University of Sussex

Internal migration and labour markets in Thailand: Insights from policy evaluations

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Thesis submitted for the degree of Doctor of Philosophy

Department of Economics

University of Sussex

June 2017

UNIVERSITY OF SUSSEX
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Doctor of Philosophy in Economics

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SUMMARY

This thesis investigates how labour markets respond to a range of national policies in Thailand. It deepens understanding of the behavioural changes of households towards internal migration and of labour market dynamics during the 2000s. It focuses on two policy themes, one on the access to credit and the other on the minimum wage policy.

The first essay investigates the relationship between borrowing and internal migration. It evaluates the short and medium term effects of the introduction of a village-based micro-finance scheme (Village Fund), assessing the impact of borrowing on households' migration decision. Using a panel instrumental variables model, the essay shows that internal migration is not a credit constrained decision in Thailand. Migration interacts with credit over time. While not affecting migration at introduction of the scheme, borrowing is found to reduce the likelihood of migration in the medium term.

The second and third essays investigate the effects of the minimum wage policy in Thailand from two complementary angles. The essays provide insights on labour market responsiveness to changes in the minimum wage during the last decade (2002-2013), also focusing on the short term effects of the recent introduction of a National Minimum Wage (2012-2013) which generated an unprecedented hike in the country. The essays evaluate the policy effects on the private sector, focusing on the wage distribution and employment.

The second essay evaluates the impact of the minimum wage on the wage distribution. Its novelty is to propose a variant of the Unconditional Quantile Regression, in which the Recentered Influence Function is applied to the provincial wage distributions. The method allows for the identification of the wage response while accounting for the geographic heterogeneity of Thai wage schedules. It shows that provincial wage distributions are affected by the minimum wage policy up to the 60th percentile, suggesting that minimum wage levels act as a *numeraire* for wage renegotiation. The evidence further suggest that the 2012-2013 policy change was especially beneficial for workers between the 15th and 45th percentiles. However, the results show no discernible effects of the policy change on the lowest quantiles, suggesting some degree of non-compliance with the law.

The third essay explores the employment effects of the minimum wage policy. Using a panel of provincial employment measures, it finds that aggregate private sector employment is not affected by the minimum wage policy. However, the results for 2002-2013 show minor adjustments in youth low-skilled employment, stronger for the female population. The findings also suggest that the latest policy change (2012-2013) had no immediate negative effects on employment.

Declaration

I hereby declare that this thesis has not been and will not be, submitted in whole or in part to another University for the award of any other degree.
Chapter 4 and Chapter 5 are joint work with Dilaka Lathapipat.

Signature: Cecilia Poggi

Acknowledgements

My journey in labour and development economics received guidance by many individuals in and outside of academia which made the discipline my passion and the context my inspiration. I would like to thank my main supervisor, Prof. Richard Tol, for pushing me in being curious and for discussing my ideas with rigour, integrity and humour. Thanks to my second supervisor Dr. Iftikhar Hussain for advice. A further mention is due to many faculty members of the Economics Department at Sussex for the discussions and support throughout the process. Particularly, thanks to my academic advisor Prof. Barry Reilly for his encouragement.

This work has greatly benefited from the collaboration to the Thailand Systematic Country Diagnostics Report (SCD) at the World Bank Group, Bangkok Office. I would like to express my gratitude to the National Statistics Office of Thailand to allow the use of invaluable statistical data during the period of my collaboration with the World Bank Group for the background research for the Thailand SCD 2016. Parts of this research, in collaboration with Dilaka Lathapipat, are part of this thesis (Chapter 4 and 5). The findings, interpretations, and conclusions presented in the chapters of the thesis should not be considered reflecting the views of the institutions providing access to the data.

I would like to thank Reena Badiani-Magnusson, Lars Sondergaad and Xubei Luo for sharing with me their expertise, time, trust and dedication. Many thanks to Theepakorn Jithitikulchai and Dilaka Lathapipat for all the shared knowledge, dialogue, time, laughs and encouragement. The collaboration with Dilaka and the SCD Poverty Team not only enabled me to have a better understanding of the Thai economy, but also generated research which was shared in different arenas and hopefully reached well different audiences to enhance the discussion on the lively and prosperous labour markets in Thailand.

The visits to researchers at Mahidol University (IPSR), Thammasat University, Chulalongkorn University and IOM Thailand are greatly acknowledged. Especially, thanks to Hataya Sibunruang, Phakpoom Tippakoon, Sastarum Thammaboosadee, Charamporn Holumyong, Jerry Huguet and Yuko Hamada for their time. I would also like to express my gratitude to Art BA Pongpiriyakan and Vincent Leutwiler for making my visits to Thailand an unforgivable memory.

There have been many early rises and late nights which I experienced with a smile only thanks to Hector Rufrancos, Eva-Maria Egger, Elsa Valli, Samantha De Martino, Filippo Bontadini and Antonia Schwartz who taught me that to be a good researcher you must be an inspired thinker, coder, presenter, cyclist, teacher, yogi, plumber and cook. The support of more dear colleagues and friends, such as Yashodan, Michael, Ani, Tsegay, Pedro, Sarah, Mimi, the Choudury's, the Carrerita's, the Farina's and all the other Sussex PhDs has given me strength and room to discuss our research, which make of this department the Socratic idea I have of education. A group of inspirational figures deserves a big thanks: Toe, Ludo, Ale, Mase, Ila, Thili, Olga, Anna, Johanna, Cat, Nicola, Eugenio, Giulio, Livia, Katie, Mokthar, Cate, Jonas, Taka, Gratia, il Gerby, Joumana and Seb.

All of the adventures and hurdles would have not been possible without the support, smiles and happiness spread by my family and relatives. Some people have gone and others have arrived, all of you have a special place in my hearth. Alessandra and Lamberto, thanks for being the support every daughter would dream of. Cucca, Cami, Luca and the little ones: you are the reason why I would cross mountains to catch a high-five! And a final very special thanks goes to Javier, my *petit voyageur*. Your support, openness to discussion, smiles and dedication make you the best *compañero* I could ever ask for.

This thesis is dedicated to Mimma and Poppo, passionate travellers of a beautiful life.

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Chapter 1

Introduction

This thesis evaluates empirically how agents interact with market frictions and the role of national policies in affecting their behaviour. It investigates these issues in the context of Thailand, an emerging economy which has witnessed a fast economic transition combined with various policy reforms during the last three decades. The thesis evaluates two major national policies over the 2000s, a micro-finance scheme and the minimum wage policy. The thesis seeks to understand how household behaviour towards internal migration changes after accessing credit and it investigates on the labour market effects of variations in the minimum wage.

The thesis begins with a brief summary about Thailand. It identifies the institutions which shape the economy, relevant for the understanding of the policy environment in which the thesis expands its analysis. The thesis then conducts policy evaluations in the context of labour market participation.

The first essay (Chapter 3), of which a version is accepted for publication in the *Journal of Development Studies*, proposes an empirical assessment of the effects of formal borrowing on internal migration decisions. Migration is a risk-diversification strategy often used to mitigate market frictions both in terms of wage differentials and of capital and insurance market imperfections (Katz and Stark, 1986). The essay contributes to the literature by providing empirical evidence on the credit-migration nexus. The essay asks whether internal migration is a credit constrained decision in Thailand, and identifies the consequences of borrowing on migration decision when credit availability increases. It uses the introduction of a micro-finance scheme, the

Village and Urban Community Fund Programme (VFP), to assess the responsiveness of households to credit in their internal migration decisions. The policy was introduced in 2001 to tackle poverty by increasing access to start-up capital (de la Huerta, 2011). It disbursed funds at the village level, forming local financial institutions to disburse credit.

The essay investigates the mechanisms through which borrowing may affect household's behaviour towards migration. It identifies two main channels of influence: an alteration of the opportunity cost of migration investment (Stark and Bloom, 1985) via the direct use of credit – referred to as the economic channel of borrowing; and the interaction of borrowers with a new credit institution (Coleman, 2006; Banerjee, 2013; Fischer, 2013) – referred to as the institutional channel. It uses this framework to empirically assess how internal migration is effected by formal credit.

The essay uses an instrumental variables approach inspired by Kaboski and Townsend (2012). The VFP policy was unanticipated, it generated heterogeneous availability of credit to potential borrowers at the village level and had simple eligibility criteria. For the purpose of the analysis, these characteristics provide a valuable *quasi-experiment* for policy evaluation. The approach used accounts for issues of selection into borrowing and the presence of credit institutions (Coleman, 2006), not previously addressed by the literature on the effects of financial participation on migration. Given the time dimension of the data, it is also possible to evaluate the short and medium term effects of formal borrowing, thus adding evidence about internal migration to the micro-finance literature which investigates the prolonged effects of access to credit (Banerjee et al., 2015).

The second and third essays of the thesis, joint work with Dilaka Lathapipat, analyse the evolution and impact of the minimum wage policy in Thailand. The minimum wage is part of the set of labour market institutions put in place to mitigate the variation in labour demand and supply which affect the structure of wages (Freeman, 1996). In economies which are experiencing rapid economic changes, but do not have a full set of institutions protecting workers, the risks of increasing wage disparity have induced policy makers to focus on different practices for setting, adjusting and enforcing the minimum wage (Rani et al., 2013). Thailand has had an active minimum wage regulation since the 1970s. Over more than forty years it has experienced three types of minimum wage settings: regional bands (three bands across the geographic regions of the country), provincial minima (set according to recommendations by 76 provincial committees in the country) and very recently a single statutory wage.

The minimum wage is set in Thailand to guarantee a price for labour such that specific living standards are achieved (MOL, 2008). The two essays propose an empirical evaluation of the labour market response to the changes in the minimum wage experienced between 2002 and 2013, with a particular focus on the switch in policy regime from provincial minima to a National Minimum Wage (NMW). We assess the policy from two angles, first through the lens of the impact on the wage distribution and second through employment changes.

The second essay (Chapter 4) investigates the effects of the minimum wage policy on the wage distribution. It characterises the traits of the wage schedule in Thailand and proposes an identification strategy to reflect its attributes. The literature shows that wages tend to vary drastically across areas, reflecting the presence of 'local labour markets' (Moretti, 2011). Both employment and wages reflect different degrees of agglomeration and productivity (Moretti, 2004; Combes et al., 2008; Greenstone et al., 2010). In Thailand, there is evidence of spatial concentrations of enterprises (Felkner and Townsend, 2011) reflecting productivity and output disparities across provinces (Limpanonda, 2015).

The essay highlights the geographic disparities in wages in Thailand and performs an empirical strategy to account for this heterogeneity when evaluating the impact of the minimum wage policy. It proposes a variant of the Recentered Influence Function (RIF) regression framework (Firpo et al., 2009a) applied to provincial wage distributions. Through the RIF transformation of an individual wage observation within each province, the model captures the average provincial wage response to a minimum wage change. Exploiting the transition from geographically set minimum wages to a single statutory wage, the essay also shows evidence of the short-run effects of this policy change on wage distributions. The essay gives some short run evidence of a change in policy regime which took place in two steps: an initial hike of approximately 40 percent in nominal terms followed by a harmonisation to a single minimum which induced further 30 percent adjustments in some provinces. With the method proposed, it aims to capture a precise estimate of the policy.

The third essay (Chapter 5) complements the analysis of the minimum wage policy by proposing an empirical evaluation of its employment effects. It draws on the minimum wage literature to identify how the "elusiveness" (Manning, 2016) of the employment effects of a minimum wage policy is present in emerging economies. The essay shows how employment trends have changed over time in Thailand and identifies the rate and depth of non-compliance. Using a reduced form equation of provincial employment demand, both in a static and dynamic form, the essay identifies the provincial employment response to a policy change. It also provides insights into the state of non-wage employment in Thailand and its correlates to the minimum wage policy.

The structure of the thesis is as follows. The next chapter presents a synopsis of the characteristics of the Thai economy. Chapter 3 investigates empirically the interaction of access to credit with internal migration decisions. Chapter 4 evaluates the effects of the minimum wage policy on the wage distribution, and Chapter 5 looks at its effects on employment. The thesis concludes with Chapter 6 that brings together the different themes investigated and provides insights for policy recommendations. It also discusses the limitations of the empirical analyses and offers a future research agenda.

Chapter 2

A synopsis of the Thai economy

This chapter provides background information on the Thai economy. It lays out the economic and policy landscape in view of contextualising the different themes treated throughout the thesis. Thailand is an emerging economy (upper middle income since 2011), with a per capita Gross Domestic Product of 15,435 US$ (PPP 2011) and a population of around 67 million inhabitants as of 2013. Thailand's path to become an emerging economy has not been easy. After experiencing fast development during the 1980s-1990s, Thailand faced strong headwinds due to the Asian financial crisis in the late 1990's. However, in the 2000s the country experienced considerable growth in trade and undertook important domestic reforms, particularly on the labour and financial side, which are the subject of this thesis. The summary presented below provides further context across a broad range of economic, social and institutional dimensions.

Production and trade Export-oriented policies (including foreign direct investment) contributed to the rapid industrialisation of Thailand during the 1980s and 1990s.[1] Where manufacturing exports are concerned, the largest share is occupied by products of medium technological content (around 43 percent); resource-based exports (around 21 percent), and low-technology manufactures (around 18 percent) (Sondergaard et al., 2016). In agriculture, Thailand is a net exporter of rice and rubber as

[1]Between 1985 and 1995 a set of policies were enacted promoting the formation of industrial zones. Starting with the Eastern Seaboard Development in 1991 the country began developing an industrial base (i.e. for export-oriented industries, both light and heavy industry, logistics, transport and telecommunication facilities) through tariff exemptions and corporate tax reductions to firms locating in specific provinces in the country, in addition to receiving loans and technical assistance from abroad (Komolavanij et al. 2011 p.19-20).

well as cassava and sugar. As a member of the Association of Southeast Asian Nations (ASEAN) since 1992, Thailand has benefitted from preferential market access to neighbouring economies in South East Asia (SEA). It also enjoys broader agreements with other countries beyond the region, most notably with Australia, China, Japan, Korea and New Zealand.

Urbanisation and economic geography The country can be divided into five geographic regions (central, northern, northeastern and southern regions and the capital, Bangkok). Administratively, the country is divided into 77 provinces (76 before year 2011, used in the thesis to allow data comparability over time, named in Thai *changwats*), with smaller administrative units consisting in districts (*amphoes*), sub-districts (*tambons*) and villages. A feature of the country's development has been the slow rate of urbanisation experienced over the 2000s (World Bank, 2015).[2] Research on spatial concentration of firms (Felkner and Townsend, 2011), geographic agglomeration and inequality (Limpanonda, 2015) and on welfare dispersion (Skoufias and Olivieri, 2013) suggests that this uneven urbanisation is related to production and trade patterns across different Thai provinces.

Enterprises are regionally concentrated and within each province the proximity to main transportation arteries is associated with higher enterprise density (Felkner and Townsend, 2011). During the 1986-1996 period of strong economic growth, Felkner and Townsend (2011) show that there has been an uneven expansion of firm activity: while many regions had expanding enterprise rates, the northeast, lower north and deep south provinces have remained stagnant. A high concentration of enterprise in an area predicts high subsequent growth in and around that area (Felkner and Townsend, 2011). Limpanonda (2015) shows that this trend explains why Gross Provincial Product (GPP) per capita disparities at the province level have widened over time, even when average household income converged. Limpanonda (2015) suggests that provincial growth has been driven by the growing presence of industry in some provinces, and that high-tech manufacturing exports have been a main factor for growth. Thus, production disparities

[2]According to the World Bank (2015), except for the capital Bangkok (with a population of more than ten million inhabitants), no other city can be defined as a metropolitan area (with more than $500,000$ inhabitants). During the 2000s the country average annual growth rate of urban areas was around 1.4 percent (population growth of 2.3 percent on average), much lower than the East Asian average of 2.4 percent (population growth of 3 percent) (World Bank, 2015).

are present among the regions and provinces of Thailand. Regarding welfare, Skoufias and Olivieri (2013) show that the differences in welfare between provinces (and regions) in Thailand are due to differences in returns to characteristics of the populations in urban area, and within each area the endowment of characteristics matters to explain disparities. Skoufias and Olivieri (2013) further find a correlation between the spatial disparities in welfare among the provinces and the allocation of fiscal expenditures by the central authorities. The literature therefore suggests that the geographic element of enterprise formation, production and welfare may have been crucial in defining the Thai development process and its markets today. The evidence of the existence of local labour markets in the country, where production agglomeration seems to matter, motivates part of the methodological approach used in Chapter 4 of the thesis which investigates the behaviour of the wage distribution.

Poverty and inequality The rapid economic development of the 1980s and 1990s translated into a fast and sustained reduction in poverty and inequality, with the poverty headcount falling from 67 percent in 1986 to 10.5 percent in 2014 (Sondergaard et al., 2016).[3] However, these aggregate figures mask considerable differences in the incidence of poverty across geographic regions. In particular, the poverty incidence in the northeast and north regions remains relatively high, with more than half of the poor residing in provinces in those areas (Sondergaard et al., 2016). Inequality has been on a downward trend during the last three decades, with the Gini coefficient falling from 0.43 in 1986 to 0.38 in 2013 for real per capita household expenditure and from 0.50 to 0.46 for real per capita household income (Sondergaard et al., 2016).[4]

Employment composition The labour market in Thailand has been subject to changes in its sectoral composition. Since the economic boom of the 1980s a major shift away from agriculture and towards manufacturing took place with services gaining importance over the 2000s. At the same time, and as is the case across many emerging economies, participation of the labour force to micro-firms or Small and Me-

[3]Poverty is defined as consumption per capita below a household-specific poverty line, as delineated by the National Economic and Social Development Board (NESDB) (Sondergaard et al., 2016).

[4]According to the Thailand Systematic Country Diagnostics (SCD) report, a main difficulty in evaluating inequality measures using household data for Thailand is the underrepresentation of households in the top decile, which may be underestimating income and consumption dispersions (Sondergaard et al., 2016).

dium Enterprises (SMEs) is high.

Three observations underlie the composition of the workforce of Thailand during the 2000s: workers are becoming more educated; there is an increased participation of the female population; and the rate of informal employment is high. The 1990s and 2000s saw a sharp reduction in the low-skilled population (defined as individuals with lower than secondary education) due to rising school enrolment and to growing demand for skilled work. Some signs of polarisation in wage growth were detected between the 1987 and 2006 (Lathapipat, 2009). Lathapipat (2009) suggests that the rise of low-wage relative to the median was potentially due to migration of low-paid workers to urban areas, whereas the top-end increased due to the greater demand for high-skilled occupations. The rise in tertiary educated workers partially explains why overall wage inequality has been reducing over the period.

Female labour force participation has increased during the last two decades, contributing to a reduction in the gender wage gap. Research shows that gender inequality has improved over the period 1991 to 2007 (after the 1997 crisis), with evidence that returns to potential experience was one of the main factors inducing the gap (Adireksombat et al., 2010).[5]

Another attribute of the Thai labour market is the low unemployment and high informality. In 2013 less than 1% of individuals report to be unemployed and a rather small 0.1% reports, on average, to be seasonally unemployed (NSO, 2014). This could be attributed to the absence of a strong social protection system to assist individuals who cannot find an occupation, and to low representation of workers' unions in the bargaining process of formal employment. These elements make various forms of informal employment as an option for individuals, with figures for 2013 reporting informality at around 64 percent of total employment (NSO, 2014). Forms of unpaid work and self-employment are still spread across sectors, with particular concentrations of non-wage work in agriculture and among poor households.[6]

[5]As of 2013, female workers are paid 16 percent less than male workers, with their participation being mostly in micro or small firms, where the wage gap is highest. Both female and male workers show a wage premium which increases with education and, although there are greater number of females composing high-skilled workers, their relative premium remains lower than males (Sondergaard et al., 2016).

[6]Sondergaard et al. (2016) suggest that there could be a strong duality in the agricultural sector in the country. Commercial full-time farming has reduced since the 1990s, and today it is complemented by part-time farming activities. The reduced productivity of the agricultural sector suggests that individuals may use land as a safety net in case of hardship (Sondergaard et al., 2016).

Domestic and international migrants have also been playing a central role in shaping the labour force. Internal migration takes place in the country in forms of seasonal or permanent migration, and it plays a non-negligible role in households' financing due to remittances (Guest et al., 1994). Looking at national level data over the 2000s, approximately one-fifth of Thai households reported to have migrants. Migration trends have reduced over the period, with the highest proportions coming from households from low consumption deciles and prevalently from the northeast and northern regions (Sondergaard et al., 2016). Internal migration is found at the micro-level to be driven by low resources at home and poor access to social and physical infrastructures in the district or province of origin (Amare et al., 2012). At the macro-level, its persistence is found to reduce cross-province inequality, via redistributive effects of remittances from richer to poorer provinces (Yang, 2004). International migration has also played a critical role over the 2000s in filling labour shortages in some sectors of the country, such as seasonal work or low-paid occupations in agriculture, fishery and construction (IOM, 2011, 2014).[7]

Employment institutions Workers in Thailand are protected by the Labour Protection Act, administered by the Department of Labour Protection and Welfare which regulates the employer-employee relations. The modifications to labour laws (such as minimum wage, labour relation or labour standards) receive discussion and recommendation at the province-level trough a tripartite committee, formed of government, employer and employee representatives.

Participation to trade unions is extremely low. The International Labour Organization (ILO) reports that the trade union density is at 2% in 2015 (ILO, 2017a). This low level is due to restrictive laws governing unions formation, resistance from employers and lack of enforcement of workers' rights that weakens trade unions in representing workers effectively (ILO, 2017a). Unions are present in 34 out of 76 provinces, raising concerns on how employees in these provinces are selected to be part of the tripartite committees at the provincial level (ILO, 2017a).[8] Workers' protection comes mainly

[7]Notwithstanding the efforts to make the international migrant flows being regulated (e.g. with the stipulation of Memoranda of Understanding and the institution of centres for registration) there is still no organic migration policy protecting these workers. Data are particularly scant on international migrants (particularly on unregistered migrant workers or overstayers), preventing the research of this thesis to investigate on this type of workers.

[8]Chandoevwit (2008) reports a very similar scenario for 2006, in which there were 1,313 labour

from enrolment into the Social Security Scheme (SSS). This is the main social protection mechanism, managed by the Social Security Office, department under the Ministry of Labour of Thailand (MOL). It is a contributory scheme, financed by employees, employers and government contributions, and the benefits are transferred as a lump sum (Wedel, 2012).[9] Its main limitation are coverage (i.e. in 2008 the scheme covered 25.1% of the employed workforce), adequacy of benefits and management (Paitoonpong et al., 2010). Although data on SSS enrolment are not available for the research carried in this thesis, Chapters 4 and 5 will attempt to account for the presence of informal work in the evaluation of the minimum wage policy.

Financial institutions and their regulation The country had a relatively tight financial control prior to the 1980s. The lending interest rates were different across lending institutions, and lending activity of commercial banks to large-sized firms was segmented from that of financial institutions to SMEs (Okuda and Mieno, 1999). During the financial liberalisation between the 1980s and early 1990s many policies on financial regulation of domestic-owned and foreign-owned enterprises were relaxed. Giné and Townsend (2004) show that the country benefited from giving access to credit to would-be entrepreneurs who would have not gone into business or invested capital otherwise. Okuda and Mieno (1999) show that, on the one side, commercial banks became more capital intensive thanks to diversification of fund-raising activities. On the other side, the liberalisation induced greater unregulated competition, leading to risky behaviour. As of today, the country benefits of a more balanced commercial banking sector and a stronger rural credit market comprised of initiatives generated by Micro-finance institutions (MFIs). MFIs have been central to the financial participation of farmers and Micro Small and Medium Enterprises (MSMEs) entrepreneurs (for example, see Kaboski and Townsend 2005; Coleman 2006; Townsend 2016). One of the largest institutions created in the 2000s was the Village and Urban Community Fund Programme

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unions (among state and private enterprises) with less than 3% of state-enterprise and private-sector employees being enrolled. The author suggests that such low rate of unionisation could be due to the fact that the Labour Protection Act does not protect employees from dismissal for forming a labour union (Chandoevwit, 2008).

[9]The SSS started in 1990, covering formal sector private employees for cases of injury, sickness, maternity and invalidity and it includes other non-work related transfers. Over the years the SSS has extended its accessibility to workers in small enterprises (1993) and micro enterprises (2002). It has also extended the set of social transfers available for those registered, such as including an unemployment insurance option since 2004. (Paitoonpong et al., 2010; Wedel, 2012).

(VFP), a micro-finance scheme with village-based funds allocating short-term credit. This scheme is discussed in Chapter 3.

Thailand and the two crises In July 1997 Thailand saw its growth rate fall considerably due to the Asian financial crisis. The crisis was a result of domestic speculative investment activity in property and construction sectors over the 1990s (Chandoevwit, 2010). Already between 1995 and 1996 financial sector activity showed the characteristics of a speculative bubble that by 1997 burst and led to a contraction in overall economic activity. According to Okuda and Mieno (1999) the crisis arose from the absence of transparency and market discipline of the recently formed financial sector, in which medium-sized commercial banks were the first to fail. The repercussions to the economy were strong. The exchange rate of the Thai Baht dropped considerably, with both contractions in output, and net exports. Domestically, employment contractions where particularly visible in the construction sector, generating geographically localised repercussions in both the capital, Bangkok, and the northern and north-eastern regions (Chandoevwit, 2010).

The economy started recovering as early as year 2000, and the official recovery is considered to have taken place around 2002. This was the year where output growth recovered back to its 1996 level. As a result of the crisis, many changes in monetary, trade and social policies were enacted in the 2000s. The monetary targeting approach adopted with the floating of the currency in July 1997 was replaced in the 2000 by inflation targeting (WTO, 2003). The financial sector entered into a tighter control, while export competition policies in addition to a battery of social and labour policies were put in place to stimulate the economy.

During the 2008-2009 crisis, the country experienced a much smaller shock than during the previous crisis. Despite reductions in export demand, by the second half of 2009 the economy was already recovering.[10] According to Chandoevwit (2010), the crisis generated some short-term employment contractions in manufacturing (due to a contraction in export demand) in few quarters over these two years. However, the government responded to the crisis with two phases of stimulus packages (WTO,

[10] Additionally, this event happened just after the food price crisis of 2008, which saw the agricultural sector in Thailand with altered prices, both internationally through exports and domestically.

2011).[11]

Welfare, social assistance and agricultural policies In terms of welfare policies and social assistance, Thailand is at the forefront in many aspects like health provision, but lags in other social policies such as social protection. Over the 2000s a set of nation-wide policies were applied mostly with universal or targeted rather than mean-tested recipients.

One was the non-contributory health scheme and the second was a universal pension for the elderly. The Universal Health Coverage (UHC) provides, since 2001, universal access to healthcare, with free health services to all Thai citizens not covered by existing publicly run health insurance schemes such as the SSS and Civil Servant Medical Benefits Scheme. Second, the non-contributory allowance for the elderly (introduced in 2008 under the name of Universal 500 Baht scheme) is aimed to give transfers to all citizens aged 60 or older who do not receive other formal sector pensions. These monthly payments have been found to reach more informal workers, but due to their universal receipt, to have limited impacts on old-age poverty (see Sondergaard et al. 2016).

Additionally, the agricultural sector has been subject to a series of short or longer-term interventions, mostly through price support schemes.[12] Support schemes for rice, shallots and rubber have been subject to criticism due to problems of transparency and management (Ruengdet and Wongsurawat, 2015). Particularly, the price support to rice production has been contentious for not reaching enough poor farmers and not promoting modernisation of farm investments (Duangbootsee and Myers, 2014; Attavanich, 2016). Due to its high costs and pressures over management, the government terminate this scheme in 2014.

In addition to the aforementioned policies, the country revived its credit provision to households in rural areas through the VFP, subject of investigation of Chapter 3. It

[11]The first stimulus package targeted the poor through a combination of short-term measures. This took the form of cash transfers, low-interest loans to farmers (Agricultural price guarantee scheme), transfers to the elderly, free public transport services, reductions in water and electricity prices and other measures (see Chandoevwit (2010) for details). The second package included investment in infrastructure, transport and energy, combined with some tax measures and variations in the fiscal policy to create liquidity for the business sector (WTO, 2011).

[12]A weather index insurance was piloted for corn producers in 2006 (Mahul and Stutley, 2010) and one for rice producers was introduced in 2010 (Hongo, 2015). A financial compensation scheme was set up through the Disaster Relief Program to compensate any farmer whose crop suffered from floods or droughts since 2011 (World Bank, 2012).

also modified the minimum wage policy regime which will be investigated in Chapters 4 and 5.

Chapter 3

Credit Availability and Internal Migration: Evidence from Thailand

3.1 Introduction

Migration is a self-insurance strategy for households facing risky outcomes, particularly in rural settings (Rosenzweig, 1988). While it is often viewed as a way of overcoming insurance and credit market imperfections (Stark and Bloom, 1985; Stark and Levhari, 1982) there is little empirical evidence assessing its interaction with credit markets.

This chapter provides a household level analysis of the relationship between the decision to borrow and inter-provincial migration. Its novelty is to isolate credit decision using a unique government programme in Thailand which radically altered formal credit availability at village level. Using a detailed panel for the period 1998-2007, covering the period prior to and after the introduction of the programme, this study tests whether greater availability of credit had a direct effect on migration. It assesses whether migration is credit-constrained and whether borrowing acts as a push or pull factor on the decision to migrate.[1]

Analysing the interplay between credit and migration is complex. Borrowing encourages a diversified use of money towards consumption and investments (Carroll, 1997; Evans and Jovanovic, 1989; Lipton, 1976) and may also alter risk-coping strategies. Multiple mechanisms could be in operation. On the one hand, credit could be used to

[1]Note that a version of this chapter in article form is accepted for publication in the *Journal of Development Studies*.

support household activities, either incentivising members to stay at home or financing their migration. On the other hand, the risky nature of credit and the consequences of default could make this financial instrument of secondary importance to migration. The ambiguity in this relationship warrants empirical investigation.

The effects of borrowing on migration can be differentiated between the direct use made of credit, referred to here as the economic channel of borrowing, and the interaction of borrowers with a new credit institution, referred to here as the institutional channel. This differentiation is used throughout the chapter to allow tractability across channels of influence. Relating to the economic channels, migration, seen as an investment (Stark and Bloom, 1985), may be a credit-constrained decision. Once credit is available, households may be better able to face the upfront costs of migration leading to a higher incidence of migration. Alternatively, the opportunity cost of migrating may change in the face of relaxed credit constraints to the household, leading to a lower incidence of migration.

Borrowing can also act as an institution. That is, the presence (or absence) of credit institutions may impact the decision to borrow in the first place and, depending on the type of credit contracts available, the use made of credit (Banerjee, 2013; Coleman, 2006; Fischer, 2013). This channel may alter how households secure, accumulate and use their cash flow, in turn having an impact on factors that may condition the choice of migrating. This institutional channel is particularly complex to establish, due to unobserved traits which may affect borrowers' attachment to a new institution. This chapter aims to disentangle the complementary role of these two channels on migration decisions. Specifically, the chapter looks at internal migration episodes between Thai provinces. This type of migration includes lower costs than international migration and is frequent in Thailand (Guest et al., 1994).

The credit institution of interest is the Thailand Village and Urban Community Fund Programme (VFP) or Village Fund Program. In 2001, the Thai government introduced this micro-finance initiative which involved distributing to each village one million Baht or US$24,000 in 2001 prices.[2] It was managed by a group of village

[2]The average official exchange rate for 2001 is 44.43 Baht per one US dollar, used for all conversions in this chapter.

members providing short-term credit to fellow villagers (de la Huerta, 2011). For the purpose of this analysis, the main features of the policy were three-fold: first, it was unanticipated; second, each village received the same sum of capital regardless of its size, generating heterogeneous availability of credit to potential borrowers; third, its eligibility criteria allowed any household to opt into the scheme. The characteristics of this policy render it a *quasi-experiment* amenable to causally identifying the effect of formal borrowing on the decision to migrate.

Using longitudinal data for the period 1998-2007, this study empirically tests if migration is a credit constrained decision and examines how it is influenced by credit after the VFP introduction. The identification strategy relies on a panel instrumental variables model of migration on VFP borrowing. In order to capture any time-related component of borrowing on migration, the empirical analysis covers a short and medium time period, defined respectively as two and six years after the policy introduction. In line with the work of Kaboski and Townsend (2012), the stock of VFP credit is instrumented using interactions of the inverse number of households in each village at the start of the policy (2002) with post-programme year dummies. Village size is used as an instrument since it directly affects the perception of potential borrowers with respect to the accessibility of credit from the VFP. It does not change radically over time and does not correlate with migration. Moreover, changes in village size do not appear to be a determinant of migration.

The results reveal that there is a time-related effect of formal borrowing on internal migration from rural and semi-urban areas of Thailand. In the first two years after the scheme is introduced, borrowing does not significantly alter the decision to migrate, suggesting that internal migration in Thailand is not a credit-constrained decision. In the medium term, six years after programme implementation, borrowing lowers liquidity constraints at origin with direct impacts on migration. Accessing a VFP loan reduces the probability of migration, suggesting that households have fewer incentives to relocate one of their members once they realise the benefits from borrowing.

The institutional effects of borrowing are nuanced. The presence of a new institution leads households to make repeated use of the program, but no marked difference in migration response is found among borrowers with different frequency of borrowing.

The improvements in expectations towards borrowing availability and in the economic conditions of the villages may have assisted households who not continuously borrow from the VFP to attenuate their need for migrating internally. The economic effects are more distinct. It is only within the medium term that the opportunity cost of sending a migrant increases. This interpretation is corroborated by the analysis on the time since initial borrowing from the VFP, suggesting that the change in behaviour happens, on average, after three years.

This study contributes to the existing literature in three ways. First, it provides empirical evidence on the credit-migration nexus (Rapoport, 2002). One of the challenges for modelling this interaction is to disentangle the effects on migration which arise from market imperfections (credit, insurance or labour) from other income or employment effects considered at household level (Massey et al., 1993). The present study adds to the literature by investigating whether migration is credit constrained (Bryan et al., 2014), it investigates its opportunity cost across the whole income distribution (Bazzi, 2017) by isolating the reaction to a *positive* credit shock.

Second, it adds to the existing literature on the interaction of migration with credit institutions (Khun and Chamratrithirong, 2011; Khandker et al., 2012; Demont, 2014) through an in-depth analysis on the changes in credit availability experienced by communities. It uses a policy evaluation method which accounts for the endogeneity of selection into borrowing and the presence of credit institutions (Coleman, 2006), an issue not previously addressed in the literature.

Finally, the study shows that internal migration is influenced by policies over time. It therefore complements the programme evaluation literature on migration (for example, see Angelucci 2015, Ardington et al. 2009), showing that the implementation of policies in rural areas may reduce internal migration by increasing the opportunity cost at origin (Imbert and Papp, 2016), and that the absorption of a *positive* shocks induced by policies may take time to change this behaviour.

The chapter is organised as follows. Section 3.2 reviews the literature, Section 3.3 delineates the VFP implementation. Section 3.4 describes the data and provides selected summary statistics. Section 3.5 outlines the identification strategy and discusses the instruments. Section 3.6 presents the results and Section 3.7 concludes.

3.2 Literature overview on migration, credit constraints and credit institutions

The aim of this section is to review the contributions of the literature on the determinants of migration and the role of a credit-migration nexus, as identified across different theoretical and empirical studies. It also reviews different features of credit institutions and the use of borrowing, as per the finance literature, which can support the empirical evaluation of this chapter.

Migration prospects include two initial variations in the economic condition which the household accounts for: it loses labour capacity at origin, altering its income-generating ability, in addition to incurring costs to support the migrant at the initial stage of migration. There is evidence that migration is a self-selective process and that the household views it as an investment (for a review, see de Haan 1999; de Haas 2010a). On one side, migration is viewed as a way to overcoming insurance and credit market imperfections (Stark and Bloom, 1985; Stark and Levhari, 1982), on the other it may be affected by credit constraints in its financing (Bryan et al., 2014). Understanding the interaction between borrowing and migration poses some serious challenges. Both credit access and its use are endogenous to income generation dynamics. For example, factors like interest rates, savings and assets generation or depletion interact with both credit and investment decisions. Given the nature and multiple uses of credit, it is hard to rely on a single theoretical model to depict the behavioural interaction between borrowing and migration. Nevertheless, it is possible to generate some hypotheses on the credit-migration interaction by drawing upon the New Economics of Labour Migration (NELM) literature, combined with the predictions from the standard models of access to borrowing and of borrowing use under credit constraints.

The NELM literature on the determinants of migration has mostly relied on the analysis of wealth dynamics. The credit constraints of migration are generally captured through realised wealth or through shocks received, assuming that either borrowing has already materialised or that it is not accessible.[3] For example, Rapoport (2002), applying the

[3] An exception is Kennan and Walker (2011) who propose a model of migration as an optimal search process across locations, describing a partial equilibrium response of labor supply of an individual to wage differences across locations. Focusing on a special case in which assets do not affect migration decisions (assuming that the marginal utility of income is constant) and a fixed interest rate, the individual can borrow and lend without restriction, and will migrate by maximising the expected lifetime income across areas (Kennan and Walker, 2011).

Mesnard (2001) model of occupational choice to a setting with inequality and growth, suggests that liquidity constraints affect both entrepreneurial capacity and migration. Migration occurs if its costs can be covered with the accumulated wealth (Rapoport, 2002). Wealth is found to have a non-linear, inverted U-shaped, relationship with the likelihood to migrate (Mckenzie and Rapoport, 2007; McKenzie and Rapoport, 2010). Heterogeneity in wealth composition induces diverse effects depending both on the type of migration and on the population studied.[4]

Additionally, the literature finds that different institutions shape the decision to migrate. For example, a network at destination reduces migration costs and relaxes wealth constraints (Mckenzie and Rapoport, 2007), while risk-sharing networks at origin increase the opportunity cost of migration (Morten, 2016; Munshi and Rosenzweig, 2016). Morten (2016) reconciles the idea of coping with risk by introducing risk sharing into the analysis of household behaviour towards welfare and temporary migration.[5] Munshi and Rosenzweig (2016) show that in the absence of formal insurance, such as government programs and private borrowing, risk-sharing networks at origin will reduce migration.[6] Property rights are also relevant institutions for migration, with evidence on the relevance of landholding varying with income levels (Lee, 1985) and of greater tenure security attenuating the necessity to migrate (Mullan et al., 2011). Despite the recognition that both borrowing and credit institutions are underlying factors for migration, substantial knowledge gaps remain on how to identify and interpret their interaction.

[4]For example, Abramitzky et al. (2013) show with Norwegian historical data that higher parental wealth reduces the likelihood of international migration and that its effect becomes stronger when expected inheritance, by birth order and sibling composition, is inspected. Bazzi (2017) looks at the income elasticity of international migration in the presence of shocks (rainfall and rice prices), and shows that for villages in Indonesia international migration increases with positive agricultural income shocks, but this effect is heterogeneous across village characteristics. Positive shocks in higher opportunity cost areas (identified, for example, in villages with higher agricultural productivity) either inhibit or negatively affect migration. For internal migration, Hirvonen (2016) shows that in Tanzania temperature-induced income shocks reduce the likelihood of migrating, and identifies the existence of a gender-specific effect, suggesting that male migration is liquidity constrained.

[5]Assuming that credit is not easily accessible, Morten (2016) sets a model of migration and risk sharing determination, where both variables could have motivating or deterring effects on the other. Her findings show that risk sharing reduces the utility cost of temporary migration because households have informal insurance against bad shocks (Morten, 2016).

[6]The authors show that for households in Indian villages the loss of network insurance is greater than the income diversification gains from migration of a male member, thus explaining why India displays very low permanent internal migration for adult males (Munshi and Rosenzweig, 2016).

Within the finance literature, attention has been drawn on the mechanism underlying access to credit, with reference to specific types of credit institutions, these being either formal or informal.[7][8] In a setting of individual liability loans, **?** sets a model with formal and informal credit institutions. The model inspects four financial choices, either not to use borrowing (self-financing), to use either a formal or an informal source, or to use them simultaneously. It assumes that informal lenders compete against formal institutions and that potential borrowers have to incur transaction costs (which generally imply a collateral). The model shows that in the presence of large fixed transaction costs to access formal credit, households that need little credit may rely on informal lenders, whereas those with large borrowing needs would be better off accessing formal borrowing with a lower interest rate, by incurring the fixed transaction costs. **?** shows that, if there are efficiency gains from intermediation, once the interest rate falls, more households will opt for formal credit. He concludes that this is the core rationale used to have Micro-finance institutions (MFIs) in rural areas (**?**).[9] Thus, the type of institution and the contract terms offered does reflect how potential borrowers access and interact with the credit institution (Banerjee, 2013; Fischer, 2013), and the applied researcher needs to take account that the presence of institutions may be endogenous to the local economy and that self-selection takes place (Coleman, 2006).

Looking at the use of borrowing, the models of entrepreneurship or of consumption/income generation under credit constraints propose testable propositions on the response of households to new or greater credit. Models of entrepreneurship show that,

[7] The vast literature on contract theory suggests that for formal institutions there is relevance in contract terms to account for moral hazard, adverse selection and both monitoring and enforcement costs in the definition of a contract. Further, the creation of a financial structure within a country, assuming that access to borrowing is costly, is expected to increase income growth, to widen income distribution over time and ultimately to reduce or alt inequality (Townsend, 1983; Greenwood and Jovanovic, 1990).

[8] For informal credit markets, Banerjee (2003) nicely resumes the characteristics of access to borrowing: the price of borrowing varies (against standard neoclassical models which view a single price for capital); there is a gap between what is borrowed and the returns on borrowing (thus allowing consumption to be one of the outcomes of higher credit); and potential default is mitigated by the lender with monitoring and limited lending, both at the extensive margin in the choice of borrowers and at the intensive margin in the amount lent (Banerjee, 2003).

[9] Since the introduction of MFIs, many studies identified the positive role of group lending with joint liability. The literature suggests that it promotes screening, peer selection and monitoring with the final outcome of higher repayment than individual loans, but that it could still induce default due to limited enforcement (among many, see for example Besley and Coate 1995; Ghatak 1999; Ghatak and Guinnane 1999). Recently, given the shift away of MFIs from joint liability, predictions of group lending without joint liability (de Quidt et al., 2016) show that, when the MFIs use group repayment meetings, individual loans repayment may be higher (found in randomization studies due to a high level of social capital created across groups (Giné and Karlan, 2014) or due to the frequency of meetings (Feigenberg et al., 2014)).

due to the positive relationship between entrepreneurship and wealth, entrepreneurship choice may be credit constrained, particularly for low levels of wealth (Evans and Jovanovic, 1989). Buera (2009) proposes a dynamic entrepreneurship model, where business and borrowing are jointly determined. His model predicts variation over time in entrepreneurial capacity which has a negative relationship with wealth and may be driven by ability.[10]

For consumption and income, the buffer stock savings model (Deaton, 1991; Carroll, 1997) predicts that, under credit constraints and income uncertainty, households stockpile liquid assets. Once the credit constraints are relaxed, the model predicts a higher marginal propensity to consume out of transitory income or borrowing, and a positive correlation between savings and expected labour income growth (Carroll, 1997).[11] Fulford (2013) proposes a dynamic buffer stock model, highlighting the relevance to investigate the effects of credit through an inter-temporal lens. The model shows that, in relaxing liquidity constraints of a household, the short term effects of accessing credit are to increase consumption. However, its longer term effects are to modify both the consumption stream, shown to be reducing, and the accumulation of buffer wealth which may reduce too as a result of more credit available when needed (Fulford, 2013). Thus, the standard decision models under credit constraints show relevant insights to understand the response of households to credit, but do not generally model multiple investment portfolio decisions, as multiple interactions could create too much complexity or no finite interior solutions (Kaboski and Townsend, 2011).[12]

[10] Buera (2009) shows that individuals who become entrepreneurs have higher savings rates than individuals who expect to remain wageworkers. Further, he shows a negative relation between wealth and business start-up. At low wealth levels, business start-up increases with wealth because it relaxes the borrowing constraint, as in the standard static model (Evans and Jovanovic, 1989). For high wealth levels, entry into entrepreneurship and wealth are found to be negatively related. This relationship is associated the fact that over time individuals with high entrepreneurial ability are selected out of the pool of workers and that this selection effect increases with wealth (Buera, 2009).

[11] Kaboski and Townsend (2011, 2012) test the behaviour of Thai borrowers in the analysis of the VFP and (as discussed later) show evidence for which the policy in Thailand has reduced credit constraints and generated some of the effects predicted by this theory for consumption, but not much on the investment side, particularly at the beginning of the program.

[12] An exception is Kaboski and Townsend (2011) which adds indivisible investments in the evaluation of access to credit, and estimate the model through a structural equation. They model a lumpy investment which captures the portfolio decision between a liquid asset and a riskier illiquid asset (Kaboski and Townsend, 2011). Note that, at time of writing, no research was found in the finance literature to directly model migration as an investment outcome, conceivably due to the complexity of contemporaneously modelling investment portfolio decisions, endogenous income generation and other risk diversification strategies. This task goes beyond the scope of this study.

3.2.1 Deriving some channels of influence of borrowing on migration

Two questions remain open to debate. Is internal migration a credit-constrained decision? What are the consequences of borrowing on the decision to migrate if credit availability increases? To answer these questions, this study takes an empirical stand to the evaluation of the interaction between credit and migration. This comes with the benefit of flexibility in the empirical strategy, but at the cost of not having a more general theoretical framework from which to derive testable propositions. Still, it is possible to rely on both the migration and finance literatures to generate, without loss of generality, some hypotheses on the direction of causality helping guide the empirical work proposed here.

The view of internal migration applied is of a strategy to be evaluated in relation to a host of factors included in the portfolio of multi-local and multi-sectoral household activities (Stark, 1991). Borrowing may encourage diversified use of money at one's disposal (Lipton, 1976) and it may alter risk-coping strategies (Rosenzweig, 1988). Thus, multiple mechanisms could be at play in the interaction of borrowing and migration.

First, credit constraints could play a role in this decision. On the one hand, credit constraints may prevent households from paying up-front costs of migration, in which case a positive credit-induced shock should increase migration. On the other hand, if internal migration is not credit-constrained, borrowing could still affect migration indirectly along other investment dimensions of the household portfolio decision (such as business start-up or investment in liquid and illiquid assets), thus altering the opportunity costs of a member leaving the village. The hypothesised direction of influence is thus ambiguous: it could either be null (migration is independent of borrowing) or negative (the opportunity cost of migration increases). These potential mechanisms of influence are referred to here as the economic channel of borrowing.

Second, the presence of different credit institutions may have an impact on the choice of borrowing and, according to the type of contract available, on the use that is made of credit (Banerjee, 2013; Fischer, 2013). This is referred to as the institutional channel of borrowing. The presence of a new institution may influence the way in which households borrow, accumulate and use their stocks. Thus, the institutional attachment and frequency of borrowing may influence how they deal with outside options such as migration. However, this channel may be confounded by some intrinsic characteristics which define who will decide to borrow (Banerjee et al., 2015). Acknowledging that this latter mechanism is complex to discern, the results will consider the complementary channels proposed in affecting the decision to migrate.

The present study identifies a specific formal borrowing decision, it tests empirically if migration is credit constrained and how this financing tool influences internal migration, trying to disentangle the complementary role of the economic and institutional mechanisms over time.

On the economic channels of borrowing, very few studies directly investigate the financing costs and credit constraints of internal migration. Bryan et al. (2014) use a randomised experiment in a famine-prone region of Bangladesh to give grants or credit contracts to finance transportation cost of migration. They find that treated individuals migrate seasonally to urban areas and that households given the incentive are likely to migrate more in the future. The authors confirm empirically that households perceive migration to be risky and that, especially for households close to subsistence, migration is credit constrained.[13]

On the institutional channels, the applied literature on the role of credit institutions and their effects on internal migration is mixed. Khandker et al. (2012) report that seasonal migration in Bangladesh is deterred when there is access to microcredit institutions in a village, whereas Demont (2014) shows that for India, in the presence of an adverse climatic shock, having access to borrowing through savings groups induces households to migrate, especially those with small landholdings. The identification strategy proposed here addresses the endogeneity of selection into borrowing and the presence of credit institutions, which has not been previously addressed. For Thailand, Khun and Chamratrithirong (2011) evaluate the effect of the VFP on out-migration in Kanchanburi province, using multivariate analysis for the year 2003-2004. The authors find that credit reduces an individual's likelihood to migrate. A shortcoming of their investigation is that it cannot portray the hypothesised behavioural change with the VFP introduction. The present work improves on their contribution by using longit-

[13] Bryan et al. (2014) additionally applied an insurance treatment against climatic shocks for the loan repayment, and they evaluated the propensity to migrate for different groups with previous migration experience or with induced one. They show that risk plays a big role in driving migration, as the treated groups with previous migration experience were more likely to migrate in response to the intervention (Bryan et al., 2014).

udinal data over a broader time period and geographic coverage, identifying the extent to which the migration behaviour changes.

Further relevant insights also come from the program evaluation literature. Migration studies have focused on the role of social protection programs on migration, such as non-contributory pension schemes, cash transfers or employment guarantee schemes (e.g. Angelucci 2015, Ardington et al. 2009, Imbert and Papp 2016).[14] The effects vary according to the type of migration and are generally evaluated during a short time period post policy introduction. For example, Imbert and Papp (2016) show that the introduction of an employment guarantee scheme in India reduces internal migration, whereas the cash-transfer literature for Mexico shows mixed evidence on the impact on international migration while no impacts on internal migration.[15] A challenging task is to evaluate the effects of a scheme when this is non-random in assignment and universal in coverage, like the one investigated here. Given the long time period available after the policy implementation, the present study feeds into the evaluation literature by identifying a temporal dynamic to the absorption of positive shocks induced by policies. It complements those studies interested in long-term effects (Banerjee et al., 2015; Attanasio et al., 2017) by identifying the differences in rural households' behaviour over time on two decisions which are embedded with a high degree of risk in their outcomes.

3.3 The Village Fund Program

Thailand has had a longstanding commitment to enhance rural households' access to credit (Siamwalla et al., 1990). Borrowing in Thailand generally involves individual or joint-liability loans from either credit institutions, such as the Bank of Agriculture and

[14] Theoretical contributions of the program evaluation literature generally model migration as a household decision. For example, Angelucci (2012) models the effect of conditional and unconditional cash transfer programs related to schooling on migration, portraying a positive income effect that could be caused by both policy instruments in terms of human capital formation.

[15] Stecklov et al. (2005) finds that the programme PROGRESA reduced international migration to the US, whereas Angelucci (2015) finds in the evaluation of the programme *Oportunidades* that financial constraints are binding, as receiving the transfer increased international migration. Both studies find no effect for domestic migration, suggesting that for Mexico internal migration is an unconstrained investment.

Agricultural Cooperatives (BAAC), or from MFIs, such as production credit groups or targeted women's groups. These MFIs have been found to provide efficient means of financial intermediation (Ahlin and Townsend, 2007; Kaboski and Townsend, 2005). At the same time, informal sources of borrowing such as moneylenders or kin and friend networks continue to be used, especially when access to formal sources is constrained by the size of the loan needed or by the collaterals required by formal institutions (Coleman, 2006; Kinnan and Townsend, 2012; Kislat, 2015).

In 2001, the VFP was enacted with the objective of alleviating poverty by allowing more short-term credit to be available in rural areas. The injection of capital was substantial, totalling around US$1.8 billion (75 billion Baht) or 1.5 percent of Thai GDP in 2001 (de la Huerta, 2011). The policy was implemented rapidly after its announcement in February 2001, with the first set of funds provided as early as July 2001.[16] Given the country-wide coverage, it became complementary to other popular sources of short-term credit. The same amount of money was injected across villages with different population size, introducing heterogeneity in the level of credit available to rural and semi-urban areas at the same time.

The programme was managed in each village by a committee composed of 10-15 village members. Each VFP committee at the start of the programme opened a bank account with the BAAC. The committee received the lump-sum of one million Baht and disbursed short-term credit. Most committees followed a set of guidelines determined by the government in disbursing credit, but as these were not binding, some variation in the loan requirements emerged across villages (Menkhoff and Rungruxsirivorn, 2011). Applicants are eligible if aged 20 years and above and if they are village residents for at least two years. Once the loan application is accepted, the potential borrowers are required to become members of the VFP and open an account with an accredited institution to receive the loan (BAAC or Government Savings Bank). No collateral is required, but several village funds ask for two guarantors that are not family members. Thus, the scheme has very simple eligibility criteria to allow financial participation. Generally, each loan transaction is smaller than US$450 (20,000 Baht) with a max-

[16]Note that in the data, the scheme introduction is visible since 2002, as the survey enumeration for 2001 happened prior to July 2001.

imum duration of twelve months (de la Huerta, 2011).[17] The national average loan size from the Fund was $9,000-10,000$ Baht (US$203 – 225), equivalent to the price of a water buffalo, a common type of investment in Thai agriculture. The policy did not specify a specific interest rate to apply and only required it to be positive (nominal average at 7%, not higher than the interest on other individual loans).[18]

There have been several studies of the effects of the Village Fund. Kaboski and Townsend (2012) analyse the VFP intervention and find rising borrowing levels from other sources, short term increases in consumption and income growth. They find the strongest effect on consumption, and not only for those expenses on luxury goods. For the medium term, they find that households perceived this programme as long lasting. Credit increased, while the consumption and income effects dissipated after the first few years of funding. Comparing their findings to the theory, the authors suggest that the transitory increase in consumption follows a buffer stock savings dynamics in response to relaxed borrowing constraints (Kaboski and Townsend, 2012). Boonperm et al. (2013) conduct a similar analysis at national level, finding that expenditure increased especially at the bottom of the income distribution. Comparing VFP borrowing with loans taken from another formal credit institution (the BAAC), the authors find that having access to both enables households to have higher expenditure per capita. A similar outcome to both studies is that, no effects were found few years after policy introduction on investment start-up (Kaboski and Townsend, 2012; Boonperm et al., 2013). Both attribute these affects to the short-term nature of the loans that does not allow borrowers to engage in more remunerative activities (other than farming inputs (Boonperm et al., 2013) or frequency of agricultural activity (Kaboski and Townsend, 2012)).

The VFP studies further show that the scheme decreased households' credit constraints (Kaboski and Townsend (2011) with a structural model of consumption, Kaboski and Townsend (2012) and Boonperm et al. (2013) with a reduced form of borrowing from other sources). Moreover, no substitution of VFP is found with other types of

[17] Although the upper limit is of $50,000$ Baht (US$$1,125$) with higher values provided in the case of an emergency (de la Huerta, 2011). See Appendix A.1 Graph A.1 (p.55) for a graph of credit size over the income distribution of the sample under analysis.

[18] Additionally, the scheme does not impose rules of practice on the savings behaviour of participants to the programme, which is left to the single committees to decide. de la Huerta (2011) reports that around 61 percent of Village Fund committees from rural areas have a compulsory savings scheme.

borrowing (Kislat and Menkhoff, 2012). On the contrary, there was an increase in other types of formal credit transactions and little or no effect on default and the use of informal credit (Kaboski and Townsend, 2012). The effects found in the literature assist in the interpretation of the results of this study on migration. They suggest that the policy generated a *positive* credit availability shock.

3.4 Data and Summary Statistics

The data are obtained from two on-going household and village headmen panel surveys run by the Townsend Thai Data Project (TTDP) (Townsend et al., 1997; Townsend, 2012, 2013). Starting in 1997, these longitudinal surveys cover 64 villages in four provinces: two relatively richer in the central region, Chanchoengsao and Lop Buri, and two in the poorer Northeastern region, Buriram and Sisaket.[19] The survey instruments were designed to reflect theories on occupational choice and input financing under constraints, private information and incentives, and financial expansion (Paulson and Townsend, 2004). This unique aspect of the data allows a detailed analysis of households' financial behaviour. The household survey includes information about financial activity of the household and characteristics of migrants that are pivotal for this study. Additionally, the village headmen surveys provide data on village size.

The survey follows a sample of 960 households surveyed annually for 15 years (from 1997 to 2011 inclusive). The analysis covers the period 1998-2007. It excludes the year 1997 to avoid confounding effects arising from the Asian financial crisis which impacted Thailand and the migration flows towards the Bangkok metropolitan area (Pholphirul, 2012). The analysis also stops in the years after 2007 to avoid conflating results with the global food price crisis or the financial crisis. During this 1998-2007 period, there are information on 751 households used as a balanced panel for this analysis. In order to ensure that the estimates are not affected by this time-period choice, the use of longer panels is also investigated to assess the robustness of the estimation. Given the timing

[19]The data is not nationally representative, but solely covers rural and semi-urban areas of the country. The sampling strategy of the TTDP survey accounts for income differentials among provinces (*changwats*) and ecologically balanced characteristics among sub-counties (*tambons*) such as forested against non forested areas, to then leave the choice of villages and households at random, see Binford et al. (2004) for a detailed explanation of the sampling strategy. Townsend (2016) also offers a summary of the TTDP and a review on the research performed by the author using these data.

of the policy, it is possible to perform a short term analysis (from 1998 up to 2003) and a medium term analysis (1998-2007). The unit of observation is the household and the individual-level modules of the questionnaire are used to obtain migrant-specific and demographic characteristics.

A set of potential caveats concerning the dataset need to be clarified. As any longitudinal survey, sample selection may occur if there is no tracking of households that drop out. This potential bias is tempered by the fact that the drop out rate is small throughout the years. The attrition rate visible in the data is low (less than 3 percent per year), and in this work a set of robustness are applied to the balanced panel of households used in order to ensure that no bias is generated. Secondly, an ageing effect is seen in the data and this may bias the results towards zero. The trade-off is between seeing the life-cycle of a household over ten years or having greater statistical power with a smaller time period. It is reassuring that basic life-cycle events do occur in the households under analysis – i.e. that household head dies and its siblings take over the household. Additionally, the data on internal migration are in line with nationally representative data which show a reduction in migration over the 2000s (Sondergaard et al., 2016).

A household is defined to have an internal migrant if at least one member aged 15 years or older migrated outside the province of origin for more than a six-months period in the twelve months prior to the survey. Moreover, if an individual is a construction worker outside the province of origin, this is labelled as seasonal migration. The definition has geographic and age restrictions which capture an internal migration decision that induces direct costs, such as transportation, accommodation and ancillary costs at destination. It excludes forms of commuting to near villages or sub-districts. International migration is also excluded as this is seldom reported and is considered to be motivated by different factors.[20]

[20]Other longitudinal surveys for Thailand find similar trends, see for example Junge et al. (2015).

Table 3.1: Summary statistics for pooled sample, selected years and for migrant households (subsample). 1998-2007.

	Mean	SD	Cross SD	Obs
Main dependent and explanatory variables				
Has a migrant member	0.19	–	–	7,510
VFP borrowers	0.36			7,510
VFP loan size	6,013	9,539	8,059	7,510
Village size	172.5	314.0	67.6	7,510
VFP Borrower (since 2002)	0.60			4,506
VFP loan (since 2002)	9,981	10,559	6,317	4,506
Has a migrant (short term)	0.19			4,506
VFP borrowers (short term)	0.20			4,506
VFP loan size (short term)	3,422	7,859	7,113	4,506
Migrant characteristics				
N migrants	1.26	0.53	0.40	1,400
Male migrant	0.47	–	–	1,400
Now residing in Bangkok	0.43	–	–	1,400
Seasonal	0.16	–	–	1,400
Migrant province of origin				
Chachoengsao	0.17	–	–	1,400
Buriram	0.36	–	–	1,400
Lop Buri	0.12	–	–	1,400
Sisaket	0.35	–	–	1,400
Migrant Households' economic traits				
Net Income	106,899	266,112	128,829	1,400
VFP borrower	0.41	–	–	1,400
Average VFP Loan	6,474	9,055	6,152	1,400
Extended family	0.69	–	–	1,400
Average Kin Transfers	13,750	41,762	23,397	1,400
Reasons to migrate (subsample)*				
Work	0.76	–	–	682
Education	0.15	–	–	682
Family	0.15	–	–	682
Marriage	0.06	–	–	682

Note: Pooled data from a balanced panel of 751 households over the full sample (1998-2007, 7510 obs.), restricted to data since year 2002 (4506 obs.), or to data for the short term analysis (years 1998-2003, 4506 obs.) or to migrant households (1400 obs.). Variables in levels have both SD and cross-sectional SD, the remaining are proportions. Monetary variables are expressed in Baht and deflated by the CPI (base year 2001). The 2001 exchange rate is of 44.43 Baht per US$. *Reasons to migrate (682 obs.): a subsample of migrant-households reported qualitative information on the reasons for migrating. The shares do not add up to 1 as multiple answers were given per household.

Table 3.1 shows that 19 per cent of the households report a member that migrated in the twelve months prior to the survey. The households have one migrant at the time, among which 47 per cent are men. There is a geographic component that is noticeable in the data. More migrants leave the north-eastern region (Buriram and Sisaket provinces), which is poorer than other regions in the country and has high levels of agricultural activity.[21]

Furthermore, 43 per cent of households have migrants moving to Bangkok, a characteristic consistent with studies at national level that report high migration flows towards the greater Bangkok area (for example, see Pholphirul 2012). Among the households with migrants, 16 per cent report seasonal migrants. Since 1999 the survey asks through an open-ended question about the reasons for migration, and 76 per cent of a subsample of qualitative responses reported labour migration as the reason. If a member is reported migrating for schooling reason (15 percent of the subsample of non-missing responses), the household is flagged as educational migrant (7 percent of the overall migrant household sample). As the motives of seasonal or educational migration may differ, robustness of the main definition will be probed.[22]

Borrowing from the Village Fund is defined as total short-term borrowing, loans with duration of up to twelve months, which are taken no more than twelve months prior to the survey.[23] This definition is reflective of short-term credit in micro-finance programs, besides being the most frequent type of VFP transaction. The VFP variable is by definition subject to truncation at zero for the observations prior to 2002 (four years) and for 40 percent of the sample post 2001.[24] On average, since the policy was introduced (2002), 60 percent of the panel borrows from the VFP with an average loan

[21] For further evidence on the regional characteristics of Thai internal migration see Guest et al. (1994) and for more recent trends IOM (2011).

[22] The open-ended question on the purpose of migration is coded into four dimension: labour, schooling, family, marriage. As there may be some margins of error in the coding of this variable the data of the main specification are not trimmed of the schooling-migration observations. Robustness is performed excluding this category to ensure stability of the results. See Appendix A (p. 51) for further details on the definition of the outcome variable.

[23] Note that the VFP scheme introduction is visible in the data since year 2002, as the 2001 survey was collected in May, prior to the start of the injection of funds in July 2001.

[24] Looking at the pooled data, as shown in Table 3.1, there is 64 percent zero-reporting over the full sample, either because the policy did not exist before or because of no borrowing. As it will become clearer in the next section, this feature requires some critical thinking on the most reliable identification strategy to apply. Using a model which would deal with truncation but be subject to mis-specification could invalidate the main relationship of interest, that is why it will be argued that it is more feasible to handle this variable with an instrument which would account both for the introduction of the policy and for the selection into borrowing.

of 225 US$, sizeable as 10 percent of household net yearly income. In addition, Figure A.1 (Appendix A.1, p.55) reveals that the take-up was fairly smooth across the income distribution. Due to the simple rules of eligibility described earlier, the variable acts as proxy for formal short-term credit.

Table 3.2 (Panel A) shows that VFP borrowers are dissimilar in terms of demographic and financial traits but similar in income measures to non-borrowers. Borrowers have both a greater household size and a larger number of migrants. They have a greater proportion of male heads of household, which are more involved in agriculture, and have a slightly higher level of education than non-borrowers. Borrowers have similar average net income and assets stock to non-borrowers. However, borrowers exhibit a higher coefficient of variation, possibly suggesting they experience greater fluctuations in the outcomes of their economic activity, whereas land holdings are greater on average for non-borrowers. In terms of financial activity, VFP borrowers have a greater total borrowing from other sources, congruent with the description for north-eastern Thailand by Kislat and Menkhoff (2012), which is confirmed by a lower rate of late repayment.

Borrowing from the programme is frequent across the panel (repeated borrowing happens in 98 percent of the cases), with more than half of the VFP participants borrowing every year since 2002 (Table 3.2 Panel B). Panel C suggests that continuous borrowers, compared to those who borrow less frequently, have similar income and wealth status, live in significantly smaller villages and borrow more from both VFP as well as other institutions. Prior to the introduction of VFP, continuous borrowers raised more in loans from other formal credit institutions, suggesting that these households could have superior understanding of credit institutions and their use. The extent of this difference in behaviour will be considered in more detail in the empirical analysis.

Table 3.2: Summary statistics for VFP and non VFP borrowers and by type of VFP borrower (2002-2007).

Panel A	Non VFP				VFP				t / χ^2
	Mean	StDev	crossStDev	Obs.	Mean	StDev	crossStDev	Obs.	Tests
Migrant	0.18	–	–	1,812	0.21	–	–	2,694	0.02
Head is male	0.66	–	–	1,812	0.72	-	–	2,694	0.00
Head in Agriculture	0.49	–	–	1,812	0.57	–	–	2,694	0.00
Head education	4.08	3.18	0.60	1,812	4.28	2.59	0.93	2,694	0.02
Net Income	111,891	180,997	104,376	1,812	109,469	167,270	105,039	2,694	0.64
Assets Stock	100,631	332,897	251,648	1,812	92,432	167,553	70,762	2,694	0.28
Land stock	668,692	1,448,348	974,275	1,812	513,989	829,813	534,816	2,694	0.00
Informal loans	6,489	44,397	33,803	1,812	10,209	52,402	42,144	2,694	0.01
BAAC	9,085	26,528	17,695	1,812	18,879	44,138	29,544	2,694	0.00
Other formal loan	12,444	37,948	28,641	1,812	24,179	49,041	33,818	2,694	0.00
Late repayment[a]	0.22	–	–	975	0.16	–	–	2,683	0.00
" In Formal loans[a]	0.15	–	–	975	0.11	–	–	2,683	0.00
" In Informal loans[a]	0.04	–	–	975	0.04	–	–	2,683	0.80
Kinship Transfers	12,264	29,416	21,141	1,812	12,223	29,502	20,243	2,694	0.96
Village Size	239.65	465.28	76.98	1,812	129.27	164.32	33.46	2,694	0.00
Village Size (2002)	241.38	480.58	–	1,812	124.25	158.92	–	2,694	0.00
Panel B	**Frequency of VFP borrowing**								
2times	0.03	–	–	2,694					
3-4times	0.17	–	–	2,694					
5times	0.24	–	–	2,694					
6times	0.54	–	–	2,694					
Panel C	**Repeated VFP**				**Continuous VFP**				t / χ^2
	Mean	StDev	crossStDev	Obs.	Mean	StDev	crossStDev	Obs.	Tests
Migrant	0.21	–	–	1,842	0.21	–	–	1,464	0.93
Net Income	103,223	143,401	100,826	1,842	111,801	177,590	113,801	1,464	0.12
Assets Stock	90,847	196,040	88,322	1,842	91,682	134,180	70,099	1,464	0.89
VFP loan size	10,378	10,758	8,504	1,842	17,375	7,828	5,220	1,464	0.00
Other formal loan	19,112	48,046	33,977	1,842	26,119	44,317	30,827	1,464	0.00
" (pre 2002)	14,744	35,925	27,035	1,228	19,415	38,010	27,685	976	0.00
Village Size	144.55	217.36	43.82	1,842	115.72	63.57	22.28	1,464	0.00
Kinship Transfers	13,174	33,483	25,997	1,842	10,861	21,862	13,677	1,464	0.02
Out Transfers	1,971	10,573	8,382	1,842	2,199	12,679	10,814	1,464	0.57
Groups				307				244	

Note: Pooled sample 2002-2007 (unless specified in table). The table shows mean, standard deviation (StDev) and cross-sectional StDev (CrossStDev). P-value for tests across groups: T-test with equal or unequal variance for levels, χ^2 for binary variables. Panel A compares Non-VFP to VFP households; Panel B shows the frequency of borrowing to the program; Panel C compares VFP repeated borrowers (excluding the 2 percent of single-borrowers) to continuous borrowers (those borrowing for six years). Monetary variables are expressed in Baht and deflated by the CPI (base year 2001). The 2001 exchange rate is of 44.43 Baht per US$. [a] Loans late repayment (not paid by due date) refer to short-term credit, are calculated conditional on having made a transaction in the last twelve months.

It should be emphasised that this study does not look at other formal credit institutions as these generally impose stricter rules of eligibility and do not have the same complete geographic coverage of the VFP. A broader definition of formal credit may limit the analysis if there is endogeneity in the location of institutions (Coleman, 2006). For example, confounding effects would occur in the empirics if some areas have a specific type of institution that closes down over time or never existed. Focusing the analysis on a country-wide microcredit scheme ensures that each village is covered and that the eligibility criteria do not constrain the application for loans.

3.5 Identification Strategy

The identification strategy relies on a panel Two Stage Least Squares (2SLS) of migration on Village Fund borrowing. It applies a Linear Probability Model (LPM) for migration with instrumentation of borrowing. The identification strategy is devised to address issues of selection of borrowers into credit arrangements. Further, it accounts for unobserved heterogeneity affecting both the use of credit and migration, and potential measurement error in VFP which could bias the estimates.

The LPM with instrumentation aims to use the exogenous flows of credit made available by the scheme to obtain an estimate of the average impact of the borrowing decision on migration, without incurring in more complex modelling whose misspecification could lead to biased results. The use of a LPM to define the interaction of migration and borrowing comes at the cost of allowing for estimated probabilities which may not be bounded to the $[0, 1]$ interval (investigated in the results section). Moreover, the LPM is inherently heteroscedastic, but it can be corrected by weighting and/or allowing for heteroscedasticity-consistent standard errors. Its benefit is to avoid the non-trivial incidental parameter problem when using fixed effects in non-linear response models (see for a discussion Greene 2004).[25]

In the first stage regression, Equation (3.1), the stock of short-term VFP credit is estimated using the inverse number of households per village at the start of the policy ($invVsize_{v,t=2002}$, where the subscript is removed for brevity). This variable is interacted with a vector of post-programme year dummies (D_{t^*}), providing the set of identifying instruments. The first stage is defined as:

$$VFP_{it} = \alpha_0 + \alpha_1 invVsize * D_{t^*} + \alpha_2 X_{it} + \psi_i + \psi_t + \nu_{it} \tag{3.1}$$

where D_{t^*} stands for either the two post-programme year dummies, 2002 and 2003

[25] Additionally, the 2SLS estimator is preferred to alternative methods, such as a control function method. If a control function was used to model the zeros of the credit variable, a misspecified error term due to the nature of the borrowing variable in the first stage could make the estimator inconsistent in the second stage. As OLS is more robust than non-linear response models to mis-measurement in the dependent variable (Hausman, 2001), it seems the more confident choice of estimator.

for the short-term analysis, or the full set of six year dummies for the medium term analysis up to 2007. The vector X comprises household-level controls (described below), ψ_t and ψ_i are time and household fixed effects. In order to ensure the validity of the instruments in Equation (3.1), the variation in size and any trend in migration according to village size are discussed in Section 3.5.1 below. In the primary regression of interest, Equation (3.2), the outcome for migration (mig_{it}) is regressed on the instrumented Village Fund borrowing ($\widehat{VFP}_{it}$):

$$mig_{it} = \beta_0 + \beta_1 \widehat{VFP}_{it} + \beta_2 X_{it} + \lambda_i + \lambda_t + \varepsilon_{it} \tag{3.2}$$

The vector of controls (X) includes characteristics of the head of household, such as age and its quadratic, education, gender and a binary variable capturing whether the head's primary occupation is in agriculture. Demographic information is provided by the number of adult men, women and the number of children in the household. A variable for the stock of wealth accumulated by the household is included to control for heterogeneous selection into migration according to wealth status (McKenzie and Rapoport, 2010). This is defined as items or land purchased more than twelve months prior to each survey wave in order to avoid double-counting with the credit variable.[26] Lastly, λ_i and λ_t are household and time fixed effects (see Appendix A, p.51 for further explanation of the variables' construction). All monetary measures are deflated by a Consumer Price Index (CPI) constructed at province level and are expressed in $10,000$ Baht in the estimations in order to convey a comparable measure of one loan taken from the Fund. To ensure the consistency of the estimator applied, a comparison with Ordinary Least Squares (OLS) (with endogenous borrowing) and 2SLS model without fixed effects (including province dummies) are reported. The panel 2SLS estimates are preferred to account for borrowing decision and to control for any time-invariant characteristics at household level, such as ethnicity or religion, that could strongly

[26] Wealth stock is constructed using history on asset ownership collected at baseline (Townsend et al., 1997) and depreciated yearly by 10 percent. It is used to account for non linearities in migration choice (McKenzie and Rapoport, 2010) and for potential past borrowing behaviour (Ahlin and Townsend, 2007). According to Ahlin and Townsend (2007) which investigate for Thailand on borrowing behaviour from the BAAC, borrowers make greater use of joint liability contracts than individual contracts, and their use exhibits a U-shaped relationship with the wealth of the borrowing household, increasing with wealth dispersion. However, as wealth accumulation may be done in preparation for future migration, a preliminary analysis excludes the wealth stock variable, ensuring that it does not change any outcome found (not shown).

influence migration. All estimates are performed with clustering of the errors at village level. The empirical model is a stylised representation of the influence of borrowing on migration. The credit effects hypothesised in Section 3.2.1 suggested that migration decision may vary with the direct use made of loans (the economic channel) and the interaction of borrowers with a new credit institution (the institutional channel). The interpretation of the empirical results consider these two complementary channels likely to affect migration decisions.

3.5.1 Instrumenting borrowing

As noted earlier, the identifying instruments consist of the interactions between the inverse number of households living in each surveyed village in 2002 when the policy started ($invVsize$), and a set of dummies for each post-introduction year. The instruments represent the perception that each household had towards the availability of VFP loans in each village since credit was injected. This identification strategy owes its intellectual origins to Kaboski and Townsend (2012) who, using the same data, constructed the instruments for the first two years of the policy as used here for the short term analysis. For the medium term, the analysis uses the interactions from every post-programme year, thus providing six identifying instruments (2002–2007).

The heterogeneity of credit availability at village level is confirmed by the fact that VFP borrowers reside on average in smaller villages (last rows of Table 3.2, Panel A). Yet, any sudden change in size over time could compromise the instrumentation and affect migration. Village size variation in this dataset is fairly small, mostly between 50 and 250 households (172.5 on average).[27] Heterogeneity in size across villages arises from the administrative, environmental and infrastructural nature of the areas. The data do not show substantial variation in size over time, nor are they subject to sharp changes due, for example, to boundary modifications.[28]

[27]In the distribution of villages in 2002, two villages have size of 30 and 34 households, and other seven have a size comprised between 268 and 3,194 households, with the bigger ones considered as semi-urban. In the robustness of the main specification, the presence of village outliers will be the subject of further investigation.

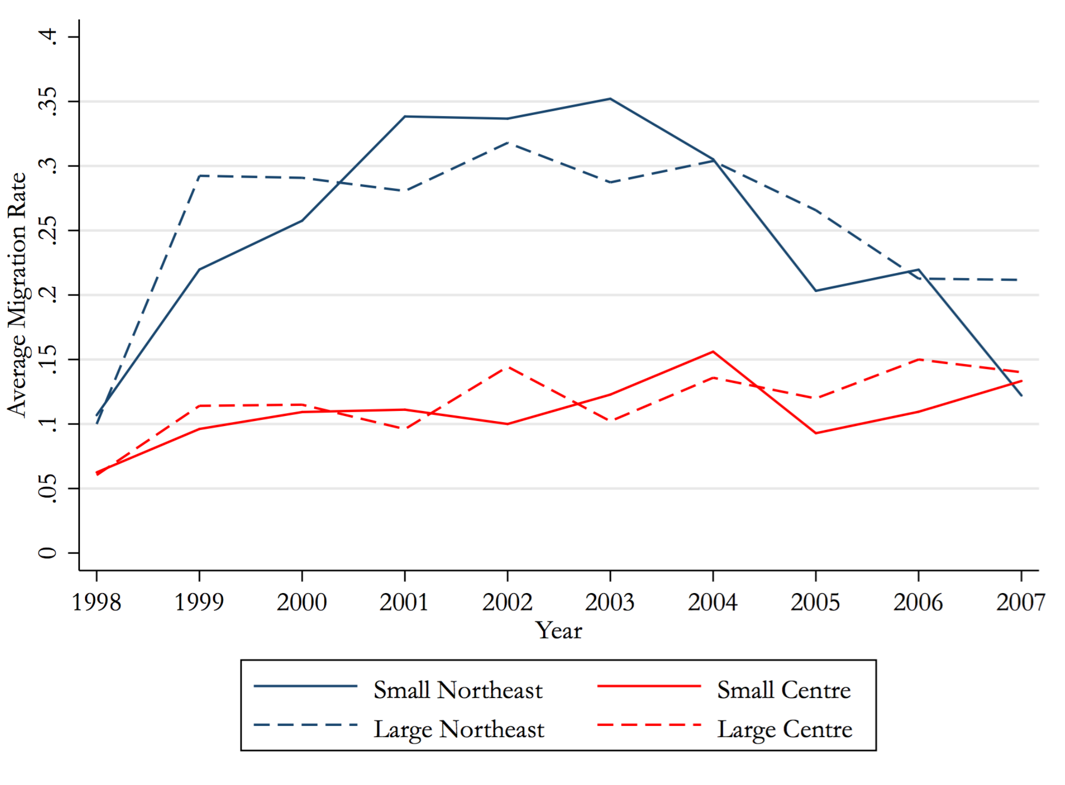
[28]To address the issue that villages may be divided and redistricted over time, official figures for the period are unavailable to the author. This should not be a major concern because, as Kaboski and Townsend (2012) report, between 2002 and 2007 the number of villages increased by 3 per cent, whereas from 1960 by 50 per cent.

A threat to identification would arise if village size growth is correlated with differential paces in local development. Then, trends in village size could lead to differing pressures to migrate and thus induce bias in the estimation. This concern is addressed through a preliminary analysis including the yearly village size as a control (Table A.6, available in Appendix A.2, p.62). This exercise reveals that yearly village size does not correlate with the migration decision nor invalidate the 2SLS instrumentation.

A further concern is that, due to small or fragmented labour markets, individuals living in smaller villages would tend to migrate more. If this were the case, the inverse number of households would not be exogenous in the current setting. Figure 3.1 graphically assesses if there are any trends in migration rates by village size at origin. As there is a geographic element to migration (more individuals migrate from the northeast), the data are split between geographic regions. The figure reveals that no trend is generated by the size of the village. This is further corroborated by the lack of a statistically significant difference among migrant and non-migrant households residing in small villages (Table A.1 in Appendix A,p.53). Thus, it appears that the economic performance of the region of origin has a major role in driving migration rather than the size of the village.

As size does not change radically over time and no trend is seen in migration according to village size, there appear good grounds for the external validity of the instruments. The knowledge that the household has about the number of families with whom they live in year 2002 (when the policy was introduced) should not be a main reason for migration. Moreover, a comparison with the wellbeing of others rather than the number of households residing in the area is a more likely driver of migration decision.

Figure 3.1: Migration Rate by Region and Village Size (1998-2007).



Notes: The figure displays average migration rate by region and village size. Small and large villages are defined according to the median size = 109 households. Northeast stands for Northeastern region (Sisaket and Buriram); Centre stands for Central region (Lop Buri and Chanchoengsao).

In line with Stark and Taylor (1991) relative deprivation theory, if the household feels economically or socially constrained, this will be based on a recent record of opportunities, social and economic events experienced. This view suggests that migration may be triggered by social and economic inequality as perceived by a reference group. The household constructs its reference point, understands its position relative to others in the village and thus decides whether or not to have a member migrating in order to reduce the level of deprivation perceived (Stark and Taylor, 1991). This view of migration choice suggests that it is the socioeconomic status, rather than the size of the village at the start of the policy, that may induce individuals to migrate.

3.6 Results

The following subsection reports the main regression analysis of migration on Village Fund borrowing, followed by an interpretation of the channels of borrowing in subsection 3.6.2. Subsection 3.6.3 examines the inter-temporal results found, and subsection 3.6.4 shows further robustness checks.

3.6.1 The effect of formal borrowing from the VFP

The first stage regressions for the short and medium term analyses (columns I and II of Table 3.3) suggest that the instruments strongly predict the VFP stock of credit with statistical significance at the one percent level. The scale of the introduction of the Fund reflects the size of an average loan given by the Fund. For example, on the basis of the short-term analysis (column I), the introduction of the Village Fund provided an average loan per borrower of $8,151$ Baht (US$ 184) *ceteris paribus*, implying an average total borrowing per village of $815,130$ Baht, close to the national average credit of $950,000$ Baht used per village (Kaboski and Townsend, 2012). A similar finding emerges for the instruments used in the medium term analysis (see column II). Thus, the policy instruments strongly predict the take-up of this type of credit (for the full first stage, see Table A.3 Appendix A.2, p. 59).

The primary regression of interest (second stage regression in the bottom panel of Table 3.3) evaluates the impact of the instrumented Village Fund on migration.[29] The short term analysis (column V) reveals that, at start of the policy, borrowing does not significantly reduce the decision to migrate. If a household applies for a loan to a new institution, it may require some time to get a satisfactory level of borrowing and make its use advantageous to production. Thus, the change in behaviour towards risk-diversification strategies, such as labour mobility, may only be visible well after the policy introduction.

[29]The Hansen J test of overidentifying restrictions and the weak instruments test are reported at the bottom of each table. The Hansen J test regresses the regression residuals on all instruments ($invVsize * D_{t^*}$). In all the main specifications the tests do not reject the null hypothesis that the instruments are uncorrelated with the error. Moreover, the tests for weak instruments reject the null hypothesis that the equation in both short and medium term is weakly identified. In addition to these tests, the orthogonality tests are reported in Table A.2, Appendix A.2 (p.58).

Table 3.3: The determinants of Migration: 2SLS (with or without FE) and OLS models of the impact of VFP credit (short and medium term analyses).

Model	2SLS		2SLS no FE			
Time period	Short	Medium	Short	Medium		
First stage	(I)	(II)	(III)	(IV)		
2002*inv V size	81.513***	81.420***	83.765***	83.518***		
	(9.664)	(9.695)	(9.038)	(9.125)		
2003*inv V size	68.448***	68.463***	70.866***	70.774***		
	(9.585)	(9.651)	(9.237)	(9.283)		
2004*inv V size		83.810***		86.134***		
		(5.886)		(5.286)		
2005*inv V size		61.717***		64.005***		
		(16.022)		(16.226)		
2006*inv V size		74.951***		77.159***		
		(6.563)		(5.984)		
2007*inv V size		61.590***		64.178***		
		(9.940)		(9.818)		
Controls	Yes	Yes	Yes	Yes		
Observations	4506	7510	4506	7510		
Model	2SLS		2SLS no FE		OLS	
Time period	Short	Medium	Short	Medium	Short	Medium
Second stage	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
VFP	-0.039	-0.043**	-0.029	-0.029*	0.007	-0.006
	(0.031)	(0.022)	(0.028)	(0.016)	(0.011)	(0.007)
Head is male	0.153***	0.065**	0.067***	0.058***	0.146***	0.061*
	(0.050)	(0.031)	(0.021)	(0.017)	(0.050)	(0.031)
Head age	0.046***	0.028***	0.031***	0.029***	0.042***	0.026***
	(0.011)	(0.007)	(0.006)	(0.005)	(0.011)	(0.007)
Head age sq.(/100)	-0.039***	-0.025***	-0.028***	-0.026***	-0.036***	-0.023***
	(0.009)	(0.006)	(0.005)	(0.004)	(0.009)	(0.006)
Head education	0.009	0.010*	0.003	0.005	0.008	0.009
	(0.007)	(0.006)	(0.004)	(0.003)	(0.006)	(0.006)
N of adults male	-0.161***	-0.096***	-0.037***	-0.038***	-0.161***	-0.098***
	(0.013)	(0.009)	(0.008)	(0.008)	(0.013)	(0.009)
N of adults female	-0.098***	-0.090***	-0.027***	-0.033***	-0.099***	-0.092***
	(0.019)	(0.014)	(0.009)	(0.007)	(0.019)	(0.014)
N of children	-0.009	-0.020**	-0.006	-0.010*	-0.012	-0.021**
	(0.014)	(0.010)	(0.006)	(0.005)	(0.014)	(0.010)
Head is farmer	-0.027	-0.020*	-0.018	-0.010	-0.025	-0.019
	(0.017)	(0.012)	(0.013)	(0.010)	(0.017)	(0.012)
Stock of Wealth	-0.00001	-0.00002	0.00001	0.00001	-0.00001	-0.00002
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Buriram			0.161***	0.123***		
			(0.021)	(0.019)		
Lop Buri			-0.004	-0.025		
			(0.016)	(0.015)		
Sisaket			0.152***	0.118***		
			(0.020)	(0.018)		
Constant			-0.736***	-0.637***	-0.774**	-0.347*
			(0.164)	(0.132)	(0.321)	(0.201)
Household FE	Yes	Yes	No	No	Yes	Yes
Observations	4506	7510	4506	7510	4506	7510
R^2	0.12	0.07	0.09	0.08	0.13	0.08
Kleibergen-Paap	41.96	47.96	51.74	68.05		
Hansen J	0.51	2.92	0.68	2.35		
p-value	0.48	0.71	0.41	0.80		

Note: 2SLS with or without household fixed effects and OLS, data for short (1998–2003) or medium term (1998–2007). Covariates in first stage: binary if the head is male, head's age and its squared term (deflated by *100*), head's years of education, number of adults male, female, children, binary if head primary occupation is in agriculture, stock of wealth, time dummies and either household fixed effects or province dummies. Standard errors in parentheses, clustered at village level. The VFP and stock of wealth are deflated by the CPI (base year 2001) and expressed in *10,000* Baht. The 2001 exchange rate is of 44.43 Baht per US$. Significance: * p<.10, ** p<.05, *** p<.01.

The medium term analysis over six post-programme years (column VI) reveals that accessing VFP borrowing reduces the likelihood of migration. On average, taking up a $10,000$ Baht loan induces a 4.3 percentage point reduction in the probability of a household member migrating internally. The magnitude is modest but entirely consistent with the decreasing migration trends found in the data (Figure 3.1). It implies that an almost doubling of VFP borrowing at its mean corresponds to a reduction in average migration to 14.3 percent over the sample. The negative sign of the coefficient suggests that those households that access VFP credit revise their opportunity costs in the medium term, conceivably investing or consuming their loan at home, thus being less prone to having members leave the household. Opportunity costs of leaving the village may reflect both direct and indirect changes at origin, such as favourable investments at household level and higher wages at village level (as found by Kaboski and Townsend 2012).

In order to further investigate the baseline estimates found, Table 3.3 reports the 2SLS instrumentation without household fixed effects. The results of both short and medium term (col. VII and VIII) are in line with the preferred specification (col. V and VI). Additionally, columns IX and X report the simple OLS correlation without instrumentation to investigate the direction of bias. The OLS estimates are not distinguishable from zero, due to either measurement error in borrowing or to the existence of a positive correlation with the error term due to self-selection into credit (or both). This upward bias could be suggestive that households with higher ability or entrepreneurship self-select into credit contracts.

For the consistency of a LPM, the predicted probabilities of Equation (3.2) are now investigated. They are found to lie within the $[0, 1]$ interval with exception of seven observations over the full sample (comprising four households over the panel). To ensure that removing those few observations which the model over-predicts or under-predicts does not alter the results, the LPM trimmed sample estimator by Horrace and Oaxaca (2006) is explored. Their approach is useful to reduce fears of a small finite sample bias found in the panel, and to ensure the consistency of the point estimates. The sensitivity estimation reported in Table A.4 (Appendix A.2, p. 60) shows the estimation of equation 3.2 with the data trimmed of the seven out-of-range observations, or with the complete removal of the four households with out-of-range prediction from the balanced panel. It suggests that the LPM may be used as its trimmed estimation produces the same results with a reduced sample bias.

3.6.2 Interpreting the channels of borrowing

There are both economic and institutional mechanisms at play. These reflect the effectiveness of credit in changing economic conditions and the nature of credit as an institution. Households that borrow at the start of the programme decide whether or not to send a member outside the place of origin without basing their decision on the expected benefits of borrowing. This suggests that internal migration is not a credit constrained decision in the Thai villages under analysis. This is consistent with the evidence on internal migration in Mexico about conditional cash transfers (Angelucci, 2012, 2015). The economic mechanism reveals that the opportunity costs of sending a migrant increase only within the medium term when the returns on borrowing are fully realised. Once improved access to credit is prevalent within a village, households reap the benefits of an improved capacity for income generation and change their behaviour towards migration. The results are consistent with Abramitzky et al. (2013), Imbert and Papp (2016) and with the heterogeneous effects due to a shock found in Bazzi (2017), further suggesting that credit may influence the internal migration process through its effect on household opportunity costs over time.

In light of theories on credit constrained environments, the results are in conformity with Kaboski and Townsend (2012). The authors fit a buffer stock model where in the short term consumption and current business investment are channelled through greater credit, but other aspects like new business start-up, as found by the authors, or migration investments, as found in this study, do not immediately respond to reduced credit constraints. These findings complement in qualitative terms a dynamic buffer stock model suggesting that credit generates inter-temporal effects (Fulford, 2013).[30]

[30]Fulford (2013) shows in his model that briefly after new credit is introduced, households have greater command on resources, become practically wealthier and consume more, as they do not need to delay consumption to maintain their buffer. Further, over time households do not need to keep as much wealth for self-insurance as they did before credit was introduced. This then results in lower consumption in the future and potentially some income effects leading beneficial investments to take

The institutional mechanism suggests that the riskiness and rigidity of repayment – generally embedded in formal credit – may not have initially induced borrowers to trade-off with other strategies for reducing their income risks. Yet, the increased presence of a new institution providing credit may have affected households through direct use of the scheme. The repeated borrowing behaviour identified in VFP households suggests that the VFP was used effectively to reduce households credit constraints and, as found in Kaboski and Townsend (2012), it did not translate into higher inability of repayment. If repeated borrowing is a relevant explanation for these results, a further question is whether the behaviour towards migration differs among types of borrowers.

One possibility is that continuous borrowing from the Fund may conceal unobserved traits, which are driving the results and are not controlled for by the household fixed effects. Finding an instrument for this behavioural pattern is non-trivial, hence Table A.5 (columns I-II, p.61) excludes continuous borrowers from the analysis. The findings are invariant to the exclusion of 54 percent of VFP borrowers (244 households), suggesting that a common behaviour occurs between different types of borrowers. Further, the result invites comparison with the view that spillover effects may occur within microfinance programs. Even those households not securing continuous streams of formal credit may be less likely to recourse to internal migration. This could occur because of enhanced expectations of credit availability when required. This view is supported by the findings in Kaboski and Townsend (2011) of reduced precautionary savings in response to the VFP introduction. Spillover effects may also occur because of economic improvements at village level, which could slow down those migration-inducing channels at origin (de Haas, 2010b).[31] In spite of that, spillover effects cannot be easily captured in the data, as one would require detailed information at the village level. For example, in order to see if the price of labour has increased in its attractiveness for household members with discontinued or no access to the Fund, a full list of wages in the local area should be used. Regrettably, the disaggregated data on this are unavailable

place. To the extent that it is possible to unpack some of the potential channels of influence coming from a reduced form equation, the investment on migration would be only altered in the medium term when other productive activities are there to be made.

[31] de Haas (2010b) shows that where a *meso* context (in this instance, greater credit) affects the communities at origin, agents' economic behaviour mutates over time with direct or indirect effects on income generation, explaining the declining migration trends.

since the village headmen survey of the TTDP data does not collect such information. Kaboski and Townsend (2012) show with monthly data for the two years after VFP introduction that the median village wage increased. Specifically, the wages increased for general nonagricultural work, construction in the village, but not for professional jobs or occupations performed outside of a village. The authors also note that there may be further general equilibrium effects as a result of the VFP which may be hard to measure, as the policy covered every village in Thailand which are segmented in their wage setting (Kaboski and Townsend, 2012).

Another possibility is that the continuous institutional participation of some borrowers is systematically different in its effects on internal migration. The ideal hypothesis to test would be whether high intensity of VFP use differs in affecting migration behaviour. To evaluate if continuous borrowers (54 percent of VFP households) behave differently than other households, a *naïve* extension of the model is performed, but its results are purely descriptive, as no direct instrument for continuous borrowing was found. Table A.5 columns III-V (with specification detailed in Appendix A.2) add to the two-step analysis a dichotomous variable for being continuous borrower which is interacted with borrowing as well as the instruments in the first stage. Although imprecise, the linear combination for continuous borrowers suggests that these households face a reduction in the likelihood to migrate, even if it is lower than other borrowers (2.1 percentage points reduction in migration on average). One major limitation is that this borrowing behaviour is not random and could be related to unobserved factors such as past or present levels of innate entrepreneurship, risk preference or trustworthiness. As it may not be possible to fully identify how borrowing behaviour differs, even by including a richer set of characteristics (Banerjee et al., 2015), the causal estimand may not be well defined and introducing interactions could mis-specify the model. Thus, this specification should not be considered as a causal relationship.

3.6.3 Exploring the temporal dimension of borrowing

To disentangle the economic channel of borrowing, there is interest in investigating how the observed behaviour changes over time. The temporal interaction between borrowing and the decision to migrate is thus assessed using two separate exercises.

The first involves an evaluation of the timing since initial borrowing within the panel, and the second is an extension of the years used to construct the panel.

Table 3.4: Borrowing behaviour: 2SLS Model with sample cut-off after first-time borrowing.

First stage: VFP on instruments					
Gap post take-up	1	2	3	4	5
2002*inv V size	81.911***	81.616***	81.403***	81.491***	81.362***
	(9.596)	(9.664)	(9.719)	(9.698)	(9.700)
2003*inv V size	50.971***	68.810***	68.607***	68.575***	68.330***
	(12.596)	(9.618)	(9.672)	(9.635)	(9.656)
2004*inv V size	41.206***	60.429***	83.967***	83.893***	83.674***
	(6.770)	(10.981)	(5.845)	(5.834)	(5.856)
2005*inv V size	31.564***	45.503***	63.722***	61.762***	61.556***
	(7.803)	(9.114)	(13.076)	(15.982)	(16.004)
2006*inv V size	42.121***	53.350***	72.114***	79.742***	74.835***
	(10.678)	(12.895)	(13.155)	(9.383)	(6.531)
2007*inv V size	35.943***	47.614***	58.384***	68.859***	72.651***
	(7.234)	(8.266)	(10.381)	(13.621)	(21.245)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	4848	5425	5990	6534	7052
Second stage: migration on VFP credit					
Gap post take-up	1	2	3	4	5
1 year after VFP	-0.038				
	(0.028)				
2 years after VFP		-0.039			
		(0.030)			
3 years after VFP			-0.047*		
			(0.025)		
4 years after VFP				-0.045*	
				(0.024)	
5 years after VFP					-0.043*
					(0.022)
Head is male	0.118**	0.101**	0.092**	0.079**	0.070**
	(0.050)	(0.044)	(0.040)	(0.038)	(0.035)
Head age	0.046***	0.044***	0.038***	0.035***	0.032***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)
Head age sq.	-0.040***	-0.039***	-0.033***	-0.030***	-0.028***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Head education	0.008	0.009	0.008	0.005	0.006
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
N of adults male	-0.130***	-0.127***	-0.121***	-0.116***	-0.108***
	(0.015)	(0.013)	(0.011)	(0.010)	(0.009)
N of adults female	-0.111***	-0.100***	-0.095***	-0.095***	-0.095***
	(0.016)	(0.017)	(0.017)	(0.016)	(0.015)
N of children	-0.012	-0.010	-0.012	-0.012	-0.016
	(0.013)	(0.012)	(0.011)	(0.011)	(0.010)
Head is farmer	-0.019	-0.021	-0.025*	-0.026**	-0.020
	(0.015)	(0.016)	(0.013)	(0.013)	(0.014)
Stock of wealth	-0.00001	-0.00001	-0.00001	-0.00003	-0.00002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year dummies	Yes	Yes	Yes	Yes	Yes
Observations	4848	5425	5990	6534	7052
R^2	0.11	0.10	0.09	0.09	0.08
Kleibergen-Paap	20.76	22.00	49.99	50.60	50.82
Hansen J	7.45	2.01	1.54	1.68	2.58
p-value	0.19	0.85	0.91	0.89	0.76

* p<.10, ** p<.05, *** p<.01

Notes: TTDP data (1998-2007). Each column drops borrowers after a specific time since initial borrowing. In both stages a set of covariates is included: dummy if the head is male, head's age and its squared term (deflated by *100*), head's years of education, number of adults male, female, children, dummy if head primary occupation is in agriculture, stock of wealth, time and household fixed effects. Standard errors in parentheses, clustered at village level. All monetary variables are deflated by the CPI (base year 2001) and expressed in *10,000* Baht.

Table 3.5: Borrowing behaviour: Second stage regressions of various balanced panels (varying end-year) of migration on VFP credit

	Short	Med		Short	Med
VFP 2003	-0.023		**VFP 2008**	-0.037	-0.041**
	(0.032)			(0.031)	(0.021)
Observations	5034		Observations	4440	8140
R^2	0.13		R^2	0.12	0.07
Kleibergen-Paap	64.35		Kleibergen-Paap	41.31	41.66
VFP 2004	-0.029	-0.039	**VFP 2009**	-0.036	-0.040*
	(0.031)	(0.026)		(0.031)	(0.021)
Observations	4890	5705	Observations	4320	8640
R^2	0.13	0.11	R^2	0.12	0.07
Kleibergen-Paap	47.89	81.82	Kleibergen-Paap	37.12	36.33
VFP 2005	-0.039	-0.047*	**VFP 2010**	-0.038	-0.039*
	(0.031)	(0.024)		(0.031)	(0.021)
Observations	4752	6336	Observations	4284	9282
R^2	0.12	0.09	R^2	0.12	0.07
Kleibergen-Paap	46.51	70.64	Kleibergen-Paap	36.12	32.27
VFP 2006	-0.040	-0.043*	**VFP 2011**	-0.039	-0.039*
	(0.031)	(0.022)		(0.031)	(0.021)
Observations	4644	6966	Observations	4230	9870
R^2	0.12	0.08	R^2	0.12	0.07
Kleibergen-Paap	45.90	59.74	Kleibergen-Paap	35.87	29.88
VFP 2007	-0.039	-0.043**			
	(0.031)	(0.022)			
Observations	4506	7510			
R^2	0.12	0.07			
Kleibergen-Paap	41.96	47.96			

Notes: Each estimate is based on a balanced panel constructed between 1998 and the end period. Short-term ends in 2003. All estimates are consistent over time. Standard errors in parentheses, clustered at village level. Additional explanatory variables: household and time fixed effects, dummy if the head is male, head's age and its squared term (deflated by *100*), head's years of education, number of adults male, female, children, dummy if head primary occupation is in agriculture, stock of wealth. Hansen J test not rejected in all instances. Sig: * p<.10, ** p<.05, *** p<.01.

First, it is worth determining exactly when the households' behaviour changes after becoming borrowers. Table 3.4 modifies the sample to reflect the time since initial borrowing. In every column of the table any VFP borrowing-household is excluded after a specific period of time since the household first borrowed. This allows identifying when the behaviour changes. Retaining the sample after one or two years from initial borrowing from the Fund (Table 3.4, col. I-II), the estimated borrowing effect is found to be statistically insignificant, as found in the short term specification (Table 3.3, col. V). Only after three years from initial borrowing, does accessing credit actually reduce migration. The estimates (from col. III onwards) exhibit a magnitude between -0.047 and -0.043, similar to the medium term results. This exercise shows that there is a time-related change in behaviour that borrowing induces after credit is secured for the first time. The findings accord with Khun and Chamratrithirong (2011), and further suggest that formal credit availability does not exacerbate uncertainty in regard to income generation after initial borrowing. Only as households receive the returns to borrowing does migration reduce.

Second, there may also be concerns that the time period selected for the panel (which excludes the years from 2008 onwards) may be an inadequate time-frame within which to infer the temporal effects of the policy. In order to mitigate this concern, Table 3.5 implements the main identification strategy, but varies the end-year of the data. Each estimation uses a distinct balanced panel from the period 1998-2003 up to a 10-year window since the VFP implementation (1998-2011). The key results are robust to this variation, with the same sign and magnitude well within the range of those obtained from the medium term analysis (ranging between -0.047 and -0.039). The results suggest a persistent reducing effect of borrowing on migration.[32]

3.6.4 Instruments and estimates robustness

The changes in variable definitions are now explored to investigate the consistency of the key migration estimates (see Appendix A.3). First, the estimates are tested against variations of the first stage regression, with a number of falsification tests and the investigation of outliers (Appendix A.3.1). Moreover, some modifications in the definition of migration are performed to determine if the estimated effects of borrowing are robust (Appendix A.3.2). The section concludes with a small note on the issues of modelling other formal or informal sources of credit (Appendix A.3.3).

Attention turns first to an assessment of the validity of the instruments. In order to test the predictive power of the instruments, a set of falsification exercises are performed (Appendix A.3, pp.64–65). Table A.7 reports the first and second stage regressions of the inverse village size interacted with dummy-years prior to the programme ($D_{t^*} = 1998, 1999, 2000, 2001$). The use of these instruments does not yield any predictive power in the reduced form equation. As second falsification, the lag value of the VFP

[32]To dispel the concern that year 1998 was still an unstable economic period for the households in the analysis, the same exercise is performed with 1999 as starting year and the results are unchanged (not shown).

variable is introduced to assess if the instrument at the start of the policy predicts the VFP stock of credit prior to the programme introduction. The results in Table A.8 reveal the absence of anticipation of the policy in the data. Thus, both falsification exercises provide evidence in support of the instruments used in the analysis.

Additionally, there could be concerns that over-instrumentation is driving the results. Appendix A.3.1 reports the results with one instrument (Table A.9, p.66), showing that the results are robust to this change. Another concern might be that the presence of outliers in the distribution of the village size variable could affect instrumentation. Thus, Table A.10 excludes those households living in 2002 in villages with fewer than 50 or more than 250 households from the sample. The estimates are unchanged when the data are trimmed in this manner, a finding which is resonant with Kaboski and Townsend (2012).

Changes in variable definitions are also investigated. There could be concerns that the truncation of the VFP measure, given its use in levels form, is affecting the estimates obtained. The VFP measure comprises a significant number of limit observations (i.e., the non-borrowers) and this may have implications for the OLS estimates used to generate the predictions. Table A.11 (p. 68) changes the dependent variable used in the first stage from a continuous measure reflecting the size of the loan to a binary measure that is equal to 1 if the household obtains a loan and zero otherwise. The results are unchanged in sign. Even if the substitution of the endogenous variable as a binary choice variable would give consistent values in the first stage, it is less efficient than taking into account the non-linear nature of the credit variable in levels. Nevertheless, the results reduce concerns that the zero-inflation of the VFP measure in levels may be confounding the estimation.

Attention then turns to an assessment of whether the results vary if the definition of migrant-household changes and if the sample is restricted to reflect this change (Appendix A.3.2, pp.69–70). There may be concerns regarding the differing motives that underlie seasonal or educational migration. It should be recalled that both types of migration were part of the definition of inter-provincial migration used in the empirical analysis. Table A.12 excludes any household that declares at least once to have migrants moving for schooling reasons. Applying this restriction does not vary the results. Additionally, as the definition of migrant also includes individuals that migrate seasonally (individuals that work in construction works outside the province of origin for more than six months), Table A.13 reports a set of specifications with restricted definitions of migrant household. The results hold, alleviating concerns over differing motives for seasonal migration.

As a final remark, this application encompasses the channels through which households make use of a specific type of formal credit, without directly modelling other formal or informal sources of credit. The choice of limiting the analysis to a single credit institution is driven by the nature of borrowing which, as exemplified here through the identification of economic and institutional channels, affects households in multiple dimensions and therefore is endogenous to households' decision. As it is tedious to find suitable instruments or exogenous variation in the presence and availability of credit institutions, below a brief commentary on the matter is reported.[33]

If total borrowing from other institutions was used in addition to VFP, it would require a more sophisticated econometric modelling. Using total formal borrowing as an endogenous variable of the model proposed, would rely on the assumption that borrowing from any institution can be fully modelled as a function of the credit availability shock of VFP, thus inducing bias in the estimation. To validate this point, Table A.14 in Appendix A.3.3 (p.71) uses total formal borrowing as endogenous regressor. It shows that the instruments merely pass the relevance tests, although a significantly reducing effect of formal borrowing persists in the medium term.

Another aspect of the financial activity of Thai households, is their interaction with informal borrowing. Among the informal institutions used in Thailand, kinship transfers are found to be used for household financing (Kislat, 2015) especially when financial access is not possible due to transactions being too large to be collateralised in the credit market (Kinnan and Townsend, 2012). Kinship transfers are defined as the receipt of transfers from extended family members. As additional exercise, it would be natural to compare participation in informal institutions to the investigation of

[33]Furthermore, in order to asses if any reverse causation takes place from the decision to migrate towards borrowing, a set of *naïve* short and medium term correlations are reported in Appendix A.3.3 (p.71). Although only representing simple correlations, the results are reported for completeness.

VFP credit. A major limitation for further exploring this channel is that it has not been possible to find an instrument that passes the tests for instruments relevance, thus any estimate with this variable included should be interpreted as non causal, leaving room for future research to address how the interaction of formal and informal financial instruments affect the decision to migrate. Table A.15 (Appendix A.3.3, p.72) reports the 2SLS specification with the addition of the lag value of kin transfers, to investigate their relevance as a migration financing tool and to see if the effect of formal credit persists. Kinship transfers appear to be negatively correlated with migration solely in the short term analysis. This result holds when a second kin transfer lag is introduced, but the effect disappears in the medium term regression. This weak outcome is representative of the fact that, due to the endogeneity induced in the model, comparing the two types of credit institutions does not establish a causal relationship between the selection and credit use from the informal source, as suggested by Banerjee (2013) when the researcher is interested in comparing credit products. Although these are imprecise estimates, VFP credit consistently maintains its effect in the medium term.

3.7 Conclusions

The chapter investigates the role of borrowing on households' internal migration decision in Thailand. The introduction of the VFP is used to assess if and how migration responds to borrowing once the availability of credit increases. Borrowing is instrumented using the inverse size of the villages at the start of the policy interacted with time. These instruments reflect credit availability within each village and are shown to exert no direct effect on internal mobility out of these villages. Therefore, the number of households present at the start of the programme is used in the specification to represent households' perception of the credit available in their village.

The empirical analysis investigates the short (1998-2003) and medium term effects (1998-2007) of the credit secured through the VFP. The results suggest that borrowing does not significantly affect the migration decision in the short term but that it has a reducing effect in the medium term. On average, accessing a VFP loan reduces the probability of migration by 4.3 percentage points six years after programme introduction. These findings suggest that migration is not credit constrained and households do not trade-off between two profitable but risky outcomes immediately after credit is injected. However, once the returns to borrowing become visible and the scheme is perceived as a stable institution, the migration probability is reduced. Further estimations confirm that the frequency of borrowing is not driving the results, and that it is only within a 3-year window since first-time borrowing that the likelihood to internally migrate falls. The results are robust and invariant to changes in variables' definition, the identifying instrument set used, the exclusion of outliers and a number of falsification tests.

The economic and institutional channels of borrowing are found to affect migration over time: information costs might be attenuated, the benefits from borrowing are eventually reaped, and potential spillover effects take place in the local economy or in the expectation of potential borrowing. These changes lead borrowers to reduce their use of this risk-diversification strategy. The results are consistent with the reduced form results from Kaboski and Townsend (2012) and show an inter-temporal effect that credit may generate on migration, analogous to the dynamic buffer stock savings model of Fulford (2013).

Notwithstanding that migration is an important livelihood strategy, the introduction of institutions that address (either directly or indirectly) market frictions may have a role in influencing internal migration decisions. The results reported here provide an additional channel through which households may be affected by increased formal credit availability within a village. If migration is not only driven by wage differentials but also by credit market imperfections, this study suggests that there is an inter-temporal dimension to account for in the credit-migration nexus where opportunity costs at origin appear to matter.

Appendix A

Appendix Credit Availability and Internal Migration

A.1 Variables definitions

Migration : An internal migrant is identified by the survey if at least one member has migrated outside the province of origin for more than six months in the twelve months prior to the survey. The information is first asked at household level, and then an individual level section of the survey is used to confirm that a member with individual ID is flagged as living outside the household (either in the "Household Members" or the "Children outside the household" sections).[1] For the purpose of this study the migration definition is restricted to working-age individuals (15+), and care is taken to see if labour mobility reflects into the occupation and location declared for the migrants.

Additionally, a restriction to migrant location is applied: the definition excludes any member who migrates within village, sub-county or same province of origin in order to exclude commuting or circular migration which could be confounding the definition. If the main occupation is construction work in Bangkok or other provinces, this is identified as seasonal migration. Thus, migration is restricted to be domestic. International migration is not included, as it is extremely low in these rural and peri-urban areas covered by the TTDP survey. Moreover, there is a variable describing

[1] As for the baseline survey (1997), in addition to be a year of instability because of the crisis, migrants can only be identified as those individuals with household ID reported in "Children Outside the Household". The number of declared migrants was extremely low, either due to measurement error at baseline or to the financial crisis that rapidly contracted migration flows over that year. As it is not possible to test which of these propositions applies for that year, the baseline survey is excluded from the analysis.

the reason for migrating (open ended question reported at the bottom of Table 3.1). Variable ‘hc12b’ asks “Why did they leave?” and the answer is extracted using regular expressions and keywords to form migration categories. As there may be some margin of error in the coding of this variable, the data of the main specification are not trimmed of the observations with schooling as motive for migration, but scrupulous checks are performed for households reporting this as a reason (i.e. assuring that individuals in working age have a job and are not in school). Due to this variable’s missing values and potential measurement error, the analysis does not strictly rely on it, but it is ensured that, with the exclusions applied to the data, the migration information satisfactorily reflects the different information provided across the survey sections.

For households that report to have a migrant but are not reporting it with household roster ID (small percent of the migrant household), an identifier is created for every member that was in the household in period $t-1$, and then is found to be in the “Children” roster the following year (t). The characteristics used to identify them are: household ID, gender, age and highest level of education attained. Observations are matched by increasing age by one year (although underreporting has been often found in the data, especially for women age) all the while adding controls in the procedure by only changing the school level by one year if the individual declares to be at school at time $t-1$. If the matched individuals are found to meet the migration criteria described above, the household is identified as having a migrant. As cross-checking, these matched individuals are screened on observable characteristics between the two periods (i.e. whether they have similar job type and are not in school).

The construction of this migration variable may be affected by measurement error, so care is taken to ensure that there is no consistent variation in number of migrants, characteristics and the estimation results once the definition of migrant is changed. Special attention is paid on the inclusion of seasonal migrants, as there could be persistent differences in between the two types of migration, thus one of the robustness checks is to remove this type of migrants from the estimations, and the results do not change in sign.

Table A.1: Summary of main variables for migrant and non migrant households

	Non Migrant		Migrant		Tests
	Mean	SD	Mean	SD	p-value
Income and assets					
Agriculture	0.55	–	0.61	–	0.00
Net Income	102,722	168,784	106,899	266,112	0.46
Assets Stock	62,338	162,966	56,771	95,684	0.22
Land stock	694,524	1,621,951	587,889	1,415,949	0.02
Kinship Transfers	18,176	30,038	22,463	51,521	0.00
Borrowing					
VFP borrower	0.35	–	0.41	–	0.00
VFP loan	16,818	9,017	15,902	7,171	0.04
Other formal loan	49,020	63,763	43,096	44,924	0.88
Informal loans	43,472	92,366	42,797	93,459	0.15
Late repayment	0.26	–	0.28	–	0.07
” Formal	0.16	–	0.17	–	0.56
” Informal	0.10	–	0.10	–	0.48
Village					
Village Size	179	334	145	201	0.00
Northern Region	0.48	–	0.71	–	0.00
Village Size(North)	122	66	121	63	0.00
Village Size(Centre)	232	454	203	353	0.00
Small village	0.50	–	0.49	–	0.43
Village Size(Small)	78	21	78	20	0.46
Village Size(Large)	279	450	208	265	0.00

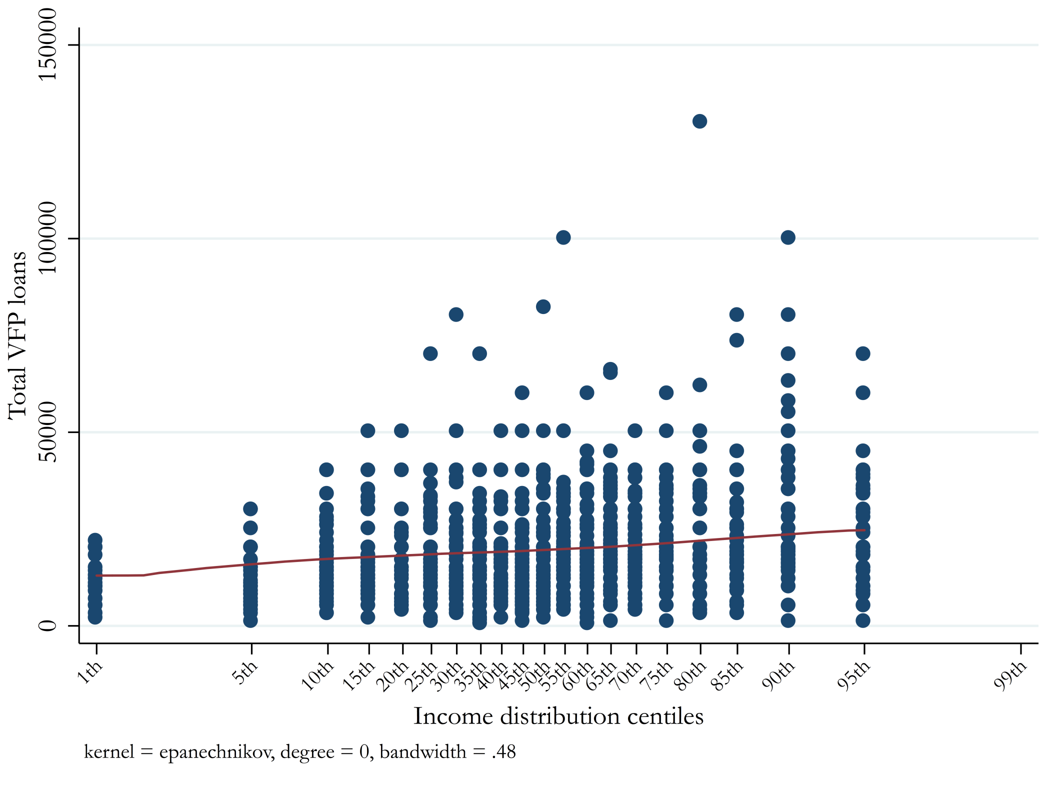
Note: TTDP data. Monetary variables are expressed in 2001 prices and are calculated conditional on having made at least one transaction.
Tests: χ^2 for binary variables, t-test with equal or unequal variance for levels.

To ensure that there is no trend in migration generated by the size of the village over time, Figure 3.1 (p.37) shows the average migration rate for villages from Northeastern region and Central region. The sample is further split between small villages (lower than the median size of 109 households) and large villages (greater than the median). The graph reflects a greater rate of migration coming from the Northeastern region as expected, with an increasing rate till 2003 and a reduction afterwards for both types of villages. For villages in the Central region, the migration rate seems to be constant and slightly increasing.

CPI and rescaling : All monetary measures are deflated by a CPI at province level (Laspeyres Index with weights constructed at base year 2001) constructed using the median deduced price of 9 consumption items (units of measurement into brackets): own-produced rice (kilos), purchased rice (kilos), other grains (kilos), milk and milk products (bottles), meat (chicken, beef, pork expressed in kilos), alcoholic beverages consumed at home (bottles), alcoholic beverages consumed away from home (bottles), tobacco (packs), and gasoline (not for business activity, expressed in litres). As there is a considerable degree of variability in deduced prices over provinces and time, the median is used to reduce possible measurement error. Similar to Kaboski and Townsend (2012), the monetary variables are expressed in *10,000* Baht so that the estimates are comparable to the average size of one VFP loan received at national level. This size was mentioned in the guidelines given by the government to the Village Fund committees and, even if they were not binding, several groups took this as the measure for standard loans (de la Huerta, 2011).

VFP Borrowing is defined as the sum of liabilities that the household has towards the Village Fund. Specifically, the stock of short-term VFP loans is defined as loans of duration of maximum 12 months. Short-term borrowing is the typical length of financing in micro-finance programs, which makes this scheme comparable to other classic types of micro-credit (e.g. Grameen Bank in Bangladesh). As this definition represents the most frequent type of VFP transaction, it is the most suited to investigate borrowing behaviour. In this way few zero-counts are generated, as the analysis does not include information on other types of borrowing that household takes from formal or informal institutions other than the Village Fund, nor those VFP loans with length greater than twelve months. Nevertheless, as visible from Figure A.1 the distribution of short-term VFP credit is well spread across the income distribution. This variable definition is also used by Kaboski and Townsend (2012) who suggest that it is well suited to the data. For consistency, the analysis is also performed using a broader VFP definition (not shown as it does not change the main results): (1) any loan made in the previous twelve months; (2) any loan of a maximum duration of twenty-four months made in the last year; (3) any loan of a maximum duration of twenty four months made in the last two years ($t-2$, for medium term analysis).

Figure A.1: Local polynomial smooth of short-term VFP credit over the income distribution. Full sample.



Controls

- Stock of assets: is defined as the monetary value of household, agricultural, business assets and land owned that were purchased more than twelve months prior to each survey wave. With the purpose of not incurring double counting with borrowing or transfer activities, the assets accumulated or the land purchased in the twelve months prior to the survey month (May of each year) are not included. The dataset contains information about household, agricultural and business assets. At baseline survey (year 1997, data from Townsend 2009), historical data on household purchases show information about the value and date of purchase of still existing assets that were purchased prior to the survey, their value is depreciated by ten percent up to 1996 in order to have the value of initial stock of wealth (for example a truck purchased in 1990 for a value of $100,000$ Baht will be depreciated by the ten percent on a yearly basis, up to its final value of 47829.7 Baht in 1997 wave). For the following waves, the household is asked to state if it has or not a specific good and if it was purchased in the last year. If the answer is no but it still owns it, the value of the good from the previous year $(t-1)$ is taken and depreciated by ten percent. Land values are not depreciated and the asset stock measure will also capture whether land was lost or purchased. To remove the concern that wealth is accumulated in preparation for future migration, a preliminary analysis excludes the wealth stock variable, ensuring that it does not alter the results (not shown).

- Binary variable if the head of household is male
- Years of education of the head of household
- Number of adult male and female (two separate variables) aged fifteen years and above
- Number of children aged fourteen and under
- Dummy if the household head primary occupation is in agriculture
- Age and age squared of the head of household (squared term scaled by 100 to allow readability of the estimates)

Kinship Transfers are used as a marginal exercise to gauge information on behaviour towards informal credit. Note that any estimate which include such measure should be interpreted as descriptive, as no reliable instrument was found to pursue further analysis of this type of transfer. Kinship transfers are defined as the sum of money received by the household in the last twelve months from individuals recoded in the "Children Outside the Household" Section. This definition of informal institution is preferred to informal borrowing as: first it does not imply strict commitment and liability from the household; second it could be a good proxy of the interaction that the household has with its network and, third if an informal loan is taken to pay back a VFP loan, the variable would convey inconsistent results if not instrumented (and simply adding lags would not be enough). Conversely, a transfer received more than one year ago should not be directly motivated by a future prospect of migration, especially because internal migration costs are relatively low once information about destination is gathered. No data on any currently declared migrants sending remittances home is found at any time t. Nonetheless, external unobserved factors affecting both, transfer receipt and the decision to migrate, cannot be completely excluded.

A.2 Estimates of borrowing on migration

First, in Table A.2 the exogeneity of regressors test is reported. Further, in Table A.3 the complete table of First and Second stage regression of migration outcome on VFP credit is reported. Table A.4 reports the sensitivity analysis of seven observations which are found with predicted linear probabilities out of unit value, aimed at justifying the LPM as a suitable estimator for the analysis.

Borrowing behaviour is examined in Table A.5 where continuous borrowers are either excluded from the analysis or investigated with an interaction term. The result being invariant to the sample restriction implies that no strong institutional effects are driving the results. However, continuous borrowers may still behave systematically differently from other repeated borrowers. To assess this conjecture, a *naïve* estimator which should not be interpreted as causal is applied. The decision to migrate is modelled using two borrowing measures: the standard VFP ($\gamma_1 B_{it} = VFP_{it}$) and the same measure interacted with a binary variable capturing continuous borrowing ($B_{it} = VFP_{it} * CB_i$):

$$mig_{it} = \gamma_0 + \gamma_1 \widehat{VFP}_{it} + \gamma_2 V\widehat{FP_{it} * C}B_i + \gamma_3 X_{it} + \Phi_i + \Phi_t + e_{it}$$

The model tests for differences in behaviour for continuous borrowers ($\gamma_1 + \gamma_2$). Nevertheless, being a repeated borrower is itself an endogenous decision and no feasible instrument for isolating this decision is found. Thus, a less precise measure to have weakly valid instrumentation is to model the two borrowing measures with the six-identifying instruments plus their interactions with the continuous-borrowing dummy, thus having in the first-stage a total of twelve instruments.

$$B_{it} = \delta_0 + \delta_1 invVsize * D_{t^*} + \delta_2 CB_i * invVsize * D_{t^*} + \delta_3 X_{it} + \rho_i + \rho_t + u_{it}$$

Although inconclusive, the linear combination from the modified 2SLS-FE specification is still in line with the causal effect of the main results. Nevertheless, the equations above may suffer from endogeneity, so these should be subject to future analysis.

Heterogeneity in village size: In the village headmen dataset there are information about the village size for each year (summary of the variable is available in Table 3.2). Putting the (time-varying) village size as a control (Table A.6) does not directly affect neither the instrumentation of VFP (1st stage) nor the migration outcome (2nd stage).

Table A.2: Orthogonality of Regressors: Migration on VFP and instruments residuals

	Short Term	Medium Term
2nd Stage		
Residuals	0.041*	0.038***
	(0.024)	(0.015)
VFP	-0.025	-0.031**
	(0.022)	(0.013)
Controls/Year dummies	Yes	Yes
Observations	4506	7510

* p<.10, ** p<.05, *** p<.01

Notes: TTDP data. Standard errors in parentheses, clustered at village level. First stage regression: VFP credit on inverse village size interacted with relevant year dummies and controls. Controls: year dummies, dummy if the head is male, head's age and its squared term (deflated by *100*), head's years of education, number of adults male, female, children, dummy if head primary occupation is in agriculture and stock of wealth. Monetary variables deflated by CPI (2001) and expressed in $10,000$.

Table A.3: Determinants of Migration: 2SLS with or without fixed effects of the impact of VFP credit (short and medium term analysis, full table)

	Short Term (1998-2003)				**Medium Term** (1998-2007)			
	2SLS		2SLS-FE		2SLS		2SLS-FE	
	1st	2nd	1st	2nd	1st	2nd	1st	2nd
2002*inv V size	83.765***		81.513***		83.518***		81.420***	
	(9.038)		(9.664)		(9.125)		(9.695)	
2003*inv V size	70.866***		68.448***		70.774***		68.463***	
	(9.237)		(9.585)		(9.283)		(9.651)	
2004*inv V size					86.134***		83.810***	
					(5.286)		(5.886)	
2005*inv V size					64.005***		61.717***	
					(16.226)		(16.022)	
2006*inv V size					77.159***		74.951***	
					(5.984)		(6.563)	
2007*inv V size					64.178***		61.590***	
					(9.818)		(9.940)	
VFP		-0.029		-0.039		-0.029*		-0.043**
		(0.028)		(0.031)		(0.016)		(0.022)
Head is male	0.045	0.067***	0.186**	0.153***	0.071*	0.058***	0.132**	0.065**
	(0.028)	(0.021)	(0.072)	(0.050)	(0.036)	(0.017)	(0.058)	(0.031)
Head age	-0.005	0.031***	0.046**	0.046***	0.003	0.029***	0.043***	0.028***
	(0.007)	(0.006)	(0.020)	(0.011)	(0.009)	(0.005)	(0.011)	(0.007)
Head age sq.	0.002	-0.028***	-0.039**	-0.039***	-0.007	-0.026***	-0.038***	-0.025***
	(0.007)	(0.005)	(0.017)	(0.009)	(0.008)	(0.004)	(0.009)	(0.006)
Head education	0.004	0.003	0.005	0.009	0.005	0.005	0.024*	0.010*
	(0.004)	(0.004)	(0.016)	(0.007)	(0.005)	(0.003)	(0.013)	(0.006)
N of adults male	0.023*	-0.037***	0.005	-0.161***	0.048***	-0.038***	0.040**	-0.096***
	(0.012)	(0.008)	(0.018)	(0.013)	(0.017)	(0.008)	(0.017)	(0.009)
N of adults female	0.050***	-0.027***	0.050**	-0.098***	0.070***	-0.033***	0.049***	-0.090***
	(0.011)	(0.009)	(0.020)	(0.019)	(0.016)	(0.007)	(0.018)	(0.014)
N of children	0.014	-0.006	0.027	-0.009	0.028*	-0.010*	0.026*	-0.020**
	(0.011)	(0.006)	(0.017)	(0.014)	(0.014)	(0.005)	(0.015)	(0.010)
Head is farmer	-0.009	-0.018	-0.014	-0.027	-0.014	-0.010	-0.013	-0.020*
	(0.022)	(0.013)	(0.029)	(0.017)	(0.028)	(0.010)	(0.029)	(0.012)
Stock of wealth	0.00000	0.00001	0.00001	-0.00001	-0.00002	0.00001	-0.00002	-0.00002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Buriram	-0.032	0.161***			-0.055	0.123***		
	(0.039)	(0.021)			(0.051)	(0.019)		
Lop Buri	-0.081***	-0.004			-0.115***	-0.025		
	(0.025)	(0.016)			(0.041)	(0.015)		
Sisaket	-0.052*	0.152***			-0.067	0.118***		
	(0.028)	(0.020)			(0.051)	(0.018)		
Constant	0.055	-0.736***			-0.156	-0.637***		
	(0.194)	(0.164)			(0.230)	(0.132)		
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4506	4506	4506	4506	7510	7510	7510	7510
R^2	0.48	0.09	0.54	0.12	0.40	0.08	0.44	0.07
Kleibergen-Paap		51.74		41.96		68.05		47.96
Hansen J		0.68		0.51		2.35		2.92
p-value		0.41		0.48		0.80		0.71

* p<.10, ** p<.05, *** p<.01

Notes: TTDP data, full table of Table 3.3. In both stages a set of covariates is included: dummy if the head is male, head's age and its squared term (deflated by *100*), head's years of education, number of adults male, female, children, dummy if head primary occupation is in agriculture, stock of wealth, time dummies (for 2SLS-FE estimates household fixed effects). Standard errors in parentheses, clustered at village level. All monetary variables are deflated by the CPI (base year 2001) and expressed in *10,000* Baht.

Table A.4: Sensitivity: Trimmed sample estimator on unit-value range. Second Stage of migration on VFP.

Second stage	A. Trimmed		B. Trimmed BP	
	S	M	S	M
VFP	-0.039	-0.044*	-0.043	-0.048**
	(0.031)	(0.022)	(0.036)	(0.024)
Head is male	0.154***	0.066**	0.156***	0.067**
	(0.051)	(0.031)	(0.052)	(0.031)
Head age	0.046***	0.029***	0.047***	0.029***
	(0.011)	(0.007)	(0.012)	(0.007)
Head age sq.	-0.039***	-0.025***	-0.039***	-0.025***
	(0.010)	(0.006)	(0.010)	(0.006)
Head education	0.009	0.010*	0.009	0.010*
	(0.007)	(0.006)	(0.007)	(0.006)
N of adults male	-0.161***	-0.097***	-0.163***	-0.098***
	(0.013)	(0.009)	(0.013)	(0.010)
N of adults female	-0.098***	-0.090***	-0.101***	-0.093***
	(0.019)	(0.014)	(0.019)	(0.014)
N of children	-0.010	-0.020*	-0.011	-0.021**
	(0.014)	(0.010)	(0.014)	(0.010)
Head is farmer	-0.026	-0.020	-0.025	-0.019
	(0.017)	(0.012)	(0.016)	(0.012)
Stock of Wealth	-0.00001	-0.00002	-0.00000	-0.00002
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Fixed Effects	Yes	Yes	Yes	Yes
Balanced Panel	N	N	Y	Y
Observations	4500	7503	4482	7470
R^2	0.42	0.30	0.42	0.30
Kleibergen-Paap	41.82	49.88	72.97	41.22
Hansen J	0.50	2.26	0.31	2.13
p-value	0.48	0.81	0.58	0.83

* p<.10, ** p<.05, *** p<.01

Notes: TTDP data. Second stage regression with trimmed sample estimator excluding out of unit-value sample (Horrace and Oaxaca, 2006). Panel A reports short (S) and medium (M) term estimations of instrumented VFP and covariates on migration with the exclusion of 7 observations; Panel B excludes completely the observations (from 4 groups). Standard errors in parentheses, clustered at village level. Monetary variables are deflated by the CPI (base year 2001) and expressed in *10,000* Baht. First stage: 2 (S) or 6 (M) instruments, dummy if the head is male, head's age and its squared term (deflated by *100*), head's years of education, number of adults male, female, children, dummy if head primary occupation is in agriculture, stock of wealth, time and household fixed effects.

Table A.5: Borrowing behaviour: 2SLS-FE with exclusion of continuous borrower, or with interactions by continuous borrower.

	Excluding continuous borrowing		Continuous borrowing interactions		
	(I)	(II)	(III)	(IV)	(V)
	1st stage *VFP*	2nd stage	1st stage *VFP*	1st stage *CB VFP*	2nd stage
2002*inv V size	84.558***		51.237**	-28.237***	
	(12.226)		(20.318)	(8.650)	
2003*inv V size	58.971***		25.631	-30.385***	
	(15.813)		(22.519)	(9.110)	
2004*inv V size	82.360***		48.214***	-28.159***	
	(9.403)		(17.119)	(8.854)	
2005*inv V size	41.518***		11.905	-28.700***	
	(15.062)		(10.403)	(8.896)	
2006*inv V size	69.667***		36.751**	-29.462***	
	(8.065)		(16.493)	(8.836)	
2007*inv V size	53.248***		21.848**	-28.944***	
	(8.177)		(9.253)	(8.269)	
invVsize 2002*CB			32.444***	62.901***	
			(8.435)	(7.550)	
invVsize 2003*CB			41.824***	62.848***	
			(8.419)	(7.434)	
invVsize 2004*CB			35.583***	61.168***	
			(8.190)	(7.607)	
invVsize 2005*CB			43.095***	59.021***	
			(5.326)	(7.117)	
invVsize 2006*CB			36.710***	60.747***	
			(7.274)	(7.651)	
invVsize 2007*CB			42.042***	63.302***	
			(6.704)	(6.953)	
γ_1 VFP		-0.038*			-0.056**
		(0.023)			(0.026)
γ_2 VFP *CB					0.034*
					(0.020)
$\gamma_1 + \gamma_2$					-0.021*
					(0.012)
Controls	Yes	Yes	Yes	Yes	Yes
Post 2001 migration		0.211			0.210
Observations	5070	5070	7510	7510	7510
R^2		0.07			0.07
Kleibergen-Paap		79.08			25.28
Hansen J		8.16			5.28
p-value		0.15			0.87

* p<.10, ** p<.05, *** p<.01

Notes: TTDP data, 1998-2007. The first two columns perform the analysis excluding continuous borrowers (who borrow for the full 6 programme years). Columns III-V report the first and second stage regression of VFP borrowing and instruments interacted with a binary variable for being continuous borrower (CB). The linear combination of VFP (γ_1) and interacted VFP (γ_2) is reported at the bottom of the table. A set of covariates is included: dummy if the head is male, head's age and its squared term (deflated by *100*), head's years of education, number of adults male, female, children, dummy if head primary occupation is in agriculture, stock of wealth, time and household fixed effects. Standard errors in parentheses, clustered at village level. All monetary variables are deflated by the CPI (base year 2001) and expressed in *10,000* Baht.

Table A.6: Robustness: Migration on VFP with yearly village size as control

First stage	Short Term		Medium Term	
	2SLS	**2SLS-FE**	2SLS	**2SLS-FE**
2002*inv V size	83.341***	81.508***	83.579***	81.417***
	(9.262)	(9.672)	(9.183)	(9.701)
2003*inv V size	70.442***	68.448***	70.835***	68.462***
	(9.503)	(9.579)	(9.442)	(9.647)
2004*inv V size			86.195***	83.808***
			(5.494)	(5.895)
2005*inv V size			64.068***	61.709***
			(16.444)	(16.017)
2006*inv V size			77.219***	74.967***
			(6.167)	(6.553)
2007*inv V size			64.230***	61.686***
			(10.024)	(9.968)
Village size	-0.00002	-0.00005	0.00000	-0.00003
	(0.00002)	(0.00007)	(0.00003)	(0.00010)
Controls	Yes	Yes	Yes	Yes
Observations	4506	4506	7510	7510
Second stage	Short Term		Medium Term	
	2SLS	**2SLS-FE**	2SLS	**2SLS-FE**
VFP	-0.033	-0.039	-0.040***	-0.043**
	(0.029)	(0.031)	(0.015)	(0.021)
Village size	-0.00001	-0.00005	-0.00003***	-0.00007
	(0.00001)	(0.00011)	(0.00001)	(0.00007)
Head is male	0.068***	0.153***	0.060***	0.065**
	(0.021)	(0.050)	(0.017)	(0.031)
Head age	0.031***	0.046***	0.029***	0.028***
	(0.006)	(0.011)	(0.005)	(0.007)
Head age sq.	-0.028***	-0.039***	-0.027***	-0.025***
	(0.005)	(0.009)	(0.004)	(0.006)
Head education	0.003	0.009	0.005	0.010*
	(0.004)	(0.007)	(0.003)	(0.006)
N of adults male	-0.037***	-0.160***	-0.037***	-0.096***
	(0.008)	(0.013)	(0.008)	(0.009)
N of adults female	-0.026***	-0.098***	-0.032***	-0.091***
	(0.009)	(0.019)	(0.008)	(0.014)
N of children	-0.006	-0.009	-0.010*	-0.020**
	(0.006)	(0.014)	(0.005)	(0.010)
Head is farmer	-0.019	-0.026	-0.011	-0.020*
	(0.013)	(0.017)	(0.010)	(0.012)
Stock of Wealth	0.00001	-0.00001	0.00000	-0.00002
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Buriram	0.161***		0.122***	
	(0.022)		(0.019)	
Lop Buri	-0.003		-0.020	
	(0.017)		(0.015)	
Sisaket	0.152***		0.117***	
	(0.020)		(0.018)	
Constant	-0.737***		-0.642***	
	(0.164)		(0.132)	
Year dummies	Yes	Yes	Yes	Yes
Observations	4506	4506	7510	7510
R^2	0.09	0.12	0.07	0.07
Kleibergen-Paap	47.70	41.94	58.27	47.90
Hansen J	0.64	0.52	2.33	3.01
p-value	0.42	0.47	0.80	0.70

Notes: TTDP data. First stage controls as in main regressions.

A.3 Robustness checks

A.3.1 Instruments robustness

Table A.7 investigates the policy-instrument interacted with the years prior to the program, to assess their interaction with VFP credit and migration outcome. The results confirm that they do not predict borrowing before the program. Table A.8 presents an estimation of the impact of lagged VFP on migration for two time periods (1998-2003 and 1998-2007) to assess if the instrument at the start of the policy reflect a change in behaviour of the households that anticipated the program. As expected, there is no prediction of the 2002 instrument.

In Table A.10 first and second stage regression are performed on a reduced sample that excludes seven villages that in 2002 were reported to include less than 50 or more than 250 households. The results are unchanged.

Following, Table A.11 reports the second stage 2SLS with or without household fixed effects of migration on VFP binary variable. The first stage regression performs less well than with the instrumented VFP variable in levels (weak instrumentation is just around 10), but still the magnitude of impact of the binary variable "being a VFP borrower" affects negatively the probability of migrating.

Table A.7: Robustness check: First stage instrumentation (*1st*) of inverse village size prior to the policy on VFP and second stage (*2nd*) of migration outcome.

	2SLS		2SLS-FE	
	1st	2nd	1st	2nd
1998*inv V size	0.335		-0.027	
	(0.259)		(0.240)	
1999*inv V size	1.771		1.437	
	(1.485)		(1.469)	
2000*inv V size	1.114		0.747	
	(0.907)		(0.883)	
2001*inv V size	0.328		0.000	
	(0.207)		(.)	
Head is male	-0.010	0.068***	0.009	0.221***
	(0.007)	(0.025)	(0.006)	(0.059)
Head age	0.001	0.032***	-0.001	0.022
	(0.001)	(0.006)	(0.002)	(0.017)
Head age sq.	-0.001	-0.029***	0.001	-0.016
	(0.001)	(0.005)	(0.002)	(0.014)
Head education	0.000	0.002	-0.000	-0.000
	(0.000)	(0.004)	(0.001)	(0.009)
N of adults male	-0.000	-0.029***	-0.012	-0.217***
	(0.001)	(0.009)	(0.008)	(0.028)
N of adults female	-0.006	-0.024**	0.001	-0.122***
	(0.003)	(0.011)	(0.001)	(0.019)
N of children	0.002	-0.004	0.006	-0.002
	(0.003)	(0.008)	(0.007)	(0.022)
Head is farmer	0.006	-0.031*	-0.000	-0.020
	(0.004)	(0.017)	(0.003)	(0.021)
Stock of wealth	-0.00000	-0.00002	-0.00000	-0.00006***
	(0.00000)	(0.00003)	(0.00000)	(0.00002)
VFP		-0.464		-2.818
		(1.084)		(2.920)
Constant	-0.024	-0.790***		
	(0.025)	(0.148)		
Year/Prov dummies	Yes	Yes	Yes	Yes
Observations	3004	3004	3004	3004
R^2		0.06		-0.80
Kleibergen-Paap		1.13		1.41
Hansen J		3.21		3.00
p-value		0.36		0.22

* p<.10, ** p<.05, *** p<.01

Notes: TTDP data. Standard errors in parentheses, clustered at village level. As expected the instruments prior to the policy do not predict the endogenous regressor.

Table A.8: Instruments robustness: Modelling Migration with Lagged VFP

	Short Term				Medium Term			
	2SLS no FE		2SLS		2SLS no FE		2SLS	
	1st	2nd	1st	2nd	1st	2nd	1st	2nd
Head is male	0.033	0.064***	0.145**	0.165***	0.067*	0.056***	0.093*	0.059*
	(0.020)	(0.024)	(0.055)	(0.063)	(0.034)	(0.018)	(0.054)	(0.035)
Head age	-0.001	0.034***	0.046**	0.051***	0.005	0.030***	0.050***	0.027***
	(0.005)	(0.006)	(0.018)	(0.016)	(0.008)	(0.005)	(0.011)	(0.009)
Head age sq.	-0.000	-0.030***	-0.039**	-0.043***	-0.009	-0.027***	-0.045***	-0.024***
	(0.005)	(0.006)	(0.016)	(0.013)	(0.007)	(0.004)	(0.010)	(0.008)
Head education	0.003	0.003	0.010	0.007	0.005	0.005	0.018*	0.011*
	(0.002)	(0.004)	(0.013)	(0.009)	(0.004)	(0.003)	(0.010)	(0.006)
N of adults male	0.010	-0.040***	-0.017	-0.188***	0.046***	-0.040***	0.030*	-0.105***
	(0.008)	(0.009)	(0.018)	(0.017)	(0.017)	(0.009)	(0.016)	(0.011)
N of adults female	0.031***	-0.031***	0.032*	-0.102***	0.060***	-0.036***	0.015	-0.098***
	(0.008)	(0.010)	(0.018)	(0.023)	(0.015)	(0.008)	(0.020)	(0.016)
N of children	0.005	-0.008	0.004	-0.001	0.020	-0.011**	0.006	-0.016
	(0.008)	(0.006)	(0.022)	(0.014)	(0.015)	(0.005)	(0.019)	(0.010)
Head is farmer	-0.013	-0.012	-0.036	-0.031	-0.002	-0.006	0.006	-0.018
	(0.017)	(0.015)	(0.029)	(0.022)	(0.025)	(0.011)	(0.028)	(0.013)
Stock of wealth	0.00000	0.00001	-0.00000	-0.00002	-0.00005	0.00000	-0.00009	-0.00003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2002*inv V size	0.777		-1.159		0.913		-1.326	
	(0.736)		(0.859)		(1.304)		(0.919)	
2003*inv V size	83.680***		81.550***		84.103***		81.545***	
	(9.015)		(9.466)		(9.065)		(9.724)	
2004*inv V size					71.185***		68.591***	
					(9.258)		(9.569)	
2005*inv V size					86.123***		83.560***	
					(5.392)		(5.847)	
2006*inv V size					63.630***		61.241***	
					(16.326)		(16.095)	
2007*inv V size					77.656***		74.777***	
Lag VFP		-0.011		-0.009		-0.024		-0.027
		(0.030)		(0.035)		(0.015)		(0.027)
					(5.911)		(6.437)	
Constant	0.191	-0.666***			0.105	-0.578***		
	(0.189)	(0.177)			(0.224)	(0.140)		
Year/Prov dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3755	3755	3755	3755	6759	6759	6759	6759
R^2	0.54	0.09	0.58	0.11	0.42	0.07	0.47	0.07
Kleibergen-Paap		48.53		53.22		75.09		49.22
Hansen J		1.55		2.48		6.57		11.09
p-value		0.21		0.12		0.26		0.05

* p<.10, ** p<.05, *** p<.01

Notes: TTDP data. Standard errors in parentheses, clustered at village level.

Table A.9: Robustness: First & Second stage migration on VFP credit (one instrument)

First stage: VFP credit on one instrument				
	Short Term		Medium Term	
	2SLS	**2SLS-FE**	2SLS	**2SLS-FE**
inv V size	77.31***	75.00***	74.29***	72.00***
	(7.686)	(8.264)	(4.498)	(4.968)
Controls	Yes	Yes	Yes	Yes
Observations	4506	4506	7510	7510
R^2	0.48	0.54	0.40	0.44

Second stage: migration on VFP credit				
	Short Term		Medium Term	
	2SLS	**2SLS-FE**	2SLS	**2SLS-FE**
VFP	-0.03	-0.04	-0.03*	-0.04*
	(0.029)	(0.032)	(0.015)	(0.023)
Controls	Yes	Yes	Yes	Yes
Observations	4506	4506	7510	7510
R^2	0.09	0.12	0.08	0.07
Kleibergen-Paap	101.18	82.36	272.74	210.04

* p<.10, ** p<.05, *** p<.01

Notes: TTDP data. Standard errors in parentheses, clustered at village level. First stage regression: VFP credit on inverse village size in 2002. Explanatory variables: dummy if the head is male, head's age and its squared term (deflated by *100*), head's years of education, number of adults male, female, children, dummy if head primary occupation is in agriculture and stock of wealth, province and time dummies for 2SLS, household and year fixed effects for 2SLS-FE model. Monetary variables deflated by CPI (2001) and expressed in $10,000$.

Table A.10: Robustness check: First and Second stage regression of migration on VFP credit. Reduced sample: 654 groups with village size in between 50 and 250 households.

First stage: VFP on instruments

	Short Term		Medium Term	
	2SLS(noFE)	2SLS	2SLS(noFE)	2SLS
Head is male	0.019	0.171**	0.043	0.124**
	(0.026)	(0.075)	(0.036)	(0.061)
Head age	-0.010	0.055**	-0.004	0.045***
	(0.008)	(0.023)	(0.009)	(0.011)
Head age sq.	0.006	-0.047**	-0.002	-0.040***
	(0.007)	(0.019)	(0.008)	(0.009)
Head education	0.004	0.002	0.006	0.025*
	(0.004)	(0.019)	(0.005)	(0.015)
N of adults male	0.029**	0.012	0.054***	0.044**
	(0.013)	(0.020)	(0.017)	(0.019)
N of adults female	0.049***	0.042**	0.074***	0.041**
	(0.012)	(0.021)	(0.016)	(0.020)
N of children	0.009	0.013	0.021*	0.020
	(0.008)	(0.016)	(0.012)	(0.015)
Head is farmer	0.005	-0.001	0.003	-0.009
	(0.023)	(0.028)	(0.029)	(0.030)
Stock of wealth	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
2002*inv V size	76.220***	72.972***	75.772***	72.661***
	(10.095)	(11.515)	(10.202)	(11.573)
2003*inv V size	59.489***	56.064***	59.368***	56.052***
	(18.757)	(19.068)	(18.499)	(19.163)
2004*inv V size			84.857***	81.495***
			(11.477)	(12.382)
2005*inv V size			90.963***	87.790***
			(14.110)	(14.381)
2006*inv V size			83.911***	81.224***
			(10.041)	(11.197)
2007*inv V size			83.053***	80.413***
			(11.267)	(11.997)
Constant	0.218		0.034	
	(0.188)		(0.223)	
Year dummies	Yes	Yes	Yes	Yes
Observations	3924	3924	6540	6540
R^2	0.47	0.53	0.38	0.44

Second stage: migration on VFP credit

	Short Term		Medium Term	
	2SLS(noFE)	2SLS	2SLS(noFE)	2SLS
VFP	-0.019	-0.029	-0.049*	-0.074*
	(0.049)	(0.057)	(0.025)	(0.038)
Head is male	0.074***	0.151***	0.058***	0.050
	(0.023)	(0.058)	(0.018)	(0.033)
Head age	0.031***	0.046***	0.029***	0.029***
	(0.007)	(0.013)	(0.005)	(0.008)
Head age sq.	-0.028***	-0.039***	-0.027***	-0.026***
	(0.006)	(0.011)	(0.005)	(0.007)
Head education	0.004	0.015**	0.006*	0.014**
	(0.004)	(0.007)	(0.004)	(0.006)
N of adults male	-0.044***	-0.162***	-0.043***	-0.096***
	(0.010)	(0.014)	(0.009)	(0.010)
N of adults female	-0.027***	-0.110***	-0.031***	-0.094***
	(0.009)	(0.021)	(0.008)	(0.016)
N of children	-0.007	-0.010	-0.012*	-0.020*
	(0.007)	(0.015)	(0.006)	(0.011)
Head is farmer	-0.022	-0.035*	-0.013	-0.021
	(0.014)	(0.019)	(0.011)	(0.013)
Stock of wealth	0.00000	-0.00002	-0.00001	-0.00002
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.738***		-0.625***	
	(0.186)		(0.149)	
Year dummies	Yes	Yes	Yes	Yes
Observations	3924	3924	6540	6540
R^2	0.09	0.13	0.07	0.07
Kleibergen-Paap	31.01	21.48	24.60	16.76
Hansen J	1.22	0.92	2.32	1.99
p-value	0.27	0.34	0.80	0.85

* p<.10, ** p<.05, *** p<.01. *Notes*: TTDP data. The estimates are performed with a balanced panel that excludes seven villages: two with size of 30 and 34 households, and other seven with size comprised between 268 and 3194 households. The real VFP credit and wealth are expressed in *10,000* Baht, age squared is deflated by (*100*), clustered SE(village).

Table A.11: Determinants of Migration: Second stage 2SLS estimates (with or without FE) of migration on VFP binary variable. Short and medium term analyses.

	Short Term		Medium Term	
	2SLS(noFE)	2SLS	2SLS(noFE)	2SLS
VFP borrower	-0.119	-0.168	-0.107*	-0.161**
	(0.120)	(0.131)	(0.056)	(0.074)
Head is male	0.066***	0.156***	0.058***	0.071**
	(0.022)	(0.052)	(0.017)	(0.031)
Head age	0.031***	0.049***	0.029***	0.030***
	(0.006)	(0.012)	(0.005)	(0.007)
Head age sq.	-0.028***	-0.041***	-0.027***	-0.027***
	(0.005)	(0.010)	(0.004)	(0.007)
Head education	0.003	0.010	0.005	0.011*
	(0.004)	(0.007)	(0.003)	(0.006)
N of adults male	-0.037***	-0.162***	-0.037***	-0.095***
	(0.008)	(0.012)	(0.008)	(0.009)
N of adults female	-0.026***	-0.097***	-0.032***	-0.090***
	(0.009)	(0.019)	(0.008)	(0.014)
N of children	-0.006	-0.009	-0.009	-0.018*
	(0.006)	(0.014)	(0.005)	(0.010)
Head is farmer	-0.017	-0.026	-0.008	-0.019
	(0.013)	(0.017)	(0.010)	(0.012)
Stock of Wealth	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Buriram	0.161***		0.124***	
	(0.022)		(0.019)	
Lop Buri	-0.004		-0.025	
	(0.016)		(0.015)	
Sisaket	0.153***		0.119***	
	(0.021)		(0.019)	
Constant	-0.736***		-0.643***	
	(0.164)		(0.133)	
Year dummies	Yes	Yes	Yes	Yes
Observations	4506	4506	7510	7510
R^2	0.08	0.10	0.06	0.05
Kleibergen-Paap	14.53	13.43	13.97	10.82
Hansen J	0.27	0.09	1.58	2.00
p-value	0.60	0.77	0.90	0.85

* p<.10, ** p<.05, *** p<.01. *Notes*: TTDP data. First stage regression: VFP binary on inverse village size interacted with relevant year dummies (short term: 2002,2003; medium term 2002–2007) and controls. Additional explanatory variables: time dummies, dummy if the head is male, head's age and its squared term (deflated by *100*), head's years of education, number of adults male, female, children, dummy if head primary occupation is in agriculture and stock of wealth. The Instruments Tests are weaker, thus the interpretation of this table must be cautious. Standard errors in parentheses, clustered at village level. Monetary variables deflated by CPI (2001) and expressed in $10,000$.

A.3.2 Migration definition robustness

As robustness to the definition of migration, Table A.12 reports a specification with the exclusion of educational migrants from the analysis. In order to have a balanced panel, any household that declares at least once to have a educational migrant or a migrant currently attending school is excluded. Second stage of the 2SLS regression of migration outcome on VFP credit shows the same results as in the main specifications. Then, in Table A.13 a migrant-household is defined to be without seasonal migrants. The results do not change in significance and direction.

Table A.12: Robustness check: Second stage regression of migration on VFP credit. Reduced sample: balanced panel (680 groups) with non-educational migrants only

	Short	Medium
VFP	-0.026	-0.033*
	(0.027)	(0.018)
Head is male	0.136***	0.061**
	(0.053)	(0.028)
Head age	0.040***	0.023***
	(0.012)	(0.006)
Head age sq.	-0.034***	-0.021***
	(0.010)	(0.005)
Head education	0.005	0.006
	(0.007)	(0.006)
N of adults male	-0.154***	-0.096***
	(0.014)	(0.010)
N of adults female	-0.090***	-0.080***
	(0.018)	(0.014)
N of children	-0.003	-0.012
	(0.014)	(0.009)
Head is farmer	-0.019	-0.007
	(0.017)	(0.013)
Stock of Wealth	-0.000	-0.000
	(0.000)	(0.000)
Year dummies	Yes	Yes
Observations	4080	6800
R^2	0.11	0.07
Kleibergen-Paap	46.46	58.61
Hansen J	0.25	5.94
p-value	0.62	0.31

* p<.10, ** p<.05, *** p<.01

Notes: TTDP data. The estimates are performed with a balanced panel that excludes any household that declares to have a member migrating for educational reasons or that is currently in school (71 households are excluded). The stock of short-term VFP credit and stock of wealth are deflated by the CPI (base year 2001) and expressed in *10,000* Baht. Age squared is deflated by (*100*). Standard errors in parentheses, clustered at village level.

Table A.13: Robustness: Second Stage Regression of Migration on VFP borrowing, with non-seasonal migrant as dependent variable over the panel, excluding schooling migrant households or village outliers.

	(I)		(II)		(III)	
	Short	Medium	Short	Medium	Short	Medium
VFP	-0.030	-0.038*	-0.015	-0.064*	-0.025	-0.026*
	(0.030)	(0.021)	(0.052)	(0.036)	(0.026)	(0.017)
Head is male	0.111**	0.035	0.105*	0.020	0.109**	0.028
	(0.047)	(0.026)	(0.055)	(0.027)	(0.048)	(0.024)
Head age	0.049***	0.029***	0.050***	0.031***	0.045***	0.023***
	(0.009)	(0.006)	(0.010)	(0.007)	(0.009)	(0.005)
Head age sq.	-0.042***	-0.025***	-0.043***	-0.028***	-0.038***	-0.021***
	(0.008)	(0.005)	(0.009)	(0.006)	(0.008)	(0.005)
Head education	0.005	0.009	0.010	0.013**	0.002	0.004
	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.005)
N of adults male	-0.135***	-0.073***	-0.138***	-0.072***	-0.129***	-0.074***
	(0.013)	(0.009)	(0.014)	(0.010)	(0.013)	(0.009)
N of adults female	-0.098***	-0.093***	-0.106***	-0.094***	-0.089***	-0.083***
	(0.016)	(0.012)	(0.018)	(0.013)	(0.014)	(0.011)
N of children	-0.014	-0.021**	-0.018	-0.022**	-0.010	-0.015*
	(0.011)	(0.009)	(0.013)	(0.010)	(0.011)	(0.008)
Head is farmer	-0.001	0.002	-0.007	0.002	-0.003	0.015
	(0.016)	(0.011)	(0.018)	(0.013)	(0.015)	(0.012)
Stock of wealth	-0.00003	-0.00001	-0.00004	-0.00001	-0.00004	-0.00000
	(0.00004)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4506	7510	3924	6540	4260	6800
R^2	0.11	0.06	0.12	0.06	0.10	0.06
Kleibergen-Paap	41.96	47.96	21.48	16.76	43.53	58.61
Hansen J	0.60	4.05	1.20	2.77	0.54	7.46
p-value	0.44	0.54	0.27	0.74	0.46	0.19

* p<.10, ** p<.05, *** p<.01

Notes: TTDP data. Explanatory variables in first stage: household fixed effects, year dummies, dummy if the head is male, head's age and its squared term (deflated by *100*), head's years of education, number of adults male, female, children, dummy if head primary occupation is in agriculture and stock of wealth. All monetary variables are deflated by the CPI (base year 2001) and expressed in *10,000* Baht. Dependent variable: non-seasonal migrants (reported to have left the household in the last twelve months). Standard errors in parentheses, clustered at village level. Columns description: (I) stands for estimates with non-seasonal migrant as dependent variable and stock of short-term credit from VFP as explanatory variable; (II) estimates with non-seasonal migrant as dependent variable and a balanced panel that excludes seven village outliers; (III) estimates with a balanced panel that excludes any household that declares to have a member migrating for educational reasons or that is currently in school.

Table A.14: Robustness: Use of official credit as endogenous regressor.

First stage: Official Credit on instruments		
	Short Term	Medium Term
2002*inv V size	149.033***	149.096***
	(38.891)	(38.641)
2003*inv V size	101.400***	101.189***
	(28.071)	(27.812)
2004*inv V size		103.201***
		(21.662)
2005*inv V size		102.307
		(73.903)
2006*inv V size		125.335***
		(38.218)
2007*inv V size		88.702***
		(34.132)
Controls	Yes	Yes
Observations	4506	7510
Second stage: migration on Official credit		
	Short Term	Medium Term
Official borrowing	-0.024	-0.026**
	(0.016)	(0.013)
Controls	Yes	Yes
Observations	4506	7510
R^2	0.07	0.00
Kleibergen-Paap	10.78	4.59
Hansen J	0.17	3.03
p-value	0.68	0.70

A.3.3 Total formal borrowing, kinship and reverse causality estimates

The results with the use of total borrowing from formal sources of Table A.14 shows that the instrumentation behaves much worse than with the sole source of VFP borrowing, but the results keep being in line with the main specification.

The results of kinship transfers (Table A.15), although not to be interpreted as causal, confirm the strength of the VFP measure in the medium term.

As a last *naïve* exercise, I report in Table A.16 a short and medium-term Fixed Effects analysis of VFP on instruments, controls and migration. In regressing VFP stock of credit on the set of controls, the instruments and migration I find no direct correlation of the migration variable at time t, and a positive correlation once the lag of migration is introduced in the short term analysis. No correlation in medium term. These estimates should not be considered as causal, as migration is endogenous to household decision and it goes beyond the scope of this study to model the consequences of the decision to migrate.

Table A.15: Determinants of Migration: Second stage Fixed Effects estimates of migration on VFP credit and transfers variable plus simple model with VFP excluded. Short and medium term analyses.

Dependent variable: migration	Short Term		Medium Term	
	2SLS	**2SLS-FE**	2SLS	**2SLS-FE**
Transfers (1 lag)				
VFP	-0.029	-0.045	-0.029*	-0.046*
	(0.027)	(0.029)	(0.015)	(0.024)
lag Transfer	0.003	-0.010**	0.000	-0.006
	(0.005)	(0.005)	(0.003)	(0.004)
Year dummies	Yes	Yes	Yes	Yes
Observations	3755	3755	6759	6759
Transfers (2 lags)				
VFP	-0.034	-0.070**	-0.031**	-0.069***
	(0.026)	(0.027)	(0.016)	(0.026)
lag Transfer	0.001	-0.012*	0.002	-0.004
	(0.006)	(0.007)	(0.003)	(0.004)
2nd lag Transfer	0.004	0.000	-0.003	-0.007**
	(0.005)	(0.007)	(0.002)	(0.003)
Year dummies	Yes	Yes	Yes	Yes
Observations	3004	3004	6008	6008
Only Kin Transfer(1 lag)	OLS	FE	OLS	FE
Lag Transfer	0.003	-0.009**	0.000	-0.006
	(0.005)	(0.005)	(0.003)	(0.004)
Year dummies	Yes	Yes	Yes	Yes
Observations	3755	3755	6759	6759
Only Kin Transfer(2 lags)	OLS	FE	OLS	FE
Lag Transfer	0.001	-0.011*	0.002	-0.004
	(0.006)	(0.007)	(0.003)	(0.004)
2nd lag Transfer	0.004	0.000	-0.003	-0.007**
	(0.005)	(0.007)	(0.002)	(0.003)
Year dummies	Yes	Yes	Yes	Yes
Observations	3004	3004	6008	6008

* $p<.10$, ** $p<.05$, *** $p<.01$

Notes: TTDP data. Standard errors in parentheses, clustered at village level. Additional controls: time dummies, dummy if the head is male, head's age and its squared term (deflated by *100*), head's years of education, number of adults male, female, children, dummy if head primary occupation is in agriculture and stock of wealth (for 2SLS-FE estimates household fixed effects). First stage regression: VFP credit on inverse village size interacted with relevant year dummies (short term: 2002,2003; medium term 2002–2007) and controls. Monetary variables deflated by CPI (2001) and expressed in $10,000$.

Table A.16: Reverse causality check of VFP: Fixed Effects estimates on instruments, migration and its lags

Dependent variable: VFP		
	Short Term	Medium Term
migration		
Migrant	0.022	-0.024
	(0.032)	(0.030)
Controls	Yes	Yes
Observations	4506	7510
R^2	.45357	.373006
lagged migration		
Migrant (*one lag*)	0.073*	-0.004
	(0.037)	(0.032)
Controls	Yes	Yes
Observations	3755	6759
R^2	.448368	.34676
first & second lag migration		
Migrant (*one lag*)	0.094**	-0.003
	(0.045)	(0.033)
Migrant (*two lags*)	0.004	-0.004
	(0.052)	(0.032)
Controls	Yes	Yes
Observations	3004	6008
R^2	.440161	.305784

* p<.10, ** p<.05, *** p<.01. *Notes*: TTDP data. Controls: household and year fixed effects, instruments, dummy if the head is male, head's age and its squared term (deflated by *100*), head's years of education, number of adults male, female, children, dummy if head primary occupation is in agriculture, stock of wealth. Monetary variables deflated by CPI (2001) and expressed in 10,000. Standard errors in parentheses, clustered at village level.

Chapter 4

The Minimum wage policy in Thailand: the effects on provincial wage distributions

Joint work with Dilaka Lathapipat. [1]

4.1 Introduction

There is widespread acceptance that a minimum wage can alleviate issues such as distributional frictions or low compensation to specific groups of the labour force (Card and Krueger, 1995; Freeman, 1996). However, there is still debate on the policy features that support such outcomes. The next two chapters of this thesis tackle this issue by looking at the distributional and employment effects of changes in the minimum wage policy in Thailand. The analyses aim to give an account of the most recent policy regime change, moving from geographically defined minimum wages to a national statutory one.

Between 2012 and 2013 the minimum wage was raised nationwide to 300 Baht per day (9.65 US$) – an unprecedented average increase over two years of around 60-70 percent. With its introduction, media reports portrayed public fear that such large and precipitous increase in the minimum wage could curtail jobs, and that the harmonisation of the provincial minimum wages to a single one would lead to non-

[1] **Disclaimer**. An earlier version of this work is circulated in article form under the title "From Many to One: Minimum Wage Effects in Thailand". The findings, data manipulation, interpretations and conclusions presented in this chapter do not necessarily reflect the views of the World Bank Group (WBG) nor of the National Statistics Office of Thailand (NSO) or other government agencies.

compliance and not translate into higher wages. The aim of this chapter is to empirically test whether these concerns were justified through an analysis of the responsiveness of the Thai labour market to the policy change by looking at wages, while Chapter 5 looks at this from the perspective of employment.

This chapter contributes in understanding the labour market in Thailand, its wage structure and its response to the changes in minimum wage regulation. It uses the Thai Labour Force Survey (2002 to 2013) to identify the wage effects of changes in the minimum wage over the entire period, and over a shorter time frame (2011-2013), capturing the latest move towards the National Minimum Wage (NMW).

In order to evaluate how a change in the minimum wage policy affects wages, the characterisation of the labour market and its institutions may be of relevance. Characteristics of the economy, such as the presence of firms' agglomeration and informality, may reflect into wages paid.[2] Research at the cross-road between labour, urban and regional economics emphasise how different mechanisms may generate local labour markets through firms' agglomeration.[3] Factors related to agglomeration, such as productivity and skills composition may reflect in wages paid in a local area (Moretti, 2011).[4] Thailand has shown since its economic boom signs of spatial differentiation in enterprise formation, productivity and growth across its provinces (Felkner and Townsend, 2011; Limpanonda, 2015). Thus, we expect agglomeration forces to have generated heterogeneous characteristics which reflect on the wages paid and we aim to apply

[2]The concept of informality has been widely discussed in the literature, it reflects the dichotomy of wage differences across formal and informal sectors, as in the standard two-sectors model (Welch, 1974; Gramlich, 1976; Mincer, 1976). This framework has been used to characterise not only the duality of wage contracting, but also the traits of firms which form the informal sector (Rauch, 1991). As reviewed in the next chapter, the dual labour market theory has been challenged to be too restrictive in explaining the dynamics and persistence of informal employment (Maloney, 1999, 2004). Alternatively, the informal sector may be seen as a competitive fringe of the labour market (Magnac, 1991).

[3]For example, in the taxonomy of Duranton and Puga (2004) for urban agglomeration theories, they classify three branches of theories deriving the motives for agglomeration. The one investigating mechanisms of 'sharing', such as indivisible resources or the gains from inputs, where gains appear from narrower specialisation. The second one is the 'matching' mechanism where agglomeration, defined as an increase in the number of agents trying to match, improves the expected quality and likelihood of each match. The third theory is of 'learning', in which generation, accumulation and diffusion of knowledge are investigated into outputs, like product and process innovations or geographic specialisation (Duranton and Puga, 2004).

[4]The agglomeration effects on local labour markets are identified in the literature trough changes happening to firms, such as their density in an area or other characteristics of firm behaviour, including wages. These effects are identified by exogenous variations in inflow of public investment (Kline and Moretti, 2014) or infrastructure in the local market (Severnini, 2014), or by changes in the competitive environment, such as changes in competitors (Greenstone et al., 2010) or job displacement (Gathmann et al., 2014). Additionally, the skills composition of the labour force is found to be relevant both for the productivity gains of firms (Moretti, 2004) and wage disparities across areas (Combes et al., 2008).

an empirical strategy that accounts for this.

Additionally, in the absence of strong labour institutions influencing wage contracting, the minimum wage may be used by workers to anchor their wages (Saget, 2008), even if they are well above the threshold mandated by the law. Thus, we could expect that in the Thai labour market this could create spillovers across the wage distribution.[5] This study takes into account these traits of the Thai economy to evaluate empirically the distributional effects of the minimum wage policy.

The contribution of the chapter is three-fold. First, we document some degree of geographic heterogeneity in the wage schedule of the Thai labour market, suggesting that provinces may constitute in Thailand a form of 'local labour market', with a wide variation in employment and the wage schedule reflecting different degrees of agglomeration and productivity spillovers (Moretti, 2004; Greenstone et al., 2010; Gathmann et al., 2014). This adds to the literature which shows industrialisation and firms' production in the country to be geographically distributed across provinces (Felkner and Townsend, 2011; Limpanonda, 2015) and complements those studies which look at local labour and financial markets in a smaller dimension such as the village (see Samphantharak and Townsend 2010; Townsend 2016).

Second, we apply a method that accounts for these heterogeneous wage distributions at geographic level to evaluate the policy effects. We propose a variant of the Recentered Influence Function (RIF) regression framework (Firpo et al., 2009a) which we apply to wage distributions at the province level instead of the national level. Through the RIF transformation of an individual wage observation within each province, we aim to capture what is the average local wage response to a minimum wage change.

Third, to the best of our knowledge, this is the first study to perform for an emerging economy an in-depth evaluation of the effects of the harmonisation of geographic minima to a statutory minimum with an unusual hike. Variations of a similar magnitude were only previously reported for the whole labour force in Hungary (Harasztosi and Lindner, 2017) and for youth workers in Portugal (Portugal and Cardoso, 2006)

[5] Institutions such as trade unions or the use of collective bargaining contracts are not strongly present in the country. Thus, the minimum wage adjustments could act as one of the main instruments with other forms of labour protection for wage negotiation. Its enforcement, as later discussed in Chapter 5, is central to the discussion on labour market dynamics of many emerging and developing economies (Basu et al., 2010; Bhorat et al., 2015).

and New Zealand (Hyslop and Stillman, 2007). The study provides some evidence to the literature comparing the effectiveness of different minimum wage policy regimes across countries (i.e. Saget 2008; Garnero et al. 2015) by inspecting the short term effects generated by the policy change.

We find positive effects of an increase in the minimum wage on private sector wages over the full period under analysis (twelve years, 2002-2013). The multiple variations in the minimum wage affect the provincial wage distributions between the 15$^{\text{th}}$ and the 60$^{\text{th}}$ percentile. On average, a 10 percent increase in the minimum wage increases the average wage below the median by 2.5 percent, with the effect being stronger between the 25$^{\text{th}}$ and 45$^{\text{th}}$ percentiles and with signs of spillovers. In terms of the short term impact of the NMW introduction (analysed from 2011 to 2013), the results suggest that the shift in the minimum wage strongly affected the average provincial distribution from the 15$^{\text{th}}$ to the 45$^{\text{th}}$ percentiles, halving around around the 50$^{\text{th}}$-60$^{\text{th}}$ percentiles. The impact is strongest between the 15$^{\text{th}}$ and 25$^{\text{th}}$ percentiles, where the 70 percent increase in the minimum wage induces an increase in wages by 35 percent. This suggests that the minimum wage change reached wages of private sector workers in the lower half of the distribution, thus benefiting parts of its intended beneficiaries. However, the latest minimum wage hike did not translate in short term increases in wages for the lowest fraction of provincial wage earners at the 5$^{\text{th}}$ and 10$^{\text{th}}$ provincial percentile. The analysis evaluates which mechanisms could induce such no response, showing that there is some degree of non-compliance among smaller firms.

The work is organised as follows: Section 4.2 introduces the minimum wage setting in Thailand. Section 4.3 describes the data and provides some descriptive analysis of the Thai labour market. Section 4.4 briefly revises the econometric literature on wage analysis and presents the Recentered Influence Function (RIF) methodology. Section 4.5 introduces the province RIF model, followed by results and a series of robustness checks in Section 4.6. Concluding remarks are given in Section 4.7.

4.2 Minimum wages in Thailand

The minimum wage is defined in Thailand as “the payment sufficient for a “skill-needed worker” to make a living in the current social and economic condition and to have a living standard that is appropriate with the capability of businesses in that locality" (Labour Protection Act, MOL 2008). The minimum wage is set as daily rate and applies for a working day of eight hours (seven hours for occupations involving potential danger for the employee's health and safety). Occupations covered are all those in formal sector industries, except for agricultural work, fishery, any government administration or state-owned enterprises, homeworkers and domestic workers. No restrictions on age, gender or nationality are applied (Labour Protection Act, MOL 2008).

The minimum wage legislation was first enacted in 1973 in Bangkok and its vicinities and later, in 1974, extended throughout the country. Minimum wage bands were set across geographic regions to account for differences in the cost of living and other socioeconomic factors such as inflation (as reflected initially by the CPI and, since 1990, economic growth) (Del Carpio et al., 2014). In 1998 the Labour Protection Act (No. 2) introduced changes, setting the ground for a two-tiered system intended to further differentiate minimum-wage levels by province and industry again adjusted to reflect provincial differences in the cost of living and other socioeconomic factors (e.g. inflation). However, no further implementation of industrial differentiation took place, and the effective implementation of the provincial minimum wages started after year 2001.[6] A committee involving government and province representatives set the wage yearly for each province.[7]

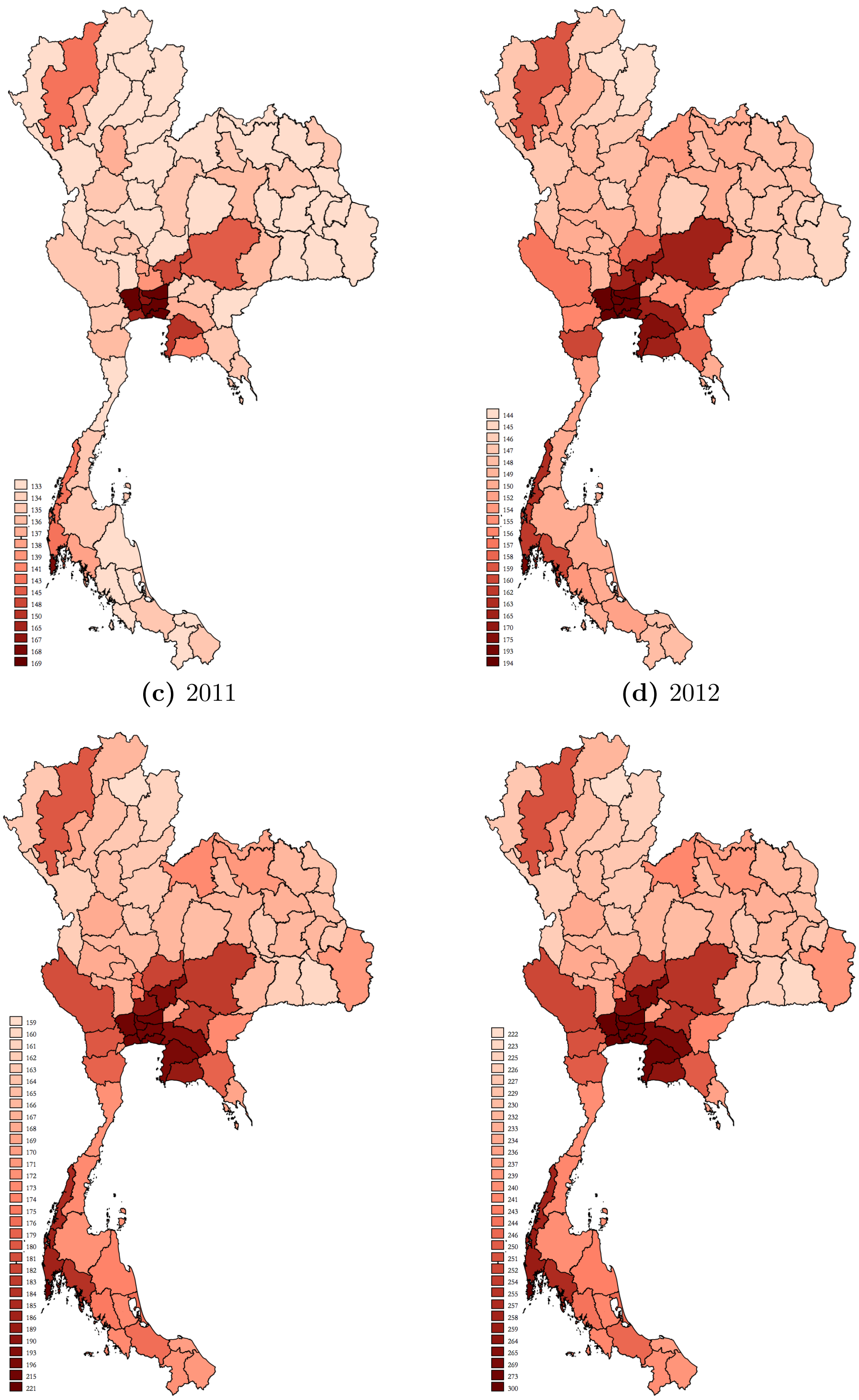
[6]The effective implementation of The Labour Protection Act (No. 2) started in 2001, with yearly adjustments except for years 2005, 2008 and 2010 in which it was amended twice, and year 2009 with no change. See Figure 4.2 below for a graphic visualisation of the mean yearly provincial minima in real terms.

[7]Del Carpio et al. (2014) argue that due to the complex decision-making system, the wage setting was reflecting more political bargaining than real labour market events.

Figure 4.1: Evolution of the minimum wage: map of provincial daily rates over time.

(a) 2003 **(b)** 2008

(c) 2011 **(d)** 2012



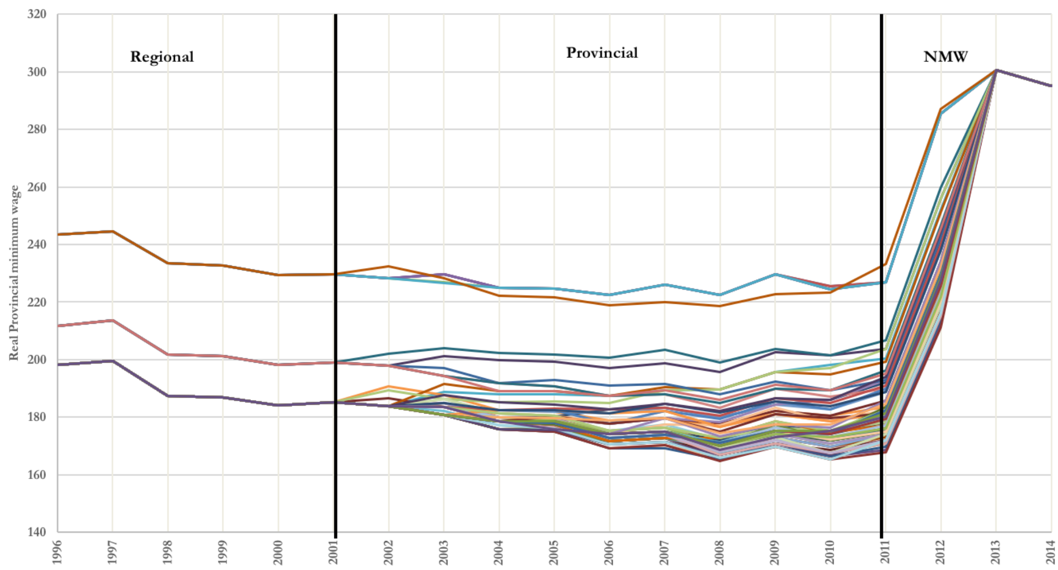
Source: MOL 2003-2012, nominal daily minimum wage in Q2.

In November 2011 the government announced a change in the regulation with the purpose of harmonising wages to one national minimum wage (NMW) following a two-step procedure. In April 2012 a daily minimum wage of 300 Baht (9.65 US$)[8]

[8]Exchange rate in 2012 was of one US dollar for 31.08 Baht.

was applied in seven pilot provinces (Bangkok and vicinities plus Phuket province, as shown in Figure 4.1(d)), and at the same time an uptick of approximately 40 percent was applied to the minima in the other provinces, from approximately US$ 5.12-6.30 to US$ 7.14-8.78 a day. The policy lasted for 9 months and was followed by the introduction in January 2013 of a statutory minimum of 300 Baht per day for the whole kingdom. This second step of the policy increased by a further 30% the nominal minimum across some areas.[9] The different revisions to the minimum wage and wage levels across provinces are summarised in Table B.1 (Appendix B.1) and Figure 4.2 which show, respectively, the different minimum wage regimes and the levels at which these were set across different provinces.

Figure 4.2: Real daily minimum wage by province, 1996-2014.



Note: Authors' own calculations using daily minimum wage data 1996-2014 (annual average) from the Ministry of Labour. Mean provincial daily wages (represented by the solid lines) are expressed in constant 2013 Thai Baht. The vertical lines represent the different minimum wage regimes applied (regional, provincial, single statutory minimum (NMW).

The NMW regime was kept for four years, until the beginning of 2017 in which it was used as the base for four minimum wage levels, attributed to provinces according to their economic performance (ranging between 300 and 310 Baht per province, see Table B.1). Additionally, as of Q4 2016 the country further introduced some skill-specific minimum wage rates. This rates are solely for skilled workers in twenty occupations of five industries, and eligibility is conditional on passing specific tests and certification (two bands between 340 Baht and 550 Baht per day, depending on the skill levels

[9] A report from Bank of Thailand (BOT) suggests in the first step that the immediate lay-off levels were not bigger than previous quarters and the pass-through of labour costs to retail prices was not higher than usual (BOT, 2012).

and experience). The latest data available extend until 2013, thus allowing to show the short-run effects of moving from provincial minima to the national minimum wage, where the hike induced by the switching in regime will be the focus of this investigation.

In developing or emerging economies, potential factors threatening the minimum wage effectiveness are: the low pressure exerted by trade unions; low enforcement by the government; and a complex legislation on minimum wages (Rani et al., 2013). All but one of these features have been prominent in the Thai settings: the latest policy simplified the legislation and also introduced some incentives to comply and to cope with increasing costs. Three complementary policies were used to help firms comply to the minimum wage: i) a reduction in employers contributions to the Social Security Scheme (SSS) from 5 to 4 percent; ii) a decrease in the withholding tax for Small and Medium Enterprises (SMEs) from 3 to 2 percent; and iii) a reduction in corporate income tax from 30 to 23 percent (tax year starting in 2012) which was further reduced to 20 percent for the subsequent tax years.

These complementary measures can be instruments which induce the absorption of greater factor costs by the firms, and are found in the literature to effectively increase firms' investment according to their tenure (Abel, 1982; Auerbach, 1989).[10] These measures are not uncommon in the presence of a minimum wage hike, as was seen in the case of Hungary where the government introduced a temporary subsidy to firms and a permanent removal of the minimum wage from personal income tax (Harasztosi and Lindner, 2017).[11]

Different studies have assessed the impacts of the minimum wage in Thailand at different points in time. In a cross-country comparison, Saget (2008) describes the Thai minimum wage policy structure to follow a "maxi minimum wage set-up", where the minimum is set relatively high to act as an effective wage paid to most low-skilled or

[10] Moreover, the literature investigating the motives behind tax reductions, suggests that a sustained political power of businesses could explain measures like a corporate income tax cut (Sobel, 1999).

[11] At the same time of the national minimum wage introduction, the non-covered agricultural sector was subject to other interventions. Between 2011 and 2014 a series of government-funded pledging schemes (rice, shallots and cassava) were active. The rice policy has been found to be subject to low take-up rate from small farmers (Duangbootsee and Myers, 2014), which for the purpose of this analysis could represent private sector wage workers leaving the private sector to go farming. We do not see any increase in the number of self-employed or wage workers in the period of policies' enactment, but actual decrease in the participation to agricultural work over the period. Thus, these interventions should not contaminate our results.

semi-skilled workers, thus potentially substituting for collective bargaining and also potentially increasing room for non-compliance. Leckcivilize (2015) investigates the effect of the minimum wage policy on wage inequality in the period between the 1980s and 2010 (between regional and provincial regimes), finding no discernible wage compressions for the overall labour market or in sectors covered by the policy.[12] Del Carpio et al. (2014) shows for the period prior to the change to a statutory minimum (1998-2010) some employment contractions for female, elderly, and less-educated workers, also finding large positive effects on the wages of prime-age male workers and a reduction in consumption inequality. Ariga (2016) compares the effect of minimum wage changes over the introduction of the NMW on a sample of daily-paid workers against monthly-paid workers and finds that there is a positive effect of the policy only for daily-wage workers, and rising employment among some groups.[13] Our work differs from this last article in several ways. First, in the emphasis given to the characterisation of the Thai labour market. As we will show, wages in Thailand are diversified geographically. The method we propose is amenable to represent the effect of this policy change on heterogeneous wage structures. Second, in the interest we have in understanding the switch of policy regime. The period of analysis that we choose includes all of the quarters of data available for the latest nationwide enactment of the national minimum wage. This allows us to inspect different facets of the most recent change and the adjustments generated in this first quarters of policy implementation. Although we believe more years of data are necessary to get a full picture, to the best of our knowledge this is the first study for an emerging economy which evaluates such type of change in minimum wage regime with care to its geographic component.

[12] However, Leckcivilize (2015) finds signs of marginal wage compression for workers participating in large firms. The author suggests that the non-responsiveness in wage inequality could be due to the level of non-compliance in the formal sector. We will discuss in the next chapter whether, over the national minimum wage period, the low levels of labour inspections and sanctions still persist and if they could affect policy outcomes.

[13] As robustness to the wage analysis, we assess whether the claim about workers' characteristics raised by Ariga (2016) creates concerns to our identification strategy, but we find that separating workers by their type of wage does not alter the results for the wage distribution (not shown). In the following chapter we will compare the employment estimates found by the author with the ones proposed in the thesis.

4.3 Data and characteristics of the Thai private sector

4.3.1 Data

For the distributional analysis of the minimum wage we use pooled individual-level quarterly cross-sectional data from the Labour Force Survey (LFS) for the years 2002-2013 provided by the NSO of Thailand.[14]

The time period used and geographic areas covered in our sample is conditioned by different features of the dataset. First, since 2001 the LFS is representative at provincial level. However, during this year there is a miscoding of the firm size variable during the first three quarters. In order to allow comparability and to remove any potential measurement error, the main results are reported for the period 2002Q1 - 2013Q4. The sample excludes the latest three years of data for one province (Nong Khai) as its jurisdiction was separated into two during year 2011. This prevents any over-sampling of the population surveyed (i.e. if we were to aggregate both provinces into one since 2011).[15]

The wage analysis is performed using two time periods. The first covers the complete twelve years (2002-2013) of data that is representative at province level. The second covers a shorter window around the NMW introduction (2011-2013). We make the conservative choice of using 2011 Q1 as the starting point for evaluating the NMW introduction. This avoids capturing potential labour market adjustment arising from the 2008-2009 recession.[16]

As additional data for the analysis we make use of quarterly minimum wage levels provided by the Ministry of Labour of Thailand (MOL). The data is converted from

[14]LFS data is available since 1986, but it was subject to various revisions in its enumeration and representative sample sizes over time. Between 1986 and 1996 data is available for Q1 and Q3, since 1998 for all quarters. Data prior to the 2000s are solely used in this study for descriptive purposes (such as in Table B.1 or Appendix B.1.3). Since year 2001 the data are representative at province level with a fairly constant sample size per quarter (around 15,000-25,000 per quarter, or between 72,000 and 80,000 per year). In previous versions of this work we explored data around the Asian financial crisis, but we choose not to report these first years as (1) sample representativeness and weights are not the same (2) we are interested in examining what happened in the 2000s, after the recovery from the financial crisis, particularly in gauging the short-term effects of the latest policy regime change.

[15]Extensive checks with specifications either fully including or excluding this province do not alter the results proposed in the following sections.

[16]Given that in Thailand only minor contractions to production were experienced up to the first half of 2009, the estimations could be performed for a longer time period (for example with an equal number of quarters before or after 2012 Q2), but we choose this more cautious approach to avoid contamination of the policy effect from other macro-economic adjustments.

daily rate to hourly rate (following the law of a 8-hour working day) to match the LFS data. During the years under analysis, the changes in the minimum wage occur generally once per year since 2001 (generally during Q1 or Q2), except for years 2005, 2008 and 2010 in which it was adjusted twice, and with no change in year 2009. The total number of revisions was 13 (2002-2013) with a minimum of 3 minima applied (excluding 2013 with one) and a maximum of 32. Thus, it appears that the number of revisions gives enough power to the policy to be investigated (as visible from the mean yearly provincial minima in real terms plotted in Figure 4.2).

In order to account for production output at the provincial level, we use Gross Provincial Product (GPP) from the National Economic and Social Development Board (NESDB), measured as yearly total value added of sixteen sectors aggregated together, available since year 1995. We use the GPP expressed in its lag per capita terms to represent past performance. We use the national Consumer Price Index (CPI) at quarter-year level (base-year 2013 Q3, BOT) to express the monetary variables in real terms. In order to further test the results of the wage analysis, we apply as robustness the yearly Spatial Consumer Price Index (SCPI), base year 2011, which is calculated for the five geographic regions and at urban/rural levels (NESDB).

Wages from the LFS are expressed in hourly rate.[17] We restrict the main sample to males aged 15-65 employed in the private sector (excluding students), representing both formally and informally hired workers.[18] We include both full- and part-time workers (the cut-off in Thailand between the two definitions is 40 hours per week).[19]

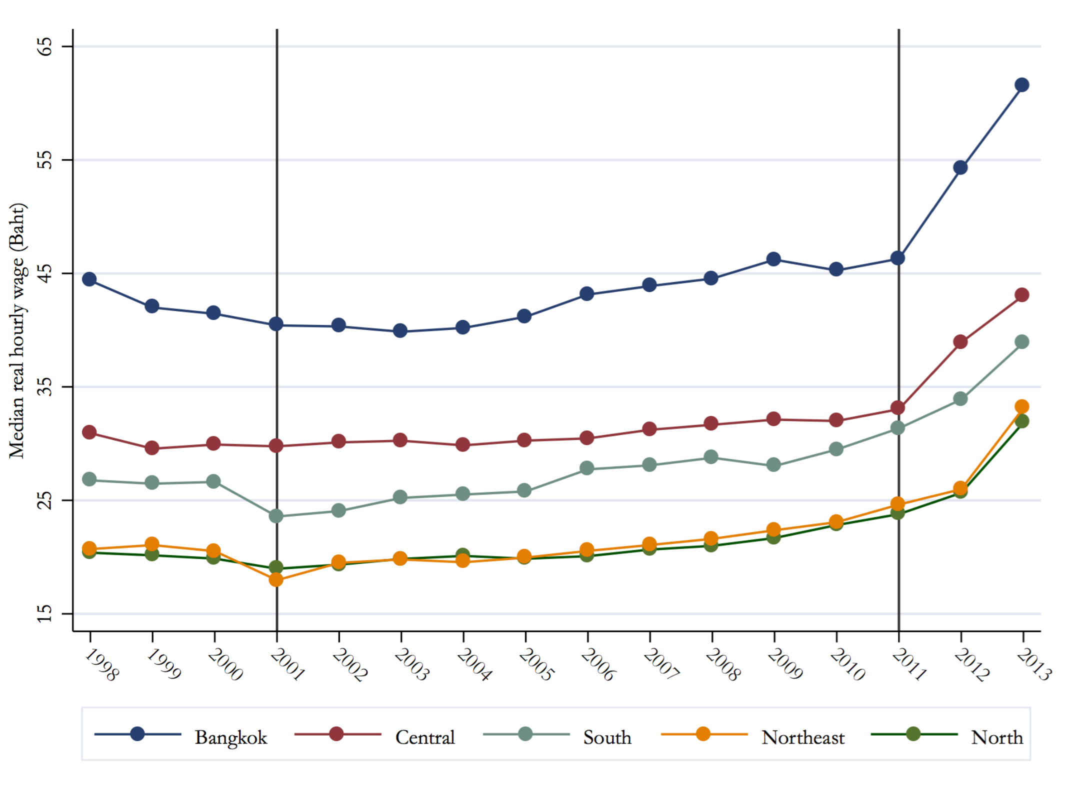
[17]The wage data is reported in the survey both as wage earned in the last month and in its rate by type of wage received, while the hours worked reflect the recall period of the previous week. We calculate the hourly wage as monthly earnings divided by 4.286 (converted to weekly) and by the hours worked during the last week. We ensure that the transformation is consistent with the wage rate reported (i.e. if the wage is reported daily or weekly, we check that the conversion matches with the wage reported). We believe this measure to be more reliable than the wage rate variable, as there may be higher measurement error in the wage rate reported by the interviewee.

[18]A shortcoming of this dataset is that it is limited in differentiating between the formal and informal sectors. The official definition of informality identifies workers (such as wage employees, unpaid family members or self-employed) not covered by the Social Security Scheme (SSS) contribution. The information is not provided in the LFS data, with exception of a special section collected for one quarter (since 2005) not available to the authors. We use as proxy for informal work the employment in micro-enterprises with less than five employees (for which we have wage information), or non-wage work (not disposing of wage, that will be used in the following chapter). We draw inference on specific behaviour correlated to informal workers in the regressions, while keeping in mind the strong assumption we have to apply to the definition (in the absence of the SSS information which would have been better suited to the investigation).

[19]Part-time workers are a very minor share of private sector wage employees (9 percent) and when we exclude these from the analysis as robustness, the results do not change.

To represent the coverage of the minimum wage law, the main specifications exclude the agricultural sector (around 17% of the private sector population), but we use this category in some robustness checks. Table B.2 (Appendix B.1.1, p. 134) reports a summary of the data used. In order to construct the wage distributions we use survey weights multiplied by hours worked over a week (DiNardo et al., 1996).[20] Similar to Autor et al. (2016), we pool the individual observations in each location-time period (province-quarter) and construct the wage distributions. Applying a variant of the RIF transformation of Firpo et al. (2009a), detailed later in the chapter, these quarterly provincial measures for the private sector population are expressed into quantiles, our primary outcomes of interest.[21] Further in the chapter we also investigate briefly on the female labour force, in addition to conducting specifications with sample splits by firm or province characteristics.

Figure 4.3: Median hourly wage by geographic region, 1998-2013.



Note: Authors' own calculations using LFS 1998-2013. The figure reports median real hourly wage by geographic region for private sector workers (all quarters except for 1998, using Q1 and Q3) deflated by national CPI (2013). The vertical lines refer to the three minimum wage regimes applied.

The provincial minimum wage rates (Figure 4.2) followed relatively flat adjustments

[20]For the weights we follow the approach of DiNardo et al. (1996), extensively applied in the wage inequality literature (Autor et al., 2016), and we ensure that the results are robust to the use of population weights in place of population-hours weights.

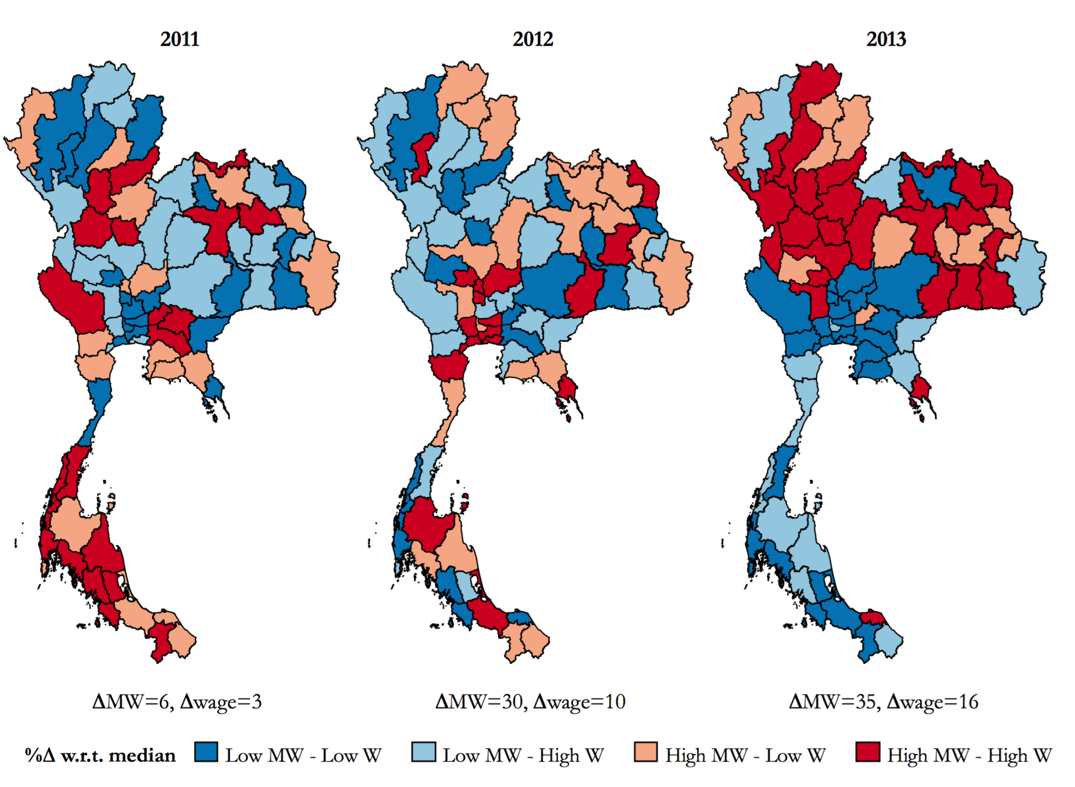
[21]Additionally, we perform robustness of the wage analysis by using only one quarter of data (Q3, enumerated during the wet season) and the results are not distant to the ones reported (not shown).

in real terms over the period 2002-2011, with signs of reduction for some provinces, and never adjusted to the levels experienced before the Asian financial crisis until the NMW introduction. The flat minimum wage floor appears to have been reflected also in median private sector wages. As shown in Figure 4.3, the real median hourly wages in the five geographic regions of Thailand have grown slowly but steadily over the decade of a provincial minimum wage regimes, while after 2011 they have jumped. Noticeably, regional median private sector earnings follow marked trends, feature which suggests a wage structure that differs across areas of the country, but that co-moves over time. There could be strong linkages between the increase in median wages and the hike in the minimum wages which led to the statutory wage. In order to understand the mechanisms in place, we first report some statistics on the minimum wage bite and the labour markets, followed by regression analysis.

4.3.2 The latest minimum wage bite and non-compliance

We now investigate on the characteristics of the NMW policy introduction. Attention turns first to the nominal changes in the minimum wage and to the changes in provincial median wage (for male private sector workers). We seek to identify the year-on-year change induced by the NMW 2-step policy. In order to do so, we create a 'regime quadrant' of high versus low regimes in Minimum wage (MW) level changes and median earnings for each year between 2011 and 2013 which we plot in Figure 4.4. The figure shows that prior to the policy change in 2011 (with a MW change ranging from a min=4% to a max=9%) there is some heterogeneity among provincial median changes. As visible from the first map, in 2011 provinces with stagnant or decreasing changes in median wages (those in low W category, min=-12%,max=2.4%) are spread across the country (no sign of geographic clustering is seen in the data). The maps for 2012 and 2013 help to form a better understanding of where and how the policy correlates with market behaviour. In 2012 the seven pilot provinces (Bangkok, its surroundings and Phuket) have a much higher nominal minimum wage and earnings (red coloured on the map). The map further shows that also other provinces saw a a co-movement of MW changes due to the first hike (Q2 2012) and median wage changes (for example, the provinces in the north-east). The map for 2013, with the NMW at 300 Baht or 9.65 US$ for the whole country, indicates that some wage response occurred across the whole economy. For example, regions known for having a very flat private sector wage such as the North, North-east and the deep South saw movement in their median earnings.

Figure 4.4: Maps of high versus low changes in the minimum wage and median earnings (2011, 2012, 2013).



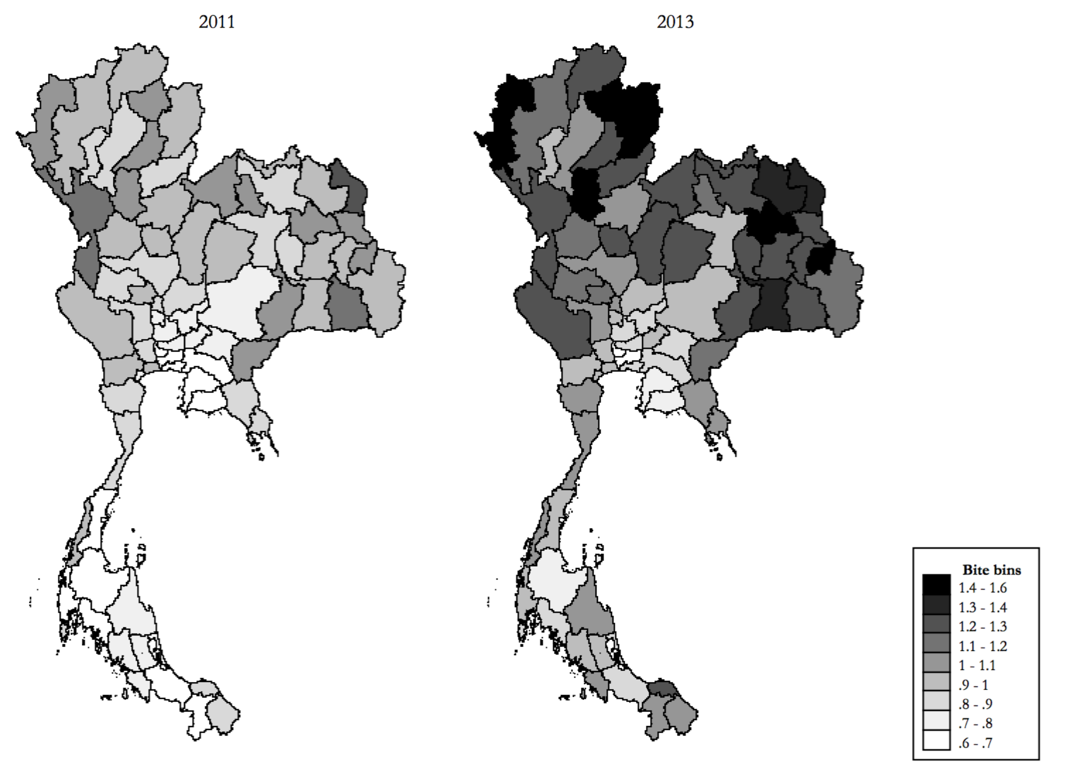
Notes: LFS 2010-2013 at province level. The data capture the yearly change (from $t-1$ to t) in average MW and median male hourly wage at province-level. Each map reports the Δ% median value of MW changes and median wages, used as cut-offs for high vs. low regimes in each year. Then a 'regime quadrant' for each year is created: The low values represent any province having less than median change. Any high value is greater or equal to the median change of each year.

Further evidence of the wage effect of the latest policy change can be seen from calculating the minimum wage bite (median Kaitz index) at provincial level for private sector wages and comparing the pre (2011) and post (2013) introduction years as is shown in Figure 4.5.[22] The average provincial Kaitz Indices for 2011 and 2013 are 87% and 108% respectively. The degree of variation in the index suggests that, in several provinces the statutory 300 Baht minimum was greater than the median private sector wage (in 48 provinces out of 76). Thus, we can already expect that the proportion of wageworkers under the minimum wage to have increased, and the bite to be less effective the higher the share of workers not paid at or above the minimum wage. Even if these measures seem unusually high when compared to developed economies, they

[22]The minimum wage bite or Kaitz index, is the ratio of nominal minimum wage to the median wage level, following the definition in Garnero et al. (2013).

are in line with other economies. Comparing these magnitudes with measures for other developing and emerging countries (taken from measures for the late 2000s as shown in Rani et al. 2013, p.392-393), Thailand has moved from a bite in the mid-range of the minimum being at 80 percent of the median wage (Brazil and Costa Rica) to high-range at or above 100% (Indonesia, South Africa and Turkey).

Figure 4.5: Maps of the minimum wage bite at province level, 2011 and 2013.



Note: The maps report the minimum wage bite per province in year 2011 and 2013. The bite is defined as the ratio of nominal minimum wage over nominal median wage for private sector workers. The median is calculated using survey weights multiplied by hours worked. In 2013 a total of 48 provinces has a bite greater than one (9 in Central region, 16 North, 17 Northeast, 6 South). In 2011 these were 14.

Where the presence and characteristics of workers paid sub-minimum wage are concerned, there seems to have been an increase in the rate of non-compliance over the latest three years of data available (approximately by 20 percentage points for low-skilled and young low-skilled workers) as is shown in Table B.5 (Appendix B.1.3, p. 142). Table 4.1 identifies the composition of non-compliance by worker characteristics compared to workers at the minimum or above. Individuals paid below the minimum are low-educated (80 percent on average), mostly residing in the Northeast, North or Central regions in provinces with relatively low GPP per capita. They are full time workers and more than 50 percent work in firms with less than 10 employees (suggesting a higher degree of non-compliance for this type of firm). They mostly work in manufacturing, construction or wholesale and retail (with the last two sectors seeing their shares increase between 2011 and 2013). Their average wage has increased during the period (although less than for other groups), and their average hours worked per week is the highest compared to individuals paid at or above the minimum (though significantly reducing during the policy shift).[23]

Table 4.1: Summary statistics for private sector wage workers by relative position to the minimum wage level, Q3 2011-2012-2013.

	2011			2012			2013			Tests for workers below MW			
Pop. +/- 5% of the MW	Below	At	Above	Below	At	Above	Below	At	Above	Test 2011-12 test	p-val	Test 2013-12 test	p-val
Age	35.59	33.99	35.00	35.25	34.07	35.53	34.86	33.83	35.70	2.41	0.02	-2.33	0.02
Male	0.46	0.47	0.58	0.52	0.54	0.57	0.54	0.56	0.56	47.25	0.00	7.43	0.01
Edu < 2^{ary}	0.84	0.81	0.52	0.81	0.78	0.44	0.78	0.77	0.43	14.35	0.00	27.42	0.00
Bangkok	0.12	0.12	0.23	0.09	0.11	0.26	0.05	0.08	0.28	35.92	0.00	31.43	0.00
Central	0.27	0.42	0.38	0.26	0.46	0.41	0.24	0.55	0.40	14.10	0.00	1.53	0.22
North	0.22	0.15	0.12	0.22	0.12	0.10	0.23	0.11	0.08	2.12	0.15	1.67	0.20
Northeast	0.30	0.21	0.17	0.31	0.23	0.14	0.34	0.20	0.14	2.52	0.11	14.37	0.00
South	0.10	0.10	0.11	0.13	0.08	0.09	0.14	0.05	0.10	25.98	0.00	1.52	0.22
Micro Firm	0.59	0.36	0.28	0.57	0.33	0.21	0.57	0.24	0.19	10.09	0.00	0.32	0.57
SME Firm	0.28	0.26	0.33	0.29	0.29	0.34	0.29	0.30	0.34	0.17	0.68	5.28	0.02
Large Firm	0.13	0.38	0.39	0.14	0.38	0.45	0.14	0.46	0.48	16.37	0.00	4.85	0.03
Manufacture	0.32	0.47	0.39	0.28	0.48	0.42	0.29	0.57	0.41	1.52	0.22	0.06	0.81
Construction	0.21	0.15	0.15	0.26	0.19	0.12	0.26	0.16	0.10	65.32	0.00	6.73	0.01
Wholesale	0.17	0.14	0.20	0.19	0.17	0.18	0.21	0.15	0.20	3.29	0.07	0.00	0.99
Hospitality	0.13	0.09	0.06	0.09	0.06	0.05	0.09	0.04	0.05	26.30	0.00	1.77	0.18
Services	0.07	0.07	0.13	0.07	0.06	0.14	0.05	0.06	0.16	3.00	0.08	0.74	0.39
Other	0.11	0.08	0.08	0.11	0.05	0.08	0.10	0.03	0.08	17.07	0.00	3.51	0.06
Full time	0.94	0.98	0.94	0.94	0.97	0.93	0.94	0.99	0.92	5.63	0.02	5.89	0.02
Married	0.56	0.62	0.61	0.60	0.63	0.63	0.61	0.64	0.63	-5.00	0.00	-0.52	0.60
Hourly wage	17.60	24.65	58.17	23.58	33.46	72.92	27.94	37.79	81.00	-58.87	0.00	-48.53	0.00
Weekly hours	55.33	52.90	49.04	53.48	50.02	48.26	51.05	50.58	47.93	8.72	0.00	16.67	0.00
Log MW	3.16	3.19	3.21	3.46	3.50	3.53	3.62	3.62	3.62	-198.42	0.00	-207.31	0.00
Log GPPpc	11.33	11.61	11.79	11.29	11.65	11.95	11.17	11.72	11.99	3.07	0.00	10.16	0.00
Obs.	5,524	2,605	22,752	10,397	3,131	19,364	9,767	2,952	17,634	15,921		20,164	

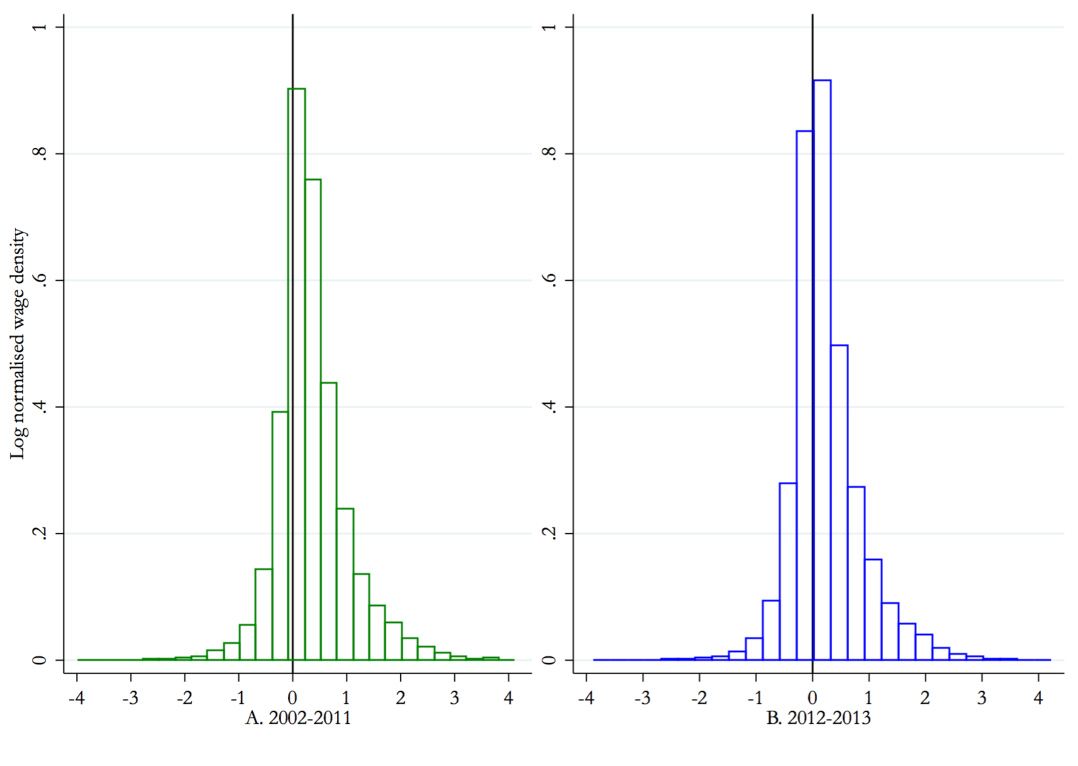
Note: LFS Q3 2011-2013. The table reports summary statistics for private sector workers (including female, excluding agriculture) by year and real hourly wage relative position to the real hourly minimum wage (+/- 5% of the minimum wage). Means are evaluated using survey weights, monetary variables are deflated by CPI (Q3 2013). Sectors: Manufacture (including mining), Construction, Wholesale (and retail), Hospitality (restaurants), Services, Other. Tests for population of individuals below the minimum wage by years (either 2011-2012 or 2012-2013), reporting test and p-value (equal or unequal variance test for levels, χ_2 test for binary variables).

Nevertheless, a comparison of the normalised (log) wage of private sector workers (Figure 4.6 below) during the provincial minimum wage regime (2002-11) and the NMW regime (2012-13) shows for both policy periods the presence of bunching at and around the provincial levels dictated by the policy in each year. This gives ground for an

[23] The issue of non-compliance is central to theoretical and empirical evidence for emerging and developing economies (Basu et al., 2010; Bhorat et al., 2012b; Rani et al., 2013). In the next chapter, we review the contributions of the literature about non-compliance (Section 5.2), we further investigate on the incidence and depth of non-compliance (Section 5.3.1) and report some evidence about firms' interaction with the authorities (Appendix C.4). Additionally, a broader description of the theoretical models behind the minimum wage literature will be described in the following chapter, so to keep the wage analysis focused on the challenges of identification of provincial wage distributions.

analysis on the responsiveness of wages to the policy shift. Overall, the statistics shown in this section suggest that some change is already happening only six quarters after the policy regime shift. But this also implies that further data might be needed in order to assess the full effect of the policy.

Figure 4.6: Log Normalised wages, years 2002-2011 and 2012-2013.



Source: LFS 2002-2013 (pooled data by time period, 02-11 or 12-13). Normalised log wage density, 0=Minimum Wage.

4.3.3 The features of the Thai labour market

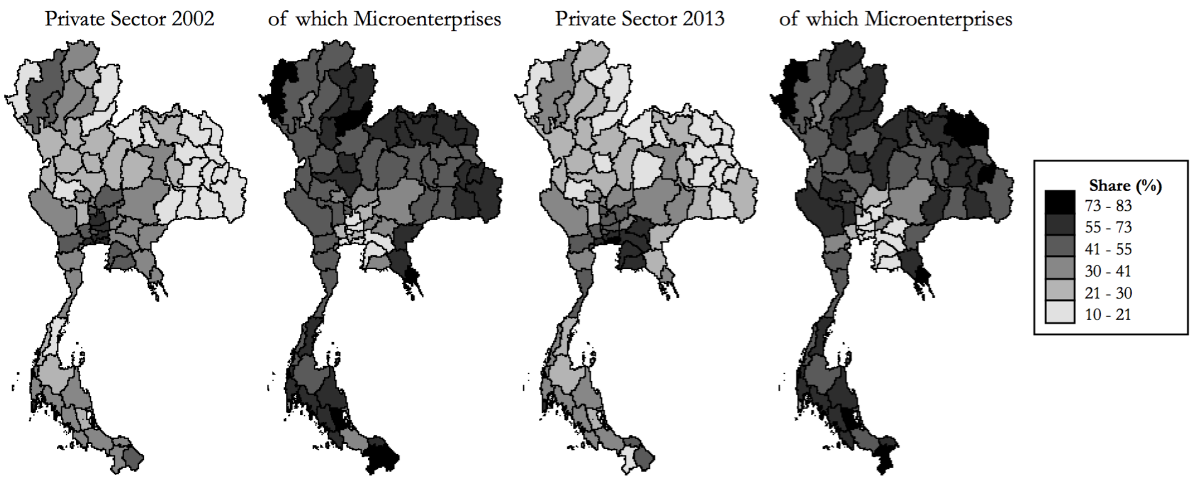
The Thai economy is diversified in terms of types of production and firms' location (Felkner and Townsend, 2011; Limpanonda, 2015). We report some evidence about how the labour market can be broadly classified as partially segmented to motivate the analyses we perform at the province-level.[24] This section gives an overview of labour market participation in the private sector and shows how the notion for '*local*' labour markets is applicable to provinces in the country as a result of differentiation across

[24]We loosely define segmentation to apply if a high degree of heterogeneity is present in some labour-related factors across workers' characteristic (labour-unit segmentation) and/or across locations where they work (geographic segmentation). The term segmentation is used to identify diversity across agents or markets, thus overarching across the definitions typically used either in the dualistic or in the spatial approaches to labour market analysis. Note that it goes beyond the scope of this work to explain the full characteristics of segmentation for Thailand (e.g. as in Sussangkarn 1987) or its motives (e.g. Heidenreich 2015 for long-term unemployment in European economies).

firms and production that characterise participation.[25]

Thai private sector employment is not massive in size nor homogeneously distributed, as is the case for many emerging and developing economies. On average private sector employment accounts for 35 percent of the total population employed per province over the period under analysis (similar to countries like Indonesia, Viet Nam and Peru, with an average wage employees around 30-40% over the 2000s, as reported by Rani et al. 2013). There is a high degree of variation across areas of the country, as shown in Figure 4.7. The industrial hotspots in the Central region show the highest average share of workers in the private sector (e.g. Samut Prakan with 72 percent), while many provinces in the Northern and Northeastern regions have an average below or around 20 percent. In those areas, non-wage work accounts for around 70-75 percent of employment, either being declared as self-employment or unpaid family work.[26]

Figure 4.7: Private Sector and Micro-enterprise employment shares, 2002-13.



Source: LFS 2002; 2013. The map reports the average private sector share (%) over total employment by province and the participation within micro-enterprises (with less than ten employees) over total private sector employment. The first two figures refer to year 2002 and the last to 2013, survey weights applied.

High informality may explain this heterogeneity, with official figures for 2013 at

[25]The local labour markets and agglomeration effects are generally studied in the literature trough changes in the economic activity of firms (Kline and Moretti, 2014; Greenstone et al., 2010; Gathmann et al., 2014). In this study, due to the limitation in accessing firm-level data and no availability of nationally representative longitudinal data, we solely aim to account for geographic heterogeneity in realised employment and wage dynamics, without specifically looking into the motives of firms agglomeration. This means that we have to rely on the literature for Thailand (Felkner and Townsend, 2011) and implicitly assume that geographic agglomeration has taken place independently of the policy under analysis. To the best of our knowledge, this is the first attempt to characterise local labour markets in Thailand from an evaluation of labour market outcomes.

[26]This implies that an institution such as the minimum wage may have different degree of direct impact to covered workers across areas.

around 64.3 percent of total employment, with prevalence in the North and Northeast (NSO 2014 pp.78-79). Informality is found across education groups – particularly among the low-educated but with a post-1997 rising share of higher educated workers taking up informal employment (Lathapipat and Chucherd, 2013) – and across both low and higher income groups, although the largest share of informally employed is in the lowest income deciles (Dasgupta et al., 2015).[27] However, high informality may hide some unemployment (it is reported at less than 1 percent in 2013) which is not well captured by standard survey questionnaires (Sussangkarn, 1987) and may be reported as self-employment or part-time employment in agriculture.[28]

In addition to high levels of informal employment, the Thai labour market saw important changes in the educational composition of the labour force during the 2000s. During this period the share of private sector workers with completed secondary or higher education rose from 23% to 34% (Table B.3, p.135). There are also marked differences in the wage structure by education and in the growth rates by type of education achieved (Lathapipat, 2009).[29] As in many emerging economies, the 2000s for Thailand brought about a more educated population and a shift away from agricultural work into services with a relatively stagnant industrial sector participation (see Figure B.2, p.137). At the same time, these years were characterised by a slower pace of participation of the labour force in large private sector firms, whose rate only returned to previous levels after 2011 with a reduction in participation in micro-enterprises.

Different economic mechanisms motivate firms' location decisions (e.g. prices and demand for goods, transport networks or housing and amenities) and their demand for labour leading to differences in wage schedules across provinces. Geographic agglomeration of firms is one of the factors explaining the concentration of productions

[27]The wage premium in 2011 of formal workers relative to informal is found to grow across the income distribution, and it is highest for those in the upper income groups of minimum-wage covered industries such as services or manufacturing (Dasgupta et al., 2015).

[28]The high informality rate and the diversified private employment shares across the country are strictly linked to the duality of agriculture in Thailand, in which commercial full-time farmers coexist with part-time farmers using land as a safety net (Sondergaard et al., 2016).

[29]Figure B.1 (p.136) displays these trends. The composition-adjusted real hourly wage (Panel A) had a much higher premium for workers with post-secondary education than for those in secondary or lower education. However, the hourly wage index (wages are indexed to 1 in 1986) reveals some interesting trends for non-agricultural wages (Panel C). After 2005, the commodity price boom and the relative decline in primary-educated labour supply put upward pressure on the low-skilled hourly wages despite stagnant or falling provincial minimum wages.

in some areas of the country and therefore the employment patterns across provinces (e.g. the case of automotive industry as detailed in Pholphirul 2006; Kohpaiboon and Poapongsakorn 2013). It also explains why economic development has been spatially concentrated across and within provinces (Felkner and Townsend, 2011) and why growth divergence and inequality has been so different across different areas of the country (Limpanonda, 2015). Felkner and Townsend (2011) find that during the pre-1997 period numerous industries and enterprises clustered in Bangkok, its surroundings and in a central national corridor along the main transportation arteries (Felkner and Townsend, 2011). Further on this line, during the 2000s public intervention may have also favoured concentration of private sector firms. For example, the Industrial Estate Authority of Thailand (I-EA-T) promoted the creation of industrial estates (industrial areas or export processing areas) according to perceived comparative advantage (see I-EA-T 2012). Such place-based policies aim to attract manufacturing or service firms to a specific jurisdiction (an approach which is also used in the United States, European and other Asian countries, see Kline and Moretti 2014).[30]

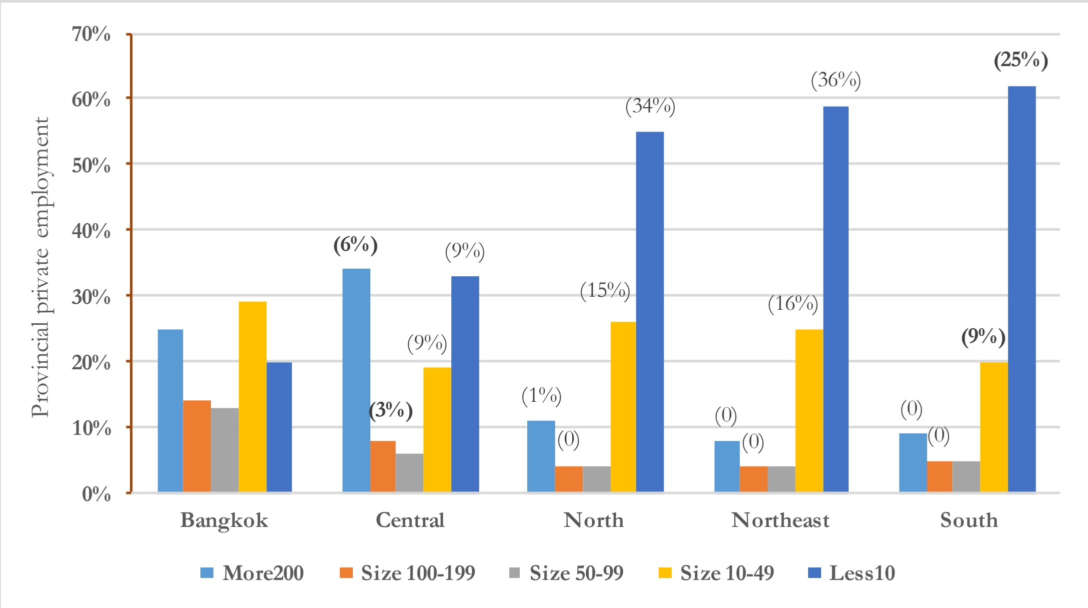
Employment and wages are therefore expected to reflect these provincial differences. A closer look at private employment shares between 2002 and 2013 (Figure 4.7 above) reveals that where private sector employment is relatively low the participation in micro-enterprises (with less than ten employees) is highest. An indication of possible agglomeration is likely to have a direct effect on wage negotiation in those areas given that bargaining is likely to happen without the participation of worker representatives or trade unions. Figure 4.8 also highlights the heterogeneity of employment composition across regions in 2013. It shows the average share of provincial private sector employment in a specific type of firm according to size. The central region has a concentration of both very large (more than 200 employees) and micro (less than 10) firms with a noticeably high variance across provinces (some having less than 10% employment either in the biggest firms or in micro firms). By contrast, the North,

[30]What we aim to emphasise is that some geographic heterogeneity is present in the data and we ascribe it to the level of provincial markets. With the data at our disposal we can only identify the difference across provinces as reflected in their different economic activity, but we cannot delineate if this happens because of agglomeration spillovers or natural advantages. Such type of exploration of local labour market generation could be only consistently estimated with the use of firm-level data, not available to the authors. Thus, it goes beyond the objective of this study to define the reasons of why, where and how place-based policies have taken place in Thailand.

Northeast and South employ, on average, more private sector workers in either small or micro enterprises. Bangkok, as expected, is the most heterogeneous.

Firm location appears to matters. It seems to lead to partially segmented labour markets with employment participation not clustered in single regions, but rather dispersed across provinces. For example, employment in large firms accounts for the highest share of employment in thirteen industrial provinces of the central region, and in two provinces with industrial estates in the north (Lamphun) and northeast (Nakhom Phanom). These areas not only are served by a solid transport network, but they also enjoy an greater economic activity than other provinces in the region.

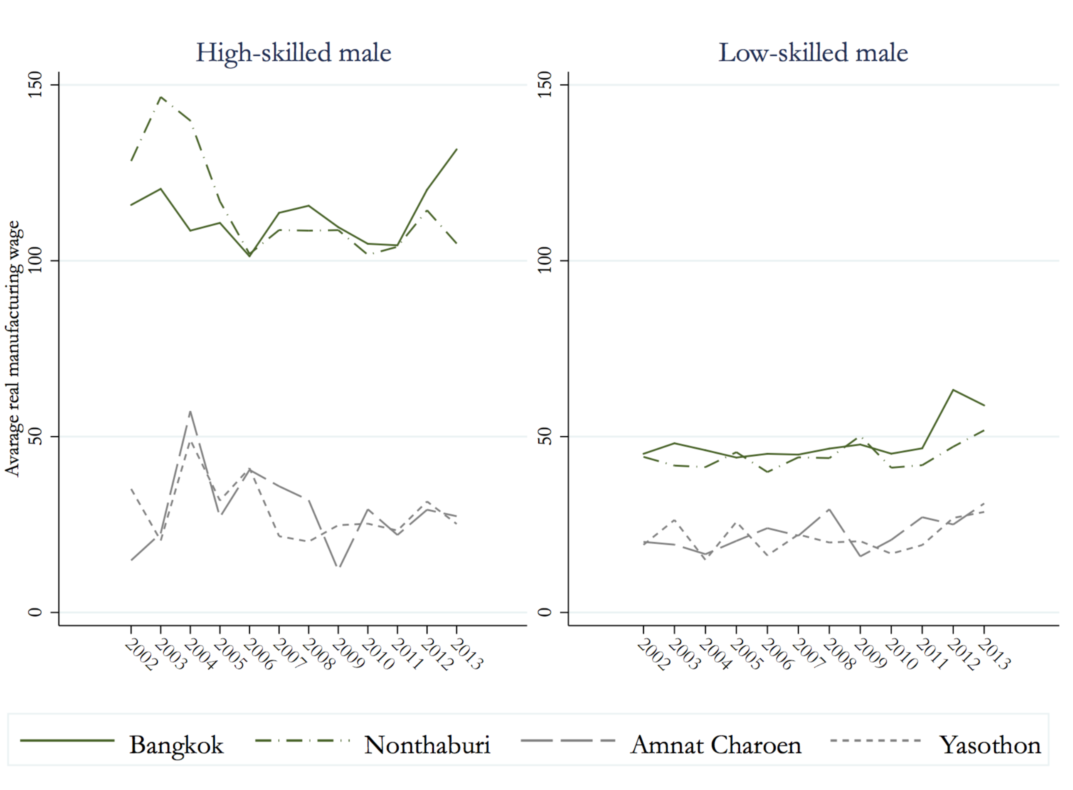
Figure 4.8: Provincial private employment share by firm size and region, 2013.



Notes:LFS 2013. The figure gives a snapshot of the regional private employment share by firm size in 2013. It reports the average provincial private-sector employment by firm-size (with the minimum provincial share in brackets). For full table, see Table B.4 (p.138).

The provincial agglomeration of employment by type of sector also offers interesting insights. Given that we do not have access to firm-level data or statistics on firms presence by province, we use a *naive* measure of employment concentration called the Location Quotient (LQ) for three aggregated sectors (further detailed in Appendix B.1.2, p.138 with definition and limitations). The LQ for the Industry sector suggests that employment specialisation has remained spatially clustered in the Central provinces surrounding Bangkok, with increased employment above the national average in 2013 for provinces with industrial estates established over the 2000s. Services are the biggest specialisation in Bangkok (as expected), but the there was widespread increase in specialisation for this sector across provincial labour markets between 2002 and 2013.

Figure 4.9: Average real wage in Manufacturing by education. Selected provinces.



Source: LFS 2002-2013. Real average provincial hourly wage for male private sector workers in the Manufacturing sector is depicted for four provinces, selected according to their relative rank for private-sector wages at beginning and end of the period (Bangkok and Nonthaburi in Central region with high wage rates, and Amnat Charoen and Yasothon in the Northeast with low wage rates).

The statistics above suggest that private sector employment is heterogeneous across provinces in terms of firm size, production type and characteristics of labour force hired. A further question to explore is whether this heterogeneity translates into different wage structures across geographic areas. In Figure 4.9 we take as example male manufacturing workers with high (education above secondary) or low skills (secondary or lower) across four provinces, two with a relatively high average real hourly wage (Bangkok and Nonthaburi), and two with a relatively low one (Amnat Charoen and Yasothon). The figure suggests that within the same industry, the wage schedule of observationally similar workers varies widely across provinces. Such heterogeneity, discounting the cost of living across localities, is generally attributed to differences in productivity (Moretti, 2011), within-industry interactions and in the skill composition across areas (Combes et al., 2008). While these provincial differences may arise from different wage structures as a result of greater wage inequality within the sector, headline measures (reported and commented in Appendix B.1.3, page 140) show that wage inequality has been stable (or even reducing) over time across sector and gender groups.

All the elements highlighted above suggest that provinces are not only different in terms of production, but they also have different wage schedules for private sector work. This is important in the context of identifying the wage impacts of the minimum wage. The econometric analysis we perform aims to account for heterogeneity in the data while delivering a population effect in the estimation. In the next two sections we propose a variant of the computationally simple RIF method to account for this.

4.4 Modelling wage distributions: the RIF methodology

A vast literature has investigated how to evaluate the impact on distributions going beyond the mean regression. The method which has generated much interest and use in the economics discipline is the Conditional Quantile Regression (CQR), as first proposed and tested by Koenker and Bassett (1978, 1982), where a quantile estimator is applied to examine the effects of observable covariates on the distribution of an outcome variable.[31]

The core idea behind the CQR is to model the quantiles of the conditional distribution of the response variable as functions of a set of observed covariates. It provides a framework for robust inference when the researcher is interested in evaluating the heterogeneity of conditional response across a distribution to a change in covariates. The main limitation of this methodology is that it cannot apply the Law of iterated expectations, so the conditional quantiles do not average up to their unconditional population counterparts (Firpo et al., 2007). For an empirical application this would imply that the effect generated by a policy is interpreted on the *conditional* quantile of the outcome variable, which may not always be desirable. Additionally, the presence of measurement error in the outcome variable biases the quantile estimator, and this bias can be substantial when conditional heteroscedasticity is present (Hausman, 2001).

[31] A vast literature (not exhaustively reported here) has extended the usability of the CQR model, for example to semi- and non-parametric structures, with multiple contributions on applications with longitudinal data (Koenker, 2004), instrumentation (Harding and Lamarche, 2009), dynamic modelling (Galvao Jr., 2011), interactive effects (Harding and Lamarche, 2014) or selection correction (Arellano and Bonhomme, 2017). For a list of selected empirical examples, see for example Koenker and Hallock (2001), p.151.

Much effort has been put forward in the literature to convey a transition from conditional to unconditional quantile effects. The literature on decomposition methods has generated a series of stepping stones in the investigation of distributions (see Fortin et al. 2011 for a review). The objective of such studies is to evaluate the impact of a counterfactual change in the distribution of some covariates on the (un)conditional distribution of the variable of interest (see for example the re-weighting approach by DiNardo et al. (1996) for aggregate distributions, or the distribution regression approach by Chernozhukov et al. (2013) for estimating the conditional distribution). An example is Machado and Mata (2005), who propose a method based on the estimation of marginal wage distributions consistent with a conditional distribution estimated by quantile regression as well as with any hypothesised distribution for the covariates. Although this work has been seminal in moving from conditional to unconditional distributions, it is cumbersome in its estimation, as it requires numerical integrations to globally create the unconditional effect.[32]

Firpo Fortin Lemieux (FFL) or Firpo et al. (2009a), propose the Unconditional Quantile Regression (UQR) method, in which the parameters capture changes in the unconditional quantile distribution of the dependent variable in the presence of exogenous regressors. They develop a method to estimate the Unconditional Quantile Partial Effect (UQPE) of the explanatory variables of interest on the functional (quantile) of an outcome variable (the log wage distribution). The method proposes a solution to the lack of linearity condition in CQR analysis. The aim is to extract a population effect of X variables on the quantile of Y, proposing a simple and flexible method based on the Recentered Influence Function (RIF). In a nutshell, their method estimates the unconditional (marginal) effect of X on the functional $\nu(.)$ of the marginal distribution of Y, regressing the transformation known as the Recentered Influence Function (RIF) on covariates: $\mathrm{RIF}\,(Y;\ \nu, F_Y) = X\beta + e$.

[32]The calculation of the provincial wage analysis using the Machado and Mata (2005) method is prevented by two facts: we aim to represent unconditional effects generated by subgroups of the population, and the method proposed by the authors would need to be modified to perform initially a CQR for each province, to then generate the "global" transformation back (with multiple integrations), assuming we have fully accounted for idiosyncratic factors affecting each provincial distribution; the large sample size which we consider in this analysis objectively prevents us from presenting this methodology as a further robustness to the analysis. Nevertheless, we acknowledge the importance of the authors' work.

Their approach got resonance in the literature as it is a computationally simple regression method to estimate the impact of changing the distribution of explanatory variables on the marginal quantiles of the outcome variable. Following FFL work, extensions have been proposed to allow the estimator in non-separable models, when an explanatory variable is endogenous (Rothe, 2010; Ghosh, 2016) or when the analysis is carried with aggregate data (Nicoletti and Best, 2012). We choose the RIF as our estimation procedure due to its computational simplicity in evaluating a population effect using an Ordinary Least Squares (OLS) framework, in which potential measurement error does not bias the estimates and, as we will show, since the RIF transformation can be adjusted to the local labour markets that we can identify with the data at our disposal. Below we summarise the core definitions behind the Recentered Influence Function.

4.4.1 The Unconditional Quantile Regression

Using FFL notation, we assume that a random sample of Y is observed in the presence of continuous covariates X, such that they have a joint distribution $F_{Y,X}(.,.) : \mathbb{R}\times\mathcal{X} \rightarrow [0,1]$ with $\mathcal{X} \subset\mathbb{R}^k$ being the support of X. We assume that the interaction of Y and X follows a general structural model $Y = h(X, \varepsilon)$, where $h(.,.)$ is a mapping function invertible in the second argument and ε an unobservable component of Y.

The RIF is defined as $\text{RIF}(y;\ \nu, F_Y) = \nu(F_Y) + IF(y;\ \nu, F_Y)$, the sum of a distributional statistic $\nu(F_Y)$ and the Influence Function $IF(y;\ \nu, F_Y)$, representing the influence of an individual observation on that distributional statistic of Y (Hampel, 1974). The functional $\nu(F_Y)$ is any function of F_Y , part of $\mathcal{F}_v \rightarrow \mathbb{R}$, a class of distribution functions, such that $F_Y \in \mathcal{F}_v$ if $|\nu(F_Y)| < +\infty$.[33]

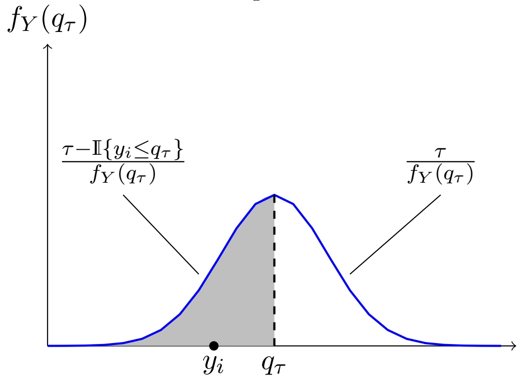
Choosing as functional the quantile, the transformation for the τ^{th} quantile, q_τ, is defined as:

$$RIF(y_i, q_\tau, F_Y) = q_\tau + \frac{\tau - \mathbb{I}\{y_i \leq q_\tau\}}{f_Y(q_\tau)} \tag{4.1}$$

[33]For further details on the Influence Function, see Appendix B.2.1 (p. 143) and Firpo et al. (2009a,b).

Where $f_Y(q_\tau)$ is the kernel density estimator of outcome Y in the τ^{th} quantile q_τ and $\mathbb{I}\{Y_i \leq q_\tau\}$ is an identity measuring if each observation is at or below the q_τ cut-off.

Figure 4.10: Visual example of a RIF transformation



Source: Author own calculation. The figure displays an illustrative distribution from which the researcher aims to find the RIF measure at the τ^{th} quantile.

The transformation is performed locally, moving from proportions to quantiles by dividing the proportions by the relevant density. As shown in Figure 4.10 (using an illustrative distribution), the RIF measure for a specific q_τ attributes the fraction of Equation 4.1 to the observation at or below the cut-off (shaded grey area), while weighting for every y_i observation above (by the constant density at the cut-off). FFL show that an important property of the RIF is that it integrates up to the quantile q_τ of interest. That is:

$$\int_{\mathbb{R}} \mathrm{RIF}\left(y; q_\tau, F_Y\right) dF_Y\left(y\right) = q_\tau \tag{4.2}$$

where $F_Y(y)$ is the marginal (or unconditional) distribution function of outcome variable Y.

For a small change in the X vector, FFL show that regression analysis permits to find the impact on the marginal distribution of Y by integrating over $E\left[\mathrm{RIF}\left(Y;\ \nu, F_Y\right)|X\right]$, assuming $F_{Y|X}\left(.\right)$ is unaffected and Theorem 1 of FFL holds.[34] Applying the Law of Iterated Expectations to the previous expression yields:

$$E\left[\mathrm{RIF}\left(y; q_\tau, F_Y\right)|X\right)] = m^{q_\tau}\left(X\right) = q_\tau \tag{4.3}$$

where the conditional effect on the covariate space of X averages up to the unconditional population mean, and $m^{q_\tau}(X)$ is the RIF regression model (Firpo et al., 2009a). The model is easily estimated using conventional parametric regression methods such as

[34]Theorem I (FFL,p.957) is reported in Appendix B.2.1 (p. 143).

OLS[35], where the RIF regression is defined as:

$$E\left[\mathrm{RIF}\left(y; q_\tau, F_Y\right)|X\right)] = X'\gamma \tag{4.4}$$

The OLS regression provides an estimate for γ which represents the effect of the covariates X on the unconditional quantile τ of the outcome Y.

In the presence of a specific change in the X vector of continuous covariates, the Unconditional Quantile Partial Effect (UQPE) is the average derivative of a projection of the RIF of the quantile of interest on the regressors:

$$\alpha\left(\tau\right) = \int \frac{\mathrm{dE}\left[\mathrm{RIF}\left(Y; \upsilon\right)|X = x\right]}{\mathrm{dx}} \cdot dF\left(x\right) = \frac{1}{f_Y(q)} \cdot \int \frac{\mathrm{d}\ Pr[Y > q_\tau|X = x]}{\mathrm{dx}} \cdot dF\left(x\right) \tag{4.5}$$

corresponding to the marginal effect on the unconditional quantile of a small location shift in the distribution of continuous covariates, *ceteris paribus* (Firpo et al., 2009a).

Let's now look at the characteristics of this estimator and the main motivation for our variant. First, the RIF method shows for a continuous explanatory variable the impact of a marginal location shift in the variable as we highlighted above, whereas for binary explanatory variables it evaluates the impact of a marginal change in their conditional distribution in the presence of other covariates (Rothe, 2009, 2012).[36] We report the definition in the following section.

Second, as in any OLS specification, the RIF regression assumes that the covariates are independent of the unobserved noise (independence assumption), which still allows for the presence of heteroscedasticity, but it may require serious evaluation of

[35] Firpo et al. (2009a) also report the application of the estimator to other parametric methods such as probit, logit or non-parametric estimators.

[36] In their working paper version, Firpo et al. (2007), p. 16, show that it is possible to define the UQPE for a binary variable as a small increase in the probability of $X = 1$. Rothe (2009) clarifies in his working paper the conditions under which the interpretation can be the same in the presence of other covariates. The author shows that, as long as the dichotomous variable is strictly independent of the other covariates, the unconditional effect can then be determined. This notion may be seen as a weakness of the approach when applied as a linear model. Yet, it also reveals how complex is to define an unconditional effect further than the mean, which is also found in general non-linear models such as the one of the same Rothe (2012).

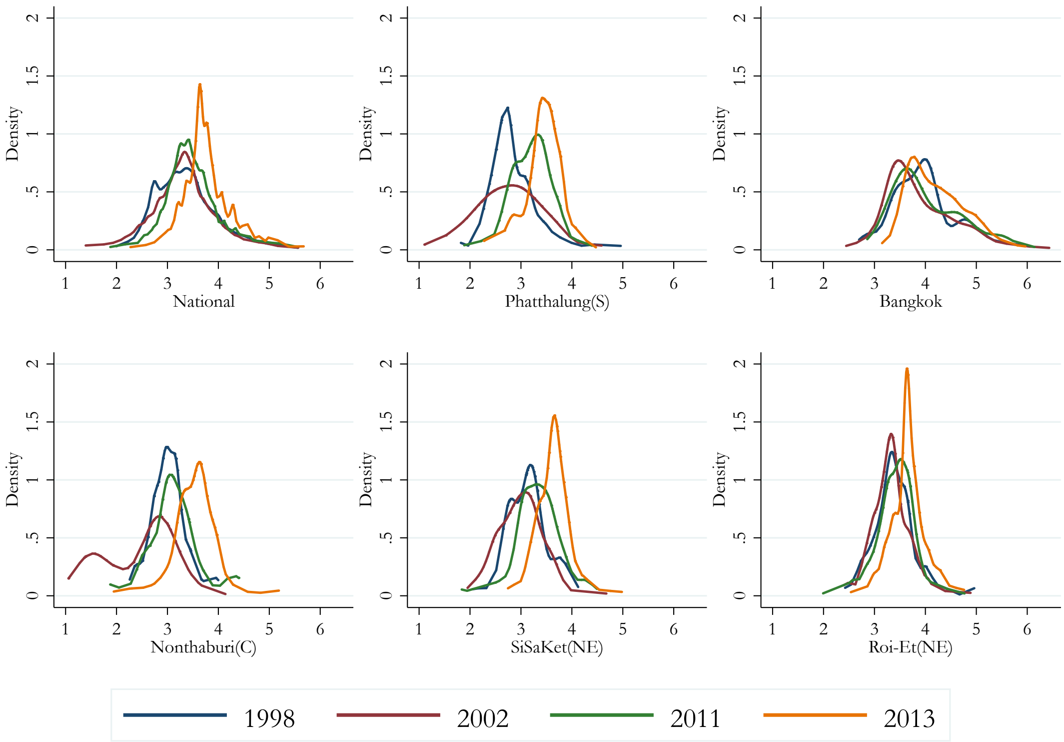
the exogeneity of the explanatory variables. The independence assumption is not inevitable, and it can be relaxed in two ways: either by assuming Conditional Independence Assumption (CIA) (Firpo et al., 2007)[37] or by defining the model in a more flexible manner, such as a non-separable model as proposed by Rothe (2010) (detailed for completeness in Appendix B.2.1, p.145) where an endogenous regressor can be modelled via a control function (see also Ghosh (2016) for non-separable models applied to both linear and non linear additive separable models).

Third, the RIF regression coefficients only provide a local approximation for the effect of changes in the distribution of a covariate on the quantile of interest, assuming invariance of the conditional distribution (Fortin et al., 2011).[38] There could be issues on how good the linear approximation of the effects on the dependent variable looks like. According to Fortin et al. (2011), this approximation may be subject to inaccuracy for a non-smooth dependent variable such as the wage distribution, and they warrant its investigation. This last remark is of main importance to our investigation because, given the heterogeneity in provincial labour markets for Thailand, a linear approximation of the minimum wage effects on the national wage distribution could both be captured with higher error and could mask heterogeneous response of local labour markets.

[37] Firpo et al. (2007) note that if we assume that in $Y = h(X, \varepsilon)$ the vector X is composed for example of $X = (X_1, X_2)$ of which only X_1 is manipulated in the regression framework, then we can assume that ε is independent of X_1 conditional on X_2, or simply $X_1 \perp \varepsilon | X_2$ to get consistent estimates. This is called the Conditional Independence Assumption (CIA), also known as the *ignorability* of the treatment in the treatment effects literature (*unconfoundedness* or *selection on observables* in the program evaluation literature).

[38] That is, the conditional distribution of Y given X remains invariant under manipulations of the marginal distribution of X.

Figure 4.11: Kernel wage density distributions, national and for selected provinces.

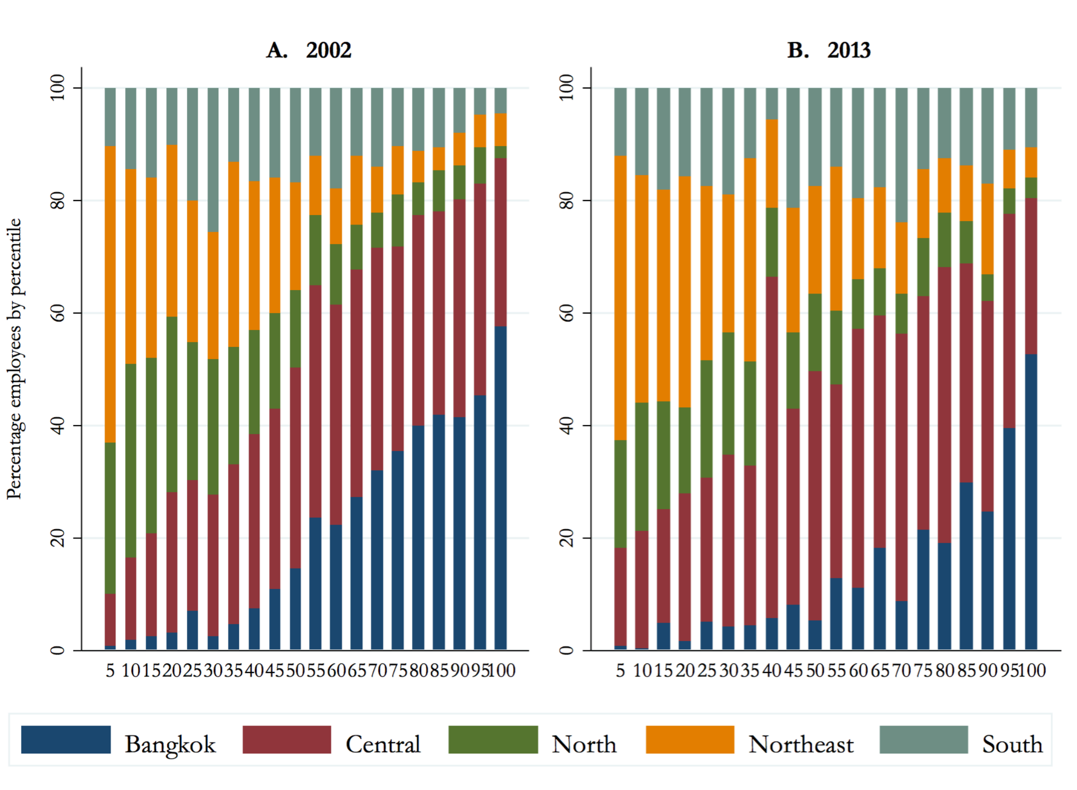


Source: LFS Q3 for years 1998 2002 2011 2013; Epanechnikov kernel applied with default bandwidth based on Silverman's rule-of-thumb, survey weights are multiplied by hours supplied. In this table we plot the distribution of log real hourly wage for private sector workers (CPI, base Q3 2013) at national level (top left figure) and compare it to the kernel density for the capital (top right figure) and other selected provinces (displayed with the geographic region acronym into parenthesis). The provincial distributions show a high degree of between and within variation.

When we evaluate the log hourly wage densities at the national level compared to the provincial ones, heterogeneous wage distributions appear across provinces and over time. Figure 4.11 depicts the provincial wage densities of private sector wages at the national level compared to those from selected provinces.[39] Taking this information in addition to the evidence found in Section 4.3.3, all point to diversified labour markets which we will identify as relative distributions and investigate in their heterogeneity.

[39]The figure, though being a simple kernel density, conveys a very strong message: with year 1998 as benchmark (period of instability and private sector employment contraction experienced in some Thai labour markets at the height of the Asian financial crisis), the response of the wage structure of each province has been extremely diversified. The difference in densities suggests that applying a single RIF transformation to the distribution may hide variations within local labour markets in terms of wage structure and its composition over time.

Figure 4.12: Wageworkers composition across the national wage percentile distribution by geographic region, 2002 and 2013.



Source: LFS Q3 for years 2002 and 2013. The bar charts represent the percentage of wageworkers by region in each year (weights applied) over the national wage distribution.

Additionally, if we were to use the national distribution we would be assuming that the poorer and richer wage workers are clustered in specific geographic areas but can influence each other's wage. For example, as visible from the first two percentiles of bar chart A in Figure 4.12, the low paid occupations in year 2002 would only be represented by specific areas of the country, the northern and north-eastern regions, which have been influenced by a different minimum wage regime before the NMW introduction. Lastly, the data allow representativeness at more granular level of analysis, and the fact that the minimum wage has always been set to reflect the provincial labour market structures, both render an evaluation of the provincial wage distribution compelling.

4.5 Applying the RIF to provincial distributions

We aim to account for geography in the construction of the wage distributions by asking the following question: What is the effect of a 1% rise in the provincial minimum wage on the τ^{th} quantile of provincial wage earnings, *ceteris paribus*? Thus, we aim to identify provincial labour market dynamics while exploiting the heterogeneity in the magnitude of the policy over time.

We set for simplicity a general structural model of the type $Y = h(X, \varepsilon)$. We now assume that X is a vector $X = (W, G)$ composed by a vector of continuous variables (W) and by a vector of dichotomous variables (G) representing participation to a group $g \in G$. The thought experiment we try to address is: supposing that individual i belonging to a group g of non-overlapping G groups in a same population experiences a marginal increase in one of the observable characteristics, how does this affect the mean unconditional distribution of the outcome for these groups?

The core assumption we impose is that the distributions are independent across g groups, that is, the wage pattern for private sector employment across provinces is independent of each other. With this assumption we can keep the independence assumption in place ($X \perp \varepsilon$, thus implying $E[\varepsilon|X] = 0$).[40]

Next we define the province RIF. We assume there exist for the population of individuals under analysis a set of distributions per group (Y_g), allowing to keep the conditional distribution invariance assumption valid. For each group g and time t the RIF transformation of individual wage i is defined as:

$$\text{RIF}\left(Y_{i,g,t}; q_{\tau,g,t}, F_{Y,g,t}\right) = q_{\tau,g,t} + \frac{\tau}{f_{Y,g,t}(q_{\tau,g,t})} - \frac{\mathbb{I}(Y_i \leq q_{\tau,g,t})}{f_{Y,g,t}(q_{\tau,g,t})} \tag{4.6}$$

The transformation is performed locally so that the proportions divided by the relative density are transformed into provincial quantile values. The transformation is then regressed on the explanatory variables of interest using OLS.

To evaluate the UQPE for this RIF measure, we simply re-interpret Corollary 1 of FFL. For a small location shift in the distribution of a continuous variable W, the unconditional grouped quantile effect $\alpha(\tau_g)$ can be estimated as the slope coefficient of

[40] Alternatively, as we will be able to assume and test in regression framework with the two-way clustering, the set-up of the error independence could be relaxed to be conditional on belonging to the groups $(W \perp \varepsilon|G)$.

W in a RIF-OLS framework:

$$\alpha\left(\tau_g\right) \;= E\left[\frac{dE[RIF\left(Y_g; q_{\tau g}\right)|W]}{\text{d w}}\right] \;= \int \frac{\partial E\left[\text{RIF}\left(Y_g; q_{\tau g}\right)|W\right]}{\partial W} dF_W\left(w\right) \qquad (4.7)$$

For dichotomous variables, we follow Nicoletti and Best (2012) and express the UQPE through the definition of Generalized Average Partial Effect (GAPE) (Rothe, 2009), in which we can evaluate the effect of any binary variable g when another continuous variable W is present. Relabelling the UQPE of the FFL framework described above in (4.7) as $Q_\tau(F_{Y_g}) = \int E[RIF\left(Y_g; q_{\tau g}\right)|W]dF_W(w)$, the slope coefficient of g is interpreted as:

$$\beta\left(Q_\tau(F_{Y_g}), g\right) = \int \left[Q'_\tau\left(F_{Y_g|g,W}\left(\cdot,1,w\right)\right) - \; Q'_\tau(F_{Y_g|g,W}(\cdot,0,w))\right] \cdot dF_W(w) \qquad (4.8)$$

Where $dF_W(w)$ is the joint cumulative distribution for vector W.[41] The derivation of equations (4.7) and (4.8) can be found in Firpo et al. (2009b) and Rothe (2009). Additionally, to further confirm that the assumptions on the distributions are valid for getting a consistent estimation, Appendix B.2.1 (p. 147) shows how FFL define the UQPE as a weighted average of the Conditional Quantile Partial Effect (CQPE).

4.5.1 Empirical estimation of the province RIF

For the RIF estimation we proceed to identify as our main group g variable the province ($p = 1, ..., n$) belonging to a group of independent distributions P ($P = \sum_1^n p$). For each individual i in province p at time t we define the RIF transformation for the contribution of the individual observation on the provincial quantile q of interest:

$$\text{R}\,\hat{\text{I}}\,\text{F}\left(Y_{i,p,t}; \hat{q}_{\tau,p,t}, F_{Y,p,t}\right) = \hat{q}_{\tau,p,t} + \frac{\tau}{\hat{f}_{Y,p,t}(\hat{q}_{\tau,p,t})} - \frac{\mathbb{I}(y_i \leq \hat{q}_{\tau,p,t})}{\hat{f}_{Y,p,t}(\hat{q}_{\tau,p,t})} \qquad (4.9)$$

We first compute each sample quantile $\hat{q}$, then estimate its density using kernel methods and then evaluate for each individual the RIF transformation. For the choice of

[41]Note that the response to a binary variable is similar to a conditional Average Partial Effect $E[E(Y|G = 1, X) - E(Y|G = 0, X)]$. Rothe (2009) shows that if the dichotomous variable is independent of the other covariates, the interpretation of GAPE is the same as the UQPE in the presence of other covariates. If the variables are not fully independent, the interpretation can be made as a marginal change in the conditional distribution of the binary variable given the other covariates.

the density estimation method we use a kernel density (Gaussian distribution) with Silverman rule of thumb for the bandwidths, and we ensure to thoroughly assess estimation consistency to a change in bandwidths in the robustness section.[42] Since $\hat{q}_{\tau,p,t}$, $\hat{f}_{Y,p,t}(\hat{q}_{\tau,p,t})$, and $\mathbb{I}(Y_i \leq \hat{q}_{\tau,p,t})$ all vary across province and time, we include province (ψ_p) and time (ψ_t) fixed effects to the RIF-OLS, together with individual and provincial time-varying covariates, performing the following regression with pooled cross-sections:

$$\mathrm{RIF}_{Y_{ipt},q_{\tau pt}} = \beta_0 + \beta_1 \ln(\mathrm{MW}_{\mathrm{p\ t}}) + \beta_2 X_{\mathrm{i\ t}} + \beta_3 Z_{p\ t} + \psi_t + \psi_p + \phi_{p*t} + \mu_{\mathrm{i\ p\ t}} \quad (4.11)$$

Specifically, for the main estimations we introduce as vector X of controls a set of individual characteristics (years of schooling, marital status, a quadratic in years of potential experience, whether in full-time work) interacted with time dummies. We also include a set of industry indicators (6 groups if excluding agriculture), firm size indicators (5 groups, respectively of size with less than 10 employees, 10-49, 50-99, 100-199 and 200 or more). Vector Z comprises province-level information (share of young population, share of elderly population, share of individuals in the labour force with secondary education or greater, past yearly log per capita GPP). We include a rural binary variable in addition to time and geographic controls (ψ_t quarter-year and ψ_p province fixed effects and ϕ_{p*t} province-specific time trends) to account for geography and unobserved time varying confounders.[43] We refer to this model as the most saturated version of equation (4.11) as it includes time interactions and province-specific trends. We report the estimations from the fifth to the ninety-fifth percentiles in intervals of five.[44] Regarding the measure for the minimum wage policy, we choose to

[42]Specifically we apply the following kernel density formula:

$$\hat{f_K} = \frac{1}{Wh}\sum_{i=1}^{n} w_i K \frac{(y - Y_i)}{h} \quad (4.10)$$

where K is the Gaussian kernel function $K = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}$, $W = \sum_i w_i$ are weights, h is the bandwidth (driving how many values are included in the density at each point) which we identify with Silverman rule of thumb (equation provided in the note of Figure 4.16, Sec. 4.6.2).

[43]The introduction of time-interactions controls for quarter-specific characteristics of the population in LFS cross-sectional data. The linear trends are introduced to account for economic fluctuations at geographic level which are not captured by past value added, following Autor et al. (2016) and Magruder (2013).

[44]See Table B.2 (p. 134) for a summary statistics of the variables and main sample used, and Table B.3 (p.135) for a comparison across selected years (sample with agricultural work which will be used as robustness).

use a direct measure of log real hourly rate (MW_{pt}) for three reasons. First, there is enough within and between variation for the variable to be meaningfully altering the regression framework (as shown in Section 4.3). Second, there could be concerns that economy-wide feedbacks or province-specific economic shocks may alter the minimum wage adjustments and thus confound the estimation. When we investigate the determinants of the province-level minima (Table 4.2) it emerges that MW adjustments are dependent on inflation (as determined by the law, Section 4.2). As visible from Figure 4.2, the minima adjustments in real terms were mostly stagnant for many years. However, we find that they do not depend on the market output generated by the economy. This alleviates concerns that a direct use of the policy measure could be capturing overall economic performance. However, as we cannot ensure its full exogeneity in the econometric model, we ensure with province-specific controls and province fixed effects to capture the local variation of the economy. Third, we refrain from using some transformations of the minimum wage for reasons related to the context under analysis. A measure such as the 'fraction affected' (Card and Krueger, 1995) assumes that workers should be paid exactly at the prevailing minimum wage in every period t to then calculate the number of potentially affected from $t-1$ to t. However, it assumes no influence of those workers paid sub-minimum wage which, as we aim to assess with the specification, may or may not be affected by policy variations.[45] Another way to address the endogeneity of the policy variable could be to use the 'effective' minimum wage (Lee, 1999), defined as the gap between the minimum and median wages, which is then instrumented with past minimum wage levels (Autor et al., 2016). A shortcoming of this measure is that it implicitly assumes that median earnings are not affected by the policy, but as visible from the minimum wage bite reported in Figure 4.5, in some areas of the country this may not be the case. Thus, we keep a more conservative approach and use the minimum wage in levels, and we ensure with the inclusion of province-specific controls that the dynamics of the local economies under analysis are controlled for.

[45] The minimum wage variable varies over time and between distributions (provinces), thus allowing to directly identify the average provincial quantile response to a policy change. If we were to use the fraction of workers affected (such as in Pérez Pérez 2015 for RIF transformations for city-industry pairs in Colombia), it could induce misspecification if due to local labour market dynamics, people which were paid sub-minimum in period $t-1$ still do not move up the distribution, and the explanatory variable would not account for this.

Table 4.2: The correlates of minimum wage adjustments (2002-2013).

A. Time&Prov FE	I		II		III	
	FE	Diff	FE	Diff	FE	Diff
GPP	0.155		0.178			
	(0.394)		(0.384)			
1st lag GPP	0.037		0.021		-0.383	
	(0.367)		(0.364)		(0.441)	
Δ GPP		0.205		0.212		
		(0.411)		(0.416)		
Δ 1st lag GPP		-0.118		-0.117		-0.098
		(0.164)		(0.157)		(0.148)
4th lag GPP					0.600	
					(0.537)	
Δ 4th lag GPP						-0.316
						(0.542)
CPI	16.735***		16.437***		-0.863	
	(3.748)		(3.692)		(3.356)	
1st lag CPI	-16.095***		-16.255***			
	(3.605)		(3.607)			
Δ CPI		20.247***		20.431***		28.680***
		(4.197)		(4.195)		(5.087)
Δ 1st lag CPI		4.173***		4.182***		
		(0.846)		(0.815)		
4th lag CPI					-9.197***	
					(2.964)	
Δ 4th lag CPI						-29.585***
						(4.514)
N	3572	3496	3572	3496	3344	3268
Controls	N	N	Y	Y	Y	Y
B. Prov trends	I		II		III	
	FE	Diff	FE	Diff	FE	Diff
GPP	0.172		0.173			
	(0.422)		(0.414)			
1st lag GPP	-0.104		-0.105		-0.490	
	(0.362)		(0.361)		(0.344)	
Δ GPP		0.223		0.231		
		(0.409)		(0.414)		
Δ 1st lag GPP		-0.105		-0.105		-0.105
		(0.199)		(0.192)		(0.171)
4th lag GPP					0.486	
					(0.614)	
Δ 4th lag GPP						-0.360
						(0.518)
CPI	15.268***		15.380***		-5.704	
	(4.164)		(4.110)		(5.673)	
1st lag CPI	-17.459***		-16.920***			
	(3.400)		(3.349)			
Δ CPI		18.959***		19.154***		28.827***
		(3.971)		(3.969)		(5.080)
Δ 1st lag CPI		3.204***		3.192***		
		(0.719)		(0.746)		
4th lag CPI					-19.715***	
					(4.160)	
Δ 4th lag CPI						-30.561***
						(4.663)
N	3572	3496	3572	3496	3344	3268
Controls	N	N	Y	Y	Y	Y

Note: Quarterly province data from MOL, NESDB, LFS (2002-2013). The table reports the semi-elasticity of nominal minimum wage to a change in GPP and CPI. GPP is defined as yearly log GPP per capita (metadata for this measure is available from NESDB (2013)). CPI is defined as yearly log average regional CPI for urban and rural areas (SCPI), used to capture local price variations. All regressions have quarter-year and province fixed effects, in panel B province-specific time trends are added. Model I investigates variables in levels and first lag; Model II the forth lag (to reflect the yearly change); Model III 1st and 4th lag. Each first column is a panel fixed effects model, each second a differenced model. Additional controls: total population and share of high-skilled workforce. Robust standard errors applied.

4.5.2 Differences between national and province RIF

One concern is that by using the provincial data to generate distributions, the measurement may be subject to error due to small samples, outliers or misreporting.

To tackle the small sample issue, we make sure that in every quarter-year the number of observations is large enough to maintain statistical power. For the measurement issue, such as accounting for outliers or misreporting, we expect to find the size (of each quantile value) or observations (mass of individuals falling under a cut-off) for the provincial distributions to give evidence of whether a bias exists with respect to the national wage distribution.

A preliminary investigation of the behaviour of province wage distributions suggests that this issue is not a major concern. The data behaves as expected: the average gap across cut-off values is constant for each year within the national and provincial distributions (Table 4.3). The province RIF measures capture a higher proportion of workers in the quantiles below the provincial median (Figure 4.13), and the national RIF has a larger right-hand tail both in terms of workers included and size of average quantile values for the whole time period under analysis and during the latest policy change (Figure 4.14).

The main difference between the two types of distributions (national and provincial) is that the provincial distributions, by construction, give on average greater weight to the percentiles at the bottom half of the wage distributions. By contrast, the national distribution is relatively more right-skewed, giving greater weight around and after the median quantile and especially at the top tail.

We report in Table 4.3 a comparison over time of the average value for selected provincial quantile values and their distance to the national values (with tests). On average the provincial (national) distribution displays more concentration below (above) the 45^{th} percentile, both in terms of number of individuals falling in greater (smaller) number within the percentile cut-off, and of average value of the mean quantile. In addition, the mean yearly difference between the average provincial quantile and the national quantile values, as shown in the table, highlights that that the provincial means are slightly smaller than the national one. This is expected for two reasons: one is statistical, each quantile depicts more precisely the distribution of smaller areas, as it puts less weight on outliers at both ends of the distribution; another is context-specific,

Table 4.3: Comparison of selected distributional cut-offs for province RIF means, their distance to the national RIF and test statistics (2002-2013).

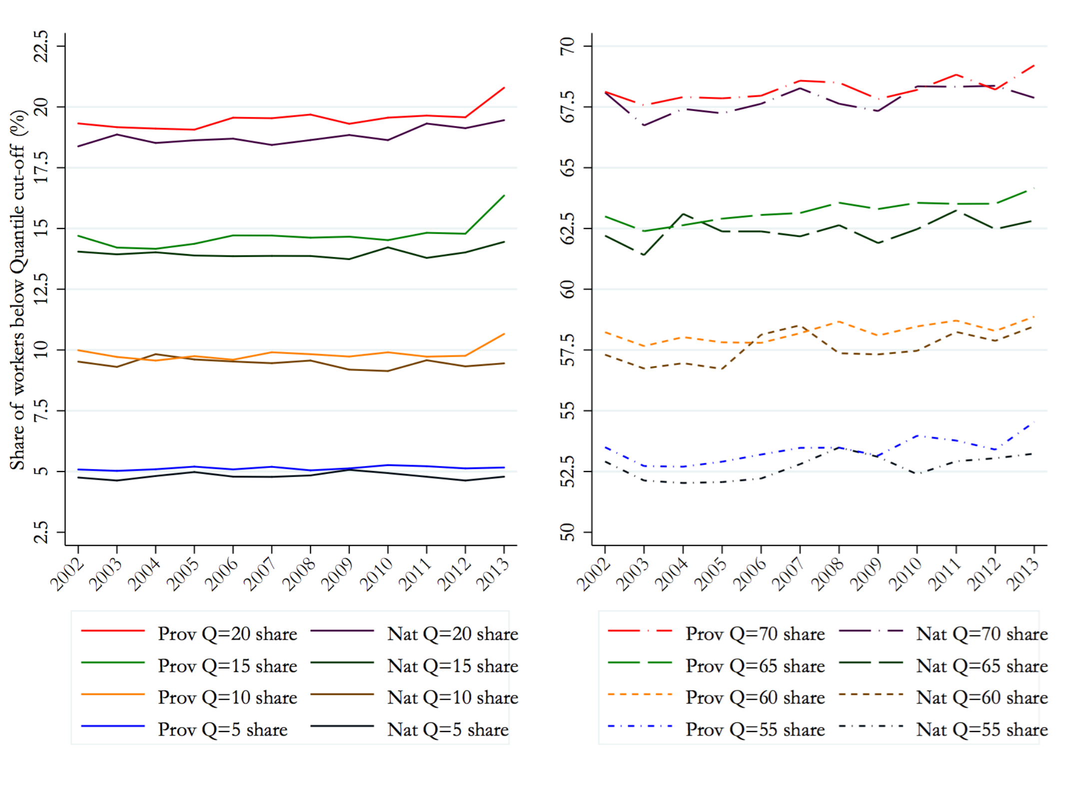
	5th			45th			90th			Mean
	P	P-N	t	P	P-N	t	P	P-N	t	Y gap
2002	2.63	0.13	0.00	3.36	-0.01	0.00	4.23	-0.14	0.00	-0.01
2003	2.65	0.12	0.00	3.37	0.00	0.26	4.29	-0.14	0.00	-0.01
2004	2.64	0.12	0.00	3.35	0.00	0.49	4.27	-0.12	0.00	-0.01
2005	2.66	0.09	0.00	3.37	0.00	0.28	4.28	-0.13	0.00	-0.01
2006	2.70	0.10	0.00	3.37	0.01	0.00	4.24	-0.12	0.00	-0.01
2007	2.74	0.12	0.00	3.39	0.01	0.00	4.24	-0.15	0.00	-0.01
2008	2.75	0.12	0.00	3.39	0.02	0.00	4.21	-0.16	0.00	-0.02
2009	2.78	0.13	0.00	3.42	0.02	0.00	4.26	-0.16	0.00	-0.01
2010	2.79	0.11	0.00	3.43	0.01	0.00	4.24	-0.13	0.00	-0.01
2011	2.83	0.07	0.00	3.45	0.02	0.00	4.23	-0.11	0.00	-0.01
2012	2.95	0.09	0.00	3.55	-0.01	0.00	4.33	-0.12	0.00	-0.01
2013	3.12	0.08	0.00	3.69	0.02	0.00	4.41	-0.12	0.00	-0.01

Note: The table above aims to compare how the average provincial quantiles (mean of 76) differ in size to the national quantiles over time. Here we report statistics for log real hourly wages of male private sector workers excluding agriculture, evaluated at 5^{th}, 45^{th} and 90^{th} percentile means for provincial (P) or national (N) distributions. The first column ("P") reports the mean value for provincial quantile, the second ("P-N") reports the difference in means between provincial and national means at the specific percentile and column "t" reports the t-test (with equal or unequal variance). The 5^{th} percentile column shows that there is a statistically greater value for the provincial quantile mean over time, but this gets reversed around the 45^{th} percentile (with no statistically significant difference between the distribution means, with this event changing over the years with lowest switching at the 35^{th} and highest at 65^{th}). After the 45^{th} percentile greater magnitude is seen in the national means over time. This is suggestive of greater nuance (weights) captured by the provincial quantiles for the lower tail of wage distribution and higher nuance (weights) for the national around and after the median quantile and especially at the top tail. The last column ("Mean Y gap") reports the average yearly gap among 19 percentiles (taking the average of percentile mean gaps from the 5^{th} to 95^{th} with 5 percentiles intervals), showing that overall average provincial wages are only slightly smaller than the national one.

in an economy where wage negotiation may be segmented according to geographic areas (and physical location of industries), using the local distribution of wages as representative of the relative status of a worker may be more appropriate to gauge relative shifts in its wage with respect to others.

However, we cannot fully rule out whether measurement error may induce noise in the estimation of the province RIF transformation. This would occur if, for example, measurement error is intrinsically greater at the bottom of the distribution or if measurement error is systematic in specific provinces. Figures 4.13 and 4.14 show that more individuals fall under the lower percentile categories and they show a higher mean percentile wage, so we would expect the direction of the bias to be towards zero in the lowest percentile.

Figure 4.13: Annual share of workers below the quantile cut-offs of Provincial and National log wage distributions, 2002-2013.



Source: LFS quarterly data 2002-2013. The figure above reports the share of male private employees over total number (excluding agricultural workers) with log wage below a quantile cut-off (for selected quantile cut-offs at percentiles 5, 10, 15, 20, 55, 60, 65, 70) of either quarter-year distributions at provincial level (labeled "Prov") or quarter-year distribution at national level (labeled "Nat"). In other words, we look for each RIF transformation of quantile q_τ, what is the share of individuals with identity measure $\mathbb{I}(Y \leq q_\tau)$. The shares are cumulative (i.e. the 15^{th} percentile cut-off will include the share of workers of the 5^{th} and 10^{th} cut-offs). The visual comparison of the population in both distributions suggests that with the province RIF transformation the private workers are more spread across the distribution, and a greater number of individuals compose the bottom 5 and 15 of the provincial wage distribution.

Since we impose the transformation of the wage distributions to be geographically determined but not conditioned by any other covariate, we may potentially induce idiosyncrasies in the error terms. A simple one-way clustering in the regression analysis may therefore not be enough to control for simultaneous clustering. In order to ensure statistical inference we apply a multiway clustering method (Cameron et al., 2011), which allows the error dependence to account for multiple dimensions or layers (in our case related to the location of the wage earners and the time) and to test the robustness of the estimation.[46] Allowing the standard errors to be multi-way clustered

[46]Multiway clustering is a type of cluster-robust inference. When this error structure is used, it relies on a weak distributional assumption of independence of observations that share no clusters in common. In order to understand its functioning in an intuitive matrix form, let's think of defining in a regression of y on X the variance matrix estimates based on the interaction of two cluster groups called a and b. The method constructs a cluster-robust variance matrix for each group ($\hat{V}^a]\hat{\beta}$ and $\hat{V}^b]\hat{\beta}$), sums them and then it subtracts the matrix for being "jointly" in both groups ($\hat{V}^{a\cap b}]\hat{\beta}$), thus leaving the remaining variance to be of a multi-dimensional nature (Cameron et al., 2011).

Figure 4.14: Average mean quantile differences between provincial and national wage distributions, years 2002-2013 and 2011-2013.

Source: LFS 02-13. The figure aims to compare how the average provincial quantiles (mean of 76) differ in size to the national quantiles over time. The point estimates plotted on the graph refer to the average gap between the average value at provincial level and the national value. The first line (darker, in dash-dot) refers to the average difference per quantile between 2002-2013, the second line (red, in dot) refers to years 2011-2013. The figure shows that provincial distributions have higher mean quantile levels on average than national quantile means. However, passed the median the provincial mean becomes smaller than the national one. This difference is persistent by applying the comparison with different time periods.

will account for: (i) specific within-geographic clustering (i.e. due to shocks) affecting some grouped observations; and (ii) for the potential non-random assignment of the provincial level minima.

To sum up, the province RIF model is used to capture provincial wage distributions and to assess their changes resulting from the minimum wage policy. This simple variant of the FFL model can be helpful to use when wage data behave heterogeneously across groups. We see it as a complement to the standard RIF and to other conditional distribution estimators. It is useful to apply particularly when the data available are not longitudinal and their sampling strategy allows representativeness to be drawn in a dimension lower than the country as a whole.

This estimator could be used when researchers are interested in assessing what is the population effect generated by a policy/treatment on grouped samples that represent a feasible space in which one of the covariates is defined and where the dependent variable behaves.[47] If a policy acts "locally" to modify the distributions of specific groups, the estimator will account for the average functional of these groups. It delivers a marginal effect which accounts for the specific distributions, without having to fully condition on all the covariates as in the conditional quantile case (Koenker and Bassett, 1978; Koenker, 2004).

4.6 Results

In the following section we report the main results of our analysis. In section 4.6.2 we compare the province RIF to the standard RIF estimator and we perform some robustness checks. In section 4.6.3 we investigate on any heterogeneous effect from the economic conditions and location of the provinces of interest, and in section 4.6.4 we investigate wage performance by firm types. Lastly, in section 4.6.5 we investigate some sample modifications.

4.6.1 Wage effects: minimum wage as a *numeraire*

In Figure 4.15 we report the baseline estimates. We find positive effects of an increase in the minimum wage on the private sector wage distribution. Over the full period under analysis (twelve years, 2002-2013) the multiple variations in the minimum wage appear to affect the provincial wage distributions, almost progressively increasing wages between the 15$^{\text{th}}$ and the 60$^{\text{th}}$ percentiles (Figure 4.15, left hand graph).

On average, an increase in the minimum wage of 10 percent increases the wage below the median by 2.5 percent. The effect appears to be stronger between the 25$^{\text{th}}$ and 45$^{\text{th}}$ percentiles. The effect starts to decline around the median and does not bite

[47] This framework is applicable to several settings in applied economics, where the investigator believes there is a strong connection between how an explanatory variable affects the dependent variable, and in response how its distribution behaves. For example, in evaluating the effect of an agricultural fertiliser program on yields, the yields are strictly dependent on the type of topography where farmers produce, which can be identified and grouped according to non-overlapping characteristics. This feature may directly influence the production performance, and using a simple average would miss useful information on the within-group performance. Alternatively, in the case when we are interested to evaluate policies which are geographically disbursed, the local-level definition of the policy may strictly interact with the outcome of a program, e.g. school-vouchers effect on exam scores or an employment policy on wages, making attractive to look at the average functional in a set of grouped distributions.

beyond the 60th percentile.[48]

Focusing on the latest policy change, we investigate the time period 2011-2013, five quarters before the first big hike in Q2 2012 and then covering the introduction of the national minimum in 2013 Q1 until the end of the year.

Figure 4.15: Comparison of the minimum wage effects at provincial level, 2002-2013; 2011-2013.

Note: province RIF regressions of hourly wage for male private sector workers (excluding agricultural workers, pooled quarterly LFS 2002-2013). The left figure displays coefficient and confidence intervals for log real hourly minimum wage for the period 2002-2013, and the right figure for the period 2011-2013. Other controls and clustering follow the main saturated specification reported. All monetary variables are deflated by national CPI (base 2013 Q3). For the point estimates, see Table 4.4 below ("Saturated" row), or in Appendix B.3 (Table B.6 and Table B.7, p.148).

The RIF regression (Figure 4.15, right hand graph) suggests that the shift in the minimum wage strongly affects the mean provincial quantiles from the 15th to the 45th percentiles. The effect then roughly halves around the 50th-60th percentiles and gets weaker in terms of significance. In between the 15th and 25th percentiles, on average, an increase in the minimum wage of 10 percent increases the hourly wage by 5 percent. The effect extends until the 45th percentile with an average increase of 3 to 4 percent.

[48] With exception for the 95th percentile which may be more prone to measurement error. We rely on findings of previous literature (see Lemieux (2008) for a discussion on top-coding and Autor et al. (2016) on measurement error) and consider the effects on the top tale of wage distributions as potentially spurious.

Two evidence emerge for the Thai labour market. First, the results suggest that the minimum wage increase has benefited parts of its intended beneficiaries in the lower half of the distribution and the magnitude of the NMW is pronounced. For an average 70% nominal increase in the minimum wage over these two years, between 21% to 45% increase in the provincial wages is generated on average. In other words, for every 10 Baht increase in the minimum wage experienced between 2012 and 2013, between 3 to 5 Baht are redistributed to the affected workforce in each province on average.

Second, the change introduced between year 2012 and 2013 did not translate in short term increases in wages for the lowest fraction of provincial wage earners (Figure 4.15, right hand graph). The most saturated model suggests that the 5^{th} and 10^{th} provincial quantile average wages were not significantly affected by the hike. One explanation is that some workers are kept at a sub-minimum wage, as shown in the descriptive statistics on non-compliance. This however suggests that only the reward of the lowest-paid workers is unaffected, warranting further inspection on whether this is linked to work-specific characteristics. A second explanation could be the low sampling power, either due to low number of observations in the left tail of the provincial distributions, or to measurement error which may reduce the precision and statistical power of the estimator (visible in the larger standard errors of Figure 4.15).[49]

In order to ensure that the chosen controls do not affect the results, we report in Table 4.4 a comparison of the estimates for male private sector workers using different sets of controls from least- to most-saturated specifications. The effects over 2002-2013 (Panel A) from the most saturated model appear to be smaller in magnitude than without province-specific trends, and have smaller standard errors.[50]

For the period 2011-2013 (Table 4.4 Panel B), all specifications point to no statistically significant effect on the lowest (5^{th}) percentile of the provincial wage distribution,

[49]Notwithstanding that lower power generated by fewer cross-sectional data points between 2011 and 2013 may be also affecting the estimates, for any type of specification (changing the saturation of the model with controls) and clusters applied, we find no effect at the lowest 5^{th} percentile.

[50]The province-specific linear time trends are introduced to account for omitted variable bias which could affect the provincial wage structures over time. However, they could act as confounders, as they are defined linearly in time and not allowed to have points of inflection. If we assume that the introduction of a province-specific time trend adds spuriousness to the regressors, the estimates from the saturated model should be considered upper bound of the policy effect.

corroborating the result that the lowest percentile has not been affected. Noting that the literature on minimum wage argues for the use of large time periods to allow markets to react fully, our results suggest that as little as six quarters after the introduction of a statutory minimum wage there has been a positive effect on provincial wage distributions below the median. Additionally, estimations with different sets of controls over both time periods suggest positive effects up to the 60$^{\text{th}}$ percentile.

Further, we report a comparison of the specification with single or multi-way clustering (Cameron et al., 2011), used to ensure that the estimates are not sensitive to multiple geographic and temporal error dependence. The two-way clustering allows the correlation in the error being driven by common shocks, having a factor structure rather than a decaying dependence as in spatial analysis, and also tolerates clusters which are non-nested (Cameron and Miller, 2015). Hence, we can assess if specific within-geographic clustering, for example due to shocks, affects the grouped observations and the specification.

We apply several types of two-way clustering which assume that there could be a specific within-geographic clustering (i.e. due to shocks) affecting some grouped observations. Specifically, we focus on cluster groups based on Province-Year or Region-Year (looking at spatial-time error dependence) and Province with Region-year grouping (accounting for within province and across region-time dependence).The estimates appear to be stable across specifications. For the period 2002-2013 (Table 4.5) the cluster groups increase the standard errors and show significance of the estimator from the 15$^{\text{th}}$ to 60$^{\text{th}}$ percentile, thus strengthening the reliance of the estimates found with one-way clustering. For the 2011-2013 period (Table 4.6), the multi-way clustering procedure suggests that reliance on the one-way clustering is enough to interpret the estimators, as the significance of the coefficients resembles the one of the main results reported using one-way clustering.[51]

[51] If we allow the error structure to capture the co-movement in the minimum wage levels visible in Figure 4.2, clustering the provinces under the old policy of regional minimum wage bands and time clusters, we find the estimates to underperform than any other cluster of Tables 4.5 and 4.6. Thus, we can exclude this clustering on "past minimum wage policy" to be driving the variance in the data, and do not report it.

Table 4.4: Province RIF regressions of log minimum wage with a diverse set of controls, 2002-2013; 2011-2013.

Panel A:	**Years 2002 - 2013**									
Percentile	5	10	15	20	25	30	35	40	45	50
Simple	0.262	0.262**	0.327***	0.293***	0.320***	0.341***	0.325***	0.321***	0.318***	0.249***
	(0.165)	(0.108)	(0.078)	(0.069)	(0.082)	(0.077)	(0.074)	(0.061)	(0.058)	(0.057)
Interactions	0.260	0.232**	0.305***	0.262***	0.277***	0.306***	0.289***	0.297***	0.295***	0.230***
	(0.162)	(0.105)	(0.075)	(0.065)	(0.077)	(0.077)	(0.076)	(0.074)	(0.073)	(0.057)
P Trends	0.061	0.103	0.210***	0.200***	0.249***	0.279***	0.260***	0.250***	0.244***	0.175***
	(0.137)	(0.085)	(0.065)	(0.056)	(0.069)	(0.065)	(0.058)	(0.043)	(0.039)	(0.041)
Saturated	0.085	0.085	0.201***	0.179***	0.219***	0.260***	0.244***	0.249***	0.247***	0.184***
	(0.141)	(0.083)	(0.063)	(0.052)	(0.066)	(0.065)	(0.062)	(0.058)	(0.059)	(0.038)
Percentile	55	60	65	70	75	80	85	90	95	
Simple	0.250***	0.238***	0.180**	0.197***	0.180**	0.198**	0.150*	0.180**	0.458***	
	(0.056)	(0.060)	(0.071)	(0.059)	(0.071)	(0.088)	(0.088)	(0.087)	(0.155)	
Interactions	0.218***	0.181***	0.111	0.106*	0.081	0.104	0.052	0.059	0.251**	
	(0.058)	(0.063)	(0.083)	(0.061)	(0.071)	(0.087)	(0.107)	(0.100)	(0.123)	
P Trends	0.166***	0.154***	0.077	0.123**	0.091	0.121	0.097	0.098	0.323**	
	(0.042)	(0.042)	(0.052)	(0.050)	(0.057)	(0.074)	(0.082)	(0.089)	(0.137)	
Saturated	0.165***	0.122***	0.036	0.062	0.030	0.088	0.089	0.094	0.249*	
	(0.041)	(0.044)	(0.068)	(0.047)	(0.059)	(0.073)	(0.090)	(0.099)	(0.127)	

Panel B:	**Years 2011 - 2013**									
Percentile	5	10	15	20	25	30	35	40	45	50
Simple	0.123	0.233**	0.360***	0.321***	0.355***	0.357***	0.313***	0.316***	0.310***	0.241***
	(0.118)	(0.098)	(0.070)	(0.056)	(0.058)	(0.050)	(0.041)	(0.039)	(0.034)	(0.045)
Interactions	0.131	0.210**	0.349***	0.305***	0.334***	0.349***	0.297***	0.315***	0.305***	0.234***
	(0.111)	(0.093)	(0.066)	(0.053)	(0.062)	(0.056)	(0.042)	(0.049)	(0.049)	(0.033)
P Trends	-0.257	0.143	0.479***	0.416***	0.527***	0.364***	0.461***	0.326***	0.317***	0.203*
	(0.318)	(0.156)	(0.139)	(0.123)	(0.110)	(0.105)	(0.097)	(0.103)	(0.093)	(0.105)
Saturated	-0.234	0.166	0.499***	0.449***	0.548***	0.383***	0.473***	0.341***	0.323***	0.188
	(0.301)	(0.146)	(0.143)	(0.121)	(0.121)	(0.107)	(0.112)	(0.099)	(0.108)	(0.115)
Percentile	55	60	65	70	75	80	85	90	95	
Simple	0.249***	0.307***	0.187***	0.233***	0.218***	0.194**	0.202	0.232**	0.557***	
	(0.042)	(0.033)	(0.062)	(0.043)	(0.060)	(0.095)	(0.129)	(0.115)	(0.136)	
Interactions	0.235***	0.250***	0.153***	0.160***	0.143***	0.112	0.093	0.102	0.344***	
	(0.031)	(0.033)	(0.052)	(0.040)	(0.053)	(0.085)	(0.130)	(0.112)	(0.108)	
P Trends	0.279***	0.284**	0.168*	0.287**	0.141	0.184*	0.044	0.306	0.423***	
	(0.102)	(0.127)	(0.089)	(0.116)	(0.097)	(0.098)	(0.212)	(0.197)	(0.148)	
Saturated	0.245**	0.230*	0.128	0.206	0.052	0.042	-0.033	0.116	0.333**	
	(0.109)	(0.136)	(0.117)	(0.138)	(0.130)	(0.136)	(0.169)	(0.184)	(0.155)	

Note: Sample of pooled quarterly LFS data for male private sector workers excluding agriculture, Panel A for 2002-2013 data (791,542 obs.), Panel B for 2011-2013 (205,075 obs.). The table reports the β coefficient of log real hourly minimum wage on the RIF measure from a set of estimation with different controls from least to most saturated models. Each cell is a separate regression. Standard errors in parenthesis are clustered at province level (* p<.10 ** p<.05 *** p<.01). All monetary variables are deflated by quarterly CPI (base year 2013 Q3). In each sub-panel the first row ("Simple") uses as controls: individual-level variables (years of schooling, marital status, potential experience and its squared, whether in full-time work), industry dummies (6 groups), firm size dummies (5 groups), provincial-level variables (share of young population, share of elderly population, share of individuals in labour force with secondary education or greater, log per capita GPP), rural binary, time and province fixed effects. In the second row ("Interactions") the individual-level variables of the first specification are interacted with quarter-year dummies. In the third row ("P Trends") we add to the first specification the province-specific time trends. In the last row ("Saturated") we jointly add the individual-level variables interacted with time and the province-specific time trends, used for Figure 4.15.

Table 4.5: One versus two-way clustering comparison of minimum wage standard errors, saturated model 2002-2013.

Cluster (mat size)	5th	10th	15th	20th	25th	30th	35th	40th	45th	50th
No cluster	0.052	0.034**	0.027***	0.024***	0.022***	0.021***	0.020***	0.020***	0.020***	0.021***
Province (76)	0.141	0.083	0.063***	0.052***	0.066***	0.065***	0.062***	0.058***	0.059***	0.038***
Region (5)	0.158	0.067	0.023***	0.026***	0.051**	0.059**	0.064**	0.062**	0.066**	0.043**
Prov-Year (76x12)	0.179	0.091	0.064***	0.059***	0.063***	0.058***	0.053***	0.039***	0.041***	0.039***
Reg-Year (5x12)	0.181	0.08	0.049***	0.052***	0.060***	0.057***	0.061***	0.051***	0.059***	0.042***
Prov-Regyr (76x60)	0.168	0.098	0.071***	0.055***	0.068***	0.072***	0.072***	0.069***	0.074***	0.055***

Cluster (mat size)	55th	60th	65th	70th	75th	80th	85th	90th	95th
No cluster	0.022***	0.023***	0.024	0.027**	0.03	0.035**	0.041**	0.051*	0.073***
Province (76)	0.041***	0.044***	0.068	0.047	0.059	0.073	0.09	0.099	0.127*
Region (5)	0.051**	0.065	0.102	0.069	0.086	0.101	0.135	0.118	0.083**
Prov-Year (76x12)	0.044***	0.059**	0.067	0.057	0.054	0.088	0.146	0.099	0.126**
Reg-Year (5x12)	0.050***	0.065*	0.091	0.065	0.072	0.098	0.209	0.166	0.100**
Prov-Regyr (76x60)	0.062***	0.069*	0.093	0.089	0.099	0.112	0.138	0.143	0.141*

Note: The standard errors with significance level are reported. This table reports a comparison of standard errors for minimum wage variable (starting with no cluster) or clustered either at province or regional level (one-way cluster in the second and third rows of each sub-panel, but note that single region clustering suffers of too reduced number of cells created) against two-way clustering (Cameron et al., 2011) of the Province variable clustered with either a time control (Year), or a group variable of Region and Year (Regyr) or the Region variable clustered with Year. Estimations come from a RIF regression of log wages for male private sector workers (excluding agriculture) using pooled quarterly data from LFS 2002-2013 (791,542 observations, controls from the saturated model). The size of the joint matrix is reported into parenthesis. The two-way clustering appears to increase the standard error. The Reg-Year and Prov-Regyr cluster groups are the ones of most interest at they assume there could be a specific within-geographic clustering (i.e. due to shocks) affecting some grouped observations. Both clustering types increase the standard error and show significance of the estimator from the 15^{th} to 60^{th} percentile, thus strengthening the reliance of the estimates.

Table 4.6: One versus two-way clustering comparison of minimum wage standard errors, saturated model 2011-2013.

Cluster (mat size)	5th	10th	15th	20th	25th	30th	35th	40th	45th	50th
No cluster	0.127*	0.080**	0.058***	0.051***	0.046***	0.044***	0.043***	0.043***	0.044***	0.046***
Province (76)	0.301	0.146	0.143***	0.121***	0.121***	0.107***	0.112***	0.099***	0.108***	0.115
Region (5)	0.233	0.047**	0.087***	0.069***	0.086***	0.079***	0.080***	0.059***	0.059***	0.052**
Prov-Year (76x3)	0.223	0.115	0.093***	0.083***	0.052***	0.076***	0.065***	0.067***	0.047***	0.049***
Reg-Year (5x3)	0.214	0.087*	0.068***	0.063***	0.041***	0.066***	0.038***	0.042***	0.027***	0.035***
Prov-Regyr (76x15)	0.248	0.089*	0.109***	0.092***	0.105***	0.100***	0.118***	0.121***	0.131**	0.147
Cluster (mat size)	55th	60th	65th	70th	75th	80th	85th	90th	95th	
No cluster	0.048***	0.051***	0.054**	0.061***	0.068	0.078	0.089	0.105	0.154**	
Province (76)	0.109**	0.136*	0.117	0.138	0.13	0.136	0.169	0.184	0.155**	
Region (5)	0.069**	0.112	0.078	0.111	0.05	0.095	0.205	0.213	0.096**	
Prov-Year (76x3)	0.044***	0.059***	0.038***	0.043***	0.065	0.063	0.098	0.109	0.119***	
Reg-Year (5x3)	0.034***	0.043***	0.026***	0.040***	0.042	0.041	0.074	0.095	0.108***	
Prov-Regyr (76x15)	0.163	0.199	0.206	0.243	0.239	0.268	0.292	0.25	0.161**	

Note: The standard errors with significance level are reported. This table reports a comparison of standard errors for the minimum wage variable (starting with no cluster) or clustered either at province or regional level (one-way cluster in the second and third rows of each sub-panel) against two-way clustering (Cameron et al., 2011) of the Province variable clustered with either a time control (Year), or a group variable of Region and Year (Regyr) or the Region variable clustered with Year. Estimations come from a RIF regression of log wages for male private sector workers (excluding agriculture) using pooled quarterly data from LFS 2011-2013 (205,075 observations, controls from the saturated model). The size of the joint matrix is reported into parenthesis. The two-way clustering appears not to improve the one-way clustering, with only a modest change in the standard errors created in the Province x Region-year clustering. This may be indicative of either no strong geographic clustering in the error structure (except for intrinsic province-specific noise accounted by the single clustering and the controls) or to too little number of clusters created. Thus, the results suggest that single clustering at province-level best captures the variance in the data.

4.6.2 Model comparisons and robustness

We now compare the province RIF measure to the standard RIF. The UQPE is reported in Table B.13 (Appendix B.5 p. 153). The estimation for the 2002-2013 period (Panel A) shows with the standard RIF some significant minimum wage effects concentrated around the median, between the 30$^{\text{th}}$ and the 65$^{\text{th}}$ percentiles (these are of greater magnitude than the province RIF regressions by roughly 0.1 percent on average, although they are not directly comparable in magnitude due to the different distribution these estimates refer to). The 2011-2013 national RIF analysis seems to inflate the effect of the minimum wage around the 40$^{\text{th}}$ percentile (i.e. where the actual minimum wage value lies when looking at quantile values for the national distribution in 2013). As expected, the national RIF attributes greater weight to the upper tail of the distribution, and the results display inconsistencies particularly in the top percentiles (for both time periods). The explained variation of the models (R^2) and the precision of the estimates (standard errors) suggest that the province RIF (Table B.6 and B.7, p.148) performs relatively better than the national RIF (Table B.13). More formally, we perform the Davidson–Mackinnon–White P_E test statistic (MacKinnon et al., 1983) to assess which of two outcome variables (drawn from the same distribution) performs better given a specific set of variables.[52] Table 4.7 reports the P_E test statistics, which shows that the province RIF is preferred (hypothesis not rejected at the 1 to 5 percent confidence). Thus, we sustain the use of provincial wages to investigate the policy effect since the linear approximation generated within the standard RIF-OLS estimates is found to be less precise than the province RIF.

[52] The P_E test stands for extended P test, as proposed by MacKinnon et al. (1983). As its name suggests, it is a generalisation of the P test regression (Davidson and MacKinnon, 1981) for nested models, set to test the case where two non-nested models involve different transformations of the dependent variable. Formally, we follow the notation in MacKinnon et al. (1983) and assume we are interested in testing the specification of a nonlinear regression model against the evidence provided by a non-nested alternative. We define the first model as $H_0 : y_t = f_t(X_t, \beta) + \epsilon_{0t}$, and the alternative as $H_1 : h_t(y_t) = g_t(Z_t, \gamma) + \epsilon_{1t}$, where $h(\cdot)$ is any continuously differentiable function which does not depend on any unknown parameter. MacKinnon et al. (1983) set an artificial compound model to test the two specifications: $H_c : (1 - \alpha)(y_t - f_t(\beta))\alpha(h_t(y_t) - g_t(\gamma)) = \epsilon_t$. Taking the derivative of the left-hand side of H_c with respect to α, evaluated at $(\hat{\beta}, 0)$ and simplifying the equation, leads to the following testable expression: $y_t - \hat{f}_t = \alpha(\hat{g}_t - h_t(\hat{f}_t)) + \hat{F})tb + \epsilon_t$ (see Davidson and MacKinnon 1981; MacKinnon et al. 1983 for further details). This test is generally used for testing the difference between a linear and a log linear specification of the dependent variable. We adapt it to accommodate a case of two log-transformations by assuming that, instead of y_t, we are testing a model with $l(y_t)$ which is a function with same properties as $h(\cdot)$, as is the actual case of our two dependent variables. For the empirical application we adapt the Stata ado-file by Shehata and Mickaiel (2012).

Table 4.7: P_E test statistic for province RIF versus standard RIF.

A. 2002-2013										
Percentile	5	10	15	20	25	30	35	40	45	50
Test	6.82	5.83	0.95	0.63	0.00	0.50	0.55	1.65	2.54	3.44
P-value	0.01	0.02	0.33	0.43	0.99	0.48	0.46	0.20	0.12	0.07
Percentile	55	60	65	70	75	80	85	90	95	
Test	0.72	1.00	0.00	0.29	0.35	1.31	3.07	1.51	0.38	
P-value	0.40	0.32	0.98	0.59	0.56	0.26	0.08	0.22	0.54	
B. 2011-2013										
Percentile	5	10	15	20	25	30	35	40	45	50
Test	0.11	0.15	4.01	3.29	0.41	2.13	0.05	0.90	0.57	1.36
P-value	0.74	0.70	0.05	0.07	0.53	0.15	0.82	0.35	0.45	0.25
Percentile	55	60	65	70	75	80	85	90	95	
Test	1.54	1.26	0.66	0.30	1.53	0.16	0.88	0.19	0.05	
P-value	0.22	0.27	0.42	0.59	0.22	0.69	0.35	0.66	0.82	

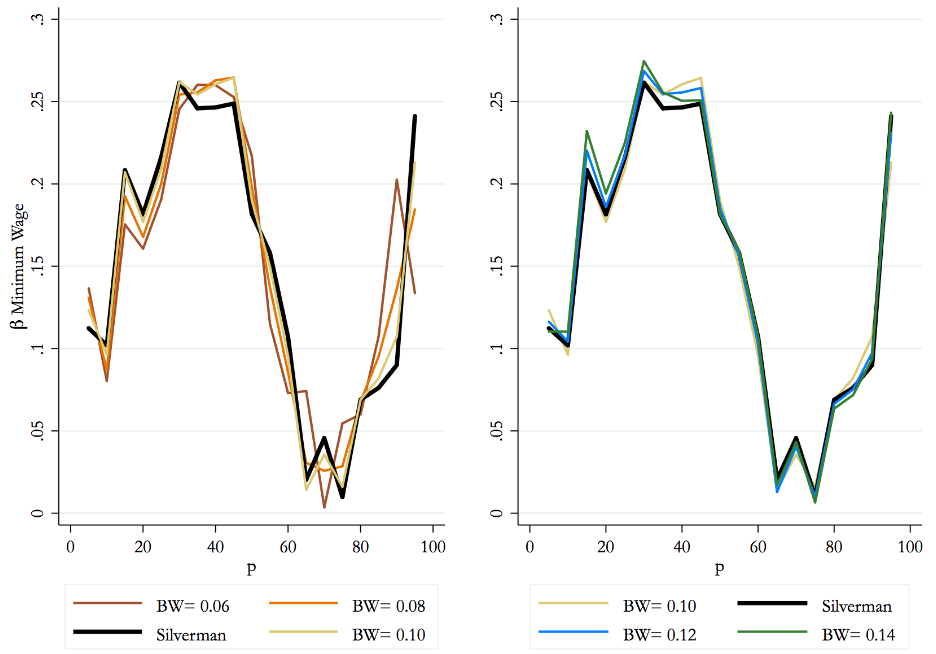
Note: LFS male cross-sections excluding agriculture, 2002-2013 (791,542 obs) or 2011-2013 (205,075 obs). This table reports the test and p-value for the P_E test statistic (MacKinnon et al., 1983). $H0 : \hat{F} = 0$ (choose province RIF Model as opposed to the standard RIF). The controls, weights and clustering are the same as the main model, excluding the intercept.

Following, we assess the strength of the estimator across several dimensions. For the choice of the density estimation method in the construction of the province RIF transformations we relied on a kernel density (Gaussian distribution), with Silverman rule of thumb for the bandwidths.[53] However, as the RIF transformation for quantile values may be sensitive to the choice of bandwidth, we report the same estimations with different bandwidths applied in the construction of distributions. Fortin et al. (2011) suggests that for a non-smooth dependent variables such as the wage distribution, it may be advisable to "oversmooth" the density estimates (increase the bandwidth) and compare the stability of the estimates (Fortin et al., 2011). We report below in Figure 4.16 a comparison of the minimum wage coefficient applied on the provincial wage distributions from various bandwidths with respect to the ones with Silverman's bandwidth.

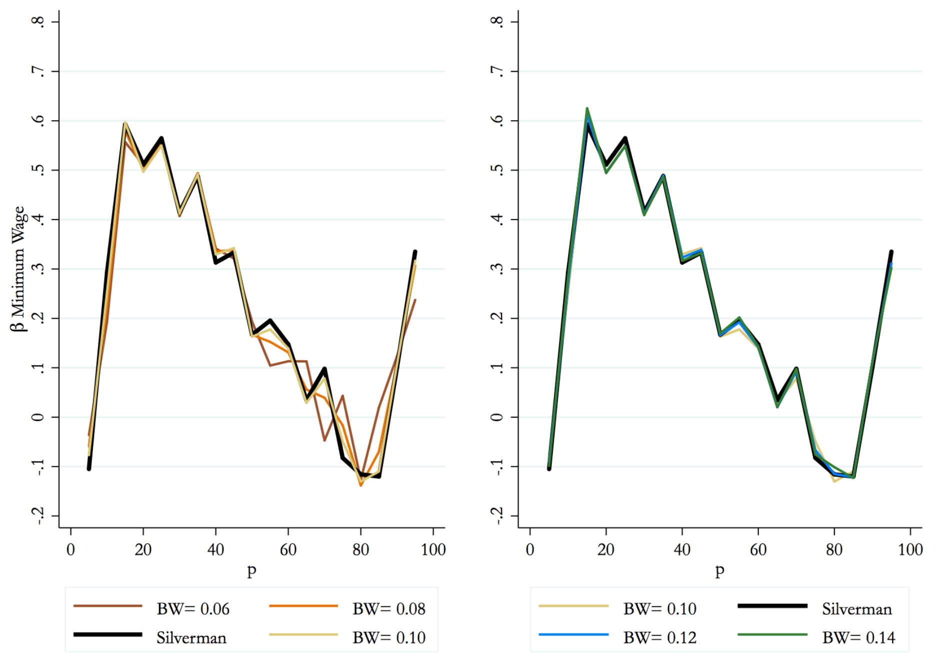
[53] Baltagi and Ghosh (2015) show that performing the RIF with different density estimators does not alter the performance (for example, using the kernel density via diffusion from Botev et al. (2010)). We rely on the evidence proposed by their replication study and not perform further investigation on other density estimators.

Figure 4.16: Comparison of the minimum wage coefficient on province wage distribution with different bandwidths, 2002-2013 and 2011-2013.

(A) 2002-2013



(B) 2011-2013



Note: Province RIF regressions of hourly wage for male private sector workers (excluding agricultural workers, pooled quarterly LFS (A) 2002-2013 or (B) 2011-2013). Different bandwidths (BW) applied. For each RIF we apply the kernel density as in Eq. (4.10). The left figure (warm colours) displays the MW coefficients from BW=0.06 to BW=0.10 and Silverman rule. The right figure (cold colours) displays the MW coefficients from BW=0.10 to BW=0.14 and Silverman rule. Silverman bandwidth is defined as $h = 0.9m/n^{1/5}$, where $m = min(\sqrt{var_x}, IQR_x/1.349)$. Controls and clustering follow the main saturated specification.

The estimates from Figure 4.16 accord with the main specification used. Any bandwidth between 0.08 and 0.14 performs very close to the Silverman rule, whereas for 0.06 and lower widths, some greater noise is captured especially at the tails. However, in all instances, the statistical significance of the coefficients matches the main estimates. Particularly for the introduction of the NMW (2011-2013) the estimates appear to be very stable to a bandwidth change. We further report in Figure B.7 and Figure B.8 (Appendix B.5, pp.153–154) the regressions for provincial distributions subject to a larger range of widths, from 0.02 to 0.16, displaying graphs with point estimates and confidence intervals. Thus, we can be assured that the bandwidth choice does not drastically alter our estimator.

A potential issue in pooling individual observations for different provincial percentiles together is that we may be capturing some "aggregation" bias in different wage structures, that is the noise in individual observations which is not controlled for by the geographic dimension of each wage distribution and its controls. Addressing this concern, we perform an eyeballing exercise and compare the estimation with a two-step procedure, in a fashion similar to a selection model (see Appendix B.5.1, p. 154 for equations and further explanation). We first model the RIF transformation for each quantile in each year on a set of individual characteristics, quarter and province dummies. Then we take the predicted value of the provincial binary variables, pool them together over time and regress them on our policy variable and a set of geographic-specific controls using weighted least squares (WLS), where the weights are provided by the inverse of the standard error for the corresponding provincial fixed effect. The results of this exercise go in line with the province RIF, as the estimates convey an effect which is similar in significance (for the two-step approach significant up to the 55^{th} percentile) albeit smaller in magnitude (on average 0.84 percentage points smaller in between the 15-60 percentiles). More importantly, the two-step minimum wage effects fall within the confidence interval of the province RIF specification up to the median of the distribution, that is where the effect are sizeable in both specifications. Thus, even if this exercise does not constitute a formal testing, it suggests that no strong aggregation bias is driving the results.

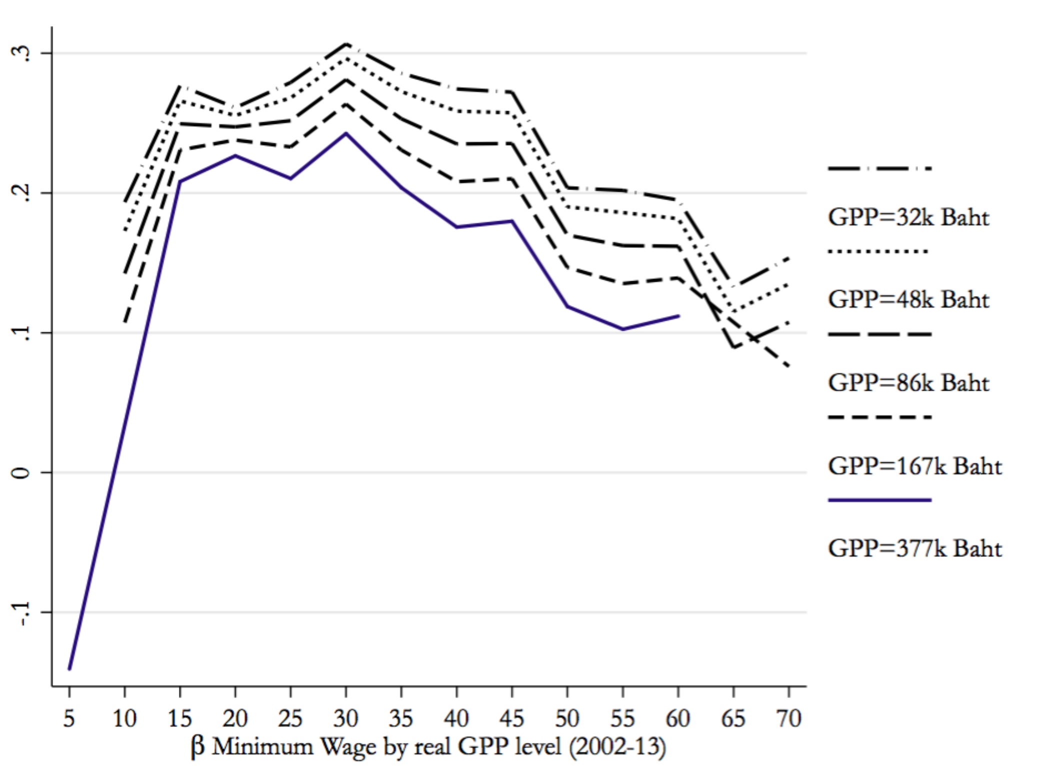
Lastly, we test the robustness of the estimation by substituting the deflator used for monetary variables (quarterly CPI) with a yearly spatial CPI (SCPI , see Appendix B.5.2, p.156-160). The robustness suggests similar effects, although of less precision. As we apply a yearly SCPI to quarterly data, the transformation performed in this exercise accounts more for the geographic specificity of pricing over time, but it ignores its seasonality.

4.6.3 Inspecting the heterogeneous response of provincial wages

Most of the research of the chapter has inspected descriptively the differences among Thai local labour markets, and it has proposed an estimator which, whilst giving a single average population effect, accounts simultaneously for the province-specific characteristics. The reason behind this choice of empirical strategy is that, although interesting on their own, performing 76 single-province distributional regressions would fall short on two aspects: firstly, they do not convey a clear policy message on the effectiveness of the different regimes, and secondly, may be more prone to statistical issues such as lower sampling power or higher measurement error in a sampled area. Therefore, our approach employs a small, econometrically-feasible, modification to the RIF framework, which we believe allows to more precisely identify the traits of the data at our disposal than a standard RIF estimator. Whilst we present an overall policy effect, we are also interested in further investigating if there are any heterogeneous effects stemming from some main characteristics of the Thai labour markets. Two attributes appear to be relevant to the analysis: over the 2000s provinces experienced different levels of economic performance; and as a result of differential economic and production spill-overs, the latest policy regime switch implies that some areas may have been more or less responsive in their wage adjustments. The present analysis further elucidates these heterogeneous effects, and it evaluates two aspects of the minimum wage policy. We investigate how economic conditions interact with the policy to affect wages, and examine the minimum effectiveness according to levels of economic activity of the last decade. Then we evaluate for the latest policy regime switch whether there is any heterogeneous effect from belonging to different geographic regions.

We have shown that firms are spatially clustered in their production, as expressed by their employment trends, and that provinces reflect this in their economic performance. Hence we would expect that, at different levels of provincial output, the wage responsiveness to a similar magnitude of minimum wage increase may differ among local labour markets. To formally assess this, we introduce an interaction term between the log of past GPP per capita and the minimum wage to our main specification (Equation 4.11). This allows us to evaluate the minimum wage effect as a function of GPP and to capture differences across diverse economic conditions experienced. In practice, we evaluate for the sample over the entire decade this interaction with GPP and then calculate the marginal effects of the minimum wage at the median GPP for each region.[54]

Figure 4.17: Wage elasticities to the minimum wage at selected GPP levels (2002-2013).



Note: Sample of male population 2002-2013 excluding agriculture; Province RIF regression model (covariates as main specification with an additional interaction term between MW and GPP. The graph reports the wage elasticity to the minimum wage for specific past GPP per capita rates. Each level (reported in ascending order) is chosen by calculating the median real GPP per capita over the period for the regions, spanning from the lowest in the Northeastern region (32 thousand Baht) to Bangkok (377 thousand Baht). The reported effects cover between the 5th and 70th percentiles, and are statistically significant at 10 percent or lower.

Figure 4.17 plots the marginal effects of the interaction term as evaluated at the region specific GPP levels. It is notable that the minimum wage has stronger effects

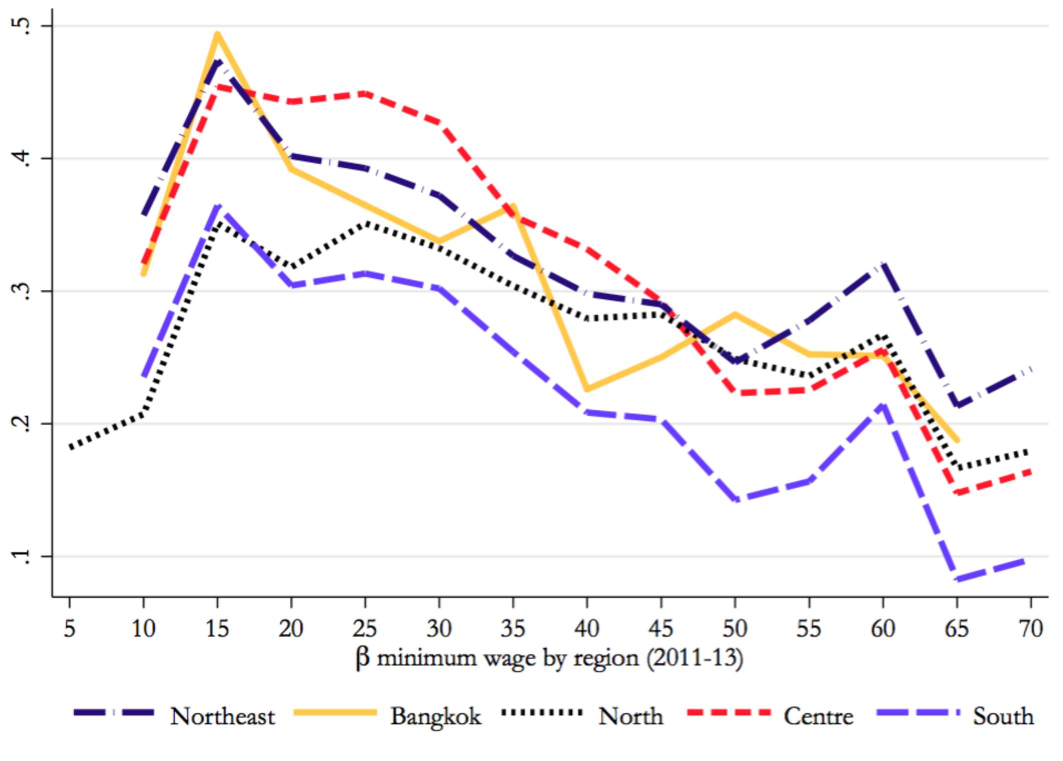
[54]Note that either performing the main regression accounting for non-linearity in GPP or calculating the elasticities at other levels of GPP (for example, GPP values at the 15th, 50th and 75th percentiles of its distribution) do not alter the results.

in those provinces where the past GPP per capita is weakest, whereas it has lower magnitude the better an area performs. A direct implication of this is that during the decade the areas with lower economic activity may have benefited more from a same percentage increase to the provincial minimum wage relative to richer areas. The graph also suggests that in the absence of the latest minimum wage adjustments the wage rate of private sector workers in the less wealthy areas could have potentially stagnated or even shrank, as those areas with lowest GPP are also the ones experiencing small rates of minimum wage adjustments prior to 2012.

Now we turn our focus to the latest policy change and inspect the heterogeneity in its effects across geographic areas. The regional heterogeneity could reveal which areas may have been more influenced by the jump in the wage floor, particularly as some regions have experienced different size of minimum wage adjustment than others. Figure 4.18 shows the wage elasticity of the minimum wage as a function of being in each of the five geographic regions during the NMW introduction (2011-2013).[55] The figure shows that the strong effects found in our main results for the NMW introduction stem mostly from three out of five geographic areas. For the lowest significantly affected percentiles, the 10^{th} and 15^{th}, the policy effects are stronger for Bangkok, the Central and Northeastern regions. The former two regions comprise those wealthier areas which experienced the NMW increase to 300 Baht first, in April 2012, and where we would expect to see the strongest effects (and compliance) for the lowest fraction of the population (as in the 10^{th} and 15^{th} percentiles). It is also remarkable the responsiveness of the Northeast, as both those workers at the bottom and top of the pay distribution benefited the most from the rising minimum wage rate when compared to areas from the North or South. In Northeastern provinces, the average 70 percent minimum wage increase provokes for the lowest percentiles a 25 percent increase in the 10^{th} percentile and a 33 percent wage rise in the 15^{th} percentile (with elasticities at 0.36 and 0.47 respectively).

[55] The estimation is slightly modified to include the fixed effects for being in one of the five geographic regions of Thailand and its interaction term with the minimum wage. This estimation excludes the province dummies, as they would remove the variance for being in one region otherwise, and not allow to inspect the regional minimum wage slopes of each percentile.

Figure 4.18: Wage elasticities to the minimum wage as a function of being in a geographic region, province RIF, 2011-2013.



Note: Sample of male population 2011-2013 excluding agriculture. The province RIF regression models covariates include region fixed effects and interaction term with the minimum wage level. The graph reports the marginal effects of the minimum wage variable evaluated for being in a specific geographic region. The reported effects cover between the 5^{th} and 70^{th} percentiles, and are statistically significant at 10 percent or lower.

For the 20^{th} to 35^{th} percentiles of provincial wage distributions, the Central region workers have the highest elasticity, from 0.35 to 0.45 (average 0.42). For a 70 percent increase in the minimum wage, the wages in these areas grow on average between 25 and 32 percent. Being in the Northeast and Bangkok in this segment of the distribution displays a statistically similar wage response at 26 percent (0.37 elasticity) to the 70 percent NMW rise, whilst the other two areas show some lower trends in policy responsiveness. With the 70 percent NMW increase, the average impact between the 20^{th} and 35^{th} percentiles are of 23 percent response for wages in the North (elasticity of 0.33) and 20 percent increase in the South (elasticity 0.29). At higher levels of the wage distribution, being in the Northeastern region means having had a higher push to own salary. Tentatively, this may reflect a higher propensity to wage negotiation being bound to minimum wage changes in the Northeastern provinces than in the rest of the country. Therefore, the two estimations suggest some degree of heterogeneity across the provinces of Thailand, in which wages from relatively poorer provinces have benefited more of a policy change during the 2000s. The latest minimum wage harmonisation seems to have generated stronger effects for the wages below the median of the provincial distributions in Bangkok, the Central and Northeastern regions.

Lastly, in Appendix B.6 we perform an ancillary exercise seeking to identify heterogeneous time correlations. We report some preliminary evidence on whether the NMW wage effects are more correlated to the hike period (Q2-Q4 2012) or to the policy harmonisation to a single regime (Q1-Q4 2013). In order to disentangle this time effect we use a Difference-in-Differences approach in a non-experimental policy environment, to identify whether the NMW intervention correlates with the wage response according to provinces' exposure to the hike. We find indications that, relative to the seven provinces which were piloted to the 300 Baht minimum already in April 2012, the non-piloted provinces show a higher wage correlation with the introduction of the NMW harmonisation. The attempt of using some observations as control group is subject to major caveats and does not pass the robustness checks performed, so it should not be considered as causal. As more extensively explained in the Appendix, future extensions could use other statistical procedures to make more precise inference than using observational data.

4.6.4 Is non-compliance localised? Investigating firm-size

We now turn our attention on potential characteristics influencing non-compliance. Firms' traits, their agglomeration and production are potential factors generating local labour markets (Moretti, 2011). We could expect that firms have different types of bargaining power in affecting wage negotiation in the provinces of Thailand. The lack of impact found at the 5-10$^{\text{th}}$ percentile makes one wondering whether there are signs of localised non-compliance due to the minimum wage policy, and whether the wage effects found persist once we inspect the characteristics of the work place of wage earners. Could the effects found imply that compliance only comes from specific types of firms? To answer this question, we look at workers' wage distributions by firm size (Appendix B.4, pp.150-152). Initially, we rule out that the effect on wage distributions is coming only from participation in large-sized firms. This could be a concern in a scenario where only relatively wealthier firms comply with the law. Table B.11 reports the province-RIF regression with sample split by firm size, comparing large versus Micro Small and Medium Enterprises (MSMEs) together. The results suggest positive effects for both types of workers, with statistically significant effect for the 10$^{\text{th}}$ quantile value of workers participating to large firms and with some statistically greater effects for large firms (only between the 25-35 percentiles). Furthermore, we investigate firms with less than 100 employees. Figure B.6 compares workers in micro-enterprises (less than 10 employees) versus SMEs (10-99). The results suggest that most of the improvements in provincial wage distributions apply to SMEs and are not different from zero in micro enterprises during the 2002-2013 decade. However, the micro firm estimation could simply be the result of the uneven distribution of micro enterprises, so that when we separate its sample and run the estimation alone, the statistical power is weakened. Table B.12 further assesses this issue. If there was absolute non-compliance by this type of firms, a specification for MSMEs with an additional variable for being a worker in a micro-firm and its interaction with the minimum wage should reveal joint negative effects on the distribution. Table B.12 (Panel A) shows that in 2002-2013 the MW effect for Micro firms is lower than for SMEs, but the slope is not statistically different from zero in all instances. Participation in micro enterprises, where the likelihood of informal employment is highest, seems to be less responsive and thus reflecting lower level of compliance which could curtail the overall effectiveness of changes in the policy. However, for the latest hike (Table B.12, Panel B), the wage responsiveness appears for micro enterprise as well: the slope for being in a micro-firm (relative to SMEs) is positive and the joint significance with the MW interaction is different from zero in some parts of the distribution (25-35$^{\text{th}}$ percentiles), tentatively implying that some but not all workers in micro firms have benefited from the minimum wage hike in the short-term.

4.6.5 Province RIF sample modifications

We now evaluate the consistency of the sample used. The main findings are drawn from the most saturated model (Equation 4.11) restricted to male private sector workers excluding workers in the agricultural sector. In Appendix B.4 (p.149) we test whether the effects of the minimum wage policy are robust to sample modification. Initially, we report an expansion of the sample including agricultural workers, then we investigate on all private sector workers, briefly investigating the gender dimension.

The inclusion of agricultural private sector workers (a non-covered sector which employs approximately 17 percent of the private sector workers, Table B.8, p.149) appears to be consistent with expectations. In the medium-run analysis (2002-2013, Panel A) the estimates are slightly smaller, the minimum wage affects the distribution from the 20^{th} to the 60^{th} percentile, suggesting that the population of agricultural wageworkers lies in the lower tail of the wage distribution and thus weakens the policy effect. In the latest policy shift (Panel B), the distribution is affected between the 15^{th} and 60^{th} percentile, where a 10 percent increase in the minimum induces more than 4 percent increase in average wage between the 15^{th}-45^{th} percentiles on average. The effect then decreases to around 2 percent in between the 50^{th} and 60^{th} percentile.

We then expand to all private sector employees, including female workers (Table B.9, p. 149). The medium-run analysis (Panel A) suggests that on average the minimum wage induces a 3 to 3.5 percent rise in average wage between the 5^{th} and 50^{th} percentiles, with effects up to the 60^{th} percentile.[56] For the short-run analysis of private sector workers (Panel B) we still find no effect at the lowest two percentiles (5^{th}-10^{th}).

In Table B.10 we further investigate the wage effects for the female population separately over the latest policy change. The results are in line with the male wage RIF regressions. The effects on the first three quantile groups (5^{th} to 15^{th}) are not significantly different from zero. Greater effects are found between the 20^{th} and 50^{th} percentiles (a 10 percent increase in the minimum leading to 4.5 to 6 percent increase) with a decreasing (and weakly statistically significant) positive effect persisting until the 75^{th} percentile. Thus, it appears that for the female wage distribution the latest minimum wage hike has a strong positive effect, failing to affect wages at the very bottom of the distribution, but strongly benefitting female wageworkers up to the provincial median.

[56] Note that for the private sector RIF regression, we identify greater spuriousness in the top wage distribution with positive and strongly statistically significant results between the 80^{th} and 95^{th} percentiles. Additionally, although in line with the more saturated model estimates, this result should be interpreted with caution as the female wage structure has been changing drastically over the 2000s and in this estimation we do not model selection if not by controlling for observables.

4.7 Conclusions

This chapter investigates the wage effects of the changes in the minimum wage policy in Thailand. The evaluation disentangles the effects of the application of multiple minima at provincial level since 2002 and the fastest rise in the country's history to a statutory rate after April 2012, providing an account of the short run effects induced by the policy change. The work explores the labour market characteristics of Thailand and identifies some traits of segmentation in the composition of private sector participation across provinces, with evidence of heterogeneity in the composition by firms size and sectors' participation. We show that these differences translate into diverse provincial private sector wage schedules.

With the objective of accounting for provincial wage heterogeneity, we propose an application of the RIF regression (Firpo et al., 2009a) to provincial wage distributions. This framework captures the heterogeneity of geographic distributions and offers a better description of the policy effects. We find positive effects of the minimum wage on the provincial wage distributions, with effects spanning between the 15$^{\text{th}}$ and 60$^{\text{th}}$ percentile, but with no effect on the lowest percentile. We ascribe the latter result to non-compliance in micro enterprises, which could have reduced the total effectiveness of the provincial minimum wage policy in redistributing to the less well-off. Our estimates for both 2002-2013 and 2011-2013 periods suggest that the minimum wage in Thailand is used as a *numeraire* for renegotiation. For the latest policy hike, we find that the introduction of the NMW induced a strong short term effect on provincial wages. The magnitude of the NMW effect is pronounced, as for every 10 Baht increase in the minimum wage over these two years, between 3 to 5 Baht are redistributed to the workforce in each province on average. We show that the policy impacts have been heterogeneous according to the economic performance over the decade and also stronger in Bangkok, Central and Northeastern regions during the latest NMW policy change. Additionally, we find that compliance happens among firms with different employee size, but we find weaker effects for micro-enterprises, suggesting some degree of non-compliance for this group. While we cannot focus on private sector wages in the informal sector due to data limitations, our estimates suggest that there may be interest in the future to understand the inequality impacts of the national minimum wage introduction, to both formal and informal wages once more data are available.

Notwithstanding that the geographic estimator proposed is complementary to the standard RIF (Firpo et al., 2009a), two last issues need to be iterated. Given the type of nationally representative data available (cross-sections) and potentials for measurement error, the ambition we had is to propose a simple estimator that identifies the distributional characteristics of the Thai labour market, while avoiding the use of a CQR, which does not capture population effects and may not be robust to a mis-measured outcome variable (Hausman, 2001). With the RIF transformation (Firpo et al., 2009a) instead, in a OLS regression a moderate measurement error does not create substantial issues. As potential extension to the distributional analysis, it could be interesting to assess the local-level heterogeneity of the results by testing if and how a modification to the minimum wage variable – such as a transformation to reflect the importance of local level changes in wages or economic performance – would alter the results found. Additionally, future research could inspect on forms of selection correction to the estimation, thus matching the latest literature which applies it to the CQR (Arellano and Bonhomme, 2017), assessing the strength of the linear results proposed in the UQR.

Overall, albeit not being effective for the lowest tail of the distribution, we conclude that the harmonisation to a NMW has generated a positive wage effect in the provincial labour markets of Thailand.

Appendix B

Appendix for the wage analysis

B.1 Additional descriptive tables and figures

Table B.1: Minimum Wage Policies in Thailand, 1973-2017.

Law	Years	Institutions *	Coverage	MW type
Revolutionary Party Decree No. 103	1973/4 - 1998	NWC	Bangkok, and three provinces**(1973), Kingdom (1974)	Bands by geographic region
Labour Protection Act B.E. 2541 (1998)	1998-2008	NWC, PSMWs, STAR	Kingdom (2001)	Province-specific
Labour Protection Act B.E. 2551 (2008)	2008-2012	NWC, PSMWs, STAR	Kingdom (2008)	Province-specific
Notification of the Wage Committee on the Minimum Wage Rate(No.6)	2012/3- 2016	NWC, PSMWs, STAR	Bangkok and six provinces*** (2012), Kingdom (2013)	Province-specific (Q2 2012), Statutory wage (Q1 2013)
Notification on Wage Rates for Skilled Workers According to Skills Standards (No. 5)	2016-	NWC, PSMWs, STAR	Kingdom (2016)	Skill-specific (Q4 2016) 5 industries**** with eligibility
Notification of the Wage Committee on the Minimum Wage Rate(No.8)	2017-	NWC, PSMWs, STAR	Kingdom (2017)	Province-specific (1^{st} Jan 2017)*****

Note: * NWC stands for National Wage Committee, which includes government, employer, and employee representatives, it recommends minimum wage adjustments; PSMWs stand for Provincial Subcommittees on Minimum Wages, which are tripartite subcommittees composed of government, employer, and employee representatives at provincial level, which recommend minimum wage adjustments; STAR stands for Subcommittee on Technical Affairs and Review, the body submitting technical reviews of the recommendations. Final recommendations are handed over the deciding authority that is the Ministry of Labour that announces the law on the Royal Gazette (source: MOL 2008; Del Carpio et al. 2014). ** Nonthaburi, Pathum Thani and Samut Prakan. *** Nakhon Pathom, Nonthaburi, Pathum Thani, Phuket, Samut Prakan, Samut Sakhon. **** The Notification has increased the new minimum wage rates for skilled workers between 340 Baht and 550 Baht per day (two bands), depending on their skill levels and experience, for 20 professional branches of 5 industries:(1) Electrical and electronics (2) Parts and spare parts of motor vehicles (3) Motor vehicle (4) Jewellery (5) Logistics; Eligibility: employees must pass the professional skill standards tests and obtain relevant certificates from the authorities, they must be employed to work in positions that require usage of such skills (entirely or partly). ***** Minimum wage rates as of January 2017: 300 Baht, 305 Baht, 308 Baht, 310 Baht (MOL, 2016).

B.1.1 Summary statistics

Table B.2: Descriptive statistics for male private sector workers (pooled quarterly data).

	2002-13		2011-13	
	Mean	SD	Mean	SD
Schooling(years)	8.69	4.09	9.08	4.18
Experience(years)	17.46	11.17	18.50	11.52
Married	0.63		0.62	
Full time	0.91		0.92	
Sector				
Manufacturing	0.35		0.34	
Construction	0.25		0.26	
Wholesale	0.20		0.20	
Hospitality	0.04		0.04	
Services	0.11		0.12	
Other	0.04		0.05	
Firm size				
less 10	0.37		0.37	
10-49	0.25		0.24	
50-99	0.07		0.07	
100-199	0.08		0.08	
more 200	0.23		0.23	
Geo Info				
Rural	0.55		0.54	
Bangkok	0.19		0.17	
Central	0.34		0.35	
North	0.14		0.14	
Northeast	0.22		0.23	
South	0.10		0.11	
Wage & Pop.				
Hourly wage	51.42	105.61	56.11	107.40
Weekly hours	49.66	11.34	49.68	10.57
Log MW	3.25	0.17	3.41	0.21
Log GPP pc	11.68	0.95	11.64	0.88
Youth pop sh	0.22	0.04	0.20	0.04
Elderly pop sh	0.09	0.02	0.12	0.02
High skilled sh	0.19	0.10	0.21	0.10
Obs.	791,701		205,190	

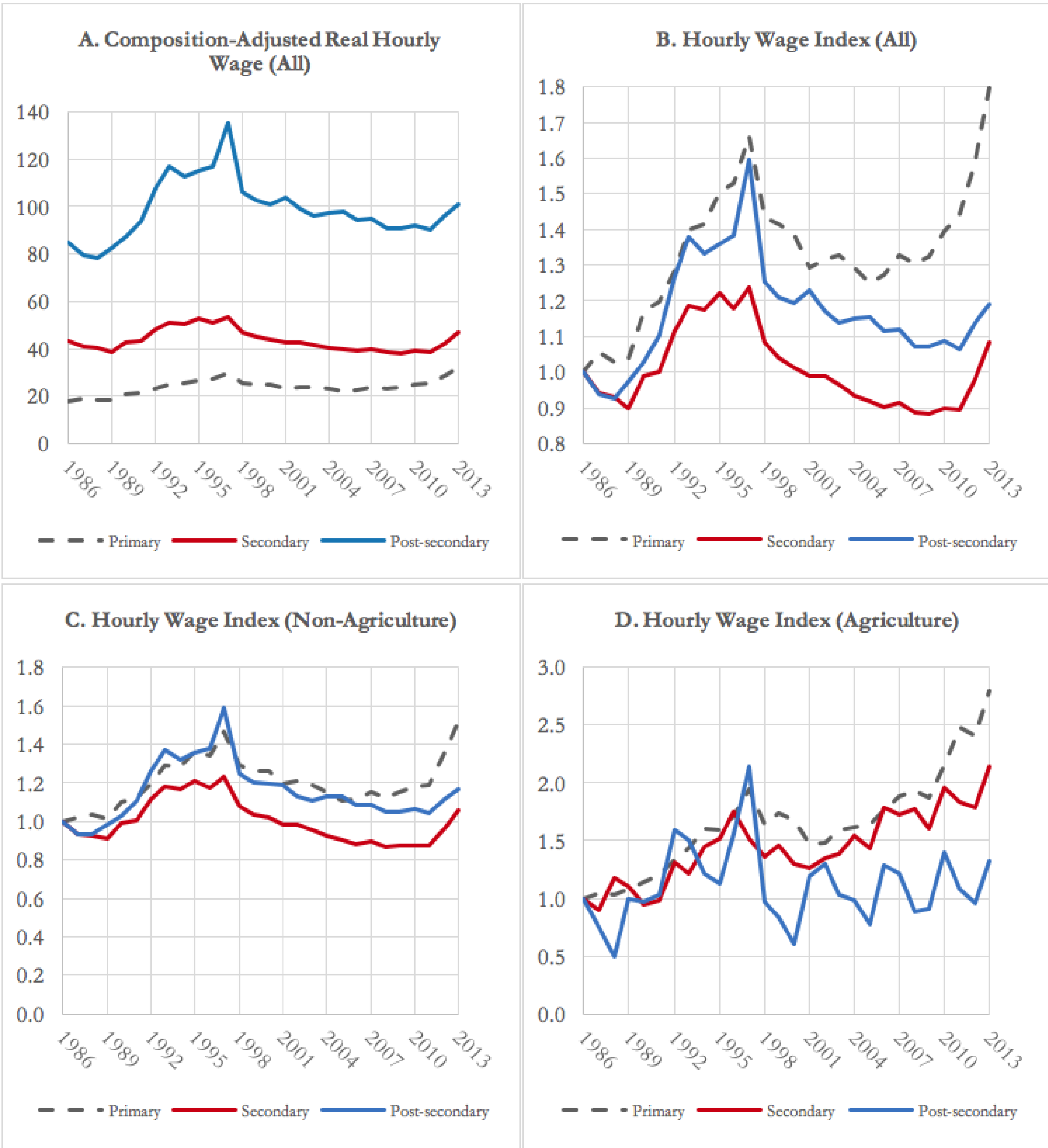
Note: LFS data at individual level for private sector male workers aged 15-65 excluding agriculture (pooled Q1-Q4 for years 2002-13 or 2011-13). The table reports the mean (and standard deviation) for levels, proportions for binary variables. Monetary variables are in Thai Baht, expressed in real terms (quarterly CPI, base Q3-2013). Manufacture includes mining and electricity. All variables are at individual level with exception of log minimum wage, youth, elderly and high-skilled shares (expressed in province-quarter) or log GPP (in province-year). The data report mean and standard deviation (using survey weights).

Table B.3: Descriptive statistics for male private sector workers (pooled quarterly data, including agriculture), selected years.

	2002		2011		2013		Test 02-11		Test 11-13	
Post	Mean	SD	Mean	SD	Mean	SD	test	p-val	test	p-val
Age(years)	33.15	10.65	35.30	11.24	35.66	11.30	-39.45	0.00	-6.42	0.00
Edu below 2^{ary}	0.77	–	0.69	–	0.66	–	920.01	0.00	47.24	0.00
Bangkok	0.20	–	0.14	–	0.14	–	32.23	0.00	1.65	0.20
Central	0.30	–	0.33	–	0.34	–	54.25	0.00	39.51	0.00
North	0.16	–	0.15	–	0.14	–	8.58	0.00	22.74	0.00
Northeast	0.22	–	0.24	–	0.25	–	2.89	0.09	71.26	0.00
South	0.12	–	0.14	–	0.14	–	0.64	0.42	31.02	0.00
Firm S10	0.43	–	0.45	–	0.42	–	0.00	0.98	83.75	0.00
Firm S99	0.32	–	0.30	–	0.30	–	10.29	0.00	0.14	0.70
Firm S100	0.25	–	0.25	–	0.28	–	7.04	0.01	133.65	0.00
Agriculture	0.20	–	0.17	–	0.15	–	81.36	0.00	8.16	0.00
Manufacture	0.29	–	0.28	–	0.30	–	27.09	0.00	28.83	0.00
Construction	0.20	–	0.22	–	0.22	–	3.44	0.06	12.63	0.00
Wholesale	0.16	–	0.16	–	0.17	–	4.15	0.04	3.60	0.06
Hospitality	0.03	–	0.04	–	0.03	–	6.37	0.01	16.58	0.00
Services	0.08	–	0.10	–	0.10	–	125.40	0.00	13.73	0.00
Other	0.04	–	0.04	–	0.04	–	4.98	0.03	1.12	0.29
Not in agri.	0.80	–	0.83	–	0.85	–	81.36	0.00	8.16	0.00
Full time	0.87	–	0.88	–	0.88	–	49.56	0.00	4.01	0.05
Married	0.64	–	0.62	–	0.62	–	132.19	0.00	21.94	0.00
Hourly wage	44.33	75.44	46.92	86.39	58.29	115.84	-8.78	0.00	-18.77	0.00
Weekly hours	48.82	12.48	48.75	11.85	47.87	11.36	4.36	0.00	17.18	0.00
Log MW	3.21	0.10	3.19	0.10	3.63	0.00	29.99	0.00	-1,271	0.00
Log GPP pc	11.61	1.01	11.53	0.85	11.56	0.86	3.72	0.00	1.06	0.29
Youth pop sh	0.26	0.02	0.21	0.04	0.20	0.04	287.83	0.00	32.89	0.00
Elderly pop sh	0.08	0.02	0.11	0.02	0.12	0.02	-301.52	0.00	-134.43	0.00
High skilled sh	0.15	0.08	0.20	0.09	0.21	0.10	-139.51	0.00	-26.54	0.00
Obs.	72,339		79,099		80,069					

Note: LFS data at individual level for male private sector workers aged 15-65 (pooled Q1-Q4 for years 2002, 2011, 2013). Monetary variables are in Thai Baht expressed in real terms (quarterly CPI, base Q3-2013). Manufacture includes mining and electricity. All variables at individual level with exception of log minimum wage, youth, elderly and high-skilled shares (expressed in province-quarter) or log GPP (in province-year). The data report yearly means and standard deviations for continuous variables, the rest are proportions (survey weights applied). Test statistics are performed between year 2002 and 2011 or 2011 and 2013 reporting test and p-value (equal or unequal variance test for levels, χ_2 test for binary variables).

Figure B.1: Composition-adjusted real hourly wage and Index, 1986-2013.



Notes: LFS Q3 1986-2013, adapted from Lathapipat (2009) and updated up to 2013. We report the composition-adjusted real hourly wage (using a regression of real hourly wages with experience held constant at all-year-average levels) split by education level (Panel A); Indexed for its 1986 value for all private sector employment (Panel B), any non-agricultural (Panel C) or agricultural work (Panel D).

Figure B.2: Average employment shares by sectors or firm type, 2002-2013.

Source: LFS 2002-2013, average yearly private sector employment (A) by aggregated sector (including agriculture) (B) by firm type (only Industry and Service). Survey weights applied and shares expressed as %.

Table B.4: Provincial private employment share by firm size and region, 2013.

	Bangkok	Central	North	Northeast	South
Less10	0.20	0.33	0.55	0.59	0.62
min		0.09	0.34	0.36	0.25
max		0.74	0.77	0.79	0.85
Sh-aboveM		0.52	0.53	0.47	0.64
Size 10-49	0.29	0.19	0.26	0.25	0.20
min		0.09	0.15	0.16	0.09
max		0.26	0.40	0.36	0.33
Sh-aboveM		0.48	0.41	0.53	0.50
Size 50-99	0.13	0.06	0.04	0.04	0.05
min		0.03	0.00	0.01	0.01
max		0.14	0.08	0.07	0.09
Sh-aboveM		0.44	0.41	0.47	0.57
Size 100-199	0.14	0.08	0.04	0.04	0.05
min		0.03	0.00	0.00	0.00
max		0.16	0.08	0.08	0.16
Sh-aboveM		0.44	0.35	0.63	0.36
More200	0.25	0.34	0.11	0.08	0.09
min		0.06	0.01	0.00	0.00
max		0.62	0.46	0.37	0.21
Sh-aboveM		0.48	0.41	0.26	0.43
Provinces	1	25	17	19	14

Note: LFS 2013. The table reports for each region the mean provincial private-sector employment by firm-size, minimum, maximum and share of provinces with value above regional mean (Sh-aboveM). Categories: micro (less than 10 employees); small (10-49 employees); medium (50-99); large (100-199); large with more than 200 employees. The final row reports the total number of provinces per region. This table is used to create Fig. 4.8 (p.94).

B.1.2 Location Quotients

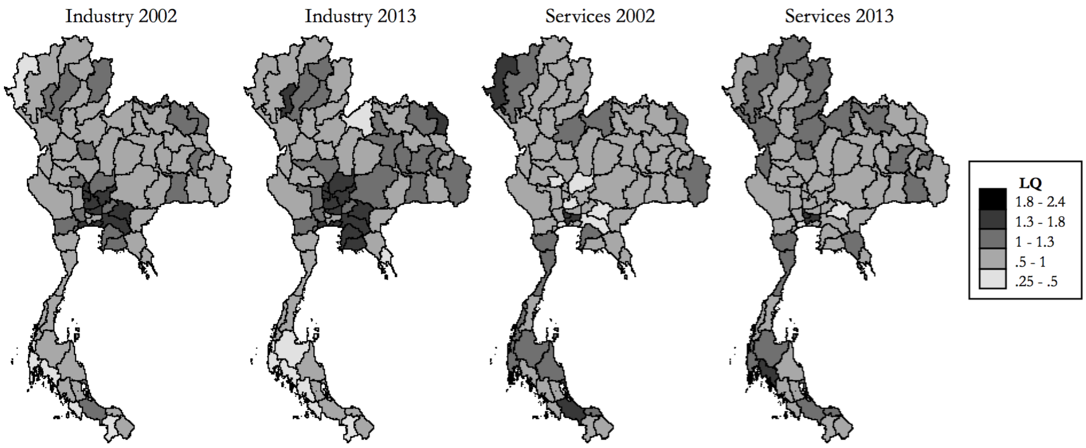
To identify the geographic segmentation of industries, the economic geography and urban economics literatures have proposed several measures of dispersion or concentration, of which the Location Quotient (LQ) is one of the simplest in its assumptions, calculation and data requirements (Isserman, 1977; Leigh, 1970). It is a measure of dispersion which provides a way of assessing the relative specialisation of a particular characteristic within a population. Often used in regional spatial analysis of firms' agglomeration, the LQ may show limitations in the choice of its cut-offs for comparison (Crawley et al., 2013), which for the descriptive purpose of this section should not be an issue.

We choose as smallest location unit under analysis the province (given the nature of the data at our disposal). In order to apply this measure we need to assume that each province represents a micro-structure of the nation in the generation of employment. Specifically we define: $\mathrm{LQ}_{\mathrm{sp}} = \frac{e_{\mathrm{sp}}}{e_p} / \frac{E_s}{E}$. LQ is the ratio of employment share of the sector of interest in the geographic scale of interest (in our case $\frac{e_{\mathrm{sp}}}{e_p}$ represents employment in sector s over total private sector employment of province p) and the employment share of sector s in a reference area (in our case the nation, with its employment labelled as E). We calculate the LQ for employment in the private sector of each province, aggregating private sector employment in three sectors (aggregations of Industry, Services and Agriculture).

The reference of this index is the value 1, meaning that sectoral employment s in province p behaves as the national average. Any value below (above) 1 suggests that the province is less (more) specialised in this sector than the national average. As illustration, we report in Figure B.3 below the LQ for Industry and Services at beginning and end of our data analysis period (2002 and 2013).

The LQ for the Industry sector suggests that employment specialisation has remained spatially clustered in the Central provinces surrounding Bangkok over the 2000s, with increased employment above national average in 2013 for those provinces with industrial estates established over the period. The LQ for the Service sector shows instead that the biggest specialisation is in Bangkok (as expected), with widespread increase in Service specialisation across the country between 2002 and 2013 (complementing the understanding of the growing aggregate employment share in Services shown in Figure B.2 panel A). Thus, the map for 2013 suggests that Service employment has spread among provincial labour markets.

Figure B.3: Map of Location Quotients for Industry and Services, 2002-2013.

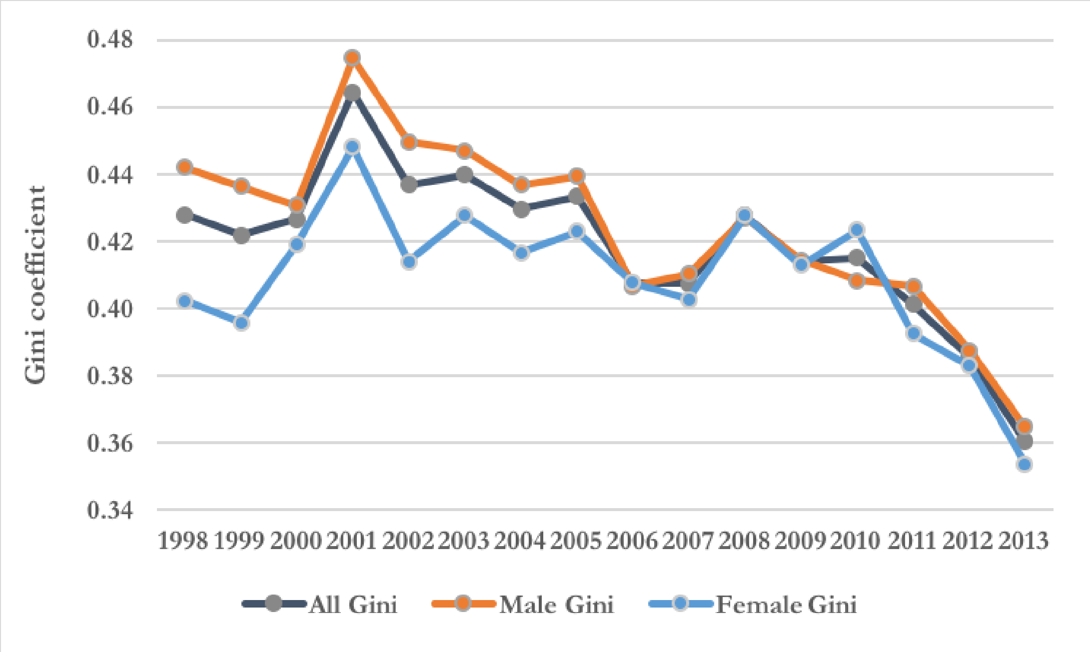


Source: LFS 2002,2013. Location Quotients for private sector employment for Industry and Services, see above for more details.

B.1.3 Gini coefficient and the provincial wage distribution

As reported in Section 4.3.3 (p.90), we inspect inequality measures to understand how private sector workers have behaved over the decade of the 2000s. The Gini coefficient for hourly wage in the private sector (Figure B.4) shows that in more than a decade private sector wage inequality has fallen but at a very slow rate (declining from 0.46 in 2001 to 0.36 in 2013). Next we examine in Figure B.5 the evolution of quantile ratios p10/p50 (defined as the ratio of 10^{th} percentile to the median, describing the volume of the lower half of the distribution) and the p90/p50 (ratio of 90^{th} percentile to the median, describing the volume of the upper half of the distribution). Both male and female p10/50 show that, at the start of recovery from the financial crisis, the bulk of the lower part of the distribution has only slightly increased, but the top gap p90/p50 has reduced, suggesting some degree of wage inequality reduction.

Figure B.4: Wage Gini for private sector workers: all, male and female, 1998-2013.

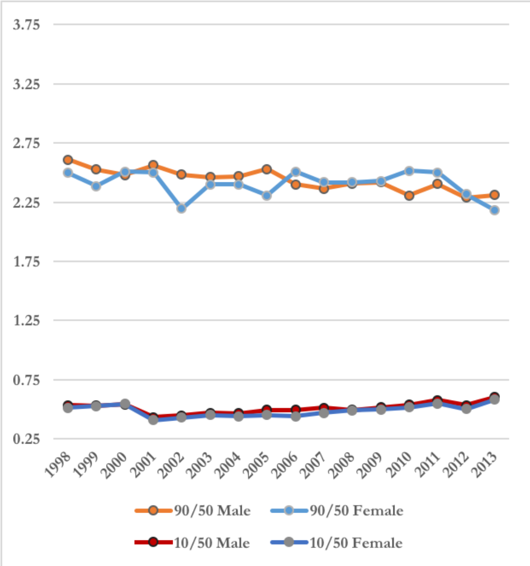


Source: LFS private sector workers 1998-2013. Gini coefficient (y-axis) for hourly wage which is defined as the comparison of cumulative proportions of a population against cumulative proportions of log hourly wage they receive (using survey weights multiplied by hours supplied), ranging between 0 (perfect equality) and 1 (perfect inequality). The measure suggests moderate reduction in wage inequality. The Gini formula: $G = 1 + (1/N) - [2/(m \cdot N^2)][\sum (N - i + 1)y_i]$, where obs are ranked in ascending order of y_i.

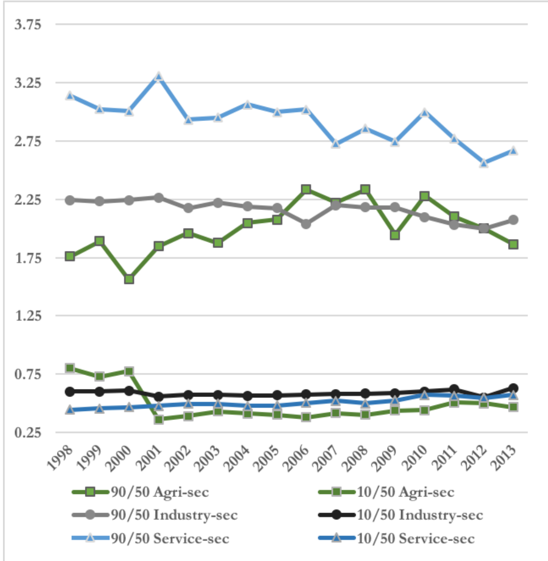
Looking at wage differentials for three broadly defined production sectors (Industry, Agriculture, Services) it appears that most of the reduction in wage inequality has taken place in the Services sector (with sizeable reductions in the p90/p50 ratio) and that in all three aggregate sectors the p10/p50 ratio has slightly increased after 2001. This statistics has to be interpreted with the evolution of employment composition across sectors in Thailand (reported in Figure B.2) which has seen workers moving out of agriculture and entering in the service sector. Over the period, employment composition by firm size has also varied, with reductions in participation in micro-enterprises after 2009 and revived participation in large firms since 2011.

Figure B.5: p10/p50 and p50/p90 ratios by gender and aggregate sectors for private sector workers, 1998-2013.

(a) Gender



(b) Sectors



Source: LFS 1998-2013 Q3. Annual ratios constructed for private sector workers. The graph (a) reports the ratios by gender, graph (b) for sectors: Agriculture (including forestry and fishery), Industry (including manufacturing, mining, construction) and Services.

Table B.5: Non-compliance – share of private sector workers with wage below the minimum (%), 2002-2013.

Year	Overall	Low skilled	Young	Young low skilled
2002	28.1	32.1	39.1	42.4
2003	27.7	31.8	40.3	43.9
2004	27.6	31.5	38.6	41.8
2005	27.8	32.1	38.9	42.7
2006	24.7	28.5	35.3	38.4
2007	23.3	27.0	33.4	36.3
2008	21.0	24.6	30.8	33.3
2009	21.9	25.6	33.5	36.1
2010	20.2	23.6	30.9	33.4
2011	18.6	21.9	28.8	31.1
2012	28.3	33.8	41.6	45.2
2013	35.6	42.3	49.8	53.4

Note: LFS data 2002-2013 for male private sector employees excluding agriculture. Shares in percentages (%). Young stands for aged 15-24; Low skilled stands for individuals with less than secondary education.

B.2 Wage distributional analysis

B.2.1 FFL RIF Regression method

More on the Influence Function and the RIF transformation

Assume the following general structural model $Y = h(X,\ \varepsilon)$. The (marginal) unconditional distribution of Y is defined as $F_Y\,(y) = \int F_{Y|X}\,(y|X=x) \cdot dF_X\,(x)$.

Under the assumption that a small location shift of the distribution of X $(G_X\,(x))$ does not affect the conditional distribution $F_{Y|X}\,(.)$, a counterfactual distribution of Y is obtained:

$G^*_Y\,(y) \equiv \int F_{Y|X}\,(y|X=x) \cdot dG_X\,(x)$.

Let R be a real separable metric space and let $\nu(.)$ be a real-valued functional and F_Y representing a probability measure on R for which $\nu(.)$ is defined. Let the functional $\nu(F_Y)$ be any function of F_Y part of $\mathcal{F}_v \rightarrow\ \mathbb{R}$, a class of distribution functions, such that $F_Y \in \mathcal{F}_v$ if $|\nu\,(F_Y)| < +\infty$, and let also G_Y be from the same class.

The Influence Function (IF) is used to investigate the effect of contaminating a distribution with a small amount of additional unit (Hampel, 1974). The definition of an influence function $IF\ (y;\ \nu, F_Y)$ of a distributional statistic $\nu(F_Y)$ represents the influence of an individual observation on that distributional statistic of Y. From a special case of the Gâteaux distribution (where contamination takes place by a point mass), we assume that there exists a probability measure Δ_y for every point $y \in R$ of mass point one. For a small location shift $0 \leq t < 1$ of the F_Y distribution towards the G_Y distribution (known as the mixing distribution $F_{Y,t\cdot G_Y}$), the directional derivative of ν towards G_Y is:

$$\frac{\nu\left(F_{Y,t\cdot G_Y}\right)-\nu(F_Y)}{t} = \frac{\partial\nu(F_{Y,t\cdot G_Y})}{\partial t}|_{t=0} = \int \text{IF}\ \ (y;\ \nu, F_Y)\cdot d(G_Y - F_Y)(y)$$

where IF $(y;\ \nu, F_Y) = \frac{\partial v(F_{Y,t\cdot\Delta_y})}{\partial t|_{t=0}}$ (Firpo et al. (2009a) p.956). Applying the von Mises linear approximation of the functional $\nu(F_{Y,t\cdot G_Y})$:

$$\nu\left(F_{Y,t\cdot G_Y}\right) = \nu\left(F_Y\right) + t\cdot \int \text{IF}\ \ (y;\ \nu, F_Y)\cdot d\left(G_Y - F_Y\right)(y) + r(t;\nu;G_Y,F_Y)$$

Simplifying the equation above, FFL define the RIF to be the special case where $G_Y = \Delta_y$ and $t = 1$:

$$\text{RIF}\ \ (y;\ \nu, F_Y) = \nu(F_Y) + IF\ \ (y;\ \nu, F_Y)$$

Theorem I of FFL (p. 957, Firpo et al. 2009a) states how the impact of a marginal change in the distribution of X on the functional is obtained by integrating the conditional expectation of RIF with respect to the changes in distribution of the covariates $d(G_X - F_X)$:

$$\frac{\partial\nu((1-t)\cdot F_Y + t\cdot G_Y^{*})}{\partial t}|_{t=0} = \int E[\text{RIF}(y;\ \nu, F_Y)\,|X = x]\cdot d(G_X - F_X)$$

In choosing the statistical functional, FFL extensively analyse the quantile and in Firpo et al. (2009b) show the properties.[1] The Recentered Influence Function (RIF) from FFL is generated by adding back the statistic $\upsilon\left(F\right)$ to the influence function. The RIF for the τ^{th} quantile, q_τ, is given by:

$$\text{RIF}\left(Y_i; q_\tau, F_Y\right) = q_\tau + \frac{\tau}{f_Y(q_\tau)} - \frac{\mathbb{I}(Y_i \leq q_\tau)}{f_Y(q_\tau)}$$

where $f_Y(q_\tau)$ is the kernel density estimator of outcome Y in the τ^{th} quantile q_τ and $\mathbb{I}\left(Y_i \leq q_\tau\right)$ is the identity function identifying if each observation is below the q_τ cut-off. In order to go from proportions to quantiles all that is needed is to divide through the proportions by the relevant density. The main feature of the RIF is that its expectation is equal to the functional $\upsilon\left(F\right)$, and FFL shows that this also applies to the quantile RIF which integrates up to the quantile q_τ of interest. Formally:

$$\text{(generic)} \int \text{RIF}\left(y;\upsilon\right)\cdot\ dF\left(y\right) = \int\left(\upsilon\left(F\right) + IF\left(y;\upsilon\right)\right)\cdot\ dF\left(y\right) =\ \upsilon\left(F\right)$$

[1] See Firpo et al. (2009b) for a full description of the asymptotic properties of the estimator. Firpo et al. (2009a) argues that as the influence function can be computed for most distributional statistics, easily extending to other measures such as the Gini or other commonly used inequality measures, see Essama-Nssah and Lambert (2012) for a review.

(quantile) $\int \text{RIF}\left(y; q_\tau, F_Y\right) \cdot\ dF_Y\left(y\right) = q_\tau$

where $F_Y\left(y\right)$ is the marginal distribution function of outcome variable Y. The reciprocal of the relevant density is the derivative of the inverse of the CDF. In presence of covariates, we can express the RIF in terms of conditional expectations:

$$\upsilon\left(F_Y\right) = \int \text{RIF}\left(Y_i; q_\tau, F_Y\right) \cdot dF_Y\left(y\right) = \iint \text{RIF}\left(Y_i; q_\tau, F_Y\right) \cdot dF_{Y|X}\left(y|X = x\right)$$

$$= \int E[RIF\left(Y_i; q_\tau, F_Y\right)|X = x] \cdot dF_X\left(x\right)$$

The second equality follows from the fact that the influence function integrates to zero, and the third equality shows that, when we are interested in the impact of covariates on a specific quantile, it is possible to integrate over the $E[\cdot]$ of the transform to find the effect of covariates, which can be done using regression methods. Applying the Law of Iterated Expectation to the quantile RIF expression yields:

$$E\left[\text{RIF}\left(y; q_\tau, F_Y\right)|X)\right] = m^{q_\tau}(X) = q_\tau$$

where the conditional effect on the covariate space of X averages up to the unconditional population mean, and $m^{q_\tau}(X)$ is the RIF regression model. The model is easily estimated using Ordinary Least Squares:

$$E\left[\text{RIF}\left(y; q_\tau, F_Y\right)|X)\right] = X'\gamma$$

where the OLS regression provides an estimate for γ which represents the effect of the covariates X on the unconditional quantile τ of the outcome Y (Firpo et al., 2009a).

The RIF in non-separable models

Rothe (2010) shows that for any functional $\nu(.)$ it is possible to define the UQPE with a more flexible structural equation, through general non separable models using the insights and properties of the control variable approach (Imbens and Newey, 2009). It assumes that $Y = l(X, \xi)$ where X is a potentially endogenous regressor (or a vector with one or more endogenous variables), making the function non-additive in ξ.

Assuming that $X = h(Z, \mu)$ where Z is an instrument and μ a continuously distributed unobserved disturbance, and the function $h(.)$ is strictly increasing in Z, we can define a control variable to be $V = F_{X|Z}(X, Z) = F_{\mu}(\mu)$ the conditional CDF of X given Z, where the instrument $(Z \perp (\xi, \mu))$ is independent from the errors, and so $(\xi \perp X|V)$ the source of dependence between ξ and X exists only in their joint dependence on the unobserved disturbance μ (Imbens and Newey, 2009).[2]

Under the condition that the functional $\nu(.)$ is Hadamard differentiable at F_Y[3], the Unconditional Partial Effect (UPE) of X on $\nu(F_Y)$ is:

$$\theta_{\nu} = \frac{\nu(F_{Y,\delta} + \delta h_{\delta}) - \nu(F_Y)}{\delta} = \nu^{'}(\theta_{\text{id}}) = \nu^{'}\left(\mathbb{E}(\partial_X F_{Y|X,V}(., X, V))\right)$$

The Unconditional Partial Effect (UPE) θ_{ν} of X on F_Y is the average derivative of the conditional CDF of Y given X and V.

where $\theta_{\text{id}} = \mathbb{E}(\partial_X F_{Y|X,V}(., X, V))$ and V is the control variable, constructed with a conditional independence assumption (conditioning on an unobservable variable, see for details Rothe (2010) Lemma I) which allows to derive the CDF of the counterfactual variable Y_{δ}, where $Y_{\delta} = l(X + \delta, \xi)$ (Rothe, 2010).

In Lemma I and Lemma II (Rothe, 2010) the author shows that the functional $\nu(.)$ is Hadamard differentiable (at F_Y) if there is a continuous linear map $\nu^{'}(.)$ such that, for a sufficiently small constant $\delta \neq 0$, in all sequences of function $h_{\delta} \to h$, where $h_{\delta} = \frac{(F_{Y,\delta} - F_Y)}{\delta}$, the shift $F + \delta h_{\delta}$ is contained in the domain of $\nu(.)$, or in other words, there exist a value of $\nu^{'}(h)$ which sets the equation to zero:

$$\left\| \frac{\nu(F_Y + \delta h_{\delta}) - \nu(F_Y)}{\delta} - \nu^{'}(h) \right\| = 0$$

The functional which transfers a CDF into its quantile function is:

---

[2]Note that if the objective function $Y = l(X, \xi) = l_0(X) + \xi$ is additive separable in ξ, we would have a case where X depends on Z but not on μ, thus X would become an (instrumented) exogenous regressor of Y (Imbens and Newey, 2009).

[3]Hadamard requires a single quotient $\nu^{'}(.)$ for each direction of the F, equivalent to a Gâteux differentiability being uniform over the perturbation δ (no matter the direction).

$\nu(Y) = F_Y{}^{-1}(\tau) = inf\{y : F(y) \geq \tau\} = q.$

From Theorem 1 (Rothe, 2010) we can show that, under the assumption that the quantiles are unique, the $\nu'(.)$ map is Hadamard differentiable at F_Y with derivative:

$$\phi \to \nu'_{F_Y}(\phi) = -(\frac{\phi}{\partial_Y F_Y}) \circ F_Y^{-1}$$

Thus, the UPE of X on the quantile of Y is

$$\theta_\nu(\tau) = \nu'(\theta_{\text{id}}) = -\frac{\theta_{\text{id}}(q_\tau)}{f_Y(q_\tau)} = \frac{\mathbb{E}[f_{Y|XV}(q_\tau, X, V)\partial l(X, \xi_\tau(X)]}{f_Y(q_\tau)}$$

The UQPE as a weighted average of CQPE

As final remark about the RIF methodology, we show how Firpo et al. (2009a) define their estimator (the UQPE) with respect to the Conditional Quantile (CQPE).

Let's define the τ^{th} quantile of the distribution of Y as $Q_\tau = (h(X, \varepsilon))$ and the conditional quantile of Y given $X = x$ to be: $Q_\tau(Y|X = x) = (h(X, \varepsilon)|X = x)$. The conditional quantile partial effects (CQPE) is then defined as:

$$CQPE(\tau, x) = \frac{\partial Q_\tau[h(X, \varepsilon)|X = x]}{\partial x} = \frac{\partial h(X, Q_\tau[\varepsilon])}{\partial x}$$

Where $Q_\tau[Y|X = x] \equiv inf_q\{q : F_{Y|X}(q|X) \geq \tau\}$ is the conditional quantile operator. FFL (p.956) shows that the UQPE can be written as a weighted average of the CQPE:

$$UQPE(\tau) = E[\omega_\tau(X) \cdot \frac{\partial h(X, \varepsilon_\tau(X))}{\partial x}] = E[\omega_\tau(X) \cdot CQPE(\xi_\tau(X), X)]$$

This equality exists thanks to three auxiliary functions: $\omega_\tau(x) \equiv f_{Y|X}(q_\tau|x)/f_Y(q_\tau)$ is a weighting function of the ratio between the conditional density given $X = x$ and the unconditional density; ε_τ is the inverse function $h^{-1}(., q_\tau)$ which exists under the assumption that h is monotonic in ε; and ξ_τ is the matching function which indicates where the unconditional quantile falls in the conditional distribution of Y:

$$\xi_\tau(X) \equiv \{s : Q_s[Y|X = x] = q_\tau\} = F_{Y|X}(q_\tau|X = x)$$

(Firpo et al., 2009a). This thus show that the conversion of the partial effects is valid, and it could be applied without violations if the conversion was performed for the conditional density of $X = g$ (conditional on independence from the error).[4]

B.3 Province RIF Regression tables

Table B.6: The effect of the minimum wage on provincial wage distributions, 2002-2013.

Percentile	5	10	15	20	25	30	35	40	45	50
Log MW	0.085	0.085	0.201***	0.179***	0.219***	0.260***	0.244***	0.249***	0.247***	0.184***
	(0.141)	(0.083)	(0.063)	(0.052)	(0.066)	(0.065)	(0.062)	(0.058)	(0.059)	(0.038)
R^2	0.11	0.18	0.23	0.26	0.28	0.30	0.32	0.34	0.35	0.37
Percentile	55	60	65	70	75	80	85	90	95	Obs.
Log MW	0.165***	0.122***	0.036	0.062	0.030	0.088	0.089	0.094	0.249*	
	(0.041)	(0.044)	(0.068)	(0.047)	(0.059)	(0.073)	(0.090)	(0.099)	(0.127)	
R^2	0.37	0.38	0.38	0.39	0.38	0.36	0.34	0.29	0.20	791,542

Note: The summary table reports the point estimates of log hourly minimum wage on the RIF transformation of log hourly wage for a specific percentile q. Data: pooled quarterly LFS 2002-2013 for male private sector workers (excluding agricultural workers, 791,542 obs.). Robust standard error reported in parenthesis, clustered at province level (* p<.10 ** p<.05 *** p<.01). Each column represents a separate regression. All monetary variables are deflated by quarterly CPI (base year 2013 Q3). Controls: individual-level variables (years of schooling, marital status, potential experience and its squared, whether in full-time work, all interacted with quarter-year dummies), industry dummies (6 groups), firm size dummies (5 groups), provincial-level variables (share of young population, share of elderly population, share of individuals in labour force with secondary education or greater, log per capita GPP), rural binary, time and province fixed effects, province-specific time trends.

Table B.7: The effect of the minimum wage on provincial wage distributions, 2011-2013.

Percentile	5	10	15	20	25	30	35	40	45	50
Log MW	-0.234	0.166	0.499***	0.449***	0.548***	0.383***	0.473***	0.341***	0.323***	0.188
	(0.301)	(0.146)	(0.143)	(0.121)	(0.121)	(0.107)	(0.112)	(0.099)	(0.108)	(0.115)
R^2	0.08	0.15	0.23	0.27	0.29	0.32	0.33	0.35	0.36	0.37
Percentile	55	60	65	70	75	80	85	90	95	Obs.
Log MW	0.245**	0.230*	0.128	0.206	0.052	0.042	-0.033	0.116	0.333**	
	(0.109)	(0.136)	(0.117)	(0.138)	(0.130)	(0.136)	(0.169)	(0.184)	(0.155)	
R^2	0.37	0.38	0.38	0.38	0.37	0.35	0.33	0.29	0.19	205,075

Note: The summary table reports the point estimates of log hourly minimum wage on the RIF transformation of log hourly wage for a specific percentile q. Data: pooled quarterly LFS 2011-2013 for male private sector workers (excluding agricultural workers, 205,075 obs.). Robust standard error reported in parenthesis, clustered at province level (* p<.10 ** p<.05 *** p<.01). All monetary variables are deflated by quarterly CPI (base year 2013 Q3). Controls as in table above.

[4] As a last note about the difference between the CQR and the UQR, note that the CQR expectation (where $Q_\tau(.)$ is quantile operator): $Q_\tau(y) = Q_\tau(X)'\beta$ which is not $Q_\tau(y) = (X)'\beta$ and the $\beta(\tau)$ is chosen to minimise the Weighted Sum of Absolute Errors (WSAE):

$$WSAE = \sum_{i=1}^{n} |y_i - x_i'\beta(\tau)|[(\tau)I(y_i x_i'\beta(\tau)) + (1-\tau)I(y_i x_i'(\tau))]$$

Whereas with the application of the transformation, in the RIF-OLS we aim to minimise the Sum of Squared Errors (SSE):

$$SSE = \sum_{i=1}^{n} [y_i - x_i'\beta]^2$$

B.4 Province RIF sample modifications

Table B.8: The effect of the minimum wage on provincial wage distributions for male private sector workers (including agriculture), 2002-2013; 2011-2013.

Panel A:	**Years 2002 - 2013**									
Percentile	5	10	15	20	25	30	35	40	45	50
Log MW	0.217	0.133	0.133	0.161**	0.189***	0.237***	0.212***	0.202***	0.213***	0.149***
	(0.158)	(0.096)	(0.080)	(0.061)	(0.057)	(0.060)	(0.062)	(0.062)	(0.065)	(0.042)
R^2	0.15	0.24	0.28	0.31	0.33	0.35	0.36	0.37	0.38	0.39
Percentile	55	60	65	70	75	80	85	90	95	
Log MW	0.178***	0.144***	0.020	0.044	0.031	0.082	0.063	0.115	0.155	
	(0.040)	(0.044)	(0.066)	(0.053)	(0.058)	(0.069)	(0.092)	(0.099)	(0.115)	
R^2	0.39	0.39	0.39	0.39	0.38	0.36	0.34	0.29	0.21	

Panel B:	**Years 2011 - 2013**									
Percentile	5	10	15	20	25	30	35	40	45	50
Log MW	0.113	0.153	0.428***	0.396***	0.517***	0.422***	0.463***	0.296***	0.349***	0.233**
	(0.263)	(0.150)	(0.138)	(0.113)	(0.110)	(0.098)	(0.109)	(0.097)	(0.088)	(0.110)
R^2	0.13	0.21	0.26	0.29	0.32	0.33	0.35	0.36	0.37	0.38
Percentile	55	60	65	70	75	80	85	90	95	
Log MW	0.236**	0.245**	0.090	0.133	0.082	0.048	-0.070	0.139	0.302*	
	(0.110)	(0.116)	(0.114)	(0.128)	(0.125)	(0.125)	(0.152)	(0.171)	(0.154)	
R^2	0.38	0.39	0.38	0.38	0.37	0.35	0.33	0.27	0.18	

Note: The summary table reports the point estimates of log hourly minimum wage on the RIF transformation of log hourly wage for a specific percentile q. Data: Panel A pooled quarterly LFS 2002-2013, Panel B for years 2011-2013. The sample represents male private sector workers (including agricultural workers). Robust standard errors (parenthesis) are clustered at province level (* p<.10 ** p<.05 *** p<.01). All monetary variables are deflated by quarterly CPI (base year 2013 Q3). Controls: individual-level variables (years of schooling, marital status, potential experience and its squared, whether in full-time work, all interacted with quarter-year dummies), industry dummies (7 groups), firm size dummies (5 groups), provincial-level variables (share of young population, share of elderly population, share of individuals in labour force with secondary education or greater, log per capita GPP), rural binary, time and province fixed effects, province-specific time trends.

Table B.9: The effect of the minimum wage on provincial wage distributions for private sector workers (female and male, excluding agriculture), 2002-2013; 2011-2013.

Panel A:	**Years 2002 - 2013**									
Percentile	5	10	15	20	25	30	35	40	45	50
Log MW	0.09	0.13	0.19***	0.23***	0.25***	0.23***	0.29***	0.31***	0.31***	0.31***
	(0.16)	(0.10)	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
R^2	0.12	0.20	0.25	0.28	0.31	0.33	0.35	0.37	0.38	0.39
Percentile	55	60	65	70	75	80	85	90	95	
Log MW	0.169***	0.181***	0.089	0.100*	0.119**	0.238***	0.275***	0.208***	0.239*	
	(0.059)	(0.042)	(0.092)	(0.054)	(0.046)	(0.053)	(0.082)	(0.069)	(0.123)	
R^2	0.40	0.40	0.40	0.40	0.39	0.37	0.34	0.29	0.20	

Panel B:	**Years 2011 - 2013**									
Percentile	5	10	15	20	25	30	35	40	45	50
Log MW	-0.26	0.14	0.49***	0.55***	0.55***	0.47***	0.42***	0.48***	0.40***	0.39***
	(0.33)	(0.16)	(0.13)	(0.14)	(0.10)	(0.09)	(0.09)	(0.13)	(0.10)	(0.11)
R^2	0.12	0.19	0.25	0.29	0.32	0.35	0.36	0.38	0.39	0.40
Percentile	55	60	65	70	75	80	85	90	95	
Log MW	0.105	0.269**	0.135	0.189	0.205	0.208	0.200	0.005	0.026	
	(0.134)	(0.118)	(0.135)	(0.152)	(0.137)	(0.140)	(0.144)	(0.136)	(0.192)	
R^2	0.40	0.40	0.40	0.39	0.39	0.36	0.33	0.28	0.19	

Note: The summary table reports the point estimates of log hourly minimum wage on the RIF transformation of log hourly wage for a specific percentile q. Data: Panel A pooled quarterly LFS 2002-2013, Panel B for years 2011-2013. The sample represents male and female private sector workers (excluding agricultural workers). Robust standard errors in parenthesis are clustered at province level (* p<.10 ** p<.05 *** p<.01). All monetary variables are deflated by quarterly CPI (base year 2013 Q3). Controls: individual-level variables (female binary, years of schooling, marital status, potential experience and its squared, whether in full-time work, all interacted with quarter-year dummies), industry dummies (6 groups), firm size dummies (5 groups), provincial-level variables (share of young population, share of elderly population, share of individuals in labour force with secondary education or greater, log per capita GPP), rural binary, time and province fixed effects, province-specific time trends.

Table B.10: The effect of the minimum wage on provincial wage distributions for female private sector workers (excluding agriculture), 2011-2013.

Percentile	5	10	15	20	25	30	35	40	45	50
Log MW	-0.020	-0.086	0.233	0.511***	0.445***	0.585***	0.457***	0.495***	0.460***	0.445***
	(0.326)	(0.214)	(0.150)	(0.139)	(0.110)	(0.100)	(0.104)	(0.098)	(0.097)	(0.104)
R^2	0.14	0.23	0.29	0.33	0.36	0.39	0.41	0.43	0.44	0.45
Percentile	55	60	65	70	75	80	85	90	95	
Log MW	0.225*	0.309**	0.340**	0.266*	0.281*	0.092	-0.085	-0.273*	-0.276	
	(0.123)	(0.136)	(0.146)	(0.155)	(0.168)	(0.145)	(0.131)	(0.148)	(0.170)	
R^2	0.45	0.45	0.43	0.43	0.42	0.39	0.35	0.29	0.19	

Note: The summary table reports the point estimates of log hourly minimum wage on the RIF transformation of log hourly wage for a specific percentile q. Data: pooled quarterly LFS 2011-2013. The sample represents female private sector workers (excluding agricultural workers). Standard errors in parenthesis are clustered at province level (* p<.10 ** p<.05 *** p<.01). All monetary variables are deflated by quarterly CPI (base year 2013 Q3). Controls: individual-level variables (years of schooling, marital status, expected experience and its squared, whether in full-time work, all interacted with quarter-year dummies), industry dummies (6 groups), firm size dummies (5 groups), provincial-level variables (share of young population, share of elderly population, share of individuals in labour force with secondary education or greater, log per capita GPP), rural binary, time and province fixed effects, province-specific time trends.

Table B.11: RIF regression with sample break by firm size: M-SME versus Large firms, 2002-2013 and 2011-13.

Panel (A)	**Years 2002 - 2013**									
Percentile	5	10	15	20	25	30	35	40	45	50
For SME	0.193	0.067	0.239***	0.192***	0.209**	0.231***	0.230**	0.268***	0.275***	0.222***
	(0.188)	(0.127)	(0.087)	(0.067)	(0.079)	(0.084)	(0.091)	(0.090)	(0.087)	(0.053)
R^2	0.08	0.14	0.19	0.21	0.24	0.26	0.28	0.29	0.30	0.31
For LE	0.002	0.258***	0.313***	0.372***	0.493***	0.574***	0.500***	0.429***	0.371***	0.259***
	(0.160)	(0.089)	(0.073)	(0.066)	(0.074)	(0.069)	(0.066)	(0.074)	(0.070)	(0.096)
R^2	0.15	0.20	0.22	0.23	0.26	0.28	0.30	0.32	0.34	0.36
β diff (χ^2-pval)	0.38	0.24	0.55	0.07	0.00	0.00	0.03	0.24	0.45	0.78
Percentile	55	60	65	70	75	80	85	90	95	
For SME	0.196***	0.159***	0.061	0.112**	0.076	0.151**	0.142	0.125	0.261**	
	(0.050)	(0.044)	(0.070)	(0.053)	(0.055)	(0.065)	(0.097)	(0.095)	(0.122)	
R^2	0.32	0.32	0.32	0.32	0.32	0.31	0.29	0.26	0.19	
For LE	0.235***	0.185**	0.109	0.121	0.074	0.091	0.024	0.020	0.178	
	(0.083)	(0.082)	(0.099)	(0.123)	(0.136)	(0.165)	(0.171)	(0.200)	(0.283)	
R^2	0.38	0.39	0.40	0.40	0.40	0.39	0.36	0.31	0.22	
β diff (χ^2-pval)	0.71	0.78	0.65	0.95	0.99	0.74	0.51	0.63	0.80	
Panel (B)	**Years 2011 - 2013**									
Percentile	5	10	15	20	25	30	35	40	45	50
For SME	-0.351	-0.071	0.479**	0.408***	0.540***	0.405***	0.548***	0.377***	0.351***	0.226**
	(0.398)	(0.286)	(0.185)	(0.150)	(0.185)	(0.146)	(0.163)	(0.107)	(0.129)	(0.112)
R^2	0.06	0.13	0.18	0.21	0.24	0.26	0.28	0.29	0.30	0.31
For LE	0.030	0.826*	0.591***	0.576***	0.669***	0.437**	0.352**	0.263	0.252*	0.149
	(0.272)	(0.434)	(0.197)	(0.151)	(0.131)	(0.190)	(0.146)	(0.175)	(0.146)	(0.184)
R^2	0.14	0.21	0.24	0.26	0.28	0.30	0.31	0.33	0.35	0.36
β diff (χ^2-pval)	0.36	0.19	0.70	0.46	0.62	0.91	0.43	0.62	0.61	0.71
Percentile	55	60	65	70	75	80	85	90	95	
For SME	0.265***	0.251**	0.162*	0.229*	0.084	0.059	0.008	0.275	0.448**	
	(0.093)	(0.105)	(0.094)	(0.120)	(0.142)	(0.147)	(0.108)	(0.183)	(0.198)	
R^2	0.31	0.33	0.33	0.33	0.32	0.31	0.30	0.28	0.19	
For LE	0.258	0.270	0.207	0.351	0.159	0.251	0.004	0.171	0.808*	
	(0.182)	(0.233)	(0.187)	(0.235)	(0.223)	(0.256)	(0.525)	(0.396)	(0.421)	
R^2	0.37	0.38	0.38	0.39	0.38	0.36	0.33	0.28	0.18	
β diff (χ^2-pval)	0.97	0.93	0.81	0.59	0.77	0.51	0.99	0.77	0.50	

Note: Estimates for pooled quarterly LFS (male, no agri) split by Micro-SME (M-SME, 1-99 employees) or Large enterprises (LE, with 100 or more). Every row is a different sample: Panel A data 2002-13 for M-SME (557,641 obs.) or LE (233,901); Panel B Data 2011-13 for M-SME (142,486 obs.) or LE (62,589 obs.). Robust standard errors in parenthesis clustered at province level (* p<.10 ** p<.05 *** p<.01). We report a χ^2 test p-value for joint equality of the minimum wage variable on the two samples. All monetary variables are deflated by quarterly CPI (base year 2013 Q3). Same controls as saturated model excluding firm size.

Figure B.6: Comparison of the minimum wage effects for Micro and SME firms, 2002-2013.

Note: Province RIF regressions of hourly wage for male private sector workers (excluding agricultural workers, pooled quarterly LFS 2002-2013) split by firm size. The left figure displays the MW coefficient and confidence intervals for Micro enterprises (313,756 obs), and the right figure for SMEs (243,885 obs). Controls and clustering follow the main saturated specification, excluding firm size.

Table B.12: RIF regression for M-SME sample, with interaction term for being in a Micro Enterprises, 2002-2013 and 2011-13.

Panel (A)	**Years 2002 - 2013**									
Percentile	5	10	15	20	25	30	35	40	45	50
MW*Micro	-0.012	-0.012	-0.019	-0.053*	-0.063**	-0.087**	-0.101**	-0.133***	-0.131**	-0.154**
	(0.072)	(0.033)	(0.025)	(0.030)	(0.027)	(0.034)	(0.038)	(0.048)	(0.055)	(0.062)
Micro(d)	-0.153	-0.122	-0.081	0.038	0.082	0.165	0.210*	0.311**	0.308*	0.379*
	(0.225)	(0.112)	(0.084)	(0.097)	(0.089)	(0.109)	(0.122)	(0.152)	(0.172)	(0.193)
Ln MW	0.186	0.062	0.242***	0.223***	0.249***	0.292***	0.302***	0.365***	0.371***	0.336***
	(0.214)	(0.132)	(0.084)	(0.071)	(0.086)	(0.098)	(0.110)	(0.115)	(0.119)	(0.085)
R^2	0.08	0.14	0.19	0.22	0.25	0.26	0.28	0.29	0.31	0.32
β diff (χ^2-pval)	0.93	0.01	0.13	0.11	0.01	0.36	0.39	0.50	0.74	0.98
Percentile	55	60	65	70	75	80	85	90	95	
MW*Micro	-0.170**	-0.190**	-0.212**	-0.237**	-0.257**	-0.227**	-0.165**	-0.092**	0.038	
	(0.069)	(0.077)	(0.089)	(0.098)	(0.098)	(0.095)	(0.065)	(0.040)	(0.037)	
Micro(d)	0.427*	0.489**	0.559**	0.636**	0.693**	0.592*	0.389*	0.150	-0.265**	
	(0.215)	(0.241)	(0.278)	(0.306)	(0.305)	(0.299)	(0.206)	(0.127)	(0.118)	
Ln MW	0.324***	0.302***	0.222***	0.293***	0.273***	0.323***	0.264***	0.186**	0.217*	
	(0.083)	(0.059)	(0.042)	(0.054)	(0.058)	(0.074)	(0.072)	(0.084)	(0.124)	
R^2	0.32	0.33	0.33	0.33	0.32	0.31	0.30	0.26	0.20	
β diff (χ^2-pval)	0.86	0.84	0.75	0.40	0.39	0.38	0.42	0.34	0.05	

Panel (B)	**Years 2011 - 2013**									
Percentile	5	10	15	20	25	30	35	40	45	50
MW*Micro	-0.150	-0.061	-0.083**	-0.103***	-0.101***	-0.131***	-0.126***	-0.145***	-0.145***	-0.159***
	(0.092)	(0.057)	(0.036)	(0.034)	(0.028)	(0.032)	(0.031)	(0.034)	(0.042)	(0.049)
Micro(d)	0.370	0.053	0.148	0.218*	0.220**	0.326***	0.305***	0.368***	0.371***	0.415***
	(0.301)	(0.205)	(0.127)	(0.120)	(0.096)	(0.107)	(0.102)	(0.109)	(0.133)	(0.155)
lnMW	-0.291	-0.049	0.510***	0.448***	0.579***	0.457***	0.598***	0.435***	0.409***	0.290**
	(0.394)	(0.290)	(0.175)	(0.142)	(0.177)	(0.142)	(0.162)	(0.107)	(0.132)	(0.118)
R^2	0.06	0.13	0.18	0.22	0.25	0.27	0.29	0.30	0.31	0.32
β diff (χ^2-pval)	0.35	0.44	0.26	0.11	0.01	0.00	0.06	0.16	0.32	0.55
Percentile	55	60	65	70	75	80	85	90	95	
MW*Micro	-0.153***	-0.170***	-0.166***	-0.169***	-0.170**	-0.146**	-0.088**	-0.033	0.030	
	(0.053)	(0.054)	(0.060)	(0.064)	(0.065)	(0.071)	(0.040)	(0.037)	(0.053)	
Micro(d)	0.394**	0.448***	0.437**	0.440**	0.434**	0.353	0.157	-0.024	-0.237	
	(0.166)	(0.169)	(0.187)	(0.201)	(0.207)	(0.229)	(0.132)	(0.132)	(0.178)	
lnMW	0.326***	0.319***	0.229**	0.296**	0.152	0.117	0.042	0.286	0.432**	
	(0.093)	(0.109)	(0.095)	(0.124)	(0.145)	(0.152)	(0.103)	(0.184)	(0.186)	
R^2	0.32	0.34	0.33	0.34	0.33	0.31	0.30	0.28	0.19	
β diff (χ^2-pval)	0.84	0.86	0.29	0.03	0.51	0.22	0.06	0.45	0.54	

Note: Estimates for pooled quarterly LFS (male, no agri) with sample restriction for workers in Micro (less than 10 employees) or SME (10-99). The model adds a binary term (d) for being in a Micro firm and its interaction term with MW, in addition to same controls as saturated model excluding firm size. Panel A data 2002-13 (tot: 557,641 obs.) ; Panel B Data 2011-13 (tot: 142,486 obs.). Robust standard errors in parenthesis clustered at province level (* p<.10 ** p<.05 *** p<.01). We report a χ^2 test p-value for joint equality of the dichotomous Micro variable and the interaction.

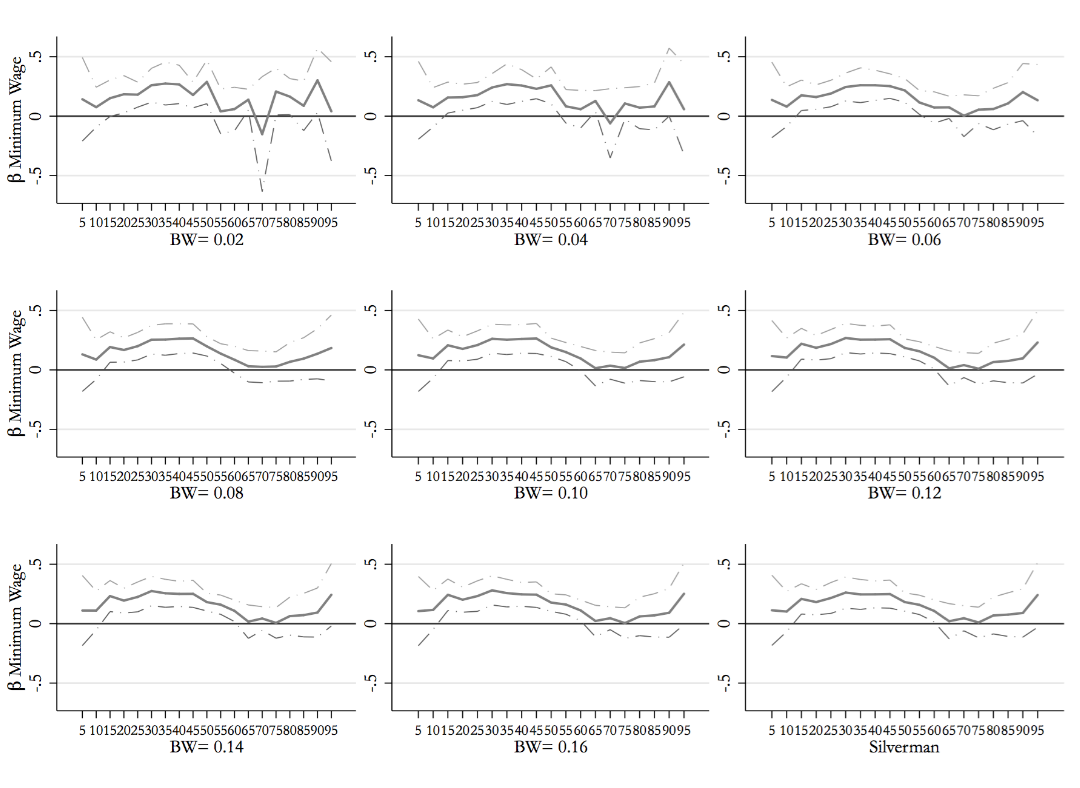
B.5 Robustness for distributional analysis

Table B.13: National RIF regression (excluding agriculture), 2002-2013; 2011-2013.

Panel (A)	**Years 2002 - 2013**									
Percentile	5	10	15	20	25	30	35	40	45	50
Ln MW	-0.005	0.104	-0.115	-0.146	-0.013	0.170**	0.348***	0.386***	0.378***	0.476***
	(0.122)	(0.082)	(0.095)	(0.096)	(0.080)	(0.073)	(0.049)	(0.045)	(0.035)	(0.053)
R^2	0.10	0.16	0.21	0.25	0.28	0.31	0.34	0.35	0.35	0.36
Percentile	55	60	65	70	75	80	85	90	95	
Ln MW	0.408***	0.366***	0.192***	-0.135***	0.011	-0.320***	0.444***	0.437***	0.513***	
	(0.056)	(0.063)	(0.056)	(0.041)	(0.055)	(0.076)	(0.082)	(0.099)	(0.191)	
R^2	0.37	0.37	0.38	0.38	0.37	0.35	0.33	0.29	0.21	
Panel (B)	**Years 2011 - 2013**									
Percentile	5	10	15	20	25	30	35	40	45	50
Ln MW	0.068	-0.010	-0.186	0.121	0.382***	0.594***	0.931***	1.023***	0.852***	0.486***
	(0.274)	(0.192)	(0.133)	(0.130)	(0.111)	(0.104)	(0.117)	(0.125)	(0.146)	(0.097)
R^2	0.10	0.17	0.21	0.26	0.30	0.33	0.34	0.36	0.37	0.38
Percentile	55	60	65	70	75	80	85	90	95	
Ln MW	0.276**	0.383***	0.217**	0.057	0.351***	-0.398***	0.470***	0.156	-0.994***	
	(0.113)	(0.107)	(0.103)	(0.081)	(0.111)	(0.121)	(0.143)	(0.191)	(0.187)	
R^2	0.38	0.39	0.39	0.38	0.37	0.36	0.33	0.28	0.19	

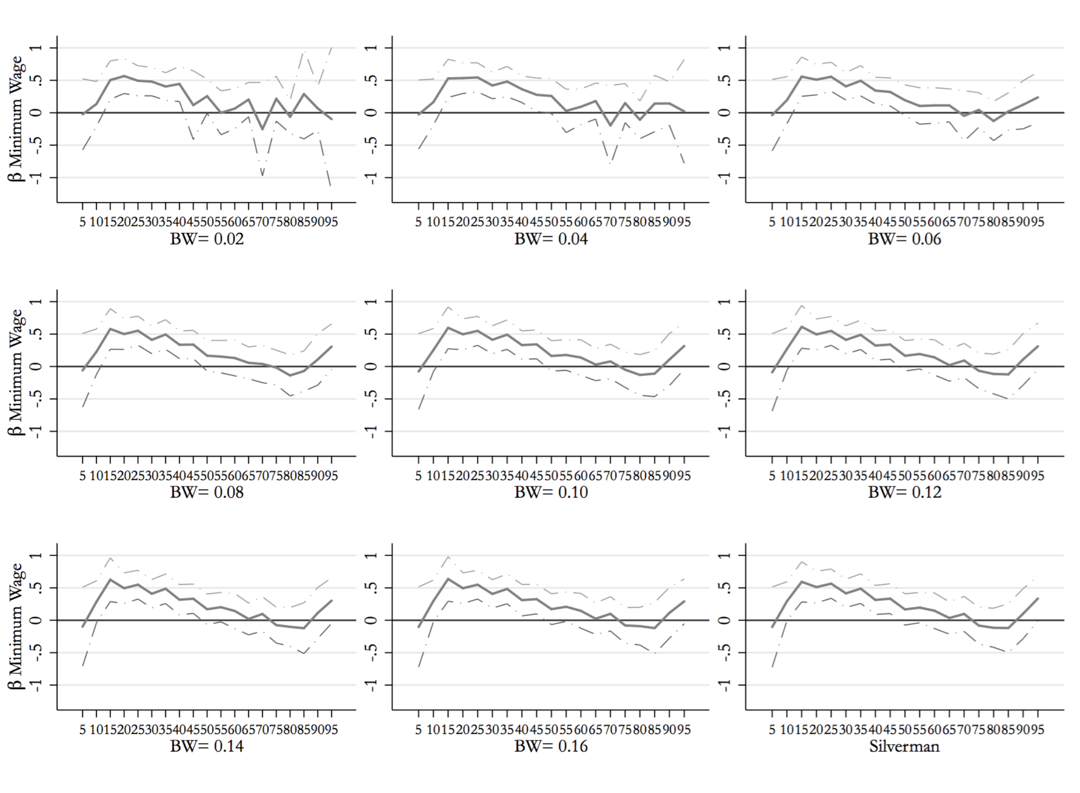
Note: The summary table reports the point estimates of log hourly minimum wage on the National RIF transformation (FFL, 2009) of log hourly wage for a specific percentile q. Data: Panel (A) pooled quarterly LFS 2002-2013, Panel (B) for years 2011-2013. The sample represents male private sector workers (excluding agricultural workers). Robust standard errors (parenthesis) are clustered at province level (* p<.10 ** p<.05 *** p<.01). All monetary variables are deflated by quarterly CPI (base year 2013 Q3). Controls applied from the most saturated model.

Figure B.7: Comparison of the minimum wage coefficient (and CIs) on province wage distribution with different bandwidths, 2002-2013.



Note: Province RIF regressions of hourly wage for male private sector workers (excluding agricultural workers, pooled quarterly LFS 2002-2013) with different bandwidths (BW) applied. For each RIF we apply the kernel density as in Eq. (4.10). Each figure displays the MW coefficients and confidence intervals (CIs) from BW=0.02 to BW=0.16 and Silverman rule. The Silverman bandwidth is defined as $h = 0.9m/n^{1/5}$, where $m = min(\sqrt{var_x}, IQR_x/1.349)$. Controls and clustering follow the main saturated specification.

Figure B.8: Comparison of the minimum wage coefficient (and CIs) on province wage distribution with different bandwidths, 2011-2013.



Note: Province RIF regressions of hourly wage for male private sector workers (excluding agricultural workers, pooled quarterly LFS 2011-2013) with different bandwidths (BW) applied. For each RIF we apply the kernel density as in Eq. (4.10). Each figure displays the MW coefficients and confidence intervals (CIs) from BW=0.02 to BW=0.16 and Silverman rule. The Silverman bandwidth is defined as $h = 0.9m/n^{1/5}$, where $m = min(\sqrt{var_x}, IQR_x/1.349)$. Controls and clustering follow the main saturated specification.

B.5.1 Comparison with Two-step prediction

In order to address the concern that by pooling individual observations for different provincial percentiles together we may capture some "aggregation" bias in different wage structures we report a two-step procedure to evaluate the effect of the minimum wage on the provincial wage structure. Note that the "aggregation" bias that we refer to is the potential bias represented by aggregation of different provincial wage structures over time in the reduced form equation, allowing the error structure to contain the noise within each labour market. The two-step procedure, in a fashion similar to a selection model (Oaxaca-Blinder), first models the RIF transformation and then regresses the yearly provincial binary predicted value on the policy variable and controls. The hypothesis that we aim to confute with this exercise is that, in the presence of noisy provincial distributions, the linear effect of the minimum wage on the province predicted values would reveal much different beta coefficients of the policy variable.

We perform the first-step of the estimation yearly. Each individual i in each time period (quarter) has a wage (transformed) falling in a specific provincial percentile τ. For each quantile in each year the province-RIF transformation is regressed on a set of individual characteristics, quarter t and province p dummies:

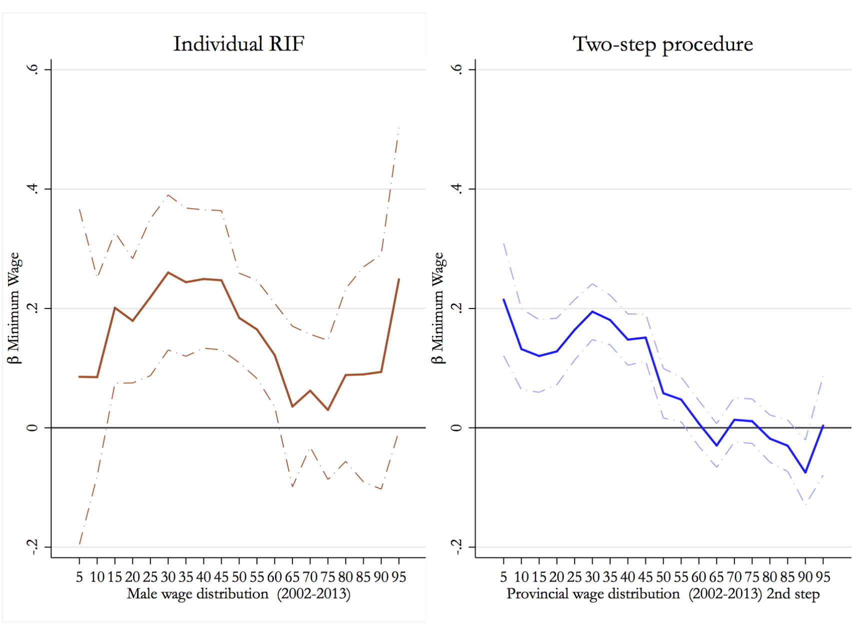
$$\text{RIF}_{y_{\text{i p t}},q_{\tau pt}} = \alpha_0 + \alpha_1 X_{\text{i p t}} + \psi_p + \psi_t + \mu_{\text{i p t}} \tag{B.1}$$

For the second-step of the analysis we take the coefficient of the provincial binary variables ($\hat{\psi_{pt,q_{\tau pt}}}$) and we pool them over time and use them as the outcome variable of a regression on the policy of interest and a set of geographic-specific controls. The regression is weighted, where the weights are provided by the inverse of the standard error for the corresponding provincial fixed effects of the first step, thus using Weighted Least Squares (WLS) we perform the following regress (data at province-year level):

$$\hat{\psi_{pT,q_{\tau pt}}} \;=\; \beta_0 \;+\; \beta_1 \ln\left(\text{MW}_{\text{p t}}\right) + \;\beta_2\; X_{\text{p t}} \;+\; \xi_{\text{p t}} \tag{B.2}$$

In Figure B.9 we compare the province RIF measure (2002-13) with the second stage of the two-step procedure. The eye-balling exercise reveals that the two-step minimum wage values fall within the confidence interval of the RIF regression, thus suggesting that no evidence of aggregation bias is generated by pulling the different distributions together.

Figure B.9: Two-step procedure: Comparison of province RIF to the (second stage) MW effect on the predicted provincial binary variables, 2002-2013.



Source: LFS 2002-2013. The figure compares (LHS) the province RIF measure (2002-13) with the second stage of the two-step procedure (RHS)

Table B.14: Two-step procedure: Second stage of the effect of minimum wage on the predicted provincial binary variables, 2002-2013.

	5th	10th	15th	20th	25th	30th	35th	40th	45th	50th
Ln MW	0.215***	0.132***	0.120***	0.128***	0.164***	0.195***	0.181***	0.148***	0.151***	0.058***
	(0.047)	(0.034)	(0.030)	(0.028)	(0.025)	(0.023)	(0.021)	(0.022)	(0.020)	(0.021)
R^2	0.83	0.86	0.88	0.89	0.90	0.90	0.91	0.92	0.92	0.93
	55th	60th	65th	70th	75th	80th	85th	90th	95th	
Ln MW	0.047**	0.007	-0.030	0.013	0.011	-0.018	-0.030	-0.075***	0.004	
	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.020)	(0.022)	(0.027)	(0.042)	
R^2	0.93	0.93	0.94	0.93	0.94	0.92	0.90	0.86	0.80	

Note: LFS 2002-13, second step regression of predicted provincial dummies on log real minimum wage, using weighted least squares (WLS) where the weights are provided by the inverse of the standard error for the corresponding provincial fixed effect, robust standard errors clustered in parenthesis. Controls 1st stage: provincial dummies, individual level variables interacted with quarter dummies (schooling, married, experience and its squared, full-time), rural, industry dummies, firm dummies, round dummies. Controls 2nd stage: log real hourly MW, share of youth, share of elderly, share of high skilled, log per capita GPP, province-specific trends. Note that (1) the main difference between the estimation proposed here and the single province RIF estimation is that here we predict the provincial wage structure year by year rather than in each quarter-year (2) the exclusion of the trends does not alter the significance reported here, but slightly increases the magnitude of the point estimates.

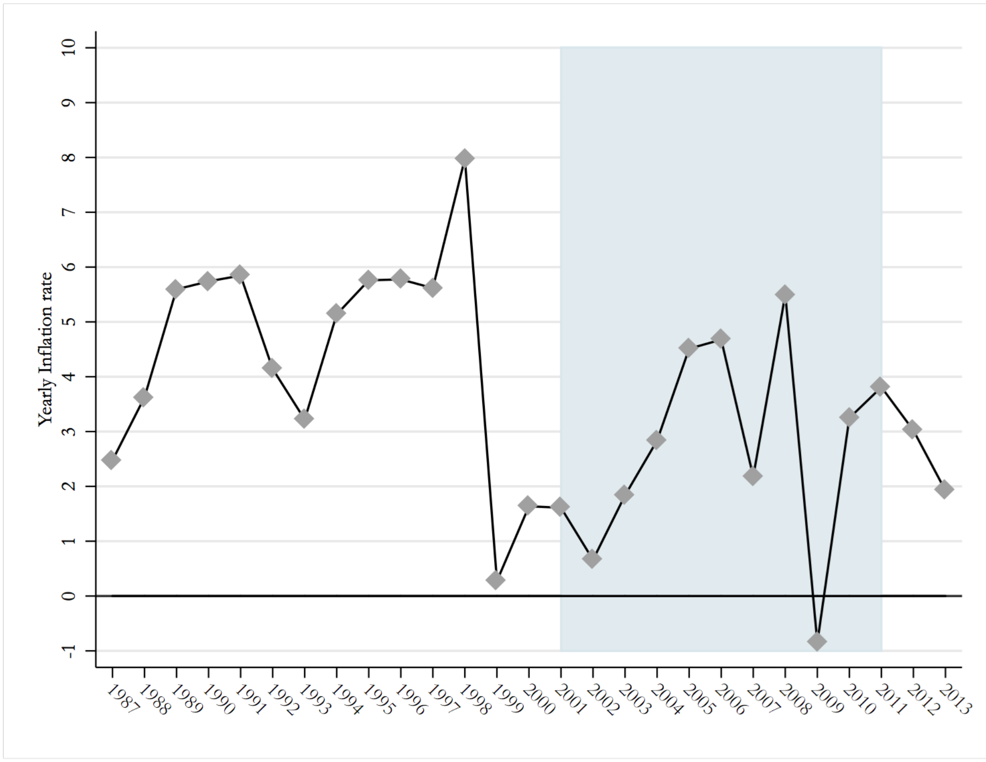
B.5.2 Inflationary effects, spatial and national CPI comparisons

To address the reliability of our estimation results we proceed to change the type of deflator used for constructing the wage distribution. In our main results we proposed a deflator which reflects the quarterly variations (quarterly national CPI with base year 2013 Q3). However, over the decade under analysis Thailand experienced an economic recovery from the Asian financial crisis, partially reflected in price changes. Additionally, both the 2007-2008 world food price crisis, the oil price hikes and the 2008 global financial crisis may have affected (in)directly domestic price movements with different strength and variation across areas. Thus, a national CPI may be underestimating the wage effects if some areas have recovered rapidly or if purchasing power has grown with different trends between rural and urban areas.

To account for this, we assess whether there have been highs or lows in inflation. Figure B.10 shows that after the Asian financial crisis, the national inflation stayed fairly stable until 2001, followed by a hike until year 2008, then returning to more stability afterwards. Ideally, we would look for province-quarter specific CPIs across rural-urban areas. As this information is not readily available from national authorities, we apply to the monetary variables of the main specification the most refined geographic CPI available, a yearly SCPI , with regional and urban-rural deflators.

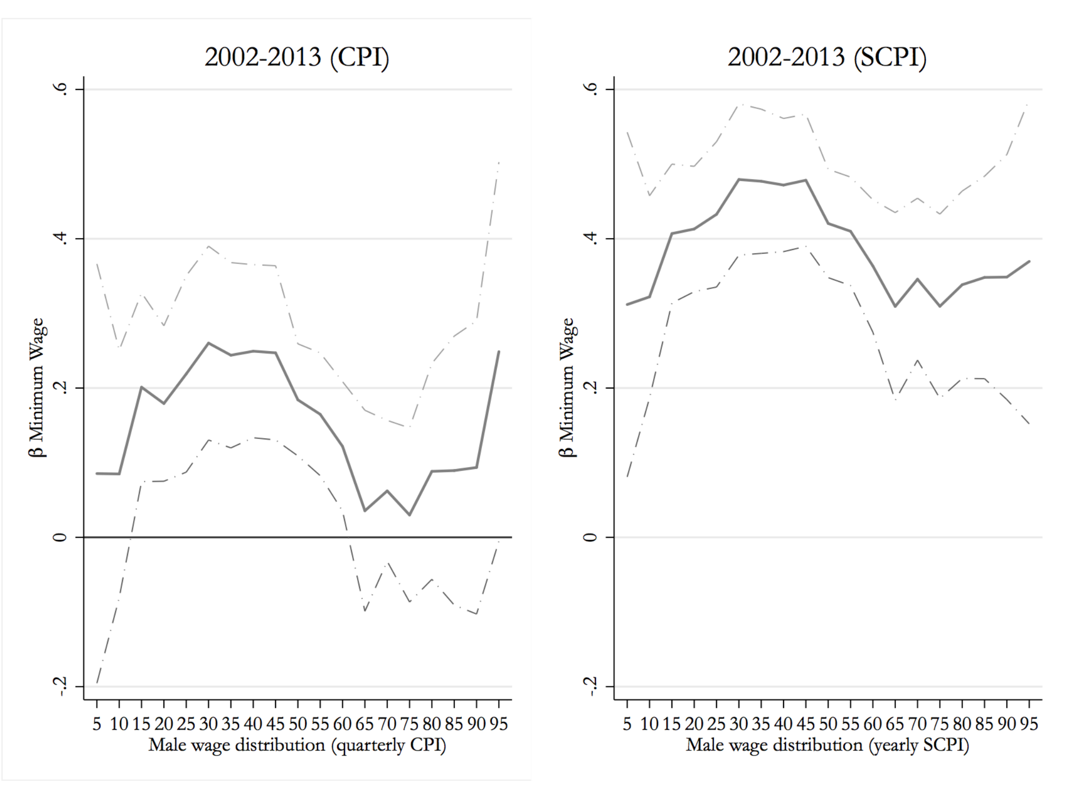
Noting that a yearly SCPI does not fully capture the seasonality in prices if applied to quarterly data, we interpret the SCPI estimations with caution. The estimates for the full time period under analysis (2002-2013) in Figure B.11 suggest that the minimum wage effect to be larger than the ones using quarterly CPI by approximately 0.21 (0.17 between the 5-50 percentiles and 0.25 between the 55-95 on average). Looking at a shorter time period of more stability in inflation (2011-2013, 12 quarters), the two specifications (Figure B.12) display very similar results (with a beta average 0.04 log-points greater for the estimation using national CPI). Thus, although the long-run analysis might be over-inflated, we assert that the estimates go in a similar direction over the latest policy hike, providing further robustness to the results found.

Figure B.10: National yearly inflation rate, 1987-2013.



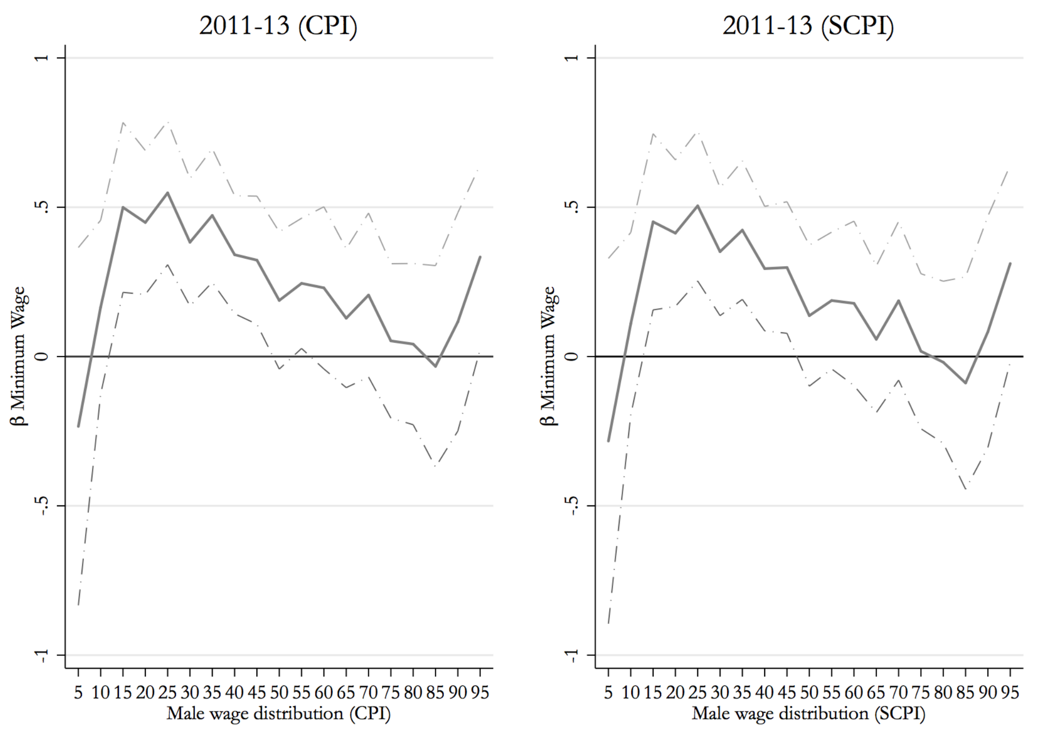
Source: Authors calculation using 1986-2013 yearly Consumer Price Index data for all commodities (TDRI). Inflation as captured by the CPI represents the annual percentage change in the cost to a representative consumer of acquiring a basket of goods and services. Change (in %, reported on y-axis) for consumer prices is calculated for the whole Kingdom. The figure displays the average yearly inflation rate to be high till the financial crisis (1997), then low in the recovery phase (till 2002), high again till 2008 and reducing after 2011. The shaded area in the graph represents the period of provincial minima being in vigour (prior introduction of the National Minimum between 2012 and 2013).

Figure B.11: Comparison of the effect of Minimum wage on CPI-deflated versus SCPI-deflated distributions, 2002-2013.



Source: LFS quarterly data (2002-2013) for male private sector workers (excluding agriculture). The wage distributions are reported on the x-axis, and the regression coefficient from log real minimum wage is reported on the y-axis. The left panel reports the estimation for all monetary variables deflated by quarterly CPI (base 2013Q3). The right panel reports the estimation for all monetary variables deflated by yearly spatial CPI (SCPI, base 2011).

Figure B.12: Comparison of the effect of Minimum wage on CPI-deflated versus SCPI-deflated distributions, 2011-2013.



Source: LFS quarterly data (2011-2013) for male private sector workers (excluding agriculture). The wage distributions are reported on the x-axis, and the regression coefficient from log real minimum wage is reported on the y-axis. The left panel reports the estimation for all monetary variables deflated by quarterly CPI (base 2013Q3). The right panel reports the estimation for all monetary variables deflated by yearly spatial CPI (SCPI, base 2011).

B.6 Do wage changes correlate more with the hike or the harmonisation?

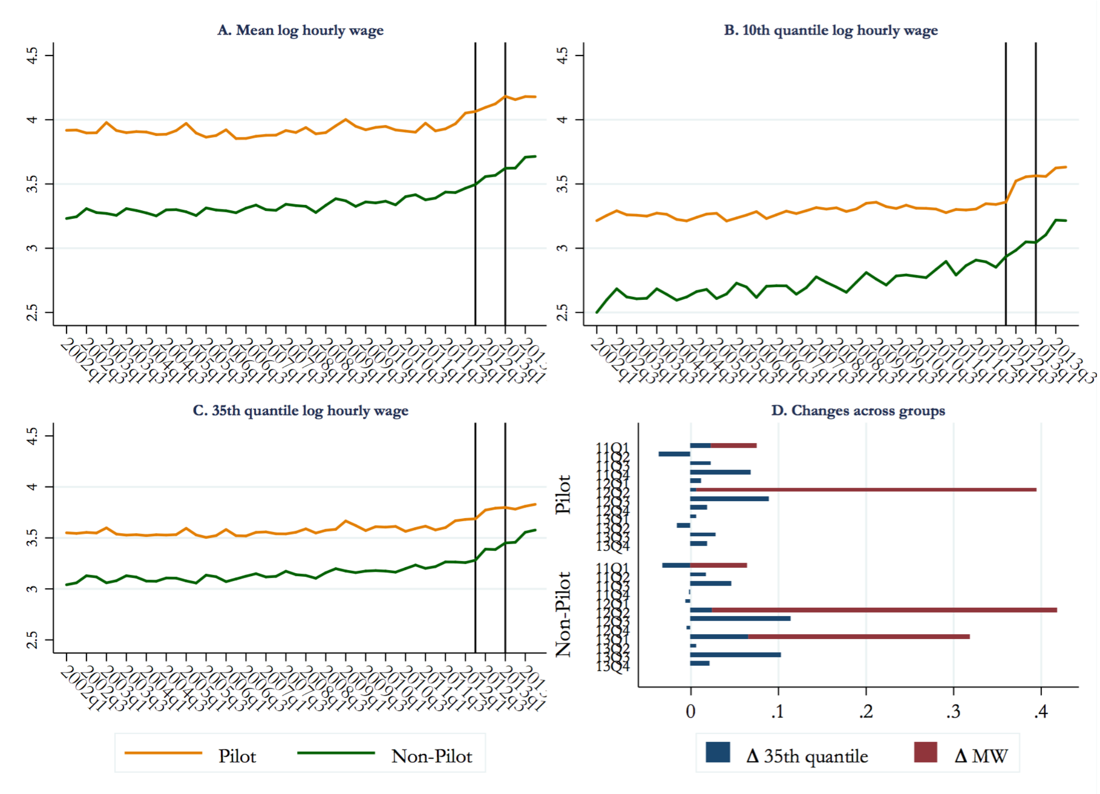
As final ancillary exercise, we aim to get a sense of how the shift from many geographic minimum wages to one generated the positive effects in wages found in this analysis. This is relevant for evaluating this policy, as it could suggest whether the responsiveness of labour markets has been generated through the magnitude of increase in the minimum wage or through a simpler single policy instrument used. Due to the characteristics of the NMW policy implementation, set in two-steps to harmonise the mandated wages to a statutory minimum, we propose some simple correlations to see whether the wage changes are correlated to the hike or the policy harmonisation experienced in the country. Discerning the two interventions is not simple because (i) all minimum wages were increased simultaneously in both policy steps; and (ii) provinces have a different wage structure, reflecting differences in local labour market characteristics (such as firms location and employment patterns). However, most provinces were subject to a varying intensity in the adjustments of April 2012 and January 2013, so we exploit this distinction to see which of the two effects correlates with the wage changes.

We use a Difference-in-Differences (DiD) model as a descriptive exercise to characterise how the wage response varied. To identify the interventions we contrast two groups of provinces differentially exposed to the policy change. From April to December 2012 a minimum wage hike was applied to all provinces. Seven provinces, named here the 'pilot' provinces, were pushed to the 300 Baht floor (Bangkok, Nakhon Pathom, Nonthaburi, Pathum Thani, Phuket, Samut Prakan, Samut Sakhon) while the rest of the country received a hike of approximately 40 percent. The NMW of 300 Baht was applied to all in January 2013, with the remaining provinces' legal minimum being pushed by further 30 percent.

In a standard DiD the researcher would compare the difference in outcomes after and before the policy for the group affected by the treatment to the same difference for the unaffected group (Bertrand et al., 2004). In this exercise, the 'treatment' and 'control' groups for this policy are imperfect (everyone experienced the policy change) and subject to many limitations discussed below, thus we do not claim causality but treat this as a descriptive exercise. We report these results to illustrate which of the two policy jumps may have affected the more exposed areas. This application assumes that the pilot provinces which received the increase in April 2012 to 300 Baht are the control group, as they were subject to a single and relatively lower hike in this first step of the policy. Although imperfect, we use the observational data on these provinces as benchmark for the analysis of the policy intervention. The remaining 68 areas, defined as the treated, or non-pilot provinces, experienced a much lower minimum prior to 2012, being in a relatively low provincial minimum wage regime. We are interested in seeing how the two-step intervention might have changed the wage schedule of those areas over the 2011-2013 period. In April 2012 these were subject to a change which increased their legal minimum by 40 percent, the intensive margin of the policy, and then by a second 30 percent nominal increase to a single minimum in January 2013, the extensive margin of harmonisation.

As visible from Figure 4.3 (p.85), the median wages displayed parallel trends at the regional level. To perform the estimation we have to assume that in absence of the two treatments the wage trends would be the same in the two groups of provinces. We investigate whether these parallel trends exist when we look at the treatment variable of not belonging to a pilot province.[5]

Figure B.13: Parallel trends in wages between pilot and non-pilot provinces (2002-2013) and their changes (2011-2013).



Note: Graphs A-B-C refer to trends in log wage (mean, 10th or 35th percentile); Graph D evaluates per quarter the change for the 35th percentile (blue bars) and average nominal minimum wage (red bars). Pilot (control) areas are Bangkok, Nakhon Pathom, Nonthaburi, Pathum Thani, Phuket, Samut Prakan, Samut Sakhon. Non-pilot (treated) areas are the remaining 69 provinces. The two vertical lines capture the policy jump and the introduction of the 300 Baht policy.

Figure B.13 investigates the log hourly wage trends among the two groups and also shows the changes in both wages and minimum wages per quarter. Graphs A-B-C show that there have been parallel trends between the two groups prior to April 2012. Eval-

[5]We acknowledge that the control chosen is imperfect. One option which may achieve causal inference would be to apply synthetic control methods (Abadie et al., 2010) to identify an average province control, or the method could be combined to matching techniques to identify groups of similar individuals. These methods could be also subject to limitations – such as confoundedness generated by indirect effects in the control areas which could influence the matching, or to issues of interpolation bias for a synthetic control. However, as we show below, they are preferred future avenues to improve the estimator. Applying a series of robustness to falsify the correlations proposed, suggests that is better not to rely on the standard observational data at our disposal. We thus confine the results proposed to represent correlations and not to imply causal inference.

uated at the mean (graph A) it seems that average wages have risen for both groups since 2011 and have stayed constant even during the policy implementation.[6] When we look at the percentiles lower than the median, there seems to be a change in the slope of the non-pilot group in both April 2012 and after January 2013. Moreover, graph D (Figure B.13) shows the quarter-on-quarter change for the 35^{th} wage percentile (blue bars) with the nominal minimum wage change stacked next to it (red bars). For the April 2012 change the non-pilot provinces have a statistically higher jump than the pilot group (on average 40% versus 39%) and in January 2013 the non-pilot (treated) group gets pushed up by an average of 30% in nominal terms to the 300 Baht rate.[7]

Even though the parallel trends assumption appears fulfilled, there are two issues which weaken the persuasiveness of the DiD analysis. First, there is reason to believe that treatment and control groups are not good comparators and, second the slope of the control also changes over both policy steps. The core issue of having a weak control is that its population has underlying characteristics which are intrinsically different from the ones of the population in the treated group, thus leaving uncertainty on whether they reflect the counterfactual wages in the absence of the policy interventions.[8] With this major limitation in mind, the figure above shows that, although the size of wages between the before and after April 2012 differ for the two groups, the intervention altered the trajectory of the non-pilot (treated) group even if the two groups have been on different wage growth trajectories. We attempt with this exercise to see which of the two periods correlates with the change seen in wages.

In the empirical strategy we define two types of intervention. The first intervention is defined as a binary variable ($hike_{\{t=2012Q2-Q4\}}$) taking the value of one in between April and December 2012, zero otherwise. The second intervention is the wage harmonisation to the 300 Baht wage, defined as a binary variable ($NMW_{\{t\geq 2013Q1\}}$) which takes the value of one from January to December 2013, zero otherwise. Our treatment (T_i) is defined as being a resident in a province which was not piloted to raise its min-

[6] This could be due to the slightly higher minimum increase in nominal minimum wages in 2011Q1 (average at 6.5%) which in previous revisions was between 3 to 5%.

[7] We perform a t-test and a two-sample variance-comparison at province-level of both the levels and changes in the MW, finding that in April 2012 (and after) the non-pilot (treatment) group has a higher MW change than the pilot (control).

[8] Performing a summary statistics on the observable characteristics of wage earners in the two groups shows statistically significant differences, given the underlying characteristics identified in Section 4.3.3.

imum at 300 Baht in the first step of the policy. We perform the following regression:

$$\begin{aligned} w_{ipt} = \alpha_0 + \alpha_1 T_i \times hike_{\{t=2012Q2-Q4\}} + \alpha_2 T_i \times NMW_{\{t \geq 2013Q1\}} \\ + \alpha_3 T_i + \alpha_4 hike_{\{t=2012Q2-Q4\}} + \alpha_5 NMW_{\{t \geq 2013Q1\}} \\ + \alpha_6 X_{it} + \alpha_7 Z_{pt} + \phi_p + \epsilon_{ipt} \end{aligned} \tag{B.3}$$

Where w_{ipt} is the wage outcome variable (wage in logs or as a province RIF log transformation) of individual i in province p and quarter-year t. The vector X_{it} comprises individual-level controls (years of schooling, marital status, potential experience and its squared, binaries for type of industry and firm size, binary variables for being full-time, in rural areas and for quarter of interview), the vector Z_{pt} stands for province controls (demographics for youth and elderly population shares and the past log per capita GPP) and ϕ_p are province fixed effects. In order to have correct standard errors we apply a pair-cluster bootstrap (province cluster, 400 repetitions).[9]

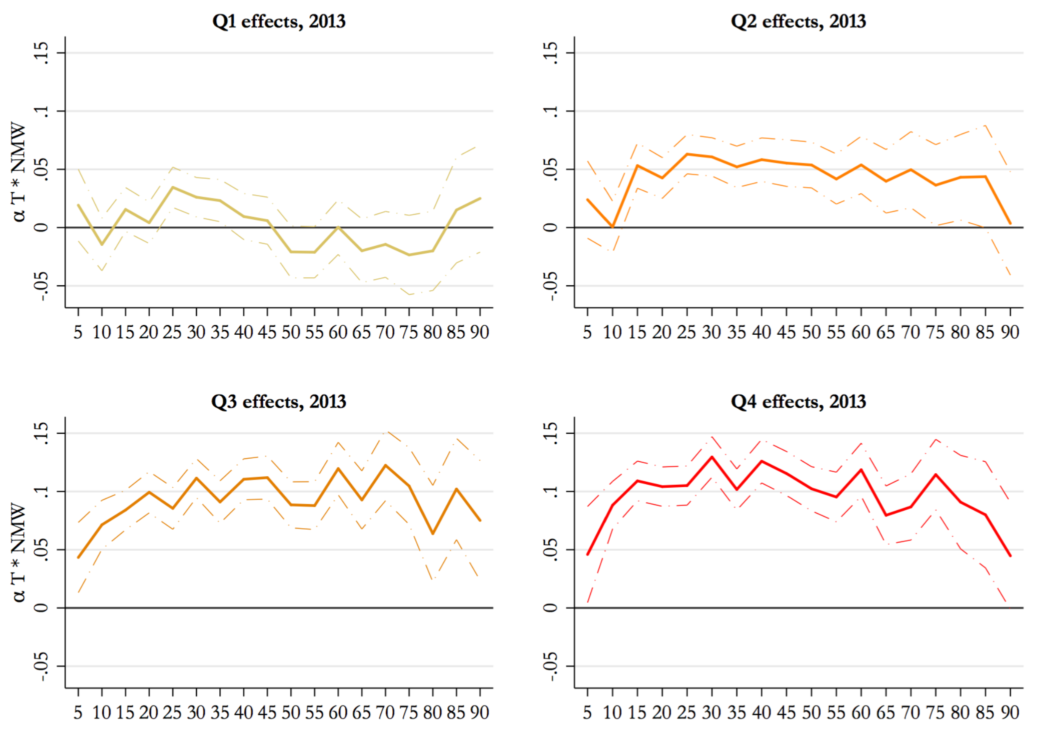
Table B.15 reports a specification performed for the period 2011Q1-2013Q4. It reports the coefficients of interest, α_1 and α_2, representing respectively the policy outcome for the non-pilot provinces during the hike or in the year of NMW harmonisation relative to the pilot provinces. The table shows that, relative to the control areas, the wage schedules in the pilot provinces have reacted to the harmonisation rather than to the hike. Evaluated at the national mean, log wages have a lower response to the policy hike than for those of the control provinces by -1.8 percentage points. The province RIF estimates further show that this negative performance is perceived between the 10th and 55th percentile (excluding the 40th). Instead, the harmonisation in 2013 correlates with an average rise of 5 percentage points more for the treated provinces. When we look into the provincial distributions, we find a positive effect from the the 5th to the 85th percentile (with spurious significance at the 95th, potentially due to low sample in this wage bin). The third column calculates the difference $\alpha\Delta = \alpha_2 - \alpha_1$, showing a statistically higher coefficient between the 5th and 75th provincial percentiles (point estimates are between 3 and 11 percentage points higher in the harmonisation period).

[9]In a preliminary estimation without bootstrap, both the log wage and RIF transformations show no differential correlations than the control provinces with the hike period, and show a positive correlation of wages with the NMW period. These may be subject to bias due to serial correlation which may induce standard errors to understate the standard deviations of the estimators (Bertrand et al., 2004). We thus apply the pair-cluster bootstrap, which resamples the clusters with replacement from the original sample. See (Cameron and Miller, 2015, p. 344) for the steps of the bootstrap procedure.

Given that the control group was pushed at the same time as the treatment during 2012, it may be that the negative correlations of the interaction term for the hike are simply the result of a change which may have taken time to happen (due to wage negotiation or slow adoption). Alternatively, this could simply reflect the different characteristics of wage earners among the two groups, thus showing a negative wage correlation during the quarters of the policy hike. Given that the two interventions exist for three and four quarters respectively, we explore the correlations for time of adjustment to the policy. In order to allow for time-varying heterogeneous effects across the two groups, we employ a flexible DiD specification on Equation (C.3), modifying the NMW binary variable to represent each quarter of minimum wage harmonisation ($NMW_{\{t=2013Q_{j=1,..,4}\}}$), similar to the one proposed in Autor (2003). Table B.16 column (I) suggests that when we account for multiple slopes for year 2013, the negative hike correlation of the first intervention period is no longer statistically different from zero. Whereas, the harmonisation intervention still stays significantly higher than the control group, with the treatment having a stronger wage response between the second and the fourth quarters of the NMW.

Looking at the same identification for the provincial wage distributions, we find that by disaggregating year 2013, no differential effect is found for the treatment interaction with the hike policy. Instead, Figure B.14 shows that the adjustment to the NMW policy show signs of correlations for the treatment provinces one quarter after introduction (with no statistically significant effect except for the 25-35$^{\text{th}}$ percentiles). This suggests that either wage contracting took place after introduction, or simply that firms in the treatment provinces needed some time to adjust to the harmonisation. Additionally, the figure reveals that in Q2 the provincial wage distributions were affected between the 15th and 60th percentile (similar to the main province RIF specification) with a magnitude of around 5 percentage points difference, and the policy effect further increased in Q3 and Q4 at around 10-12 percentage points more than the control group.

Figure B.14: DiD model for province RIF effect of NMW quarter-treatment interactions (2011-2013).



Note: DiD model for province RIF performed with the coefficients α_1 of Equation (C.3) and a disaggregation of α_NMW by quarters which are separately reported in each graph. The dotted lines are the 95% confidence intervals.

In column (II) (Table B.16) we interact the quarters for $hike_{\{t=2012Q_{j=2,..,4}\}}$, allowing the estimation to have a single time treatment interaction per quarter. The results show again no differential correlation with the log wage for the treatment group over this period. We take this as an indication that the harmonisation might have a stronger correlation with the non-pilot provincial wage changes than the hike.

Nevertheless, as the policy was discussed during year 2011 and announced in November 2011, we could potentially find no correlations in the 2012 hike because adjustments took place before the actual policy introduction. To address this concern, columns (III) and (IV) (Table B.16) perform an anticipation test. The results suggest that there was neither anticipation for these provinces at announcement (col III), nor four quarters before introduction (col IV).[10] Thus, these consistency checks on the correlations present no clear pattern of anticipation to the policy. The policy change for the non-pilot provinces was double the size of the pilot group and we show some indications that the

[10]For column (IV) Table B.16 the $T \times NMW_{\{t=2011Q3\}}$ shows a marginal significance at 10%, however it may be induced by the multiple binary variables and interactions which we add for two-thirds of the data under analysis, thus we consider that specific result as not stable.

policy harmonisation effects may have prevailed over the initial intensity of the hike in explaining the wage distributional change found in our main results. Putatively, the fact that the 300 Baht minimum wage was advertised in media outlets could have induced a more transparent wage negotiation which reflects in the higher rise in wages of the non-pilot provinces. The correlations found through the DiD estimation are in line with studies showing that policy effectiveness tends to be stronger for countries with a statutory minimum wage (Saget, 2008; Rani et al., 2013; Garnero et al., 2015).

However, when performing some falsification tests on the estimates, by varying the time period under analysis (Appendix section B.6.1), the results do not appear fully stable, increasing the concerns on the reliability of the estimator used for this exercise. First, in Table B.17 (p.171) we perform three placebo exercises using data from 2009 onwards, showing that the correlations do not pass placebo interventions randomly applied over time.[11] Second, we report in Table B.18 (p.B.18) a placebo exercise using the full dataset available (2002-2013) and again, no stability is found to the correlations.[12] Thus, the estimation results do not pass the two falsification tests applied to different length of data, further cautioning on the reliability of the estimates of Tables B.15 and B.16.

Therefore, the results are subject to the aforementioned caveats and we caution in attributing any causality to the estimates. Some further refinements to the estimation strategy are needed to give unbiased results. The fact that control individuals may not be sufficiently similar to those in the treated areas and that the control provinces were subject themselves to minimum wage variations could undermine the parallel trends

[11] Table B.17 reports the correlations with extended data (2009). Two specifications attribute the two policy interventions to data in gaps of two (we distinguish the placebo by using the letter *beta*). Model (I) reports the coefficients $\beta_{hike} = 2009$ and $\beta_{NMW=2011}$, showing a statistically lower slope for both 2009 (period of potential instability due to the crisis) and year 2011 (pre-intervention year). Similarly model (II) shows that inducing the policies to be in year 2010 (3 quarters) and 2012 (4 quarters) reveals negative slopes below the median wage in both periods, even if at the mean the policy interaction $\beta_{NMW=2012}$ does not detect any significant result on log wages. Finally, model (III) uses the actual hike over the three quarters of 2012, but now excludes the 2013 data from the analysis. In this instance, the treatment intensity interaction is significantly lower for the treated provinces, being in line with the results found in Table B.15.

[12] We attribute to the data the placebo policies starting in 2004 ($\beta_{hike} = 2004$ and $\beta_{NMW=2005}$) and shift it in intervals of three till 2010. Models (I) to (III) reveal statistically negative slopes for both mean wage and the province RIF below the median, potentially capturing the lower magnitude of wage growth experienced in these areas. Model (IV) reports the actual treatment interactions applied in Equation (C.3) to the full dataset, showing that over both periods there are statistically higher increases for the treated areas.

in the wages seen in the data. A future application for identifying a better control group could be achieved using synthetic control methods (Abadie et al., 2010) or with matching techniques (Smith and Todd, 2005). This would ensure that each control unit mirrors every treated observation, so to have a counterfactual distribution of wages unaffected by the law. Moreover, the division of 75 local labour markets into two could be dismissing the fact that prices and other economic conditions may be similar across neighbouring provinces, these being in either of the two groups. As future extension, a DiD model with matched data at province-level with a spatial nuisance parameter across contiguous provinces (similar to the spatial regression discontinuity by Magruder 2013) could be used to test whether the NMW wage effects still diverge between the two groups. This could enlighten on whether the harmonisation effects still persist after accounting for economic similarities, but it would potentially suffer of small sample bias as we cannot disaggregate the data to a lower administrative level than the province. In sum, we take the results presented here as indication of a stronger correlation of wages in non-piloted areas to the harmonisation period, but we do not interpret these correlations as causal effects.

Table B.15: DiD model for wage or province RIF on policy-treatment interactions, 2011-2013.

	α_hike	α_NMW	$\alpha\Delta$
Log wage	-0.018***	0.046***	0.065***
	(0.007)	(0.006)	(0.006)
RIF5	0.004	0.034***	0.030**
	(0.012)	(0.012)	(0.013)
RIF10	-0.056***	0.023***	0.079***
	(0.009)	(0.009)	(0.008)
RIF15	-0.042***	0.064***	0.105***
	(0.007)	(0.006)	(0.007)
RIF20	-0.046***	0.057***	0.103***
	(0.006)	(0.006)	(0.006)
RIF25	-0.044***	0.065***	0.109***
	(0.006)	(0.006)	(0.006)
RIF30	-0.026***	0.073***	0.099***
	(0.006)	(0.006)	(0.006)
RIF35	-0.026***	0.059***	0.085***
	(0.007)	(0.006)	(0.006)
RIF40	-0.007	0.069***	0.076***
	(0.006)	(0.006)	(0.006)
RIF45	-0.015**	0.060***	0.075***
	(0.006)	(0.006)	(0.006)
RIF50	-0.015**	0.042***	0.057***
	(0.007)	(0.007)	(0.007)
RIF55	-0.014*	0.036***	0.050***
	(0.008)	(0.007)	(0.008)
RIF60	-0.003	0.055***	0.058***
	(0.008)	(0.008)	(0.008)
RIF65	0.001	0.033***	0.033***
	(0.009)	(0.009)	(0.009)
RIF70	0.001	0.042***	0.041***
	(0.010)	(0.010)	(0.010)
RIF75	0.013	0.041***	0.028**
	(0.012)	(0.011)	(0.012)
RIF80	0.008	0.028**	0.019
	(0.015)	(0.012)	(0.014)
RIF85	0.018	0.039***	0.021
	(0.016)	(0.014)	(0.016)
RIF90	-0.033*	0.019	0.052***
	(0.019)	(0.017)	(0.019)
RIF95	-0.036	0.095***	0.131***
	(0.025)	(0.025)	(0.025)

Note: DiD regression 2011-2013, pooled male LFS at individual level (205,075 obs). The table reports the coefficients α_1 and α_2 of Equation (C.3) and a linear combination of the two ($\alpha\Delta = \alpha_2 NMW - \alpha_1 hike$). Pair cluster bootstrapped standard errors reported in parenthesis.

Table B.16: DiD model for log wage on policy quarter-treatment interactions, 2011-2013.

	(I)	(II)	(III)	(IV)
T × 2011Q2				-0.001
				(0.010)
T × 2011Q3				0.017*
				(0.010)
T × 2011Q4			0.007	0.011
			(0.009)	(0.010)
T × 2012-Q1			0.006	0.010
			(0.010)	(0.010)
T × hike-Q2		-0.015		
		(0.010)		
T × hike-Q3		0.004		
		(0.009)		
T × hike-Q4		0.009		
		(0.009)		
T × hike	-0.001			
	(0.007)			
T × NMW-Q1	0.018*	0.018*	0.018**	0.023***
	(0.010)	(0.009)	(0.009)	(0.009)
T × NMW-Q2	0.039***	0.039***	0.040***	0.043***
	(0.009)	(0.009)	(0.008)	(0.009)
T × NMW-Q3	0.081***	0.081***	0.083***	0.086***
	(0.009)	(0.010)	(0.009)	(0.009)
T × NMW-Q4	0.087***	0.087***	0.089***	0.092***
	(0.010)	(0.009)	(0.009)	(0.009)
H0: NMW($\sum Q1 - Q4$)=0	0.000	0.000	0.000	0.000
R^2	0.45	0.45	0.45	0.45
Obs	205,075	205,075	205,075	205,075

Note: Flexible DiD regression with pair cluster bootstrapped standard errors, pooled male LFS 2011-2013. Column (I) reports the coefficients α_1 of Equation (C.3) and a disaggregation of α_NMW by quarter; column (II) disaggregates both α_hike and α_NMW by quarter; column (III) disaggregates α_NMW by quarter and checks for anticipation (at announcement Q4 and before introduction); column (IV) disaggregates α_NMW by quarter and checks for anticipation 4 quarters prior introduction. We report a test for joint significance of quarterly α_NMW and R^2.

B.6.1 Tables for hike-harmonisation placebo tests

Table B.17: DiD placebo with policy quarter-treatment interactions, 2009-2013.

	(I)		(II)		(III)
	$\beta hike2009$	$\beta nmw2011$	$\beta hike2010$	$\beta nmw2012$	$\alpha hike$
Log wage	-0.044***	-0.013**	-0.028***	-0.004	-0.012***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.003)
RIF5	-0.086***	-0.014*	-0.024**	0.038***	0.025***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.007)
RIF10	-0.063***	0.006	-0.018**	-0.017***	0.003
	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)
RIF15	-0.054***	-0.009	-0.025***	-0.033***	0.011***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.004)
RIF20	-0.049***	-0.007	-0.026***	-0.032***	0.005
	(0.005)	(0.005)	(0.006)	(0.005)	(0.004)
RIF25	-0.049***	-0.010**	-0.039***	-0.037***	0.006*
	(0.005)	(0.005)	(0.006)	(0.005)	(0.003)
RIF30	-0.057***	-0.023***	-0.030***	-0.022***	-0.001
	(0.006)	(0.005)	(0.006)	(0.005)	(0.003)
RIF35	-0.055***	-0.008	-0.041***	-0.017***	-0.001
	(0.005)	(0.005)	(0.006)	(0.005)	(0.003)
RIF40	-0.051***	-0.020***	-0.034***	-0.015***	-0.000
	(0.006)	(0.005)	(0.006)	(0.005)	(0.003)
RIF45	-0.046***	-0.021***	-0.034***	-0.006	-0.006*
	(0.005)	(0.005)	(0.006)	(0.005)	(0.003)
RIF50	-0.045***	-0.019***	-0.012**	-0.005	-0.007**
	(0.006)	(0.005)	(0.006)	(0.006)	(0.003)
RIF55	-0.051***	-0.011*	-0.015**	0.002	-0.013***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.003)
RIF60	-0.032***	-0.029***	-0.002	-0.011*	-0.017***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.003)
RIF65	-0.041***	-0.014*	-0.004	0.014*	-0.017***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.004)
RIF70	-0.028***	-0.021**	-0.008	0.010	-0.029***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.004)
RIF75	-0.012	-0.026***	-0.021**	0.013	-0.041***
	(0.011)	(0.009)	(0.010)	(0.009)	(0.004)
RIF80	0.009	-0.020*	-0.033**	0.016	-0.051***
	(0.012)	(0.010)	(0.013)	(0.011)	(0.006)
RIF85	-0.015	-0.046***	-0.035***	0.042***	-0.053***
	(0.013)	(0.012)	(0.013)	(0.012)	(0.006)
RIF90	-0.051***	-0.017	-0.056***	0.019	-0.041***
	(0.016)	(0.014)	(0.017)	(0.014)	(0.008)
RIF95	-0.082***	-0.013	-0.125***	-0.012	-0.037***
	(0.021)	(0.020)	(0.027)	(0.018)	(0.011)

Note: DiD placebo regressions (pair cluster bootstrap). Model (I) uses LFS 2009-2013 (336,715 obs) and reports the coefficients $\beta hike = 2009$ and $\beta NMW = 2011$; Model (II) with LFS 2009-2013 (336,715 obs) reports the coefficients $\beta hike = 2010$ and $\beta NMW = 2012$; Model (III) uses data for 2009-2012 (198,177 obs) and reports the actual α_{hike} variable.

Table B.18: DiD placebo with policy quarter-treatment interactions, 2002-2013.

	(I)		(II)		(III)		(IV)	
	$\beta hike2004$	$\beta nmw2005$	$\beta hike2007$	$\beta nmw2008$	$\beta hike2010$	$\beta nmw2011$	$\alpha hike$	αNMW
Log wage	-0.021***	-0.021***	0.004	-0.015***	-0.012**	0.008*	0.021***	0.085***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
RIF5	-0.039***	-0.040***	-0.034***	-0.051***	0.022**	0.055***	0.094***	0.126***
	(0.011)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.010)	(0.008)
RIF10	-0.051***	-0.038***	-0.034***	-0.016***	0.036***	0.065***	0.036***	0.119***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.005)
RIF15	-0.044***	-0.033***	-0.027***	-0.009*	0.024***	0.041***	0.016***	0.124***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
RIF20	-0.050***	-0.029***	-0.018***	-0.008*	0.016***	0.035***	0.009*	0.115***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
RIF25	-0.030***	-0.015***	-0.008	-0.013***	-0.003	0.024***	0.004	0.116***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
RIF30	-0.021***	-0.014***	-0.015***	-0.026***	-0.002	0.011**	0.016***	0.117***
	(0.006)	(0.005)	(0.005)	(0.004)	(0.006)	(0.004)	(0.005)	(0.004)
RIF35	-0.023***	-0.018***	-0.018***	-0.024***	-0.013***	0.022***	0.024***	0.110***
	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
RIF40	-0.017***	-0.016***	-0.006	-0.017***	-0.010*	0.009**	0.030***	0.106***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
RIF45	-0.024***	-0.018***	-0.008	-0.010**	-0.014**	0.005	0.028***	0.102***
	(0.006)	(0.005)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)
RIF50	-0.013**	-0.015***	0.011**	-0.013***	0.004	0.006	0.025***	0.080***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
RIF55	-0.027***	-0.013**	0.012**	-0.017***	-0.002	0.010*	0.029***	0.077***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
RIF60	-0.007	-0.002	0.008	-0.001	0.006	-0.013**	0.017**	0.073***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
RIF65	-0.009	-0.008	0.039***	-0.015**	-0.001	0.000	0.034***	0.063***
	(0.008)	(0.007)	(0.007)	(0.006)	(0.008)	(0.007)	(0.007)	(0.007)
RIF70	-0.003	0.006	0.032***	-0.020***	-0.014	-0.017**	0.021***	0.058***
	(0.009)	(0.007)	(0.009)	(0.007)	(0.009)	(0.007)	(0.008)	(0.007)
RIF75	-0.007	-0.016*	-0.009	-0.021**	-0.022**	-0.020**	0.033***	0.056***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.008)	(0.009)	(0.009)
RIF80	-0.010	-0.030***	0.046***	-0.027***	-0.036***	-0.022**	0.029**	0.044***
	(0.011)	(0.011)	(0.011)	(0.009)	(0.011)	(0.009)	(0.011)	(0.010)
RIF85	-0.032**	-0.017	0.068***	-0.030***	-0.064***	-0.060***	0.026**	0.043***
	(0.015)	(0.013)	(0.012)	(0.011)	(0.013)	(0.010)	(0.012)	(0.011)
RIF90	-0.057***	-0.059***	0.032**	0.030**	-0.070***	-0.024*	0.003	0.055***
	(0.019)	(0.016)	(0.016)	(0.013)	(0.016)	(0.013)	(0.015)	(0.013)
RIF95	-0.024	-0.026	0.057***	0.014	-0.126***	-0.020	-0.006	0.121***
	(0.024)	(0.021)	(0.021)	(0.019)	(0.025)	(0.019)	(0.020)	(0.017)

Note: DiD placebo regressions (pair cluster bootstrap), LFS 2002-2013 (791,542 obs). Model (I) reports the coefficients $\beta hike = 2004$ and $\beta NMW = 2005$; Model (II) reports the coefficients $\beta hike = 2007$ and $\beta NMW = 2008$; Model (III) reports the coefficients $\beta hike = 2010$ and $\beta NMW = 2011$; and Model (IV) the actual α_{hike} and α_{NMW} (note that this last model implicitly assumes that over the decade is possible to interpret the interaction term of treatment to be representative of the minimum wage policy).

Chapter 5

The Minimum wage Policy in Thailand: the employment effects and interactions with institutions

Joint work with Dilaka Lathapipat. [1]

5.1 Introduction

The final chapter of this thesis analyses the employment effects of the minimum wage policy during the 2000s and assesses the short-run effects of the introduction of the National Minimum Wage (NMW).

The chapter first reviews the contributions of the literature focusing on developed economies which identifies some "elusiveness" in the employment effects of a Minimum wage (MW) policy (Manning, 2016). It shows that similar trends are found for emerging and developing economies, due to two possible channels. First, workers may shift from formal to informal occupations as a result of the policy, thus altering the composition and remuneration of workers (Cunningham, 2007; Maloney and Nuñez Mendez, 2003). Second, non-compliance with the law may act as a partial buffer in response to a policy change, which implies that institutional enforcement and the probability of being sanctioned can drive employment effects (Basu et al., 2010; Bhorat et al., 2015).

In the empirical estimation, we apply a set of models to investigate the employment

[1] **Disclaimer**. An earlier version of this work is circulated in article form under the title "From Many to One: Minimum Wage Effects in Thailand". The findings, data manipulation, interpretations and conclusions presented in this chapter do not necessarily reflect the views of the World Bank Group (WBG) nor of the National Statistics Office of Thailand (NSO) or other government agencies.

response to a minimum wage increase. The main results use a reduced form equation at province level (panel fixed effects regression) presenting estimates for employment and hours worked. Using information on age and education we explore, following the adjustments to the minimum wage, whether any change or substitution in provincial employment composition take place. There is an ongoing debate on the correct econometric specification to account for the geographic dimension of labour markets. The use of geographic-specific trends following a reduced form labour demand equation has been central to the discussion (see for example Addison et al. 2015; Allegretto et al. 2013; Dube et al. 2010; Meer and West 2016; Neumark et al. 2014a,b). The econometric literature also warns that estimations using geographic aggregates may cause issues related to cross-sectional dependence within panels (De Hoyos and Sarafidis, 2006; Sarafidis and Wansbeek, 2012). We control for these issues through the use of province-specific trends and tests implemented to identify cross-sectional dependence in the data (Frees, 1995; Pesaran, 2004). In addition to the main findings, the chapter also investigates the temporal dynamics of minimum wage changes and assesses the reliance of the results using employment response models at individual level. Specifically, we perform analyses on non-wage employment, channel which could highlight further policy effects on informal employment in an emerging economy setting. Non-wage work, defined as self-employment or unpaid family work, is the main outside option relative to unemployment in countries such as Thailand. We assess whether this proxy for informality acts as a buffer as predicted by the two-sector model (Welch, 1974; Gramlich, 1976; Mincer, 1976). Complementing the previous chapter, we perform an ancillary exercise inspecting whether differential patterns in employment among provinces correlates with the sharp rise in the minimum wage or the harmonisation to the NMW.

We find for the entire period of analysis (2002-2013) that increases in the minimum wage have little impact on aggregate employment. Moreover, no evidence of a negative short run adjustments to labour demand was identified after the introduction of the NMW (2011-2013). Over the entire sample period, we find minor signs of contraction in employment for low-skilled youth with stronger effects for the female population. We show that when there is employment contraction it is geographically localised in areas subject to a low minimum wage regime over the 2000s. Over the NMW time period, both panel and individual-level regressions show no evidence of reductions in employment, but actual increase in hours worked. We also find no detectable effects of the NMW policy on non-wage employment, in line with the literature rejecting the standard duality model (Lemos, 2009). However, this might arise from the inability of detecting informal wage employees in the data available for analysis. Overall, we conclude that Thai labour markets have been flexible in absorbing the policy change, with no strong evidence of negative short-run effects after the NMW introduction. We contrast these results with the findings from the wage analysis in the previous chapter by identifying that non-compliance across types of firms may be playing a considerable role and we compare this with descriptive evidence on labour inspections for the year of the NMW introduction.

The chapter is organised as follows. Section 5.2 reviews the literature on the minimum wage impact on employment and explores the different channels of influence of the policy. Section 5.3 describes the data and variables used for the analysis, and explores the trends in employment and the extent of non-compliance. Section 5.4 presents the empirical models and the findings, and Section 5.5 compares the evidence found with the wage analysis. Section 5.6 presents some concluding remarks.

5.2 Review of the employment effects of the minimum wage

5.2.1 Brief survey of the literature

The employment effects of minimum wage policies have received widespread attention in the labour economics literature. A variety of conceptually distinct but complementary explanations for the interaction of supply and demand for labour is available. We confine our review to three key models (competitive, monpsonistic and institutional) which inform on the active role of the minimum wage legislations as a policy tool for labour markets. Then we highlight the relevance of informality and non-compliance in an emerging economy setting.

The standard argument on the impact of the minimum wage on employment relates to a perfectly competitive framework, where firms cannot modify prices or wages. The model predicts that the introduction of a minimum wage will alter wages above the market-clearing level and firms will modify their labour demand. The excess labour supply is then predicted to generate unemployment (Hamermesh, 1996). However, this accepted wisdom does not always find empirical evidence for some markets (e.g. Card 1992; Card and Krueger 1995). The predictions become more nuanced once one accounts for a set of market frictions.[2]

Through the monopsonistic lens we may infer further nuances of the policy effects on the employment decision of the employer (i.e. Dickens et al. 1999; Manning 2003).[3] Accounting for market imperfections, theoretical and empirical contributions have broaden the attention to the incentives for job search (i.e. Manning 2003; Flinn 2006, 2010)[4], and redistributive aspects like wage inequality (Lee, 1999; Dickens and Manning, 2004; Butcher et al., 2012; Autor et al., 2016).

The institutional approach to labour markets complements both the competitive and monopsonistic views of the market economy by investigating the role of institutions and market imperfections.[5] It posits that labour demand may have a non-monotonic discontinuous relationship with wages (e.g. allowing for vertical or positively sloped sections) (Kaufman, 2010). Broadly, it shows that the costs of adjustments on the production side and the transmission channels within the firm's organisational structure, may play an important role in determining the effects of a minimum wage policy on employment.[6]

How do these frameworks match the labour market traits of an emerging economy? To the extent that labour contracting can be informal and also not fully monitored,

[2]For example, in a context of efficiency wage theories (which investigate how workers' productivity relates to their wages), the minimum wage could be used as a tool to reduce information asymmetries in wage bargaining, where an improvement in average quality of the workforce more than offsets the rising average labour cost (Drazen, 1986).

[3]The standard monopsony model assumes that one firm sets wages and that there are frictions in the market. An increased minimum wage may induce higher wages and employment levels, at the cost of a reduction in firm welfare. Beyond the single producer, monopsonistic models help to understand how frictions (e.g. costs to the employee or employer, heterogeneity in preference over occupations or asymmetries in market opportunities) affect the equilibrium. There may be circumstances where a firm (even one of some employers in a nominally competitive market) employs workers which are faced with mobility costs (pecuniary or not) in changing jobs. The firm has some degree of monopsony power over its workforce and for a low enough level of the minimum wage the employment in an oligopsonistic-type of market may not necessarily rise or fall (Manning, 2003).

[4]Those in low-wage occupations may have less incentives to look for alternative jobs than before as the wage gap between new vacancies and their current occupation is reduced (Manning, 2003). Further, Flinn (2006) formalises how the minimum wage can be investigated in a job search and wage bargaining model. His model predicts that a minimum wage increase may have ambiguous effects to unemployment, and it can be welfare-improving to both supply and demand side.

[5]See Kaufman (2010), for an extract of the key concepts developed within this framework.

[6]Such adjustments may apply to product prices (e.g. Hirsch et al. 2015 find to respond similarly within a same sector), internal wage structure compressions (such as of those above the minimum), efficiency of production (e.g. found in the UK, Riley and Rosazza Bondibene 2017), changes in non-labour inputs or customer services, and profits.

the duality of labour markets and non-compliance are at the heart of theoretical and empirical analysis for emerging economies. The dual labour market theory posits that, with the introduction of a minimum wage, the employment in the uncovered or informal sector could explain why reserves of workers do not enter unemployment (Welch, 1974). Informality may exist due to rationing of formal sector occupations (Gramlich, 1976; Mincer, 1976) or to the characteristics of the firm such as size (Rauch, 1991). The dualistic view has however been challenged by the notion that informal occupations may be part of a competitive environment themselves (Magnac, 1991; Maloney, 1999; Pratap and Quintin, 2006; Lemos, 2009), and may also be affected by market frictions (Meghir et al., 2015).[7] Informality has played a central role in explaining the labour markets of developing economies (see Maloney 2004 for a discussion), and it is also modelled as a distinctive component of labour relations (e.g. see Perry et al. (2007) for a discussion).

However, even formal employers may choose to violate minimum wage regulations. The standard profit-maximising model of compliance shows that violation takes place if the expected monetary costs attached to it are less than the expected savings on wage costs (Ashenfelter and Smith, 1979). Further extended in Chang and Ehrlich (1985), non-compliance is manifested as law evasion (reduced wages) as well as law avoidance (modified employment). Yaniv (2001) further shows that it is possible to relax the assumptions of these models, which relate to non-compliance towards the whole workforce employed. The author applies a portfolio-choice approach to the non-compliance problem, and introduces the probability of inspection and a penalty dependent on the number of workers not paid at MW. This literature is challenged in Basu et al. (2010) because it takes a determined sub-minimum wage as given, while not addressing the issue of sub-minimum wage dispersion. Basu et al. (2010) introduce a model with imperfect competition, imperfect commitment and imperfect enforcement of the minimum wage. They set the theoretical predictions of some stylised facts found in the literature for emerging economies (including the wage analysis in the previous chapter): there can be co-existence of compliant and non-compliant firms; there is wage clustering around the minimum wage; there may be a dispersion of firm-specific equilibrium

[7] Meghir et al. (2015) include frictions between the formal and informal sector, explaining how could low-skilled workers transition in between the two, and how firms' productivity determines whether they are formal or not. The size of frictions determine the higher wage given in the formal sector and the search costs prevent workers for waiting for a formal occupation (Meghir et al., 2015).

sub-minimum wages and co-movements with minimum wage levels. Additionally, as stressed in Polinsky and Shavell (2000), the type and amount of sanctions applied may translate into a different propensity of detection and compliance of the firm. Modifying the competitive framework model, Bhorat et al. (2015) show that it is possible to have partial compliance when there is imperfect enforcement.

While the literature is diverse, all the theoretical predictions about non-compliance emphasise that there may be partial equilibria where firms may not fully comply but still generate welfare-enhancing effects. Moreover, no matter which model structure is chosen, the enforcement allocation effort of the authority matters in determining how firms behave.

5.2.2 The empirical evidence and identification issues of the employment effects

The challenge of moving from theory to empirical predictions is to ensure that the reduced form equation of demand for labour is identified for meaningful inference to be made with the available data.

In the literature on the US (and its European counterpart) the discussion of the employment effects concentrates on identifying the groups most affected, on the conditions of the economy over the time period under analysis, and on the model specifications which best accounts for heterogeneity in labour markets and in minimum wage settings.[8] Manning (2016) gives an overall review on the “elusiveness” of employment reported by many studies. Two key aspects are highlighted: the demand elasticity may be small and the way in which unemployment is interpreted must include forms of frictions. Even for groups which one can estimate a sizeable wage effect, such as specific age-groups or industries as relevant for the US literature, the employment effect is not always robustly identified (Manning, 2016).

The literature for emerging and developing economies encounters different challenges for identification. It is common to have major portions of the population being paid sub-minimum wages (see for example Rani et al. 2013). Not all sectors of private-sector employment are covered by national legislations (see for example Bhorat et al.

[8]The US debate is lively on which methods best suit specific employment scenarios, and the effects are still not fully agreed. Not aiming to be a comprehensive list, but see Addison et al. (2015); Allegretto et al. (2013); Meer and West (2016); Neumark and Wascher (2006); Neumark et al. (2014b).

2017 for Sub-Saharan Africa). Due to the presence of informality, which continues to be contentious not just in definition but also in its contribution to the economy (Maloney, 2004), many studies have investigated the differential effects across informal and formal markets.[9] Some have shown that informal workers may be positively affected by policies even if by definition they should not since they would not qualify as recipients of the minimum wage (Cunningham, 2007; Lemos, 2009). But the complexity of defining 'informal' markets makes comparison across studies difficult (see for example Broecke et al. 2015). Nevertheless, the "elusiveness" of employment is also found for emerging markets. Aggregate employment effects do not emerge, but marginal negative effects tend to be visible for vulnerable groups, namely the youth and low-skilled workers (Broecke et al., 2017). In the South East Asian context, mixed evidence emerges on the effect of minimum wage adjustments. For Indonesia, small or no negative effects on employment are reported after hikes in the minimum wage (Alatas and Cameron, 2008; Comola and De Mello, 2011; Del Carpio et al., 2012; Rama, 2001), but these are found to be positive when controlling for spatial clustering within districts (Magruder, 2013). For Vietnam, Sakellariou and Fang (2014) show that during the Renovation Reform the minimum wage policy had no effect on employment, whereas Nguyen (2017) shows that during 2008-2010 firms reduced their workforce slightly, substituting it for fixed assets and modifying worker composition.

Attempts to identify and assess non-compliance have been prominent during the latest decade for developed, emerging and developing economies. Generally the share of covered workers paid sub-minimum wages is used to capture non-compliance (as proposed in the descriptive statistics of the previous chapter). Compliance may be less enforced in specific sectors, such as in agriculture for Kenya (Andalon and Pages, 2008), or in specific geographic areas, such as in South Africa or Italy (Bhorat et al., 2012a; Garnero, 2017). Bhorat et al. (2013) propose a measure of depth of minimum wage violation (analogous to poverty indices) which they find in Bhorat et al. (2012b) to vary drastically by occupation and location of employment.[10] Rani et al. (2013) show that

[9] A vast literature has looked into informality and minimum wage policy in Latin America (Cunningham, 2007; Maloney and Nuñez Mendez, 2003). For the South East Asian context, the literature is less developed, but some exceptions exist. For example, in Indonesia informality has been the subject of minimum wage research on a decentralisation of powers which induced a hike with multiple geographically set minima. For 1996–2004, Comola and De Mello (2011) construct data at district level, showing that employment is pushed to the informal sector. For 1997–2007, Hohberg and Lay (2015) show that formal employment is not affected while wage effects do not perpetrate to the informal sector.

[10] We make use of this measurement later in the chapter to assess the country's performance over the

the least complex is the minimum wage set-up, the higher the compliance takes place, showing that countries with a national minimum wage set at a meaningful level show higher compliance than countries with occupation- or industry-specific minimum wage systems. Although there are exceptions, such as countries with a NMW in Central and Eastern Europe, where vulnerable groups (low-skilled, female and temporary workers) are more likely to be paid sub-minimum wage (Goraus-Tanska and Lewandowski, 2016).

Enforcement by the authorities is also relevant to understand the effective implementation of the law. However, good data on labour inspections is a major limitation in the empirical literature. Many methods have been proposed to capture enforcement (see Ronconi 2010 for a review on different proxies used). Ronconi (2010) finds for Argentina, that the more labour inspectors are in an area the higher the compliance found. This trend is also found in Costa Rica (Gindling et al., 2015) but not in South Africa (Bhorat et al., 2012b). However, there seems to be consensus that, when it comes to full enforcement, "turning a blind eye" (Basu et al., 2010) may be a way to make the policy fulfil its efficiency purposes in terms of employment.

Lastly, studies for emerging economies need to take into account issues arising from measurement error (less emphasised for developed economies with few exceptions, e.g. Ritchie et al. 2016 for the UK), and other data limitations. The difficulty of isolating the effects of the minimum wage in such settings requires an approach which can triangulate results, either through the use of multiple data sources when available or by using multiple empirical models.

5.3 Data for employment analysis and labour inspections

The main data used in the analysis are aggregated cross-sections from the Labour Force Survey (LFS) for the years 2002-2013 provided by the National Statistics Office (NSO) of Thailand. We construct a quarterly panel (48 quarters) of employment information at province-level (76 groups) to evaluate the minimum wage effects on employment and hours worked. As mentioned in the previous chapter, since year 2001 the data are representative at provincial level. Over this year a miscoding of one variable (firm

NMW period.

size) was detected in the first three quarters. In order to ensure comparability and to remove any potential measurement error, we perform the estimations for the period 2002Q1-2013Q4.

The dataset constructed also excludes the latest three years of data for one province as its jurisdiction was split into two from 2011 (Nong Khai, with a new province created called Bueng Kan). This leaves us with an unbalanced panel of 75 provinces with 48 quarters of data and one province with 36 quarters, for a total of 3,636 observations. This choice avoids any double sampling of population (if the provinces were combined) and missing market information (such as GPP) for the new province. For the investigations of the NMW introduction, we use 75 provinces (900 obs.) with information five quarters before and seven after the policy change (2011Q1-2013Q4). Specifications with full inclusion or exclusion of the provinces do not alter the results reported in the chapter.

The population under analysis is composed of individuals aged 15-65 (excluding students). We report information for male and female workers separately for the main results, and we aggregate them together for secondary specifications. The main outcome variable is the employment-to-population ratio in each Thai province. This measure defines the ratio of the labour force employed over the total working-age population. Employment-to-population is chosen instead of a direct employment measure because the latter displays a unitary effect of the population variable in some of the main specifications. This allows for a more efficient econometric model for estimation. Nonetheless, as log employment is easier to interpret as an elasticity, when we interpret some of the results, we convert the estimates by dividing the estimation coefficients by the average measure of each outcome variable.

We distinguish between overall employment (including both wageworkers and non-wageworkers) and private sector employment (only wageworkers). Employment-to-population is calculated for either the working-age population (any individual of age 15-65), or the low-skilled population (those individuals with education lower than secondary). Further, the latter group is differentiated by age between youth low-skilled (individuals aged 15-24 with education lower than secondary) or older low-skilled population (aged 25 and above with education lower than secondary). The demographic characteristics used to investigate the employment effects are chosen on the basis that there may be substitution across workers' types, or stronger effects concentrated in a single group. Due to the very low rate of unemployment reported in the data (i.e. below 1 percent in year 2013), we would expect that when the minimum wage increases, those workers laid off from covered jobs (in Industry or Services) may seek employment in the primary sector or may shift to forms of non-wage employment. Thus, we examine the evolution of non-wage occupations, defined as self-employment and unpaid work, to assess if they appear to act as a buffer.[11] Additionally, we report estimates for private sector employment in agriculture.[12] According to the different specifications considered, indications in the chapter are given about further splits by firm characteristics which may provide a better understanding of the compositional effects of the MW policy on workers' demand.

Besides the LFS data, we make use for the estimations of minimum wage levels from the Ministry of Labour of Thailand (MOL) to capture the policy change, and we use Gross Provincial Product (GPP) data from the National Economic and Social Development Board (NESDB), estimated as yearly per capita value-added aggregated from 16 sectors from the previous year, to capture past provincial market outputs. In addition to these, one other source of data is used to perform a descriptive evaluation of the labour inspections in the country (Appendix C.4), reporting statistics from the Department of Labour Protection and Welfare (MOL) over the year of introduction of the national minimum wage (MOL, 2013).

5.3.1 Employment trends and the depth of non-compliance

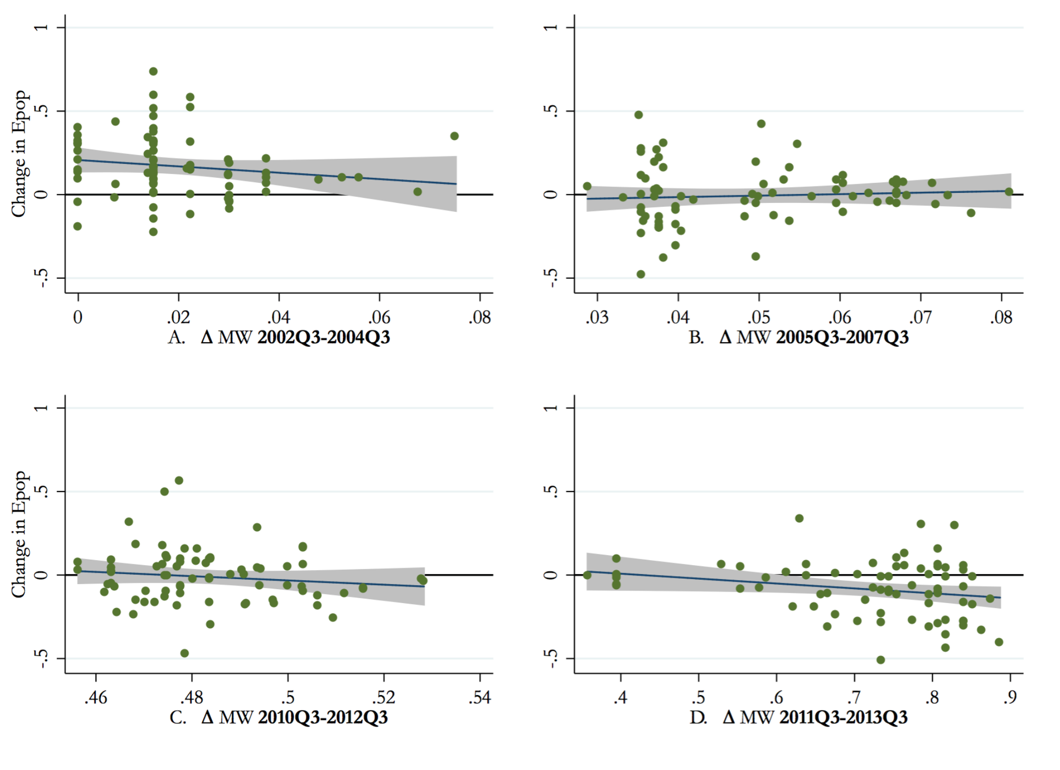
To begin the employment analysis, we first explore using descriptive statistics how the changes in the minimum wage correlate with private employment changes in the provinces under analysis. Figure 5.1 presents a scatterplot with line of best fit for selected years. We plot the change in employment-to-population (Epop) against the

[11] As discussed in the previous chapter, a main shortcoming of this dataset is that it is limited in differentiating between the formal and informal sector. Informal work in this chapter is proxied by non-wage work (not disposing of wage information in the LFS data). An incomplete proxy for informal wage-work employment is participation to micro-enterprises (with less than five employees).

[12] As mentioned in the previous chapter, the MW policy in Thailand does not cover the agricultural sector. In the event that a change in the minimum wage prevents workers from keeping or finding an occupation in the industries covered by the policy, workers without land to return to as non-wage employees may still seek employment as wageworkers in agriculture. Conversely, if the employment attractiveness in covered industries increases due to the MW, we may find that agricultural private sector employment to shrink. That is why in some specifications we investigate private sector employment in agricultural occupations as one of our outcome variables of interest.

change in the minimum wage (MW) between Q3 of year t and two years before (Q3 $t-2$). In graphs A and B the time periods represent a relatively small MW increase (x-axis less than 10%). Graphs C and D show the NMW introduction in its two steps of implementation, with substantial minimum wage variations in the range of 60-70% between 2011 and 2013.

Figure 5.1: Changes in Epop and the minimum wage by province, Q3 of selected years.



Notes: LFS province level (2002-2004,2005-2007,2010-2012,2011-2013). Scatterplot with line of best fit for selected years. Each graph plots the change in private sector employment-to-population Epop of the whole population (y-axis) and the change in the nominal hourly minimum wage (MW, x-axis). Time: each graph evaluates the Δ between Q3 of year t and two years before (Q3 $t-2$). Each grey shaded area represents the confidence intervals of the lfit.

Graphs A and B show that changes to employment-to-population do not seem to strongly correlate with the adjustments in the minimum wage experienced between 2002 and 2007.

In graph C the correlation between changes in 2010 to 2012 is not statistically different from zero, tentatively because the first hike was introduced shortly before in Q2 April, and contracts renegotiation may have occurred before or after. Graph D shows a more pronounced correlation with the harmonisation to the NMW: with exception of Bangkok and its surroundings (observations in the left-tail of the graph), some negative correlation is found in changes of MW and employment. Nevertheless, given the size of change of the MW in just two years, the correlation reveals that there have been no major reductions in private sector employment.[13]

From the review of the employment literature it emerges that differential effects on employment may occur due to country-specific composition of wageworkers and to the liability of firms to pay at the minimum wage.

In order to complement the description of the employment trends and compliance to the law investigated in the previous chapter, we now explore the gender dimension of provincial employment. We report in Table 5.1 the average employment-to-population and log hours worked which are used as main outcome variables in the empirics of the chapter. The table shows that, on average, 95 percent of the male population reports to be employed versus 77 percent of the female population. Wage employment in the private sector (excluding public sector employment) is at around 35-36 percent for males and only 25 percent for females. Private sector employment among the provinces of Thailand shows that industry is the main sector of employment, while services employs more than agriculture. The most salient change between the provincial MW regime and the NMW introduction period is visible in private employment by firm type. On aggregate, employment in micro enterprises and Small and Medium Enterprises (SMEs) fell over the 2011-2013 period.

[13] In Figure C.1 and Figure C.2 (Appendix C, pp.210–211) we repeat the same exercise, now separating the employment data by gender and show that, with a quadratic prediction of changes in the MW, the same interpretation applies to both male and female populations separately.

Table 5.1: Summary statistics: Provincial employment-to-population and hours worked across workers (male and female).

	Working-age						Low-skilled					
	2002-13		2011-13		Test		2002-13		2011-13		Test	
	M	F	M	F	M	F	M	F	M	F	M	F
Overall	0.95	0.77	0.95	0.78	0.00	0.00	0.95	0.76	0.95	0.77	0.00	0.00
St.dev.	0.03	0.06	0.02	0.05			0.03	0.07	0.03	0.06		
NonWage	0.51	0.46	0.52	0.46	0.12	0.25	0.54	0.49	0.55	0.51	0.03	0.00
St.dev.	0.13	0.12	0.14	0.12			0.14	0.13	0.14	0.13		
Self-employment	0.36	0.20	0.35	0.21	0.06	0.00	0.38	0.22	0.38	0.23	0.18	0.00
St.dev.	0.09	0.05	0.09	0.04			0.09	0.05	0.09	0.05		
Unpaid	0.15	0.25	0.16	0.25	0.00	0.81	0.15	0.27	0.17	0.28	0.00	0.09
St.dev.	0.06	0.10	0.07	0.11			0.06	0.11	0.07	0.12		
Private	0.35	0.25	0.35	0.24	0.06	0.08	0.36	0.25	0.36	0.24	0.02	0.03
St.dev.	0.13	0.12	0.14	0.12			0.13	0.12	0.14	0.12		
Industry	0.17	0.11	0.17	0.11	0.80	0.05	0.18	0.12	0.18	0.11	0.77	0.05
St.dev.	0.11	0.10	0.11	0.10			0.10	0.10	0.11	0.10		
Service	0.10	0.09	0.10	0.09	0.15	0.00	0.10	0.07	0.10	0.08	0.46	0.00
St.dev.	0.06	0.06	0.06	0.06			0.06	0.05	0.06	0.05		
Agri.	0.08	0.05	0.07	0.05	0.00	0.00	0.09	0.06	0.08	0.05	0.00	0.00
St.dev.	0.06	0.04	0.05	0.04			0.06	0.04	0.06	0.04		
Micro	0.17	0.10	0.17	0.10	0.00	0.00	0.19	0.11	0.18	0.11	0.01	0.17
St.dev.	0.07	0.05	0.07	0.04			0.07	0.05	0.08	0.05		
SME	0.10	0.06	0.09	0.06	0.00	0.19	0.10	0.06	0.09	0.06	0.00	0.00
St.dev.	0.05	0.03	0.05	0.04			0.05	0.03	0.05	0.03		
Large	0.08	0.08	0.09	0.08	0.17	0.73	0.07	0.08	0.08	0.08	0.39	0.34
St.dev.	0.11	0.10	0.11	0.10			0.10	0.10	0.10	0.10		
Ln hrs	3.77	3.74	3.76	3.73	0.01	0.20	3.77	3.74	3.76	3.74	0.01	0.17
St.dev.	0.12	0.13	0.13	0.13			0.13	0.14	0.14	0.15		
Ln hrs(Priv)	3.87	3.86	3.88	3.87	0.01	0.05	3.88	3.87	3.88	3.88	0.01	0.01
St.dev.	0.07	0.08	0.07	0.07			0.07	0.08	0.07	0.08		

Note: LFS, pooled province-level panel. Average employment-to-population and log hours worked (overall or for the private sector) are reported with their standard deviation (St.dev.) for male (M) and female (F) population in working-age (15-65) or low-skilled (less than secondary). Data for 2002-2013 (3636 obs) and 2011-2013 (900 obs). T-test (with equal or unequal variance) p-value is reported for each group. $H0$: equality in means of 2011-2013 with 2002-2010 period. For splits by age-groups, see Appendix C, Table C.1 (p.211).

In addition to the features of provincial employment, a crucial aspect to inspect is whether the extent of non-compliance varies across gender and other work characteristics. The measures reported in Table 5.2 investigate the incidence of non-compliance (the share of private sector workers paid below the minimum) and the depth of non-compliance, measure which shows how far from the minimum wage each worker earns on average (Bhorat et al., 2012b, 2013).[14]

[14]The depth of non-compliance (also known as depth of violation) $v_{\alpha=1}$ is measured as follows: $v_\alpha = (mw - w)^\alpha / mw$ if $w < mw$, zero otherwise. The ratio v_1/v_0 of the depth ($\alpha = 1$) to the incidence ($\alpha = 0$) gives a measure the average shortfall (Bhorat et al., 2013). We report these measures in Table 5.2 for either the full period (2002 Q1-2013 Q3 in panel A and B) or for a 6-quarter window before and after the minimum wage hike (2010 Q3-2012 Q1 and 2012 Q2-2013 Q4 in panel C and D). We choose this time period for this descriptive analysis to ensure no stronger depth of violation is detected before the NMW period, noting that if we use as starting year Q1 2011 the table results are practically the same (not shown).

Table 5.2: Compliance with the MW: Incidence and depth of compliance for male and female wageworkers

	Overall	Industry	Services	Micro	SME	Large
A. Incidence						
Male	0.25	0.26	0.25	0.39	0.23	0.11
Female	0.31	0.31	0.31	0.57	0.29	0.14
B. Depth						
Male	0.06	0.06	0.06	0.11	0.05	0.02
Female	0.08	0.08	0.08	0.18	0.07	0.02
C. Incidence pre/post NWM						
Male Pre	0.18	0.18	0.18	0.28	0.16	0.08
Male Post	0.34	0.36	0.32	0.55	0.32	0.14
Female Pre	0.24	0.25	0.23	0.45	0.20	0.11
Female Post	0.35	0.36	0.35	0.66	0.33	0.16
D. Depth pre/post NMW						
Male Pre	0.04	0.04	0.04	0.07	0.03	0.01
Male Post	0.08	0.08	0.08	0.14	0.07	0.02
Female Pre	0.06	0.06	0.05	0.12	0.04	0.02
Female Post	0.10	0.10	0.09	0.21	0.08	0.03

Note: LFS, covered private sector employees. Panel A and B refer to the whole time period Q1 2002-Q4 2013 (female sample 682,885 obs., male sample 791,542 obs.), Panel C and D refer to a 6-quarter window around the NMW (pre period: Q3 2010-Q1 2012; post: Q2 2012-Q4 2013, female sample:196,848 ; male: 232,938 obs.). The statistics compare the wage earned with each quarter-specific minimum wage. The incidence is calculated as a headcount of any wage below the legally mandated (shares). The depth (Bhorat et al., 2013) calculates the gap between the actual wage and the MW, expressed as a fraction of the MW.

The incidence rates (Panel A) suggest that both overall and across work characteristics, female wageworkers are subject to higher non-compliance than male over the 2000s (31 percent versus 25 percent). Particularly high non-compliance rate for female workers appears in micro-enterprise work (at 57 percent). However, we find evidence of only mild depth of non-compliance. For both male and female private sector workers, the depth of non-compliance is lower than 10 percent (Panel B). Only exception is micro-enterprise participation. Looking in more detail only around the NMW introduction (Panel C and D, Table 5.2), two details become apparent. First, there has been some homogeneous increase in non-compliance by gender (in both incidence and depth) across the sectors covered by the policy. During the *before-after* NMW introduction, the average shortfall (v_1/v_0) for workers paid sub-minimum wage has moved from 22.2 to 23.5% for male workers and from 25 to 28.6% for female. Second, catching up with the policy change appears to be more difficult for micro firms as well as SMEs (with a two-fold increase in the depth of non-compliance), whereas large firms seem to have abided more easily with the law.

With respect to emerging and developing economies, the Thai labour market seems much more compliant than other poorer economies such as Honduras (with 39% or 74% of wage earners in large and small firms respectively paid below the minimum in the late 2000s, see Ham 2017), or richer countries like South Africa with a more complex minimum wage set-up and 44% of covered workers paid sub-minimum (Bhorat et al., 2012b). There still is a higher incidence of non-compliance than in developed economies, for example found to be 7% in France (Garnero et al., 2015). However, the depth of non-compliance in Thailand is much less severe than the average for Central and Eastern European countries during the 2000s, resembling the average monthly violation experienced in Lithuania which has a NMW regime (Goraus-Tanska and Lewandowski, 2016). Moreover, it has a similar average distance from the minimum wage for workers paid sub-minimum to the shortfall of Italy (Garnero, 2017), country with wage floors set by collective bargaining. The relatively low depth of violation (8-10% post NMW introduction) for Thailand may be suggestive of little dispersion in sub-minimum wages imposed. Still, the descriptive evidence presented herein shows that Thai workers tend to suffer of non-compliance to some degree. This may play a role in attenuating both the responsiveness of wages (as found in the previous chapter) and the employment to a variation of the policy.

5.4 Model specifications for the employment analysis

5.4.1 Panel Fixed Effects at province level

The main specification of the impact of the minimum wage on employment uses a quarterly panel fixed effects model at province-level. We use different employment outcomes which we regress on log minimum wage and covariates, representing a reduced form labour demand equation. The specification uses provincial panel data (48 quarters from 2002 to 2013 for the full period or 12 quarters from 2011 to 2013), identifying the effect of the policy on the outcome variable E_{pt} in province p and time t:

$$E_{\mathrm{pt}} = \beta_0 + \beta_1 \mathrm{MW}_{\mathrm{pt}} + \beta_2 X_{\mathrm{pt}} + \phi_p + \phi_t + \varepsilon_{\mathrm{pt}} \tag{5.1}$$

As outcome variable E, we use employment-to-population ratios ($E = Epop_{\mathrm{pt}}$) or the log weekly hours worked ($E = ln(hrs)_{\mathrm{pt}}$). As minimum wage policy variable we rely on a direct measure of log real hourly minimum wage level. As provincial-level controls X_{pt} we include as labour demand shifter a variable controlling for market performance, yearly log per capita GPP from the previous period, in addition to provincial population characteristics such as: the share of youth and elderly out of the total 15-65 population to account for the ageing population over the decade; the female or male share; and the share of population with above secondary education. We also use population group-specific controls such as the average years of schooling, the average years of potential work experience and share of rural population.[15] In order to control for unobserved provincial and time heterogeneity, we include in the reduced form equation province (ϕ_p) and time (ϕ_t) fixed effects and report robust standard errors clustered at the province level.[16] We investigate the differential effects across gender, level of education and age, and identify changes in employment by production type or firm size.[17]

[15] Population group-specific controls refer to the age and gender group under analysis.

[16] In preliminary estimations we applied as policy variable the minimum wage bite (median Kaitz Index) as it aims to produce a relative price for labour which may not be fully reflected in the minimum wage alone. As the Kaitz Index implicitly assumes that the minimum wage increase should not affect the mean (or median) wages (Lemos, 2005), we also applied a bite to the 60$^{\mathrm{th}}$ provincial wage percentile to reflect the results of the previous chapter. In both instances, the results do not change to the ones of the main specification, that is why they are not reported. Moreover, we test that adding demand shifters other than the one in the main specification, such as the unemployment rate or the log median wage, do not affect the results.

[17] Firm size is agglomerated in three groups: micro enterprises are defined as those with less than 10 employees, small-medium size firms employ between 10 and 99 people, while large firms employ 100 or more.

The results for male and female in the working-age population (15-65), the secondary or less-educated population (low-skilled), and the young or older low-skilled populations are reported in Tables 5.3 and 5.4. We focus particularly on the low-skilled since this type of workers is the most likely to be directly affected by variations in the minimum wage.

Our estimates suggest that there are minor aggregate employment effects in the full time period under analysis (2002-2013). These are mostly driven by reduction in employment in the agricultural sector, not covered by the minimum wage law. Wage employment in agriculture has been reducing over the 2000s (for a representation of the employment trends, see Figure B.2, p. 137) and the results suggest that only a marginal reduction in this sector is due to minimum wage adjustments. For an average 5% increase in the minimum wage over the period, low-skilled employment in agriculture is reduced by -0.11% for the male population (with an average Epop of 9%) and by -0.12% for the female low-skilled population (average Epop of 6%). These results suggest that the MW may have played a marginal role in attracting Thai wage workers out of agriculture.[18] Looking at non-wage employment, the estimates reveal semi-elasticities which are insignificantly different from zero, suggesting that there was no shift to this proxy of informal sector work directly generated by minimum wage adjustments. For male private employment-to-population ratios, overall there seems to be no direct impact for the male working-age population or for the male low-skilled in general. In addition to shifts outside of agriculture, no statistically significant contractions either by sector of production or firm type are found for males (Panel B).

However, the minimum wage changes generate some contractions for female private sector employment. A negative and statistically significant effect is found for the female young low-skilled group (Panel A). For an average 5% increase in the minimum wage over the period the employment-to-population in the industry sector reduces by -0.2%, with an elasticity of -0.244 (coefficient -0.041, mean Epop 0.168). The employment-to-population in micro enterprises (Panel B), which is the greatest share among firm types where low-skilled females work, seems to be marginally affected as well.

[18] This evidence is complemented by studies on international migration to Thailand which show that foreign workers have been replacing Thai workers in the non-covered agricultural sector, see IOM (2014) for further details.

Table 5.3: The effects of the MW: Fixed effects 2002-2013 for male and female employment-to-population and log weekly hours worked

Panel (A)						
	All	Non wage	Private	Indus.	Service	Agri.
Male Working-age	-0.008	-0.005	0.008	0.008	-0.00006	-0.021*
	(0.006)	(0.016)	(0.012)	(0.010)	(0.007)	(0.011)
Male Low-skilled	-0.011*	-0.009	0.006	0.002	0.004	-0.020*
	(0.006)	(0.017)	(0.012)	(0.010)	(0.007)	(0.012)
Male Young-lowskilled	-0.047**	-0.014	-0.048	-0.035	-0.013	-0.009
	(0.018)	(0.032)	(0.030)	(0.030)	(0.019)	(0.020)
Male Older-lowskilled	-0.004	-0.001	0.009	0.004	0.005	-0.021*
	(0.006)	(0.017)	(0.012)	(0.010)	(0.008)	(0.011)
	All	Non wage	Private	Indus.	Service	Agri.
Female Working-age	-0.031***	-0.019	0.001	-0.002	0.003	-0.022***
	(0.010)	(0.014)	(0.008)	(0.008)	(0.006)	(0.008)
Female Low-skilled	-0.034***	-0.019	-0.004	-0.007	0.004	-0.023**
	(0.011)	(0.015)	(0.008)	(0.008)	(0.005)	(0.009)
Female Young-lowskilled	-0.054**	0.005	-0.039	-0.041*	0.002	-0.026*
	(0.026)	(0.027)	(0.028)	(0.023)	(0.021)	(0.013)
Female Older-lowskilled	-0.032***	-0.023	0.000	-0.003	0.003	-0.021**
	(0.012)	(0.015)	(0.009)	(0.009)	(0.005)	(0.009)

Panel (B)					
	Micro	SM	Large	Log Hrs	Hrs(Priv.)
Male Working-age	-0.014	-0.005	0.006	-0.040**	-0.038*
	(0.011)	(0.010)	(0.008)	(0.018)	(0.021)
Male Low-skilled	-0.012	-0.004	0.001	-0.043**	-0.041*
	(0.013)	(0.011)	(0.008)	(0.019)	(0.023)
Male Young-lowskilled	-0.016	-0.016	-0.025	-0.061**	0.005
	(0.026)	(0.023)	(0.021)	(0.030)	(0.037)
Male Older-lowskilled	-0.013	-0.004	0.005	-0.046**	-0.054**
	(0.012)	(0.011)	(0.008)	(0.020)	(0.023)
	Micro	SM	Large	Log Hrs	Hrs(Priv.)
Female Working-age	-0.018**	-0.011	0.008	-0.049***	-0.040**
	(0.008)	(0.007)	(0.008)	(0.018)	(0.019)
Female Low-skilled	-0.016*	-0.013*	0.003	-0.047**	-0.037*
	(0.009)	(0.007)	(0.007)	(0.020)	(0.021)
Female Young-lowskilled	-0.001	-0.029*	-0.032	-0.041	0.003
	(0.022)	(0.017)	(0.022)	(0.037)	(0.039)
Female Older-lowskilled	-0.018**	-0.011	0.008	-0.050**	-0.043**
	(0.009)	(0.007)	(0.008)	(0.021)	(0.021)

Note: LFS at province-quarter level 2002-2013 (3,636 obs., 76 groups). Fixed effects models for male or female employment measures. Reported are the coefficient for log hourly minimum wage and cluster robust standard error. Each row represent an employment measure for either the for working-age, low-skilled or youth low-skilled population of male or female. Dependent variables in Panel (A): Employment-to-population of aggregate employment (All), Non-wage work occupations (i.e. self-employment or unpaid work), Wage-work in the private sector (covered) and by industry or services, private sector participation into the non-covered sector (Agri). Dependent variables in Panel (B): Employment-to-population by private sector occupations in Micro enterprises, Small-medium firms, Large firms; log weekly hours for any worker or for (covered) private sector employees. Population group-specific controls: average years of schooling, average years of experience and rural share. Provincial controls: share of youth, share of elderly, female/male share, share of high-skilled out of the total population, log per capita GPP, province and time fixed effects (significance: * p<.10, ** p<.05, *** p<.01).

Table 5.4: The effects of the NMW: Fixed effects 2011-2013 for low-skilled male and female employment-to-population and log weekly hours worked.

Panel (A)						
	All	Non wage	Private	Indus.	Service	Agri.
Male Low-skilled	0.008	0.001	-0.003	0.001	-0.004	0.002
	(0.006)	(0.016)	(0.011)	(0.010)	(0.007)	(0.012)
Male Young-lowskilled	0.020	0.003	-0.024	-0.018	-0.005	0.023
	(0.022)	(0.038)	(0.033)	(0.027)	(0.022)	(0.024)
Male Older-lowskilled	0.005	0.002	-0.001	0.004	-0.005	-0.003
	(0.006)	(0.015)	(0.012)	(0.010)	(0.007)	(0.011)
	All	Non wage	Private	Indus.	Service	Agri.
Female Low-skilled	0.020*	0.009	0.006	0.001	0.005	-0.005
	(0.011)	(0.015)	(0.009)	(0.009)	(0.005)	(0.008)
Female Young-lowskilled	0.007	0.015	0.006	0.017	-0.011	-0.028**
	(0.030)	(0.033)	(0.027)	(0.024)	(0.021)	(0.013)
Female Older-lowskilled	0.021*	0.007	0.006	-0.001	0.007	-0.001
	(0.011)	(0.014)	(0.010)	(0.009)	(0.005)	(0.008)
Panel (B)						
	Micro	SM	Large	Log Hrs	Hrs(Priv.)	
Male Low-skilled	0.016	-0.004	-0.013**	0.041**	0.025	
	(0.014)	(0.010)	(0.006)	(0.018)	(0.023)	
Male Young-lowskilled	0.009	-0.002	-0.012	0.044	0.072*	
	(0.030)	(0.021)	(0.019)	(0.034)	(0.041)	
Male Older-lowskilled	0.016	-0.007	-0.013*	0.042**	0.017	
	(0.012)	(0.010)	(0.008)	(0.017)	(0.023)	
	Micro	SM	Large	Log Hrs	Hrs(Priv.)	
Female Low-skilled	0.007	-0.002	-0.004	0.043**	0.050**	
	(0.009)	(0.007)	(0.007)	(0.019)	(0.023)	
Female Young-lowskilled	0.012	-0.019	-0.013	0.073*	0.058	
	(0.022)	(0.021)	(0.020)	(0.041)	(0.036)	
Female Older-lowskilled	0.006	0.001	-0.002	0.044**	0.051**	
	(0.009)	(0.007)	(0.008)	(0.019)	(0.025)	

Note: LFS at province-quarter level 2011-2013 (900 obs., 75 groups). Fixed effects models for male or female employment measures. Reported are the coefficients for log hourly minimum wage and cluster robust standard errors. Each row represents an employment measure for either the low-skilled or an age-specific population of male or female. Dependent variables in Panel (A): Employment-to-population of aggregate employment (All), Non-wage work occupations (i.e. self-employment or unpaid work), Wage-work in the private sector (covered) and by industry or services, private sector participation into the non-covered sector (Agri). Dependent variables in Panel (B): Employment-to-population by private sector occupations in Micro enterprises, Small-medium firms, Large firms; elasticities are reported for log weekly hours for any worker or for (covered) private sector employees. Population group-specific controls: average years of schooling, average years of experience and rural share. Provincial controls: share of youth, share of elderly, female/male share, share of high-skilled out of the total population, log per capita GPP, province and time fixed effects (significance: * p<.10, ** p<.05, *** p<.01).

A 5% increase in the minimum wage induces a -0.08% reduction in provincial low-skilled female employment-to-population ratio in micro firms. This effect is slightly stronger for older low-skilled female (-0.09%), with an implied elasticity of -0.139 (coefficient -0.018, mean 0.13).

However, these results might be considered relatively low with respect to the literature and they may arise for several reasons. First, over the decade, minimum wage adjustments in real terms before Q2 2012 have been decreasing if not stagnant, so it might not be surprising to find relatively small effects on employment. Second, as visible from Panel B (last two columns), adjustments seem to have taken place in weekly hours worked. We report the elasticity for both weekly hours in any type of employment and only for the private sector. Average low-skilled hours worked in private sector employment have decreased due to minimum wage adjustments both for male (0.9 hours reduction at the mean of 46.04) and female (0.89 hours reduction at the mean of 44.63). Third, the non-compliance rates which we documented may partly explain why the provincial employment response is attenuated.

Looking at the period around the introduction of the NMW (2011-2013), Table 5.4 reports the semi-elasticities of provincial employment response to the minimum wage change for the low-skilled population. Panel A shows no statistically significant effect for overall and private sector employment at province-level, neither for male nor for female participation. Except for some minor contractions in agriculture, not covered by the policy, for female low-skilled youth participation and some contraction for older male low-skilled employment in large firms (significance at 10 percent), the effects tend to be close to zero. However, significantly positive effects are detected in average hours worked for the low-skilled female population (0.050) and for the male young low-skilled group (0.072). In spite of the fact that non-compliance has been increasing in the country, these results are suggestive of two other likely factors playing at the same time. One is the fact that tax breaks were applied contemporaneously to the NMW, and the other is the potential productivity changes on the side of firms to cope with these changes. The short-run effects of the NMW (2011-2013) on provincial employment, although of weak statistical power, suggest no immediate negative effects of the policy switch on provincial private-sector employment.

High versus low regimes and identification issues

In order to further investigate the mechanisms underpinning employment responsiveness, we split the province sample by their trends in minimum wage regimes over the period 2002-2013. Given the local labour market characterisation which we have attributed to provincial differences in their employment and wage schedule, we expect some differences in employment response to occur across areas of the country. To test this hypothesis, we perform separate employment demand regressions for areas with high or low minimum wage regimes. High (low) minimum wage provinces are defined as those provinces with a real average minimum wage which is higher (lower) than the national average over the period.[19] Table 5.5 shows that, in provinces which experienced a low minimum wage regime (56 of them) there are signs of contraction in low-skilled youth employment and in older workers' hours in the private sector during the 2002-2013 period. Additionally, in provinces with low minimum wage regimes the youth employment in Industry shows some contraction, while Services has responded positively with rises in older workers' employment. By contrast, in high-regime provinces youth low-skilled workers appear to shift from SMEs to micro enterprises.[20]

The results suggest that over the 2000s, the areas under a lower minimum wage regime have been subject to downward adjustments in employment. These geographically localised employment effects suggest that the adjustments to a policy change have been better absorbed in the relatively wealthier provinces of the country.

Performing a separate analysis for the two groups around the NMW period (not reported), reveals positive hours worked elasticity and no statistically significant effects on employment for both groups. This may either due to the fact that adjustments may have taken place after 2013 – thus not visible from the data at our disposal – or because even firms in low minimum wage regime provinces were able to keep their workers by adjusting workers' productivity levels (potentially linked to the higher average hours worked), on other cost margins, or by partially complying to the new minimum wage.

[19] We inspect the minimum wage time series and identify 20 provinces (including the pilot areas) which benefited of a high minimum wage regime (Bangkok, 13 provinces from the Centre, 1 from the North, 1 from Northeast, and 4 from the South) versus a lower than average regime for the other 56 provinces. Note that if we perform the specification excluding the pilot provinces (7) we still find small contractions in aggregate provincial demand (not shown).

[20] As the separate estimations may be confounded by low power due to sample size, Table C.2 (Appendix C.1, p.212) checks the robustness by using the full province-sample and performing Equation 5.1 with an additional binary variable for being a low-regime province L_p, which is interacted to the minimum wage levels ($L_p \times \mathrm{MW}_{\mathrm{pt}}$).

Table 5.5: Fixed effects of employment-to-population in high versus low minimum wage regime provinces, 2002-2013.

	A. LOW regime						**B. HIGH regime**					
	All	No W	Priv.	Agri.	Indus.	Serv.	All	No W	Priv.	Agri.	Indus.	Serv.
All	-0.140**	-0.110	0.032	0.023	-0.084	0.093***	0.044*	0.108	-0.087	-0.045	-0.004	-0.037
	(0.055)	(0.095)	(0.081)	(0.055)	(0.063)	(0.032)	(0.023)	(0.091)	(0.087)	(0.049)	(0.068)	(0.045)
LS	-0.150**	-0.163	-0.008	0.034	-0.121*	0.079**	0.050	0.098	-0.079	-0.045	-0.012	-0.022
	(0.058)	(0.108)	(0.084)	(0.060)	(0.064)	(0.031)	(0.030)	(0.095)	(0.099)	(0.053)	(0.073)	(0.042)
Y-LS	-0.129	0.158	-0.335**	-0.028	-0.381***	0.075	-0.093	0.059	-0.154	-0.061	0.014	-0.108
	(0.115)	(0.164)	(0.140)	(0.094)	(0.118)	(0.076)	(0.092)	(0.139)	(0.205)	(0.084)	(0.183)	(0.110)
O-LS	-0.133**	-0.223**	0.072	0.056	-0.067	0.082**	0.062**	0.087	-0.055	-0.029	-0.004	-0.022
	(0.052)	(0.105)	(0.082)	(0.057)	(0.063)	(0.035)	(0.029)	(0.095)	(0.092)	(0.045)	(0.067)	(0.037)
	Micro	SME	Large	Log Hrs	P Hrs		Micro	SME	Large	Log Hrs	P Hrs	
All	-0.007	-0.030	0.069*	-0.225	-0.317*		0.016	-0.081	-0.020	-0.110	0.013	
	(0.060)	(0.048)	(0.036)	(0.149)	(0.186)		(0.039)	(0.049)	(0.071)	(0.108)	(0.084)	
LS	0.005	-0.042	0.029	-0.270	-0.365*		0.023	-0.073	-0.029	-0.122	0.003	
	(0.068)	(0.051)	(0.032)	(0.162)	(0.197)		(0.047)	(0.049)	(0.070)	(0.121)	(0.088)	
Y-LS	-0.133	-0.143	-0.064	-0.499**	-0.409		0.168**	-0.157*	-0.166	-0.104	0.033	
	(0.099)	(0.090)	(0.086)	(0.224)	(0.248)		(0.071)	(0.083)	(0.181)	(0.138)	(0.093)	
O-LS	0.045	-0.031	0.059*	-0.265	-0.391*		0.005	-0.072	0.013	-0.143	-0.012	
	(0.067)	(0.049)	(0.030)	(0.160)	(0.199)		(0.048)	(0.050)	(0.066)	(0.139)	(0.096)	

Note: LFS 2002-2013 (low regime= 2,676 obs; high regime= 960 obs). High (Low) minimum wage provinces are defined as those provinces with a real mean minimum wage higher (lower) than the national average over the period. High regime provinces are 20: Bangkok, 13 from the Centre, 1 from the North, 1 from Northeast, and 4 from the South (low regime are the remaining 56 provinces). Samples: Overall population (All); Low-skilled (LS); Young low-skilled (Y-LS); Older low-skilled (O-LS). The table reports the minimum wage coefficient (labeled by sample name). Controls and clustering as in main specification (significance: * p<.10, ** p<.05, *** p<.01).

However, the relatively localised employment effects found could be masked by some identification issues. These could be due to the small sample at our disposal (76 provinces with no possibility of disaggregation at a lower administrative level). The aggregation which we impose at the province level over both time periods could mask within-province dynamics which we cannot fully capture with a panel regression. Time is also an issue for the latest policy regime change, in which we investigate a specification with only twelve quarters of data and the power of the model may be low.

Thus, we further complement the main specification proposed in four ways. First, in Section 5.4.2 we assess whether the estimates would require the use of province-specific trends and we test for cross-sectional dependence in the data.

Second, in Section 5.4.3 we investigate specifications at the individual level using the LFS cross-sections at our disposal. A non-linear response model is used to see if the results are in line with the panel regression and with the literature on the employment effects for Thailand (Del Carpio et al., 2014; Ariga, 2016). Even if only representing correlations, we also inspect two forms of informal employment in the analysis of the MW policy.

Third, we perform an ancillary exercise for the 2002-2013 data applying a dynamic specification reported in Appendix C.2 (p.224, reporting the model specification and its caveats). Following Allegretto et al. (2011), we apply a distributed leads and lags model to the data in levels and seek the effect of a cumulative response over time to a minimum wage change. This model is chosen to identify if there is any influence from the past – reflecting any adjustment period – and to detect any anticipation effect associated with the leading minimum wage terms. The results show more pronounced correlations than the standard panel fixed effect model. The results underline some signs of contraction in low-skilled employment following a minimum wage adjustment and no strong anticipatory effects. The dynamic specification also provides evidence of some delayed downward adjustments in employment in SMEs. Additionally, it shows that as a response to minimum wage adjustments, large firms tend to substitute from low to high-skilled employment. However, we caution to interpret the results as causal, as there could be issues of multicollinearity induced in the estimations. This implies that the correlation between the leading and lagged terms of the minimum wage variable could confound the cumulative estimation we perform. We take those results as indications rather than causal effects, though suggesting that no strong anticipatory effects were found as a response to a policy change.

Lastly, in Appendix C.3 (p.230) we focus on the latest policy change, and complement the Difference-in-Differences exercise proposed in Chapter 4 with some correlations about the employment changes across groups of provinces. We do not consider the estimates as causal, but pure correlations, as we use aggregate employment information among observational data to perform the exercise. The Appendix suggests how future analysis could more precisely investigate on any heterogenous time effects.

As subsidiary consideration, we inspect a potential threat to identification arising from internal labour mobility. Over the 2000s the policy may have played a role in altering workers' flows outside their province of origin. The expected effect on employment mobility in principle is ambiguous. The minimum wage, according to the change in its rate, may either reduce migration (if it increases the expected wage in the province of origin) or induce it (if push factors – lower jobs at origin – or pull factors – higher expected wages outside – induce more people to move). In order to identify whether this issue raises concerns over the results, we look at labour migration trends from a set of household-level cross-sections available for the whole country, the Socio Economic Survey (SES). Given the minor size of adjustments in the provincial wage minima experienced prior to 2012, the employment estimates should not be particularly affected by internal migration across areas. During the 2000s the share of households reporting a labour migrant within or outside the province of origin have reduced across the provinces of Thailand (for further details at the national level, see Pholphirul 2012; Punpuing 2012; Sondergaard et al. 2016), thus alleviating concerns about the robustness of the results.[21]

5.4.2 Province-specific trends and Discroll-Kraay estimator

We now investigate on the use of province time trends and potential cross-sectional dependence in the panel fixed effects specification.

The use of geographic linear trends has been advised for identifying geographic-specific patterns over time when the data are aggregated or when a specific type of workers or markets is investigated (Allegretto et al., 2011; Addison et al., 2012). The intuition behind including trends is to account for heterogeneous patterns not captured in other control variables for the geographic areas under analysis. These trends should be tested against those of higher order to ensure the estimates are stable (Neumark et al., 2014b). We perform a comparison of the panel specification for private employment, for different workers' characteristics (age and education) with or without trends. We report in Appendix C.1.1, p.216–217) the estimations for male-female employment, whereas below we report the estimations split by gender. The polynomials are defined up to their quadratic form for the 2002-2013 sample. For the 2011-2013 data (reported below) the estimation is performed with trends up to cubic form, as the degrees of freedom would be considerably reduced in the estimation with quartic trends, thus be uninformative.

The inclusion of linear trends alter the magnitude and significance of the estimates, but does not appear to be stable once polynomials higher than the quadratic order are added. For the full decade under analysis (Table 5.6), the inclusion of linear trends reveals a significantly negative semi-elasticity of the low-skilled male and

[21]We do not dispose of migration or place of birth information in the LFS data, so we cannot perform an evaluation of the in/outflows of labour force. However, in preliminary analyses (not shown), we explored the Thai SES household-level data which reports information on members living outside the household for a subset of years (2009; 2011; 2013). We could not compute standard net migration measures used in the literature (Giulietti, 2014; Edo and Rapoport, 2016), so we looked at the likelihood of outmigration. Using the household survey data for the closest years to the NMW introduction (2009;2011) and its year of implementation (2013), we found no clear correlations between the minimum wage levels or changes and provincial out-migration rates.

female employment measures, confirming the negative sign found for young low-skilled employment.

For the period around the NMW introduction (Table 5.7), the inclusion of either linear or quadratic province-specific trends shows a positive semi-elasticity of employment. The low-skilled coefficients increase from insignificant near-zero magnitudes to 0.127 elasticity for male (+0.045, with mean outcome 0.355) and 0.086 elasticity for female low-skilled employment (+0.021 with mean 0.243). Tentatively, the short-term effects of the NMW could be interpreted as having retained if not attracted more participation in the private sector.

However, to ensure the validity of the results, we test for the presence of Cross-sectional Dependence (CD) in the data (for a comprehensive review, see Sarafidis and Wansbeek 2012 and Pesaran 2015, Chapter 29). Following De Hoyos and Sarafidis (2006), we perform the Pesaran CD test for the panel fixed effect model without trends, and the Frees test when linear trends are included. The estimations for 2002-2013 are reported in Appendix C.1.1 (pp.212-217) with an explanation of the tests. For both 2002-2013 (Tables C.5 and C.6) and 2011-2013 samples (Tables 5.8 and 5.9) the estimation results show that most of the specifications without trends do not suffer from CD (with exception of overall participation to the private sector, micro and large firms), whereas the inclusion of trends does generate CD (cross-sectional independence is rejected in all but one instance). In case some cross-sectional dependence is detected, the coefficients are still consistent (but inefficient) while the standard error estimates are invalid. In order to ensure that the estimates are robust to CD, we follow Hoechle (2007) and apply the Discroll-Kraay standard errors (also reported in Appendix C.1.1).

The results performed with robust standard errors in the presence of CD are in line with the main specification proposed above (Section 5.4.1). For the NMW introduction the estimates show no overall effects on private employment and a positive response of weekly hours worked both with or without trends (as reported in Table 5.8-5.9 below). Overall, the test for CD suggests that for the quarter-province panel under analysis, a model without province-specific time trends is preferred.

Table 5.6: The effects of the MW: Fixed effects 2002-2013 for male and female employment-to-population with or without trends.

(A) Male Trend	None	Linear	Quadratic	Cubic	Quartic
Working-age Male	-0.013	-0.023	0.006	0.014	0.017
	(0.016)	(0.015)	(0.016)	(0.016)	(0.015)
R^2	0.24	0.35	0.40	0.44	0.46
Ftest(p)		0.00	0.00	0.00	0.00
Low-skilled Male	-0.015	-0.026	0.008	0.017	0.018
	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)
R^2	0.24	0.35	0.41	0.44	0.47
Ftest(p)		0.00	0.00	0.00	0.00
Young-lowskilled Male	-0.057	-0.068*	-0.007	0.016	0.013
	(0.035)	(0.035)	(0.034)	(0.034)	(0.034)
R^2	0.09	0.15	0.20	0.24	0.26
Ftest(p)		0.00	0.00	0.00	0.00
Older-lowskilled Male	-0.012	-0.023	0.011	0.017	0.018
	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)
R^2	0.25	0.37	0.43	0.46	0.48
Ftest(p)		0.00	0.00	0.00	0.00
(B) Female Trend	None	Linear	Quadratic	Cubic	Quartic
Working-age Female	-0.021*	-0.021*	0.004	0.011	0.016
	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)
R^2	0.17	0.30	0.38	0.42	0.44
Ftest(p)		0.00	0.00	0.00	0.00
Low-skilled female sample	-0.026**	-0.030**	0.003	0.010	0.014
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
R^2	0.17	0.29	0.37	0.41	0.44
Ftest(p)		0.00	0.00	0.00	0.00
Young-lowskilled female	-0.065**	-0.047*	-0.027	-0.014	-0.014
	(0.030)	(0.026)	(0.029)	(0.032)	(0.034)
R^2	0.07	0.14	0.18	0.22	0.25
Ftest(p)		0.00	0.00	0.00	0.00
Older-lowskilled female	-0.021	-0.028**	0.010	0.016	0.021*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
R^2	0.20	0.34	0.41	0.45	0.48
Ftest(p)		0.00	0.00	0.00	0.00

Note: LFS at province-quarter level 2002-2013 (3,636 obs., 76 groups). The table reports the β coefficient for log MW. Other controls are as those set for Equation 5.1 with no trends (col I of each panel) or with addition of linear to higher order polynomials. Each row represents an employment measure for either the for working-age, low-skilled , youth or older low-skilled population of male or female. For each trend included, an F-test is performed with the null hypothesis of the trends being jointly equal to zero (p-value reported).(significance: * p<.10, ** p<.05, *** p<.01).

Table 5.7: The effects of the NMW: Fixed effects 2011-2013 for male and female employment-to-population with or without trends.

(A) Male Trend	None	Linear	Quadratic	Cubic
Working-age Male	-0.002	0.039**	0.043**	0.012
	(0.016)	(0.016)	(0.016)	(0.017)
R^2	0.26	0.44	0.55	0.63
Ftest(p)		0.00	0.00	0.00
Low-skill Male	-0.001	0.045***	0.049***	0.015
	(0.017)	(0.016)	(0.017)	(0.018)
R^2	0.28	0.46	0.56	0.64
Ftest(p)		0.00	0.00	0.00
Young-lowskill Male	-0.001	0.048	0.057	-0.030
	(0.040)	(0.036)	(0.037)	(0.053)
R^2	0.13	0.32	0.41	0.49
Ftest(p)		0.00	0.00	0.00
Older-lowskill Male	-0.003	0.042**	0.046***	0.025
	(0.016)	(0.016)	(0.017)	(0.017)
R^2	0.28	0.45	0.55	0.63
Ftest(p)		0.00	0.00	0.00
(B) Female Trend	None	Linear	Quadratic	Cubic
Working-age female	0.006	0.023*	0.026**	-0.010
	(0.011)	(0.012)	(0.012)	(0.015)
R^2	0.20	0.37	0.51	0.60
Ftest(p)		0.00	0.00	0.00
Low-skilled female	0.001	0.021*	0.026*	-0.016
	(0.012)	(0.013)	(0.014)	(0.016)
R^2	0.21	0.39	0.52	0.61
Ftest(p)		0.00	0.00	0.00
Young-lowskilled female	-0.022	-0.002	-0.001	-0.073
	(0.028)	(0.035)	(0.037)	(0.054)
R^2	0.05	0.20	0.30	0.38
Ftest(p)		0.00	0.00	0.00
Older-lowskilled female	0.005	0.027**	0.033**	-0.003
	(0.012)	(0.013)	(0.014)	(0.016)
R^2	0.23	0.40	0.55	0.63
Ftest(p)		0.00	0.00	0.00

Note: LFS at province-quarter level 2011-2013 (900 obs., 75 groups). The table reports the β coefficient for log MW. Other controls are as those set for Equation 5.1 with no trends (col I of each panel) or with addition of linear to higher order polynomials. Each row represent an employment measure for either the for working-age, low-skilled , youth or older low-skilled population of male or female. For each trend included, an F-test is performed with the null hypothesis of the trends being jointly equal to zero (p-value reported).(significance: * p<.10, ** p<.05, *** p<.01).

Table 5.8: Robustness: CD tests and Driscoll-Kraay for FE 2011-2013 with or without trends.

Working-age employment-to-pop						
	Private	Indus.	Service	Private	Indus.	Service
log MW-FE	0.003	0.006	-0.002	0.030**	0.019***	-0.000
	(0.012)	(0.008)	(0.005)	(0.012)	(0.007)	(0.005)
CD tests	5.38	0.25	-0.09	3.43	4.28	1.77
pval	0.000	0.804	0.931	0.000	0.000	0.000
R^2	0.26	0.12	0.13	0.43	0.32	0.40
log MW-DK	0.003	0.006	-0.002	0.030	0.019	-0.000
	(0.020)	(0.010)	(0.002)	(0.020)	(0.013)	(0.002)
PxT trend	N	N	N	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Low-skilled employment-to-pop						
	Private	Indus.	Service	Private	Indus.	Service
log MW-FE	-0.000	0.001	0.001	0.033**	0.017**	0.003
	(0.013)	(0.008)	(0.005)	(0.013)	(0.008)	(0.006)
CD tests	6.22	1.29	-0.35	3.01	3.97	1.60
pval	0.000	0.198	0.729	0.000	0.000	0.000
R^2	0.28	0.14	0.11	0.46	0.33	0.36
log MW-DK	-0.000	0.001	0.001	0.033	0.017	0.003
	(0.023)	(0.012)	(0.002)	(0.022)	(0.014)	(0.002)
PxT trend	N	N	N	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Young-lowskilled employment-to-pop						
	Private	Indus.	Service	Private	Indus.	Service
log MW-FE	-0.009	-0.002	-0.008	0.026	0.008	0.004
	(0.028)	(0.021)	(0.014)	(0.027)	(0.019)	(0.017)
CD tests	0.77	-0.74	-0.45	0.72	0.97	1.30
pval	0.441	0.458	0.652	0.000	0.000	0.000
R^2	0.11	0.03	0.07	0.29	0.24	0.25
log MW-DK	-0.009	-0.002	-0.008	0.026*	0.008	0.004
	(0.018)	(0.010)	(0.009)	(0.013)	(0.012)	(0.010)
PxT trend	N	N	N	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Older-lowskilled employment-to-pop						
	Private	Indus.	Service	Private	Indus.	Service
log MW-FE	0.001	0.002	0.001	0.035**	0.020**	0.002
	(0.013)	(0.008)	(0.005)	(0.013)	(0.008)	(0.006)
CD tests	6.52	1.30	0.47	3.19	4.20	1.37
pval	0.000	0.192	0.638	0.000	0.000	0.000
R^2	0.28	0.15	0.11	0.46	0.34	0.34
log MW-DK	0.001	0.002	0.001	0.035	0.020	0.002
	(0.025)	(0.013)	(0.002)	(0.026)	(0.015)	(0.002)
PxT trend	N	N	N	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013

Note: LFS at province-quarter level 2011-2013 (900 obs., 75 groups). The table reports the β coefficient for log MW with CD tests and Driscoll-Kraay specification (log MW DK). Other controls are as those set for Equation 5.1. Pesaran CD test is performed for specifications without trends, Frees test for specifications with linear trends (critical values for Q distribution: alpha(0.10)=0.2136; alpha(0.05)=0.2838; alpha(0.01)=0.4252).(significance: * p<.10, ** p<.05, *** p<.01). For 2002-2013 estimation, see Appendix C.1.1.

Table 5.9: Robustness: CD tests and Driscoll-Kraay for Firm-type Epop and log hours FE 2011-2013 with or without trends.

Working-age Epop by firm size and log hours								
	Micro	SM	Large	Ln Hrs(P)	Micro	SM	Large	Ln Hrs(P)
log MW-FE	0.009	-0.001	-0.006	0.046**	0.020**	0.003	0.006	0.055**
	(0.009)	(0.007)	(0.006)	(0.021)	(0.009)	(0.007)	(0.006)	(0.023)
CD tests	5.96	0.00	-0.20	-0.21	2.89	1.41	2.02	1.79
pval	0.000	0.997	0.845	0.832	0.000	0.000	0.000	0.000
R^2	0.25	0.11	0.08	0.14	0.41	0.30	0.37	0.29
log MW-DK	0.009	-0.001	-0.006	0.046***	0.020	0.003	0.006**	0.055***
	(0.015)	(0.004)	(0.006)	(0.004)	(0.014)	(0.004)	(0.002)	(0.009)
PxT trend	N	N	N	N	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Low-skilled employment-to-pop								
	Micro	SM	Large	Ln Hrs(P)	Micro	SM	Large	Ln Hrs(P)
log MW-FE	0.011	-0.003	-0.009*	0.049**	0.024**	0.002	0.006	0.057**
	(0.010)	(0.007)	(0.006)	(0.023)	(0.010)	(0.008)	(0.006)	(0.024)
CD tests	5.78	0.31	0.47	-0.44	2.81	1.40	2.39	1.50
pval	0.000	0.754	0.636	0.661	0.000	0.000	0.000	0.000
R^2	0.24	0.11	0.08	0.13	0.41	0.32	0.37	0.28
log MW-DK	0.011	-0.003	-0.009	0.049***	0.024	0.002	0.006**	0.057***
	(0.018)	(0.005)	(0.007)	(0.005)	(0.016)	(0.004)	(0.002)	(0.009)
PxT trend	N	N	N	N	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Young-lowskilled employment-to-pop								
	Micro	SM	Large	Ln Hrs(P)	Micro	SM	Large	Ln Hrs(P)
log MW-FE	0.015	-0.011	-0.014	0.070*	0.018	-0.005	0.012	0.083**
	(0.019)	(0.016)	(0.015)	(0.036)	(0.021)	(0.019)	(0.013)	(0.040)
CD tests	-0.03	-0.59	-1.10	-0.46	0.97	0.65	1.54	0.99
pval	0.973	0.557	0.273	0.648	0.000	0.000	0.000	0.000
R^2	0.08	0.04	0.04	0.07	0.24	0.18	0.32	0.20
log MW-DK	0.015	-0.011	-0.014	0.070***	0.018*	-0.005	0.012**	0.083***
	(0.009)	(0.014)	(0.015)	(0.015)	(0.008)	(0.012)	(0.006)	(0.015)
PxT trend	N	N	N	N	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Older-lowskilled employment-to-pop								
	Micro	SM	Large	Ln Hrs(P)	Micro	SM	Large	Ln Hrs(P)
log MW-FE	0.011	-0.003	-0.008	0.045**	0.025**	0.002	0.006	0.050**
	(0.009)	(0.007)	(0.007)	(0.021)	(0.010)	(0.007)	(0.007)	(0.023)
CD tests	6.87	-0.16	1.00	-0.64	3.61	1.57	2.92	0.31
pval	0.000	0.873	0.315	0.524	0.000	0.000	0.000	0.005
R^2	0.26	0.12	0.07	0.13	0.42	0.31	0.32	0.28
log MW-DK	0.011	-0.003	-0.008	0.045***	0.025	0.002	0.006*	0.050***
	(0.020)	(0.004)	(0.006)	(0.008)	(0.020)	(0.004)	(0.003)	(0.013)
PxT trend	N	N	N	N	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013

Note: LFS at province-quarter level level 2011-2013 (900 obs., 75 groups). The table reports the β coefficient for log MW with CD tests and Driscoll-Kraay specification (log MW DK). Other controls are as those set for Equation 5.1. Pesaran CD test is performed for specifications without trends, Frees test for specifications with linear trends (critical values for Q distribution: alpha(0.10)=0.2136; alpha(0.05)=0.2838; alpha(0.01)=0.4252).(significance: * p<.10, ** p<.05, *** p<.01). For 2002-2013 estimation, see Appendix C.1.1.

5.4.3 Individual-level specification and non-wage work

We complement the provincial-level reduced form equation proposed in Equation (5.1) by reporting a specification at individual level using a Logit model (Appendix C.1.2 p.218, reports the model specification and a comparison with a Probit model). The marginal effects of the minimum wage levels, with or without trends, are reported using pooled LFS individual data.[22] In this way, we confirm the results of the provincial fixed effects model which may suffer of a small sample reducing the power for statistical inference, and also we can compare our estimates to the other two studies on the employment effects of the Thai minimum wage policy (Del Carpio et al., 2014; Ariga, 2016), which exclusively use pooled individual level regressions. Similar to Del Carpio et al. (2014) (which propose estimations for the period 2001-2010 with higher level of disaggregation by age or education), we find that over the decade, the change in minimum wages is negatively associated with the employment response for low-skilled individuals, which we find to be consistent to inclusion or exclusion of linear trends for youth low-skilled workers.

When the data are investigated for the period around the NMW, no statistically significant effect is found neither for overall private sector employment probabilities nor for low-skilled employment, as suggested from the province-level findings. When province linear-trends are included, the results on the NMW period are in line with Ariga (2016) (which uses only Q2 of each year) in suggesting a positive employment probability response for the low-skilled workers involved in the Industry sector. Overall, the estimations confirm the main results with or without trends. However, as emerged from the previous section, the province-specific trends induce cross-sectional dependence once applied to the panel dimension of the data, thus we interpret with caution the results with province-specific trends and keep as our preferred estimate the model without trends.

Given the settings of the Thai economy, with low unemployment and high rates

[22] We acknowledge the fact that the use of a logit or probit regressions may not fully capture the behavioural choice linked to different forms of employment. Applying a different estimation such as a multinomial logit (with status options being employment in the private sector versus public, self-employment, unpaid work, unemployment and not in the labour force) leads to similar results to the one of the standard logit, but does not satisfy the property of Independence of Irrelevant Alternatives in all of its outcomes (tested through a Small-Hsiao test), thus it is not reported.

of informal work, we want to test with the individual level data if there are any signs of modification to types of non-wage employment. We test whether the adjustments in the minimum wage resulted in higher rates of participation to self-employment or unpaid work. Non-wage work is the main outside option in place of unemployment in the country, so we would expect a job loss by specific types of workers to be visible in this proxy of informal work. Table 5.10 (Panel A) below reveals that over the decade (2002-2013), no statistically significant effect is found.

Around the NMW introduction (Panel B), a marginally significant positive effect is found for male low-skilled participation to unpaid work, suggesting that for a 70% increase in the log minimum wage the probability of being an unpaid worker raises by almost 4%. For young low-skilled female, a 70% increase in the wage floor reduces the probability of self-employment by 6.37%. However, no other significant effect is found when the female population is investigated or when both male and female populations are investigated by age. The table is suggestive of a minor adjustments of non-wage employment in response to the policy change, confirming the aggregate province-level results reported in Table 5.4 for low-skilled employment. Therefore, we can exclude that shifts outside of the private sector into forms of informality have been generated by the policy hike. However, due to data limitations in identifying informal wageworkers, we are not able to test how the overall informal sector behaved as the the results may be confounded by the narrow definition of non-wage employment used.

Table 5.10: Marginal effects of log MW on self-employment and unpaid work, Logit regression, individual level.

Panel A. 2002-2013				
	Male		Female	
	Self	Unpaid	Self	Unpaid
Working-age	-0.042	-0.004	-0.021	-0.008
	(0.038)	(0.021)	(0.022)	(0.034)
Obs	2,793,533	2,793,533	3,295,684	3,295,684
LL	-5.02e+08	-3.33e+08	-4.48e+08	-4.88e+08
Low-skilled	-0.054	-0.008	-0.035	-0.005
	(0.042)	(0.025)	(0.024)	(0.036)
Obs	2,316,010	2,316,010	2,684,519	2,684,519
LL	-4.45e+08	-2.97e+08	-4.02e+08	-4.39e+08
Young-lowskilled	-0.036	0.023	-0.002	-0.107
	(0.037)	(0.083)	(0.043)	(0.080)
Obs	307,786	307,786	270,903	270,903
LL	-40187185	-79885959	-27124734	-59594230
Older-lowskilled	-0.060	-0.008	-0.040	0.011
	(0.048)	(0.026)	(0.025)	(0.034)
Obs	2,008,224	2,008,224	2,413,616	2,413,616
LL	-4.04e+08	-2.16e+08	-3.74e+08	-3.72e+08
Panel B. 2011-2013				
	Male		Female	
	Self	Unpaid	Self	Unpaid
Working-age	-0.045	0.038	-0.027	0.006
	(0.038)	(0.030)	(0.021)	(0.053)
Obs	732,226	732,226	842,875	842,875
LL	-1.33e+08	-92690234	-1.20e+08	-1.27e+08
Low-skilled	-0.052	0.057*	-0.030	0.032
	(0.043)	(0.032)	(0.024)	(0.052)
Obs	604,148	604,148	674,768	674,768
LL	-1.15e+08	-81522682	-1.04e+08	-1.11e+08
Young-lowskilled	-0.038	0.128	-0.091*	-0.063
	(0.049)	(0.105)	(0.049)	(0.079)
Obs	74,655	74,655	60,620	60,620
LL	-9284367	-19260684	-6299842	-13576945
Older-lowskilled	-0.059	0.046	-0.022	0.046
	(0.049)	(0.029)	(0.026)	(0.053)
Obs	529,493	529,493	614,148	614,148
LL	-1.05e+08	-61824010	-97646913	-96289608

Note: LFS individual level 2002-2013 and 2011-2013 (male or female pop.), Logit model. The table reports the marginal effects for log MW. Each cell represents a non-wage employment response model for either the working-age, low-skilled, youth or older low-skilled population of males or females. Controls: years of schooling, married binary, potential experience and its squared, population characteristics (share of other gender in prime-age, of overall youth, elderly and high skilled), log GPP pc, rural binary, quarter-year and province dummies. Observations and Log Likelihood are reported with robust SE (unconditional variance), survey weights are applied (significance: * p<.10, ** p<.05, *** p<.01).

5.5 Interpreting the effects of the minimum wage

The distributional analysis showed that the minimum wage has a positive effect on provincial wages, perpetrating until the 60^{th} percentile of the distribution, but with non-response at the lowest percentiles. The employment analysis showed signs of minor contractions, localised towards low-skilled female individuals over the decade under analysis, with no strong employment effects generated by the sizeable increase in the latest statutory minimum wage. In light of the insights of the short-run effects of the latest policy change, two elements are worth noting.

On the one side, due to the sizeable hike induced to otherwise relatively stagnant provincial real minimum wages, the reductions to Social Security Scheme (SSS) contributions, withholding and corporate income taxes may have played a substantial role in allowing complying firms to adjust to the rising price of labour. Understanding the mechanisms behind this combination of policies would require firm-level data (unavailable to the authors at time of writing).[23] Tentatively we would expect that the average increase in hours worked due to the NMW may be reflected in higher firm productivity (measured as output per worker for example) after the policy change. It would be interesting for future research to inspect if the policy hike has indeed generated higher efficiency of production as is found in the United Kingdom (Riley and Rosazza Bondibene, 2017). On the other side, the lack of strong effects found in employment and the descriptive evidence of higher localised wage non-compliance between 2011 and 2013 raise concerns that the low probability of detection may not be deterring non-complying behaviour. In Appendix C.4 we report the statistics on labour inspections available for year 2013. The literature stresses that firms will respond to policies according to the probability of being detected and to the size of the expected penalty (Polinsky and Shavell, 2000). The statistics show a disaggregation of nation-wide labour inspections by firm size (Table C.13, p.238), revealing that out of the 13.7% of population of firms inspected, on average only the 7.2% of micro-firms with less than 5 employees were actually visited, followed by the 11.9% of firms with 5-9 employees, and in contrast to the 24.4% of firms with 10-19 employees. We take this as an indication that smaller firms are less likely to receive a labour inspection (and this trend is common across

[23] At time of writing the last firm level dataset available is for 2012 and a new survey is expected to come out next year covering 2017.

countries, see Almeida and Ronconi 2016).[24] Out of the number of inspected firms found in non-compliance of any type of regulation, only the 4.5% of them received either a penalty or a prosecution. The law states that, under infringement of labour regulations, the employers may be subject to a penalty up to US$ 643.50 (20,000 Bhat, 2012 exchange rate). Putting this in perspective of payments at the 300 Baht minimum wage, it would account for 67 days (around three months) of payment to a single worker. Due to the low number of inspections visible for year 2013, and the increased rate of non-compliance detected in the data, there may be signs that "turning a blind eye" (Basu et al., 2010) has contributed to avoid employment losses at the cost of some redistributive deficiency, and that the threat of the penalty may not be enough to deter unlawful behaviour.

Thus, we reconcile our findings for Thailand with a scenario of imperfect competitive markets with imperfect commitment and imperfect enforcement (Basu et al., 2010). Once a higher minimum is introduced, the effects on aggregate employment are minimally damaging because some firms are able to comply, while others can retain workers at the cost of some violations of the law. This does not prevent the generation of sizeable positive effects on the wage distribution, as those reported in the previous chapter. The results show that prior to the NMW change some firms moved away from low-skilled workers, and some may have been acting with some degree of market power. Through a higher minimum wage imposed through the NMW, they either redistribute some of the rents that were available prior to the policy change, or manage to absorb, through the tax reductions, any rent loss. This then would explain the sizeable wage effects, no massive employment effects and higher hours worked by their employees. At the same time, the results in the thesis show that particularly smaller firms may be acting in partial compliance, expressed at a sub-minimum equilibrium which is not fully catching up with the policy due to low enforcement (Basu et al., 2010; Bhorat et al., 2015).

The immediate policy implication is that, due to the localised non-compliance found,

[24] According to the ILO (2017b), information collection on firms activity in Thailand is carried either through self-assessments for SMEs on the implementation of labour laws or through standard labour inspection visits. The self-assessment covers all SMEs which are required to address a set of 50 questions on 19 areas of conduct of the Labour Protection Act. If in the review of the questionnaire more than 70% of the answers show compliance, no inspection of the enterprise takes place. For official inspections, two types of inspections are generally carried, one to verify the general conditions of work (in which wage contracting and minimum wage compliance enter) and another for occupational health and safety. Visits can be initiated by request or complaint, as part of the general or provincial plans or as a follow-up visit to a previous inspection (ILO, 2017b).

more inspections may be needed to realign firms' incentives towards higher commitment. On the one side, the approach of complementing a minimum wage adjustment with tax rebates may have generated no employment contractions. On the other side, the low probability of detection for non-complying firms and the low institutional protection of workers (in the absence or sparse presence of trade unions) raise some concerns over the sustainability of the redistributive effects of the policy. If labour inspections continue to be as low as in 2013, we might expect some groups of wage earners being kept at the low-end of the wage distribution in the future, thus increasing wage inequality. This income gain gaps may realise even with the present return to geographically determined wage floors, and future inspections on this issue are warranted. Additionally, as workers paid sub-minimum wage are more likely to be informal, thus not covered by the SSS, concerns over potential increases in old-age poverty in the future might arise. Given that only the first quarters of NMW data are available at time of writing, we also acknowledge that more data points are needed for the full policy effect to emerge.

5.6 Conclusion

This chapter evaluates the employment effects of the minimum wage policy in Thailand. The work draws on the minimum wage literature and applies various econometric methods to a reduced form equation of provincial labour market demand, both in a static and dynamic form. We evaluate the effects generated by the policy over the 2000s and give some insights on the short run effects of the NMW introduction, presenting estimates for employment, labour force composition and hours worked.

We find some evidence of small but significant negative employment effects for the low-skilled, particularly young female population, with no major contraction for other groups of the population over the 2002-2013 decade. Additionally, secondary estimations show that these employment contractions appear to be geographically concentrated in provinces which have experienced a low minimum wage regime. Aggregate private sector employment seems stable over the 2000s, and some small downward adjustments are also provoked to the non-covered agricultural sector. Investigating on the dynamic response of employment over the 2000s, we show some evidence of higher participation of high-skilled individuals, of some delayed low-skilled employment contractions in micro-enterprises and SMEs, but no signs of strong anticipatory effects to a policy change.

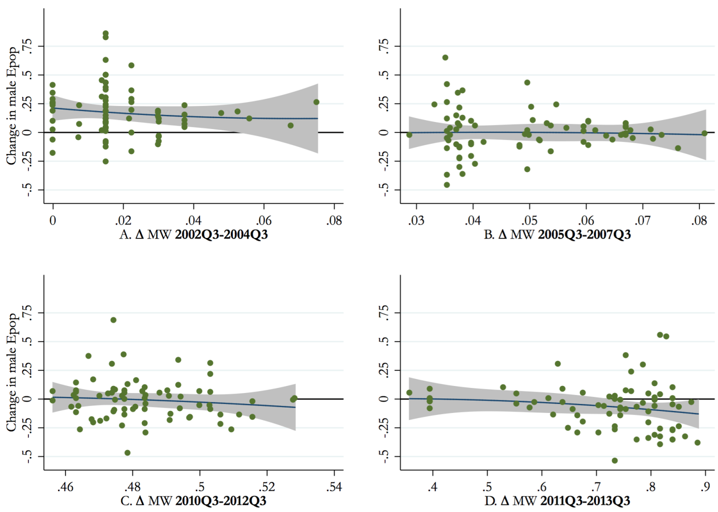
For the 2011-2013 period, we find that the introduction of the NMW has generated no visible short-term effect on provincial employment, but some positive effects on average hours worked for both the low-skilled female and male populations. We interpret this increase of the intensive margin of employment as a positive short-term market absorption of the minimum wage rise. Nevertheless, we think more data are needed to better understand the employment response to the Thai minimum wage harmonisation. We also find that non-wage employment is not affected by variations in the policy, during the whole decade as well as during the latest regime change. This results go in line with other studies (Lemos, 2009) which reject the predictions of the dual labour market theory. However, as discussed in the chapter, these effects may be confounded by the inability in identifying the size of informal wage employment, an interesting avenue for future research aiming to address the impact of the policy on this type of informal work.

Putting together the main findings on the wage and employment effects, the application of a higher minimum wage appears to induce some mixed responses. After a prolonged period of stagnation in real minimum wages, some gains arise for wage workers who obtain through the regime change a higher reward for their labour. Further gains arise for firms, which may find a bigger pool of candidates in the market available for work. The losses appear to be the fair reward of those paid at the bottom of the wage distribution, as firms may easily not comply with the law, and the localised contraction in work affecting particularly low skilled females over the 2000s. From a social planner perspective, the minimum wage policy appears to have partially increased social welfare, with positive distributional effects around the minimum and localised employment losses during the first policy regime. This happens in a situation of imperfect enforcement and commitment, in which the social planner is more interested in efficiency than in distribution (Basu et al., 2010). We cautiously conclude that workers could be penalised in the future if rising rates of non-compliance are not tackled. Although we are only able to show some evidence for the early stages of the new policy, this work suggests that the fast increase and harmonisation to a single minimum wage was useful in reviving the wage distribution without damaging employment. Future adjustments could be coupled with new sets of guidelines for employers on the risks of non-compliance and potentially better enforcement activity.

Appendix C

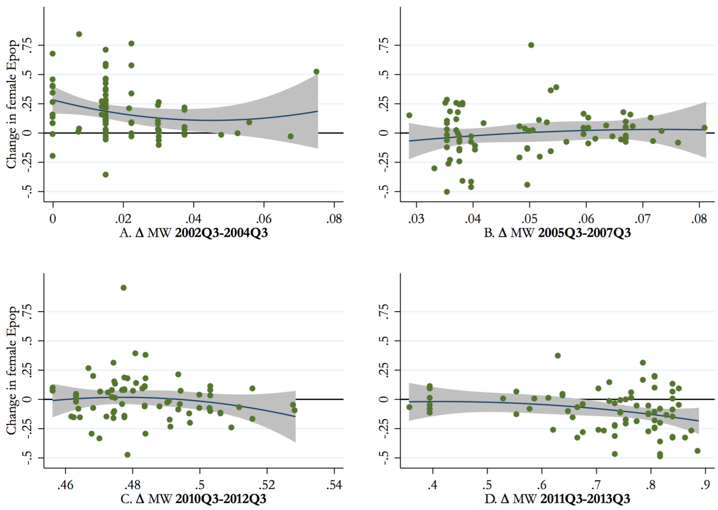
Appendix for Employment analysis

Figure C.1: Changes in male Epop and the minimum wage by province, Q3 of selected years.



Notes: Scatterplot with quadratic prediction of the change between the nominal hourly minimum wage (MW) and changes in private sector employment-to-population Epop of the male population. For linear prediction, see Fig.5.1

Figure C.2: Changes in female Epop and the minimum wage by province, Q3 of selected years.



Notes: Scatterplot with quadratic prediction of the MW Δ and private Epop Δ of the female population.

Table C.1: Summary statistics: Average employment-to-population across low-skilled workers (male and female) by age.

	Young-lowskilled						Older-lowskilled					
	2002-13		2011-13		Test		2002-13		2011-13		Test	
	M	F	M	F	M	F	M	F	M	F	M	F
Overall	0.88	0.66	0.89	0.64	0.00	0.00	0.88	0.66	0.89	0.64	0.00	0.00
St.dev.	0.07	0.12	0.07	0.11			0.07	0.12	0.07	0.11		
NonWage	0.41	0.31	0.43	0.31	0.02	0.78	0.41	0.31	0.43	0.31	0.02	0.78
St.dev.	0.18	0.16	0.18	0.16			0.18	0.16	0.18	0.16		
Private	0.46	0.35	0.45	0.33	0.11	0.00	0.46	0.35	0.45	0.33	0.11	0.00
St.dev.	0.17	0.18	0.17	0.17			0.17	0.18	0.17	0.17		
Industry	0.22	0.17	0.21	0.14	0.19	0.00	0.22	0.17	0.21	0.14	0.19	0.00
St.dev.	0.14	0.17	0.13	0.14			0.14	0.17	0.13	0.14		
Service	0.14	0.13	0.15	0.14	0.08	0.00	0.14	0.13	0.15	0.14	0.08	0.00
St.dev.	0.09	0.09	0.09	0.10			0.09	0.09	0.09	0.10		
Agri.	0.10	0.05	0.09	0.05	0.00	0.00	0.10	0.05	0.09	0.05	0.00	0.00
St.dev.	0.08	0.06	0.08	0.05			0.08	0.06	0.08	0.05		
Micro	0.24	0.13	0.24	0.13	0.21	0.45	0.24	0.13	0.24	0.13	0.21	0.45
St.dev.	0.11	0.08	0.11	0.08			0.11	0.08	0.11	0.08		
SME	0.12	0.08	0.12	0.08	0.00	0.83	0.12	0.08	0.12	0.08	0.00	0.83
St.dev.	0.08	0.06	0.08	0.07			0.08	0.06	0.08	0.07		
Large	0.10	0.13	0.09	0.11	0.14	0.00	0.10	0.13	0.09	0.11	0.14	0.00
St.dev.	0.13	0.16	0.13	0.14			0.13	0.16	0.13	0.14		
Ln hrs	3.74	3.74	3.74	3.74	0.98	0.16	3.74	3.74	3.74	3.74	0.98	0.16
St.dev.	0.17	0.20	0.17	0.19			0.17	0.20	0.17	0.19		
Ln hrs(Priv)	3.87	3.89	3.87	3.89	0.65	0.68	3.87	3.89	3.87	3.89	0.65	0.68
St.dev.	0.11	0.13	0.10	0.10			0.11	0.13	0.10	0.10		

Note: LFS, pooled province-level panel. Average employment-to-population and standard deviation (St.dev.) are reported for low-skilled population of young (15-24) or older (25-65) male (M) and female (F) population. Data for 2002-2013 (3636 obs) and 2011-2013 (900 obs). T-test (with equal or unequal variance) p-value is reported for each group. H0: equality in means of 2011-2013 with previous period.

C.1 Fixed effects regression

Table C.2: Fixed effects of employment-to-population with interaction term for being in low minimum wage regime province, 2002-2013.

	All	No W	Priv.	Indus.	Serv.	Agri.	Micro	SME	Large	Log Hrs	P Hrs
L*WA	0.003	0.004	-0.036*	-0.025	-0.011	0.005	0.003	0.007	-0.040**	-0.005	-0.027
	(0.009)	(0.023)	(0.020)	(0.016)	(0.013)	(0.012)	(0.011)	(0.012)	(0.018)	(0.032)	(0.027)
WA	-0.044*	-0.044	0.078	0.039	0.039	-0.052	-0.017	-0.044	0.087*	-0.104	-0.029
	(0.026)	(0.064)	(0.048)	(0.043)	(0.027)	(0.032)	(0.029)	(0.028)	(0.045)	(0.076)	(0.066)
L*LS	0.005	0.017	-0.034	-0.022	-0.011	0.007	0.005	0.009	-0.040*	-0.005	-0.028
	(0.010)	(0.026)	(0.022)	(0.018)	(0.013)	(0.014)	(0.013)	(0.013)	(0.020)	(0.035)	(0.029)
LS	-0.049*	-0.071	0.070	0.024	0.046*	-0.053	-0.016	-0.042	0.073	-0.120	-0.042
	(0.029)	(0.069)	(0.054)	(0.047)	(0.025)	(0.035)	(0.034)	(0.029)	(0.048)	(0.082)	(0.072)
L*Y-LS	0.022	-0.016	0.008	0.041	-0.033	0.021	-0.002	0.016	0.015	0.013	-0.025
	(0.022)	(0.038)	(0.046)	(0.043)	(0.025)	(0.022)	(0.020)	(0.021)	(0.041)	(0.038)	(0.033)
Y-LS	-0.185***	0.012	-0.134	-0.178	0.045	-0.082	0.016	-0.107**	-0.126	-0.194**	-0.090
	(0.061)	(0.097)	(0.117)	(0.117)	(0.045)	(0.057)	(0.053)	(0.044)	(0.099)	(0.095)	(0.089)
L*O-LS	-0.00022	0.027	-0.049**	-0.041**	-0.008	0.005	0.006	0.007	-0.056***	-0.014	-0.032
	(0.01122)	(0.027)	(0.022)	(0.017)	(0.012)	(0.013)	(0.013)	(0.012)	(0.020)	(0.035)	(0.028)
O-LS	-0.015	-0.080	0.104*	0.064	0.040	-0.040	-0.020	-0.039	0.123**	-0.133	-0.056
	(0.030)	(0.069)	(0.053)	(0.045)	(0.025)	(0.031)	(0.033)	(0.029)	(0.049)	(0.086)	(0.072)

Note: LFS 2002-2013 province panel (3,636 obs). Samples: Overall population (WA); Low-skilled (LS); Young low-skilled (Y-LS); Older low-skilled (O-LS). The table reports the minimum wage coefficient (labeled by sample name) or its interaction with a binary for being in a low minimum wage regime (L). Low minimum wage provinces are defined as those provinces with a real mean minimum wage lower than the national average over the period (56 provinces). Controls as main specification (significance: * p<.10, ** p<.05, *** p<.01).

C.1.1 Tables for Province-trends and Discroll-Kraay estimations

In this section we provide a fuller account of the estimations using linear and polynomial trends and of the inspection for potential cross-sectional dependence in the panel fixed effects specification.

For the full decade under analysis (Table C.3), the inclusion of linear trends reveals a significantly negative semi-elasticity of the employment measures, confirming the main results by the negative sign found for young low-skilled employment (Panel C, Table C.3). For the period around the NMW introduction (Table C.4), some positive effects are found.

As standard procedure to ensure validity of the statistical results, in the main specification we adjust the standard errors to control for possible dependence in the residuals, producing, with robust standard errors, a heteroscedasticity-consistent covariance estimator. However, there could still be the presence of cross-sectional dependence. We apply the Pesaran (2004) CD test for the Fixed Effects (FE) regression without trends, which is a parametric test for both balanced and unbalanced panels. When the trends are included, we apply the Frees (1995) test statistic (a nonparametric test following a

Q distribution).[1] The Frees test though has the limitation to account for dependency only in the balanced component of the data, thus for the 2002-2013 estimations it will test for 75 groups (see De Hoyos and Sarafidis (2006) for further explanation on the tests). The null hypothesis for both tests is that the product-moment correlation coefficient of the disturbances of any observations i and j is equal to zero (cross-sectional independence).

Both the 2002-2013 estimations (Tables C.5–C.6) and the 2011-2013 estimations (Section 5.4.2) show that the specifications without trends do not suffer of CD (with exception of participation to private sector, micro and large firms), whereas the inclusion of trends does generate CD (cross-sectional independence is rejected in all but one instance).

To account for CD in panel data, Driscoll and Kraay (1998) propose a non-parametric covariance matrix estimator which allows for autocorrelation that is robust to spatial and temporal dependence in addition to heteroscedasticity. Their core improvement on other non-parametric estimators is to allow for N (number of groups) to be larger than T (number of time periods), thus not constraining the feasibility of the estimator (Driscoll and Kraay, 1998). However, Hoechle (2007) suggests caution in applying the estimator to a panel dataset with a large number of N and a very small number of T (it relies on large T asymptotic property). In our case, with a N(all)=76 T(all)=48 and a N(NMW)=75 T(NMW)=12 we are particularly cautious in the reliability of the estimator for the NMW analysis. Acknowledging this limitation of the estimator for the time period available, we perform the application to test for robustness of the estimates. The results are commented in Section 5.4.2.

[1]The Frees test is a test statistic based on the sum of the squared rank correlation coefficients across observations, which follows a Q distribution. The Q distribution is a weighted sum of the χ^2 distributions of two random variables and depends on the size of time under analysis. When time is not too small (time greater than 30) the test can be approximated to follow a normal distribution (De Hoyos and Sarafidis, 2006). The procedure of this test solves a limitation of the Pesaran test, which is not to be able to detect cases of cross-sectional dependence when the sign of the correlations across observations is alternating, that is why De Hoyos and Sarafidis (2006) suggests its use when trends are included as variables in the analysis.

Table C.3: Comparison of fixed effects estimates with or without trends: 2002-2013 private employment-to-population by groups.

Trend	None	Linear	Quadratic	Cubic	Quartic
A. Working-age sample					
	(I)	(II)	(III)	(IV)	(V)
β MW	-0.017	-0.022*	0.005	0.012	0.016
	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)
R^2	0.23	0.36	0.43	0.47	0.49
Ftest(p)		0.00	0.00	0.00	0.00
B. Low-skilled sample					
	(I)	(II)	(III)	(IV)	(V)
β MW	-0.021	-0.028**	0.006	0.014	0.016
	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
R^2	0.24	0.36	0.43	0.47	0.49
Ftest(p)		0.00	0.00	0.00	0.00
C. Young-lowskilled sample					
	(I)	(II)	(III)	(IV)	(V)
β MW	-0.061**	-0.059**	-0.016	0.002	0.001
	(0.027)	(0.025)	(0.025)	(0.025)	(0.026)
R^2	0.09	0.17	0.23	0.27	0.29
Ftest(p)		0.00	0.00	0.00	0.00
D. Older-lowskilled sample					
	(I)	(II)	(III)	(IV)	(V)
β MW	-0.017	-0.026**	0.012	0.018	0.020
	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)
R^2	0.25	0.39	0.46	0.50	0.52
Ftest(p)		0.00	0.00	0.00	0.00

Note: LFS 2002-2013 at province level, unbalanced panel (3,636 obs.,76 groups). The table reports the β coefficient for log MW. Other controls are as those set for Equation 5.1 with no trends (col I of each panel) or with addition of linear to higher order polynomials. Panel A reports private sector employment-to-population (both male and female) for the whole working-age sample, Panel B for the low-skilled population, Panel C for young (15-24) low-skilled, Panel D for older low-skilled (25-65). For each trend included, an F-test is performed with the null hypothesis of the trends being jointly equal to zero (p-value reported).

Table C.4: Comparison of fixed effects estimates with or without trends: 2011-2013 private employment-to-population by groups.

Trend	None	Linear	Quadratic	Cubic
A. Working-age sample				
	(I)	(II)	(III)	(IV)
β MW	0.003	0.030**	0.034**	-0.001
	(0.012)	(0.012)	(0.013)	(0.014)
R^2	0.26	0.43	0.56	0.64
Ftest(p)		0.00	0.00	0.00
B. Low-skilled sample				
	(I)	(II)	(III)	(IV)
β MW	-0.00004	0.033**	0.037**	-0.002
	(0.01307)	(0.013)	(0.014)	(0.014)
R^2	0.28	0.46	0.57	0.66
Ftest(p)		0.00	0.00	0.00
C. Young-lowskilled sample				
	(I)	(II)	(III)	(IV)
β MW	-0.009	0.026	0.031	-0.049
	(0.028)	(0.027)	(0.028)	(0.043)
R^2	0.11	0.29	0.38	0.46
Ftest(p)		0.00	0.00	0.00
D. Older-lowskilled sample				
	(I)	(II)	(III)	(IV)
β MW	0.001	0.035**	0.040***	0.010
	(0.013)	(0.013)	(0.014)	(0.014)
R^2	0.28	0.46	0.58	0.66
Ftest(p)		0.00	0.00	0.00

Note: LFS 2011-2013 at province level, balanced panel (900 obs., 75 groups). The table reports the β coefficient for log MW. Other controls (delineated in note of Table **??**) with no trends (col I of each panel) or with addition of linear to cubic order polynomials. Panel A reports private sector employment-to-population for the whole working-age sample, Panel B for the low-skilled population, Panel C for young (15-24) low-skilled, Panel D for older low-skilled (25-65). For each trend included, an F-test is performed with the null hypothesis of the trends being jointly equal to zero (p-value reported).

Table C.5: Robustness: CD tests and Driscoll-Kraay for FE 2002-2013 with or without trends.

Working-age employment-to-pop						
	Private	Indus.	Service	Private	Indus.	Service
log MW-FE	-0.017	0.002	0.002	-0.022*	-0.000	0.001
	(0.013)	(0.008)	(0.006)	(0.012)	(0.008)	(0.005)
CD tests	4.84	-1.54	-1.16	3.06	3.70	1.23
pval	0.000	0.124	0.245	0.000	0.000	0.000
R^2	0.23	0.20	0.24	0.36	0.30	0.34
log MW-DK	-0.017	0.002	0.002	-0.022	-0.000	0.001
	(0.014)	(0.008)	(0.005)	(0.013)	(0.009)	(0.004)
PxT trend	N	N	N	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Low-skilled employment-to-pop						
	Private	Indus.	Service	Private	Indus.	Service
log MW-FE	-0.021	-0.003	0.004	-0.028**	-0.005	0.002
	(0.014)	(0.008)	(0.005)	(0.013)	(0.008)	(0.004)
CD tests	5.65	-1.03	-1.17	3.08	3.38	1.09
pval	0.000	0.301	0.241	0.000	0.000	0.000
R^2	0.24	0.20	0.16	0.36	0.30	0.27
log MW-DK	-0.021	-0.003	0.004	-0.028*	-0.005	0.002
	(0.014)	(0.008)	(0.006)	(0.015)	(0.010)	(0.005)
PxT trend	N	N	N	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Young-lowskilled employment-to-pop						
	Private	Indus.	Service	Private	Indus.	Service
log MW-FE	-0.061**	-0.039	-0.006	-0.059**	-0.033	-0.006
	(0.027)	(0.024)	(0.015)	(0.025)	(0.020)	(0.013)
CD tests	0.70	-1.42	-1.17	0.68	0.73	0.37
pval	0.486	0.155	0.241	0.000	0.000	0.000
R^2	0.09	0.10	0.07	0.17	0.21	0.15
log MW-DK	-0.061**	-0.039	-0.006	-0.059*	-0.033	-0.006
	(0.027)	(0.024)	(0.012)	(0.030)	(0.021)	(0.007)
PxT trend	N	N	N	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Older-lowskilled employment-to-pop						
	Private	Indus.	Service	Private	Indus.	Service
log MW-FE	-0.017	-0.001	0.005	-0.026**	-0.003	0.002
	(0.013)	(0.008)	(0.005)	(0.012)	(0.008)	(0.005)
CD tests	6.79	-0.91	-0.65	2.77	3.59	1.27
pval	0.000	0.363	0.515	0.000	0.000	0.000
R^2	0.25	0.24	0.18	0.39	0.35	0.29
log MW-DK	-0.017	-0.001	0.005	-0.026*	-0.003	0.002
	(0.016)	(0.009)	(0.006)	(0.015)	(0.009)	(0.004)
PxT trend	N	N	N	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013

Note: LFS at province-quarter level 2002-2013 (3,636 obs., 76 groups). The table reports the β coefficient for log MW with CD tests and Driscoll-Kraay specification (log MW DK). Other controls are as those set for Equation 5.1. Pesaran CD test is performed for specifications without trends, Frees test for specifications with linear trends (with approximation to a normal distribution as $T \geq 30$).(significance: * p<.10, ** p<.05, *** p<.01).

Table C.6: Robustness: CD tests and Driscoll-Kraay for Firm-type Epop and log hours FE 2002-2013 with or without trends.

Working-age employment-to-pop								
	Micro	SM	Large	Ln Hrs(P)	Micro	SM	Large	Ln Hrs(P)
log MW-FE	-0.015*	-0.007	0.005	-0.014	-0.019**	-0.002	-0.001	0.008
	(0.009)	(0.008)	(0.007)	(0.022)	(0.008)	(0.007)	(0.006)	(0.021)
CD tests	8.29	0.71	4.05	1.74	2.04	1.01	2.01	1.91
pval	0.000	0.477	0.000	0.082	0.000	0.000	0.000	0.000
R^2	0.13	0.12	0.15	0.13	0.26	0.21	0.33	0.28
log MW-DK	-0.015	-0.007	0.005	-0.014	-0.019*	-0.002	-0.001	0.008
	(0.009)	(0.007)	(0.008)	(0.026)	(0.011)	(0.004)	(0.005)	(0.018)
PxT trend	N	N	N	N	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Low-skilled employment-to-pop								
	Micro	SM	Large	Ln Hrs(P)	Micro	SM	Large	Ln Hrs(P)
log MW-FE	-0.014	-0.008	0.001	-0.017	-0.020**	-0.004	-0.004	0.013
	(0.010)	(0.008)	(0.007)	(0.023)	(0.010)	(0.008)	(0.006)	(0.022)
CD tests	8.41	1.46	2.79	1.36	2.00	1.14	1.98	1.89
pval	0.000	0.145	0.005	0.173	0.000	0.000	0.000	0.000
R^2	0.14	0.12	0.13	0.12	0.27	0.20	0.29	0.28
log MW-DK	-0.014	-0.008	0.001	-0.017	-0.020	-0.004	-0.004	0.013
	(0.011)	(0.006)	(0.007)	(0.028)	(0.012)	(0.004)	(0.005)	(0.019)
PxT trend	N	N	N	N	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Young-lowskilled employment-to-pop								
	Micro	SM	Large	Ln Hrs(P)	Micro	SM	Large	Ln Hrs(P)
log MW-FE	-0.007	-0.023	-0.030	-0.002	-0.017	-0.014	-0.027*	0.034
	(0.019)	(0.016)	(0.019)	(0.032)	(0.019)	(0.015)	(0.015)	(0.032)
CD tests	-0.47	-0.24	2.77	-0.83	0.37	0.25	2.00	0.80
pval	0.637	0.813	0.006	0.408	0.000	0.000	0.000	0.000
R^2	0.06	0.06	0.12	0.06	0.12	0.10	0.24	0.15
log MW-DK	-0.007	-0.023*	-0.030	-0.002	-0.017	-0.014	-0.027	0.034*
	(0.015)	(0.013)	(0.022)	(0.033)	(0.011)	(0.012)	(0.023)	(0.017)
PxT trend	N	N	N	N	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Older-lowskilled employment-to-pop								
	Micro	SM	Large	Ln Hrs(P)	Micro	SM	Large	Ln Hrs(P)
log MW-FE	-0.016*	-0.007	0.005	-0.027	-0.021**	-0.003	-0.002	0.005
	(0.009)	(0.008)	(0.007)	(0.023)	(0.009)	(0.007)	(0.007)	(0.023)
CD tests	9.75	1.53	5.85	1.89	2.04	1.00	1.90	1.58
pval	0.000	0.126	0.000	0.059	0.000	0.000	0.000	0.000
R^2	0.15	0.12	0.16	0.12	0.28	0.21	0.36	0.28
log MW-DK	-0.016	-0.007	0.005	-0.027	-0.021	-0.003	-0.002	0.005
	(0.011)	(0.007)	(0.010)	(0.031)	(0.013)	(0.004)	(0.003)	(0.021)
PxT trend	N	N	N	N	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013

Note: LFS at province-quarter level 2002-2013 (3,636 obs., 76 groups). The table reports the β coefficient for log MW with CD tests and Driscoll-Kraay specification (log MW DK). Other controls are as those set for Equation 5.1. Pesaran CD test is performed for specifications without trends, Frees test for specifications with linear trends (with approximation to a normal distribution as T$\geq$30).(significance: * p<.10, ** p<.05, *** p<.01).

C.1.2 Individual level regression: Logit and Probit models with marginal effects

Below we report the results from a pooled Logit and a Probit models for the male population. For both specifications we define the response probability $P(y = 1|x) = P(y = 1|x_1, ...x_k)$ using the following specification:

$$P(y_{\text{ipt}} = 1|x) = \beta_0 + \beta_1 \text{MW}_{\text{pt}} + \beta_2 X_{\text{ipt}} + \phi_t + \phi_p + \omega_{pt} + \varepsilon_{\text{pt}} \tag{C.1}$$

Where the response variable y for individual i in province p in quarter-year t is the employment probability which is regressed against the log minimum wage (MW_{pt}), a set of covariates X, province and time intercepts (ϕ_p and ϕ_t respectively) and an error term. The outcome variable y captures the employment probability, first for overall employment (any form of work) and later for different categories such as: non-wage employment (being self-employment or in unpaid work); private sector wage employment (MW covered sectors). These are further split across aggregate sectors (industrial or services), in addition to agriculture. The X vector includes individual characteristics (age, experience and its squared, and a binary variable capturing marital status); province-specific demographic shifters (share of female in prime age, 25-54; share of youth males; share of elderly males and the share of high-skilled population); past log GPP per capita; and a binary variable taking the value 1 when the individual comes from a rural area. In some of the specifications, a province specific trend (ω_{pt}) is also introduced and compared to a model without trends (see Table C.10 against Table C.9).

Across different specifications, we modify the population sample to identify the working-age population which is low-skilled (lower than secondary education) and the low-skilled youth (aged 24 and under). We report the marginal effects of the minimum wage on the probability of employment. As we have a representative sample of the population and we use survey weights in both Logit and Probit models (with clustered standard errors at province level), we perform the standard error calculation for the marginal effects based on linearisation to estimate the unconditional variance instead of the delta method (Korn and Graubard, 1999).[2]

[2]For the Logit model the response probability is the logistic function evaluated as a linear function of the covariates. For the Probit model the response probability is the standard normal CDF evaluated

The Logit model without trends (Table C.7) shows a negative marginal effect only for youth low-skilled participation in the private sector. Over the 2002-2013 period it shows that a 10 percent increase in the minimum wage induces a contraction of -1.6 percent in the probability of employment. This relationship remains statistically significant for the NMW period (2011-2013) with a -1.34 percent reduction (significance at 10 percent), but there is no indication of which sector is driving the results.

The Logit model with the inclusion of linear trends (Table C.8) gives a more pronounced picture on the introduction of the NMW (2011-2013). It shows that, for the working-age population, there is a negative marginal effect on non-covered occupations such as non-wage work. However, this is counterbalanced by a positive marginal effect on private sector participation, especially in the Industry sector for the low-skilled population (a 10 percent increase in the MW induces a 1.86 increase in the probability of employment). With regards to the young low-skilled, over the entire period (2002-2013) the specification confirms the negative marginal effect on participation to the private sector. However, the specification shows no statistically significant effect for the NMW period, suggesting that the fast increase in the minimum did not negatively affect participation of the potentially most vulnerable group of low educated youth.[3]

as a linear function of the covariates. The main difference between the binary response models Logit and Probit lies on the nonlinear function used to model the interaction of covariates $P(y = 1|x) = G(\beta_0 + x\beta)$: Logit applies a logistic distribution ($G(z) = exp(z)/[1 + exp(z)] = \Lambda(z)$), whereas Probit uses the standard cumulative distribution function ($G(z) = \Phi(z) = \int_{-\infty}^{z} \phi(v)dv$). We thus expect the results across models to be similar and report the Probit solely for completeness.

[3]The Probit model delivers similar results, reported here for completeness. Without trends, the Probit model (Table C.9) also shows a negative marginal effect on employment for the whole period (2002-2013) for youth low-skilled participation in the private sector only (contraction by -0.159 percent). However, it detects, for the NMW period (2011-2013), a contraction in agriculture (not covered by the NMW). A contraction in youth low-skilled participation (-0.131 significant at 10 percent) is also identified but there is no indications of what sectors are driving this reduction. Again, the inclusion of linear trend in the Probit model (Table C.10) displays a more diversified story about the NMW (2011-2013): it confirms that, for the working-age population, contraction in non-wage work seems to be counterbalanced by positive marginal effects on private sector participation, especially for the low-skilled population in Industry (0.186). For the low-skilled youth, over 2002-2013 it confirms that some contraction took place. As was the case earlier, the specification shows no statistically significant effect for 2011-2013.

Table C.7: Marginal Effects of Minimum Wage Policy, Logit Regression.

(A) WA Pop 02-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.010	-0.054	-0.051	0.019	-0.002	-0.010
	(0.012)	(0.049)	(0.032)	(0.032)	(0.027)	(0.012)
Controls	Y	Y	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Obs.	2793533	2793533	2793533	2793533	2793533	2793533
Pseudo R^2	0.10	0.11	0.11	0.15	0.09	0.11
LL	-1.86e+08	-5.79e+08	-5.44e+08	-1.94e+08	-4.00e+08	-3.03e+08
2011-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.010	-0.060	-0.050	-0.051	0.019	-0.005
	(0.014)	(0.056)	(0.040)	(0.036)	(0.032)	(0.012)
Controls	Y	Y	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Obs.	732226	732226	732226	732226	732226	732226
Pseudo R^2	0.11	0.10	0.12	0.15	0.10	0.11
LL	-4.63e+07	-1.52e+08	-1.40e+08	-4.63e+07	-1.03e+08	-7.92e+07
(B) Low-skill 02-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.016	-0.063	-0.040	0.019	-0.005	-0.010
	(0.013)	(0.051)	(0.039)	(0.036)	(0.032)	(0.014)
Controls	Y	Y	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Obs.	2316010	2316010	2316010	2316010	2316010	2316010
Pseudo R^2	0.10	0.09	0.11	0.12	0.09	0.10
LL	-1.534e+08	-5.027e+08	-4.719e+08	-1.897e+08	-3.502e+08	-2.444e+08
2011-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.011	-0.054	-0.045	-0.063	0.018	-0.004
	(0.016)	(0.057)	(0.050)	(0.042)	(0.035)	(0.015)
Controls	Y	Y	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Obs.	604148	604148	604148	604148	604148	604148
Pseudo R^2	0.11	0.09	0.11	0.12	0.09	0.10
LL	-3.68e+07	-1.28e+08	-1.19e+08	-4.50e+07	-8.87e+07	-6.18e+07
(C) Young Low-skill 02-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.090*	-0.046	-0.160**	0.003	-0.047	-0.057
	(0.053)	(0.083)	(0.073)	(0.069)	(0.072)	(0.040)
Controls	Y	Y	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Obs.	307786	307786	307786	307786	307786	307786
Pseudo R^2	0.06	0.08	0.08	0.11	0.08	0.07
LL	-4.918e+07	-8.775e+07	-8.898e+07	-3.880e+07	-6.684e+07	-5.545e+07
2011-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.055	-0.023	-0.134*	-0.012	-0.002	-0.055
	(0.062)	(0.081)	(0.077)	(0.085)	(0.065)	(0.040)
Controls	Y	Y	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Obs.	74655	74655	74655	74655	74655	74655
Pseudo R^2	0.08	0.08	0.08	0.11	0.07	0.06
LL	-1.09e+07	-2.08e+07	-2.10e+07	-8897244.65	-1.56e+07	-1.31e+07

Note: LFS 2002-2013 or 2011-2013 at individual level, Logit model. The table reports the marginal effects of the minimum wage with standard error clustered at province level. Controls from Equation (C.1) exclude province-time trends. Panel (A) uses as sample the working-age population (WA Pop); Panel (B) only individuals with lower than secondary education; Panel (C) individuals aged 15-24 with lower than secondary education. Each column is an outcome variable: "Any" stands for any type of employment; "Non-wage" to self-employment or unpaid work; "Private" to wage-employment; "Agri" to wage employment in agriculture; "Indus" to wage employment in Industry; "Service" to wage employment in Services.

Table C.8: Marginal Effects of Minimum Wage Policy, Logit Regression with trends.

(A) WA Pop 02-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.015	-0.041	-0.075***	-0.047	-0.023	-0.007
	(0.013)	(0.038)	(0.028)	(0.031)	(0.021)	(0.013)
Controls & PxT trend	Y	Y	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Obs	2793533	2793533	2793533	2793533	2793533	2793533
Pseudo R^2	0.10	0.11	0.11	0.15	0.10	0.11
LL	-1.855e+08	-5.785e+08	-5.441e+08	-1.935e+08	-3.993e+08	-3.023e+08
2011-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.075***	-0.264***	0.202***	-0.024	0.171***	0.011
	(0.016)	(0.058)	(0.046)	(0.034)	(0.039)	(0.020)
Controls & PxT trend	Y	Y	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Obs	732226	732226	732226	732226	732226	732226
Pseudo R^2	0.11	0.10	0.12	0.15	0.10	0.11
LL	-4.622e+07	-1.515e+08	-1.403e+08	-4.607e+07	-1.032e+08	-7.906e+07
(B) Low-skill 02-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.018	-0.041	-0.067*	-0.057*	-0.018	-0.008
	(0.014)	(0.042)	(0.035)	(0.035)	(0.023)	(0.014)
Controls & PxT trend	Y	Y	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Obs	2316010	2316010	2316010	2316010	2316010	2316010
Pseudo R^2	0.10	0.09	0.11	0.12	0.09	0.10
LL	-1.530e+08	-5.021e+08	-4.716e+08	-1.892e+08	-3.501e+08	-2.440e+08
2011-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.067***	-0.289***	0.240***	-0.032	0.186***	0.028
	(0.017)	(0.065)	(0.054)	(0.040)	(0.040)	(0.024)
Controls & PxT trend	Y	Y	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Obs	604148	604148	604148	604148	604148	604148
Pseudo R^2	0.12	0.09	0.11	0.12	0.09	0.11
LL	-3.675e+07	-1.282e+08	-1.186e+08	-4.477e+07	-8.864e+07	-6.168e+07
(C) Young Low-skill 02-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.098	-0.000	-0.228***	-0.083	-0.067	-0.072
	(0.062)	(0.082)	(0.073)	(0.061)	(0.064)	(0.048)
Controls & PxT trend	Y	Y	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Obs	307786	307786	307786	307786	307786	307786
Pseudo R^2	0.07	0.08	0.09	0.12	0.09	0.07
LL	-4.901e+07	-8.761e+07	-8.884e+07	-3.868e+07	-6.667e+07	-5.528e+07
2011-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.029	-0.084	0.065	0.059	0.013	0.000
	(0.050)	(0.110)	(0.116)	(0.082)	(0.107)	(0.058)
Controls & PxT trend	Y	Y	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Obs	74655	74655	74655	74655	74655	74655
Pseudo R^2	0.09	0.09	0.08	0.12	0.08	0.06
LL	-1.080e+07	-2.069e+07	-2.094e+07	-8822618.112	-1.556e+07	-1.307e+07

Note: LFS 2002-2013 or 2011-2013 at individual level, Logit model. The table reports the marginal effects of the minimum wage with standard error clustered at province level. Controls from Equation (C.1) include province-time trends. Panel (A) uses as sample the working-age population (WA Pop); Panel (B) only individuals with lower than secondary education; Panel (C) individuals aged 15-24 with lower than secondary education. Outcome variable details (columns) available in footnote of Table C.7 above.

Table C.9: Marginal Effects of Minimum Wage Policy, Probit Regression.

(A) WA Pop 02-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.011	-0.050	-0.047	0.004	0.002	-0.005
	(0.012)	(0.049)	(0.032)	(0.028)	(0.027)	(0.012)
Controls	Y	Y	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Observations	2793533	2793533	2793533	2793533	2793533	2793533
Pseudo R^2	0.10	0.11	0.11	0.15	0.09	0.11
LL	-1.86e+08	-5.79e+08	-5.45e+08	-1.94e+08	-4.00e+08	-3.02e+08
2011-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.011	-0.057	-0.049	-0.056*	0.020	-0.005
	(0.014)	(0.057)	(0.040)	(0.031)	(0.032)	(0.012)
Controls	Y	Y	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Observations	732226	732226	732226	732226	732226	732226
Pseudo R^2	0.11	0.10	0.12	0.15	0.10	0.11
LL	-4.63e+07	-1.52e+08	-1.40e+08	-4.63e+07	-1.03e+08	-7.91e+07
(B) Low-skill 02-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.016	-0.061	-0.035	0.002	-0.000	-0.004
	(0.013)	(0.052)	(0.040)	(0.032)	(0.032)	(0.015)
Controls	Y	Y	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Observations	2316010	2316010	2316010	2316010	2316010	2316010
Pseudo R^2	0.10	0.09	0.11	0.12	0.09	0.10
LL						
2011-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.011	-0.051	-0.043	-0.070*	0.021	-0.003
	(0.016)	(0.058)	(0.050)	(0.036)	(0.035)	(0.016)
Controls	Y	Y	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Observations	604148	604148	604148	604148	604148	604148
Pseudo R^2	0.11	0.09	0.11	0.12	0.09	0.10
LL	-3.68e+07	-1.28e+08	-1.19e+08	-4.50e+07	-8.88e+07	-6.18e+07
(C) Young Low-skill 02-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.093*	-0.037	-0.159**	-0.011	-0.043	-0.054
	(0.052)	(0.080)	(0.072)	(0.062)	(0.074)	(0.042)
Controls	Y	Y	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Observations	307786	307786	307786	307786	307786	307786
Pseudo R^2	0.06	0.08	0.08	0.11	0.08	0.07
LL						
2011-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.050	-0.019	-0.131*	-0.021	-0.002	-0.057
	(0.062)	(0.077)	(0.076)	(0.079)	(0.065)	(0.042)
Controls	Y	Y	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Observations	74655	74655	74655	74655	74655	74655
Pseudo R^2	0.08	0.08	0.08	0.11	0.07	0.06
LL	-1.09e+07	-2.08e+07	-2.10e+07	-8904714.43	-1.56e+07	-1.31e+07

Note: LFS 2002-2013 or 2011-2013 at individual level, Probit model. The table reports the average partial effects of the minimum wage on the probability of employment (using covariates from Equation (C.1) excluding province-time trends). Panel (A) uses as sample the working-age population (WA Pop); Panel (B) only individuals with lower than secondary education; Panel (C) individuals aged 15-24 with lower than secondary education. Each panel is divided in sample 2002-2013 or 2011-2013. Each column is an outcome variable for employment: "Any" stands for any type of employment; "Non-wage" to self-employment or unpaid work; "Private" to wage-employment; "Agri" to wage employment in agriculture; "Indus" to wage employment in Industry; "Service" to wage employment in Services.

Table C.10: Marginal Effects of Minimum Wage Policy, Probit Regression with trends.

(A) WA Pop 02-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.015	-0.041	-0.075***	-0.047	-0.023	-0.007
	(0.013)	(0.038)	(0.028)	(0.031)	(0.021)	(0.013)
Controls & PxT trend	Y	Y	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Obs	2793533	2793533	2793533	2793533	2793533	2793533
Pseudo R^2	0.10	0.11	0.11	0.15	0.10	0.11
LL	-1.855e+08	-5.785e+08	-5.441e+08	-1.935e+08	-3.993e+08	-3.023e+08
2011-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.075***	-0.264***	0.202***	-0.024	0.171***	0.011
	(0.016)	(0.058)	(0.046)	(0.034)	(0.039)	(0.020)
Controls & PxT trend	Y	Y	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Obs	732226	732226	732226	732226	732226	732226
Pseudo R^2	0.11	0.10	0.12	0.15	0.10	0.11
LL	-4.622e+07	-1.515e+08	-1.403e+08	-4.607e+07	-1.032e+08	-7.906e+07
(B) Low-skill 02-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.018	-0.041	-0.067*	-0.057*	-0.018	-0.008
	(0.014)	(0.042)	(0.035)	(0.035)	(0.023)	(0.014)
Controls & PxT trend	Y	Y	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Obs	2316010	2316010	2316010	2316010	2316010	2316010
Pseudo R^2	0.10	0.09	0.11	0.12	0.09	0.10
LL	-1.530e+08	-5.021e+08	-4.716e+08	-1.892e+08	-3.501e+08	-2.440e+08
2011-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.067***	-0.289***	0.240***	-0.032	0.186***	0.028
	(0.017)	(0.065)	(0.054)	(0.040)	(0.040)	(0.024)
Controls & PxT trend	Y	Y	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Obs	604148	604148	604148	604148	604148	604148
Pseudo R^2	0.12	0.09	0.11	0.12	0.09	0.11
LL	-3.675e+07	-1.282e+08	-1.186e+08	-4.477e+07	-8.864e+07	-6.168e+07
(C) Young Low-skill 02-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.098	-0.000	-0.228***	-0.083	-0.067	-0.072
	(0.062)	(0.082)	(0.073)	(0.061)	(0.064)	(0.048)
Controls & PxT trend	Y	Y	Y	Y	Y	Y
Years	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013	2002-2013
Obs	307786	307786	307786	307786	307786	307786
Pseudo R^2	0.07	0.08	0.09	0.12	0.09	0.07
LL	-4.901e+07	-8.761e+07	-8.884e+07	-3.868e+07	-6.667e+07	-5.528e+07
2011-13	Overall		Private Sector			
MFX for	Any	Non wage	Private	Agri.	Indus.	Service
log MW	-0.029	-0.084	0.065	0.059	0.013	0.000
	(0.050)	(0.110)	(0.116)	(0.082)	(0.107)	(0.058)
Controls & PxT trend	Y	Y	Y	Y	Y	Y
Years	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013	2011-2013
Obs	74655	74655	74655	74655	74655	74655
Pseudo R^2	0.09	0.09	0.08	0.12	0.08	0.06
LL	-1.080e+07	-2.069e+07	-2.094e+07	-8822618.112	-1.556e+07	-1.307e+07

Note: LFS 2002-2013 or 2011-2013 at individual level, Probit model. The table reports the average partial effects of the minimum wage on the probability of employment (using covariates from Equation (C.1) including province-time trends). Panel (A) uses as sample the working-age population (WA Pop); Panel (B) only individuals with lower than secondary education; Panel (C) individuals aged 15-24 with lower than secondary education. Outcome variable details (columns) available in footnote of Table C.9 above.

C.2 Dynamic employment response

In order to assess the anticipatory or delayed effects to a policy change over the 2002-2013 period we use a specification similar to Allegretto et al. (2011), which introduces finite leads and lags of the MW variable:

$$E_{\text{pt}} = \sum_{k=-4}^{6} \beta_k \text{MW}_{pt+k} + \gamma X_{\text{pt}} + \phi_p + \phi_t + \varepsilon_{\text{pt}} \tag{C.2}$$

Where E is the variable identifying the employment outcome, $\sum_{k=-4}^{6} \beta_k \text{MW}_{pt+k}$ are the leads and lags of the MW. The vector X captures a set of: provincial-level variables; provincial population characteristics; and population group-specific controls (see discussion around Equation 5.1). ϕ_p is a province level shifter, ϕ_t time dummies and ε the error term. Robust standard errors are clustered at the province level.

The specification covers a ten quarter window to assess whether any anticipation or delayed effects took place. The window length in the leads (one year or 4 quarters) is chosen to capture any potential future anticipation of a policy change. The length of the lags (a year and a half or 6 quarters) reflects the maximum gap between minimum wage changes. Similar to Allegretto et al. (2011), we estimate the cumulative response of the outcome variable from a log point increase in the minimum wage by successively summing the coefficients β_{-4} to β_6 to show the time path of adjustment. While the individual quarterly $\beta_{\pm k}$ coefficients are informative, they do not give a sense of the full adjustment path. However, summing these gives an indication of the the average effect over time.[4]

However, by introducing the minimum wage leads and lags we might expect some correlation to come from the quarterly data with yearly adjustments. A preliminary inspection of this possible collinearity reveals that variance inflation factors do worsen (as expected) but not by a huge margin (between 8 and 18 for the minimum wage leads and lags).[5] The presence of correlation does not bias the coefficients, but it can inflate

[4]The implicit assumption made by Allegretto et al. (2011), which propose this specification for US state-level employment regressions, is that every time period t can be influenced by previous or future adjustments. They set a model with leads and lags and then sum for every point in time the coefficients, so that the value for every time t is cumulated to past response.

[5]The (centered) variance inflation factor (VIF) is defined: $VIF = (X_j) = 1/(1 - \hat{R}_j^2)$ where $\hat{R}_j^2$ is the square of the centred multiple correlation coefficient that results when the explanatory variable X_j is regressed with intercept against all the other explanatory variables. According to Chatterjee and Hadi (2012) there is evidence of multicollinearity if the largest VIF is greater than 10 (with an upper bound threshold value of 30) and if the mean VIF across all independent variables is considerably larger

their standard errors and affect the significance of the individual coefficients even when a statistical relation exists. Therefore, we do not take this results at face value, but simply assess them to understand if there are any indications of strong anticipatory or delayed effects. We are aware that this is not the only way to look at dynamic path responses, but with the limited time period available we are constrained in the empirical strategy to use.[6]

Figure C.3 reports the cumulative response to the minimum wage of employment and weekly working hours elasticities. The left-hand column presents the elasticities for all working age population, while the right-hand column shows the results for the young (15-24) low-skilled subgroup.

Panel I (Figure C.3) shows that the employment elasticity time path throughout much of the time horizon (the sum of the betas) is just slightly negative for the working age population, while the response for the young low-skilled group is larger. Six quarters after the minimum wage increase, the magnitudes of the cumulative employment elasticity for both population groups are negative and significant, with an elasticity of -0.140 and -0.367 respectively.

Panel II shows that private sector employment elasticities adjust downward by a greater magnitude for the low-skilled youth group. For the whole working age population, there is evidence of some anticipation (by a magnitude of -0.069 three quarters prior to a minimum wage change) with further downward adjustments by the sixth quarter (-0.273).

The private sector cumulative employment elasticity of the youth also shows signs of anticipation and even greater adjustments at the sixth quarter after the policy change (-0.688). This evidence suggests that an increase in the minimum wage produces stronger delayed adjustments for the low-skilled youth population.

The time paths for private sector weekly working hours are presented in Panel III (Figure C.3). They show a small negative but significant reduction in weekly working hours for both population groups of interest prior to policy introduction. The effects persist at the time of introduction (with elasticities of -0.095 and -0.087 respectively).

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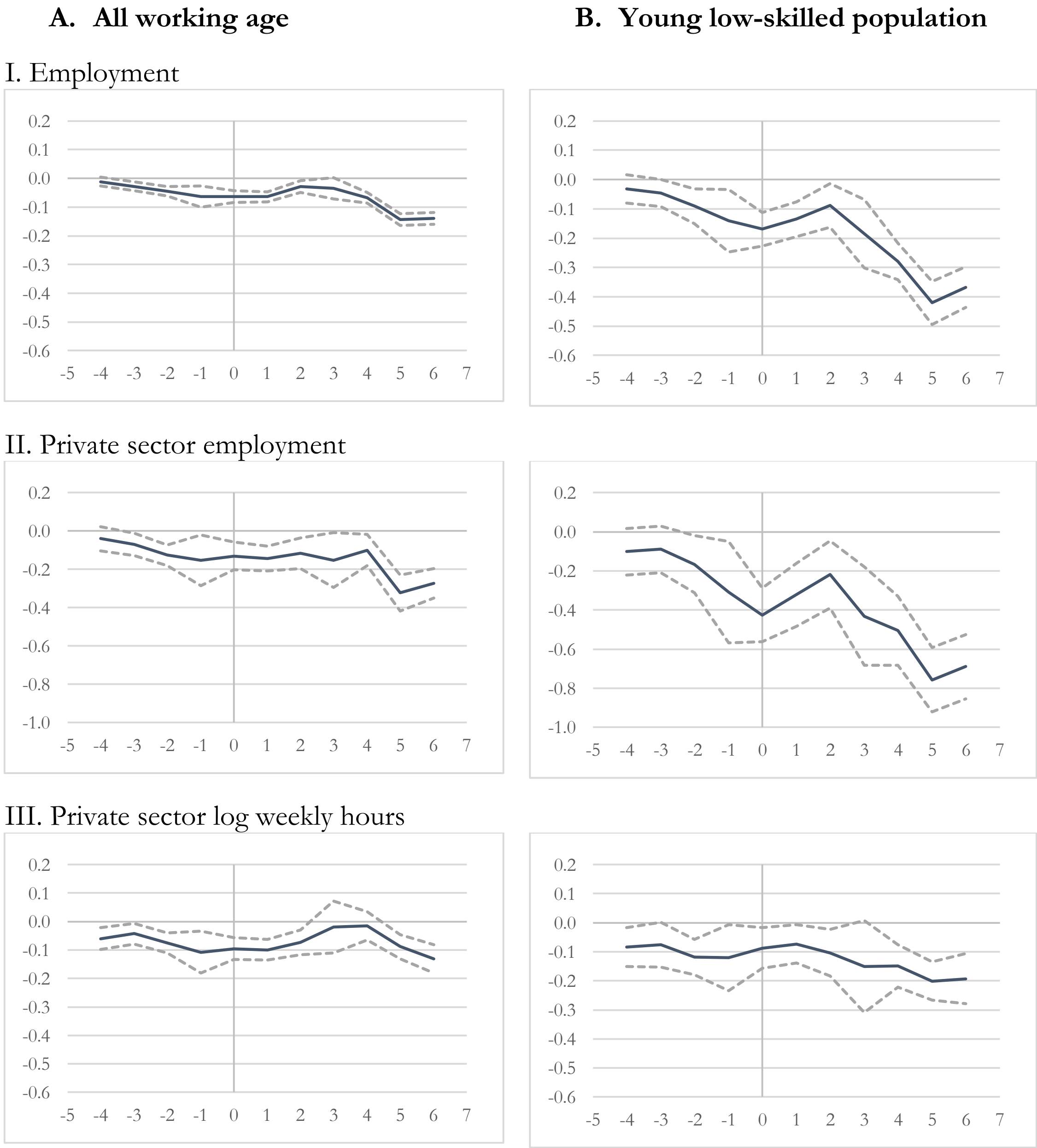
[6] In preliminary estimations, we attempt to perform growth regressions (such as differenced models with or without distributed lags like Meer and West 2016), and the specifications are not supported by robustness checks.

Figure C.3: Cumulative response to changes in the minimum wage of employment and log weekly hours elasticities

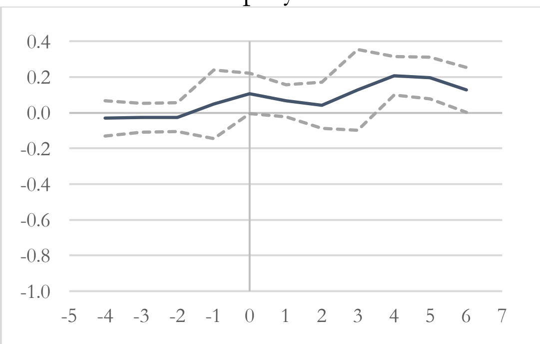


Note: Quarterly LFS. Dynamic provincial panel model with distributed leads and lags in log real minimum wage. The specification covers a 10-quarter window (reported on y-axis, four quarters before the change in the minimum wage reported with negative sign and lags till six quarters after the change reported with positive sign). The solid line graphs represent the cumulative response of selected outcomes to a minimum wage increase. For employment, coefficients are divided by average employment-to-population ratio, so to represent employment elasticities. Each regression equation includes controls at province level for average years of schooling, female composition, average potential work experience, population shares of youth (less than 25 years of age), senior (more than 55 years of age), share of rural population and share of high skilled labour force (completed post-secondary education), lagged yearly log real GPP per capita, year and quarter dummies, and provincial fixed effects. The dotted lines represent the 95% confidence intervals, computed using robust standard errors clustered at the provincial level.

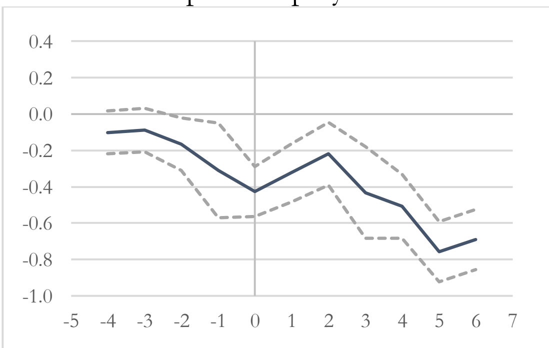
Figure C.4: Cumulative response to changes in the minimum wage of employment elasticity for high versus young low skilled populations.

A. High skilled population **B. Young low-skilled population**

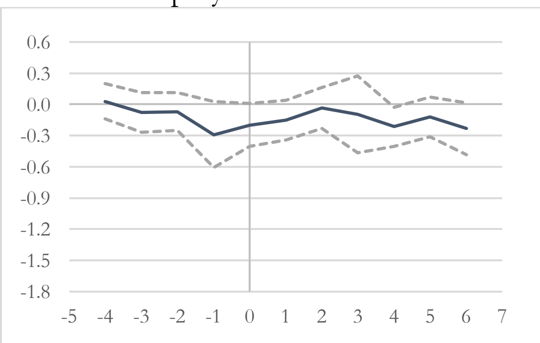
I. Private sector employment

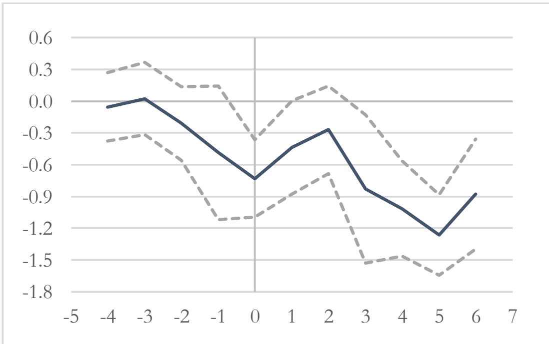


II. Micro enterprise employment

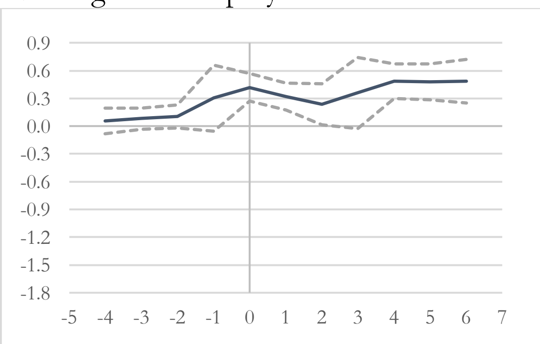


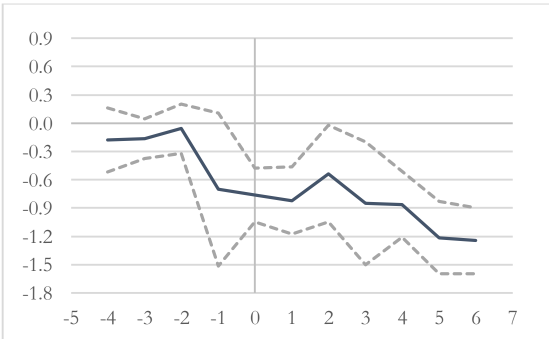
III. SMEs employment





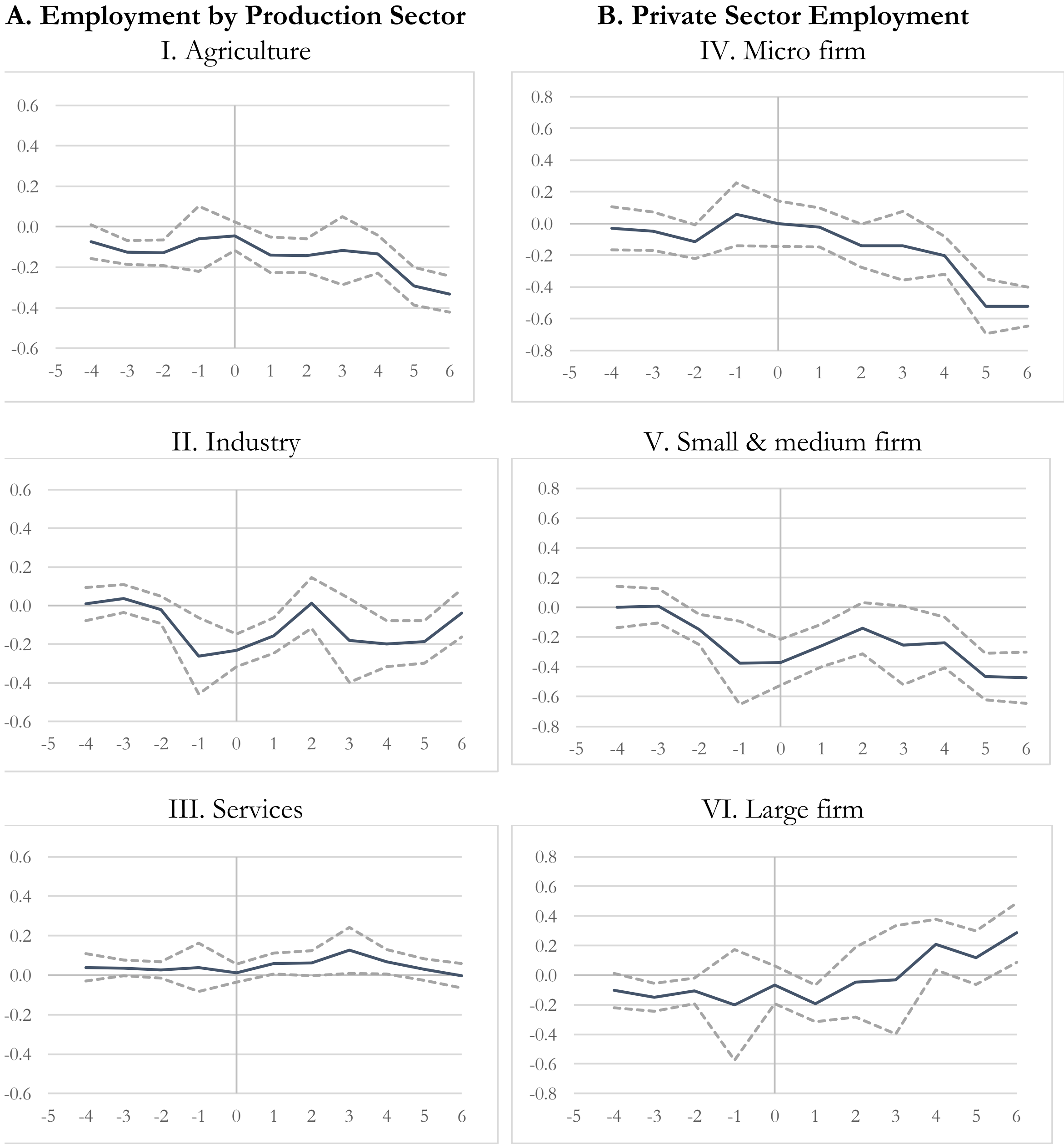
IV. Large firm employment





Note: Quarterly LFS. Dynamic provincial panel model with distributed leads and lags in log real minimum wage. Left column refers to private sector employment of high skilled workers, right column for young low skilled employment. The specification covers a 10-quarter window (reported on y-axis, four quarters before the change in the minimum wage reported with negative sign and lags till six quarters after the change reported with positive sign). The solid line graphs represent the cumulative response of selected outcomes to a minimum wage increase. Coefficients are divided by average employment-to-population ratio, so to represent employment elasticities. The dotted lines represent the 95% confidence intervals, computed using robust standard errors clustered at the provincial level. See figure above for details on controls used.

Figure C.5: Cumulative response to changes in the MW, working age population.



Note: Quarterly LFS 2002-2013. Dynamic provincial panel model with distributed leads and lags in log real minimum wage. Left column refers to private sector employment by aggregate sector, right column by firm size. The specification covers a 10-quarter window (reported on y-axis, four quarters before the change in the minimum wage reported with negative sign and lags till six quarters after the change reported with positive sign). The solid line graphs represent the cumulative response of selected outcomes to a minimum wage increase. Coefficients are divided by average employment-to-population ratio, so to represent employment elasticities. The dotted lines represent the 95% confidence intervals, computed using robust standard errors clustered at the provincial level. See Figure C.3 for details on controls used.

The cumulative effects continue six quarters after the increase in the minimum wage, where the respective elasticities are -0.131 for the whole working-age population and -0.193 for the low-skilled hours. The findings suggest that some substitution away from low-skilled youth employment is taking place.

In Figure C.4 we compare the low-skilled youth group to the high skilled group (working-age individuals with more than secondary education), finding that the employment elasticity time paths of high skilled workers have reacted positively to the increase in the minimum wage (Panel I), and their estimated time paths for employment in large enterprises are almost a mirror image of those of the low-skilled youth group, (Panel IV) revealing an adjustment in employment composition in response to the minimum wage increase.

The cumulative response of employment for the working-age population in three broadly-defined production sectors (Agriculture, Industry, Services) is reported in the left-hand column of Figure C.5. Figure C.5 provides further evidence that the Thai labour market has been flexible in absorbing the policy changes through no systematic contraction in the covered sectors (Industry and Services), and partial employment adjustments between large and smaller sized firms. There seems to be no sign of anticipation with the exception of employment in Agriculture, where an elasticity of -0.068 is estimates three quarters before the minimum wage increase. At policy introduction, some negative adjustments occur for the Industry sector (-0.232), which persist after one quarter. Conversely, Services show a positive though not statistically significant trend in its cumulative response. Over the entire time path, Agriculture seems to be the only sector responsive six quarters after the policy change, with an elasticity of -0.332.

Private sector elasticities by firm size (right-hand column of Figure C.5) reveals that, at the time of the minimum wage increase, the employment response of small and medium enterprises (SMEs) is negative and significant (-0.370). Adjustments to employment in the different private sector firms appear to take different trends. Micro firms and SMEs see a contraction in employment six quarters after introduction by -0.523 and -0.472 respectively, whereas large firm elasticity increases by 0.287. These graphs therefore provide some evidence that the Thai labour market has been flexible in absorbing the policy changes through no systematic contraction in the covered sectors (Industry and Services), and partial employment adjustments between large and smaller sized firms.

The results show more nuanced effects than the standard panel fixed effect model. However, as we cautioned earlier, there could be issues of multicollinearity induced in the estimations from the lead and lag terms of the minimum wage variable, which implies that the correlation between a variable and its previous values could confound the estimation. We take these results as indications rather than causal effects, though confirming that no strong anticipatory effects were found. We also attempted to compare these results with growth models in preliminary estimations. Growth dynamics have been suggested for the US literature to uncover employment effects using a levels equation (Meer and West, 2016). Due to the time period under analysis, two issues have emerged. First, the time period we investigate is relatively small for a growth analysis, as we cover a 48 quarters period, or 12 years. Second, the NMW change may have a great weight on a growth specification. When we assessed with a Generalized Method of Moments (GMM) estimator the robustness of the growth results, these appeared not stable, so these models are not reported in the thesis.

C.3 Inspection of the policy hike *vs* harmonisation

Following the Difference-in-Differences (DiD) model presented in the previous chapter (Appendix B.6), we now investigate descriptively whether the employment trends correlate with any of the two types of interventions which led to the NMW.

Although we present an imperfect specification, we aim to identify whether there are any signs that the policy change induced changes in private and non-wage employment as well as hours worked across the two periods. We apply a DiD model at province level for the male or female populations with wild bootstrapped standard errors clustered at province level (400 replications).[7]

It is however important to begin with a note of caution. As also noted in Chapter 4, the estimations are subject to several caveats and solely aim to show correlations. First, the control group areas were also exposed to the policy change during the hike period (2012 Q2-Q4). Second, we assume that the control group provinces should not have underlying characteristics which are inherently different from the treated group. Given that these areas are diverse in their production and employment offer,

[7] The use of wild cluster bootstrap-t procedure is advised by Cameron et al. (2008) which show that when the regressor of interest is an indicator variable that is highly correlated within cluster (such as the province, given that treatment is defined for a group of provinces), the standard errors should be corrected for such clustering. We also ensure that if the standard errors are clustered in a greater geographic dimension of the data (region) the correlations reported do not change.

uncertainty on whether they exactly reflect the counterfactual employment outcome in the absence of the policy interventions remains. Keeping this main limitation in mind, we pool together the province panel and report the Ordinary Least Squares (OLS) correlations of the two interventions below. The first big hike is defined as a binary variable ($hike_{\{t=2012Q2-Q4\}}$) taking the value of one in between April and December 2012, which is the first period of variation of the MW, zero otherwise. The second intervention is the wage harmonisation to the 300 Baht wage, defined as a binary variable ($NMW_{\{t\geq 2013Q1\}}$) which takes the value of one from January to December 2013, zero otherwise. Our treatment (T_p) is defined as being a province which received variations in the minimum twice to raise it to 300 Baht. We apply the following model:

$$\begin{aligned} Y_{pt} = \beta_0 + \beta_1 T_p \times hike_{\{t=2012Q2-Q4\}} + \beta_2 T_p \times NMW_{\{t\geq 2013Q1\}} \\ +\beta_3 T_p + \beta_4 hike_{\{t=2012Q2-Q4\}} + \beta_5 NMW_{\{t\geq 2013Q1\}} \\ +\beta_6 X_{pt} + \phi_p + \phi_t + \epsilon_{pt} \end{aligned} \tag{C.3}$$

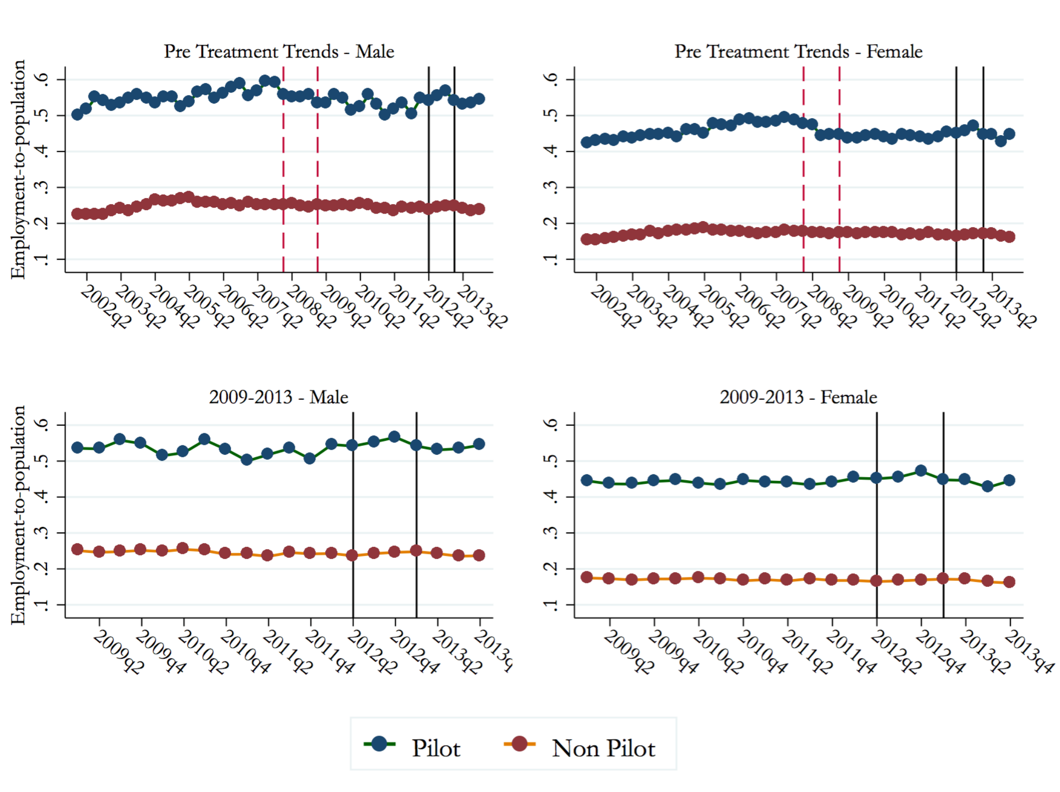
Where Y_{pt} is the employment-to-population or average log hours of province p in quarter-year t either for the male or female populations. The vector X_{pt} comprises population-specific controls (share of rural population, share of population of other gender, high-skilled share) and past log per capita GPP, ϕ_p and ϕ_t are province and quarter-year binaries.

The key identifying assumption we need to evaluate for the DiD model is that the treatment provinces have similar trends to the control provinces in the absence of treatment. Figure C.6 shows private sector employment in covered sectors (excluding agriculture) for both male and female populations.[8] The employment adjustments have been fairly aligned between the selected groups in the ten years preceding 2012. However, the top graphs also show that the 2008-2009 crisis (represented by the dashed vertical lines) has modified the employment trends in the pilot (control) provinces (as found in Adireksombat et al. 2010 for contraction in specific areas of the country). Taking a closer look around the NMW period (bottom graphs) reveals that for male

[8]The graphs in Figure C.6 are constructed by netting out from the average employment-to-population (Epop) shares a linear trend-cycle (per quarter-year) and its seasonal component (dummies for quarter). The Epop for the pilot (control) group is slightly noisier due to the low number of provinces as compared to the treatment. The inspection for parallel trends across types of non-wage employment and average hours work are available below in Appendix C.3.1, p.235.

employment in the treatment (non-pilot) has been more stable than the control. The pilot provinces therefore are an imperfect representation of a control group for the analysis, so we keep the estimations for illustrative purposes rather than causal effects of the policy.

Figure C.6: Parallel trends in Epop between pilot and non-pilot provinces (2002-2013).



Notes: quarterly provincial LFS data for male or female, private sector employment to population (Epop, excluding agriculture) net of a linear trend-cycle and its seasonal component. The top graphs refer to Epop trends across groups between 2002-2013. The bottom graphs refer to 2009-2013. Pilot (control) areas are Bangkok, Nakhon Pathom, Nonthaburi, Pathum Thani, Phuket, Samut Prakan, Samut Sakhon. Non-pilot (treated) areas are the remaining 68 provinces. The dotted vertical lines represent the 2008q1-2009q1 period, the two solid vertical lines capture the policy hike and the introduction of the 300 Baht policy.

The estimates in Table C.11 indicate that there are no difference in private employment across the two groups. The average hours worked between the two interventions seem to be positively affected during the harmonisation, particularly for low-skilled female (both young and older) and for male older low-skilled hours. With regard to non-wage employment, there are some signs of increased participation in the hike period for the female population in the more exposed provinces, but it does not persist if we separate on any of the two types of non-wage work.[9] We also investigate whether these correlations persist if we disaggregate the interventions by quarters, performing a flexible DiD specification (see Table C.12 below), and we find that only hours worked for

[9]The estimates keep being stable when the wild bootstrap-t is applied with the geographic region as cluster (5 groups, 400 repetitions) or if a pair cluster bootstrap is applied instead.

Table C.11: The effect of the NMW policy on private employment, hours and non-wage work, DiD regression.

	A. Male					B. Female				
All										
	Priv.	P Hrs	No-Wage	Self	Unpaid	Priv.	P Hrs	No-Wage	Self	Unpaid
T × hike	-0.014	0.020*	0.017	0.009	0.007	-0.011	0.018	0.024	0.015	0.008
	(0.018)	(0.011)	(0.025)	(0.009)	(0.017)	(0.013)	(0.015)	(0.018)	(0.015)	(0.009)
T × NMW	0.00043	0.027***	-0.001	0.009	-0.003	0.006	0.036***	0.003	-0.001	0.010
	(0.003)	(0.000)	(0.013)	(0.013)	(0.014)	(0.013)	(0.000)	(0.101)	(0.010)	(0.010)
Low-skill population										
	Priv.	P Hrs	No-Wage	Self	Unpaid	Priv.	P Hrs	No-Wage	Self	Unpaid
T × hike	-0.017	0.012	0.019	0.007	0.012	-0.012	0.013	0.030*	0.019	0.010
	(0.023)	(0.014)	(0.023)	(0.011)	(0.016)	(0.016)	(0.018)	(0.018)	(0.016)	(0.009)
T × NMW	-0.001	0.020*	0.003	0.013	-0.001	0.006	0.035***	0.010	0.004	0.011
	(1.304)	(0.010)	(0.026)	(0.012)	(0.010)	(0.016)	(0.000)	(0.020)	(0.025)	(0.010)
Young low-skill population										
	Priv.	P Hrs	No-Wage	Self	Unpaid	Priv.	P Hrs	No-Wage	Self	Unpaid
T × hike	0.002	0.007	-0.009	-0.006	-0.004	-0.039	0.022	0.047*	0.035	0.011
	(0.009)	(0.024)	(0.037)	(0.029)	(0.011)	(0.032)	(0.042)	(0.027)	(0.023)	(0.013)
T × NMW	-0.002	0.009	-0.013	-0.004	-0.001	-0.023	0.039*	0.001	0.010	-0.006
	(0.016)	(0.023)	(0.026)	(0.041)	(0.040)	(0.037)	(0.023)	(0.019)	(0.017)	(0.016)
Older low-skill population										
	Priv.	P Hrs	No-Wage	Self	Unpaid	Priv.	P Hrs	No-Wage	Self	Unpaid
T × hike	-0.020	0.014	0.024	0.007	0.016	-0.009	0.010	0.028	0.018	0.009
	(0.023)	(0.016)	(0.024)	(0.008)	(0.017)	(0.017)	(0.019)	(0.018)	(0.016)	(0.009)
T × NMW	-0.001	0.026**	0.004	0.016	-0.004	0.008	0.039***	0.011	0.001	0.015*
	(1.304)	(0.012)	(0.057)	(0.010)	(0.016)	(0.014)	(0.000)	(0.020)	(1.304)	(0.009)

Note: LFS province level 2011-2013 (male or female pop., 900 obs), DiD model with wild cluster bootstrapped standard errors (province). The table reports the β coefficient for the two interaction terms. Dependent variables: private Epop (Private); mean log hours worked in private sector (P Hrs); non-wage Epop (Non-Wage); self-employment Epop (Self); unpaid Epop (Unpaid). Controls: share of rural population, share of population of other gender, high-skilled share), past GPP, quarter-year and province dummies (significance: * p<.10, ** p<.05, *** p<.01).

the female private sector employees seems to be affected during the policy harmonisation, with no adjustments taking place prior to year 2012 or in the same quarters of the hike.

The analysis is limited in its ability to provide an exact estimate, but it shows a trend about the more exposed group of provinces which warrants future investigation with more robust methods. These extensions could be the application of a synthetic control approach to define the control group (Abadie et al., 2010), matching techniques (Smith and Todd, 2005) or the application of a feasible GLS combined with robust inference (Brewer et al., 2013) to check if gains in power of the model estimation could be achieved with the limited number of observations at our disposal.[10]

[10] Brewer et al. (2013) show with Monte Carlo simulations that it is possible to apply a feasible Generalized Least Square (GLS) estimation to improve the power of a DiD model with aggregate data and small number of groups. The procedure is to perform individual level regressions for each group-time cell, then take the average residual within each group-time cell as the outcome variable of a group-level regression on treatment and time dummies, where its variation will be explained by the variation in the group-time shocks (Brewer et al., 2013).

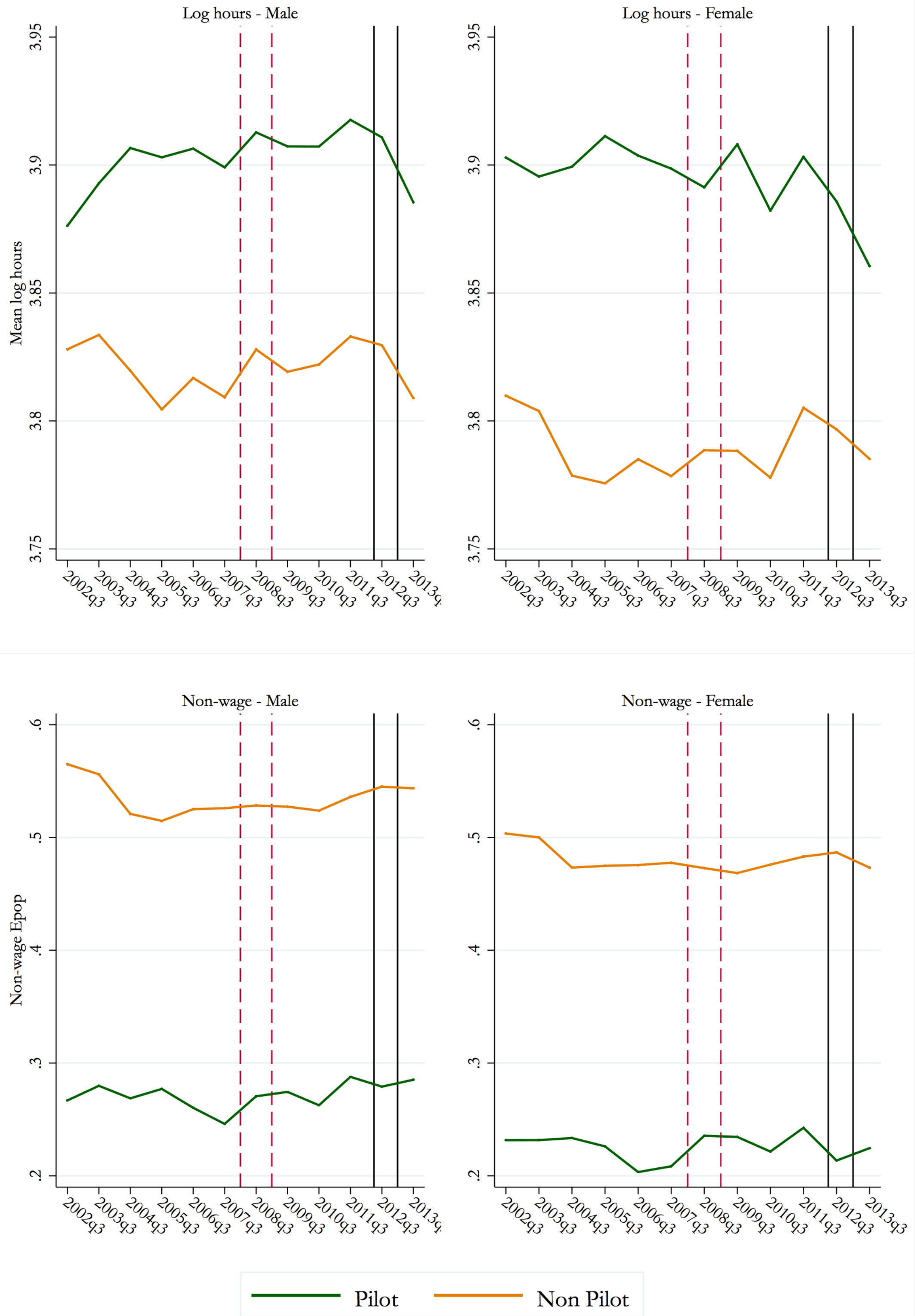
Table C.12: The effect of the NMW policy on log hours by quarter of intervention, flexible DiD regression.

A. Male low-skilled				
	(I)	(II)	(III)	(IV)
T*2011-Q2				-0.003
				(0.012)
T*2011-Q3				0.005
				(0.038)
T*2011-Q4			0.018	0.018
			(0.011)	(0.015)
T*hike-Q1			-0.027	-0.027
			(0.020)	(0.020)
T*hike-Q2		0.010		
		(0.020)		
T*hike-Q3		0.019		
		(0.013)		
T*hike-Q4		0.006		
		(0.018)		
T × hike	0.012			
	(0.012)			
T*NMW-Q1	0.032	0.032	0.026	0.026
	(0.024)	(0.024)	(0.027)	(0.025)
T*NMW-Q2	0.015	0.015	0.009	0.009
	(0.017)	(0.017)	(0.015)	(0.014)
T*NMW-Q3	0.023	0.023	0.016	0.017
	(0.015)	(0.015)	(0.014)	(0.014)
T*NMW-Q4	0.008	0.008	0.002	0.002
	(0.021)	(0.021)	(0.049)	(0.016)
R^2	0.78	0.78	0.78	0.78
Obs	900	900	900	900
B. Female low-skilled				
	(I)	(II)	(III)	(IV)
T*2011-Q2				-0.003
				(0.014)
T*2011-Q3				-0.008
				(0.032)
T*2011-Q4			0.008	0.006
			(0.016)	(0.024)
T*hike-Q1			0.006	0.005
			(0.018)	(0.019)
T*hike-Q2		0.016		
		(0.016)		
T*hike-Q3		0.022		
		(0.017)		
T*hike-Q4		0.011		
		(0.022)		
T × hike	0.016			
	(0.016)			
T*NMW-Q1	0.058*	0.058*	0.054	0.052*
	(0.033)	(0.033)	(0.034)	(0.031)
T*NMW-Q2	0.016	0.016	0.011	0.009
	(0.019)	(0.019)	(0.013)	(0.012)
T*NMW-Q3	0.042***	0.042***	0.037***	0.035**
	(0.015)	(0.015)	(0.013)	(0.016)
T*NMW-Q4	0.044***	0.044***	0.040***	0.038**
	(0.016)	(0.016)	(0.015)	(0.018)
R^2	0.82	0.82	0.82	0.82
Obs	900	900	900	900

Note: LFS province level 2011-2013 A. male or B. female population (900 obs), flexible DiD model with wild cluster bootstrapped standard errors (province). The table reports the β coefficient for the multiple interaction terms of T (non-pilot areas) with quarter of intervention. Dependent variable is mean log hours worked in the private sector. Additional controls as in the main DiD specification (significance: * p<.10, ** p<.05, *** p<.01).

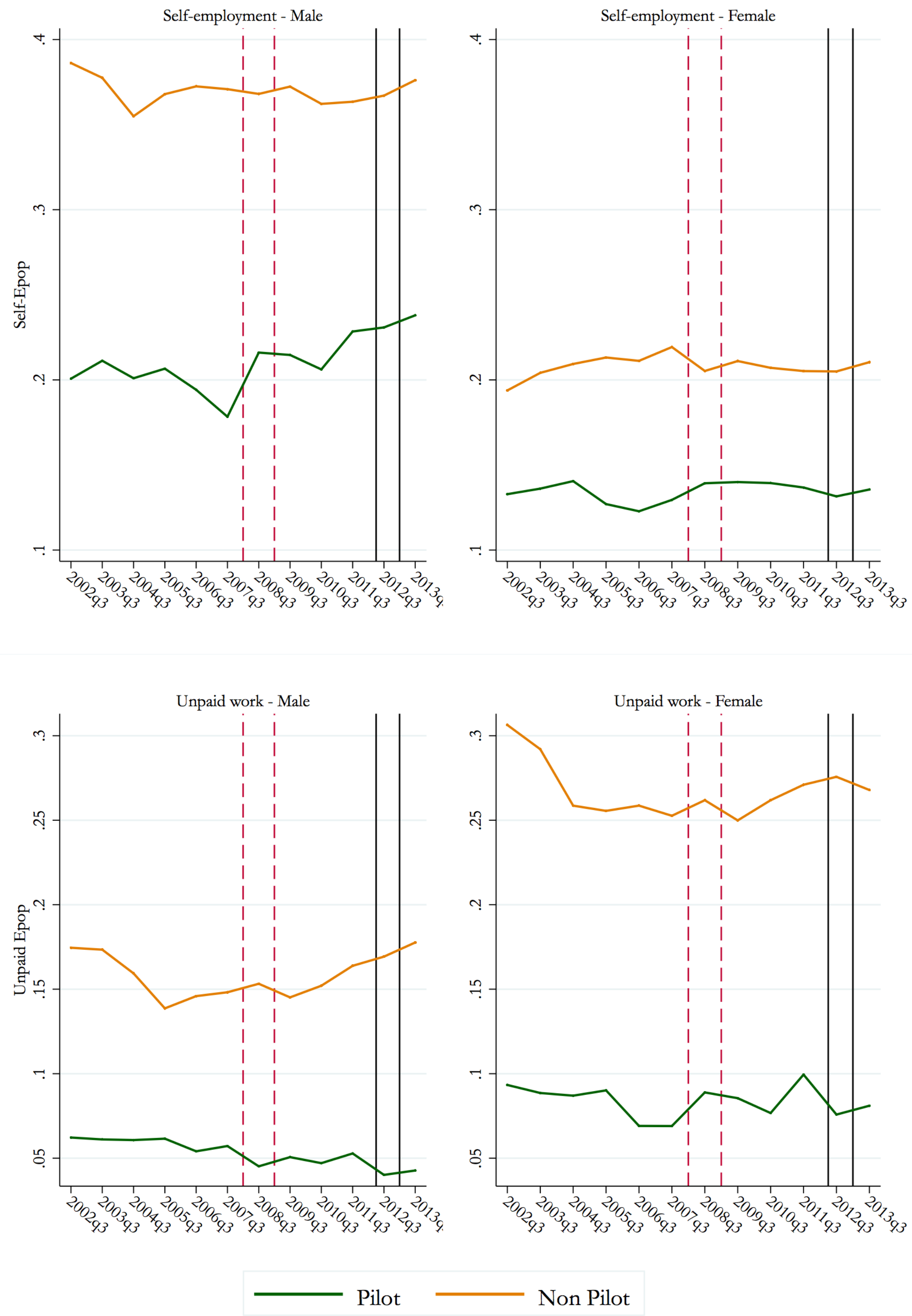
C.3.1 Employment parallel trends inspection

Figure C.7: Parallel trends in hours worked and non-wage Epop between pilot and non-pilot provinces (2002-2013).



Notes: Q3 2002-2013 provincial LFS data (male or female), log hours worked (top) or non-wage Epop (bottom), net of a linear trend-cycle and its seasonal component. See next graph for groups definition.

Figure C.8: Parallel trends in self-employment and unpaid Epop between pilot and non-pilot provinces (2002-2013).



Notes: Q3 2002-2013 provincial LFS data for male or female, private sector self and unpaid employment to population (Epop, excluding agriculture) net of a linear trend-cycle and its seasonal component. The top graphs refer to self-employment; the bottom graphs refer to unpaid employment-to-population trends across groups. Pilot (control) areas are Bangkok, Nakhon Pathom, Nonthaburi, Pathum Thani, Phuket, Samut Prakan, Samut Sakhon. Non-pilot (treated) areas are the remaining 68 provinces. The dotted vertical lines represent the 2008q1-2009q1 period, the two solid vertical lines capture the policy hike and the introduction of the 300 Baht policy.

C.4 Labour inspections

To complement the results on the response in the wage distributions and employment, we now examine whether the overall policy environment might have been affected by the lack of labour inspections. A limitation in this analysis relates to potential measurement and sampling errors arising from the LFS data which could reduce the precision of the estimated wage earners paid sub-minimum wages. Since we are unable to compare the headline measures reported in Section 5.3.1 with alternative data sources, such as firm-level surveys or social security data, we turn to labour inspections to infer the possible likelihood of being caught infringing the law.

Statistics for the period 2006-2010 show signs of weak law enforcement. Out of 12-13% of inspections, only 0.3 percent of firms found to be in violation of any labour law, including, but not limited to the MW, were fined or prosecuted. Most of the rest (94%) received a warning only (Leckcivilize, 2015). We analyse the trends in labour inspections for the year of introduction of the national minimum wage, using the 2013 Yearbook of Labour Protection and Welfare statistics (MOL, 2013). Table C.13 reports that around 13.7% of all registered firms in the country were inspected, implying a marginal increase in labour inspections over the year of the NMW introduction, with approximately 4000 firms inspected per month (MOL, 2013). The uneven inspection across firms size is common across countries (Almeida and Ronconi, 2016). Difficulty of inspecting small or micro-enterprises may be due to their lower survival rates, and potentially because the first screening happens through self-assessment.[11] Inspecting Micro Small and Medium Enterprises (MSMEs) may therefore be more procedurally complex. Still, in 2013, SMEs are found to be amongst the highest in terms of firms inspected which are found to be in violation of any labour law (highest proportions among the 1.63% of firms with 10-19 employees and the 2.17% of firms with 50-99). Table C.13 also shows that the outcome of the inspection is mostly biased towards warnings. On average, 4.5% of non-complying firms got either a fine or prosecution in 2013. The low fines applied (1.7%) as opposed to warnings, may suggest that the

[11] Almeida and Ronconi (2016) compare the characteristics of formal-sector firms inspected in a set of developing and emerging economies, finding that larger firms are more likely to be inspected. They tentatively suggest that this could reflect the inspection agencies's behaviour in being pushed for collecting revenues and also to avoid creating job destruction, as large firms tend to comply more than smaller ones. They also show that firms operating in sectors with less tax compliance are less likely to be inspected and that there is no distinction in the likelihood of inspection according to skill composition of workers (Almeida and Ronconi, 2016).

threat of sanctions may be too low to enforce full compliance.

Table C.13: Labour inspections and actions by firm size, 2013.

Firm size	% of inspections	N of est. inspected	N of est. non-compliant with the law	Conduction of Labour inspection				
				Advice	Order of presentation	Order of compliance	Fine	Criminal action submission
Overall	13.7 %	48749	465	164	32	248	8	13
1 - 4	7.2 %	12635	75	25	1	44	3	2
5 - 9	11.9 %	10457	68	31	1	32	-	4
10 - 19	24.4 %	9139	149	76	13	57	1	2
20 - 49	26.6 %	9299	116	58	9	47	1	1
50 - 99	37.1 %	3453	75	31	5	36	1	2
100 - 499	33.6 %	3614	54	18	3	29	2	2
500 - 999	30.4 %	379	3	1	-	2	-	-
$\geq$ 1,000	26.5 %	190	2	-	-	1	-	-

Note: Own calculations based on MOL (2013). Combination of Table 4.1 (total establishments); Table 7.3 (inspections and actions). The table reports the inspections by firm size (number of employees) and the number of firms which received a specific action by the inspection in year 2013.

The labour inspections in Thailand cover many aspects of firm management – from holiday to leave or welfare provisions to contracting issues. In Table C.14 we focus specifically on the non-compliance with the minimum wage legislation and other selected regulations. On average only 0.35% of establishments inspected are found to be violating the NMW. This is somehow at odds with the reported 34-35% of private sector workers found to be paid sub-minimum wages (Table 5.2). However, in terms of violations found, non-compliance with the MW is only second to the 0.47% of non-complying firms with welfare regulations (not shown). Other salient traits of the transparency of labour relation, such as the provision of work rules and the records of employees and their wages, are found to be among the main non-complying activities of firms, particularly of SMEs. Although descriptive in its nature, Table C.14 tentatively suggests that the lack of transparency of wage contracting may explain some of the non-responsiveness found in the employment analysis.

Table C.14: Non-compliance detected for selected regulations by firm size, 2013.

	Minimum Wage			The work rules		
Firm size	% MW violations	Est.	Persons	Provide	Announce	Deliver a copy
Overall	0.35 %	171	1927	146	69	81
1 - 4	0.35 %	44	135	2	1	1
5 - 9	0.34 %	36	224	3	2	3
10 - 19	0.39 %	36	351	74	32	38
20 - 49	0.38 %	35	564	60	23	31
50 - 99	0.35 %	12	479	11	10	11
100 - 499	0.22 %	8	174	12	10	8
500 - 999	0	-	-	-	-	-
≥ 1,000	0	-	-	-	-	-
	Records of			Overtime and holiday		
Firm size	Employees	Working time	Wages payment	Overtime pay	Holiday overtime	Holiday pay
Overall	43	19	24	18	8	5
1 - 4	1	1	1	5	2	1
5 - 9	3	3	4	3	2	1
10 - 19	19	8	11	7	3	-
20 - 49	20	8	10	3	2	2
50 - 99	6	2	2	3	1	-
100 - 499	1	-	-	2	1	2
500 - 999	-	-	-	-	-	-
≥ 1,000	-	-	-	-	-	-

Note: Own calculations based on MOL (2013). Combination of Table 7.3 (inspections) and selections of Table 7.7 (part2). The table reports the number of establishments found in infringement with selected regulations (minimum wage, provision of work rules, record of employees, overtime and holiday pay). Additionally we report the share of firms violating the MW (out of those inspected) and the number of workers found to be paid sub-minimum wage. Statistics are expressed by firm size (number of employees) in year 2013.

Chapter 6

Conclusion

The thesis assesses whether the introduction or modification of specific policies can assist agents in their labour market decisions. It uses Thailand as a case-study for policy evaluation in a context of national policies implemented to solve market frictions and improve the country's development process. The thesis identifies how households interact with a formal credit institution in their migration decisions, and then evaluates how the minimum wage policy affects both wages and employment.

Chapter 3 performs an empirical evaluation of the effects of formal borrowing on internal migration decisions in Thailand. The introduction of the Village and Urban Community Fund Programme (VFP) is used to assess whether migration responds to borrowing once credit availability increases. Borrowing is instrumented using the inverse size of the villages at the start of the policy interacted with time (Kaboski and Townsend, 2012). These instruments reflect credit availability within each village and are shown to exert no direct effect on internal mobility out of these villages. The chapter identifies the short (1998-2003) and medium term effects (1998-2007) of the credit secured through the VFP. The results suggest that internal migration is not credit constrained. Households did not trade-off between two profitable but risky outcomes immediately after credit was injected. However, once the returns to borrowing became visible, and the scheme was perceived as a stable institution, the migration probability reduced. These medium term effects could arise from delays in reaping the benefits from borrowing, potential spillover effects taking place in the economic environment, such as greater economic activity within a village, or from increased expectations about potential borrowing. The results support the view that these likely channels may have modified households' behaviour in the medium term leading to changes towards a risk-diversification strategy such as migration.

Among potential extensions to this study, a future contribution could build on the empirical results to inform a theoretical model of the inter-temporal credit-migration nexus. For example, the dynamic models proposed by Fulford (2013) or Buera (2009) could be extended to address investments and migration decision as outcomes of borrowing dynamics. This would provide a theoretical grounding of how credit-constrained households trade-off between activities in and outside of the place of origin when faced with formal credit arrangements. As Deaton (2010) suggests in the case of quasi-experimental policies, the definition of a theoretical basis for the inter-temporal migration-borrowing nexus could support replicability of similar policy environments in other contexts.

Another potential extension to the analysis could be to compare VFP borrowing with other credit institutions. This could help explain whether the credit-migration nexus changes in a setting with different contractual arrangements. Additionally, since the chapter only looked at internal movements (seasonal or of longer length), future extensions could seek to cover other types of migration. An extension to other types of migration with nationally representative data would help answer the question of whether credit shocks produce different reactions to international as opposed to internal migration, and whether they alter trends in return migration. Given the paucity of data in terms of quality and frequency, no analysis has been found assessing whether foreign workers accessed VFP credit or whether they indirectly benefited from the scheme.

The chapter also puts forward new evidence on the medium term impacts of the policy, a facet that has been rarely studied in the evaluation literature (with the exception of some randomisation studies such as Banerjee et al. (2015) for a micro-finance institution and Attanasio et al. (2017) for a training and job placement programme). The results show an inter-temporal aspect which could be useful for the design of financial inclusion policies, as the involvement with Micro-finance institutions (MFIs) may alter risk-diversification strategies only some time after programme introduction. The VFP was recently complemented by the implementation of a country-wide savings scheme – the National Savings Fund (see Chandoevwit et al. 2016). Future research could also look at the potential complementarities of these programmes in changing savings and long-term borrowing behaviour of Thai households.

The chapter exclusively investigates the implications for migration and does not assess the sustainability of the scheme, but some conjectures can be made on potential roll-outs in other contexts. From a welfare perspective, the results point towards reduced credit constraints after greater exposure to micro-credit availability where contractual terms do not require collaterals. However, the heterogeneous outlook of the policy regarding single-sized fund allocation to self-selected groups of fund committees at the local level may create unintended consequences in other environments. This could happen in the event of take-up not being distributed across income groups or if funds are not allocated fairly by the local committees. As Townsend (2016) suggests, the allocation of future funds could be better planned to reflect the credit needs and market frictions across areas.

Chapters 4 and 5 explore the impacts of the minimum wage policy in Thailand. Chapter 4 provides some evidence of geographic heterogeneity in private sector employment and wages across Thai provinces, complementing the literature showing that growth and productivity are spatially concentrated in Thailand (Felkner and Townsend, 2011; Limpanonda, 2015). The empirical strategy is specifically devised to account for this heterogeneity when deriving the policy effects of a minimum wage change. It applies a variant of the Recentered Influence Function (RIF) regression framework (Firpo et al., 2009a) to provincial wage distributions. The chapter shows that this modification gives better linear approximations for the Thai data. The simplicity of the approach could provide a useful tool for analysis in other contexts. This method could be applied as a complementary estimator when national data are available as cross-sections, with lower level of geographic or administrative representativeness.

The province RIF evaluates the marginal effect of a shift in the covariates, and our policy variable is used in its log minimum wage per hour level to calculate the direct elasticity or wage responsiveness. As an extension to the empirical strategy performed, the minimum wage variable could be expressed as a weighted measure of the economic conditions in the local economy. As argued in the chapter, some standard modifications to the minimum wage measure proposed by the literature are not suitable to correctly capture the heterogeneous geographic wage settings and potential forms of informal labour relations attached to them. However, it may be useful to test the strength of the results by capturing within the same policy variable what are the local level conditions – at the province level – accounting for differential effects which may be stemming in low- versus high-wage areas. Additionally, all of the estimations are performed for the population of wage employees without considering the potential selection of private sector workers. Though not central to the policy evaluation *per se*, it could be interesting to modify the Unconditional Quantile Regression (UQR) with selection-correction methods, such as those applied to the Conditional Quantile Regression (CQR) case (Arellano and Bonhomme, 2017). This would account for the fact that samples of wage earners are non-random while assessing if this affects the linear approximations generated through the RIF model.

The chapter shows that during the 2000s the minimum wage had a positive effect on provincial wage distributions. The effects are however weak at the lowest percentiles (5^{th} and 10^{th}), and perpetrate from the 15^{th} to the 60^{th} percentile of the distribution. This suggests that the minimum wage in Thailand is used as a *numeraire* for wage negotiation. The weak effects found for the bottom of the provincial wage distributions, could be due to the low power of the model in providing linear approximations of the policy at the bottom tail of the distribution, and could also reflect signs of localised non-compliance for the least-paid employees. We show that the policy impacts have been heterogeneous according to the provinces' economic performance over the decade. Additionally, we find that compliance happens among firms with different employee size, but we find weaker effects for micro-enterprises, suggesting some degree of non-compliance for this group.

For the latest policy shift, which harmonised the minimum wage across provinces between 2012 and 2013, the chapter shows that the combination of a steep increase in the minimum and a move towards a single statutory minimum had strong positive effects on the wage distributions in the short-run. The results show sizeable effects between the 15^{th} and 60^{th} percentiles. The effects are particularly strong between the 15^{th} and 45^{th} percentiles of provincial distributions, where for every 10 Bath increase in the minimum, 3 to 5 Bath are redistributed to the workers in these percentiles. Moreover, we find that these effects due to the National Minimum Wage (NMW) policy change have been stronger in Bangkok and provinces from the Central and Northeastern regions. Although prior research suggests that the minimum wage has not altered wage inequality in Thailand (Leckcivilize, 2015), the findings proposed in the chapter indicate that future research might be needed. Future research questions should address whether inequality increased after the latest national minimum wage introduction, both across individuals in a same area and among different areas, and what role can be attributed to the variation in the policy versus other institutions guiding the labour market.

Chapter 5 investigates the employment effects of the minimum wage policy. The chapter draws on the theoretical and empirical literature highlighting that, in an emerging economy setting, both informal sector participation and enforcement matter for explaining the adaptiveness to a minimum wage policy change. The main results, obtained using a reduced form demand equation at province level, show that aggregate private sector employment was not affected by policy changes over the 2000s. There are signs of small but significant contractions in low-skilled employment, particularly for female youth, revealing that over the last decade the adjustments have generated some negative effects. However, no indication of major changes in sectoral workforce composition due to the minimum wage changes are found. The estimations indicate that some of the adjustments took place in hours worked for private sector employment, but most of the estimates suggest that minimum wage adjustments were well absorbed.

The employment demand in the provinces also appeared to be stable during the NMW policy period. On aggregate, no major short-run adjustments are visible at provincial level neither for private nor for non-wage employment. The average hours worked is positively affected during the regime change, suggesting some signs of increased employment participation at the intensive margins. The results from the employment analysis of the latest NMW policy are partly driven by non-compliance and partly by the tax breaks applied over the period, which may have increased firms' capacity to absorb change.

A key limitation of both chapters is data related, as these do not track informal wage employment in the Thai economy. Not accounting for informal wage work is an issue for two reasons. From the empirical standpoint, it is not possible to gauge for

Thailand how informal wage, self-employment and unpaid work act as substitutes to formal wage employment. The Labour Force Survey (LFS) does not collect information on social security coverage nor wage data for the self-employed. A quarterly collection of such information could better help policy makers devise social security coverage strategies across age, geographic and occupational groups. The effects of the minimum wage on dual labour markets is thus still not clear for Thailand, as not all of the types of informal employment, particularly informal wage employment, can be identified in the data. From the theoretical standpoint, for most workers in emerging economies being unemployed is not an option, and this raises challenges related to which characterisation of other forms of status should be used for thinking of their employment options. Aside from the evidence that the standard supply-and-demand model may not be enough for understanding the low-paid labour market (Card and Krueger, 1995; Manning, 2016), there still seems to be an inadequate understanding of the diverse forms of informal work and underemployment in emerging economies. Future analysis on this issue would provide a more refined understanding of the minimum wage policy.

As further paths of research, there are three important aspects of the response to a minimum wage policy change that were beyond the scope of the thesis but which could be extended in the future. The first is an evaluation of hiring versus layoffs, which could provide more information on whether any substitution of the labour force took place across sectors and geographic areas in the country. The second aspect relates to adjustment costs on the side of firms. The lack of employment contraction found in Chapter 5 raises several questions on which margins did firms adjust – being profits or non-labour inputs for example – and how effective were the lower social security contributions and corporate income tax rates to aide the change. The third, and related, aspect is a screening of the survival of firms over time. Although it was not possible to assess with the data used in this thesis, perhaps some firms (particularly micro enterprises) either closed down or de-registered due to the increased costs of formally hiring, increasing the rate of informal firms present in the country. More research on these three aspects, once more firm-level data become available, could be extremely beneficial for understanding Thai firms' behaviour and for assessing future minimum wage revisions.

The work of Chapters 4 and 5 suggests that the increase of a minimum wage level well above inflation did not create strong contractionary effects on employment and had a positive wage effects. However, the chapters also show evidence of partial compliance in Thailand. The labour inspection system, with low levels of sanctions and probability of detection, may have not been completely apt to ensure that minimum wage increases are effectively reflected into wage increases for employees at the bottom of the distribution. The strategy of "turning a blind eye" (Basu et al., 2010) appears to be the mechanism used to ensure that job losses are at a minimum. However, this fact raises concerns. In the future rising inequality could become an issue if the wage keeps being stagnant for a fraction of low-paid workers. Additionally, as the Thai population is ageing and other forms of labour protection are limited, this portion of low-paid workers may end up being more vulnerable once they exit the labour force.

Regarding the set-up of the latest policy change, two features have emerged from the short-term evaluation of this thesis. First, the use of a single minimum may have reduced information asymmetries for workers when bargaining their wage. Second, there are indications that some firms (particularly larger ones) have responded better to the policy change by increasing wages and retaining their workers. This could be due to the complementary policies on tax concessions and social contributions which were applied with the NMW. Future research should look into the fiscal sustainability of the two measures combined. This aspect would help Thailand, as well as many other economies with a small tax base, to plan complementary fiscal adjustments in addition to labour policies.

The Chapters attempt a series of ancillary exercises, among which one investigates whether the wage or employment effects found are correlated with any time period of the two steps of the NMW introduction, the hike period or the move from many to a single minimum wage. The exercise is considered as a non-causal and preliminary heterogeneity investigation, due to the use of observational data to compare groups. Future research with a more accurate econometric methodology could provide a better understanding of the latest intervention in terms of its policy traits. A synthetic control approach (Abadie et al., 2010) at the province level or matching techniques (Smith and Todd, 2005) across individual cross-sections could help attenuate the uncertainty in the selection of comparator groups. This would both be relevant for Thailand as well as for those countries using geographic (i.e. Indonesia) or sector-specific minimum wages (i.e. South Africa) to assess their regime adjustments.

A final aspect of the policy, not evaluated in the thesis *per se* but highlighted elsewhere in the literature (Rani et al., 2013; Bhorat et al., 2015), is coverage. The minimum wage in Thailand does not cover agricultural, fishery or domestic work. Partial coverage may allow some sectors to benefit from a lower cost of labour, but at the price of creating uneven rewards for workers. Future research is warranted on the regulation of such sectors which are mostly composed of foreign labour. Although it was not covered in this thesis, much more effort should be pursued to collect information on international workers' inflows and their conditions.

Some simple actions to improve the protection of the labour force could be recommended from the work of this thesis. The thesis gave some evidence that the modification of the policy has translated into positive short-term wage redistribution. The fact that the 300 Baht minimum wage was advertised in media outlets could have induced more transparent wage negotiations which reflect in the results found here. Research shows that the simpler is a minimum wage legislation, in the presence of forms of enforcement and sanctions, the lower is the rate of non-compliance (Saget, 2008; Rani et al., 2013). Thailand could take the example of other countries (such as Costa Rica) and implement inexpensive campaigns to advertise the minimum wage adjustments. Employer-employee relations could be enhanced by demanding greater transparency on the contract terms and ensuring mediation through labour representatives, so as to ensure that the legal minimum is received by workers. All these avenues could be set as experimentation of information campaigns and help lines for those who are subject to discrimination. This is particularly relevant today, as since 2017 the re-introduction of four minimum wages and the addition of sector-specific skill-based floors may create further complexities. Future adjustments of the minimum wage should be kept at a higher rate than inflation, to avoid wage erosion as prior to the NMW introduction.

The final message which stems from this thesis, is that the labour market of this emerging economy is characterised by considerable heterogeneity, absorption capacity and dynamism. The thesis characterised many aspects of the Thai labour market and raised many more questions on the mechanisms and the institutions needed to alleviate present and possibly future market frictions. A key challenge identified for policy making is the need for a holistic view on the labour market in both its legal and redistributive contours. Policies which are well thought to solve market imperfections may fall short without complementarities from other institutions in guaranteeing workers' protection and reward.

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