Three Essays in Environmental Economics

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Three Essays on Individual Responses to Weather and Climate

Summary

Motivated by the desire to inform climate policy, this dissertation consists of a compilation of three essays devoted to unravelling the significance of weather and climate as drivers of social welfare in two different contexts: the impact of weather fluctuations on labour markets and the importance of heterogeneity in determining individuals' preferences for climate. Chapter 2 investigates the existence of weather-related changes in earnings and working times in the Mexican labour market. Leveraging quasi-random day-to-day variation in an individual's exposure to weather, I provide evidence of extreme-rainfall days causing economy-wide meaningful reductions in working times. However, I observe no average heat effects on either earnings or working times, but only a small cold-related drop in minutes worked. Further analysis reveals considerable heterogeneity in temperature and precipitation effects across industries as well as job- and individual-specific characteristics, with non-trivial earnings losses observed for individuals working in unprotected working environments. Applying a residential choice model, Chapter 3 tests for the importance of origin climates in driving climate preferences of Mexican migrants to the United States (U.S.). I find temperature preferences to differ significantly between migrants originating from colder and warmer Mexican municipalities. Building upon the findings from Chapter 3, Chapter 4 further investigates heterogeneity in the amenity value of temperatures and individuals' willingness to pay (WTP) for mitigation of global warming. The study employs a two-stage random utility sorting model to analyse location choice decisions of Mexican migrants to the U.S. The econometric model captures both observed heterogeneity and unobserved preference heterogeneity in temperatures. Evaluation of the first stage is done following a Bayesian estimation procedure. Examining heterogeneity in individual climate valuations reveals significant differences in the marginal willingness to pay (MWTP) for preferable temperatures across both demographic and clinal characteristics.

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”Und so ist es denn nicht das Streben nach Glück, was auf der Erde uns leiten soll. Streben nach dem Unendlichen, Ausbildung seiner Seele, dies ist es, was wir ohne Hinsicht auf Lust und Ruhe unbedingt ausüben müssen.”

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To my beloved

Valerie, Adelheid,

and Marius.

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Acronyms

ACS American Community Survey *see Glossary:* American Community Survey (ACS), 107, 112, 113

CCSM3 Community Climate System Model *see Glossary:* Community Climate System Model (CCSM3), 102, 140, 145

CPI Consumer Price Index 80, 81, 87

CRU Climatic Research Unit *see Glossary:* Climatic Research Unit (CRU), 4, 83, 84, 118, 145

ENOE Encuesta Nacional de Ocupación y Empleo *see Glossary:* Encuesta Nacional de Ocupación y Empleo (ENOE), 2, 7, 8, 23, 25, 27, 28

GDP Gross Domestic Product 12

HDD Harmful-Degree Days *see Glossary:* Harmful-Degree Days (HDD)

HI Heat Index 21, 58, 59, 175, 183

hPa Hectopascal 85, 86

IIA Independence from Irrelevant Alternatives 73, 74, 107, 110

IID Identically and Independently Distributed 5, 72, 73, 74, 107, 109, 110, 303

INEGI Instituto Nacional de Estadística, Geografía e Informática *see Glossary:* Instituto Nacional de Estadística, Geografía e Informática (INEGI), xviii, 23

IPCC Intergovernmental Panel on Climate Change *see Glossary:* Intergovernmental Panel on Climate Change (IPCC), 1

IPUMS Integrated Public Use Microdata Series *see Glossary:* Integrated Public Use Microdata Series (IPUMS), 70, 71, 112

IV Instrumental Variable 5, 101, 113, 121, 123, 141, 149

MMP Mexican Migration Project *see Glossary:* Mexican Migration Project (MMP), 4, 68, 77, 87, 91, 112, 114, 120

MSA Metropolitan Statistical Area 4, 5, 6, 66, 67, 68, 69, 73, 75, 76, 77, 78, 80, 81, 82, 84, 87, 88, 89, 99, 101, 105, 106, 107, 110, 111, 112, 113, 114, 115, 118, 120, 121, 123, 136, 141, 149, 313

MWTP Marginal Willingness to Pay iii, 5, 99, 101, 102, 104, 106, 128, 133, 134, 135, 136, 137, 138, 139, 150, 345, 346, 347

NARR North American Regional Reanalysis *see Glossary:* North American Regional Reanalysis (NARR), 2, 7, 8, 25, 26, 145

NCEP National Centers for Environmental Prediction *see Glossary:* National Centers for Environmental Prediction (NCEP), 26

NOAA National Oceanic Atmospheric Administration *see Glossary:* National Oceanic Atmospheric Administration (NOAA)

OLS Ordinary Least Squares 5, 101, 113, 114, 121, 123, 133

sd Standard Deviation 27, 84, 85, 116

SRES Special Report on Emission Scenarios *see Glossary:* Special Report on Emission Scenarios (SRES), 140

TFP Total Factor Productivity 11

U.S. United States iii, xi, 4, 9, 11, 12, 28, 62, 66, 67, 68, 69, 70, 71, 72, 73, 74, 76, 77, 78, 79, 80, 81, 82, 84, 85, 86, 87, 88, 89, 97, 99, 100, 102, 103, 104, 105, 110, 114, 116, 117, 135, 136, 141, 146, 148, 149, 151, 183

UNDP United Nations Development Programme 2, 10

WBGT Wet Bulb Globe Temperature 21, 58, 59, 175, 177, 200

WTP Willingness to Pay iii, 4, 5, 6, 66, 67, 68, 92, 98, 99, 100, 101, 102, 105, 107, 109, 115, 123, 126, 135, 137, 140, 142, 148, 149, 150, 151

Glossary

American Community Survey (ACS) Ongoing annual U.S. household survey, run by the U.S. Census Bureau. The survey has been conducted since 2000. 107

Climatic Research Unit (CRU) Research institute established in the School of Environmental Sciences at the University of East Anglia in Norwich in 1972. The CRU is widely recognised as one of the world's leading institutions concerned with the study of natural and anthropogenic climate change. 4

clinal The term *clinal* goes back to Sir Julian Huxley, a British evolutionary biologist (Huxley 1938). The human-biology literature uses the term *clinal* to refer to a gradual change in a character or feature across the distributional range of a species or population, usually correlated with an environmental transition such as humidity, rainfall, and temperature. For example, it has been observed that pigmentation changes with distance from the equator, due to different levels of UV radiation. In this thesis, the term *clinal-preference heterogeneity* is used to indicate systematic differences in the valuation of climate over geographical variation in migrants' origin climates. 3, 4, 5, 6, 66, 67, 68, 70, 71, 74, 83, 87, 88, 89, 90, 91, 92, 97, 98, 99, 100, 101, 105, 128, 136, 137, 140, 141, 142, 143, 148, 149, 150, 151, 152

Community Climate System Model (CCSM3) Coupled global climate model developed by the University Corporation for Atmospheric Research with funding from the National Science Foundation, the Department of Energy, and the National Aeronautics and Space Administration. 102

Encuesta Nacional de Ocupación y Empleo (ENOE) National Survey of Employment and Occupation. A Mexican Household Survey, run by Instituto Nacional de Estadística, Geografía e Informática (INEGI). 2

Harmful-Degree Days (HDD) defined as the sum of the difference in the daily mean temperature and the threshold of 32°C on days with temperatures exceeding the threshold. *HDD* captures the excessive heat beyond healthy levels. 11

Instituto Nacional de Estadística, Geografía e Informática (INEGI) The Mexican Statistics Agency. xviii, 23

Integrated Public Use Microdata Series (IPUMS) The world's largest individual-level population database, IPUMS includes all persons enumerated in the United States Censuses from 1790 to 2010 and from the ACS since 2000 and the Current Population Survey since 1962. IPUMS is housed at the Institute for Social Research and Data Innovation, an interdisciplinary research centre at the University of Minnesota. 70

Intergovernmental Panel on Climate Change (IPCC) Intergovernmental body of the United Nations, dedicated to providing the world with an objective, scientific view of climate change, its natural, political and economic impacts and risks, and possible response options. The IPCC was established in 1988 by the World Meteorological Organization and the United Nations Environment Programme, and later endorsed by the United Nations General Assembly. 1

Mexican Migration Project (MMP) Migration survey conducted in collaboration between Princeton University and the University of Guadalajara since 1982. 4

National Centers for Environmental Prediction (NCEP) Arm of the National Oceanic Atmospheric Administration's National Weather Service. The centre is comprised of nine distinct research centres and the Office of the Director. The National Centers for Environmental Prediction provides a wide variety of national and international weather guidance products. 26

North American Regional Reanalysis (NARR) Reanalysis dataset run over the North American Region originally produced by NOAA's NCEP. The NARR model uses the very high resolution NCEP Eta Model (32km/45 layer) together with the Regional Data Assimilation System. 2

Special Report on Emission Scenarios (SRES) Report by the IPCC published first in 2000 describing different greenhouse gas emissions scenarios used to make projections of possible future climate change. 140

Chapter 1

Introduction

The year 2019 has seen a global uprising of youth demonstrating for a greater effort by politicians to combat global warming. The Fridays-for-Future movement comes after years of stagnation in the international effort to develop effective global policies to prevent average temperatures from rising above a threshold of 2°C higher than pre-industrial levels. Climate change remains a prominent issue in global politics. Uncertainty around the social cost of carbon has led to significant disagreement among political leaders with respect to committing to climate-change mitigation. However, that uncertainty does not preclude consensus about the existence of climate change.

In fact, the scientific literature provides persuasive evidence that global warming has reached between 0.8 to 1.2°C above pre-industrial temperature levels. The Intergovernmental Panel on Climate Change (IPCC) projects that with unchanged trends in global warming, average temperatures will reach 1.5°C above pre-industrial levels between 2030 and 2052 (Intergovernmental Panel on Climate Change 2013, hereafter IPCC). Alongside rises in average temperatures, scientists further project warming of extreme temperatures and likely increases in the frequency and intensity of extreme precipitation events and droughts in certain regions of the globe.

While the scientific literature at large acknowledges the importance of climate as a determinant of economic and social well-being, measuring the damage of climate change remains an intractable problem in the climate-policy debate. In this regard, developing a better understanding of current impacts of climate and weather has the potential to discipline damage estimates and contribute to evidence-based policy responses to climate change (Dell et al. 2014; Deschênes and Greenstone 2007). Motivated by the desire to inform climate policy, this dissertation consists of a compilation of three essays devoted to unravelling the significance of weather and climate as drivers of individuals' welfare in two different contexts: the impact of weather fluctuations on labour markets and the importance of heterogeneity in determining individuals' preferences with respect to climate.

A recent strand of research documents a causal relationship between local labour-market outcomes and short-term weather fluctuations. A report by the United Nations Development Programme (UNDP) identifies Central America as an area highly exposed to weather-related labour-market effects (Kjellstrom et al. 2016). However, research on the region is limited largely to impacts on the agricultural labour market. Chapter 2 seeks to fill the gap in the literature by investigating the existence of weather-related changes in earnings and working time in the Mexican labour market over the period 2000 to 2016. The analysis draws upon comprehensive data from the Mexican labour-force survey Encuesta Nacional de Ocupación y Empleo (ENOE) (Instituto Nacional de Estadística y Geografía 2011, hereafter INEGI) combined with fine-scaled temperature and precipitation data from the North American Regional Reanalysis (NARR) model (National Centers for Environmental Prediction 2017, hereafter NCEP).

I employ a high-dimensional fixed-effects regression model controlling for time-, industry- and municipality-specific confounding factors. Leveraging quasi-random day-to-day variation in an individual's exposure to weather (within sector, municipality, and season), I provide evidence of extreme-rainfall days causing economy-wide meaningful reductions in working times. While the results presented in Chapter 2 indicate no average heat effects on either earnings or working times, but only a small cold-related drop in minutes worked, further analysis reveals considerable heterogeneity in temperature and precipitation effects.

Particularly workers employed in labour-intensive and service-oriented industries experience weather-related earnings and working-time fluctuations. Concerning precipitation, I estimate reductions of up to 70 minutes in response to heavy rainfall in weather-exposed sectors (e.g. Agriculture and Construction) and labour-intensive manual industries (e.g. Manufacturing and Trade). Moreover, I observe nontrivial earnings losses for individuals working in unprotected working environments. The design of relevant climate-change mitigation policies should carefully consider the latter regressive dimension of weather-related labour-market fluctuations.

A final contribution of the chapter is the provision of a rough cost estimate of predicted annual labour-market changes based on a counterfactual analysis. The hope is that providing a rough measure of associated welfare implications ultimately helps to inform decisions on designing protective labour-market policies targeted at those most vulnerable to weather-related earnings losses.

A second strand of literature within environmental economics aims to measure the amenity value of climate. Despite the suggestive evidence on the significance of climate in shaping an individual's life, very little is known about the value that people attach to living in a comfortable climate. In light of rising climate-change awareness, the topic recently saw a resurgence as monetary measures of individuals' valuation of climate today provide numerical estimates of the potential benefits of limiting global warming. Compared with the costs of greenhouse-gas abatement, the latter estimates allow for cost-benefit comparisons of alternative climate-change abatement policies and, thus, help inform the climate-change policy debate.

A potentially serious drawback of most of the earlier work on the topic is the assumption of preference homogeneity among individuals from different climatic regions. The human-biology literature provides ample evidence of systematic differences in human thermal comfort and sensitivity across climatic zones.[1] Economic research on the amenity value of climate largely ignores these findings.[2] Chapter 3 aims to provide new insights into the importance of accounting for clinal[3] heterogeneity in climate preferences. For this purpose, I estimate a residential location choice model of bilateral migration movements

1. See James (2010) for an overview of research on climate-related morphological variation and physiological adaptations of humans.

2. During a comprehensive review of the literature using the relevant research databases and library catalogues as well as back and forward tracing of related journal articles, only two studies by Scott et al. (2005) and Fan et al. (2012) were found to allow for heterogeneous differences in climate preferences by origin region. See Chapter 3 for more detail.

3. The term *clinal* goes back to Sir Julian Huxley, a British evolutionary biologist (Huxley 1938). The human-biology literature uses the term *clinal* to refer to a gradual change in a character or feature across the distributional range of a species or population, usually correlated with an environmental transition such as humidity, rainfall, and temperature. For example, it has been observed that pigmentation changes with distance from the equator, due to different levels of UV radiation. In this thesis, the term *clinal-preference heterogeneity* is used to indicate systematic differences in the valuation of climate over geographical variation in migrants' origin climates, i.e. the climate to which an individual is accustomed.

between Mexico and the United States (U.S.) over the period 1970 to 2016, allowing for clinal variation in the weight given to climate amenities in the decision.

I draw upon a unique dataset with detailed geographical information on both origin and destination locations of migrants, which I combine with Metropolitan Statistical Area (MSA)-specific social and economic data and information on the local climate. Information on migration movements, including coordinates of the origin and the destination, is taken from the Mexican Migration Project (MMP) (The Princeton University and the University of Guadalajara 2017, hereafter MMP) and combined with data from the U.S. census and other official data sources. Climate data is retrieved from the CRU TS4.01 dataset produced by the Climatic Research Unit (CRU) at the University of East Anglia (University of East Anglia Climatic Research Unit, Harris, Ian C. and Jones, Philip D. 2017, hereafter CRU). The empirical estimation method builds upon McFadden's Residential Location Choice Model (McFadden 1974), which I modify by including a vector of the ratio between origin and destination climate allowing identification of clinal preference heterogeneity directly through measurable spatial variation in origin climate.

Results from the study emphasise the importance of accounting for heterogeneity in climate preferences. The findings reveal a general preference among migrants for settling in locations with warmer summer and winter temperatures relative to their origin climate. Employing a split-sample analysis shows that the utility of migrants from warmer origins is five times more responsive to both average and extreme temperatures, while preferences regarding precipitation are similar between the two samples. Consequently, to assume preference homogeneity across different climatic regions may result in biased estimates of the amenity value of temperatures. This finding is relevant for measuring the social cost of carbon, where local amenity estimates have been used to generalise the benefits of climate-change mitigation for the rest of the world.

Chapter 4 builds upon the findings of the previous chapter by investigating the importance of preference heterogeneity in driving individuals' temperature valuations and their willingness to pay (WTP) for mitigation of global warming. Benefitting from recent advancements in estimation procedures, I apply a two-stage random utility sorting model to analyse location-choice decisions. The analysis exploits the same migration survey as appears in Chapter 3, but with the sample limited to migration taking place between 2000 and 2012, due to lack of individual-level wage data for the previous years.

The first stage consists of a mixed logit model of the discrete location choice, which overcomes the restrictive identically and independently distributed (IID) error structure assumed in Chapter 3. Evaluation of the mixed logit model follows a Bayesian estimation procedure, given the computational advantages of the Bayesian approach over the classical frequentist method (Train 2001). The model captures both observed heterogeneity related to clinal and demographic characteristics of the migrant and unobserved individual heterogeneity in temperature preferences. It further controls for individual earnings, the cost of migration, the prevalence of migrant networks, and destination- and time-specific confounding factors. Similarly to Chapter 3, clinal preference heterogeneity is identified by exploiting the spatial gradient in migrants' origin temperatures, however, with the difference that in Chapter 4 temperature tastes are allowed to vary randomly across individuals.

In the second stage, estimated MSA fixed effects from the first stage are regressed on local amenities, including climate. Location-specific constants represent the composite part of utility attributed to local amenities in the location choice. I address the potential issue of endogeneity in the second-stage regression by, on the one hand, including a large set of location-specific amenities aside from climate in the regression and, on the other hand, by exploiting an instrumental variable (IV) estimation method developed by Bayer and Timmins (2007). Results from the specification tests indicate a bias in Ordinary Least Squares (OLS) estimates. As a last step, coefficients from the first and second stage are converted into WTP estimates for local amenities to provide a monetary measure for observed differences in climate valuations.

Examining heterogeneity in individual climate valuations, I observe significant differences in the marginal willingness to pay (MWTP) for friendlier summer temperatures across both the life cycle and differences in origin temperatures. I find migrants from warmer Mexican regions to be willing to pay for living in cities with lower summer and winter temperatures, while migrants from colder Mexican regions are willing to forgo earnings to experience warmer winters. These results suggest that greater awareness among individuals of the negative impacts of higher seasonal temperatures causes migrants to prefer locations with colder temperatures. By contrast, lack of exposure to warmer temperatures prior to the migration makes individuals choose MSAs with warmer winters.

I supplement these results by providing estimates of the WTP for projected future changes in mean summer and winter temperatures for the period 2040 to 2069. Increases in summer temperatures are estimated to result on average in a welfare reduction of between US$423 and $596 per person. At the same time, warmer winter temperatures increase people's welfare by between $660 and $1,246. Importantly, studying heterogeneity in the WTP for warming of winter temperatures, I find predicted welfare gains of migrants from colder regions to exceed predicted gains of individuals from warmer regions. Overall, the findings lend support to the hypothesis that clinal preference heterogeneity is an important driver of individuals' temperature valuations. Insofar as the WTP for the abatement of global warming is largest among individuals aware of the negative impacts of heat, measurements derived from populations with access to air conditioning and relatively moderate temperatures will underestimate the WTP for climate-change mitigation.

Finally, Chapter 5 provides a summary of the conclusions from the preceding empirical chapters. Moreover, I reflect on the limitations of each study and discuss an agenda for the potential of future research in light of the findings of this thesis.

Chapter 2

Labour-Market Responses to Weather Fluctuations:

Evidence from Mexico

Abstract

This chapter examines Mexican labour-market responses to temperature and precipitation fluctuations to gain insight into the potential labour-productivity consequences of climate change. I apply a higher-dimensional fixed-effect model to identify weather-driven changes in earnings and working time, exploiting the plausibly exogenous within sector, municipality and season day-to-day variation in an individual's exposure to temperatures and precipitation. Using data from the Mexican labour force survey ENOE (INEGI 2011) combined with fine-scaled climate data from the NARR model (NCEP 2017), I find that average working-time responses are limited to cold days and days with heavy rainfall. Temperatures below 10°C reduce working times of Mexicans by just three minutes, while extreme rainfall causes working days to shorten by 30 minutes ($> 30\,\mathrm{mm}$). Focusing on heterogeneity in the weather effects, I estimate heat- and extreme-rainfall effects of up to 70 minutes for industries exposed to the weather and workers in unprotected employment situations; this type of workers are further vulnerable to weather-induced earnings fluctuations. Providing a rough impact assessment, I conduct a counterfactual analysis to estimate annual weather-related losses due to weather conditions deviating from the optimal level. On average, extreme heat and heavy precipitation reduce potential earnings by 0.20% and 0.05%, respectively. The calculated total loss in annual working times due to cold days amounts to 0.02% and 0.12% for extreme rainfall. Assuming no future adaptation and mitigation of labour markets to climate change, an increase in average temperatures by 2°C is projected to result in an additional heat-related earnings loss of 0.02% for Mexico, with losses concentrated in the least protected segments of the Mexican labour force.

2.1 Introduction

Growing climate-change awareness has given rise to an emerging body of literature on the impact of weather on economies. Several studies identify a causal link between adverse weather and aggregate economic slowdowns in developing countries.[1,2] These findings gave rise to an emerging body of literature aimed at isolating the underlying mechanisms of weather-driven aggregate productivity changes. Early studies of the field focus primarily on uncovering the relationship between agricultural yield and the phenomena of extreme temperatures and precipitation shocks. Empirical evidence confirms economically meaningful agricultural productivity losses in response to sustained heat and lack of rainfall (see Burke and Emerick 2016; Deschênes and Greenstone 2007; Feng et al. 2010; Mendelsohn et al. 1994; Schlenker and Roberts 2009; Solomou and Wu 1999). However, volatility of crop growth cannot explain temperature-driven productivity losses in manufacturing observed for both developing and developed countries. For example, a study by Hsiang (2010) covering the Caribbean identifies a causal relationship between increasing temperatures and non-agricultural production losses (−2.4% per 1°C) that considerably exceed those experienced by the agricultural industry (−0.1% per 1°C).

This chapter examines the direct impact of short-term weather fluctuations on labour markets as one channel of weather-driven productivity changes. Leveraging quasi-random day-to-day weather fluctuations in a fixed-effects model, I examine the impact of precipitation and temperature changes on weekly working times and earnings in Mexico for the period 2005 to 2016.[3] The analysis draws upon comprehensive individual-level information from the Mexican labour-force survey ENOE (INEGI 2011) combined with fine-scaled climate data from the NARR model (NCEP 2017). Exploiting detailed information on municipal-, individual- and job-specific characteristics, this chapter sheds new light on the heterogeneity of weather-induced labour-market changes.

The identification strategy employed in this chapter follows closely to the influential work by Graff Zivin and Neidell (2014).[4] I apply a higher-dimensional fixed-effect estima-

1. Using an international panel dataset covering 125 countries, Dell et al. (2012) find higher annual average temperatures to cause reductions in both agricultural and non-agricultural output growth in developing countries, with some suggestive evidence of a permanent effect. Focusing on rainfall impacts, Barrios et al. (2010) identify reductions in annual precipitation levels to be a critical determinant of the poor economic performance of African countries during the second half of the 20th century.

2. Dell et al. (2014), Carleton and Hsiang (2016) and Cavallo and Noy (2009) provide comprehensive reviews of the current body of literature.

3. In this chapter, *earnings* refers to any income generated within the working week; this could include tips or bonuses paid within the reference week. Income earned over longer periods, such as salaries, is rescaled to the week level.

4. Using data from the American Time Use Survey, Graff Zivin and Neidell (2014) exploit spatial variation in temperatures and precipitation to examine daily temperature impacts on individual time-allocation choices. The authors find heat-related reductions in working times for weather-exposed industries of over one hour on days with temperatures above 37.8°C (100°F).

tion strategy which allows causal identification of weather-driven changes in earnings and working time by exploiting the plausibly exogenous within sector, municipality and season day-to-day variation in an individual's exposure to temperatures and precipitation. To isolate weather impacts, I control for various worker and job characteristics, seasonality by industry, year and month, as well as municipality-specific confounding factors. In line with Graff Zivin and Neidell (2014), I avoid specifying the functional form of weather variables by assuming a nonparametric structure of the weather variables in the form of weather bins. To further isolate potential channels of weather effects—that is, direct weather exposure, high ambient temperatures, or possible demand-side changes—I explore heterogeneity in predicted weather effects by industry and work location as well as individual and employment characteristics.

The analysis reveals three sets of results. First, I find no evidence of average heat effects on within-municipality earnings or working times, but only a small cold-related drop in minutes worked, caused by days with temperatures below 10°C. The lack of heat-effects is surprising, given contradictory evidence of significant labour-supply reductions for the U.S. (Graff Zivin and Neidell 2014) and Australia (Kjellstrom et al. 2009). Second, the results indicate strong economy-wide working-time responses to heavy-rainfall days. Extreme-precipitation days (> 30 mm) reduce working times by around 30 minutes.

Second, further analysis reveals considerable heterogeneity in temperature and precipitation effects across industries and job- and individual-specific characteristics. Particularly workers employed in labour-intensive and service-oriented industries experience weather-related earnings and working-time fluctuations. Similar to Connolly (2008), the results suggest a strong link between rainfall and working times in weather-exposed (Agriculture and Construction) and manual labour-intensive industries (Manufacturing). An important revelation of this study is the nontrivial earnings losses observed for individuals working in unprotected employments. Particularly informal workers, those with temporary employment contracts and flexible earnings, are affected by adverse weather.

The results, while suggestive, highlight the distributional dimension of extreme temperatures and rainfall impacts on labour markets, which should be taken into consideration for the design of climate-change mitigation and adaptation policies. Although estimates of short-term weather impacts should not be generalised to make an inference with regard to climate change, they nevertheless highlight current policy shortcomings leaving the least protected workers most vulnerable to adverse weather. Thus, labour-market policies aimed at mitigating the adverse impacts of climate change can learn from today's estimates to protect workers now and in the future.

Lastly, the chapter provides a rough cost estimate to establish the magnitude and the welfare implications of weather fluctuations. A better understanding of the total welfare loss attributable to weather fluctuations is essential for providing sound policy advice on mitigating adverse labour-market effects. Back-of-the envelope calculations estimate annual heat-related earnings losses to amount to around 0.2%, while working times are reduced by roughly 0.02%. Cold days (<14°C) account for a reduction of around 0.04%, which, however, is offset by longer working time on warmer days. Again, the heterogeneous estimates highlight distributional implications of weather impacts on labour markets. For instance, workers with incomes below the official minimum wage are estimated to earn 20% less per year due to temperature impacts. Similarly, extreme-rainfall days reduce potential earnings for these workers by roughly 50%.

Projecting a future two-degree temperature (°C) increase over the previous estimates, I predict heat-related earnings losses (>30°C) to rise by about 0.02% (assuming zero adaptation and unchanged labour market characteristics). The reduced frequency of cold days under a two-degree scenario results in an overall small positive effect on total annual working hours. However, the projections emphasise the disproportionate burden of climate change on the least protected workers. For those with earnings falling below the official minimum wage rate, I predict a two-degree temperature (°C) rise to cause an additional income loss of around 10% due to temperatures above 22°C, causing a total loss of 43% of potential annual earnings.

This chapter contributes to a growing body of literature examining the direct impact of short-term weather fluctuations on labour markets—effects on labour supply and demand, labour and firm-level productivity and earnings.[5] To the best of my knowledge, this is the first study to explore weather impacts on non-agricultural earnings and working times for a Latin American country.[6] A report published by the UNDP on the impacts of heat

5. See Heal and Park (2016) for a reflection on the current state of the literature.

6. A literature review was conducted using the relevant research databases and library catalogues as well as back and forward tracing of related journal articles to identify relevant articles examining the relationship between weather and labour markets.

and climate change on the workplace identifies Central America as an area highly exposed to weather-related labour-market effects (Kjellstrom et al. 2016). Despite the growing interest in the field, empirical studies are mainly focussed on the U.S. and Asia.[7]

Empirical evidence on the role of weather fluctuations in shaping Latin American labour markets is limited to the rural labour market.[8] While the agricultural sector is arguably affected by weather fluctuations, adverse impacts of rainfall and temperature will likely extend beyond rural labour markets, affecting both urban[9] and non-agricultural labour markets. In Mexico only about 10% of the labour force is employed in the agricultural sector, compared to 20% in trade, 15% in manufacturing and 12% in nonfinancial services. Recent studies focussing on the manufacturing sector document economically meaningful heat-related short-run labour and firm-level productivity losses, reductions in earnings and labour supply responses (Adhvaryu et al. 2018; Cachon et al. 2012; Cai et al. 2018; Chen and Yang 2019; Park and Behrer 2016; Sudarshan et al. 2015; Zhang et al. 2018).[10] Therefore, disregarding consequences outside the agrarian sector might substantially underestimate weather-related costs to labour markets. Hence, this chapter sheds new light on impacts for this understudied part of the world, examining both urban and rural labour markets and covering a wide spectrum of industries and occupations.

This study, further, provides new evidence on individual-level heterogeneity in labour-market responses to weather. Sensitivity of earnings and working times to weather fluctuations likely varies by individual and job-specific characteristics. For instance, previous country- and region-level studies document a negative relationship between extreme

7. An exception is a recent interdisciplinary study of weather-effects on outdoor work in the European Union by Orlov et al. (2019).

8. Jessoe et al. (2018) identify a negative causal relationship between Harmful-Degree Days (HDD) during the growing season and rural employment in Mexico, with the strongest impact estimated for older and off-farm workers.

9. Urban heat island effects, caused by heat absorption in road tar-seal or concrete surfaces (Oke 1973), can have severe implications for working conditions in cities becoming increasingly problematic with global warming (IPCC 2013).

10. Using firm-level data from Chinese manufacturing plants, Chen and Yang (2019) and Zhang et al. (2018) document an inverted-U shape relationship between temperatures and firm-level total factor productivity (TFP) and output, with evidence of a significant heterogeneity in the effects across industry and season (Chen and Yang 2019). Studying administrative employment data from China, Cai et al. (2018) find heat-related labour-productivity losses with no evidence of work-time adjustments. Cachon et al. (2012) document weather-related plant-level production losses for the U.S. automobile sector. Studying production line data for the Indian garment sector, Adhvaryu et al. (2018) observe a negative, non-linear temperature effect on production-line efficiency, highlighting the productivity and energy-saving benefits associated with the introduction of heat-saving technology (LED). A second study identifies negative impacts of heat on worker productivity and absenteeism in Indian diamond cutting factories (Sudarshan et al. 2015).

weather and income as well as Gross Domestic Product (GDP) per capita (Barrios et al. 2010; Dell et al. 2012). Studies examining individual-level impacts on earnings outside the agricultural sector are rare, with empirical research relying primarily on average district wages.[11] However, regional studies may mask heterogeneity in the response of earnings at a lower geographical level.

In this regard, this chapter explores the link between job and employment characteristics and the sensitivity of individual earnings to weather fluctuations. For example, I investigate the role of payment flexibility in weather-related earnings fluctuations. If pay is not tightly linked to workers' performance, one would expect earnings of employees with long-term fixed-wage contracts to be unaffected by day-to-day weather changes. A further question touched upon in this context is the distributional implications of weather impacts on labour markets. Households in less developed regions are particularly vulnerable to detrimental weather effects, due to their primary employment in weather-exposed industries and their limited access to adaptation and mitigation mechanisms available to less deprived households (e.g. air conditioning and heating) (IPCC 2013). Studying differences among workers within an industry can shed important light on the distributional consequences of weather-driven earnings fluctuations.[12]

The rest of the chapter is organised as follows: Section 2.2 summarises the relationship between both temperatures and rainfall and labour market outcomes. In Section 2.3, I describe a theoretical model explaining weather impacts on labour supply decisions and optimal wage setting. Section 2.4 briefly discusses the empirical strategy, followed by a description of the different datasets employed in the regression analysis. The empirical results are presented in Section 2.6, including counterfactual cost estimates, followed by a discussion of various robustness checks. The chapter closes with a summary of the key findings, any caveats of the study and a brief note on the implications for policy and research.

11. Colmer (2020) finds a direct negative impact of temperature increases on Indian district agricultural and manufacturing wages, with the effect size varying by the rigidity of the local labour market. County-level annual payroll data for the U.S. suggest that heat exposure significantly reduces payroll per capita in weather-exposed industries (Park and Behrer 2016). In contrast, a study by Burgess et al. (2014) on Indian mortality find no evidence of urban wage responses to adverse weather. Using Brazilian household data, Mueller and Osgood (2009) find long-term drought effects on wages to be limited to the rural sample.

12. See Park et al. (2018) for a discussion of the distributional welfare implications of heat exposure.

2.2 Background: Weather Fluctuations and Labour Market Performance

Prolonged heat exposure has been identified as an occupational health problem for a considerable time (Kjellstrom et al. 2009). The epidemiological literature provides substantial scientific evidence of a causal relationship between heat exposure and reduced physical work capacity (Kerslake 1972), diminished mental task performance (Ramsey 1995), adverse health effects, such as heat stress and heat strokes (Bouchama and Knochel 2002) and increased mortality (Centers for Disease Control and Prevention, USA 2008). Natural human response mechanisms, such as thermoregulatory control mechanisms that include sweating, shivering and vasoactivity, prevent the body from severe damage caused by heat exposure (e.g. brain and heart failure). Higher external temperatures diminish the ability to transfer body heat to the external environment, thereby increasing the risk of heat exhaustion and heat stroke. To prevent such life-threatening outcomes, the body reacts by reducing physical activity, including brain activity, resulting in diminished mental ability. Work involving heavy physical exertions is particularly prone to heat impacts, as physically active workers experience less effective thermoregulation and faster onset of fatigue.

Similar processes apply to the exposure to harmful cold temperatures. Exposure to cold temperatures during working hours results in vasoconstriction and drops in tissue temperatures, causing numbness in the extremities, reduced dexterity in hands and loss in strength (Parsons 2014). Controlled experiments and empirical studies stress the negative relationship between adverse temperatures and labour productivity (Niemelä et al. 2002; Piil et al. 2019), cognitive performance (Graff Zivin et al. 2018), mental task ability (Seppänen et al. 2006; Wargocki and Wyon 2007) and the risk of workplace accidents (Binazzi et al. 2019).

Besides temperatures, one further expects rainfall to impede labour markets. Heavy showers may endanger external work, render weather-exposed activities more physically intense, cause environmental degradation, interrupt supply chains by delaying transportation and destroying infrastructure, disrupt the daily commute or cause closure of schools, which forces parents to remain at home with their miners. Higher levels of precipitation also likely reduce the attractiveness of outdoor recreational activities, thus incentivising the substitution of indoor work for leisure (Connolly 2008). Using data from the American Time Use Survey, Connolly (2008) assesses work-leisure substitution effects attributed to daily rainfall fluctuations. She finds working hours to increase by an additional 30 min per day on rainy days, with a corresponding earnings increase. However, for weather-exposed industries, Connolly (2008) estimates a reversed relationship, with working times falling by more than one hour on rainy days.

Understanding the responsiveness of Mexican labour markets to weather fluctuations can shed new light on the current costs of adverse temperatures and precipitation in a different climatic and cultural context. Moreover, the rich data exploited in this study allow investigating the multiple channels through which day-to-day changes in weather influence earnings and working times.

2.3 Conceptual Framework

To motivate the empirical strategy, this section describes a simple formal model illustrating the impact of weather on both labour supply and demand. The discussion closely follows the model developed by Hanna and Oliva (2011) on the impact of polution on labour markets. I start by describing a worker's optimal choice of working time under the influence of an environmental condition. The environmental variable in the model is defined as the realisation of weather during the working week. Considering the above biological and non-biological mechanisms through which weather can affect labour markets, it is reasonable to assume that most adverse effects of temperature and rainfall will be concentrated at the extremes of the distribution. Hence, for simplification, I focus on adverse-weather days in the discussion of model predictions. The simple model developed in the section allows me to predict how workers' labour-supply decisions are affected by the weather.

2.3.1 Labour Supply and Adverse Weather

Consider a partial equilibrium framework where individuals maximise their utility with respect to consumption, c, and hours worked, h. Utility is given by $u(c, h; \alpha)$ and is separable in c and h. I further assume that utility is increasing in consumption and decreasing in hours worked, so $u_c > 0$ and $u_h < 0$. Moreover, the utility function is assumed to be concave and, thus, $u_{cc} < 0$ and $u_{hh} < 0$.

The random variable α represents the realisation of weather during the working week, which affects the marginal utility of both consumption and hours worked. The relationship between the environmental condition and working time as well as consumption is ambiguous.

The individual faces the following optimisation problem:

$$\max_{h,c} u(c, h; \alpha) \quad \text{s.t.} \quad mc = wh + y^* \,, \tag{2.1}$$

where w is the hourly wage rate and m the price of consumption. Individuals are assumed to be wage takers. At this point, wages are defined exogenously and, hence, are unaffected by the environmental variable. I will discuss the implications of relaxing the assumption in Section 2.3.2.

The maximisation problem can be rewritten using the indirect utility function:

$$\max_{h} v(h) = \lambda(\alpha) \cdot wh - g(h; \alpha) \tag{2.2}$$

The first term, $\lambda(\alpha)$, represents the optimal path of the marginal utility of income. It captures changes in an individual's income in response to an individual's re-optimisation decision of working time and consumption. The function $g(h; \alpha)$ captures the disutility of hours worked for a given level of α:

$$g(h; \alpha) = -\int_0^h u_h(x; \alpha) dx \,. \tag{2.3}$$

Solving the maximisation problem in (2.2) yields the following first-order condition:

$$\lambda(\alpha) w = g_h(h; \alpha) \tag{2.4}$$

The relationship between the optimal level of working time and the environmental variable can be inferred by the derivative of (2.4) with respect to α. Rearranging the resulting expression to solve for $dh/d\alpha$ I obtain the following:

$$\frac{dh}{d\alpha} = \frac{-g_{h\alpha} + \frac{\partial \lambda}{\partial \alpha} w}{g_{hh}} \tag{2.5}$$

From the assumptions about the concavity of the utility function, it follows that g_{hh} is positive. Therefore, the sign of the change in hours worked in response to worsening weather depends on the two terms in the nominator. The first term captures an individual's "substitution" between leisure and work as the environmental variable changes. The nature of the impact of α on the marginal disutility of work likely depends on a combination of the extent of weather exposure during the working day and the physical intensity of the job. Following Graff Zivin and Neidell's (2014) approach, I distinguish between two types of workers according to the extent of weather exposure: those who are sheltered from negative impacts of weather during the working day ('low risk') and those that are not ('high risk'). This category also includes physical-intensive work in insufficiently ventilated facilities. If the indoor climate is strongly correlated with the outdoor climate, manual labour-intensive work will be affected by outdoor weather conditions.

It is fair to assume that the disutility of work for high-risk labourers increases as the weather conditions deteriorate. Working conditions for this type of workers are optimal for midrange temperatures and low levels of precipitation. Therefore, $g_{h\alpha}$ is convex. In contrast, low-risk workers work primarily indoors. As such, they are not directly affected by the weather and, thus, might respond to adverse weather conditions by substituting indoor work for outdoor recreational activities. Hence, for low-risk workers, $g_{h\alpha}$ is concave with positive values for adverse-weather days. Consequently, I expect the substitution effect of adverse weather to work in the opposite direction for the two risk groups.

The second term in the numerator of (2.5) captures the "income effect". The direction of the term depends on a combination of several underlying factors.[13] First, income grows with the number of hours worked, enabling a higher level of consumption. However, as the number of hours worked increase, so does the disutility of work relative to the marginal utility of consumption, thereby reducing an individual's willingness to work additional hours. Consequently, changes in the income level imply a re-optimisation of both working

13. See Appendix A.1 for the mathematical derivation of $\partial\lambda/\partial\alpha$.

time and consumption, affecting both the disutility of work[14] and the utility of additional consumption.

Second, the re-optimisation of consumption in response to adverse weather results in a change in the marginal utility of income ($\lambda(\alpha)$). The direction of the change depends on whether consumption is a substitute or complement for adverse weather. I expect consumption, on average, to fall on days with bad weather, since consumption in such weather conditions is less attractive.[15] Hence, I expect $u_{c\alpha}$ to be concave with a single peak at comfortable temperatures and precipitation.

Assuming adverse weather is a substitute for consumption, the direction of the income effect ($\partial\lambda/\partial\alpha w$) of adverse weather for high-risk workers is ambiguous due to two opposing effects: an increase in the disutility of work and a reduction in the marginal utility of consumption. If the effect of adverse weather on consumption exceeds the effect on the disutility of work, the income effect will be positive and vice versa. In contrast, I expect the income effect to be negative for low-risk workers as both the disutility of work and the utility of consumption decreases with adverse weather.

In sum, the partial equilibrium model predicts adverse-weather days to decrease working times of high-risk workers except if adverse weather is a strong substitute for consumption and the positive income effect dominates. Similarly, as long as the positive substitution effect dominates the negative income effect, the model predicts a positive impact of adverse-weather days on labour supply of low-risk workers. Next, I will relax the assumption that wages are unaffected by adverse weather.

2.3.2 Optimal Wages Setting and Weather

In the previous section, I have assumed that wages are unaffected by weather fluctuations. In this case, changes in earnings are purely caused by adjustments in the number of hours worked. However, this assumption likely does not hold in certain contractual structures,

14. As discussed above, adverse weather will increase the disutility of work for high-risk workers ($g_{h\alpha}$ is convex), while reducing it for those employed in low-risk professions ($g_{h\alpha}$ is concave).

15. You could also argue the opposite, that the marginal utility of consumption increases on bad weather days. For example, weather-exposed workers might use bad weather days for shopping and to run other errands. However, research on the retail sector suggests that consumption on average responds negatively to adverse weather (Starr-McCluer 2000). In terms of the model, changes in the assumption would affect the sign of the income effect. However, it is fair to assume that the income effect will only dominate the substitution effect at high-income levels or if consumption responds heavily to adverse weather. Except for the case of severe natural disasters, this is unlikely to be the case.

where wages reflect workers productivity (i.e. a piece-rate contract). Under a productivity-mapped wage regime, labour-productivity losses on adverse-weather days will lead to reductions in hourly wages.

Assume a profit-maximising firm that produces output using the following production function $Q(h \cdot \phi(\alpha), K)$, where $\phi(\alpha)$ is the number of labour-efficiency units per hour worked. For simplicity, I assume the production function is homogeneous of degree one. The firm sells the product at a price p and pays an hourly wage of w. The profit-maximisation problem yields the following optimal wage rate:

$$w(\alpha) = f(h \cdot \phi(\alpha), K)\phi(\alpha)p \quad . \tag{2.6}$$

Here, $f(\cdot, K)$ is defined as the marginal productivity of labour-efficiency units for a given K. If labour productivity of weather-exposed workers falls on adverse-weather days, then ${}^{\partial}\!/\!_{\partial\alpha}\phi(\alpha) < 0$. In equilibrium, $f(h \cdot \phi(\alpha), K)$ is equal to the labour supply S_L. Therefore,

$$\frac{\partial w(\alpha)}{\partial \alpha} = S_L \frac{\partial \phi(\alpha)}{\partial \alpha} p < 0 \tag{2.7}$$

Considering the above result, the optimal labour-supply response for someone under a productivity-mapped wage regime will be sensitive to weather-related wage fluctuations. Besides the effects discussed in Section 2.3.1, labour supply for such workers will depend on a wage-substitution effect and a wage-income effect (see Appendix A.1 for a full derivation). The first is unambiguously negative. Lower wages for each additional hour worked will decrease the substitution effect on the labour supply. Thus, lower wages amplify the negative substitution effect of adverse weather on labour supply for high-risk workers and weaken the positive impact for low-risk workers.

At the same time, the marginal utility of income increases due to a lower wage for current hours worked and every additional hour spent working. Therefore, lower wages yield a positive income effect on labour supply, reducing the negative income effect for low-risk professions and increasing the positive impact for the high-risk type (assuming adverse weather is not a strong substitute).

Above, I have assumed that prices are unaffected by weather. Allowing for demand shocks in response to adverse weather changes (2.7) to:

$$\frac{\partial w(\alpha)}{\partial \alpha} = S_L \frac{\partial \phi(\alpha)}{\partial \alpha} p(\alpha) + S_L \phi(\alpha) \frac{\partial p(\alpha)}{\partial \alpha} \tag{2.8}$$

On average, I expect customer demand to fall on adverse-weather days and, thus, $\partial p(\alpha)/\partial \alpha < 0$. Allowing for customer-demand shocks in the model amplifies the negative productivity shock on wages under a flexible-wage regime.

2.4 Empirical Strategy

The identification strategy of weather impacts on local labour markets exploits the temporal and spatial variation of weather. The impact of short-term fluctuations in weather is isolated using a higher-dimensional fixed-effect identification method. I estimate the reduced-form baseline regression specified as follows:

$$Y_{it} = \alpha + \Theta W_{rt} + \Phi X_{it} + \delta_r + \gamma_s \times \eta_{yq} + \lambda_m + \epsilon_{it} \tag{2.9}$$

where Y denotes the outcome of interest, here weekly earnings (in 2010 Mexican pesos) and working time (in minutes), for individual i at time t, where t is the survey calendar reference week. W is a vector of weather bins for municipality r. The vector Θ measures the effect of weather on the outcome variable Y. The model comprises a vector X of individual characteristics, which includes age, age squared, education, marriage status and gender, as well as job-specific characteristics, such as the industry, the firm size, whether the individual works in formal employment, has a permanent or temporary contract and lives in a rural or urban area. These variables are not expected to be affected by day-to-day weather fluctuations but are likely to influence the outcome variable.

The regressions further include three sets of fixed effects: municipality δ_r, sector-specific quarter and year $\gamma_s \times \eta_{yq}$ as well as month fixed effects λ_m. Municipality fixed effects control for observable and potential unobservable confounding variables at the municipality level, such as time-invariant municipality labour-market characteristics. They further account for historical climate at location r and, thus, for adaptation to the climatic conditions at a municipal level. Year fixed effects in η_{yq} control for time-varying changes in the dependent variable, which are common across Mexico, such as time-specific cross-regional macroeconomic shocks. Quarter and month fixed effects capture seasonality in labour markets and weather.[16] Moreover, considering industry-specific business cycles, such as harvest periods in the agricultural sector, additional industry-specific seasonal and annual controls are added to the regression. Under this higher-dimensional fixed-effect strategy, time-invariant municipality-specific confounding factors and time-specific cross-regional sectoral changes will not bias the estimates.[17] Therefore, assuming weather realisations are randomly distributed over time, then Equation (2.9) yields unbiased estimates of the vector Θ (Burgess et al. 2014; Deschênes and Greenstone 2007; Guerrero Compeán 2013).

A major concern when working with weather data is the choice of the appropriate functional form of the weather variables. Past studies often apply simple measures, such as 'levels' (Dell et al. 2012; Feng et al. 2010; Hsiang and Jina 2014; Hsiang 2010; Yang and Choi 2007), anomalies (Anderson et al. 2013; Barrios et al. 2010; Fishman et al. 2019; Hidalgo et al. 2010; Theisen 2012) and degree-days definitions (Aroonruengsawat and Auffhammer 2011; Burke and Emerick 2016; Deschênes and Greenstone 2007; Graff Zivin et al. 2018; Jessoe et al. 2018). Averaging weather across the working week provides a straightforward measure of weather. However, weekly averages may mask daily fluctuations and extremes. Equally, degree-days potentially miss the complexity of the impact of weather by excluding medium-range temperatures from the assessment. Nonlinearities may be crucial in the context of human behavioural responses to weather, considering the nonlinear sensitivity of the human body to weather.[18]

Following the current standard in the literature, the issue of nonlinearity in responses is overcome by binning the temperature and precipitation data (W_{rt}). This approach avoids specifying the functional form of weather variables by assuming a nonparametric structure of the variables.[19] The weather bins are defined as the weekly sum of days

16. The robustness section tests the sensitivity of the findings to alternative fixed effects and time-trend specifications.

17. A further decision concerning the empirical specification relates to the inclusion of a lagged dependent variable. In light of the short time span of the panel structure with $t = 5$ (five quarters per individual), a lagged dependent variable approach is inadequate as it would likely suffer from Nickell bias (Nickell 1981).

18. Many recent studies highlight the importance of accounting for nonlinearities in the impact of weather. Examples are Burgess et al. (2014), Burke et al. (2015), Deschênes (2014), Kjellstrom et al. (2009), Seppänen et al. (2006) and Wargocki and Wyon (2007).

19. For alternative studies exploiting a binned weather-variable approach see Barreca et al. (2016), Burgess et al. (2014), Graff Zivin and Neidell (2014), Guerrero Compeán (2013), Guiteras (2009) and Schlenker

in which temperature and precipitation fall into the corresponding bin. The analysis is limited to daily mean temperatures and total precipitation, due to data limitations on daily maximum and minimum temperatures.[20,21]

Daily average temperatures are distributed over 16 bins, defined as follows: temperatures below 10°C and above 34°C. Temperatures between these two extremes are spread over 12 two-degree-wide bins (i.e. 10-12°C, 12-14°C, ..., 32-34°C), with the 20-22°C bin defined as the base temperature. Hence, coefficient estimates are interpreted as the impact of temperature deviations from the optimal temperature bin of 20-22°C. For rainfall, the range of daily accumulated precipitation is divided into nine bins: five two-millimetre-wide bins 0-2 mm, 2-4 mm, ..., 8-10 mm; one bin for zero-rainfall days; three bins for days with extreme rainfall of 10-20 mm, 20-30 mm and exceeding 30 mm. I expect the direction of zero-rainfall days to vary by workers' exposure. Hence, exclusion of the 2-4 mm bin from the regressions allows a straightforward interpretation of heterogeneous dry-day effects.

Due to the low frequency of extreme-weather days, higher temperatures and precipitation levels are collapsed into above 34°C and 10-20 mm, 20-30 mm and above 30 mm bins in an effort to obtain precise estimates, while allowing a meaningful interpretation of effects. There is an apparent trade-off between including bins with a low frequency of observations and collapsing the bins into greater units. Low-frequency bins result in low precision in the estimates, while excluding bins limits the prediction of nonlinearities at extreme levels of the distribution. Given the existing evidence of adverse heat effects setting in at around 30°C (Barreca et al. 2016; Deschênes and Greenstone 2011; Graff Zivin and Neidell 2014), heat-stress effects in the regressions should be identified by bins exceeding this threshold. Likewise, precipitation levels above 10 mm fall into the top 5% of the Mexican rainfall distribution and, thus, the top three precipitation bins will cap-

and Roberts (2009).

20. Ideally, one would like to use maximum as opposed to mean temperatures, considering that heat stress is associated with extreme temperatures, and given that for most jobs the highest productivity is reached during the daytime (Deschênes and Greenstone 2011; Graff Zivin and Neidell 2014; Park and Behrer 2016). The length of the study period and the wide geographical area covered in the research prohibits the use of hourly data for the construction of maximum and minimum temperature variables. In light of the lack of high-resolution homogenised weather data on daily maximum and minimum temperature for the study period, the analysis relies on mean temperatures.

21. In addition to mean temperatures, alternative temperature measures employed in the robustness section are the Heat Index (HI) and the Wet Bulb Globe Temperature (WBGT) Index as measures of apparent temperature. Both indices combine the effect of temperature and humidity. The WBGT is recommended by the International Standard Organisation as a measure of occupational heat-stress. By and large, the results are consistent across different temperatures measures, though precision in weather coefficients is greatest using an average temperatures specification.

ture 'extreme' rainfall events. Despite collapsing bins at the top end of the distribution, the final bin structure should provide enough flexibility for nonparametric estimation of weather impacts without suffering from lack of precision.

The empirical analysis further intends to isolate the potential channels of weather effects by examining heterogeneity in weather sensitivity. I estimate different model specifications which include interactions between weather bins and information on the industry, work location (office and outdoor work), employment formality and contract length, as well as differences in age, gender and education.[22]

A potential methodological issue is the problem of 'over-controlling', which in this context becomes problematic when control variables are directly or indirectly influenced by the weather (Dell et al. 2014, 743) . For example, individuals might consider average weather conditions in their job choice. An individual sensitive to heat might choose not to work in a weather-exposed occupation. Therefore, industry fixed effects will partially capture an individual's responsiveness to weather exposure. Consequently, while including other time-varying characteristics will increase the precision of the estimates, the *ceteris-paribus* assumption of the coefficient interpretation may not be valid. Hence, careful choices must be made about including further controls in the regression.[23]

One key limitation of this study is the inability to differentiate between demand- and supply-side effects in driving changes in earnings and labour supply as discussed in the theoretical model (see Section 2.3 and Appendix A.1). For instance, rainfall will reduce demand for outdoor activities or services, such as car cleaning. Moreover, labour demand for workers may fall in response to weather-related labour-productivity losses. If demand for a particular service or output is positively (negatively) affected by extreme temperatures or precipitation, this would result in an indirect positive (negative) effect of adverse weather on working times and earnings, which cannot be differentiated from a direct effect caused by weather exposure.

Research on the retail sector provides some evidence of non-permanent weather-related

22. The robustness section provides results based on alternative subsample and individual fixed-effects regressions. Yet, the low precision in estimates suggests that the more restrictive fixed-effects specifications significantly reduce the variation in the weather bins, rendering estimation problematic. See Appendix A.6 for an more in-depth discussion of the problematic.

23. To address the issue, I follow Dell et al.'s (2014, 743) advice and estimate separate models with and without control variables. On the whole, estimates are robust to the exclusion of additional controls.

changes in customer demand (Starr-McCluer 2000). However, there remains a gap in the literature regarding demand-side responses for non-retail industries. Unfortunately, firm-level records with information on customer demand behaviour is rare for Mexico and access is restricted. Therefore, I attempt to address this issue by differentiating between industries for which demand is more or less sensitive to within-season weather fluctuations.

2.5 Description of the Data

Labour-market observations

The empirical analysis draws upon labour-market data from the ENOE (Mexican Labour Force Survey) conducted by the Instituto Nacional de Estadística, Geografía e Informática (INEGI) from 2005 till 2016. ENOE is a nationally representative labour-force survey comprising a rotating panel of five consecutive quarters. The sampling of survey respondents follows a two-stage procedure: geographical stratification of areas, followed by a random selection of households into the survey sample. During each survey round, one-fifth of the sample households are dropped from the study, and a new cohort is added. The rolling panel structure implies that each quarterly release of the survey contains information on five different survey cohorts.

ENOE provides a rich dataset of information on individuals' employment situation, their job characteristics, as well as the sociodemographic characteristics of the household. The final sample consists of 2,632,000 individuals located in 1,251,954 households spread over 1,676 municipalities.[24] Appendix A.2 provides a map of surveyed municipalities visualising the spatial variation in the data.

Table 2.1 presents summary statistics of baseline characteristics for the sample individuals.[25] The empirical analysis is confined to the legal working population between the ages of 14 and 98.[26] The sample is equally split between men and women, with an average

24. The ENOE stratification process excluded 780 of Mexico's 2,456 municipalities. This process implies that ENOE is nationally representative at the state level.

25. In view of the labour-force survey being a rotating panel, the summary statistics are generated using the first interview round for each surveyed individual.

26. An advantage of ENOE is the extensive data cleaning and verification effort by INEGI, resulting in a very clean dataset with few missing information. Besides validating the accuracy of the data entries and deleting duplicates, data cleaning for this research project included limiting the dataset to the working population between the age 14 and 98 – the official Mexican government definition of the working age. Workers absent from work for holidays, educational training, and health or family reasons were dropped from the dataset to reduce measurement error in the outcome variable. Moreover, merging of the weather

Table 2.1: Summary Statistics Labour Market Survey

Variable	Mean	Std. Dev.	5th	95th %ile
individual characteristics				
age	38.13	14.21	18.00	64.00
female (%)	52.01			
married (%)	38.99			
rural (%)	15.80			
macro area (%)	64.61			
education				
max secondary (%)	55.79			
preparatory (%)	17.01			
university (%)	25.31			
postgraduate (%)	1.56			
labour-market characteristics				
weekly wage in 2010 prices	1,006.70	1,406.22	0.00	2,924.5
weekly working hours (h)	42.24	18.00	8.00	72.00
days worked per week	5.45	1.30	2.00	7.00
unemployment rate (municipality)	0.04	0.02	0.00	0.08
firm size				
micro (%)	61.93			
small (%)	14.62			
medium (%)	9.42			
large (%)	14.03			
contract type				
informal (%)	27.66			
permanent (%)	29.83			
piecework (%)	13.24			
weekly earnings (%)	50.28			
< minimum wage (%)	19.75			
work location				
office (%)	39.44			
outdoor (%)	14.22			
domestic (%)	10.42			
sector				
agriculture (%)	10.79			
extractive industry (%)	1.00			
manufacturing (%)	15.26			
construction (%)	8.17			
trade (%)	20.54			
restaurants (%)	7.54			
transport & communication (%)	4.90			
professional & financial services (%)	6.33			
social services (%)	8.47			
diverse services (%)	11.13			
government (%)	5.88			

age of around 38 years. Around 40% of the sample has completed tertiary education. On average, individuals earn about 1,000 pesos per hour (in 2010 prices), with the top 5% of earners in the sample receiving almost three times as much. Average working times are 42.24 hours per week spread over five and a half working days. The largest employment

data with the labour-force survey involved several verification tests to ensure the merge happened on the correct calendar week. Similar attention was paid to the calculation of polygon averages for the weather variables.

sector by far is the trade industry, followed by manufacturing and diverse services. The agricultural sector employs only around 10% of the labour force, which emphasises the importance of analysing weather impacts outside of the agricultural industry.

Of interest is further information on the employment situation of workers. Almost one-third of respondents work in informal employment and only one-third of workers have a permanent contract. Moreover, half of the sample reported being paid on a weekly basis, and almost 20% earn an hourly wage that falls below the official minimum wage. Regarding work locations, roughly 40% of workers report to work indoors, while 15% are exposed to elements during working hours. The remaining share of labourers either work from home or have no consistent work location.[27]

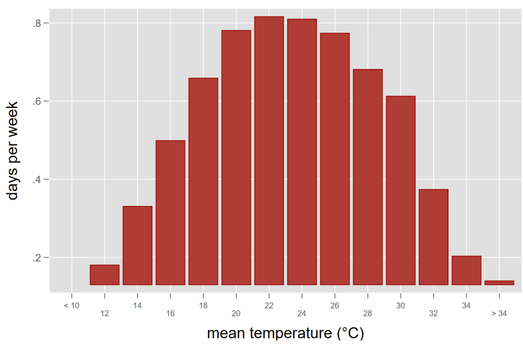
Weather Data

Table 2.2: Summary Statistics Weather Variables

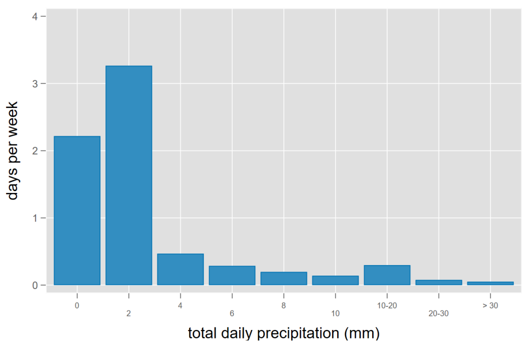
	Mean	Std. Dev.	5th–95th %ile	
avg. temperature (°C)	22.24	5.75	12.78	31.42
avg. daily Heat Index (°C)	25.52	6.33	17.62	38.02
avg. Wet Bulb Globe Temp. (°C)	19.78	4.69	12.39	27.75
avg. daily total percip. (mm)	2.10	3.38	0.00	9.05

Figure 2.1: Distribution of daily mean temperature and total precipitation over bins per week

(a) Temperature



(b) Precipitation



Notes: Period of observation 2005-2016. The bar height captures the incidence of days with weather falling into the respective bin across municipality per week.

Using the calendar reference week of the survey, I match observations from the labour-force survey to fine-scaled weekly weather data from the NARR model (NCEP 2017)

27. To the extent that the information provided in ENOE only allows a rough categorisation of weather exposure, I expect the analysis to underestimate the true effect of weather on working times and earnings. For instance, plumbing work may take place indoors or outdoors and, thus, cannot be easily categorised as ‘exposed’ or ‘nonexposed’.

developed by the National Centers for Environmental Prediction (NCEP). The NARR dataset consists of a long-term, high-frequency, high-resolution, and dynamically consistent meteorological and land-surface hydrology dataset. It covers climate data from 1979 to 2017, with weather data provided eight times daily in the form of a 0.3°-resolution grid (32 km at the lowest latitude). Reanalysis data collects information from ground stations, satellites and other sources, such as rawinsondes. The use of reanalysis data for empirical research has several advantages compared to station data. Firstly, reanalysis data does not suffer from missing observations as often incurred with station data. Moreover, homogenising of the data implies that values are comparable across regions and time. Lastly, consideration of the topography in reanalysis models can reduce the inaccuracy in the temperature and precipitation measurements across physical features of an area. At the same time, the validity of using reanalysis data in this study hinges on the accuracy of the model in predicting weather across the study region.[28] As shown by Mesinger et al. (2006), NARR has a good track record of accurately measuring extreme-weather events for Mexico.

The weather data is aggregated to weekly bins (Monday to Sunday) at the municipality level to match the survey reference period.[29] Mexican municipalities present useful geographic units of local economic characteristics, providing uniform measures of, for example, local labour- and housing-market conditions. Treating place characteristics of states as uniform is inadequate, given the vast variation in within-state topography, climate and industrial structure. It is reasonable to assume that municipalities experience homogeneous weather considering the average size of municipalities of around 800 km^2—about the size of New York City. Nevertheless, depending on the topography, weather can vary substantially even within small geographical areas. Along with the potential issue of inaccuracy in reanalysis data, it is likely that the final temperature and precipitation variables entail some measurement error, causing an attenuation bias in the impact estimates.

This study follows the current standard method for geographical aggregation of reanalysis data, by using a two-step procedure that first generates weekly bins for every grid point and then averages grid points over municipality polygons (Dell et al. 2014, p.

28. See Auffhammer et al. (2013) on potential pitfalls of using reanalysis data for empirical research.

29. The robustness section examines the implications of applying alternative temporal aggregations to the weather variables. The regressions exhibit very similar impacts, with some loss in precision and a decline in the effect size with lengthening of the measurement period.

745).[30,31] This sequence is essential for correctly accounting for nonlinear effects of weather. Averaging over the geographic area before binning the observations could lead to a misrepresentation of the extreme-weather days due to smoothing over extreme observations (Dell et al. 2014, p. 745). To better understand the reasoning behind the aggregation steps, consider this simplified example, where municipality r includes only two grid points with temperatures of 27°C and 34°C with equal weights. Assume that labour supply drops significantly for temperatures above 32°C. The mean temperature for the municipality is 30.5°C. Averaging temperature before aggregation would imply an incorrect prediction of a reduction in labour supply caused by temperatures of 30.5°C. Instead, binning the temperature before aggregation would assign half a day to each of the corresponding bins and, thus, allows correct identification of heat effects associated with temperatures exceeding 32°C. Note that the sequential aggregation method results in fractional days in bins, but total days per week and municipality sum to seven days.

Between 2005 and 2016 Mexico experienced average temperatures of 22.35°C with a standard deviation (sd) of 5.75°C. Daily precipitation totals on average 2.10 mm (sd 3.37 mm), with the 95th percentile of the distribution reaching 9.04 mm. Figure 2.1 depicts the incidence of days falling into the respective temperature and precipitation bins on average per municipalities over the survey time.[32] As expected, few days fall into the extreme temperature and precipitation bins.

2.6 Results

I begin the analysis by estimating a basic regression specification including the weather variables, additional controls and the higher-dimensional fixed effects, with December, quarter four in the year 2010 in Mexico City as the base.[33] Standard errors are clustered at the municipality level, due to the stratification method of ENOE and to control for

30. Note that in 2011, municipality Othón P. Blanco in the South-Eastern state Quintana Roo lost 40% of its territory to the newly founded municipality Bacalar. The original municipality boundaries from 2005 are kept throughout the study to ensure consistency in the geographic boundaries and characteristics of municipalities over time.

31. Raster point weights used to calculate the geometric averages per polygon were generated using the `extract` command of the `raster` package in R.

32. Studying summary statistics by Mexican macro-regions in Appendix A.3 reveals significant spatial variation in the number of days per bin.

33. As mentioned in the data section, the correct functional form of the weather variables is heavily debated. Following the literature, the discussion focusses on the preferred specification using weather bins. Appendix A.5 provides alternative estimates based on simpler linear and polynomial variable specifications.

geographical clustering in the climate variables (Abadie et al. 2017; Cameron and Miller 2015).[34] Subsequently, I test for heterogeneity in the predicted weather effects by including interaction terms between the weather bins and different variables of interest.

2.6.1 Baseline Results

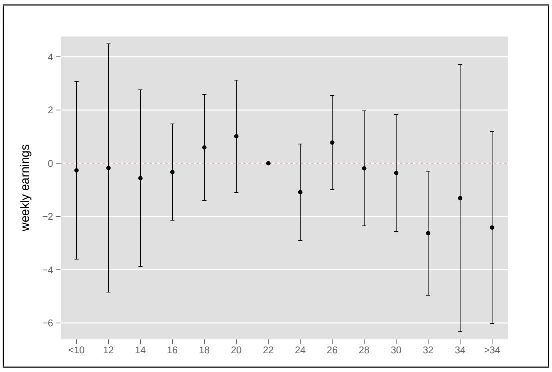
Figures 2.2 and 2.3 present coefficient plots of weather impacts for earnings and working-time regressions, respectively. The baseline results indicate a negative but small effect of cold days, with temperatures below 10°C causing a working-time reduction of around two minutes. Contrary to findings for the U.S. (Graff Zivin and Neidell 2014), coefficient estimates in Plot 2.3a suggest no distinct relationship between heat and working time. In contrast, the rainfall coefficients in 2.3b reveal strong impacts of extreme rainfall days. On days with precipitation exceeding 30 mm economy-wide working times are on average 30 min shorter. Concerning earnings, the coefficient plots in Figure 2.2 indicate no average effect of weather fluctuations on weekly earnings.

The municipality estimates mask potentially important heterogeneity in weather impacts. For example, the extent of occupational weather exposure is likely to be an important determinant of the sensitivity of earnings and working times to weather fluctuations. The analysis exploits the detailed information of ENOE on individual and job-specific characteristics to test for differentials in weather effects using interaction effects. Tables 2.3 and 2.4 provide a summary of significant heterogeneous weather effects estimated using interaction terms. I will discuss the summarised findings in more detail for the remainder of this section.

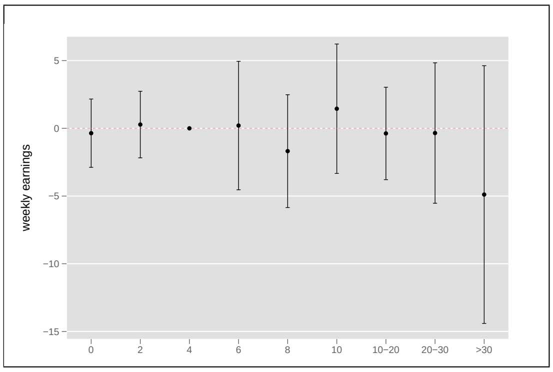
34. The robustness section demonstrates the validity of the results to two-dimensional cluster specifications such as at the sate-year level. In light of the stratification method and the robustness of results, municipality-level clusters is the preferred specification in the analysis.

Figure 2.2: Weather Bins Coefficient Plots - Earnings Regression

(a) Temperature



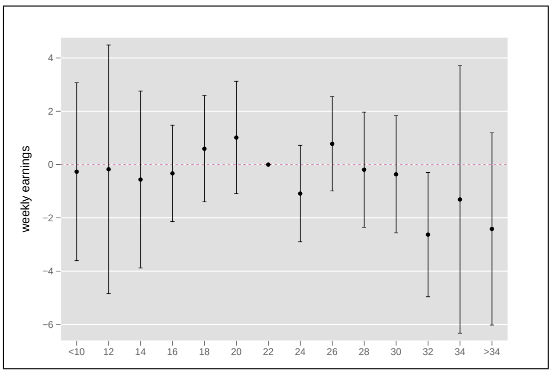
(b) Precipitation



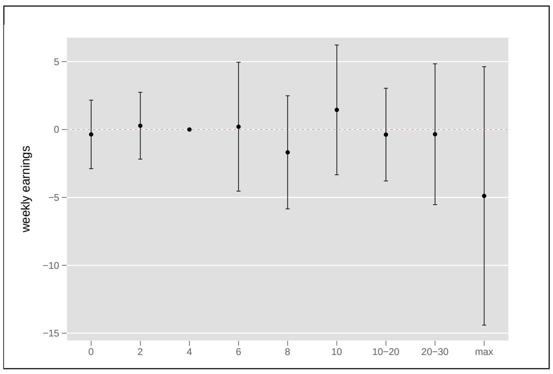
Notes: Figure depicts marginal effects of weather bins on weekly earnings (in 2010 pesos). N=7,390,147 and i=2,632,000. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly earnings based on Equation 2.9 in the methodology section. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] °C and (2-4] mm precipitation. Appendix A.4 provides the corresponding regression tables. Standard errors are clustered at the municipality level.

Figure 2.3: Weather Bins Coefficient Plots - Working Time Regression

(a) Temperature



(b) Precipitation



Notes: The figure depicts marginal effects of weather bins on weekly minutes worked. For all regressions N=7,390,147 and i=2,632,000. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly minutes worked based on Equation 2.9 in the methodology section. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] °C and (2-4] mm precipitation. Appendix A.4 provides the corresponding regression tables. Standard errors are clustered at the municipality level.

Table 2.3: Summary Table Significant Impacts - Earnings Regressions

	Temperature Impacts in 2010 Mexican Pesos			
	positive		**negative**	
Cold	*industry*			
	Restaurant Services	6.512*	Extractive	-37.55**
	Trade[a]	12.19***	Construction	-15.63***
			Agriculture[a]	-8.007***
			Social Services[a]	-13.58**
	work location			
	domestic[a]	8.041*		
	job characteristics			
	< minimum wage[a]	8.033**	weekly pay	-9.290**
			union[a]	-6.631*
	individual characteristics			
	14-19 years old[a]	8.994*		
	tertiary schooling	6.107*	max secondary	-5.098*
Heat	*industry*			
	Extractive	157.7***	Manufacturing	-16.88***
	Professional Services	9.861*	Trade	-9.128***
	Social Services	20.74*	Restaurant Services	-17.99**
	Agriculture[a]	8.555*	Diverse Services	-11.94***
	work location			
	office work[a]	6.751*	non-office work	-9.371***
			domestic	-16.82***
			rural	-9.858**
	job characteristics			
	union	10.88***	non-union	-14.70***
	less frequent than weekly pay	12.66***	weekly pay	-20.91***
			informal	-16.62***
			temporary	-6.382***
			< minimum wage	-22.82***
			piecework	-18.23***
	individual characteristics			
			female	-8.635***
	40-49 years old	9.022*	14-19 years old	-23.32***
	50-59 years old	8.640**	20-29 years old	14.08***
			> 60 years old	-7.223*
	university	18.28**	max secondary	-13.98***
	postgraduate	86.67***	tertiary	-3.560*

Table continues on next page

2.6.2 Industry Estimates

As discussed in the theoretical section, workers' weather sensitivity likely varies with the extent of weather exposure and physical intensity of the job, both of which can roughly be identified by the employment industry. Figures 2.4 and 2.5 present the marginal effects for interactions between the weather bins and industrial dummies. As predicted by the model outlined in Section 2.3, the industry estimates indicate significant working-time responses

Table 2.3: Summary Table - Earnings Regressions *(Continued)*

	Precipitation Impacts in 2010 Mexican Pesos			
	positive		**negative**	
Dry	*industry*			
	Agriculture	20.36***	Extractive Industry	-59.86***
	Government	18.04**	Social Services[a]	-9.641**
	work location			
	outdoor	8.823***	non-office work	-3.876***
			domestic	-12.69***
	job characteristics			
	formal	3.232*	informal	-9.945***
	permanent	6.426*	temporary	-3.367**
	union	8.352*	non-union	-8.801***
	less frequent than weekly pay	3.895*	weekly pay	-7.674***
			piecework	-10.31***
	individual characteristics			
	male	5.702***	female	-9.763***
	40-49 years old	5.938**	14-19 years old	-18.29**
	50-59 years old	6.477**	20-29 years old	-6.328***
Wet	*industry*			
	Extractive Industry	81.55*	Diverse Services	-17.91*
			Restaurant Services[a]	-18.72***
	work location			
	office work[a]	14.12**	non-office work	-13.90***
			domestic	-17.21**
			rural	-12.39***
	job characteristics			
	permanent[a]	12.55**	temporary	-12.55***
	union	17.32*	non-union	-22.29***
			informal	-15.03***
			< minimum wage	-26.77***
			piecework	-18.23**
			weekly pay	-33.06***
	individual characteristics			
			female	-16.81***
	30-39 years old	9.022*	14-19 years old	-27.68***
			20-29 years old	-13.34**
	university[a]	16.34*	max secondary	-13.51***
	postgraduate[a]	89.77*		

[a] Impact for other than maximum (minimum) bin. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors are clustered by municipality. Covariates include marital status, age, gender, education, rural, contract type, and firm size, as well as municipality, month, and industry-year-quarter fixed effects.

Table 2.4: Summary Table Significant Impacts - Working Time Regressions

	Temperature Impacts in Minutes Worked			
	positive		**negative**	
Cold	*industry*			
	Social Services	8.640*	Manufacturing	-9.721***
	Transport[a]	23.54***	Construction	-16.35***
			Agriculture[a]	-18.84***
	work location			
			office	-3.053***
			urban	-3.607***
			metro area	-2.533**
			outdoor[a]	-20.43***
	job characteristics			
	informal[a]	6.306***	formal	-3.051**
			permanent[a]	-2.922**
			non-union	-3.049*
			non-piecework	-2.674**
			piecework	-9.802**
			weekly pay	-7.451***
			less frequent than weekly pay[a]	-3.167**
	individual characteristics			
			male	-6.792***
	14-19 years old	14.65***	30-39 years old	-9.102***
			40-49 years old	-5.019**
			50-59 years old[a]	-3.780*
	university	4.161*	max secondary	-6.975***
Heat	*industry*			
	Professional Services	6.545*	Manufacturing	-8.683**
	Government[a]	11.10**	Transport	-30.03***
	work location			
	office[a]	6.954***	non-office	-4.987***
			rural[a]	-10.20***
	job characteristics			
	formal	4.968***	informal	-18.67***
	permanent[a]	8.604***	temporary	-3.594**
	union[a]	4.442**	non-union[a]	-5.742**
			< minimum wage	-12.48***
	individual characteristics			
	20-29 years old	4.166**	> 60 years old	-5.926*
	tertiary[a]	3.866*	max secondary	-4.544***
	university	6.943**		
	postgraduate[a]	14.76***		

Table continues on next page

Table 2.4: Summary Table - Working Time Regressions *(Continued)*

	Precipitation Impacts in Minutes Worked			
	positive		**negative**	
Dry	*industry*			
	Agriculture	40.36***	Construction	-9.075***
	Social Services	13.89***	Trade	-13.37***
			Restaurant Services	-7.619**
			Transport	-30.34***
	work location			
	outdoor	31.52***		
	office work	3.733***		
	domestic	5.426*		
	job characteristics			
	formal	5.404***	informal	-12.90***
	permanent	7.335***	temporary	-2.570**
	non-union	2.737*	union[a]	-3.304***
			< minimum wage	-8.414***
	less frequent than weekly pay	3.979***	weekly pay	-6.212***
	individual characteristics			
	female	3.126**		
	40-49 years old	2.847*	14-19 years old	-14.03***
	> 60 years old	10.15***		
	university	5.446****		
	postgraduate	8.603*		
	negative			
Wet	*industry*			
	Agriculture	-69.49***	Manufacturing	-30.71***
	Construction	-70.92***	Trade	-20.90***
	Restaurant Services[a]	-17.82**	Transport	-23.53**
	Professional Services	-13.35*	Social Services	-17.65**
	work location			
	outdoor	-63.91***	non-office work	-42.47***
	urban	-19.35***	rural	-63.39***
	metro area	-21.07***		
	job characteristics			
	formal	-16.07***	informal	-58.77***
	temporary	-39.73***		
	non-union	-32.73***	union	14.17***
	< minimum wage	-46.47***	non-piecework	-31.65***
	less frequent than weekly pay	-21.57***	weekly pay	-42.11***
	individual characteristics			
	male	-35.52***	female	-16.26***
	14-19 years old	-42.92***	20-29 years old	-16.32***
	30-39 years old	-23.90***	40-49 years old	-32.62***
	50-59 years old	-36.61***	> 60 old	-34.57***
	max secondary	-42.45***	tertiary	-9.686**

[a] Impact for other than maximum (minimum) bin. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors are clustered by municipality. Covariates include marital status, age, gender, education, rural, contract type, and firm size, as well as municipality, month, and industry specific year and quarter fixed effects.

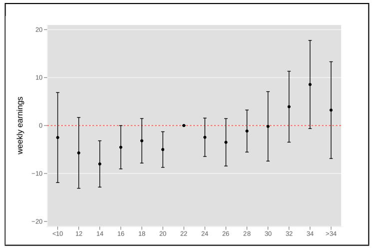
to both heat and cold days for weather-exposed and manual labour-intensive industries. Days with temperatures exceeding 22°C reduce working times by around eight minutes in the manufacturing sector and by more than half an hour in the transport sector. In contrast, working times in the government and the professional service sector (low risk industries) are prolonged by around three to twelve minutes. The results provide some suggestive evidence of heat-related increases in working times in the extractive sector, but the coefficient for the maximum-temperature bin is insignificant.

Predicted cold effects are more consistent. I find working-time reductions to range roughly between 10 to 19 min per day with temperatures below 12°C for agricultural, construction and manufacturing workers.[35] Similar to Connolly (2008) and in line with the theoretical model, I observe rainfall-related working-time reductions during heavy-rainfall days of up to 70 min in weather-exposed industries, including agriculture 69.49 min (−16.19% of daily working time), construction 70.92 min (−14.29%) and transport 23.53 min (−4.20%); half an hour for physical-intensive work in manufacturing (−6.40%); and up to 20 min in service-oriented industries (−2 to −4%).

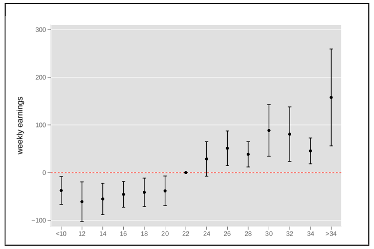
35. Note that the marginal effect for the minimum temperature bin is insignificant for the agricultural sector. Agricultural production in Mexico is primarily located in regions with moderate or tropical climate all year round. Hence, the number of observations in the lowest temperature bin for the industry is small, limiting the identification of effects for the temperature range.

Figure 2.4: Industry Marginal Effects on Earnings - Temperature

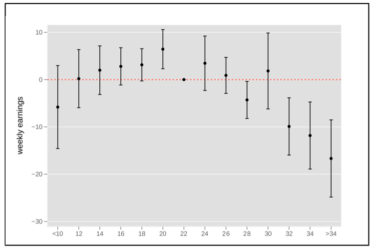
(a) Agriculture



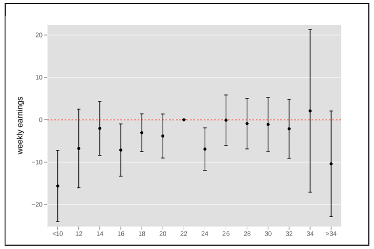
(b) Extractive Industry



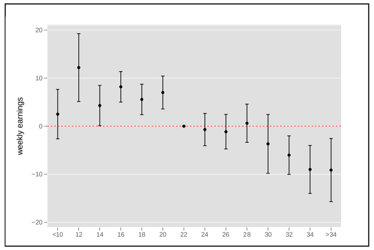
(c) Manufacturing



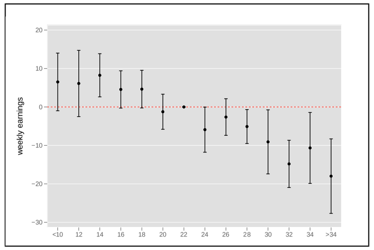
(d) Construction



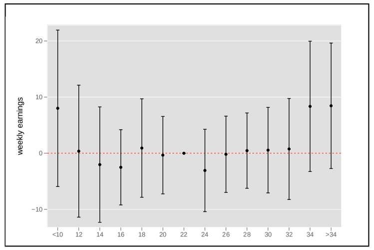
(e) Trade



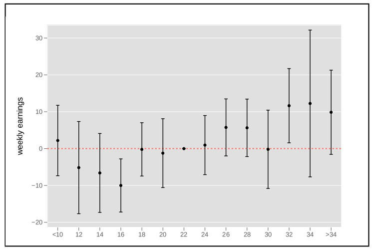
(f) Restaurant Services



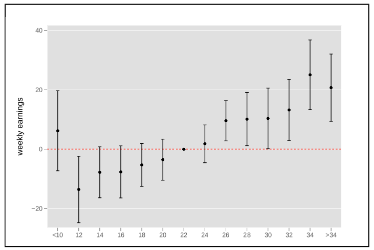
(g) Transport



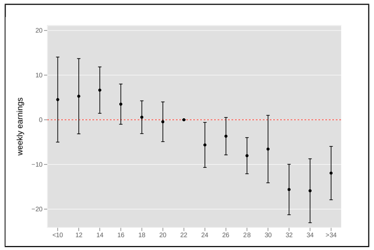
(h) Professional Services



(i) Diverse Services



(j) Social Services



(k) Government

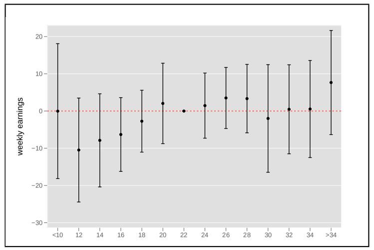
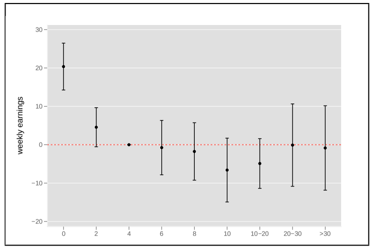
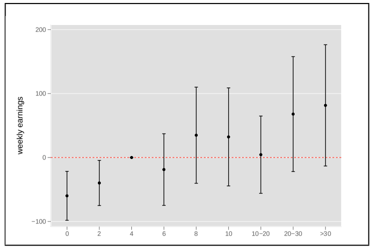


Figure 2.4: Industry Marginal Effects on Earnings - Precipitation *(continued)*

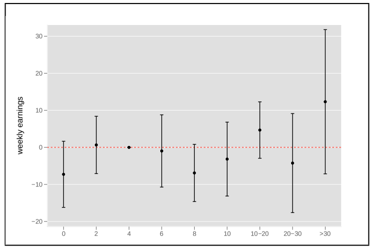
(l) Agriculture



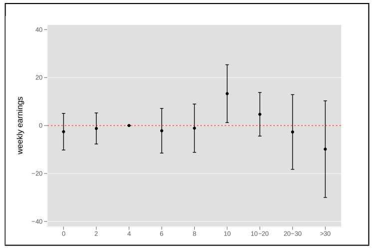
(m) Extractive Industry



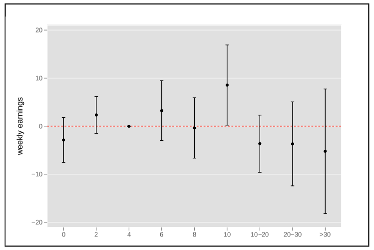
(n) Manufacturing



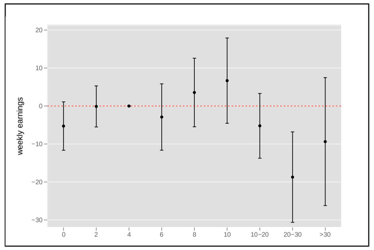
(o) Construction



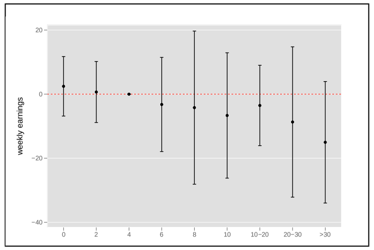
(p) Trade



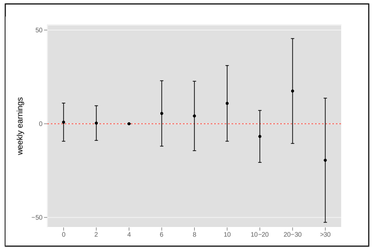
(q) Restaurants Services



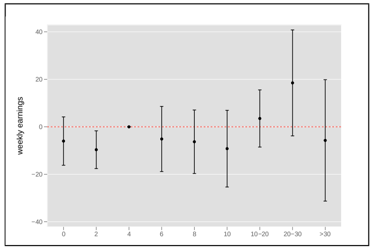
(r) Transport



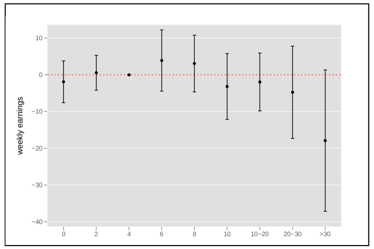
(s) Professional Services



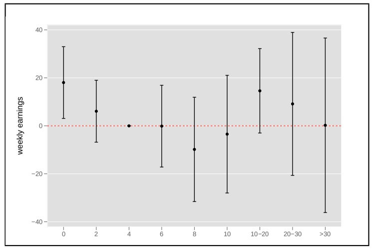
(t) Diverse Services



(u) Social Services



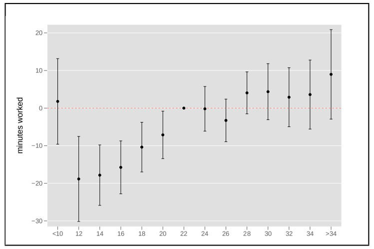
(v) Government



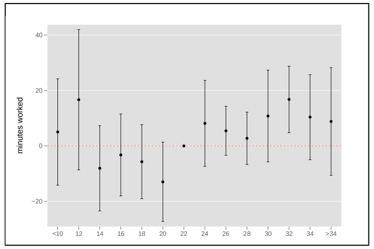
Statistics: Adjusted R^2=0.116, F Stat=2273.5, # clusters=1,676, N=7,390,147, Ind.=2,632,000.
Notes: Figure depicts marginal effects of weather bins on weekly earnings (in 2010 pesos). The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] °C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Figure 2.5: Industry Marginal Effects on Working Time - Temperature

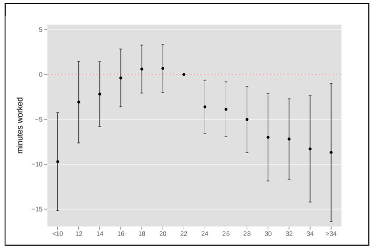
(a) Agriculture



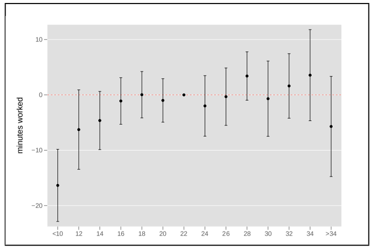
(b) Extractive Industry



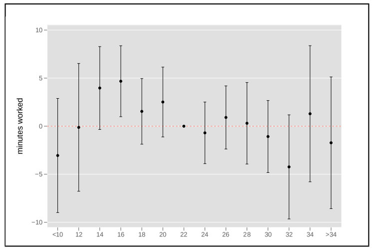
(c) Manufacturing



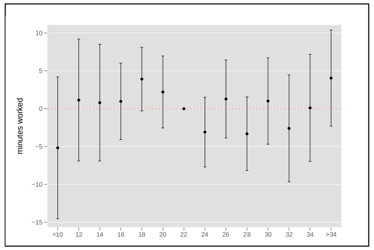
(d) Construction



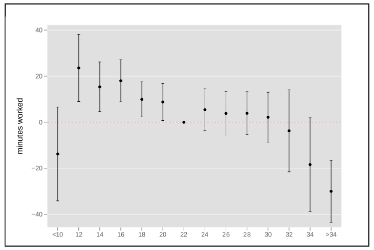
(e) Trade



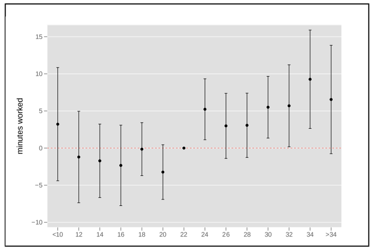
(f) Restaurant Services



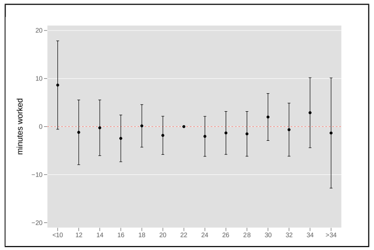
(g) Transport



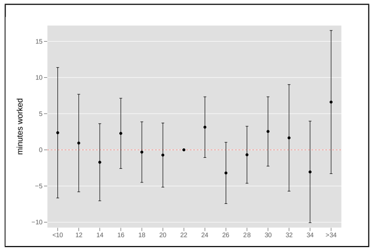
(h) Professional Services



(i) Diverse Services



(j) Social Services



(k) Government

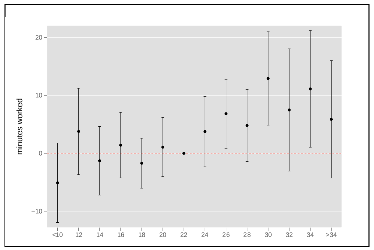
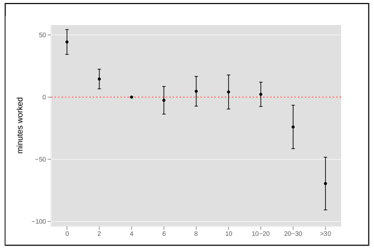
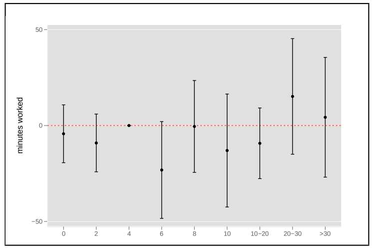


Figure 2.5: Industry Marginal Effects on Working Time - Precipitation *(continued)*

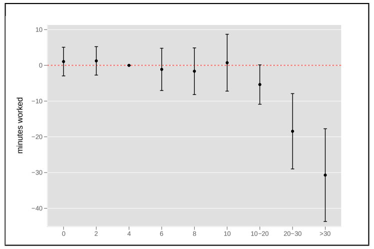
(l) Agriculture



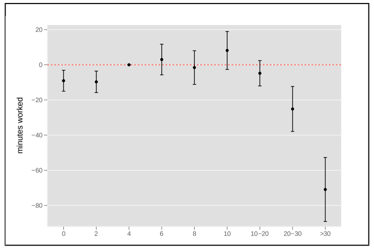
(m) Extractive Industry



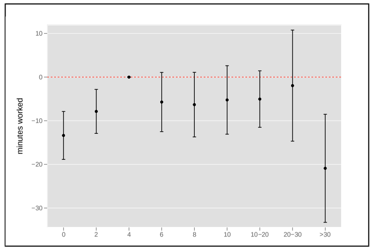
(n) Manufacturing



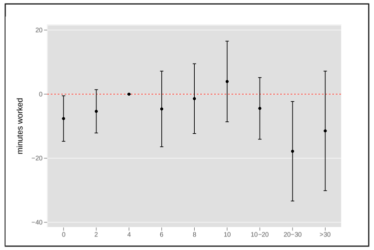
(o) Construction



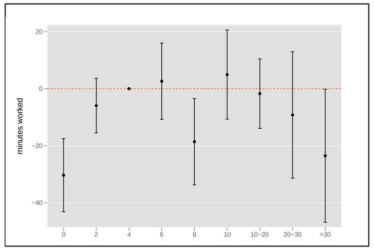
(p) Trade



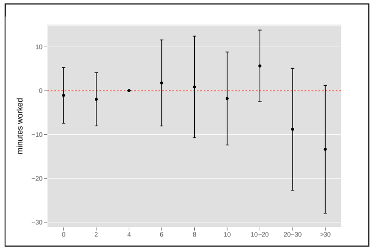
(q) Restaurant Services



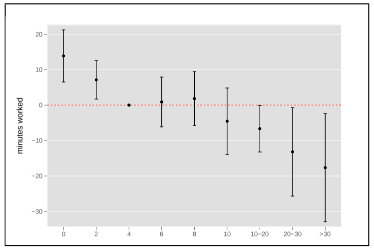
(r) Transport



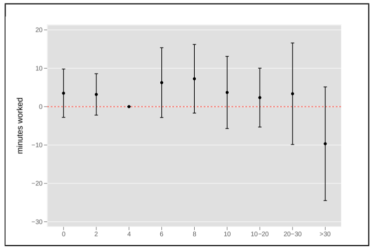
(s) Professional Services



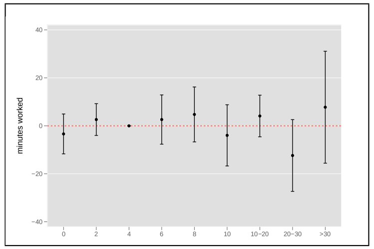
(t) Diverse Services



(u) Social Services



(v) Government



Statistics: Adjusted R^2=0.147, F Stat=980.1, # clusters=1,676, N=7,390,147, Ind.=2,632,000.
Notes: The figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] °C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

As expected, zero-rainfall days have a strong positive effect on working times in the agricultural sector of an additional 40 min per day (+10.33%), with a corresponding increase in daily earnings by 23.40%. In terms of the model, this suggests that the substitution effect of a lower disutility of agricultural work on dry days dominates the income effect of a higher utility from recreational activities. However, the impact of day-to-day changes in weather on the agricultural sector will likely vary by season. During harvest season, agricultural workers will react very differently to extreme rainfall than outside the growing season. Moreover, prolonged heat and drought will, for example, result in greater usage of irrigation. Hence, aside from direct effects on labour productivity and the disutility of work, weather fluctuations will likely cause agricultural production line adjustments. Therefore, observed responses in working times and earnings should be interpreted as the equilibrium outcome of the re-optimisation of the firm and the individual maximisation problem.

In contrast to the agricultural sector, I observe minor adverse effects of dry days on working times in the construction (−1.83%), trade (−2.91%) and restaurant services industry (−1.64%), suggesting substitution effects between recreational activities and working time on zero-rainfall days in line with Connolly (2008). Similarly, working times in the transport industry drop by half an hour on zero-rainfall days (−5.41%).

While the impacts on weather-exposed and manual labour-intensive industries can be attributed to direct weather impacts, it is uncertain, whether work-time reductions in service-oriented industries are caused by lower customer demand or changes in labour productivity.[36,37] For example, shorter working hours in the transportation sector on zero-rainfall days could result both from lower traffic congestion (higher labour productivity) as well as fewer passengers (lower output price). Research on the retail sector demonstrates a negative relationship between extreme-weather days and customer-demand (Starr-McCluer 2000), speaking in favour of demand-side driven working-time responses

36. In terms of the model, a fall in customer demand would result in a lower price in the output sector and a lower equilibrium level of labour supply for workers under a flexible wage regime. Similarly, labour-productivity impacts would cause changes in productivity-mapped wages and, through equilibrium mechanisms, in the optimal level of labour supply.

37. I assume here that service-oriented industries belong to the low-risk category. However, in the context of Mexico, this categorisation might not be appropriate considering the low air-conditioning penetration rate. A high correlation between outdoor and indoor climate may imply that nonfinancial-service industries belong in the high-risk category. In this case, labour supply would respond directly to adverse weather days. As working time falls, so would earnings for workers paid on an hourly basis.

for occupations with customer contact. However, a study on the impact of rainfall on labour supply in the New York taxi market shows that despite higher returns per hour (higher occupancy rate and shorter mileage travelled) supply drops on rainy days (Farber 2015). This suggests that taxi drivers dislike driving in the rain (higher disutility of work relative to the utility of consumption) and, therefore, cut short working days. Heat could have similar effects on labour supply in the transport sector.

The corresponding earnings estimates provide some evidence of demand-side effects for service-oriented industries. Aside from direct heat and cold effects on earnings of manual labour-intensive industries (agricultural, construction and manufacturing),[38] impacts on earnings are limited to trade and nonfinancial services, such as the restaurant sector. In contrast to working times, earnings in the transport sector are unaffected by adverse weather. In terms of the model, this suggests that higher customer demand and labour productivity in the transport sector result in higher hourly wages. This causes a re-optimisation of working times to a lower level given the negative income effect, thus, leaving earnings in the transport sector unaffected. In contrast, reductions both in earnings and working times for other nonfinancial service industries suggest negative customer-demand responses on adverse-weather days causing a fall in earnings and, consequently, labour supply. Nevertheless, adverse weather impacts on labour productivity of nonfinancial service employees cannot be ruled out as an explanation (see Equation 2.8). Observed effects likely result from a combination of both demand- and supply-side impacts.

A surprising result in Figure 2.4 is the unusual earnings increases (declines) in response to heat (cold) days in the extractive industry. While extreme-rainfall and heat days raise average earnings in the sector by around 81.55 pesos (+21.14%) and 157.7 pesos (+41.3%), zero-rainfall days and cold temperatures lower income by −59.86 pesos (−15.68%) and −37.55 pesos (−9.84%), respectively. The results indicate no corresponding working-time adjustments for the industry. This suggests the implementation of heat- and rainfall-related effort-compensation schemes in the Mexican extractive industry as a means of incentivising employees to work in adverse temperatures and rain despite a higher disutility of work. Unfortunately, I have not come across any anecdotal evidence of weather-dependent compensation programs in the sector. However, Kahn (2016) em-

38. These findings are consistent with scientific evidence of temperature-related reductions in cognitive ability, physical task performance and higher injury risk for weather-exposed and physically-active jobs.

phasises that compensating wage differentials will rise with future climate change and deteriorating work conditions in weather-exposed industries.

Occupational health problems caused by prolonged heat exposure are not uncommon among Mexican miners (Trabajo y Previsión Social 2017). High external temperatures can result in life-threatening underground temperatures in mines. Similarly, surface mining is directly exposed to the elements with limited possibilities of shelter. At the same time, employment in the extractive industry is disproportionally well protected, with over 95% workers having a formal work contract and 78% being union members with a permanent position. Therefore, workers in the extractive industry seem to posses the bargaining strength to demand compensation for working in adverse weather.

2.6.3 Work Location

To better understand the underlying mechanisms of the observed industry differentials, I explore information on work locations and occupational codes to categorise individuals into office, domestic and outdoor workers. An outdoor dummy variable identifies occupations predominantly exposed to the elements (e.g. agricultural-field and external-construction workers). Moreover, I investigate differentials between rural, urban and metropolitan locations. Figure 2.7 presents marginal effects on weekly working time by job location. Days with temperatures between 10-12°C lower working times of outdoor workers by 20 min (-4.80%), while heat days prolong working days for both outdoor and office workers. Models 3 to 5 provide some evidence for heat-stress impacts on non-office, domestic and rural work. However, the effects are small and predicted effects of maximum-temperature bins are mostly insignificant.

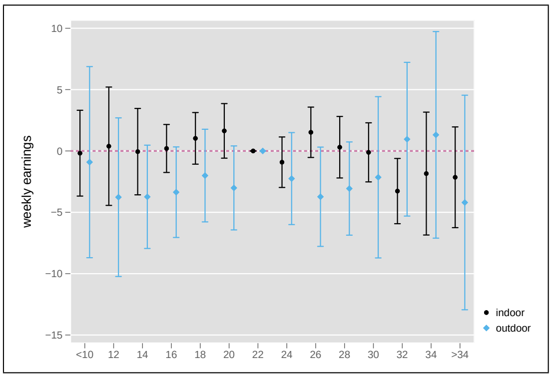
More revealing are the precipitation estimates. As expected, the precipitation results depict a strong association between rainfall and weather-exposed working times (high risk). Extreme-rainfall days (> 30 mm) shorten rural and outdoor working days by approximately one hour (14%). In contrast, outdoor labourers work roughly half an hour longer on zero-rainfall days.

Earnings effects presented in Figure 2.6 are consistent with a story of labour-productivity losses in response to heat exposure. The results indicate heat- and rainfall-related reductions in earnings for outdoor, non-office and rural workers. As expected, rainfall impacts on

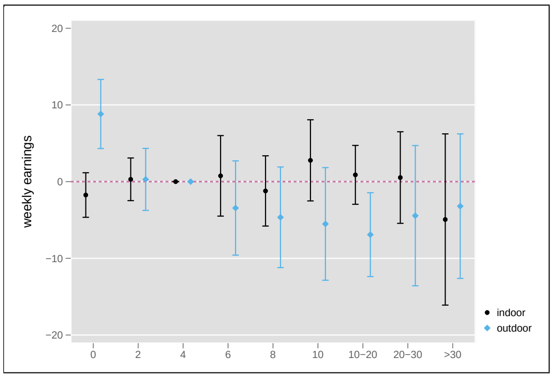
Figure 2.6: Work Location Marginal Effects on Earnings

outdoor vs indoor

(a) temperature

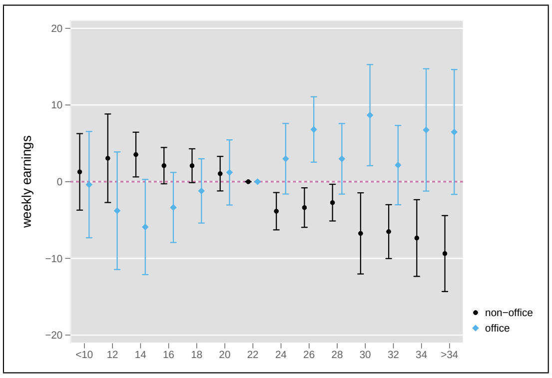


(b) precipitation

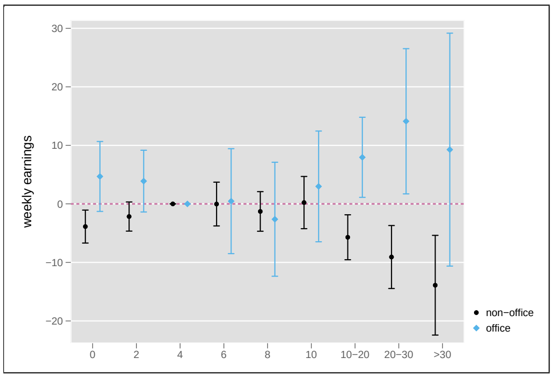


office vs non-office

(c) temperature

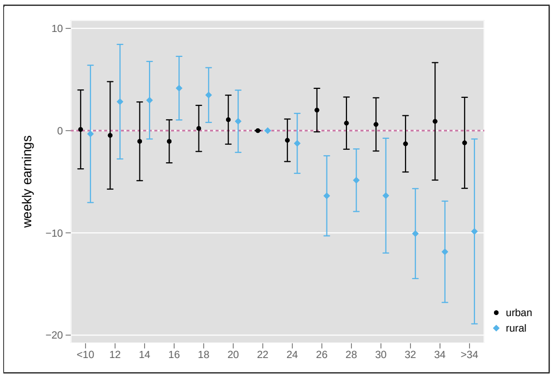


(d) precipitation



urban vs rural

(e) temperature



(f) precipitation

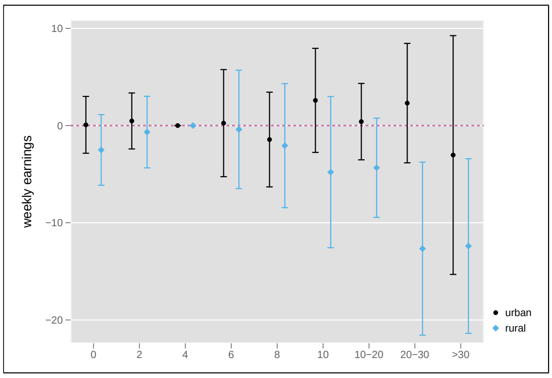
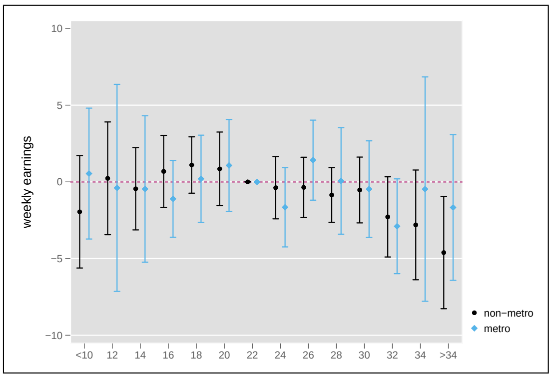


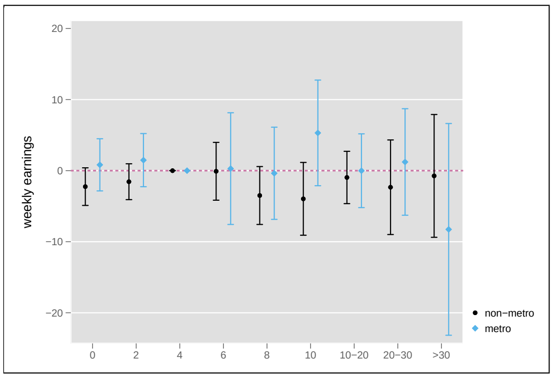
Figure 2.6: Work Location Marginal Effects on Earnings *(continued)*

metro vs non-metro area

(g) temperature

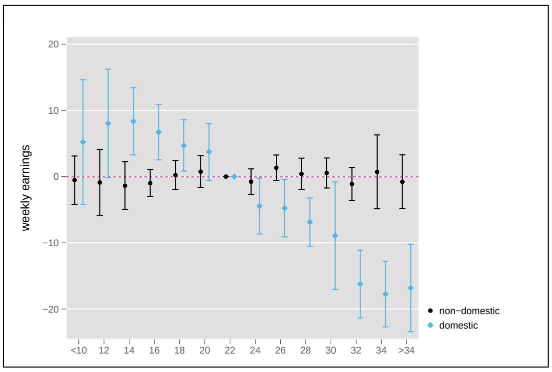


(h) precipitation

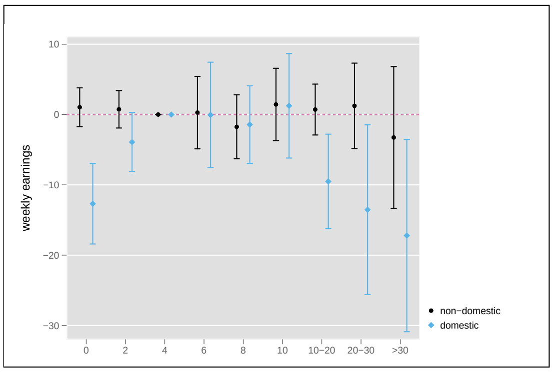


domestic vs non-domestic

(i) temperature



(j) precipitation

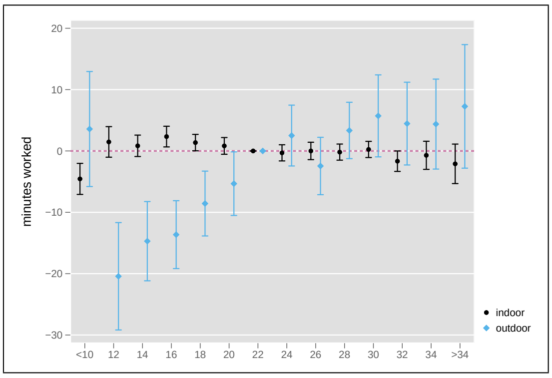


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly earnings (in 2010 pesos). The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] °C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

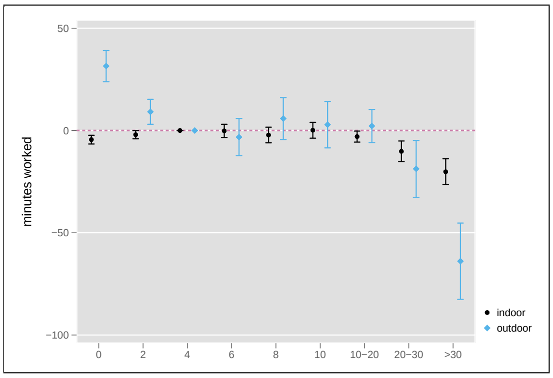
Figure 2.7: Work Location Marginal Effects on Working Time

outdoor vs indoor

(a) temperature

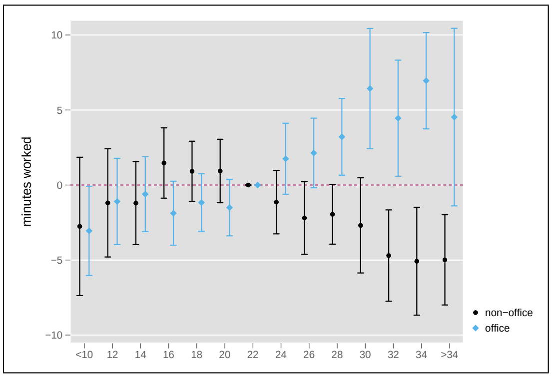


(b) precipitation

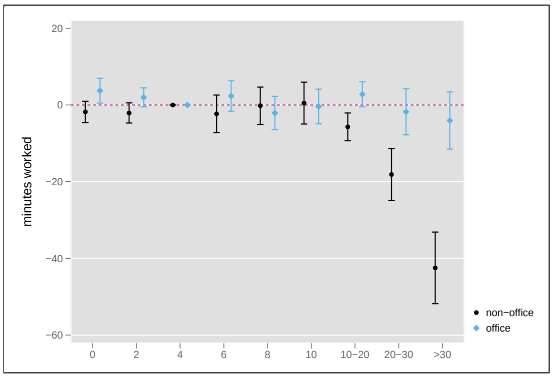


office vs non-office

(c) temperature

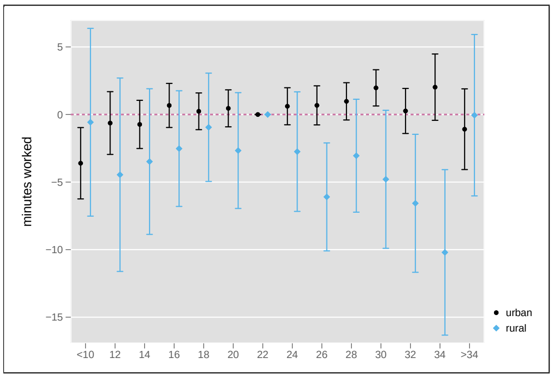


(d) precipitation



urban vs rural

(e) temperature



(f) precipitation

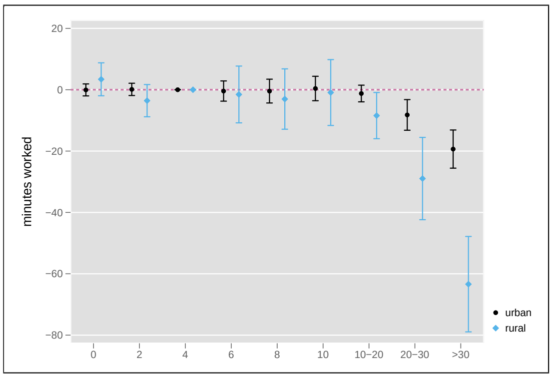
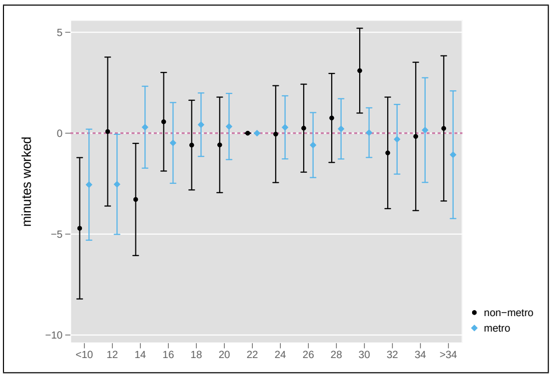


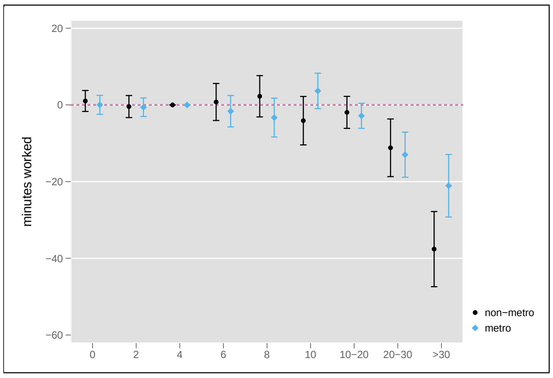
Figure 2.7: Work Location Marginal Effects on Working Time *(continued)*

metro vs non-metro area

(g) temperature

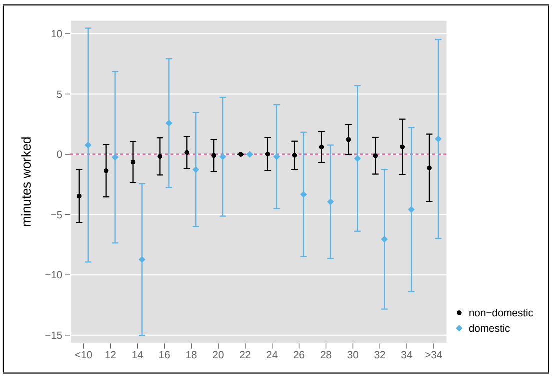


(h) precipitation

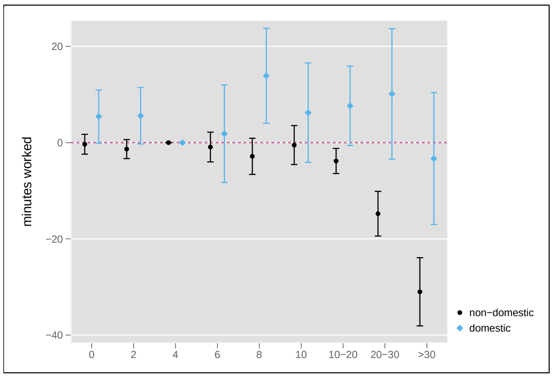


domestic vs non-domestic

(i) temperature



(j) precipitation



Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] °C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

earnings are stronger for the rural labour market which employs the majority of weather-exposed workers. Zero-rainfall days raise earnings of outdoor workers by 8.27%, resembling earlier findings for the agricultural sector. Similarly, domestic workers benefit from dry days, with a small increase in earnings, despite shorter working times. This increase in earnings likely stems from a rise in customer demand for domestically produced products considering that 60% of domestic workers are employed in service industries. Considering the positive effect of heat on working times of office workers, the small rise in earnings on days with temperatures between 32°and 34°C for this type of worker indicates the existence of work-leisure substitution effects and the remuneration of overtime.

2.6.4 Employment Characteristics

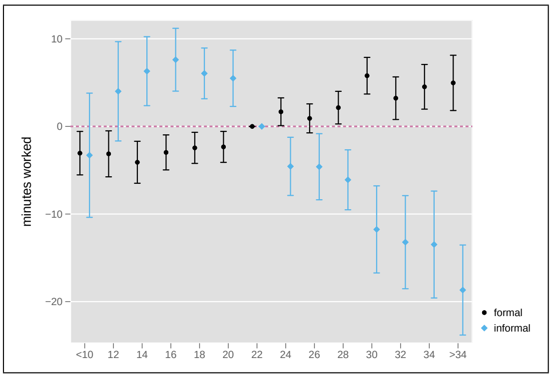
From a policy perspective, it is important to identify potential distributional welfare consequences of weather-driven labour-market changes. In this respect, I study differentials between protected and unprotected groups of workers, exploring heterogeneity by job formality, contact duration and earnings levels below the legally binding minimum wage. Results are presented in Figures 2.9 and 2.8. Negative heat-stress effects on minutes worked are limited to individuals working in unprotected employments (informal, temporary, non-union member and below-minimum-wage earners). As predicted by the model, heat days have a prolonging effect on working times of formal workers (low risk). I predict the largest heat-stress effect for informal workers with a work-time decline of 19 min on days with temperatures above 34°C (−4.33%). Moreover, adverse precipitation effects are considerably larger for unprotected workers. On days with precipitation exceeding 30 mm, working times of informal workers fall by around an hour (13.64%), whereas formal workers are unaffected.

Similarly, the marginal effects in Table 2.9 reveal nontrivial earnings losses for individuals working in unprotected work environments. Informal workers experience a significant drop in earnings of up to 16.62 pesos (11.01%) on days with temperatures exceeding 22°C or precipitation above 10 mm. Similar impacts are observed for temporary workers and non-union members. Workers in vulnerable work environments are primarily employed in the trade, construction, manufacturing and nonfinancial service industries. As such, they are either directly affected by weather or indirectly through changes in product demand. I observe the largest relative earnings loss for labourers with hourly earnings falling be-

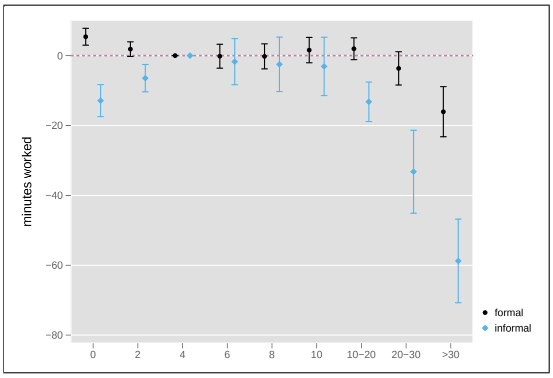
Figure 2.8: Job Characteristics Marginal Effects on Working Time

formal vs informal

(a) temperature

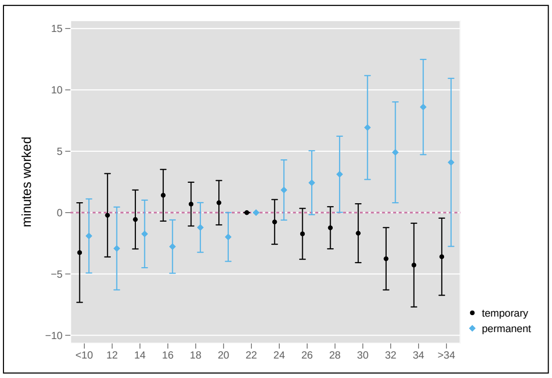


(b) precipitation

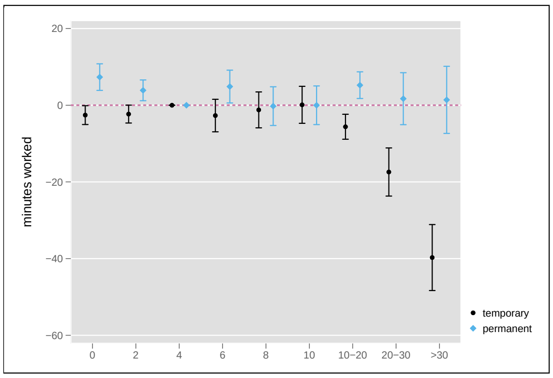


permanent vs temporary

(c) temperature

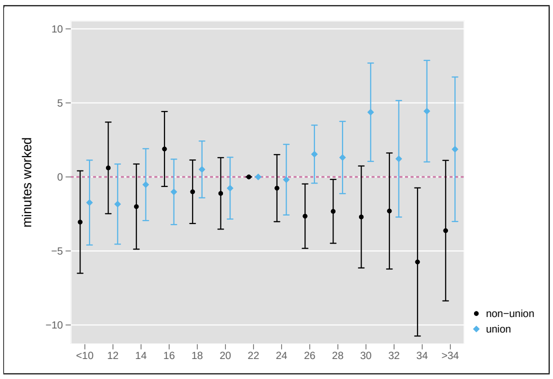


(d) precipitation



union vs non-union

(e) temperature



(f) precipitation

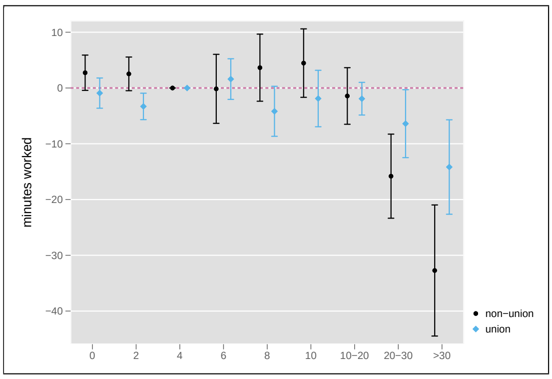
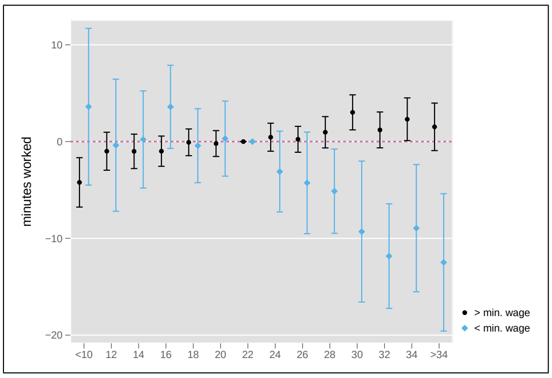


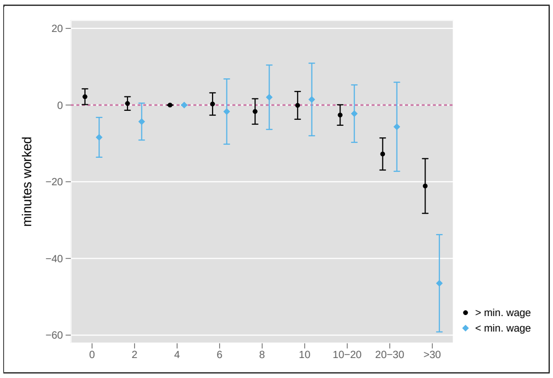
Figure 2.8: Job Characteristics Marginal Effects on Working Time *(continued)*

above vs below official minimum wage

(g) temperature

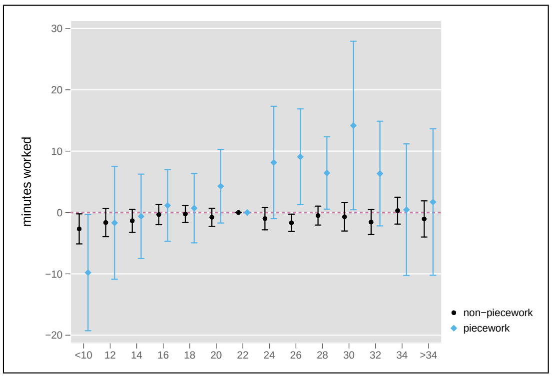


(h) precipitation

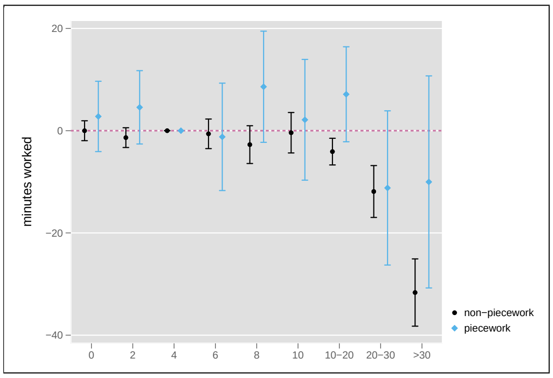


piecework vs non-piecework

(i) temperature

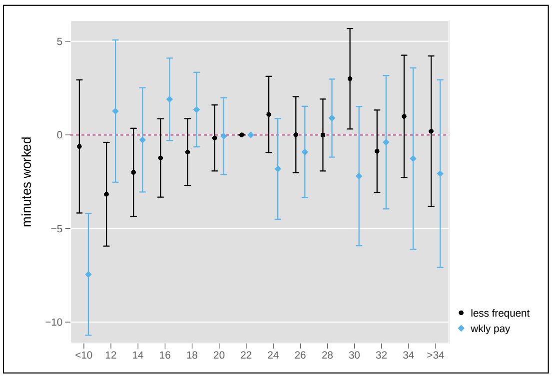


(j) precipitation

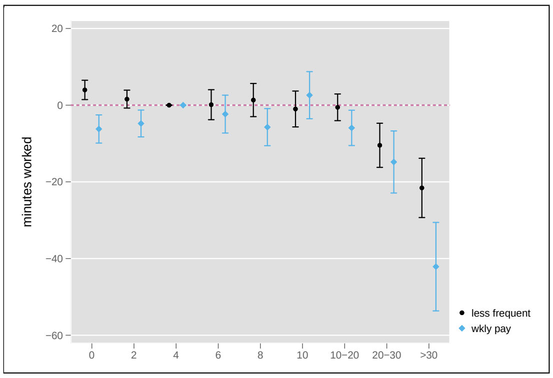


weekly vs less frequent pay

(k) temperature



(l) precipitation



Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] °C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

low the official minimum wage, employed mainly in agriculture, manufacturing and trade. Days with temperatures exceeding 34°C or with rainfall exceeding 30 mm reduce daily earnings of below-minimum-wage earners by more than 50%. These findings raise concern about distributional welfare implications of weather impacts on labour markets, considering that predominantly poor workers are employed in unprotected work environments. As such, it is important to understand who's earnings are affected.

2.6.5 Wage Rigidity and Weather Impacts on Earnings

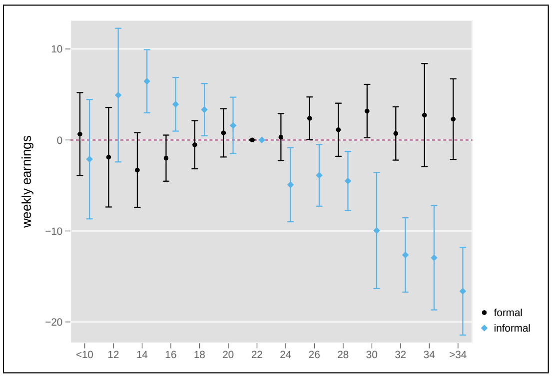
Well-documented short-run wage rigidities may limit the flexibility of earnings to adjust to temperature-induced productivity changes (Castellanos et al. 2004; Crawford 2001; Dwyer, Leong et al. 2000; Kahn 1997; McLaughlin 1994). I exploit information on payment frequency to identify workers with piece-rate contracts and those receiving weekly payments, compared to salaried workers with fixed-payment contracts. Notably, industries with significant earnings responses have relatively large shares of workers with earnings paid on a weekly or more frequent basis (construction 80.9%, diverse services 73.6%, manufacturing 68.4%, restaurant services 61.2% and transport 60.5%). As predicted by the model, negative temperature and precipitation effects on earnings are limited to workers with flexible-payment contracts. At the same time, the results suggest that heat has a positive impact on earnings for salaried employees (i.e. non-piecework and less frequent payment contracts in Figure 2.9). In terms of the model, this suggests that salaried (low risk) employees substitute work time for leisure on adverse weather days. The increase in labour supply leads to an increase of earnings due to remuneration of overtime.

Interestingly, estimates in Figure 2.8 indicate no corresponding heat effect on working time for workers on flexible-earnings contracts (piece-work and weekly-payment contracts). However, negative cold and rainfall effects on working times are stronger for this type of worker, which indicates a reduction in labour demand and wages paid to workers with flexible-payment contracts on adverse-weather days. Interestingly, the negative impact of extreme rainfall on working times is largest for workers with flexible weekly earnings, while the effect on working times of those paid by number of units produced is insignificant despite losses in earnings. This suggests that employees on piecework contracts are unable to mitigate adverse labour-productivity effects by adjusting working times during adverse-

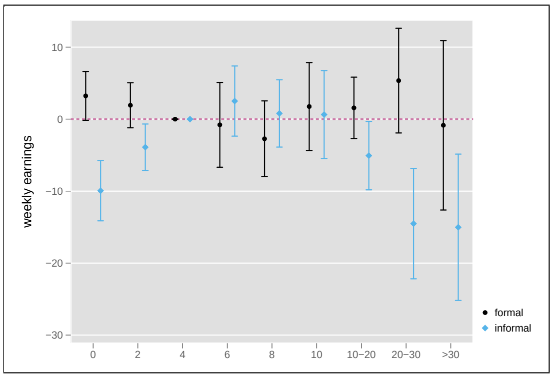
Figure 2.9: Job Characteristics Marginal Effects on Earnings

formal vs informal

(a) temperature

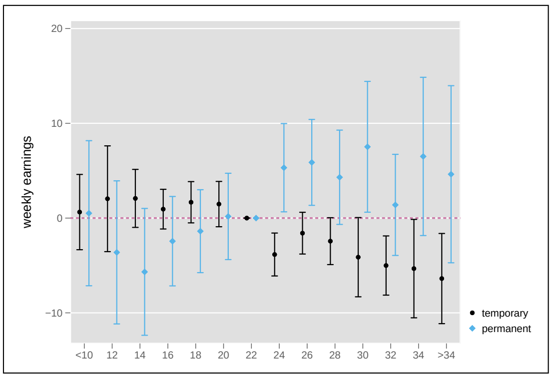


(b) precipitation

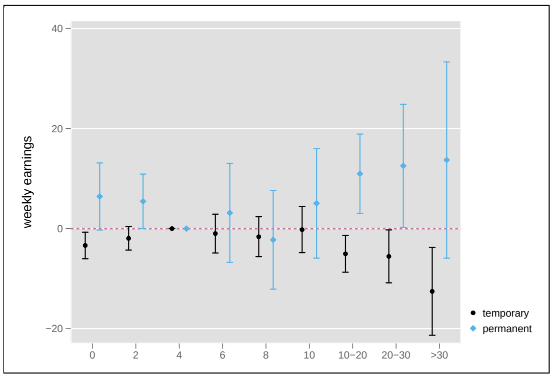


permanent vs temporary

(c) temperature

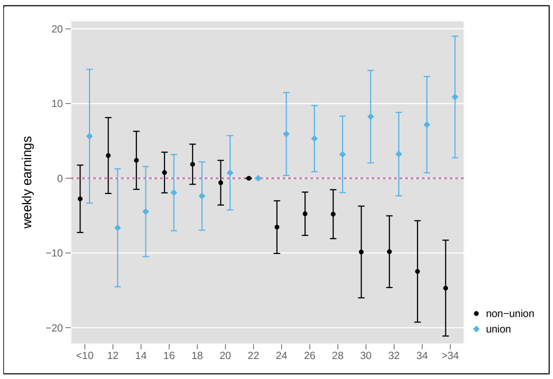


(d) precipitation



union vs non-union

(e) temperature



(f) precipitation

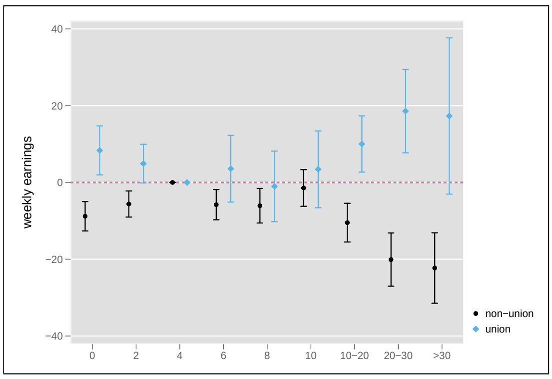
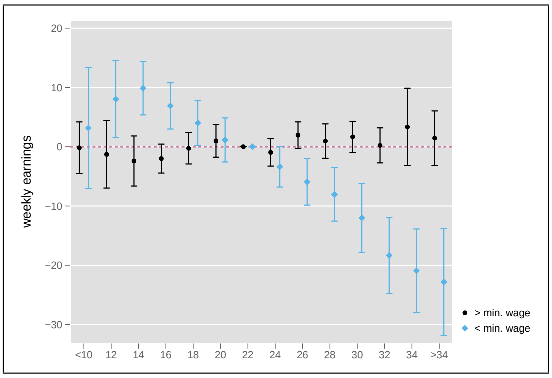


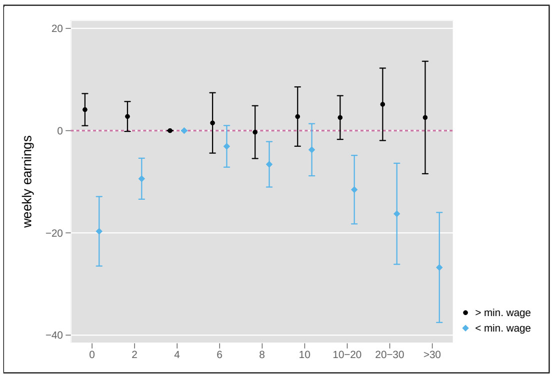
Figure 2.9: Job Characteristics Marginal Effects on Earnings *(continued)*

above vs below official minimum wage

(g) temperature

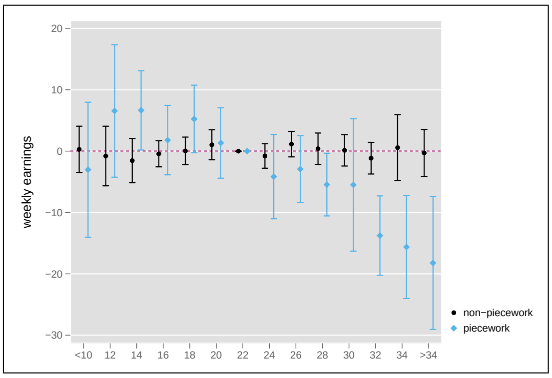


(h) precipitation

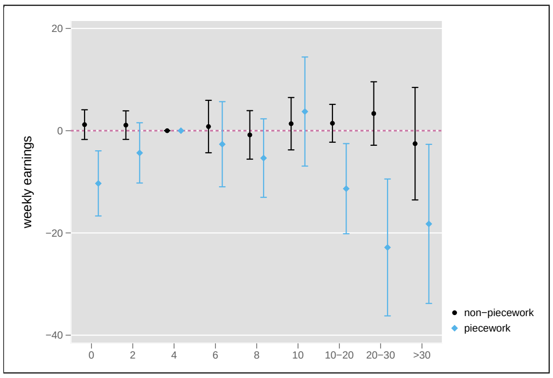


piecework vs non-piecework

(i) temperature

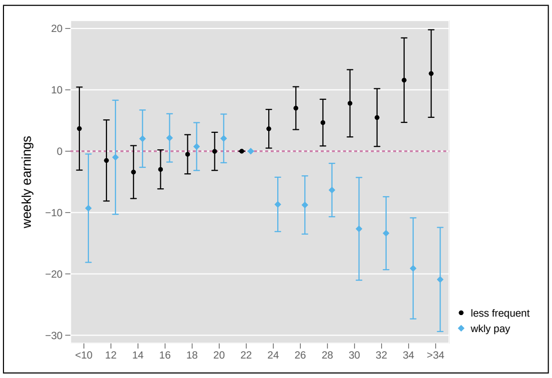


(j) precipitation

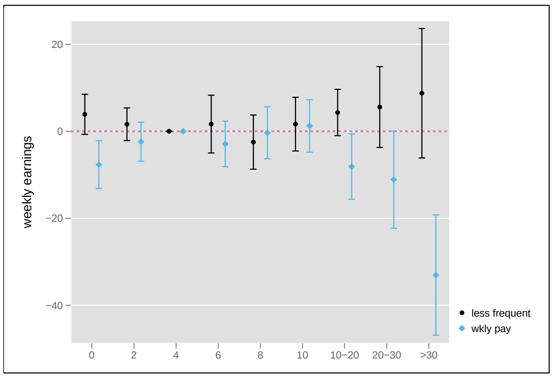


weekly vs less frequent pay

(k) temperature



(l) precipitation



Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly earnings (in 2010 pesos). The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] °C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

weather days.[39]

2.6.6 Individual Characteristics

The human-biology literature reports significant gender and age differences in the body's ability to cope with temperature stress. Together with unequal employment selection by different demographic groups, particularly into vulnerable and weather-exposed working environments, I expect potential significant demographic differentials in weather impacts. Figures 2.10 and 2.11 present estimates by gender, age and education level. In line with scientific evidence, heat stress causes significant declines in working times of women and elderly workers. In contrast, days with temperatures below 10°C only significantly alter working times of male workers and those aged 14 to 49, with the cold effect reversing direction at the age of 29 (from positive to negative). Given the lower employment share of women in weather-exposed occupations, female working times unsurprisingly are less sensitive to extreme-rainfall days. Estimates by level of education demonstrate a reversal of heat-related working-time adjustments from a reduction to a prolonging effect for education levels beyond secondary education, while rainfall effects disappear for more highly educated individuals.

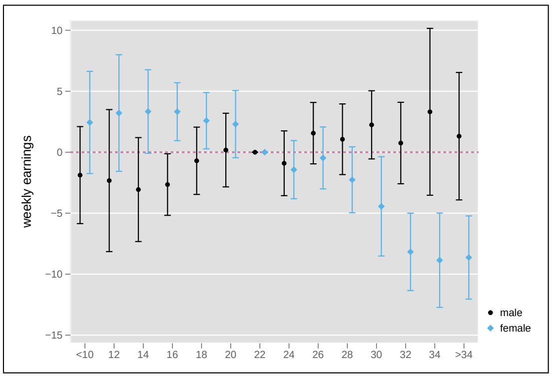
Regarding earnings, estimates in Figure 2.10 further stress the distributional dimensions of weather impacts, with women, the young and the least educated being disproportionately affected by adverse weather conditions. Female earnings fall by 16.81 pesos (10.11%) and 8.64 pesos (5.19%) on extreme rainfall and heat days, whereas earnings of men are unaffected except for a small positive effect of zero-rainfall days. Women are primarily employed in manufacturing and service-oriented industries, with female workers having twice as frequent direct customer contact, compared to their male counterpart (40.3% versus 21.1%). Hence, besides biological differences in temperature sensitivity, female earnings might be more responsive to weather-related customer-demand changes. Moreover, women carry out a greater share of care responsibilities and domestic tasks, which may prevent recovery from heat strain during non-working hours, resulting in greater tiredness and other symptoms of heat exhaustion during the next working day (Pogačar et al. 2018). Similarly, the share of women paid on a pro rata basis is significantly larger.

39. These results are in line with findings for blueberry pickers on piece-rate contracts in California, who's productivity drops significantly at temperatures above 25°C and below 15°C, whereas labour supply remains unaffected (Stevens 2017).

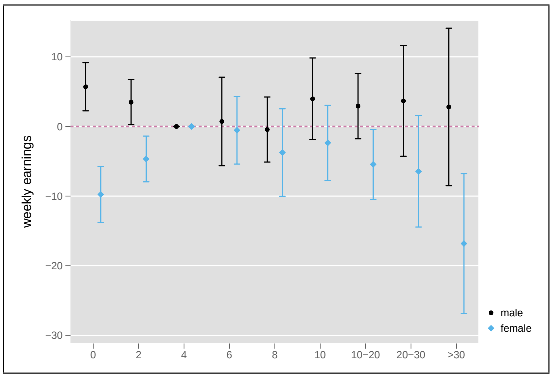
Figure 2.10: Individual Characteristics Marginal Effects on Earnings

male vs female

(a) temperature

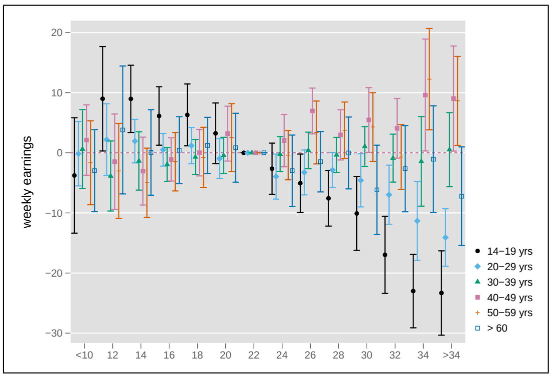


(b) precipitation

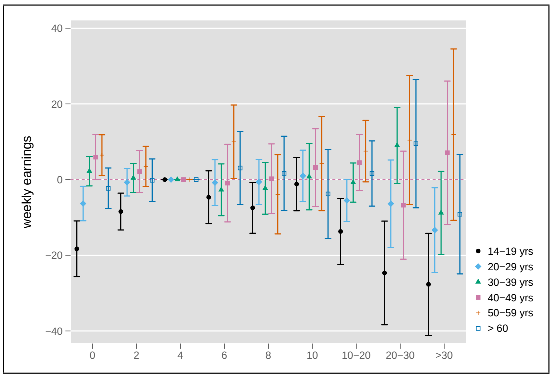


by age group

(c) temperature

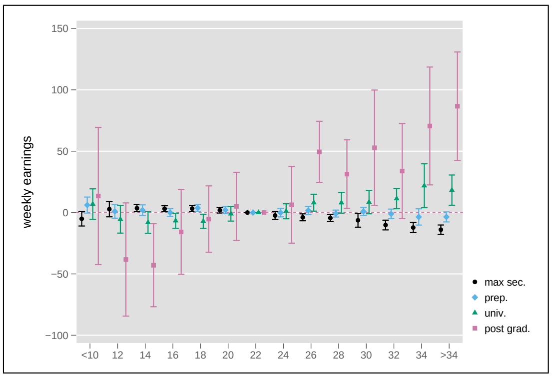


(d) precipitation

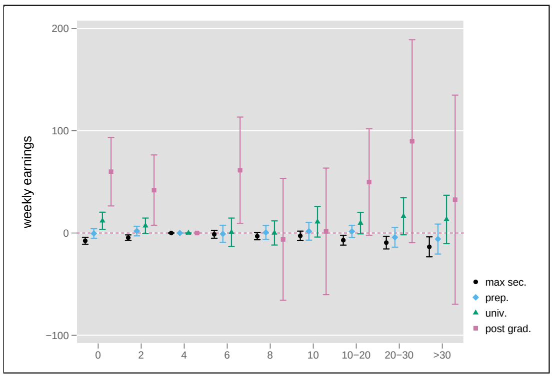


by education

(e) temperature



(f) precipitation



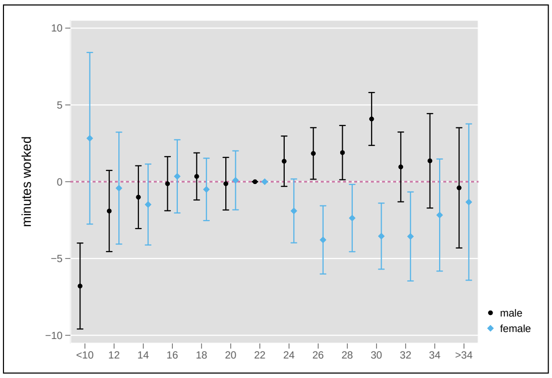
Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly earnings (in 2010 pesos). The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] °C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Hence, the loss in earnings and the reduction in working times is likely the consequence of a combination of a negative wage effect due to reduced labour productivity and the direct impact of heat exposure.

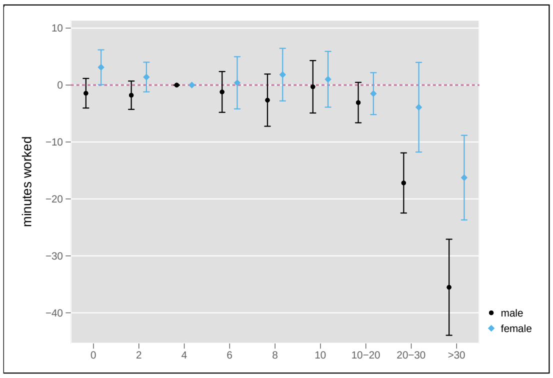
Figure 2.11: Individual Characteristics Marginal Effects on Working Time

male vs female

(a) temperature

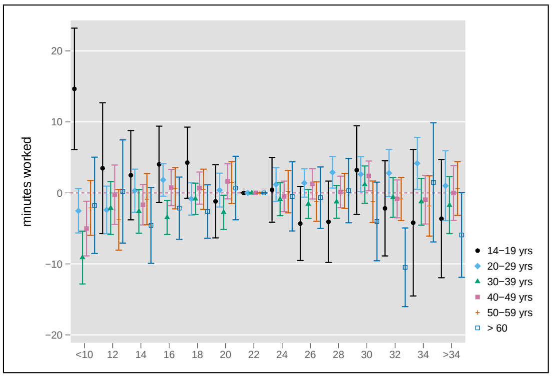


(b) precipitation

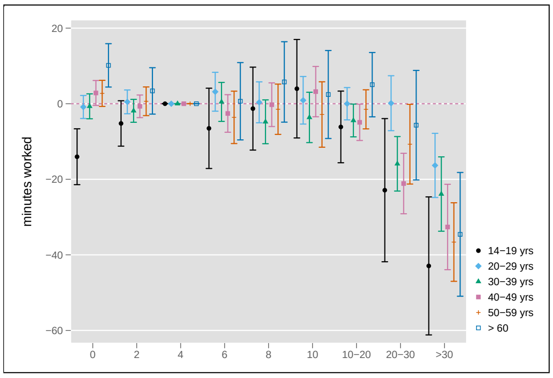


by age group

(c) temperature

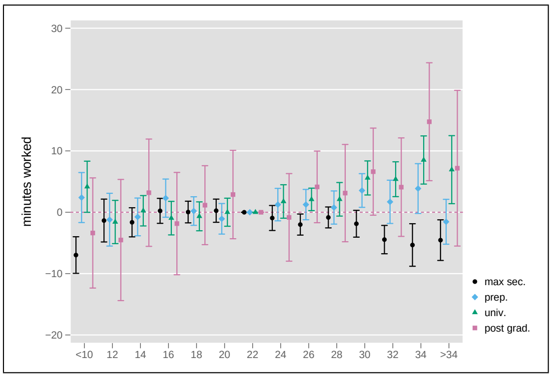


(d) precipitation

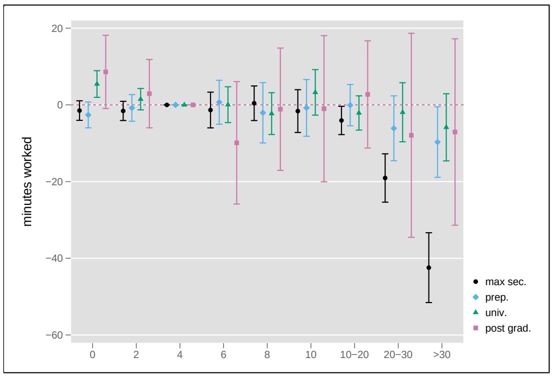


by education

(e) temperature



(f) precipitation



Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] °C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

2.6.7 Counterfactual Cost Estimate

The final set of results consists of a counterfactual analysis intended to provide a rough estimate of the annual cost associated with the above weather impacts.[40] A better understanding of the total costs implied by weather-induced working time and earnings fluctuations to the Mexican economy provides valuable information to policymakers. Such numerical figures allow cost-benefit comparisons with potential policy interventions protecting workers from adverse impacts, such as mandatory insurance policies. Nonetheless, it is important to stress at this point that any figures provided in this section are crude back-of-the-envelope estimates as the calculation is based on a highly abstract counterfactual scenario. Consequently, the results presented here should be considered as an indication of the importance of labour market impacts for the Mexican economy rather than absolute values.

I calculate weather-driven annual changes in earnings and working times in 2016 using the information on the total number of days per weather bin in 2016 and the coefficient estimates from the previous regressions. I compare these cost estimates with the potential annual earnings and working times, assuming a counterfactual scenario with year-round temperatures of 20-22°C and 2-4 mm precipitation. Estimated reductions in earnings provide an indicative monetary valuation of the annual costs of weather impacts to employees, while working-time losses represent costs to employers.

Three important conclusions can be drawn from the cost estimates (see Appendix A.10 for the results). First, average effects are relatively small. Annual weather-related losses in working times amount to 1 million days in 2016 (around -0.037% of total annual potential working days), of which half is lost due to temperatures below 10°C. The predicted annual temperature-related losses in earnings total 3.5 billion pesos (-0.175% or approximately US\$279.9 million). Slightly lower are the cost estimates for rainfall impacts. Estimated changes in earnings caused by rainfall fluctuations total just 571.8 million pesos (-0.029% or \$46.2 million), despite zero-precipitation days costing more than 1.75 billion pesos (-0.088% or approximately \$141.5 million).

40. This section is the result of the fruitful discussion with Olivier Deschênes and other participants at the 6th IZA Workshop on Environment and Labour Markets. One key result of the workshop was that research in this field should aim to provide numerical measures of the economic costs as an orientation for policymakers.

Second, the largest accumulated annual weather-driven cost is estimated for bins with small marginal effects but a high annual frequency of days in the corresponding temperature and precipitation range. For example, zero-rainfall days cost almost 2 billion pesos in annual earnings, while the loss in earnings due to extreme-rainfall days (> 10 mm) amounts to 1 billion pesos. Accordingly, the accumulation of minor daily weather impacts can result in considerable medium- and long-term losses in earnings and working times.

Third, the findings reveal considerable earnings losses for the most vulnerable part of the labour force. Again, the largest relative reduction in potential earnings and working times is predicted for below-minimum-wage earners—up to 2% for working times and over 50% for earnings.[41] From the industry estimates one can infer that the largest absolute temperature-driven earnings losses are incurred in the nonfinancial service industry, and the agricultural and construction sector. However, in relative terms, temperatures fluctuations have the largest (positive) impact on earnings in the extractive industry, despite the smaller share of workers being employed by the sector. This again highlights the importance of compensation schemes in motivating employees to work in adverse weather conditions.

Projecting a future two-degree temperature (°C) increase over the previous set of estimates, predicted economy-wide annual heat-related (>30°C) earnings losses increase by roughly 0.02%, with a similar total effect. The lower number of cold days, however, has a small positive effect on the total hours lost due to extreme temperatures (see Tables A.10.9 and A.10.10 in Appendix A.10). The heterogeneous estimates highlight the distributional aspects of climate change impacts with disproportionate increases in costs for the most vulnerable. For example, I predict an additional income loss for workers with earnings falling below the official minimum wage rate of around 4%, whereas total earnings of permanent workers at the same time rise due to reimbursement of overtime.

Evidently, these cost predictions must be considered with extreme caution. Not only is the counterfactual scenario far from reality (constant temperatures and rainfall), but the estimation also does not allow for substitution of labour across working weeks (aside from effects captured by sector-specific temporal fixed effects). Moreover, the calculation does

41. Considering the large temporal variation in earnings for workers in this income group, counterfactual earnings are estimated with a large uncertainty. Consequently, the estimate of 50% is likely overestimated. However, the result demonstrates the large uncertainty surrounding weather-induced earnings fluctuations for low-income earners.

not account for holidays or sick leave. A further limitation is the assumption of homogeneity in individual responses to weather impacts and the lack of job-switches or changes in employment characteristics within a quarter. Nevertheless, the results show that minor daily effects can potentially accumulate to substantial annual costs if encountered frequently. Without any adaptation and mitigation, both a higher frequency of extreme events and the higher intensity of weather events would imply a surge in the economic costs associated with weather-driven changes in the Mexican labour market. Furthermore, the predictions emphasise the distributional implications of global warming on labour markets, which should be taken into consideration by policymakers, with low-income workers being disproportionately affected by adverse weather.

2.7 Robustness Checks

In this section, I implement several specification checks to test the structural validity of the key findings.

Alternative Cluster and Fixed-Effects Specification

I find the main results to be robust to more complex two-dimensional clustering at the regional and panel level (see estimates with alternative cluster specifications in Appendix A.12). Second, the estimates are robust to the inclusion of time trends in lieu of fixed effects (see Appendix A.11 for results), suggesting that the higher-dimensional fixed effects adequately control for seasonal time correlation.

One concern with the municipality-level fixed-effects specification is potential individual selection bias driving the results. Workers sensitive to adverse temperatures may select into employment in climate-controlled environments, causing a downward bias in estimates. Ideally, one would like to apply an individual fixed-effects specification to control for confounding factors at the worker level. Applying this specification, I observe significant differences between subsample estimates and the previous results. For example, after controlling for individual unobservables, temperatures above 34°C significantly reduce outdoor working times. Likewise, adverse rainfall and heat effects on unprotected workers are noticeably smaller. In addition, contrary to the findings in the previous section, heat and extreme-rainfall days have a positive effect on earnings for most industries.

These contradictory findings may result from individual fixed effects removing a sizeable portion of the variation in individuals' exposure and sensitivity to weather, thereby prohibiting inference of impacts on labour-market segments with limited within-group variation.[42] For example, individual fixed effects control for individual- and job-specific characteristics, which are shown to be important drivers of weather-sensitivity. Similarly, industry-specific municipality fixed effects control for geographical differences in the industry's exposure and preparedness to cope with weather shocks. While one cannot rule out individual selection bias, the contradicting results under an individual fixed-effects specification may arise purely from construction. More frequent panel survey data with large within-individual weather variation can help overcome the trade-off between controlling for individual selection bias and identification of heterogeneous effects.

Subsample Regressions

In addition to modelling interaction effects, I estimate subsample regressions for the variables of interest. Results presented in Appendix A.8 are largely consistent with estimates presented in the previous section. Similar to individual fixed effects, I observe a loss in precision, in particular for the industry regressions. Again, industry-specific municipality fixed effects remove much of the within-sector variation in weather exposure and readiness to cope with weather fluctuations, causing weather effects to disappear in industry-specific regressions.

Alternative Temperature Measures

Following the literature, I further test whether alternative measures of apparent temperature are better predictors of heat impacts. Apparent temperature composites have the advantage of taking into account humidity and provide a better estimate of the temperature effect on the human body. Alternative measures applied as a robustness check are the HI and the WBGT. The calculation used for construction of both apparent temperature measures and the main results are provided in Appendices A.7.1 and A.7.2. Note that the two new measures yield noticeably different distributions of days per bin, compared to the original mean temperature measure. Studying the distribution of the HI bins reveals

42. As discussed in Appendix A.6, individual fixed effects remove a sizeable portion of weather-bin variation.

a large spike in days with temperatures above 34°C. Moreover, there is a small increase in the average number of days below 10°C. In contrast, the WBGT indicates fewer days with temperatures above 22°C, with significantly more days in the lowest bin.

Estimates based on the HI are very similar to the baseline temperature predictions. Cold effects are slightly stronger, while heat effects on average are smaller. The WBGT estimates again are comparable to the baseline temperature estimates, although I observe minor changes in the size of predicted heat impacts (See Appendix A.7.2). The WBGT estimates seem to do better at capturing effects at the top end of the distribution, while the HI is a stronger predictor of cold effects. However, discrepancies in effects are to a large extent explained by differences in the distributions of days per bin across the alternative temperature measures. Overall, the gains from using the more complex temperature measurements seem to be minimal in the case of Mexico. Considering the negligible differences in estimates, I chose to present results using mean temperatures in the main analysis, as the specification provides a readily interpretable unit of measurement for policymakers.

Temporal Aggregation of Weather Variables

As briefly touched upon in the data section, estimated weather impacts are likely sensitive to the temporal aggregation of the climate variables. Provided that wages are rigid in the medium term, one would expect earnings of salaried workers to respond to weather changes with some delay. Salaries may only be affected by prolonged heat waves or extreme-rainfall periods. To test for medium-term impacts, the regressions are re-estimated using weather variables aggregated over one month and three months before the survey reference date (Appendix A.13). Overall, the new regressions exhibit very similar impacts despite some loss in precision and effect size as the measurement period increases. Overall, the findings suggest that temperature has a sustained medium-term impact, while rainfall affects earnings and working times only in the short term. Examining industry differences using the alternative temporal specifications yields robust estimates for all but the transport sector, where the negative extreme cold effects with prolonged time periods turn significant. Moreover, low temperatures in the recent past (one and three months) are predicted to increase current working times of agricultural workers. The results suggest that workers in the agricultural (transport) industry mitigate negative weather impacts by shifting working time from days with adverse (comfortable) weather to those with more comfortable (adverse) working conditions.

Short-Term Substitution Effects

Given the previous findings, I test for unobserved working time substitution outside the reference week, offsetting short-term impacts. To do so, I add lagged weather bins to the regression. Results are presented in Appendix A.14. Average municipality effects indicate a lasting effect of extreme-rainfall and heat days on working time beyond the reference week, with no effect on earnings. The lagged industry-specific marginal effects indicate some short-term substitution of working time in response to heat days among agricultural workers, but the effects are insignificant. More interesting are the results for the trade sector, where heat days in the previous week significantly increase working time in the next week, while heat during the reference week has the opposite effect. This finding further supports the notion of working-time fluctuations in the trade sector being primarily caused by weather-related short-term fluctuations in customer demand. A study by Starr-McCluer (2000) shows that adverse weather leads to a postponement of purchasing decisions but causes no long-term losses in retail demand. Exploring substitution effects by job characteristics, I find union workers to shift working times across weeks in response to adverse temperatures, while non-union members show no such behaviour. Hence, union membership seems to provide protection against adverse-weather effects or the flexibility to substitute working time for leisure to optimise utility in light of adverse weather effects.

Long-Term Adaptation Effects

Aside from substitution effects, I am interested in identifying potential adaptation effects across Mexico. For this reason, I split the dataset into municipalities with temperatures below and above the historical Mexican average temperature of 24.94°C. As expected, coefficient plots in Appendix A.15 reveal that heat (cold) effects on earnings and working times are stronger in areas with colder (warmer) historical mean temperature. The results hint at industries adapting to some extend to the local climatic conditions to reduce the negative impacts of heat and cold shocks.[43] However, the differences are predominantly

43. Evidently, this is a crude differentiation of climate zones that might mask adaptation beyond simple temperature effects. However, studying adaptation effects to temperature, Park and Behrer (2016) find averages to yield similar results to more complex classifications by heat days. Nevertheless, splitting regions

insignificant.

Municipality-Level Regressions

As a final robustness check, the dataset is collapsed to municipality level. The reduced sample size enables the use of daily, as opposed to weekly, weather bins. Accordingly, the dependent variables change to total minutes worked per day and daily earnings, calculated as weekly earnings divided by the number of days worked in the reference week.[44] A disadvantage of using aggregate data is potential information-aggregation bias through the loss of heterogeneous variation provided on the individual level.[45] Hence, the municipality level results should be interpreted with caution.

Several notable observations can be made about the municipal estimates presented in Appendix A.16. Different from the individual-level regressions, days with temperatures exceeding 28°C cause a small negative reduction in average daily municipality earnings (see Figure A.16.1). Moreover, the effect of heavy rainfall on working times decreases to a seven-minute reduction on days with precipitation exceeding 30 mm (Figure A.16.2). Thus, using daily as opposed to weekly working time data seems to provide a more precise measure of extreme temperature effects, while failing to capture prolonged extreme rainfall effects beyond the working day. However, results based on interaction effects between weather bins and job characteristics reaffirm earlier findings of significant heterogeneity in effects.

To conclude this section, the main results are shown to be robust to all but the individual-level fixed-effects specification, where the lack of within-individual variation in weather may preclude identification of impacts. Given the largely consistent results, the robustness checks substantiate the finding of both temperature- and rainfall-driven fluctuations in working times and earnings in Mexican labour markets.

by climatic zones may yield stronger adaptation effects.

44. This approximation likely introduces measurement error causing an attenuation bias in the earnings results.

45. See Goodfriend (1992) and more recent Blundell and Stoker (2005) for a discussion of information-aggregation bias.

2.8 Discussion and Conclusion

In this chapter, individual-level information taken from the Mexican labour-force survey is combined with a fine-scale weekly weather dataset to investigate the impact of day-to-day weather changes on weekly earnings and working times in Mexico. The results suggest the sensitivity of labour markets to both daily temperatures and rainfall changes. Unusually high levels of rainfall significantly reduce hours worked throughout the economy. During days with precipitation exceeding 30 mm, the average working time across the economy drops by half an hour. Responses to daily changes in temperatures are more complex. Contrary to findings for the U.S. (Graff Zivin and Neidell 2014), the results presented here suggest no average impacts of heat on the economy, while working times drop by just three minutes on days with temperatures below 10°C. To better understand the mechanisms behind contrasting temperature results, interaction effects are exploited to examine heterogeneity in weather impacts. The results provide suggestive evidence that individual and job-specific characteristics play an essential role in determining workers' sensitivity to temperature and precipitation impacts.

Similar to Connolly (2008) and Graff Zivin and Neidell (2014), I identify a strong link between weather-driven working-time fluctuations and direct rainfall and temperature exposure. On days with precipitation exceeding 30 mm, working times of weather-exposed workers drop by more than one hour (e.g. agriculture, construction and trade). Sectoral estimates further depict minor heat-related working-time reductions for the manufacturing sector on heat days, with a corresponding minor decline in earnings. This result emphasises the often inadequate industrial ventilation and air conditioning in Mexican factories. Effective climate control is an important instrument for preventing heat stress of physically active workers. Without appropriate ventilation, indoor factory temperatures can rise to unhealthy levels due to a combination of high external temperatures, waste heat from machinery and heat strain from physical work.

A further intriguing finding of this study is sizeable heat-related earnings increases in the extractive industry, indicating the existence of temperature-related compensation schemes in the sector (Rosen 2002). Workers in Mexico's mining industry are known to be particularly vulnerable to heat stress (Trabajo y Previsión Social 2017). High external temperatures raise underground temperatures in mines to life-threatening levels. Meanwhile, surface miners are directly exposed to the sun and heat.

An important revelation of this study is the estimation of nontrivial earnings losses for individuals working in unprotected work environments. Particularly informal workers, those in temporary employment contracts, or with flexible incomes are vulnerable to earnings fluctuations caused by adverse weather. The result, while suggestive, reaffirms the distributional dimension of weather impacts on labour markets. The distributional consequences of weather effects should be taken into consideration in the design of climate-change mitigation and adaptation policies.

The final contribution is the provision of a rough cost estimate to establish the magnitude and the welfare implications of weather-driven labour-market changes. These estimates helps to inform the climate-change policy debate by quantifying the costs of day-to-day weather impacts on earnings and working times. Using a counterfactual analysis, I estimate that heat-related earnings losses in 2016 amount to 0.2% of potential earnings, while annual working times throughout the Mexican economy are reduced by roughly 0.02% by days with temperatures above 30°C. Cold days alone account for a reduction by around 0.04%, which is offset partly by longer working times on warmer days.

The cost calculations further underline the economically meaningful losses in earnings for the most vulnerable part of the labour force. For instance, below-minimum-wage earners lose about 30% of potential annual income due to days with temperatures exceeding 22°C. Heavy-rainfall days with precipitation exceeding 10 mm reduce potential yearly earnings of informal workers by 0.62%.

Projecting a future two-degree temperature (°C) increase over the estimates raises predicted heat-related (>30°C) earnings losses by roughly 0.02%. However, the lower frequency of cold days has a positive effect on total annual working time. Again, some workers will be affected disproportionately by climate change. For those with earnings falling below the official minimum wage rate, a two-degree temperature rise is estimated to cause an additional heat-related income loss of approximately 10%, thus totalling earnings losses due to high temperatures to 43% for these workers.

Considering the crude assumptions underlying the estimation,[46] the above cost estim-

46. 1. Counterfactual of all-year-round constant temperatures of 20-22°C and precipitation levels of 2-4

ates should be considered with caution. Estimated impacts of day-to-day weather changes on earnings and working times should not be generalised for the expected changes caused by global warming. Adaptation and long-term changes to the labour market will mitigate future negative impacts. Changes in the structure of labour markets, such as industry employment shares, are likely to alter the importance of weather effects in the future. Therefore, an interesting line of research arising from the present study is the scope for adaptation of the Mexican labour market to future weather extremes.

Despite the inaccuracy in estimates, the cost estimates highlight current labour-market policy shortcomings. In light of the projected increase in the frequency of extreme weather event, we can learn from current cost estimates that labour-market reforms aimed at mitigating the adverse impacts of future extreme weather on workers should focus on protecting those in informal working environments. Particularly earnings of poor workers seem vulnerable to weather impacts. Hence, in terms of climate policy, preventing an increase of temperatures and the frequency of extreme events will likely protect low-income households from an increase in earnings uncertainty.

A further question which remains of interest is the identification of demand-side effects and the role of worker's health in driving results. However, the question could not be answered to full satisfaction given the lack of firm-level data and information on individuals' health. This lack of information prohibits the differentiation between demand- and supply-side effects and the causal identification of the root causes for observed changes in earnings and working times. Ideally, future research on the topic should combine firm- and work-level data to overcome the issues faced in this chapter. A better knowledge of demand-side effects and the role of physiological factors would allow for improved targeting of policies to those most vulnerable to weather shocks, rather than those with the flexibility to adapt to weather extremes.

The potential ramifications of the findings are diverse. The results demonstrate adverse effects on weather-exposed and physically active occupations. Adequate investment in insulation and air conditioning, especially for manual labour-intensive industries such as mining and manufacturing, are potential solutions to combat the negative impacts of extreme-

mm. 2. The lack of holidays or sick-leave in the estimation. 3. No job-switches or changes in employment characteristics within the quarter. 4. No heterogeneity in individual responses to adverse weather. 5. No substitution effects across time.

temperature events for these sectors. Moreover, poor households are primarily employed in weather-affected occupations and, as such, are more vulnerable to temperature and rainfall-driven income losses. Increasingly volatile weather caused by climate change will further exacerbate adverse welfare consequences, with wide-ranging adverse consequences from health, reduction in human capital and inter-generational poverty (Daoud et al. 2016; Guha-Sapir et al. 2013). Therefore, climate-change adaptation policies for the Mexican labour market should prioritise reducing impacts for the least protected workers. Provision of adequate jobs for vulnerable labourers and the development of effective labour-market policies, such as job security and risk-management strategies for weather-related uncertainties, are needed to protect workers from the negative impacts of adverse temperatures and rainfall.

Chapter 3

Clinal Heterogeneity in Climate Preferences:

A Study of Bilateral U.S.-Mexican Migration

Abstract

The central objective of this chapter is to examine the influence of origin climate on migrants' preferences regarding destination climates. I apply a McFadden residential location-choice model to a novel dataset of international migration from Mexico to U.S. MSAs between 1970 and 2016. The unique dataset provides detailed geographical information on both origin and destination locations, which I exploit to test for systematic differences in climate preferences by origin climates. Controlling for economic and demographic destination characteristics, I find Mexican migrants to prefer settlement in MSAs with warmer average temperatures but colder summers (compared to their home location). Split-sample estimates for migrants from warmer and colder Mexican regions further suggest greater responsiveness of the utility for migrants from warmer origins to both average and extreme temperatures. The findings indicate that climate change is likely to alter the desirability of locations by changing both destination and origin climates. The findings have important implications for climate-change mitigation policies. The estimated clinal variation in climate preferences implies significant differences in individuals' WTP for the mitigation of climate change depending on the climate to which an individual is accustomed. Therefore, assuming preference homogeneity in amenity models may considerably bias the predicted WTP for climate-change mitigation.

3.1 Introduction

Recent developments in the field of climate-change mitigation policies have renewed the interest in the amenity value of climate as a numerical measure for the willingness of individuals to pay for climate-change mitigation. Starting in the late 1970s, a growing body of literature attempted to derive numerical estimates of the desirability of climate. The literature finds overwhelming support for a general attraction of individuals to friendlier, more moderate climate (warmer winter months with nonextreme summer months) (Albouy et al. 2016; Alperovich et al. 1977; Brown and Scott 2012; Graves 1976; Greenwood and Hunt 1989; Scott et al. 2005; Sinha et al. 2018; Sinha and Cropper 2013). The recent resurgence of research in the field arose in response to the need to provide more accurate measurements of WTP for comfortable climate. With uncertain wealth effects of global warming, amenity-value estimates provide useful measures of the WTP for climate-change mitigation. Compared with the costs of abatement policies, such calculations can help to inform the climate-change policy debate.

One concern with the existing research on the amenity value of climate, is the typical assumption of individual preference homogeneity with respect to climate. The human-biology literature provides substantive evidence of systematic differences in individuals' climate preferences both by demographic characteristics and an individual's acclimatisation to a certain climatic environment. As early as 1848, Bergmann generalised the correlation between climate and human morphology in ecogeographic rules (Bergmann 1848; Ruff 2002). Clinical tests provide comprehensive evidence on the existence of clinal differences in human-body adaptation to climate (Beall et al. 2012). These scientific findings are largely ignored by economic research on the amenity value of climate.[1]

If climate preferences are shaped by the climate to which an individual is accustomed, location-choice models should allow for taste variation by origin climates to reduce the otherwise potential bias in climate preferences. This chapter addresses this crucial and often overlooked assumption and examines the importance of clinal[2] heterogeneity in individuals' climate valuations. Exploiting information on migration movements from Mexican municipalities to MSAs in the U.S., I estimate a residential location-choice model with climate valuations varying by the migrants' origin climate.[3]

1. During a comprehensive review of the literature using the relevant research databases and library catalogues as well as back and forward tracing of related journal articles, only two studies by Scott et al. (2005) and Fan et al. (2012) where found to allow for heterogeneous differences in climate preferences by origin region.

2. The term *clinal* goes back to Sir Julian Huxley, a British evolutionary biologist (Huxley 1938). The human-biology literature uses the term *clinal* to refer to gradual change in a character or feature across the distributional range of a species or population, usually correlated with an environmental transition such as humidity, rainfall, and temperature. For example, it has been observed that pigmentation changes with distance from the equator, due to different levels of UV radiation. In this chapter, the term *clinal-preference heterogeneity* is used to indicate systematic differences in the valuation of climate over geographical variation in migrants' origin climates.

3. Given the focus on metropolitan areas, this implies that the empirical analysis examines preference

The empirical analysis draws upon a unique dataset linking migrants' origin climate to destination climates, which consists of a migration survey of the MMP (MMP 2017) combined with information on U.S. MSAs collected from the U.S. census and other official data sources. I use micro-level geographical information provided by the MMP on both migrants' origin and destination locations to identify the climate at the migrant's origin, thus, reducing measurement uncertainty in an individual's acclimatisation to a particular climate.

I estimate a McFadden's residential location-choice model (McFadden 1974), which includes a vector of differences in origin and destination climate. To address concerns about omitted variable bias and network effects, the model further controls for economic and demographic characteristics and the presence of migrant networks at each destination, recognising the multidimensionality of individuals' migration decisions. The approach taken here differs from previous studies by linking heterogeneous preferences for destination climate directly to measurable spatial differences in origin climate.

Findings presented in this chapter demonstrate the importance of accounting for heterogeneity in climate preferences. The results suggest that Mexican migrants prefer locating in MSAs with warmer average temperatures but colder summers, compared to their home municipality. Results from split-sample regressions for migrants from warmer and colder Mexican regions provide further support for clinal heterogeneity in climate preferences. The utility of migrants from warmer origins is estimated to be five times more responsive to both average and extreme temperatures, while the results indicate no differences in preferences for rainfall. Future changes in temperature and precipitation will affect the desirability of locations with potential long-term effects on the direction of migration streams. Moreover, observed clinal variation in climate preferences indicates considerable differences in individuals' WTP for climate-change mitigation. Assuming preference homogeneity in choice models may, therefore, bias the predicted WTP for abating climate change.

The remainder of this chapter is organised as follows: The next section provides a short review of the existing literature on climate preferences in Section 3.2, followed by a discussion of the McFadden residential location-choice model employed in the empirical

heterogeneity for migrants residing in urban areas.

analysis in Section 3.3. Section 3.4 describes the data sources used to compile the final dataset and explains the construction of the climate variables. Estimation results are presented in Section 3.5 with subsequent robustness checks. The chapter ends with a brief conclusion highlighting the implications of this chapter's findings for future research in the field.

3.2 Literature Review

Grounded in Lee's (1966) seminal study of the determinants of migration, researchers have been studying the influence of amenities on migrants' location decisions. Coming from urban economic theory, during the late 1970s, models were developed explicitly including climate as a push- or pull-factor of migration. Greenwood (1969) tested for the impact of temperatures on interstate U.S. migration between 1955 and 1960, finding that migrants preferentially move to hotter states. Graves (1976) improved upon Greenwood's research by analysing changes in more disaggregated census data on inter-MSA migration rates between 1960 and 1968. Profiting from greater precision in the climate variables, Graves finds below-zero-degrees Celsius temperature frequencies to be negatively correlated with net migration rates. Graves (1980) improves upon earlier research by including several climate regressors and splitting the census sample into different demographic groups. The author finds older individuals to prefer modest, constant temperatures in contrast to younger people, who are attracted by warmer temperatures.[4] A more recent study by Rappaport (2007) examines changes in U.S. county populations since the Second World War and finds evidence for increasing migration toward areas with on average warm winters and with cooler, less humid summers. Rappaport motivates his findings with a possible increased valuation of nice weather as a consumption amenity, probably due to broad-based rising per-capita income (Rappaport 2007, p. 375).

Several recent studies have attempted to measure the value of climate amenities following a traditional hedonic income approach. These studies compute the amenity value of climate—what people are willing to forgo for experiencing friendlier climate—by measuring the implicit price of destination amenities, which is estimated by exploiting the

4. Similar studies were conducted by Alperovich et al. (1977), Clark and Hunter (1992), Cushing (1987), Greenwood and Hunt (1989), Greenwood et al. (1991) and Mueser and Graves (1995), as well as Renas and Kumar (1983).

spatial distribution of characteristics and the revealed preferences of migrants for some places over others. Alternatively, Cragg and Kahn (1997) run a hedonic estimation of the implicit demand for climate based on observed interstate migration from the 1990 U.S. Integrated Public Use Microdata Series (IPUMS) sample. Assuming perfect within-state labour mobility, the authors test whether wages and housing prices compensate for the superior climate. Cragg and Kahn (1997) find individuals' marginal utility to be positively correlated with higher winter temperatures, while higher summer temperatures are negatively correlated.

A common problem with earlier studies is the failure to control for location-specific unobservables. Exclusion of location controls is likely to bias estimates for climate variables due to the inherent spatial correlation between climate and other local characteristics, such as the industrial composition of the local economy (e.g. the size of the local tourism sector). Recent technological improvements in the computational strength of statistical software packages, as well as more advanced estimation techniques, have given rise to improved studies on residential location choices allowing the inclusion of complex fixed effects and modelling preference heterogeneity. Albouy et al. (2016) estimate a hedonic model, regressing a vector of destination-specific characteristics, including climate, on a quality-of-life index by U.S. IPUMS. Again Albouy et al. (2016) confirm a preference of individuals for moderate temperatures.

Several studies allow for systematic differences in preferences by including interaction terms between location-specific variables and individual demographic characteristics (Brown and Scott 2012; Fan et al. 2012), or by estimating their migration model for separate demographic groups (Beine and Parsons 2015; Clark and Hunter 1992; Clark et al. 1996; Graves 1979, 1980). Brown and Scott (2012) predict a weaker impact of local climate amenities for highly educated Canadian labour migrants. A recent study by Sinha et al. (2018) finds significant age differences in the marginal willingness of U.S. intra-state migrants to pay for summer and winter temperatures. However, little evidence exists on clinal heterogeneity in climate preferences. The amenity-value literature has widely ignored the issue, the main reason being the lack of computational power or access to micro-level data providing location-specific information on the origin of migrants.

Studies by Scott et al. (2005) and Fan et al. (2012) are rare exceptions. Scott et al. (2005) allow individual preferences to vary by region of origin. The authors study the implications of differences in human capital on residential location choices by running separate regressions for different immigrant nationalities in the U.S. Their findings suggest individuals' preferences for destination climate differ by nationalities. Besides the broad climatic definition of origin climates by nationality, an additional drawback of Scott et al.'s (2005) study is the use of an arbitrary climate index, restricting the identification of heterogeneity in preferences to overall climate composition instead of specific climatic factors.

An alternative study allowing for heterogeneous climate preferences was conducted by Fan et al. (2012). The authors run a two-stage random utility sorting model to examine the relationship between temperature extremes and residential choice of different demographic groups for the 2000 IPUMS sample. In the regressions, Fan et al. (2012) include interaction terms between destination climate and the migrant's birthplace, categorised in U.S. macro-regions Northeast, West, South, and state of California. Fan et al. (2012) find that on average, individuals throughout the U.S. get disutility from extreme heat. However, the extent of disutility differs by U.S. region, with people born in the Western macro-region disliking extreme heat most.

Although both papers provide some first evidence for the existence of a relation between clinal preference heterogeneity and the location choice of migrants, both studies fall short providing a comprehensive explanation of these observed differences. The geographic dimension used by Scott et al. (2005) (nations) and Fan et al. (2012) (macro-regions) comprise a large variety of regional climates and, thus, are inadequate geographic units for identification of clinal climate-preference heterogeneity. Consequently, the relationship between origin climates and immigrants' preferences for destination climates has not yet been examined satisfactorily.

Unlike previous studies, this chapter exploits micro-level geographical origin information on Mexican migrants to the U.S. to examine clinal variation in climate preferences. My approach differs from Scott et al. (2005) and Fan et al. (2012) inasmuch as it links clinal differences in climate preferences directly to the spatial gradient in origin climates and, thus, to the human-biological explanation for heterogeneity in climate preferences.

3.3 Residential Location-Choice Model

The analysis relies upon the concept of random utility maximisation as the underlying decision rule of migrants in the residential location-choice model (Anas 1983; Anderson and Papageorgiou 1994; Ben-Akiva and Lerman 1985; Halperin and Gale 1984). Following McFadden (1974), the model considers rational, utility-maximising individuals faced with the choice over a finite, discrete set of alternative locations with location-specific attributes. Assuming uncertainty about alternative specific payoffs, at any given time individuals maximise the expected present value of the realised future payoffs for the full set of alternative locations subject to moving costs.[5] The model extends the McFadden's alternative-specific choice model (McFadden 1978), by including a climate vector consisting of climate differences between the migrants' origin and the destination location.

Consider a population of individuals $i = 1, \ldots, I$ with homogeneous preferences, choosing their optimal location among a set of locations, with U_{idot} being the utility for a migrant from origin location o moving to location d in time period t. U_{idot} can be written as:

$$\mathrm{U}_{idot} = V_{idot} - C_{idot}(.) + \varepsilon_{idot} \tag{3.1}$$

where V_{idot} is the observable, deterministic utility, C_{idot} denotes the migration cost of moving from origin location o to destination d (assumed to be constant across individuals), and ε_{idot} is a random error component accounting for the unobservable component of utility.

For a utility-maximising migrant V_{idot} depends on a linear combination of the destination-specific factors Z_{dt}, including controls for the presence of migrant networks, and differences in climate between origin and destination location A_{dot}. Assuming an IID Type I Extreme Value (Gumbel) distribution for the error term (McFadden 1974), the parameters of the above utility function are obtained through maximum likelihood estimation, where the

5. An implicit assumption of the model is full information about the quality of local amenities—including climate—and the moving costs to each destination. This is arguably a strong assumption. However, given the focus on climate valuations and the long history of migration between the Mexico and the U.S., I expect migrants to have on average enough information to rank locations by the attractiveness of their climate.

log-likelihood function is given by:

$$\ln L = \sum_{IDOT} H_{idot} \ln \frac{\exp[z'_{dt}\beta + a'_{dot}\delta - c'_{dot}\mu]}{\sum_{d=1}^{D} \exp[z'_{Dt}\beta + a'_{Dot}\delta - c'_{Dot}\mu]}, \tag{3.2}$$

where

$$\mathrm{H}_{idot} = \begin{Bmatrix} 1 & \text{if individual } i \text{ from origin } o \text{ chooses destination } d \text{ in time period } t \\ 0 & \text{otherwise.} \end{Bmatrix}$$

See Appendix B.1 for a discussion of the intermediary steps. Note that individual characteristics contained in ε_{idot} drop out, when taking the ratio of the exponentiated linear combinations. Therefore, individual characteristics can only enter the model through interaction effects with the destination-specific controls or fixed effects.

The universal choice set in this study consists of 321 U.S. MSAs. Considering the large number of alternatives in the dataset, estimating the above location-choice model over the full set of destinations is not computationally feasible.[6] Moreover, it would be undesirable, as such a model would be behaviourally unrealistic, as migrants unlikely consider the universal set of alternatives in their decision process (Fotheringham 1988). A solution for the computational problem is provided by McFadden (1978) and Ben-Akiva and Lerman (1985), who show that the choice set can be restricted under the assumption of an IID structure of the error term across alternatives. This assumption requires the model to fulfil the Independence from Irrelevant Alternatives (IIA) property, which necessitates individual choice probabilities for any two alternatives to remain unaffected (independent) by the inclusion or exclusion of any alternative from the universal choice set. The IIA is a very restrictive requirement, and alternative models have been developed, which do not rely on the IIA assumption, such as the multinomial probit and the more complex mixed logit model.

The size of the universal choice set in this study renders the application of a multinomial probit infeasible. The model requires solving a multidimensional integral over the universal choice set for the evaluation of choice probabilities, which precludes the estimation in this

6. Repeated attempts to estimate the model over the full set of alternatives failed to converge. Therefore, I decided to apply a choice-pruning method to reduce the number of alternatives to a feasible number.

context (Ben-Akiva and Lerman 1985; Train 2009). Alternatively, one could apply a mixed logit model structure, which allows for a random component in the utility function removing the IIA restriction.[7] There are, however, two drawbacks to this method. First, the introduction of the random component makes the computation increasingly difficult. Secondly, the estimation of the model over a large choice set is again infeasible. Therefore, the conventional approach is to use some choice set pruning methods. However, studies find that the potential bias introduced from choice set restrictions is more severe in a mixed logit model. Application of a mixed logit model, therefore, necessitates the selection of a larger sample of alternatives (Guevara et al. 2014), which complicates the estimation considerably. Experimenting with a mixed logit model in the present context, I experienced problems with the concavity of the likelihood function due to the inclusion of a large number of fixed effects.

Bearing in mind the computational difficulties of the above models, I opted to rely on the more simplistic standard logit model, assuming an IID structure for the random error term. As Train points out in his discussion of the advantages and disadvantages of an IID error structure, the logit model is known to do fairly well in approximating the average tastes of the population (Train 2009, p. 44). This research aims to develop a better understanding of clinal preference heterogeneity and, thus, to estimate systematic taste variations in the population. The logit model may provide a useful approximation of average taste variation, given the robustness of the logit formula to misspecification (Train 2009, p. 44). I gain further confidence in this approach from the findings by Scott et al. (2005), who using a model similar to the one applied in this chapter, test for possible violations of the IIA and find the assumption to hold for their approach.

The literature proposes two types of choice set pruning for logit models. The first approach ignores the behavioural complexity of a dynamic social search process and assumes that individuals choose from the global set of alternatives. The computational burden of using the universal set is reduced by drawing a random subset of alternatives for each individual (Train 2009, p. 49). McFadden (1978) shows that this simple choice set restriction mechanism yields asymptotically consistent parameter estimates. The second, less frequently applied method attempts to model the underlying dynamic search process by

7. A recent study by Sinha et al. (2018) uses a two-stage mixed model strategy to estimate the amenity value of climate using U.S. census data.

formulating behaviourally plausible rules describing individuals' decision processes. These rules are then used to reduce the universal choice set to a feasible size. While the deterministic approach has greater behavioural plausibility, conducting a comparison test between the two different pruning methods Zolfaghari et al. (2012) find no evidence of a better performance of the deterministic method in predicting choice outcomes. The authors conclude that the underperformance of the deterministic method likely results from the inaccuracy of the model in describing individual behaviour. In view of missing information on individual decision processes, I refrain from modelling the dynamic search process and opt for a random choice set restriction.[8]

I assume individuals form their residential location choice based on the universal choice set and draw a random subset of destination locations, including the migrant's chosen MSA. For the purpose of this research, the utility-maximising decision of migration is treated as weakly separable from the settlement decision to concentrate on modelling the second decision stage. This approach is commonly applied in the location-choice literature (Brown and Scott 2012; Scott et al. 2005; Sinha et al. 2018; Sinha and Cropper 2013). My estimation, nevertheless, entails a computational trade-off, as the estimation becomes increasingly computationally expensive the larger the set of alternatives. Nerella and Bhat (2004) use simulation methods to examine the model performance of a multinomial logit for different sample sizes of alternatives. The Monte Carlo results from the study suggest that the optimal level of drawn alternatives lies at around one-quarter of the universal choice set (with a minimum of one-eighth). Following Nerella and Bhat's (2004) suggestion, the number of alternatives is restricted to a subset of 74 random destinations per individual which are added to the chosen destination.[9]

A caveat of the alternative-specific choice model that should be highlighted here is

8. As a robustness check, I apply a more complex matching procedure for the choice set pruning, where alternatives are matched to the chosen destination based on the similarity in socioeconomic and geographical characteristics. Estimates based on the matching technique are comparable to those retrieved using random choice set pruning. Given the similarity in results, I chose to rely on the random choice sampling approach, given its theoretical foundation.

9. As part of the robustness checks, I experiment with the choice set size. I find that increasing the number of random alternatives beyond 49 MSAs yields no significant changes in parameter estimates. Given the recommendation by Nerella and Bhat (2004), I decided to draw 74 random destinations to reduce any potential bias. To further test the robustness of the results with respect to the choice set composition, I developed a bootstrap program calculating standard errors by resampling the set of random alternatives in each iteration process. The bootstrap standard errors based on this estimation method are similar to the standard logit model with clustered standard errors at the municipality level. Given the high computational burden of the bootstrap program, I rely on the standard method for the main analysis.

the complicated way in which individual characteristics can be included in the model. The only way in which individual regressors can enter the logistic regression is through interaction effects with the alternative-specific constants. Inclusion of such interaction effects is highly computational expensive, causing significant problems with convergence. Moreover, the interpretation of the parameters is not intuitive in a location-choice setting, where effects of individual characteristics imply a change in the average attractiveness of a location.

An additional problematic issue stems from the natural correlation in climate variables. For instance, winter and summer temperatures are naturally related. Multicollinearity in logit models is problematic, as it can lead to unreliable and unstable coefficient estimates. Correlation in the climate variables will increase the variance of the estimator, thus reducing precision in estimates. To reduce the problem, regressors are demeaned which increases the precision in estimates. However, the problem of multicollinearity cannot be overcome completely given the relatively small sample size. Hence, small changes in the underlying sample could potentially cause significant changes in the estimated coefficients. This could be particularly problematic in subsample regressions. As the underlying sample changes, so might imprecise coefficients. Therefore, interpretation of coefficients with a large variance should be done with caution, particularly in subsample comparisons.

3.4 Data and Variables

Considering the context of the bilateral migration between Mexico and the U.S., I consider MSAs and Mexican municipalities as the appropriate geographical level of analysis.[10] Any higher regional aggregation level (e.g. states) would introduce measurement error in amenity variables and, thus, reduce the precision of the estimates. It would be inadequate to treat place characteristics of states such as California as uniform, given the vast within-state variation in topography, climate, and economic factors. Besides, census statistics of the year 2000 highlight that 95% of all foreign-born individuals living legally in the U.S. reside in metropolitan areas (Wilson and Singer 2011). Besides, MSAs present useful geographic units of local economic characteristics, providing uniform measures such as for local labour and housing-market conditions.

10. Maps of Mexican municipalities and U.S. MSAs are provided in Appendix B.2 and B.3, respectively.

The set of MSAs is further reduced to the contiguous U.S. Based on the economic, cultural and demographic differences, I expect migration to the islands of Hawaii and Puerto Rico to be motivated differently compared to migration to the contiguous U.S. Further, the state of Alaska is excluded from the analysis due to the distance from Mexico and limited availability of location-specific information for Alaskan MSAs.[11]

The final dataset is compiled from various sources. Information on migration movements from Mexico to the U.S. was retrieved from the MMP survey dataset, which was merged with official statistics on MSAs coming from the U.S. census and other publicly available datasets. I used interpolated raster weather data to construct the climate variables. The rest of the section provides more detailed information on different data sources and the variables used in the empirical estimation.

Mexican Migration Data

The MMP is a collaborative research project based at Princeton University and the University of Guadalajara and run by Princeton University (MMP 2017).[12] It provides a unique cross-sectional database collecting information on social as well as economic factors of Mexican-U.S. migration. It consists of annual household surveys conducted since 1982. In each wave, a small number of households from selected communities are interviewed, with additional communities added in each consecutive survey round. One important aspect of the MMP is the coverage of illegal migration. Over 85% of the observed migration in the sample is illegal.[13]

The MMP covers a comprehensive set of survey questions on demographic character-

11. Appendix B.3 provides a full list of U.S. destinations.

12. The analysis focusses on international as opposed to internal migration for two reasons: First, limited information on origin locations of internal migrants limits identification of origin climates. Second, the smaller variation in origin and destination climates within a single country may prevent identification of clinal heterogeneity in climate tastes. The use of international migration data necessitates careful modelling of networks at destination locations as well as migration costs as both will have greater importance in international migration. One argument against the use of international migration data could be a potential selection bias causing climate preferences of international migrants to differ from those migrating nationally. Considering the similarity in climate across Mexico, this could suggest that only migrants with preferences for a different climate move internationally. However, as discussed in the results section, I find migrants to prefer settling in locations with similar temperatures (if not warmer) to origin locations. In line with the human-biology literature (Beall et al. 2012), this suggests that climate preferences are developed through exposure and adaptation to a specific climate, speaking against the possibility of systematic differences in climate tastes among the two sets of migrants.

13. Migration movements between the U.S. and Mexico during the 1980s and 1990s were primarily illegal (Durand and Massey 2019). Considering the study period, the MMP provides a more accurate representation of migration movements compared to official administrative, which captures mainly documented migration movements.

istics of household heads and spouses. A unique feature of the dataset is the provision of detailed information on individual bilateral migration experiences for almost 170,000 Mexicans, including the geographical origin and destination information. This geographic information is exploited to identify the origin and destination climates corresponding to each migration. The survey provides retrospective life-history migration information of household heads corresponding to 66,818 person-years. For the empirical analysis, the study relies on 46 years of bilateral migration movements between Mexico and the U.S. between 1970 and 2016,[14] covering 161 communities in 126 Mexican municipalities.[15]

The final sample comprises 13,013 individuals with complete information on 21,624 movements between Mexico and the U.S. These movements consist of 1,909 unique origin and destination combinations. Figure 3.1 shows a map of reported migration movements within the survey, separated into northern and southern Mexican municipalities for better visibility. Darker coloured lines imply a larger flow of migrants for this particular route. Observed migrations exhibit a clear preference for the states of California (62.7%) and Texas, both historical destinations of Mexican migrants.[16] The most frequent sample destinations are: Los Angeles-Long Beach (25.6%), Chicago 9.0%), San Diego (6.7%), Fresno (4.6%), and Houston (4.1%). Historically, Fresno has the highest population share of Mexican migrants among U.S. MSAs.

The analysis is further restricted to prime-aged adults (16-70 years) participating in the labour force. Moreover, I exclude migration for education, family reunion and retirement reasons. Residential location choices related to these migration types are likely to differ from labour migration and should be analysed separately.[17] Table 3.1 describes the characteristics of the sample migrants. Around 73% of the recorded migration in the sample is permanent (defined as migration with a duration of at least 12 months). More than 40% of sample individuals migrated more than once. The sample primarily consists of unmarried men (85%) with an average age of 30 years at the time of migration. Eighty-five percent of the recorded border crossings in the sample are illegal. Almost 50% of individuals have

14. Due to lack of readily accessible location-specific data for U.S. MSAs before 1970, only migration starting from 1970 is considered in the empirical analysis.

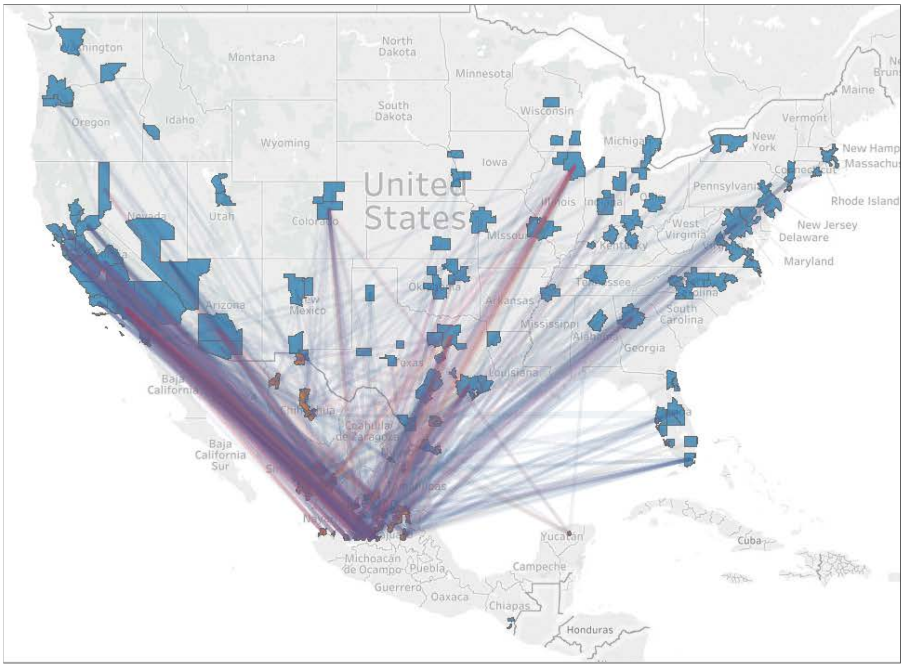
15. Appendix B.2 provides a full list of surveyed Mexican municipalities with a corresponding map illustrating the wide geographical distribution in survey municipalities.

16. Census data show that in 2012, roughly 59% of all foreign-born living in Texas were from Mexico (41% in California).

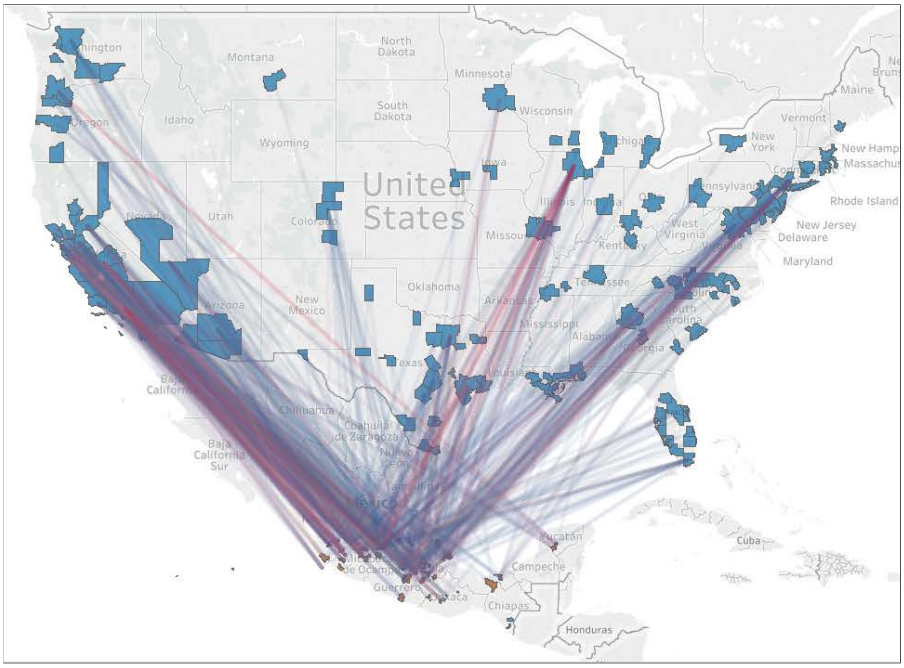
17. The majority of reported migration movements in the dataset is work-related, with only 9% of migrants not participating in the workforce, among whom female homemakers account for 7%.

Figure 3.1: Sample Migration Flows split by Origin in Northern and Southern Mexican Municipalities

(a) *Migration from Northern Mexican Municipalities*



(b) *Migration from Southern Mexican Municipalities*



Notes: The saturation of the lines between the Mexican origin community and the U.S. metropolitan area varies by the size of the flow.

Table 3.1: Sample Summary Statistics Mexican Migrants

	U.S. Total		**West**		**Midwest**		**South**		**North East**	
variables	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
age	30.03	*9.47*	29.97	*9.47*	30.80	*9.51*	30.07	*9.58*	28.08	*8.58*
duration (months)	47.87	*68.39*	46.92	*68.09*	59.71	*75.20*	43.12	*64.69*	42.65	*56.96*
migration distance (km)	2,722.6	*887.3*	2,798.3	*759.2*	3,213.2	*239.2*	1,650.2	*800.1*	4,227.3	*251.7*
migration time (h)	28.86	*28.40*	29.47	*31.62*	26.88	*15.84*	28.28	*23.44*	26.78	*12.87*
male (%)	85.92		85.62		84.16		87.22		92.91	
working (%)	91.05		91.65		87.10		92.33		88.42	
legal migration (%)	12.81		12.97		12.49		12.88		10.40	
secondary (%)	25.44		24.26		26.44		29.91		25.06	
tertiary (%)	11.19		10.79		12.96		10.97		13.48	
higher (%)	5.46		5.40		6.12		5.51		3.78	
permanent migration (%)	72.99		71.35		85.04		68.59		79.91	
married (%)	26.60		24.22		31.63		31.96		30.97	
relative in U.S. (%)	46.10		47.68		43.76		42.13		41.13	
trip 1 (%)	55.44		53.14		64.72		56.36		61.94	
trip 2-5 (%)	33.72		35.14		29.51		32.62		26.00	
trip 6-10 (%)	5.05		5.28		3.65		5.76		2.60	
trip $\geq$ 10 (%)	4.08		4.43		1.53		3.61		9.22	
N	12,986		8,869		1,698		1,996		423	
Frequency (%)	100.00		68.30		13.08		15.37		3.26	

Notes: Sample statistics are based on working-age population during first year of migration from the Mexican Migration Project Survey 161 restricted over the period 1970-2016.

a relative or friend who previously migrated to the U.S.

Other studies stress the importance of controlling for migration costs in location-choice models (Bayer and Timmins 2007). To limit the potential bias associated with moving costs, the model controls for the road-travel distance between the origin and destination locations as a proxy for moving expenses.[18] On average, individuals migrated a distance of 2,723.31 km to their new home, which corresponds to a travel time of 28.5 hours by car. Road distance provides only a rough proxy of migration costs. However, MSA fixed effects further control for differences in the administrative costs of settlement between states and MSAs, as well as the availability of low-cost long-distance transport to a specific location.

MSA Location-Specific Data and Variables

Non-climate control variables included in the regressions are summarised in Table 3.2.[19] I control for demographic and economic characteristics, such as the population size, the unemployment rate, per capita income and the Consumer Price Index (CPI), as well as network effects.[20] Population size will capture the benefits of larger cities that come along

18. The road-distance and travel-time measures are retrieved by querying the Google Distance Matrix API V3 with the help of the `traveltime3` Stata command written by Stefan Bernhard.

19. More geographically disaggregated statistics by state can be found in Table B.4.1 in Appendix B.4.

20. The economic and demographic information was collected from different official U.S. statistical offices. Data on the CPI and unemployment statistics are retrieved from the U.S. Bureau of Labour Statistics (U.S.

with urban agglomeration, such as access to public services, including public transport. Given the focus on labour migration, it is important to control for differences in unemployment to capture the availability of jobs at the destination. The regressions further include per capita earnings and the CPI to control for earnings and living cost differentials between MSAs.

In light of the historical context of bilateral migration flows between Mexico and the U.S., one might be concerned about networks playing an important role in driving location decisions of Mexican migrants (Bauer et al. 2002). The presence of network effects is problematic if climate preferences of historical and current networks are systematically different from those of sample migrants. Studying the relationship between seasonal temperatures and U.S. county population growth, Rappaport (2007) finds that starting in the 1920s U.S. residents have moved to places with nicer weather. Rappaport explains this change in migration flows with the introduction of air conditioning, a shift in the industrial composition of U.S. employment from agriculture to manufacturing, population ageing and the overall rise in incomes. Hence, climate preferences of today's Mexican migrants may differ systematically from preferences of their ancestors.

I address the issue of potential bias due to network effects by controlling for the population share of residents with Mexican roots and the migration experience of the origin municipality. The Mexican population share accounts for the size of local migrant networks as well as immigration and integration policies of the local government. Furthermore, I follow the approach by Bauer et al. (2002) and include two origin-specific measures of migration networks controlling for the stock and the flow of migrants from municipality o to MSA d at the moment of the migrants location decision at time t. I first calculate the cumulative migration experience of migrants from municipality o to each MSA d for each year t:

$$EXP_{doT} = \sum_{t=0}^{T} \sum_{i=1}^{N} M_{iodt} \tag{3.3}$$

Here, M_{iodt} is a dummy variable indicating, whether a migrant from municipality o mi-

Bureau of Labor Statistics 2014). Information on the population size and the ethnic compositions stems from the U.S. Census (Manson et al. 2011). Unemployment rates are collected from the Local Area Unemployment Statistics and the U.S. Census (Manson et al. 2011; U.S. Bureau of Labor Statistics 2014). Historical data on average wages are from the Quarterly Census of Employment and Wages (Bureau of Labor Statistics 2017). Appendix B.5 provides a complete variable list, with definitions, and the respective source.

grated to the MSA d at time t. As a next step, I divide the cumulative stock variable by the total U.S. experience of migrants from that municipality. This yields a measure of the concentration of a municipality's migration experience to a particular MSA at time t (stock).

$$\text{Municipality Migration Experience} = NET_{dot} = \frac{EXP_{doT}}{\sum_{o=1}^{O} EXP_{doT}} \times 100\,. \tag{3.4}$$

Lastly, I calculate the percentage difference in the relative size of networks between two consecutive years to capture changes in the flow of migrants across time (herd effects):

$$Herd = H_{dot} = NET_{dot} - NET_{do(t-1)}\,. \tag{3.5}$$

Together with information on the Mexican MSA population share, EXP_{doT} and H_{dot} will control for both origin- and ethnicity-related network effects as well as for the historical climate preferences of Mexican immigrants.

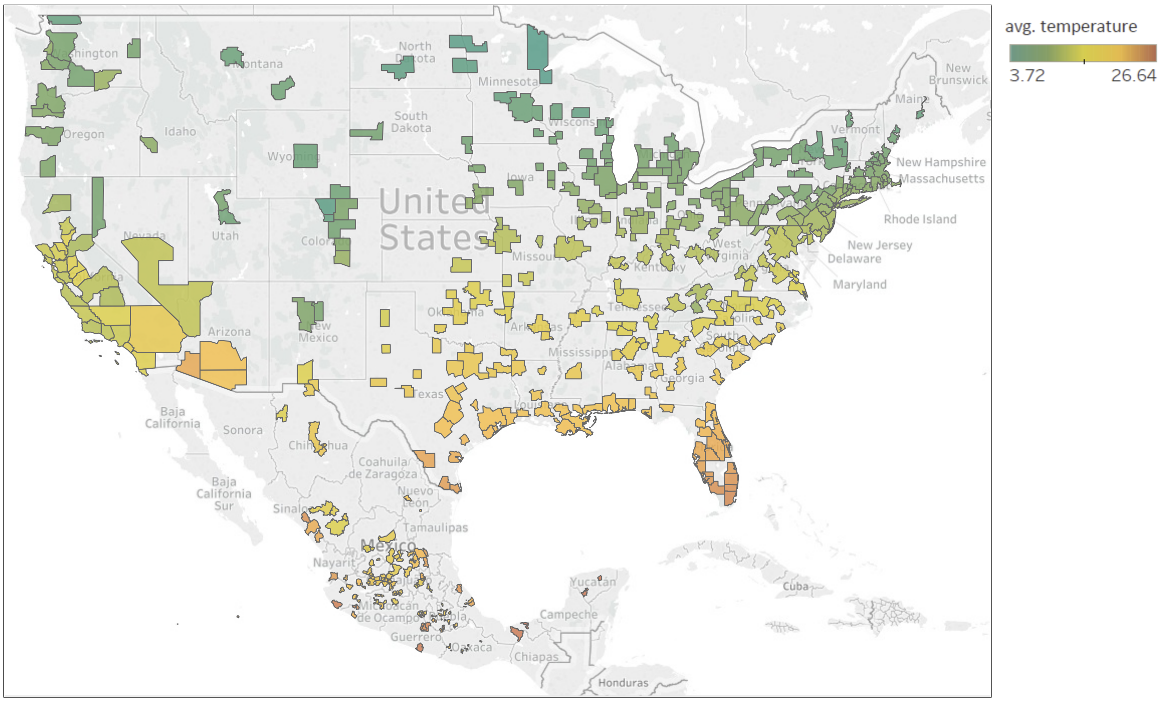
Table 3.2: Summary Statistics on Location Specific Characteristics by U.S. Census Region

	Total		**West**		**Midwest**		**South**		**North East**	
variables	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
pc income (in 1000s)	15.47	*9.55*	16.07	*9.87*	15.42	*8.73*	14.29	*8.61*	17.37	*11.51*
population (in 1000s)	693.9	*1,127.6*	809.9	*1,329.6*	583.5	*1,091.5*	548.0	*777.5*	1,020.6	*1,442.2*
Mexicans (%)	5.73	*11.82*	14.86	*13.02*	1.97	*2.50*	6.37	*14.72*	0.54	*0.89*
municipality migration experience (%)	0.05	*0.31*	0.16	*0.55*	0.03	*0.24*	0.03	*0.26*	0.01	*0.08*
herd (%)	-0.01	*0.19*	-0.02	*0.31*	-0.01	*0.14*	-0.00	*0.18*	-0.00	*0.05*
rural housing (%)	77.64	*13.23*	84.21	*10.94*	78.14	*10.30*	75.88	*13.41*	74.38	*15.74*
unemployment rate	5.16	*2.45*	6.20	*3.35*	4.81	*2.00*	4.97	*2.28*	5.00	*1.98*
CPI	265.6	*132.0*	374.4	*189.2*	227.8	*82.2*	234.3	*84.9*	274.0	*138.9*
N	15,018		2,713		3,644		5,802		2,859	
Frequency (%)	100.0		18.1		24.3		38.6		19.0	

Climate Data and Variables

Previous studies in the field primarily focus on different seasonal temperature measures, such as mean summer and winter temperatures. In line with the research question, I focus on climate variables with significant variation over the alternative destinations, as well as between origin and destination locations. Following the standard in the literature, the

Figure 3.2: Historical Average Temperature 1940-2016



Notes: The figure shows 1940-2016 average temperature normals in °C. Data from CRU TS3.21, Climatic Research Unit, East Anglia University.

analysis uses both seasonal climate measures and annual averages.[21] [22]

Regressions further include proxies for humidity (vapour pressure) and daily sunshine exposure (cloudy days).[23] Appendix B.5 provides a full variables list with definitions and sources. Due to the inherent correlation between different climate factors, it is impossible to include all climate regressors simultaneously in the regression. Therefore, I estimate separate regressions with different sets of climate variables.

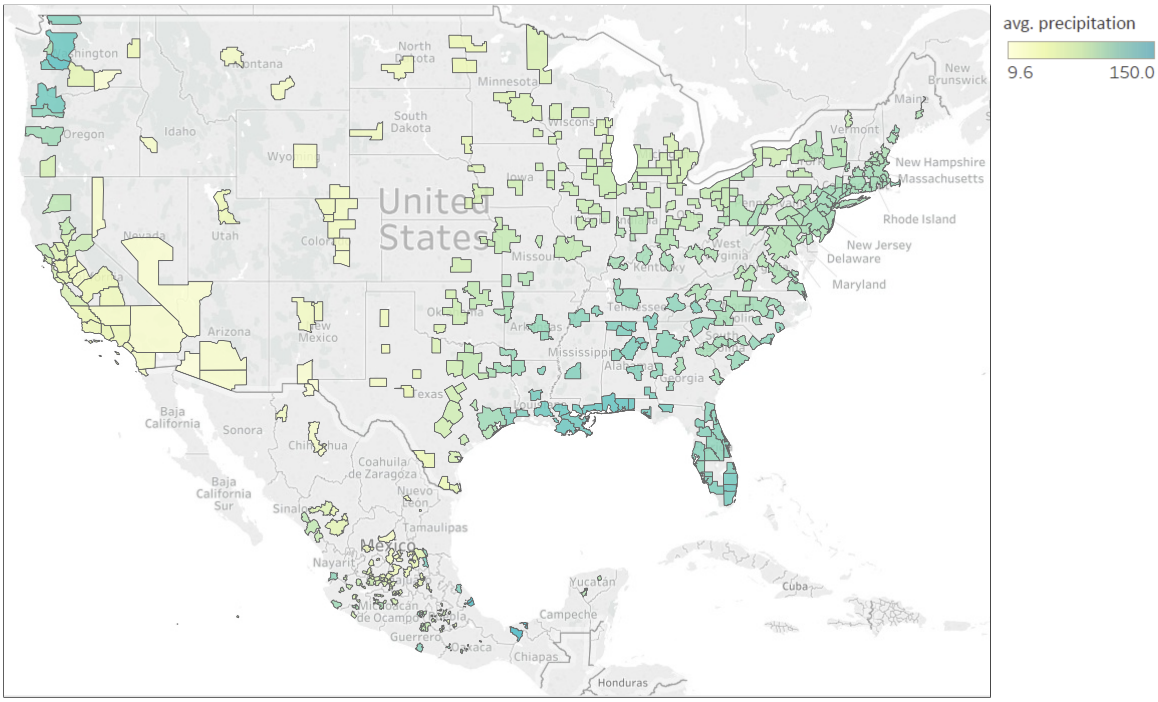
For the construction of the climate normals, I rely on interpolated weather data from the CRU TS4.01 dataset produced by the CRU at the University of East Anglia (CRU

21. Graves (1980), for example, uses measures of cold and warmth as well as temperature deviation, wind speed and humidity. Rappaport (2007) uses mean temperatures for January and July, the middle of the climatological winter and summer, as well as average precipitation. Cragg and Kahn (1997, 1999) use average February and July temperatures. Scott et al. (2005) generate a climate index for their estimation. Sinha et al. (2018) and Sinha and Cropper (2013) focus on average winter (December to February) and summer (June to August) temperatures.

22. Alternatively, one could use heating and cooling degree days. However, given the considerable time and spatial dimension of the climate data, the computation of degree-day variables was impractical, as it requires aggregation of daily weather data to compute the thirty-year climate normals.

23. In the context of Mexico, humidity may be an important factor influencing individuals' thermal comfort by limiting human thermoregulatory control mechanisms, such as sweating and precapillary vasodilation. While short-term heat acclimatisation, on average, takes around two weeks, complete acclimatisation to an unfamiliar thermal climate may take several years, depending on physiological and psychological factors such as age, sex, body composition, metabolic rate, diet and fitness (Koppe et al. 2004). The traits vary with clinal differences in human bodies (Makinen 2010).

Figure 3.3: Historical Total Monthly Precipitation 1940-2016



Notes: The figure shows 1940-2016 average total precipitation normals in *mm*. Data from CRU TS3.21, Climatic Research Unit, University of East Anglia.

2017). The CRU time-series dataset provides monthly, homogenised, high-resolution grids (0.5x0.5 degree[24]) created from historical climate observations of more than 4,000 weather stations. All climate variables are constructed as thirty-year arithmetic averages over Mexican municipality and MSA polygons prior to the year of migration.

U.S. Climate

Figures 3.2 and 3.3 present maps of average temperature and monthly precipitation for the period 1940 to 2016. Mean temperatures for the 321 U.S. MSAs average at 13.34°C, with a sd of 5.01°C (see Table 3.3). Studying seasonal climate variables exhibits mean winter temperatures (December to February) of 2.92°C (sd of 7.30°C) compared to summer temperatures of around 23.03°C (sd of 3.51°C). Statistics in columns five to eight highlight significant regional differences in temperatures. Minimum and maximum temperatures range from a daily high of 31°C in the Yuma MSA (AZ) to a low of minus 4°C in the western Fort Collins-Loveland MSA (CO). Total monthly precipitation averages 83 mm (sd of 29.87 mm). Summer and winter precipitation differ by roughly 25 mm. Tacoma MSA (WA) has the highest monthly rainfall among destination locations with an average

24. The grid corresponds to a geographic area of approximately 56x52km^2 to 56x42km^2.

of 137.3 mm per month. In contrast, Yuma MSA (AZ) on average experiences only 9.7 mm monthly precipitation. Around 50% of days in the U.S. are covered by clouds. Daily vapour pressure averages 123.3 Hectopascal (hPa).

Table 3.3: Historical Climate Normals United States

	U.S. Total		**West**		**Midwest**		**South**		**North East**	
variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
average temperature (°C)	13.34	5.01	11.77	3.60	9.73	2.31	17.80	3.30	9.51	1.57
maximum temperature (°C)	19.42	5.03	18.80	3.91	15.52	2.40	23.97	3.03	15.11	1.54
minimum temperature (°C)	7.29	5.18	4.78	3.71	3.97	2.32	11.67	3.66	3.94	1.70
summer (Jun-Aug) temperature (°C)	23.03	3.51	19.91	3.28	21.92	1.68	26.30	1.94	20.75	1.25
winter (Dec-Feb) temperature (°C)	2.92	7.30	3.92	5.05	-3.84	3.34	8.41	4.93	-2.37	2.15
sd mean temperature (°C)	8.00	2.09	6.52	1.79	10.18	0.87	7.12	1.38	9.13	0.39
average precipitation (mm)	83.40	29.87	51.40	30.69	73.22	11.99	97.42	23.14	92.51	7.04
summer (Jun-Aug) precipitation (mm)	91.78	45.42	22.73	19.42	96.25	10.75	115.79	41.14	97.85	8.45
winter (Dec-Feb) precipitation (mm)	75.72	40.26	87.21	64.02	44.97	18.37	85.11	33.33	83.07	12.21
cloud cover (%)	59.77	7.15	52.52	9.85	63.83	3.53	57.99	4.12	65.26	3.38
vapour pressure (hPa)	12.33	4.37	8.79	2.14	10.23	1.27	16.00	3.28	9.83	0.74

Notes: All climate variables are calculated 30-year averages prior to the migration year.

Mexican Climate

As expected, average temperatures for Mexico are significantly higher at almost 20°C (sd 2.95 °C). Table 3.4 exhibits significant temperature variation across sample municipalities. Tenango Del Valle in state México (2,600 m above sea level) experiences mean temperature of just 13°C. The highest maximum temperature is reached in the Mexican municipality of Huitzuco de los Figueroa (958 m above sea level) in the Southern state of Guerrero. Mexican average monthly precipitation is significantly lower compared to the U.S., with 73.5 mm. Moreover, the partially tropical country experiences greater seasonality in rainfall levels. Winter precipitation comes to just 16.46 mm, while summer precipitation amounts to over 150 mm. The municipality of Huimanguillo in the state of Tabasco experiences the highest average rainfall in the sample, with 206.0 mm per month. Vapour-pressure normals range from a minimum of 70 hPa (Nuevo Casas Grandes, Chihuahua) to a maximum

Table 3.4: Historical Climate Normals Mexico

	Mexico		**Baja California**		**Zona Norte**		**Occidental y Bajio**		**Central Mexico**		**South Mexico**	
variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
average temp. (°C)	19.87	2.95	17.85	0.10	18.68	2.84	19.54	2.00	20.46	3.37	22.44	3.83
maximum temp. (°C)	27.64	2.55	26.71	0.08	26.71	1.80	27.72	1.66	27.75	3.30	28.92	2.67
minimum temp. (°C)	12.15	3.64	9.04	0.28	10.70	4.07	11.40	2.47	13.23	3.93	16.00	5.00
summer temp. (°C)	22.14	2.97	20.89	0.19	24.07	2.81	21.78	1.78	21.94	3.31	23.75	4.43
winter temp. (°C)	16.44	3.49	13.63	0.21	12.54	3.97	16.08	2.44	17.75	3.49	20.04	3.20
sd mean temp. (°C)	2.63	0.96	3.11	0.06	4.67	1.58	2.57	0.38	2.16	0.37	1.86	0.35
average precip. (mm)	73.51	34.25	42.51	6.25	48.53	22.61	63.27	16.11	88.31	35.48	144.00	55.26
summer precip. (mm)	159.38	60.80	102.53	18.70	114.49	54.36	161.62	44.65	174.19	50.71	221.94	91.70
winter precip. (mm)	16.46	23.32	9.03	1.27	17.13	8.27	9.18	2.40	18.85	24.57	66.42	61.31
cloud cover (%)	57.01	5.32	51.50	0.16	48.74	2.62	53.64	2.51	62.11	4.60	62.51	1.25
vapour pressure (hPa)	14.46	4.48	10.93	0.42	11.62	4.56	13.63	2.95	15.75	4.50	20.10	5.89

Notes: All climate variables are calculated 30-year averages prior to the migration year.

of 260 hPa (Jalpa de Méndez, Tabasco), more than double the U.S. average.

Table 3.5: Ratio of U.S. / Mexican Climate Normals

variable $^{US}/_{Mex}$	Mean	St. Dev.	90% Conf. Int		P-Value
avg temperature (°C)	0.68	0.27	0.32	1.18	0.000
max temperature (°C)	0.71	0.19	0.45	1.04	0.000
min temperature (°C)	0.63	0.48	-0.00	1.57	0.000
summer temperature (°C)	1.06	0.21	0.75	1.42	0.000
winter temperature (°C)	0.16	0.46	-0.47	0.97	0.000
sd temperature (°C)	3.37	1.28	1.45	5.64	0.000
avg precipitation (mm)	1.40	0.84	0.40	2.97	0.000
summer precipitation (mm)	1.01	3.11	0.04	1.75	0.000
precipitation Dec-Feb (mm)	7.82	6.19	0.99	19.39	0.000
cloud cover (%)	1.08	0.17	0.78	1.34	0.000
vapour pressure (hPa)	0.93	0.40	0.42	1.72	0.000

Notes: All variables are calculated ratios in 30-year averages prior to the migration year. The ratio is calculated as the U.S. devided the Mexican climate

Deviations U.S.-Mexican Climate

The identification strategy necessitates significant variation in climate across the U.S. and Mexico, and between origin-destination pairs. Table 3.5 provides summary statistics for calculated ratios in climate normals between U.S. destination and Mexican origin locations.

All ratios are statistically different from zero. On average, temperatures in U.S. MSAs is 6.5°C colder than for the Mexican sample locations. However, summer temperatures are higher for the U.S. As expected, the U.S. experiences lower daily minimum temperatures. As noted earlier, Mexico experiences greater variation in annual precipitation, higher levels of vapour pressure and more frequent cloudy days. The geographical variation in destination or origin ratios in climate builds the basis for the subsequent empirical test for clinal heterogeneity in climate preferences.

3.5 Results

To make the results comparable to other studies, I begin the analysis by estimating a simple regression model including U.S. destination climate. All regressions include MSA fixed effects, with the base location Los Angeles MSA (California). The alternative-specific constants represent the destination-specific composite part of utility attributed to unobserved local amenities. Considering the sampling procedure applied to the MMP, I follow the advice of the literature by clustering the standard errors at the Mexican state-year level (Abadie et al. 2017; Cameron and Miller 2015; Wooldridge 2003). State-year clusters will control for systematic correlation in the unobservables among migrants from the same origin state and migration wave.[25] Table 3.6 presents the estimated odds ratios for the baseline regression of the residential location-choice model. The coefficients for the alternative specific regressors are interpreted as follows: An odds ratio higher than one implies that a positive change in the regressor for one metropolitan area increases the frequency at which the destination is chosen, while the relative attractiveness of alternative locations declines (i.e. an increase in the odds of the destination being selected). Accordingly, an increase in the population size at location d increases the probability of a migrant choosing this location and reduces the likelihood of settlement in any alternative destination (on average and inter alia).

Estimated odds ratios for all destination-specific controls except log per capita income are statistically significant. As expected, higher costs of migration reduce the likelihood of settlement. Lower living costs (CPI) and lower unemployment levels increase the de-

25. The Appendix reports the robustness of the results to alternative clusters. Destination specific amenities are cluster robust to the introduction of municipality level clusters. However, given the small number of sample municipalities, clustering at the municipality level is too restrictive for the identification of origin specific tastes.

sirability of an MSA. Moreover, migrants prefer MSAs with relatively larger populations and lower levels of urbanisation (share of rural housing). Contrary to the initial belief, increases in the relative population share of the Mexican community reduce the desirability of a destination. However, the odds ratio for the net migration experience for the municipality, capturing the relative U.S. experience of the origin municipality, suggests that a large stock of migrants from the same origin increase the likelihood of settlement at a location. The contrasting results may be explained by intensified job competition from a large Mexican population share, while a larger network of migrants stemming from the same municipality make a location more attractive for settlement. Contrary to Bauer et al. (2002), I find that an increased flows of migrants to a location (relative to all other destinations) reduces the chances of a new migrant moving to this particular MSA. This suggests that migrants move in waves causing herd effects to be negative, with recent larger streams of migrants leaving to a location reducing the likelihood of future migrations following the same direction.

Of interest are the different climate variables included in Models 1 to 8. The estimated odds ratios for the U.S. climate variables are comparable to the findings of other studies, such as Fan et al. (2012) and Sinha and Cropper (2013). In absolute terms, Mexican migrants settle in cities with warmer mean temperatures (Model 1 and 2) and avoid extreme temperatures (Model 3 to 7) (reduction from increasing maximum temperatures and increase from rising minimum temperatures). Moreover, the results indicate that locations with year-round lower rainfall levels see a greater inflow of migrants, but the coefficients for the alternative precipitation measures are insignificant (Model 6 to 9). However, the percentage rate of cloud days per month has a positive impact on a location's attractiveness.

To test for clinal heterogeneity, I estimate a further set of regressions, replacing the U.S. destination climate variables with climate ratios between destination and origin locations. The interpretation of the estimates of climate ratios is very different from the US climate variables. Keeping in mind the construction of the variables as the ratio between U.S. and Mexican climate normal, the estimated odds ratios in Table 3.7 should be interpreted as follows: Referring to the predicted odds ratio for average temperatures in Model 1, the warmer the U.S. destination compared to the Mexican origin location (i.e. ${}^{U.S.}/_{Mexico}$) the more likely for a migrant to settle at this particular destination. Estimates for Models 1 and 2 indicate a preference of individuals for locations with, on average, warmer temperatures than origin municipalities and a dislike for colder places. The odds ratios for minimum and maximum temperature differences further support the result. Similarly, the larger the ratio in the maximum and minimum temperatures the greater the likelihood of settlement. Consequently, locations with colder extreme temperatures relative to the origin are chosen less frequently.

As discussed in the data section, Mexican average and maximum temperatures exceed those of the sample MSAs, while U.S. summers are slightly warmer than those of the Mexican municipalities. Therefore, the temperature effects suggest a general desire of Mexicans to locate in destinations with, if not warmer, at least similar temperature variation. Locations with historically colder summer temperatures (compared to the origin) are more appealing to migrants (Models 7 to 9), however only the estimate for summer temperatures in Model 8 is significant. Concerning precipitation, I observe an attraction of migrations to locations with lower average and winter but higher summer precipitation levels (Models 5 to 8). Interestingly, the odds ratio for the destination-origin climate ratio for percentage cloud cover is less than one. Hence, the lower the sunshine exposure of a destination relative to the origin, the less attractive the location becomes to a migrant. A final important observation is that models using differences perform slightly better than the models restricting tastes to be uniform across different origin climates. This finding lends further support to the hypothesis of clinal differences in climate preferences.

Besides the ratio-specifications, I further estimate split-sample regressions for migrants from Mexican municipalities with temperatures above and below the historical mean temperature of 19.23°C. Regressions including U.S. destination climate are presented in Table 3.8. In general, the interpretation of the split-sample results is nontrivial. The variance of the latent variable in nonlinear models is unidentified. Therefore, the underlying scaling factor for coefficients in each regression differs, therefore precluding direct comparison of the predicted odds ratios.

The scaling problem in nonlinear models is well known in the literature (Allison 1999; Cramer 2003; Train 2009; Williams 2009). To make the results interpretable, I follow the advice by Train (2009, p.25) and rescale the odds ratios by the estimate for the percentage share of the Mexican population[26] to retrieve relative odds of the climate variables compared to the percentage share of residents with Mexican ethnicity.[27] Assuming identical weights given to the Mexican population share in both samples, rescaling the coefficients cancels out the difference in the unobserved variance for each regression.

Rescaled odds ratios are presented in Table 3.9. Note that the direction of the effect should be inferred from the unscaled odds ratio, while scaled effects should only be considered to identify systematic differences in the effect size across the two samples. I find the odds ratio of average temperatures to be larger for migrants from colder Mexican regions. For every additional degree in destination temperatures, individuals from cold regions gain 1.1 times the utility of those from warm regions. However, allowing for nonlinearity in the temperature effects reveals that the utility of individuals from warm regions is more sensitive to maximum temperatures, while migrants from cold regions have stronger preferences regarding minimum temperatures.

I observe a general attraction of individuals from warmer (colder) origins to places with higher (lower) maximum temperatures. The impact of maximum temperatures is roughly four times stronger for the hot sample, although this result must be considered with caution considering the insignificant estimate for the alternative regression. Migrants from cold regions are up to ten times more sensitive to changes in minimum temperatures, yet the direction of the impact is the same for both samples. The relative importance given to precipitation levels in Models 6,7 and 8 is similar for the hot and cold sample, with migrants from warmer regions having slightly stronger preferences for lower levels of precipitation. Again, the result should be treated with caution, given the lack of precision in the cold-sample estimates. The relative size of the predicted odds ratios for vapour pressure suggests a negative impact of humidity on utility, but the predicted effect is only statistically different from zero for the cold sample.

To get a feeling for the importance of clinal climate-preference heterogeneity, I estimate subsample regressions by age, education, the migration duration (i.e. permanent versus

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26. This variable was chosen as the difference between the two subsamples is statistically indifferent from zero.

27. The relative scale of estimates from each regression reflects the relative size of the unobserved variance of the two subsamples. Rescaling the estimates using the prediction for the Mexican population share allows us to compare their relative importance in each model (For a more detailed discussion of the scaling issue see Train 2009, p.25). Hence, differences in the coefficients between the two subsamples are interpreted relative to the weight given to the Mexican population share in the location choice of migrants.

temporary migration) and by the existence of personal networks. Migrants are split into those migrating at an age above or below 35 years, migrants with an education level of up to tertiary schooling or above, those migrating permanently or only temporarily and migrants with and without a network at the chosen destination. Table B.7.1 in Appendix B.7 displays the subsample regression results for the preferred model specifications, with corresponding rescaled odds ratios in Table B.7.2.

Again, overall, migrants prefer destinations with higher average temperatures. However, the utility of temporary migrants is more sensitive to warmer destination temperatures as the utility of permanent migrants. Similarly, migrants younger than 35 years and migrants with higher education levels have stronger preferences regarding average temperatures, compared to the alternative subsample. The same is true for winter temperatures. However, interestingly, summer temperatures have a stronger effect on higher educated migrants potentially due to better access to air conditioning. Interestingly, differences for migrants without and with networks are small, suggesting that networks have no influence on climate tastes. Overall, differences in the effect size by age, education, migration duration and networks are comparable to predicted clinal differences.

Several specification tests were conducted to check the robustness of the results. First, the US-climate and subsample results are robust to more conservative cluster specifications. However, the climate-ratio estimates loose significance once clusters are restricted to the municipality or state level. This is unsurprising considering that the sample consists of 161 communities located in 109 municipalities in 24 states. Restricting clusters to the municipality level, therefore, precludes the identification of taste variation by origin climates (see Table B.9.1 in Appendix B.9). Given the sampling procedure of the MMP survey and the construction of the origin climate variables, I believe that state-year clusters are the appropriate specification in this study.

One further potential weakness of the identification strategy in this chapter could stem from the choice-set restriction, of randomly selecting a subsample of 74 alternatives. I inspect the sensitivity of the results to alternative choice-set sizes by experimenting with the number of alternatives. Table B.8.1 in Appendix B.8 provides results for the preferred model specification using different numbers of alternatives. As noted earlier, increasing the number of alternatives beyond 59 does not significantly alter the results. Alternatively, I apply a different choice-pruning mechanism, where alternatives are matched to the chosen location by similarity in non-climate amenities. The estimates based on matching are comparable to those based on random choice-set pruning (see Appendix B.10), therefore, supporting the implementation of a more simplistic random choice-pruning approach.

As a further test of the validity of the random choice set pruning method, I developed a bootstrap program that re-estimates the regression model, drawing a new set of 74 random alternatives for each iteration.[28] The results in Appendix B.11 highlight the robustness of the findings to bootstrapping of the random alternative choice-set. Given the high computational burden of the bootstrap program and the indistinguishable results from the more complex method, the main analysis relies on the evaluation of the standard logit model.

In summary, the findings suggest systematic clinal differences in climate preferences of Mexican migrants. The predicted deviations in climate preferences between the two subsamples closely resemble differences in the two regions' origin climates. Warmer areas of Mexico, referred to as Tierras Calientes, offer year-round warmth with tropical levels of humidity and heavy precipitation during the rainfall season lasting from June to October. Therefore, migrants from tropical areas are accustomed to heat and moisture, explaining the results for predicted effects of maximum temperatures, precipitation, and vapour pressure. The results presented in this study suggest that ignoring clinal climate-preference heterogeneity in amenity-value estimates could overestimate the WTP for climate-change mitigation for individuals living in warmer climatic regions. This finding, however, does not conflict with the general recommendation to invest in climate-change mitigation. The baseline results confirmed that on average sample migrants gain disutility from extreme temperatures. However, the extent to which extreme temperatures reduce welfare differs by an individual's climate familiarity.

28. The code for the bootstrap program `bsasclogit` is provided in Appendix B.12.

Table 3.6: U.S. Destination Climate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Location specific characteristics									
migration	0.795^{***}	0.796^{***}	0.795^{***}	0.795^{***}	0.794^{***}	0.795^{***}	0.796^{***}	0.795^{***}	0.796^{***}
distance	(-12.07)	(-12.06)	(-12.18)	(-12.13)	(-12.27)	(-12.20)	(-12.13)	(-12.18)	(-12.03)
log	0.976	0.952	1.000	0.979	0.978	0.856	0.862	0.866	0.896
pc income	(-0.07)	(-0.15)	(0.00)	(-0.06)	(-0.07)	(-0.49)	(-0.47)	(-0.45)	(-0.34)
unemployment	0.913^{***}	0.909^{***}	0.906^{***}	0.903^{***}	0.915^{***}	0.904^{***}	0.928^{***}	0.918^{***}	0.922^{***}
rate	(-4.18)	(-4.35)	(-4.46)	(-4.56)	(-4.14)	(-4.51)	(-3.60)	(-4.05)	(-3.86)
CPI	0.616^{***}	0.616^{***}	0.578^{***}	0.578^{***}	0.735^{***}	0.604^{***}	0.653^{***}	0.625^{***}	0.627^{***}
	(-5.50)	(-5.50)	(-6.18)	(-6.19)	(-3.39)	(-5.36)	(-4.56)	(-4.99)	(-5.30)
% rural	1.035^{***}	1.034^{***}	1.030^{**}	1.030^{**}	1.019	1.020	1.007	1.009	1.018
housing	(3.39)	(3.34)	(2.94)	(2.95)	(1.45)	(1.74)	(0.51)	(0.72)	(1.45)
log	2.583^{***}	3.110^{***}	2.697^{***}	2.961^{***}	2.521^{***}	3.056^{***}	2.576^{***}	2.997^{***}	2.528^{***}
population	(4.04)	(4.87)	(4.27)	(4.75)	(3.88)	(4.58)	(3.91)	(4.29)	(3.76)
% population	0.871^{***}	0.870^{***}	0.872^{***}	0.872^{***}	0.889^{***}	0.875^{***}	0.887^{***}	0.880^{***}	0.879^{***}
Mexican	(-12.78)	(-12.87)	(-12.95)	(-12.95)	(-9.55)	(-12.30)	(-9.66)	(-11.63)	(-11.56)
net migration	1.621^{***}	1.620^{***}	1.616^{***}	1.615^{***}	1.623^{***}	1.617^{***}	1.621^{***}	1.619^{***}	1.621^{***}
municipality	(17.64)	(17.61)	(17.65)	(17.61)	(17.58)	(17.58)	(17.55)	(17.61)	(17.54)
herd	0.966	0.966	0.965	0.965	0.967	0.964	0.965	0.965	0.966
	(-1.51)	(-1.52)	(-1.57)	(-1.58)	(-1.48)	(-1.57)	(-1.53)	(-1.57)	(-1.53)
Climate variables									
avg temperature	7.573^{***}	34.96^{***}							
US	(6.05)	(4.50)							
avg temperature^2		0.953^{*}							
US		(-2.24)							
max temperature			0.797	3.732	9.505	6.544			
US			(-0.74)	(1.13)	(1.87)	(1.57)			
min temperature			9.584^{***}	10.20^{***}		8.132^{***}			
US			(8.23)	(8.16)		(4.93)			
max temperature^2				0.964	0.976	0.970			
US				(-1.37)	(-0.93)	(-1.08)			
summer temp.							2.065^{*}	3.204^{**}	2.417^{*}
US							(2.00)	(3.00)	(2.41)
winter temp.							2.091^{***}	1.831^{**}	2.040^{**}
US							(3.35)	(2.65)	(3.12)
precipitation						0.958		0.954	0.963
US						(-1.68)		(-1.82)	(-1.46)
summer precip.					0.974		0.973		
US					(-1.57)		(-1.69)		
winter precip.					0.969^{**}		0.975^{*}		
US					(-2.83)		(-2.26)		
cloud cover						1.627^{**}		1.745^{***}	
US						(2.66)		(4.60)	
vapour press.						0.345^{*}		0.618	
US						(-2.46)		(-1.41)	
MSA FE	×	×	×	×	×	×	×	×	×
LL	-33,163.6	-33,155.4	-33,128.8	-33,125.0	-33,179.0	-33,097.1	-33,116.0	-33,100.4	-33,135.7
# cluster	683	683	683	683	683	683	683	683	683
N	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800
Cases	21,624	21,624	21,624	21,624	21,624	21,624	21,624	21,624	21,624

Notes: The table presents odds ratios with the respective significance level of * $p<0.1$; ** $p<0.05$; *** $p<0.01$. T-statistics presented in parentheses.

Table 3.7: Climate Ratios U.S. Destination / Mexican Origin

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
avg temperature US	5.976***	11.83**							
	(5.29)	(2.81)							
avg temperature ratio $^{US}/_{Mex}$	1.477***	3.024*							
	(4.65)	(2.42)							
avg temperature^2 US		0.973							
		(-1.22)							
avg temperature^2 ratio $^{US}/_{Mex}$		0.793							
		(-1.65)							
max temperature US			0.698	1.238	2.619	2.745			
			(-1.03)	(0.16)	(0.69)	(0.76)			
max temperature ratio $^{US}/_{Mex}$			1.454	5.202	11.10	1.521			
			(1.11)	(1.07)	(1.63)	(0.29)			
min temperature US			8.826***	9.180***		6.678***			
			(7.90)	(7.63)		(4.31)			
min temperature ratio $^{US}/_{Mex}$			1.058*	1.056		1.177*			
			(2.00)	(1.91)		(2.09)			
max temperature^2 US				0.981	0.992	0.984			
				(-0.67)	(-0.30)	(-0.57)			
max temperature^2 ratio $^{US}/_{Mex}$				0.664	0.580	0.911			
				(-0.85)	(-1.18)	(-0.21)			
summer temp. US							2.365*	3.387**	2.434*
							(2.33)	(3.18)	(2.45)
summer temp. ratio $^{US}/_{Mex}$							0.832	0.744*	0.894
							(-1.40)	(-2.25)	(-0.85)
winter temp. US							1.906**	1.830**	1.951**
							(2.86)	(2.66)	(2.90)
winter temp. ratio $^{US}/_{Mex}$							1.071	0.928	1.043
							(1.96)	(-1.41)	(1.23)
summer precip. US					0.972		0.971		
					(-1.64)		(-1.81)		
summer precip. ratio $^{US}/_{Mex}$					1.015***		1.015***		
					(7.94)		(7.70)		
winter precip. US					0.970**		0.976*		
					(-2.67)		(-2.09)		
winter precip. ratio $^{US}/_{Mex}$					0.999		0.999		
					(-0.57)		(-0.86)		
precipitation US						0.963		0.960	0.967
						(-1.45)		(-1.51)	(-1.27)
precipitation ratio $^{US}/_{Mex}$						0.970		0.952*	0.961*
						(-1.54)		(-2.46)	(-2.13)
cloud cover US						1.686**		1.993***	
						(2.87)		(5.09)	
cloud cover ratio $^{US}/_{Mex}$						0.614		0.468*	
						(-1.38)		(-2.21)	
vapour press. US						0.451		0.630	
						(-1.85)		(-1.34)	
vapour press. ratio $^{US}/_{Mex}$						0.855		1.168**	
						(-1.75)		(2.97)	
MSA FE	×	×	×	×	×	×	×	×	×
controls	×	×	×	×	×	×	×	×	×
LL	-33,129.9	-33,121.2	-33,100.7	-33,097.6	-33,135.7	-33,014.3	-33,085.7	-33,032.7	-33,099.7
# cluster	683	683	683	683	683	683	683	683	683
N	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800
Cases	21,624	21,624	21,624	21,624	21,624	21,624	21,624	21,624	21,624

Notes: The table presents odds ratios with the respective significance level of * p<0.1; ** p<0.05; *** p<0.01. T-statistics presented in parentheses. Regression tables including full destination controls are presented in Appendix B.6.

Table 3.8: Subsample Regressions Hot and Cold Mexican Origin - U.S. climate

	(1)		**(2)**		**(3)**		**(6)**		**(7)**		**(8)**	
	hot	cold	hot	cold	hot	cold	hot	cold	hot	cold	hot	cold
avg temperature US	6.428***	8.791***	115.0***	13.53*								
	(5.07)	(4.71)	(4.81)	(2.32)								
avg temperature^2 US			0.908**	0.987								
			(-3.21)	(-0.44)								
max temperature US					2.794**	0.669	1107.0***	0.420				
					(2.68)	(-0.98)	(4.38)	(-0.51)				
min temperature US					2.299*	13.18***	0.846	15.37***				
					(2.10)	(6.57)	(-0.30)	(4.65)				
max temperature^2 US							0.889***	1.032				
							(-3.33)	(0.80)				
summer temperature US									2.051	2.048	2.066	4.500**
									(1.49)	(1.37)	(1.35)	(2.68)
winter temperature US									1.719*	2.475**	1.698*	1.983*
									(2.07)	(2.90)	(2.00)	(2.16)
precipitation US							0.940*	0.977			0.946	0.961
							(-2.06)	(-0.79)			(-1.90)	(-1.33)
summer precip. US									0.985	0.959*		
									(-0.69)	(-2.08)		
winter precip. US									0.981*	0.976		
									(-1.99)	(-1.59)		
cloud cover US							1.736*	1.662*			1.195	1.903***
							(2.48)	(2.17)			(1.01)	(4.24)
vapour press. US							0.769	0.178**			1.025	0.406*
							(-0.51)	(-2.91)			(0.05)	(-1.97)
MSA FE	×	×	×	×	×	×	×	×	×	×	×	×
controls	×	×	×	×	×	×	×	×	×	×	×	×
LL	-10,862.1	-20,744.2	-10,849.3	-20,743.8	-10,861.9	-20,715.2	-10,834.4	-20,687.6	-10,856.5	-20,702.7	-10,854.3	-20,690.6
# cluster	442	418	442	418	442	418	442	418	442	418	442	418
N	607,650	1,014,150	607,650	1,014,150	607,650	1,014,150	607,650	1,014,150	607,650	1,014,150	607,650	1,014,150
Cases	8,102	13,522	8,102	13,522	8,102	13,522	8,102	13,522	8,102	13,522	8,102	13,522

Notes: Notes: The table presents odds ratios with the respective significance level of * p<0.1; ** p<0.05; *** p<0.01. T-statistics presented in parentheses. Regression tables including full destination controls are presented in Appendix B.6.

Table 3.9: Subsample Regressions Hot and Cold Mexican Origin - U.S. climate *(rescaled)*

	(1)		**(2)**		**(3)**		**(6)**		**(7)**		**(8)**	
	hot	cold	hot	cold	hot	cold	hot	cold	hot	cold	hot	cold
% pop Mexican	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
avg temperature US	7.358***	10.105***	131.279***	15.570*								
avg temperature^2 US			1.037**	1.135								
max temperature US					3.198**	0.769	1253.016***	0.481				
min temperature US					2.631*	15.139***	0.958	17.596***				
max temperature^2 US							1.006***	1.182				
summer temperature US									2.310	2.317	2.335	5.120**
winter temperature US									1.937*	2.800**	1.919*	2.257*
precipitation US							1.064*	1.118			1.069	1.093
summer precip. US									1.109	1.086*		
winter precip. US									1.105*	1.104		
cloud cover US							1.965*	1.902*			1.350	2.166***
vapour press. US							0.870	0.204**			1.158	0.462*
MSA FE	×	×	×	×	×	×	×	×	×	×	×	×
controls	×	×	×	×	×	×	×	×	×	×	×	×
LL	-10,862.1	-20,744.2	-10,849.3	-20,743.8	-10,861.9	-20,715.2	-10,834.4	-20,687.6	-10,856.5	-20,702.7	-10,854.3	-20,690.6
# cluster	442	418	442	418	442	418	442	418	442	418	442	418
N	607,650	1,014,150	607,650	1,014,150	607,650	1,014,150	607,650	1,014,150	607,650	1,014,150	607,650	1,014,150
Cases	8,102	13,522	8,102	13,522	8,102	13,522	8,102	13,522	8,102	13,522	8,102	13,522

Notes: The table presents rescaled odds ratios for the regressions presented in Table 3.8 with the respective significance level of * p<0.1; ** p<0.05; *** p<0.01. T-statistics presented in parentheses. Assuming identical weights given to the Mexican population share in both samples, rescaling of coefficients cancels out the difference in the unobserved variance for each regression. Rescaled odds ratios should only be considered to identify systematic differences in the effect size across the two samples.

3.6 Conclusion

This chapter estimates a discrete location-choice model to examine clinal heterogeneity in climate preferences exploiting a newly constructed dataset. The findings suggest that the value attached to destination climates in residential location choices of Mexican migrants to the U.S. differs by the climate at the migrant's origin. I find that Mexican migrants prefer settling in cities with warmer average and extreme temperatures, but colder summer temperatures, compared to their home locations. Migrants dislike moving to destinations with colder temperatures than their home municipality. Split sample regressions for migrants from warm and cold Mexican climatic areas further support these results. Migrants on average gain disutility from extreme temperatures. Studying heterogeneity in the predicted effect by origin climates reveals significant differences in the size of the impact. Estimates suggest that the utility of migrants from warmer Mexican regions is more sensitive to increases in average temperatures. The observed differences become more pronounced if considering temperature extremes. Comparing results across different split-sample regressions, I find estimated clinal differences to be comparable to those over age, education, migration duration and differences across migrants with and without networks.

While the results provide some initial evidence of clinal heterogeneity, several methodological drawbacks should be highlighted here. In light of the historical context of bilateral migration flows between Mexico and the U.S., a concern could be network effects driving location choices. Given the interest in population averages, the presence of network effects is problematic if climate preferences of networks are systematically different from current migrants. Although I control for network effects by including measures of the migrant stock and flow, unobserved individual variation in network strengths are unaccounted for.

A further concern is unobserved individual heterogeneity in preferences. Individual location choices are likely influenced by migrants' characteristics and individual tastes. For example, an important determinant of location choices are family structures, i.e. whether migrants are joined by their family or migrating alone. Due to the complexity of including individual characteristics in the alternative-specific choice model, the link between individual characteristics and climate valuations cannot be explored further in this chapter.

Moreover, modelling heterogeneity in preferences, aside from clinal differences, is limited to subsample regression analysis. Given the unknown underlying scaling factor used in the logit model, comparison of coefficients across two samples is problematic. Chapter 4 aims at disentangling complex interlinkages between individual characteristics and climate preferences, exploiting a Bayesian approach for the estimation of the location-choice model. The Bayesian method overcomes both the problem of convergence and the restrictiveness in modelling individual heterogeneity experienced in this chapter.

A line of research not exploited in this thesis, but of great value to the climate-change debate, is replication of this study in a different climatic context. Generalisation of the findings presented here to different climatic areas might shed important light on how climate change will alter future location choices of migrants due to adaptation of climate preferences to new climatic environments in the long term. Further data collection on climate-related migration is essential to replicate this study in a different context.

Despite the limitations, the findings presented in this chapter have several policy implications. Although climate preferences only play a minor role in location decisions, the results suggest that climate change will alter the attractiveness of locations by affecting temperatures and precipitation and, in the long term, climate preferences. Concerning migration, this might imply changes in the direction of future migration flows. Moreover, the results provide suggestive evidence of significant clinal variation in climate preferences which implies non-negligible differences in individuals' WTP for the mitigation of climate change. Assuming preference homogeneity in choice models may considerably bias the predicted WTP for abating climate change, with the direction of the bias depending on the origin climate. This question will be explored in the next chapter.

Chapter 4

Capturing Heterogeneity in Individual Temperature Valuations:

A Two-Stage Random Utility Approach

Abstract

This chapter investigates the importance of preference heterogeneity in driving individuals' temperature valuations and their WTP for mitigation of global warming. I apply a two-stage random utility sorting model to analyse location-choice decisions, drawing on survey data of Mexican migration to the U.S. The econometric model captures both observed heterogeneity related to clinal and demographic characteristics of the migrant and unobserved preference heterogeneity in temperatures. The first stage consists of a mixed logit model of the discrete-location choice, controlling for the cost of migration, the prevalence of migrant networks and MSA fixed effects. Heterogeneous preferences are modelled using interaction effects and allowing for random individual variation in climate regressors, capturing unexplained individual-taste variation. Evaluation of the mixed logit model follows a Bayesian estimation procedure. In the second stage, estimated MSA-specific fixed effects, capturing destination-specific mean utility, are regressed on local amenities. On average, I find migrants to value warmer winters and cooler summers. Further, the results demonstrate significant differences in the MWTP for friendlier summer temperatures across both demographic and clinal characteristics, lending support to the hypothesis of clinal preference heterogeneity playing an important part in forming individuals' temperature valuations. I supplement these results with estimates of the WTP for projected future temperature changes. Increases in summer temperatures are estimated to cause welfare losses of between US$1,245 and $1,755 per person per year. At the same time, warmer winter temperatures increase people's welfare only by between $102 and $193 (per person and year). Moreover, the predictions highlight that heterogeneity plays an important part in driving individuals' WTP for climate change. Insofar as the WTP for the abatement of global warming is largest among individuals aware of the negative impacts of heat, measurements derived from populations with access to air conditioning and relatively moderate temperatures will underestimate the WTP for climate change mitigation.

4.1 Introduction

A growing scientific consensus projects that climate change will alter local climates by, on the one hand, raising average temperatures and, on the other hand, increasing the intensity and frequency of extreme weather events (IPCC 2013). In light of these projections, an emerging body of literature examines potential impacts of future adverse climate, as well as people's WTP for the mitigation of negative welfare effects. Despite the suggestive evidence on the significance of climate in shaping an individual's life (see literature reviews by Dell et al. 2014; Parker 1995), very little is known about people's climate preferences and the value they attach to living in a more preferential climate.

As discussed in the previous chapter, a potentially serious drawback of earlier work is the assumption of preference homogeneity among individuals. Chapter 3 presents suggestive evidence of clinal[1] and demographic differences in climate tastes of Mexican immigrants to the U.S. This chapter intends to provide further insights into the importance of heterogeneous differences in driving the amenity value of temperatures and, thus, an individual's WTP for mitigation of global warming.

Benefiting from recent advancements in estimation procedures, I apply a two-stage random utility sorting model to analyse location-choice decisions of Mexican migrants to the U.S. over the period 2000 to 2012, using the same migration survey as in Chapter 3.[2] The model captures both observed heterogeneity attributed to demographic characteristics and clinal differences in migrants' acclimatisation as well as unobserved heterogeneity related to individual tastes. Results from the two-stages are used to calculate individuals' current WTP for living in a preferred climate, which in turn is used to project the welfare effects of predicted global warming for the sample locations.

The first stage consists of a mixed logit model of the discrete location choice, which among climate amenities controls for migration costs, the prevalence of networks and

1. The term *clinal* goes back to Sir Julian Huxley, a British evolutionary biologist (Huxley 1938). The human-biology literature uses the term *clinal* to refer to gradual change in a character or feature across the distributional range of a species or population, usually correlated with an environmental transition such as humidity, rainfall, and temperature. For example, it has been observed that pigmentation changes with distance from the equator, due to different levels of UV radiation. In this chapter, the term *clinal-preference heterogeneity* is used to indicate systematic differences in the valuation of climate over geographical variation in migrants' origin climates.

2. As in Chapter 3, the utility-maximising decision of migration is treated as weakly separable from the migration decision.

destination-specific confounding factors. MSA fixed effects included in the first stage capture destination-specific mean utility after accounting for individual heterogeneity. The approach taken here differs from Chapter 3, as individual taste variation in climate preferences is modelled using interaction effects and random variation in coefficients. Clinal-preference heterogeneity again is identified through the spatial gradient in origin temperatures. The mixed logit model is evaluated following a Bayesian estimation procedure due to the computational advantages over the classical frequentist method (Train 2001).

Analogous to the traditional hedonic approach, in the second stage the MSA fixed effects from the first stage are regressed on destination-specific amenities, including climate. I address the potential issue of endogeneity in the second stage by including a large set of destination characteristics into the regression and exploring alternative model specifications, including an IV approach. The IV results indicate that OLS estimates suffer from an endogeneity bias.

Results from the first-stage regressions indicate that migrants are more likely to settle in locations with warmer summer and colder winter temperatures. Moreover, the baseline estimates exhibit, on average, a positive relationship between seasonal temperature preferences, i.e. individuals preferring warmer winters also enjoy warmer summers and vice versa. Studying climate impacts from the second stage reveals that the composite mean utility declines with warmer summer temperatures but rises with warmer winters.

Combining estimates from the first and second stage, I find individuals on average are willing to pay between US$371 and $686 per person per year to live in a location with one degree lower summer temperatures. At the same time, migrants are willing to forgo annual earnings of between $70 and $133 to enjoy one degree warmer winters. Examining heterogeneity in the MWTP for temperatures, the results indicate that the WTP for living in preferential temperatures changes considerably over the life cycle. Moreover, I find migrants from warmer Mexican regions willing to forgo income to live in locations with colder summer and winter temperatures. However, individuals originally from colder Mexican regions see warmer winter temperatures as an amenity. It seems that greater awareness in individuals of the adverse effects of heat due to previous exposure at the origin makes migrants prefer locations with colder seasonal temperatures. These findings lend support to the notion that clinal-preference heterogeneity is an important driver of individual temperature valuations.

As a last step, based on MWTP measures I calculate the WTP for projected changes in mean summer and winter temperature under alternative climate scenarios for the period 2040 to 2069. Modelled temperature data was retrieved from the ECHAM5 (Roeckner et al. 2003) and the Community Climate System Model (CCSM3) (Collins et al. 2006). On average, the projected future increase in summer temperatures is estimated to reduce welfare by between \$1,245 to \$1,755 per person per year. At the same time, warmer winter temperatures result in welfare gains of between \$102 and \$193 per person per year. As expected, heterogeneity in the WTP for global warming is large, with predicted welfare gains due to warming of winter temperatures reaching up to \$10,320 annually per migrant aged 55 and above.

The remainder of this chapter is organised as follows: First, I provide a short summary of the relevant literature, followed by a detailed description of the model and the empirical strategy employed in the analysis. Section 4.5 provides a short description of the different data sources used to create the final dataset. The results of the two-stage sorting model are presented in Section 4.6, followed by an analysis of the estimated MWTP for temperature changes and, lastly, by a discussion of projected welfare effects of global warming. The chapter ends with a brief conclusion highlighting the implications of the findings for future empirical work.

4.2 Literature Review

Deliberate attempts to measure the amenity value of climate date back to Hoch and Drake (1974) and Nordhaus (1996), who found interstate net migration to decline with rising temperatures, indicating a general attraction of U.S. residents to warmer climates. In light of rising climate-change awareness, the topic recently saw a resurgence also due to methodological innovations and advances in computing power. Deriving a monetary measure of individuals' valuation of climate today can be used to predict the negative (or positive) effect of temperature changes under alternative climate-change scenarios on individual well-being. Such estimates provide a numerical measure for the potential benefits of limiting further temperature rises. Compared with the abatement costs of interventions, estimates of the amenity value of climate can help inform the climate-change policy debate, where the costs and benefits of policy interventions remains a much-debated topic.

Measuring climate valuations poses an econometric challenge, considering that the amenity is not marketed. Traditionally, two alternative approaches using revealed preference techniques have been used to measure climate preferences: hedonic-regression methods (Rosen 1974) and the discrete-choice approach (Cragg and Kahn 1997, 1999). Both approaches can be used to derive a monetary estimate of individuals' or households' valuation of climate, i.e. how much a person is willing to pay for friendlier climate. Revealed preference methods are particularly attractive for deriving numerical measures of climate valuations, as their estimates rely on observed behaviour and market prices in contrast to potentially arbitrary survey responses evaluated in conjoint analyses.

Based on the seminal work of Lancaster (1966) and Rosen (1974) and the important contributions of Roback (1982), the hedonic-price approach assumes that in a frictionless world, individuals would relocate to alternative locations if they offer preferable combinations of amenities. Hence, under hedonic theory, location-specific earnings and living-cost differentials will compensate individuals for less favourable amenities at a location. In terms of climate, the theory would imply that individuals are willing to forgo some of their earnings to live in a favourable climate, or the minimum compensation a household would need to be paid in order to be willing to relocate to a place with inferior climate. The hedonic literature refers to this as the 'compensating surplus' measures of welfare change (Hicks 1939). Consequently, an individual's implicit valuation of marginal changes in the level or quality of a nonmarketed amenity can be inferred from regressing location-specific amenities on the hedonic property and wage price.

Over the past two decades, various papers have applied the hedonic approach to deliberately measure the amenity value of climate. For example, Englin (1996) and Mendelsohn (2001) provide estimates for the U.S. and Cavailhès et al. (2009), Maddison (2001), Maddison and Bigano (2003), Meier and Rehdanz (2017) and Rehdanz and Maddison (2009) for Europe. Englin (1996) uses the approach to measure the amenity value of rainfall using information on housing prices in Washington State. Englin's (1996) results suggest that house owners are willing to pay more for properties in locations with, on average, lower annual rainfall levels, but larger seasonal variation. Using an international dataset covering 79 countries, Maddison and Rehdanz (2011) analyse the influence of temperature and precipitation on life satisfaction and estimate a negative relationship between degree days and well-being. A recent study by Albouy et al. (2016) estimates a hedonic model for U.S. public-use microdata areas with an index of life quality as the hedonic outcome variable. Albouy et al. find individuals prefer moderate temperatures with the predicted MWTP for abating excess heat being significantly larger than that for extreme cold.

Aside from the hedonic-regression method, researchers have implemented a discrete-choice approach to capture households' attraction to location-specific amenities in the residential-location choice. Going back to Cragg and Kahn (1997), the discrete-choice approach assumes that households choose their residence based on the relative utility they receive from alternative locations, where utility depends on potential earnings, living costs and other location-specific attributes of each destination. If individuals are free to choose where to live, climate becomes a choice variable. Residential-location choice models identify individual preferences by exploiting the variation in characteristics across space and time and the revealed choice of residence. In their seminal work, Cragg and Kahn (1997) examine the impact of different climate variables on individuals' propensity to move across U.S. states. Controlling for wages, the costs of housing and employment prospects, Cragg and Kahn (1997) observe people to be attracted to moderate temperatures (warmer winters and modest summer temperatures).[3]

Considering the primary research aim, the discrete-choice approach offers several advantages over the hedonic approach. Most importantly, the method allows for greater flexibility in incorporating heterogeneous individual preferences through the inclusion of interactions effects and random coefficients in a mixed logit model specification. Secondly, Bayer et al. (2009) demonstrate the importance of controlling for migration costs in the analysis of amenity values. Ignoring market frictions can substantially bias estimates of amenity values. Compared to the hedonic approach, explicit modelling of market frictions in a choice model is trivial.

A small number of studies attempt to identify heterogeneous differences in the amenity value of climate through estimation of subsample regressions and modelling of interaction effects. This literature provides suggestive evidence of significant taste variation by age, level of education, and by origin nation and state (Brown and Scott 2012; Cragg and

3. Alternative studies with similar results were conducted by Bayer et al. (2009), Brown and Scott (2012), Fan et al. (2012), Scott et al. (2005), Sinha et al. (2018) and Sinha and Cropper (2013).

Kahn 1997; Fan et al. 2012; Scott et al. 2005; Sinha et al. 2018; Sinha and Cropper 2013). Recently, Sinha et al. (2018) apply a mixed logit model approach allowing for random variation in households' climate valuations to estimate a location-choice model of households sorting into U.S. MSAs. Exploiting U.S. Census data, the authors find preferences for winter and summer temperatures to be antagonal, i.e. households preferring warm winters gain disutility from warmer summers and vice versa. Moreover, the WTP for living in comfortable climate is considerably larger among older residents.

Although the above studies provide evidence of the importance of heterogeneity in driving temperature valuations, clinal differences have largely been ignored in the literature.[4] Given the findings of the previous chapter, this chapter aims to provide further insights into the significance of clinal heterogeneity in driving temperature valuations and, thus, the WTP for the abatement of global warming. Considering the rising global concern about climate change, a better understanding of today's amenity value of temperatures is an important contribution to the climate-change policy debate.

4.3 Methodology: A Random Utility Sorting Model

The theoretical framework for specifying the underlying decision rule of migrants' residential-location choice is based on the concept of random utility maximisation. In line with the theory, migrants form a relative judgement about alternative locations based on their preferences regarding potential housing and consumption, as well as other destination-specific amenities. These preferences, in turn, are a function of individual-specific tastes for destination attributes and demographic and socioeconomic characteristics. Individual-specific tastes influence how the migrant evaluates alternative-specific characteristics.

Individual location choices are modelled using a structural approach developed by Timmins (2007) and extended by Fan et al. (2012) and Sinha et al. (2018) to explicitly model individual-preference heterogeneity. The first stage consists of a discrete-choice model of migrants' residential-location choices including location-specific fixed effects. MSA-specific constants represent the composite part of utility attributed to local amenities.

4. During a comprehensive review of the literature using the relevant research databases and library catalogues as well as back and forward tracing of related journal articles, only two studies by Scott et al. (2005) and Fan et al. (2012) where found to allow for heterogeneous differences in climate preferences by origin region.

In the second stage, estimated fixed effects are regressed on local amenities to retrieve individuals' MWTP for preferable climate.

The analysis assumes the following utility function for migrant i moving to destination j:

$$U_{ij} = C_i^{\beta_c} H_i^{\beta_H} Z_j^{\beta_z} e^{\beta_{qi}^T (X_i \times T_j) + \beta_m M_{ij} + N_{ij} + \zeta_j + \eta_{ij}} \tag{4.1}$$

where C_i and H_i are the consumption level of the numeraire good and housing, respectively. Z_j is a vector of location-specific amenities, including information on local climate T_j. Preference heterogeneity is modelled by including a vector X_i containing individual-specific variables interacted with T_j. The coefficient on the interaction, β_{qi}^T, is random with distribution $N(b, \Omega)$. The standard interpretation of the β_{qi}^T's is taste-parameters specifying the weight given by individuals to different amenities in their location-choice decisions. M_{ij} denotes migration costs from the migrant's origin to location j, while N_{ij} indicates the presence of networks at the destination. ζ_j represents the location-specific unobservable heterogeneity and η_{ij} denotes the individual-specific idiosyncratic error term.

Migrants maximize their utility subject to a destination-specific budget constraint given by:

$$C_i + \rho_j H_i = I_{ij} \,.\text{[5]} \tag{4.2}$$

I_{ijt} represents income at MSA j, whereas ρ_{jt} denotes the location-specific price of housing. Solving the first order conditions and taking logs yields the following indirect utility function[6]:

$$\ln V_{ij} = \beta_I \ln I_{ij} + \beta_{qi}^T (X_i \times T_j) + \beta_m M_{ij} + N_{ij} + \Theta_j + \eta_{ij} \,, \tag{4.3}$$

where

$$\Theta_j \equiv -\beta_H \ln \rho_j + \beta_z \ln Z_j + \zeta_j \,. \tag{4.4}$$

The fixed effects Θ_j capture the composite part of utility for MSA j that is constant across migrants. In the second stage, I decompose this average effect by regressing Θ_j on location-specific amenities, including destination climates.

5. Traditionally, migration costs do not enter the budget constraint as these are a one-off cost often financed through savings.

6. See Bayer et al. (2009) and Fan et al. (2012) for the complete mathematical derivation.

Retrieving MSA fixed effects requires information on a migrant's income I_{ij} for all potential locations in the choice set. In reality, one only observes income for migrant i at the final destination j. However, I use information from the American Community Survey (ACS) on similar persons residing in the alternative destinations to predict potential income $\hat{I}_{ij}$ of migrant i for non-chosen destinations. Section 4.4.3 describes the hedonic regression used to retrieve earnings estimates. Inserting $\hat{I}_{ij}$ into Equation 4.3 yields

$$\ln V_{ij} = \beta_I \ln \hat{I}_{ij} + \beta_{qi}^T (X_i \times T_j) + \beta_m M_{ij} + N_{ij} + \Theta_j + \upsilon_{ij}\,. \tag{4.5}$$

The above error term υ_{ij} is composed by the idiosyncratic error from the utility η_{ij} and the income equation ε_{ij}^I.

As discussed in Chapter 3, the stochastic error component of the utility function υ_{ij} in the standard logit model is assumed to be IID in accordance with the Generalized Extreme Value distribution Type-I (Gumbel). This error specification is very restrictive, as it requires two individuals who, based on observable characteristics, are indistinguishable to have identical tastes for amenities entering the model. Hence, the coefficients β_{qi}^T (individual climate preference) would be required to be fixed across migrants. Given the research aim of identifying heterogeneity across the population, it is undesirable to assume constant taste parameters across the population. As noted earlier, climate valuations likely vary not only by observed but also by unobserved individual characteristics. Ignoring this taste variation might lead to biased estimates of the WTP for comfortable climate.

In addition, the IID assumption gives rise to the IIA property. This property requires that the relative probability of choosing one alternative over another is unaffected by the addition or omission of a location to the choice set. In the presence of vast contrasts in attributes among destinations, this could be violated as changes in the composition of the choice set might alter relative valuations of attributes.

The analysis makes an attempt at relaxing the IID error specification using a mixed logit model, which resolves the limitation of the standard logit model by explicitly allowing for random taste parameters, substitution among alternatives, and correlation in unobserved covariates.[7] In contrast to the standard logit model, the stochastic component

7. See Train (2009) Chapter 6 for an comprehensive description of the mixed logit model.

of the utility $\eta_{ijt} \equiv \beta^T_{qi} + \upsilon^I_{ij}$ in RUMs is allowed to be correlated across alternatives with

$$Cov(\eta_{ij}, \eta_{ik}) = E(\beta^T_{q_j i}(X_i \times T_j) + \upsilon_{ij})(\beta^T_{q_k i}(X_i \times T_k) + \upsilon_{ik}) = \beta^T_{q_j i}{}' \, \Omega \, \beta^T_{q_k i} \,, \tag{4.6}$$

where Ω is the covariance of β^T_{qi}. As such, the mixed logit provides the highly desirable flexibility to model individual choice situations with various substitution patterns among alternatives.

In the presence of random effects, the probability of choice j is the integral of standard logit probabilities over a density of the random parameters β^T_{qi}. Assuming a log-linear indirect utility function as in Equation 4.5, the conditional logit probability is given by

$$\begin{aligned} &P(\ln V_{ij} \geq \ln V_{ik} \, \forall \, k \neq j) = \\ &\qquad \int \frac{e^{\beta_I \ln \hat{I}_{ij} + \beta^T_{q_j i}(X_i \times T_j) + \beta_m M_{ij} + N_{ij} + \Theta_j}}{\sum\limits_{k=1}^{J} e^{\beta_I \ln \hat{I}_{ik} + \beta^T_{q_k i}(X_i \times T_k) + \beta_m M_{ik} + N_{ik} + \Theta_k}} f(\beta^T_{q_j i} | \bar{\beta}, \Omega) d\beta^T_{q_j i}. \end{aligned} \tag{4.7}$$

Thus, the probability of the model is defined as a mixture of the standard logit function integrated over all values of β^T_{qi} and weighted by the mixing distribution $f(\beta^T_{qi})$.

The choice probability in Equation 4.7 has no closed-form solution. Consequently, evaluation of the choice probability requires simulation for the close approximation of the integral.

4.4 Estimation of the Model

4.4.1 Estimation Method for the First Stage

The first stage of the model (Equation 4.7) is evaluated using Bayesian estimation procedures. Bayesian methods were first introduced to the estimation of choice models by Albert and Chib (1993), Allenby and Lenk (1994) and McCulloch and Rossi (1994).[8] The use of the Bayesian approach in mixed logit estimations is known to benefit from two computational advantages over classical frequentist procedures (Train 2009). First, Bayesian methods do not require the maximisation of a likelihood function, which is known to be numerically difficult, as convergence can be sensitive to the appropriate specification of

8. See Train (2009, Chapter 12) for an introduction into Bayesian statistical methods for choice analysis.

starting values.[9] Besides, successful convergence does not guarantee maximisation, due to the issue of local versus global maxima.

A second desirable property is the relatively simple conditions under which Bayesian estimation procedures yield consistent and efficient estimates. Train (2009, Chapter 12) shows that Bayesian estimation procedures for mixed logit models can lead to asymptotically equivalent estimates to the maximum likelihood approach if the conditions of the Bernstein-von Mises theorem are satisfied.[10] In addition, individual-level parameters can be easily obtained. A further important advantage is that Bayesian procedures are considerably faster to compute under most model specifications. Bearing in mind these advantages, the Bayesian approach is preferred over the frequentist approach.

As discussed in detail by Ruud (1996) and later by Train (2001), mixed logit models with only random parameters are nearly unidentified empirically, given that in logit models only ratios of parameters are economically meaningful, due to the underlying scaling parameter. Thus, at least one coefficient in a mixed logit model should be held constant across cases (here migrants). In the context of a residential location-choice model, the optimal strategy is to keep the alternative-specific constants fixed across individuals. Moreover, Train (2009) advises to keep the coefficient for the hedonic income measure fixed across individuals. Random variation in the price index introduces further complexity in measuring the WTP distribution, due to variation in the scale across individuals (Train 2009, p.351).[11] The remaining IID error term constitutes the random component of these constants.

Introducing fixed coefficients in a Bayesian mixed logit framework considerably complicates the estimation method (Train 2001). A second layer of Gibbs sampling is required in the simulation to ensure that fixed parameters are kept constant across the population, while the algorithm draws the random coefficients for each individual.[12] I apply Train's (2001) estimation procedure which, using Bayes rule, yields the following posteriors for

9. As noted in Chapter 3, I was unable to achieve convergence experimenting with a mixed logit approach evaluated using simulated maximum likelihood estimation techniques.

10. See Train (2009, pp. 327) for a detailed description of the Bernstein-von Mises theorem in the context of discrete choice models.

11. As a sensitivity analysis, the results include estimates of a location-choice model allowing for random variation in the income variable. Removing the restriction of constant income weights across individuals inflates coefficients on summer and winter temperatures with a negative covariance between the coefficient on income and temperatures.

12. See Train (2001, pp. 7-8) for a comprehensive explanation of the estimation procedure.

the Gibbs sampling:

$$\Lambda(\beta_i|\alpha, \bar{\beta}, \Omega) \propto L(y_i|\alpha, \beta_i) f(\beta_i|\bar{\beta}, \Omega) \tag{4.8}$$

As a simplification, α and β_i indicate composite vectors containing fixed and random parameters in (4.7). Metropolis-Hastings sampling is used to draw the β_i's, respectively. Moreover, I assume individual β_i's to be IID with a multivariate normal distribution of mean $\bar{\beta}$ and covariance matrix Ω. For convenience, I assume natural conjugate priors, with the prior for $\bar{\beta}$ being normal and the prior on Ω being the inverted Wishart distribution.

Therefore, $\Lambda(\bar{\beta}|\Omega, \beta_i \forall i) = N(0, \Omega/N)$, where draws of Ω are obtained from its posterior conditional on $\bar{\beta}$ and β_i for all N. $\Lambda(\Omega|\bar{\beta}, \beta_i)$ is the posterior of the inverted Wishart with $K+N$ degrees of freedom and scale matrix $(KI+N\bar{S})/(K+N)$. K is the number of random parameters with K-dimensional identity matrix I. $\bar{S}$, defined as $(1/N)\sum_i(\beta_i - \bar{\beta})(\beta_i - \bar{\beta})'$, is the sample variance of the β_i's around the known mean $\bar{\beta}$.[13]

Finally, the posterior for the fixed effects α conditional on the β_i's is defined as

$$\Lambda(\alpha|\beta_i) \propto \prod_i L(y_i|\alpha, \beta_i)\,. \tag{4.9}$$

Draws of (4.8) and (4.9) and are obtained through Metropolis-Hastings sampling.

4.4.2 Choice-Set Pruning in Large Choice Sets

The choice set of alternatives in this study consists of 255 U.S. MSAs. Estimation of a mixed logit model with alternative-specific characteristics, therefore, results in a prohibitively large dataset, rendering evaluation of the model over the full set of destinations highly computationally expensive. Besides, as noted in Chapter 3, such a model is behaviourally unrealistic, considering that individuals are unlikely to consider the full set of alternatives in their decision (Fotheringham 1988).

As discussed in the previous chapter, the problem of unrealistically large sets of alternatives in the case of a simple logit model with an IID error term can be overcome through sampling a random subset of alternatives (Ben-Akiva and Lerman 1985; McFadden 1978). Relaxation of the IIA property in the mixed logit model, however, implies that McFadden's

13. See Train (2009, pp. 337–340) for a detailed description of how to obtain a draw of the inverted Wishart.

(1978) theoretical proof of parameter consistency under random sampling of alternatives is no longer valid. The pruning method introduces further noise into the mixed logit model, causing potential bias in parameter estimates.

With the renewed interest in the application of mixed logit models, several studies have set out to examine empirically how choice-set sampling affects parameter and standard error estimates (Brownstone et al. 2000; Keane and Wasi 2013; Nerella and Bhat 2004; von Haefen and Domanski 2013). Facing a universal choice set of 689 alternative vehicles, Brownstone et al. (2000) performed experiments to evaluate the effect of increasing the number of alternatives in a mixed logit regression from 28, and found no systematic bias in estimated parameter coefficients. Nerella and Bhat (2004) examine the bias in coefficient estimates of mixed logit models based on a simulation study with 200 alternatives and random samples of alternatives varying between 2.5% and 75%. Estimated coefficients vary considerably by size of the choice set. Based on their findings, Nerella and Bhat (2004) recommend drawing a minimum of 25% of alternatives to limit potential bias from the choice-set pruning.

A more in-depth analysis of the potential sampling bias for different latent-class models was conducted by von Haefen and Domanski (2013), who found random sampling to perform well in mixed logit models as the number of alternatives increases. Lastly, Guevara et al. (2014) formally demonstrate the consistency of parameters under random sampling of alternatives in mixed logit models as the number of drawn alternatives approaches the universal choice set. Using simulation methods, the authors observe that the naïve approach outperforms alternative sampling methods, correcting for the sampling probability of alternatives. However, the simulation results stress that the potential bias introduced from choice-set restrictions is more severe in a mixed logit model than in the standard logit. Thus, application of a mixed logit model necessitates the selection of a larger sample of alternatives.

Considering the theoretical and empirical evidence of the viability of the naïve choice pruning approach in the context of a mixed logit model choice, the analysis draws a random sample of 74 alternatives in addition to the migrant's chosen location.[14]

14. Experimentation with the choice-set size reveals no significant changes in parameter estimates from increasing the number of random alternatives beyond 59 MSAs.

4.4.3 Hedonic Price Regressions and Endogeneity

Before estimating the first-stage choice model in Equation 4.7, one requires individual-level information on earnings $\hat{I}_{ij}$ and location-specific housing prices for all alternative locations. Since information on earnings is only observed for the chosen alternative, I follow the literature by estimating a location-specific hedonic income equation to compute potential earnings of individuals for the full set of alternatives (Bayer et al. 2009; Bayer and Timmins 2007; Fan et al. 2018; Sinha et al. 2018). I use information from the IPUMS of the ACS (U.S. Census Bureau 2018) to estimate an MSA-level regression, controlling for non-random sorting as in Dahl (2002):

$$\ln w_{ij} = \delta_j + \lambda_j M_i + \kappa_{1j} P(D_j, MI|EDU) + \kappa_{1j}[P(D_j, MI|EDU)]^2 + \varsigma_{ij}^I \,. \tag{4.10}$$

Here, w_{ij} is measured as annual wage earnings of individual i residing at MSA j. The vector M_i includes a set of individual characteristics: age, gender, level of education and occupation type,[15] as well as whether the individual is of Mexican ethnicity and a migrant, and whether the immigration took place within the relevant study period (2000 to 2012).

A common problem in hedonic income regressions is the selection bias stemming from more highly educated individuals choosing locations with higher returns to schooling, potentially causing a problematic upward bias in the returns to education. To address this issue, I apply the semi-parametric control mechanism suggested by Dahl (2002), where $P(D_r, MI|EDU)$ measures the percentage of Mexican immigrants MI with education level EDU residing in region D_r.[16] Results for the hedonic income regression are presented in Appendix C.2.

15. Mexican occupation codes are converted into two-digit ISCO-88 occupation codes based on the cross-walk provided by Mahutga et al. (2018, Appendix D) to match occupations between the MMP and the ACS.

16. The control mechanism requires observations for each combination of education level and destination to function correctly. This requirement is fulfilled at the Census Region level. Regions are defined as: New England (CT, ME, MA, NH, RI, VT), Middle Atlantic (NJ, NY, PA), East North Central (IL, IN, MI, OH, WI), West North Central (IA, KS, MN, MO, NE, SD, ND), South Atlantic (DE, DC, FL, GA, MD, NC, SC, VA, WV), East South Central (AL, KY, MS, TN), West South Central (AR, LA, OK, TX, WY), Mountain (AZ, CO, ID, MT, MV, NM, UT), and Pacific (AK, CA, HI, OR, WA).

4.4.4 Estimation of the Second Stage

Having obtained estimates of the composite utility measures θ_j from the first-stage regression, evaluation of the second stage

$$\Theta_j \equiv -\beta_H \ln \rho_j + \beta_z \ln Z_j + \zeta_j \qquad \text{(4.4 revsited)}$$

requires information on location-specific housing prices ρ_j. Following Sinha et al. (2018), the natural log of annual housing costs P_{hj} of household h in MSA j is regressed on information on property ownership O_h and a vector of dwelling characteristics D_h using data from the ACS.

$$\ln P_{hj} = \ln \rho_j + \lambda_j O_h + \gamma_j D_h + \varsigma_{ij}^H \, . \qquad (4.11)$$

Annual housing costs are computed as the sum of annual rent or mortgage payments, property taxes and insurance, and utility costs, such as water and gas. The dummy O_h indicates whether the property is owned or rented. After netting out dwelling attributes, the parameter ρ_j captures the effective housing price index in location j. $\ln \rho_j$ is estimated as the MSA-specific constants from the hedonic housing price regression in (4.11).

Complications in the estimation of Equation 4.4 could further arise from endogeneity in ρ_j and Z_j caused by people's sorting into locations with preferential amenities. Housing prices and amenities are likely correlated with unobserved attributes in ζ_j leading to biased OLS estimates. The problem of endogeneity in ρ_j can be overcome by moving $\beta_H \hat{\ln} \rho_j$ to the left-hand side of the equation. Equation 4.4 then becomes:

$$\Theta_j - \beta_H \hat{\ln} \rho_j = \beta_z \ln Z_j + \zeta_{ij} \qquad (4.12)$$

By means of the Cobb-Douglas properties of the utility function, the coefficient β_H can be approximated by multiplying the income coefficient from the first-stage regression with the median share of income spent on housing in the ACS sample used to estimate Equation 4.11.

The remaining issue of endogeneity in Z_j is addressed by testing the sensitivity of estimates to inclusion of additional controls and the implementation of an IV approach after Bayer and Timmins (2007). The instrument is constructed as follows:

$$IV_j = \frac{1}{N}\sum_{i=1}^{N}\tilde{P}_{ij} = \frac{1}{N}\sum_{i=1}^{N}\frac{\tilde{V}_{ij}}{\sum_{k=1}^{J}\tilde{V}_{iJ}}\,,\text{[17]} \tag{4.13}$$

where $\tilde{P}_{ij}$ captures the proximity of substitute locations determined by the utility space. $\tilde{V}_{ij}$ is the utility an individual receives from location j based on exogenous amenities. $\tilde{V}_{ij}$ is retrieved by, first, estimating Equation 4.12 using simple OLS, which yields biased estimates of the indirect utility. Second, coefficient estimates from the first- and second-stage regressions are used to calculate each migrant's indirect utility $\tilde{V}_{ij}$ at location j, based on only exogenous amenities.[18] The predicted share of similar locations based on exogenous location attributes will provide a good approximation of agglomeration effects if the impact of location size on utility is not large compared to that of the exogenous amenities.

4.5 Choice Setting and Data

The primary data on migration movements are again taken from the MMP, the same migration survey as in Chapter 3. Different from the previous chapter, the analysis is limited to migration movements which took place between 2000 and 2012. Lack of MSA-specific individual-level earnings and property prices data, required for the estimation of $\hat{I}_{ij}$ and ρ_j, implies that information on earlier migration movements is lost.[19] The reduced sample consists of 1,128 individuals from 59 different municipalities and a total of 1,254 observed migration movements. Again, alternative destinations in the location choice of migrants are defined as contiguous U.S. MSAs, excluding the state of Alaska. Due to unavailability of price data for some locations, the final set of alternatives consists of 255 MSAs. The total number of observations after drawing a random subset of alternative

17. Different from Bayer and Timmins (2007) the $\tilde{V}_{ij}$'s in the numerator and denominator are not exponentiated due to large values prohibiting the application of an exponential transformation. Alternative methods of normalisation were exploited, but differences compared to results based on absolutes were considered negligible.

18. Following Bayer and Timmins (2007), besides population measures also the parameters sectoral earnings are excluded from the construction of the instrument, as they likely do not fulfil the exogeneity criterion.

19. Although the loss of earlier migration movements considerably reduces the sample size, the restriction implies that estimated climate valuations reflect today's preferences. Changes in the access to air conditioning as well as to protective clothing during the last two decades may likely have altered climate preferences in the recent past, likely changing climate valuations.

destinations is 94,050.

Mexican Migration Data

Table 4.1: Sample Summary Statistics Mexican Migrants

	U.S. Total		West		Midwest		South		North East	
variables	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
age	30.79	*9.07*	30.85	*8.75*	30.61	*9.30*	31.17	*9.75*	29.68	*7.90*
duration	31.13	*32.77*	36.47	*38.33*	30.06	*26.34*	23.07	*23.40*	25.50	*33.37*
migration distance	3,152.1	*989.1*	3,428.9	*984.9*	3,273.6	*227.6*	2,198.8	*952.9*	4,108.5	*188.9*
migration time	39.30	*42.43*	38.00	*34.15*	35.12	*30.13*	38.08	*27.09*	69.00	*113.43*
$\hat{I}$	3,341.0	*2,386.9*	3,212.5	*2,259.5*	3,326.6	*2,316.3*	3,764.5	*2,761.2*	2,806.3	*1,870.3*
male	90.43		89.10		90.51		91.12		97.22	
married	53.72		51.63		52.19		57.92		59.72	
parent	3.55		2.49		0.73		5.79		13.89	
legal migration	11.08		10.52		8.03		14.67		13.89	
college graduate	20.66		20.08		20.07		22.39		20.83	
permanent	78.19		83.37		82.12		69.11		58.33	
network	38.48		37.67		37.96		38.22		47.22	
trip 1	58.95		59.85		62.77		56.76		45.83	
trip 2-5	35.46		34.99		33.58		37.07		40.28	
trip 6-10	3.55		3.44		2.55		4.63		4.17	
trip $\geq$ 10	1.24		0.57		0.73		0.77		9.72	
mean temperature Mex	20.16	*2.85*								
N	1,128		523		274		259		72	
Frequency (%)	100		46.4		24.3		23.0		6.4	

Notes: Sample statistics are based on working-age population during first year of migration from the Mexican Migration Project Survey 161 restricted over the period 2000-2012.

As in Chapter 3, the analysis is restricted to prime-aged adults (16-75 years) participating in the labour force. Estimates of amenity values based on the two-stage model rely on the capitalisation of amenities into incomes and housing prices.[20] This approach may not be appropriate for retirement migration, as this type of migrants do not draw their income purely from wages earnings. As such, the estimated income coefficient might not be representative for retired migrants leading to biased WTP-estimates. Individual-level characteristics considered in the analysis are migrants' age, the marital status, the education level, the occupation, whether the migrant resided in the same location during a previous trip, and finally whether the individual has relatives living in the MSA.[21]

Table 4.1 provides summary statistics for sample migrants. The minor differences in the statistics compared with Table 3.1 in Chapter 3 are explained by the loss in observations prior to 2000. Interestingly, the average migration distance is longer for movements

20. The two-stage model explicitly controls for income, while housing prices are only captured implicitly through the implemented price correction in the second-stage regression (see Equation 4.12).

21. Information on migrants' marital status and occupation are considered for the estimation of potential earnings $\hat{I}_{ij}$.

starting in 2000. While age and gender composition of the sample remain almost unchanged, a larger share of migrants is married with completed college education at the time of emigration. Moreover, the share of legal migration crossing is lower. Interestingly, Mexicans that migrated between 2000 and 2012 are more likely to migrate to the U.S. for more than one year. Furthermore, fewer migrants benefit from a personal network in the U.S. Studying regional differences across census regions reveals that migration to the South and North Eastern census regions tends to be less permanent with a higher prevalence of repeated circular migration. Moreover, the share of legal migrants is larger compared to other census regions.

Mexican temperature normals are relatively warm throughout the year, with annual mean temperatures of 20.16°C (sd of 2.85°C). I exploit information on Mexican temperatures to differentiate between migrants originating in municipalities with warmer and colder temperatures than the historical median.

MSA Location-Specific Data and Variables

Non-climate control variables included in the second-stage regressions are summarised in Table 4.2. Ideally, one would like to include population size as an explanatory variable in the second-stage regression to capture benefits that come along with agglomeration effects of large cities. However, measures of population size should be used with caution, due to the simultaneity problem discussed earlier. Alternatively, studies have suggested using population density or land area to control for agglomeration effects (Sinha et al. 2018). I examine the sensitivity of estimates to the inclusion of the alternative population measures. The model further includes hourly wages earned in business service, construction and production occupations, and the violent crime rate.[22] Additional amenities included in the second stage are information on city scores from the *Places Rated Almanac; Millennium Edition* (Savageau and D'Agostino 2000) on health, transportation, education, arts and recreational facilities. Lastly, I control for elevation and distance to the nearest coast.[23]

22. The economic and demographic information was collected from different official U.S. statistical offices. Data on hourly wages are retrieved from the U.S. Bureau of Labour Statistics (U.S. Bureau of Labor Statistics 2014). Information on the population size was collected from the U.S. Census (Manson et al. 2011). Crime rates stem from the United States Department of Justice, Federal Bureau of Investigation (2019, hereafter FBI).

23. Both variables are generated by querying the Google Elevation and Distance Matrix API.

Table 4.2: Summary Statistics on Location Specific Characteristics by U.S. Census Region

	U.S. Total		**West**		**Midwest**		**South**		**North East**	
variables	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
population (in 1,000s)	873.49	*1,300.75*	1,042.56	*1,538.59*	695.14	*1,235.98*	739.62	*920.97*	1,276.08	*1,739.23*
population density	190.75	*340.19*	128.04	*180.16*	122.46	*95.28*	124.08	*91.99*	526.89	*711.72*
area (km^2)	6.32	*8.74*	12.47	*17.37*	4.94	*4.58*	5.33	*3.46*	3.81	*3.02*
hourly wage business	1,644.4	*308.0*	1,792.5	*263.3*	1,837.8	*220.5*	1,359.4	*131.4*	1,842.8	*259.5*
hourly wage construction	1,333.2	*171.3*	1,321.1	*138.7*	1,434.1	*198.7*	1,261.9	*157.6*	1,356.8	*91.9*
hourly wage production	2,268.8	*257.0*	2,398.1	*261.3*	2,210.8	*187.2*	2,188.7	*207.2*	2,400.9	*338.5*
violent crime (per 1000)	3,939.2	*1,403.6*	4,109.1	*1,037.1*	3,994.9	*1,494.0*	4,347.8	*1,338.2*	2,709.7	*1,071.0*
health score	1,250.7	*1,081.7*	1,023.4	*1,022.3*	1,373.8	*1,005.8*	1,080.5	*803.2*	1,718.2	*1,589.6*
transportation score	4,295.4	*1,476.7*	4,656.2	*1,593.0*	4,470.7	*1,269.5*	3,963.1	*1,437.4*	4,390.8	*1,621.2*
education score	2,827.75	*322.04*	2,669.69	*332.53*	2,799.48	*241.82*	2,813.80	*303.84*	3,085.73	*321.25*
arts score	3,469.9	*5,044.3*	3,593.1	*4,065.8*	3,327.3	*3,813.6*	2,650.7	*3,029.3*	5,483.8	*9,373.8*
recreational score	1,912.1	*834.9*	2,489.7	*1,019.4*	1,750.4	*481.6*	1,792.4	*827.8*	1,788.3	*799.0*
distance to coast (km)	209.21	*273.68*	353.06	*450.27*	211.73	*207.51*	201.24	*216.37*	59.64	*64.20*
elevation (m)	302.23	*384.75*	737.31	*640.60*	266.31	*65.30*	166.70	*234.27*	180.92	*159.99*
N	255		48		66		99		42	
Frequency (%)	100		18.8		25.9		38.8		16.4	

Notes: Sample statistics are based 255 Metropolitan Statistical Areas in the year 2010.

Climate Data and Variables

Table 4.3: Summary Statistics Climate variables

	Total		**West**		**Midwest**		**South**		**North East**	
variables	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
average temperature (°C)	13.21	*4.73*	11.82	*3.61*	9.49	*2.08*	17.86	*3.25*	9.71	*1.54*
max temperature (°C)	19.27	*4.89*	18.75	*4.06*	15.14	*2.18*	23.98	*3.02*	15.26	*1.51*
min temperature (°C)	7.19	*4.73*	4.92	*3.60*	3.88	*2.06*	11.78	*3.58*	4.18	*1.67*
summer temperature (Jun-Aug)	0.86	*3.43*	-2.27	*3.52*	-0.44	*1.59*	4.15	*1.84*	-1.29	*1.24*
winter temperature (Dec-Feb)	-14.07	*6.75*	-12.90	*4.79*	-20.79	*2.98*	-8.15	*4.82*	-18.82	*2.08*
precipitation (mm)	84.45	*27.41*	55.59	*32.37*	75.43	*10.09*	100.49	*24.39*	93.81	*7.22*
cloud cover (%)	60.00	*7.19*	53.07	*10.25*	64.56	*3.45*	57.91	*3.77*	65.68	*3.67*
vapour pressure (hPa)	121.88	*39.39*	87.95	*20.31*	101.70	*11.56*	161.28	*33.02*	99.49	*7.73*
N	255		48		66		99		42	
Frequency (%)	100		18.8		25.9		38.8		16.4	

Notes: All climate variables are calculated 30-year averages prior to the migration year.

Table 4.3 summarises the climate variables included in the empirical analysis. As in Chapter 3, climate variables are constructed as thirty-year arithmetic averages over MSA polygons based on interpolated weather data taken from the CRU TS4.01 dataset provided by the CRU at the University of East Anglia (CRU 2017). Considering the evidence of nonlinearity in climate preferences in Chapter 3, the empirical analysis tests for heterogeneous preferences using both seasonal climate specifications, such as summer and winter temperatures, and annual means, maxima and minima.[24] Besides temperature measures, the regressions include measures for mean total monthly precipitation, humidity (vapour pressure) and daily sunshine exposure (percentage rate of cloud cover).

4.6 Results from the Two-Stage Sorting Model

The Baseline: Testing for Endogeneity

Table 4.4 presents the posterior means and distributions of the coefficient estimates for the baseline first-stage mixed logit model.[25] In a classical sense, the results can be interpreted as the coefficient estimate and the standard deviation. I performed 40,000 iterations of the Gibbs Sampling, with the first 30,000 considered as a burn-in. The posterior means are based on the next 10,000 draws, of which every tenth draw is retained. The distribution of random coefficients is simulated using 10,000 draws from $N(\bar{\beta}, \Omega)$ per individual. The simulated log-likelihood value is calculated based on 5,000 draws per migration movement. Convergence was confirmed via visual inspection of trace and density plots. Running the procedure using three chains with different starting values yields very similar posterior means.

Table 4.4 reports the mean and the standard deviation of the distribution of the random variables as well as the correlation between coefficient estimates for summer and winter temperatures. The first-stage model includes fixed parameters for the natural log of income and migration distance as well as MSA and year fixed effects. Throughout all models, the base location is defined as Chicago (IL) in 2010. Random parameters in the model

24. Due to the high natural correlation in climate, issues of collinearity in parameters render it impossible to include all temperature variables simultaneously in the regression. Consequently, alternative model specifications are evaluated, including different sets of temperature variables.

25. Note that the concept of null-hypothesis significance testing is not appropriate in a Bayesian context. Therefore, to be consistent in the presentation of results across the two-stages, significance stars are not provided throughout the chapter.

Table 4.4: First Stage: Bayesian Mixed Logit Model

	Model (1)	
	Hierarchical Bayes	
1st Stage		
	Coef (Std Err)	*Std* Ω
fixed coefficients		
ln $\hat{I}$	1.142	
	(0.359)	
ln migration	-6.645	
distance	(0.724)	
random coefficients		
same location	15.95	99.15
previous migration	(2.016)	(29.18)
relative	10.70	60.70
same MSA	(1.321)	(17.02)
summer	2.150	3.280
temperature	(0.484)	(1.77)
winter	-7.030	5.690
temperature	(0.45)	(1.825)
precipitation	-0.610	0.367
	(0.089)	(0.08)
vapour	2.670	16.48
pressure	(1.003)	(5.589)
cloud	1.918	2.044
cover	(0.482)	(0.871)
correlation: winter summer temperature	0.4384	
MSA FE	×	
year FE	×	
simulated LL	-1910.9	
N	94,050	
cases	1,254	

Notes: The table presents the posterior means and distributions of the coefficient estimates, the mean and the standard deviation of the distribution of the random variables and the correlation between coefficient estimates for summer and winter temperatures. To improve convergence, climate variables have been rescaled in units of 10. Model is evaluated using 40,000 iterations of the Gibbs Sampling, with the first 30,000 considered as a burn-in. The posterior means are based on the next 10,000 draws, of which every tenth draw is retained. The distribution of random coefficients is simulated using 10,000 draws from $N(\bar{\beta}, \Omega)$ per individual. The simulated log-likelihood value is calculated based on 5,000 draws per migration movement.

are: mean summer and winter temperature normals, average monthly precipitation, mean vapour pressure, average number of cloud days per month, and two dummies for the presence of networks (same location and relatives).[26] The two variables indicate repeated migration movements to the same destination and the presence of any relatives or friends at a destination.[27] In the first stage, coefficients should be interpreted as relative changes in the attractiveness of a location after controlling for the location-specific composite utility, captured by the MSA fixed effects.

Studying results from the first stage, I find parameter estimates for income and migration distance to have the expected sign, with higher earnings increasing the attractiveness of a location, while moving farther away from home reduces the likelihood of settlement. Turning to the random coefficients, the presence of relatives in the MSA or previous migration trips to the same location are important drivers of migrants' location choices. Concerning climate, migrants are attracted to locations with on average warmer summers and colder winters. This result differs from findings in Chapter 3, where I found the coefficient for winter temperatures to be positively related to the probability of settlement. A further difference to previous results is the positive coefficient for vapour pressure. The contrasting results may stem from the difference in the model specification, with the approach taken here not only allowing for random variation in coefficients, but also explicitly modelling correlations in the random variation across climate regressors. Given the natural correlation in climate variables, the weight a person gives to temperatures in the migration decision is likely to be correlated with preferences for humidity and sunshine. Accounting for such correlations may considerably alter predicted preferences. Therefore, observed differences between Chapter 3 and the baseline results indicate the presence of significant individual taste variation in climate preferences.

Unobserved individual heterogeneity in the first stage is captured through the variance-covariance matrix Ω. Appendix C.1 provides the variance-covariance matrix for the baseline model. Elements along the diagonal of the matrix indicate unexplained variation in the corresponding amenity's influence on choice probabilities, while off-diagonal (covariance) elements explain how sensitive the tastes for attributes are to changes in other amenities (i.e. changes in preferences for summer temperatures in response to changes in vapour pressure). The variance-covariance estimates reveal several significant elements,

26. To improve convergence, climate variables have been rescaled in units of 10.

27. The approach taken here differs from Chapter 3, as the mixed logit specification allows for the exploitation of individual-level information on the presence of networks provided by the MMP.

particularly with respect to networks and the main variables of interest, summer and winter temperature. Diagonal elements for summer temperature and vapour pressure show large unexplained heterogeneity in the weight given to both amenities in individuals' location decisions. Unsurprisingly, coefficients for temperature and vapour pressure have a negative covariance. Humidity directly affects human thermal comfort by reducing the ability of the body to cope with external heat stress. Therefore, the stronger an individual's taste for warmer temperatures, the greater the disutility the person experiences from rising humidity levels.

Moreover, I observe a large heterogeneity in the weight given to networks in the choice process. An intriguing finding is the positive covariance between the presence of network ties and the coefficients for all climate amenities except vapour pressure. This suggests that stronger networks ties increase the relative weight given to summer and winter temperatures and precipitation. At the same time, greater weight given to the presence of networks reduces the coefficient for vapour pressure. These observations emphasise the existence of significant individual taste variation in climate preferences, which remains unaccounted for in the standard logit.

Table 4.5 presents estimates for the second-stage. Besides climate variables, the regressions include amenities listed in Table 4.2. Columns one to five present OLS estimates with robust standard errors. In Models 2 to 5, I include additional region fixed effects and test for agglomeration effects by adding alternative measures of population size to the regression. Model 6 reports estimates using the IV estimation method outlined in Section 4.4.3. Before going into detail regarding the differences across models, it is important to note that the interpretation of coefficients differs from the first-stage regression. In the second stage, coefficient estimates explain changes in the composite utility of a destination.

I find warmer summer temperatures reduce the composite utility of a destination, while locations with warmer winter temperatures on average have a higher composite utility. While the number of cloud days and vapour pressure are negatively related to the composite utility of an MSA, precipitation has a small positive effect. Across the different models, most of the coefficients for non-climate amenities are significant with the expected sign. Exceptions are the coefficients for production wages, violent crimes and for the arts and recreational-facilities scores. I estimate a negative impact of production

Table 4.5: Second Stage: Specification Tests OLS versus IV

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	OLS	region FE	region & ln pop	region & pop dens	region & ln area	region & IV
2nd Stage	*Coef* *(Std Err)*	*Coef* *(Std Err)*	*Coef* *(Std Err)*	*Coef* *(Std Err)*	*Coef* *(Std Err)*	*Coef* *(Std Err)*
summer temperature	-5.898 (0.088)	-4.914 (0.119)	-5.736 (0.122)	-5.267 (0.124)	-6.902 (0.138)	-4.721 (0.121)
winter temperature	7.557 (0.068)	7.515 (0.114)	6.592 (0.108)	7.710 (0.114)	7.952 (0.116)	7.648 (0.114)
precipitation	0.190 (0.010)	0.120 (0.012)	0.156 (0.011)	0.113 (0.012)	0.131 (0.011)	0.147 (0.011)
cloud cover	-1.045 (0.140)	-0.938 (0.192)	0.257 (0.184)	-0.884 (0.192)	-0.244 (0.188)	-1.419 (0.191)
vapour pressure	-3.240 (0.038)	-3.257 (0.042)	-3.497 (0.040)	-3.270 (0.042)	-3.451 (0.042)	-3.159 (0.042)
ln hourly wage business	4.775 (0.544)	3.195 (0.581)	0.619 (0.585)	3.105 (0.580)	3.176 (0.582)	3.363 (0.580)
ln hourly wage production	-6.614 (0.436)	-2.183 (0.448)	-2.056 (0.446)	-2.926 (0.448)	-2.693 (0.442)	-2.661 (0.450)
ln hourly wage construction	24.07 (0.472)	25.92 (0.591)	24.20 (0.591)	27.45 (0.571)	26.87 (0.594)	26.13 (0.594)
violent crime rate	0.097 (0.005)	0.145 (0.005)	0.105 (0.005)	0.150 (0.005)	0.118 (0.005)	0.143 (0.005)
health score	0.104 (0.003)	0.082 (0.003)	0.037 (0.003)	0.078 (0.003)	0.062 (0.003)	0.079 (0.003)
transport score	0.068 (0.001)	0.061 (0.001)	0.050 (0.001)	0.058 (0.001)	0.052 (0.001)	0.059 (0.001)
education score	0.002 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.002 (0.000)
the arts score	-0.007 (0.000)	-0.001 (0.000)	-0.001 (0.000)	0.004 (0.001)	0.002 (0.000)	-0.001 (0.000)
recreational facilities score	-0.100 (0.002)	-0.112 (0.003)	-0.134 (0.003)	-0.117 (0.003)	-0.136 (0.003)	-0.108 (0.003)
distance to coast	-0.002 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.001 (0.000)
elevation	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)
ln population			1.015 (0.028)			
population density				-0.001 (0.000)		
land area					0.960 (0.022)	
region FE		×	×	×	×	×
IV						×
adjusted R^2	0.568	0.603	0.609	0.604	0.609	0.604
N	94,050	94,050	94,050	94,050	94,050	94,050

Notes: Robust standard errors presented in parentheses. Models 1 to 5 are estimated using Ordinary Least Squares. Model 6 is evaluated using the Instrumental Variableestimation method outlined in Section 4.4.3. Models 2 to 6 include region fixed effects. Regions are defined as: New England (CT, ME, MA, NH, RI, VT), Middle Atlantic (NJ, NY, PA), East North Central (IL, IN, MI, OH, WI), West North Central (IA, KS, MN, MO, NE, SD, ND), South Atlantic (DE, DC, FL, GA, MD, NC, SC, VA, WV), East South Central (AL, KY, MS, TN), West South Central (AR, LA, OK, TX, WY), Mountain (AZ, CO, ID, MT, MV, NM, UT), and Pacific (AK, CA, HI, OR, WA). Models 3 to 5 include alternative population controls as specified. Climate variables have been rescaled in units of 10.

wages on the composite utility indicating that MSAs with a large production sector on average have a lower living quality (measured in utility terms). The positive coefficient for the violent crime rate is likely explained by the correlation between this type of crimes and economic inequality. Research has shown that inequality, which generally rises with higher living standards, increases violent crime rates, with social deprivation increasing the propensity to engage in violence (see for example Kelly 2000). The negative relationship between arts and recreational-facilities scores and composite utility may be explained by local authorities in less attractive locations investing more in local facilities to improve the living quality of the MSA.

Ideally, one would like to control for the location's population size in the second stage, as the provision and quality of services and amenities changes as cities grow (agglomeration effects). However, population size itself is an outcome variable of a sorting process among locations. Therefore, adding measures of population size to the model may introduce an endogeneity bias to the OLS regression. Including the natural log of population in Model 3 results in a significant drop in the coefficient for business wages indicating that the estimates suffer from an endogeneity bias. As an alternative to population size, studies have suggested to use population density and land area, which might be less correlated with the error term since both are only indirectly an outcome of the sorting process (Sinha et al. 2018). Models 4 and 5 yield more similar coefficient estimates for business wages. Comparing estimates based on the IV method (Model 6) and the simple OLS estimates (Model 1), I observe small differences in the estimated coefficients for both climate and non-climate amenities, with some suggestive evidence of a bias in OLS estimates.

Except for Model 3, differences across the alternative models (2-6) are small. However, small changes in coefficients can cause considerable differences in the estimates of WTP for amenities. Considering the econometric rationale for the IV approach and the similarity of results, the remainder of the analysis will be evaluated using IV estimation methods as in Model 6. For completeness, alternative estimates using simple OLS are provided in Appendix C.3.

Table 4.6: First Stage: Alternative Mixed Logit Specification

	Base Model		**(7)**		**(8)**		**(9)**		**(10)**		**(11)**	
	region & IV		RD: $\hat{I}$		linear mig distance		mig distance married		no mig distance		RD: ln mig distance	
1st Stage	*Coef* (Std Err)	*Std* Ω	*Coef* (Std Err)	*Std* Ω	*Coef* (Std Err)	*Std* Ω	*Coef* (Std Err)	*Std* Ω	*Coef* (Std Err)	*Std* Ω	*Coef* (Std Err)	*Std* Ω
ln $\hat{I}$	1.142		1.622	1.866	1.258		1.861		-0.957		-0.016	
	(0.359)		(0.603)	(0.55)	(0.722)		(0.677)		(0.612)		(0.473)	
ln migration distance	-6.645		-7.294				-7.760				-8.499	4.114
	(0.724)		(0.761)				(0.627)				(0.507)	(1.634)
migration distance					-1.476							
					(0.202)							
ln migration distance ×married							-0.031					
							(0.328)					
same location previous migration	15.95	99.15	22.20	264.3	29.95	514.5	21.52	241.0	82.27	5122.6	20.40	196.7
	(2.016)	(29.18)	(1.901)	(50.67)	(2.041)	(77.04)	(1.761)	(47.32)	(18.45)	(2256.0)	(2.733)	(70.84)
relative same MSA	10.70	60.70	6.577	15.65	8.819	38.16	10.28	56.27	43.29	666.8	8.304	29.98
	(1.321)	(17.02)	(0.561)	(6.647)	(0.596)	(8.48)	(1.011)	(21.04)	(6.5)	(276.1)	(0.788)	(8.234)
summer temperature	2.150	3.280	-0.002	2.122	1.323	2.574	2.189	5.416	2.159	71.64	0.335	4.465
	(0.484)	(1.77)	(0.271)	(0.761)	(0.159)	(0.832)	(0.526)	(0.906)	(1.046)	(29.8)	(0.338)	(1.296)
winter temperature	-7.030	5.690	-5.628	1.991	-6.458	3.137	-9.491	4.452	-6.476	34.02	-6.225	5.350
	(0.45)	(1.825)	(0.199)	(0.945)	(0.404)	(1.11)	(0.469)	(1.789)	(0.662)	(12.73)	(0.354)	(1.769)
precipitation	-0.610	0.367	-0.895	0.330	-0.753	0.273	-0.571	0.349	-0.657	0.451	-0.209	0.353
	(0.089)	(0.081)	(0.137)	(0.075)	(0.061)	(0.049)	(0.082)	(0.079)	(0.14)	(0.119)	(0.077)	(0.071)
vapour pressure	2.670	16.48	0.543	1.708	3.336	7.149	2.314	12.84	2.630	14.19	0.079	4.144
	(1.003)	(5.589)	(0.254)	(0.879)	(0.571)	(3.34)	(0.705)	(4.297)	(0.712)	(4.931)	(0.45)	(1.236)
cloud cover	1.918	2.044	2.540	1.480	1.075	1.354	0.613	2.734	1.724	7.501	1.620	3.884
	(0.482)	(0.871)	(0.399)	(0.539)	(0.346)	(0.499)	(0.211)	(0.754)	(0.211)	(3.359)	(0.429)	(1.195)
correlation: temperature	0.438		0.006		0.396		0.241		-0.921		0.245	
MSA FE	×		×		×		×		×		×	
year FE	×		×		×		×		×		×	
simulation LL	-1910.9		-1908.6		-1965.7		-1905.8		-2033.2		-1902.6	
N	94,050		94,050		94,050		94,050		94,050		94,050	
cases	1,254		1,254		1,254		1,254		1,254		1,254	

Notes: The table presents the posterior means and distributions of the coefficient estimates, the mean and the standard deviation of the distribution of the random variables and the correlation between coefficient estimates for summer and winter temperatures. To improve convergence, climate variables have been rescaled in units of 10.

Alternative Specifications of the First-Stage Mixed Logit Model

Next, I examine the sensitivity of the baseline climate estimates to alternative specifications of the first-stage mixed logit model (Tables 4.6 and 4.7). Allowing for random variation in $\hat{I}$ changes climate coefficients in both the first and second stage of Model 7. The coefficient for summer temperatures shrinks considerably in the first stage of the model and loses its significance. Moreover, I find summer temperatures to explain less of

Table 4.7: Second Stage: Alternative Mixed Logit Specification

	Base Model	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
	region & IV	RD: $\hat{I}$	linear mig distance	mig distance married	no mig distance	RD: ln mig distance
2nd Stage	*Coef (Std Err)*	*Coef (Std Err)*	*Coef (Std Err)*	*Coef (Std Err)*	*Coef (Std Err)*	*Coef (Std Err)*
summer temperature	-5.898 (0.088)	-4.159 (0.094)	-3.357 (0.074)	-5.911 (0.098)	0.866 (0.108)	-2.267 (0.087)
winter temperature	7.557 (0.068)	8.653 (0.072)	7.359 (0.052)	10.73 (0.074)	8.504 (0.075)	9.161 (0.072)
precipitation	0.190 (0.010)	0.438 (0.009)	0.370 (0.008)	0.210 (0.009)	0.238 (0.012)	0.295 (0.008)
cloud cover	-1.045 (0.140)	-4.260 (0.151)	-4.128 (0.107)	-4.662 (0.133)	-7.755 (0.147)	-6.009 (0.128)
vapour	-3.240 (0.038)	-3.063 (0.044)	-1.885 (0.030)	-1.215 (0.037)	-1.643 (0.048)	-2.679 (0.038)
ln hourly wage business	4.775 (0.544)	-4.165 (0.614)	-0.580 (0.474)	5.576 (0.572)	5.693 (0.608)	-6.196 (0.526)
ln hourly wage production	-6.614 (0.436)	-0.347 (0.478)	-14.72 (0.460)	-4.108 (0.421)	-4.139 (0.483)	-3.095 (0.434)
ln hourly wage construction	24.07 (0.472)	24.19 (0.628)	26.99 (0.400)	14.78 (0.519)	6.897 (0.557)	28.792 (0.486)
violent crime rate	0.097 (0.005)	0.072 (0.005)	0.024 (0.004)	0.041 (0.007)	0.224 (0.006)	-0.160 (0.006)
health score	0.104 (0.003)	0.076 (0.003)	0.059 (0.002)	0.084 (0.003)	0.070 (0.003)	0.104 (0.003)
transport	0.068 (0.001)	0.005 (0.001)	0.032 (0.001)	0.029 (0.001)	0.028 (0.001)	0.055 (0.001)
education	0.002 (0.000)	0.001 (0.000)	0.002 (0.000)	0.001 (0.000)	0.001 (0.000)	0.002 (0.000)
the arts	-0.007 (0.000)	0.010 (0.001)	0.001 (0.000)	0.008 (0.001)	0.008 (0.001)	-0.005 (0.000)
recreational facilities	-0.100 (0.002)	-0.044 (0.003)	-0.014 (0.002)	0.012 (0.002)	0.030 (0.003)	-0.026 (0.002)
distance to coast	-0.002 (0.000)	0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	0.001 (0.000)	-0.002 (0.000)
elevation	-0.001 (0.000)	-0.004 (0.000)	-0.001 (0.000)	-0.003 (0.000)	-0.003 (0.000)	-0.002 (0.000)
region FE	×	×	×	×	×	×
adjusted R^2	0.568	0.556	0.576	0.611	0.498	0.576
N	94,050	94,050	94,050	94,050	94,050	94,050

Notes: Robust standard errors presented in parentheses. Regressions include additional region fixed effects. All regressions are estimated using the Instrumental Variable estimation method outlined in Section 4.4.3. Climate variables have been rescaled in units of 10.

the observed differences in mean utility across locations, while winter temperature have a stronger effect.

Misspecification of migration costs causes notable changes in the first-stage estimates. Applying a linear specification (Model 8), dropping costs all together (Model 10) or allowing random variation in the coefficient for migration distance (Model 11) turns the coefficient for income insignificant. Introducing random variation in the coefficient for migration costs causes the effect of summer temperatures and vapour pressure to disappear. This change is explained by the natural correlation of the instrument for migration costs (distance to the origin) with distance from the equator, which itself is a strong predictor of the local climate. Therefore, allowing for random variation in the coefficient for migration distance will remove some of the individual choice variation attributed to variation in local temperatures in the base model. Since migrants, on average, prefer more southern locations, the correlation between migration distance and winter temperatures is weaker. This explains why the coefficient for winter temperatures remains largely unaffected. In Model 9, I test for differences in the impact of migration cost by marital status. However, the interaction term is small and insignificant.

These results highlight the importance of accounting for migration costs in the estimation of climate valuations, as misspecification not only affects climate variables, but also the precision of the income estimate. Precise estimation of the income coefficient is essential for accurate capitalisation of amenity estimates for the calculation of WTP measures.

Alternative Temperature Measures

In Tables 4.8 and 4.9 I examine differences across alternative temperature specifications. First, I test the sensitivity of temperature estimates to the omission of non-temperature climate variables. Dropping precipitation, vapour pressure and cloud cover variables from the regression reduces the size of both temperature coefficients and increases the coefficient for income in the first stage. In the second stage, the coefficient for summer temperature changes its sign from negative to positive. As noted earlier, in the baseline mixed logit model the coefficients for seasonal temperatures and vapour pressure are negatively correlated (see Appendix C.1). Moreover, the coefficients for cloud cover and winter temperatures have a large positive covariance. Both cloud cover (i.e. sunshine exposure) and the exposure to humidity are known to directly affect well-being. Therefore, failure to control for other climate variables in the model results in biased temperature coefficients.

Restricting temperature tastes to be constant across seasons (Model 13) increases the

Table 4.8: First Stage: Alternative Climate Specifications

	Base Model		**(12)**		**(13)**		**(14)**		**(15)**	
	region & IV		no alt climate		avg tmp		avg tmp^2		max min tmp	
1st Stage	*Coef* (Std Err)	*Std Ω*	*Coef* (Std Err)	*Std Ω*	*Coef* (Std Err)	*Std Ω*	*Coef* (Std Err)	*Std Ω*	*Coef* (Std Err)	*Std Ω*
ln $\hat{I}$	1.142 (0.359)		2.297 (1.017)		1.550 (0.469)		2.096 (0.664)		0.716 (0.498)	
ln migration distance	-6.645 (0.724)		-4.980 (0.496)		-7.725 (0.417)		-8.127 (0.77)		-6.452 (0.758)	
same location previous mig	15.95 (2.016)	99.15 (29.18)	29.18 (5.422)	462.3 (165.3)	29.33 (2.934)	454.1 (85.67)	34.71 (6.6)	650.3 (343.4)	20.02 (2.97)	185.4 (72.05)
relative same MSA	10.70 (1.321)	60.70 (17.02)	9.035 (1.193)	52.93 (20.71)	14.36 (2.262)	162.90 (70.86)	18.61 (2.034)	208.2 (51.9)	11.17 (1.036)	72.76 (17.54)
summer temperature	2.150 (0.484)	3.280 (1.770)	1.503 (0.640)	1.805 (1.053)						
winter temperature	-7.030 (0.45)	5.690 (1.825)	-6.566 (0.297)	1.238 (0.436)						
average temperature					-8.646 (0.602)	12.11 (4.916)	7.565 (0.561)	16.71 (5.941)		
average temperature^2							-1.102 (0.026)	0.148 (0.016)		
maximum temperature									-8.752 (0.428)	4.040 (1.984)
minimum temperature									-0.126 (0.445)	3.949 (2.234)
precipitation	-0.610 (0.089)	0.367 (0.081)			-1.023 (0.095)	0.296 (0.061)	-0.270 (0.095)	0.314 (0.104)	-0.609 (0.075)	0.393 (0.075)
cloud cover	2.670 (1.003)	16.48 (5.589)			3.569 (0.518)	11.46 (3.24)	9.462 (0.433)	8.141 (4.078)	3.302 (0.421)	11.46 (3.436)
vapour pressure	1.918 (0.482)	2.044 (0.871)			2.518 (0.293)	1.035 (0.273)	-1.316 (0.228)	2.177 (0.836)	1.473 (0.367)	1.328 (0.385)
correlation temperature	0.4384		0.5161				-0.0269		0.1044	
MSA FE	×		×		×		×		×	
year FE	×		×		×		×		×	
simulated LL	-1910.9		-1901.8		-1900.1		-1941.1		-1902	
N	94,050		94,050		94,050		94,050		94,050	
cases	1,254		1,254		1,254		1,254		1,254	

Notes: The table presents the posterior means and distributions of the coefficient estimates, the mean and the standard deviation of the distribution of the random variables and the correlation between coefficient estimates for summer and winter temperatures. To improve convergence, climate variables have been rescaled in units of 10.

coefficients for the non-temperature climate controls across the two stages. Results from the first stage depict a large unexplained variation in the coefficient for mean temperatures. Alternatively, Model 14 tests for nonlinearity in mean temperatures. In line with findings from Chapter 3, the estimates indicate a concave relationship between mean temperatures and the probability of settlement. However, composite utility grows at an increasing rate with rising mean temperatures. Lastly, using annual means of daily extreme temperatures yields a negative effect of average daily maximum and minimum temperatures on the location choice and a positive effect on the composite utility. However, the coefficient for income in Model 15 is insignificant. Therefore, estimates of the MWTP for changes in daily minimum and maximum temperatures should be considered with caution.

Overall, the results demonstrate the importance of accounting for nonlinearity in temperature preferences across seasons and daily peak temperatures, which are masked using annual means. Although Model 13 overall performs best among the different specifications, the remainder of the discussion will focus on the baseline model to allow comparison of the results with other studies.

Heterogeneity in Temperature Valuations

Turning next to examining heterogeneity in climate valuations, Tables 4.10 and 4.11 present results including interaction terms with age, education and a control for origin temperatures. In Model 16, I interact seasonal temperatures with a dummy indicating whether a migrant is younger or older than 55 years at the time of emigration. Estimates from the first stage suggest that older migrants have weaker preferences for temperatures in the location choice. However, much of the variation in the tastes of older migrants remains unexplained. Turning to the second stage, I find winter and summer temperatures to have a strong positive impact on the composite utility of older migrants that significantly differs from the effect for younger migrants. The result suggests that temperatures are more important for the overall well-being of older migrants. Unsurprisingly, differentiating between migrants with and without college education (Model 17) reveals that temperatures matter less in location choices and overall well-being of better educated migrants.

Model 18 tests for clinal heterogeneity in temperature preferences. The model includes an interaction term between both seasonal temperatures variables and a dummy indicating whether mean temperatures at the migrant's origin municipality exceed the historical Mexican median temperature (19.23°C). Studying results from the first stage, I find migrants from warmer Mexican locations to give less weight to temperatures in the location choice. This finding contradicts with results from Chapter 3, where I observed a stronger positive preference of migrants from warmer locations for summer temperatures.

The contrasting findings may be explained by the relatively large unexplained variation in the temperature variables. Again, requiring preference to be constant across the population may mask significant taste variation, an important driver of temperature preferences. Concerning composite utility, I observe colder summer and warmer winter temperatures to have a positive impact on the composite utility of migrants from colder Mexican regions. In contrast, the composite utility of migrants from warmer origins decreases with lower summer and winter temperatures. Altogether, results from Models 16 to 18 highlight differences in temperature valuations across the life-cycle and the temperatures to which an individual is accustomed.

Table 4.9: Second Stage: Alternative Climate Specifications

	Base Model	**(12)**	**(13)**	**(14)**	**(15)**
	region & IV	no alt climate	avg tmp	avg tmp^2	max min tmp
2nd Stage	*Coef* *(Std Err)*	*Coef* *(Std Err)*	*Coef* *(Std Err)*	*Coef* *(Std Err)*	*Coef* *(Std Err)*
summer temperature	-4.721 (0.121)	2.452 (0.108)			
winter temperature	7.648 (0.114)	7.398 (0.079)			
average temperature			7.939 (0.116)	11.24 (0.281)	
average temperature^2				0.294 (0.010)	
maximum temperature					6.744 (0.160)
minimum temperature					1.094 (0.171)
precipitation	0.147 (0.011)		0.808 (0.010)	0.091 (0.012)	0.296 (0.010)
cloud cover	-1.419 (0.191)		-5.618 (0.143)	-10.50 (0.179)	-0.765 (0.164)
vapour pressure	-3.159 (0.042)		-3.612 (0.047)	-0.244 (0.041)	-2.447 (0.039)
ln hourly wage business	3.363 (0.580)	-0.832 (0.619)	4.421 (0.552)	-1.847 (0.590)	-6.501 (0.555)
ln hourly wage production	-2.661 (0.450)	1.326 (0.477)	-2.978 (0.424)	2.193 (0.478)	-6.148 (0.479)
ln hourly wage construction	26.13 (0.594)	13.45 (0.611)	14.00 (0.580)	21.20 (0.568)	32.08 (0.512)
violent crime rate	0.143 (0.005)	0.034 (0.006)	0.026 (0.005)	0.112 (0.007)	0.168 (0.005)
health score	0.079 (0.003)	0.075 (0.003)	-0.019 (0.003)	0.094 (0.003)	0.050 (0.003)
transport score	0.059 (0.001)	0.050 (0.001)	0.033 (0.001)	0.042 (0.001)	0.036 (0.001)
education score	0.002 (0.000)	0.002 (0.000)	0.003 (0.000)	0.001 (0.000)	0.002 (0.000)
the arts score	-0.001 (0.000)	0.000 (0.000)	0.012 (0.000)	0.006 (0.000)	0.005 (0.000)
recreational facilities score	-0.108 (0.003)	0.024 (0.002)	0.050 (0.002)	-0.135 (0.003)	-0.069 (0.002)
distance to coast	-0.001 (0.000)	0.000 (0.000)	-0.001 (0.000)	0.000 (0.000)	0.002 (0.000)
elevation	-0.001 (0.000)	0.002 (0.000)	-0.001 (0.000)	0.000 (0.000)	0.000 (0.000)
region FE	×	×	×	×	×
IV	×	×	×	×	×
adjusted R^2	0.604	0.545	0.605	0.606	0.560
N	94,050	94,050	94,050	94,050	94,050

Notes: Robust standard errors presented in parentheses. Regressions include additional region fixed effects. All regressions are estimated using the Instrumental Variable estimation method outlined in Section 4.4.3. Climate variables have been rescaled in units of 10.

Table 4.10: First Stage: Heterogeneous Climate Differences

	Base Model		**(16)**		**(17)**		**(18)**	
	region & IV		age $\geq$ 55		education		clinal	
1st Stage	*Coef* (Std Err)	*Std* Ω	*Coef* (Std Err)	*Std* Ω	*Coef* (Std Err)	*Std* Ω	*Coef* (Std Err)	*Std* Ω
ln $\hat{I}$	1.142 (0.359)		2.100 (0.698)		2.406 (0.834)		1.779 (0.686)	
ln migration distance	-6.645 (0.724)		-8.460 (0.674)		-7.605 (0.495)		-8.198 (0.61)	
same location previous migration	15.95 (2.016)	99.15 (29.18)	35.63 (3.038)	761.89 (137.64)	15.72 (2.183)	100.53 (37.28)	30.27 (2.978)	540.86 (117.32)
relative same MSA	10.70 (1.321)	60.70 (17.02)	9.886 (0.799)	43.59 (7.992)	11.92 (1.221)	97.26 (28.76)	9.903 (0.816)	50.17 (9.87)
summer temperature	2.150 (0.484)	3.280 (1.77)	5.418 (0.308)	2.897 (1.109)	2.589 (0.31)	5.200 (2.045)	1.727 (0.223)	2.144 (0.569)
winter temperature	-7.030 (0.45)	5.690 (1.825)	-5.601 (0.385)	3.327 (0.975)	-4.334 (0.396)	2.470 (0.942)	-3.922 (0.363)	3.346 (1.54)
age $\geq$ 55 summer tmp			-0.265 (1.809)	183.65 (33.75)				
age $\geq$ 55 winter tmp			1.385 (1.24)	82.09 (16.07)				
college graduate summer tmp					-0.147 (0.316)	2.119 (0.798)		
college graduate winter tmp					0.246 (0.39)	4.059 (1.939)		
mex hot summer tmp							-1.942 (0.275)	2.169 (0.552)
mex hot winter tmp							0.803 (0.278)	2.077 (1.024)
precipitation	-0.610 (0.089)	0.367 (0.081)	-0.193 (0.095)	0.361 (0.088)	-0.868 (0.123)	0.323 (0.066)	-0.684 (0.09)	0.376 (0.073)
vapour pressure	2.670 (1.003)	16.48 (5.589)	-5.952 (0.269)	5.191 (1.941)	-1.167 (0.273)	2.105 (1.278)	-2.275 (0.298)	3.961 (1.709)
cloud cover	1.918 (0.482)	2.044 (0.871)	3.320 (0.279)	3.167 (1.214)	4.307 (0.581)	1.913 (0.621)	4.157 (0.294)	1.922 (0.569)
MSA FE	×		×		×		×	
year FE	×		×		×		×	
simulated LL	-1910.9		-1900.8		-1904.6		-1878.1	
N	94,050		94,050		94,050		94,050	
cases	1,254		1,254		1,254		1,254	

Notes: The table presents the posterior means and distributions of the coefficient estimates, the mean and the standard deviation of the distribution of the random variables and the correlation between coefficient estimates for summer and winter temperatures. To improve convergence, climate variables have been rescaled in units of 10.

Table 4.11: Second Stage: Heterogeneous Climate Differences

	Base Model	**(16)**	**(17)**	**(18)**
	region & IV	age $\geq$ 55	education	clinal
2nd Stage	*Coef* (*Std Err*)	*Coef* (*Std Err*)	*Coef* (*Std Err*)	*Coef* (*Std Err*)
summer temperature	-4.721 (0.121)	-6.680 (0.153)	-3.654 (0.136)	-2.145 (0.258)
winter temperature	7.648 (0.114)	5.117 (0.154)	9.071 (0.135)	31.37 (0.713)
age $\geq$ 55 summer temperature		11.80 (1.150)		
age $\geq$ 55 winter temperature		59.99 (5.076)		
college graduate summer temperature			0.021 (0.018)	
college graduate winter temperature			-0.064 (0.064)	
mex hot summer temperature				0.939 (0.368)
mex hot winter temperature				-40.49 (1.164)
precipitation	0.147 (0.011)	-0.085 (0.011)	0.623 (0.011)	0.353 (0.011)
cloud cover	-1.419 (0.191)	2.244 (0.196)	-7.298 (0.181)	-6.070 (0.205)
vapour pressure	-3.159 (0.042)	-4.086 (0.044)	-4.430 (0.042)	-4.292 (0.046)
ln hourly wage business	3.363 (0.580)	10.63 (0.614)	12.36 (0.656)	4.412 (0.650)
ln hourly wage production	-2.661 (0.450)	-5.149 (0.480)	-5.133 (0.489)	-2.087 (0.494)
ln hourly wage construction	26.13 (0.594)	16.82 (0.626)	11.34 (0.606)	18.04 (0.634)
violent crime rate	0.143 (0.005)	0.150 (0.005)	0.054 (0.005)	0.152 (0.006)
health score	0.079 (0.003)	0.089 (0.003)	0.062 (0.003)	0.101 (0.003)
transport score	0.059 (0.001)	0.038 (0.001)	0.063 (0.001)	0.055 (0.001)
education score	0.002 (0.000)	0.001 (0.000)	0.000 (0.000)	0.001 (0.000)
the arts score	-0.001 (0.000)	0.001 (0.000)	0.007 (0.001)	0.003 (0.001)
recreational facilities score	-0.108 (0.003)	0.015 (0.002)	0.007 (0.002)	-0.004 (0.002)
distance to coast	-0.001 (0.000)	0.000 (0.000)	0.001 (0.000)	0.000 (0.000)
elevation	-0.001 (0.000)	-0.003 (0.000)	-0.002 (0.000)	-0.001 (0.000)
region FE	×	×	×	×
IV	×	×	×	×
adjusted R^2	0.604	0.675	0.622	0.611
N	94,050	94,050	94,050	94,050

Notes: Robust standard errors presented in parentheses. Regressions include additional region fixed effects. All regressions are estimated using the Instrumental Variable estimation method outlined in Section 4.4.3. Climate variables have been rescaled in units of 10.

4.7 The Marginal Willingness to Pay for Preferential Temperatures

In this section, I measure the MWTP for preferential location amenities combining results from the first- and second-stage regression. Following the approach by Sinha et al. (2018), coefficients of amenity variables have been converted to the MWTP by dividing the mean coefficient and the standard error from the first and second stage by the coefficient on income from the mixed logit regression. The result is multiplied by the sample mean predicted income to yield a monetary measure of the amenity value of a marginal change in the amenity. Non-linear amenities have been evaluated at the population weighted average.[28]

Endogeneity and the Marginal Willingness to Pay

As we can see from Table 4.12, estimates of the MWTP for a one-degree reduction in summer temperatures across alternative specifications of the second-stage regression range between US$371 and $686 per person per year.[29] Estimates of the MWTP for warmer winter temperatures lie between $70 and $133 per person per year, ignoring the negative value for Model 3 as it likely suffers from an endogeneity bias. Overall, the estimates of the MWTP for warmer winter temperatures are insignificant. Concerning endogeneity, controlling for agglomeration effects and potential endogeneity in Models 2 to 6 reduces MWTP estimates for non-climate amenities. If we believe in the strength of the instrument, these observations suggest that the simple OLS yields biased estimates.

Comparing the baseline IV estimates with other studies, I find the general observation of individuals preferring colder summers and warmer winters to resemble findings of Cragg and Kahn (1997) and Fan et al. (2012) and Sinha et al. (2018). The predicted MWTP for summer and winter temperatures here is notably smaller than, for example, those estimated by Sinha et al. (2018). Part of the discrepancy between Sinha et al.'s

28. For example, the MWTP for summer temperature in Model 6 was calculated as follows: $MWTP\,summer\,temperature = [\frac{1}{2}(2.150 - 4.721)/1.142] * 3298.32/10 \approx -371$, where 3298.32 is the sample mean predicted income, divided by 10 to rescale the unit of measurement to changes by one °C.

29. This result should be interpreted as the willingness to forgo annual earnings for a 1°C reduction in mean temperatures during the months June to August. Given the inherent correlation in temperatures across the year, the coefficient on summer temperatures will also capture changes in temperatures of adjacent months.

Table 4.12: Marginal Willingness to Pay First-Stage Specification

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	region FE	region & ln pop	region & pop dens	region & ln area	region & IV
	MWTP	*MWTP*	*MWTP*	*MWTP*	*MWTP*	*MWTP*
mean: summer temperature	$ -541 ($ 83)	$ -399 ($ 87)	$ -518 ($ 88)	$ -450 ($ 88)	$ -686 ($ 90)	$ -371 ($ 87)
mean: winter temperature	$ 76 ($ 75)	$ 70 ($ 81)	$ -63 ($ 81)	$ 98 ($ 81)	$ 133 ($ 82)	$ 89 ($ 81)
mean: preciptation	$ -61 ($ 14)	$ -71 ($ 15)	$ -66 ($ 14)	$ -72 ($ 15)	$ -69 ($ 15)	$ -67 ($ 15)
mean: cloud cover	$ 235 ($ 165)	$ 250 ($ 173)	$ 423 ($ 171)	$ 258 ($ 173)	$ 350 ($ 172)	$ 181 ($ 172)
mean: vapour pressure	$ -191 ($ 75)	$ -193 ($ 76)	$ -228 ($ 75)	$ -195 ($ 76)	$ -221 ($ 76)	$ -179 ($ 76)
ln hourly wage business	$ 1 ($ 0)	$ 1 ($ 0)	$ 0 ($ 0)	$ 1 ($ 0)	$ 1 ($ 0)	$ 1 ($ 0)
ln hourly wage production	$ -1 ($ 0)	$ -0 ($ 0)	$ -0 ($ 0)	$ -1 ($ 0)	$ -1 ($ 0)	$ -1 ($ 0)
ln hourly wage construction	$ 5 ($ 0)	$ 5 ($ 0)	$ 5 ($ 0)	$ 5 ($ 0)	$ 5 ($ 0)	$ 5 ($ 0)
violent crime rate	$ 281 ($ 14)	$ 419 ($ 14)	$ 304 ($ 15)	$ 434 ($ 14)	$ 340 ($ 15)	$ 412 ($ 14)
health score	$ 301 ($ 8)	$ 237 ($ 8)	$ 106 ($ 9)	$ 226 ($ 8)	$ 178 ($ 7)	$ 229 ($ 8)
transport score	$ 197 ($ 3)	$ 177 ($ 3)	$ 145 ($ 4)	$ 168 ($ 4)	$ 151 ($ 3)	$ 170 ($ 3)
education score	$ 7 ($ 0)	$ 4 ($ 0)	$ 4 ($ 0)	$ 4 ($ 0)	$ 3 ($ 0)	$ 4 ($ 0)
the arts score	$ -20 ($ 1)	$ -3 ($ 1)	$ -3 ($ 1)	$ 11 ($ 2)	$ 6 ($ 1)	$ -4 ($ 1)
recreational facilities score	$ -289 ($ 7)	$ -325 ($ 7)	$ -386 ($ 7)	$ -338 ($ 7)	$ -392 ($ 8)	$ -313 ($ 7)
distance to coast	$ -5 ($ 0)	$ -1 ($ 0)	$ -1 ($ 0)	$ -1 ($ 0)	$ 1 ($ 0)	$ -2 ($ 0)
elevation	$ -3 ($ 0)	$ -3 ($ 0)	$ -3 ($ 0)	$ -3 ($ 0)	$ -4 ($ 0)	$ -3 ($ 0)
ln population			$ 0 ($ 0)			
population density				$ -3 ($ 0)		
land area					$ 0 ($ 0)	

Notes: Standard errors provided in parentheses. Amenity coefficients have been converted to the MWTP by dividing the mean coefficient and the standard error from the first and second stage by the coefficient on income from the mixed logit regression. The result is multiplied by the sample mean predicted income to yield a monetary measure of the amenity value of a marginal change in the amenity.

a Nonlinear amenity variables are evaluated at population-weighted means in order to compute the Marginal Willingness to pay.

(2018) estimates and the results presented here is explained by the lower predicted income level of Mexican immigrants. If one considers the MWTP for changes in temperatures relative to mean predicted income, the results suggest that Mexican migrants attach a considerably larger relative value to summer temperatures compared to the average U.S. citizen. Moreover, the insignificant estimate for winter temperatures may be explained by the shorter duration of migration from Mexico to the U.S. On average, sample migrants remain in the U.S. for two and a half years. Hence, other factors, such as economic considerations, might play a greater role in driving location choices. Moreover, requiring tastes for winter temperatures to be homogeneous masks heterogeneity in the valuation of winter preferences across sample migrants.

Alternative Temperature Measures

With respect to alternative temperatures, I find the MWTP estimates for non-linear temperature specifications in Table 4.13 to be similar. Note that for low temperature ranges the MWTP for increases in mean temperatures using a quadratic specification (Model 14) is positive, with the value turning negative as the mean temperature rises. Requiring temperature valuations to be constant across seasons and the temperature range changes the MWTP for cloud days, vapour pressure and the score for provision of health services and recreational services. The first two changes are again explained by the natural correlation in climate variables. The change in the MWTP of recreational activities suggests that the attractiveness of such facilities is closely related to the average temperature of a location. Locations with all year-round comfortable weather may provide lower quality indoor facilities etc. The link between temperatures and the quality of recreational facilities is weaker for seasonal and daily peak temperatures and, as such, remains unaccounted for in the base model. The drop in the estimate of the MWTP for improved health facilities indicates that mean temperature is a poor predictor of the prevalence of temperature-related illnesses in a particular location. Heat- and cold-related illnesses can result in significant costs to the health care sector. Consequently, uncontrolled seasonal variation in temperature-related illnesses causes biased estimates of the WTP for better health care provision.

Individual Heterogeneity

The final set of results in this section concerns heterogeneity in temperature valuations across age, education and differences in the temperature to which an individual is accustomed. The MWTP estimates are presented Table 4.14. I find older migrants to be willing to pay $806 per year to live in locations with one degree warmer summer temperatures and $4,782 for those with warmer winters. In contrast, prime-aged migrants are willing to forgo $99 of their annual wage income to live in locations with one degree lower summer temperatures. Moreover, younger migrants have no significant preferences over winter temperatures. The large difference in the magnitude of MWTP between prime-aged migrants and migrants aged 55 may stem from the use of wage income and housing prices as the hedonic price measure for the two-stage model. The capitalisation of amenities based on the two price measures might not be appropriate for older migrants, who can rely on alternative income sources aside from wage earnings. Moreover, wages of older migrants may differ less across U.S. locations than those of younger migrants. If older migrants still sort across locations based on climate preferences, climate valuations for this group of migrants are likely overestimated. Moreover, the relatively small sample share of older migrants (5%) may imply that the estimates are not representative for the rest of the population.

Results from Model 17 indicate no significant differences in the MWTP for temperatures by education. However, introducing interaction terms between education and temperatures reduces the MWTP for lower summer temperatures and increases the MWTP for warmer winters across the two sub-groups (compared to the base model). Testing for clinal heterogeneity, I observe significant differences in the MWTP for winter temperatures between migrants from warmer and colder Mexican municipalities. Migrants from colder areas are willing to forgo $2,545 to live in an MSA with one degree warmer winter temperatures (per year). In contrast, migrants from warmer locations are willing to pay $1,135 annually to live somewhere with one degree colder winter temperatures. One would expect individuals accustomed to warmer climates to be less sensitive to heat. However, the estimates indicate that migrants from warmer regions are more aware of the negative impact of warm winters on well-being and, thus, prefer locations with year-round lower temperatures. Estimates of the MWTP for rising summer temperatures are both negative but insignificant.

Interestingly, controlling for demographic and clinal differences in temperatures significantly affects the MWTP for non-temperature climate amenities. Most importantly, the MWTP for fewer cloud days becomes negative and significant. At the same time, the MWTP for lower rainfall and humidity levels declines and turns insignificant for the latter. This observation again highlights the problem of multicollinearity in logistic regressions as discussed in Chapter 3 on page 76.

Overall, the large differences in preferences for winter temperatures explains to some extent the insignificant result found in the baseline model. The results suggest a greater variation in tastes regarding winter temperatures. While differences in tastes for summer temperatures are limited to life cycle differences. In general, the results highlight the importance and complexity of accounting for heterogeneity in individuals WTP for climate amenities. Despite the application of a more flexible mixed logit approach, issues arising from multicollinearity render disentangling of heterogeneous differences problematic.

Table 4.13: Marginal Willingness to Pay Alternative Climate Specification

	Base Model	**(13)**	**(14)**	**(15)**
	region & IV	avg tmp	avg tmp^2	max min
	MWTP *(Std Err)*	*MWTP* *(Std Err)*	*MWTP* *(Std Err)*	*MWTP* *(Std Err)*
mean: summer temperature	\$ -371 (\$ 87)			
mean: winter temperature	\$ 89 (\$ 81)			
mean: average temperature		\$ -75 (\$ 76)		
mean: average temperature^{2}[a]			\$ -37 (\$ 9)	
mean: maximum temperature				\$ -463 (\$ 136)
mean: minimum temperature				\$ 223 (\$ 142)
mean: precipitation	\$ -67 (\$ 15)	\$ -23 (\$ 11)	\$ -14 (\$ 8)	\$ -72 (\$ 19)
mean: cloud cover	\$ 181 (\$ 172)	\$ -218 (\$ 70)	\$ -82 (\$ 48)	\$ 585 (\$ 135)
mean: vapour pressure	\$ -179 (\$ 76)	\$ -116 (\$ 36)	\$ -123 (\$ 21)	\$ -224 (\$ 93)
ln hourly wage business[a]	\$ 1 (\$ 0)	\$ 1 (\$ 0)	\$ -0 (\$ 0)	\$ -2 (\$ 0)
ln hourly wage production[a]	\$ -1 (\$ 0)	\$ -0 (\$ 0)	\$ 0 (\$ 0)	\$ -2 (\$ 0)
ln hourly wage construction[a]	\$ 5 (\$ 0)	\$ 2 (\$ 0)	\$ 2 (\$ 0)	\$ 10 (\$ 0)
violent crime rate	\$ 412 (\$ 14)	\$ 56 (\$ 11)	\$ 177 (\$ 10)	\$ 773 (\$ 21)
health score	\$ 229 (\$ 8)	\$ -40 (\$ 7)	\$ 149 (\$ 4)	\$ 232 (\$ 13)
transport score	\$ 170 (\$ 3)	\$ 71 (\$ 2)	\$ 66 (\$ 2)	\$ 166 (\$ 6)
education score	\$ 4 (\$ 0)	\$ 6 (\$ 0)	\$ 2 (\$ 0)	\$ 7 (\$ 0)
the arts score	\$ -4 (\$ 1)	\$ 26 (\$ 1)	\$ 10 (\$ 1)	\$ 25 (\$ 2)
recreational facilities score	\$ -313 (\$ 7)	\$ 107 (\$ 4)	\$ -213 (\$ 5)	\$ -318 (\$ 11)
distance to coast	\$ -2 (\$ 0)	\$ -2 (\$ 0)	\$ -0 (\$ 0)	\$ 11 (\$ 0)
elevation	\$ -3 (\$ 0)	\$ -2 (\$ 0)	\$ 0 (\$ 0)	\$ 1 (\$ 0)

Notes: Standard errors provided in parentheses. Amenity coefficients have been converted to the MWTP by dividing the mean coefficient and the standard error from the first and second stage by the coefficient on income from the mixed logit regression. The result is multiplied by the sample mean predicted income to yield a monetary measure of the amenity value of a marginal change in the amenity.

a Nonlinear amenity variables are evaluated at population-weighted means in order to compute the Marginal Willingness to pay.

Table 4.14: Marginal Willingness to Pay Heterogeneous Climate Specification

	Base Model	**(16)**	**(17)**	**(18)**
	region & IV	age ≥ 55	education	clinal
	MWTP *(Std Err)*	*MWTP* *(Std Err)*	*MWTP* *(Std Err)*	*MWTP* *(Std Err)*
mean: summer temperature	$ -371 ($ 87)	$ -99 ($ 36)	$ -73 ($ 31)	$ -39 ($ 45)
mean: winter temperature	$ 89 ($ 81)	$ -38 ($ 42)	$ 325 ($ 36)	$ 2,545 ($ 100)
mean: age ≥ 55 summer temperature		$ 806 ($ 269)		
mean: age ≥ 55 winter temperature		$ 4,782 ($ 538)		
mean: college graduate summer temperature			$ -82 ($ 53)	
mean: college graduate winter temperature			$ 337 ($ 67)	
mean: mex hot summer temperature				$ -132 ($ 104)
mean: mex hot winter temperature				$ -1,135 ($ 233)
mean: precipitation	$ -67 ($ 15)	$ -22 ($ 8)	$ -17 ($ 9)	$ -31 ($ 9)
mean: cloud cover	$ 181 ($ 172)	$ -291 ($ 37)	$ -580 ($ 31)	$ -774 ($ 47)
mean: vapour pressure	$ -179 ($ 76)	$ -60 ($ 25)	$ -8 ($ 43)	$ -13 ($ 32)
ln hourly wage business	$ 1 ($ 0)	$ 1 ($ 0)	$ 1 ($ 0)	$ 1 ($ 0)
ln hourly wage production	$ -1 ($ 0)	$ -1 ($ 0)	$ -0 ($ 0)	$ -0 ($ 0)
ln hourly wage construction	$ 5 ($ 0)	$ 2 ($ 0)	$ 1 ($ 0)	$ 2 ($ 0)
violent crime rate	$ 412 ($ 14)	$ 236 ($ 8)	$ 75 ($ 7)	$ 282 ($ 10)
health score	$ 229 ($ 8)	$ 140 ($ 4)	$ 85 ($ 4)	$ 187 ($ 6)
transport score	$ 170 ($ 3)	$ 60 ($ 2)	$ 86 ($ 2)	$ 103 ($ 2)
education score	$ 4 ($ 0)	$ 1 ($ 0)	$ -0 ($ 0)	$ 1 ($ 0)
the arts score	$ -4 ($ 1)	$ 2 ($ 1)	$ 10 ($ 1)	$ 5 ($ 1)
recreational facilities score	$ -313 ($ 7)	$ 23 ($ 4)	$ 9 ($ 3)	$ -7 ($ 5)
distance to coast	$ -2 ($ 0)	$ 0 ($ 0)	$ 2 ($ 0)	$ -1 ($ 0)
elevation	$ -3 ($ 0)	$ -5 ($ 0)	$ -3 ($ 0)	$ -3 ($ 0)

Notes: Standard errors provided in parentheses. Amenity coefficients have been converted to the MWTP by dividing the mean coefficient and the standard error from the first and second stage by the coefficient on income from the mixed logit regression. The result is multiplied by the sample mean predicted income to yield a monetary measure of the amenity value of a marginal change in the amenity.

[a] Nonlinear amenity variables are evaluated at population-weighted means in order to compute the Marginal Willingness to pay.

4.8 The Willingness to Pay for Projected Warming

In order to assess individuals' WTP for future climate change, results from the two-stage sorting model are used to predict the WTP for projected changes in mean summer and winter temperatures over the period 2040 to 2069. Temperature projections stem from the ECHAM5 (Roeckner et al. 2003) and the CCSM3 (Collins et al. 2006) model under the A2 and B1 climate scenarios defined by the Special Report on Emission Scenarios (SRES) (Nakicenovic et al. 2000). Projected increases in summer and winter temperatures for the sample destinations range between 3.36°C to 4.73°C and 1.14°C to 2.16°C. Based on estimates from the baseline model, I predict warming of summer temperatures to reduce welfare by between $1,245 and $1,755 per person per year. At the same time, increases in winter temperatures are estimated to boost welfare by $102 to $193 per person per year. Once I allow for heterogeneity in temperature valuations, predicted welfare effects increase in size.

Accounting for life-cycle effects, younger individuals are estimated to pay $333 to $469 per year to prevent summer temperatures from rising and $44 to $82 to keep winter temperatures at the current level. In contrast, estimated welfare gains for migrants aged 55 resulting from warmer summers range between $2,707 and $3,813 annually per person. In addition, the welfare of older migrants would benefit considerably from rising winter temperatures, with welfare predicted to rise by up to $10,320 per migrant per year.

Concerning clinal differences, I find welfare gains of migrants from colder regions caused by warming of winter temperatures to outweigh welfare losses of migrants from warmer regions. Migrants from warm municipalities are willing to pay up to $2,449 under ECHAM7 SRA2 to prevent winter temperatures from rising. However, welfare gains for migrants from colder regions are estimated to reach up to $5,492 per person per year. As discussed in Chapter 3, the division of migrants into warmer and colder regions does not capture the full diversity in origin climates and, as such, is only a crude measure of clinal variation in origin climates. Nevertheless, the results further lend support to the notion of clinal differences in temperature preferences.

Notwithstanding, the above estimates of the WTP for rising temperatures must be considered with caution. Adaptation to global warming, such as the installation of air conditioning, will likely reduce the adverse effects of rising temperatures. Such changes are only captured in this study as long as they mirror recent adaptation to climate change by today's generation. However, unprecedented technological change leading to changes in climate tastes would not be accounted for in the model. Moreover, the natural correlation in climate variables implies that estimates change significantly due to the inclusion and exclusion of variables or changes in the variable specification. Further research into alternative estimation methods for measuring the amenity value of climate—which overcome the problem of multicollinearity but do not suffer from selection bias as the hedonic income approach—is required.

4.9 Conclusion

This chapter employs a two-stage location-choice model to examine heterogeneity in individual temperature valuations using information on bilateral migration movements between Mexico and the U.S. The first stage consists of mixed logit model allowing for variation in climate valuations both by observed attributes, such as age, education and the climate to which an individual is accustomed, as well as unobserved individual tastes. Analogous to the traditional hedonic approach, the second stage regresses estimated MSA fixed effects from the mixed logit model on destination-specific amenities, including climate. The study implements an IV estimation technique to account for endogeneity in the second-stage regression. Estimates from the baseline model suggest that Mexican migrants on average are willing to forgo earnings to avoid warmer summer temperatures (\$371 per year for every °C decrease) and to enjoy warmer winter temperatures (\$89), although the estimate is not significantly different from zero.

Examining demographic and clinal heterogeneity in individual climate valuations, I observe significant life-cycle differences in temperature preferences. While older migrants are willing to pay around \$5,000 per year in order to enjoy living in a location with warmer summer and winter temperatures, prime-aged migrants give up earnings in order to live in places with lower summer and winter temperatures. Moreover, migrants from warmer Mexican regions regard colder summer and winter temperatures as an amenity, while individuals from colder regions are willing to pay to increase winter temperatures. This suggests that exposure to warmer temperatures, and thus awareness of the negative impacts of heat, yields a negative relationship between individuals' utility and temperatures. In contrast, lack of exposure prior to the migration causes individuals to prefer locations with on average warmer winters.

Using climate forecasts under two alternative climate scenarios, the study predicts individuals' WTP for future changes in mean summer and winter temperature over the period 2040 to 2069. Estimates from the baseline model yield predicted welfare losses between \$1,245 and \$1,755 per person per year due to increases in summer temperatures. At the same time, I forecast annual welfare gains of between \$102 to \$193 per individual due to raised winter temperatures. Again, the magnitude of the WTP for warming fluctuates significantly across observable characteristics of migrants. I predict an additional annual welfare of up to \$10,230 per person due to rising winter temperatures for migrants aged 55 and above. Although the large positive welfare impact is substantially greater than predicted losses, it is important to remind oneself that only a handful migrants fall into this category. Therefore, the absolute welfare effect is unclear.

Lastly, origin climates play an important role in determining individuals' idea of optimal temperatures and consequently their WTP for the abatement of global warming. The results suggest that migrants from warmer Mexican regions are willing to forgo earnings to prevent both summer and winter temperatures from rising, while migrants from colder regions would pay up to \$5,492 to increase winter temperatures by 2.16°C over the next 50 years. Notably, the estimated welfare gains of migrants from colder regions exceed predicted losses of those immigrating from warmer regions.

These results underscore the importance of taking preference heterogeneity into account when thinking about the potential welfare gains of abating global warming. Assuming preference homogeneity across demographic and clinal differences in populations may considerably bias the predicted welfare gains from abating climate change. Insofar as the WTP for the abatement of global warming is largest among individuals aware of the negative impacts of heat, measurements derived from populations with access to air conditioning and relatively moderate temperatures will underestimate the WTP for the mitigation of climate change. The natural question arises, whether clinal differences documented here are reflective of what one might expect across other climatic zones. Replication of this study based on a larger sample, with migrants from diverse climatic origins, has the potential to give further insights into the extent of clinal differences in temperatures valuations of today's population.

Lastly, alternative estimation methods to the mixed logit model should be explored, which may overcome the problem of multicollinearity experienced in this study. Consequently, more careful research is needed to, on the one hand, verify the magnitude of demographic and clinal differences and, on the other hand, to ensure external validity of the climate-amenity estimates.

Table 4.15: Marginal Willingness to Pay for Projected Temperature Changes

Model	**Base Model**				**(15)**				**(16)**			
	region FE & IV				age $\geq$ 55				mex hot			
Panel A: Baseline Values												
summer temperature	23.11				23.11				23.11			
MWTP	($ -371)				($ -99)				($ -39)			
winter temperature	2.92				2.92				2.92			
MWTP	($ 89)				($ -38)				($ 2,545)			
summer temperature					23.11							
age $\geq$ 55 MWTP					($ 806)							
winter temperature					2.92							
age $\geq$ 55 MWTP					($ 4,782)							
summer temperature									23.11			
mex hot MWTP									($ -132)			
winter temperature									2.92			
mex hot MWTP									($ -1,135)			
Panel B: Projections 2040 to 2069												
	ECHAM5		**CCSM3**		**ECHAM5**		**CCSM3**		**ECHAM5**		**CCSM3**	
Scenario:	SRA2	SRB1	SRA2	SRB1	SRA2 2	SRB1	SRA2	SRB1	SRA2	SRB1	SRA2	SRB1
Δ summer temperature	3.81	3.36	4.73	3.78	3.81	3.36	4.73	3.78	3.81	3.36	4.73	3.78
WTP	($ -1,413)	($ -1,245)	($ -1,755)	($ -1,401)	($ -378)	($ -333)	($ -469)	($ -374)	($ -147)	($ -130)	($ -183)	($ -146)
Δ winter temperature	2.16	2.10	1.48	1.14	2.16	2.10	1.48	1.14	2.16	2.10	1.48	1.14
WTP	($ 193)	($ 188)	($ 132)	($ 102)	($ -82)	($ -80)	($ -56)	($ -44)	($ 5,492)	($ 5,346)	($ 3,763)	($ 2,910)
Δ summer temperature					3.81	3.36	4.73	3.78				
age $\geq$ 55 WTP					($ 3,071)	($ 2,707)	($ 3,813)	($ 3,044)				
Δ winter temperature					2.16	2.10	1.48	1.14				
age $\geq$ 55 WTP					($ 10,320)	($ 10,045)	($ 7,071)	($ 5,468)				
Δ summer temperature									3.81	3.36	4.73	3.78
mex hot WTP									($ -501)	($ -442)	($ -622)	($ -497)
Δ winter temperature									2.16	2.10	1.48	1.14
mex hot WTP									($ -2,449)	($ -2,384)	($ -1,678)	($ -1,297)

Notes: Table presents estimates of the willingness to pay for projected global warming for the ECHAM5 and the CCSM3 model under the A2 and B1 climate scenarios defined by the SRES. Estimates of the willingness to pay for changes in temperature have been derived by dividing the mean coefficient and the standard error from the first and second stage of the sorting model by the coefficient on the hedonic income variable from the mixed logit regression. The result is multiplied by the sample mean predicted income and the projected temperature change from the alternative climate models.

Chapter 5

Conclusion

This thesis is a collection of three empirical chapters in the field of environmental economics, investigating climate impacts on individuals' welfare. I address this overarching question in two separate research contexts: first, by studying weather-related fluctuations in labour markets and, second, by examining the importance of heterogeneity in people's climate preferences.

In the following, I will provide a short summary of the key findings from the three empirical chapters, identify any challenges faced in conducting the research and provide a short outlook into further research prompted by this thesis.

Before going in detail into each essay, it is worth discussing a shared concern in all three empirical studies. The empirical analysis in all three chapters relies on gridded weather data in the form of reanalysis (NARR), interpolated (CRU) and modelled climate data (ECHAM5 and CCSM3). Auffhammer et al. (2013) discuss in detail the pitfalls of using modelled weather data in empirical analysis and note the inherent measurement error associated with the data type. These are particularly concerning in Chapter 2, which studies day-to-day weather deviations in contrast to climate normals used in the later chapters, which are less prone to error. However, a study by Mesinger et al. (2006) finds that the NARR has a good track record of accurately measuring extreme weather events for Mexico, supporting the use of the dataset in the present research context. Nevertheless, climate and weather variables exploited in this thesis should be regarded as approximations, and interpretation of coefficients should be done in light of potential errors in the data.

Chapter 2 investigates the impact of day-to-day weather changes on weekly earnings and working times in Mexico. Leveraging quasi-random day-to-day changes in weather, I find unusually high levels of rainfall cause a meaningful reduction in working times across the Mexican economy. Contrary to findings for the U.S. (Graff Zivin and Neidell 2014), results from Chapter 2 suggest no average impacts of heat across the economy, whilst revealing a drop in working times by just three minutes on days with temperatures below 10°C. On further examination, regressions allowing for heterogeneity in weather impacts indicate that individual and job-specific characteristics play an essential role in determining workers' sensitivity to temperature and precipitation impacts. In particular, the results confirm earlier findings in the literature of adverse heat and rainfall effects on weather-exposed and physically active occupations.

An important revelation of Chapter 2 is the estimation of nontrivial earnings losses for individuals working in unprotected working environments. Particularly informal workers, those in temporary employment contracts or with flexible incomes are vulnerable to earnings fluctuations caused by adverse weather. Whilst costs estimates indicate that annual heat-related earnings losses in the year 2016 roughly amount to just 0.3% of potential earnings and 0.04% of working times, I find these losses to be overwhelmingly borne by the poor. This result provides suggestive evidence of regressive weather impacts on labour markets, which ought to be considered in the design of climate-change adaptation policies.

A key limitation of the paper is the inability to account for weather-related labour-productivity changes. For instance, the results suggest that formal workers increase their working time in response to heat. However, if labour productivity falls with increasing temperatures, the economic impact of heat in formal working environments is uncertain and could well be negative. A further important caveat in the study is the limited information concerning workers' health and changes in product demand. This lack of data hinders identification of physiological mechanisms and differentiation between demand versus supply effects. The inclusion of additional data, particularly on the firm level, is an important area for improvement, given the very different policy implication related to the two alternative channels. A better understanding of the underlying mechanisms would allow for improved targeting of policies to those most vulnerable to weather shocks, rather than those with the flexibility to adapt to weather extremes. In this respect, future research should aim to link labour-market data with information on firm-level productivity and product demand to differentiate between demand and supply effects.

Adaptation to adverse weather unquestionably will partly offset negative future impacts of weather on labour markets. For example, in the long-run workers adversely affected by weather might decide to switch jobs in order to mitigate negative welfare consequences.[1] Consequently, the presented evidence on wage and working-hour responsiveness to day-to-day weather changes should not be generalised for the expected changes due to global warming. However, there are a few lessons to be learned from the findings. First, these results document the negative impact of heat exposure on outdoor and manual-labour intensive work. Adequate ventilation and air conditioning, whilst effective instruments for preventing workers' heat stress, are largely non-existent in Mexican factories. A combination of high external temperatures, waste heat from machinery, and heat strain from physical work can raise body temperatures to unhealthy levels with potentially serious health effects. Equally, lack of protection from direct sunlight and external heat leaves outdoor workers particularly vulnerable to heat stress. While evidence from the extraction sector suggests the existence of temperature-related compensation schemes in the industry, such schemes seem to be absent in other industries.

Traditional methods, such as long lunch-breaks ('siesta') during peak temperatures of the day or flexible working-time schemes can reduce some of the strain. However, with continued global warming, such methods will become less effective as rises in daily minimum temperatures will render work outside peak temperatures equally unhealthy. Considering these results, these traditional methods seem to be ineffective to prevent earnings losses of workers in unprotected work environments. Furthermore, increasingly volatile weather due to climate change will further exacerbate adverse welfare consequences indicated by these results. An important step toward mitigating negative weather effects will be to reduce informal employment to ensure better protection of workers from earnings volatility. Given the complexity of weather effects, labour-market programs aimed at protecting workers from adverse temperatures and precipitation, such as weather insurance programs, should be made accessible to workers across all industries and employment types. Besides,

1. A study by Colmer (2020) demonstrate that Indian agricultural workers mitigate adverse welfare effects of weather shocks by switching to manufacturing jobs.

stricter policies on workplace health and safety standards, especially with regard to heat exposure, are potential solutions to combat the negative impacts of extreme temperature. Tax incentives for firms investing in proper workplace temperature regulation could be used to ensure compliance.

Unlike Chapter 2, the remaining empirical chapters investigate individual climate preferences. Chapters 3 and 4 address a crucial assumption in research on the amenity value of climate, clinal-preference homogeneity. This assumption is often overlooked in research. Evidence from the human-biology literature emphasises systematic differences in human thermal comfort and sensitivity across climatic zones. Motivated by these scientific findings, Chapter 3 provides initial evidence of systematic differences in preferences regarding temperatures, driven by the climate to which an individual is accustomed. Building upon this research, Chapter 4 investigates how the assumption may cause biased estimates of the WTP for the abatement of climate change.

Exploiting a unique dataset of bilateral migration movements between Mexico and the U.S., Chapter 3 estimates a discrete location-choice model to examine clinal heterogeneity in climate preferences. The chapter identifies clinal heterogeneity by using climate differences between origin and destination location, as well as subsample regressions. The results provide suggestive evidence that climate valuations vary by temperatures at the migrant's origin. Relative to their home location, Mexican migrants prefer settling in cities with warmer average and minimum temperatures but colder summer temperatures compared to their home municipality. Moreover, results from the subsample regressions reveal a greater temperature sensitivity of the utility of migrants from warmer Mexican regions, compared to migrants from colder areas. The observed differences become more pronounced in the case of temperature extremes. Estimated clinal differences in temperature preferences are comparable to those related to age, education and migration duration.

Whilst the results provide some initial evidence of clinal heterogeneity, several methodological drawbacks should be highlighted here. Ideally, one would like to control for individual characteristics in the regressions, as they likely influence individuals' location choice. Yet, since individual characteristics are constant across alternatives, identification of the importance of individual-level characteristics in driving location decisions is difficult within the standard logit framework. While in theory other models such as the mixed logit provide greater flexibility in incorporating individual characteristics into the model, I found these models fail to converge. The problem of convergence of more complex models is not uncommon within the location-choice literature, given the inclusion of a large number of fixed effects.

A more pressing concern is the natural correlation in climate variables. For instance, winter and summer temperatures are naturally related. Multicollinearity in regressors within a logit setting is problematic, as it can lead to unreliable and unstable coefficient estimates. Ideally, one would want to increase the sample size to reduce the problem of collinearity in regressions. However, this is not possible in the present context. Alternatively, demeaning of variables can reduce the collinearity in variables. This is the approach followed here. However, while improving precision in estimates, this method cannot fully overcome the issue of collinearity.

In this respect, it is important to consider the implications of the issue for estimates in Chapter 3. Correlation in the climate variables will increase the variance of the estimator, thus reducing precision in estimates. Hence, small changes in the underlying sample could potentially cause significant changes in the estimated coefficients. This could be particularly problematic in subsample regressions. As the underlying sample changes, so might imprecise coefficients. Therefore, interpretation of coefficients with a large variance should be done with extreme caution, particularly in subsample comparisons. Ideally, other estimation methods allowing for collinearity should be exploited.

Motivated by these insights, Chapter 4 applies a different methodological approach, allowing for both individual heterogeneity and correlation among climate regressors. The chapter employs a two-stage random utility sorting model to investigate the importance of clinal heterogeneity in driving individuals' WTP for preferential temperatures, using the same dataset as Chapter 3. In the first stage, I estimate a mixed logit model of the discrete location choice of Mexican migrants to the U.S. The model allows for heterogeneity in the climate valuations by both observed attributes, such as age, education and the climate to which an individual is accustomed, and unobserved individual tastes.

Analogous to the traditional hedonic approach, in the second stage, MSA fixed effects retrieved from the mixed logit model are regressed on destination-specific amenities, including climate. I further implement an IV estimation technique to account for endogeneity in the second-stage regression. Estimates from the baseline model suggest that Mexican migrants on average are willing to forgo earnings to avoid warmer summer temperatures (US$371 per °C per person per year) and to enjoy warmer winters ($89).

In-depth analysis of heterogeneity in individual climate valuations reveals significant differences in the MWTP for friendlier temperatures. Chapter 4 further substantiates the notion that origin climates play an important role in determining individuals' idea of optimal temperatures and consequently their WTP for the abatement of global warming. Results from the sorting model indicate that migrants from warmer regions gain disutility from increasing summer and winter temperatures, while individuals from colder regions enjoy warmer winter temperature. This suggests that exposure to warmer temperatures and, hence, greater awareness of adverse heat effects, yields a negative relationship between individuals' utility and temperatures. At the same time, lack of exposure prior to the migration causes individuals to prefer locations with warmer winter temperatures.

These estimates of the amenity value of temperatures can help to inform the climate-change debate by providing a numerical estimate of the benefits of abating global warming. In this respect, I use climate forecasts under two alternative climate scenarios to predict individuals' WTP for future changes in mean summer and winter temperature over the period 2040 to 2069. On average, I predict welfare losses of between $1,245 to $1,755 per person per year due to increases in summer temperatures, and welfare gains of around $102 to $193 due to warmer winters. Again, the magnitude and direction of the WTP for warming fluctuate significantly across observable characteristics of migrants. Concerning clinal differences, I find estimated welfare gains of migrants from colder regions to exceed losses predicted for individuals from warmer regions.

As shown here, the Bayesian hierarchical-model approach provides a solution to some of the computational issues faced in Chapter 3. The greater flexibility in the hierarchical structure of the regression model and the considerably smaller computational burden makes the method particularly useful in the analysis of climate valuations. The approach facilitates the study of some of the interlinkages between individual characteristics and the amenity value of temperatures. A remaining issue is the problem of choice-set pruning. With greater diversity in potential locations, choice-set restrictions will become even more problematic. Some efforts made in the transport theory might be promising, but more research is required to identify the merits of alternative methods within the location-choice literature. Moreover, the mixed logit model cannot overcome some of the issues caused by multicollinearity in amenity attributes. Therefore, research on the amenity value of climate should concentrate on the development of alternative estimation methods, which are more stable in the presence of natural correlation in regressors.

Several important conclusions can be drawn from the findings in Chapter 4. Comparison to other studies shows that the estimated WTP for temperature changes based on the sample migrants are considerably smaller than estimates produced based on the U.S. Census (Sinha et al. 2018). This finding is unsurprising, given the considerably lower income level of migrants. With regard to climate-change policy, we learn that estimates from developed countries should not be generalised to less developed countries, not even if adjusting measures by the relative size of earnings across countries. Robustness checks indicate a negative correlation between the relative weight given to income and temperatures in location decisions. Hence, the more a person considers income in her choice, the less weight is given to temperatures. Consequently, the WTP of global warming is likely to change disproportionately with rising income.

Moreover, the evidence presented here emphasises the need to account for clinal-preference heterogeneity in the estimation of the WTP for abating climate change. Insofar as the WTP for the abatement of global warming is largest among individuals aware of the negative impacts of heat, measurements derived from populations with access to air conditioning and relatively moderate temperatures may result in a serious underestimation of the WTP for mitigation of climate change. The natural question arises of whether clinal differences documented here are reflective of what one might expect across other climatic zones. In consequence, more careful research is needed to verify the magnitude of clinal differences and to ensure external validity of climate-amenity estimates. This is essential for accurate cost-benefit analyses of climate-change mitigation policies. In this sense, it is important to replicate this study on a global scale to allow for generalisation of the results and to improve identification and precision in heterogeneous effects.

A further line of research is the extent to which climate change will influence migration flows by altering the attractiveness of locations in the long term. In this context, one might ask how quickly temperature valuations will adapt to global warming and whether preferences assimilate as global temperatures rise above a certain threshold. To address these research questions, further data collection on climate-related migration is essential. Lack of detailed information on the origins of migrants in census data prevents the identification of clinal differences in climate valuations. Instead, global migration surveys with greater diversity in origin and destination climates are required. In conclusion, further research on the amenity value of temperatures is required in order to provide useful insights for the climate-change policy debate, and there is much scope for improvements.

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Three Essays in Environmental Economics

Volume II

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Appendices

Appendix A

Appendix to Chapter 2

A.1 Mathematical Derivation

A.1.1 Worker Utility-Maximisation Problem

A worker faces the following utility-maximisation problem:

$$\max_{h,c} u(c, h; \alpha) \quad \text{s.t.} \quad mc = wh + y^* \,. \tag{2.1 revisited}$$

where m is the cost of consumption and w is the hourly wage rate. The first order conditions are given by:

$$u_c(c, h; \alpha) = \lambda m \tag{A.1}$$
$$-u_h(c, h; \alpha) = \lambda w \tag{A.2}$$
$$wh - mc = 0 \tag{A.3}$$

Next, I derive an expression for ${}^{de}/_{d\alpha}$ and ${}^{dc}/_{d\alpha}$ by differentiating (A.1) and (A.2) with respect to α and rearranging the resulting expressions.

$$\frac{dh}{d\alpha} = \frac{\frac{\partial \lambda}{\partial \alpha} w + u_{h\alpha}}{-u_{hh}} \tag{A.4}$$
$$\frac{dc}{d\alpha} = \frac{\frac{\partial \lambda}{\partial \alpha} m - u_{c\alpha}}{u_{cc}} \tag{A.5}$$

To derive an expression for ${}^{d\lambda}/_{d\alpha}$, I totally differentiate the budget constraint (A.3) to obtain:

$$w\frac{dh}{d\alpha} - \frac{dc}{d\alpha} = 0 \tag{A.6}$$

Inserting (A.4) and (A.5) into (A.6) and solving for $\frac{\partial\lambda}{\partial\alpha}$ yields:

$$\frac{\partial\lambda}{\partial\alpha} = \frac{w\frac{u_{h\alpha}}{u_{hh}} - m\frac{u_{c\alpha}}{u_{cc}}}{-[\frac{w^2}{u_{hh}} + \frac{m^2}{u_{cc}}]} \tag{A.7}$$

Given that both $u_{cc} < 0$ and $u_{hh} < 0$, the denominator in (A.7) is positive. It is easy to show that $\frac{\partial\lambda}{\partial\alpha}$ of adverse weather days is positive for high-risk workers [negative for low-risk workers], except if consumption and extreme weather are a strong substitute [compliment]. If $u_{h\alpha}$ is concave (high-risk workers) [convex for low-risk workers], the first term in the numerator is positive [negative] for adverse weather days. Consumption and adverse weather are substitutes if $u_{c\alpha}$ is concave (with negative values at weather extremes) and strong substitutes if for extreme weather days $0 > \frac{w}{p}\frac{u_{h\alpha}}{u_h h}u_{cc} > u_{c\alpha}$. Only in the latter case, $\frac{\partial\lambda}{\partial\alpha}$ is positive for high-risk workers for adverse-weather days. For low-risk workers, $\frac{\partial\lambda}{\partial\alpha}$ is negative as long as consumption and adverse weather are no strong compliments $u_{c\alpha} > \frac{w}{p}\frac{u_{h\alpha}}{u_{hh}} > 0$.

The effect of hours worked can now be inferred from equation (A.4). First, note that the denominator is positive. Hence, the sign of $dh/d\alpha$ depends on the two terms in the nominator. Remember that for high-risk workers, $u_{h\alpha}$ is negative and positive for low-risk workers. If consumption and adverse weather days are strong substitutes, both terms in the numerator are negative for high-risk workers and $\frac{dh}{d\alpha} < 0$. If $\frac{\partial\lambda}{\partial\alpha} > 0$, then $\frac{dh}{d\alpha}$ is negative for weather-exposed workers if the substitution effect dominates the income effect ($\frac{\partial\lambda}{\partial\alpha}w < -u_{h\alpha}$). For low-risk workers, $\frac{dh}{d\alpha} > 0$ if consumption and adverse weather are strong compliments, or the positive substitution effect dominates the negative income effect $-\frac{\partial\lambda}{\partial\alpha}w < u_{h\alpha}$.

A.1.2 Productivity-Mapped Wage Regimes

When labour productivity is reduced by adverse weather and wages are adjusted for changes in productivity, then adverse weather days affect equilibrium wages. In this case, equation (A.4) and (A.6) become:

$$\frac{dh}{d\alpha} = \frac{\frac{\partial\lambda}{\partial\alpha}w + \frac{\partial w}{\partial\alpha}\lambda + u_{h\alpha}}{-u_{hh}} \tag{A.8}$$

$$w\frac{dh}{d\alpha} + \frac{\partial w}{\partial\alpha}h - \frac{dc}{d\alpha} = 0 \tag{A.9}$$

and finally, $\partial\lambda/\partial\alpha$ becomes

$$\frac{\partial\lambda}{\partial\alpha} = \frac{w\frac{u_{h\alpha}}{u_{hh}} - m\frac{u_{c\alpha}}{u_{cc}}}{-[\frac{w^2}{u_{hh}} + \frac{m^2}{u_{cc}}]} + \frac{dw}{d\alpha}\frac{[\frac{w\lambda}{u_{hh}} - h]}{-[\frac{w^2}{u_{hh}} + \frac{m^2}{u_{cc}}]} \tag{A.10}$$

Equation A.10 now consists of two terms. The first is identical to (A.7). The second term is explained by the traditional relationship between increased wages and income: since adverse weather days decrease earnings per hour worked ($\frac{dw}{d\alpha}h$) and reduce income from each additional hour worked ($\frac{dw}{d\alpha}\frac{w\lambda}{u_{hh}}$), the marginal utility of income will increase. Therefore, productivity-mapped wages will amplify the negative substitution effect of high-risk workers and reduce the positive effect for low-risk workers, given the additional negative term ($\frac{\partial w}{\partial\alpha}h$) in (A.9). As discussed above, depending on the complementarity of consumption and adverse-weather days, the income effect might work in the opposing direction of the substitution effect. At high levels of hours worked, the income effect could potentially dominate the substitution effect. In this case, the labour supply elasticity would be negative. However, I consider this situation unlikely to apply to the Mexican labour force due to the lack of empirical evidence of a negative elasticity (see Arceo Gómez and Campos-Vázquez (2010)).

A.2 Maps of Mexican Municipalities

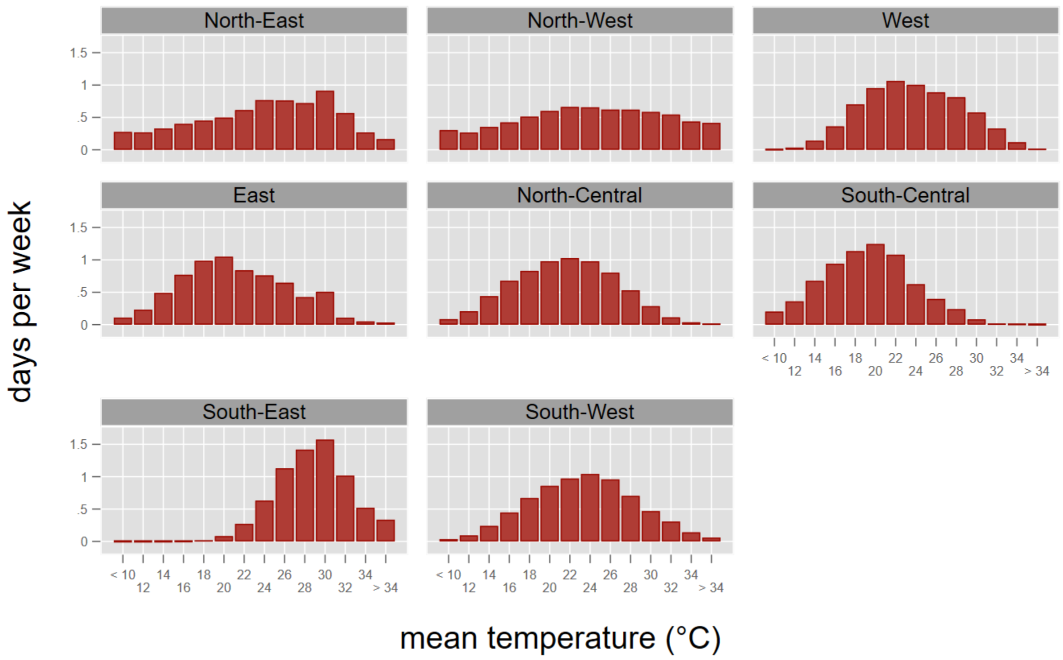
Figure A.2.1: Map of Mexican Municipality

Notes: 780 municipalities coloured in green are not included in the final sample.

A.3 Distribution of Temperatures and Precipitation across Region and Season

Figure A.3.1: Regional differences in temperatures and precipitation

(a) Temperature (°C)



(b) Precipitation (mm)

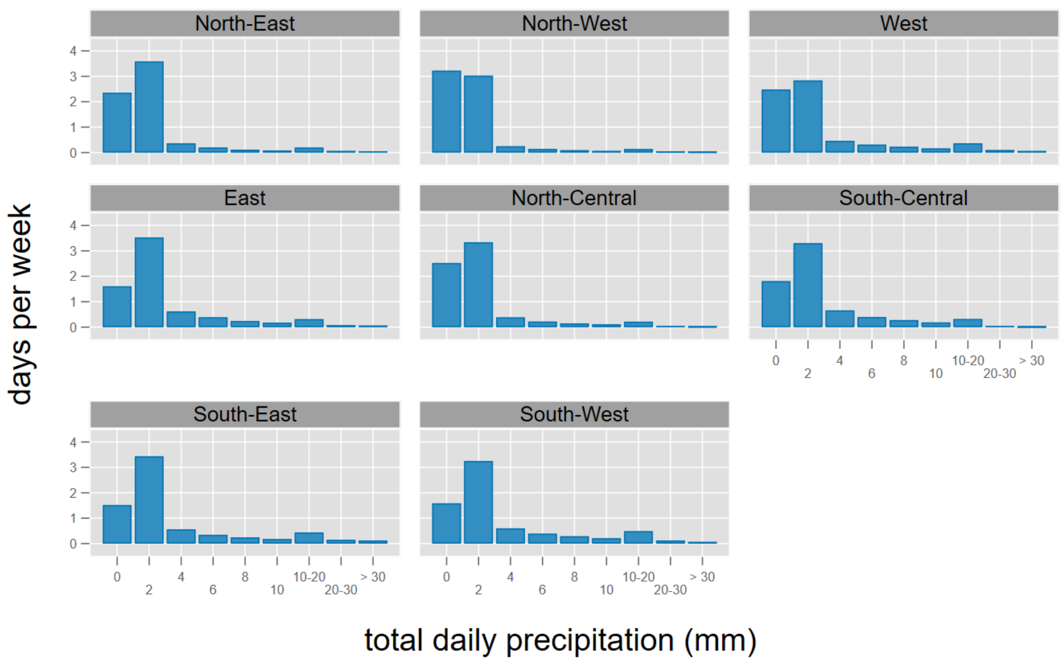
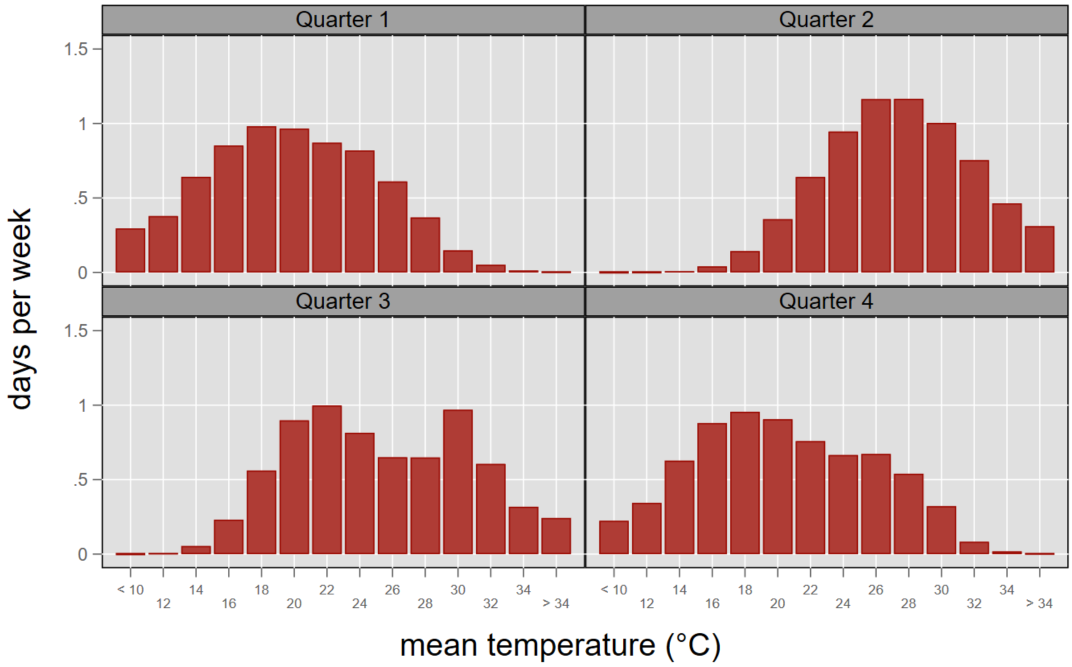
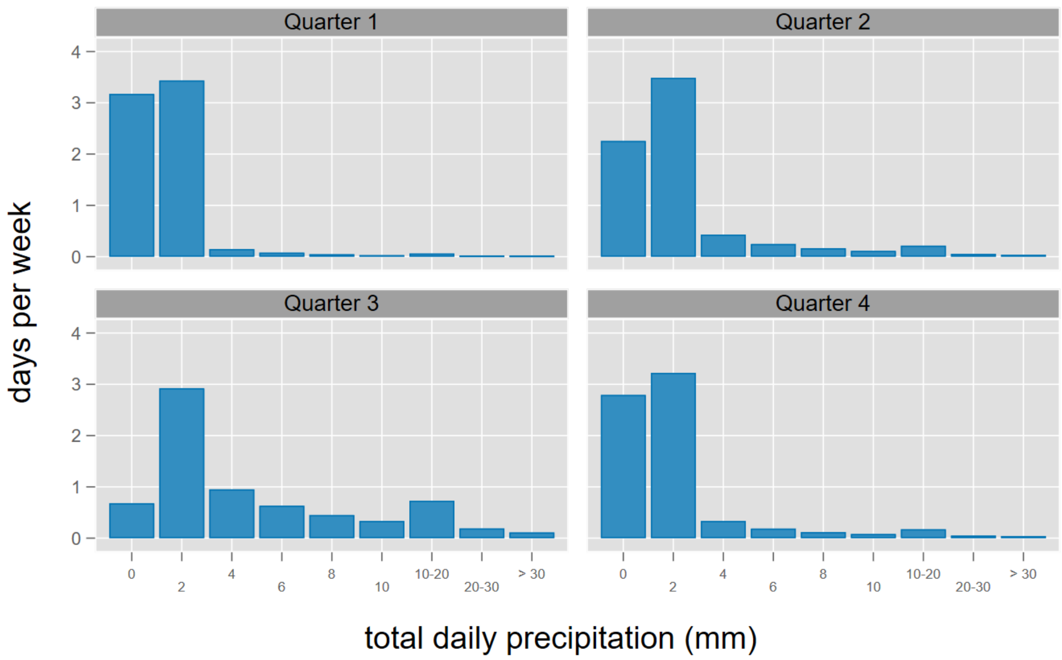


Figure A.3.2: Quarterly differences in temperatures and precipitation

(a) Temperature (°C)



(b) Precipitation (mm)



A.4 Baseline Model Regression Tables

Table A.4.1: Baseline Model Regression Table

	(1)	(2)
	weekly earnings	minutes worked
Temperature:		
$\leq$ 10°C	-0.267	-3.293***
	(-0.16)	(-2.74)
10-12°C	-0.177	-1.345
	(-0.07)	(-1.21)
12-14°C	-0.562	-1.222
	(-0.33)	(-1.38)
14-16°C	-0.331	0.0356
	(-0.36)	(0.04)
16-18°C	0.594	-0.00098
	(0.58)	(-0.00)
18-20°C	1.014	-0.0502
	(0.94)	(-0.07)
20-22°C	–	–
22-24°C	-1.088	0.0726
	(-1.18)	(0.11)
24-26°C	0.778	-0.351
	(0.86)	(-0.54)
26-28°C	-0.191	0.257
	(-0.17)	(0.39)
28-30°C	-0.367	1.136*
	(-0.33)	(1.86)
30-32°C	-2.628{**}	-0.754
	(-2.21)	(-0.98)
32-34°C	-1.31	0.0207
	(-0.51)	(0.02)
> 34°C	-2.415	-0.781
	(-1.31)	(-0.60)
Precipitation:		
= 0 mm	-0.36	0.366
	(-0.28)	(0.38)
0-2 mm	0.279	-0.522
	(0.22)	(-0.55)
2-4 mm	–	–
4-6 mm	0.205	-0.595
	(0.08)	(-0.37)
6-8 mm	-1.683	-0.894
	(-0.79)	(-0.48)
8-10 mm	1.447	0.232
	(0.59)	(0.12)
10-20 mm	-0.377	-2.464*
	(-0.22)	(-1.87)
20-30 mm	-0.347	-12.05***
	(-0.13)	(-5.08)
> 30 mm	-4.89	-28.12***
	(-1.01)	(-8.48)

Table continues on next page

Table A.4.1: *(Continued)*

	(1)	(2)
	weekly earnings	minutes worked
Controls:		
married	110.7***	-20.53***
	(24.34)	(-9.08)
female	-320.7***	-468.6***
	(-42.92)	(-67.03)
age	39.33***	42.45***
	(25.81)	(48.86)
age^2	-0.413***	-0.491***
	(-29.31)	(-52.22)
secondary	89.09***	9.415***
	(15.65)	(2.82)
preparatory	178.5***	-36.95***
	(16.36)	(-7.16)
university	509.5***	-150.1***
	(22)	(-20.29)
postgraduate	961.3***	-13.82**
	(24.92)	(-2.32)
unemp. rate	-405.1***	-494.2***
	(-2.96)	(-10.03)
rural	-61.66***	-48.05***
	(-6.38)	(-5.99)
medium	67.12***	97.36***
	(9.03)	(14.24)
large	158.0***	54.09***
	(12.17)	(6.12)
informal	-186.3***	-505.2***
	(-27.08)	(-48.21)
permanent	168.2***	77.20***
	(23.58)	(12.78)
constant	8.603	1895.9***
	(0.21)	(73.04)
mun. fe	×	×
sec time fe	×	×
year fe	×	×
qtr fe	×	×
adjusted R^2	0.115	0.146
F Stat.	1216.4	599.5
DF	-5731675	-5731675
# clusters	1676	1676
N	7390147	7390147

Notes: Standard errors (in parentheses) are clustered by municipality. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects.

A.5 Simple Weather Variables

Considering the controversy around the correct specification, prior to implementing a more flexible functional-form approach, I estimate several initial regressions using noncomplex specifications of weather variables. These more simple regressions serve the purpose of comparability of the estimates with other studies, as well as providing a reference point for the more complex structural models in the main regression analysis. I employ four different temperature indicators in the analysis: (1) weekly mean temperatures (in ° C), (2) weekly mean Wet Bulb Globe Temperature (WBGT) (in ° C), (3) weekly mean Heat Index (HI) (in ° C), and (4) weekly total harmful degree-days (HDD) (in ° C). Harmful degree-days capture the detrimental impact of extreme heat, taking into account the duration of the heat wave by summing excessive degrees over an upper threshold over time. This heat indicator is constructed as the sum of the difference in temperatures above 35°C and the threshold. Alternative measures suggested by the literature are the WBGT (Kjellstrom et al. 2018) measure and the HI (Heyes and Saberian 2019; Kim et al. 2006), which measures the apparent temperature by factoring relative humidity with actual air temperature. The formulas for the calculation for each alternative temperature measure are provided in Appendices A.7.2 and A.7.1. Moreover, all the regressions include weekly total precipitation (in mm).

A.5.1 Simple Linear Weather Variables

Table A.5.1 summarises the key predictions for the effect of linear weather variables on earnings. We estimate a significant negative impact of the heat index on weekly earnings in the municipality fixed-effects regression. An increase of 1°C measured in the form of the HI reduces weekly earnings by 0.504 Mexican pesos, or one standard deviation increase in the heat index reduces average weekly earnings by 3.19 pesos. Note that the predicted coefficients for mean temperature and WBGT are of comparable size but insignificant. Secondly, the results indicate no significant linear relationship between precipitation and earnings. Similarly, the work-time estimates suggest a negative linear relationship between HI and working time. A one-standard-deviation increase in the HI reduces average weekly working time by 2.78 minutes. Contrary to the earnings regressions, I predict a negative association between precipitation and weekly working times. An increase in total weekly precipitation by one standard deviation (3.38 mm) reduces average working times in the municipality by 1.40 minutes.

Table A.5.1: Linear Weather Specification – Earnings Regression

	(1)	(2)	(3)	(4)
mean tempeartue (°C)	-0.486			
	(-0.88)			
WBGT (°C)		-0.501		
		(-0.69)		
HI (°C)			-0.504***	
			(-2.68)	
HDD (°C)				0.00426
				(0.16)
total wkly precip (mm)	-0.0311	-0.0236	-0.0300	-0.0116
	(-0.54)	(-0.41)	(-0.48)	(-0.18)
mun. fe	×	×	×	×
sec time fe	×	×	×	×
year fe	×	×	×	×
qtr fe	×	×	×	×
adjusted R^2	0.115	0.115	0.115	0.115
F Stat.	1176.1	1169.6	1171.3	1166.0
DF	(554,1675)	(554,1675)	(554,1675)	(554,1675)
# clusters	1,676	1,676	1,676	1,676
N				
Ind.	2,632,000	2,632,000	2,632,000	2,632,000

Notes: Standard errors (in parentheses) are clustered by municipality. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] ° C and (2-4] *mm* precipitation.

Table A.5.2: Linear Weather Specification – Working Time Regression

	(1)	(2)	(3)	(4)
mean tempeartue (°C)	-0.00471			
	(-0.02)			
WBGT (°C)		-0.0572		
		(-0.15)		
HI (°C)			-0.441***	
			(-3.33)	
HDD (°C)				-0.0419
				(-0.78)
total wkly precip (mm)	-0.415***	-0.417***	-0.431***	-0.419***
	(-12.14)	(-12.11)	(-12.48)	(-12.44)
mun. fe	×	×	×	×
sec time fe	×	×	×	×
year fe	×	×	×	×
qtr fe	×	×	×	×
adjusted R^2	0.146	0.146	0.146	0.146
F Stat.	580.4	581.3	582.5	581.2
DF	(554,1675)	(554,1675)	(554,1675)	(554,1675)
# clusters	1,676	1,676	1,676	1,676
N				
Ind.	2,632,000	2,632,000	2,632,000	2,632,000

Notes: Standard errors (in parentheses) are clustered by municipality. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] ° C and (2-4] *mm* precipitation.

Polynomial Weather Variables

Before moving to the preferred weather-variable specification, I estimate further sets of regressions, including polynomial weather specifications. Table A.5.3 lists the earnings regression estimates. Including squared and cubic terms, I predict a statistically significant concave relationship between mean temperatures and earnings, with the optimal temperature reached at around 17.81°C, after which income starts declining. Our predictions for the impact of precipitation remain insignificant.

Our predictions for the working-time polynomial regressions indicate nonlinearities in the impact of temperatures on minutes worked (see Table A.5.4). Both mean temperatures and the WBGT estimates outline a cubic relationship between working times and temperature. Based on mean temperature estimates, working times increase up to a temperature of approximately 22°C, after which they decline until reaching a temperature of 40°. Once this extreme level is reached, working times again rise rapidly. Our results further suggest that rainfall decreases working times at an increasing rate, with the quadratic specification providing the best fit for the relationship between rainfall and working times.

Table A.5.3: Polynomial Weather Specification – Earnings Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
mean temp. (°C)	2.238	3.165						
	(1.61)	(0.73)						
mean temp.^{2} (°C)	-0.0609**	-0.106						
	(-2.28)	(-0.50)						
mean temp.^{3} (°C)		0.000671						
		(0.21)						
WBGT (°C)			3.705**	7.665				
			(1.97)	(0.90)				
WBGT^2 (°C)			-0.104**	-0.312				
			(-2.39)	(-0.70)				
WBGT^3 (°C)				0.00345				
				(0.45)				
HI (°C)					-0.186	4.239		
					(-0.14)	(0.82)		
HI^2 (°C)					-0.00548	-0.162		
					(-0.22)	(-0.87)		
HI^3 (°C)						0.00175		
						(0.82)		
HDD (°C)							-0.133	-0.0953
							(-1.21)	(-0.55)
HDD^2 (°C)							0.0004*	0.0001
							(1.83)	(0.15)
HDD^3 (°C)								0.0000
								(0.46)
total wkly	-0.0213	-0.0661	-0.0002	-0.0373	-0.0039	-0.0439	0.0269	0.0035
precip. (mm)	(-0.27)	(-0.48)	(-0.00)	(-0.25)	(-0.04)	(-0.29)	(0.31)	(0.02)
total wkly	-0.0002	0.0007	-0.0003	0.0004	-0.000248	0.0005	-0.0004	0.0001
precip.^{2} (mm)	(-0.23)	(0.34)	(-0.34)	(0.22)	(-0.31)	(0.27)	(-0.52)	(0.03)
total wkly		-0.0000		-0.0000		-0.0000		-0.0000
precip.^{3} (mm)		(-0.48)		(-0.40)		(-0.45)		(-0.26)
mun. fe	×	×	×	×	×	×	×	×
sec time fe	×	×	×	×	×	×	×	×
year fe	×	×	×	×	×	×	×	×
qtr fe	×	×	×	×	×	×	×	×
adjusted R^2	0.115	0.115	0.115	0.115	0.115	0.115	0.115	0.115
F Stat.	1212.8	1213.3	1205.2	1211.1	1190.6	1198.7	1201.6	1222.8
DF	(556,1675)	(558,1675)	(556,1675)	(558,1675)	(556,1675)	(558,1675)	(556,1675)	(558,1675)
# clusters	1,676	1,676	1,676	1,676	1,676	1,676	1,676	1,676
N 7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147
Ind.	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000

Notes: Standard errors (in parentheses) are clustered by municipality. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] ° C and (2-4] *mm* precipitation.

Table A.5.4: Polynomial Weather Specification – Working Time Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
mean temp. (°C)	2.778***	5.592**						
	(3.42)	(1.99)						
mean temp.^{2} (°C)	-0.0592***	-0.196						
	(-3.25)	(-1.47)						
mean temp.^{3} (°C)		0.00209						
		(1.02)						
WBGT (°C)			3.421***	12.12***				
			(2.89)	(2.71)				
WBGT^2 (°C)			-0.0834***	-0.542**				
			(-2.91)	(-2.37)				
WBGT^2 (°C)				0.0077**				
				(2.02)				
HI (°C)					-0.313	0.238		
					(-0.50)	(0.11)		
HI^2 (°C)					-0.00132	-0.0201		
					(-0.12)	(-0.26)		
HI^2 (°C)						0.0002		
						(0.25)		
HDD (°C)							0.0415	0.0983
							(0.36)	(0.87)
HDD^2 (°C)							-0.0002	-0.0006
							(-1.01)	(-1.22)
HDD^2 (°C)								0.0000
								(0.82)
total wkly	-0.193***	-0.112	-0.192***	-0.110	-0.211***	-0.135	-0.183***	-0.0920
precip. (mm)	(-2.95)	(-1.13)	(-2.90)	(-1.11)	(-3.22)	(-1.38)	(-2.85)	(-0.96)
total wkly	-0.0021***	-0.0036**	-0.0021***	-0.0036**	-0.0020***	-0.0035**	-0.0022***	-0.0038**
precip.^{2} (mm)	(-3.60)	(-2.28)	(-3.58)	(-2.26)	(-3.46)	(-2.19)	(-3.70)	(-2.46)
total wkly		0.0000		0.0000		0.0000		0.0000
precip.^{2} (mm)		(0.92)		(0.91)		(0.88)		(1.04)
mun. fe	×	×	×	×	×	×	×	×
sec time fe	×	×	×	×	×	×	×	×
year fe	×	×	×	×	×	×	×	×
qtr fe	×	×	×	×	×	×	×	×
adjusted R^2	0.146	0.146	0.146	0.146	0.146	0.146	0.146	0.146
F Stat.	595.3	595.8	596.1	595.8	599.3	598.0	597.3	612.2
DF	(556,1675)	(558,1675)	(556,1675)	(558,1675)	(556,1675)	(558,1675)	(556,1675)	(558,1675)
# clusters	1,676	1,676	1,676	1,676	1,676	1,676	1,676	1,676
N 7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147
Ind.	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000

Notes: Standard errors (in parentheses) are clustered by municipality. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] ° C and (2-4] *mm* precipitation.

A.6 Residual Variation

In view of the spatiotemporal higher dimensional fixed-effects structure of the regression specification, it is essential to analyse how much variation in the weather variables is stripped away by the fixed effects. Following Guiteras (2009) and Jessoe et al. (2018), I regress each weather measure on various definitions of fixed effects and time trends (none; municipality fixed effects; municipality fixed effects and year trend; municipality fixed effects and higher polynomial year trends; municipality, quarter, and year fixed effects; municipality, region×year, and quarter fixed effects; municipality and state×year, and quarter fixed effects; individual, year and quarter fixed effects). The residual variation of each regression provides a measure of the remaining variation left for the identification of weather impacts. I follow Guiteras's (2009) approach and run separate regressions for each bin b on the various fixed-effects specifications. I next calculate the absolute value of the residuals from each regression. Each entry in Table A.6.1 depicts the mean across municipalities over time. The mean value times the number of municipality-by-quarter observations yields the number of observations available to identify the weather impact for the respective interval. The final numbers in Table A.6.1 can be interpreted as the mean number of days per district-year-quarter available for the identification of the impact of each bin, after controlling for the particular spatiotemporal error structure. The larger the number of remaining observations, the better and more precise will be the identification of the weather-bin impacts.

Ideally, one would like to have a significant residual variation above reasonable cut-off points. As becomes evident from the results, the remaining variation declines substantially with more complex time fixed effects. Results differ only a little between time trends and year fixed effects, with year fixed effects removing slightly more variation in the weather variables. Considering the short period of data collection, the loss in variation suggests abnormal weather for one or more years compared to the overall trend. Year dummies will remove some of this unusual variation. However, in light of the modest difference in residual variation between year trends and year fixed effects, I prefer to include year fixed effects, as this specification more appropriately controls for exogenous shocks to labour markets. The sector-specific year and quarter fixed effects reduce the residual variation in the climate variables substantially. In light of seasonality both in climate and in sectoral productivity, dropping industry-specific quarterly fixed effects from the regression could generate substantial bias in the estimates.

The final specification test based on individual fixed effects again results in a significant loss in variation, which may render the identification of weather impacts using this empirical strategy difficult. In light of the previous findings, all the regressions include industry-specific year and quarter, as well as month and municipality fixed-effects specification.[1] It is important to note that given the loss in weather variation under the preferred fixed effects strategy, any interpretation of large weather fluctuations should be made with caution. The latter requires a large variation in individual weather exposure over the five weekly observations in the panel.

1. Section 2.7 tests the robustness of the preferred specification to the introduction of different fixed-effects structures.

Table A.6.1: Residual Variation of Weekly Weather Bins

Panel 1: Temperature Bins

	Bin													
Regressors	≤ 10	(10-12]	(12-14]	(14-16]	(16-18]	(18-20]	(20-22]	(22-24]	(24-26]	(26-28]	(28-30]	(30-32]	(32-34]	(> 34]
constant	0.24	0.32	0.54	0.73	0.87	0.96	0.98	0.98	0.97	0.90	0.89	0.60	0.36	0.26
municipality fe	0.24	0.32	0.54	0.73	0.87	0.96	0.98	0.98	0.97	0.90	0.89	0.60	0.36	0.26
mun & qtr fe year trend	0.23	0.28	0.45	0.62	0.78	0.92	0.97	0.98	0.94	0.84	0.79	0.52	0.32	0.25
mun & qtr fe year^2	0.23	0.29	0.45	0.62	0.78	0.92	0.97	0.98	0.94	0.84	0.79	0.52	0.32	0.25
mun & qtr fe year^3	0.23	0.29	0.45	0.62	0.78	0.92	0.97	0.98	0.94	0.84	0.79	0.52	0.32	0.26
mun year & qtr fe	0.24	0.29	0.46	0.62	0.78	0.92	0.97	0.98	0.94	0.84	0.79	0.52	0.33	0.26
mun year qtr & mth fe	0.22	0.27	0.43	0.60	0.78	0.91	0.95	0.96	0.93	0.82	0.77	0.52	0.32	0.26
mun state×year qtr & mth fe	0.24	0.28	0.44	0.60	0.77	0.90	0.94	0.96	0.92	0.82	0.81	0.55	0.34	0.26
mun., sector×year×qtr & mth fe	0.22	0.26	0.42	0.60	0.77	0.91	0.95	0.96	0.93	0.82	0.77	0.52	0.32	0.25
ind year & qtr fe	0.25	0.31	0.46	0.62	0.78	0.92	0.97	0.98	0.94	0.84	0.79	0.53	0.33	0.26

Panel 2: Precipitation Bins

	Bin								
Regressors	= 0	(0-2]	(2-4]	(4-6]	(6-8]	(8-10]	(10-20]	(20-30]	(> 30]
constant	1.70	1.32	0.55	0.38	0.28	0.22	0.44	0.14	0.09
municipality fe	1.70	1.32	0.55	0.38	0.28	0.22	0.44	0.14	0.09
mun & qtr fe year trend	1.40	1.30	0.46	0.32	0.24	0.19	0.36	0.12	0.09
mun & qtr fe year^2	1.40	1.30	0.46	0.32	0.24	0.19	0.36	0.12	0.09
mun & qtr fe year^3	1.40	1.30	0.46	0.32	0.24	0.19	0.36	0.12	0.09
mun year & qtr fe	1.39	1.30	0.46	0.32	0.24	0.19	0.36	0.12	0.09
mun year qtr & mth fe	1.32	1.29	0.44	0.31	0.23	0.18	0.34	0.12	0.09
mun state×year qtr & mth fe	1.33	1.30	0.45	0.31	0.24	0.19	0.35	0.13	0.09
mun., sector×year× & mth fe	1.28	1.27	0.43	0.30	0.23	0.18	0.34	0.12	0.09
ind year & qtr fe	1.41	1.30	0.46	0.32	0.24	0.19	0.36	0.12	0.09

Notes: This table assesses the extent of residual variation available after removing district fixed effects and other controls. For each bin, the number of days in that bin is regressed on the controls given in the row heading. The absolute value of the residual is then averaged over all district × year observations. The result can be interpreted as the mean number of days per district × year available to identify the effect of that bin. Years: 2005-2016; Sample: 2456 districts (8720 total year × district observations)

Table A.6.2: Residual Variation of Weekly Weather Bins

Panel 1: Wet Bulb Globe Temperature Bins

	Bin													
Regressors	≤ 10	(10-12]	(12-14]	(14-16]	(16-18]	(18-20]	(20-22]	(22-24]	(24-26]	(26-28]	(28-30]	(30-32]	(32-34]	(> 34]
constant	0.19	0.42	0.82	1.08	1.23	1.26	1.17	1.02	0.90	0.84	0.46	0.17	0.02	0.00
municipality fe	0.19	0.42	0.82	1.08	1.23	1.26	1.17	1.02	0.90	0.84	0.46	0.17	0.02	0.00
mun & qtr fe year trend	0.18	0.38	0.66	0.93	1.21	1.24	1.13	0.99	0.87	0.76	0.42	0.16	0.02	0.00
mun & qtr fe year^2	0.18	0.38	0.66	0.93	1.21	1.24	1.13	0.99	0.87	0.76	0.42	0.16	0.02	0.00
mun & qtr fe year^3	0.18	0.38	0.66	0.93	1.21	1.24	1.13	0.99	0.87	0.76	0.42	0.17	0.02	0.00
mun year & qtr fe	0.19	0.39	0.66	0.93	1.21	1.24	1.13	0.99	0.87	0.76	0.42	0.17	0.02	0.00
mun year qtr & mth fe	0.18	0.35	0.62	0.91	1.18	1.22	1.12	0.99	0.85	0.75	0.42	0.17	0.02	0.00
mun state×year qtr & mth fe	0.19	0.36	0.63	0.90	1.16	1.21	1.11	0.96	0.85	0.80	0.44	0.18	0.03	0.00
mun., sector×year× & mth fe	0.17	0.34	0.62	0.91	1.17	1.21	1.11	0.99	0.85	0.75	0.42	0.16	0.02	0.00
ind year & qtr fe	0.20	0.41	0.67	0.93	1.21	1.24	1.13	0.99	0.87	0.76	0.42	0.17	0.02	0.00

Panel 2: Heat Index Bins

	Bin													
Regressors	≤ 10	(10-12]	(12-14]	(14-16]	(16-18]	(18-20]	(20-22]	(22-24]	(24-26]	(26-28]	(28-30]	(30-32]	(32-34]	(> 34]
constant	0.04	0.06	0.18	0.44	0.80	0.91	0.91	0.90	0.90	0.79	0.73	0.58	0.48	1.37
municipality fe	0.04	0.06	0.18	0.44	0.80	0.91	0.91	0.90	0.90	0.79	0.73	0.58	0.48	1.37
mun & qtr fe year trend	0.04	0.06	0.17	0.41	0.75	0.88	0.91	0.89	0.88	0.75	0.71	0.57	0.48	1.32
mun & qtr fe year^2	0.05	0.06	0.17	0.41	0.75	0.88	0.91	0.89	0.88	0.75	0.71	0.57	0.48	1.32
mun & qtr fe year^3	0.05	0.06	0.17	0.41	0.75	0.88	0.91	0.89	0.88	0.75	0.71	0.57	0.48	1.32
mun year & qtr fe	0.05	0.06	0.17	0.40	0.75	0.88	0.91	0.89	0.88	0.75	0.71	0.57	0.48	1.31
mun year qtr & mth fe	0.05	0.06	0.17	0.40	0.74	0.87	0.89	0.89	0.87	0.75	0.70	0.56	0.47	1.29
mun state×year qtr & mth fe	0.05	0.06	0.18	0.41	0.73	0.85	0.89	0.88	0.86	0.74	0.70	0.56	0.47	1.34
mun., sector×year× & mth fe	0.05	0.06	0.17	0.40	0.73	0.86	0.89	0.88	0.87	0.74	0.70	0.56	0.47	1.28
ind year & qtr fe	0.06	0.07	0.18	0.42	0.75	0.88	0.91	0.90	0.88	0.76	0.71	0.57	0.48	1.32

Notes: This table assesses the extent of residual variation available after removing district fixed effects and other controls. For each bin, the number of days in that bin is regressed on the controls given in the row heading. The absolute value of the residual is then averaged over all district × year observations. The result can be interpreted as the mean number of days per district × year available to identify the effect of that bin. Years: 2005-2016; Sample: 2456 districts (8720 total year × district observations)

A.7 Apparent Temperature Measures

A.7.1 The Heat Index

An alternative measure suggested by the literature is the HI (Heyes and Saberian 2019; Kim et al. 2006), which measures the perceived temperature by factoring relative humidity with actual air temperature. In the construction of the HI, I follow the U.S. National Weather Service approach (National Oceanic and Atmospheric Administration and National Weather Service 2017, hereafter NOAA and NWS) by using Lans P. Rothfusz (Rothfusz 1990) equation and applying several adjustments to it. The Rothfusz equation is given by:

$$\begin{aligned} HI = & -42.379 + 2.04901523 \times T + 10.14333127 \times RH - 0.22475541 \times T \times RH \\ & - 0.00683783 \times T^2 - 0.05481717 \times RH^2 + 0.00122874 \times T^2 \times RH \\ & + 0.00122874 \times T \times RH^2 - 0.00000199 \times T^2 RH^2 \, , \end{aligned}$$

where T is temperature in °F and RH is relative humidity in percent. Further adjustments must be made for the following combinations of RH and T.

If RH less than 13 per cent and temperature between 80 and 112°F

$$HI_{adj} = HI - \frac{13 - RH}{4} \times \sqrt{\frac{17 - |T - 95|}{17}} \, . \tag{A.11}$$

If RH is greater than 85 per cent and the temperature is between 80 and 87°F:

$$HI_{adj} = HI + \frac{RH - 85}{10} \times \frac{87 - T}{5} \, . \tag{A.12}$$

The use of the Rothfusz regression is not appropriate for temperatures below 80°F. At these temperatures, a more simple formula is used:

$$HI = 0.5 \times (T + 61 + (T - 68) \times 1.2 + RH * 0.094) \, . \tag{A.13}$$

Finally, for the purpose of comparability with the average temperature measurement, I transformed the unit of measurement from °F to ° C.

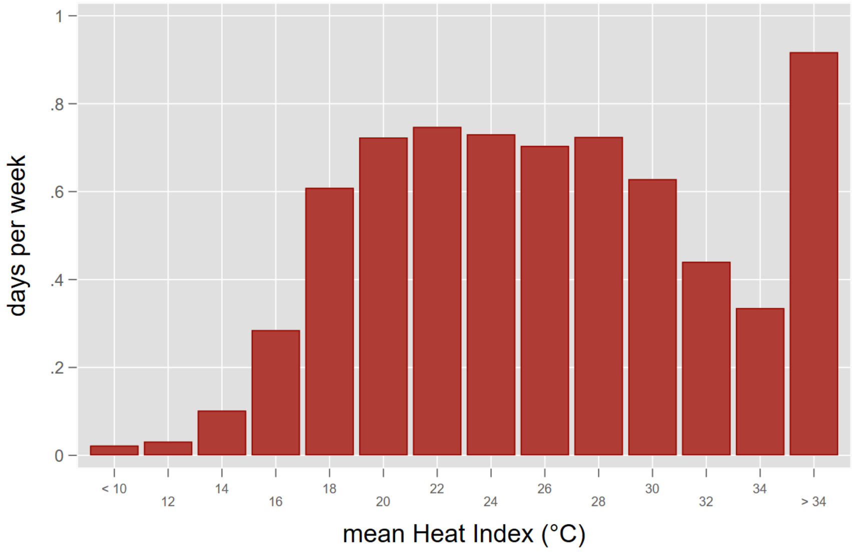
Table A.7.1 below shows the implication of different temperature ranges for health.

Table A.7.1: Health effects of different Heat Index bands

27-32°C	Caution: Fatigue is possible with prolonged exposure and or physical activity.
32-41°C	Extreme Caution: Sunstroke, muscle cramps, and/or heat exhaustion possible with prolonged exposure and/or physical activity.
41-54°C	Danger: Sunstroke, muscle cramps, and/or heat exhaustion likely. Heatstroke possible with prolonged exposure and/or physical activity.
over 54°C	Extreme Danger: Heatstroke likely.

Results

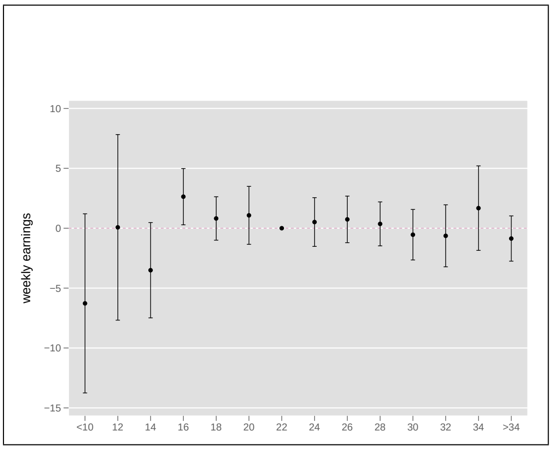
Figure A.7.1: Distribution of daily Heat Index bins per week



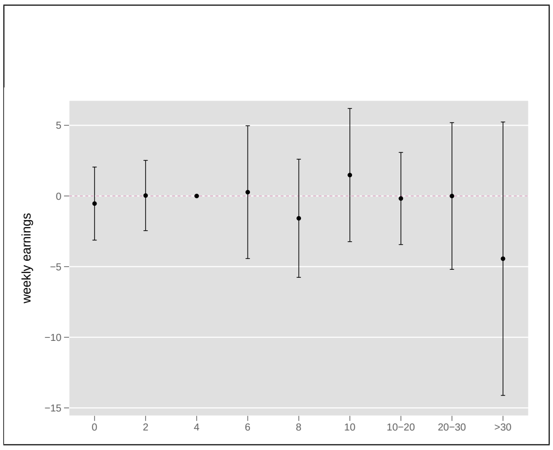
Notes: Period of observation 2005-2016. The bar height captures the incidence of days with weather falling into the respective bin across municipality per week.

Figure A.7.2: HI Weather Bins Coefficient Plots - Earnings Regression

(a) Temperature



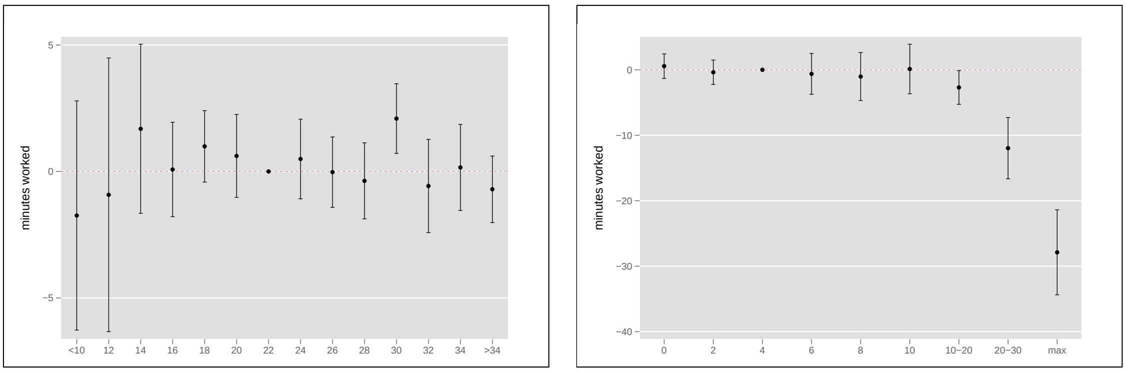
(b) Precipitation



Notes: Figure depicts marginal effects of weather bins on weekly earnings. N=7,390,147, Ind.=2,632,000. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Figure A.7.3: HI Weather Bins Coefficient Plots - Working Time Regression

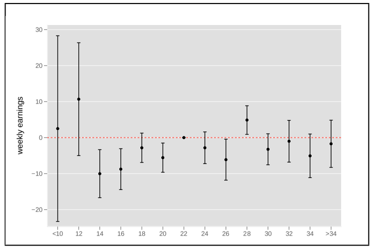
(a) Temperature **(b)** Precipitation



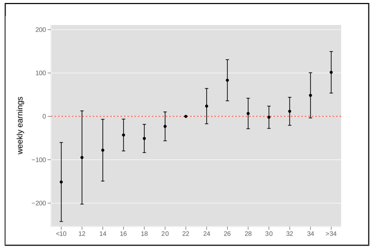
Notes: The figure depicts marginal effects of weather bins on weekly minutes worked. N=7,390,147, Ind.=2,632,000. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Figure A.7.4: HI Industry Marginal Effects on Earnings - Heat Index

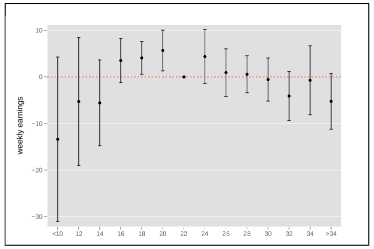
(a) Agriculture



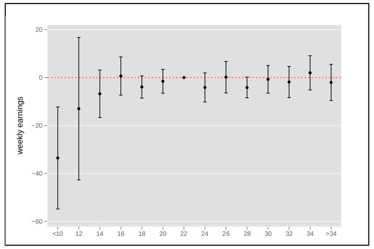
(b) Extractive Industry



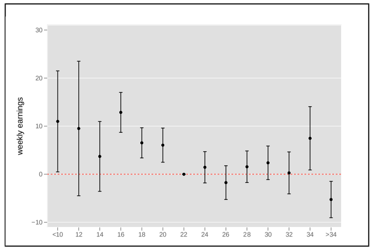
(c) Manufacturing



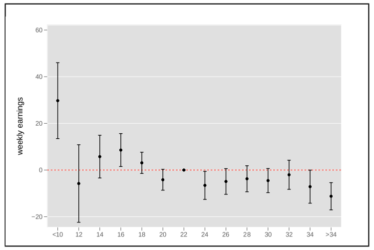
(d) Construction



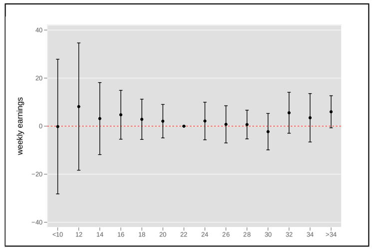
(e) Trade



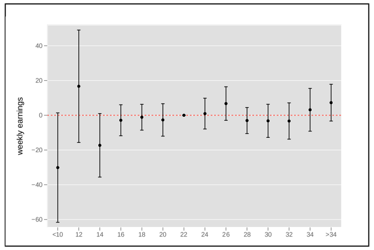
(f) Restaurant Services



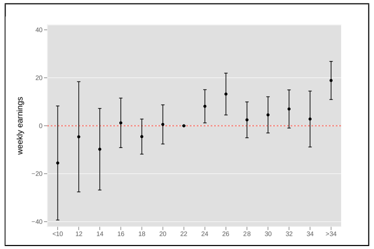
(g) Transport



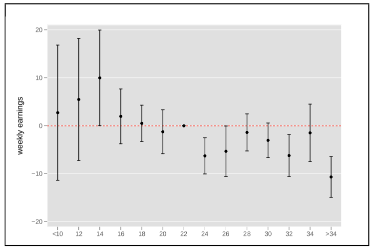
(h) Professional Services



(i) Diverse Services



(j) Social Services



(k) Government

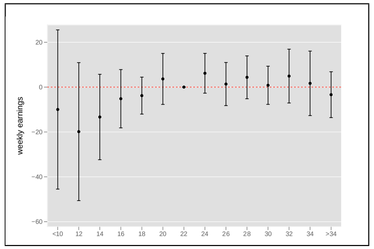
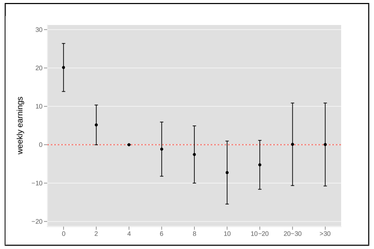
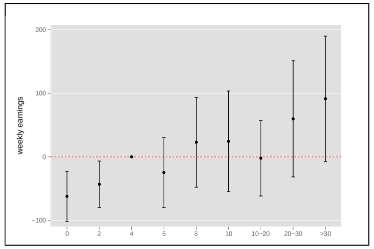


Figure A.7.4: HI Industry Marginal Effects on Earnings - Precipitation *(continued)*

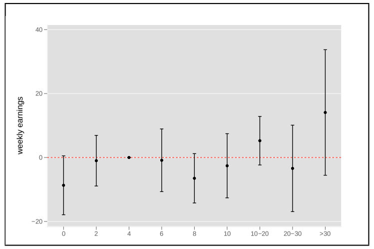
(l) Agriculture



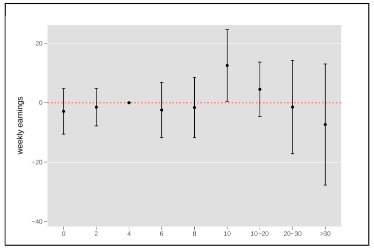
(m) Extractive Industry



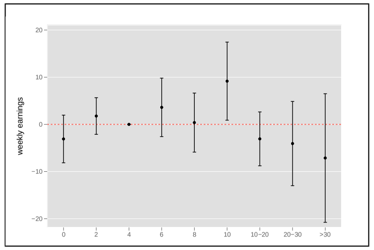
(n) Manufacturing



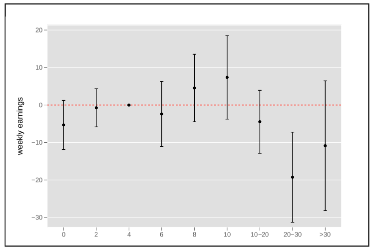
(o) Construction



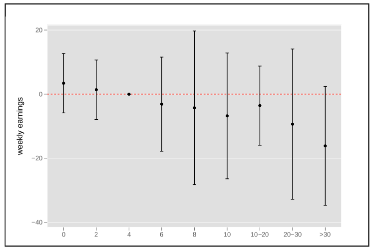
(p) Trade



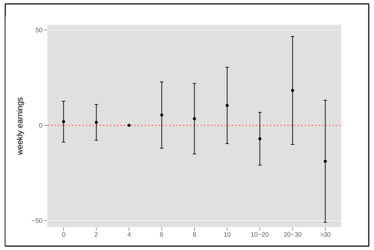
(q) Restaurants Services



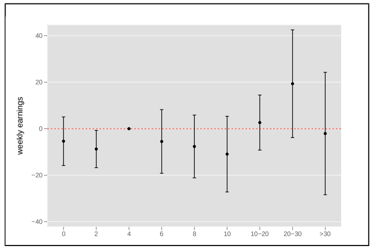
(r) Transport



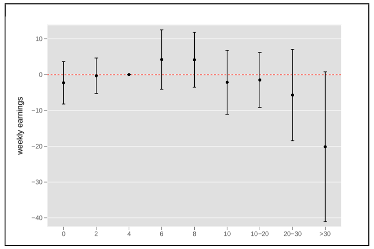
(s) Professional Services



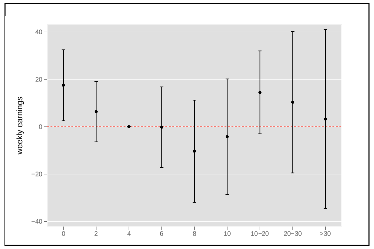
(t) Diverse Services



(u) Social Services



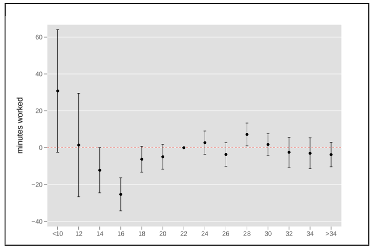
(v) Government



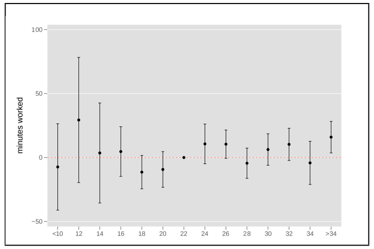
Statistics: Adjusted R^2=0.116, F Stat=2273.5, # clusters=1,676, N=7,390,147, Ind.=2,632,000.
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Figure A.7.5: HI Industry Marginal Effects on Working Time - Heat Index

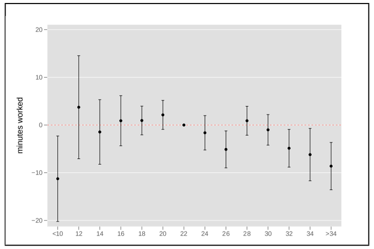
(a) Agriculture



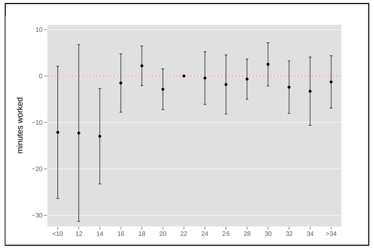
(b) Extractive Industry



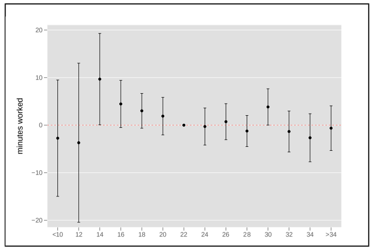
(c) Manufacturing



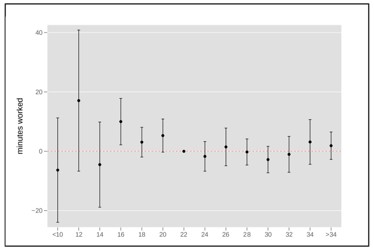
(d) Construction



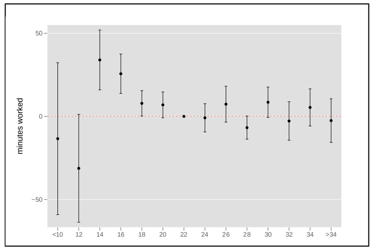
(e) Trade



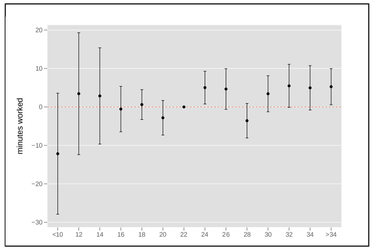
(f) Restaurant Services



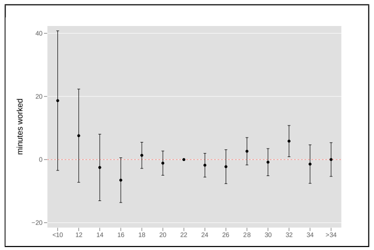
(g) Transport



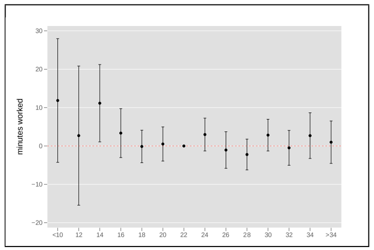
(h) Professional Services



(i) Diverse Services



(j) Social Services



(k) Government

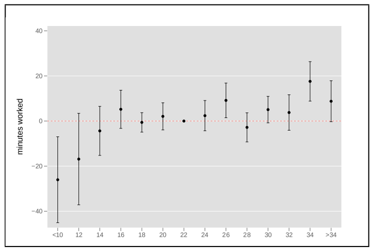
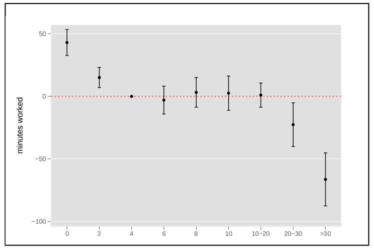
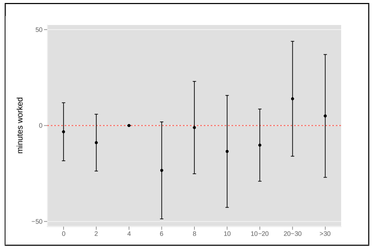


Figure A.7.5: HI Industry Marginal Effects on Working Time - Precipitation *(continued)*

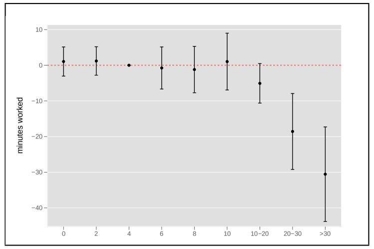
(l) Agriculture



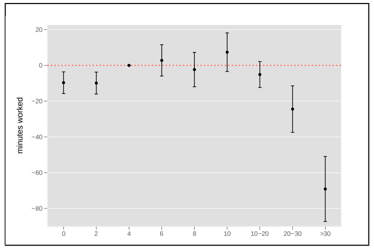
(m) Extractive Industry



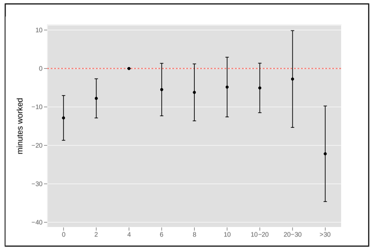
(n) Manufacturing



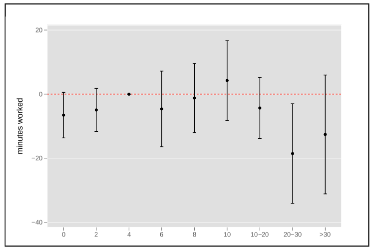
(o) Construction



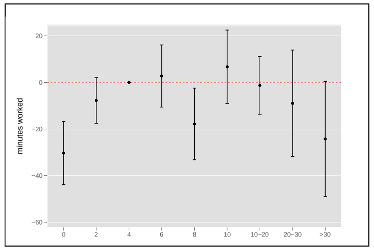
(p) Trade



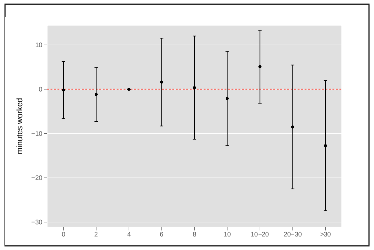
(q) Restaurant Services



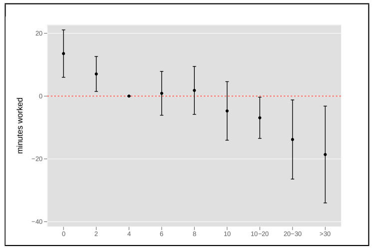
(r) Transport



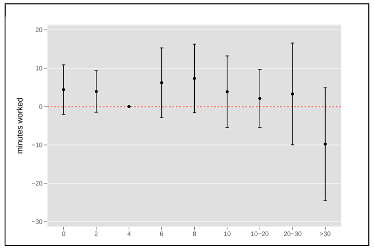
(s) Professional Services



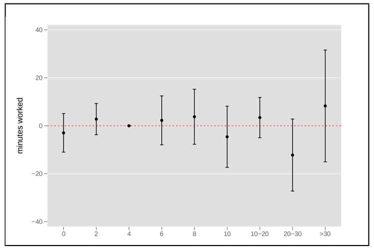
(t) Diverse Services



(u) Social Services



(v) Government

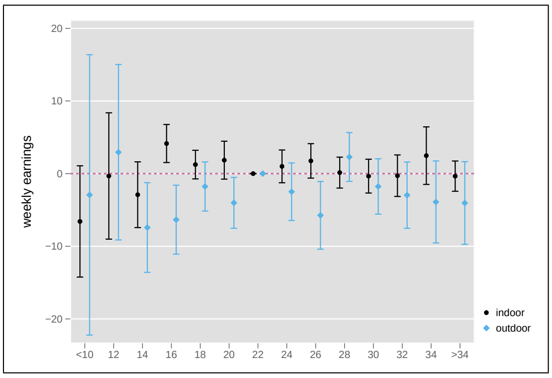


Statistics: Adjusted R^2=0.147, F Stat=980.1, # clusters=1,676, N=7,390,147, Ind.=2,632,000.
Notes: The figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

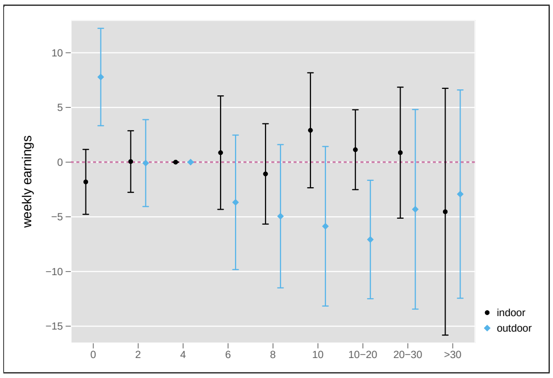
Figure A.7.6: HI Work Location Marginal Effects on Earnings

outdoor vs indoor

(a) Heat Index

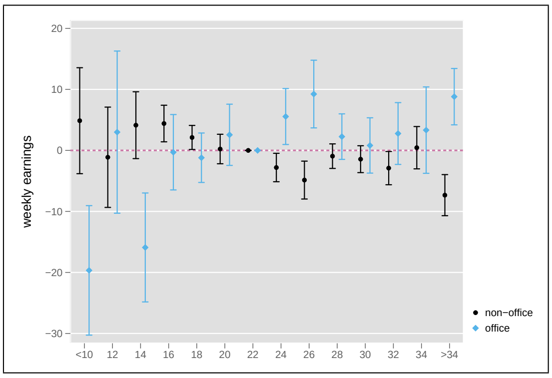


(b) precipitation

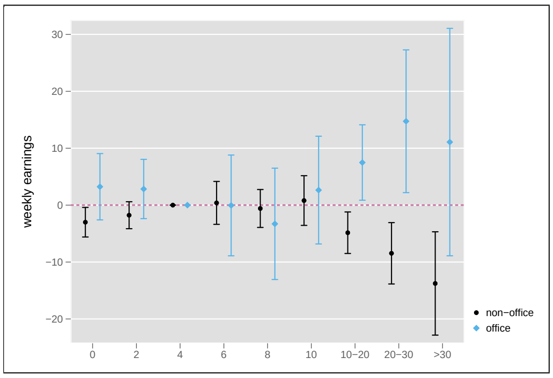


office vs non-office

(c) Heat Index

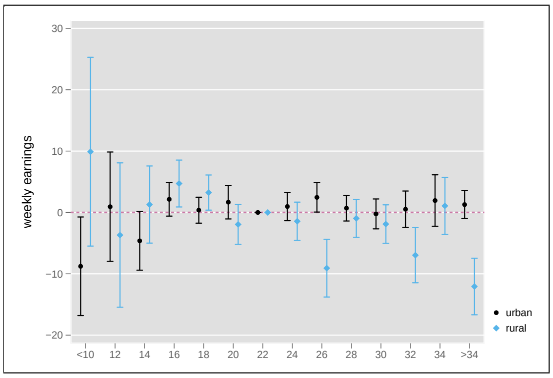


(d) precipitation



urban vs rural

(e) Heat Index



(f) precipitation

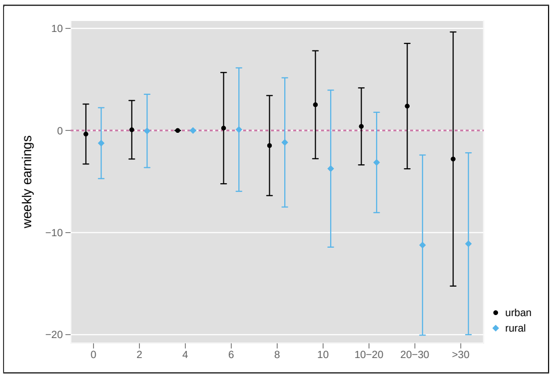
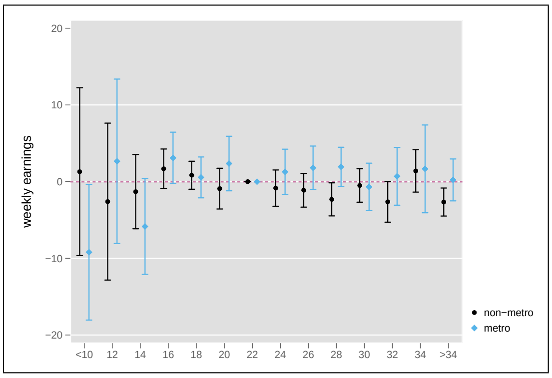


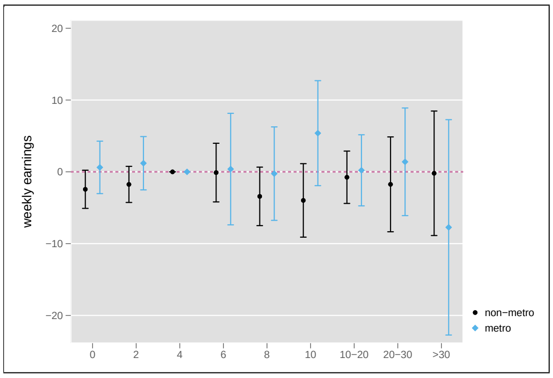
Figure A.7.6: HI Work Location Marginal Effects on Earnings *(continued)*

metro vs non-metro area

(g) Heat Index

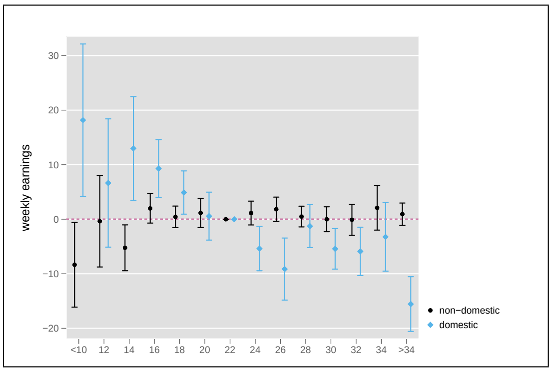


(h) precipitation

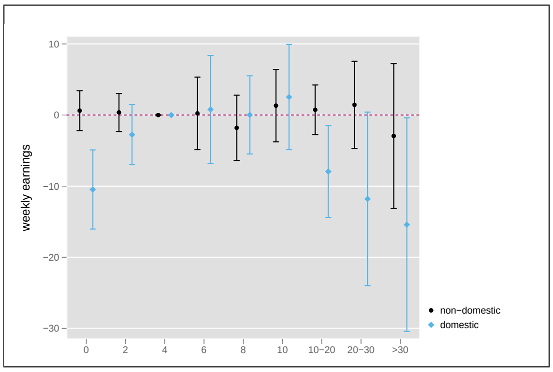


domestic vs non-domestic

(i) Heat Index



(j) precipitation



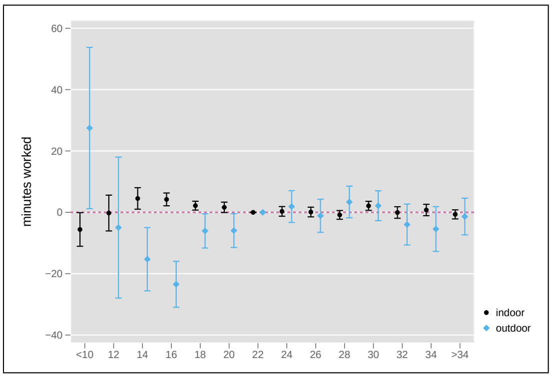
Statistics: N=7,390,140, Ind.=2,631,998.

Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

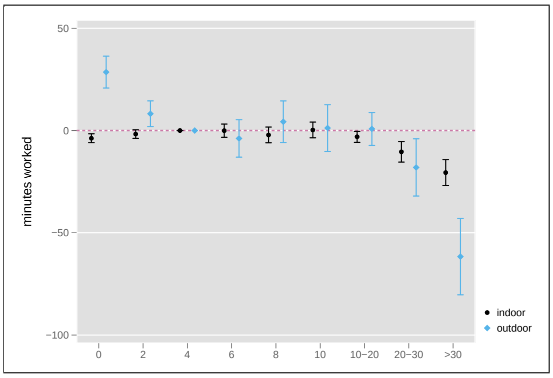
Figure A.7.7: HI Work Location Marginal Effects on Working Time

outdoor vs indoor

(a) Heat Index

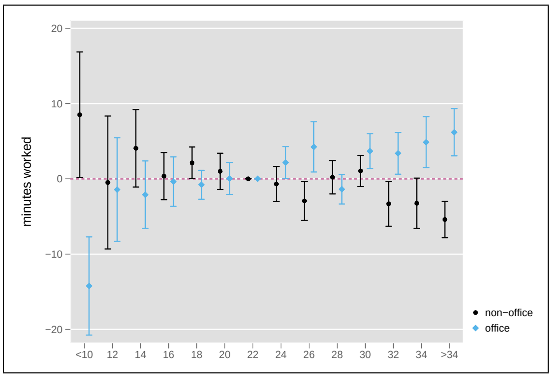


(b) precipitation

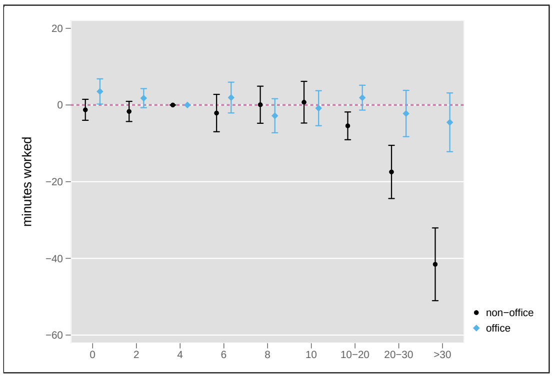


office vs non-office

(c) Heat Index

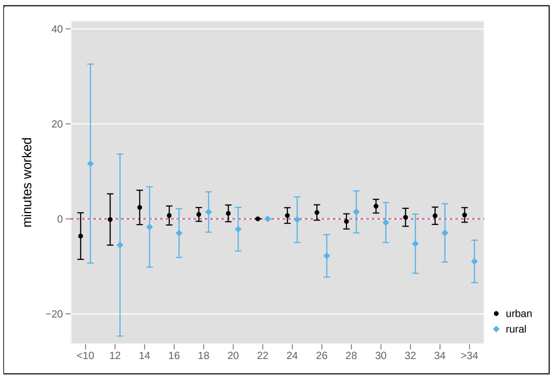


(d) precipitation



urban vs rural

(e) Heat Index



(f) precipitation

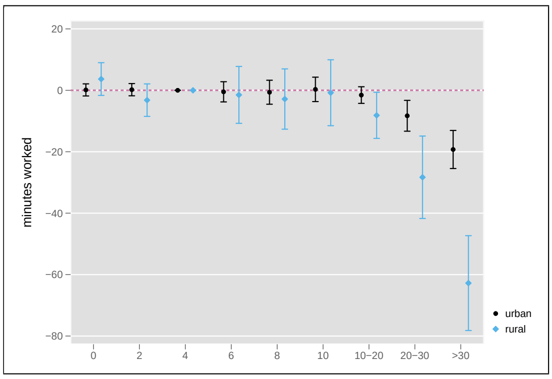
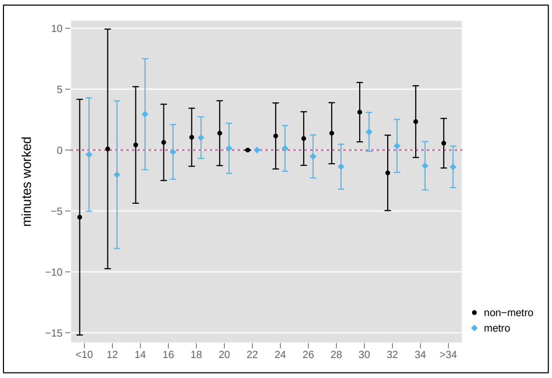


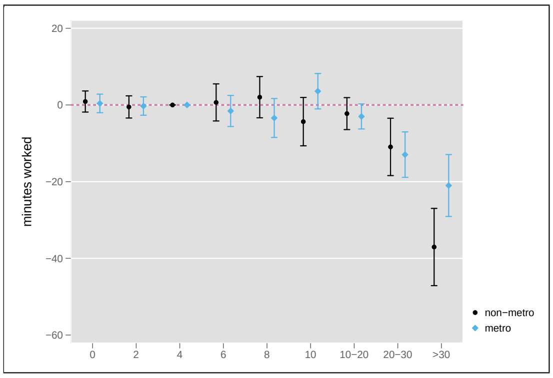
Figure A.7.7: HI Work Location Marginal Effects on Working Time *(continued)*

metro vs non-metro area

(g) Heat Index

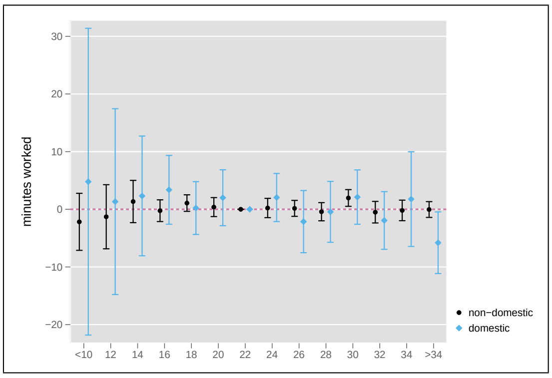


(h) precipitation

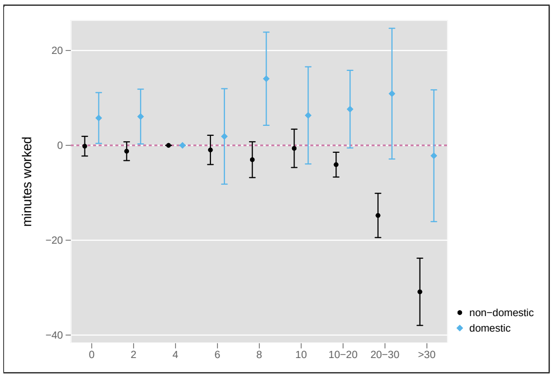


domestic vs non-domestic

(i) Heat Index



(j) precipitation



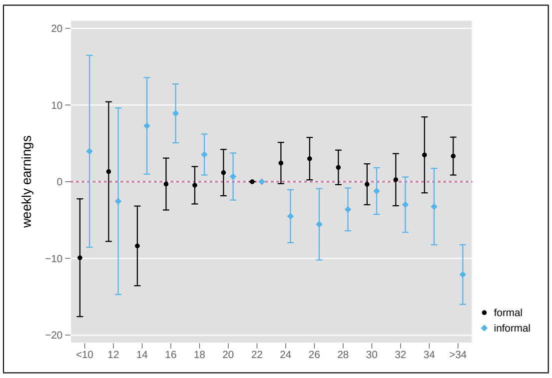
Statistics: N=7,390,140, Ind.=2,631,998.

Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

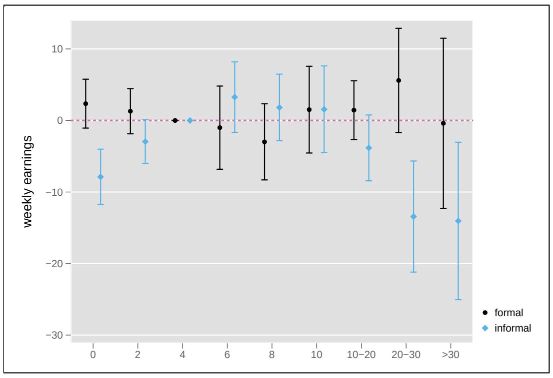
Figure A.7.8: HI Job Characteristics Marginal Effects on Earnings

formal vs informal

(a) Heat Index

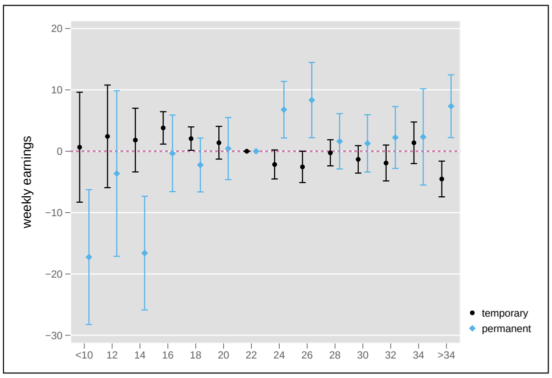


(b) precipitation

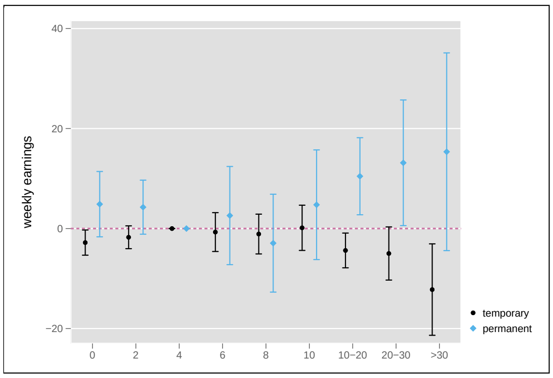


permanent vs temporary

(c) Heat Index

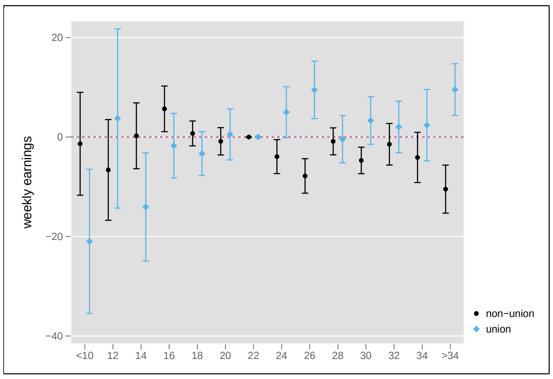


(d) precipitation



union vs non-union

(e) Heat Index



(f) precipitation

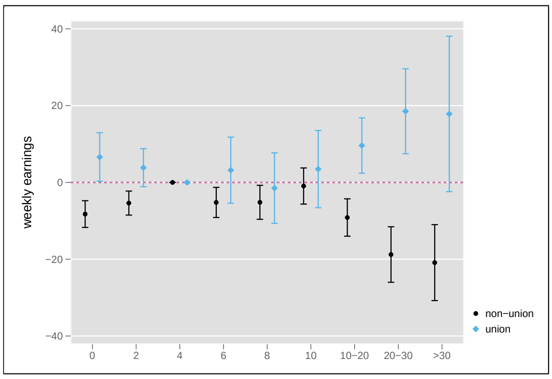
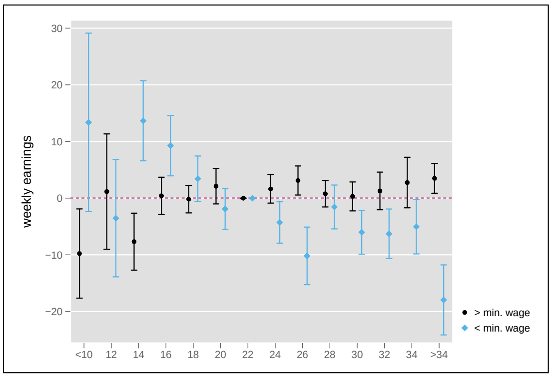


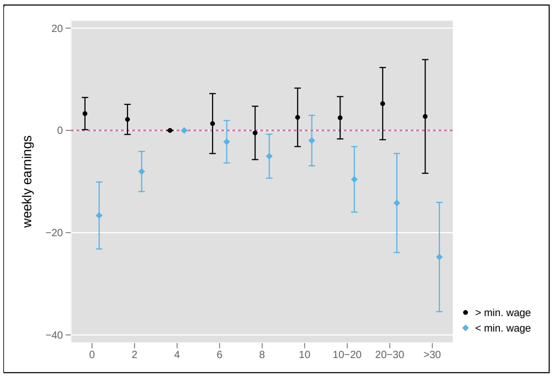
Figure A.7.8: HI Job Characteristics Marginal Effects on Earnings *(continued)*

above vs below official minimum wage

(g) Heat Index

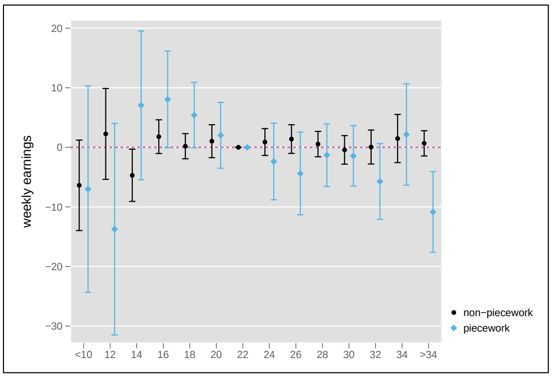


(h) precipitation

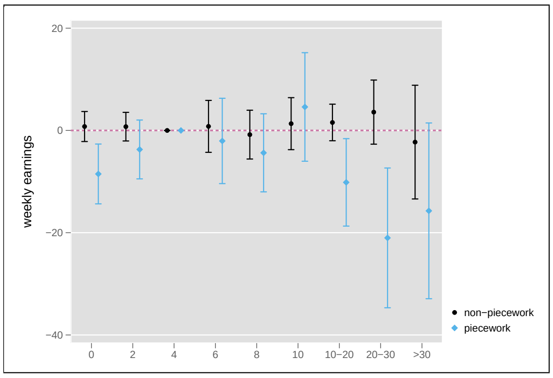


piecework vs non-piecework

(i) Heat Index

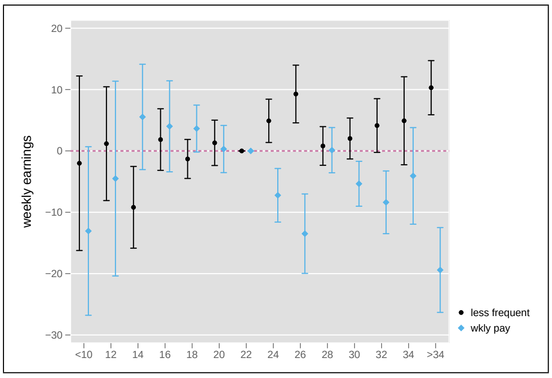


(j) precipitation

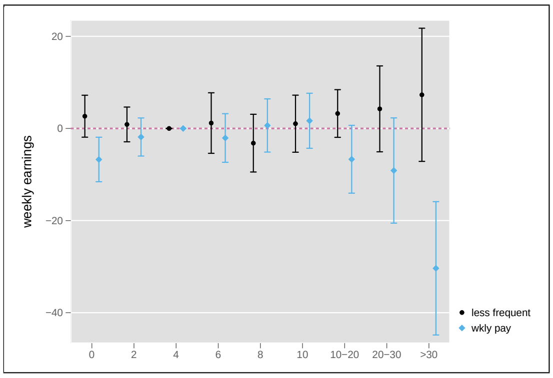


weekly vs less frequent pay

(k) Heat Index



(l) precipitation

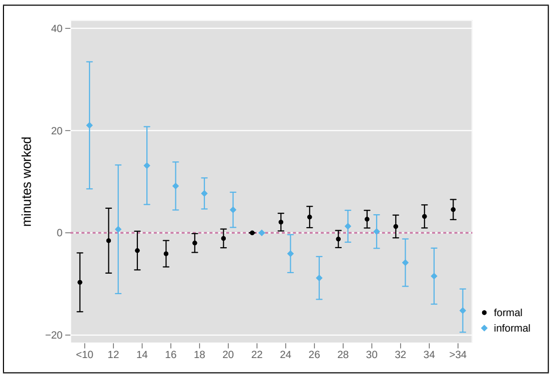


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

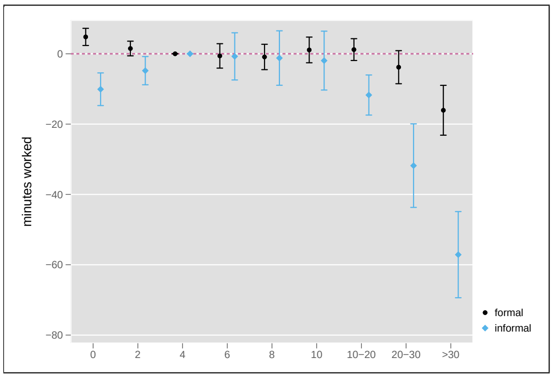
Figure A.7.9: HI Job Characteristics Marginal Effects on Working Time

formal vs informal

(a) Heat Index

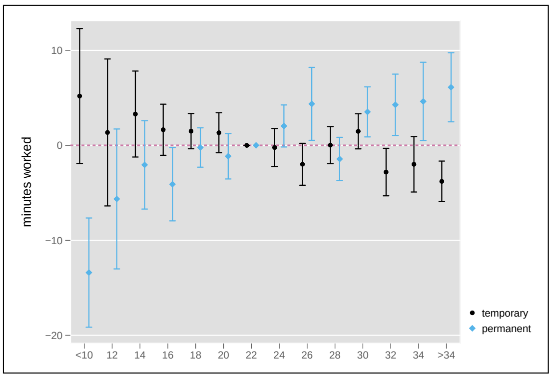


(b) precipitation

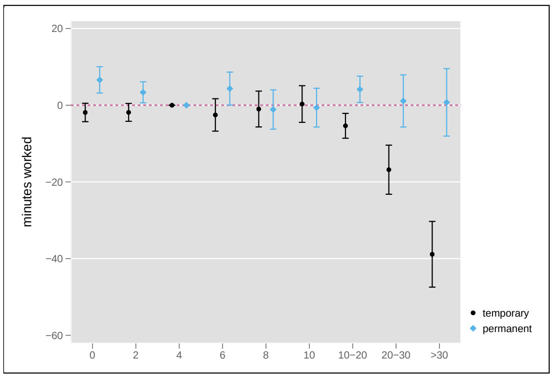


permanent vs temporary

(c) Heat Index

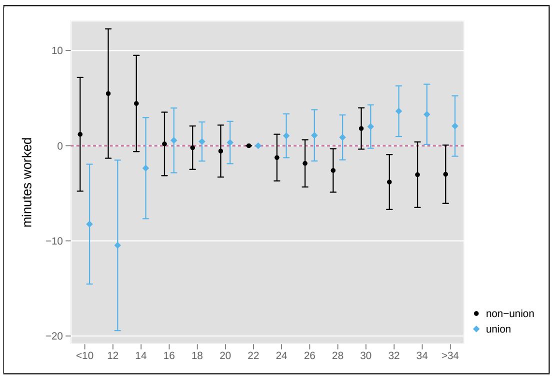


(d) precipitation



union vs non-union

(e) Heat Index



(f) precipitation

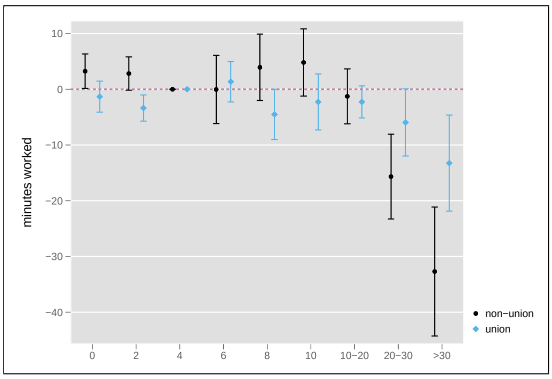
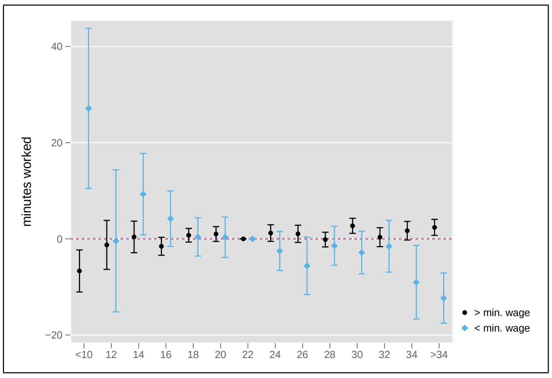


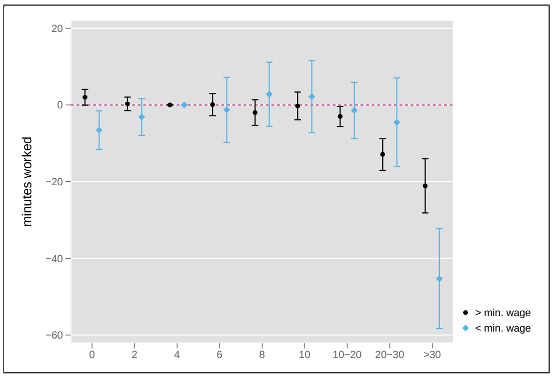
Figure A.7.9: HI Job Characteristics Marginal Effects on Working Time *(continued)*

above vs below official minimum wage

(g) Heat Index

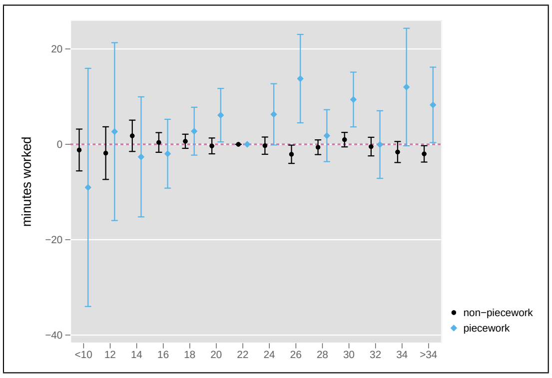


(h) precipitation

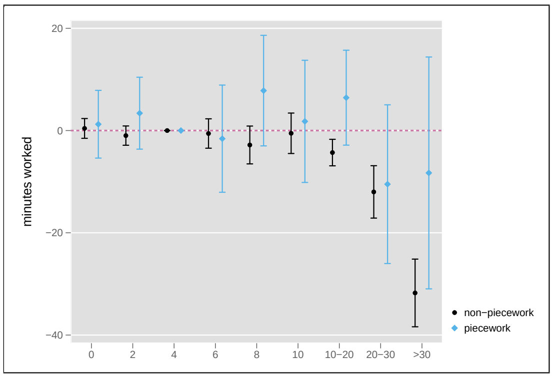


piecework vs non-piecework

(i) Heat Index

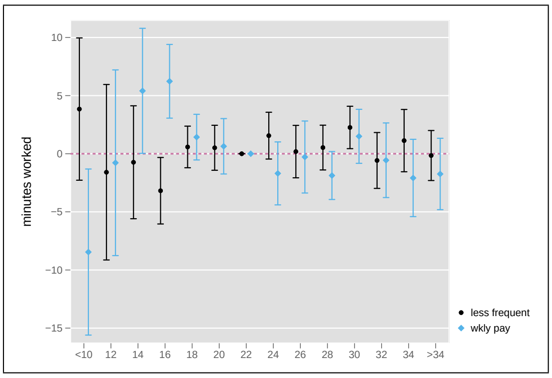


(j) precipitation

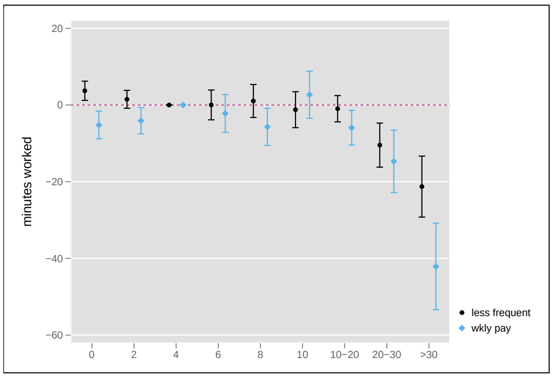


weekly vs less frequent pay

(k) Heat Index



(l) precipitation

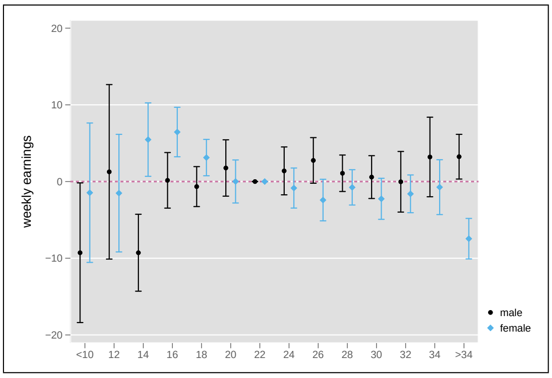


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

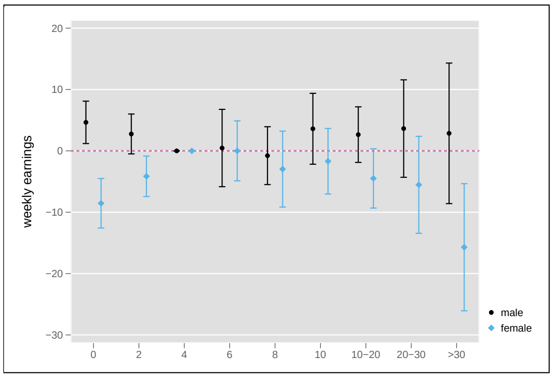
Figure A.7.10: HI Individual Characteristics Marginal Effects on Earnings

male vs female

(a) Heat Index

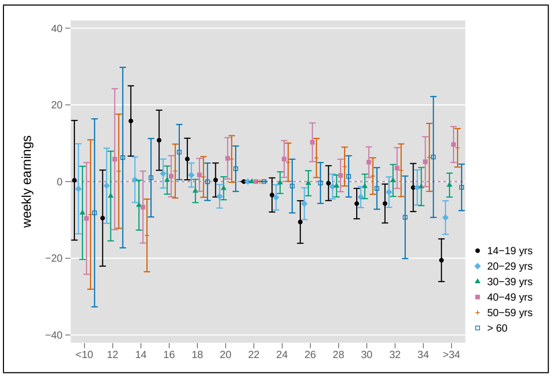


(b) precipitation

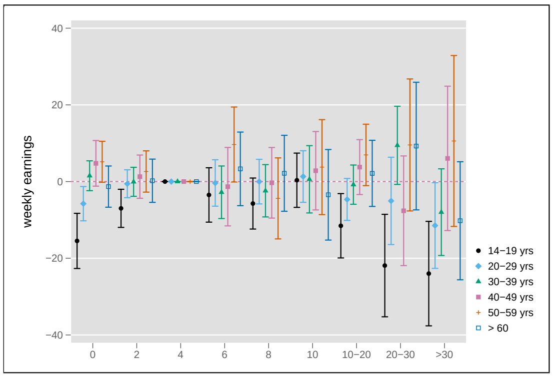


by age group

(c) Heat Index

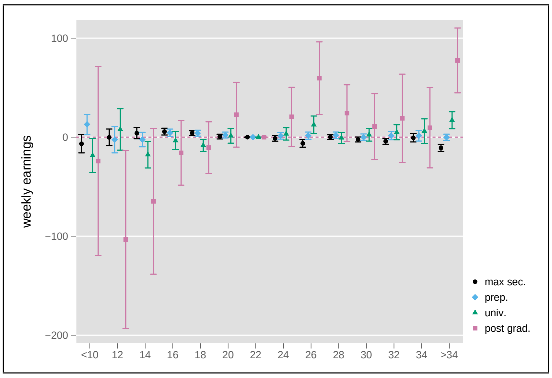


(d) precipitation

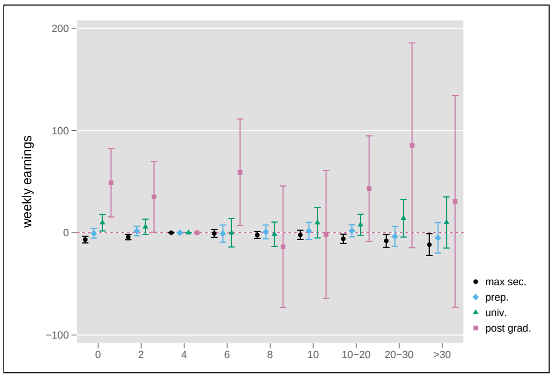


by education

(e) Heat Index



(f) precipitation

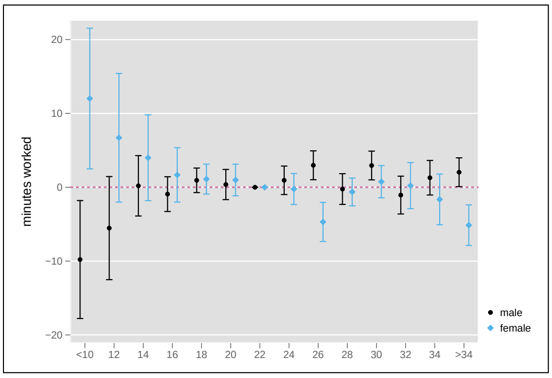


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] $^\circ$ C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

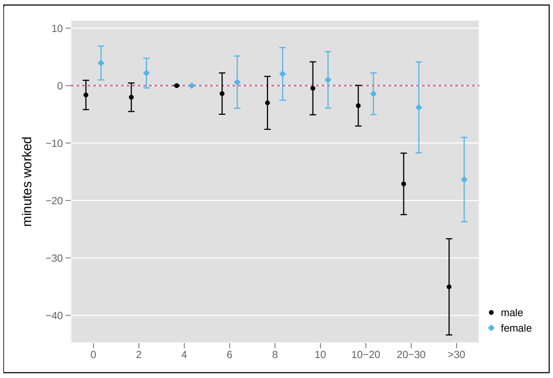
Figure A.7.11: HI Individual Characteristics Marginal Effects on Working Time

male vs female

(a) Heat Index

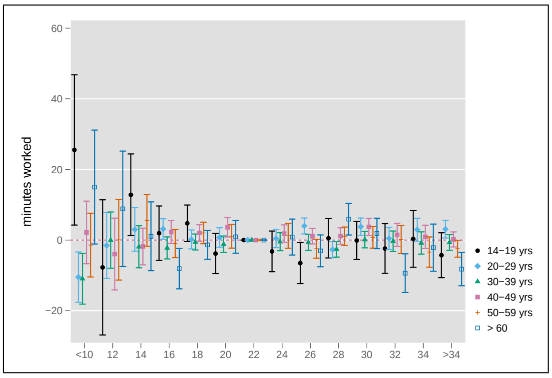


(b) precipitation

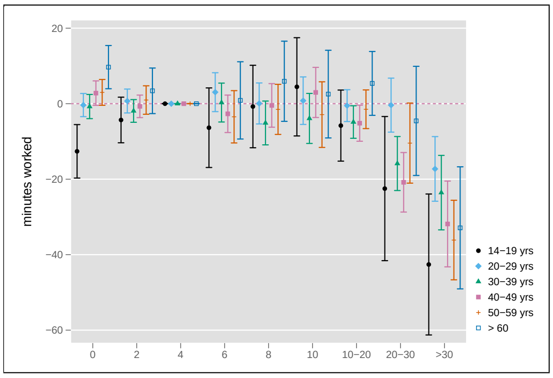


by age group

(c) Heat Index

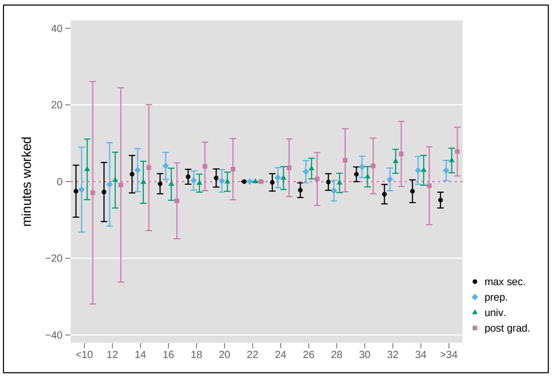


(d) precipitation

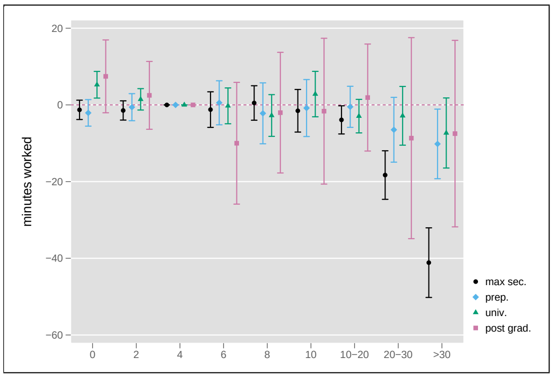


by education

(e) Heat Index



(f) precipitation



Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

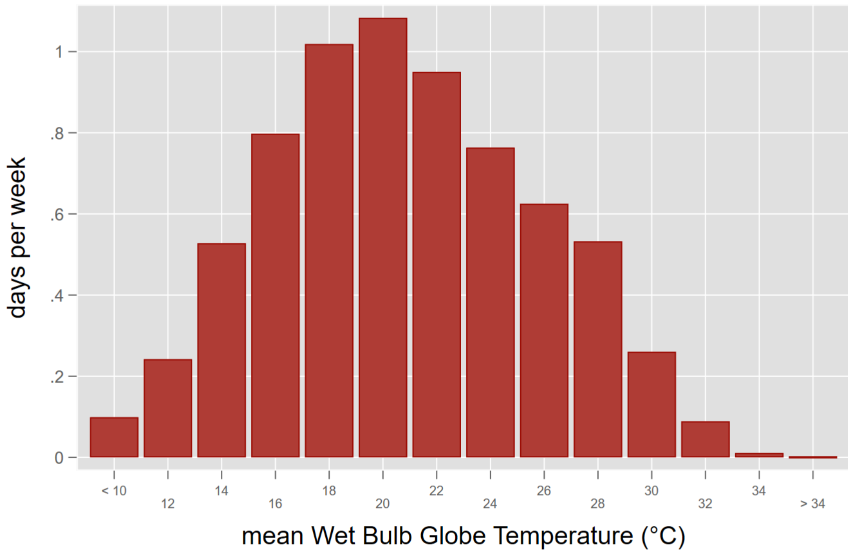
A.7.2 Wet Bulb Globe Temperature

This Appendix presents results using the WBGT as an alternative measure of temperature. The WBGT measure traditionally is constructed using the information on temperature, humidity, wind speed, sun angle and cloud cover (solar radiation) and is recommended by the International Standard Organisation as occupational heat-stress index (Standardization 2017). In contrast to the heat index, WBGT attempts to measure heat stress in the sunlight while the heat index is calculated for shady areas. The WBGT has been applied frequently as an apparent temperature measure in the context of labour markets (Kjellstrom et al. 2009; Lemke and Kjellstrom 2012; Sudarshan et al. 2015). Lemke and Kjellstrom (2012) show that the WBGT can be approximated using the following formula:

$$WBGT = 0.567T_a + 0.216\rho + 3.38,$$
$$\rho = (RH/100) \times 6.105 \exp(\frac{17.27T_a}{237.3 + T_a}) \tag{A.14}$$

where T_a represents air temperature in $^\circ$ C and ρ vapour pressure calculated from relative humidity (RH).

Figure A.7.12: Distribution of Wet Bulb Globe Temperature bins per week

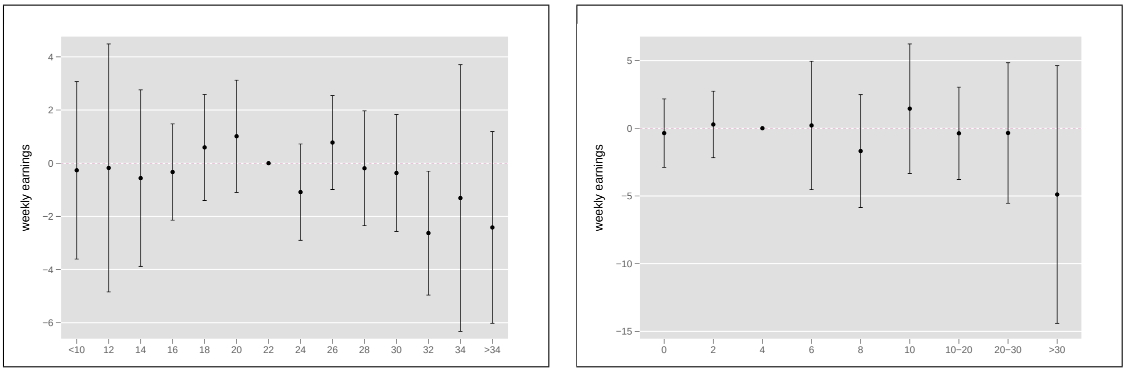


Notes: Period of observation 2005-2016. The bar height captures the incidence of days with weather falling into the respective bin across municipality per week.

Results

Figure A.7.13: WBGT Weather Bins Coefficient Plots - Earnings Regression

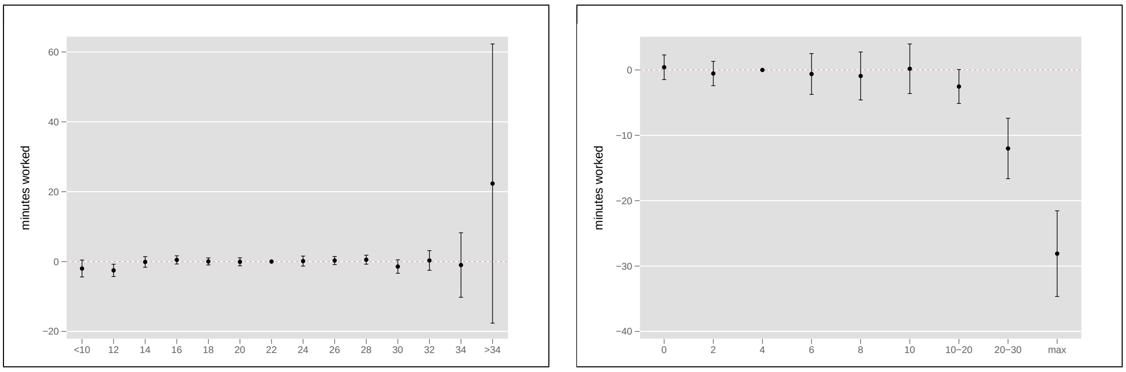
(a) WBGT **(b)** precipitation



Notes: Figure depicts marginal effects of weather bins on weekly earnings. N=7,390,147, Ind.=2,632,000. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Figure A.7.14: WBGT Weather Bins Coefficient Plots - Working Time Regression

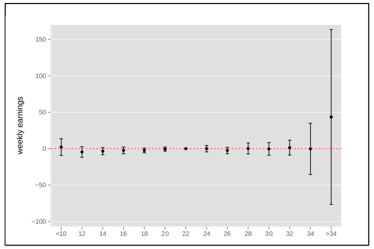
(a) WBGT **(b)** precipitation



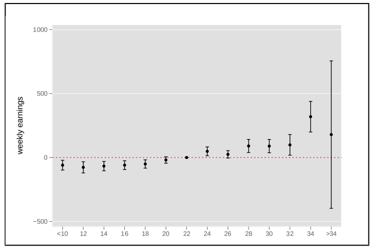
Notes: The figure depicts marginal effects of weather bins on weekly minutes worked. N=7,390,147, Ind.=2,632,000. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Figure A.7.15: WBGT Industry Marginal Effects on Earnings - WBGT

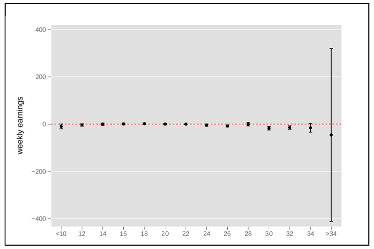
(a) Agriculture



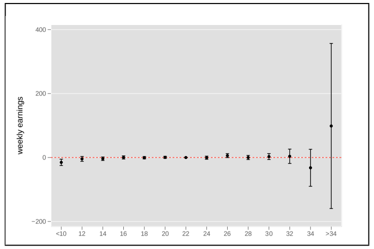
(b) Extractive Industry



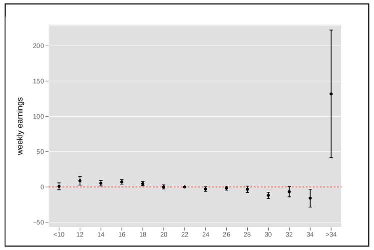
(c) Manufacturing



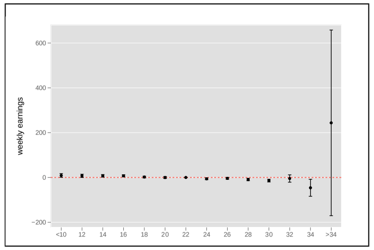
(d) Construction



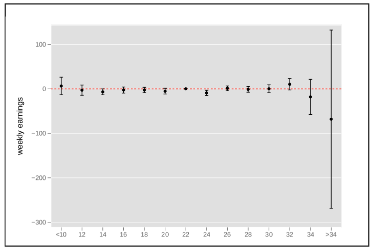
(e) Trade



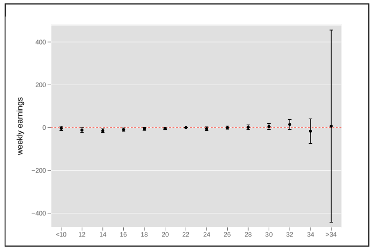
(f) Restaurant Services



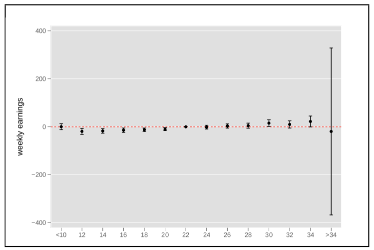
(g) Transport



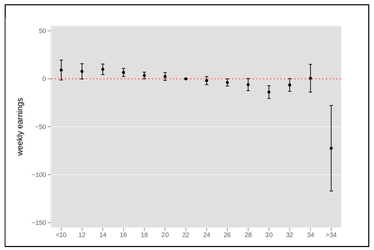
(h) Professional Services



(i) Diverse Services



(j) Social Services



(k) Government

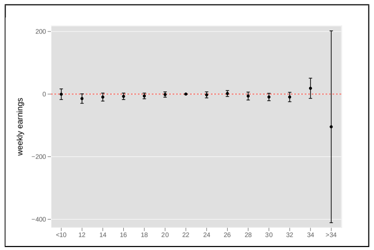
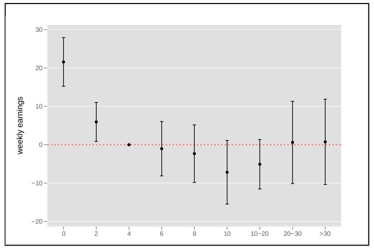
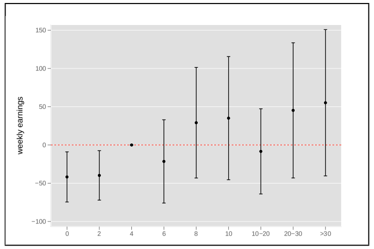


Figure A.7.15: WBGT Industry Marginal Effects on Earnings - Precipitation *(continued)*

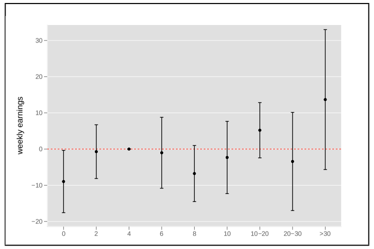
(l) Agriculture



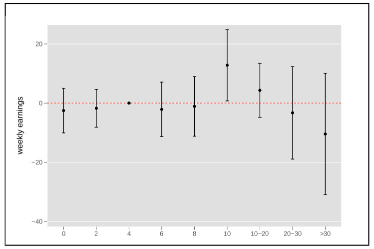
(m) Extractive Industry



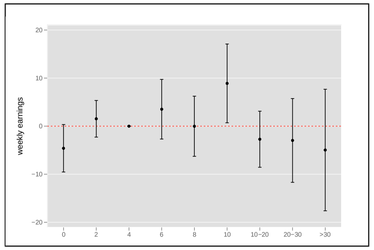
(n) Manufacturing



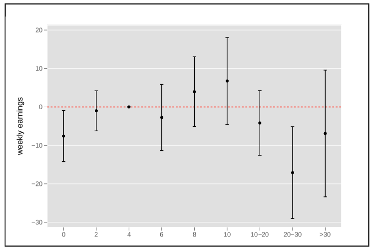
(o) Construction



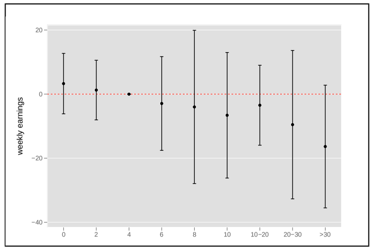
(p) Trade



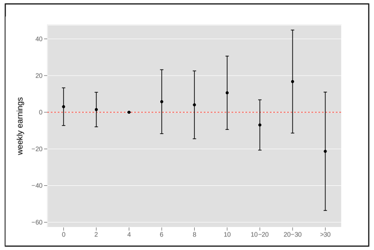
(q) Restaurants Services



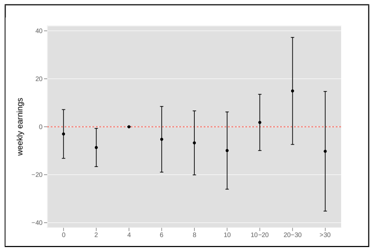
(r) Transport



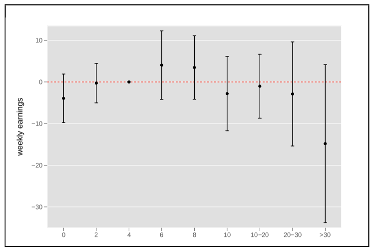
(s) Professional Services



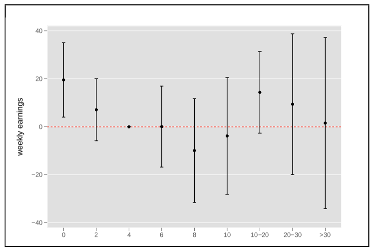
(t) Diverse Services



(u) Social Services



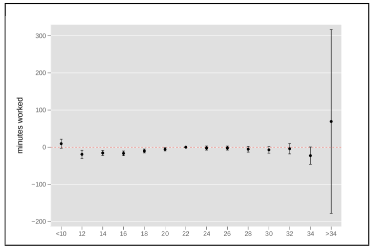
(v) Government



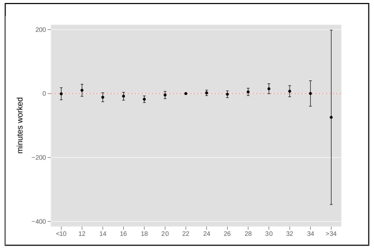
Statistics: Adjusted R^2=0.116, F Stat=2273.5, # clusters=1,676, N=7,390,147, Ind.=2,632,000.
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Figure A.7.16: WBGT Industry Marginal Effects on Working Time - WBGT

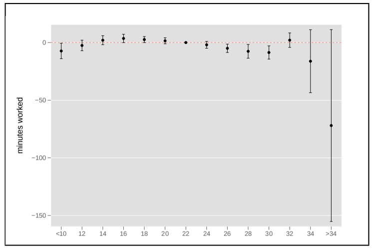
(a) Agriculture



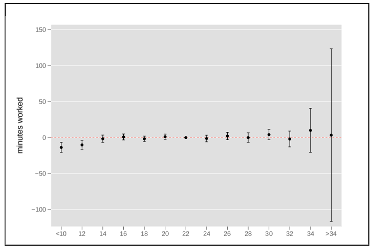
(b) Extractive Industry



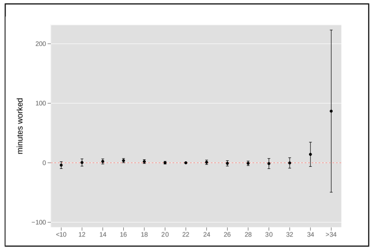
(c) Manufacturing



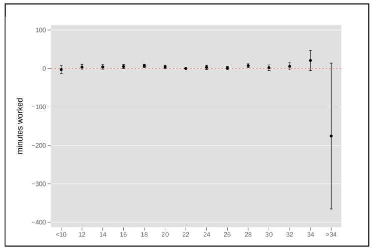
(d) Construction



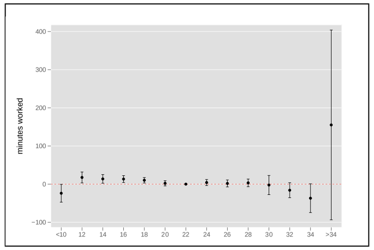
(e) Trade



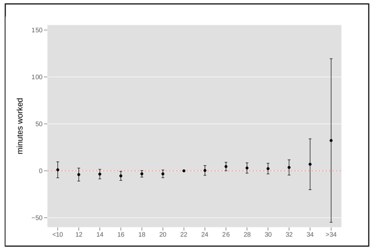
(f) Restaurant Services



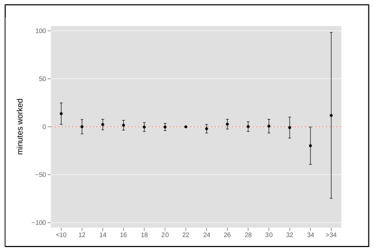
(g) Transport



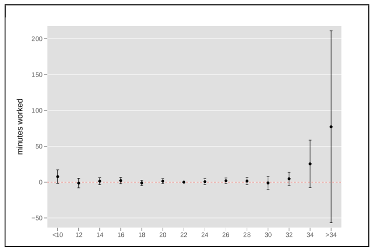
(h) Professional Services



(i) Diverse Services



(j) Social Services



(k) Government

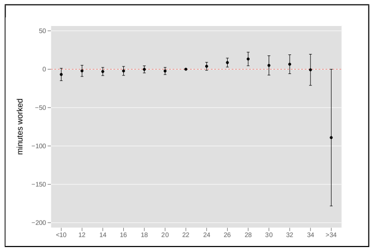
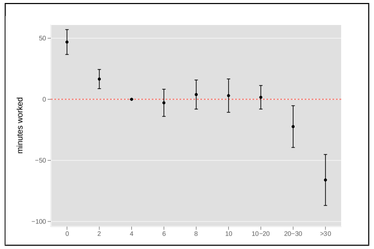
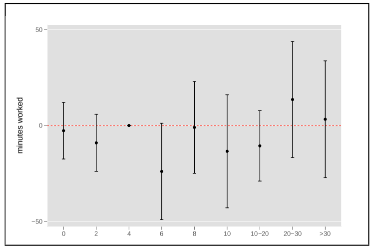


Figure A.7.16: WBGT Industry Marginal Effects on Working Time - Precipitation *(continued)*

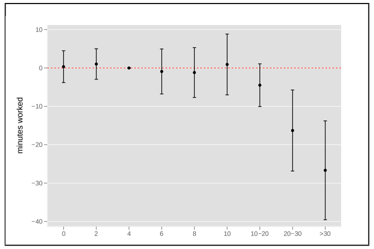
(l) Agriculture



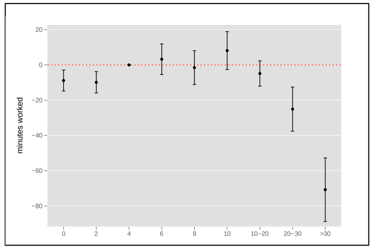
(m) Extractive Industry



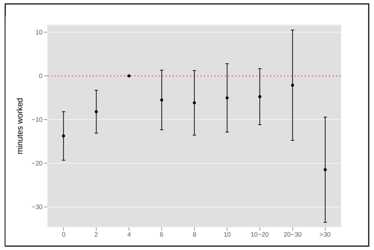
(n) Manufacturing



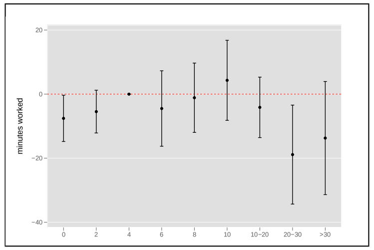
(o) Construction



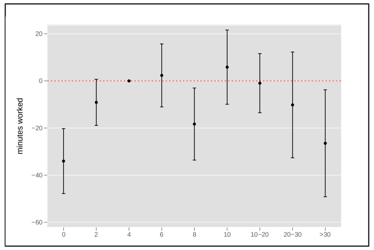
(p) Trade



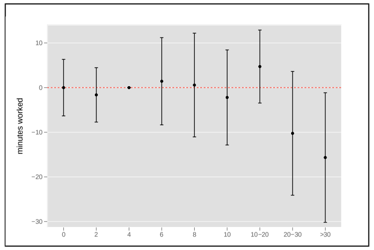
(q) Restaurant Services



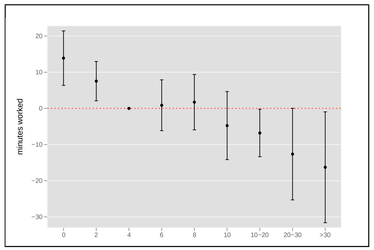
(r) Transport



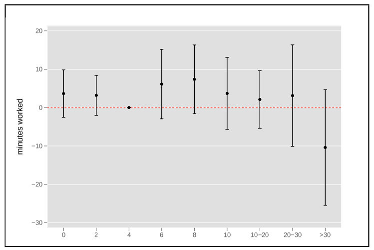
(s) Professional Services



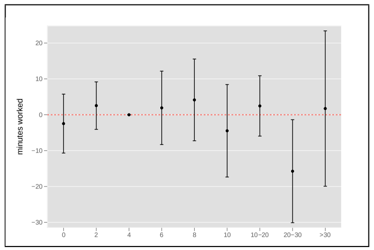
(t) Diverse Services



(u) Social Services



(v) Government

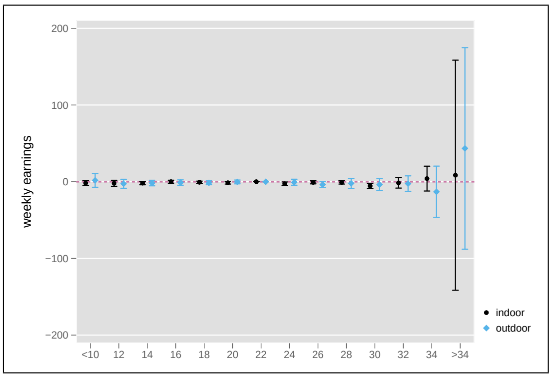


Statistics: Adjusted R^2=0.147, F Stat=980.1, # clusters=1,676, N=7,390,147, Ind.=2,632,000.
Notes: The figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

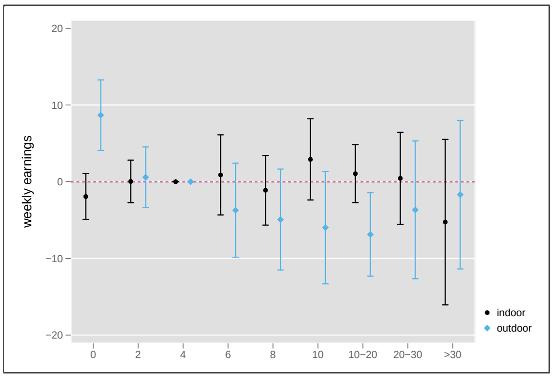
Figure A.7.17: WBGT Work Location Marginal Effects on Earnings

outdoor vs indoor

(a) WBGT

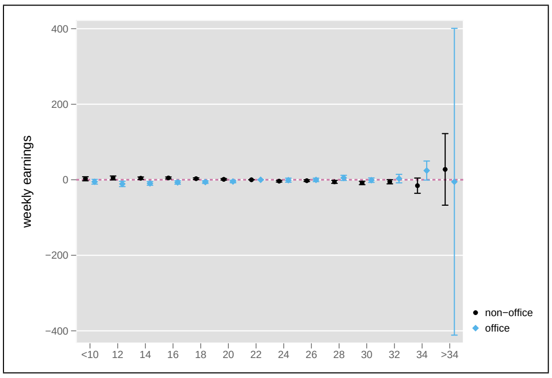


(b) precipitation

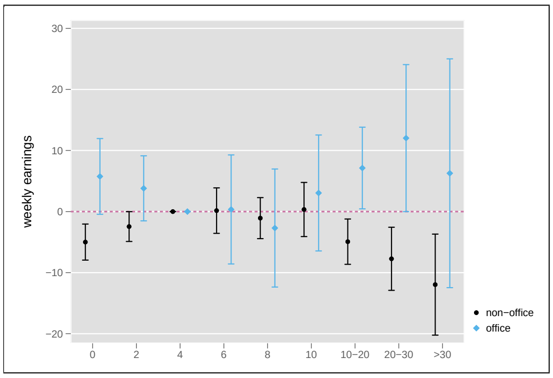


office vs non-office

(c) WBGT

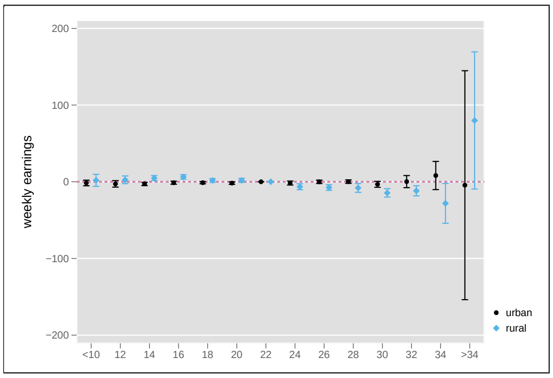


(d) precipitation



urban vs rural

(e) WBGT



(f) precipitation

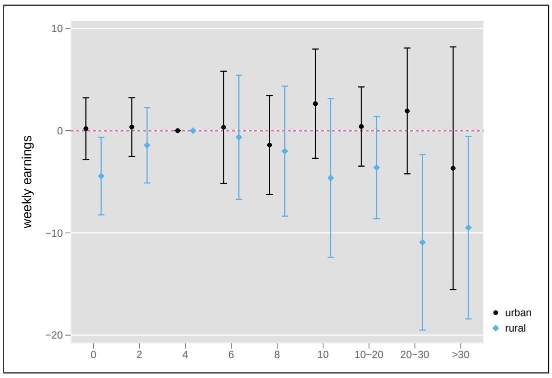
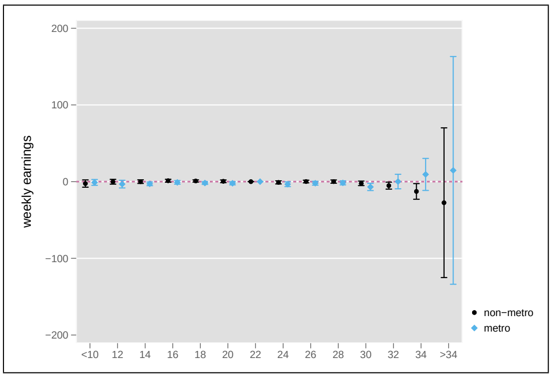


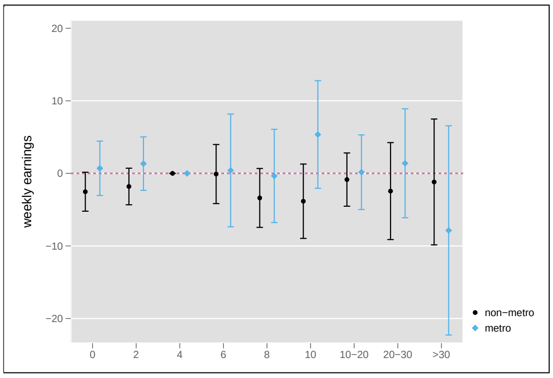
Figure A.7.17: WBGT Work Location Marginal Effects on Earnings *(continued)*

metro vs non-metro area

(g) WBGT

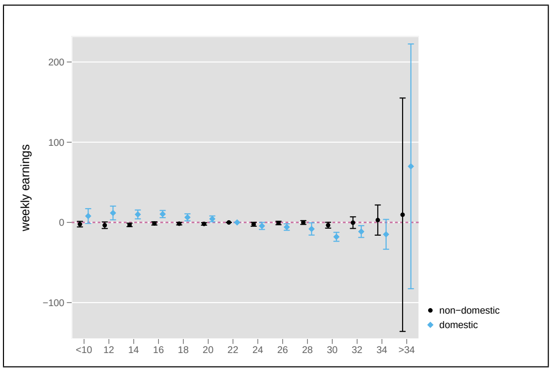


(h) precipitation

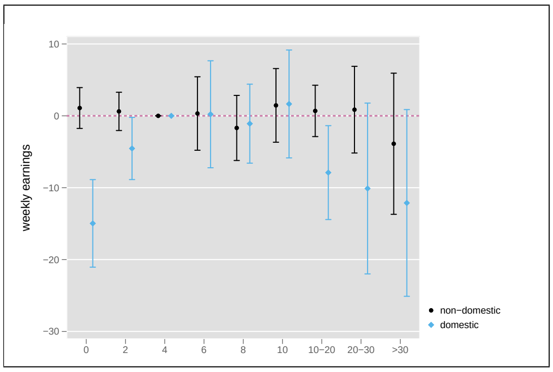


domestic vs non-domestic

(i) WBGT



(j) precipitation



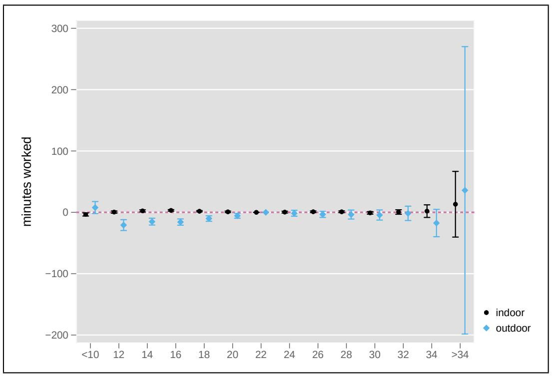
Statistics: N=7,390,140, Ind.=2,631,998.

Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

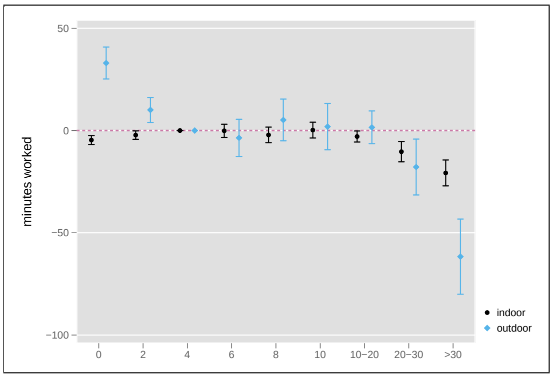
Figure A.7.18: WBGT Work Location Marginal Effects on Working Time

outdoor vs indoor

(a) WBGT

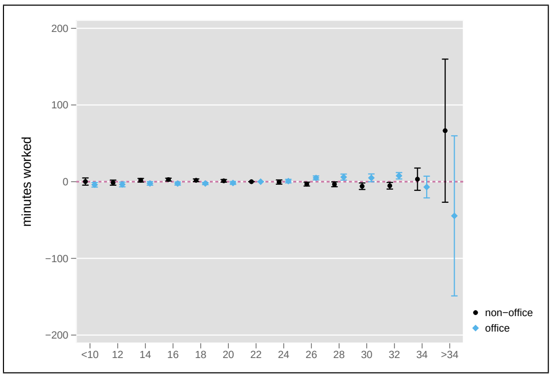


(b) precipitation

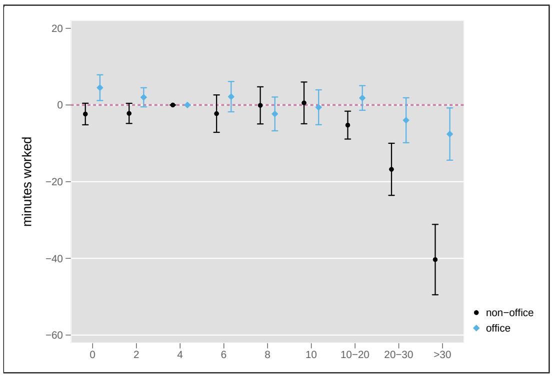


office vs non-office

(c) WBGT

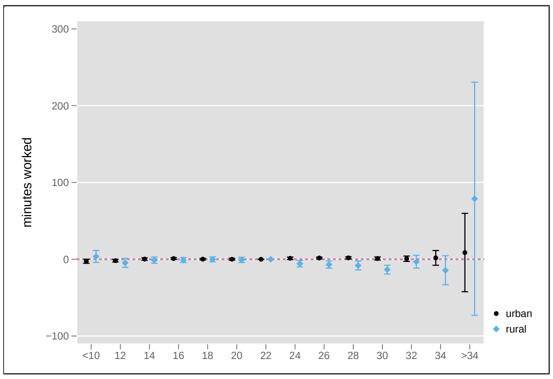


(d) precipitation



urban vs rural

(e) WBGT



(f) precipitation

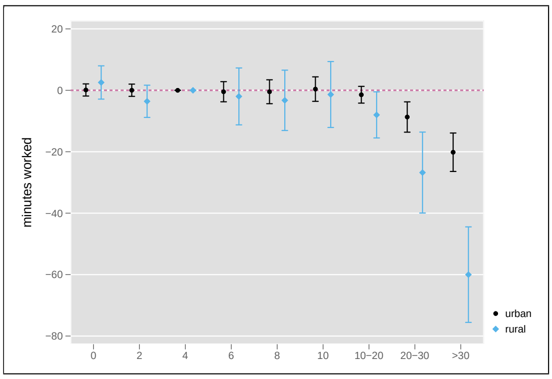
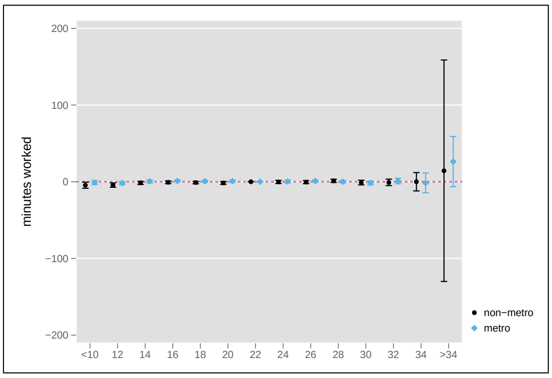


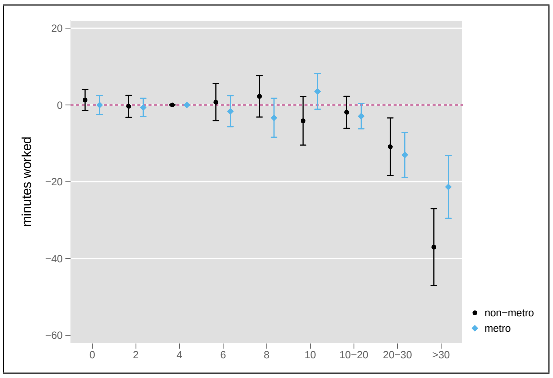
Figure A.7.18: WBGT Work Location Marginal Effects on Working Time *(continued)*

metro vs non-metro area

(g) WBGT

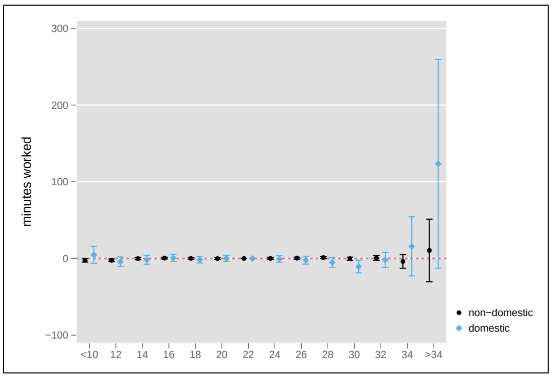


(h) precipitation

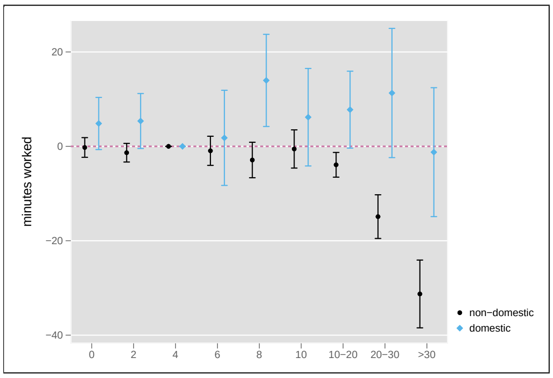


domestic vs non-domestic

(i) WBGT



(j) precipitation

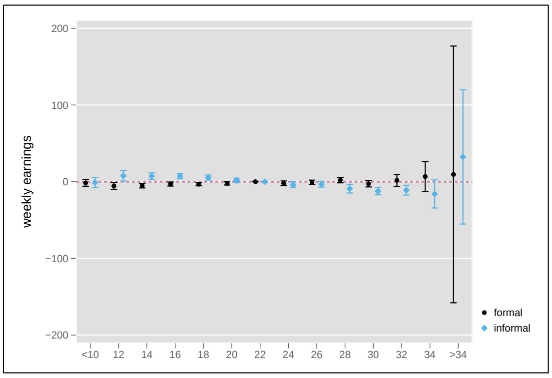


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

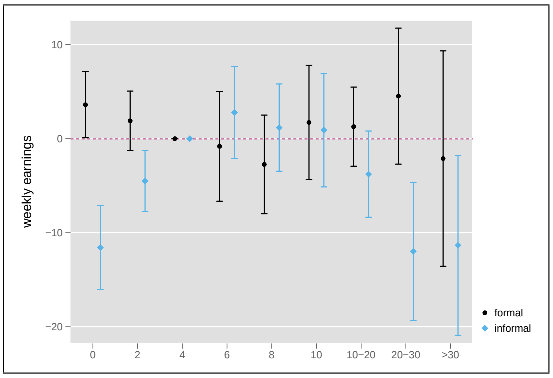
Figure A.7.19: WBGT Job Characteristics Marginal Effects on Earnings

formal vs informal

(a) WBGT

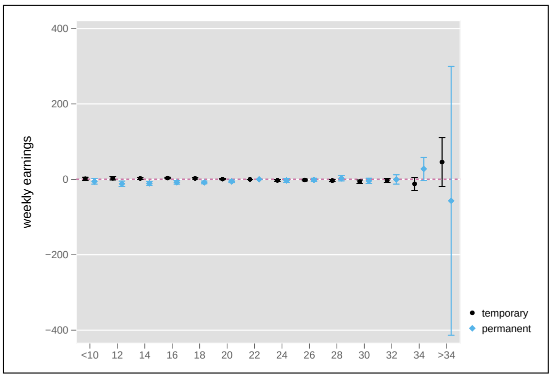


(b) precipitation

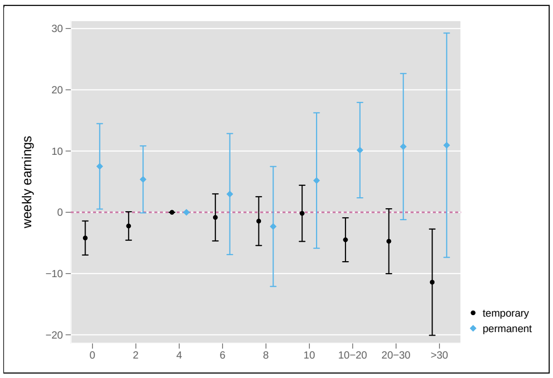


permanent vs temporary

(c) WBGT

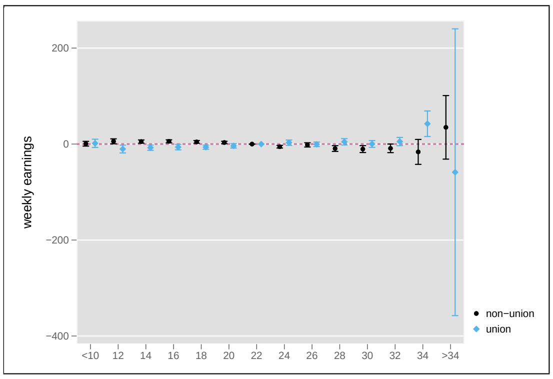


(d) precipitation



union vs non-union

(e) WBGT



(f) precipitation

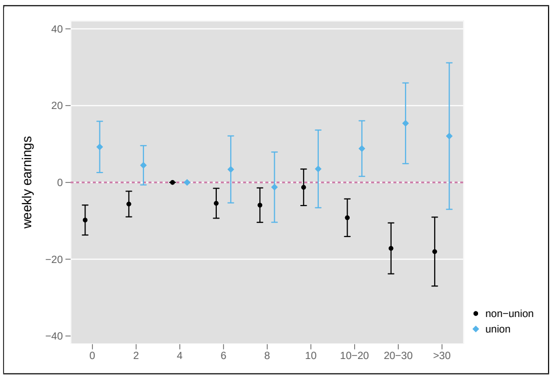
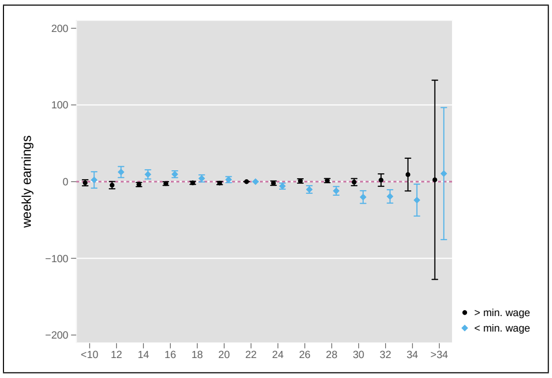


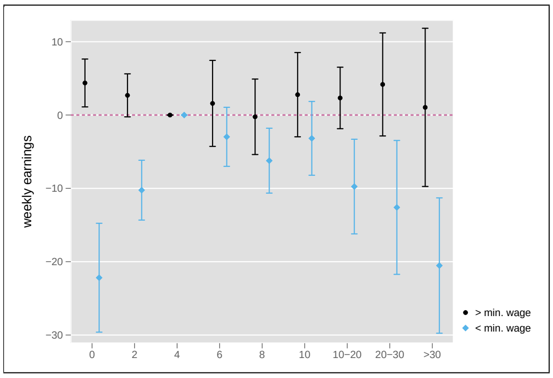
Figure A.7.19: WBGT Job Characteristics Marginal Effects on Earnings *(continued)*

above vs below official minimum wage

(g) WBGT

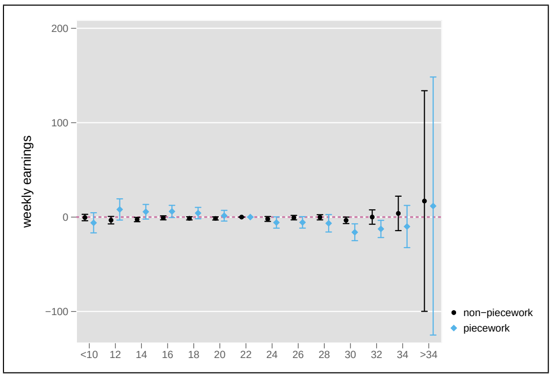


(h) precipitation

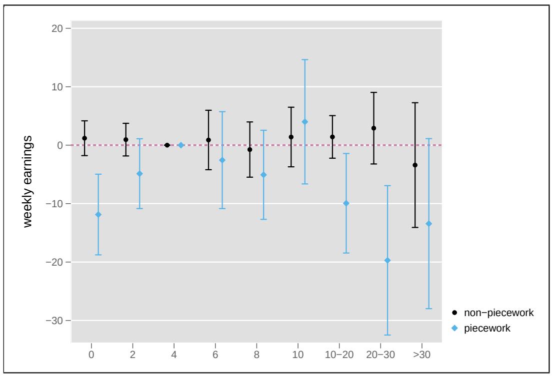


piecework vs non-piecework

(i) WBGT

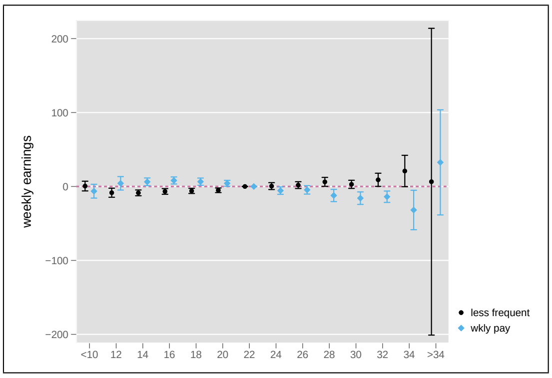


(j) precipitation

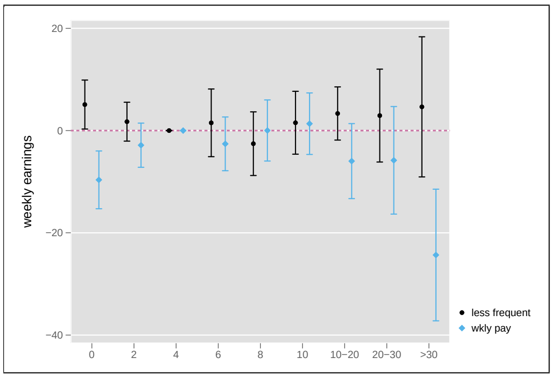


weekly vs less frequent pay

(k) WBGT



(l) precipitation

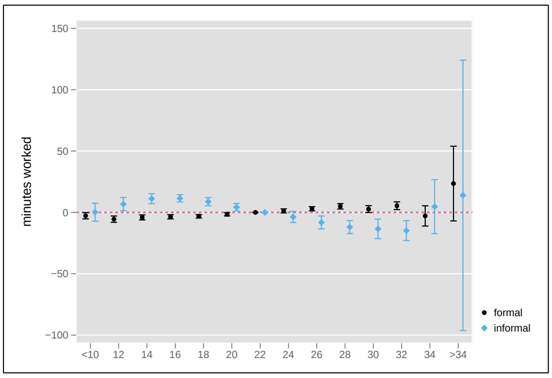


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

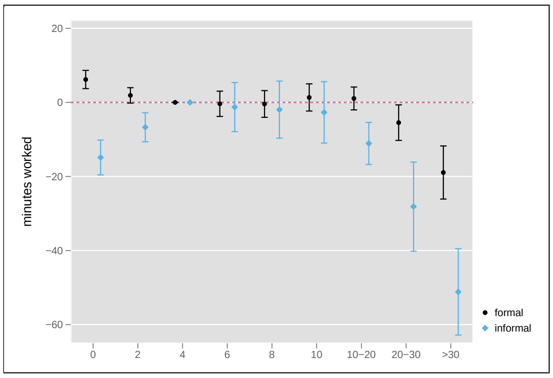
Figure A.7.20: WBGT Job Characteristics Marginal Effects on Working Time

formal vs informal

(a) WBGT

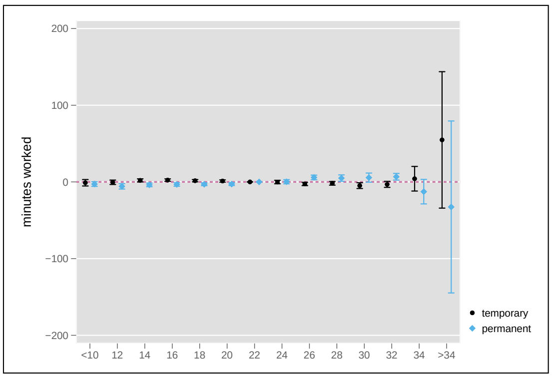


(b) precipitation

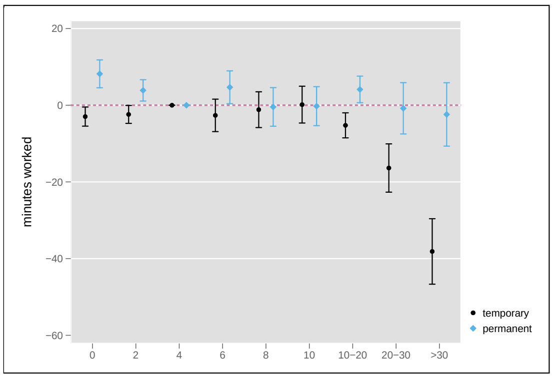


permanent vs temporary

(c) WBGT

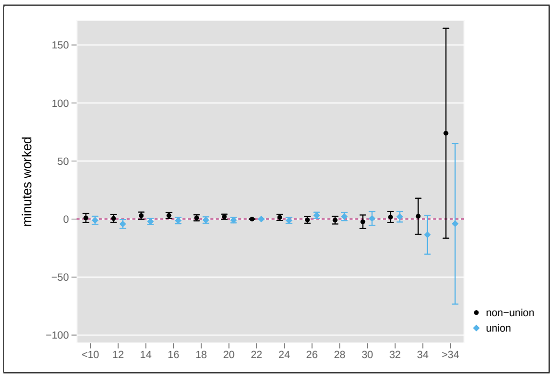


(d) precipitation



union vs non-union

(e) WBGT



(f) precipitation

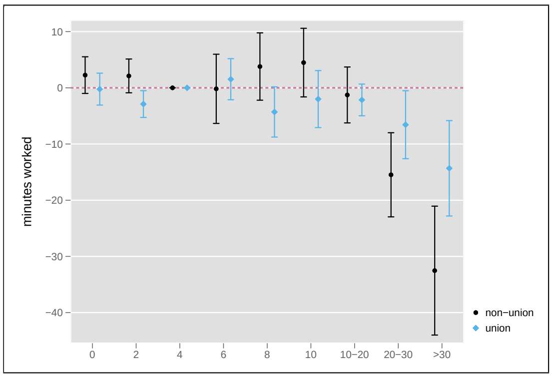
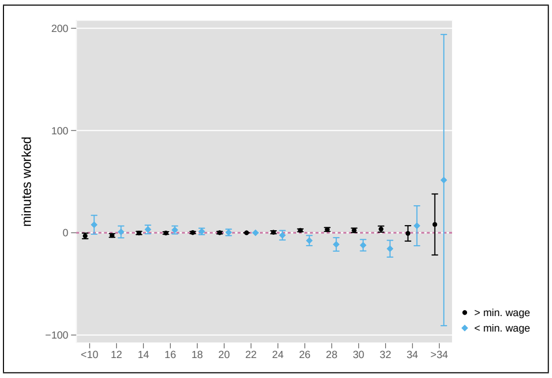


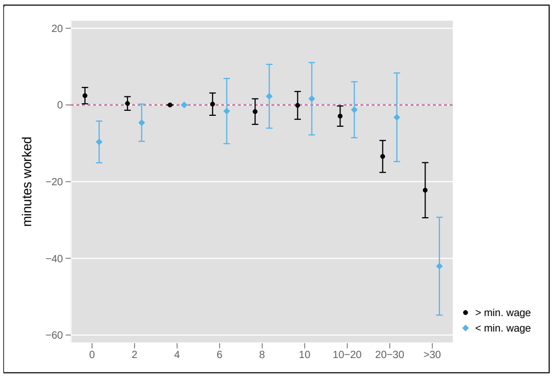
Figure A.7.20: WBGT Job Characteristics Marginal Effects on Working Time *(continued)*

above vs below official minimum wage

(g) WBGT

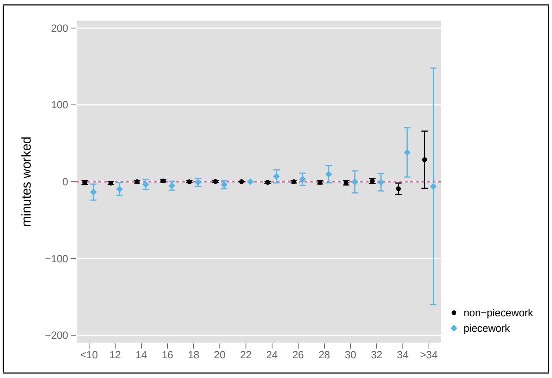


(h) precipitation

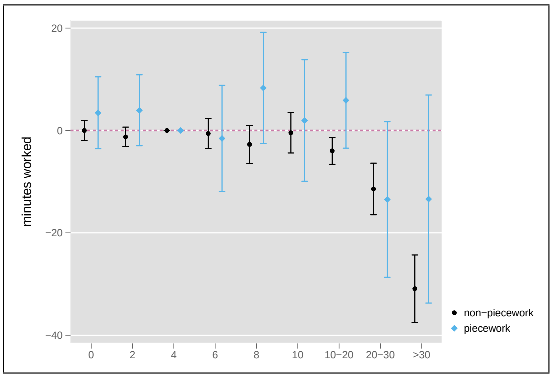


piecework vs non-piecework

(i) WBGT

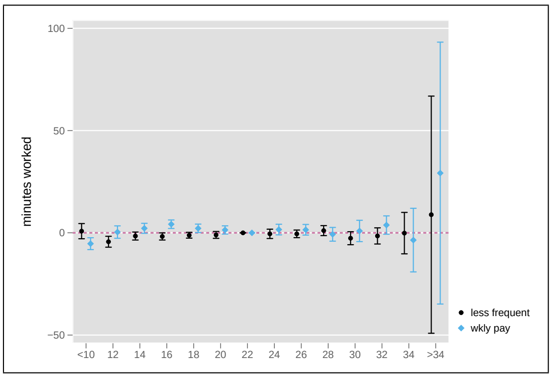


(j) precipitation

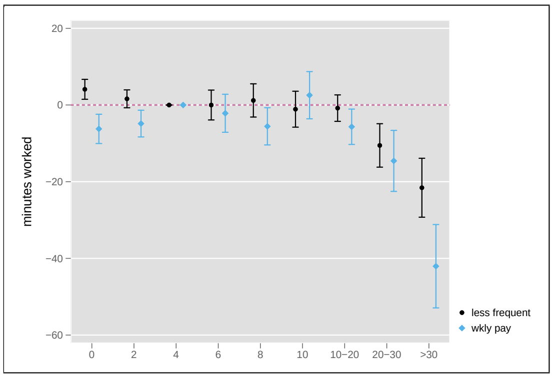


weekly vs less frequent pay

(k) WBGT



(l) precipitation

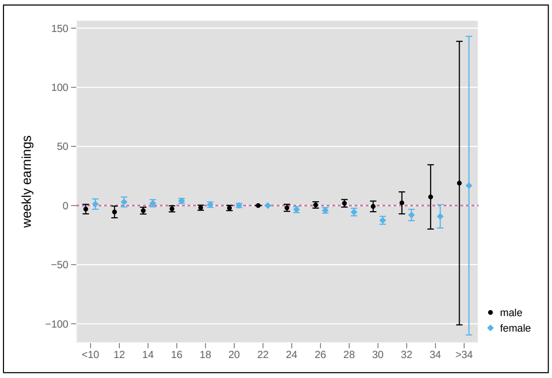


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

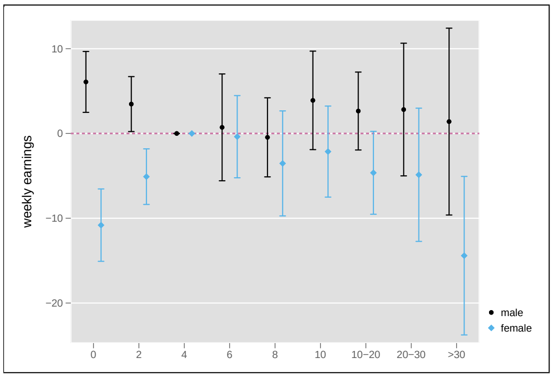
Figure A.7.21: WBGT Individual Characteristics Marginal Effects on Earnings

male vs female

(a) WBGT

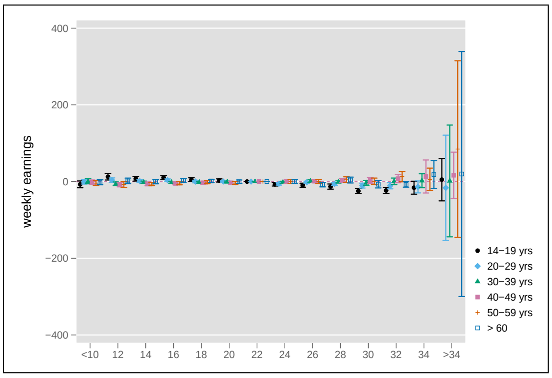


(b) precipitation

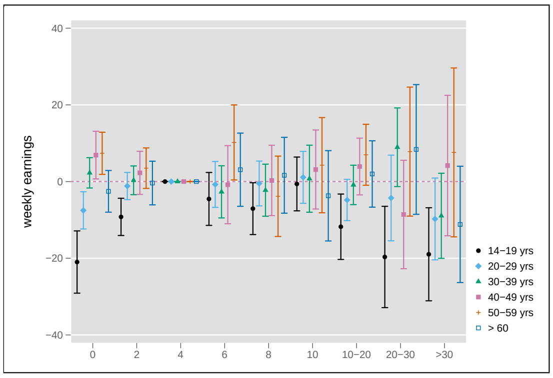


by age group

(c) WBGT

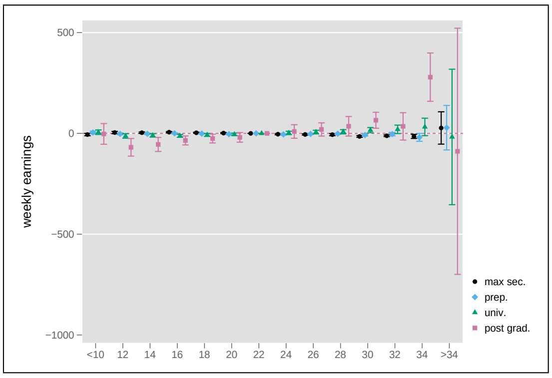


(d) precipitation

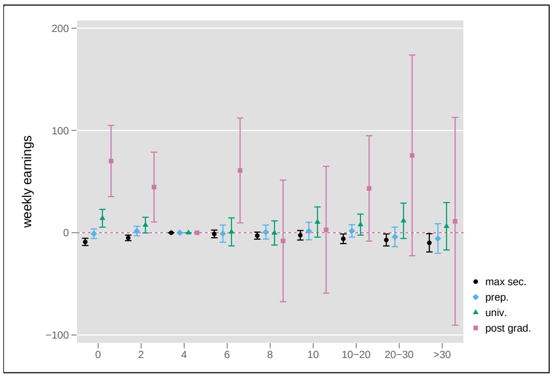


by education

(e) WBGT



(f) precipitation

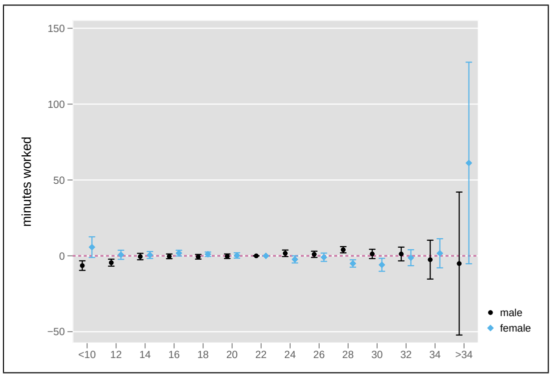


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] $^\circ$C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

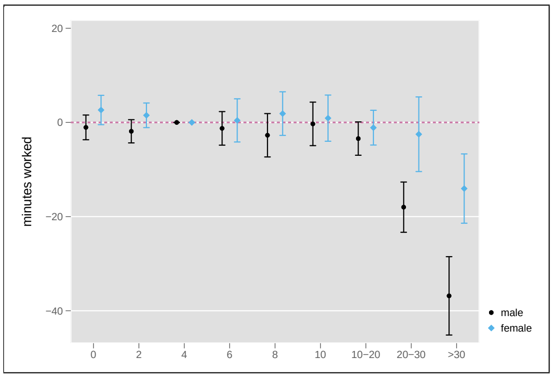
Figure A.7.22: WBGT Individual Characteristics Marginal Effects on Working Time

male vs female

(a) WBGT

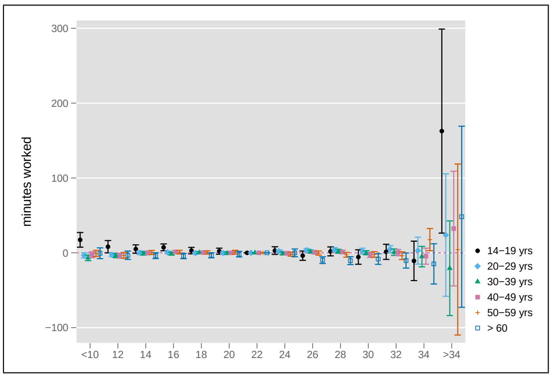


(b) precipitation

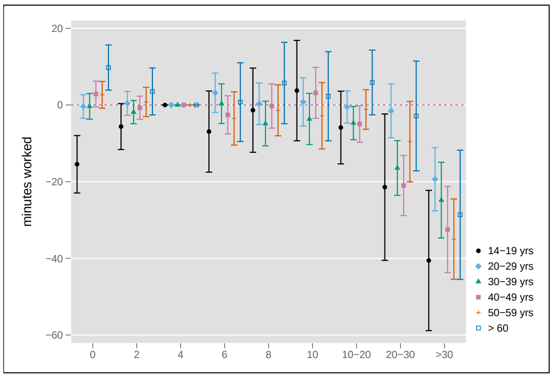


by age group

(c) WBGT

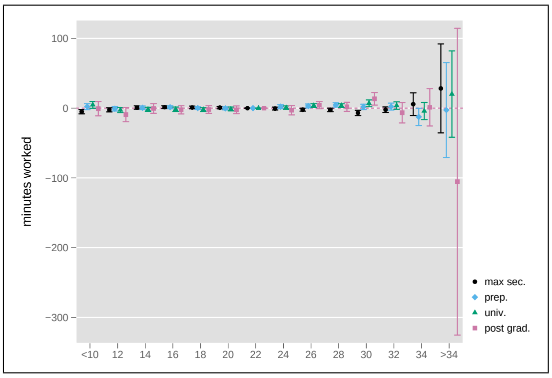


(d) precipitation

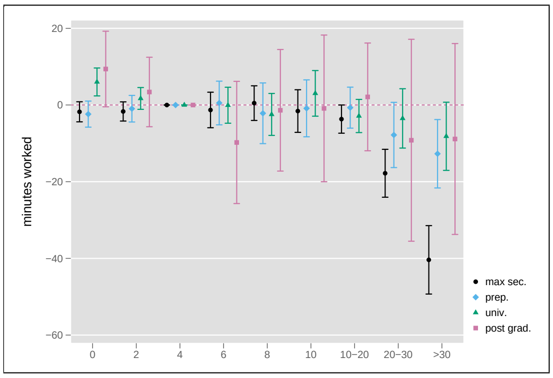


by education

(e) WBGT



(f) precipitation

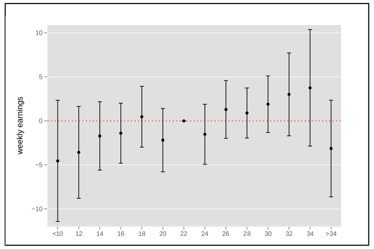


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

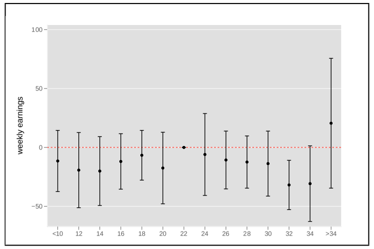
A.8 Subsample Regressions

Figure A.8.1: Industry Subsample Effects on Earnings - Temperature

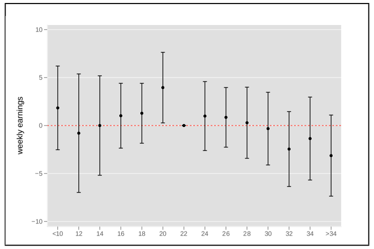
(a) Agriculture



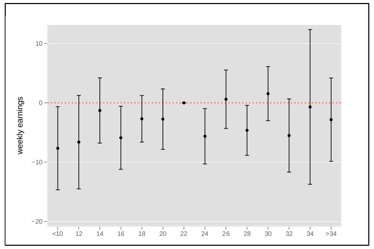
(b) Extractive Industry



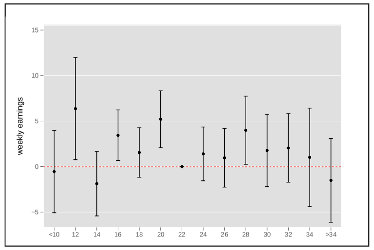
(c) Manufacturing



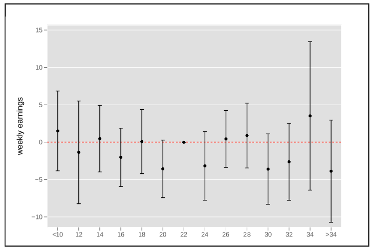
(d) Construction



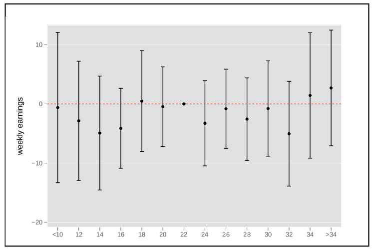
(e) Trade



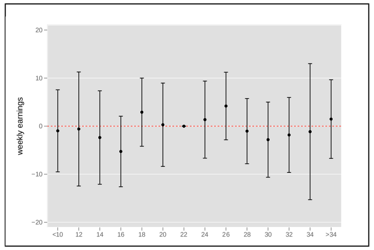
(f) Restaurant Services



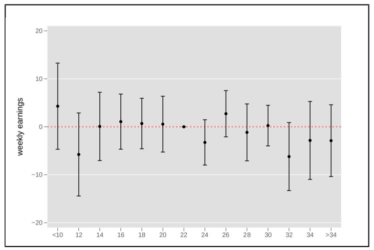
(g) Transport



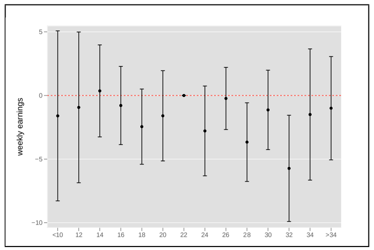
(h) Professional Services



(i) Diverse Services



(j) Social Services



(k) Government

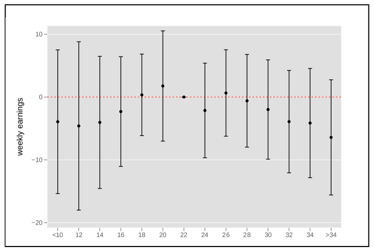
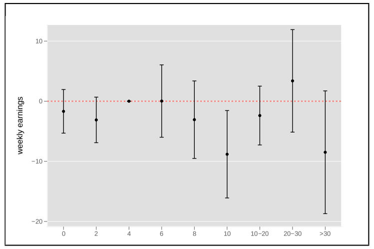
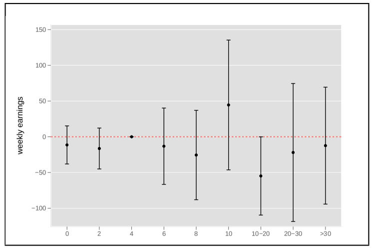


Figure A.8.1: Industry Subsample Effects on Earnings - Precipitation *(continued)*

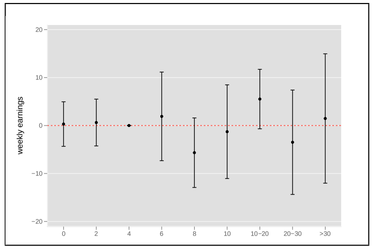
(l) Agriculture



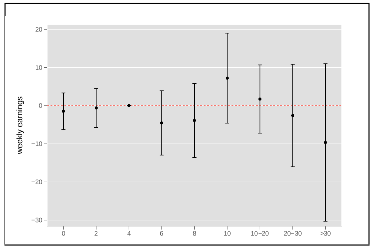
(m) Extractive Industry



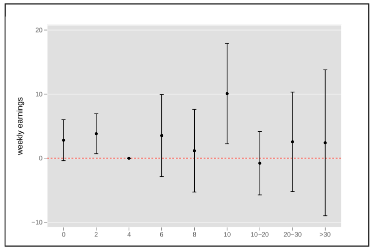
(n) Manufacturing



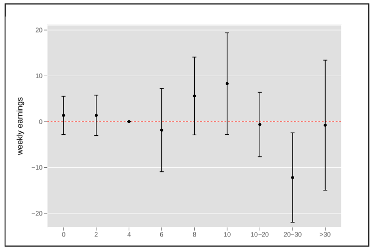
(o) Construction



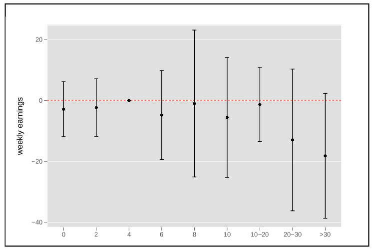
(p) Trade



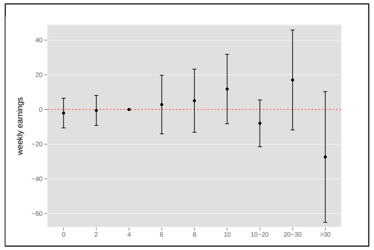
(q) Restaurants Services



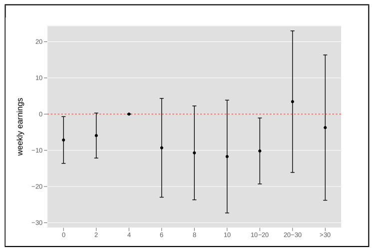
(r) Transport



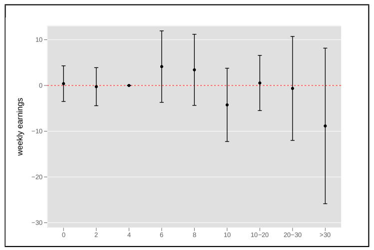
(s) Professional Services



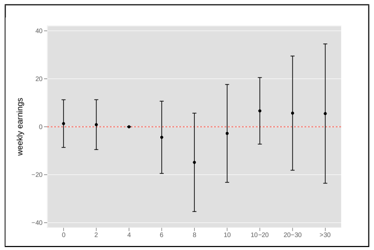
(t) Diverse Services



(u) Social Services



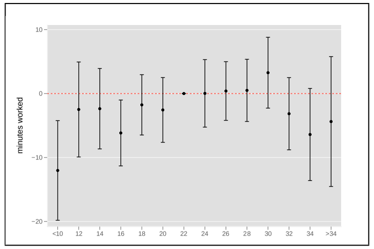
(v) Government



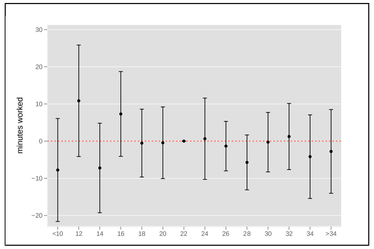
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Figure A.8.2: Industry Subsample Effects on Working Time - Temperature

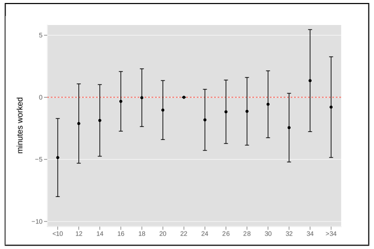
(a) Agriculture



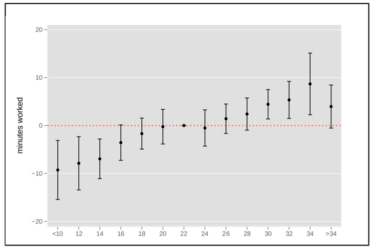
(b) Extractive Industry



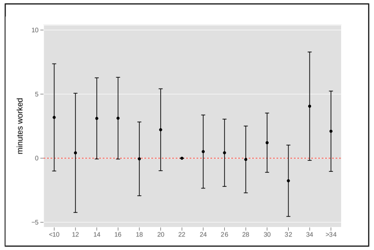
(c) Manufacturing



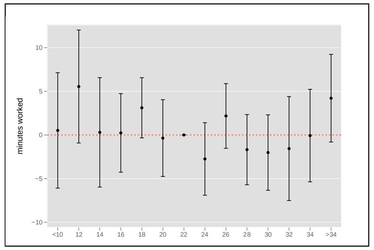
(d) Construction



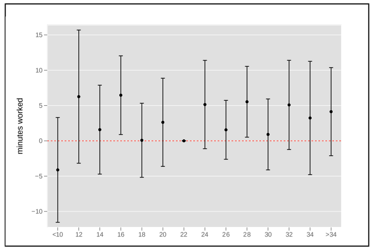
(e) Trade



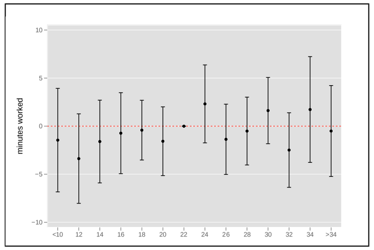
(f) Restaurant Services



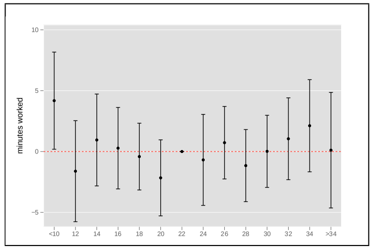
(g) Transport



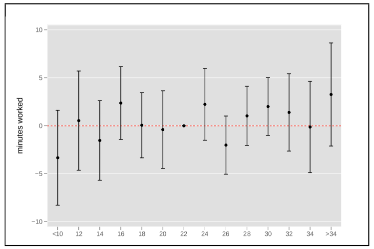
(h) Professional Services



(i) Diverse Services



(j) Social Services



(k) Government

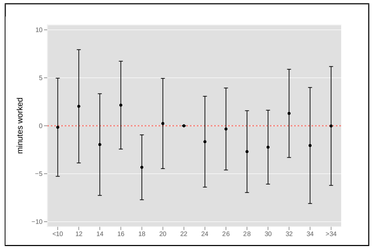
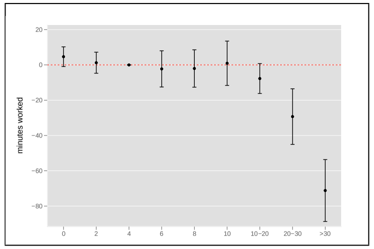
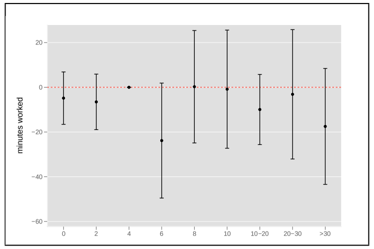


Figure A.8.2: Industry Subsample Effects on Working Time - Precipitation *(continued)*

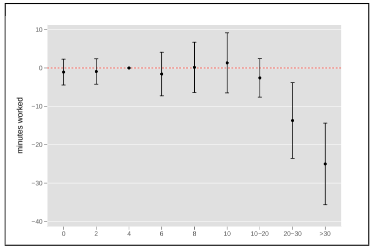
(l) Agriculture



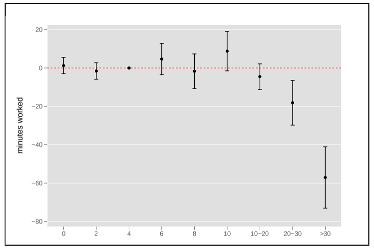
(m) Extractive Industry



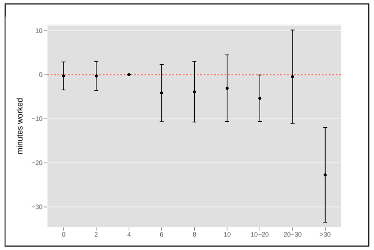
(n) Manufacturing



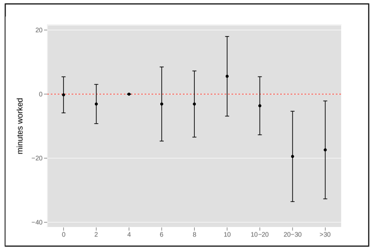
(o) Construction



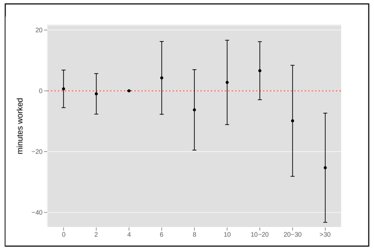
(p) Trade



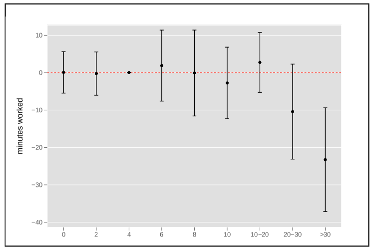
(q) Restaurant Services



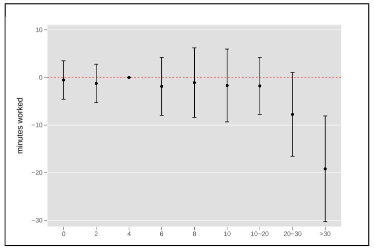
(r) Transport



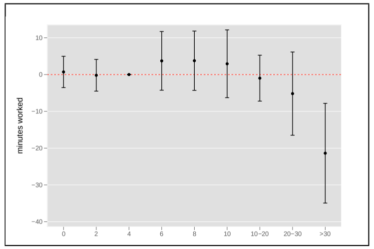
(s) Professional Services



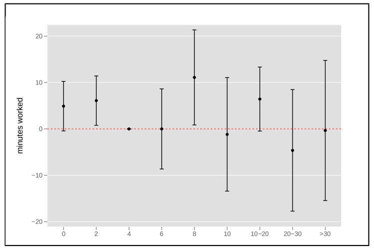
(t) Diverse Services



(u) Social Services



(v) Government

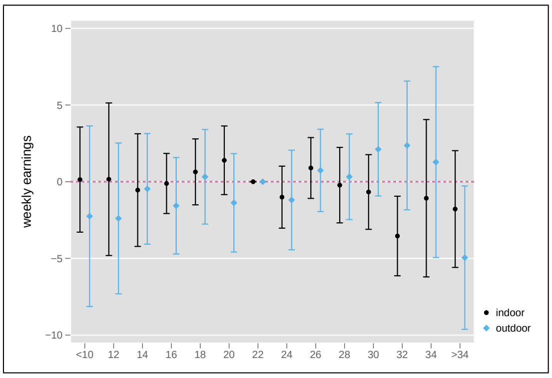


Notes: The figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

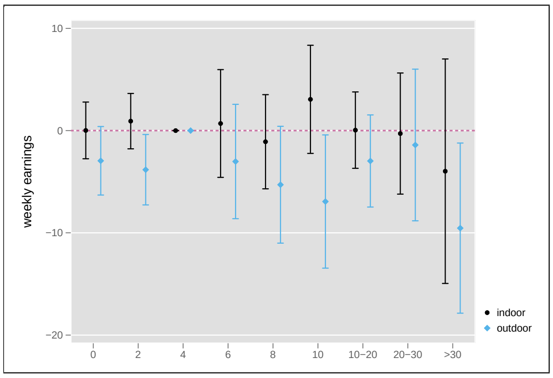
Figure A.8.3: Work Location Subsample Effects on Earnings

outdoor vs indoor

(a) temperature

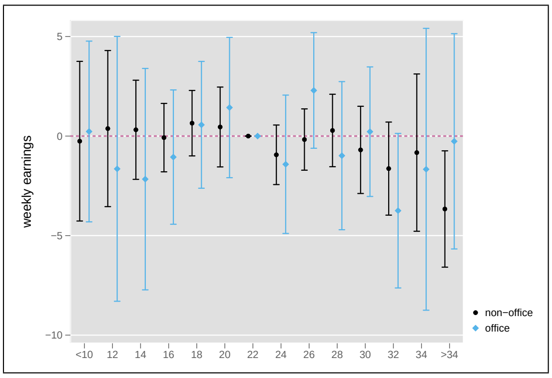


(b) precipitation

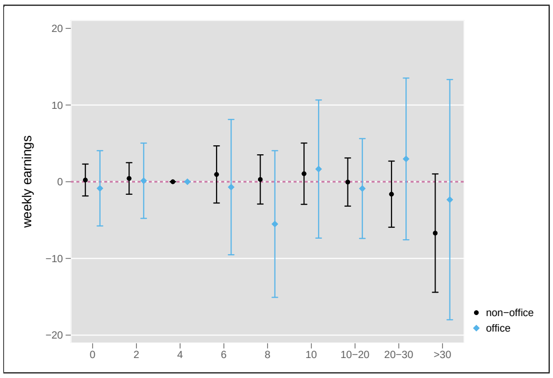


office vs non-office

(c) temperature

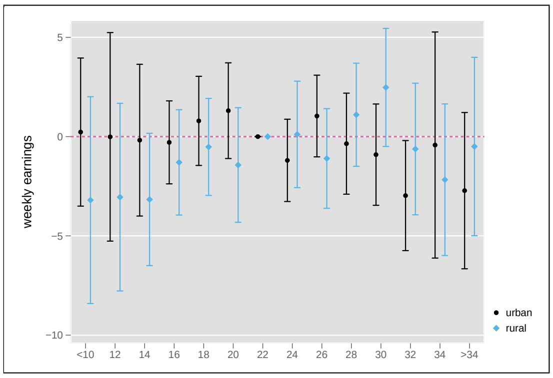


(d) precipitation



urban vs rural

(e) temperature



(f) precipitation

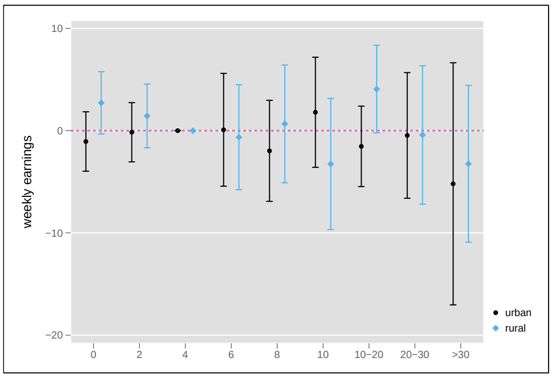
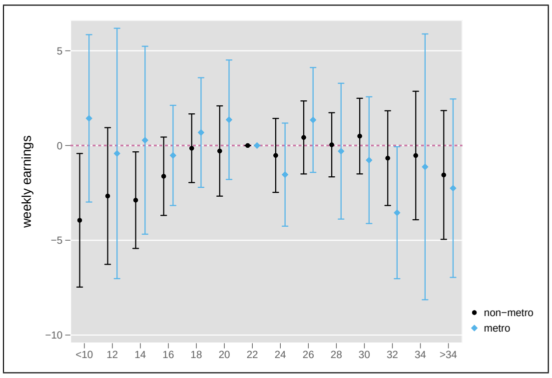


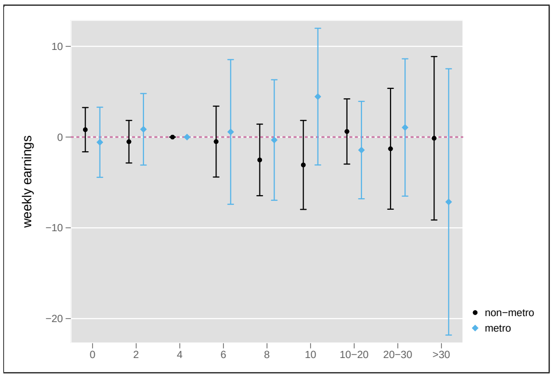
Figure A.8.3: Work Location Subsample Effects on Earnings *(continued)*

metro vs non-metro area

(g) temperature

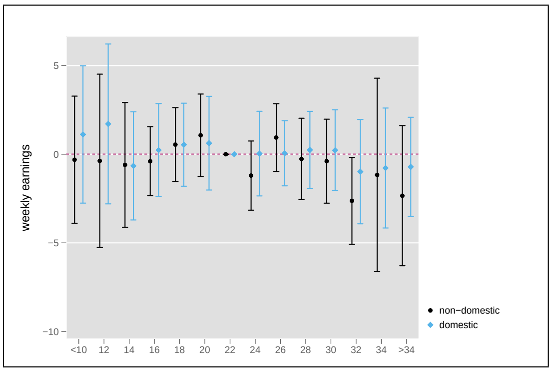


(h) precipitation

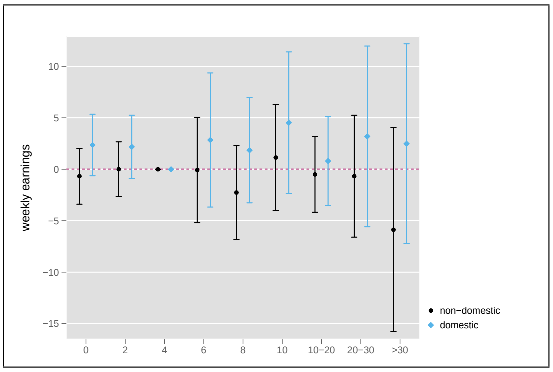


domestic vs non-domestic

(i) temperature



(j) precipitation

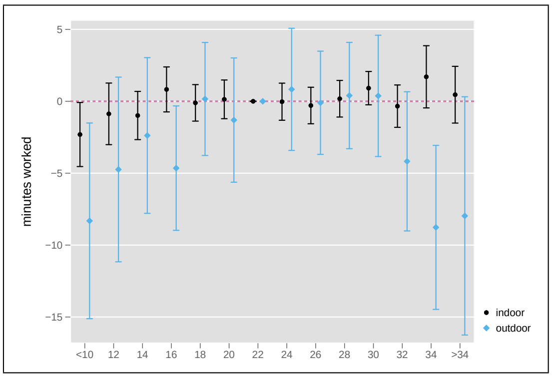


Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

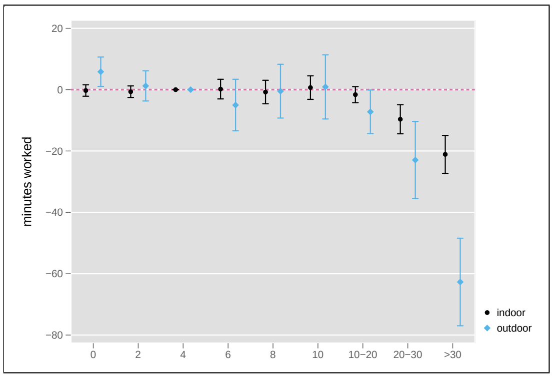
Figure A.8.4: Work Location Subsample Effects on Working Time

outdoor vs indoor

(a) temperature

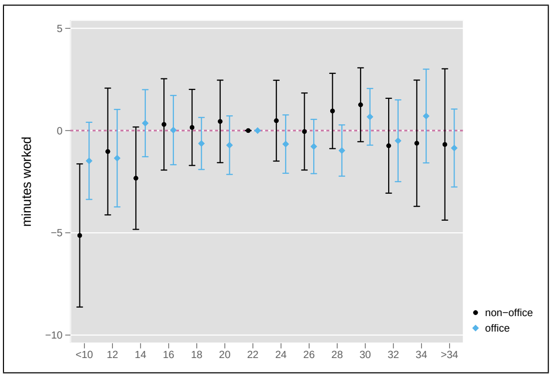


(b) precipitation

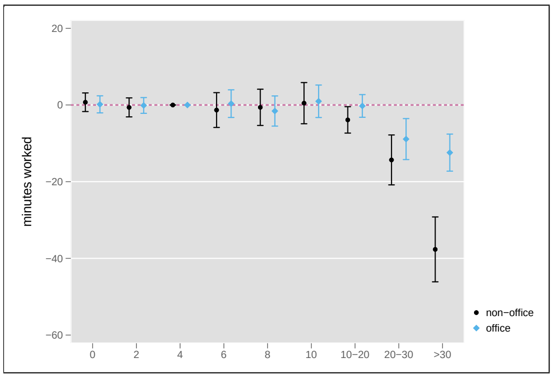


office vs non-office

(c) temperature

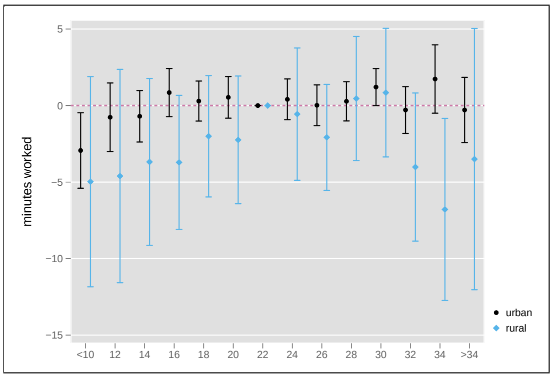


(d) precipitation



urban vs rural

(e) temperature



(f) precipitation

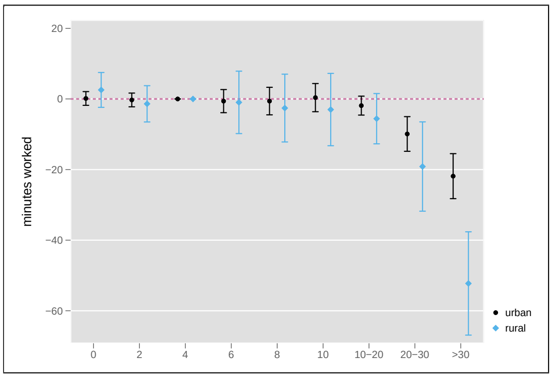
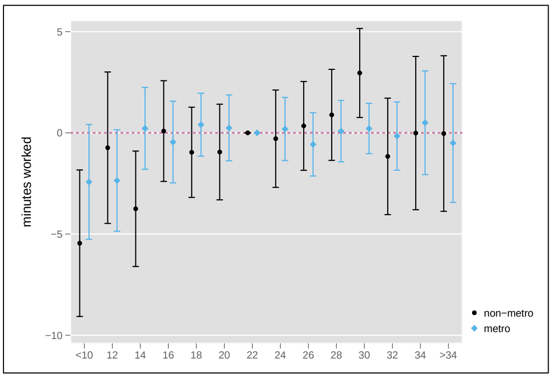


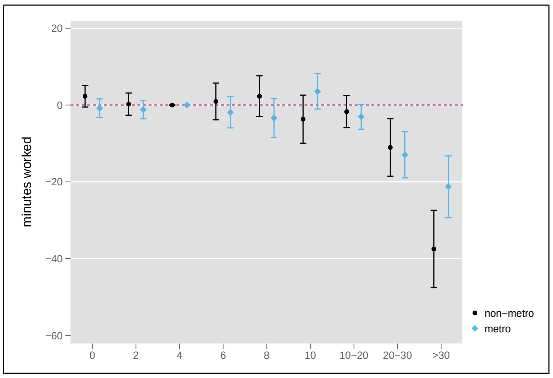
Figure A.8.4: Work Location Subsample Effects on Working Time *(continued)*

metro vs non-metro area

(g) temperature

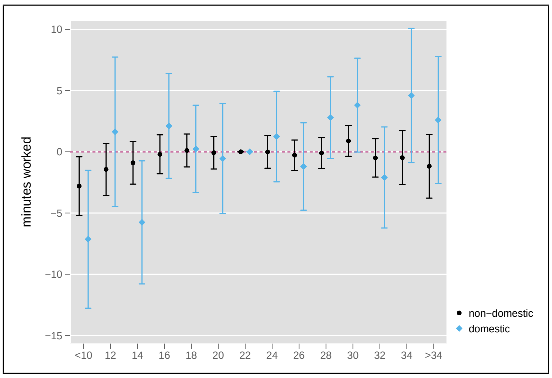


(h) precipitation

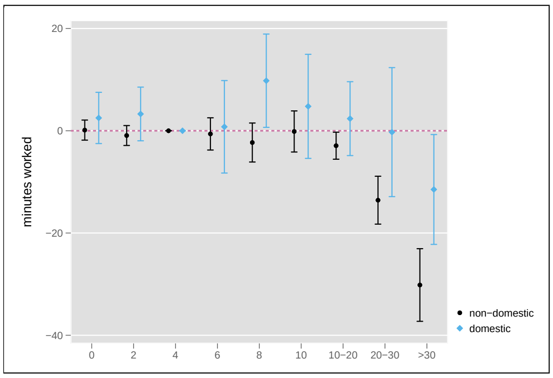


domestic vs non-domestic

(i) temperature



(j) precipitation



Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

A.9 Individual Fixed Effects

This Appendix presents individual fixed-effects regressions. Estimated average effects are comparable to the baseline results with municipality fixed effects. A striking result is split-sample industry-specific weather effects on earnings (Figure A.9.3). After controlling for individual-specific temperature and rainfall sensitivity and exposure, extreme heat consistently has a positive effect on earnings. Cold temperatures above 10°C reduce earnings across sectors, while extreme cold effects are more diverse. Similarly, I find extreme and zero-rainfall days have a positive effect on earnings. In contrast to earnings, sectoral working-time subsample impacts are very similar to the municipality regressions (Figure A.9.4).

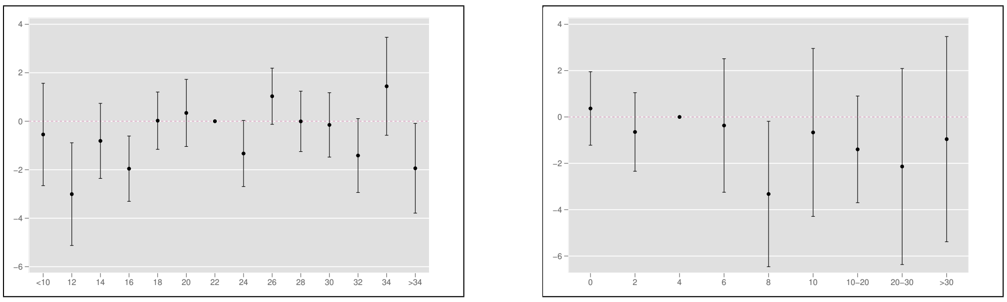
Similar to the preferred specification, I observe heat- and extreme-rainfall-related earnings losses for outdoor and non-office work with corresponding reductions in working times (see Figure A.9.5 and A.9.6). Estimated heat impacts on outdoor working times increase in size and significance. On average, extreme rainfall impacts become stronger using an individual fixed-effects specification. Cold effects affect both outdoor and indoor working times.

Heterogeneous estimates by job and individual characteristics again differ significantly from the municipality-level results. Earlier strong effects on informal workers, minimum-wage earners, and those with flexible earnings disappear. Moreover, after controlling for unobserved individual heterogeneity, systematic gender, age and education differences in the weather impact on earnings disappear. Again, heat effects on working times turn negative or insignificant, while extreme precipitation impacts are mostly consistent with the earlier findings.

In summary, the individual fixed-effects regressions results suggest that individual sensitivity and exposure to temperature are an essential determinant of the direction and size of weather-related earnings and working-time fluctuations. The latter should be taken into consideration when estimating labour-market effects.

Figure A.9.1: Ind. FE Weather Bins Coefficient Plots – Earnings Regressions

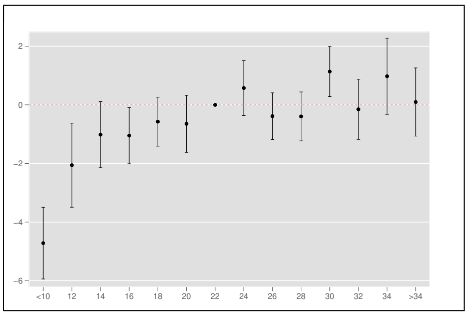
(a) Temperature **(b)** Precipitation



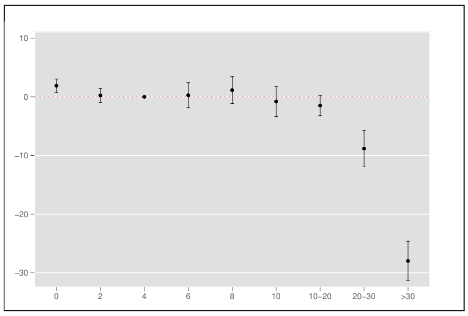
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly earnings. Covariates include individual, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] *mm* precipitation. Standard errors are clustered at the municipality level.

Figure A.9.2: Ind. FE Weather Bins Coefficient Plots – Working Time Regressions

(a) Temperature



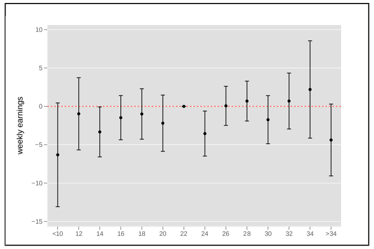
(b) Precipitation



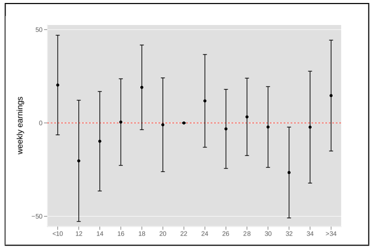
Notes: The figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly earnings. Covariates include individual, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] *mm* precipitation. Standard errors are clustered at the municipality level.

Figure A.9.3: Ind. FE Industry – Earnings Regressions

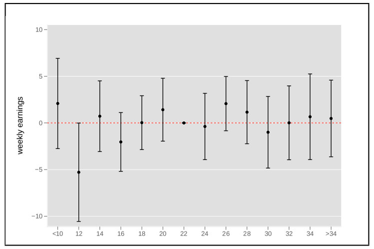
(a) Agriculture



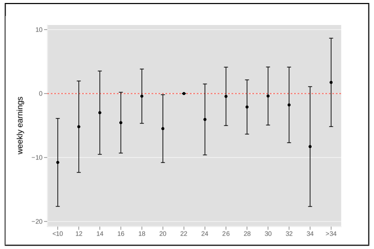
(b) Extractive Industry



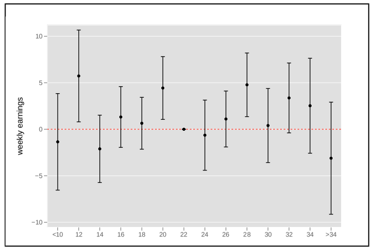
(c) Manufacturing



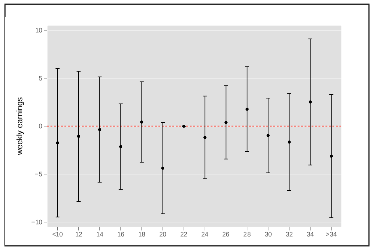
(d) Construction



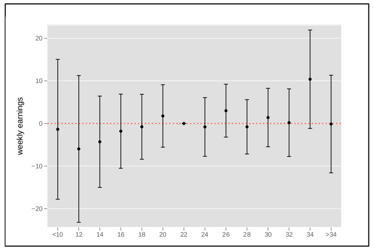
(e) Trade



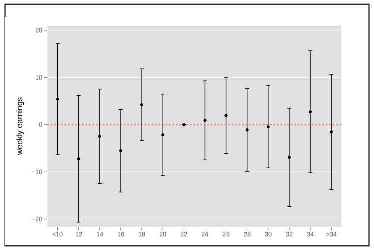
(f) Restaurant Services



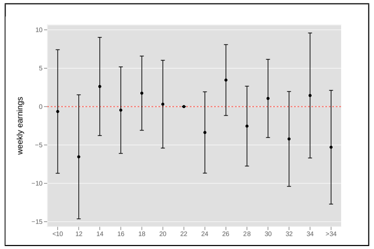
(g) Transport



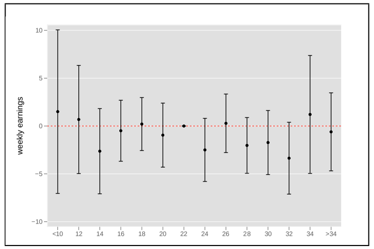
(h) Professional Services



(i) Diverse Services



(j) Social Services



(k) Government

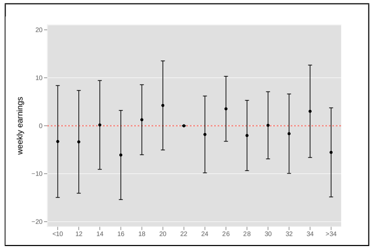
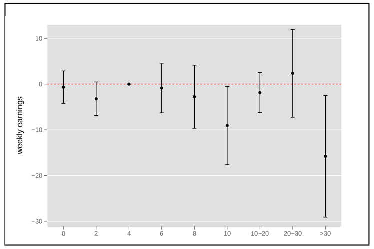
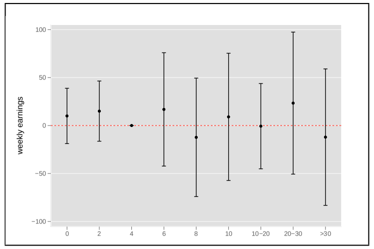


Figure A.9.3: Ind. FE Industry – Earnings Regressions *(continued)*

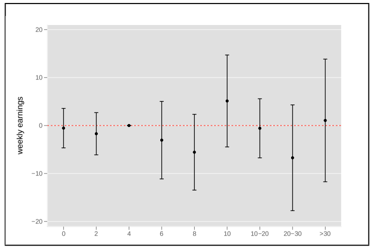
(l) Agriculture



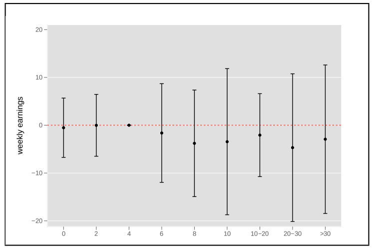
(m) Extractive Industry



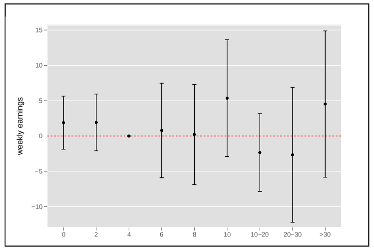
(n) Manufacturing



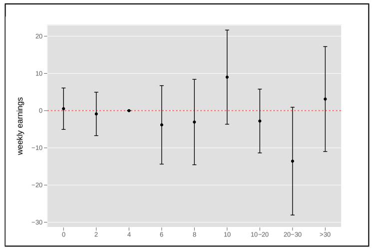
(o) Construction



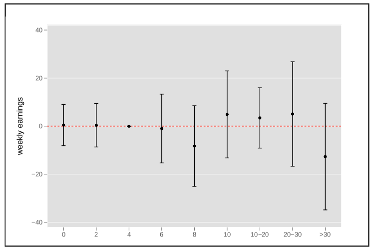
(p) Trade



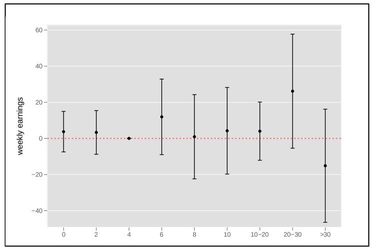
(q) Restaurants Services



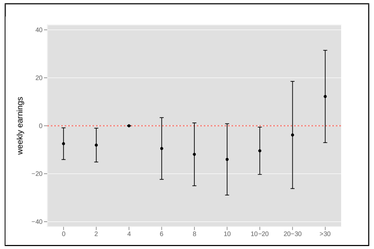
(r) Transport



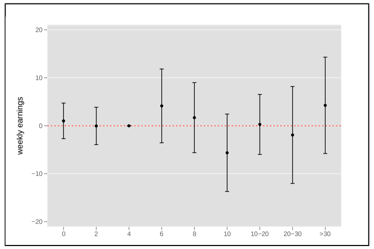
(s) Professional Services



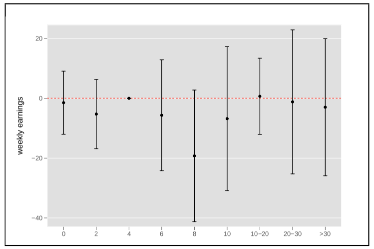
(t) Diverse Services



(u) Social Services



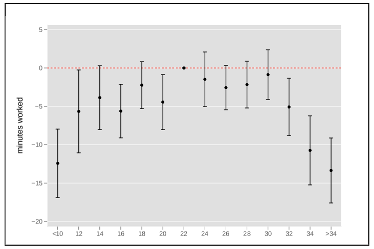
(v) Government



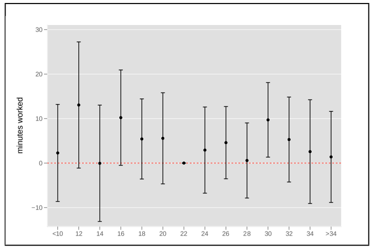
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include individual, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] $^\circ$ C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Figure A.9.4: Ind. FE Industry – Working Time Regressions

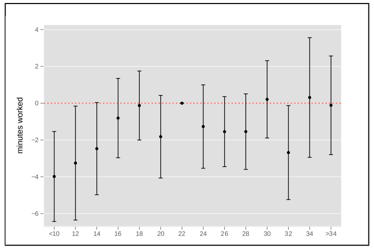
(a) Agriculture



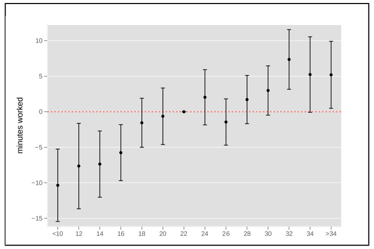
(b) Extractive Industry



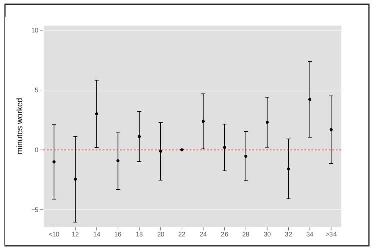
(c) Manufacturing



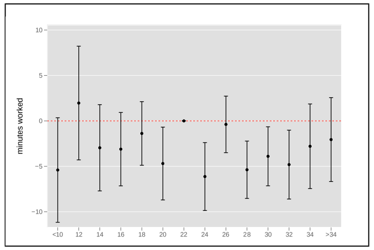
(d) Construction



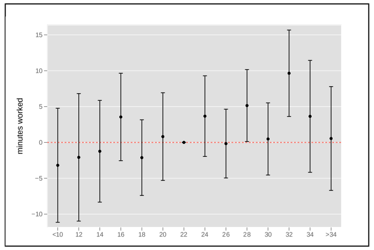
(e) Trade



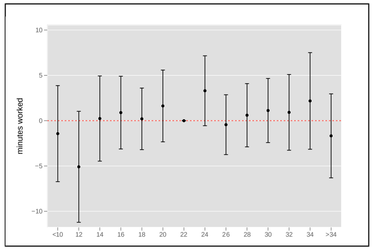
(f) Restaurant Services



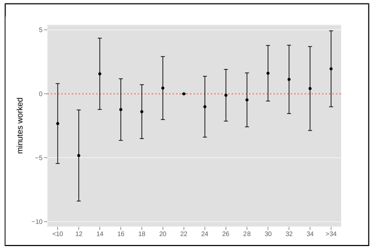
(g) Transport



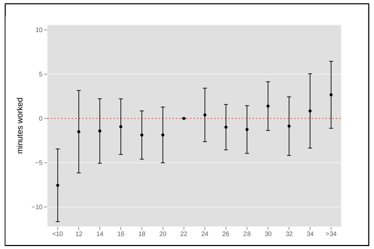
(h) Professional Services



(i) Diverse Services



(j) Social Services



(k) Government

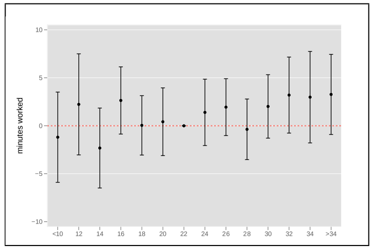
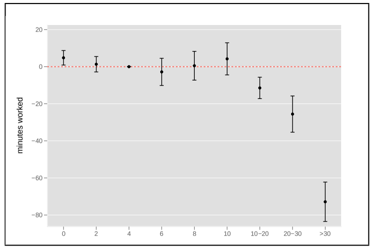
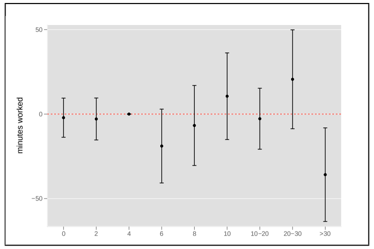


Figure A.9.4: Ind. FE Industry – Working Time Regressions *(continued)*

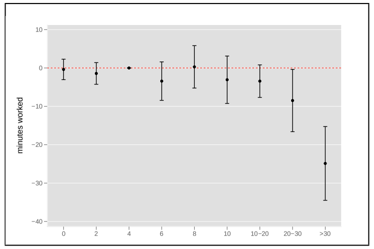
(l) Agriculture



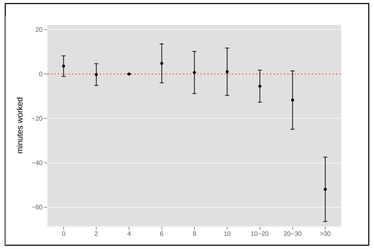
(m) Extractive Industry



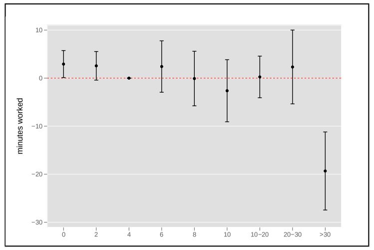
(n) Manufacturing



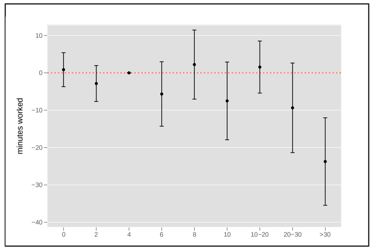
(o) Construction



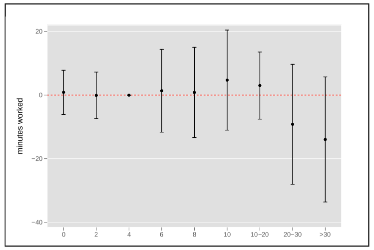
(p) Trade



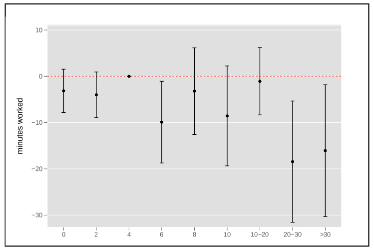
(q) Restaurant Services



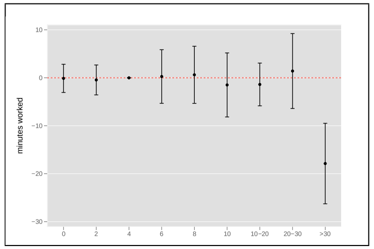
(r) Transport



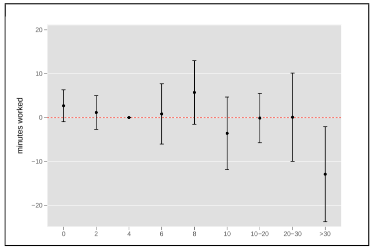
(s) Professional Services



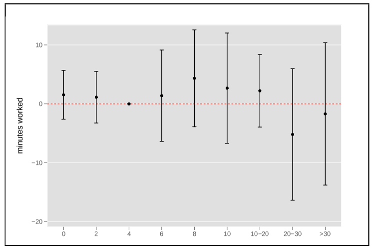
(t) Diverse Services



(u) Social Services



(v) Government

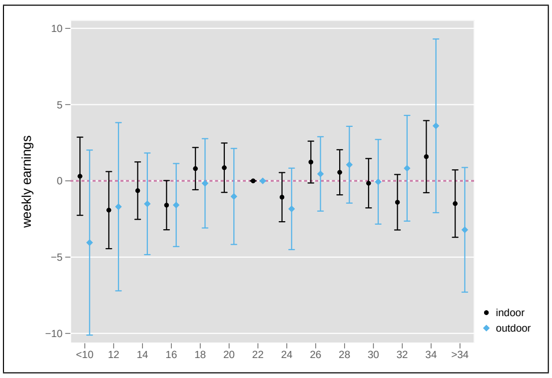


Notes: The figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include individual, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

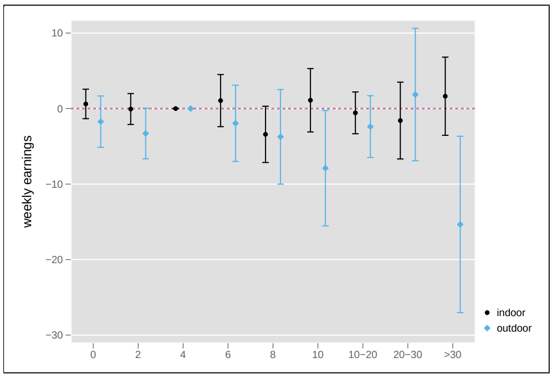
Figure A.9.5: Ind. FE Work Location – Earnings Regressions

outdoor vs indoor

(a) temperature

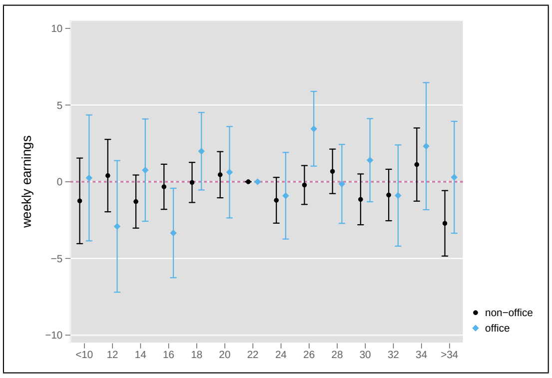


(b) precipitation

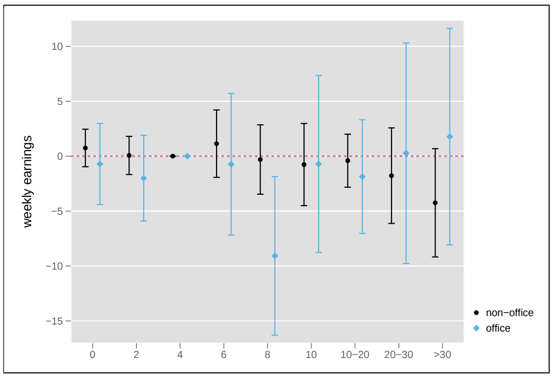


office vs non-office

(c) temperature

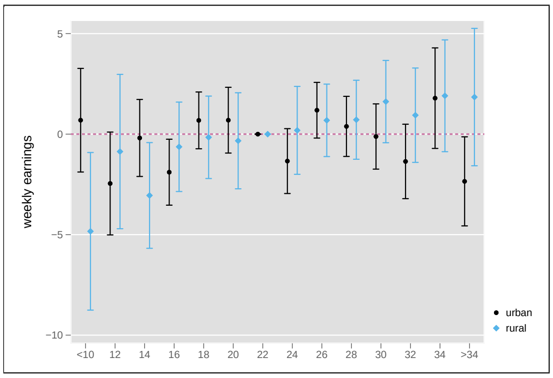


(d) precipitation



urban vs rural

(e) temperature



(f) precipitation

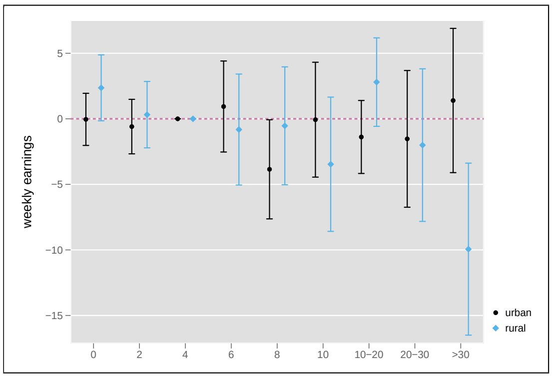
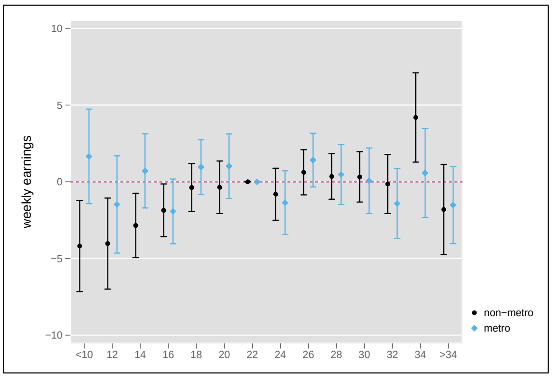


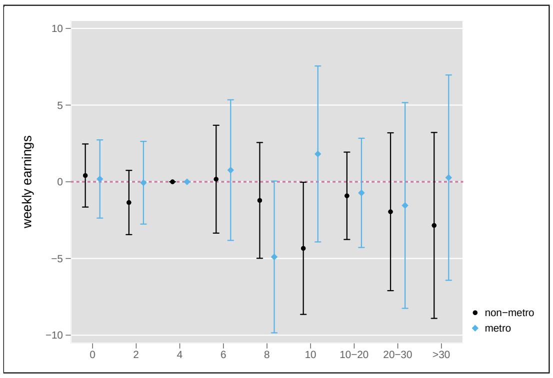
Figure A.9.5: Ind. FE Work Location – Earnings Regressions *(continued)*

metro vs non-metro area

(g) temperature

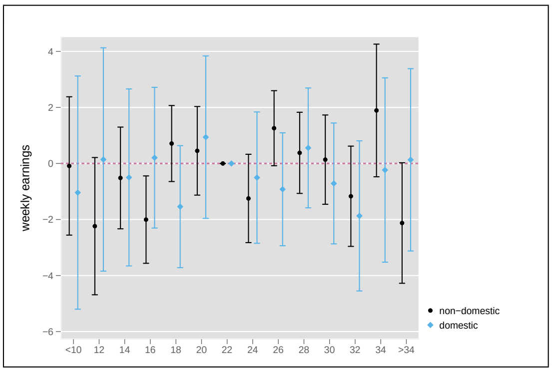


(h) precipitation

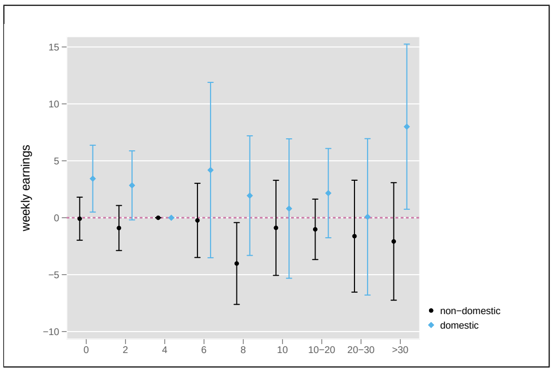


domestic vs non-domestic

(i) temperature



(j) precipitation

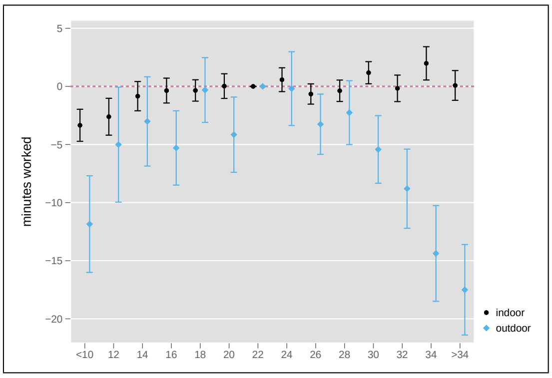


Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include individual, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

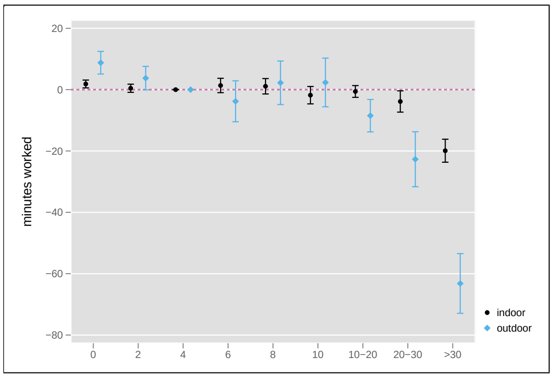
Figure A.9.6: Ind. FE Work Location – Working Time Regressions

outdoor vs indoor

(a) temperature

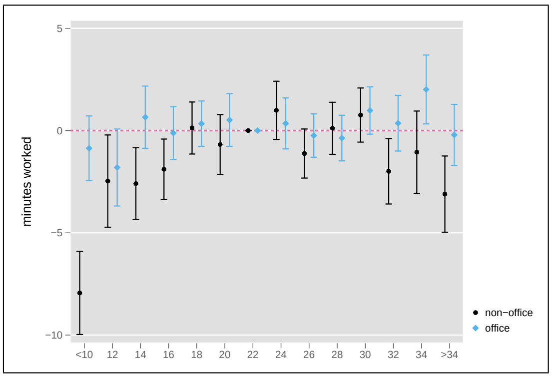


(b) precipitation

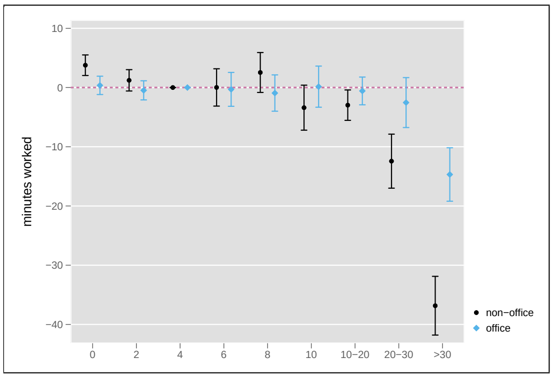


office vs non-office

(c) temperature

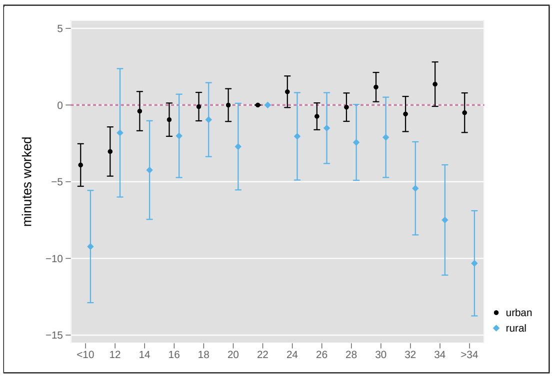


(d) precipitation



urban vs rural

(e) temperature



(f) precipitation

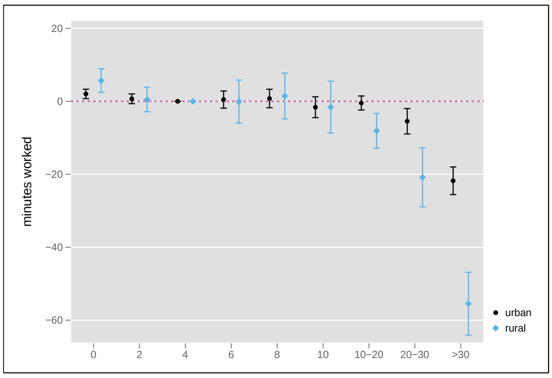
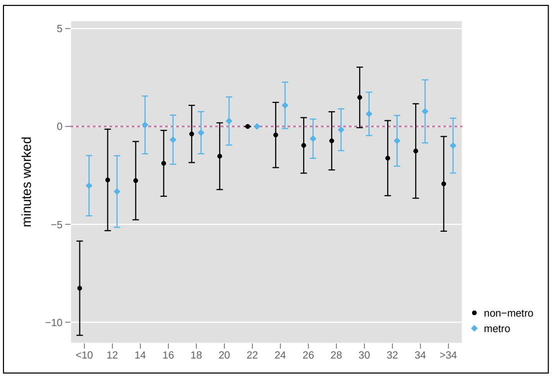


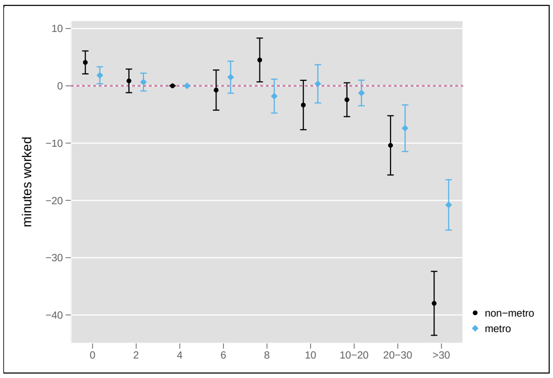
Figure A.9.6: Ind. FE Work Location – Working Time Regressions *(continued)*

metro vs non-metro area

(g) temperature

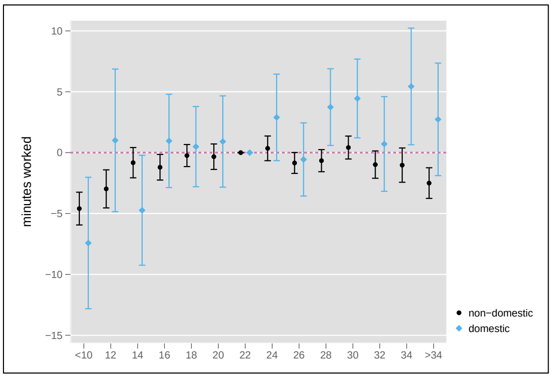


(h) precipitation

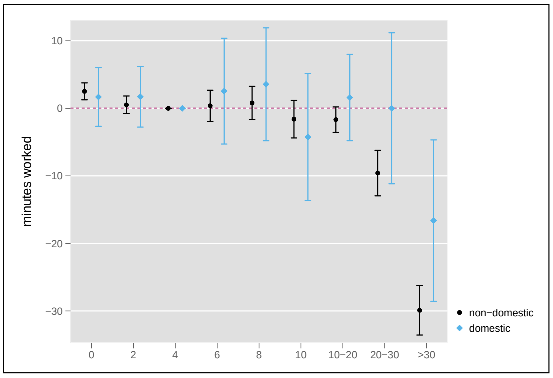


domestic vs non-domestic

(i) temperature



(j) precipitation

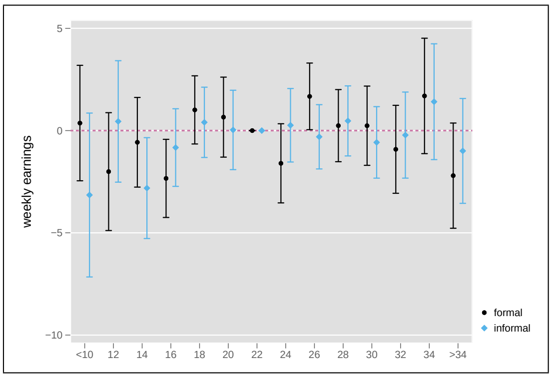


Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include individual, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

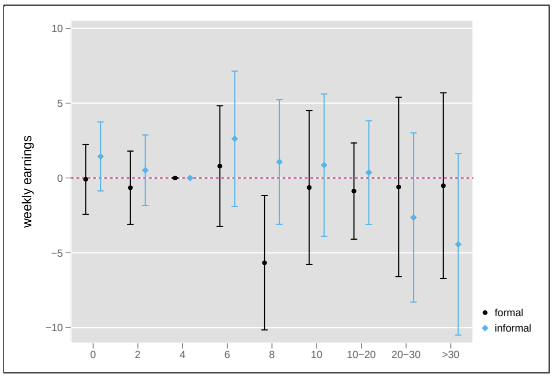
Figure A.9.7: Ind. FE Job Characteristics – Earnings Regressions

formal vs informal

(a) temperature

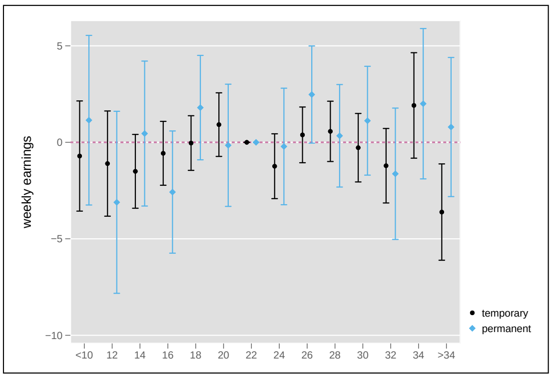


(b) precipitation

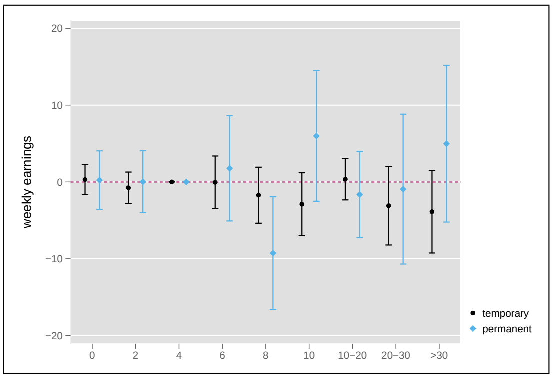


permanent vs temporary

(c) temperature

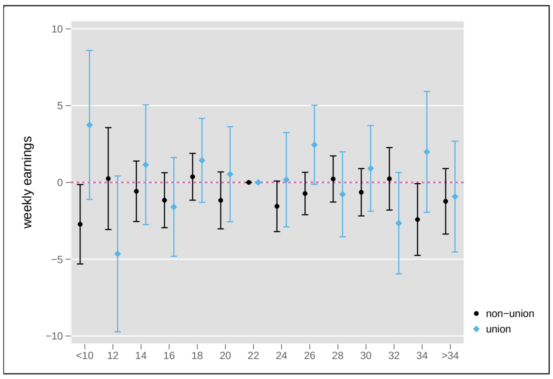


(d) precipitation



union vs non-union

(e) temperature



(f) precipitation

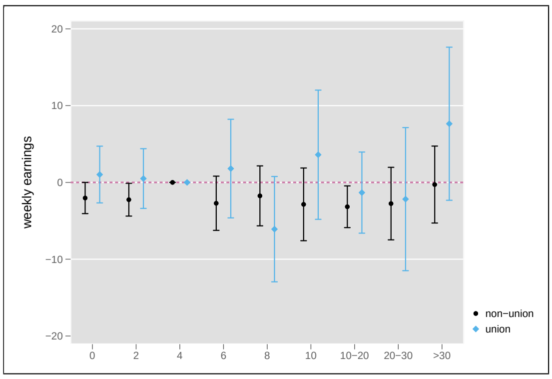
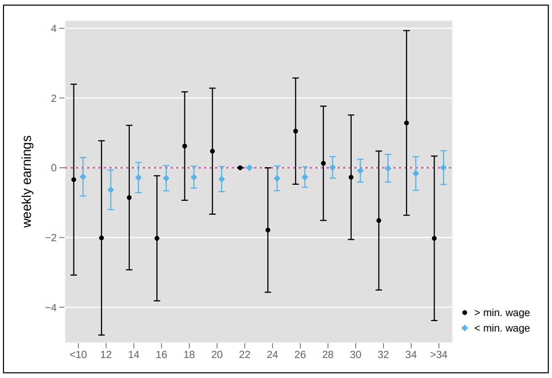


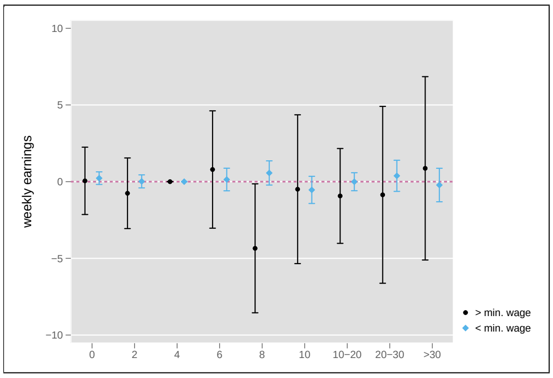
Figure A.9.7: Ind. FE Job Characteristics – Earnings Regressions *(continued)*

above vs below official minimum wage

(g) temperature

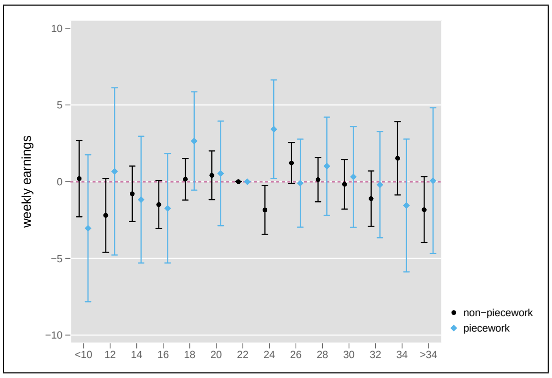


(h) precipitation

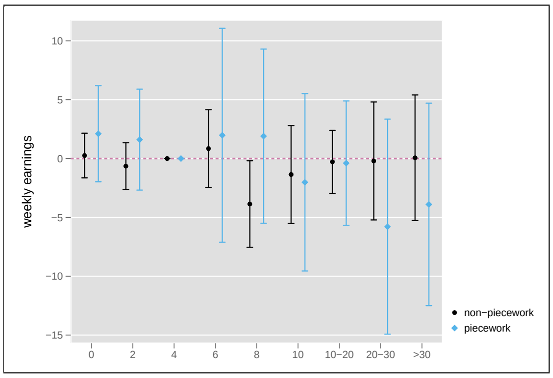


piecework vs non-piecework

(i) temperature

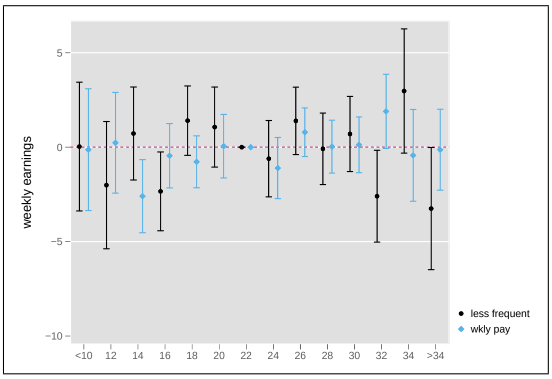


(j) precipitation

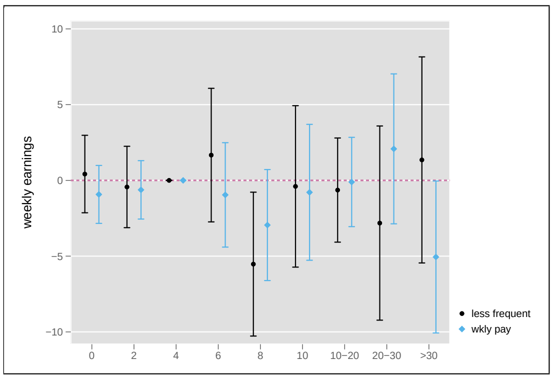


weekly vs less frequent pay

(k) temperature



(l) precipitation

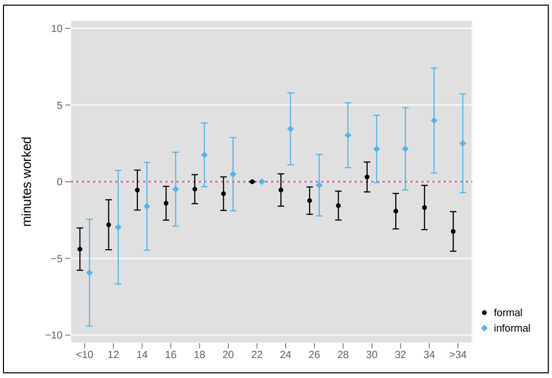


Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include individual, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

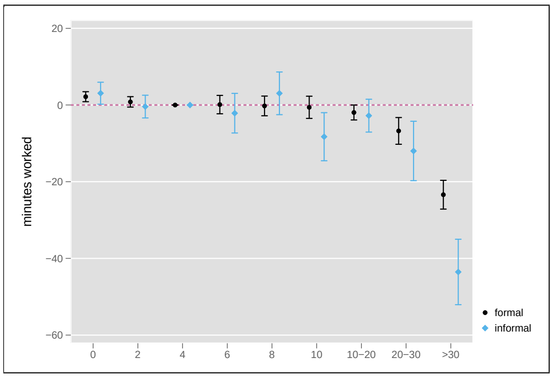
Figure A.9.8: Ind. FE Job Characteristics – Working Time Regressions

formal vs informal

(a) temperature

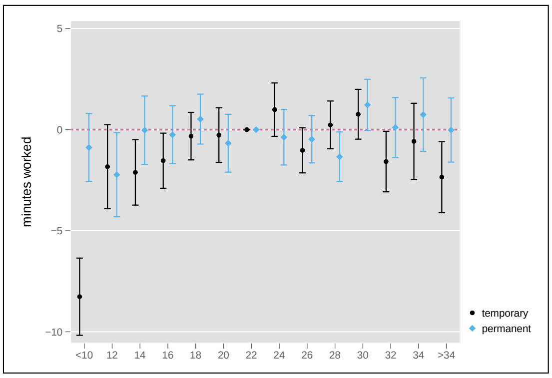


(b) precipitation

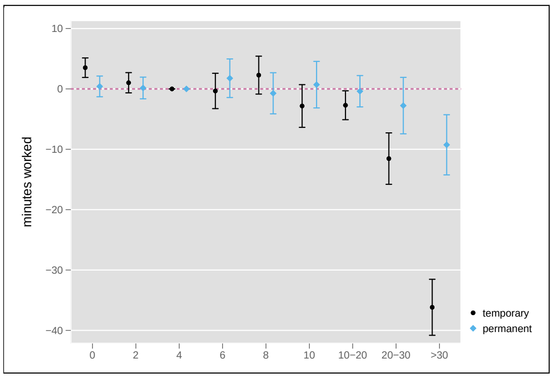


permanent vs temporary

(c) temperature

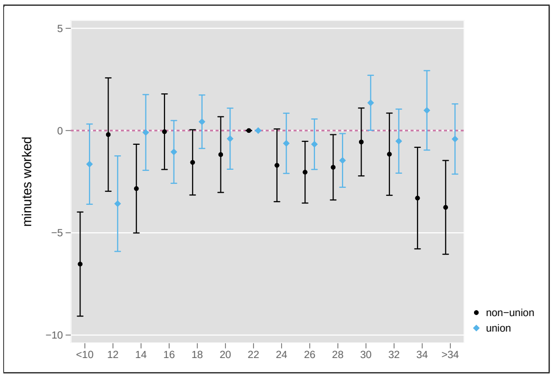


(d) precipitation



union vs non-union

(e) temperature



(f) precipitation

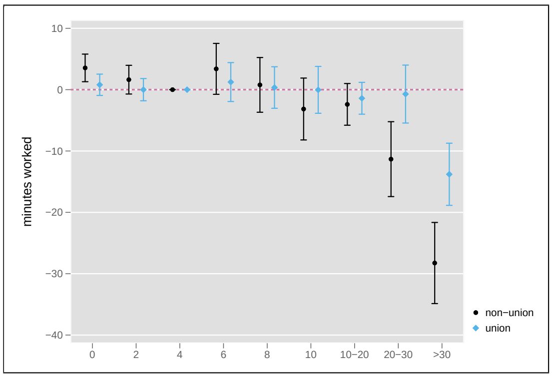
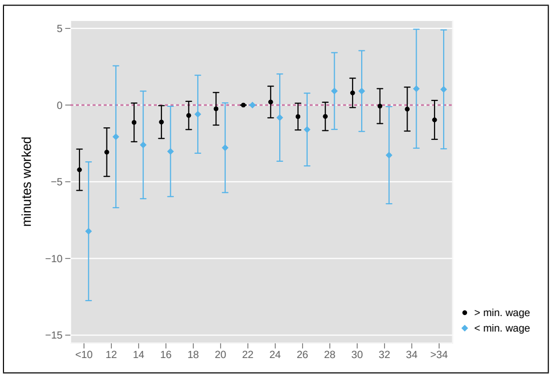


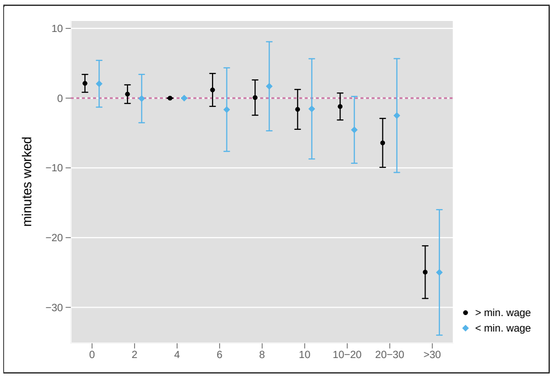
Figure A.9.8: Ind. FE Job Characteristics – Working Time Regressions *(continued)*

above vs below official minimum wage

(g) temperature

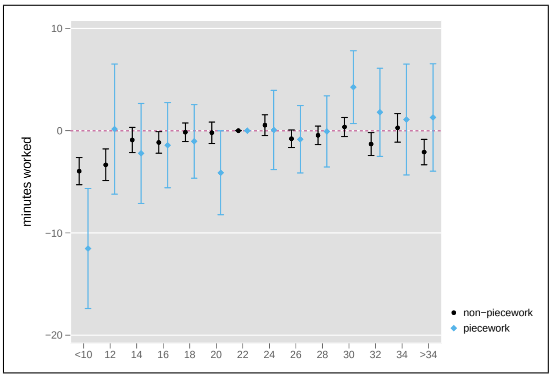


(h) precipitation

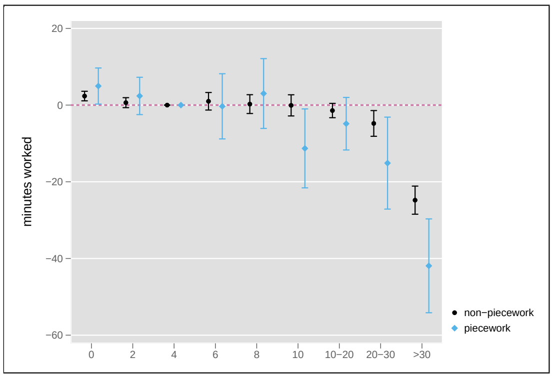


piecework vs non-piecework

(i) temperature

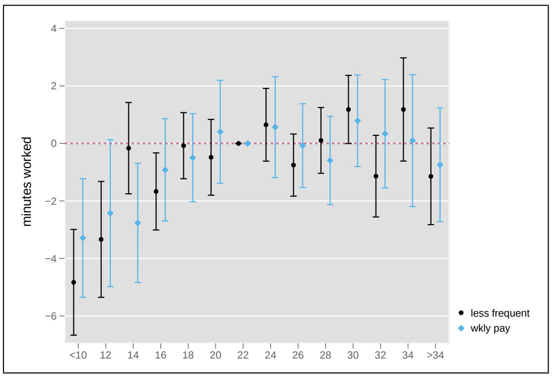


(j) precipitation

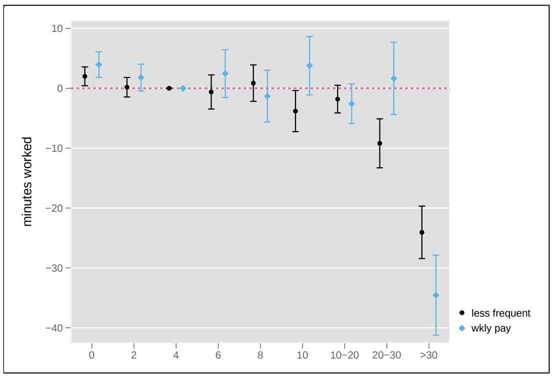


weekly vs less frequent pay

(k) temperature



(l) precipitation

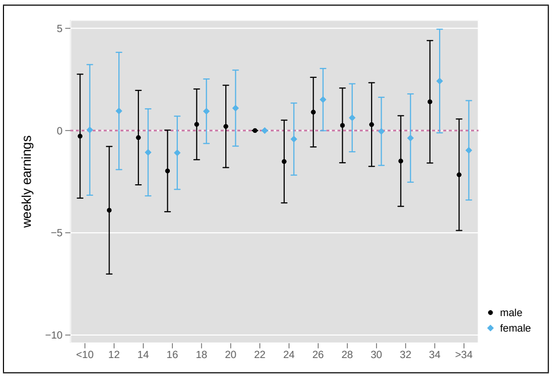


Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include individual, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

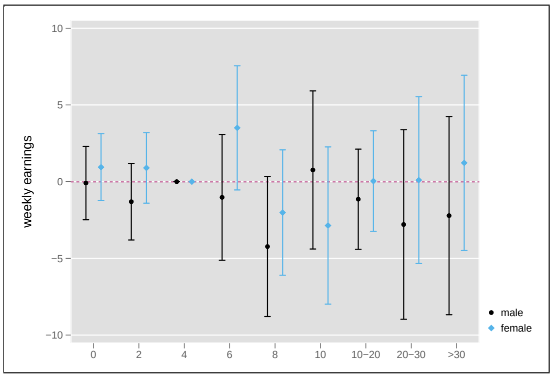
Figure A.9.9: Ind. FE Individual Characteristics – Earnings Regressions

male vs female

(a) temperature

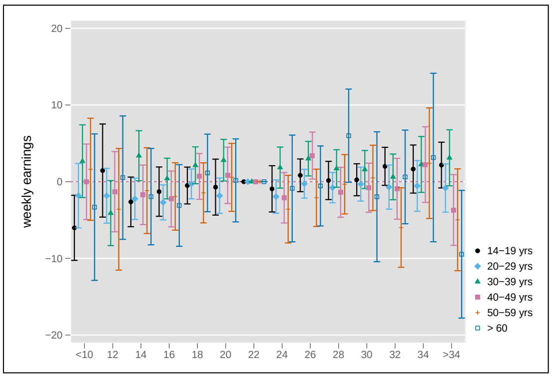


(b) precipitation

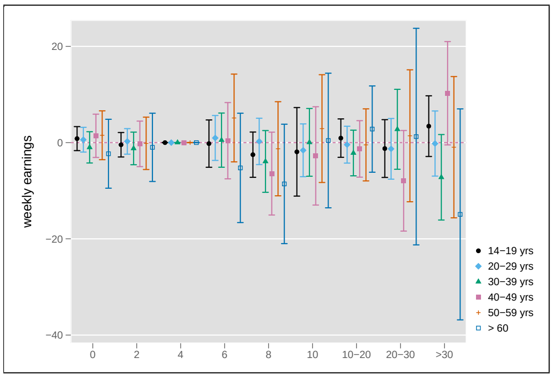


by age group

(c) temperature

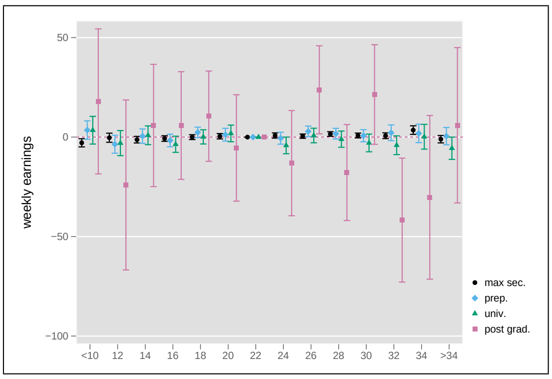


(d) precipitation

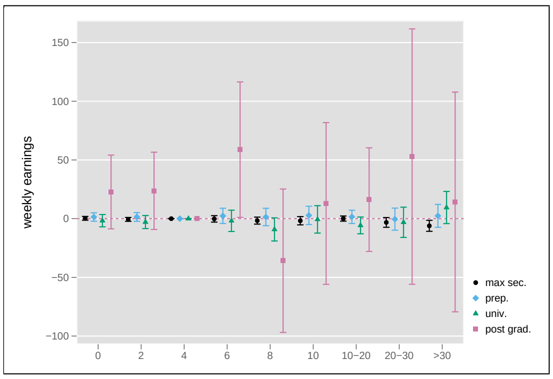


by education

(e) temperature



(f) precipitation

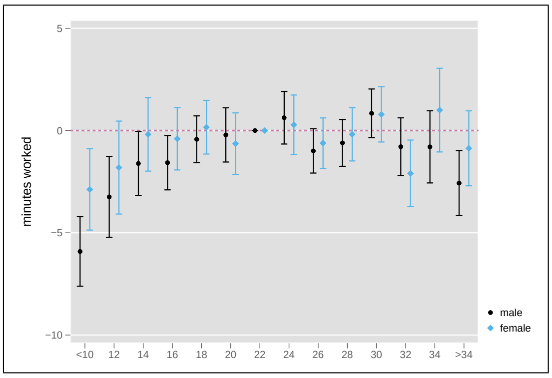


textitNotes: Figure depicts marginal effects of weather bins on weekly earnings (in 2010 pesos). The 95% confidence interval indicated by markers. Covariates include individual, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

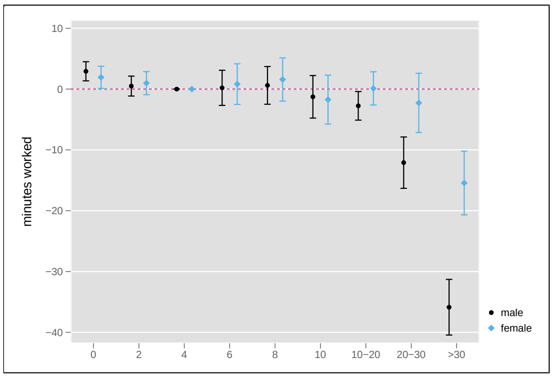
Figure A.9.10: Ind. FE Individual Characteristics – Working Time Regressions

male vs female

(a) temperature

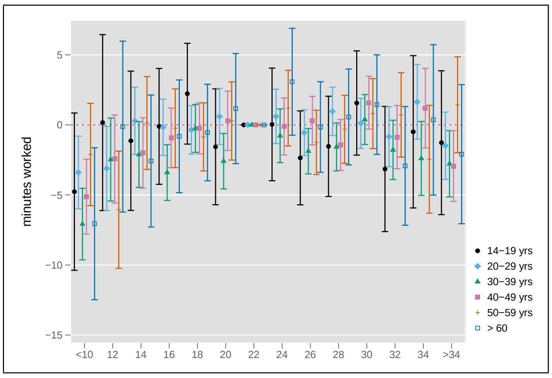


(b) precipitation

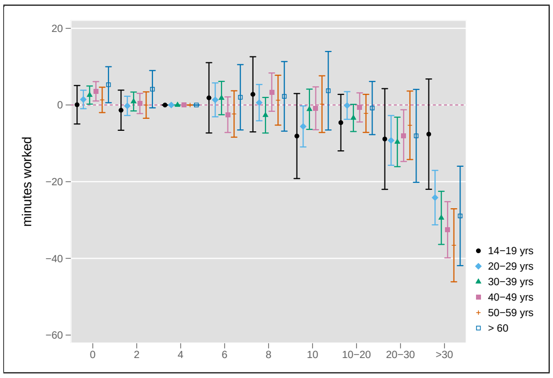


by age group

(c) temperature

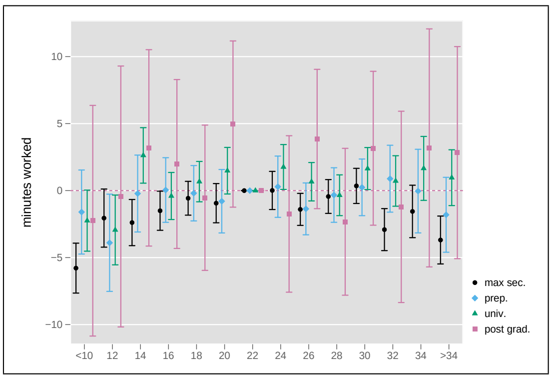


(d) precipitation

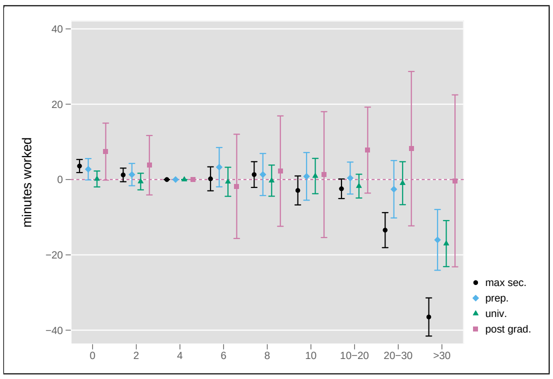


by education

(e) temperature



(f) precipitation



Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include individual, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

A.10 Counterfactual Cost Estimates

A.10.1 2016 Weather Cost Estimates

Table A.10.1: Earnings Losses by Temperature Bin

	Bins													Total	
Regressors	(≤ 10]	(10-12]	(12-14]	(14-16]	(16-18]	(18-20]	(22-24]	(24-26]	(26-28]	(28-30]	(30-32]	(32-34]	(> 34]	Δ	potential earnings
municipio	-78.12	-80.29	-556.06	-452.22	1,083.55	2,318.28	-2,259.08	1,368.42	-312.14	-507.62	-2,474.76	-622.73	-893.66	-3,466.4	1,984,499.5
std. error	(54.97)	(79.86)	(91.78)	(55.35)	(73.3)	(89.29)	(72.19)	(62.99)	(76.77)	(74.18)	(64.91)	(93.09)	(74.25)		(1737.6)
%	*-0.004%*	*-0.004%*	*-0.028%*	*-0.023%*	*0.055%*	*0.117%*	*-0.114%*	*0.069%*	*-0.016%*	*-0.026%*	*-0.125%*	*-0.031%*	*-0.045%*	*-0.175%*	*100%*
outdoor	-35.22	-235.91	-490.62	-682.04	-566.43	-1,030.39	-796.80	-1,197.15	-879.68	-520.94	152.20	110.13	-264.05	-6,436.9	254,265.6
	(47.36)	(41.34)	(41.46)	(44.5)	(54.77)	(54.03)	(59.97)	(60.97)	(55.62)	(91.3)	(69.66)	(66.34)	(73.56)		(695.1)
	-0.014%	*-0.093%*	*-0.193%*	*-0.268%*	*-0.223%*	*-0.405%*	*-0.313%*	*-0.471%*	*-0.346%*	*-0.205%*	*0.060%*	*0.043%*	*-0.104%*	*-2.532%*	*100%*
office	-52.57	-693.20	-2,319.97	-1,740.18	-815.58	1,046.97	2,302.80	4,354.88	1,833.96	4,493.53	792.44	1,250.44	1,023.07	11,476.6	1,016,174.0
	(79.58)	(82.46)	(108.07)	(84.81)	(93.35)	(112.07)	(112.43)	(91.36)	(101.08)	(135.84)	(90.81)	(91.67)	(111.)		(1154.1)
	-0.005%	*-0.068%*	*-0.228%*	*-0.171%*	*-0.080%*	*0.103%*	*0.227%*	*0.429%*	*0.180%*	*0.442%*	*0.078%*	*0.123%*	*0.101%*	*1.129%*	*100%*
informal	-148.23	641.64	1,866.59	1,575.39	1,799.43	1,052.13	-2,776.19	-1,847.93	-1,933.46	-3,625.90	-3,079.41	-1,578.08	-1,413.76	-9,467.8	374,545.4
	(51.16)	(68.83)	(52.29)	(49.33)	(57.98)	(70.94)	(85.05)	(63.43)	(59.22)	(111.23)	(57.95)	(54.37)	(46.85)		(910.8)
	-0.040%	*0.171%*	*0.498%*	*0.421%*	*0.480%*	*0.281%*	*-0.741%*	*-0.493%*	*-0.516%*	*-0.968%*	*-0.822%*	*-0.421%*	*-0.377%*	*-2.528%*	*100%*
permanent	56.77	-500.44	-1,673.52	-947.45	-703.67	113.77	3,148.95	2,885.71	2,060.99	3,043.41	404.11	972.10	609.90	9,470.6	831,987.0
	(79.4)	(69.9)	(100.64)	(75.6)	(84.22)	(104.43)	(99.93)	(85.)	(96.56)	(125.6)	(83.65)	(86.26)	(116.87)		(1029.5)
	0.007%	*-0.060%*	*-0.201%*	*-0.114%*	*-0.085%*	*0.014%*	*0.378%*	*0.347%*	*0.248%*	*0.366%*	*0.049%*	*0.117%*	*0.073%*	*1.138%*	*100%*
temporary	115.52	641.42	1,444.27	920.94	2,198.05	2,406.34	-5,707.54	-2,016.30	-2,805.42	-4,041.00	-3,260.32	-1,737.33	-1,519.94	-13,361.3	1,153,312.3
	(50.83)	(80.39)	(71.)	(54.58)	(68.21)	(85.12)	(76.1)	(66.71)	(73.68)	(118.77)	(71.88)	(80.05)	(77.85)		(1433.3)
	0.010%	*0.056%*	*0.125%*	*0.080%*	*0.191%*	*0.209%*	*-0.495%*	*-0.175%*	*-0.243%*	*-0.350%*	*-0.283%*	*-0.151%*	*-0.132%*	*-1.159%*	*100%*
minimum wage	145.05	715.38	1,962.87	2,032.73	1,639.91	585.30	-1,649.80	-2,532.79	-3,045.08	-3,804.96	-3,820.66	-2,190.97	-1,569.47	-11,532.5	57,503.9
	(64.36)	(50.25)	(55.62)	(56.41)	(66.48)	(73.5)	(65.21)	(69.12)	(76.54)	(93.56)	(82.82)	(62.)	(77.81)		(846.9)
	0.252%	*1.244%*	*3.413%*	*3.535%*	*2.852%*	*1.018%*	*-2.869%*	*-4.405%*	*-5.295%*	*-6.617%*	*-6.644%*	*-3.810%*	*-2.729%*	*-20.055%*	*100%*
piecework	-110.57	415.67	914.97	354.80	1,407.94	442.67	-1,308.18	-814.90	-1,375.04	-1,225.20	-2,003.18	-1,188.94	-972.83	-5,462.8	270,349.4
	(63.3)	(70.5)	(66.7)	(66.66)	(77.81)	(91.42)	(105.68)	(77.59)	(70.77)	(147.61)	(69.93)	(63.56)	(83.64)		(705.7)
	-0.041%	*0.154%*	*0.338%*	*0.131%*	*0.521%*	*0.164%*	*-0.484%*	*-0.301%*	*-0.509%*	*-0.453%*	*-0.741%*	*-0.440%*	*-0.360%*	*-2.021%*	*100%*
weekly earnings	-1,165.33	-162.07	670.12	981.41	449.19	1,539.22	-6,131.52	-5,274.76	-3,581.82	-6,340.98	-4,763.76	-3,742.29	-3,538.19	-31,060.8	890,220.9
	(97.99)	(94.93)	(72.77)	(69.05)	(80.72)	(93.72)	(101.62)	(97.88)	(89.64)	(167.02)	(100.58)	(98.18)	(119.97)		(1225.5)
	-0.131%	*-0.018%*	*0.075%*	*0.110%*	*0.050%*	*0.173%*	*-0.689%*	*-0.593%*	*-0.402%*	*-0.712%*	*-0.535%*	*-0.420%*	*-0.397%*	*-3.489%*	*100%*
metro	100.06	-103.90	-277.94	-850.98	206.48	1,418.50	-1,899.61	1,311.93	55.70	-330.72	-1,460.07	-115.97	-382.58	-2,329.1	1,230,214.1
	(55.33)	(85.88)	(102.75)	(55.45)	(77.21)	(97.78)	(76.84)	(66.52)	(91.34)	(73.62)	(63.59)	(94.88)	(78.23)		(1307.1)
	0.008%	*-0.008%*	*-0.023%*	*-0.069%*	*0.017%*	*0.115%*	*-0.154%*	*0.107%*	*0.005%*	*-0.027%*	*-0.119%*	*-0.009%*	*-0.031%*	*-0.189%*	*100%*
rural	-16.52	250.18	541.07	1,157.48	1,325.11	411.67	-568.58	-2,619.20	-1,752.53	-1,991.44	-2,070.42	-1,300.97	-729.59	-7,363.8	311,686.4
	(47.5)	(42.98)	(44.32)	(44.44)	(45.33)	(54.94)	(53.18)	(66.71)	(49.93)	(88.35)	(55.58)	(45.38)	(81.03)		(811.1)
	-0.005%	*0.080%*	*0.174%*	*0.371%*	*0.425%*	*0.132%*	*-0.182%*	*-0.840%*	*-0.562%*	*-0.639%*	*-0.664%*	*-0.417%*	*-0.234%*	*-2.363%*	*100%*

Notes: Counterfactual estimate based on annual weather of 20-22°C and precipitation of 2-4 mm precipitation.

Table A.10.2: Earnings Losses by Precipitation Bin

	Bins								Total	
Regressors	[=0]	(0-2]	(4-6]	(6-8]	(8-10]	(10-20]	(20-30]	(> 30]	Δ	potential earnings
municipio	-1,752.73	2,390.96	190.35	-1,104.12	649.57	-326.76	-61.76	-557.29	-571.8	1,981,743.0
std. error	(178.54)	(235.63)	(86.88)	(60.11)	(51.59)	(64.38)	(34.53)	(53.17)		(1786.9)
%	*-0.088%*	*0.121%*	*0.010%*	*-0.056%*	*0.033%*	*-0.016%*	*-0.003%*	*-0.028%*	*-0.029%*	*100%*
outdoor	6,595.81	403.64	-554.24	-516.88	-426.92	-1,128.07	-171.40	-82.27	4,119.7	244,253.3
	(124.5)	(153.14)	(46.43)	(37.83)	(32.56)	(45.96)	(28.35)	(25.64)		(763.4)
	2.700%	*0.165%*	*-0.227%*	*-0.212%*	*-0.175%*	*-0.462%*	*-0.070%*	*-0.034%*	*1.687%*	*100%*
office	9,071.41	12,730.86	153.98	-623.35	480.13	2,407.51	822.78	343.91	25,387.2	1,003,025.2
	(267.43)	(312.96)	(97.98)	(85.16)	(61.27)	(74.99)	(47.06)	(62.25)		(1244.3)
	0.904%	*1.269%*	*0.015%*	*-0.062%*	*0.048%*	*0.240%*	*0.082%*	*0.034%*	*2.531%*	*100%*
informal	-12,776.04	-9,277.97	676.23	150.88	82.93	-1,241.41	-703.70	-465.92	-23,555.0	388,583.9
	(151.33)	(163.12)	(48.6)	(36.65)	(35.79)	(47.86)	(26.77)	(29.69)		(970.4)
	-3.288%	*-2.388%*	*0.174%*	*0.039%*	*0.021%*	*-0.319%*	*-0.181%*	*-0.120%*	*-6.062%*	*100%*
permanent	9,747.62	13,708.19	778.87	-399.93	602.37	2,500.49	562.88	387.38	27,887.9	814,675.3
	(265.64)	(282.85)	(93.13)	(74.5)	(60.68)	(75.14)	(41.18)	(53.33)		(1113.8)
	1.197%	*1.683%*	*0.096%*	*-0.049%*	*0.074%*	*0.307%*	*0.069%*	*0.048%*	*3.423%*	*100%*
temporary	-11,300.62	-11,788.77	-669.79	-775.24	-68.41	-3,214.20	-737.63	-1,075.68	-29,630.3	1,169,216.4
	(156.26)	(188.19)	(61.01)	(49.08)	(42.72)	(59.76)	(30.47)	(42.87)		(1483.)
	-0.967%	*-1.008%*	*-0.057%*	*-0.066%*	*-0.006%*	*-0.275%*	*-0.063%*	*-0.092%*	*-2.534%*	*100%*
minimum wage	-19,478.78	-17,988.54	-711.41	-1,060.99	-416.12	-2,570.66	-798.88	-850.78	-43,876.2	89,292.4
	(214.39)	(181.02)	(37.32)	(31.41)	(27.35)	(65.36)	(34.64)	(32.27)		(932.1)
	-21.815%	*-20.146%*	*-0.797%*	*-1.188%*	*-0.466%*	*-2.879%*	*-0.895%*	*-0.953%*	*-49.138%*	*100%*
piecework	-6,897.45	-5,612.19	-391.74	-557.69	267.91	-1,610.52	-708.63	-397.93	-15,908.2	280,637.7
	(164.96)	(219.58)	(60.93)	(43.81)	(45.89)	(67.85)	(36.97)	(38.86)		(797.4)
	-2.458%	*-2.000%*	*-0.140%*	*-0.199%*	*0.095%*	*-0.574%*	*-0.253%*	*-0.142%*	*-5.669%*	*100%*
weekly earnings	-14,239.43	-7,085.92	-841.51	-69.37	166.66	-2,205.88	-647.03	-1,177.73	-26,100.2	885,604.3
	(242.01)	(250.48)	(52.61)	(46.23)	(35.13)	(78.51)	(42.3)	(42.49)		(1263.8)
	-1.608%	*-0.800%*	*-0.095%*	*-0.008%*	*0.019%*	*-0.249%*	*-0.073%*	*-0.133%*	*-2.947%*	*100%*
metro	2,337.47	7,064.06	140.58	-132.41	1,285.35	-5.09	97.76	-422.42	10,365.3	1,218,248.6
	(200.05)	(268.32)	(104.75)	(70.3)	(58.55)	(67.98)	(33.34)	(54.14)		(1341.7)
	0.192%	*0.580%*	*0.012%*	*-0.011%*	*0.106%*	*0.000%*	*0.008%*	*-0.035%*	*0.851%*	*100%*
rural	-2,428.95	-1,204.59	-83.02	-298.33	-475.07	-919.64	-647.45	-406.93	-6,464.0	310,823.8
	(113.9)	(159.96)	(52.17)	(41.64)	(38.87)	(48.76)	(31.73)	(27.31)		(848.4)
	-0.781%	*-0.388%*	*-0.027%*	*-0.096%*	*-0.153%*	*-0.296%*	*-0.208%*	*-0.131%*	*-2.080%*	*100%*

Notes: Counterfactual estimate based on annual weather of 20-22°C and precipitation of 2-4 mm precipitation.

Table A.10.3: Working Time Losses by Temperature Bin

	Bins													Total	
Regressors	(≤ 10]	(10-12]	(12-14]	(14-16]	(16-18]	(18-20]	(22-24]	(24-26]	(26-28]	(28-30]	(30-32]	(32-34]	(> 34]	Δ	potential working t
municipio	-669.66	-422.75	-840.01	33.79	-1.24	-79.72	104.78	-429.15	291.16	1,091.66	-492.76	6.84	-200.72	-1,607.8	4,370,075.8
std. error	(32.27)	(30.99)	(40.07)	(39.92)	(40.43)	(47.85)	(43.54)	(38.19)	(37.88)	(33.58)	(35.06)	(33.12)	(43.75)		(897.1)
%	*-0.015%*	*-0.010%*	*-0.019%*	*0.001%*	*0.000%*	*-0.002%*	*0.002%*	*-0.010%*	*0.007%*	*0.025%*	*-0.011%*	*0.000%*	*-0.005%*	*-0.037%*	*100%*
outdoor	95.98	-888.25	-1,340.29	-1,922.55	-1,680.23	-1,266.63	617.00	-546.22	665.88	964.07	492.20	255.02	317.20	-4,236.8	677,707.0
	(47.51)	(46.62)	(53.01)	(55.59)	(63.86)	(68.19)	(66.11)	(58.72)	(56.04)	(77.34)	(62.5)	(48.14)	(70.6)		(477.2)
	0.014%	*-0.131%*	*-0.198%*	*-0.284%*	*-0.248%*	*-0.187%*	*0.091%*	*-0.081%*	*0.098%*	*0.142%*	*0.073%*	*0.038%*	*0.047%*	*-0.625%*	*100%*
office	-290.82	-138.97	-164.51	-675.26	-548.22	-904.98	936.43	949.15	1,371.59	2,313.21	1,133.40	894.49	496.11	5,371.6	1,731,624.0
	(28.47)	(25.78)	(36.25)	(33.)	(35.57)	(41.41)	(48.18)	(41.43)	(46.81)	(68.73)	(56.58)	(30.76)	(67.22)		(531.4)
	-0.017%	*-0.008%*	*-0.010%*	*-0.039%*	*-0.032%*	*-0.052%*	*0.054%*	*0.055%*	*0.079%*	*0.134%*	*0.065%*	*0.052%*	*0.029%*	*0.310%*	*100%*
informal	-160.73	362.04	1,266.21	2,122.22	2,265.62	2,516.02	-1,787.34	-1,522.12	-1,817.04	-2,975.32	-2,236.28	-1,141.15	-1,103.26	-4,211.1	1,083,330.4
	(46.05)	(44.27)	(49.41)	(50.01)	(48.71)	(61.15)	(57.77)	(58.77)	(51.95)	(72.15)	(62.86)	(48.24)	(41.6)		(572.)
	-0.015%	*0.033%*	*0.117%*	*0.196%*	*0.209%*	*0.232%*	*-0.165%*	*-0.141%*	*-0.168%*	*-0.275%*	*-0.206%*	*-0.105%*	*-0.102%*	*-0.389%*	*100%*
permanent	-146.31	-280.50	-355.56	-747.53	-427.84	-904.52	758.07	830.27	1,038.20	1,947.73	990.69	892.78	374.66	3,970.1	1,354,822.8
	(26.08)	(26.04)	(34.5)	(29.03)	(32.46)	(37.99)	(43.82)	(40.71)	(50.17)	(64.2)	(53.68)	(33.4)	(71.36)		(469.6)
	-0.011%	*-0.021%*	*-0.026%*	*-0.055%*	*-0.032%*	*-0.067%*	*0.056%*	*0.061%*	*0.077%*	*0.144%*	*0.073%*	*0.066%*	*0.028%*	*0.293%*	*100%*
temporary	-412.07	-47.15	-269.86	959.02	632.71	911.97	-781.92	-1,522.41	-989.08	-1,142.64	-1,700.43	-967.93	-594.43	-5,924.2	3,015,757.7
	(43.27)	(40.76)	(46.41)	(45.69)	(46.58)	(53.58)	(51.01)	(52.32)	(42.57)	(56.79)	(48.7)	(43.8)	(42.87)		(777.2)
	-0.014%	*-0.002%*	*-0.009%*	*0.032%*	*0.021%*	*0.030%*	*-0.026%*	*-0.050%*	*-0.033%*	*-0.038%*	*-0.056%*	*-0.032%*	*-0.020%*	*-0.196%*	*100%*
minimum	114.88	-23.14	29.85	736.22	-120.40	110.49	-1,049.42	-1,268.67	-1,347.83	-2,047.87	-1,712.18	-650.06	-596.07	-7,824.2	722,522.1
wage	(42.46)	(43.84)	(51.81)	(51.71)	(55.58)	(63.91)	(66.28)	(76.86)	(61.51)	(97.55)	(58.09)	(48.09)	(51.13)		(504.9)
	0.016%	*-0.003%*	*0.004%*	*0.102%*	*-0.017%*	*0.015%*	*-0.145%*	*-0.176%*	*-0.187%*	*-0.283%*	*-0.237%*	*-0.090%*	*-0.082%*	*-1.083%*	*100%*
piecework	-248.45	-74.32	-59.74	157.42	131.31	987.54	1,780.65	1,756.84	1,129.31	2,191.92	641.30	24.18	63.39	8,481.4	569,470.8
	(45.39)	(50.01)	(59.15)	(57.35)	(66.55)	(79.63)	(117.42)	(92.45)	(68.12)	(156.53)	(76.84)	(67.59)	(76.76)		(462.5)
	-0.044%	*-0.013%*	*-0.010%*	*0.028%*	*0.023%*	*0.173%*	*0.313%*	*0.309%*	*0.198%*	*0.385%*	*0.113%*	*0.004%*	*0.011%*	*1.489%*	*100%*
weekly	-649.07	144.62	-60.60	598.86	557.08	-34.90	-890.79	-380.59	352.17	-766.56	-96.49	-172.26	-243.23	-1,641.8	1,603,739.7
earnings	(30.06)	(32.31)	(36.15)	(32.11)	(34.38)	(40.44)	(51.36)	(41.96)	(35.75)	(61.8)	(50.22)	(48.14)	(59.02)		(582.)
	-0.040%	*0.009%*	*-0.004%*	*0.037%*	*0.035%*	*-0.002%*	*-0.056%*	*-0.024%*	*0.022%*	*-0.048%*	*-0.006%*	*-0.011%*	*-0.015%*	*-0.102%*	*100%*
metro	-327.80	-467.20	123.68	-257.29	298.74	303.96	229.09	-379.08	132.63	12.63	-105.50	26.30	-169.98	-579.8	2,475,459.3
	(29.72)	(26.3)	(36.41)	(36.95)	(35.55)	(44.57)	(38.78)	(34.21)	(32.74)	(23.98)	(29.58)	(28.03)	(43.42)		(672.1)
	-0.013%	*-0.019%*	*0.005%*	*-0.010%*	*0.012%*	*0.012%*	*0.009%*	*-0.015%*	*0.005%*	*0.001%*	*-0.004%*	*0.001%*	*-0.007%*	*-0.023%*	*100%*
rural	-20.58	-273.59	-440.19	-488.38	-250.35	-834.10	-871.23	-1,739.37	-764.83	-1,043.04	-938.10	-778.06	-2.61	-8,444.4	895,755.2
	(40.95)	(45.76)	(52.49)	(50.95)	(56.56)	(64.52)	(66.89)	(56.69)	(56.83)	(67.01)	(53.77)	(46.74)	(44.62)		(455.)
	-0.002%	*-0.031%*	*-0.049%*	*-0.055%*	*-0.028%*	*-0.093%*	*-0.097%*	*-0.194%*	*-0.085%*	*-0.116%*	*-0.105%*	*-0.087%*	*0.000%*	*-0.943%*	*100%*

Notes: Counterfactual estimate based on annual weather of 20-22°C and precipitation of 2-4 mm precipitation.

Table A.10.4: Working Time Losses by Precipitation Bin

	Bins								Total	
Regressors	[=0]	(0-2]	(4-6]	(6-8]	(8-10]	(10-20]	(20-30]	(> 30]	Δ	potential working time
municipio	1,237.33	-3,109.13	-383.60	-407.39	72.49	-1,481.80	-1,488.02	-2,225.05	-7,785.2	4,377,639.8
std. error	(110.27)	(148.59)	(47.85)	(44.04)	(34.17)	(40.6)	(25.8)	(30.24)		(940.2)
%	*0.028%*	*-0.071%*	*-0.009%*	*-0.009%*	*0.002%*	*-0.034%*	*-0.034%*	*-0.051%*	*-0.178%*	*100%*
outdoor	16,363.64	8,677.51	-360.56	452.20	154.04	249.81	-502.59	-1,141.80	23,892.3	650,206.3
	(175.73)	(192.65)	(57.47)	(49.24)	(42.02)	(56.82)	(35.96)	(42.33)		(600.4)
	2.517%	*1.335%*	*-0.055%*	*0.070%*	*0.024%*	*0.038%*	*-0.077%*	*-0.176%*	*3.675%*	*100%*
office	5,017.39	4,528.29	539.42	-345.60	-43.98	584.65	-71.73	-104.16	10,104.3	1,731,734.2
	(120.84)	(122.22)	(36.06)	(31.82)	(24.45)	(29.72)	(19.)	(19.45)		(613.3)
	0.290%	*0.261%*	*0.031%*	*-0.020%*	*-0.003%*	*0.034%*	*-0.004%*	*-0.006%*	*0.583%*	*100%*
informal	-11,507.29	-10,676.79	-324.80	-328.45	-279.94	-2,246.80	-1,118.45	-1,265.57	-27,748.1	1,106,575.0
	(138.65)	(166.25)	(54.99)	(50.83)	(40.73)	(47.28)	(34.51)	(29.16)		(605.2)
	-1.040%	*-0.965%*	*-0.029%*	*-0.030%*	*-0.025%*	*-0.203%*	*-0.101%*	*-0.114%*	*-2.508%*	*100%*
permanent	7,725.94	6,777.82	836.83	-29.02	-0.90	828.11	53.18	27.47	16,219.4	1,345,878.6
	(114.44)	(117.3)	(33.47)	(31.81)	(23.29)	(27.47)	(18.91)	(19.83)		(535.4)
	0.574%	*0.504%*	*0.062%*	*-0.002%*	*0.000%*	*0.062%*	*0.004%*	*0.002%*	*1.205%*	*100%*
temporary	-5,990.09	-9,712.02	-1,273.03	-403.20	24.97	-2,487.86	-1,607.44	-2,364.89	-23,813.6	3,038,863.9
	(120.27)	(156.73)	(55.6)	(47.96)	(37.23)	(44.23)	(30.11)	(35.)		(815.8)
	-0.197%	*-0.320%*	*-0.042%*	*-0.013%*	*0.001%*	*-0.082%*	*-0.053%*	*-0.078%*	*-0.784%*	*100%*
minimum	-5,779.51	-5,729.16	-271.95	228.12	112.41	-345.07	-193.13	-1,025.76	-13,004.1	726,683.8
wage	(136.49)	(181.17)	(64.95)	(49.45)	(42.32)	(60.87)	(33.92)	(31.69)		(555.6)
	-0.795%	*-0.788%*	*-0.037%*	*0.031%*	*0.015%*	*-0.047%*	*-0.027%*	*-0.141%*	*-1.790%*	*100%*
piecework	1,294.13	4,101.67	-123.85	621.28	105.91	702.06	-241.28	-151.92	6,308.0	573,036.5
	(148.5)	(222.69)	(64.05)	(51.69)	(42.33)	(59.59)	(34.71)	(43.16)		(555.6)
	0.226%	*0.716%*	*-0.022%*	*0.108%*	*0.018%*	*0.123%*	*-0.042%*	*-0.027%*	*1.101%*	*100%*
weekly	-8,004.46	-9,771.49	-466.48	-789.25	246.73	-1,117.42	-598.74	-1,041.88	-21,543.0	1,623,136.0
earnings	(135.)	(163.1)	(41.31)	(31.28)	(29.82)	(40.18)	(25.56)	(29.52)		(634.)
	-0.493%	*-0.602%*	*-0.029%*	*-0.049%*	*0.015%*	*-0.069%*	*-0.037%*	*-0.064%*	*-1.327%*	*100%*
metro	50.15	-1,988.33	-558.89	-820.44	614.20	-861.89	-721.69	-747.81	-5,034.7	2,480,590.1
	(112.52)	(144.93)	(45.54)	(45.71)	(30.33)	(35.72)	(21.76)	(24.69)		(736.1)
	0.002%	*-0.080%*	*-0.023%*	*-0.033%*	*0.025%*	*-0.035%*	*-0.029%*	*-0.030%*	*-0.203%*	*100%*
rural	2,288.21	-4,444.68	-225.07	-304.45	-62.93	-1,240.81	-1,028.15	-1,445.13	-6,463.0	892,774.8
	(140.23)	(190.18)	(66.04)	(53.5)	(44.73)	(59.94)	(39.87)	(39.41)		(559.01)
	0.256%	*-0.498%*	*-0.025%*	*-0.034%*	*-0.007%*	*-0.139%*	*-0.115%*	*-0.162%*	*-0.724%*	*100%*

Notes: Counterfactual estimate based on annual weather of 20-22°C and precipitation of 2-4 mm precipitation.

A.10.2 Industry Cost Estimates

Table A.10.5: Industry Earnings Losses by Temperature Bin

	Bins													Total	
Regressors	(≤ 10]	(10-12]	(12-14]	(14-16]	(16-18]	(18-20]	(22-24]	(24-26]	(26-28]	(28-30]	(30-32]	(32-34]	(> 34]	Δ	potential earnings
municipio	- 78.12	- 80.29	- 556.06	- 452.22	1,083.55	2,318.28	- 2,259.08	1,368.42	- 312.14	- 507.62	- 2,474.76	- 622.73	- 893.66	- 3,466.43	1,985,071.4
std. error	(54.97)	(79.85)	(91.78)	(55.35)	(73.29)	(89.29)	(72.19)	(62.99)	(76.77)	(74.18)	(64.91)	(93.09)	(74.25)		(1778.4)
%	*-0.004%*	*-0.004%*	*-0.028%*	*-0.023%*	*0.055%*	*0.117%*	*-0.114%*	*0.069%*	*-0.016%*	*-0.026%*	*-0.125%*	*-0.031%*	*-0.045%*	-0.17%	*100%*
Agriculture	- 76.67	- 284.50	- 826.17	- 747.39	- 737.47	- 1,396.07	- 724.02	- 947.60	- 276.62	- 35.77	519.03	600.98	167.26	- 4,765.01	167,840.9
	(50.94)	(42.01)	(41.83)	(49.24)	(61.11)	(52.49)	(58.11)	(68.38)	(58.7)	(91.81)	(74.47)	(66.36)	(76.97)		(802.7)
	-0.046%	*-0.170%*	*-0.492%*	*-0.445%*	*-0.439%*	*-0.832%*	*-0.431%*	*-0.565%*	*-0.165%*	*-0.021%*	*0.309%*	*0.358%*	*0.100%*	-2.84%	*100%*
Extractive Industry	- 126.93	- 208.20	- 354.91	- 375.48	- 429.08	- 525.68	435.12	741.98	553.96	1,294.79	769.97	238.99	637.49	2,652.02	30,414.0
	(56.19)	(59.96)	(71.49)	(63.04)	(79.55)	(98.64)	(120.15)	(116.79)	(88.24)	(193.71)	(157.87)	(53.18)	(213.98)		(434.0)
	-0.42%	-0.68%	-1.17%	-1.23%	-1.41%	-1.73%	1.43%	2.44%	1.82%	4.26%	2.53%	0.79%	2.10%	8.72%	
Manufacturing	- 375.23	17.07	348.06	662.07	949.63	2,427.86	1,138.18	243.44	- 1,056.83	371.48	- 1,460.32	- 925.78	- 1,190.61	1,149.02	355,418.4
	(69.93)	(45.91)	(59.1)	(50.27)	(50.81)	(71.39)	(91.39)	(53.21)	(53.83)	(101.13)	(67.17)	(53.12)	(75.87)		(933.5)
	-0.106%	*0.005%*	*0.098%*	*0.186%*	*0.267%*	*0.683%*	*0.320%*	*0.068%*	*-0.297%*	*0.105%*	*-0.411%*	*-0.260%*	*-0.335%*	0.32%	*100%*
Construction	- 392.91	- 257.35	- 165.47	- 817.12	- 467.34	- 715.44	- 1,170.56	- 14.25	- 121.66	- 129.90	- 171.14	83.39	- 302.97	- 4,642.72	226,360.3
	(40.58)	(45.98)	(50.16)	(54.93)	(47.72)	(62.6)	(57.07)	(60.59)	(60.71)	(63.39)	(56.95)	(102.91)	(71.35)		(620.5)
	-0.174%	*-0.114%*	*-0.073%*	*-0.361%*	*-0.206%*	*-0.316%*	*-0.517%*	*-0.006%*	*-0.054%*	*-0.057%*	*-0.076%*	*0.037%*	*-0.134%*	-2.05%	*100%*
Trade	132.42	1,050.68	838.12	2,179.38	1,988.72	3,147.85	- 279.80	- 380.39	188.92	- 949.49	- 1,059.90	- 782.02	- 603.31	5,471.18	298,353.5
	(35.71)	(52.9)	(51.7)	(42.85)	(51.55)	(64.49)	(58.98)	(55.72)	(61.3)	(89.36)	(48.52)	(39.63)	(56.98)		(843.9)
	0.044%	*0.352%*	*0.281%*	*0.730%*	*0.667%*	*1.055%*	*-0.094%*	*-0.127%*	*0.063%*	*-0.318%*	*-0.355%*	*-0.262%*	*-0.202%*	1.83%	*100%*
Restaurant Service	115.69	184.93	566.28	426.53	586.22	- 203.54	- 919.19	- 363.31	- 702.11	- 1,121.56	- 1,230.89	- 433.16	- 499.40	- 3,593.51	125,714.4
	(29.67)	(38.19)	(41.16)	(38.5)	(47.)	(51.78)	(63.92)	(47.7)	(46.01)	(84.88)	(51.06)	(50.14)	(53.91)		(584.9)
	0.092%	*0.147%*	*0.450%*	*0.339%*	*0.466%*	*-0.162%*	*-0.731%*	*-0.289%*	*-0.558%*	*-0.892%*	*-0.979%*	*-0.345%*	*-0.397%*	-2.86%	*100%*
Transport	112.32	8.67	- 112.12	- 185.66	90.51	- 42.90	- 309.74	- 15.73	37.06	37.48	34.57	187.42	139.56	- 18.56	125,789.1
	(48.6)	(45.83)	(68.24)	(47.17)	(75.11)	(69.54)	(65.33)	(53.46)	(53.57)	(58.5)	(56.1)	(47.05)	(48.69)		(511.8)
	0.089%	*0.007%*	*-0.089%*	*-0.148%*	*0.072%*	*-0.034%*	*-0.246%*	*-0.013%*	*0.029%*	*0.030%*	*0.027%*	*0.149%*	*0.111%*	-0.01%	*100%*
Professional Services	40.98	- 158.30	- 496.74	- 981.12	- 27.69	- 212.92	136.91	651.24	613.07	- 16.19	681.83	323.99	202.31	757.37	148,295.3
	(38.22)	(55.23)	(83.35)	(58.28)	(72.11)	(112.55)	(86.87)	(70.55)	(73.51)	(89.82)	(71.89)	(85.83)	(55.28)		(587.9)
	0.028%	*-0.107%*	*-0.335%*	*-0.662%*	*-0.019%*	*-0.144%*	*0.092%*	*0.439%*	*0.413%*	*-0.011%*	*0.460%*	*0.218%*	*0.136%*	0.51%	*100%*
Social Services	135.39	- 457.41	- 578.71	- 767.14	- 706.68	- 584.52	270.58	1,214.52	1,213.52	1,040.05	896.35	830.01	537.18	3,043.14	203,053.6
	(59.8)	(51.93)	(65.21)	(72.08)	(71.56)	(79.)	(68.9)	(64.98)	(87.12)	(94.11)	(77.26)	(57.27)	(61.34)		(714.3)
	0.067%	*-0.225%*	*-0.285%*	*-0.378%*	*-0.348%*	*-0.288%*	*0.133%*	*0.598%*	*0.598%*	*0.512%*	*0.441%*	*0.409%*	*0.265%*	1.50%	*100%*
Diverse Services	130.45	249.50	708.61	509.83	111.24	- 107.59	- 1,245.43	- 672.73	- 1,365.81	- 955.86	- 1,541.09	- 788.07	- 449.76	- 5,416.71	187,086.0
	(47.86)	(46.6)	(47.35)	(44.76)	(43.88)	(61.55)	(66.06)	(48.24)	(46.65)	(83.51)	(50.98)	(42.89)	(39.09)		(640.3)
	0.070%	*0.133%*	*0.379%*	*0.273%*	*0.059%*	*-0.058%*	*-0.666%*	*-0.360%*	*-0.730%*	*-0.511%*	*-0.824%*	*-0.421%*	*-0.240%*	-2.90%	*100%*
Government	- 0.32	- 212.19	- 345.65	- 362.43	- 207.04	200.13	123.03	250.45	216.71	- 110.15	17.03	10.43	109.47	- 310.53	121,222.6
	(61.36)	(51.5)	(73.75)	(61.87)	(62.23)	(96.19)	(70.55)	(59.22)	(65.05)	(98.24)	(64.58)	(48.4)	(55.62)		(524.6)
	0.000%	*-0.175%*	*-0.285%*	*-0.299%*	*-0.171%*	*0.165%*	*0.101%*	*0.207%*	*0.179%*	*-0.091%*	*0.014%*	*0.009%*	*0.090%*	-0.26%	*100%*

Notes: Counterfactual estimate based on annual weather of 20-22°C and precipitation of 2-4 mm precipitation.

Table A.10.6: Industry Earnings Losses by Precipitation Bin

	Bins								Total	
Regressors	[=0]	(0-2]	(4-6]	(6-8]	(8-10]	(10-20]	(20-30]	(> 30]	Δ	potential earnings
municipio	- 1,752.73	2,390.96	190.35	- 1,104.12	649.57	- 326.76	- 61.76	- 557.29	- 571.78	1,985,071.4
std. error	(178.54)	(235.63)	(86.88)	(60.11)	(51.59)	(64.38)	(34.53)	(53.16)		(1778.4)
%	*-0.088%*	*0.120%*	*0.010%*	*-0.056%*	*0.033%*	*-0.016%*	*-0.003%*	*-0.028%*	*-0.029%*	*100%*
Agriculture	12,457.53	5,127.85	- 101.47	- 162.79	- 427.97	- 679.99	- 3.20	- 18.89	16,191.07	154,715.9
	(152.54)	(174.81)	(48.91)	(39.13)	(33.68)	(50.44)	(31.01)	(27.94)		(871.7)
	8.052%	*3.314%*	*-0.066%*	*-0.105%*	*-0.277%*	*-0.440%*	*-0.002%*	*-0.012%*	*10.465%*	*100%*
Extractive Industry	- 2,372.72	- 2,610.21	- 120.63	157.17	98.03	28.41	109.36	83.76	- 4,626.83	37,784.2
	(244.49)	(293.78)	(81.8)	(84.29)	(65.5)	(95.79)	(55.74)	(49.31)		(743.1)
	-6.280%	*-6.908%*	*-0.319%*	*0.416%*	*0.259%*	*0.075%*	*0.289%*	*0.222%*	*-12.245%*	*100%*
Manufacturing	- 6,150.92	925.35	- 136.59	- 670.62	- 210.43	601.24	- 105.14	183.89	- 5,563.22	368,323.1
	(264.32)	(300.31)	(69.69)	(42.75)	(41.13)	(54.72)	(33.52)	(38.86)		(990.5)
	-1.670%	*0.251%*	*-0.037%*	*-0.182%*	*-0.057%*	*0.163%*	*-0.029%*	*0.050%*	*-1.510%*	*100%*
Construction	- 1,025.60	- 865.42	- 167.59	- 59.39	489.48	333.67	- 38.98	- 91.76	- 1,425.59	226,838.5
	(154.49)	(179.1)	(49.13)	(41.64)	(37.35)	(49.08)	(29.5)	(32.01)		(705.8)
	-0.452%	*-0.382%*	*-0.074%*	*-0.026%*	*0.216%*	*0.147%*	*-0.017%*	*-0.040%*	*-0.628%*	*100%*
Trade	- 1,025.60	- 865.42	- 167.59	- 59.39	489.48	333.67	- 38.98	- 91.76	- 1,425.59	226,838.5
	(154.49)	(179.1)	(49.13)	(41.64)	(37.35)	(49.08)	(29.5)	(32.01)		(705.8)
	-0.452%	*-0.382%*	*-0.074%*	*-0.026%*	*0.216%*	*0.147%*	*-0.017%*	*-0.040%*	*-0.628%*	*100%*
Restaurant Service	- 1,959.84	- 72.03	- 198.51	173.19	222.68	- 342.72	- 267.81	- 88.40	- 2,533.44	128,737.9
	(124.46)	(143.47)	(43.05)	(35.21)	(32.81)	(44.05)	(22.48)	(27.25)		(575.0)
	-1.522%	*-0.056%*	*-0.154%*	*0.135%*	*0.173%*	*-0.266%*	*-0.208%*	*-0.069%*	*-1.968%*	*100%*
Transport	581.66	299.00	- 154.79	- 147.22	- 156.49	- 153.36	- 70.57	- 81.76	116.47	127,648.4
	(143.57)	(209.78)	(62.08)	(81.35)	(48.69)	(52.21)	(33.17)	(23.06)		(579.6)
	0.456%	*0.234%*	*-0.121%*	*-0.115%*	*-0.123%*	*-0.120%*	*-0.055%*	*-0.064%*	*0.091%*	*100%*
Professional Services	278.05	212.81	362.87	202.11	360.38	- 390.94	174.28	- 124.94	1,074.62	150,533.9
	(187.09)	(234.53)	(86.56)	(75.37)	(61.17)	(66.79)	(43.95)	(43.34)		(702.1)
	0.185%	*0.141%*	*0.241%*	*0.134%*	*0.239%*	*-0.260%*	*0.116%*	*-0.083%*	*0.714%*	*100%*
Social Services	- 2,181.72	- 6,041.92	- 331.78	- 289.58	- 291.58	207.11	218.20	- 43.78	- 8,755.05	216,988.1
	(197.49)	(206.91)	(66.35)	(51.47)	(46.54)	(58.99)	(38.37)	(36.74)		(763.5)
	-1.005%	*-2.784%*	*-0.153%*	*-0.133%*	*-0.134%*	*0.095%*	*0.101%*	*-0.020%*	*-4.035%*	*100%*
Diverse Services	- 972.98	505.68	382.14	215.13	- 152.97	- 177.64	- 86.65	- 210.62	- 497.91	187,086.0
	(130.79)	(148.16)	(49.77)	(36.73)	(31.95)	(48.11)	(26.67)	(34.32)		(640.3)
	-0.520%	*0.270%*	*0.204%*	*0.115%*	*-0.082%*	*-0.095%*	*-0.046%*	*-0.113%*	*-0.266%*	*100%*
Government	3,498.20	2,149.27	- 5.16	- 291.66	- 70.09	528.20	63.26	1.00	5,873.02	117,079.9
	(210.88)	(251.35)	(65.8)	(67.79)	(56.91)	(67.55)	(38.48)	(38.39)		(691.1)
	2.988%	*1.836%*	*-0.004%*	*-0.249%*	*-0.060%*	*0.451%*	*0.054%*	*0.001%*	*5.016%*	*100%*

Notes: Counterfactual estimate based on annual weather of 20-22°C and precipitation of 2-4 mm precipitation.

Table A.10.7: Industry Working Time Losses by Temperature Bin

	Bins													Total	
Regressors	(≤ 10]	(10-12]	(12-14]	(14-16]	(16-18]	(18-20]	(22-24]	(24-26]	(26-28]	(28-30]	(30-32]	(32-34]	(> 34]	Δ	potential working t
municipio	- 669.66	- 422.75	- 840.01	33.79	- 1.24	- 79.72	104.78	- 429.15	291.16	1,091.66	- 492.76	6.84	-200.72	- 1,607.78	4,377,639.8
std. error	(32.27)	(30.99)	(40.07)	(39.92)	(40.43)	(47.85)	(43.54)	(38.19)	(37.88)	(33.58)	(35.06)	(33.12)	-43.75		(940.2)
%	*-0.015%*	*-0.010%*	*-0.019%*	*0.001%*	*0.000%*	*-0.002%*	*0.002%*	*-0.010%*	*0.007%*	*0.025%*	*-0.011%*	*0.000%*	*-0.005%*	*-0.037%*	*100%*
Agriculture	38.10	- 652.92	-1,277.50	- 1,806.2	- 1,671.6	- 1,379.5	- 37.11	- 616.73	679.79	618.97	265.97	175.86	324.52	- 5,338.31	545,415.5
	(51.45)	(53.61)	(57.96)	(64.03)	(72.39)	(74.35)	(71.78)	(65.33)	(62.2)	(78.75)	(65.83)	(55.2)	(75.64)		(582.1)
	0.007%	*-0.120%*	*-0.234%*	*-0.331%*	*-0.306%*	*-0.253%*	*-0.007%*	*-0.113%*	*0.125%*	*0.113%*	*0.049%*	*0.032%*	*0.059%*	*-0.979%*	*100%*
Extractive Industry	11.80	39.49	- 35.96	- 18.63	- 41.07	- 123.63	85.77	55.10	27.48	109.65	111.37	37.84	24.76	283.97	36,104.6
	(30.65)	(30.45)	(27.85)	(28.67)	(29.7)	(37.79)	(42.78)	(23.74)	(26.16)	(49.31)	(27.55)	(25.09)	(34.08)		(213.5)
	0.033%	*0.109%*	*-0.100%*	*-0.052%*	*-0.114%*	*-0.342%*	*0.238%*	*0.153%*	*0.076%*	*0.304%*	*0.308%*	*0.105%*	*0.069%*	*0.787%*	*100%*
Manufacturing	- 435.51	- 183.49	- 265.33	- 63.35	127.30	177.26	- 824.46	- 728.89	- 857.75	- 985.17	- 736.53	- 450.99	- 430.45	- 5,657.36	737,771.6
	(36.24)	(28.37)	(34.52)	(34.25)	(33.25)	(38.61)	(39.43)	(35.57)	(42.35)	(51.08)	(41.33)	(36.95)	(59.58)		(558.1)
	-0.059%	*-0.025%*	*-0.036%*	*-0.009%*	*0.017%*	*0.024%*	*-0.112%*	*-0.099%*	*-0.116%*	*-0.134%*	*-0.100%*	*-0.061%*	*-0.058%*	*-0.767%*	*100%*
Construction	- 285.55	- 165.51	- 261.77	- 87.37	3.31	- 129.27	- 233.87	- 32.23	316.71	- 56.62	90.48	98.41	- 115.55	- 858.83	380,289.2
	(26.31)	(29.63)	(34.52)	(31.24)	(37.43)	(39.42)	(51.88)	(43.98)	(37.)	(56.59)	(39.75)	(36.8)	(43.16)		(402.9)
	-0.075%	*-0.044%*	*-0.069%*	*-0.023%*	*0.001%*	*-0.034%*	*-0.061%*	*-0.008%*	*0.083%*	*-0.015%*	*0.024%*	*0.026%*	*-0.030%*	*-0.226%*	*100%*
Trade	- 111.67	- 7.35	537.52	863.97	382.53	784.61	- 193.42	209.67	64.70	- 192.99	- 517.63	78.13	- 79.24	1,818.83	877,425.4
	(34.32)	(41.52)	(44.39)	(41.47)	(46.37)	(56.91)	(47.02)	(42.43)	(54.41)	(45.61)	(54.68)	(46.87)	(49.51)		(608.4)
	-0.013%	*-0.001%*	*0.061%*	*0.098%*	*0.044%*	*0.089%*	*-0.022%*	*0.024%*	*0.007%*	*-0.022%*	*-0.059%*	*0.009%*	*-0.009%*	*0.207%*	*100%*
Restaurant Service	- 63.67	24.07	38.42	63.32	343.86	251.73	- 333.60	123.84	- 316.75	87.67	- 149.69	3.33	77.93	150.46	324,142.5
	(30.86)	(29.72)	(47.06)	(33.38)	(33.69)	(44.94)	(41.77)	(42.92)	(42.23)	(48.44)	(48.86)	(31.99)	(29.42)		(433.2)
	-0.020%	*0.007%*	*0.012%*	*0.020%*	*0.106%*	*0.078%*	*-0.103%*	*0.038%*	*-0.098%*	*0.027%*	*-0.046%*	*0.001%*	*0.024%*	*0.046%*	*100%*
Transport	- 134.53	386.26	588.40	923.23	675.29	756.87	376.55	224.76	215.58	102.61	- 119.55	- 287.22	- 344.31	3,363.94	271,441.5
	(59.2)	(47.25)	(59.61)	(53.54)	(54.43)	(67.43)	(67.53)	(61.7)	(62.17)	(69.31)	(92.45)	(68.66)	(48.86)		(431.2)
	-0.050%	*0.142%*	*0.217%*	*0.340%*	*0.249%*	*0.279%*	*0.139%*	*0.083%*	*0.079%*	*0.038%*	*-0.044%*	*-0.106%*	*-0.127%*	*1.239%*	*100%*
Professional Services	41.71	- 25.68	- 89.72	- 159.04	- 13.35	- 388.56	522.16	235.51	231.49	326.76	231.76	170.30	93.24	1,176.58	295,525.1
	(25.42)	(22.68)	(32.08)	(36.5)	(29.65)	(36.94)	(37.05)	(33.32)	(33.99)	(29.31)	(32.85)	(23.8)	(29.46)		(371.7)
	0.014%	*-0.009%*	*-0.030%*	*-0.054%*	*-0.005%*	*-0.131%*	*0.177%*	*0.080%*	*0.078%*	*0.111%*	*0.078%*	*0.058%*	*0.032%*	*0.398%*	*100%*
Social Services	131.31	- 27.92	- 12.88	- 170.26	13.69	- 209.75	- 212.87	- 116.49	- 125.69	139.15	- 30.31	66.45	- 24.01	- 579.58	255,296.1
	(33.97)	(26.02)	(36.71)	(33.31)	(36.6)	(37.84)	(37.56)	(35.74)	(37.65)	(37.49)	(34.75)	(29.58)	(51.72)		(375.7)
	0.051%	*-0.011%*	*-0.005%*	*-0.067%*	*0.005%*	*-0.082%*	*-0.083%*	*-0.046%*	*-0.049%*	*0.055%*	*-0.012%*	*0.026%*	*-0.009%*	*-0.227%*	*100%*
Diverse Services	47.37	30.87	- 126.92	230.02	- 41.68	- 122.08	481.53	- 406.78	- 80.36	257.54	113.65	- 105.13	172.82	450.85	414,566.5
	(37.76)	(31.08)	(40.48)	(40.2)	(41.74)	(51.14)	(45.81)	(40.66)	(37.84)	(44.17)	(55.42)	(35.06)	(54.02)		(487.0)
	0.011%	*0.007%*	*-0.031%*	*0.055%*	*-0.010%*	*-0.029%*	*0.116%*	*-0.098%*	*-0.019%*	*0.062%*	*0.027%*	*-0.025%*	*0.042%*	*0.109%*	*100%*
Government	-43.44	52.98	-39.47	55.91	-90.32	71.97	218.42	337.97	216.31	494.81	191.09	148.47	58.16	1,672.86	192,188.5
	-19.37	-22.94	-29.09	-29.49	-26.92	-37.85	-40.85	-35.81	-36.74	-45.6	-47.47	-31.11	-33.57		(277.5)
	-0.023%	*0.028%*	*-0.021%*	*0.029%*	*-0.047%*	*0.037%*	*0.114%*	*0.176%*	*0.113%*	*0.257%*	*0.099%*	*0.077%*	*0.030%*	*0.870%*	*100%*

Notes: Counterfactual estimate based on annual weather of 20-22°C and precipitation of 2-4 mm precipitation.

Table A.10.8: Industry Working Time Losses by Precipitation Bin

	Bins								Total	
Regressors	[=0]	(0-2]	(4-6]	(6-8]	(8-10]	(10-20]	(20-30]	(> 30]	Δ	potential working t
municipio	1,237.3	- 3,109.1	- 383.60	- 407.39	72.49	- 1,481.8	- 1,488.0	- 2,225.1	- 7,785.2	4,377,639.8
std. error	(110.27)	(148.59)	(47.85)	(44.04)	(34.17)	(40.6)	(25.8)	(30.24)		(940.2)
%	*0.028%*	*-0.071%*	*-0.009%*	*-0.009%*	*0.002%*	*-0.034%*	*-0.034%*	*-0.051%*	*-0.178%*	*100%*
Agriculture	18,846.2	11,392.8	- 237.30	304.28	186.75	216.74	- 559.82	- 1,077.2	29,072.4	516,733.7
	(207.07)	(225.81)	(63.98)	(52.06)	(46.29)	(63.38)	(42.06)	(44.81)		(619.9)
	3.647%	*2.205%*	*-0.046%*	*0.059%*	*0.036%*	*0.042%*	*-0.108%*	*-0.208%*	*5.626%*	*100%*
Extractive	- 118.12	- 413.25	- 103.11	- 1.48	- 27.48	- 41.18	16.97	3.07	- 684.58	37,278.3
Industry	(80.32)	(104.36)	(30.71)	(22.38)	(20.96)	(24.34)	(15.58)	(13.52)		(254.5)
	-0.317%	*-1.109%*	*-0.277%*	*-0.004%*	*-0.074%*	*-0.110%*	*0.046%*	*0.008%*	*-1.836%*	*100%*
Manufacturing	621.25	1,219.5	- 110.67	- 110.97	34.14	- 480.05	- 317.48	- 318.33	537.40	737,448.5
	(98.95)	(128.64)	(35.23)	(30.12)	(27.36)	(33.)	(22.02)	(21.58)		(554.4)
	0.084%	*0.165%*	*-0.015%*	*-0.015%*	*0.005%*	*-0.065%*	*-0.043%*	*-0.043%*	*0.073%*	*100%*
Construction	- 2,518.9	- 4,800.1	160.13	- 59.63	208.60	- 238.70	- 253.68	- 459.22	- 7,961.4	389,835.9
	(100.42)	(140.61)	(38.28)	(32.97)	(27.82)	(32.29)	(20.18)	(24.09)		(444.7)
	-0.646%	*-1.231%*	*0.041%*	*-0.015%*	*0.054%*	*-0.061%*	*-0.065%*	*-0.118%*	*-2.042%*	*100%*
Trade	- 8,702.3	- 8,977.4	- 704.88	- 553.67	- 313.06	- 575.33	- 44.92	- 303.25	- 20,174.8	905,430.8
	(142.46)	(176.69)	(45.43)	(39.29)	(30.73)	(44.24)	(30.74)	(24.63)		(598.2)
	-0.961%	*-0.992%*	*-0.078%*	*-0.061%*	*-0.035%*	*-0.064%*	*-0.005%*	*-0.033%*	*-2.228%*	*100%*
Restaurant	- 1,964.5	- 2,434.7	- 219.73	- 47.46	91.42	- 202.46	- 177.04	- 75.08	- 5,029.54	331,844.6
Service	(115.68)	(149.44)	(48.48)	(35.39)	(30.62)	(41.42)	(24.44)	(25.13)		(440.2)
	-0.592%	*-0.734%*	*-0.066%*	*-0.014%*	*0.028%*	*-0.061%*	*-0.053%*	*-0.023%*	*-1.516%*	*100%*
Transport	- 4,996.0	- 1,832.3	87.73	- 452.03	80.84	- 52.07	- 51.96	- 88.95	- 7,304.7	283,253.5
	(165.15)	(175.07)	(47.07)	(42.84)	(32.38)	(42.31)	(26.09)	(23.63)		(476.0)
	-1.764%	*-0.647%*	*0.031%*	*-0.160%*	*0.029%*	*-0.018%*	*-0.018%*	*-0.031%*	*-2.579%*	*100%*
Professional	- 241.47	- 800.72	81.46	29.07	- 40.61	227.08	- 60.86	- 59.51	- 865.56	299,686.6
Services	(97.08)	(128.1)	(40.56)	(39.3)	(26.75)	(32.78)	(18.19)	(15.89)		(426.7)
	-0.081%	*-0.267%*	*0.027%*	*0.010%*	*-0.014%*	*0.076%*	*-0.020%*	*-0.020%*	*-0.289%*	*100%*
Social	3,502.9	3,108.2	40.40	58.81	- 99.85	- 272.14	- 107.99	- 93.78	6,136.6	251,565.7
Services	(118.62)	(117.53)	(28.32)	(24.41)	(22.52)	(26.88)	(17.89)	(18.28)		(368.9)
	1.392%	*1.236%*	*0.016%*	*0.023%*	*-0.040%*	*-0.108%*	*-0.043%*	*-0.037%*	*2.439%*	*100%*
Diverse	1,246.2	2,002.1	427.33	354.26	123.54	148.77	42.60	- 78.95	4,265.9	414,566.5
Services	(120.4)	(140.26)	(45.31)	(35.5)	(27.98)	(39.)	(23.44)	(22.02)		(487.0)
	0.301%	*0.483%*	*0.103%*	*0.085%*	*0.030%*	*0.036%*	*0.010%*	*-0.019%*	*1.029%*	*100%*
Government	- 453.14	642.37	74.17	98.04	- 55.81	103.22	- 59.38	23.07	372.54	194,865.4
	(97.65)	(107.46)	(33.04)	(29.74)	(24.66)	(27.76)	(16.09)	(20.52)		(311.3)
	-0.233%	*0.330%*	*0.038%*	*0.050%*	*-0.029%*	*0.053%*	*-0.030%*	*0.012%*	*0.191%*	*100%*

Notes: Counterfactual estimate based on annual weather of 20-22°C and precipitation of 2-4 mm precipitation.

A.10.3 Two-Degree Temperature Increase Cost Projections

Table A.10.9: Earnings Losses by Temperature Bin + 2°C projection

	Bins													**Total**	
Regressors	(≤ 10]	(10-12]	(12-14]	(14-16]	(16-18]	(18-20]	(22-24]	(24-26]	(26-28]	(28-30]	(30-32]	(32-34]	(> 34]	Δ	potential earnings
municipio	-70.94	-71.83	-525.16	-436.88	1,018.74	2,281.41	-2,314.84	1,395.68	-318.95	-520.86	-2,606.14	-720.07	-1,046.87	-2,889.8	1,983,537.5
std. error	(51.19)	(72.64)	(86.04)	(53.19)	(67.63)	(85.35)	(70.35)	(60.56)	(73.8)	(70.79)	(62.5)	(93.63)	(78.04)		(1225.9)
%	*-0.004%*	*-0.004%*	*-0.026%*	*-0.022%*	*0.051%*	*0.115%*	*-0.117%*	*0.070%*	*-0.016%*	*-0.026%*	*-0.131%*	*-0.036%*	*-0.053%*	*-0.146%*	*100%*
outdoor	-31.99	-214.27	-457.28	-649.73	-537.95	-1,006.93	-807.29	-1,219.19	-898.43	-532.66	161.95	126.09	-311.24	-6,067.7	208,711.3
	(44.02)	(37.95)	(38.54)	(42.12)	(51.25)	(51.49)	(58.03)	(58.86)	(53.55)	(87.4)	(67.44)	(66.54)	(77.48)		(404.3)
	-0.015%	*-0.103%*	*-0.219%*	*-0.311%*	*-0.258%*	*-0.482%*	*-0.387%*	*-0.584%*	*-0.430%*	*-0.255%*	*0.078%*	*0.060%*	*-0.149%*	*-2.907%*	*100%*
office	-48.06	-619.58	-2,208.74	-1,688.65	-762.44	1,034.78	2,364.51	4,439.41	1,868.05	4,622.68	826.18	1,448.30	1,182.80	11,276.5	1,010,218.9
	(74.53)	(74.94)	(101.7)	(81.95)	(85.63)	(107.46)	(109.85)	(87.81)	(96.98)	(129.79)	(86.93)	(92.18)	(116.21)		(988.2)
	-0.005%	*-0.061%*	*-0.219%*	*-0.167%*	*-0.075%*	*0.102%*	*0.234%*	*0.439%*	*0.185%*	*0.458%*	*0.082%*	*0.143%*	*0.117%*	*1.116%*	*100%*
informal	-133.01	572.03	1,758.11	1,523.10	1,694.09	1,035.71	-2,858.65	-1,885.00	-1,986.86	-3,718.50	-3,258.49	-1,822.97	-1,685.72	-9,080.4	423,837.2
	(47.19)	(62.48)	(49.02)	(47.4)	(53.5)	(67.73)	(82.82)	(60.84)	(57.16)	(106.01)	(55.97)	(54.61)	(49.53)		(575.2)
	-0.031%	*0.135%*	*0.415%*	*0.359%*	*0.400%*	*0.244%*	*-0.674%*	*-0.445%*	*-0.469%*	*-0.877%*	*-0.769%*	*-0.430%*	*-0.398%*	*-2.142%*	*100%*
permanent	52.05	-447.81	-1,596.23	-918.52	-657.15	112.48	3,226.98	2,940.32	2,093.50	3,132.39	420.35	1,119.71	702.21	9,478.1	829,033.5
	(74.46)	(63.59)	(94.78)	(73.07)	(77.15)	(100.2)	(97.7)	(81.7)	(92.46)	(120.11)	(79.97)	(86.56)	(122.21)		(886.8)
	0.006%	*-0.054%*	*-0.193%*	*-0.111%*	*-0.079%*	*0.014%*	*0.389%*	*0.355%*	*0.253%*	*0.378%*	*0.051%*	*0.135%*	*0.085%*	*1.143%*	*100%*
temporary	104.29	573.85	1,358.26	888.46	2,071.93	2,363.63	-5,848.20	-2,057.26	-2,873.71	-4,141.07	-3,452.14	-2,012.45	-1,797.42	-13,024.4	1,155,307.7
	(47.11)	(73.13)	(66.42)	(52.34)	(63.1)	(81.24)	(74.05)	(64.14)	(70.96)	(113.25)	(69.44)	(80.59)	(82.07)		(908.4)
	0.009%	*0.050%*	*0.118%*	*0.077%*	*0.179%*	*0.205%*	*-0.506%*	*-0.178%*	*-0.249%*	*-0.358%*	*-0.299%*	*-0.174%*	*-0.156%*	*-1.127%*	*100%*
minimum	130.08	641.02	1,839.78	1,945.61	1,549.34	571.14	-1,687.74	-2,575.66	-3,130.02	-3,904.12	-4,059.15	-2,533.41	-1,887.63	-11,213.1	46,226.0
wage	(59.24)	(45.86)	(51.97)	(53.64)	(61.7)	(69.94)	(63.41)	(66.41)	(73.97)	(89.45)	(80.17)	(62.5)	(82.49)		(585.2)
	0.281%	*1.387%*	*3.980%*	*4.209%*	*3.352%*	*1.236%*	*-3.651%*	*-5.572%*	*-6.771%*	*-8.446%*	*-8.781%*	*-5.480%*	*-4.083%*	*-24.257%*	*100%*
piecework	-99.45	373.94	858.91	342.14	1,325.84	434.40	-1,334.65	-829.78	-1,408.15	-1,245.31	-2,126.17	-1,367.25	-1,157.75	-5,075.5	267,851.0
	(58.49)	(64.31)	(62.29)	(63.86)	(72.03)	(87.15)	(102.5)	(74.59)	(68.2)	(140.02)	(67.58)	(63.9)	(88.26)		(506.8)
	-0.037%	*0.140%*	*0.321%*	*0.128%*	*0.495%*	*0.162%*	*-0.498%*	*-0.310%*	*-0.526%*	*-0.465%*	*-0.794%*	*-0.510%*	*-0.432%*	*-1.895%*	*100%*
weekly	-1,071.75	-146.25	634.21	945.48	425.67	1,508.42	-6,226.25	-5,390.86	-3,641.61	-6,476.14	-4,988.62	-4,202.54	-4,102.34	-28,630.2	893,100.1
earnings	(92.05)	(86.6)	(68.34)	(66.15)	(75.16)	(89.38)	(98.77)	(94.6)	(86.07)	(159.92)	(96.92)	(97.36)	(125.7)		(784.2)
	-0.120%	*-0.016%*	*0.071%*	*0.106%*	*0.048%*	*0.169%*	*-0.697%*	*-0.604%*	*-0.408%*	*-0.725%*	*-0.559%*	*-0.471%*	*-0.459%*	*-3.206%*	*100%*
metro	91.17	-92.10	-264.37	-831.95	191.14	1,407.40	-1,960.42	1,340.07	56.82	-344.07	-1,518.54	-135.67	-436.03	-2,060.5	1,230,665.5
	(51.73)	(77.3)	(96.71)	(54.05)	(70.04)	(93.91)	(75.52)	(64.09)	(87.83)	(70.82)	(60.96)	(95.99)	(81.63)		(974.6)
	0.007%	*-0.007%*	*-0.021%*	*-0.068%*	*0.016%*	*0.114%*	*-0.159%*	*0.109%*	*0.005%*	*-0.028%*	*-0.123%*	*-0.011%*	*-0.035%*	*-0.167%*	*100%*
rural	-14.94	227.15	504.41	1,102.29	1,268.96	401.10	-574.94	-2,678.65	-1,796.13	-2,026.38	-2,191.74	-1,494.14	-873.94	-7,273.0	298,681.0
	(43.95)	(39.5)	(41.38)	(42.01)	(42.72)	(52.15)	(51.36)	(64.71)	(48.23)	(84.63)	(53.61)	(45.66)	(85.85)		(508.)
	-0.005%	*0.076%*	*0.169%*	*0.369%*	*0.425%*	*0.134%*	*-0.192%*	*-0.897%*	*-0.601%*	*-0.678%*	*-0.734%*	*-0.500%*	*-0.293%*	*-2.435%*	*100%*

Notes: Counterfactual estimate based on annual weather of 20-22°C and precipitation of 2-4 mm precipitation.

Table A.10.10: Working Time Losses by Temperature Bin + 2°C projection

	Bins													Total	
Regressors	(≤ 10]	(10-12]	(12-14]	(14-16]	(16-18]	(18-20]	(22-24]	(24-26]	(26-28]	(28-30]	(30-32]	(32-34]	(> 34]	Δ	potential working t
municipio	-608.11	-378.24	-793.33	32.65	-1.16	-78.45	107.37	-437.70	297.52	1,120.12	-518.92	7.91	-235.13	-1,250.3	4,366,830.7
std. error	(30.05)	(28.19)	(37.56)	(38.36)	(37.3)	(45.74)	(42.43)	(36.71)	(36.41)	(32.05)	(33.75)	(33.31)	(45.99)		(719.9)
%	*-0.014%*	*-0.009%*	*-0.018%*	*0.001%*	*0.000%*	*-0.002%*	*0.002%*	*-0.010%*	*0.007%*	*0.026%*	*-0.012%*	*0.000%*	*-0.005%*	*-0.029%*	*100%*
outdoor	87.18	-806.77	-1,249.22	-1,831.47	-1,595.75	-1,237.80	625.12	-556.28	680.07	985.76	523.74	291.99	373.89	-4,083.4	655,466.3
	(44.16)	(42.8)	(49.28)	(52.62)	(59.76)	(64.98)	(63.97)	(56.69)	(53.96)	(74.03)	(60.5)	(48.29)	(74.36)		(408.6)
	0.013%	*-0.123%*	*-0.191%*	*-0.279%*	*-0.243%*	*-0.189%*	*0.095%*	*-0.085%*	*0.104%*	*0.150%*	*0.080%*	*0.045%*	*0.057%*	*-0.623%*	*100%*
office	-265.83	-124.21	-156.62	-655.27	-512.50	-894.45	961.52	967.57	1,397.09	2,379.70	1,181.66	1,036.03	573.56	5,314.7	1,715,471.8
	(26.67)	(23.43)	(34.11)	(31.88)	(32.63)	(39.71)	(47.07)	(39.82)	(44.91)	(65.67)	(54.17)	(30.93)	(70.38)		(445.6)
	-0.015%	*-0.007%*	*-0.009%*	*-0.038%*	*-0.030%*	*-0.052%*	*0.056%*	*0.056%*	*0.081%*	*0.139%*	*0.069%*	*0.060%*	*0.033%*	*0.310%*	*100%*
informal	-267.63	129.93	708.91	1,488.77	1,569.57	2,191.21	-2,118.27	-1,744.80	-2,166.86	-3,293.11	-2,119.24	-1,192.49	-1,231.81	-6,814.0	1,154,098.0
	(40.81)	(38.41)	(45.01)	(47.8)	(47.04)	(60.21)	(56.3)	(58.14)	(51.2)	(67.75)	(64.57)	(52.52)	(46.85)		(354.)
	-0.023%	*0.011%*	*0.061%*	*0.129%*	*0.136%*	*0.190%*	*-0.184%*	*-0.151%*	*-0.188%*	*-0.285%*	*-0.184%*	*-0.103%*	*-0.107%*	*-0.590%*	*100%*
permanent	-134.14	-251.00	-339.14	-724.71	-399.55	-894.29	776.85	845.98	1,054.58	2,004.68	1,030.52	1,028.33	431.37	3,998.1	1,343,712.7
	(24.46)	(23.68)	(32.5)	(28.05)	(29.74)	(36.46)	(42.84)	(39.13)	(48.04)	(61.39)	(51.32)	(33.52)	(74.62)		(393.)
	-0.010%	*-0.019%*	*-0.025%*	*-0.054%*	*-0.030%*	*-0.067%*	*0.058%*	*0.063%*	*0.078%*	*0.149%*	*0.077%*	*0.077%*	*0.032%*	*0.298%*	*100%*
temporary	-372.00	-42.18	-253.79	925.20	596.41	895.78	-801.19	-1,553.34	-1,013.15	-1,170.93	-1,800.47	-1,121.21	-702.95	-5,710.9	3,023,622.9
	(40.1)	(37.08)	(43.42)	(43.82)	(43.09)	(51.14)	(49.64)	(50.3)	(40.99)	(54.15)	(47.04)	(44.1)	(45.19)		(621.9)
	-0.012%	*-0.001%*	*-0.008%*	*0.031%*	*0.020%*	*0.030%*	*-0.026%*	*-0.051%*	*-0.034%*	*-0.039%*	*-0.060%*	*-0.037%*	*-0.023%*	*-0.189%*	*100%*
minimum	103.02	-20.74	27.97	704.67	-113.75	107.82	-1,073.55	-1,290.14	-1,385.43	-2,101.24	-1,819.05	-751.67	-716.90	-7,612.1	723,949.0
wage	(39.08)	(40.02)	(48.41)	(49.17)	(51.59)	(60.82)	(64.45)	(73.85)	(59.45)	(93.26)	(56.24)	(48.48)	(54.2)		(398.8)
	0.014%	*-0.003%*	*0.004%*	*0.097%*	*-0.016%*	*0.015%*	*-0.148%*	*-0.178%*	*-0.191%*	*-0.290%*	*-0.251%*	*-0.104%*	*-0.099%*	*-1.051%*	*100%*
piecework	-223.46	-66.86	-56.08	151.81	123.65	969.09	1,816.67	1,788.91	1,156.51	2,227.88	680.67	27.81	75.44	8,596.6	577,964.4
	(41.94)	(45.61)	(55.23)	(54.94)	(61.61)	(75.92)	(113.89)	(88.87)	(65.64)	(148.49)	(74.26)	(67.95)	(81.)		(432.)
	-0.039%	*-0.012%*	*-0.010%*	*0.026%*	*0.021%*	*0.168%*	*0.314%*	*0.310%*	*0.200%*	*0.385%*	*0.118%*	*0.005%*	*0.013%*	*1.487%*	*100%*
weekly	-596.95	130.51	-57.36	576.94	527.91	-34.20	-904.55	-388.96	358.05	-782.90	-101.04	-193.44	-282.02	-1,466.0	1,618,904.4
earnings	(28.24)	(29.48)	(33.95)	(30.76)	(32.01)	(38.57)	(49.92)	(40.55)	(34.33)	(59.17)	(48.4)	(47.74)	(61.84)		(425.3)
	-0.037%	*0.008%*	*-0.004%*	*0.036%*	*0.033%*	*-0.002%*	*-0.056%*	*-0.024%*	*0.022%*	*-0.048%*	*-0.006%*	*-0.012%*	*-0.017%*	*-0.091%*	*100%*
metro	-298.69	-414.13	117.64	-251.54	276.56	301.58	236.43	-387.21	135.30	13.14	-109.73	30.77	-193.72	-349.9	2,473,118.2
	(27.79)	(23.67)	(34.27)	(36.01)	(32.25)	(42.81)	(38.11)	(32.96)	(31.48)	(23.07)	(28.36)	(28.35)	(45.32)		(532.7)
	-0.012%	*-0.017%*	*0.005%*	*-0.010%*	*0.011%*	*0.012%*	*0.010%*	*-0.016%*	*0.005%*	*0.001%*	*-0.004%*	*0.001%*	*-0.008%*	*-0.014%*	*100%*
rural	-18.60	-248.40	-410.36	-465.09	-239.74	-812.69	-880.97	-1,778.85	-783.86	-1,061.34	-993.07	-893.58	-3.13	-8,586.6	882,707.4
	(37.89)	(42.06)	(49.01)	(48.17)	(53.31)	(61.24)	(64.6)	(54.99)	(54.89)	(64.19)	(51.86)	(47.02)	(47.28)		(418.1)
	-0.002%	*-0.028%*	*-0.046%*	*-0.053%*	*-0.027%*	*-0.092%*	*-0.100%*	*-0.202%*	*-0.089%*	*-0.120%*	*-0.113%*	*-0.101%*	*0.000%*	*-0.973%*	*100%*

Notes: Counterfactual estimate based on annual weather of 20-22°C and precipitation of 2-4 mm precipitation.

Table A.10.11: Industry Earnings Losses by Temperature Bin + 2°C projection

Regressors	Bins (≤ 10]	(10-12]	(12-14]	(14-16]	(16-18]	(18-20]	(22-24]	(24-26]	(26-28]	(28-30]	(30-32]	(32-34]	(> 34]	Total Δ	potential earnings
municipio	- 70.94	- 71.83	- 525.16	- 436.88	1,018.74	2,281.41	- 2,314.84	1,395.68	- 318.95	- 520.86	- 2,606.14	- 720.07	- 1,046.87	- 3,936.71	1,984,109.3
std. error	(51.18)	(72.64)	(86.04)	(53.19)	(67.63)	(85.35)	(70.35)	(60.56)	(73.8)	(70.79)	(62.5)	(93.63)	(78.04)		(1255.0)
%	*-0.004%*	*-0.004%*	*-0.026%*	*-0.022%*	*0.051%*	*0.115%*	*-0.117%*	*0.070%*	*-0.016%*	*-0.026%*	*-0.131%*	*-0.036%*	*-0.053%*	*-0.198%*	*100%*
Agriculture	- 69.71	- 259.29	- 767.54	- 709.19	- 701.64	- 1,363.01	- 732.53	- 964.69	- 282.39	- 36.57	553.24	687.54	197.48	- 4,448.30	158,985.5
	(47.32)	(38.66)	(38.79)	(46.43)	(57.36)	(49.99)	(56.21)	(66.04)	(56.49)	(87.99)	(72.19)	(66.57)	(81.1)		(502.2)
	-0.044%	*-0.163%*	*-0.483%*	*-0.446%*	*-0.441%*	*-0.857%*	*-0.461%*	*-0.607%*	*-0.178%*	*-0.023%*	*0.348%*	*0.432%*	*0.124%*	*-2.798%*	*100%*
Extractive Industry	- 117.55	- 189.82	- 337.37	- 364.65	- 411.99	- 506.64	435.36	748.13	563.89	1,288.74	810.51	274.13	746.33	2,939.07	26,772.0
	(52.75)	(55.12)	(67.3)	(60.59)	(74.88)	(93.18)	(115.87)	(112.56)	(84.91)	(182.08)	(151.94)	(53.34)	(226.16)		(431.9)
	-0.439%	*-0.709%*	*-1.260%*	*-1.362%*	*-1.539%*	*-1.892%*	*1.626%*	*2.794%*	*2.106%*	*4.814%*	*3.027%*	*1.024%*	*2.788%*	*10.978%*	*100%*
Manufacturing	- 344.52	15.31	331.09	639.57	896.13	2,393.03	1,163.75	250.04	- 1,081.03	383.80	- 1,523.04	- 1,045.91	- 1,371.48	706.74	349,941.2
	(65.81)	(41.82)	(55.65)	(48.3)	(47.04)	(68.29)	(89.07)	(51.51)	(51.84)	(97.43)	(64.43)	(52.81)	(79.32)		(662.4)
	-0.098%	*0.004%*	*0.095%*	*0.183%*	*0.256%*	*0.684%*	*0.333%*	*0.071%*	*-0.309%*	*0.110%*	*-0.435%*	*-0.299%*	*-0.392%*	*0.202%*	*100%*
Construction	- 356.18	- 231.17	- 156.02	- 787.34	- 442.06	- 703.29	- 1,197.92	- 14.55	- 124.11	- 132.37	- 180.27	97.20	- 357.44	- 4,585.52	221,768.5
	(37.66)	(41.98)	(47.06)	(52.66)	(44.3)	(59.73)	(55.36)	(58.37)	(58.34)	(60.2)	(54.85)	(103.85)	(75.19)		(453.5)
	-0.161%	*-0.104%*	*-0.070%*	*-0.355%*	*-0.199%*	*-0.317%*	*-0.540%*	*-0.007%*	*-0.056%*	*-0.060%*	*-0.081%*	*0.044%*	*-0.161%*	*-2.068%*	*100%*
Trade	119.99	937.01	789.80	2,111.63	1,867.01	3,093.06	- 287.47	- 388.61	193.44	- 975.43	- 1,116.60	- 907.50	- 709.55	4,726.78	304,787.0
	(33.18)	(48.03)	(48.41)	(41.29)	(47.46)	(61.56)	(57.64)	(53.53)	(58.96)	(85.27)	(46.74)	(39.87)	(59.98)		(591.1)
	0.039%	*0.307%*	*0.259%*	*0.693%*	*0.613%*	*1.015%*	*-0.094%*	*-0.128%*	*0.063%*	*-0.320%*	*-0.366%*	*-0.298%*	*-0.233%*	*1.551%*	*100%*
Restaurant Service	104.44	164.67	534.03	413.42	548.82	- 199.71	- 940.94	- 365.85	- 711.66	- 1,142.04	- 1,297.42	- 507.10	- 595.02	- 3,994.36	128,877.6
	(27.53)	(34.64)	(38.58)	(37.11)	(43.19)	(49.41)	(62.33)	(45.47)	(44.09)	(80.48)	(49.26)	(50.87)	(56.85)		(410.8)
	0.081%	*0.128%*	*0.414%*	*0.321%*	*0.426%*	*-0.155%*	*-0.730%*	*-0.284%*	*-0.552%*	*-0.886%*	*-1.007%*	*-0.393%*	*-0.462%*	*-3.099%*	*100%*
Transport	101.02	7.64	- 106.43	- 180.46	84.33	- 42.46	- 321.66	- 15.99	37.90	38.44	36.41	218.84	164.56	22.14	129,749.0
	(45.)	(41.34)	(64.22)	(45.72)	(68.45)	(66.67)	(63.99)	(51.11)	(51.44)	(55.49)	(53.85)	(47.49)	(51.27)		(392.1)
	0.078%	*0.006%*	*-0.082%*	*-0.139%*	*0.065%*	*-0.033%*	*-0.248%*	*-0.012%*	*0.029%*	*0.030%*	*0.028%*	*0.169%*	*0.127%*	*0.017%*	*100%*
Professional Services	36.88	- 139.28	- 471.80	- 955.19	- 25.61	- 211.31	142.15	666.62	627.08	- 16.83	714.22	388.04	236.20	991.17	150,603.5
	(35.38)	(49.71)	(78.28)	(56.54)	(65.4)	(108.17)	(85.23)	(67.5)	(70.57)	(85.87)	(68.85)	(87.47)	(58.03)		(536.0)
	0.024%	*-0.092%*	*-0.313%*	*-0.634%*	*-0.017%*	*-0.140%*	*0.094%*	*0.443%*	*0.416%*	*-0.011%*	*0.474%*	*0.258%*	*0.157%*	*0.658%*	*100%*
Social Services	122.71	- 407.73	- 549.70	- 741.92	- 661.12	- 578.51	276.89	1,236.15	1,239.43	1,069.44	943.48	971.09	627.95	3,548.16	207,059.9
	(55.48)	(47.17)	(61.32)	(69.33)	(65.65)	(75.83)	(67.06)	(62.28)	(83.64)	(89.68)	(74.22)	(57.78)	(64.5)		(649.3)
	0.059%	*-0.197%*	*-0.265%*	*-0.358%*	*-0.319%*	*-0.279%*	*0.134%*	*0.597%*	*0.599%*	*0.516%*	*0.456%*	*0.469%*	*0.303%*	*1.714%*	*100%*
Diverse Services	117.57	223.19	667.88	493.75	104.45	- 105.96	- 1,276.88	- 687.11	- 1,397.32	- 979.74	- 1,622.87	- 913.74	- 528.19	- 5,904.97	182,993.9
	(44.24)	(42.34)	(44.3)	(43.16)	(40.4)	(58.89)	(64.36)	(46.3)	(44.81)	(79.43)	(49.09)	(43.19)	(41.14)		(409.8)
	0.064%	*0.122%*	*0.365%*	*0.270%*	*0.057%*	*-0.058%*	*-0.698%*	*-0.375%*	*-0.764%*	*-0.535%*	*-0.887%*	*-0.499%*	*-0.289%*	*-3.227%*	*100%*
Government	- 0.29	- 189.62	- 326.88	- 352.50	- 194.44	196.78	127.50	254.46	222.72	- 113.11	17.91	12.07	128.53	- 216.87	128,929.4
	(57.01)	(46.75)	(69.13)	(59.81)	(57.18)	(91.76)	(68.94)	(56.6)	(62.73)	(93.6)	(62.23)	(48.95)	(58.56)		(512.5)
	0.000%	*-0.147%*	*-0.254%*	*-0.273%*	*-0.151%*	*0.153%*	*0.099%*	*0.197%*	*0.173%*	*-0.088%*	*0.014%*	*0.009%*	*0.100%*	*-0.168%*	*100%*

Notes: Counterfactual estimate based on annual weather of 20-22°C and precipitation of 2-4 mm precipitation.

Table A.10.12: Industry Working Time Losses by Temperature Bin + 2°C projection

	Bins													Total	
Regressors	(≤ 10]	(10-12]	(12-14]	(14-16]	(16-18]	(18-20]	(22-24]	(24-26]	(26-28]	(28-30]	(30-32]	(32-34]	(> 34]	Δ	potential working t
municipio	- 608.11	- 378.24	- 793.33	32.65	- 1.16	- 78.45	107.37	- 437.70	297.52	1,120.12	- 518.92	7.91	- 235.13	- 1,485.47	4,374,394.7
std. error	(30.05)	(28.19)	(37.56)	(38.36)	(37.3)	(45.74)	(42.43)	(36.71)	(36.41)	(32.05)	(33.75)	(33.31)	(45.99)		(759.5)
%	*-0.014%*	*-0.009%*	*-0.018%*	*0.001%*	*0.000%*	*-0.002%*	*0.002%*	*-0.010%*	*0.007%*	*0.026%*	*-0.012%*	*0.000%*	*-0.005%*	*-0.034%*	*100%*
Agriculture	34.64	- 595.06	- 1,186.8	- 1,713.9	- 1,590.4	- 1,346.8	- 37.54	- 627.85	693.97	632.87	283.50	201.19	383.14	- 4,869.03	543,853.4
	(47.79)	(49.33)	(53.75)	(60.38)	(67.94)	(70.81)	(69.42)	(63.1)	(59.87)	(75.47)	(63.82)	(55.38)	(79.7)		(482.0)
	0.006%	*-0.109%*	*-0.218%*	*-0.315%*	*-0.292%*	*-0.248%*	*-0.007%*	*-0.115%*	*0.128%*	*0.116%*	*0.052%*	*0.037%*	*0.070%*	*-0.895%*	*100%*
Extractive	10.93	36.01	- 34.18	- 18.10	- 39.43	- 119.15	85.82	55.56	27.97	109.13	117.24	43.41	28.99	304.20	35,982.4
Industry	(28.78)	(28.)	(26.22)	(27.55)	(27.96)	(35.69)	(41.26)	(22.88)	(25.18)	(46.35)	(26.51)	(25.17)	(36.02)		(193.2)
	0.030%	*0.100%*	*-0.095%*	*-0.050%*	*-0.110%*	*-0.331%*	*0.239%*	*0.154%*	*0.078%*	*0.303%*	*0.326%*	*0.121%*	*0.081%*	*0.845%*	*100%*
Manufacturing	- 399.87	- 164.56	- 252.39	- 61.19	120.13	174.72	- 842.99	- 748.64	- 877.40	- 1,017.9	- 768.16	- 509.51	- 495.84	- 5,843.55	746,056.6
	(34.1)	(25.84)	(32.5)	(32.91)	(30.79)	(36.94)	(38.43)	(34.44)	(40.78)	(49.21)	(39.64)	(36.74)	(62.3)		(434.8)
	-0.054%	*-0.022%*	*-0.034%*	*-0.008%*	*0.016%*	*0.023%*	*-0.113%*	*-0.100%*	*-0.118%*	*-0.136%*	*-0.103%*	*-0.068%*	*-0.066%*	*-0.783%*	*100%*
Construction	- 258.86	- 148.67	- 246.83	- 84.19	3.13	- 127.08	- 239.34	- 32.91	323.09	- 57.70	95.30	114.71	- 136.32	- 795.67	378,097.9
	(24.42)	(27.05)	(32.39)	(29.95)	(34.75)	(37.61)	(50.33)	(42.37)	(35.55)	(53.74)	(38.29)	(37.13)	(45.48)		(320.4)
	-0.068%	*-0.039%*	*-0.065%*	*-0.022%*	*0.001%*	*-0.034%*	*-0.063%*	*-0.009%*	*0.085%*	*-0.015%*	*0.025%*	*0.030%*	*-0.036%*	*-0.210%*	*100%*
Trade	- 101.18	- 6.56	506.53	837.11	359.12	770.95	- 198.72	214.20	66.25	- 198.27	- 545.33	90.67	- 93.20	1,701.57	875,152.3
	(31.89)	(37.7)	(41.56)	(39.96)	(42.69)	(54.33)	(45.95)	(40.76)	(52.34)	(43.52)	(52.66)	(47.15)	(52.12)		(470.1)
	-0.012%	*-0.001%*	*0.058%*	*0.096%*	*0.041%*	*0.088%*	*-0.023%*	*0.024%*	*0.008%*	*-0.023%*	*-0.062%*	*0.010%*	*-0.011%*	*0.194%*	*100%*
Restaurant	- 57.48	21.43	36.24	61.37	321.92	246.99	- 341.49	124.71	- 321.06	89.27	- 157.78	3.90	92.85	120.87	326,620.6
Service	(28.63)	(26.96)	(44.11)	(32.18)	(30.96)	(42.88)	(40.73)	(40.91)	(40.47)	(45.93)	(47.13)	(32.46)	(31.03)		(335.9)
	-0.018%	*0.007%*	*0.011%*	*0.019%*	*0.099%*	*0.076%*	*-0.105%*	*0.038%*	*-0.098%*	*0.027%*	*-0.048%*	*0.001%*	*0.028%*	*0.037%*	*100%*
Transport	- 121.00	340.47	558.55	897.35	629.19	749.09	391.04	228.55	220.49	105.25	- 125.89	- 335.37	- 405.98	3,131.74	275,617.0
	(54.81)	(42.62)	(56.1)	(51.9)	(49.61)	(64.66)	(66.14)	(58.98)	(59.7)	(65.74)	(88.75)	(69.29)	(51.45)		(366.1)
	-0.044%	*0.124%*	*0.203%*	*0.326%*	*0.228%*	*0.272%*	*0.142%*	*0.083%*	*0.080%*	*0.038%*	*-0.046%*	*-0.122%*	*-0.147%*	*1.136%*	*100%*
Professional	37.54	- 22.60	- 85.22	- 154.84	- 12.35	- 385.61	542.15	241.07	236.78	339.68	242.77	203.97	108.86	1,292.20	295,104.0
Services	(23.53)	(20.41)	(30.13)	(35.41)	(26.89)	(35.5)	(36.35)	(31.88)	(32.63)	(28.02)	(31.46)	(24.26)	(30.92)		(279.4)
	0.013%	*-0.008%*	*-0.029%*	*-0.052%*	*-0.004%*	*-0.131%*	*0.184%*	*0.082%*	*0.080%*	*0.115%*	*0.082%*	*0.069%*	*0.037%*	*0.438%*	*100%*
Social	119.01	- 24.89	- 12.23	- 164.66	12.81	- 207.60	- 217.84	- 118.57	- 128.37	143.08	- 31.90	77.75	- 28.07	- 581.48	256,277.1
Services	(31.52)	(23.64)	(34.52)	(32.04)	(33.58)	(36.32)	(36.56)	(34.25)	(36.15)	(35.72)	(33.38)	(29.84)	(54.39)		(305.0)
	0.046%	*-0.010%*	*-0.005%*	*-0.064%*	*0.005%*	*-0.081%*	*-0.085%*	*-0.046%*	*-0.050%*	*0.056%*	*-0.012%*	*0.030%*	*-0.011%*	*-0.227%*	*100%*
Diverse	42.69	27.61	- 119.63	222.77	- 39.13	- 120.23	493.69	- 415.47	- 82.21	263.98	119.68	- 121.90	202.96	474.81	405,793.4
Services	(34.91)	(28.24)	(37.88)	(38.76)	(38.43)	(48.93)	(44.64)	(39.03)	(36.35)	(42.01)	(53.37)	(35.3)	(56.84)		(333.0)
	0.011%	*0.007%*	*-0.029%*	*0.055%*	*-0.010%*	*-0.030%*	*0.122%*	*-0.102%*	*-0.020%*	*0.065%*	*0.029%*	*-0.030%*	*0.050%*	*0.117%*	*100%*
Government	- 39.30	47.35	- 37.32	54.38	- 84.82	70.76	226.34	343.39	222.31	508.09	200.97	171.83	68.28	1,752.26	191,545.5
	(17.99)	(20.83)	(27.27)	(28.5)	(24.74)	(36.1)	(39.91)	(34.23)	(35.43)	(43.44)	(45.74)	(31.47)	(35.35)		(238.8)
	-0.021%	*0.025%*	*-0.019%*	*0.028%*	*-0.044%*	*0.037%*	*0.118%*	*0.179%*	*0.116%*	*0.265%*	*0.105%*	*0.090%*	*0.036%*	*0.915%*	*100%*

Notes: Counterfactual estimate based on annual weather of 20-22°C and precipitation of 2-4 mm precipitation.

A.11 Alternative Fixed Effects Specifications

The following tables show re-estimations of the key models using different fixed-effects specifications and alternative time trends.

Table A.11.1: Alternative Fixed Effects – Earnings Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature									
≤ 10°C	-1.066	-1.632	-1.058	-1.554	-2.237	-1.807	-2.019	-1.746	-0.267
	(-0.62)	(-0.97)	(-0.62)	(-0.90)	(-1.35)	(-1.08)	(-1.19)	(-1.10)	(-0.16)
10-12°C	-1.149	-1.549	-1.261	-1.659	-2.380	-2.214	-2.486	-3.084*	-0.177
	(-0.50)	(-0.68)	(-0.55)	(-0.72)	(-1.09)	(-1.02)	(-1.12)	(-1.93)	(-0.07)
12-14°C	-1.259	-1.793	-1.503	-1.732	-2.555*	-2.455*	-2.668*	-1.996*	-0.562
	(-0.80)	(-1.19)	(-0.99)	(-1.12)	(-1.86)	(-1.78)	(-1.88)	(-1.72)	(-0.33)
14-16°C	-0.667	-1.223	-0.863	-0.877	-1.920**	-1.730*	-1.771*	-1.875**	-0.331
	(-0.74)	(-1.34)	(-0.94)	(-0.95)	(-2.13)	(-1.90)	(-1.96)	(-2.14)	(-0.36)
16-18°C	0.131	-0.315	-0.0431	0.0291	-0.793	-0.683	-0.601	-0.368	0.594
	(0.13)	(-0.33)	(-0.04)	(0.03)	(-0.89)	(-0.76)	(-0.64)	(-0.49)	(0.58)
18-20°C	1.060	0.780	0.877	1.071	0.543	0.581	0.774	0.838	1.014
	(1.00)	(0.75)	(0.83)	(1.00)	(0.53)	(0.56)	(0.73)	(0.91)	(0.94)
20-22°C	–	–	–	–	–	–	–	–	–
22-24°C	-1.183	-1.257	-1.292	-1.304	-1.137	-1.117	-1.022	-1.152	-1.088
	(-1.28)	(-1.40)	(-1.42)	(-1.41)	(-1.25)	(-1.22)	(-1.08)	(-1.47)	(-1.18)
24-26°C	0.752	0.807	0.736	0.783	0.955	0.976	1.077	1.361*	0.778
	(0.85)	(0.92)	(0.84)	(0.87)	(1.17)	(1.18)	(1.29)	(1.68)	(0.86)
26-28°C	-0.289	-0.0198	-0.230	-0.112	0.186	0.112	0.272	0.141	-0.191
	(-0.27)	(-0.02)	(-0.21)	(-0.10)	(0.17)	(0.10)	(0.25)	(0.15)	(-0.17)
28-30°C	-0.273	0.258	-0.0644	0.0811	0.930	0.791	0.883	0.945	-0.367
	(-0.25)	(0.24)	(-0.06)	(0.07)	(0.92)	(0.79)	(0.87)	(1.00)	(-0.33)
30-32°C	-2.683**	-2.301**	-2.841***	-3.018***	-1.363	-1.619	-1.782*	-0.405	-2.628**
	(-2.47)	(-2.07)	(-2.60)	(-2.75)	(-1.36)	(-1.63)	(-1.79)	(-0.45)	(-2.21)
32-34°C	-1.296	-0.342	-0.694	-1.105	0.611	0.558	0.210	0.186	-1.310
	(-0.49)	(-0.13)	(-0.26)	(-0.42)	(0.24)	(0.22)	(0.08)	(0.12)	(-0.51)
> 34°C	-2.374	-1.970	-2.422	-2.400	-0.927	-1.110	-1.085	-0.467	-2.415
	(-1.27)	(-1.06)	(-1.32)	(-1.30)	(-0.54)	(-0.64)	(-0.63)	(-0.40)	(-1.31)
Precipitation									
= 0 mm	-0.298	-0.926	-0.466	-0.375	-1.883	-1.533	-0.929	-0.550	-0.360
	(-0.24)	(-0.76)	(-0.38)	(-0.31)	(-1.51)	(-1.23)	(-0.76)	(-0.52)	(-0.28)
0-2 mm	0.0905	-0.149	0.320	0.386	-0.901	-0.562	-0.218	-0.296	0.279
	(0.07)	(-0.12)	(0.26)	(0.31)	(-0.72)	(-0.45)	(-0.18)	(-0.25)	(0.22)
2-4 mm	–	–	–	–	–	–	–	–	–
4-6 mm	-0.131	-1.015	-0.616	-0.351	-0.936	-0.558	-0.126	-0.884	0.205
	(-0.05)	(-0.43)	(-0.26)	(-0.15)	(-0.40)	(-0.24)	(-0.05)	(-0.47)	(0.08)
6-8 mm	-1.969	-2.221	-2.044	-1.956	-2.049	-1.847	-1.597	-3.392*	-1.683
	(-0.92)	(-1.02)	(-0.95)	(-0.90)	(-0.94)	(-0.86)	(-0.73)	(-1.68)	(-0.79)
8-10 mm	1.656	1.908	2.260	1.883	2.189	2.557	2.322	2.364	1.447
	(0.67)	(0.77)	(0.92)	(0.76)	(0.90)	(1.05)	(0.95)	(1.10)	(0.59)
10-20 mm	-0.521	-0.843	-0.420	-0.818	-0.448	-0.0101	-0.242	-0.467	-0.377
	(-0.30)	(-0.47)	(-0.24)	(-0.46)	(-0.26)	(-0.01)	(-0.14)	(-0.31)	(-0.22)
20-30 mm	-0.564	-2.016	-1.352	-0.476	-1.885	-1.257	-0.272	-1.255	-0.347
	(-0.21)	(-0.72)	(-0.48)	(-0.18)	(-0.67)	(-0.45)	(-0.10)	(-0.47)	(-0.13)
> 30 mm	-4.273	-4.632	-3.862	-3.069	-4.949	-4.236	-3.450	-4.065	-4.890
	(-0.86)	(-0.89)	(-0.75)	(-0.62)	(-0.95)	(-0.81)	(-0.69)	(-1.11)	(-1.01)
controls	×	×	×	×	×	×	×	×	×
month fe									×
qtr fe	×	×	×	×				×	
year fe	×								
year trend		×	×	×					
year trend^2			×	×					
year trend^3				×					
qtr trend					×	×	×		
qtr trend^2						×	×		
qtr trend^3							×		
mun×year								×	
sector time fe									×
adjusted R^2	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.117	0.115
F Stat.	561.0	571.5	564.3	566.2	580.2	567.8	574.9	–	1216.4
DF	(59,1675)	(49,1675)	(50,1675)	(51,1675)	(46,1675)	(47,1675)	(48,1675)	(48,1675)	(573,1675)
# clusters	1,676	1,676	1,676	1,676	1,676	1,676	1,676	1,676	1,676
N	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147
# ind.	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000

Notes: Standard errors (in parentheses) are clustered by municipality. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Covariates include municipality, month, and sector specific year and quarter fixed effects.

Table A.11.2: Alternative Fixed Effects – Working Time Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature									
≤ 10°C	-2.832**	-2.919**	-2.691**	-2.602**	-2.992***	-2.823**	-2.799**	-2.849**	-3.293***
	(-2.48)	(-2.56)	(-2.39)	(-2.32)	(-2.67)	(-2.53)	(-2.52)	(-2.54)	(-2.74)
10-12°C	-0.523	-0.646	-0.531	-0.460	-0.454	-0.389	-0.359	-0.496	-1.345
	(-0.49)	(-0.61)	(-0.50)	(-0.43)	(-0.43)	(-0.36)	(-0.34)	(-0.49)	(-1.21)
12-14°C	-0.729	-0.823	-0.708	-0.667	-0.581	-0.542	-0.519	-1.077	-1.222
	(-0.86)	(-0.97)	(-0.84)	(-0.79)	(-0.70)	(-0.65)	(-0.62)	(-1.29)	(-1.38)
14-16°C	0.190	0.0705	0.213	0.216	0.339	0.414	0.419	0.114	0.0356
	(0.24)	(0.09)	(0.27)	(0.27)	(0.44)	(0.54)	(0.55)	(0.14)	(0.04)
16-18°C	-0.199	-0.297	-0.189	-0.202	-0.0416	0.00169	-0.00727	-0.314	-0.000977
	(-0.30)	(-0.45)	(-0.28)	(-0.30)	(-0.06)	(0.00)	(-0.01)	(-0.48)	(-0.00)
18-20°C	-0.381	-0.347	-0.309	-0.344	-0.160	-0.145	-0.166	-0.297	-0.0502
	(-0.52)	(-0.48)	(-0.42)	(-0.47)	(-0.22)	(-0.20)	(-0.23)	(-0.42)	(-0.07)
20-22°C	–	–	–	–	–	–	–	–	–
22-24°C	-0.0356	-0.0351	-0.0491	-0.0469	-0.541	-0.533	-0.543	-0.0610	0.0726
	(-0.05)	(-0.05)	(-0.07)	(-0.07)	(-0.75)	(-0.74)	(-0.76)	(-0.09)	(0.11)
24-26°C	-0.137	-0.174	-0.202	-0.211	-0.896	-0.887	-0.899	-0.00687	-0.351
	(-0.20)	(-0.26)	(-0.30)	(-0.31)	(-1.30)	(-1.28)	(-1.30)	(-0.01)	(-0.54)
26-28°C	-0.215	-0.0756	-0.159	-0.180	-1.171*	-1.200*	-1.218*	0.0513	0.257
	(-0.32)	(-0.11)	(-0.24)	(-0.27)	(-1.73)	(-1.78)	(-1.80)	(0.08)	(0.39)
28-30°C	0.956	1.088*	0.960	0.934	0.744	0.689	0.679	1.129*	1.136*
	(1.54)	(1.75)	(1.53)	(1.50)	(1.14)	(1.06)	(1.04)	(1.82)	(1.86)
30-32°C	-0.340	-0.263	-0.478	-0.446	-1.026	-1.127	-1.109	-0.0513	-0.754
	(-0.42)	(-0.33)	(-0.60)	(-0.56)	(-1.26)	(-1.39)	(-1.36)	(-0.07)	(-0.98)
32-34°C	0.767	0.759	0.619	0.692	-0.338	-0.359	-0.321	0.889	0.0207
	(0.67)	(0.67)	(0.55)	(0.61)	(-0.30)	(-0.32)	(-0.28)	(0.85)	(0.02)
> 34°C	0.339	0.449	0.269	0.265	0.0301	-0.0421	-0.0449	0.0468	-0.781
	(0.25)	(0.33)	(0.20)	(0.20)	(0.02)	(-0.03)	(-0.03)	(0.04)	(-0.60)
Precipitation									
= 0 mm	0.526	0.684	0.867	0.851	-1.666*	-1.528*	-1.594*	1.469	0.366
	(0.56)	(0.71)	(0.90)	(0.88)	(-1.84)	(-1.68)	(-1.76)	(1.62)	(0.38)
0-2 mm	-0.520	-0.351	-0.165	-0.177	-2.120**	-1.987**	-2.024**	-0.0182	-0.522
	(-0.56)	(-0.37)	(-0.17)	(-0.19)	(-2.27)	(-2.13)	(-2.18)	(-0.02)	(-0.55)
2-4 mm	–	–	–	–	–	–	–	–	–
4-6 mm	-0.829	-0.843	-0.685	-0.732	-1.163	-1.013	-1.061	-0.768	-0.595
	(-0.52)	(-0.53)	(-0.43)	(-0.46)	(-0.72)	(-0.63)	(-0.66)	(-0.49)	(-0.37)
6-8 mm	-0.884	-0.979	-0.908	-0.924	-1.409	-1.329	-1.356	-0.517	-0.894
	(-0.47)	(-0.51)	(-0.47)	(-0.49)	(-0.75)	(-0.70)	(-0.72)	(-0.28)	(-0.48)
8-10 mm	0.659	0.476	0.616	0.683	0.197	0.342	0.368	-0.532	0.232
	(0.34)	(0.25)	(0.32)	(0.35)	(0.10)	(0.18)	(0.19)	(-0.28)	(0.12)
10-20 mm	-2.553*	-2.618**	-2.450*	-2.378*	-2.651**	-2.479*	-2.454*	-1.660	-2.464*
	(-1.95)	(-1.98)	(-1.84)	(-1.79)	(-2.03)	(-1.88)	(-1.87)	(-1.30)	(-1.87)
20-30 mm	-12.48***	-12.12***	-11.85***	-12.01***	-12.12***	-11.87***	-11.98***	-11.37***	-12.05***
	(-5.17)	(-5.04)	(-4.93)	(-4.99)	(-5.03)	(-4.93)	(-4.98)	(-4.87)	(-5.08)
> 30 mm	-29.34***	-28.61***	-28.30***	-28.45***	-29.15***	-28.87***	-28.96***	-27.50***	-28.12***
	(-8.77)	(-8.42)	(-8.38)	(-8.46)	(-8.54)	(-8.51)	(-8.56)	(-8.33)	(-8.48)
controls	×	×	×	×	×	×	×	×	×
month fe									×
qtr fe	×	×	×	×				×	
year fe	×								
year trend		×	×	×					
year trend^2			×	×					
year trend^3				×					
qtr trend					×	×	×		
qtr trend^2						×	×		
qtr trend^3							×		
mun×year								×	
sector time fe									×
adjusted R^2	0.146	0.145	0.145	0.145	0.145	0.145	0.145	0.146	0.146
F Stat.	328.9	393.2	383.5	375.3	396.1	385.2	377.2	–	599.5
DF	(59,1675)	(49,1675)	(50,1675)	(51,1675)	(46,1675)	(47,1675)	(48,1675)	(48,1675)	(573,1675)
# clusters	1,676	1,676	1,676	1,676	1,676	1,676	1,676	1,676	1,676
N	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147
# ind.	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000

Notes: Standard errors (in parentheses) are clustered by municipality. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Covariates include municipality, month, and sector specific year and quarter fixed effects.

A.12 Alternative Cluster Specification

Results presented in this section are estimated specifying clusters at the state-panel-group level.

Table A.12.1: Alternative Cluster Specification – Earnings Regressions

	(1)	(2)	(3)	(4)	(5)
Temperature					
$\leq$ 10°C	-0.267	-0.267	-0.267	-0.267	-0.267
	(-0.16)	(-0.11)	(-0.12)	(-0.12)	(-0.11)
10-12°C	-0.177	-0.177	-0.177	-0.177	-0.177
	(-0.07)	(-0.06)	(-0.07)	(-0.06)	(-0.05)
12-14°C	-0.562	-0.562	-0.562	-0.562	-0.562
	(-0.33)	(-0.28)	(-0.33)	(-0.30)	(-0.24)
14-16°C	-0.331	-0.331	-0.331	-0.331	-0.331
	(-0.36)	(-0.21)	(-0.21)	(-0.25)	(-0.20)
16-18°C	0.594	0.594	0.594	0.594	0.594
	(0.58)	(0.40)	(0.47)	(0.47)	(0.35)
18-20°C	1.014	1.014	1.014	1.014	1.014
	(0.94)	(0.60)	(0.84)	(0.69)	(0.56)
20-22°C	–	–	–	–	–
22-24°C	-1.088	-1.088	-1.088	-1.088	-1.088
	(-1.18)	(-0.70)	(-0.77)	(-0.87)	(-0.66)
24-26°C	0.778	0.778	0.778	0.778	0.778
	(0.86)	(0.54)	(0.73)	(0.59)	(0.51)
26-28°C	-0.191	-0.191	-0.191	-0.191	-0.191
	(-0.17)	(-0.11)	(-0.15)	(-0.13)	(-0.10)
28-30°C	-0.367	-0.367	-0.367	-0.367	-0.367
	(-0.33)	(-0.23)	(-0.25)	(-0.24)	(-0.21)
30-32°C	-2.628**	-2.628	-2.628*	-2.628	-2.628
	(-2.21)	(-1.24)	(-1.82)	(-1.61)	(-1.19)
32-34°C	-1.310	-1.310	-1.310	-1.310	-1.310
	(-0.51)	(-0.43)	(-0.45)	(-0.44)	(-0.43)
> 34°C	-2.415	-2.415	-2.415	-2.415	-2.415
	(-1.31)	(-0.96)	(-1.21)	(-1.03)	(-0.90)
Precipitation					
= 0 mm	-0.360	-0.360	-0.360	-0.360	-0.360
	(-0.28)	(-0.21)	(-0.18)	(-0.21)	(-0.17)
0-2 mm	0.279	0.279	0.279	0.279	0.279
	(0.22)	(0.17)	(0.13)	(0.17)	(0.14)
2-4 mm	–	–	–	–	–
4-6 mm	0.205	0.205	0.205	0.205	0.205
	(0.08)	(0.07)	(0.06)	(0.06)	(0.06)
6-8 mm	-1.683	-1.683	-1.683	-1.683	-1.683
	(-0.79)	(-0.49)	(-0.56)	(-0.57)	(-0.47)
8-10 mm	1.447	1.447	1.447	1.447	1.447
	(0.59)	(0.40)	(0.44)	(0.46)	(0.36)
10-20 mm	-0.377	-0.377	-0.377	-0.377	-0.377
	(-0.22)	(-0.15)	(-0.17)	(-0.16)	(-0.14)
20-30 mm	-0.347	-0.347	-0.347	-0.347	-0.347
	(-0.13)	(-0.09)	(-0.09)	(-0.10)	(-0.09)
> 30 mm	-4.890	-4.890	-4.890	-4.890	-4.890
	(-1.01)	(-0.77)	(-0.96)	(-0.79)	(-0.65)
controls	×	×	×	×	×
mun. fe	×	×	×	×	×
sec time fe	×	×	×	×	×
year fe	×	×	×	×	×
qtr fe	×	×	×	×	×
clust var	munid	munid year	munid wave	munid panel	state year
adjusted R^2	0.156	0.156	0.156	0.156	0.156
DF	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147
# clusters	1,676	1,688	1,681	1,728	44
N	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147
Ind.	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000

Notes: Standard errors (in parentheses) are clustered by municipality. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Covariates include municipality, month, and sector specific year and quarter fixed effects.

Table A.12.2: Alternative Cluster Specification – Working Time Regressions

	(1)	(2)	(3)	(4)	(5)
Temperature					
$\leq$ 10°C	-3.293***	-3.293*	-3.293***	-3.293**	-3.293*
	(-2.74)	(-1.91)	(-2.77)	(-2.02)	(-1.75)
10-12°C	-1.345	-1.345	-1.345	-1.345	-1.345
	(-1.21)	(-1.17)	(-0.96)	(-0.86)	(-1.03)
12-14°C	-1.222	-1.222	-1.222	-1.222	-1.222
	(-1.38)	(-1.26)	(-1.37)	(-1.21)	(-1.02)
14-16°C	0.0356	0.0356	0.0356	0.0356	0.0356
	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)
16-18°C	-0.000977	-0.000977	-0.000977	-0.000977	-0.000977
	(-0.00)	(-0.00)	(-0.00)	(-0.00)	(-0.00)
18-20°C	-0.0502	-0.0502	-0.0502	-0.0502	-0.0502
	(-0.07)	(-0.05)	(-0.06)	(-0.05)	(-0.05)
20-22°C	–	–	–	–	–
22-24°C	0.0726	0.0726	0.0726	0.0726	0.0726
	(0.11)	(0.08)	(0.09)	(0.08)	(0.08)
24-26°C	-0.351	-0.351	-0.351	-0.351	-0.351
	(-0.54)	(-0.30)	(-0.43)	(-0.37)	(-0.29)
26-28°C	0.257	0.257	0.257	0.257	0.257
	(0.39)	(0.25)	(0.28)	(0.30)	(0.23)
28-30°C	1.136*	1.136	1.136*	1.136	1.136
	(1.86)	(1.12)	(1.66)	(1.30)	(1.12)
30-32°C	-0.754	-0.754	-0.754	-0.754	-0.754
	(-0.98)	(-0.69)	(-1.02)	(-0.81)	(-0.60)
32-34°C	0.0207	0.0207	0.0207	0.0207	0.0207
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
$>$ 34°C	-0.781	-0.781	-0.781	-0.781	-0.781
	(-0.60)	(-0.46)	(-0.50)	(-0.48)	(-0.51)
Precipitation					
= 0 mm	0.366	0.366	0.366	0.366	0.366
	(0.38)	(0.22)	(0.40)	(0.30)	(0.22)
0-2 mm	-0.522	-0.522	-0.522	-0.522	-0.522
	(-0.55)	(-0.35)	(-0.57)	(-0.44)	(-0.34)
2-4 mm	–	–	–	–	–
4-6 mm	-0.595	-0.595	-0.595	-0.595	-0.595
	(-0.37)	(-0.23)	(-0.32)	(-0.29)	(-0.24)
6-8 mm	-0.894	-0.894	-0.894	-0.894	-0.894
	(-0.48)	(-0.35)	(-0.46)	(-0.40)	(-0.31)
8-10 mm	0.232	0.232	0.232	0.232	0.232
	(0.12)	(0.09)	(0.10)	(0.09)	(0.09)
10-20 mm	-2.464*	-2.464	-2.464*	-2.464	-2.464
	(-1.87)	(-1.45)	(-1.66)	(-1.37)	(-1.20)
20-30 mm	-12.05***	-12.05***	-12.05***	-12.05***	-12.05***
	(-5.08)	(-3.35)	(-4.46)	(-3.99)	(-3.05)
$>$ 30 mm	-28.12***	-28.12***	-28.12***	-28.12***	-28.12***
	(-8.48)	(-5.87)	(-7.22)	(-6.77)	(-5.59)
controls	×	×	×	×	×
mun. fe	×	×	×	×	×
sec time fe	×	×	×	×	×
year fe	×	×	×	×	×
qtr fe	×	×	×	×	×
month fe	×	×	×	×	×
clust var	munid	munid year	munid wave	munid panel	state year
adjusted R^2	0.163	0.163	0.163	0.163	0.163
DF	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147
# clusters	1,676	1,688	1,681	1,728	44
N	7,390,147	7,390,147	7,390,147	7,390,147	7,390,147
Ind.	2,632,000	2,632,000	2,632,000	2,632,000	2,632,000

Notes: Standard errors (in parentheses) are clustered by municipality. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Covariates include municipality, month, and sector specific year and quarter fixed effects.

A.13 Alternative Time Specifications

Table A.13.1: Alternative Time Specification – Earnings Regressions

	(1)	(2)	(3)
	week	month	3 months
Temperature			
$\leq$ 10°C	-0.267	-3.943*	-11.23***
	(-0.16)	(-1.67)	(-2.85)
10-12°C	-0.177	3.969	18.81**
	(-0.07)	(0.80)	(2.12)
12-14°C	-0.562	-1.365	-1.985
	(-0.33)	(-0.44)	(-0.37)
14-16°C	-0.331	0.657	7.440**
	(-0.36)	(0.41)	(2.39)
16-18°C	0.594	-0.400	0.533
	(0.58)	(-0.18)	(0.13)
18-20°C	1.014	0.374	4.380
	(0.94)	(0.17)	(0.90)
20-22°C	–	–	–
22-24°C	-1.088	-2.242	2.250
	(-1.18)	(-1.05)	(0.50)
24-26°C	0.778	-1.311	0.482
	(0.86)	(-0.80)	(0.14)
26-28°C	-0.191	-1.496	0.267
	(-0.17)	(-0.82)	(0.08)
28-30°C	-0.367	-1.919	1.524
	(-0.33)	(-1.03)	(0.47)
30-32°C	-2.628**	-4.073*	-3.452
	(-2.21)	(-1.89)	(-0.66)
32-34°C	-1.310	-4.658	-0.248
	(-0.51)	(-1.08)	(-0.02)
> 34°C	-2.415	-4.626	-5.494
	(-1.31)	(-1.51)	(-0.90)
Precipitation			
= 0 mm	-0.360	-0.316	-0.441
	(-0.28)	(-0.41)	(-0.80)
0-2 mm	0.279	0.961	0.410
	(0.22)	(1.33)	(0.71)
2-4 mm	–	–	–
4-6 mm	0.205	-0.587	-0.730
	(0.08)	(-0.37)	(-0.56)
6-8 mm	-1.683	1.166	0.945
	(-0.79)	(0.84)	(0.91)
8-10 mm	1.447	0.110	-0.0804
	(0.59)	(0.07)	(-0.07)
10-20 mm	-0.377	0.107	0.258
	(-0.22)	(0.09)	(0.30)
20-30 mm	-0.347	-0.0603	-0.206
	(-0.13)	(-0.04)	(-0.16)
> 30 mm	-4.890	-1.091	-1.114
	(-1.01)	(-0.36)	(-0.51)
controls	×	×	×
mun. fe	×	×	×
sec time fe	×	×	×
year fe	×	×	×
qtr fe	×	×	×
month fe	×	×	×
adjusted R^2	0.115	0.115	0.115
F Stat.	1,216	1,211	1,253
DF	(573,1675)	(573,1675)	(573,1675)
# clusters	1,676	1,676	1,676
N	7,390,147	7,390,147	7,390,147
Ind.	2,632,000	2,632,000	2,632,000

Notes: Standard errors (in parentheses) are clustered by municipality. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Covariates include municipality, month, and sector specific year and quarter fixed effects.

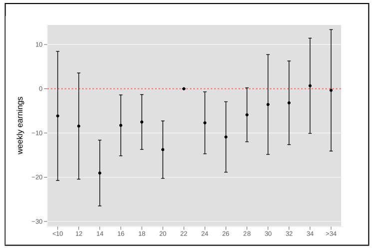
Table A.13.2: Alternative Time Specification – Working Time Regressions

	(1)	(2)	(3)
	week	month	3 months
Temperature			
≤ 10°C	-0.267	-3.943*	-11.23***
	(-0.16)	(-1.67)	(-2.85)
10-12°C	-0.177	3.969	18.81**
	(-0.07)	(0.80)	(2.12)
12-14°C	-0.562	-1.365	-1.985
	(-0.33)	(-0.44)	(-0.37)
14-16°C	-0.331	0.657	7.440**
	(-0.36)	(0.41)	(2.39)
16-18°C	0.594	-0.400	0.533
	(0.58)	(-0.18)	(0.13)
18-20°C	1.014	0.374	4.380
	(0.94)	(0.17)	(0.90)
20-22°C	–	–	–
22-24°C	-1.088	-2.242	2.250
	(-1.18)	(-1.05)	(0.50)
24-26°C	0.778	-1.311	0.482
	(0.86)	(-0.80)	(0.14)
26-28°C	-0.191	-1.496	0.267
	(-0.17)	(-0.82)	(0.08)
28-30°C	-0.367	-1.919	1.524
	(-0.33)	(-1.03)	(0.47)
30-32°C	-2.628**	-4.073*	-3.452
	(-2.21)	(-1.89)	(-0.66)
32-34°C	-1.310	-4.658	-0.248
	(-0.51)	(-1.08)	(-0.02)
> 34°C	-2.415	-4.626	-5.494
	(-1.31)	(-1.51)	(-0.90)
Precipitation			
= 0 mm	-0.360	-0.316	-0.441
	(-0.28)	(-0.41)	(-0.80)
0-2 mm	0.279	0.961	0.410
	(0.22)	(1.33)	(0.71)
2-4 mm	–	–	–
4-6 mm	0.205	-0.587	-0.730
	(0.08)	(-0.37)	(-0.56)
6-8 mm	-1.683	1.166	0.945
	(-0.79)	(0.84)	(0.91)
8-10 mm	1.447	0.110	-0.0804
	(0.59)	(0.07)	(-0.07)
10-20 mm	-0.377	0.107	0.258
	(-0.22)	(0.09)	(0.30)
20-30 mm	-0.347	-0.0603	-0.206
	(-0.13)	(-0.04)	(-0.16)
> 30 mm	-4.890	-1.091	-1.114
	(-1.01)	(-0.36)	(-0.51)
controls	×	×	×
mun. fe	×	×	×
sec time fe	×	×	×
year fe	×	×	×
qtr fe	×	×	×
month fe	×	×	×
adjusted R^2	0.115	0.115	0.115
F Stat.	1,216	1,211	1,253
DF	(573,1675)	(573,1675)	(573,1675)
# clusters	1,676	1,676	1,676
N	7,390,147	7,390,147	7,390,147
Ind.	2,632,000	2,632,000	2,632,000

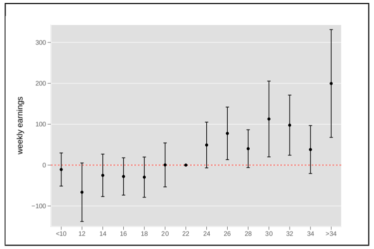
Notes: Standard errors (in parentheses) are clustered by municipality. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Covariates include municipality, month, and sector specific year and quarter fixed effects.

Figure A.13.1: Industry Marginal Effects on Earnings - Temperature (Month)

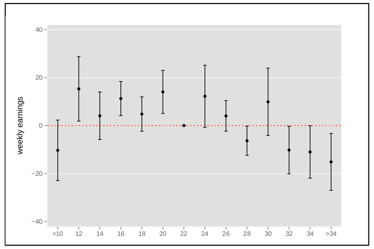
(a) Agriculture



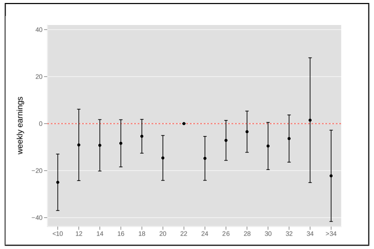
(b) Extractive Industry



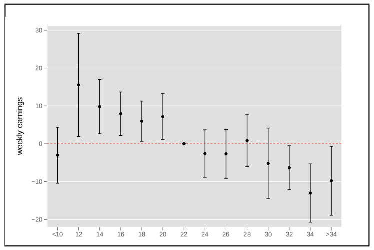
(c) Manufacturing



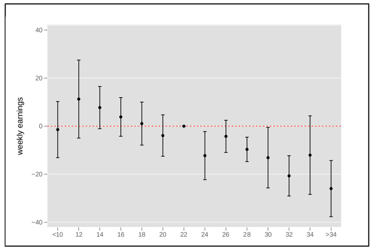
(d) Construction



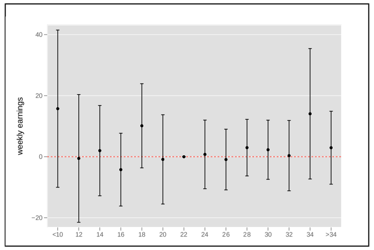
(e) Trade



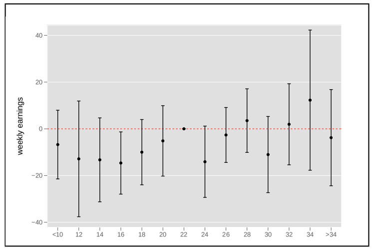
(f) Restaurant Services



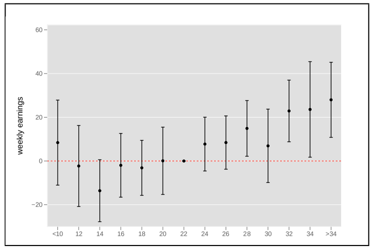
(g) Transport



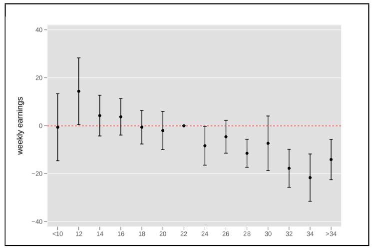
(h) Professional Services



(i) Diverse Services



(j) Social Services



(k) Government

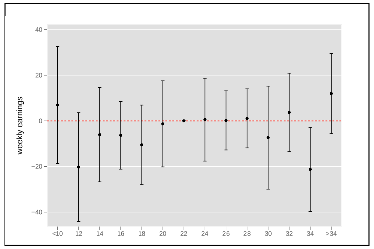
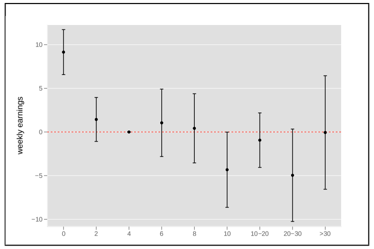
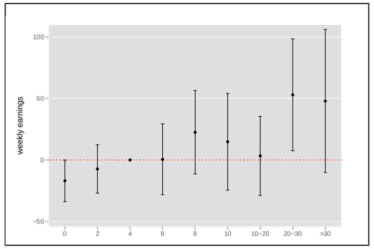


Figure A.13.1: Industry Marginal Effects on Earnings - Precipitation (Month) *(continued)*

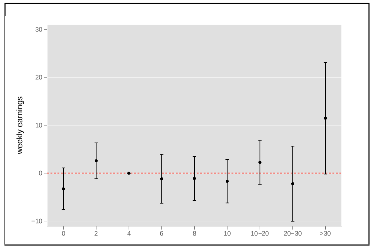
(l) Agriculture



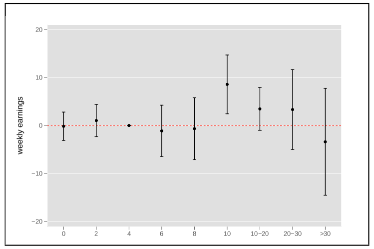
(m) Extractive Industry



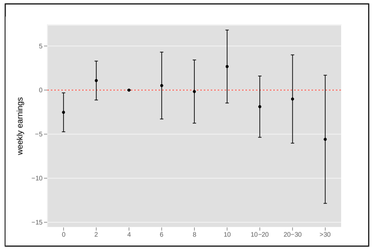
(n) Manufacturing



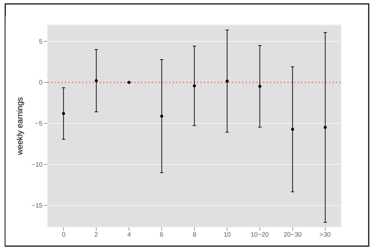
(o) Construction



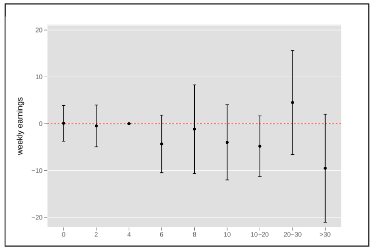
(p) Trade



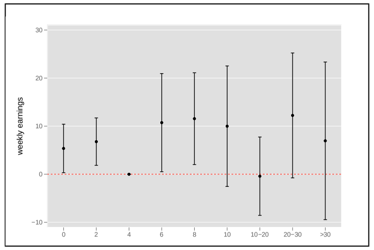
(q) Restaurants Services



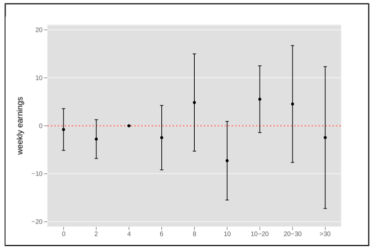
(r) Transport



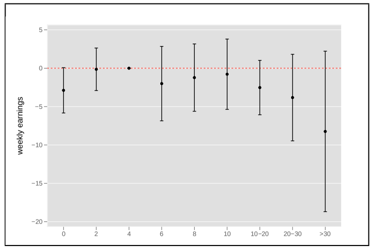
(s) Professional Services



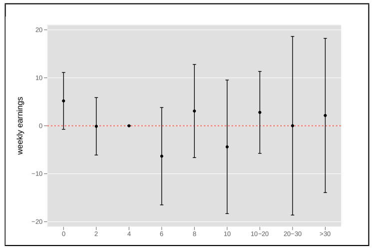
(t) Diverse Services



(u) Social Services

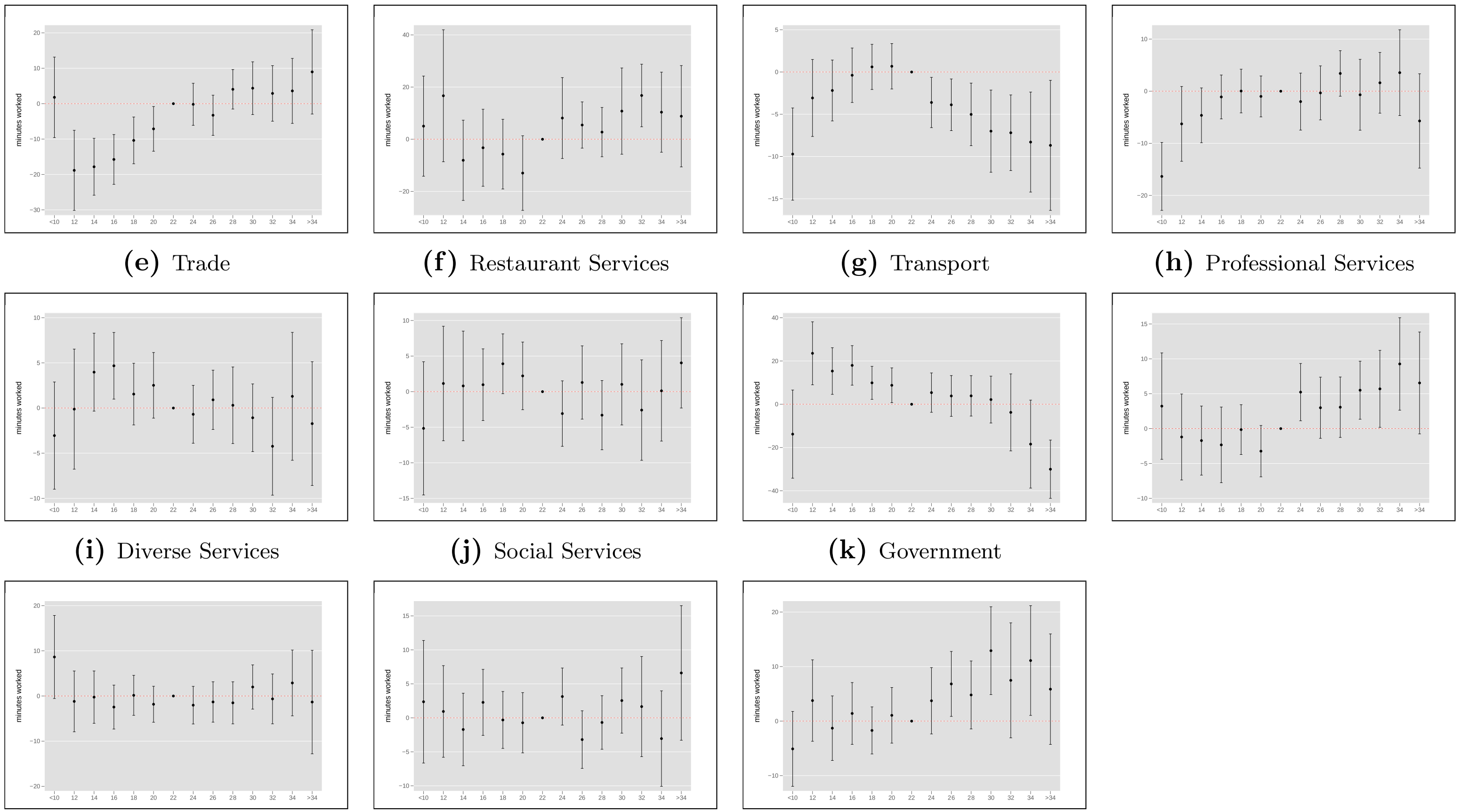


(v) Government



Statistics: Adjusted R^2=0.116, F Stat=2273.5, # clusters=1,676, N=7,390,147, Ind.=2,632,000.
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Figure A.13.2: Industry Marginal Effects on Working Time - Temperature (Month)



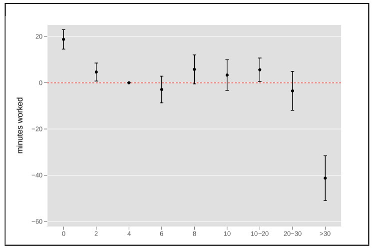
(a) Agriculture **(b)** Extractive Industry **(c)** Manufacturing **(d)** Construction

(e) Trade **(f)** Restaurant Services **(g)** Transport **(h)** Professional Services

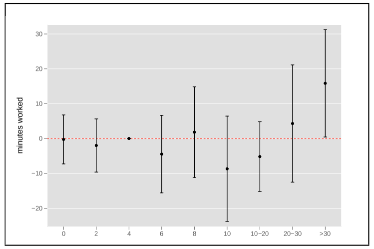
(i) Diverse Services **(j)** Social Services **(k)** Government

Figure A.13.2: Industry Marginal Effects on Working Time - Precipitation (Month) *(continued)*

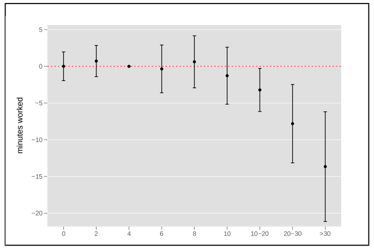
(l) Agriculture



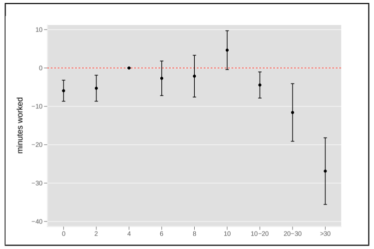
(m) Extractive Industry



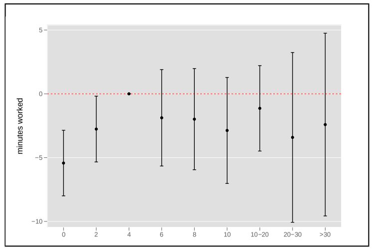
(n) Manufacturing



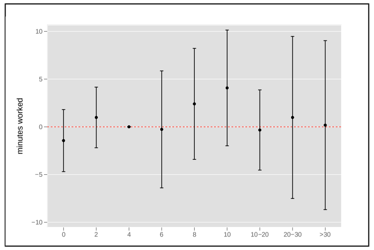
(o) Construction



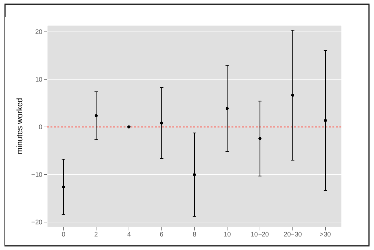
(p) Trade



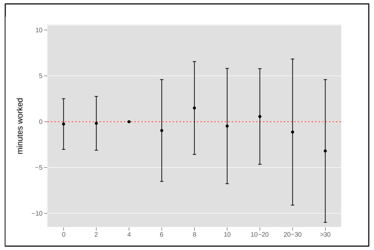
(q) Restaurant Services



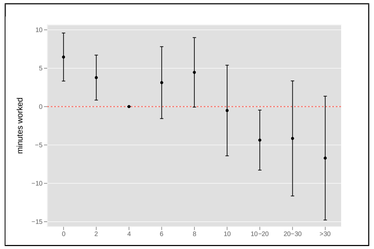
(r) Transport



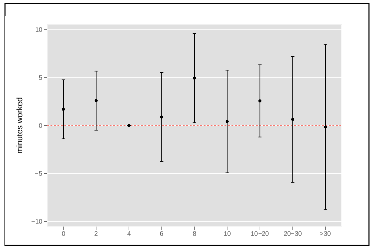
(s) Professional Services



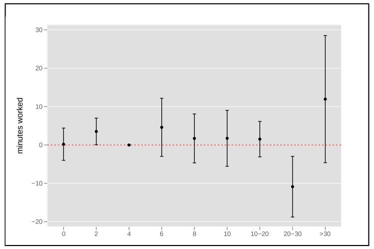
(t) Diverse Services



(u) Social Services



(v) Government

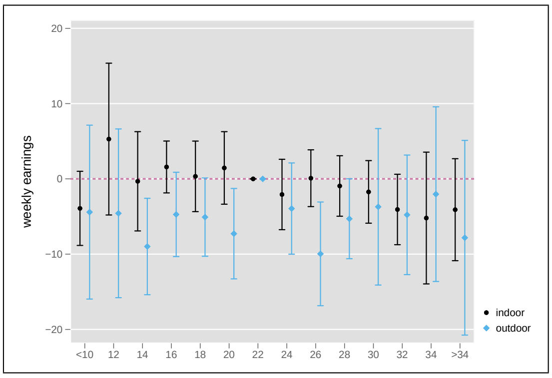


Statistics: Adjusted R^2=0.147, F Stat=980.1, # clusters=1,676, N=7,390,147, Ind.=2,632,000.
Notes: The figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] $^\circ$ C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

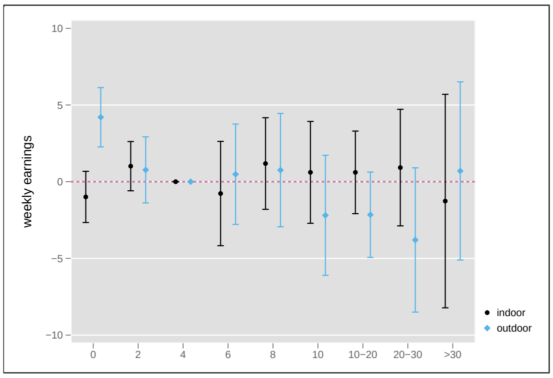
Figure A.13.3: Work Location Marginal Effects on Earnings (Month)

outdoor vs indoor

(a) temperature

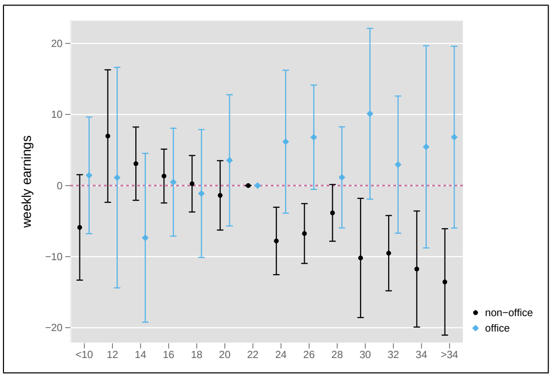


(b) precipitation

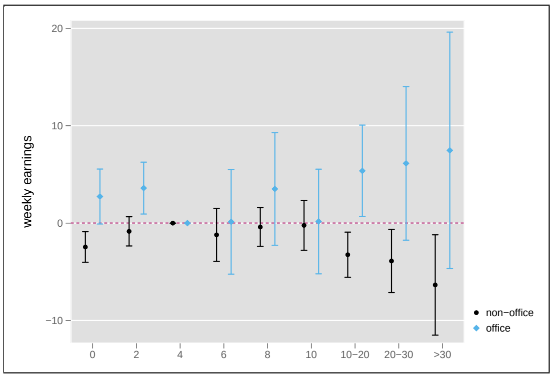


office vs non-office

(c) temperature

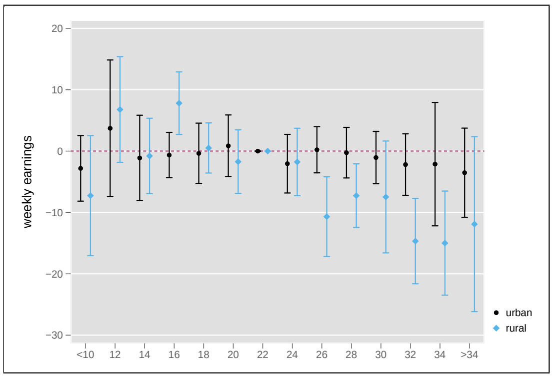


(d) precipitation



urban vs rural

(e) temperature



(f) precipitation

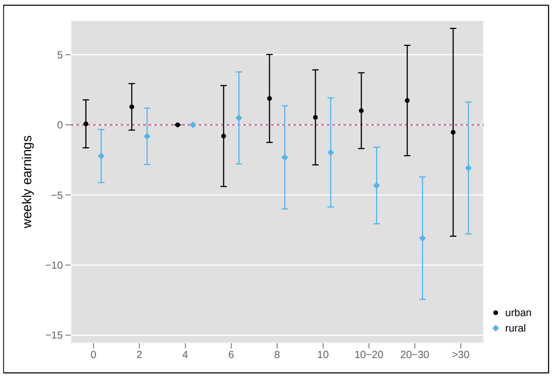
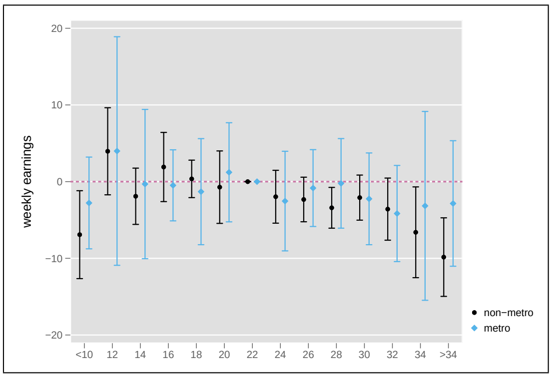


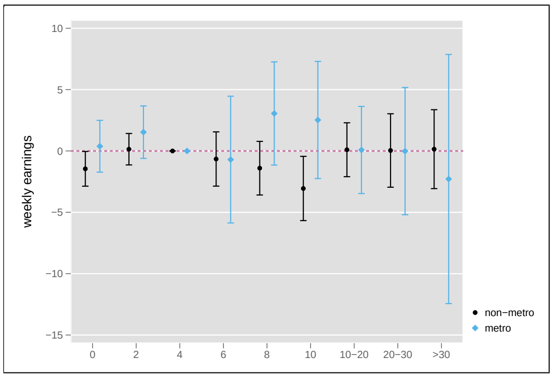
Figure A.13.3: Work Location Marginal Effects on Earnings (Month) *(continued)*

metro vs non-metro area

(g) temperature

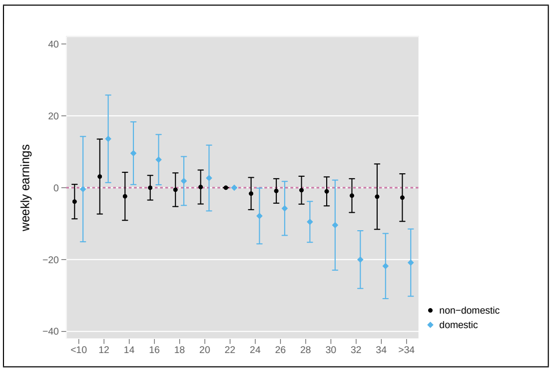


(h) precipitation

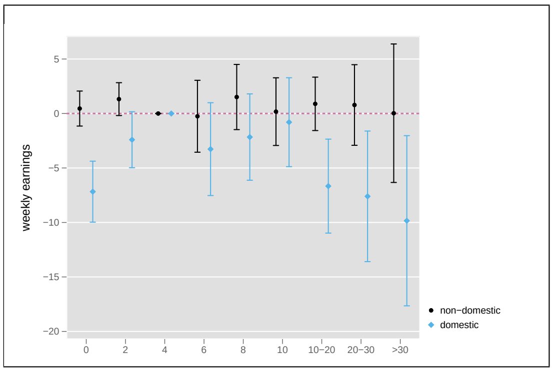


domestic vs non-domestic

(i) temperature



(j) precipitation



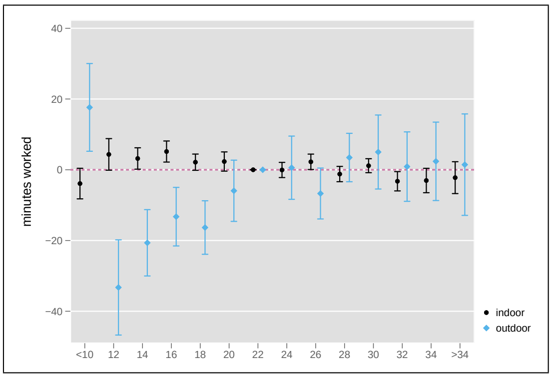
Statistics: N=7,390,140, Ind.=2,631,998.

Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

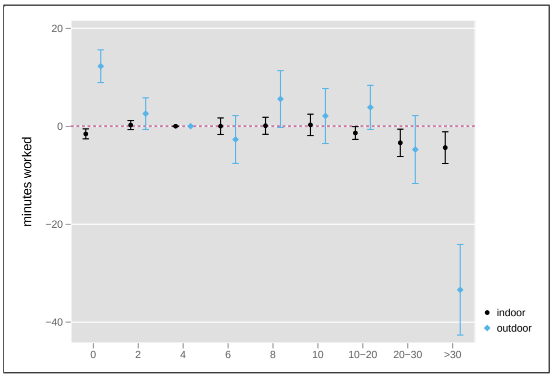
Figure A.13.4: Work Location Marginal Effects on Working Time (Month)

outdoor vs indoor

(a) temperature

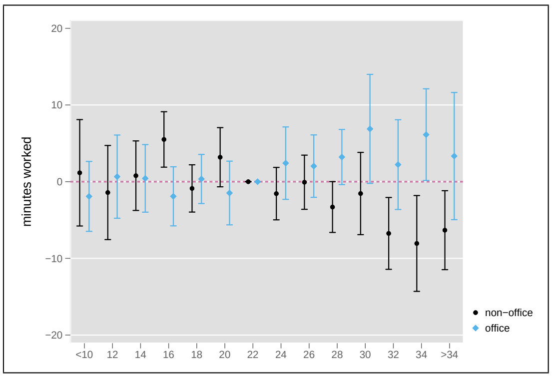


(b) precipitation

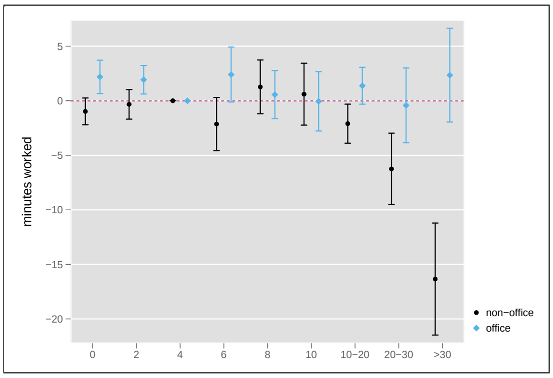


office vs non-office

(c) temperature

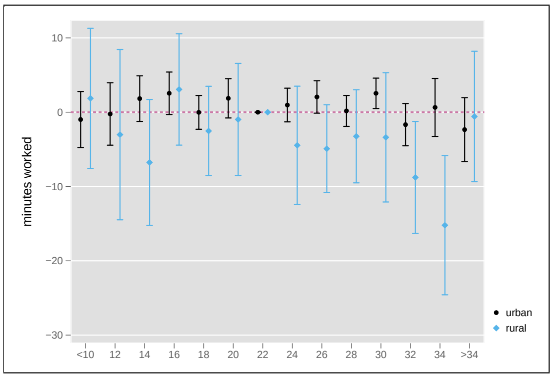


(d) precipitation



urban vs rural

(e) temperature



(f) precipitation

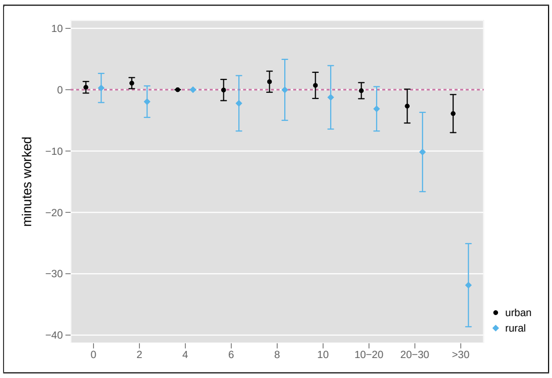
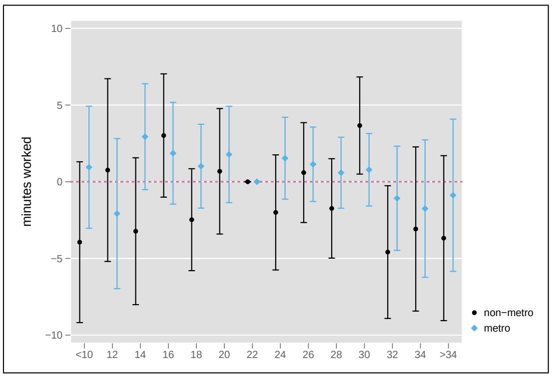


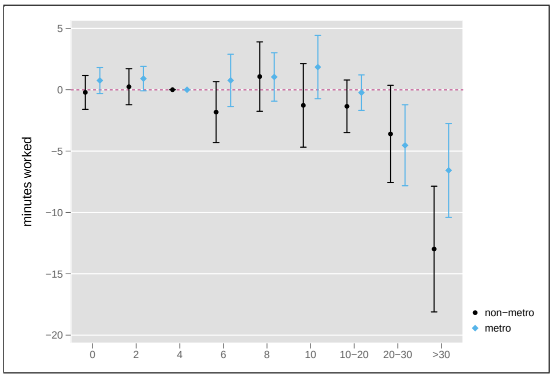
Figure A.13.4: Work Location Marginal Effects on Working Time (Month) *(continued)*

metro vs non-metro area

(g) temperature

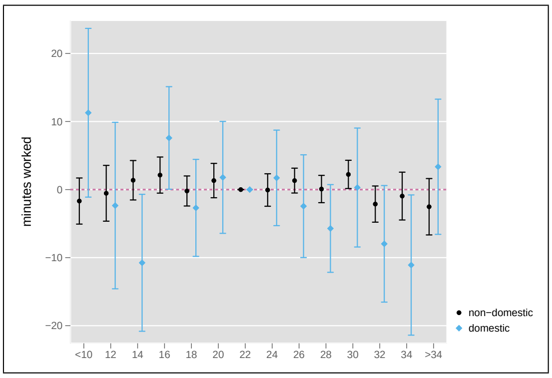


(h) precipitation

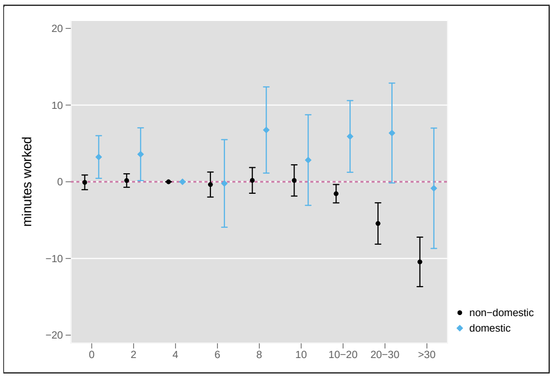


domestic vs non-domestic

(i) temperature



(j) precipitation

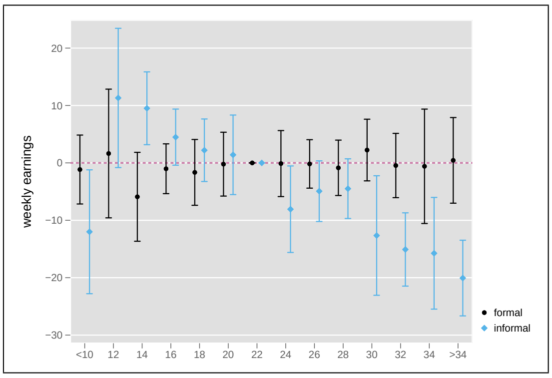


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

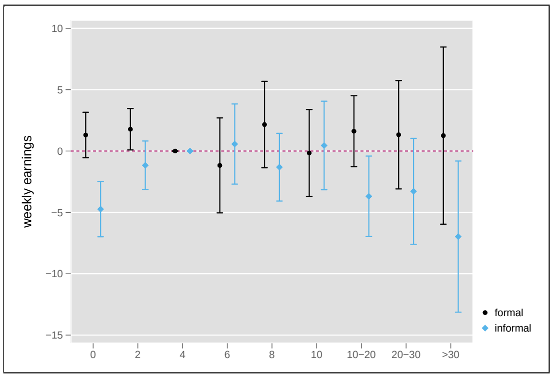
Figure A.13.5: Job Characteristics Marginal Effects on Earnings (Month)

formal vs informal

(a) temperature

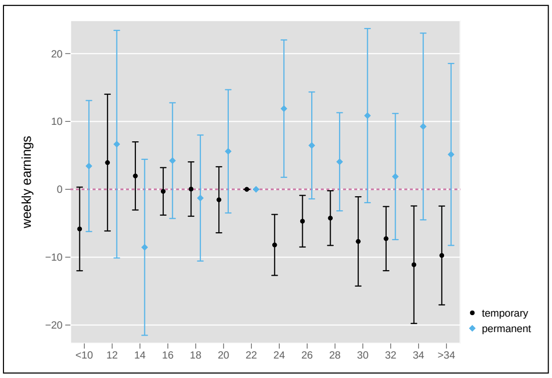


(b) precipitation

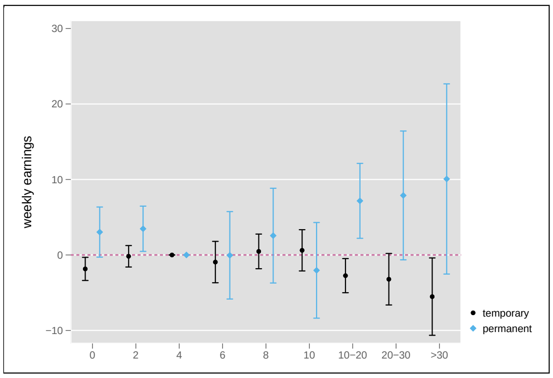


permanent vs temporary

(c) temperature

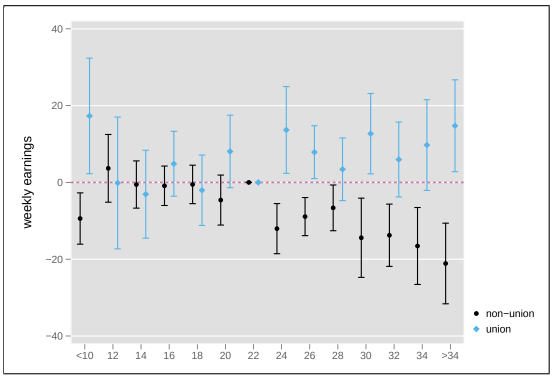


(d) precipitation



union vs non-union

(e) temperature



(f) precipitation

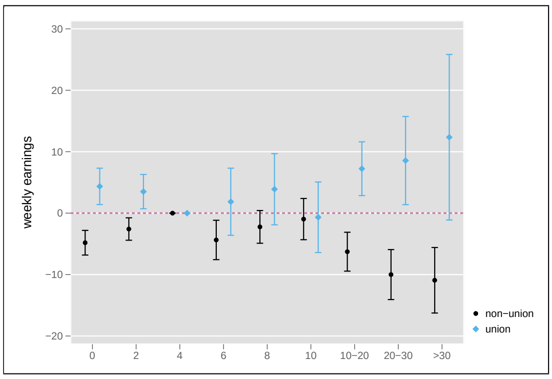
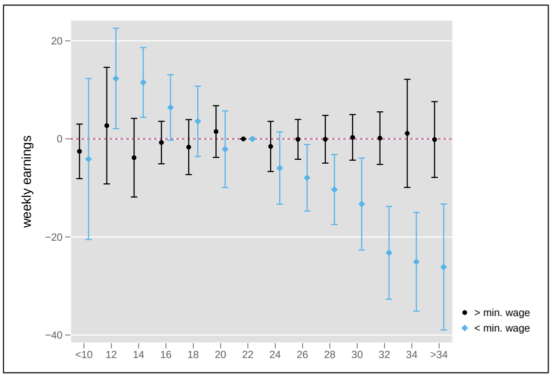


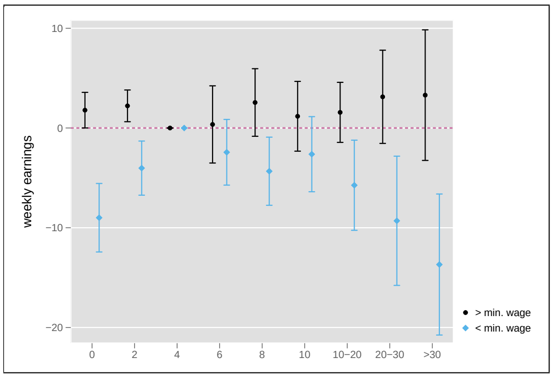
Figure A.13.5: Job Characteristics Marginal Effects on Earnings (Month) *(continued)*

above vs below official minimum wage

(g) temperature

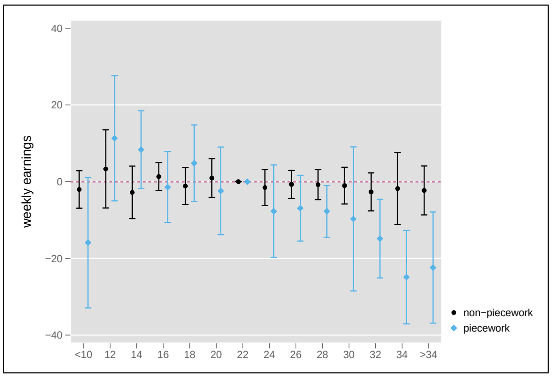


(h) precipitation

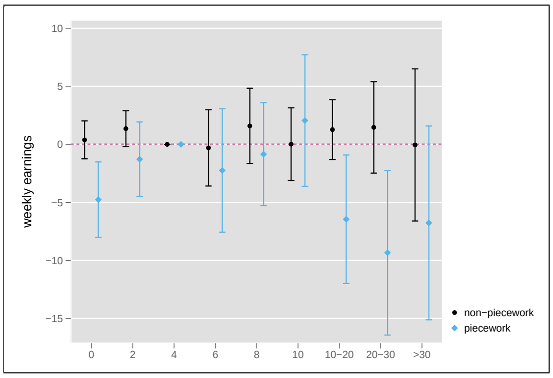


piecework vs non-piecework

(i) temperature

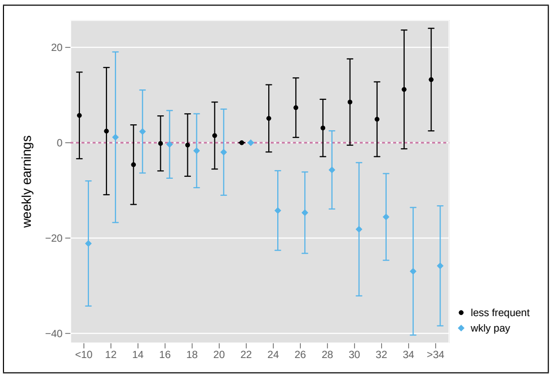


(j) precipitation

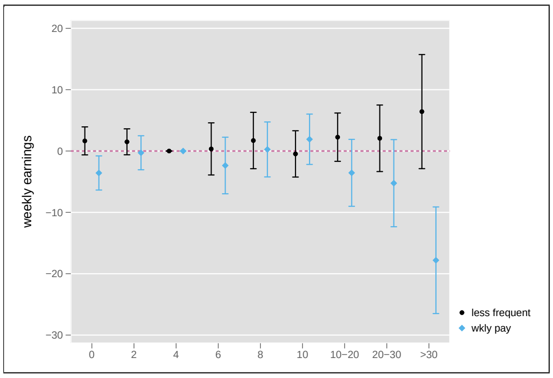


weekly vs less frequent pay

(k) temperature



(l) precipitation

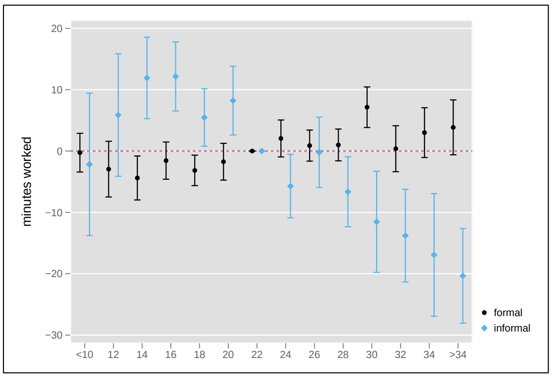


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

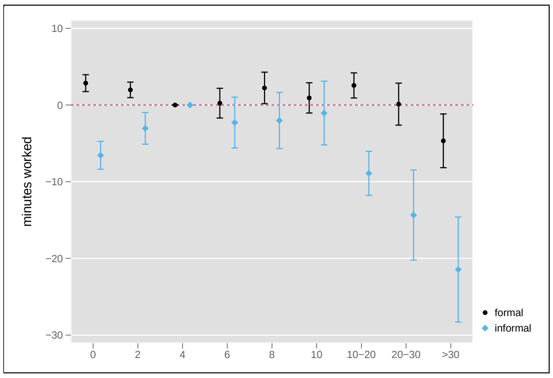
Figure A.13.6: Job Characteristics Marginal Effects on Working Time (Month)

formal vs informal

(a) temperature

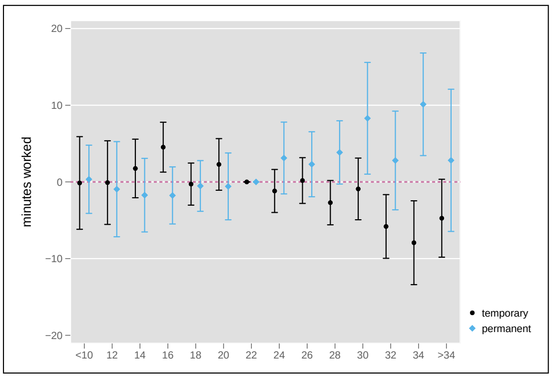


(b) precipitation

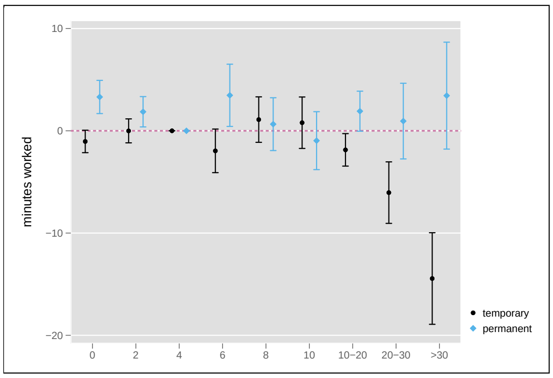


permanent vs temporary

(c) temperature

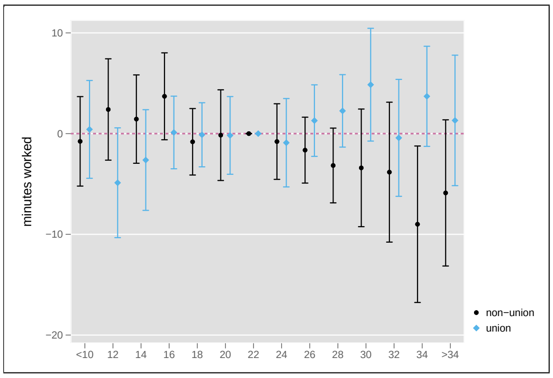


(d) precipitation



union vs non-union

(e) temperature



(f) precipitation

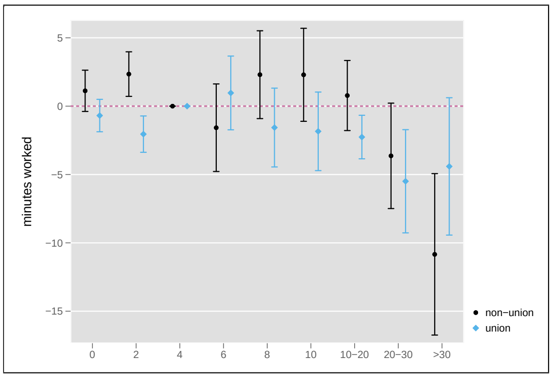
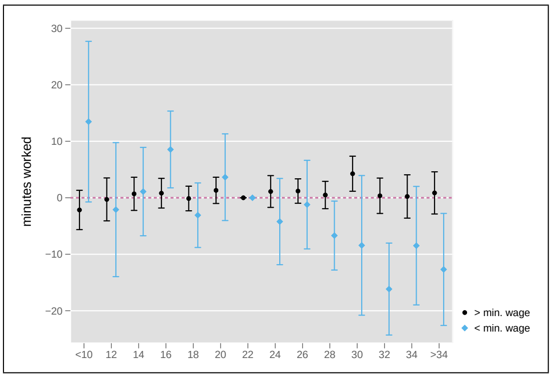


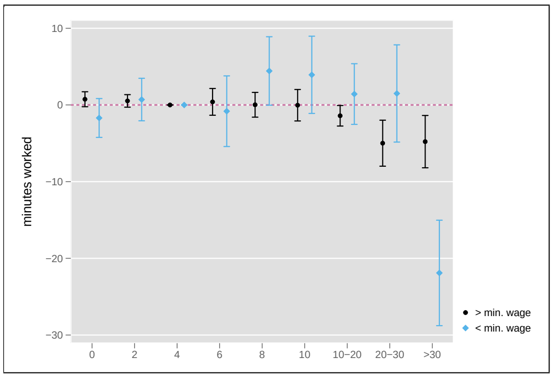
Figure A.13.6: Job Characteristics Marginal Effects on Working Time (Month) *(continued)*

above vs below official minimum wage

(g) temperature

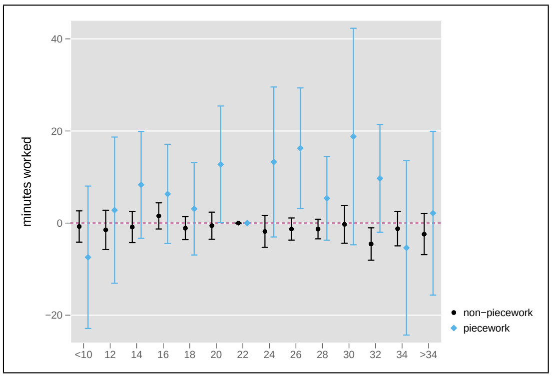


(h) precipitation

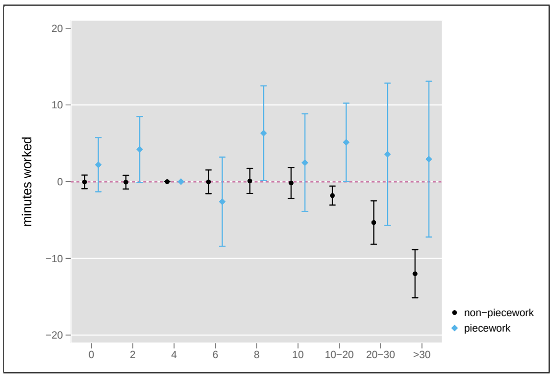


piecework vs non-piecework

(i) temperature

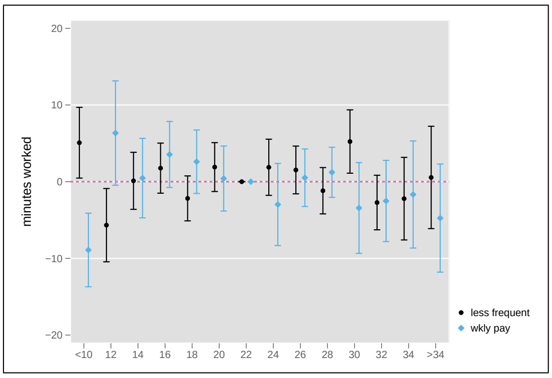


(j) precipitation

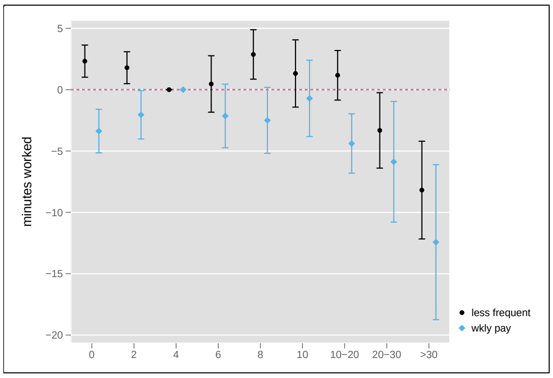


weekly vs less frequent pay

(k) temperature



(l) precipitation

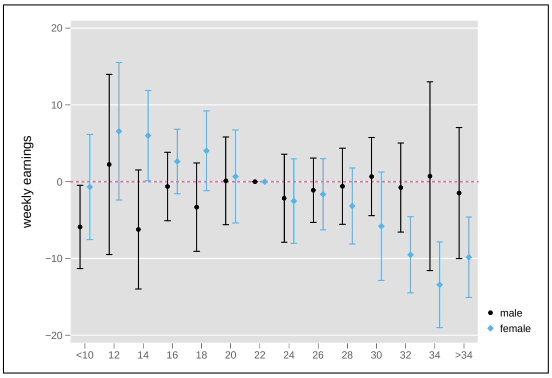


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

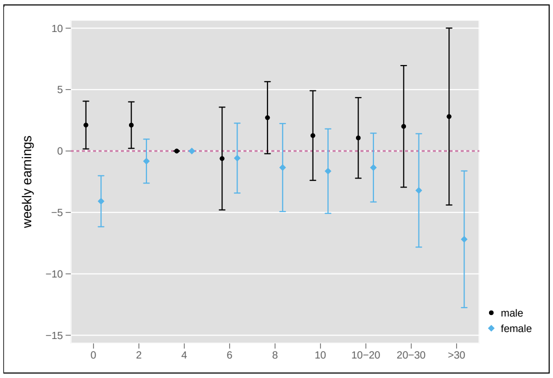
Figure A.13.7: Individual Characteristics Marginal Effects on Earnings (Month)

male vs female

(a) temperature

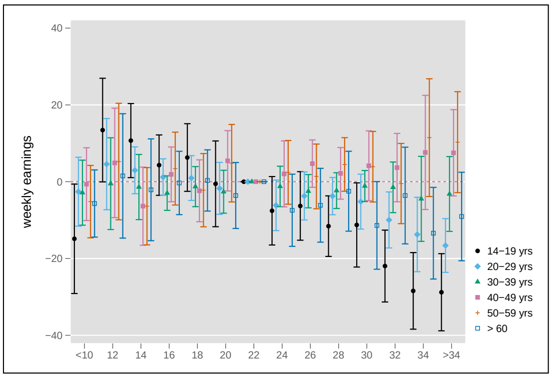


(b) precipitation

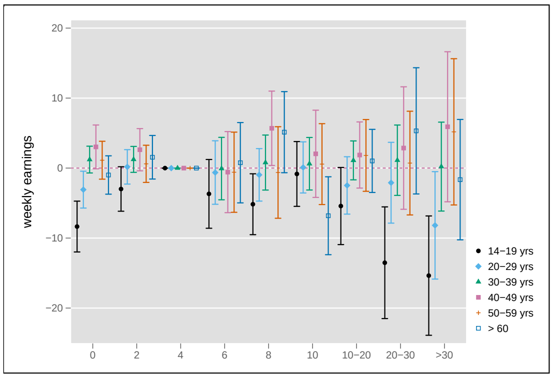


by age group

(c) temperature

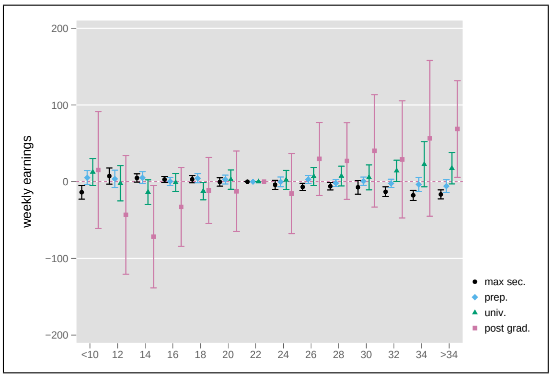


(d) precipitation

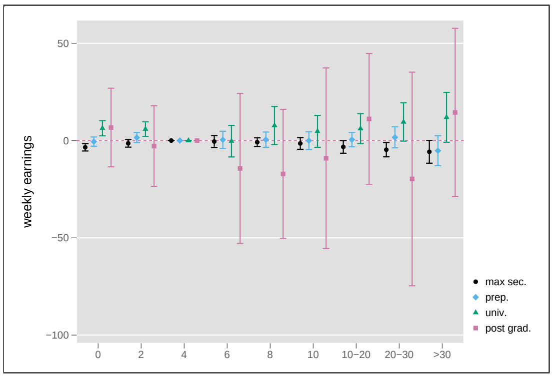


union vs non-union

(e) temperature



(f) precipitation

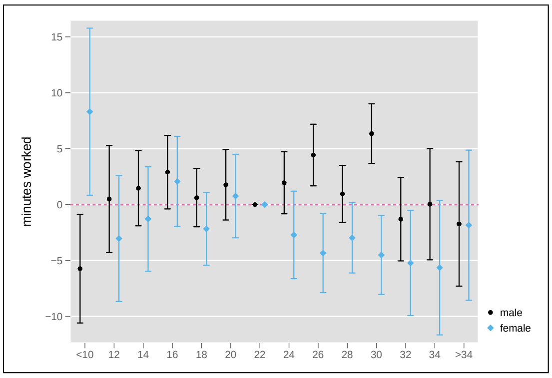


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] $^\circ$C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

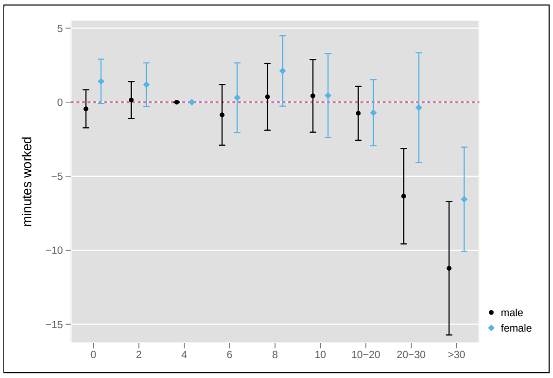
Figure A.13.8: Individual Characteristics Marginal Effects on Working Time (Month)

male vs female

(a) temperature

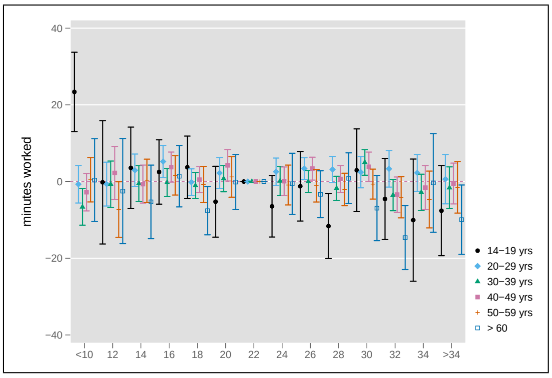


(b) precipitation

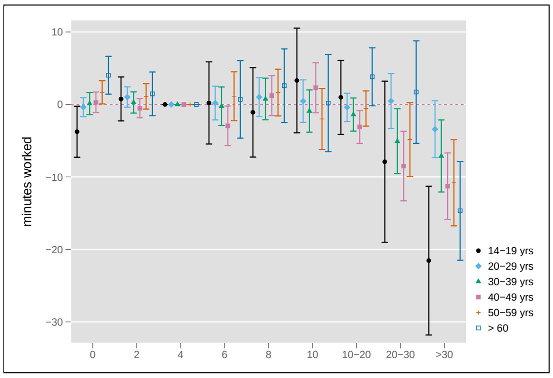


by age group

(c) temperature

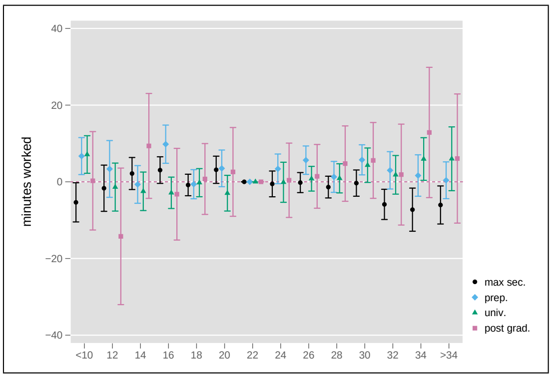


(d) precipitation

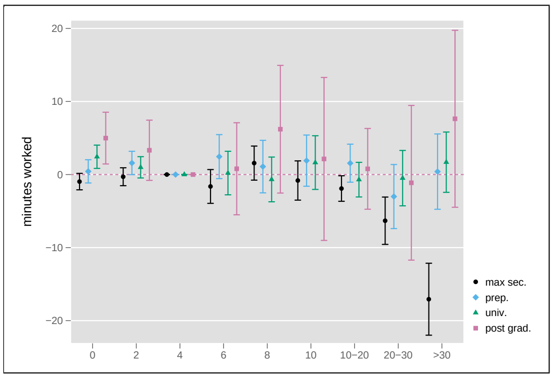


union vs non-union

(e) temperature



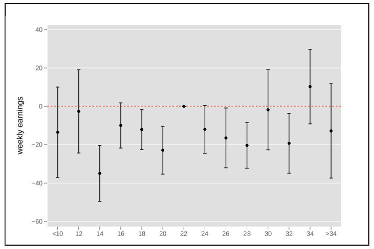
(f) precipitation



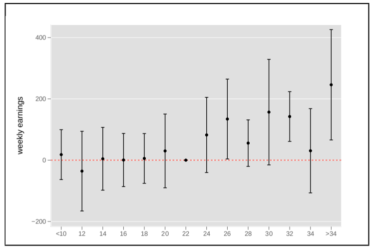
Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Figure A.13.9: Industry Marginal Effects on Earnings - Temperature (Quarter)

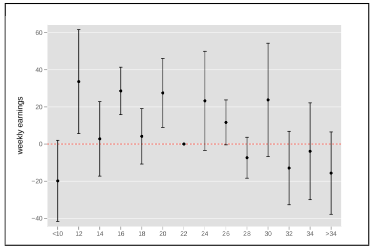
(a) Agriculture



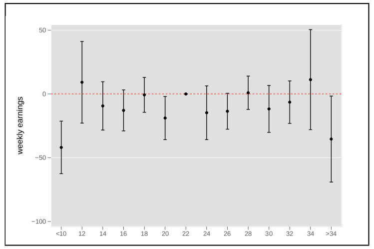
(b) Extractive Industry



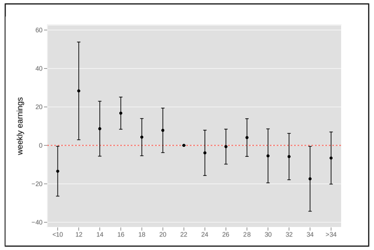
(c) Manufacturing



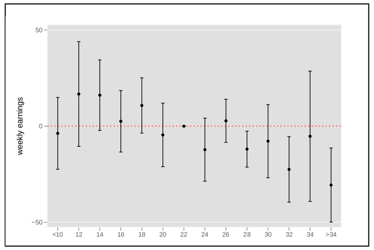
(d) Construction



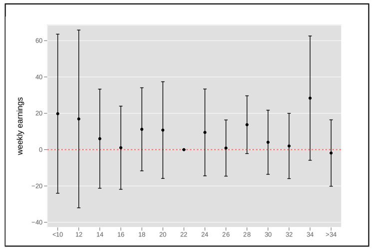
(e) Trade



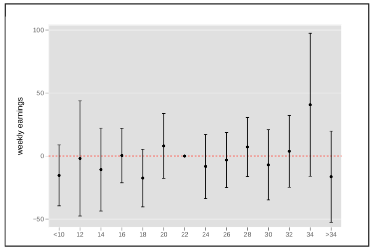
(f) Restaurant Services



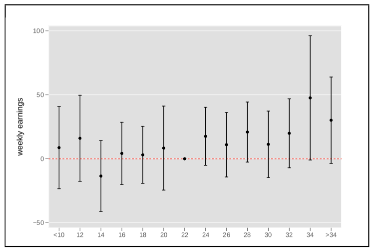
(g) Transport



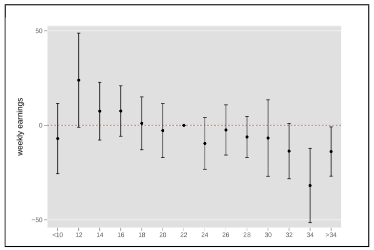
(h) Professional Services



(i) Diverse Services



(j) Social Services



(k) Government

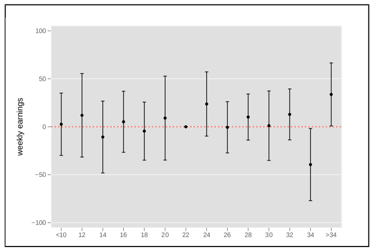
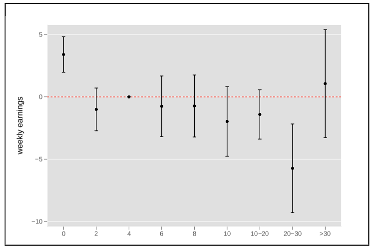
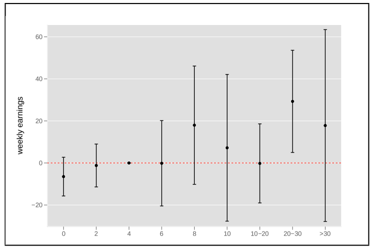


Figure A.13.9: Industry Marginal Effects on Earnings - Precipitation (Quarter) *(continued)*

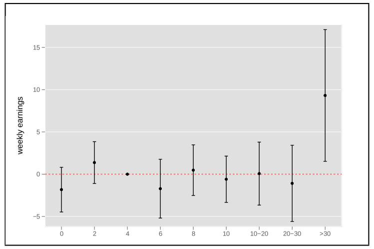
(l) Agriculture



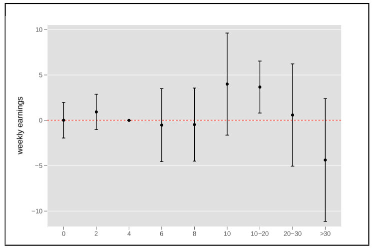
(m) Extractive Industry



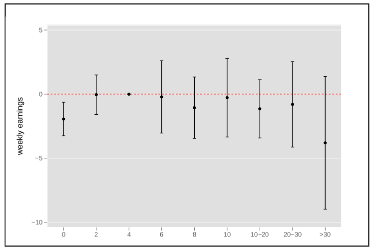
(n) Manufacturing



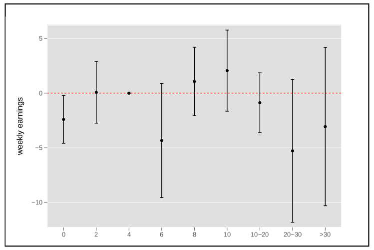
(o) Construction



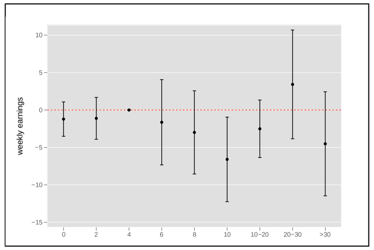
(p) Trade



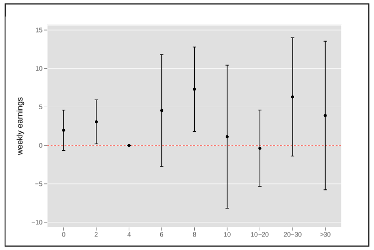
(q) Restaurants Services



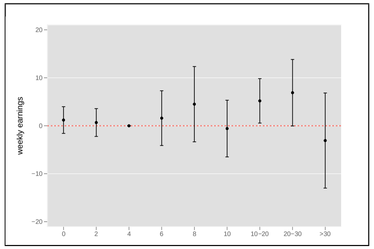
(r) Transport



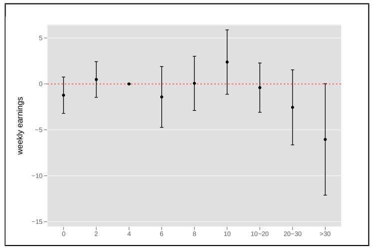
(s) Professional Services



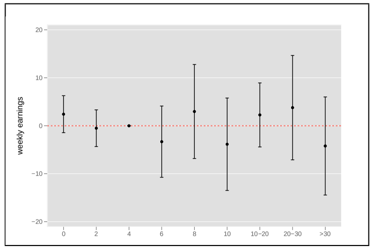
(t) Diverse Services



(u) Social Services



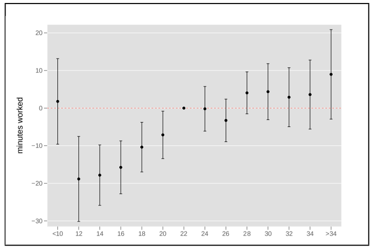
(v) Government



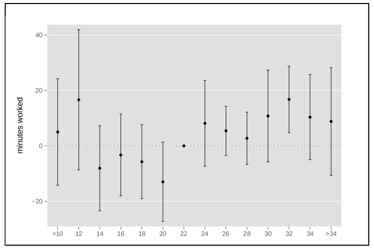
Statistics: Adjusted R^2=0.116, F Stat=2273.5, # clusters=1,676, N=7,390,147, Ind.=2,632,000.
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Figure A.13.10: Industry Marginal Effects on Working Time - Temperature (Quarter)

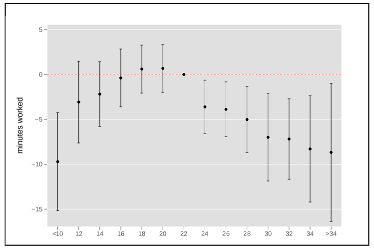
(a) Agriculture



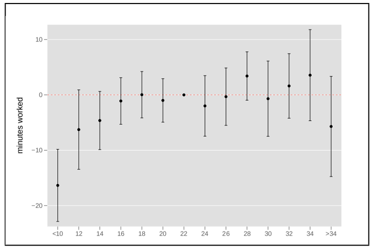
(b) Extractive Industry



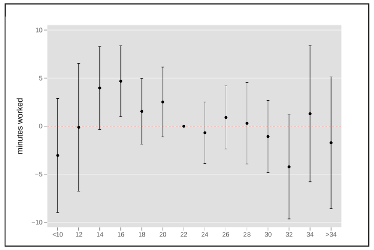
(c) Manufacturing



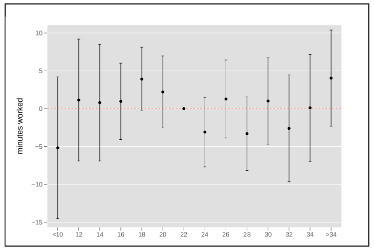
(d) Construction



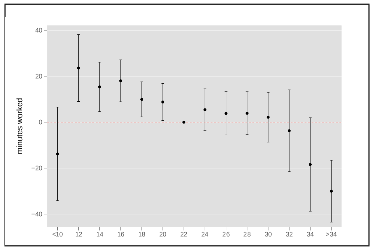
(e) Trade



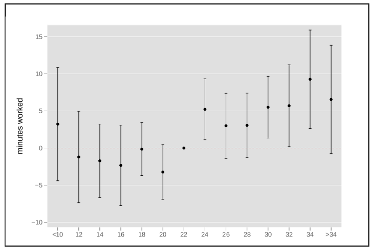
(f) Restaurant Services



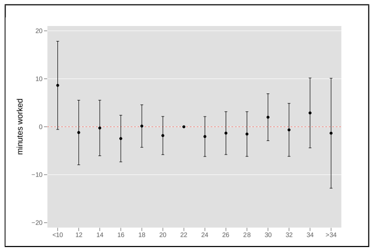
(g) Transport



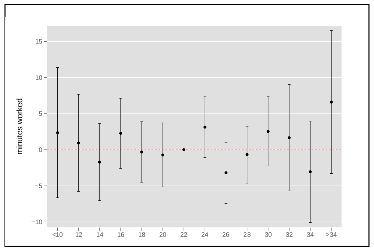
(h) Professional Services



(i) Diverse Services



(j) Social Services



(k) Government

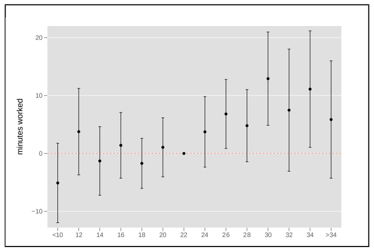
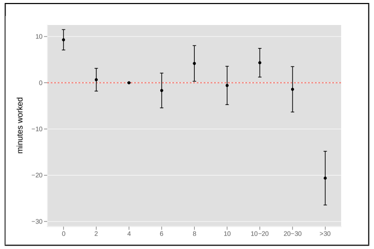
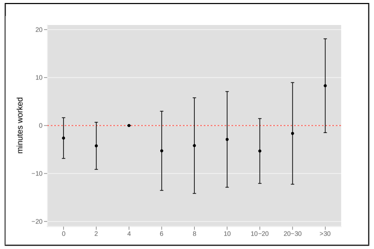


Figure A.13.10: Industry Marginal Effects on Working Time - Precipitation (Quarter) *(continued)*

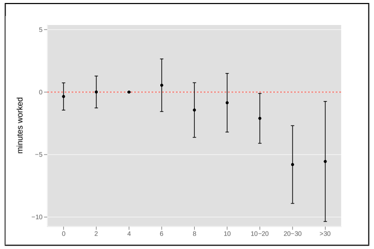
(l) Agriculture



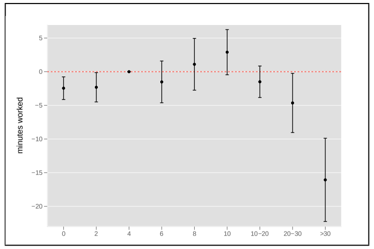
(m) Extractive Industry



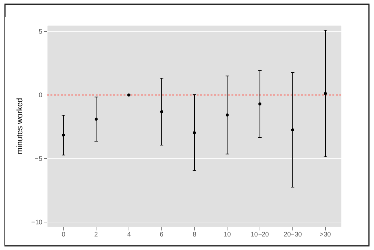
(n) Manufacturing



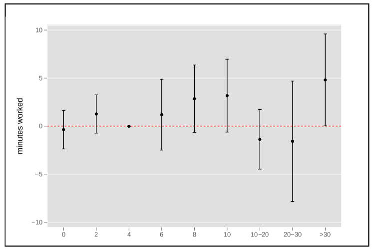
(o) Construction



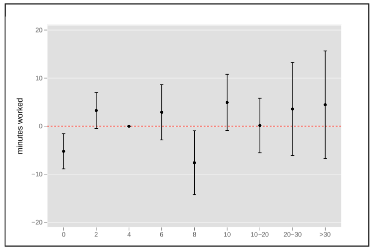
(p) Trade



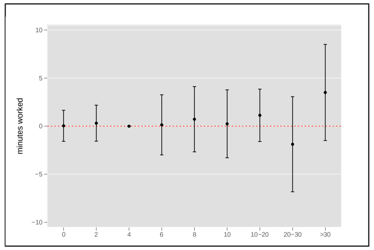
(q) Restaurant Services



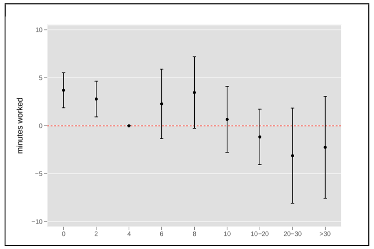
(r) Transport



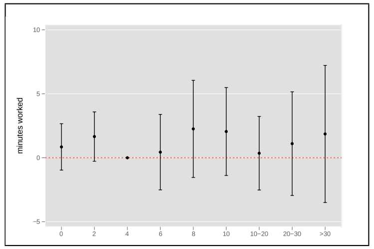
(s) Professional Services



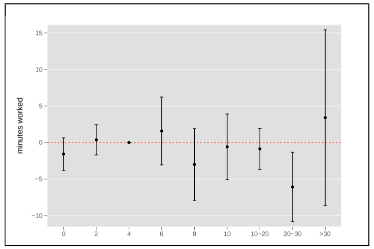
(t) Diverse Services



(u) Social Services



(v) Government

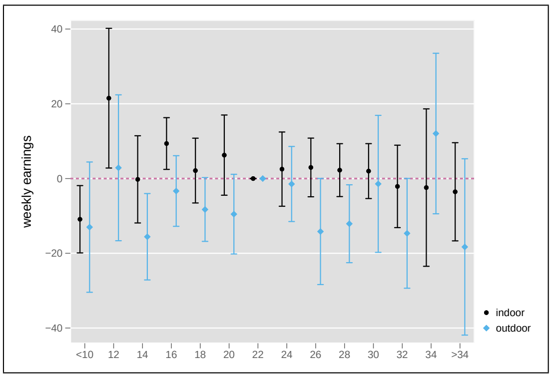


Statistics: Adjusted R^2=0.147, F Stat=980.1, # clusters=1,676, N=7,390,147, Ind.=2,632,000.
Notes: The figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

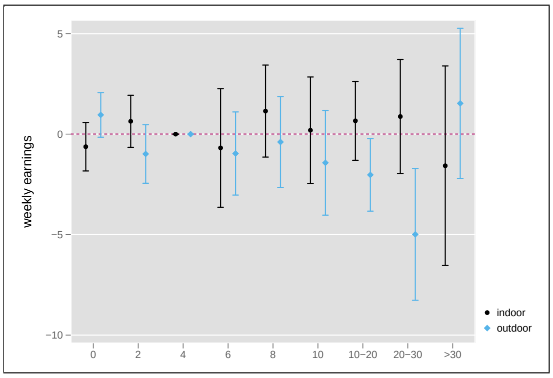
Figure A.13.11: Work Location Marginal Effects on Earnings (Quarter)

outdoor vs indoor

(a) temperature

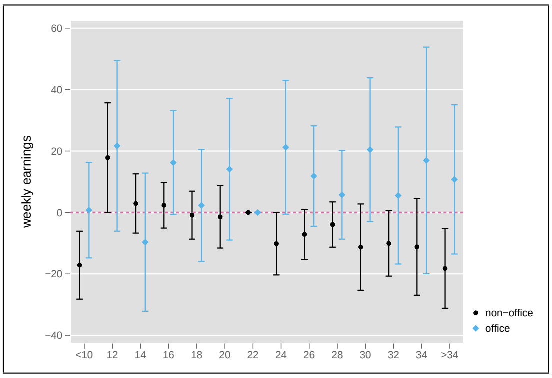


(b) precipitation

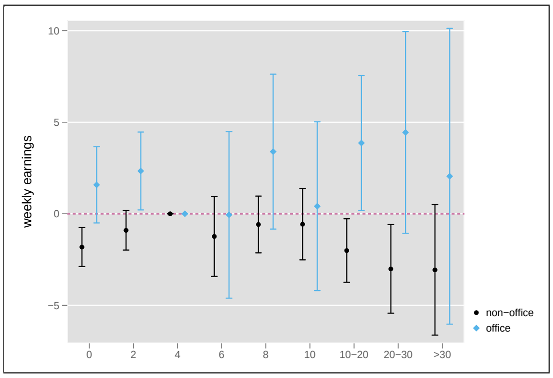


office vs non-office

(c) temperature

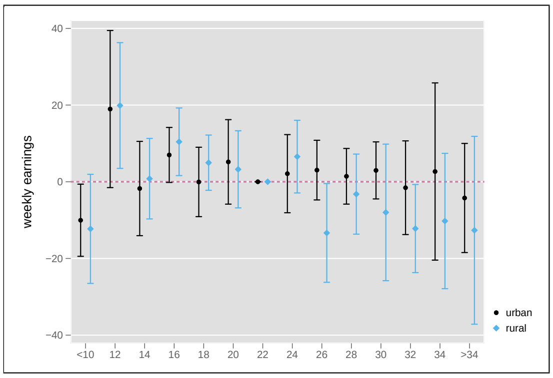


(d) precipitation



urban vs rural

(e) temperature



(f) precipitation

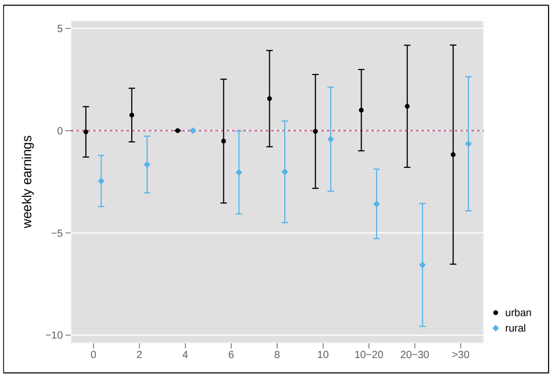
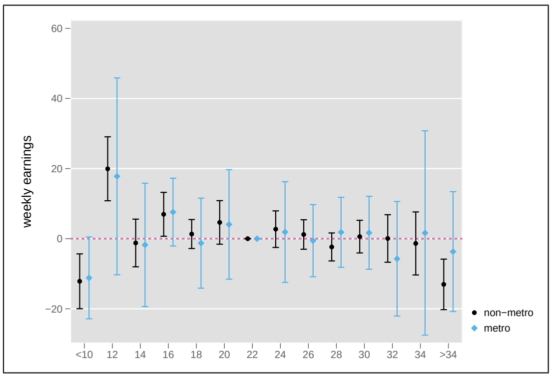


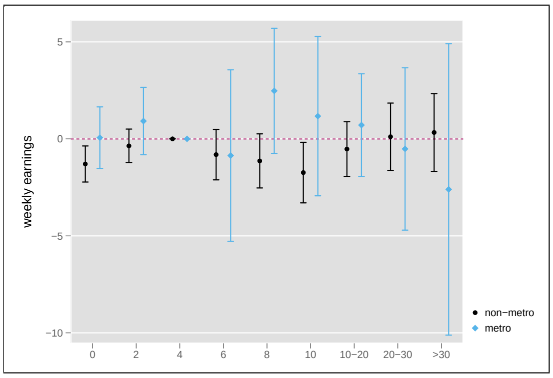
Figure A.13.11: Work Location Marginal Effects on Earnings (Quarter)
(continued)

metro vs non-metro area

(g) temperature

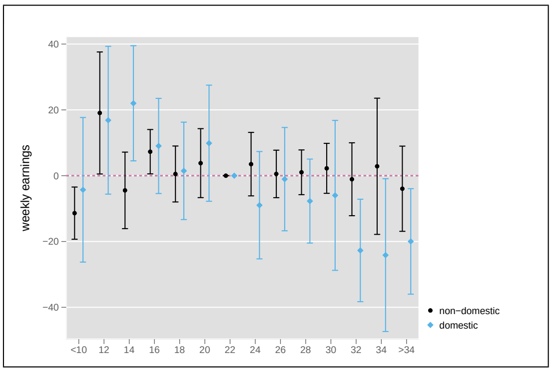


(h) precipitation

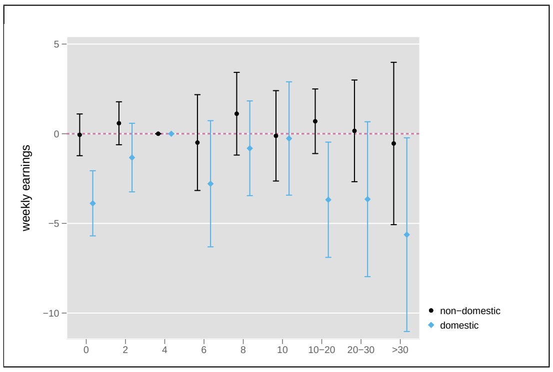


domestic vs non-domestic

(i) temperature



(j) precipitation

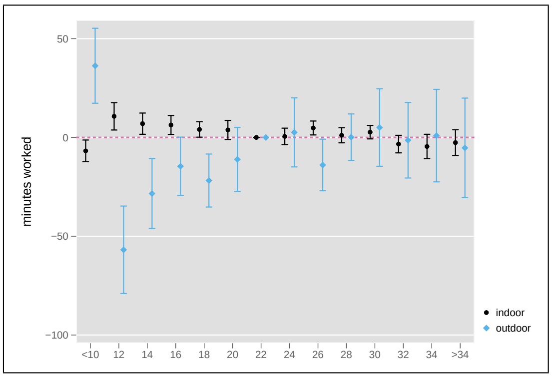


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

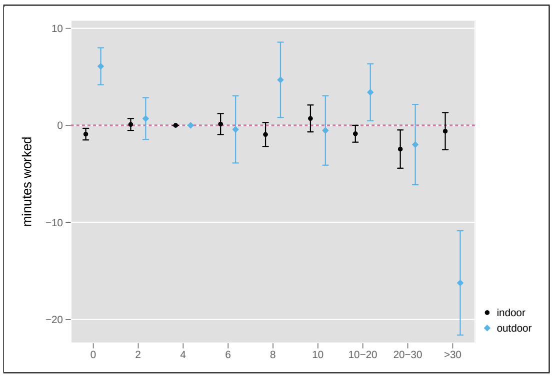
Figure A.13.12: Work Location Marginal Effects on Working Time (Quarter)

outdoor vs indoor

(a) temperature

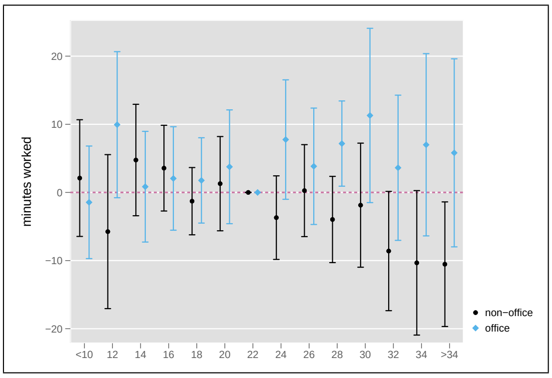


(b) precipitation

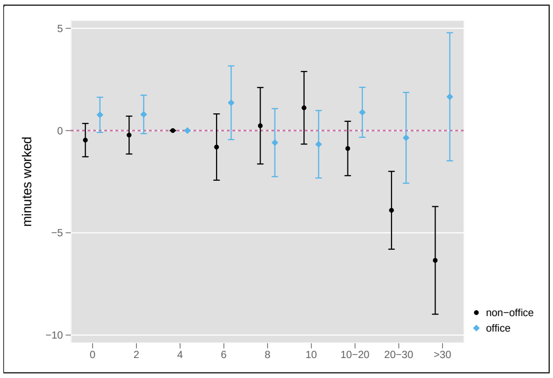


office vs non-office

(c) temperature

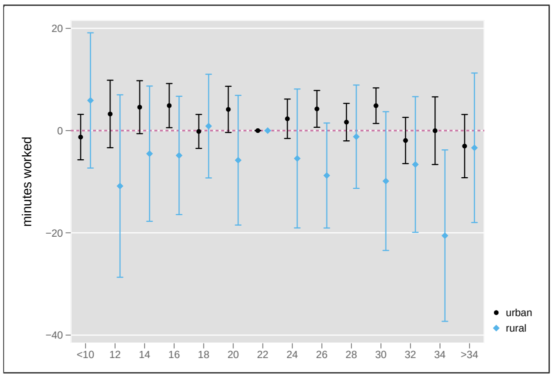


(d) precipitation



urban vs rural

(e) temperature



(f) precipitation

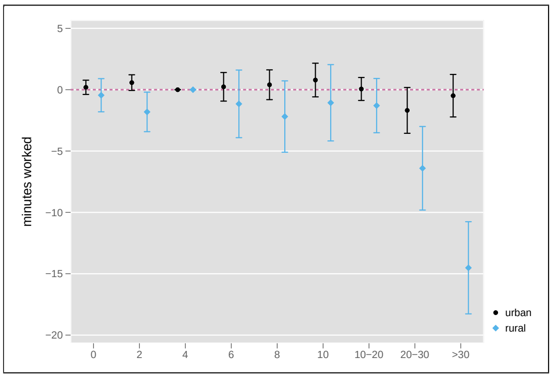
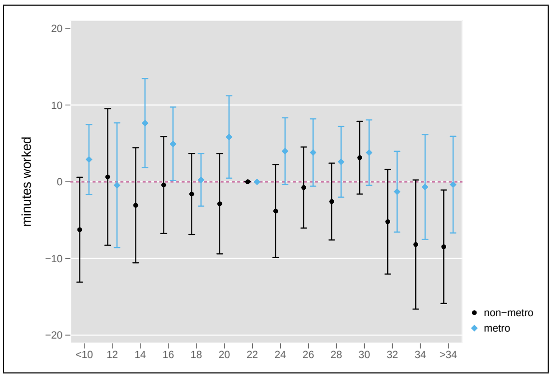


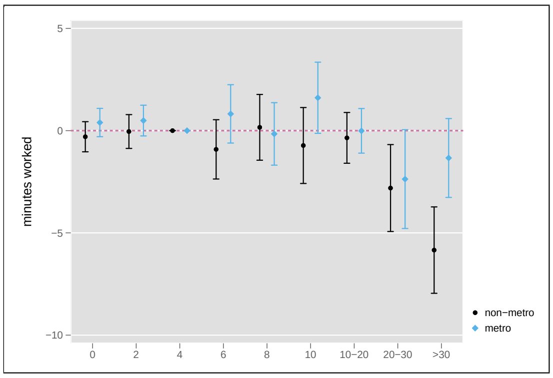
Figure A.13.12: Work Location Marginal Effects on Working Time (Quarter) *(continued)*

metro vs non-metro area

(g) temperature

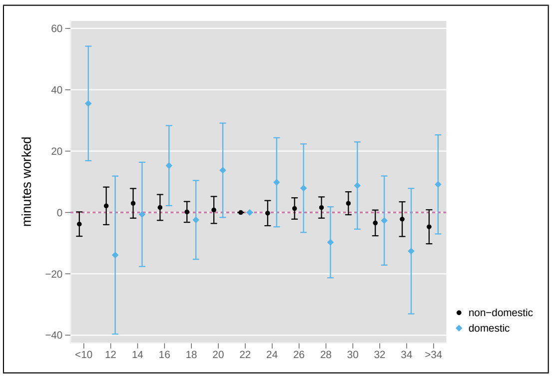


(h) precipitation

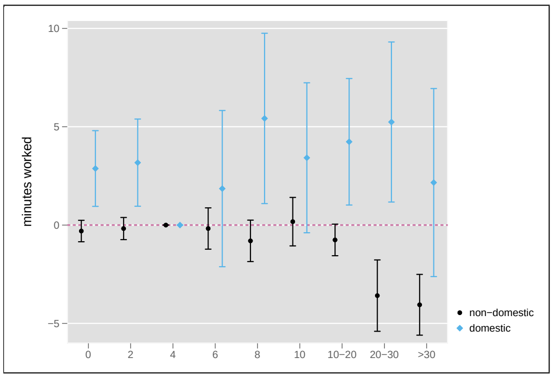


domestic vs non-domestic

(i) temperature



(j) precipitation

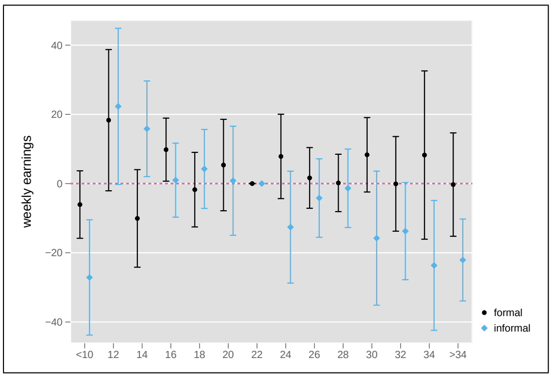


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

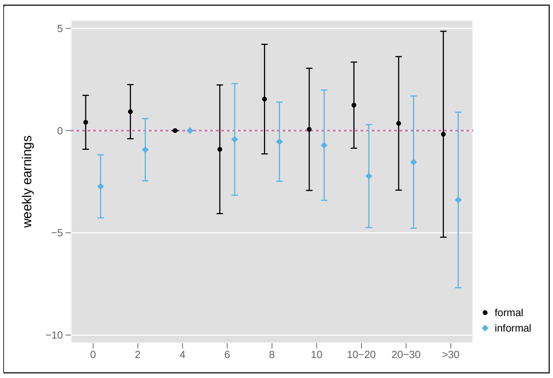
Figure A.13.13: Job Characteristics Marginal Effects on Earnings (Quarter)

formal vs informal

(a) temperature

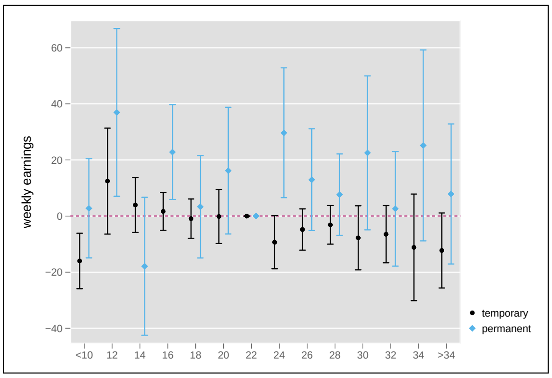


(b) precipitation

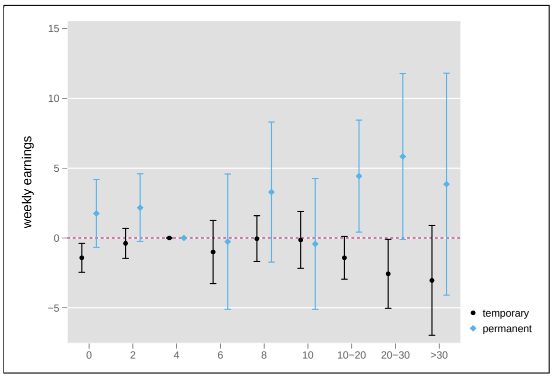


permanent vs temporary

(c) temperature

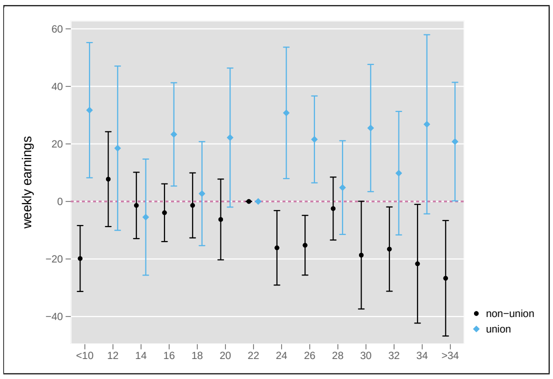


(d) precipitation



union vs non-union

(e) temperature



(f) precipitation

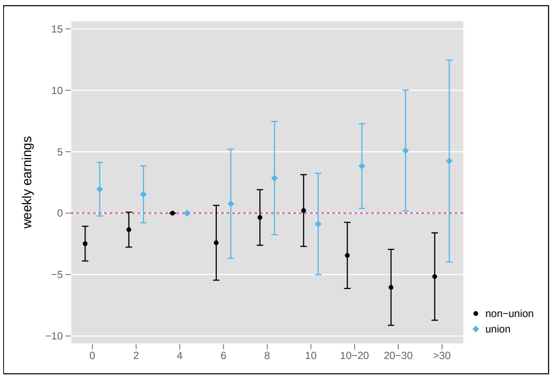
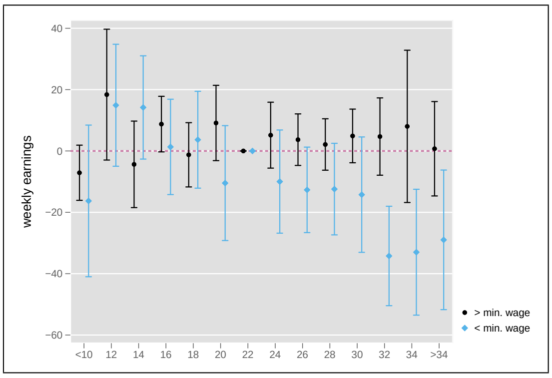


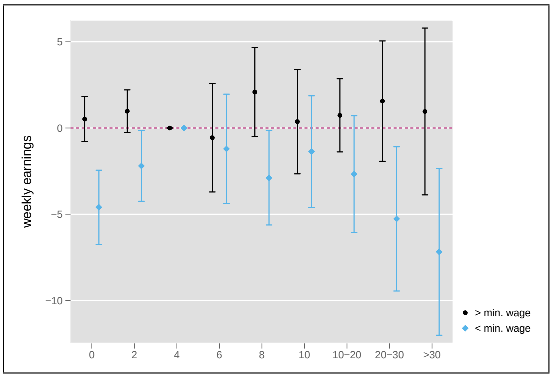
Figure A.13.13: Job Characteristics Marginal Effects on Earnings (Quarter) *(continued)*

above vs below official minimum wage

(g) temperature

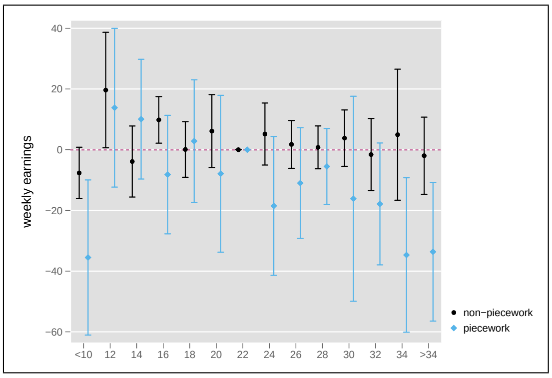


(h) precipitation

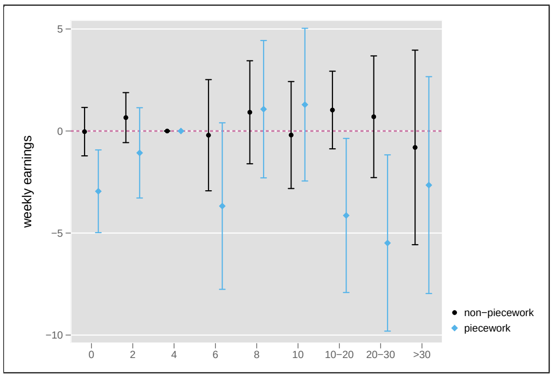


piecework vs non-piecework

(i) temperature

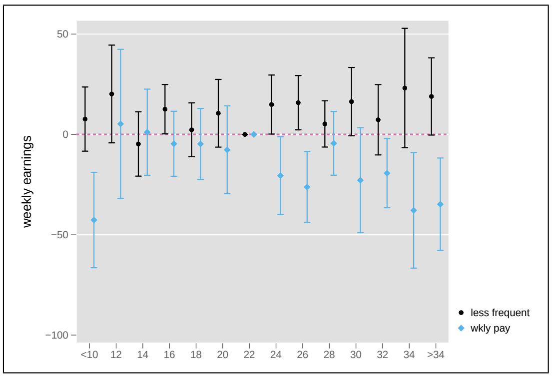


(j) precipitation

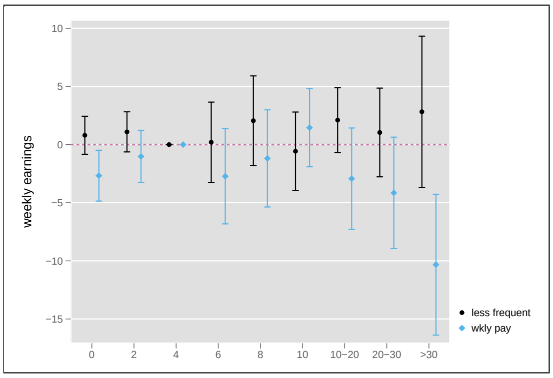


weekly vs less frequent pay

(k) temperature



(l) precipitation

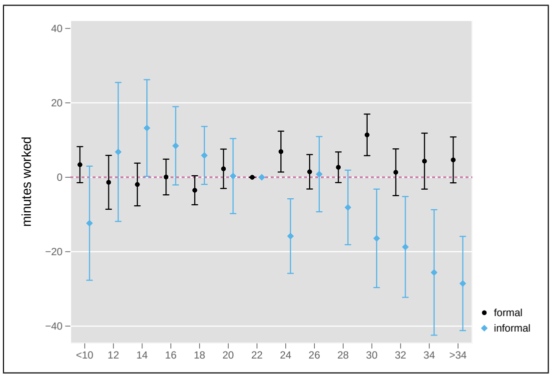


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

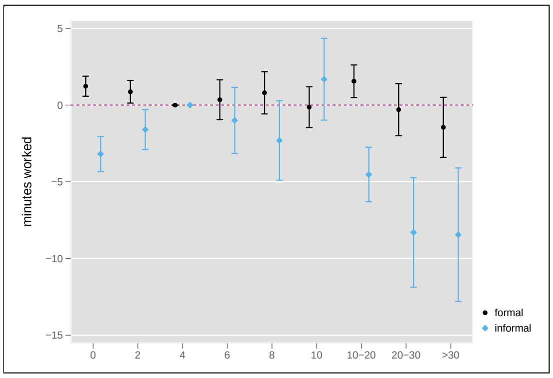
Figure A.13.14: Job Characteristics Marginal Effects on Working Time (Quarter)

formal vs informal

(a) temperature

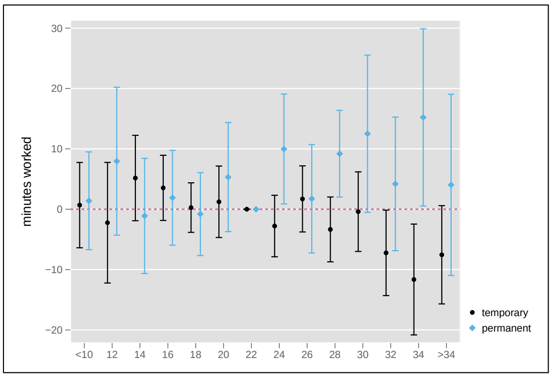


(b) precipitation

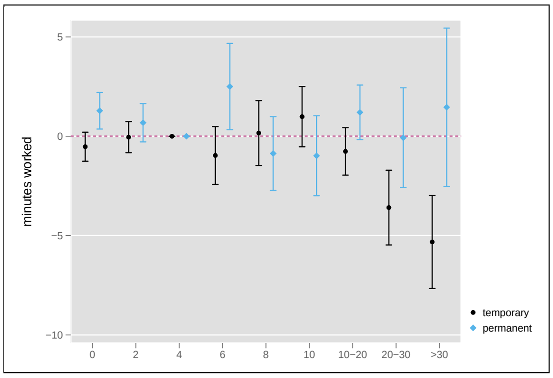


permanent vs temporary

(c) temperature

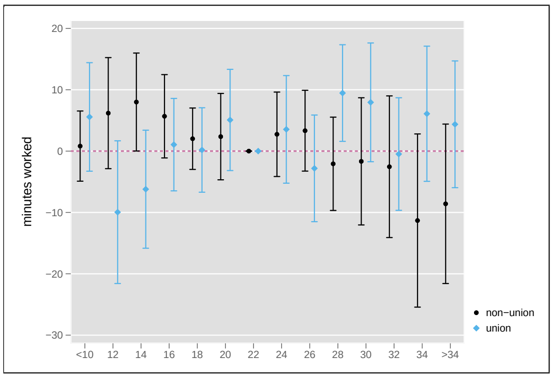


(d) precipitation



union vs non-union

(e) temperature



(f) precipitation

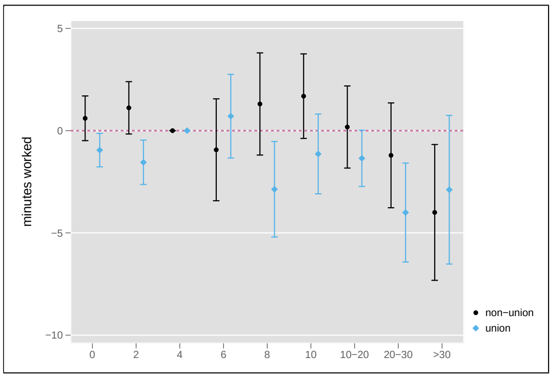
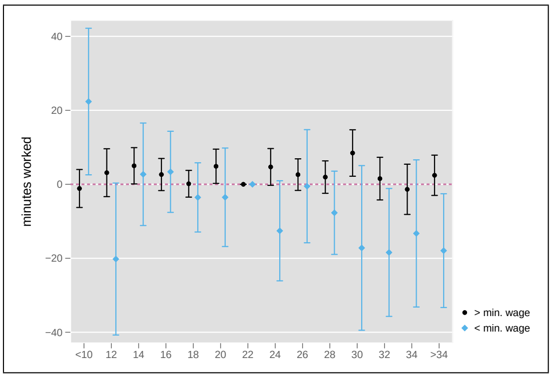


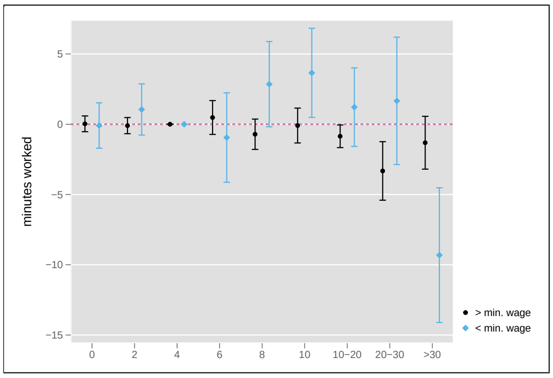
Figure A.13.14: Job Characteristics Marginal Effects on Working Time (Quarter) *(continued)*

above vs below official minimum wage

(g) temperature

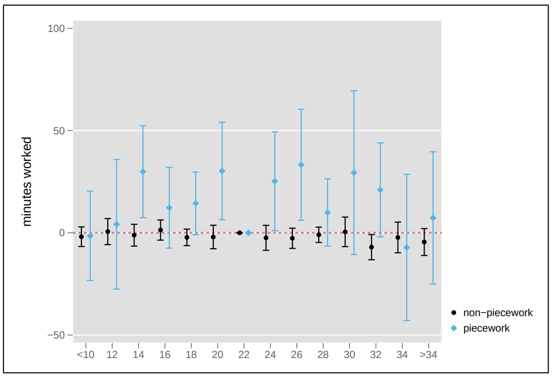


(h) precipitation

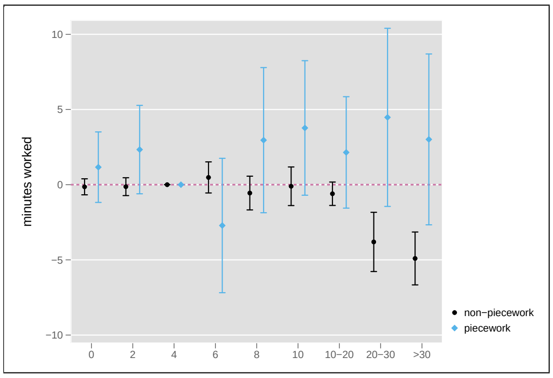


piecework vs non-piecework

(i) temperature

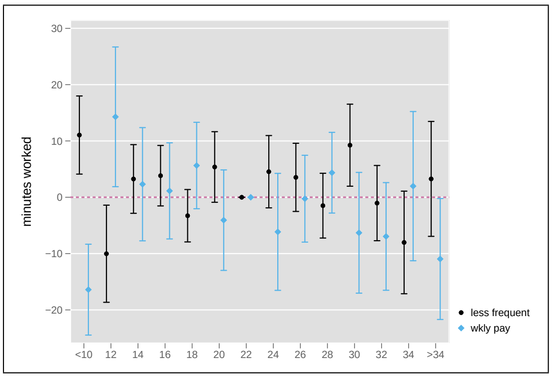


(j) precipitation

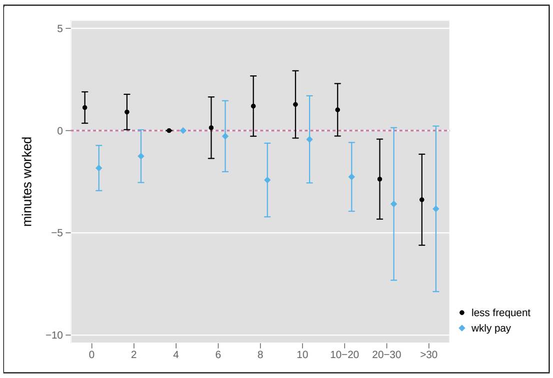


weekly vs less frequent pay

(k) temperature



(l) precipitation

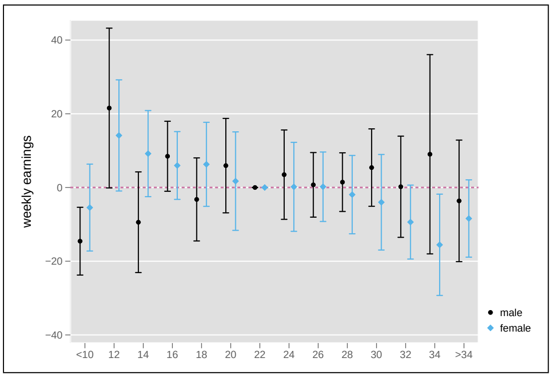


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

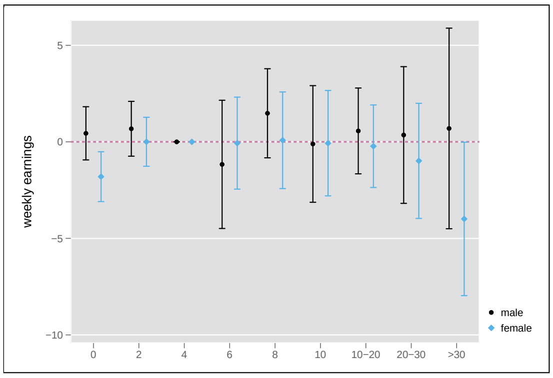
Figure A.13.15: Individual Characteristics Marginal Effects on Earnings (Quarter)

male vs female

(a) temperature

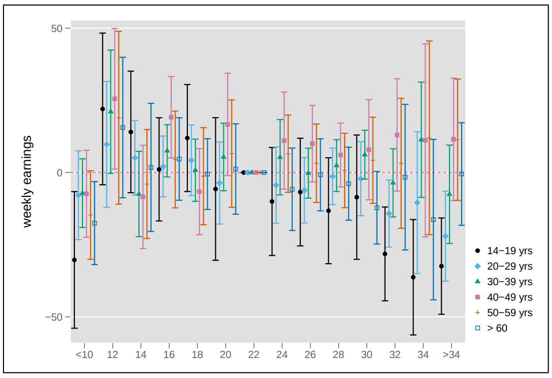


(b) precipitation

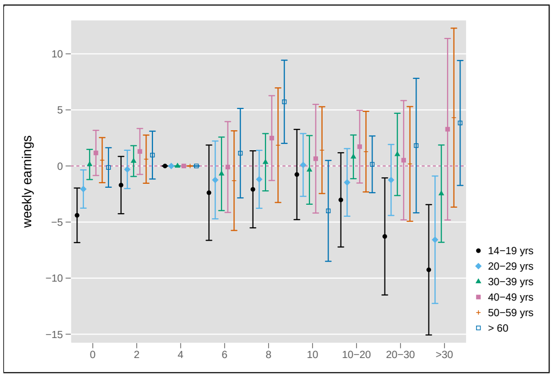


by age group

(c) temperature

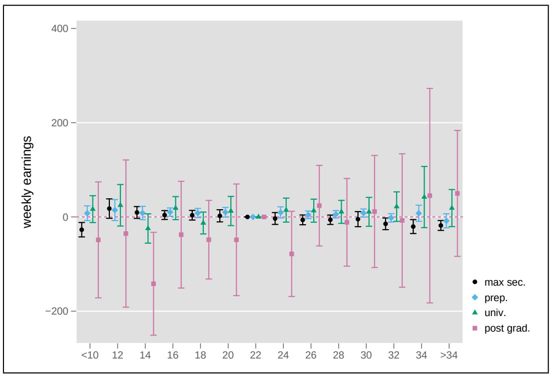


(d) precipitation

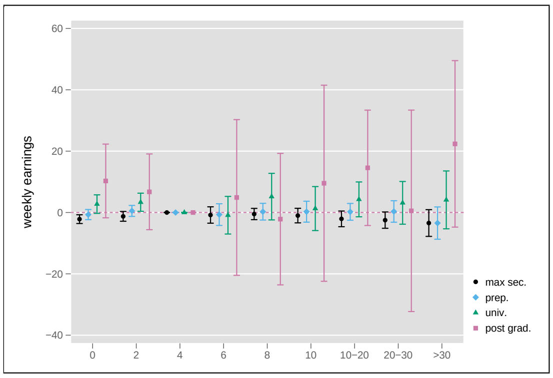


union vs non-union

(e) temperature



(f) precipitation

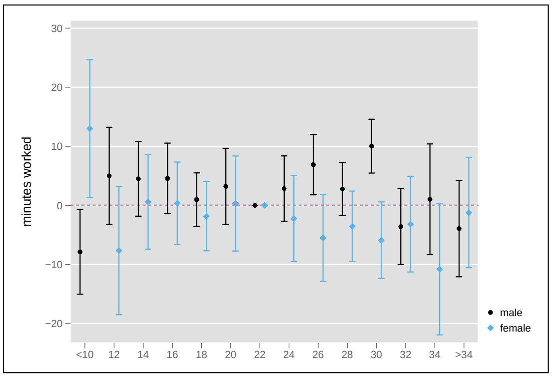


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] $^\circ$ C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

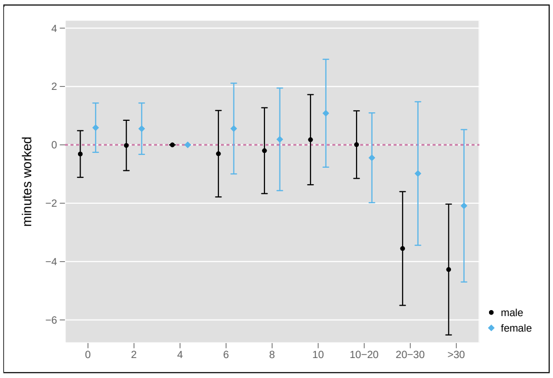
Figure A.13.16: Individual Characteristics Marginal Effects on Working Time (Quarter)

male vs female

(a) temperature

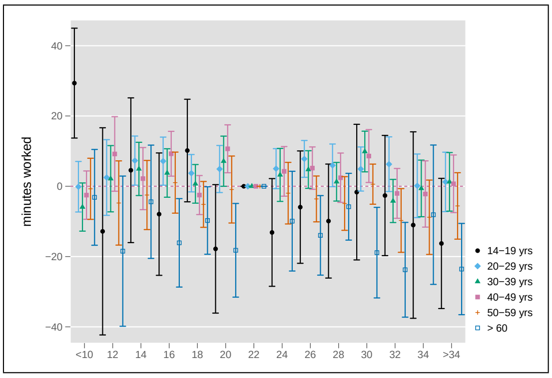


(b) precipitation

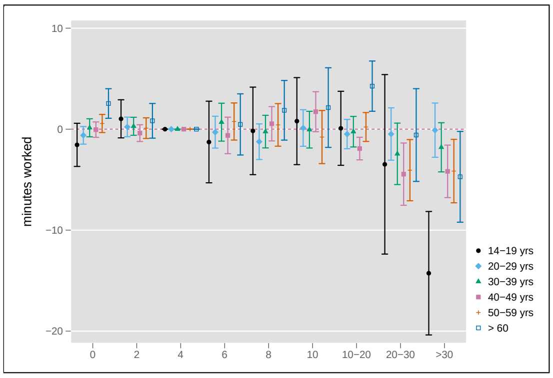


by age group

(c) temperature

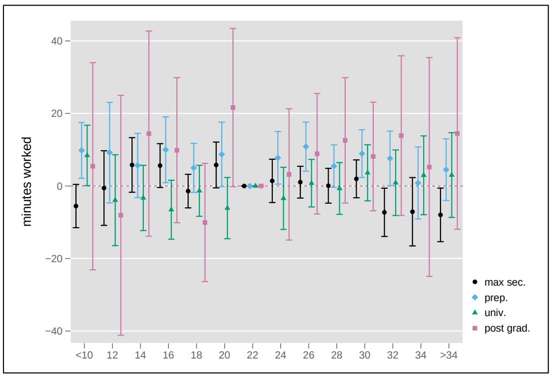


(d) precipitation

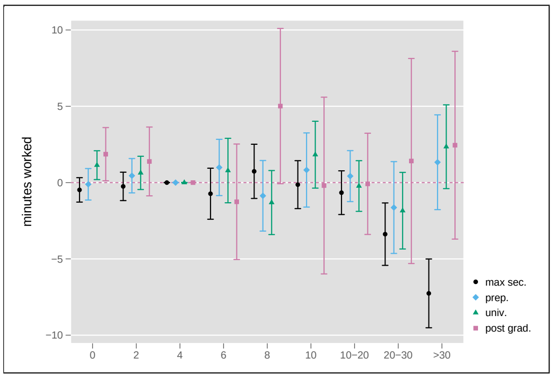


union vs non-union

(e) temperature



(f) precipitation

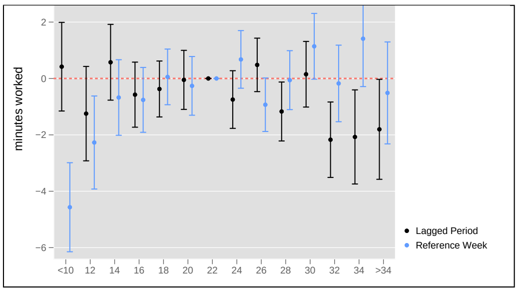


Statistics: N=7,390,140, Ind.=2,631,998.
Notes: Figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include marital status, age, gender, education, rural, industry, contract type, firm size, as well as municipality, industry-specific year and quarter as well as month fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

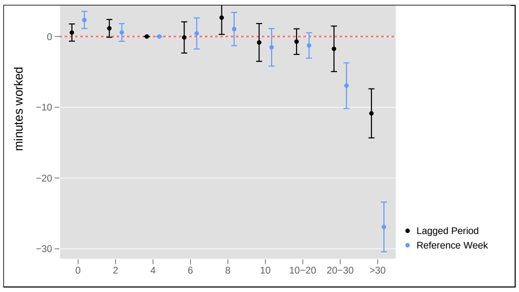
A.14 Substitution Effects

Figure A.14.1: Heterogeneous Effects Work Time with lagged weather of previous week

(a) Temperature



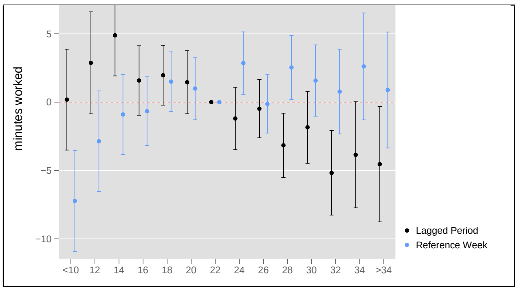
(b) Precipitation



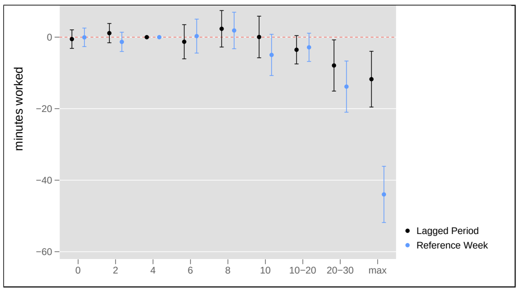
Notes: Figure depicts marginal effects for the lagged and reference week weather bins. The number of observations and of individuals for the plotted regressions are N=7,390,147 and i=2,632,000. Markers identify the 95% confidence interval. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] ° C and (2-4] *mm* precipitation. Standard errors are clustered at the municipality level.

Figure A.14.2: Lagged Working Time Effects by Job Characteristics

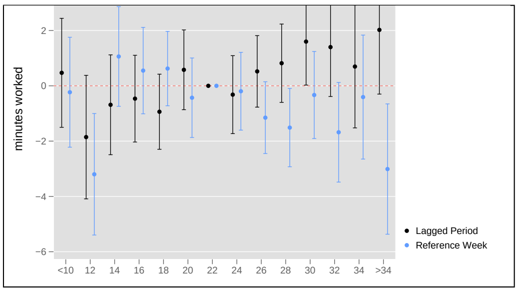
(a) Temperature



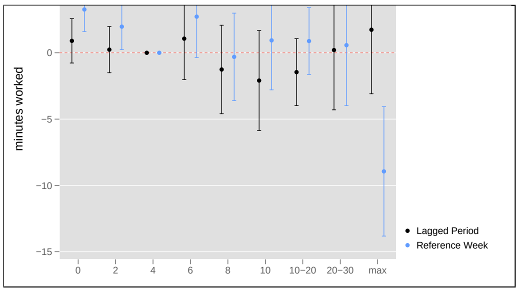
(b) Precipitation



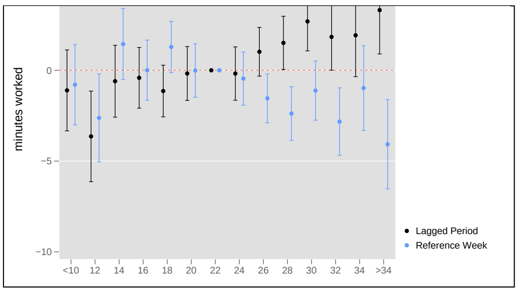
(c) Temperature



(d) Precipitation



(e) Temperature



(f) Precipitation

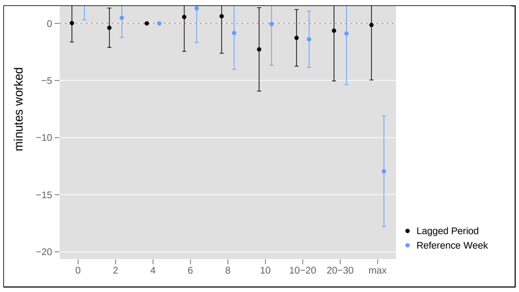
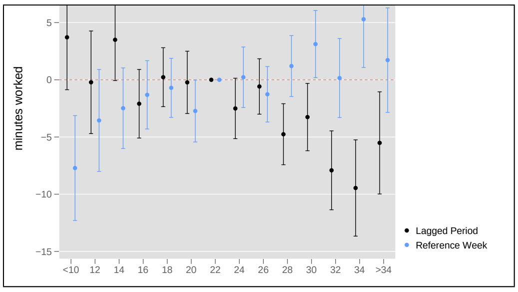
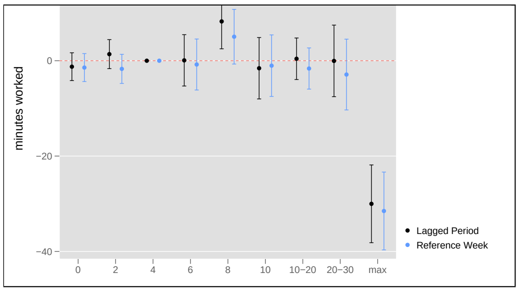


Figure A.14.2: *(continued)*

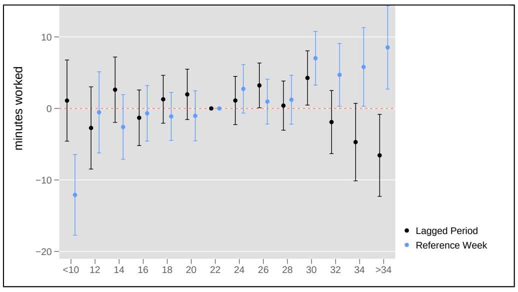
(g) Temperature



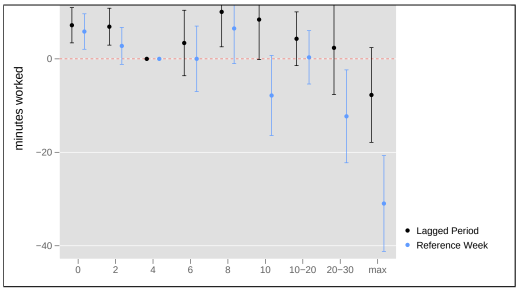
(h) Precipitation



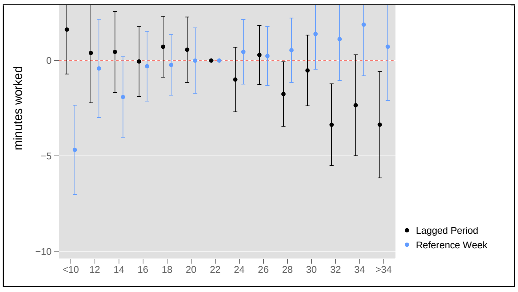
(i) Temperature



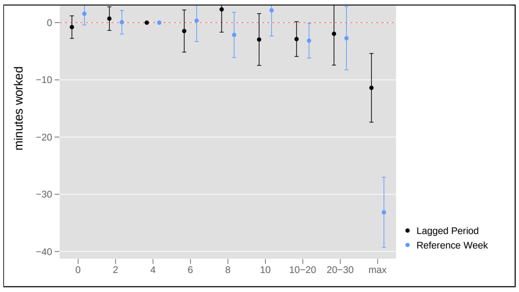
(j) Precipitation



(k) Temperature



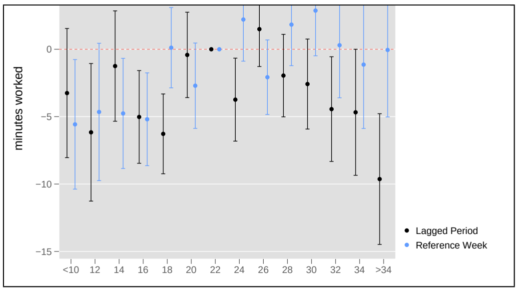
(l) Precipitation



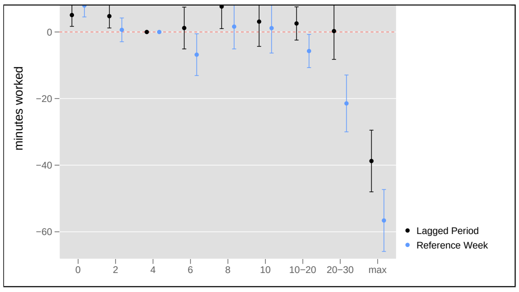
Notes: Figure depicts marginal effects for the lagged and reference week weather bins. The number of observations and of individuals for the plotted regressions are N=7,390,147 and i=2,632,000. Markers identify the 95% confidence interval. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] $^{\circ}$ C and (2-4] *mm* precipitation. Standard errors are clustered at the municipality level.

Figure A.14.3: Lagged Working Time Effects by Work Locations

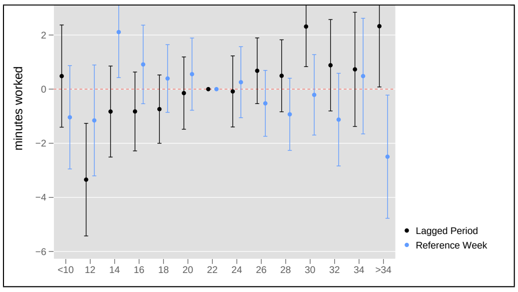
(a) Temperature



(b) Precipitation



(c) Temperature



(d) Precipitation

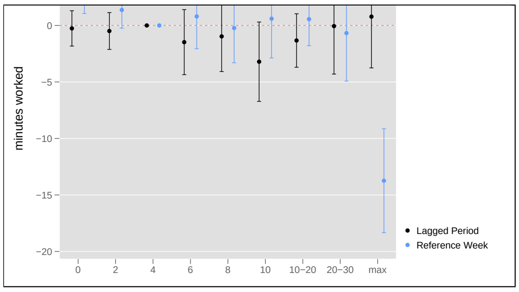
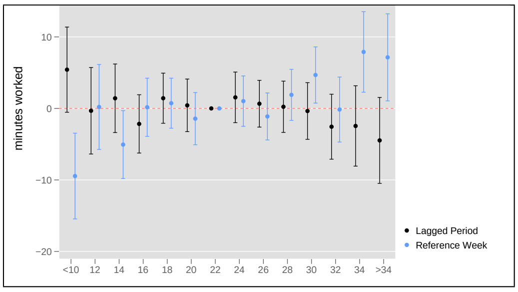
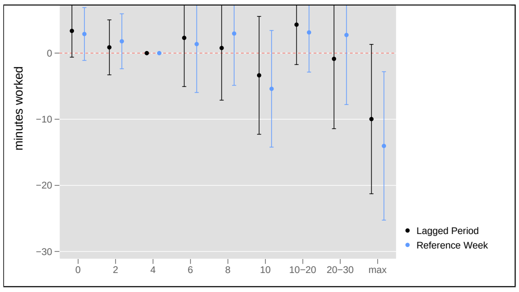


Figure A.14.3: *(continued)*

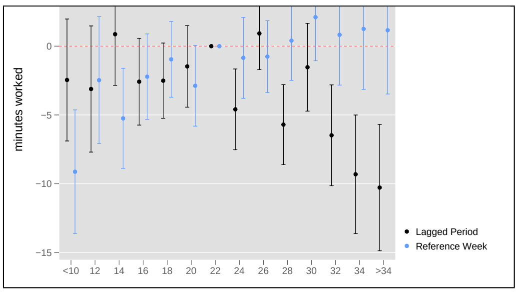
(e) Temperature



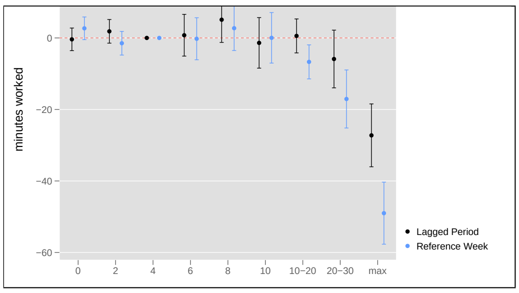
(f) Precipitation



(g) Temperature



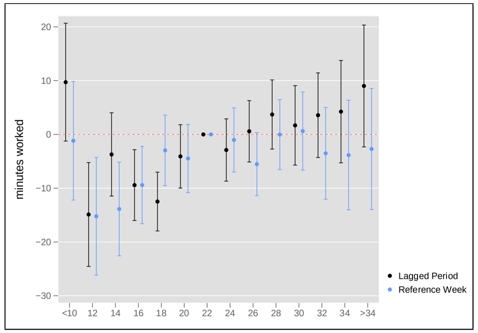
(h) Precipitation



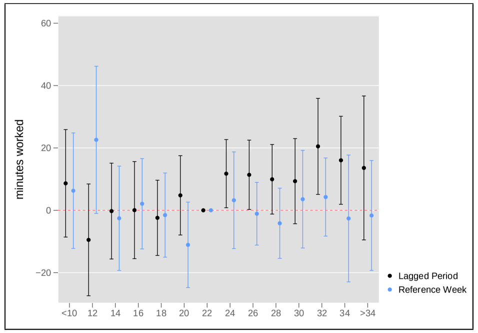
Notes: Figure depicts marginal effects for the lagged and reference week weather bins. The number of observations and of individuals for the plotted regressions are N=7,390,147 and i=2,632,000. Markers identify the 95% confidence interval. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] $^\circ$C and (2-4] *mm* precipitation. Standard errors are clustered at the municipality level.

Figure A.14.4: Lagged Working Time Effects by Sector

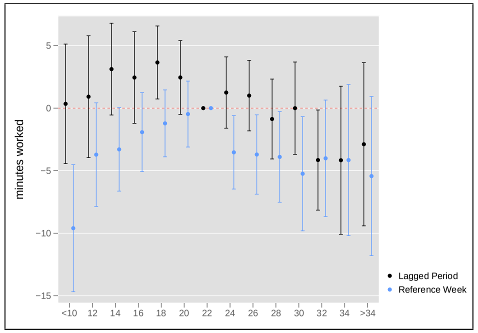
(a) Agriculture



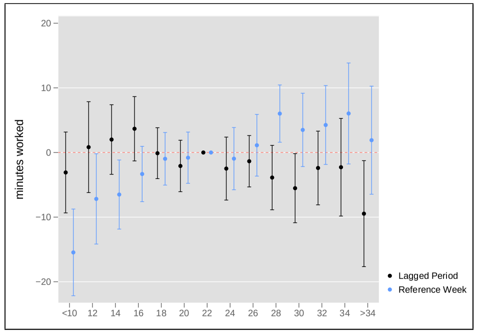
(b) Extractive



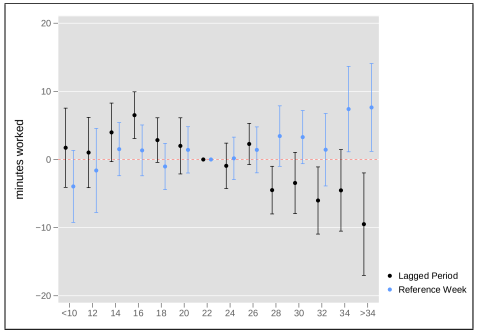
(c) Manufacturing



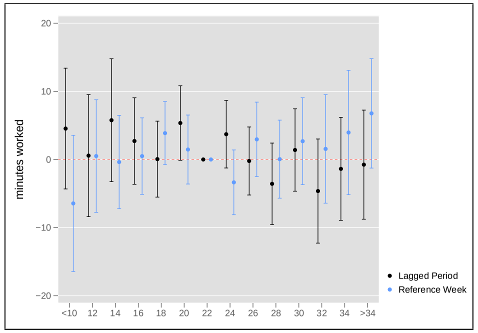
(d) Construction



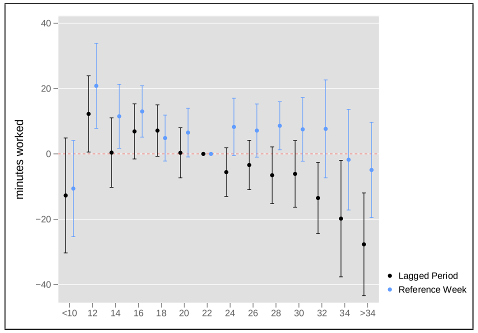
(e) Trade



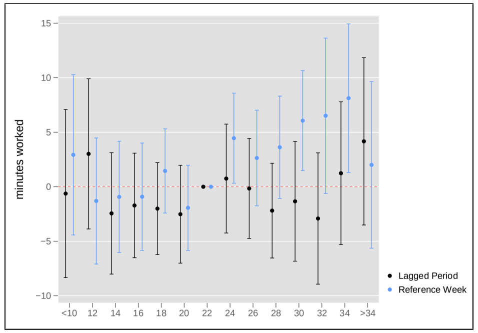
(f) Restaurant Services



(g) Transport



(h) Professional Services



(i) Diverse Services

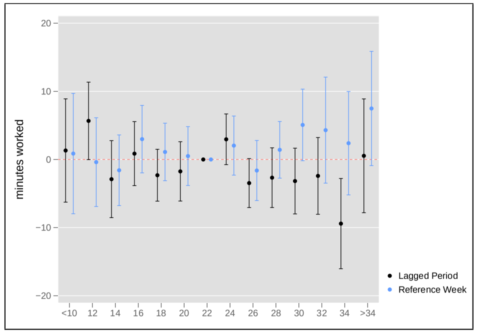
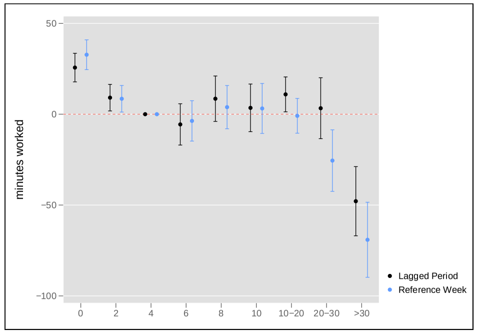
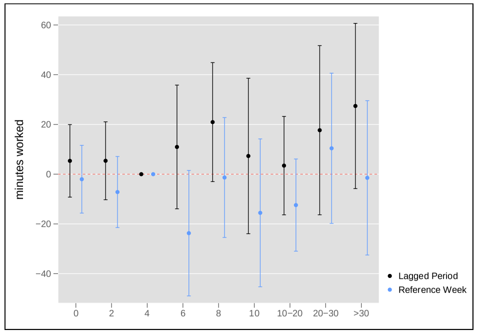


Figure A.14.4: *(continued)*

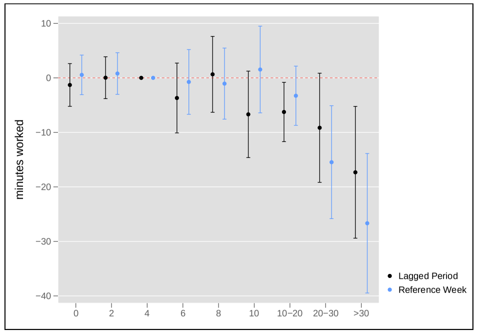
(j) Agriculture



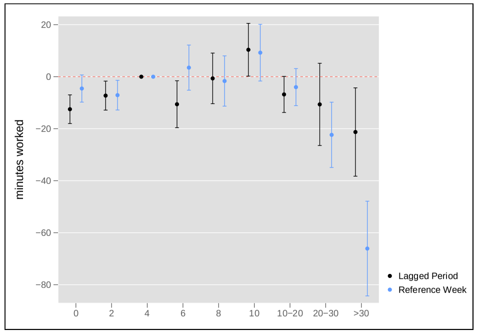
(k) Extractive



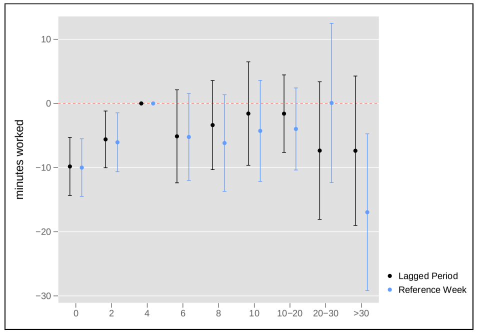
(l) Manufacturing



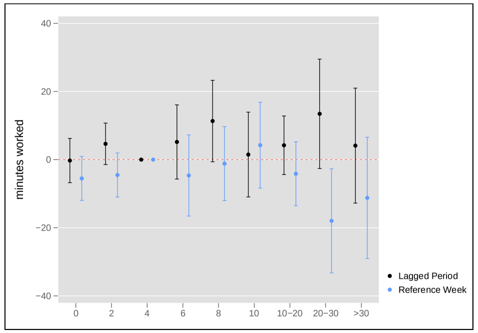
(m) Construction



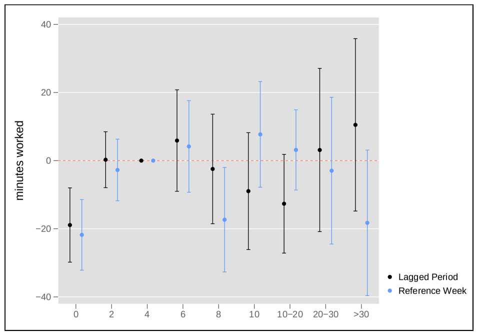
(n) Trade



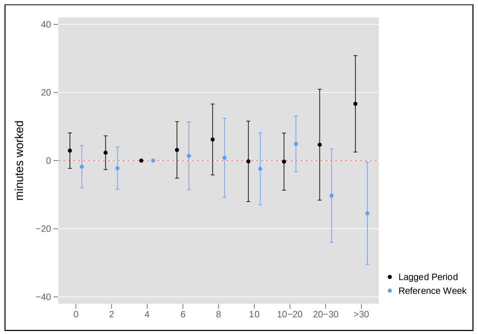
(o) Restaurant Services



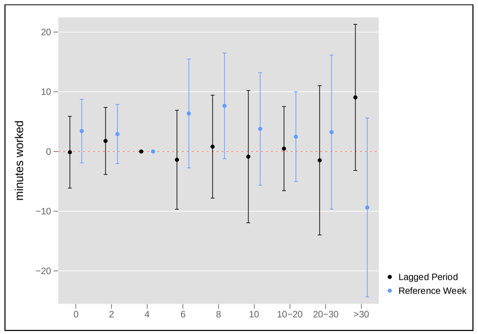
(p) Transport



(q) Professional Services



(r) Diverse Services



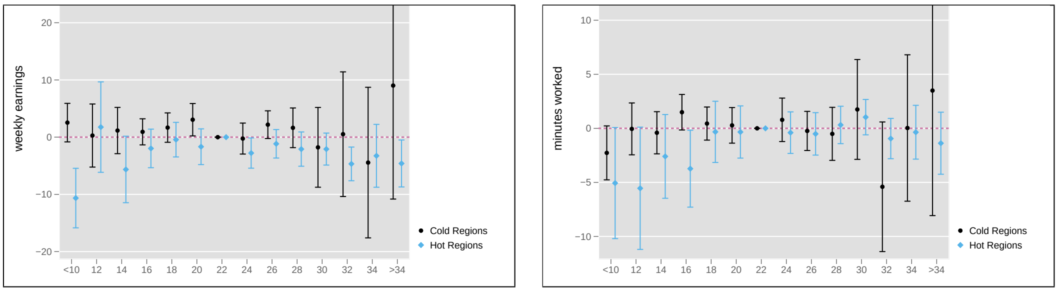
Notes: Figure depicts marginal effects for the lagged and reference week weather bins. The number of observations and of individuals for the plotted regressions are N=7,390,147 and i=2,632,000. Markers identify the 95% confidence interval. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

A.15 Adaptation Effects

Differences between historically warm and cold regions

Figure A.15.1: Average Adaptation Effects

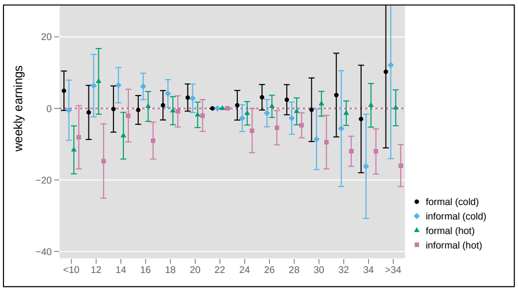
(a) earnings **(b)** working time



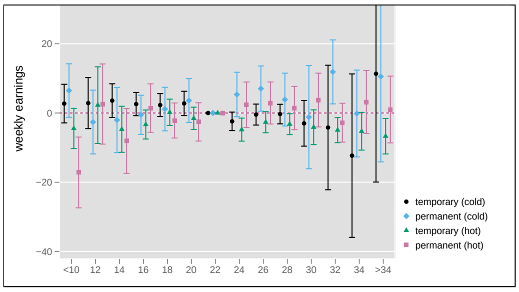
Notes: Figure depicts marginal effects for the lagged and reference week weather bins. The number of observations and of individuals for the plotted regressions are N=7,390,147 and i=2,632,000. Markers identify the 95% confidence interval. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] ° C and (2-4] *mm* precipitation. Standard errors are clustered at the municipality level.

Figure A.15.2: Adaptation Effects Earnings by Job Characteristics

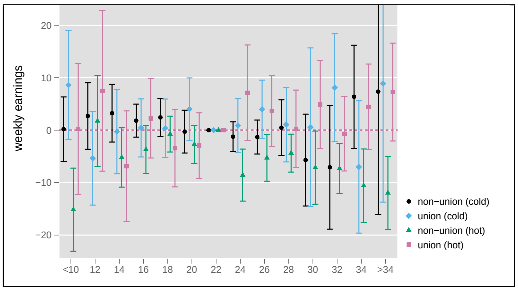
(a) informal



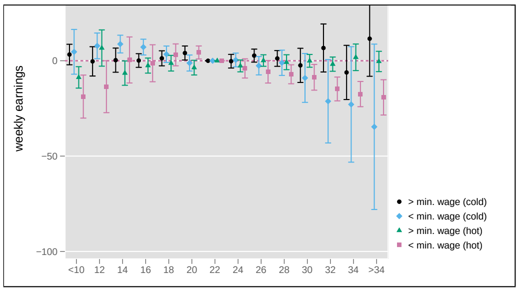
(b) permanent



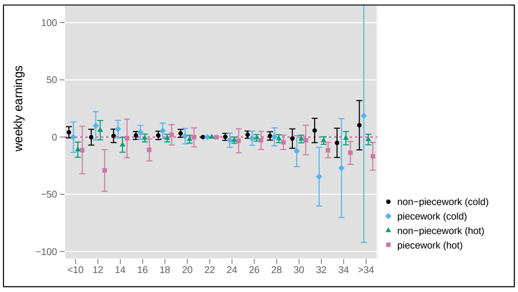
(c) union



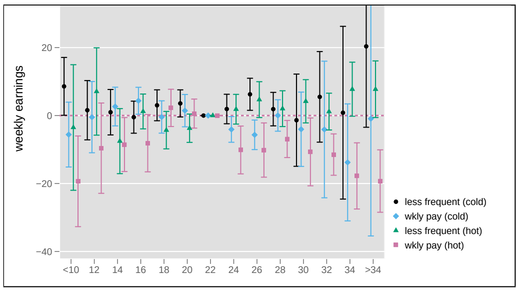
(d) minimum wage



(e) piecework



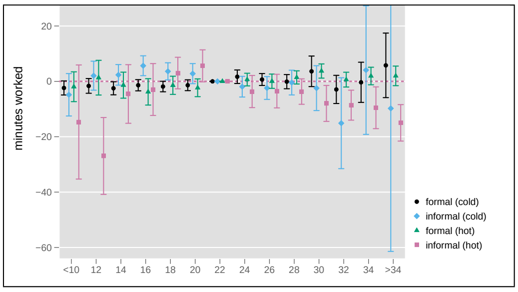
(f) weekly pay



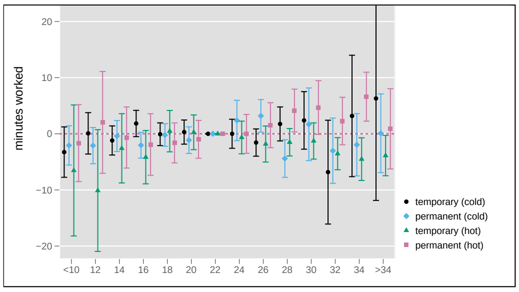
Notes: Figure depicts marginal effects for the lagged and reference week weather bins. The number of observations and of individuals for the plotted regressions are N=7,390,147 and i=2,632,000. Markers identify the 95% confidence interval. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] ° C and (2-4] *mm* precipitation. Standard errors are clustered at the municipality level.

Figure A.15.3: Adaptation Effects Working Time by Job Characteristics

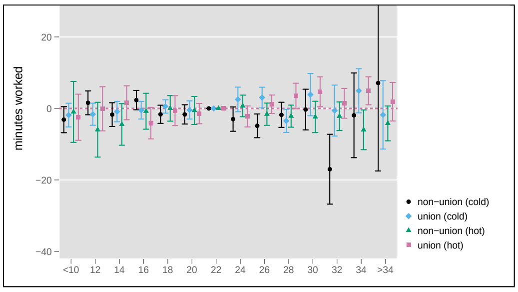
(a) informal



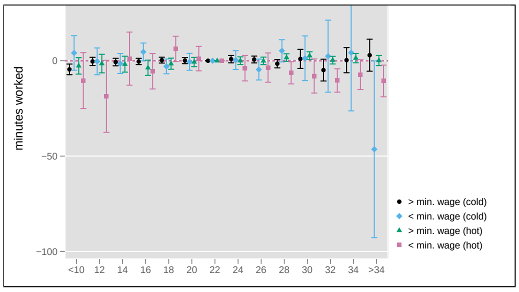
(b) permanent



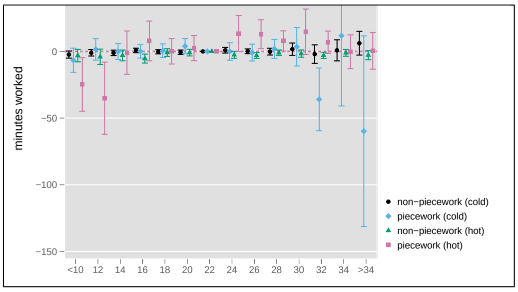
(c) union



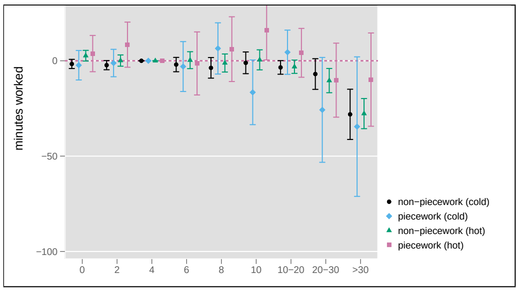
(d) minimum wage



(e) piecework



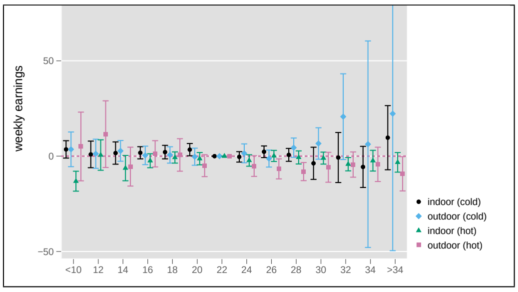
(f) Weekly pay



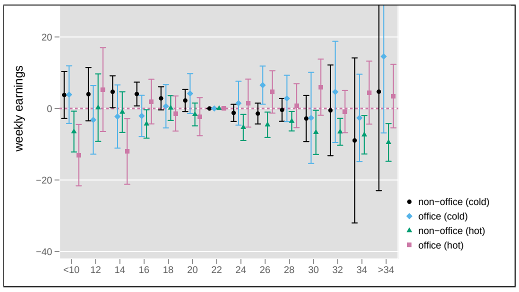
Notes: Figure depicts marginal effects for the lagged and reference week weather bins. The number of observations and of individuals for the plotted regressions are N=7,390,147 and i=2,632,000. Markers identify the 95% confidence interval. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] ° C and (2-4] *mm* precipitation. Standard errors are clustered at the municipality level.

Figure A.15.4: Adaptation Effects Earnings by Work Location

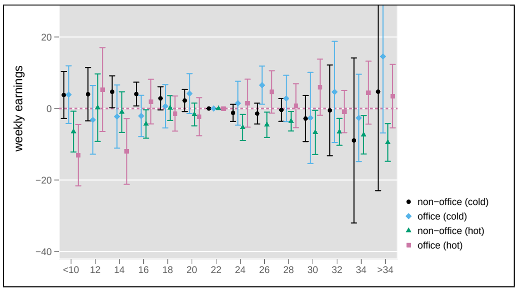
(a) outdoor



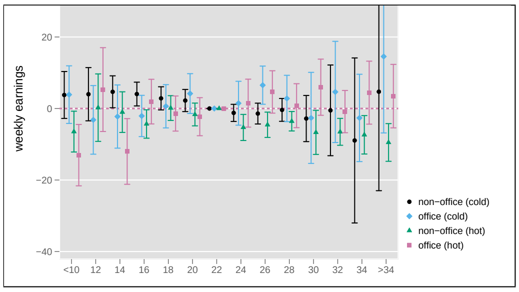
(b) office



(c) domestic



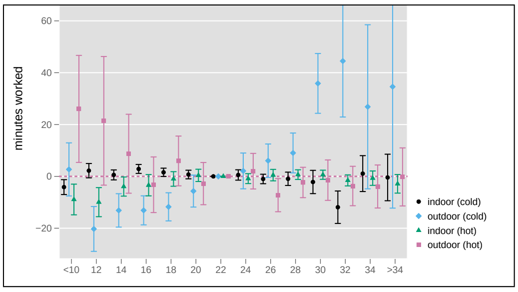
(d) rural



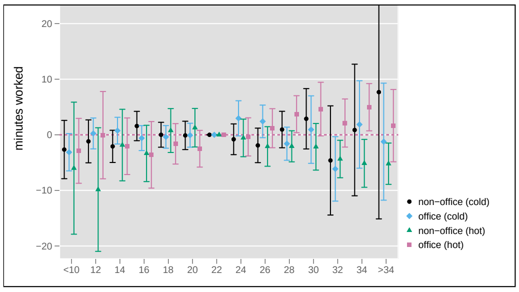
Notes: Figure depicts marginal effects for the lagged and reference week weather bins. The number of observations and of individuals for the plotted regressions are N=7,390,147 and i=2,632,000. Markers identify the 95% confidence interval. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] $^\circ$ C and (2-4] *mm* precipitation. Standard errors are clustered at the municipality level.

Figure A.15.5: Adaptation Effects Working Time by Work Locations

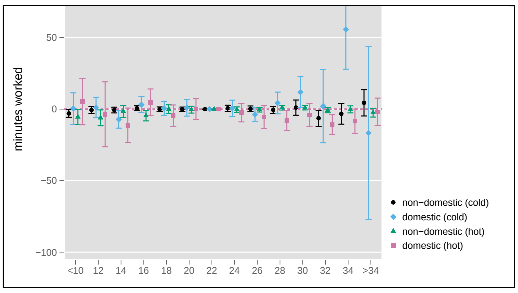
(a) outdoor



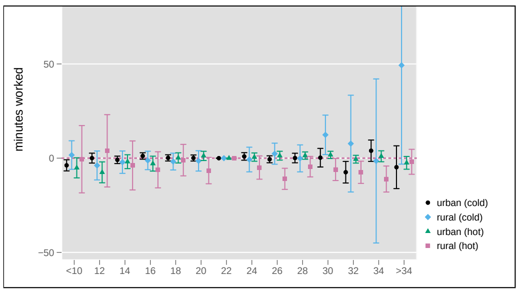
(b) office



(c) domestic



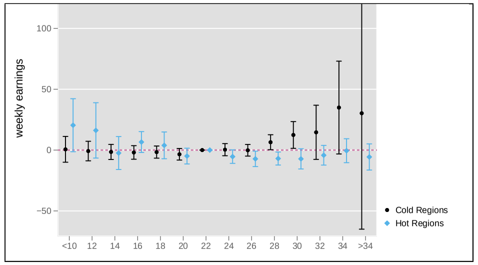
(d) rural



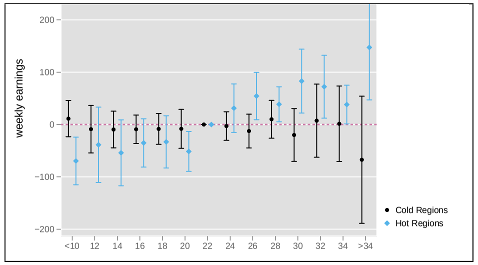
Notes: Figure depicts marginal effects for the lagged and reference week weather bins. The number of observations and of individuals for the plotted regressions are N=7,390,147 and i=2,632,000. Markers identify the 95% confidence interval. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] $^\circ$ C and (2-4] *mm* precipitation. Standard errors are clustered at the municipality level.

Figure A.15.6: Earnings Adaptation Effects by Industry

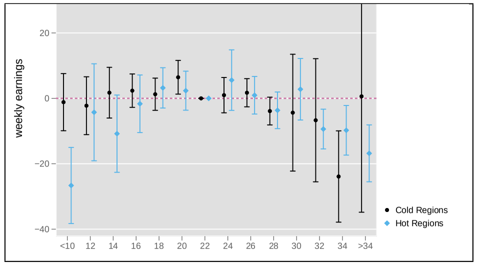
(a) Agriculture



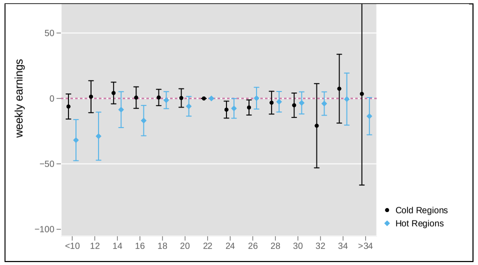
(b) Extractive



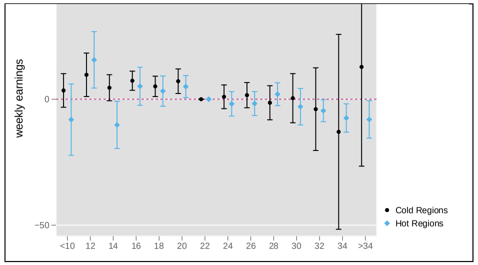
(c) Manufacturing



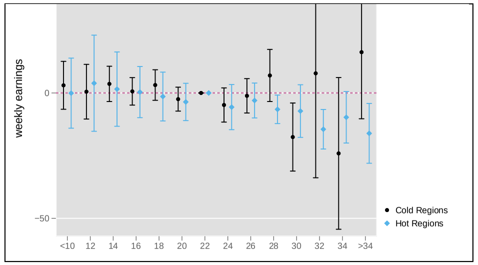
(d) Construction



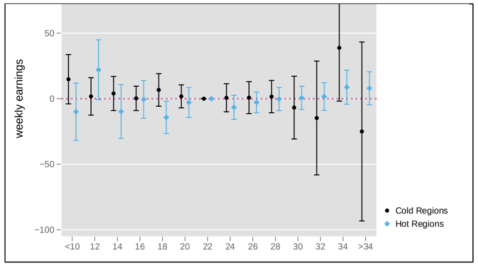
(e) Trade



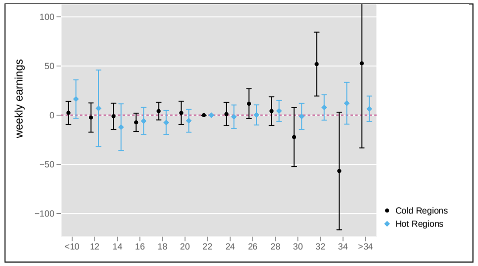
(f) Restaurant Services



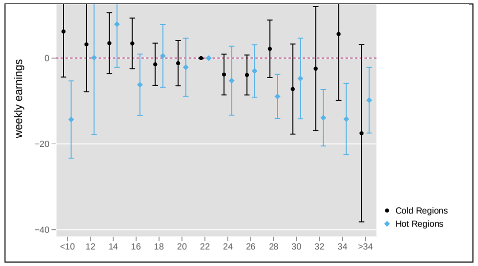
(g) Transport



(h) Professional Services

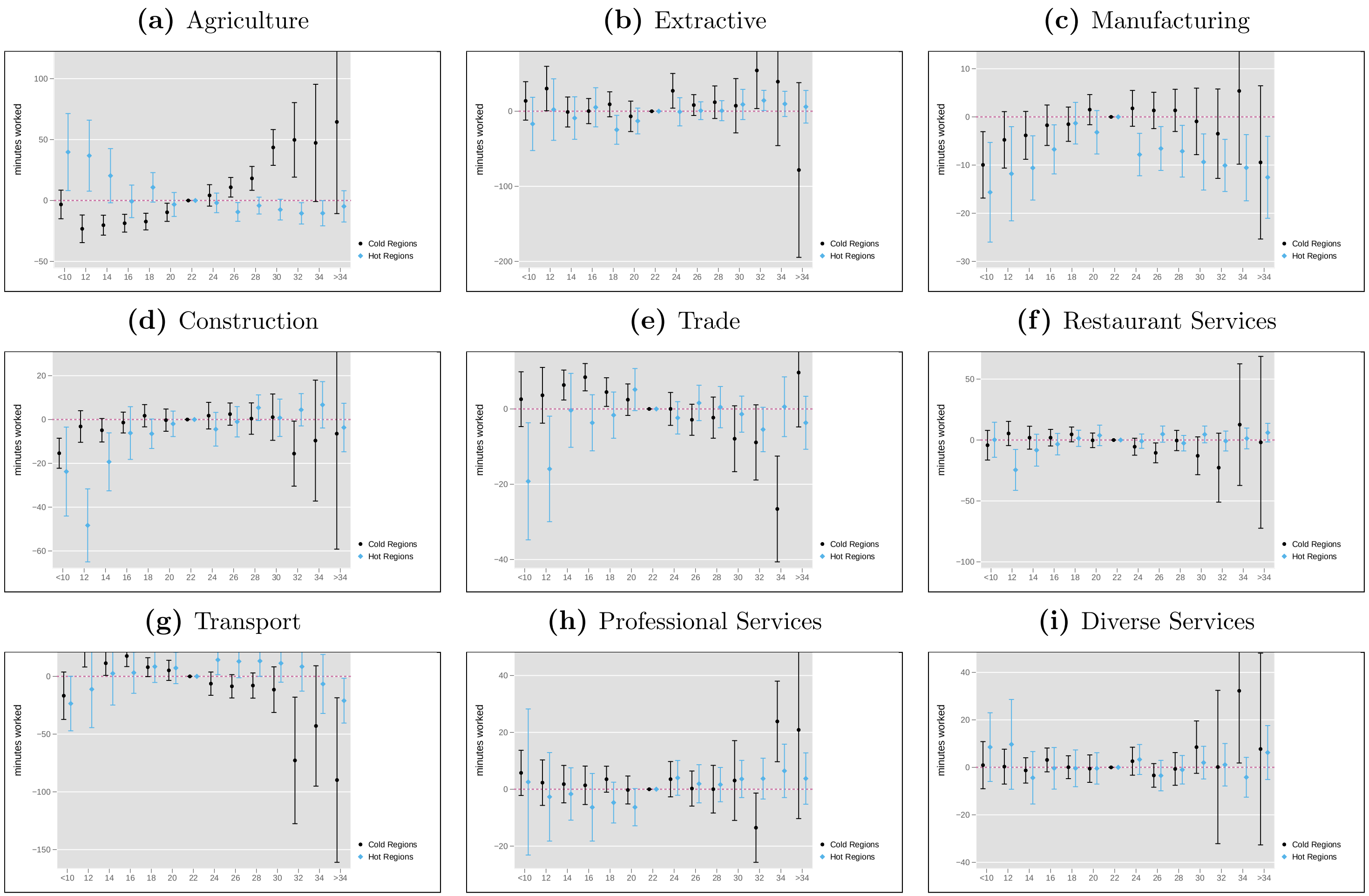


(i) Diverse Services



Notes: Figure depicts marginal effects for the lagged and reference week weather bins. The number of observations and of individuals for the plotted regressions are N=7,390,147 and i=2,632,000. Markers identify the 95% confidence interval. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] ° C and (2-4] *mm* precipitation. Standard errors are clustered at the municipality level.

Figure A.15.7: Working Time Adaptation Effects by Industry

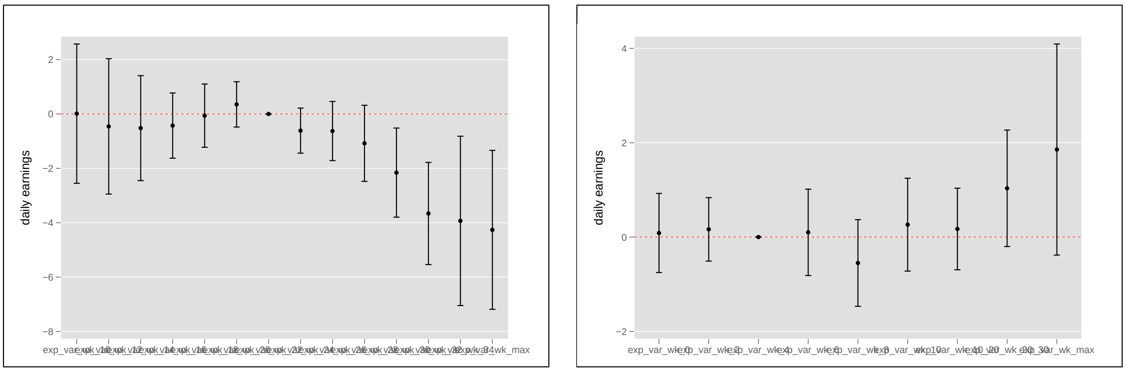


Notes: Figure depicts marginal effects for the lagged and reference week weather bins. The number of observations and of individuals for the plotted regressions are N=7,390,147 and i=2,632,000. Markers identify the 95% confidence interval. Covariates include marital status, age, gender, education, rural, sector, contract type, firm size, as well as municipality, month, and sector specific year and quarter fixed effects. The omitted category is (20-22] ° C and (2-4] *mm* precipitation. Standard errors are clustered at the municipality level.

A.16 Municipality Level Regressions

Figure A.16.1: Municipality Level Daily Earnings Regression

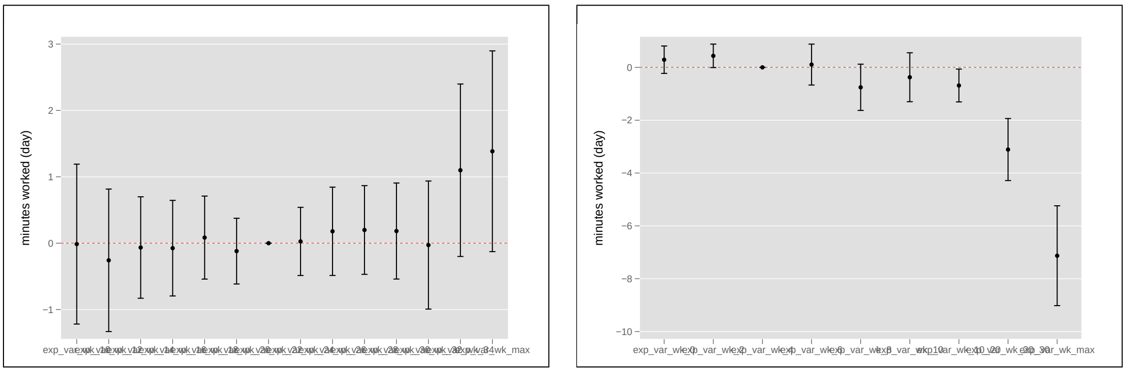
(a) Temperature **(b)** Precipitation



Notes: The figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include industry, municipality, year, quarter and day of the week fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Figure A.16.2: Municipality Level Working Time Regression

(a) Temperature **(b)** Precipitation

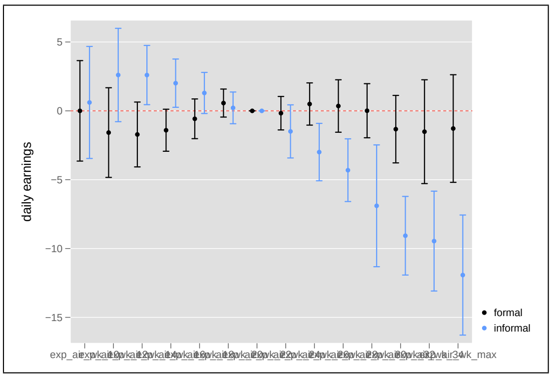


Notes: The figure depicts marginal effects of weather bins on weekly minutes worked. The 95% confidence interval indicated by markers. Covariates include industry, municipality, year, quarter and day of the week fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

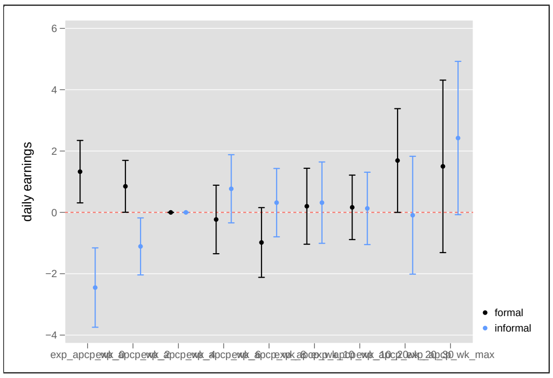
Figure A.16.3: Municipality Level Heterogeneous Effects on Daily Earnings

formal vs informal

(a) temperature

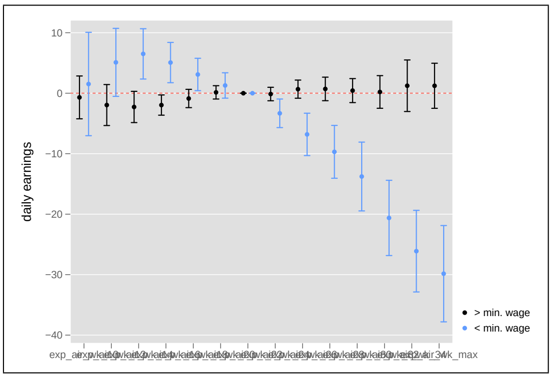


(b) precipitation

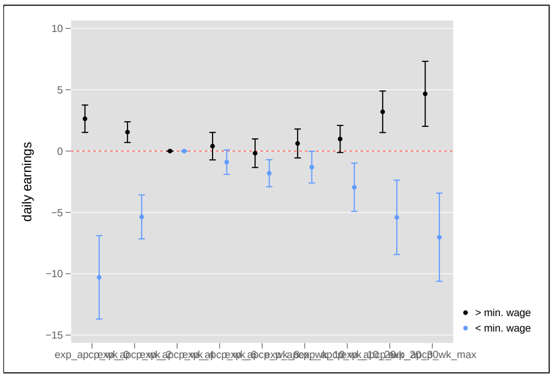


above vs below official minimum wage

(c) temperature

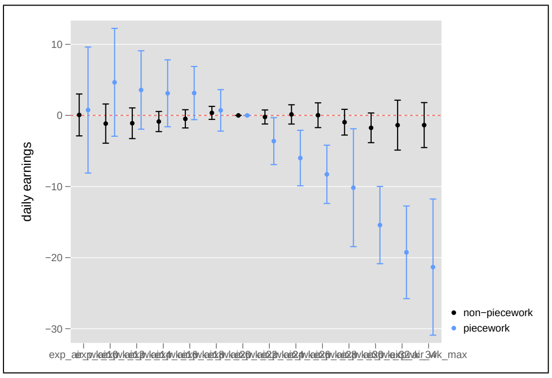


(d) precipitation

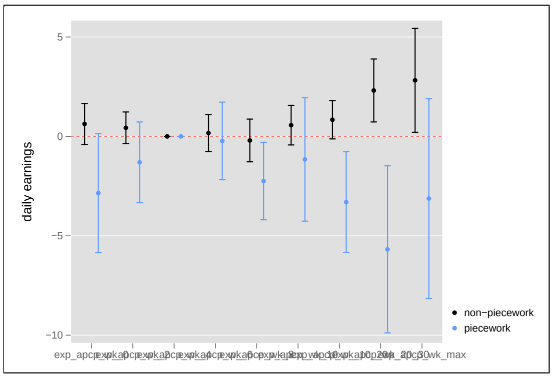


piecework vs non-piecework

(e) temperature

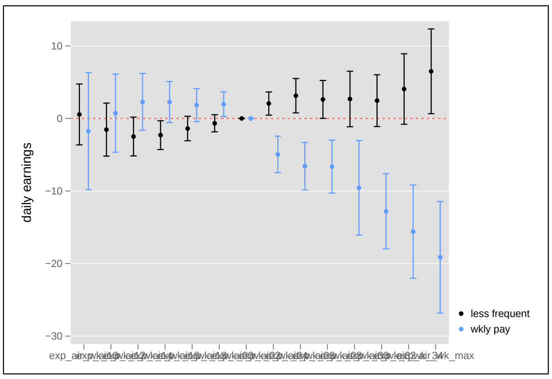


(f) precipitation

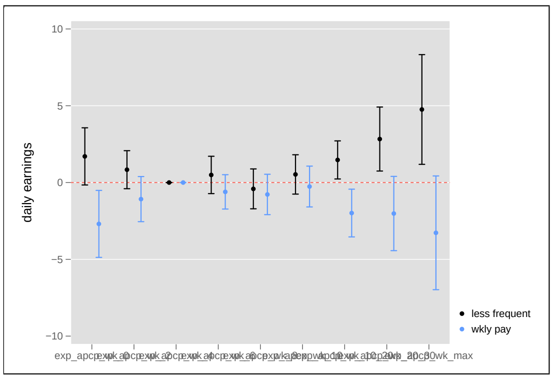


weekly vs less frequent pay

(g) temperature



(h) precipitation

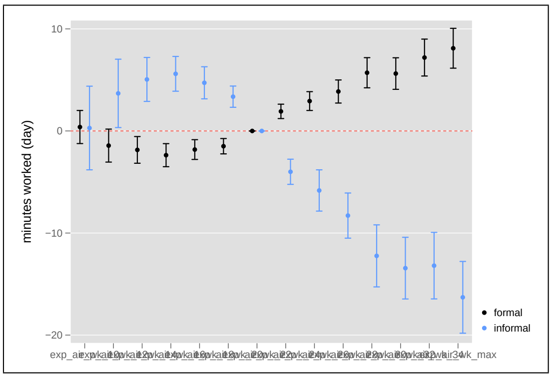


Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include industry, municipality, year and quarter as well as day of the week fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

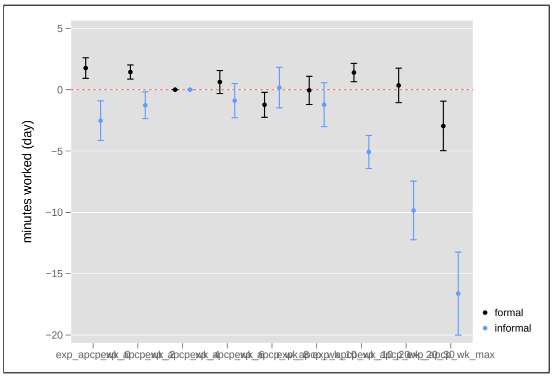
Figure A.16.4: Municipality Level Heterogeneous Effects on Daily Working Time

formal vs informal

(a) temperature

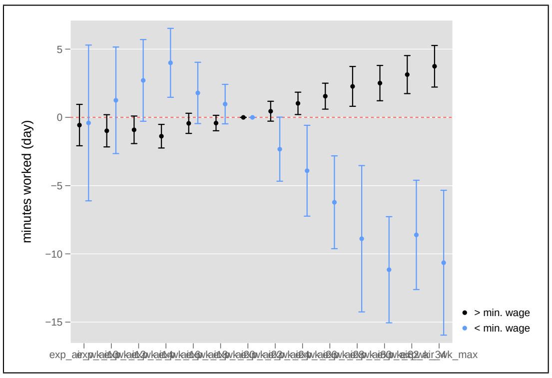


(b) precipitation

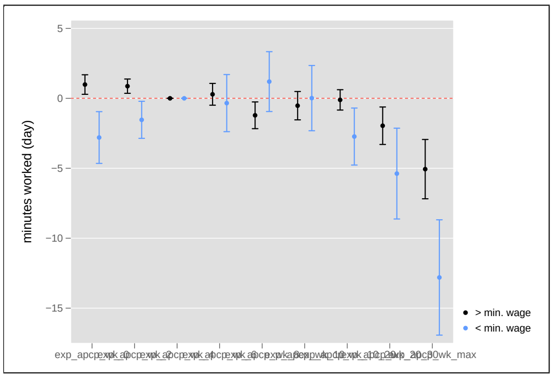


above vs below official minimum wage

(c) temperature

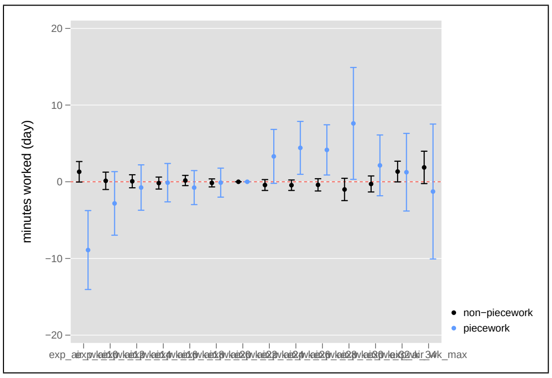


(d) precipitation

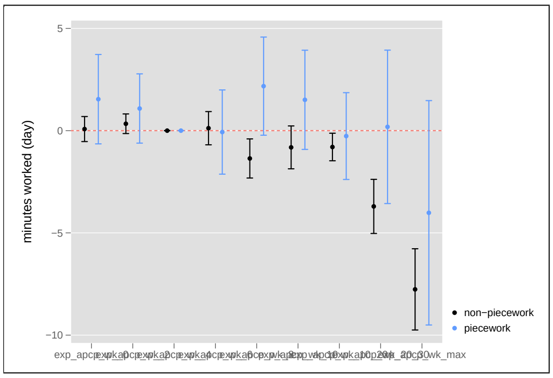


piecework vs non-piecework

(e) temperature

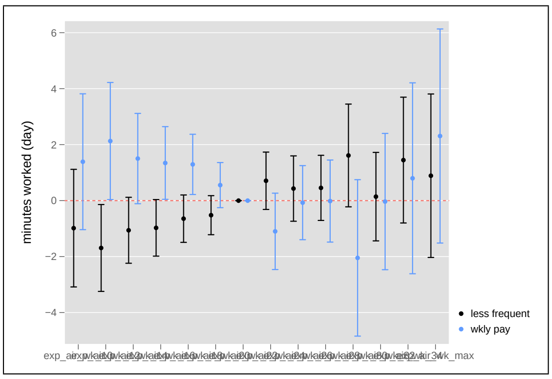


(f) precipitation

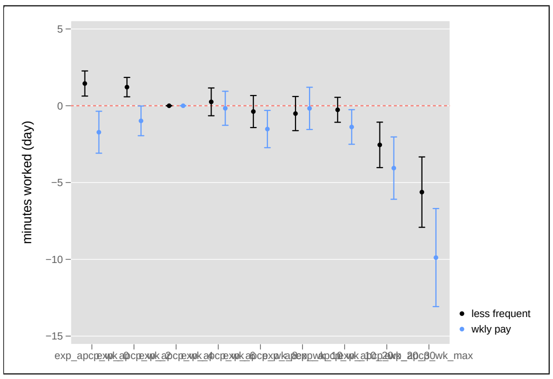


weekly vs less frequent pay

(g) temperature



(h) precipitation



Notes: Figure depicts marginal effects of weather bins on weekly earnings. The 95% confidence interval indicated by markers. Covariates include industry, municipality, year and quarter as well as day of the week fixed effects. The omitted category is (20-22] ° C and (2-4] mm precipitation. Standard errors are clustered at the municipality level.

Appendix B

Appendix to Chapter 3

B.1 McFadden Alternative-Specific Choice Model

Consider a population of individuals $i = 1, \ldots, I$ with homogeneous preferences, choosing their optimal location among a set of locations, with U_{idot} being the utility for a migrant from origin location o moving to location d in time period t. U_{idot} can be written as:

$$\mathrm{U}_{idot} = V_{dot} - C_{dot}(.) + \varepsilon_{idot} \tag{B.1}$$

where V_{dot} is the observable, deterministic utility, C_{dot} denotes the migration cost of moving from origin location o to destination d (assumed to be constant across individuals), and ε_{idot} is a random error component accounting for the unobservable component of utility. Assuming $U_{idot} \neq 0$, the migrant will choose location d over m if:

$$\mathrm{U}_{idot} > U_{imot} \quad \forall d, d \neq m. \tag{B.2}$$

The model assumes that V_{dot} for a utility-maximising migrant depends on a linear combination of the destination-specific factors Z_{dt}, and differences in climate between origin and destination location A_{dot}. This yields

$$\mathrm{U}_{idot} = Z_{dt} + A_{dot} - C_{dot} + \varepsilon_{idot}\,. \tag{B.3}$$

McFadden (1974) shows that under the assumption of the error term following an independent and IID Type I Extreme Value (Gumbel) distribution, the probability of an individual moving from o to d can be expressed as:

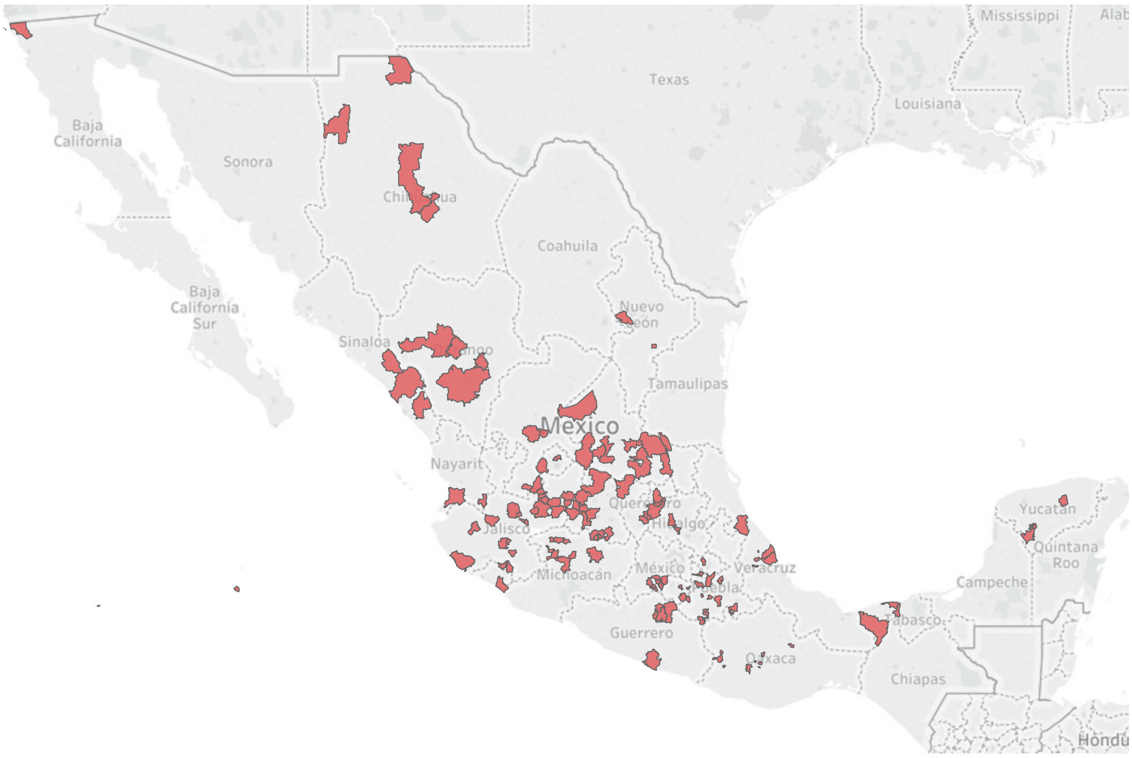
$$\mathrm{Prob}[U_{dot} = \max_{D} U_{dot}] = \frac{\exp[Z_{dt} + A_{dot} - C_{dot}]}{\sum_{d=1}^{D} \exp[Z_{Dt} + A_{Dot} - C_{Dot}]} \tag{B.4}$$

Note that individual characteristics contained in ε_{idot} drop out when taking the ratio of the exponentiated linear combinations. Therefore, the conditional probability of individual i from origin o choosing destination d is given by:

$$\mathrm{Prob}_{dot} = \frac{\exp[Z'_{dt}\beta + A'_{dot}\delta - c_{dot}\mu]}{\sum_{d=1}^{D} \exp[Z'_{Dt}\beta + A'_{Dot}\delta - c'_{Dot}\mu]} \tag{B.5}$$

B.2 Map and List of Mexican Municipalities and States

Figure B.2.1: Map of Mexican Municipalities



Mexican municipalities coloured in red.

Table B.2.1: List of Mexican Sample Municipalities

	Municipality	**State**	**Region**		**Municipality**	**State**	**Region**
1	Calvillo	Aguascal-ientes	Baja California	64	Tlazazalca	Michoacan	Occidental y Bajio
2	Pabellan De Arteaga	Aguascal-ientes	Baja California	65	Uruapan	Michoacan	Occidental y Bajio
3	Tijuana	Baja California	Baja California	66	Zamora	Michoacan	Occidental y Bajio
4	Casas Grandes	Chihuahua	Zona Norte	67	Axochiapan	Morelos	Central Mexico
5	Chihuahua	Chihuahua	Zona Norte	68	Cuautla	Morelos	Central Mexico
6	Juarez	Chihuahua	Zona Norte	69	Tepalcingo	Morelos	Central Mexico
7	Rosales	Chihuahua	Zona Norte	70	Zacualpan	Morelos	Central Mexico
8	Comala	Colima	Occidental y Bajio	71	Compostela	Nayarit	Occidental y Bajio
9	Cuauhtamoc	Colima	Occidental y Bajio	72	Ixtlan Del Rao	Nayarit	Occidental y Bajio
10	Tecoman	Colima	Occidental y Bajio	73	Hualahuises	Nuevo Leon	Zona Norte
11	Durango	Durango	Zona Norte	74	Santa Catarina	Nuevo Leon	Zona Norte
12	Nuevo Ideal	Durango	Zona Norte	75	Oaxaca De Juarez	Oaxaca	South Mexico
13	Panuco De Coronado	Durango	Zona Norte	76	Putla Villa De Guerrero	Oaxaca	South Mexico
14	Santiago Papasquiaro	Durango	Zona Norte	77	San Juan Comaltepec	Oaxaca	South Mexico
15	Coatepec Harinas	Edo Mexico	Central Mexico	78	Zimatlan De Alvarez	Oaxaca	South Mexico
16	Ixtapan De La Sal	Edo Mexico	Central Mexico	79	Atlixco	Puebla	Central Mexico

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Table B.2.1*(Continued)*

	Municipality	State	Region		Municipality	State	Region
17	Malinalco	Edo Mexico	Central Mexico	80	Chinantla	Puebla	Central Mexico
18	Ocuilan	Edo Mexico	Central Mexico	81	Coatzingo	Puebla	Central Mexico
19	Tenancingo	Edo Mexico	Central Mexico	82	Domingo Arenas	Puebla	Central Mexico
20	Tenango Del Valle	Edo Mexico	Central Mexico	83	Epatlan	Puebla	Central Mexico
21	Tonatico	Edo Mexico	Central Mexico	84	Huejotzingo	Puebla	Central Mexico
22	Abasolo	Guanajuato	Occidental y Bajio	85	Piaxtla	Puebla	Central Mexico
23	Irapuato	Guanajuato	Occidental y Bajio	86	Puebla	Puebla	Central Mexico
24	Lean	Guanajuato	Occidental y Bajio	87	Tepeaca	Puebla	Central Mexico
25	Manuel Doblado	Guanajuato	Occidental y Bajio	88	Tepexi De Rodriguez	Puebla	Central Mexico
26	Morolean	Guanajuato	Occidental y Bajio	89	Tulcingo	Puebla	Central Mexico
27	Romita	Guanajuato	Occidental y Bajio	90	Zapotitlan	Puebla	Central Mexico
28	Salvatierra	Guanajuato	Occidental y Bajio	91	Cadereyta De Montes	Queretaro	Occidental y Bajio
29	San Felipe	Guanajuato	Occidental y Bajio	92	Ezequiel Montes	Queretaro	Occidental y Bajio
30	San Francisco Del Rincan	Guanajuato	Occidental y Bajio	93	Pinal De Amoles	Queretaro	Occidental y Bajio
31	San Luis De La Paz	Guanajuato	Occidental y Bajio	94	San Joaquan	Queretaro	Occidental y Bajio
32	Uriangato	Guanajuato	Occidental y Bajio	95	Tequisquiapan	Queretaro	Occidental y Bajio
33	Yuriria	Guanajuato	Occidental y Bajio	96	Cerritos	San Luis Potosi	Occidental y Bajio
34	Acapulco De Juarez	Guerrero	Central Mexico	97	Ciudad Del Maaz	San Luis Potosi	Occidental y Bajio
35	Huitzuco De Los Figueroa	Guerrero	Central Mexico	98	El Naranjo	San Luis Potosi	Occidental y Bajio
36	Iguala De La Independencia	Guerrero	Central Mexico	99	Mexquitic De Carmona	San Luis Potosi	Occidental y Bajio
37	Tepecuacuilco De Trujano	Guerrero	Central Mexico	100	Rioverde	San Luis Potosi	Occidental y Bajio
38	Ixmiquilpan	Hidalgo	Central Mexico	101	San Luis Potosa	San Luis Potosi	Occidental y Bajio
39	San Salvador	Hidalgo	Central Mexico	102	Santo Domingo	San Luis Potosi	Occidental y Bajio
40	Acatic	Jalisco	Occidental y Bajio	103	Tamasopo	San Luis Potosi	Occidental y Bajio
41	Amacueca	Jalisco	Occidental y Bajio	104	Concordia	Sinaloa	Zona Norte
42	Ameca	Jalisco	Occidental y Bajio	105	Cosala	Sinaloa	Zona Norte
43	Arandas	Jalisco	Occidental y Bajio	106	San Ignacio	Sinaloa	Zona Norte
44	Atenguillo	Jalisco	Occidental y Bajio	107	Huimanguillo	Tabasco	South Mexico
45	Caaadas De Obregan	Jalisco	Occidental y Bajio	108	Jalpa De Mandez	Tabasco	South Mexico
46	El Salto	Jalisco	Occidental y Bajio	109	Paraaso	Tabasco	South Mexico
47	Guadalajara	Jalisco	Occidental y Bajio	110	Hueyotlipan	Tlaxcala	Central Mexico
48	Juanacatlan	Jalisco	Occidental y Bajio	111	Xicotzinco	Tlaxcala	Central Mexico

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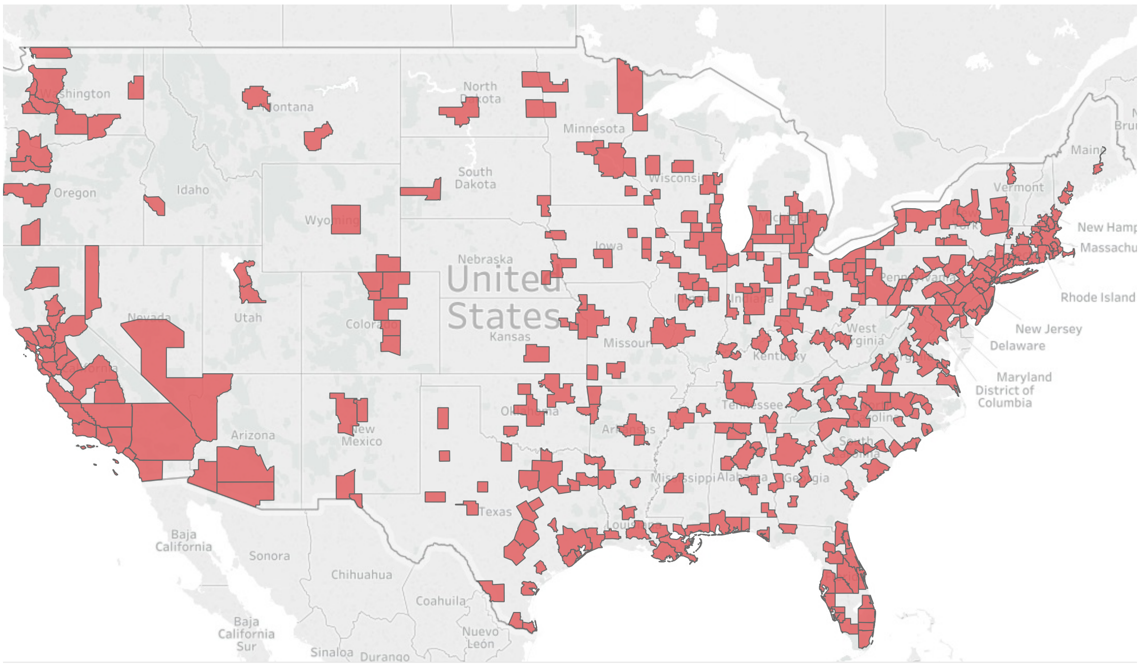
Table B.2.1*(Continued)*

	Municipality	**State**	**Region**		**Municipality**	**State**	**Region**
49	La Huerta	Jalisco	Occidental y Bajio	112	Actopan	Veracruz	Central Mexico
50	Mexticacan	Jalisco	Occidental y Bajio	113	Alto Lucero De Gutiarrez Barrios	Veracruz	Central Mexico
51	San Diego De Alejandraa	Jalisco	Occidental y Bajio	114	Landero Y Coss	Veracruz	Central Mexico
52	San Miguel El Alto	Jalisco	Occidental y Bajio	115	Papantla	Veracruz	Central Mexico
53	Tapalpa	Jalisco	Occidental y Bajio	116	Teocelo	Veracruz	Central Mexico
54	Tepatitlan De Morelos	Jalisco	Occidental y Bajio	117	Xalapa	Veracruz	Central Mexico
55	Unian De San Antonio	Jalisco	Occidental y Bajio	118	Cenotillo	Yucatan	Yucatan Peninsula
56	Valle De Guadalupe	Jalisco	Occidental y Bajio	119	Dzan	Yucatan	Yucatan Peninsula
57	Zapopan	Jalisco	Occidental y Bajio	120	Mana	Yucatan	Yucatan Peninsula
58	Zapotlan El Grande	Jalisco	Occidental y Bajio	121	Oxkutzcab	Yucatan	Yucatan Peninsula
59	Chavinda	Michoacan	Occidental y Bajio	122	Jerez	Zacatecas	Occidental y Bajio
60	Los Reyes	Michoacan	Occidental y Bajio	123	Juchipila	Zacatecas	Occidental y Bajio
61	Morelia	Michoacan	Occidental y Bajio	124	Nochistlan De Mejaa	Zacatecas	Occidental y Bajio
62	Nahuatzen	Michoacan	Occidental y Bajio	125	Pinos	Zacatecas	Occidental y Bajio
63	Tingaindan	Michoacan	Occidental y Bajio	126	Zacatecas	Zacatecas	Occidental y Bajio

B.3 List of US Metropolitan Statistical Areas and States

Figure B.3.1: Map of US Metropolitan Areas



US Metropolitan Statistical Areas coloured in red.

Table B.3.1: List of US Metropolitan Statistical Areas

	MSA	State	Region		MSA	State	Region
1	Phoenix-Mesa	Arizona	West	162	Melbourne-Titusville-Palm Bay	Florida	South
2	Tucson	Arizona	West	163	Miami	Florida	South
3	Yuma	Arizona	West	164	Naples	Florida	South
4	Bakersfield	California	West	165	Ocala	Florida	South
5	Chico-Paradise	California	West	166	Orlando	Florida	South
6	Fresno	California	West	167	Panama City	Florida	South
7	Los Angeles-Long Beach	California	West	168	Pensacola	Florida	South
8	Merced	California	West	169	Punta Gorda	Florida	South
9	Modesto	California	West	170	Sarasota-Bradenton	Florida	South
10	Oakland	California	West	171	Tallahassee	Florida	South
11	Orange County	California	West	172	Tampa-St. Petersburg-Clearwater	Florida	South
12	Redding	California	West	173	West Palm Beach-Boca Raton	Florida	South
13	Riverside-San Bernardino	California	West	174	Columbus	GA-AL	South
14	Sacramento	California	West	175	Augusta-Aiken	GA-SC	South
15	Salinas	California	West	176	Albany	Georgia	South
16	San Diego	California	West	177	Athens	Georgia	South
17	San Francisco	California	West	178	Atlanta	Georgia	South
18	San Jose	California	West	179	Macon	Georgia	South
19	San Luis Obispo-Atascadero-Paso Robles	California	West	180	Savannah	Georgia	South

Continued on next page

Table B.3.1 *(Continued)*

	MSA	State	Region		MSA	State	Region
20	Santa Barbara-Santa Maria-Lompoc	California	West	181	Louisville	KY-IN	South
21	Santa Cruz-Watsonville	California	West	182	Lexington	Kentucky	South
22	Santa Rosa	California	West	183	Owensboro	Kentucky	South
23	Stockton-Lodi	California	West	184	Alexandria	Louisiana	South
24	Vallejo-Fairfield-Napa	California	West	185	Baton Rouge	Louisiana	South
25	Ventura	California	West	186	Houma	Louisiana	South
26	Visalia-Tulare-Porterville	California	West	187	Lafayette	Louisiana	South
27	Yolo	California	West	188	Lake Charles	Louisiana	South
28	Yuba City	California	West	189	Monroe	Louisiana	South
29	Boulder-Longmont	Colorado	West	190	New Orleans	Louisiana	South
30	Colorado Springs	Colorado	West	191	Shreveport-Bossier City	Louisiana	South
31	Denver	Colorado	West	192	Baltimore	Maryland	South
32	Fort Collins-Loveland	Colorado	West	193	Hagerstown	Maryland	South
33	Greeley	Colorado	West	194	Biloxi-Gulfport-Pascagoula	Mississippi	South
34	Pueblo	Colorado	West	195	Jackson	Mississippi	South
35	Boise City	Idaho	West	196	Charlotte-Gastonia-Rock Hill	NC-SC	South
36	Billings	Montana	West	197	Asheville	North Carolina	South
37	Great Falls	Montana	West	198	Fayetteville	North Carolina	South
38	Las Vegas	NV-AZ	West	199	Goldsboro	North Carolina	South
39	Reno	Nevada	West	200	Greensboro-Winston-Salem-High Point	North Carolina	South
40	Albuquerque	New Mexico	West	201	Greenville	North Carolina	South
41	Las Cruces	New Mexico	West	202	Hickory-Morganton	North Carolina	South
42	Santa Fe	New Mexico	West	203	Jacksonville	North Carolina	South
43	Portland-Vancouver	OR-WA	West	204	Raleigh-Durham-Chapel Hill	North Carolina	South
44	Eugene-Springfield	Oregon	West	205	Rocky Mount	North Carolina	South
45	Medford-Ashland	Oregon	West	206	Wilmington	North Carolina	South
46	Salem	Oregon	West	207	Enid	Oklahoma	South
47	Provo-Orem	Utah	West	208	Lawton	Oklahoma	South
48	Salt Lake City-Ogden	Utah	West	209	Oklahoma City	Oklahoma	South
49	Bellingham	Washington	West	210	Tulsa	Oklahoma	South
50	Bremerton	Washington	West	211	Charleston-North Charleston	South Carolina	South
51	Olympia	Washington	West	212	Columbia	South Carolina	South
52	Richland-Kennewick-Pasco	Washington	West	213	Florence	South Carolina	South
53	Seattle-Bellevue-Everett	Washington	West	214	Greenville-Spartanburg-Anderson	South Carolina	South
54	Spokane	Washington	West	215	Myrtle Beach	South Carolina	South
55	Tacoma	Washington	West	216	Sumter	South Carolina	South
56	Yakima	Washington	West	217	Memphis	TN-AR-MS	South
57	Casper	Wyoming	West	218	Chattanooga	TN-GA	South

Continued on next page

Table B.3.1 *(Continued)*

	MSA	State	Region		MSA	State	Region
58	Cheyenne	Wyoming	West	219	Clarksville-Hopkinsville	TN-KY	South
59	Davenport-Moline-Rock Island	IA-IL	MidWest	220	Johnson City-Kingsport-Bristol	TN-VA	South
60	Sioux City	IA-NE	MidWest	221	Texarkana	TX-AR	South
61	Evansville-Henderson	IN-KY	MidWest	222	Jackson	Tennessee	South
62	Bloomington-Normal	Illinois	MidWest	223	Knoxville	Tennessee	South
63	Champaign-Urbana	Illinois	MidWest	224	Nashville	Tennessee	South
64	Chicago	Illinois	MidWest	225	Abilene	Texas	South
65	Decatur	Illinois	MidWest	226	Amarillo	Texas	South
66	Kankakee	Illinois	MidWest	227	Austin-San Marcos	Texas	South
67	Peoria-Pekin	Illinois	MidWest	228	Beaumont-Port Arthur	Texas	South
68	Rockford	Illinois	MidWest	229	Brazoria	Texas	South
69	Springfield	Illinois	MidWest	230	Brownsville-Harlingen-San Benito	Texas	South
70	Bloomington	Indiana	MidWest	231	Bryan-College Station	Texas	South
71	Elkhart-Goshen	Indiana	MidWest	232	Corpus Christi	Texas	South
72	Fort Wayne	Indiana	MidWest	233	Dallas	Texas	South
73	Gary	Indiana	MidWest	234	El Paso	Texas	South
74	Indianapolis	Indiana	MidWest	235	Fort Worth-Arlington	Texas	South
75	Kokomo	Indiana	MidWest	236	Galveston-Texas City	Texas	South
76	Lafayette	Indiana	MidWest	237	Houston	Texas	South
77	Muncie	Indiana	MidWest	238	Killeen-Temple	Texas	South
78	South Bend	Indiana	MidWest	239	Laredo	Texas	South
79	Terre Haute	Indiana	MidWest	240	Longview-Marshall	Texas	South
80	Cedar Rapids	Iowa	MidWest	241	Lubbock	Texas	South
81	Des Moines	Iowa	MidWest	242	McAllen-Edinburg-Mission	Texas	South
82	Dubuque	Iowa	MidWest	243	Odessa-Midland	Texas	South
83	Iowa City	Iowa	MidWest	244	San Angelo	Texas	South
84	Waterloo-Cedar Falls	Iowa	MidWest	245	San Antonio	Texas	South
85	Lawrence	Kansas	MidWest	246	Sherman-Denison	Texas	South
86	Topeka	Kansas	MidWest	247	Tyler	Texas	South
87	Wichita	Kansas	MidWest	248	Victoria	Texas	South
88	Cumberland	MD-WV	MidWest	249	Waco	Texas	South
89	Duluth-Superior	MN-WI	MidWest	250	Wichita Falls	Texas	South
90	Minneapolis-St. Paul	MN-WI	MidWest	251	Norfolk-Virginia Beach-Newport News	VA-NC	South
91	St. Louis	MO-IL	MidWest	252	Charlottesville	Virginia	South
92	Kansas City	MO-KS	MidWest	253	Danville	Virginia	South
93	Ann Arbor	Michigan	MidWest	254	Lynchburg	Virginia	South
94	Benton Harbor	Michigan	MidWest	255	Richmond-Petersburg	Virginia	South
95	Detroit	Michigan	MidWest	256	Roanoke	Virginia	South
96	Flint	Michigan	MidWest	257	Huntington-Ashland	WV-KY-OH	South
97	Grand Rapids-Muskegon-Holland	Michigan	MidWest	258	Parkersburg-Marietta	WV-OH	South

Continued on next page

Table B.3.1 *(Continued)*

	MSA	State	Region		MSA	State	Region
98	Jackson	Michigan	MidWest	259	Wheeling	WV-OH	South
99	Kalamazoo-Battle Creek	Michigan	MidWest	260	Charleston	West Virginia	South
100	Lansing-East Lansing	Michigan	MidWest	261	New London-Norwich	CT-RI	Northeast
101	Saginaw-Bay City-Midland	Michigan	MidWest	262	Bridgeport	Connecticut	Northeast
102	Rochester	Minnesota	MidWest	263	Danbury	Connecticut	Northeast
103	St. Cloud	Minnesota	MidWest	264	Hartford	Connecticut	Northeast
104	Columbia	Missouri	MidWest	265	New Haven-Meriden	Connecticut	Northeast
105	Joplin	Missouri	MidWest	266	Stamford-Norwalk	Connecticut	Northeast
106	Springfield	Missouri	MidWest	267	Waterbury	Connecticut	Northeast
107	St. Joseph	Missouri	MidWest	268	Worcester	MA-CT	Northeast
108	Fargo-Moorhead	ND-MN	MidWest	269	Boston	MA-NH	Northeast
109	Grand Forks	ND-MN	MidWest	270	Lawrence	MA-NH	Northeast
110	Omaha	NE-IA	MidWest	271	Lowell	MA-NH	Northeast
111	Lincoln	Nebraska	MidWest	272	Bangor	Maine	Northeast
112	Bismarck	North Dakota	MidWest	273	Lewiston-Auburn	Maine	Northeast
113	Cincinnati	OH-KY-IN	MidWest	274	Portland	Maine	Northeast
114	Akron	Ohio	MidWest	275	Barnstable-Yarmouth	Massachusetts	Northeast
115	Canton-Massillon	Ohio	MidWest	276	Brockton	Massachusetts	Northeast
116	Cleveland-Lorain-Elyria	Ohio	MidWest	277	Fitchburg-Leominster	Massachusetts	Northeast
117	Columbus	Ohio	MidWest	278	New Bedford	Massachusetts	Northeast
118	Dayton-Springfield	Ohio	MidWest	279	Pittsfield	Massachusetts	Northeast
119	Hamilton-Middletown	Ohio	MidWest	280	Springfield	Massachusetts	Northeast
120	Lima	Ohio	MidWest	281	Portsmouth-Rochester	NH-ME	Northeast
121	Mansfield	Ohio	MidWest	282	Newburgh	NY-PA	Northeast
122	Toledo	Ohio	MidWest	283	Manchester	New Hampshire	Northeast
123	Youngstown-Warren	Ohio	MidWest	284	Nashua	New Hampshire	Northeast
124	Rapid City	South Dakota	MidWest	285	Atlantic-Cape May	New Jersey	Northeast
125	Sioux Falls	South Dakota	MidWest	286	Bergen-Passaic	New Jersey	Northeast
126	La Crosse	WI-MN	MidWest	287	Jersey City	New Jersey	Northeast
127	Appleton-Oshkosh-Neenah	Wisconsin	MidWest	288	Middlesex-Somerset-Hunterdon	New Jersey	Northeast
128	Eau Claire	Wisconsin	MidWest	289	Monmouth-Ocean	New Jersey	Northeast
129	Green Bay	Wisconsin	MidWest	290	Newark	New Jersey	Northeast
130	Janesville-Beloit	Wisconsin	MidWest	291	Trenton	New Jersey	Northeast
131	Kenosha	Wisconsin	MidWest	292	Vineland-Millville-Bridgeton	New Jersey	Northeast
132	Madison	Wisconsin	MidWest	293	Albany-Schenectady-Troy	New York	Northeast
133	Milwaukee-Waukesha	Wisconsin	MidWest	294	Binghamton	New York	Northeast
134	Racine	Wisconsin	MidWest	295	Buffalo-Niagara Falls	New York	Northeast
135	Sheboygan	Wisconsin	MidWest	296	Dutchess County	New York	Northeast
136	Wausau	Wisconsin	MidWest	297	Elmira	New York	Northeast
137	Fort Smith	AR-OK	South	298	Glens Falls	New York	Northeast
138	Anniston	Alabama	South	299	Jamestown	New York	Northeast
139	Birmingham	Alabama	South	300	Nassau-Suffolk	New York	Northeast
140	Decatur	Alabama	South	301	New York	New York	Northeast

Continued on next page

Table B.3.1 *(Continued)*

	MSA	State	Region		MSA	State	Region
141	Dothan	Alabama	South	302	Rochester	New York	Northeast
142	Florence	Alabama	South	303	Syracuse	New York	Northeast
143	Gadsden	Alabama	South	304	Utica-Rome	New York	Northeast
144	Huntsville	Alabama	South	305	Steubenville-Weirton	OH-WV	Northeast
145	Mobile	Alabama	South	306	Philadelphia	PA-NJ	Northeast
146	Montgomery	Alabama	South	307	Allentown-Bethlehem-Easton	Pennsylvania	Northeast
147	Tuscaloosa	Alabama	South	308	Altoona	Pennsylvania	Northeast
148	Fayetteville-Springdale-Rogers	Arkansas	South	309	Erie	Pennsylvania	Northeast
149	Little Rock-North Little Rock	Arkansas	South	310	Harrisburg-Lebanon-Carlisle	Pennsylvania	Northeast
150	Pine Bluff	Arkansas	South	311	Johnstown	Pennsylvania	Northeast
151	Wilmington-Newark	DE-MD	South	312	Lancaster	Pennsylvania	Northeast
152	Dover	Delaware	South	313	Pittsburgh	Pennsylvania	Northeast
153	Washington	District of Columbia	South	314	Reading	Pennsylvania	Northeast
154	Daytona Beach	Florida	South	315	Scranton-Wilkes-Barre-Hazleton	Pennsylvania	Northeast
155	Fort Lauderdale	Florida	South	316	Sharon	Pennsylvania	Northeast
156	Fort Myers-Cape Coral	Florida	South	317	State College	Pennsylvania	Northeast
157	Fort Pierce-Port St. Lucie	Florida	South	318	Williamsport	Pennsylvania	Northeast
158	Fort Walton Beach	Florida	South	319	York	Pennsylvania	Northeast
159	Gainesville	Florida	South	320	Providence-Fall River-Warwick	RI-MA	Northeast
160	Jacksonville	Florida	South	321	Burlington	Vermont	Northeast
161	Lakeland-Winter Haven	Florida	South				

Note: Metropolitan Area Definitions according to 1999 Census definitions.

B.4 Further Summary Statistics

Table B.4.1: Summary Statistics on Location Specific Characteristics by US States

U.S. State	avg wkly wage (in 1000)	pc income (in 1000)	population (in 1000)	Mex pop (%)	unemp rate	CPI	net mig exp (%)	herd (%)	rural housing (%)
Alabama	0.49	13.67	279.55	1.10	5.45	234.91	0.00	-0.00	67.49
Arizona	0.46	12.87	272.05	2.09	5.01	233.82	0.00	0.00	68.46
Arkansas	0.48	13.51	1,197.93	28.09	8.08	356.60	0.11	-0.01	88.35
California	0.58	16.65	1,168.54	20.27	7.11	423.96	0.31	-0.04	86.03
Colorado	0.54	17.19	507.18	11.17	4.68	225.19	0.04	-0.00	84.07
Connecticut	0.62	21.93	1,108.81	0.60	4.65	234.61	0.00	-0.00	82.12
Delaware	0.58	21.25	4,506.72	1.24	3.51	235.03	0.04	-0.01	89.38
Florida	0.49	15.89	332.06	0.95	4.98	235.03	0.04	0.00	70.56
Georgia	0.49	15.95	638.14	1.96	4.88	234.44	0.01	-0.00	84.51
Hawaii	0.45	13.87	717.43	1.30	5.14	235.23	0.02	0.00	77.86
Idaho	0.50	15.85	203.53	2.77	3.77	225.25	0.00	-0.00	82.87
Illinois	0.48	13.67	372.74	7.89	4.56	409.78	0.00	-0.00	82.80
Indiana	0.45	16.35	1,158.80	2.78	5.02	225.42	0.23	-0.06	81.26
Iowa	0.47	14.63	361.55	2.15	5.04	225.92	0.01	0.00	76.48
Kansas	0.44	15.40	254.61	4.14	4.05	225.66	0.00	-0.00	86.60
Kentucky	0.46	14.50	513.51	1.04	4.87	232.02	0.03	0.01	80.07
Louisiana	0.48	13.33	403.05	0.90	4.96	232.67	0.00	-0.00	75.31
Maine	0.58	18.60	1,502.07	0.29	5.03	234.40	0.00	-0.00	80.81
Maryland	0.51	15.91	887.91	0.39	5.49	235.03	0.02	-0.00	71.92
Massachusetts	0.46	14.63	230.83	0.25	4.72	235.03	0.00	-0.00	53.40
Michigan	0.52	15.29	880.94	2.33	6.20	224.31	0.00	0.00	70.55
Minnesota	0.51	16.20	795.79	0.84	4.32	223.55	0.04	0.01	70.89
Mississippi	0.44	14.24	812.92	1.33	4.48	223.69	0.00	0.00	77.85
Missouri	0.47	14.26	367.70	0.85	5.14	235.23	0.00	-0.00	77.33
Montana	0.49	14.98	101.11	2.04	4.51	225.34	0.00	-0.00	83.13
Nebraska	0.46	13.68	462.44	2.03	4.78	234.58	0.09	-0.01	63.75
Nevada	0.46	15.28	118.19	1.21	3.55	225.66	0.00	0.00	76.35
New Hampshire	0.50	16.14	459.40	2.29	2.88	225.66	0.00	-0.00	90.31
New Jersey	0.55	18.40	512.75	0.37	3.79	233.98	0.00	0.00	64.63
New Mexico	0.63	19.32	851.62	1.38	5.68	234.23	0.00	-0.00	89.28
New York	0.49	15.92	308.03	25.02	4.97	233.54	0.01	-0.01	81.15
North Carolina	0.55	16.41	758.01	8.85	5.41	420.90	0.07	-0.04	91.82
North Dakota	0.55	16.07	1,312.93	0.50	4.99	232.94	0.03	-0.01	70.24
Ohio	0.51	14.93	772.03	0.77	5.63	242.26	0.00	0.00	80.28
Oklahoma	0.45	14.11	481.96	3.15	3.85	234.73	0.01	-0.00	82.75
Oregon	0.52	15.16	615.17	5.05	6.23	416.28	0.13	-0.07	78.19
Pennsylvania	0.52	14.91	822.77	0.40	5.05	408.97	0.02	0.00	69.23
Rhode Island	0.54	18.33	1,515.82	0.32	5.81	235.03	0.00	-0.00	87.77
South Carolina	0.46	13.57	381.94	1.13	5.24	234.17	0.00	0.00	66.70
South Dakota	0.43	15.73	120.13	1.15	3.22	224.27	0.00	0.00	78.25
Tennessee	0.45	13.49	569.76	1.08	4.94	234.22	0.00	-0.00	72.79
Texas	0.49	13.76	585.61	24.12	5.10	234.26	0.08	-0.01	82.69
Utah	0.47	13.21	754.80	4.76	3.94	425.53	0.00	0.00	95.06
Vermont	0.45	15.25	502.96	0.68	4.17	233.96	0.00	0.00	69.20
Virginia	0.46	16.58	180.88	0.22	3.77	235.03	0.00	0.00	55.02
Washington	0.54	15.95	501.17	7.57	6.12	415.44	0.00	0.00	77.11
West Virginia	0.51	16.22	306.59	2.19	4.57	224.90	0.00	-0.00	76.95
Wisconsin	0.49	13.86	221.67	0.24	5.76	234.24	0.00	0.00	63.15
Wyoming	0.52	16.57	71.90	5.00	4.21	224.24	0.00	0.00	84.06

B.5 Data Description

Table B.5.1: Variable Definitions and Data Source

Variable	Definition	Source
Individual characteristics		
age at mig.	age at migration	Mexican Migration Project
male	male migrant	"
married	married at migration	"
secondary edu.	max. secondary education (7-9 yrs)	"
tertiary edu.	max. tertiary education (10-12 yrs)	"
> tertiary	education beyond tertiary education (> 12 yrs)	"
trip duration US	duration of migration trip	"
legal migrant	legal migrant	"
same placeprev. mig.	previous migration experience to same MSA	"
migrant network	Relatives/friends with previous migration to US	"
trips #	# of trips made by migrant	"
migration dist.	Travel distance between municipality and MSA (100 km)	Google Distance
mig. travel time	Travel time between municipality and MSA (h)	Matrix API
Location characteristics		
tot. population	Total Population MSA	U.S. Census & Yearbooks
% pop. sharelatino hispanic	pop. share Hispanic or Latino origin (%)	"
% pop. share Mexican	foreign born from Mexico (%)	"
% pop. shareforeign born	Population share of foreign born (%)	
% unemployment	unemployment rate (%)	US Census &
avg. wkly wage (US$100)	average weekly income (US$100)	Bureau of Labor Statistics
CPI	Consumer Price Index	"
Climate normals: calculated as pre-migration 30 yr mean		
avg temp.	mean temperature (°C)	Climatic Research
max temp.	maximum temperature (°C)	Unit TS4.01
min temp.	minimum temperature (°C)	"
temp. Jun-Aug	mean temperature Jun-Aug (°C)[a]	"
temp. Dec-Feb	mean temperature Dec-Feb (°C)[a]	"
max temp. Jul	July maximum temperature (°C)[a]	"
min temp. Jan	January minimum temperature (°C)[a]	"
std temp.	standard deviation of mean temperature	"
precip.	total monthly precipitation (mm)	"
precip. Jun-Aug	mean total precipitation Jun-Aug (mm)[a]	"
precip. Dec-Feb	mean total precipitation Dec-Feb (mm)[a]	"
wet days	wet day frequency (Days)	"
cloud days	daily cloud cover (%)	"
vapour press.	daily vapour pressure (x10 Hectopascals)	"

[a] This variable definition from the fact that in the Northern Hemisphere January and July are the middle of the climatological winter and summer.

Total Population MSA-level population data is only available for census years and State and MSA yearbooks. Data were obtained for the years 1970, 1974, 1977, 1982, 1986, 1990, 1991, 1997, 2000, 2002, 2006, 2010 and 2012. Population data for the intercensual years was estimated assuming and exponential growth function.

Mexican Population Share Information on the size of the Mexican community in destinations is available for Census years 1970, 1980, 1990, 2000 and 2010-2012. The intercensual MSA-level Mexican population are predicted using a second-degree polynomial regression. The final share Mexican born individuals is calculated dividing the Mexican population size by the total population.

Unemployment Rate Information on employment data is available for the year 1070, 1974 and for all years starting from 1976. Data for the missing years 1971 to 1973 was predicted based on state trends and the growth rate during the subsequent years.

B.6 Full Regression Tables

Table B.6.1: Climate Ratio US Destination and Mexican Origin

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Location specific characteristics									
migration distance	0.794***	0.796***	0.795***	0.793***	0.793***	0.817***	0.798***	0.810***	0.797***
	(-12.09)	(-11.96)	(-12.19)	(-12.02)	(-13.13)	(-8.03)	(-12.78)	(-8.43)	(-11.27)
log pc income	0.966	0.951	0.990	0.976	0.975	0.848	0.853	0.856	0.880
	(-0.10)	(-0.15)	(-0.03)	(-0.07)	(-0.08)	(-0.52)	(-0.50)	(-0.49)	(-0.40)
unemployment rate	0.912***	0.909***	0.905***	0.903***	0.915***	0.901***	0.928***	0.915***	0.918***
	(-4.24)	(-4.37)	(-4.51)	(-4.58)	(-4.12)	(-4.74)	(-3.62)	(-4.17)	(-4.10)
CPI	0.617***	0.620***	0.579***	0.580***	0.732***	0.623***	0.659***	0.646***	0.638***
	(-5.49)	(-5.40)	(-6.16)	(-6.11)	(-3.47)	(-4.97)	(-4.51)	(-4.64)	(-5.05)
% rural housing	1.034***	1.034***	1.030**	1.030**	1.019	1.019	1.007	1.006	1.018
	(3.40)	(3.39)	(2.98)	(2.99)	(1.46)	(1.61)	(0.51)	(0.52)	(1.49)
log population	2.703***	3.067***	2.776***	2.958***	2.534***	3.006***	2.575***	3.110***	2.397***
	(4.20)	(4.82)	(4.34)	(4.71)	(3.87)	(4.73)	(3.91)	(4.69)	(3.69)
% population Mexican	0.871***	0.871***	0.872***	0.872***	0.889***	0.877***	0.886***	0.882***	0.879***
	(-12.80)	(-12.79)	(-12.93)	(-12.90)	(-9.53)	(-11.82)	(-9.76)	(-11.40)	(-11.46)
net migration municipality	1.618***	1.617***	1.613***	1.612***	1.617***	1.611***	1.620***	1.612***	1.619***
	(17.58)	(17.56)	(17.56)	(17.51)	(17.43)	(17.38)	(17.45)	(17.38)	(17.56)
herd	0.967	0.966	0.965	0.965	0.967	0.965	0.965	0.964	0.965
	(-1.50)	(-1.50)	(-1.56)	(-1.56)	(-1.47)	(-1.57)	(-1.53)	(-1.61)	(-1.54)

Table continues on next page

Table B.6.1: *(Continued)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Climate variables									
avg temp.	5.976***	11.83**							
US	(5.29)	(2.81)							
avg temp.	1.477***	3.024*							
ratio $^{US}/_{Mex}$	(4.65)	(2.42)							
avg temp.^{2}		0.973							
US		(-1.22)							
avg temp.^{2}		0.793							
ratio $^{US}/_{Mex}$		(-1.65)							
max temp.			0.698	1.238	2.619	2.745			
US			(-1.03)	(0.16)	(0.69)	(0.76)			
max temp.			1.454	5.202	11.10	1.521			
ratio $^{US}/_{Mex}$			(1.11)	(1.07)	(1.63)	(0.29)			
min temp.			8.826***	9.180***		6.678***			
US			(7.90)	(7.63)		(4.31)			
min temp.			1.058*	1.056		1.177*			
ratio $^{US}/_{Mex}$			(2.00)	(1.91)		(2.09)			
max temp.^{2}				0.981	0.992	0.984			
US				(-0.67)	(-0.30)	(-0.57)			
max temp.^{2}				0.664	0.580	0.911			
ratio $^{US}/_{Mex}$				(-0.85)	(-1.18)	(-0.21)			
summer temp.							2.365*	3.387**	2.434*
US							(2.33)	(3.18)	(2.45)
summer temp.							0.832	0.744*	0.894
ratio $^{US}/_{Mex}$							(-1.40)	(-2.25)	(-0.85)
winter temp.							1.906**	1.830**	1.951**
US							(2.86)	(2.66)	(2.90)
winter temp.							1.071	0.928	1.043
ratio $^{US}/_{Mex}$							(1.96)	(-1.41)	(1.23)
precipitation						0.963		0.960	0.967
US						(-1.45)		(-1.51)	(-1.27)
precipitation						0.970		0.952*	0.961*
ratio $^{US}/_{Mex}$						(-1.54)		(-2.46)	(-2.13)
summer precip.					0.972		0.971		
US					(-1.64)		(-1.81)		
summer precip.					1.015***		1.015***		
ratio $^{US}/_{Mex}$					(7.94)		(7.70)		
winter precip.					0.970**		0.976*		
US					(-2.67)		(-2.09)		
winter precip.					0.999		0.999		
ratio $^{US}/_{Mex}$					(-0.57)		(-0.86)		
cloud cover						1.686**		1.993***	
US						(2.87)		(5.09)	
cloud cover						0.614		0.468*	
ratio $^{US}/_{Mex}$						(-1.38)		(-2.21)	
vapour press.						0.451		0.630	
US						(-1.85)		(-1.34)	
vapour press.						0.855		1.168**	
ratio $^{US}/_{Mex}$						(-1.75)		(2.97)	
MSA FE	×	×	×	×	×	×	×	×	×
LL	-33,129.9	-33,121.2	-33,100.7	-33,097.6	-33,135.7	-33,014.3	-33,085.7	-33,032.7	-33,099.7
# cluster	683	683	683	683	683	683	683	683	683
N	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800
Cases	21,624	21,624	21,624	21,624	21,624	21,624	21,624	21,624	21,624

Notes: The table presents odds ratios with the respective significance level of * p<0.1; ** p<0.05; *** p<0.01. T-statistics presented in parentheses.

Table B.6.2: Subsample Regressions Hot and Cold Mexican Origin - US climate

	(1)		**(2)**		**(3)**		**(6)**		**(7)**		**(8)**	
	hot	cold	hot	cold	hot	cold	hot	cold	hot	cold	hot	cold
Location specific characteristics												
migration	0.759***	0.858***	0.759***	0.858***	0.759***	0.855***	0.758***	0.855***	0.759***	0.859***	0.759***	0.856***
distance	(-18.22)	(-4.08)	(-18.24)	(-4.08)	(-18.22)	(-4.16)	(-18.53)	(-4.16)	(-18.64)	(-4.12)	(-18.57)	(-4.16)
log	1.272	0.742	1.222	0.737	1.284	0.825	1.119	0.741	1.088	0.689	1.102	0.705
population	(0.54)	(-0.79)	(0.45)	(-0.80)	(0.55)	(-0.52)	(0.24)	(-0.82)	(0.19)	(-1.00)	(0.21)	(-0.93)
unemployment	0.920**	0.896***	0.908***	0.895***	0.921**	0.890***	0.911**	0.896***	0.927**	0.919**	0.924**	0.909***
rate	(-2.95)	(-3.71)	(-3.44)	(-3.71)	(-2.90)	(-3.85)	(-3.18)	(-3.62)	(-2.74)	(-3.01)	(-2.71)	(-3.41)
CPI	0.802*	0.528***	0.820*	0.527***	0.807*	0.500***	0.809*	0.550***	0.863	0.546***	0.784*	0.565***
	(-2.42)	(-5.09)	(-2.14)	(-5.07)	(-2.34)	(-5.53)	(-2.22)	(-4.44)	(-1.48)	(-4.65)	(-2.56)	(-4.26)
% rural	1.042**	1.031*	1.045***	1.030*	1.042***	1.025	1.034*	1.017	1.020	1.001	1.021	1.000
housing	(3.28)	(1.98)	(3.48)	(2.00)	(3.31)	(1.64)	(2.06)	(1.14)	(1.13)	(0.05)	(1.23)	(-0.00)
log population	0.977	4.005***	1.268	4.242***	0.969	3.981***	1.263	3.902***	0.952	3.931***	0.996	4.745***
	(-0.09)	(4.35)	(0.88)	(4.43)	(-0.12)	(4.37)	(0.81)	(4.16)	(-0.18)	(4.06)	(-0.01)	(4.50)
% population	0.874***	0.870***	0.876***	0.869***	0.874***	0.870***	0.883***	0.873***	0.888***	0.884***	0.885***	0.879***
Mexican	(-8.53)	(-10.30)	(-8.51)	(-9.99)	(-8.53)	(-10.47)	(-7.98)	(-9.80)	(-7.68)	(-7.58)	(-7.89)	(-9.54)
net migration	1.453***	1.669***	1.448***	1.669***	1.453***	1.660***	1.447***	1.667***	1.454***	1.667***	1.452***	1.669***
municipality	(14.17)	(12.27)	(14.29)	(12.26)	(14.17)	(12.19)	(14.27)	(12.26)	(14.21)	(12.18)	(14.24)	(12.22)
herd	0.955	0.971	0.954	0.971	0.955	0.970	0.954	0.970	0.955	0.971	0.954	0.971
	(-1.80)	(-0.92)	(-1.85)	(-0.92)	(-1.79)	(-0.96)	(-1.85)	(-0.96)	(-1.82)	(-0.93)	(-1.83)	(-0.94)

Table continues on next page

Table B.6.2: *(Continued)*

	(1)		(2)		(3)		(6)		(7)		(8)	
	hot	cold	hot	cold	hot	cold	hot	cold	hot	cold	hot	cold
Climate variables												
avg temperature US	6.428^{***}	8.791^{***}	115.0^{***}	13.53^{*}								
	(5.07)	(4.71)	(4.81)	(2.32)								
avg temperature^2 US			0.908^{**}	0.987								
			(-3.21)	(-0.44)								
max temperature US					2.794^{**}	0.669	1107.0^{***}	0.420				
					(2.68)	(-0.98)	(4.38)	(-0.51)				
min temperature US					2.299^{*}	13.18^{***}	0.846	15.37^{***}				
					(2.10)	(6.57)	(-0.30)	(4.65)				
max temperature^2 US							0.889^{***}	1.032				
							(-3.33)	(0.80)				
summer temperature US									2.051	2.048	2.066	4.500^{**}
									(1.49)	(1.37)	(1.35)	(2.68)
winter temperature US									0.981^{*}	0.976		
									(-1.99)	(-1.59)		
precipitation US							0.940^{*}	0.977			0.946	0.961
							(-2.06)	(-0.79)			(-1.90)	(-1.33)
summer precipitation US									0.985	0.959^{*}		
									(-0.69)	(-2.08)		
winter precipitation US							0.983	0.973				
							(-1.80)	(-1.39)				
cloud cover US							1.736^{*}	1.662^{*}			1.195	1.903^{***}
							(2.48)	(2.17)			(1.01)	(4.24)
vapour press. US							0.769	0.178^{**}			1.025	0.406^{*}
							(-0.51)	(-2.91)			(0.05)	(-1.97)
MSA FE	×	×	×	×	×	×	×	×	×	×	×	×
LL	-10,862.1	-20,744.2	-10,849.3	-20,743.8	-10,861.9	-20,715.2	-10,834.4	-20,687.6	-10,856.5	-20,702.7	-10,854.3	-20,690.6
# clter	442	418	442	418	442	418	442	418	442	418	442	418
N	607,650	1,014,150	607,650	1,014,150	607,650	1,014,150	607,650	1,014,150	607,650	1,014,150	607,650	1,014,150
Cases	8,102	13,522	8,102	13,522	8,102	13,522	8,102	13,522	8,102	13,522	8,102	13,522

Notes: The table presents odds ratios with the respective significance level of * $p<0.1$; ** $p<0.05$; *** $p<0.01$. T-statistics presented in parentheses.

B.7 Subsample Regressions

Table B.7.1: Alternative Subsample Regressions - US Climate

	Migrant status		**Migration age**		**Education**		**Network**	
	temporary	permanent	≥ 35	< 35	> 10	≤ 10	relative	no relative
avg temp. US	10.50***	6.001***	4.670***	9.516***	13.26***	6.702***	7.285***	7.164***
	(4.94)	(5.60)	(4.30)	(6.17)	(5.51)	(5.34)	(4.76)	(6.17)
MSA FE	×	×	×	×	×	×	×	×
controls	×	×	×	×	×	×	×	×
LL	-12,737.4	-19,468.1	-10,874.8	-22,045.7	-3,865.7	-29,046.4	-17,261.7	-15,311.1
# cluster	559	661	606	654	510	674	614	645
N	634,050	987,750	521,775	1,100,025	218,850	1,402,950	883,650	738,150
Ind.	8,454	13,170	6,957	14,667	2,918	18,706	11,782	9,842
max temp. US	1.019	0.801	0.927	0.740	0.847	0.764	0.906	0.904
	(0.04)	(-0.63)	(-0.20)	(-0.88)	(-0.29)	(-0.85)	(-0.26)	(-0.30)
min temp. US	10.88***	7.368***	4.979***	13.21***	14.76***	8.935***	8.317***	7.757***
	(4.91)	(6.99)	(4.48)	(8.54)	(5.90)	(7.27)	(5.85)	(6.81)
MSA FE	×	×	×	×	×	×	×	×
controls	×	×	×	×	×	×	×	×
LL	-12,727.0	-19,451.0	-10,869.1	-22,015.9	-3,859.9	-29,017.2	-17,248.4	-15,297.9
# cluster	559	661	606	654	510	674	614	645
N	634,050	987,750	521,775	1,100,025	218,850	1,402,950	883,650	738,150
Ind.	8,454	13,170	6,957	14,667	2,918	18,706	11,782	9,842
summer temp. US	2.480	2.126*	2.786*	2.183	5.024**	2.271*	2.553*	2.039*
	(1.75)	(2.03)	(2.47)	(1.93)	(2.91)	(2.16)	(2.03)	(1.98)
winter temp. US	2.687**	1.837**	1.463	2.442***	2.024*	1.970**	2.169**	1.942**
	(2.95)	(2.81)	(1.53)	(3.60)	(2.30)	(2.85)	(2.68)	(3.07)
precip. US	0.964	0.974	0.969	0.957	1.017	0.960	0.980	0.950*
	(-1.13)	(-1.07)	(-1.15)	(-1.60)	(0.54)	(-1.54)	(-0.70)	(-1.97)
MSA FE	×	×	×	×	×	×	×	×
controls	×	×	×	×	×	×	×	×
LL	-12,717.1	-19,460.6	-10,866.6	-22,023.9	-3,860.5	-29,022.4	-17,239.9	-15,304.0
# cluster	559	661	606	654	510	674	614	645
N	634,050	987,750	521,775	1,100,025	218,850	1,402,950	883,650	738,150
Ind.	8,454	13,170	6,957	14,667	2,918	18,706	11,782	9,842

Notes: The table presents odds ratios with the respective significance level of * p<0.1; ** p<0.05; *** p<0.01. T-statistics presented in parentheses.

Table B.7.2: Alternative Subsample Regressions - US Climate *(rescaled)*

	Migrant status		**Migration age**		**Education**		Network	
	temporary	permanent	≥ 35	< 35	> 10	≤ 10	relative	no relative
% pop Mexican	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
avg temp. US	11.630***	7.049***	5.230***	11.097***	15.371***	7.696***	8.424***	8.106***
MSA FE	×	×	×	×	×	×	×	×
controls	×	×	×	×	×	×	×	×
LL	-12,737.4	-19,468.1	-10,874.8	-22,045.7	-3,865.7	-29,046.4	-17,261.7	-15,311.1
# cluster	559	661	606	654	510	674	614	645
N	634,050	987,750	521,775	1,100,025	218,850	1,402,950	883,650	738,150
Ind.	8,454	13,170	6,957	14,667	2,918	18,706	11,782	9,842
% pop Mexican	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
max temp. US	1.128	0.939	1.038	0.861	0.980	0.876	1.046	1.022
min temp. US	12.049***	8.633***	5.576***	15.366***	17.074***	10.249***	9.608***	8.763***
MSA FE	×	×	×	×	×	×	×	×
controls	×	×	×	×	×	×	×	×
LL	-12,727.0	-19,451.0	-10,869.1	-22,015.9	-3,859.9	-29,017.2	-17,248.4	-15,297.9
# cluster	559	661	606	654	510	674	614	645
N	634,050	987,750	521,775	1,100,025	218,850	1,402,950	883,650	738,150
Ind.	8,454	13,170	6,957	14,667	2,918	18,706	11,782	9,842
% pop Mexican	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
summer temp. US	2.714	2.482*	3.094*	2.523	5.820**	2.584*	2.930*	2.285*
winter temp. US	2.940**	2.144**	1.625	2.822***	2.345*	2.241**	2.489**	2.176**
precip. US	1.055	1.137	1.076	1.107	1.178	1.092	1.125	1.065*
MSA FE	×	×	×	×	×	×	×	×
controls	×	×	×	×	×	×	×	×
LL	-12,717.1	-19,460.6	-10,866.6	-22,023.9	-3,860.5	-29,022.4	-17,239.9	-15,304.0
# cluster	559	661	606	654	510	674	614	645
N	634,050	987,750	521,775	1,100,025	218,850	1,402,950	883,650	738,150
Ind.	8,454	13,170	6,957	14,667	2,918	18,706	11,782	9,842

Notes: The table presents rescaled odds ratios for the regressions presented in Table 3.8 with the respective significance level of * p<0.1; ** p<0.05; *** p<0.01. T-statistics presented in parentheses. All predicted effects should be interpreted relative to the importance of migration distance in the respective model.

B.8 The IIA and the Number of Random Alternatives

Table B.8.1: Experimenting with the Number of Alternatives

	Number of Alternatives								
	# 30	# 40	# 50	# 60	# 70	# 75	# 80	# 90	# 100
Location specific characteristics									
migration distance	0.799***	0.800***	0.800***	0.804***	0.807***	0.810***	0.809***	0.811***	0.815***
	(-9.01)	(-8.97)	(-8.87)	(-8.78)	(-8.63)	(-8.43)	(-8.45)	(-8.36)	(-8.17)
log pc income	0.816	0.856	0.850	0.860	0.878	0.856	0.872	0.902	0.898
	(-0.75)	(-0.54)	(-0.55)	(-0.49)	(-0.42)	(-0.49)	(-0.42)	(-0.31)	(-0.31)
unemployment rate	0.918***	0.918***	0.914***	0.914***	0.914***	0.915***	0.916***	0.916***	0.915***
	(-4.19)	(-4.11)	(-4.28)	(-4.29)	(-4.24)	(-4.17)	(-4.10)	(-4.10)	(-4.09)
CPI	0.621***	0.624***	0.632***	0.638***	0.645***	0.646***	0.649***	0.649***	0.648***
	(-5.14)	(-5.00)	(-4.86)	(-4.80)	(-4.67)	(-4.64)	(-4.61)	(-4.59)	(-4.57)
% rural housing	1.015	1.011	1.011	1.010	1.008	1.006	1.005	1.003	1.003
	(1.29)	(0.90)	(0.92)	(0.81)	(0.66)	(0.52)	(0.39)	(0.26)	(0.22)
log population	2.849***	3.079***	3.178***	3.186***	3.138***	3.110***	3.073***	3.069***	3.098***
	(4.25)	(4.55)	(4.73)	(4.76)	(4.71)	(4.69)	(4.64)	(4.61)	(4.63)
% population Mexican	0.897***	0.892***	0.888***	0.885***	0.882***	0.882***	0.882***	0.883***	0.883***
	(-9.88)	(-10.70)	(-11.05)	(-11.13)	(-11.37)	(-11.40)	(-11.42)	(-11.23)	(-11.18)
net migration municipality	1.913***	1.785***	1.727***	1.699***	1.631***	1.612***	1.595***	1.551***	1.542***
	(13.33)	(14.38)	(15.67)	(16.82)	(17.02)	(17.38)	(17.59)	(17.82)	(18.27)
herd	0.956	0.962	0.967	0.978	0.962	0.964	0.957	0.944*	0.954*
	(-1.12)	(-1.21)	(-1.21)	(-0.96)	(-1.62)	(-1.61)	(-1.83)	(-2.48)	(-2.36)
summer temp. US	4.322***	3.854***	3.622***	3.349**	3.285**	3.387**	3.477**	3.339**	3.323**
	(3.78)	(3.54)	(3.34)	(3.18)	(3.11)	(3.18)	(3.23)	(3.10)	(3.08)
summer temp. $\frac{US}{Mex}$	0.674**	0.662**	0.714*	0.708**	0.739*	0.744*	0.743*	0.751*	0.742*
	(-2.93)	(-3.14)	(-2.57)	(-2.64)	(-2.32)	(-2.25)	(-2.26)	(-2.18)	(-2.25)
winter temp. US	1.661*	1.739*	1.771*	1.845**	1.848**	1.830**	1.820**	1.815**	1.832**
	(2.23)	(2.43)	(2.54)	(2.70)	(2.69)	(2.66)	(2.63)	(2.61)	(2.65)
winter temp. $\frac{US}{Mex}$	0.915	0.921	0.923	0.922	0.926	0.928	0.933	0.936	0.938
	(-1.60)	(-1.49)	(-1.46)	(-1.50)	(-1.44)	(-1.41)	(-1.31)	(-1.25)	(-1.21)
precip. US	0.962	0.962	0.964	0.961	0.960	0.960	0.959	0.957	0.957
	(-1.51)	(-1.49)	(-1.39)	(-1.49)	(-1.53)	(-1.51)	(-1.58)	(-1.62)	(-1.61)
precip. $\frac{US}{Mex}$	0.955*	0.953*	0.953*	0.953*	0.953*	0.952*	0.953*	0.953*	0.953*
	(-2.40)	(-2.52)	(-2.44)	(-2.41)	(-2.41)	(-2.46)	(-2.40)	(-2.39)	(-2.39)
cloud days US	1.878***	1.897***	1.914***	1.964***	1.988***	1.993***	2.005***	1.977***	1.980***
	(4.31)	(4.50)	(4.68)	(4.91)	(5.04)	(5.09)	(5.15)	(5.07)	(5.07)
cloud days $\frac{US}{Mex}$	0.482*	0.497*	0.516	0.489*	0.474*	0.468*	0.472*	0.472*	0.458*
	(-2.08)	(-2.01)	(-1.90)	(-2.07)	(-2.17)	(-2.21)	(-2.18)	(-2.18)	(-2.26)
vapour press. US	0.517	0.600	0.603	0.614	0.627	0.630	0.621	0.653	0.660
	(-1.87)	(-1.49)	(-1.47)	(-1.41)	(-1.35)	(-1.34)	(-1.38)	(-1.23)	(-1.21)
vapour press. $\frac{US}{Mex}$	1.208***	1.204***	1.187**	1.185**	1.170**	1.168**	1.164**	1.157**	1.156**
	(3.52)	(3.50)	(3.25)	(3.21)	(2.98)	(2.97)	(2.90)	(2.82)	(2.82)
MSA FE	×	×	×	×	×	×	×	×	×
LL	-19,471.9	-23,416.6	-26,611.4	-29,343.3	-31,850.1	-33,032.7	-34,121.2	-36,202.1	-37,949.6
# cluster	691	687	684	684	684	683	683	683	683
N	652,950	868,360	1,083,800	1,299,300	1,514,240	1,621,800	1,728,640	1,942,380	2,156,000
Ind.	21,765	21,709	21,676	21,655	21,632	21,624	21,608	21,582	21,560

Notes: The table presents odds ratios with the respective significance level of * p<0.1; ** p<0.05; *** p<0.01. T-statistics presented in parentheses.

B.9 Alternative Cluster Specifications

Table B.9.1: Alternative Cluster Specifications

	robust	mun×yr	state×yr	municipio	mex state
Location specific characteristics					
migration	0.810^{***}	0.810^{***}	0.810^{***}	0.810^{**}	0.810^{*}
distance	(-18.78)	(-10.05)	(-8.43)	(-3.02)	(-2.13)
log	0.856	0.856	0.856	0.856	0.856
pc income	(-1.22)	(-0.57)	(-0.49)	(-0.44)	(-0.35)
unemployment	0.915^{***}	0.915^{***}	0.915^{***}	0.915^{**}	0.915^{*}
rate	(-7.93)	(-4.25)	(-4.17)	(-2.86)	(-2.23)
CPI	0.646^{***}	0.646^{***}	0.646^{***}	0.646^{***}	0.646^{***}
	(-9.21)	(-5.04)	(-4.64)	(-3.64)	(-4.35)
% rural	1.006	1.006	1.006	1.006	1.006
housing	(0.94)	(0.54)	(0.52)	(0.50)	(0.56)
log poulation	3.110^{***}	3.110^{***}	3.110^{***}	3.110^{**}	3.110^{**}
	(8.18)	(4.65)	(4.69)	(2.71)	(3.23)
% population	0.882^{***}	0.882^{***}	0.882^{***}	0.882^{***}	0.882^{***}
Mexican	(-16.52)	(-11.71)	(-11.40)	(-6.43)	(-6.02)
net migration	1.612^{***}	1.612^{***}	1.612^{***}	1.612^{***}	1.612^{***}
municipality	(21.45)	(17.93)	(17.38)	(7.36)	(7.39)
herd	0.964	0.964	0.964	0.964	0.964
	(-1.88)	(-1.65)	(-1.61)	(-1.59)	(-1.38)
Climate variables					
summer temperature	3.387^{***}	3.387^{**}	3.387^{**}	3.387^{**}	3.387^{**}
US	(6.60)	(3.09)	(3.18)	(2.79)	(3.07)
summer temperature	0.744^{***}	0.744^{*}	0.744^{*}	0.744	0.744
ratio $^{US}/_{Mex}$	(-3.91)	(-2.27)	(-2.25)	(-0.76)	(-0.75)
winter temperature	1.830^{***}	1.830^{**}	1.830^{**}	1.830^{*}	1.830^{*}
US	(6.34)	(2.97)	(2.66)	(2.26)	(2.25)
winter temperature	0.928^{**}	0.928	0.928	0.928	0.928
ratio $^{US}/_{Mex}$	(-2.73)	(-1.55)	(-1.41)	(-0.55)	(-0.44)
precipitation	0.960^{***}	0.960	0.960	0.960	0.960
US	(-4.30)	(-1.88)	(-1.51)	(-1.18)	(-1.46)
precipitation	0.952^{***}	0.952^{*}	0.952^{*}	0.952	0.952
ratio $^{US}/_{Mex}$	(-6.92)	(-2.52)	(-2.46)	(-0.93)	(-0.96)
cloud cover	1.993^{***}	1.993^{***}	1.993^{***}	1.993^{**}	1.993^{*}
US	(9.61)	(5.26)	(5.09)	(2.69)	(2.57)
cloud cover	0.468^{***}	0.468^{*}	0.468^{*}	0.468	0.468
ratio $^{US}/_{Mex}$	(-6.03)	(-2.38)	(-2.21)	(-0.72)	(-0.62)
vapour pressure	0.630^{**}	0.630	0.630	0.630	0.630
US	(-2.64)	(-1.43)	(-1.34)	(-1.10)	(-0.88)
vapour pressure	1.168^{***}	1.168^{***}	1.168^{**}	1.168	1.168
ratio $^{US}/_{Mex}$	(5.26)	(3.33)	(2.97)	(1.21)	(0.90)
MSA FE	×	×	×	×	×
LL	-33,032.7	-33,032.7	-33,032.7	-33,032.7	-33,032.7
# cluster	—	2,332	683	109	24
N	1,621,800	1,621,800	1,621,800	1,621,800	1,621,800
Cases	21,624	21,624	21,624	21,624	21,624

Notes: The table presents odds ratios with the respective significance level of * p<0.1; ** p<0.05; *** p<0.01. T-statistics presented in parentheses.

B.10 Alternative Choice-Set Pruning

This Appendix presents the results for the preferred model specification using an alternative choice-set pruning mechanism based on matching destinations, using a propensity score matching technique on observable destination characteristics. I apply nearest neighbour matching of destination locations based on CPI, per capita income, poverty rate, unemployment rate, labour-force share, total population, population share of residents with Latino Hispanic background, median age of the population, population share with less than nine years of education and those with college education, geographic area, latitude and longitude, and the year.

Table B.10.1: Matched Choice Set 50 - US Climate

	(7)	**(8)**	**(9)**
Location specific characteristics			
migration distance	0.790***	0.792***	0.791***
	(-5.38)	(-5.34)	(-5.33)
log pc income	0.881	0.933	0.905
	(-0.29)	(-0.16)	(-0.23)
unemployment rate	0.910***	0.935*	0.925**
	(-3.48)	(-2.33)	(-2.75)
CPI	0.769*	0.800	0.790
	(-2.24)	(-1.87)	(-1.85)
% rural housing	1.020	1.008	1.011
	(1.40)	(0.63)	(0.76)
log population	2.204	1.711	1.938
	(1.91)	(1.32)	(1.48)
% population Mexican	0.865***	0.882***	0.873***
	(-7.66)	(-6.86)	(-7.22)
net migration municipality	2.056***	2.070***	2.063***
	(5.83)	(5.89)	(5.86)
herd	0.921	0.923	0.922
	(-0.86)	(-0.84)	(-0.84)
Climate variables			
max temperature US	24.19*		
	(2.11)		
max temperature^2 US	0.928		
	(-1.84)		
min temperature US	10.68***		
	(3.91)		
summer temperature US		1.604	2.595
		(0.91)	(1.66)
winter temperature US		2.175**	1.957*
		(3.06)	(2.34)
precipitation US	0.923**		0.920*
	(-2.58)		(-2.57)
cloud cover US	1.364		1.718**
	(1.05)		(2.63)
vapour pressure US	0.422		0.540
	(-1.31)		(-1.25)
summer precipitation US		0.955**	
		(-3.20)	
winter precipitation US		0.968	
		(-1.95)	
MSA FE	×	×	×
LL	-14190.267	-14199.145	-14195.771
# cluster	109.0	109.0	109.0
N	523,866	523,866	523,866
Cases	21,765	21,765	21,765

Notes: The table presents odds ratios with the respective significance level of * p<0.1; ** p<0.05; *** p<0.01. T-statistics presented in parentheses.

Table B.10.2: Matched Choice Set 50 - Climate Ratios US/Mexico

	(7)	**(8)**	**(9)**	**(10)**
max temperature US	8.345			
	(1.31)			
max temperature ratio $^{US}/_{Mex}$	3.261			
	(0.61)			
max temperature^2 US	0.941			
	(-1.82)			
max temperature^2 ratio $^{US}/_{Mex}$	0.687			
	(-0.63)			
min temperature US	8.806***			
	(4.59)			
min temperature ratio $^{US}/_{Mex}$	1.221*			
	(2.23)			
summer temperature US		2.148	3.264**	2.347*
		(1.82)	(2.75)	(2.09)
summer temperature ratio $^{US}/_{Mex}$		0.637**	0.567***	0.656**
		(-3.10)	(-3.70)	(-2.88)
winter temperature US		1.879*	1.802*	1.841*
		(2.50)	(2.35)	(2.43)
winter temperature ratio $^{US}/_{Mex}$		1.150***	0.996	1.115**
		(3.46)	(-0.07)	(2.74)
precipitation US	0.926**		0.923**	0.936*
	(-2.85)		(-2.90)	(-2.45)
precipitation ratio $^{US}/_{Mex}$	0.979		0.964	0.968
	(-1.12)		(-1.88)	(-1.75)
cloud cover US	1.465		2.008***	
	(1.91)		(4.53)	
cloud cover ratio $^{US}/_{Mex}$	0.497*		0.416*	
	(-2.02)		(-2.49)	
vapour pressure US	0.591		0.586	
	(-1.00)		(-1.25)	
vapour pressure ratio $^{US}/_{Mex}$	0.821*		1.138*	
	(-2.02)		(2.25)	
summer precipitation US		0.952**		
		(-2.88)		
summer precipitation ratio $^{US}/_{Mex}$		1.019***		
		(9.33)		
winter precipitation US		0.966**		
		(-2.92)		
winter percipitation ratio $^{US}/_{Mex}$		1.002		
		(1.31)		
MSA FE	×	×	×	×
controls	×	×	×	×
LL	-14,132.7	-14,151.7	-14,141.9	-14,177.5
# cluster	694	694	694	694
N	523,866	523,866	523,866	523,866
Cases	21,765	21,765	21,765	21,765

Notes: The table presents odds ratios with the respective significance level of * p<0.1; ** p<0.05; *** p<0.01. T-statistics presented in parentheses.

Table B.10.3: Matched Choice Set 50 - Hot Cold Sub-Samples

	(7)		**(8)**		**(9)**	
	hot	cold	hot	cold	hot	cold
max temperature US	2169.2***	8.880				
	(3.35)	(1.05)				
max temperature^2 US	0.856**	0.961				
	(-3.14)	(-0.72)				
min temperature US	1.768	14.04***				
	(0.55)	(3.60)				
summer temperature US			2.246	1.463	2.234	3.567
			(1.71)	(0.58)	(1.94)	(1.61)
winter temperature US			1.491	3.027**	1.415	2.670*
			(1.55)	(3.24)	(1.36)	(2.39)
precipitation US	0.920*	0.935			0.930*	0.922
	(-2.30)	(-1.66)			(-2.02)	(-1.88)
cloud cover US	1.228	1.671			1.135	1.956**
	(0.55)	(1.46)			(0.40)	(2.92)
vapour press. US	1.120	0.180			1.246	0.266
	(0.18)	(-1.91)			(0.40)	(-1.92)
summer precipitation US			0.969	0.948**		
			(-1.33)	(-2.96)		
winter precipitation US			0.974	0.971		
			(-1.66)	(-1.32)		
MSA FE	×	×	×	×	×	×
controls	×	×	×	×	×	×
LL	-4,382.8	-8,638.1	-4,396.7	-8,636.2	-4,396.5	-8,628.3
# cluster	54	55	54	55	54	55
N	195,887	327,979	195,887	327,979	195,887	327,979
Cases	8,153	13,612	8,153	13,612	8,153	13,612

Notes: The table presents odds ratios with the respective significance level of * p<0.1; ** p<0.05; *** p<0.01. T-statistics presented in parentheses.

B.11 Bootstrap Results

In this Appendix, I present the results from the bootstrap regressions using a newly written command *bsasclogit*. The internal Stata bootstrap program for *asclogit* is not appropriate for the analysis, as the program randomly drops observations, including the true chosen alternative, thereby significantly reducing the sample size during the estimation process. To test the robustness of the results to the implemented choice-set restriction, I designed a new bootstrap program that estimates standard errors by resampling the random subset of alternatives for each bootstrap iteration. The Stata code for the program is presented in the subsequent Appendix B.12.

Table B.11.1: Bootstrap Results for Model 6

	(6)			
	US/Mex	US	hot	cold
Location specific characteristics				
migration distance	0.815***	0.784***	0.757***	0.908***
	(-64.13)	(-57.61)	(-81.34)	(-20.48)
log pc income	0.773***	0.801***	0.920	0.689***
	(-9.97)	(-8.88)	(-1.82)	(-10.81)
unemployment rate	0.899***	0.908***	0.937***	0.871***
	(-25.67)	(-22.49)	(-10.97)	(-27.37)
CPI	0.631***	0.606***	0.779***	0.564***
	(-27.15)	(-23.72)	(-8.00)	(-22.52)
% rural housing	1.018***	1.022***	1.001	1.023***
	(7.01)	(7.74)	(0.28)	(9.27)
log population	2.830***	2.633***	1.794***	4.424***
	(19.05)	(16.30)	(7.07)	(19.46)
% population Mexican	0.888***	0.890***	0.907***	0.869***
	(-45.87)	(-42.99)	(-28.25)	(-35.20)
net migration municipality	1.605***	1.668***	1.469***	1.565***
	(26.02)	(18.25)	(20.15)	(15.04)
herd	0.930***	0.917**	0.920**	0.935*
	(-3.57)	(-3.11)	(-3.28)	(-2.22)
Climate variables				
max temperature US	5.702***	14.22***	220.1***	5.688***
	(5.36)	(9.71)	(17.40)	(5.08)
max temperature^2 US	0.972***	0.959***	0.911***	0.986
	(-4.57)	(-6.73)	(-13.29)	(-1.81)
min temperature US	6.051***	6.240***	1.397*	9.861***
	(24.85)	(13.92)	(2.10)	(11.72)
precipitation US	0.958***	0.959***	0.917***	0.977***
	(-15.14)	(-8.32)	(-15.80)	(-4.16)
cloud cover US	1.728***	1.552***	1.390***	1.865***
	(15.54)	(9.66)	(5.22)	(6.26)
vapour presure. US	0.388***	0.339***	0.722*	0.185***
	(-12.93)	(-9.92)	(-2.65)	(-16.37)
max temperature ratio $^{US}/_{Mex}$	1.770			
	(1.33)			
max temperature^2 ratio $^{US}/_{Mex}$	0.868			
	(-1.06)			
min temperature ratio $^{US}/_{Mex}$	1.169***			
	(14.67)			
precipitation ratio $^{US}/_{Mex}$	0.971***			
	(-13.15)			
cloud cover ratio $^{US}/_{Mex}$	0.539***			
	(-12.84)			
vapour pressure ratio $^{US}/_{Mex}$	0.874***			
	(-8.59)			
MSA FE	×	×	×	×
LL	-33,871.1	-27,437.5	-13,678.6	-18,771.1
N	1,674,668	1,116,590	740,826	933,783
Cases	22,398	22,398	9,908	12,490

Notes: The table presents odds ratios with the respective significance level of * p<0.1; ** p<0.05; *** p<0.01. T-statistics presented in parentheses.

Table B.11.2: Bootstrap Results for Model 7

	(7)			
	US-Mex	US	hot	cold
Location specific characteristics				
migration distance	0.799*** (-77.62)	0.791*** (-70.42)	0.762*** (-77.37)	0.911*** (-22.75)
log pc income	0.785*** (-9.67)	0.798*** (-9.75)	0.942 (-1.10)	0.710*** (-8.92)
unemployment rate	0.929*** (-23.73)	0.928*** (-22.72)	0.950*** (-10.74)	0.904*** (-19.41)
CPI	0.641*** (-24.98)	0.649*** (-24.82)	0.883*** (-4.51)	0.540*** (-24.88)
% rural housing	1.006* (2.46)	1.004 (1.75)	0.997 (-0.79)	1.003 (0.94)
log population	2.193*** (15.86)	2.315*** (19.51)	1.420*** (4.30)	3.889*** (19.25)
% population Mexican	0.893*** (-40.55)	0.895*** (-42.50)	0.901*** (-22.88)	0.881*** (-31.54)
net migration municipality	1.627*** (24.87)	1.590*** (23.74)	1.472*** (17.84)	1.584*** (18.92)
herd	0.969 (-1.43)	0.930** (-3.49)	0.942* (-2.27)	0.959 (-1.74)
Climate characteristics				
summer temperature US	2.636*** (14.17)	2.418*** (15.99)	2.746*** (10.11)	1.640*** (5.41)
winter temperature US	1.977*** (16.31)	1.977*** (18.65)	1.262*** (4.13)	3.094*** (21.57)
summer precipitation US	0.972*** (-11.00)	0.977*** (-9.63)	0.980*** (-4.89)	0.962*** (-10.64)
winter precipitation US	0.975*** (-16.55)	0.975*** (-15.66)	0.982*** (-7.28)	0.976*** (-12.42)
summer temperature $\frac{US}{Mex}$	0.786*** (-8.32)			
winter temperature $\frac{US}{Mex}$	1.071*** (8.99)			
summer precipitation $\frac{US}{Mex}$	1.016*** (47.49)			
winter precipitation $\frac{US}{Mex}$	1.000 (-1.24)			
MSA FE	×	×	×	×
LL	-34,037.3	-34,113.4	-13,761.9	-18,719.2
N	1,674,713	1,674,860	740,795	933,771
Ind.	22,398	22,398	9,908	12,490

Notes: The table presents odds ratios with the respective significance level of * p<0.1; ** p<0.05; *** p<0.01. T-statistics presented in parentheses.

Table B.11.3: Bootstrap Results for Model 8

	(8)			
	US/Mex	US	hot	cold
Location specific characteristics				
migration distance	0.808***	0.791***	0.753***	0.908***
	(-58.41)	(-72.08)	(-62.28)	(-18.51)
log pc income	0.770***	0.781***	0.842**	0.661***
	(-10.25)	(-11.16)	(-3.14)	(-11.48)
unemployment rate	0.914***	0.917***	0.950***	0.884***
	(-22.46)	(-25.91)	(-8.68)	(-19.79)
CPI	0.653***	0.629***	0.739***	0.587***
	(-24.29)	(-26.46)	(-7.97)	(-18.85)
% rural housing	1.004	1.006*	0.999	1.018***
	(1.75)	(2.62)	(-0.13)	(4.55)
log population	2.852***	2.683***	1.414**	4.363***
	(20.08)	(20.10)	(3.36)	(17.97)
% population Mexican	0.892***	0.890***	0.916***	0.878***
	(-43.19)	(-47.85)	(-15.08)	(-32.22)
net migration municipality	1.606***	1.589***	1.570***	1.816***
	(26.45)	(22.96)	(15.29)	(15.40)
herd	0.930***	0.929**	0.973	0.932*
	(-3.72)	(-3.44)	(-0.70)	(-2.14)
Climate variables				
summer temperature US	3.953***	3.652***	3.461***	4.297***
	(19.22)	(19.80)	(8.57)	(11.61)
winter temperature US	1.828***	1.793***	1.348***	2.594***
	(14.63)	(17.20)	(4.44)	(14.20)
precipitation US	0.959***	0.955***	0.939***	0.974***
	(-13.57)	(-12.31)	(-7.99)	(-4.59)
cloud cover US	1.948***	1.643***	1.118*	1.911***
	(23.45)	(16.02)	(2.55)	(14.76)
vapour pressure US	0.530***	0.575***	0.727	0.236***
	(-10.11)	(-7.76)	(-1.97)	(-13.00)
summer temperature ratio $^{US}/_{Mex}$	0.697***			
	(-11.51)			
winter temperature ratio $^{US}/_{Mex}$	0.925***			
	(-6.66)			
precipitation ratio $^{US}/_{Mex}$	0.953***			
	(-19.86)			
cloud cover ratio $^{US}/_{Mex}$	0.407***			
	(-16.16)			
vapour pressure ratio $^{US}/_{Mex}$	1.198***			
	(15.08)			
MSA FE	×	×	×	×
LL	-33,880.2	-34,101.6	-10,899.0	-14,733.6
N	1,674,668	1,674,860	493,934	622,544
Cases	22,398	22,398	9,908	12,490

Notes: The table presents odds ratios with the respective significance level of * p<0.1; ** p<0.05; *** p<0.01. T-statistics presented in parentheses.

B.12 Bootstrap *asclogit* Stata Program

```
***************************************************************************
**************** BSASCLOGIT BOOTSTRAP PROGRAM - ECLASS  ********************
/*  *********************************************************************  */
/*  Author:     Antonia Schwarz
    */
/*  Date:       February 18, 2015                                          */
/*  File:       bsasclogit.ado                                             */
/*  Version:    1.2                                                        */
/*  Purpose:    Bootstrap program over random choice set for asclogit      */
/*  *********************************************************************  */


/*  *********************************************************************  */
/*  Special thanks to Emmanuelle Pierard, Neil Buckley, James Chowhan from */
/*  the McMaster Research Data Centre at Statistics Canada for their PDF   */
/*  Bootstrapping Made Easy: A Stata ADO File. For the original code see   */
/*  http://www.yorku.ca/nbuckley/papers/Bootstrapping_for_Regressions_in_  */
/*      Stata_031017.pdf                                                   */
/*  *********************************************************************  */


program define bsasclogit, eclass sortpreserve byable(recall)

version 12.1
syntax varlist [if] [in] [, CMDname(string)             ///
                case(varname numeric)                   ///
                CHOICE(varlist)                         ///
                BYSample(varlist)                       ///
                Reps(integer 50)                        ///
                CMDOps(string asis)                     ///
                ITERATE(integer 500)                    ///
                NTRUE(integer 1)                        ///
                NALTern(integer 9)                      ///
                BSci                                    ///
                SAVing(string asis)                     ///
                replace                                 ///
                LEVEL(integer 90)                       ///
                noHEADer                                ///
                BOOTSample
                *]

quietly {

    _get_diopts diopts options, `options'
    mlopts mlopts rest, `options'


* Preserve the original dataset, set parameter values and set-up temporary
    matrices
    preserve
    set more 1
    tempvar esamplevar
    tempname bhat bsVC bsbhat bsbetas
```

```
* This sets the touse variable = 1 if observation is in our sample for the
    number of alternatives
    tempvar insample random sample
    marksample touse
    keep if `touse'==1
    gen `random' = runiform()
    sort `bysample' `random' `choice'
    by `bysample': gen `insample' = _n
    gen `sample'=cond(`insample'<=`naltern' | `choice'==1,1,0)
* The next line runs the wanted regression and checks for errors
    capture noi `cmdname' `varlist' if `sample'==1 `in', `cmdops'
    if _rc ~= 0 {
        noi di in red " "
        noi di in red `"Error doing: `cmdname' `varlist' `if' `in', `cmdops'"'
        noi di in red " "
        noi di in red "The regression command you have typed in resulted in an
            error, please investigate"
        error _rc
    }
    else {
* Print regression Results
        estimates store est1
        estimates table est1, se t p
        estimates stats est1
        gen `esamplevar'=e(sample)
* Collect local names for output and format table
        global title `"`e(title)'"'
        global case `=abbrev("`e(case)'",24)'
        global altvar `=abbrev("`e(altvar)'",17)'
        global k_alt `e(k_alt)'
        global N_case `e(N_case)'
        global N `e(N)'
        global alt_min `e(alt_min)'
        global alt_avg `e(alt_avg)'
        global alt_max `e(alt_max)'
        global crittype =upper(substr(`"`e(crittype)'"',1,1)) + ///
                    substr(`"`e(crittype)'"',2,.)
        global chi2type `"`e(chi2type)'"'
        global chi2 `e(chi2)'
        global dfm `e(df_m)'
        global clustvar `"`e(clustvar)'"'
        global vce `"`e(vce)'"'
        global ll `e(ll)'
        global prob `e(p)'
        global keq `e(k_eq)'
        global ic `e(ic)'
        global converged `e(converged)'


* e(b) is a 1x(k+1) coefficient vector if the model has a constant and k is
    the number of
* variables other than the constant
        matrix `bhat'=e(b)
        matrix `bsVC'=e(V)
* we store the variable names of the regressors and the number of regressors
    in local macros
```

```
        local _varnames : colfullnames(`bhat')
        local _k=colsof(`bhat')-1
        local _k1=`_k'+1

*************************************************
*****              BOOTSTRAP              *****
*************************************************

* Realboot is the actual number of successful bootstrap regressions run in
    case we get any
* convergence/regression errors etc., it starts off at the specified number of
    bootstrap weights
        local _realboot `reps'
* The main bootstrap loop will run with each bootstrap weight in the supplied
    bsweight varlist and
* exit with the matrix named BETAS containing all the bootstraps of our
    coefficients, a
        *(boot)x(k+1) dimensional matrix
        local _i 1
        tempvar sample
        gen `sample'=0

* Start of bootstrap loop for reps number of replications

* Display Bootstrap Estimation performance
        nois _dots 0, title(Bootstrap estimation running) reps(`reps')

        forvalues nreps=1/`reps' {

* This sets the touse variable = 1 if observation is in our sample for the
    number of alternatives
            replace `random' = runiform()
            sort `bysample' `random' `choice'
            by `bysample': replace `insample' = _n
            replace `sample'=cond(`insample'<=`naltern' | `choice'==1,1,0)
            if "`bootsample'"!="" {
                tempfile totfile
                save `totfile', replace
                bsample , cluster(`bysample')
            }
* Run the regression with the chosen set of bootstrap weights, only use the
    coefficients if there
* are no errors
            capture `cmdname' `varlist' if `sample'==1 `in', `cmdops'
                iterate(`iterate')
            if _rc==0 {
                if e(converged)==1 {
* Store coefficients in the bootstrap matrix
                    matrix `bsbhat'=get(_b)
* bsbhat is a 1x(`k'+1) (row) vector if the model has a constant. Need to
    transpose
                    matrix `bsbhat'=`bsbhat''
* If we have the proper number of coefficients then add them to the bootstrap
    matrix, otherwise
* do not add them (this most likely arises due to a regressor being dropped
    due to multicollinearity
```

```
                    if rowsof(`bsbhat')==`_k1' {
* If we are on the first bootstrap then create the bsbetas matrix, otherwise
  append to it
                        matrix `bsbetas'=(nullmat(`bsbetas'),`bsbhat')
                        nois _dots `nreps' 0
                    }
                    else {
                        matrix drop `bsbhat'
                        local --_realboot
                        nois _dots `nreps' 1 // shows x if dropped any
                            coefficient from regression
                    }
                }
            }
            else {
                local --_realboot
                nois _dots `nreps' 2 // shows e if error in estimation
            }
            if "`bootsample'"!="" {
                use `totfile', clear
            }
        }
* End of bootstrap loop
* All the bootstraps have been completed now calculate the new standard errors
  and display
* relevant statistics
* We must transpose the matrix to make each row now, then column, a new
  variable
        matrix `bsbetas'=`bsbetas''
* Generate the bootstrapped variance-covariance matrix, you can access this in
  e(V) after running
* the BSWREG ado file

* Prepare result matrices for programming in MATA
        tempname resmat restrue
        if "`bsci'"!="" {
            matrix `resmat'=J(`_k1',8,0)
            if "`ntrue'"!="" {
                matrix `restrue'=J(`_k1',8,0)
            }
        }
        else {
            matrix `resmat'=J(`_k1',6,0)
            if "`ntrue'"!="" {
                matrix `restrue'=J(`_k1',6,0)
            }
        }

* Generate real matrices from temporary matrices to bring them into Mata

        matrix define bhat=`bhat'
        matrix define bsbhat=`bsbhat'
        matrix define bsVC=`bsVC'
        matrix define bsbetas=`bsbetas'
        matrix define resmat=`resmat'
        matrix define restrue=`restrue'
```

```
**************************************************
*****       MATA WITHIN BOOTSTRAP           *****
**************************************************

* Calculate the new Variance Covariance Matrix from bootstrap results

        mata: covarserror
            ("bsbetas","bsVC","bhat","resmat",`_realboot',`_k1',`level',
            "restrue",`naltern',`ntrue')


        matrix rownames resmat=`varnames'
        if "`ntrue'"!="" {
            matrix rownames restrue=`varnames'
        }
        if "`bsci'"!="" {
            matrix colnames resmat=Coef StdError T-Stat low90 low90 lowbsci
                highbsci
            if "`ntrue'"!="" {
                matrix colnames restrue=Coef StdError T-Stat Conf90 Conf90
                    lowbsci highbsci
            }
        }
        else {
            matrix colnames resmat=Coef StdError T-Stat Conf90 Conf90
            if "`ntrue'"!="" {
                matrix colnames restrue=Coef StdError T-Stat Conf90 Conf90
            }
        }
    }

**************************************************
*****                RESULTS                *****
**************************************************

* Show the Results Table
    Header if "`header'"==""
    display _n in gr "Boostraped Std. Errors" _col(60)
    _coef_table , cmdextras level(`level') bmatrix(bhat) vmatrix(bsVC) //
        diparm(__sep__ )
    display _n in gr "Boostraped & Alternative Corrected Std. Errors" _col(60)
    _coef_table , cmdextras level(`level') bmatrix(bhat) vmatrix(bsVC_true) //
        diparm(__sep__ )

    quietly {
* Set the eclass variables like the coefficients and the variance-covariance
    matrix into their
* appropriate matrices so that F-tests and the like can be run
        ereturn post bhat bsVC, dof(`_realboot')
        ereturn matrix bsresult=resmat
        ereturn matrix bsrestrue=restrue
        ereturn scalar ll=$ll
        ereturn scalar N=$N
        ereturn scalar N_case=$N_case
        ereturn scalar df_m=$dfm
```

```
        ereturn scalar chi2=$chi2
        ereturn scalar N_case=$N_case
        ereturn scalar k_alt=$k_alt
        ereturn scalar k_eq=$keq
        ereturn scalar k_indvars=$k_alt
        ereturn scalar ic=$ic
        ereturn scalar converged=$converged

        ereturn local cmdline `"asclogit"'
        ereturn local case `case'
        ereturn local clustvar `cluster'
        ereturn local title "Bootstrap Alternative-specific conditional logit"
        ereturn local cmd "bsasclogit"

* Save the bootstrap raw data is the "SAVING" option has been used

        if "`saving'"~="" {
            save "`saving'", `replace'
        }
* Restore the original dataset
        restore
        mat drop bsVC_true bsbetas
        macro drop title case altvar alt_min  alt_avg  alt_max  crittype
            chi2type clustvar vce prob
    }
}
end


*************************************************
*****           PROGRAM HEADER              *****
*************************************************

* Header for result table
program define Header
        version 12
        display _n in gr `"$title"' _col(48) "Number of obs" _col(67) "= " ///
         in ye %10.0g $N
        display in gr `"Case variable: $case"' _col(48)  ///
         "Number of cases" _col(67) "= " in ye %10.0g $N_case
        display
        display in gr `"Alternative variable: $altvar"' _col(48)
            ///
         "Alts per case: min = " in ye %10.0g $alt_min _n _col(63) in gr ///
         "avg = " in ye %10.1f $alt_avg _n _col(63) in gr "max = "       ///
         in ye %10.0g $alt_max _n
        local lencr = length(`"$crittype"')
        local h help j_robustsingular:
        if `"$chi2type"' == "Wald" {
                local stat $chi2
                local cfmt=cond($chi2<1e+7,"%10.2f","%10.3e")
                if $chi2 >= . {
                        display in gr _col(51)                          ///
                         `"{`h'Wald chi2($dfm){col 67}= }"' in ye ///
                         `cfmt' $chi2
                }
```

```
                else {
                        display in gr _col(51) `"$chi2type chi2("' in ye ///
                         `"$dfm"' in gr ")" _col(67) "= " in ye    ///
                         `cfmt' $chi2
                }
        }
        else if `"$clustvar"'!="" | $vce=="jackknife" {
                /* F statistic from test after _robust */
                local stat $F
                local cfmt=cond($F)<1e+7,"%10.2f","%10.3e")
                if $F < . {
                        display in gr _col(51) "F(" in ye %3.0f $dfm in gr ///
                         "," in ye %6.0f $dfr in gr ")" _col(67) "= " ///
                         in ye $cfmt `F'
                }
                else {

                        display in gr _col(51) `"{`h' F( $dfm, $dfr)}"'
                            _col(67) ///
                         `"{`h'=           .}"'
                }
        }
        else {
                local stat $chi2
                local cfmt=cond($chi2)<1e+7,"%10.2f","%10.3e")
                display in gr _col(51) "LR(" in ye %3.0f $dfm in gr ")" ///
                 _col(67) "= " in ye $cfmt $chi2
        }
        display in gr `"$crittype = "' in ye %10.0g $ll _col(51) in gr ///
         "Prob > " %10.4f $chi2 _col(67) " = "  in ye %10.4f $prob
end


**************************************************
*****           PROGRAM MATA                *****
**************************************************

* Mata Program for calculation of new Variance Covariance Matrix of boostraped
    coefficients
version 12.1
mata:
void covarserror (string scalar bsbhatmat, string scalar bsvmatrix,  ///
 string scalar bhatmatrix, string scalar resmat,  ///
 real scalar realboot, real scalar _k1, ///
 real scalar level, | string scalar restrue, real scalar naltern, real scalar
     ntrue, string scalar bsci)
    {
    real matrix bsbhat,B,bsVC,bsV,bhat,S
    real matrix _sdx,_t,_low,_high,_p, result1
    real scalar i

    if ("ntrue"!="") {
        real matrix
            _sdx_true,_t_true,_low_true,_high_true,_p_true,result2,bsVC_true
    }
```

```
if (bsci!="") {
    real matrix _lowbsci, _highbsci,sbsbhat
    real scalar _obslow, _obshigh
}

bsbhat=st_matrix(bsbhatmat)
bsVC=st_matrix(bsvmatrix)
B=variance(bsbhat)
bsV=diagonal(B)
bsVC[.,.]=B[.,.]*(realboot-1)/realboot
bsVC_true=B[.,.]*((realboot-1)/realboot)*(naltern+1)

st_replacematrix(bsvmatrix,bsVC)
st_matrix("bsVC_true",bsVC_true)

bhat=st_matrix(bhatmatrix)
bhat=bhat'
_sdx=J(_k1,1,0)
_t=J(_k1,1,0)
_low=J(_k1,1,0)
_high=J(_k1,1,0)
_p=J(_k1,1,0)

if ("ntrue"!="") {
_sdx_true=J(_k1,1,0)
_t_true=J(_k1,1,0)
_low_true=J(_k1,1,0)
_high_true=J(_k1,1,0)
_p_true=J(_k1,1,0)
}

if (bsci!="") {
_lowbsci=J(_k1,1,0)
_highbsci=J(_k1,1,0)
}

for (i=1;i<=_k1;i++) {
    _sdx[i,1]=sqrt(((realboot-1)/realboot)* bsV[i,1])
    _t[i,1]=abs(bhat[i,1]/_sdx[i,1])
    _p[i,1]=2* norm((-1)* _t[i,1])
    _low[i,1]=bhat[i,1]-invnormal(1-((1-(level/100))/2))* _sdx[i,1]
    _high[i,1]=bhat[i,1]+invnormal(1-((1-(level/100))/2))* _sdx[i,1]

    if ("ntrue"!="") {
        _sdx_true[i,1]=sqrt(((realboot-1)/realboot)* bsV[i,1]*(naltern+1))
        _t_true[i,1]=abs(bhat[i,1]/_sdx_true[i,1])
        _p_true[i,1]=2* norm((-1)* _t_true[i,1])
        _low_true[i,1]=bhat[i,1]-invnormal(1-((1-(level/100))/2))*
            _sdx_true[i,1]
        _high_true[i,1]=bhat[i,1]+invnormal(1-((1-(level/100))/2))*
            _sdx_true[i,1]

    }

    if (bsci!="") {
        sbsbhat=sort(bsbhat,i)
```

```
            _obslow= max(round(((1-(level/100))/2)* realboot,1))
            _obshigh= max(round((1-((1-(level/100))/2))* realboot,1))

            if (_obslow<1) {
                _lowbsci[i,1]= sbsbhat[1,i]
                _highbsci[i,1]= sbsbhat[realboot,i]

            }

            else {
                _lowbsci[i,1]= sbsbhat[_obslow,i]
                _highbsci[i,1]= sbsbhat[_obshigh,i]

            }

        }
    }
    if (bsci!="") {
        result1=bhat,_sdx,_t,_p,_low,_high,_lowbsci, _highbsci

        if (" ntrue"!="") {
            result2=bhat,_sdx_true,_t_true,_p_true,_low_true,_high_true,
                _lowbsci, _highbsci
        }
    }
    else {
        result1=result1=bhat,_sdx,_t,_p,_low,_high

        if (" ntrue"!="") {
        result2=bhat,_sdx_true,_t_true,_p_true,_low_true,_high_true
        }
    }

    st_replacematrix(resmat,result1)
    st_replacematrix(restrue,result2)

    }
end
```

Appendix C

Appendix to Chapter 4

C.1 Covariance Baseline Model

Table C.1.1: Variance Covariance Matrix Random Coefficients First Stage Baseline Model

	same place	relative	summer	winter	precip	cloud	vapour
same place	99.15						
relative	-4.452	60.70					
summer temperature	-14.74	2.327	3.280				
winter temperature	-11.23	14.16	1.890	5.690			
precipitation	-1.391	1.532	0.224	0.450	0.367		
cloud cover	0.384	6.388	0.147	1.836	-0.011	2.044	
vapour pressure	31.38	-17.87	-5.205	-7.681	-1.012	-1.324	16.48

C.2 Hedonic Wage Regression

Table C.2.1: Hedonic Wage Regression

	ln wage income
age	0.266***
	(0.0000)
age^2(/100)	-0.357***
	(0.0000)
male	0.898***
	(0.0002)
married	0.124***
	(0.0003)
immigrant	-0.0662***
	(0.0004)
Mexican	0.178***
	(0.0006)
immigrant×Mexican	0.0347***
	(0.0009)
recent immigrant	-0.728***
	(0.0006)
primary	-1.925***
	(0.0004)
secondary	0.734***
	(0.0003)
tertiray	1.257***
	(0.0004)
higher	1.829***
	(0.0004)
joint prob	5.805***
	(0.015)
joint prob^2	-9.952***
	(0.038)
constant	1.612***
	(0.001)
MSA FE	×
occupation FE	×
adjusted R^2	0.313
N	1,220,093,714

Notes: Standard errors are presented in parentheses. Significance level defined as * p<0.1; ** p<0.05; *** p<0.01. Mexican occupation codes are converted into two-digit ISCO-88 occupation codes based on the crosswalk provided by Mahutga et al. (2018, Appendix D) to match occupations between the Mexican Migration Project and the American Community Survey.

C.3 Ordinary Least Square Estimates

C.3.1 Ordinary Least Square Estimates of the Marginal Willingness to Pay

Table C.3.1: Second Stage: Alternative Mixed Logit Specification (OLS)

	Base Model	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
	region & IV	RD: $\hat{I}$	linear mig distance	mig dist married	no mig distance	RD: mig distance
2nd Stage	*Coef* *(Std Err)*	*Coef* *(Std Err)*	*Coef* *(Std Err)*	*Coef* *(Std Err)*	*Coef* *(Std Err)*	*Coef* *(Std Err)*
summer temperature	-5.898 (0.088)	-4.159 (0.094)	-3.357 (0.074)	-5.911 (0.098)	0.866 (0.108)	-2.267 (0.087)
winter temperature	7.557 (0.068)	8.653 (0.072)	7.359 (0.052)	10.73 (0.074)	8.504 (0.075)	9.161 (0.072)
precipitation	0.190 (0.010)	0.438 (0.009)	0.370 (0.008)	0.210 (0.009)	0.238 (0.012)	0.295 (0.008)
cloud cover	-1.045 (0.140)	-4.260 (0.151)	-4.128 (0.107)	-4.662 (0.133)	-7.755 (0.147)	-6.009 (0.128)
vapour pressure	-3.240 (0.038)	-3.063 (0.044)	-1.885 (0.030)	-1.215 (0.037)	-1.643 (0.048)	-2.679 (0.038)
ln hourly wage business	4.775 (0.544)	-4.165 (0.614)	-0.580 (0.474)	5.576 (0.572)	5.693 (0.608)	-6.196 (0.526)
ln hourly wage production	-6.614 (0.436)	-0.347 (0.478)	-14.72 (0.460)	-4.108 (0.421)	-4.139 (0.483)	-3.095 (0.434)
ln hourly wage construction	24.07 (0.472)	24.19 (0.628)	26.99 (0.400)	14.78 (0.519)	6.897 (0.557)	28.79 (0.486)
violent crime rate	0.097 (0.005)	0.072 (0.005)	0.024 (0.004)	0.041 (0.007)	0.224 (0.006)	-0.160 (0.006)
health score	0.104 (0.003)	0.076 (0.003)	0.059 (0.002)	0.084 (0.003)	0.070 (0.003)	0.104 (0.003)
transport score	0.068 (0.001)	0.005 (0.001)	0.032 (0.001)	0.029 (0.001)	0.028 (0.001)	0.055 (0.001)
education score	0.002 (0.000)	0.001 (0.000)	0.002 (0.000)	0.001 (0.000)	0.001 (0.000)	0.002 (0.000)
the arts score	-0.007 (0.000)	0.010 (0.001)	0.001 (0.000)	0.008 (0.001)	0.008 (0.001)	-0.005 (0.000)
recreational facilities score	-0.100 (0.002)	-0.044 (0.003)	-0.014 (0.002)	0.012 (0.002)	0.030 (0.003)	-0.026 (0.002)
distance to coast	-0.002 (0.000)	0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	0.001 (0.000)	-0.002 (0.000)
elevation	-0.001 (0.000)	-0.004 (0.000)	-0.001 (0.000)	-0.003 (0.000)	-0.003 (0.000)	-0.002 (0.000)
adjusted R^2	0.568	0.556	0.576	0.611	0.498	0.576

Notes: Robust standard errors presented in parentheses. All regressions are estimated using Ordinary Least Square. Climate variables have been rescaled in units of 10.

Table C.3.2: Second Stage: Alternative Climate Specifications (OLS)

	Base Model	**(12)**	**(13)**	**(14)**	**(15)**
	simple OLS	no alt climate	mean tmp	mean tmp^2	max min
2nd Stage	*Coef (Std Err)*	*Coef (Std Err)*	*Coef (Std Err)*	*Coef (Std Err)*	*Coef (Std Err)*
summer temperature	-5.898 (0.088)	-4.695 (0.092)			
winter temperature	7.557 (0.068)	9.029 (0.041)			
temperature			7.283 (0.096)	13.00 (0.245)	
temperature^2				0.231 (0.009)	
maximum temperature					8.090 (0.147)
minimum temperature					0.198 (0.177)
precipitation	0.190 (0.010)		0.926 (0.010)	0.173 (0.010)	0.395 (0.007)
cloud cover	-1.045 (0.140)		-5.838 (0.118)	-11.73 (0.156)	-2.782 (0.131)
vapour pressure	-3.240 (0.038)		-4.175 (0.036)	-0.843 (0.036)	-2.702 (0.033)
ln hourly wage business	4.775 (0.544)	-2.825 (0.603)	6.892 (0.527)	4.965 (0.549)	-1.781 (0.516)
ln hourly wage production	-6.614 (0.436)	-10.91 (0.443)	-5.381 (0.416)	-7.138 (0.494)	-14.88 (0.501)
ln hourly wage construction	24.07 (0.472)	32.53 (0.477)	15.84 (0.475)	25.70 (0.465)	38.64 (0.446)
violent crime rate	0.097 (0.005)	0.032 (0.006)	0.011 (0.006)	0.034 (0.007)	0.088 (0.005)
health score	0.104 (0.003)	0.093 (0.003)	0.003 (0.003)	0.070 (0.003)	0.030 (0.003)
transport score	0.068 (0.001)	0.040 (0.001)	0.051 (0.001)	0.053 (0.001)	0.041 (0.001)
education score	0.002 (0.000)	0.001 (0.000)	0.003 (0.000)	0.002 (0.000)	0.002 (0.000)
the arts score	-0.007 (0.000)	-0.002 (0.000)	0.003 (0.000)	0.000 (0.000)	0.000 (0.000)
recreational facilities score	-0.100 (0.002)	-0.012 (0.002)	0.070 (0.002)	-0.090 (0.003)	-0.034 (0.002)
distance to coast	-0.002 (0.000)	0.000 (0.000)	-0.005 (0.000)	-0.004 (0.000)	-0.002 (0.000)
elevation	-0.001 (0.000)	0.001 (0.000)	-0.001 (0.000)	0.000 (0.000)	0.000 (0.000)
region FE	×	×	×	×	×
IV	×	×	×	×	×
adjusted R^2	0.568	0.499	0.550	0.560	0.505
N	94,050	94,050	94,050	94,050	94,050

Notes: Robust standard errors presented in parentheses. All regressions are estimated using Ordinary Least Square. Climate variables have been rescaled in units of 10.

Table C.3.3: Second Stage: Heterogeneous Climate Differences (OLS)

	Base Model	**(16)**	**(17)**	**(18)**
	simple OLS	age $\geq$ 55	education	clinal
2nd Stage	*Coef* *(Std Err)*	*Coef* *(Std Err)*	*Coef* *(Std Err)*	*Coef* *(Std Err)*
summer temperature	-5.898 (0.088)	-7.998 (0.102)	-4.222 (0.086)	-3.843 (0.213)
winter temperature	7.557 (0.068)	5.440 (0.120)	7.469 (0.076)	33.27 (0.701)
age $\geq$ 55 summer temperature		16.51 (1.072)		
age $\geq$ 55 winetr temperature		88.637 (4.917)		
college graduate summer temperature			0.015 (0.018)	
college graduate winter temperature			-0.057 (0.066)	
mex hot summer temperature				2.211 (0.345)
mex hot winter temperature				-44.344 (1.172)
precipitation	0.190 (0.010)	0.033 (0.009)	0.725 (0.008)	0.558 (0.009)
cloud cover	-1.045 (0.140)	0.751 (0.144)	-5.634 (0.129)	-6.022 (0.138)
vapour pressure	-3.240 (0.038)	-4.063 (0.042)	-4.454 (0.041)	-4.386 (0.043)
ln hourly wage business	4.775 (0.544)	14.35 (0.562)	13.27 (0.588)	8.338 (0.589)
ln hourly wage production	-6.614 (0.436)	-5.884 (0.464)	-8.351 (0.464)	-4.942 (0.478)
ln hourly wage construction	24.07 (0.472)	13.79 (0.472)	13.48 (0.502)	14.66 (0.502)
violent crime rate	0.097 (0.005)	0.164 (0.005)	0.070 (0.005)	0.164 (0.005)
health score	0.104 (0.003)	0.122 (0.003)	0.105 (0.003)	0.139 (0.003)
transport score	0.068 (0.001)	0.046 (0.001)	0.066 (0.001)	0.056 (0.001)
education score	0.002 (0.000)	0.000 (0.000)	-0.001 (0.000)	0.000 (0.000)
the arts score	-0.007 (0.000)	-0.002 (0.000)	0.001 (0.001)	-0.004 (0.000)
recreational facilities score	-0.100 (0.002)	0.008 (0.002)	-0.001 (0.002)	-0.017 (0.002)
distance to coast	-0.002 (0.000)	-0.001 (0.000)	0.000 (0.000)	-0.001 (0.000)
elevation	-0.001 (0.000)	-0.004 (0.000)	-0.003 (0.000)	-0.002 (0.000)
adjusted R^2	0.568	0.660	0.599	0.599
N	94,050	94,050	94,050	94,050

Notes: Robust standard errors presented in parentheses. All regressions are estimated using Ordinary Least Square. Climate variables have been rescaled in units of 10.

Table C.3.4: MWTP Alternative Climate Specification (OLS)

	Base Model	**(12)**	**(13)**	**(14)**	**(15)**
	simple OLS	no alt climate	avg tmp	avg tmp^2	max min
	MWTP	*MWTP*	*MWTP*	*MWTP*	*MWTP*
mean: summer temperature	$ -541 ($ 83)	$ -229 ($ 53)			
mean: winter temperature	$ 76 ($ 75)	$ 177 ($ 24)			
mean: average temperature			$ -145 ($ 74)		
mean: average temperature^{2a}				$ -38 ($ 9)	
mean: maximum temperature					$ -152 ($ 133)
mean: minimum temperature					$ 17 ($ 143)
mean: precipitation	$ -61 ($ 14)		$ -10 ($ 11)	$ -8 ($ 8)	$ -49 ($ 19)
mean: cloud cover	$ 235 ($ 165)		$ -241 ($ 68)	$ -179 ($ 46)	$ 120 ($ 127)
mean: vapour pressure	$ -191 ($ 75)		$ -176 ($ 35)	$ -170 ($ 21)	$ -283 ($ 92)
ln hourly wage business[a]	$ 1 ($ 0)	$ -0 ($ 0)	$ 1 ($ 0)	$ 1 ($ 0)	$ -1 ($ 0)
ln hourly wage production[a]	$ -1 ($ 0)	$ -1 ($ 0)	$ -1 ($ 0)	$ -1 ($ 0)	$ -4 ($ 0)
ln hourly wage construction[a]	$ 5 ($ 0)	$ 3 ($ 0)	$ 2 ($ 0)	$ 3 ($ 0)	$ 12 ($ 0)
violent crime rate	$ 281 ($ 14)	$ 45 ($ 9)	$ 24 ($ 12)	$ 53 ($ 11)	$ 407 ($ 22)
health score	$ 301 ($ 8)	$ 134 ($ 4)	$ 5 ($ 7)	$ 110 ($ 4)	$ 138 ($ 13)
transport score	$ 197 ($ 3)	$ 58 ($ 2)	$ 108 ($ 3)	$ 84 ($ 2)	$ 189 ($ 6)
education score	$ 7 ($ 0)	$ 1 ($ 0)	$ 6 ($ 0)	$ 3 ($ 0)	$ 11 ($ 0)
the arts score	$ -20 ($ 1)	$ -2 ($ 1)	$ 7 ($ 1)	$ -0 ($ 1)	$ 2 ($ 2)
recreational facilities score	$ -289 ($ 7)	$ -17 ($ 3)	$ 149 ($ 4)	$ -142 ($ 4)	$ -158 ($ 10)
distance to coast	$ -5 ($ 0)	$ -0 ($ 0)	$ -10 ($ 0)	$ -7 ($ 0)	$ -10 ($ 0)
elevation	$ -3 ($ 0)	$ 1 ($ 0)	$ -2 ($ 0)	$ 1 ($ 0)	$ 2 ($ 0)

Notes: Standard errors provided in parentheses. Amenity coefficients have been converted to the MWTP by dividing the mean coefficient and the standard error from the first and second stage by the coefficient on income from the mixed logit regression. The result is multiplied by the sample mean predicted income to yield a monetary measure of the amenity value of a marginal change in the amenity.

a Nonlinear amenity variables are evaluated at population-weighted means in order to compute the Marginal Willingness to Pay.

Table C.3.5: MWTP Heterogeneous Climate Specification (OLS)

	Base Model	**(16)**	**(17)**	**(18)**
	simple OLS	age $\geq$ 55	education	clinal
	MWTP	*MWTP*	*MWTP*	*MWTP*
mean: summer temperature	$ -541 ($ 83)	$ -203 ($ 32)	$ -112 ($ 27)	$ -196 ($ 40)
mean: winter temperature	$ 76 ($ 75)	$ -13 ($ 40)	$ 215 ($ 32)	$ 2,722 ($ 99)
mean: age $\geq$ 55 summer temperature		$ 1,073 ($ 43)		
mean: age $\geq$ 55 winter temperature		$ 7,057 ($ 523)		
mean: college graduate summer temperature			$ -121 ($ 50)	
mean: college graduate winter temperature			$ 228 ($ 64)	
mean: mex hot summer temperature				$ -171 ($ 57)
mean: mex hot winter temperature				$ -1,316 ($ 233)
mean: precipitation	$ -61 ($ 14)	$ -13 ($ 8)	$ -10 ($ 9)	$ -12 ($ 9)
mean: cloud cover	$ 235 ($ 165)	$ -408 ($ 32)	$ -466 ($ 28)	$ -769 ($ 40)
mean: vapour pressure	$ -191 ($ 75)	$ -58 ($ 25)	$ -10 ($ 43)	$ -21 ($ 31)
ln hourly wage business	$ 1 ($ 0)	$ 1 ($ 0)	$ 1 ($ 0)	$ 1 ($ 0)
ln hourly wage production	$ -1 ($ 0)	$ -1 ($ 0)	$ -1 ($ 0)	$ -1 ($ 0)
ln hourly wage construction	$ 5 ($ 0)	$ 1 ($ 0)	$ 1 ($ 0)	$ 2 ($ 0)
violent crime rate	$ 281 ($ 14)	$ 258 ($ 8)	$ 96 ($ 7)	$ 304 ($ 10)
health score	$ 301 ($ 8)	$ 192 ($ 4)	$ 145 ($ 4)	$ 257 ($ 5)
transport score	$ 197 ($ 3)	$ 72 ($ 2)	$ 91 ($ 2)	$ 105 ($ 2)
education score	$ 7 ($ 0)	$ 1 ($ 0)	$ -1 ($ 0)	$ 1 ($ 0)
the arts score	$ -20 ($ 1)	$ -4 ($ 1)	$ 2 ($ 1)	$ -7 ($ 1)
recreational facilities score	$ -289 ($ 7)	$ 12 ($ 3)	$ -2 ($ 3)	$ -32 ($ 4)
distance to coast	$ -5 ($ 0)	$ -1 ($ 0)	$ -0 ($ 0)	$ -3 ($ 0)
elevation	$ -3 ($ 0)	$ -6 ($ 0)	$ -4 ($ 0)	$ -4 ($ 0)

Notes: Standard errors provided in parentheses. Amenity coefficients have been converted to the MWTP by dividing the mean coefficient and the standard error from the first and second stage by the coefficient on income from the mixed logit regression. The result is multiplied by the sample mean predicted income to yield a monetary measure of the amenity value of a marginal change in the amenity.
[a] Nonlinear amenity variables are evaluated at population-weighted means in order to compute the Marginal Willingness to Pay.

Table C.3.6: MWTP Second Stage Specification (OLS)

	Base Model	(7)	(8)	(9)	(10)	(11)
	region & IV	RD: $\hat{I}$ & wage	mig distance	mig dist married	no mig distance	RD: mig distance
	MWTP	*MWTP*	*MWTP*	*MWTP*	*MWTP*	*MWTP*
mean: summer temperature	$ -541	$ -423	$ -267	$ -330	$ -521	$ 19,669
	($ 83)	($ 37)	($ 30)	($ 55)	($ -199)	($ -4,321)
mean: winter temperature	$ 76	$ 308	$ 118	$ 110	$ -349	$ -29,892
	($ 75)	($ 27)	($ 60)	($ 48)	($ -127)	($ -4,332)
mean: precip	$ -61	$ -46	$ -50	$ -32	$ 72	$ -876
	($ 14)	($ 15)	($ 9)	($ 8)	($ -26)	($ -857)
mean: cloud cover	$ 235	$ -378	$ -104	$ -208	$ 883	$ 60,370
	($ 165)	($ 41)	($ 89)	($ 74)	($ -148)	($ -5,885)
mean: vapour pressure	$ -191	$ -53	$ -106	$ -53	$ -14	$ 10,777
	($ 75)	($ 45)	($ 49)	($ 22)	($ -44)	($ -4,756)
ln hourly wage business	$ 1	$ -1	$ -0	$ 1	$ -1	$ 82
	($ 0)	($ 0)	($ 0)	($ 0)	($ -0)	($ -7)
ln hourly wage production	$ -1	$ -0	$ -3	$ -0	$ 1	$ 41
	($ 0)	($ 0)	($ 0)	($ 0)	($ -0)	($ -6)
ln hourly wage construction	$ 5	$ 3	$ 5	$ 2	$ -2	$ -382
	($ 0)	($ 0)	($ 0)	($ 0)	($ -0)	($ -6)
violent crime rate	$ 281	$ 147	$ 62	$ 72	$ -773	$ 32,494
	($ 14)	($ 11)	($ 12)	($ 13)	($ -21)	($ -1,231)
health score	$ 301	$ 155	$ 155	$ 149	$ -240	$ -21,094
	($ 8)	($ 7)	($ 6)	($ 5)	($ -11)	($ -551)
transport score	$ 197	$ 10	$ 84	$ 51	$ -98	$ -11,162
	($ 3)	($ 3)	($ 3)	($ 3)	($ -5)	($ -273)
education score	$ 7	$ 3	$ 6	$ 2	$ -4	$ -313
	($ 0)	($ 0)	($ 0)	($ 0)	($ -0)	($ -11)
the arts score	$ -20	$ 20	$ 2	$ 14	$ -29	$ 954
	($ 1)	($ 1)	($ 1)	($ 1)	($ -2)	($ -95)
recreational facilities score	$ -289	$ -89	$ -38	$ 22	$ -103	$ 5,378
	($ 7)	($ 6)	($ 5)	($ 4)	($ -9)	($ -449)
distance to coast	$ -5	$ 2	$ -2	$ -1	$ -2	$ 342
	($ 0)	($ 0)	($ 0)	($ 0)	($ -0)	($ -18)
elevation	$ -3	$ -9	$ -3	$ -5	$ 9	$ 312
	($ 0)	($ 0)	($ 0)	($ 0)	($ -0)	($ -14)

Notes: Standard errors provided in parentheses. Amenity coefficients have been converted to the MWTP by dividing the mean coefficient and the standard error from the first and second stage by the coefficient on income from the mixed logit regression. The result is multiplied by the sample mean predicted income to yield a monetary measure of the amenity value of a marginal change in the amenity.

a Nonlinear amenity variables are evaluated at population-weighted means in order to compute the Marginal Willingness to Pay.