Three essays on the Mexican Labour Market

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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.

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Summary

The present thesis aims to contribute to the understanding of labour economics in Mexico. In particular, the decisions of individuals to enter a job in the formal or informal sector and how workers differ in terms of wage and time spent unemployed. Also analysing the effect of high levels of violence on wages.

In the first chapter, search channels are analysed. The results reveal that women benefit more in securing formal jobs when searching on-line, newspaper and via allocation offices. Men benefit from friends and family to secure informal jobs. Searching online for jobs implies a wage premium of 12.3% for formal workers and 7.0% for informal ones. Searching for jobs in the newspaper, implies a wage penalty of 5.24%. These results are robust after the correction for the potential issue of selection bias.

In the second chapter, the duration of unemployment is analysed. Both the single and multiple destination models permit us to conclude that going directly to the workplace and searching for jobs via newspaper reduce the time unemployed for those exiting into a formal job. Asking friends and relatives increases the hazard for those securing an informal job. These results are robust to the inclusion of unobserved heterogeneity in the estimation.

The third chapter offers an explanation of the impact that the presence of Drug Trafficking Organizations in Mexican municipalities on the wages of individuals. It also offers an explanation of the impact for both formal and informal workers. The estimation results of the preferred specification after instrumenting violence and the presence of DTOs to address reverse causality, yields a positive effect of the presence of DTOs, but no effect of violence. More specifically, an additional DTO per municipality increases wages by 5.7%. The impact on wages is not statistically different for formal and informal workers.

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Contents

List of Tables

List of Figures

Introduction

The analysis of the duality of the labour market in Mexico has been the subject of interest of many researchers. This duality is defined as the type of jobs taken by workers which are classified as formal and informal. Informality, often referred as the underground or illegal economy, in its most simple definition refers to the lack of access to public social security and health services provided by the government.

In Mexico, informality is not considered an illegal activity. It is common to see people setting up street stalls outside their home and selling food or any other item to earn some money and this would not have any legal consequence. The facility to engage in this activities has led to approximately 60% of the total workforce to be employed as informal.[1] This sector accounts for nearly 25% of the Gross National Product according to the National Institute of Statistics and Geography (INEGI). Furthermore, the government in an effort to understand the composition and dynamics of these jobs conducts household surveys which include questions to aid in the identification and quantification of informal workers. For example, since its creation, one of the objectives of the National Survey of Occupation and Employment (ENOE) is to quantify the proportion of workers considered as informal, their earnings and personal characteristics.

The focus of the research on the labour market that is composed of these two sectors, has been on whether the informal labour market is beneficial to the economy because it diversifies the employment opportunities or it is simply the result of market failures. On the one hand, it is claimed that informality is perfectly integrated in the labour market. Workers deliberately choose these jobs because the characteristics associated to them (such as flexible working schedule, proximity to home, to avoid paying taxes) make it an attractive option (Maloney, 1999, 2004; Günther and Launov, 2006; Bargain and Kwenda,

[1]This is only one type of informal job, we can also mention that a person can be employed in both formal and informal firms as informal.

2010; Carlo et al., 2015). On the other hand, there are studies claiming that the informal sector is the result of the barriers to the entry to the formal sector, the lack of jobs in this sector creates an oversupply of labour that spills into the informal one (Serneels, 2008; Mondragón-Veléz et al., 2010).

More specifically, the literature on the search channels and duration of unemployment has focused only on the formal sector of the economy (Addison and Portugal, 2002; Woltermann, 2002; Márquez and Ruiz-Tagle, 2004; Meliciani and Radicchia, 2011). However, if the motives to access informal jobs are different to formal ones, understanding the decision of individuals to engage in one sector compared to the other can help in the design of policies to promote the formalization or to increase the productivity in the informal sector. Key aspects that can help in the understanding of this phenomena include the duration of unemployment and how wages in both sectors respond to external shocks, such as high levels of violence. Studies have documented that high levels of violence do have an effect on employment outcomes, affecting the proportion of employed individuals, the total number of hours worked and productivity (Robles et al., 2013; Cabral et al., 2016). Most of this comes from self-employed and the effect is even stronger for female workers (BenYishay and Pearlman, 2013; Fernández et al., 2014; Velásquez, 2014). In other cases, it is precisely the self-employment that serves as a coping mechanism Bozzoli et al. (2013). But the evidence on the impacts on salaried employees until now is scarce.

This thesis aims to contribute to the understanding of labour economics in Mexico, analyzing the interaction between the formal and informal sectors and how workers choose to engage in each of these. The availability of information at the household and individual level makes the Mexican case particularly apposite for this analysis. The National Survey of Occupation and Employment (ENOE), is the most complete source of information regarding employment and education for Mexican workers. It is conducted quarterly and it constitutes a nationally random sample of individuals. The period of the survey used here spans from 2005-2015. Additionally, the Mexican Family Life Survey (MxFLS) was conducted in three waves, between 2002 and 2009. This survey is nationally representative at the household level. The timing of the survey permits the analysis of the exposure of workers to the levels of violence before and after 2006 the year in which several factors increased the homicide rates in Mexico.

Given the availability of information, in the first chapter the following questions can be addressed: What is the impact of different job search channels and the means by which a person finances job search on the probability of transitioning to formal vs informal jobs? Do job searchers have any preference for the sector they wish to work in? and what is the magnitude of the gender wage gap and which factors explain the gap in formal and informal jobs? Furthermore, for the second chapter the following question can be addressed: what is the impact of search channels and means to finance job search on the duration of unemployment of formal and informal workers? Finally, for the third chapter the we enquire about the effects of the violence and presence of Drug Trafficking Organizations on wages.

In the first chapter the factors that determine the exit rates of unemployed individuals into formal and informal jobs are examined. Specifically, exploring if severance payments, government aid and assistance from family in conjunction with the search channels used have an impact on the probability of exiting unemployment. The analysis is then enriched by examining the impact of the use of different search channels on the wages of formal and informal workers. This is done correcting for selection bias in the estimation.

Some interesting findings arise from the analysis of the transitions of job searchers in the Mexican labour market. There seems to be a positive and strong correlation between being formally employed and transitioning to formal employment in period t+1. Asking directly in the workplace and asking friends or relatives to recommend for a job are the most used channels, but not the most productive in terms of securing a job. Searching on-line, via newspaper ads and using allocation offices help female workers to secure formal jobs. On the other hand, asking friends is more effective for male workers when accessing informal jobs.

The results also reveal that workers that self-select earn, on average, 16.0% and 8.2% higher wages in formal and informal jobs, respectively, than an average worker drawn at random would earn. Moreover, the results yield a positive effect of searching online for jobs of 12.3% on wages of formal workers and 7.0% on wages of informal workers. Those that secure jobs via newspaper ads experience a wage penalty of 5.24%. These results can be explained by the type of job that are secured via these channels.

The second chapter contributes to this literature by examining the overall effects of a set of personal characteristics, search channels and financial variables on the duration of unemployment. Using micro-level labour market data for Mexico the overall effects of a set of personal characteristics, search channels and financial variables on the duration of unemployment are analyzed. Individual-level heterogeneity is also accounted for in the estimation. Furthermore, given that the factors influencing the choice of one employment state impact differently the choice of another, a multiple destination or competing risk model is estimated.

Using a discrete setting model and controlling for unobserved heterogeneity, the duration of unemployment is found to be shorter for those that were previously informal workers compared to formal ones. It can be concluded that there is presence of wait unemployment, for those that are formal workers. The coefficients of the variables measuring the presence of a financial cushion yield mixed results. On the one hand, those that had access to a lump sum payment from a previous job, experience shorter unemployment duration. On the other hand, those receiving support from a government program exhibit longer unemployment periods. The results of the multiple destination model allow us to further understand that the shorter duration for those in possession of a lump sum payment happens when they exit into formal jobs. Those in receipt of a government program have a higher probability of exiting the labour force.

Regarding the search channels, those that went directly to the workplace and replied to newspaper ads experience shorter duration of unemployment when securing formal jobs. Asking friends and relatives reduces the time unemployed for individuals that exit into informal jobs. The use of other channels rather than reducing the search time seem to prolong it.

The third paper offers an explanation of the impact that the presence of DTOs in Mexican municipalities and violence have on the wages of individuals. It also explains the impact for both formal and informal workers. Given the availability of individual information from the Mexican Family Life survey (2005-2010), data from homicide rates and a unique dataset that reflects the presence of drug cartels in Mexican Municipalities from Coscia and Ríos (2012), I am able to address how the violence associated with the War on Drugs and the presence of DTOs in Mexican municipalities impacts wages. Ex-ante the effect is unknown as the impact of violence and criminal presence on labour markets is multidimensional and varies depending on whether the worker is employed as formal or informal. For example, the presence of such groups can signal the absence of the rule of law in Municipalities pushing firms to re-locate to avoid the risk of attacks, extortion or theft, thus pushing wages down. It can also mean that because these groups inject illegal money into the local economy, this could create employment opportunities and push wages up.

The estimation results of the preferred specification after instrumenting violence and the presence of DTOs to address reverse causality, yields a positive effect of the presence of DTOs, but no effect of violence. More specifically, an additional DTO per municipality increases wages by 5.7%. On further dissagregation, wages for informal workers increases by 4.9% and 3.4% for formal workers. However, it is important to highlight that these results are not statistically different, which leads to conclude that both sectors react in a similar way to these shocks.

Understanding what drives the decisions of individuals to engage in formal or informal jobs and their characteristics aids in the understanding of the mechanism through which workers access both formal and informal jobs. This ultimately leads to the design of policies to promote the formalization of jobs. One of the main characteristics of informal workers is that they do not pay taxes and this is income that the government is not receiving. Considering that almost 60% of the total workforce in Mexico is employed as informal, the loss of revenue for the government via tax avoidance is non trivial. This thesis aims to provide empirical evidence to further understand the dynamics of the Mexican labour market.

Chapter 1

Job Search Channels, employment and wages: Empirical application to Mexico's formal and informal sectors

1.1 Introduction

The Mexican labour market is widely known for having low levels of unemployment compared to other countries in the OECD (3.74% on average since year 2000). However, such rates are partially explained by the fact that much of the workforce is employed in the informal sector.[1] To understand the dynamics of a labour market with dual nature, one has to analyse how individuals allocate between the two sectors, if they have preference for one sector over the other and if so, to what extent this preferences impacts wages. Furthermore, there is a wage gap for male and female workers, but this gap is not necessarily the same for formal and informal jobs as the motives to join one sector or the other may be different by gender.

A number of studies have analysed how different search channels impact on exits out of unemployment, its duration, and the type of jobs individuals find. (Addison and Portugal, 2002; Woltermann, 2002; Meliciani and Radicchia, 2011). It is also an endogenous process

[1] According to the most recent labour report from the National Institute of Statistics and Geography, (INEGI) 57.4% of the total workforce is considered informal, which means that these individuals do not possess social security or any of the job benefits that come with being formally employed.

so most of the job searchers rely on asking directly employers for job or via friends and relatives. And these channels are also the most effective in securing a job (Addison and Portugal 2002; Woltermann 2002; Calderón-Madrid 2008; Meliciani and Radicchia 2011). There is somehow a general consensus that these search channels do not imply jobs that account for the workers personal characteristics, are low paid and short term (Addison and Portugal, 2002; Woltermann, 2002).

However, most of the existing evidence is for the formal labour market and less attention has been drawn to how search channels impact the probability of securing an informal job. If individuals face an entry barrier to formal jobs then informality can serve as "cushion" to finance job search. Alternatively, individuals might choose to be informal workers as they value certain characteristics offered by these jobs. In this sense, the literature has documented that to some extent individuals explicitly choose in which sector to work and that these are perfectly integrated (Maloney, 1999, 2004; Günther and Launov, 2006; Carlo et al., 2015).

The present study contributes to the literature by examining the factors that determine exit rates into formal and informal jobs. Specifically, I explore if severance payments, government aid (via training scholarships, aid from a government program and financial aid to start a new business) and assistance from family (via remittances or cash transfer) in conjunction with the search channels[2] used have an impact on the probability of exiting unemployment. The analysis is then enriched by examining impact of the use of different search channels on the wages of formal and informal workers. This analysis is done correcting for selection bias in the estimation using the methodology proposed by Lee (1983).

Given the availability of self-reported information in the survey I am able to address the following questions: What is the impact of different job search channels and the means by which a person finances job search on the probability of transitioning from unemployment into formal or informal jobs? Do job searchers have any preference for the sector they wish to work in? What is the magnitude of the wage returns from different search channels?

Some interesting findings arise from the analysis of the transitions of job searchers in

[2]These search channels are: asking directly in the workplace, searching on-line, replying to advertisements, asking friends and relatives, using allocation services and others.

the Mexican labour market. There seems to be a positive and strong correlation between being formally employed and transitioning to a formal employment in period $t+1$. There is a "wait unemployment", reflected by the fact that those with lower levels of education experience more transitions relative to more educated individuals. This indicates that individuals with more education have higher reservation wages and prefer to wait for a formal job offer rather than accepting an informal one.

Asking directly in the workplace and asking friends or relatives to recommend a job are the most used channels, but not the ones giving the highest returns. Searching on-line, via newspaper ads and using allocation offices help female workers to secure formal jobs. On the other hand, asking friends proves to be more productive for male workers when accessing informal jobs. The results of the selection bias correction, using the methodology proposed by Lee (1983), reveals that workers do not select randomly into jobs and earn 16.0% and 8.2% higher wages, for formal and informal respectively, than an average worker drawn at random would earn.

Regarding the wage returns of using different search channels, the results yield a positive effect of searching online for jobs of 12.3% on wages of formal workers and 7.0% on wages for informal workers. On the other hand, those securing formal jobs via newspaper ads experience a wage penalty of 5.24%. Moreover, this result is confirmed when the analysis is done separate by gender. Formal males experience a wage premium of 16.2% but experience a penalty of 4.9% when using the newspaper. These effects can be explained by the type of jobs that are secured via these channels. Jobs advertised on-line are correlated positively with the schooling level of the individual and thus are better paid. On the other hand, the jobs advertised through the newspaper are often low paid with temporary contracts.

The structure of the chapter is as follows. In section 1.2 the existing literature on search channels and job outcomes in developed and developing countries is reviewed. In section 1.3, The background to Mexican labour market is described, as well as the data used and the summary statistics are presented. In section 1.4, the econometric methodology is detailed and section 1.5 reports the empirical results of the multinomial logit model, the selection bias correction and wage differentials. Section 1.6 provides some conclusions.

1.2 Literature Review

The theoretic framework for job search derives from the economics of information and uncertainty (Mortensen, 1986). It is the modelling of the behaviour of the unemployed who are actively looking for employment. Job offers will arrive randomly from a known distribution according to a Poisson process. According to the settings of the basic model, the worker's decision problem is to maximize utility by choosing the best possible job offer. If the worker accepts, they will receive a wage continuously over the tenure of the employment and the job will last forever. If a worker rejects a job offer it cannot be recalled. A crucial implication of the Poisson arrival assumption for the basic model is that offers arrive one at a time and the probability of receiving an offer does not depend on the duration of the unemployment spell (Devine and Kiefer, 1991).

The basic model of job search can be extended and the assumption of offers that are exogenous and arrive randomly according to a Poisson process can be relaxed. One can argue that search intensity of the worker has an effect on the probability of receiving a job offer. This is because as the worker searches more intensively, the probability increases. But increasing this effort represents additional costs (Bong Joon, 1981).

Not only can the search intensity increase the arrival of job offers, the channels also have a positive impact on the probability of getting a job, as some search channels can be more effective when searching for a specific type of job, compared to others. One of the studies that provides an insight into the importance of search intensity and of the different channels used by unemployed individuals is Holzer (1988). This analysis of different search methods used by unemployed individuals aged between 16-23 years old, presents a model of job search which suggests that search method choices are related to their underlying costs and expected productivity as well as to other factors. Holzer's empirical results suggest that the search channels used more frequently are the ones associated with friends and relatives and going directly in person to the workplace and these are the more productive ones in generating job offers.

Using data from the National Longitudinal Survey (NLS) for the US in 1981, Holzer (1988) estimates using OLS an equation that captures the number of methods used and a probit model to estimate the equation that captures the specific search methods used. The results suggest that the number of methods used is affected by personal characteristics and being on lay-off. The latter presumably reflects the market opportunities as well as income sources and needs. The overall search intensity and its allocation across methods is chosen by unemployed individuals who balance the relative productivity and costs. In other words, search intensity leads to a higher job offer probability.

One would anticipate that specific methods have specific outcomes. In this sense, Chirinko (1982) analyses the impact of direct (asking for a job directly in the workplace) and indirect search methods (through friends and advertisements) on the returns to job search on the US using the Current Population Survey (CPS). Using a maximum likelihood technique, he finds that direct methods exert a positive impact on the returns to job search, whilst indirect methods yield a negative impact. There appears to be diminishing returns in the job search process when using indirect methods of job search.

Using the same dataset (CPS), Kuhn and Skuterud (2004) test for the incidence and diffusion of internet job search investigating who searches for jobs on-line and the outcomes of looking for a job through this channel. The authors use a probit model and conclude that internet job search is more common among workers with observed characteristics that are usually associated with more rapid re-employment, i.e., occupations with low unemployment rates, young and well educated workers and persons that became unemployed after finishing school or had previous job experience.

Addison and Portugal (2002), using Portugal's Labour Force Survey, assess the effects of different job search strategies on escape rates from unemployment, and measure the effectiveness of the job search strategies on obtaining a job. They find evidence indicating that the most successful methods in finding a job are approaching the employer directly and informal methods (i.e., friends and family networks). One of the implications of their empirical results is that the effectiveness of the public employment service in Portugal is low. This might be because employers tend to avoid employment service placement. Their major finding is that the public employment service has a low success rate and leads to jobs that do not last, where the pay is low and the rewards for observed human capital attributes as well as other job-finding routes are small.

The channels used for job search can be further subdivided into formal and informal ones. Presumably there are certain channels that would be more effective in ensuring a job offer given a worker's characteristics and the desire to access these type of jobs. Márquez and Ruiz-Tagle (2004) suggest that workers who come from formal jobs are more likely to use more formal methods relative to those who come from jobs in non-regulated segments of the labour market. Using a logit model and the Venezuelan Household Survey, they analyse the impact of a set of different search strategies in determining whether a worker will experience a transition into employment. They conclude that the search process is a crucial element in the functioning of the Venezuelan labour market. More effective search methods increase the efficiency of job-worker matches and certain methods would work better than others for a specific type of worker and a specific type of job. Personal characteristics (such as education, age and gender) have an impact on the choice of search strategy.

The authors also use a multinomial model to estimate the probability of individuals exiting unemployment into inactivity or employment conditional on search methods, personal characteristics and previous job status. In their findings, almost three quarters of job seekers in their sample are using either informal networks of family and friends or direct contact with employers. They find that previous job status (being employed or unemployed) has a dominant impact on transitions into employment.

The study by Meliciani and Radicchia (2011) investigate if being recruited through informal channels in the Italian labour market has both a wage penalty for job searchers. Dividing the search channels into friends and relatives and professional ties. Estimating a Mincerian wage equation and controlling for observable characteristics, they find that there is a wage penalty for those hired through the friends and family channels and a wage premium for those hired through professional ties.

Woltermann (2002) examines the effects of various job search methods on the labour market transitions of workers in Brazil (considered as a segmented developing economy) focusing particularly on the impact of search methods on exit rates into different labour force states. Part of the segmentation of the labour market originates from the lack of information on the vacancies available in the formal sector. Different search methods lead to different occupational states and that part of the labour force that enters the informal sector would be better off in a formal job if they had access to more information on labour market and assistance on application procedures. Using multinomial logit models, the study estimates the effect of the choice of a search method on the exit rates to different occupational states (informally employed, self-employed, searching and inactive) controlling for search channels, gender, position in the household, and education.

According to Woltermann (2002) most job search in Brazil relies on methods that involve directly asking either an employer or friends and family. The effects of search channels on exit rates on different labour force states are also differentiated. For example, the category 'asked employer' is the most effective in transitioning into employment, followed by 'advertisement' and 'friends and family'. The categories 'examination' and 'agency or union' do not appear to have a significant impact. According to the findings of all the search channels only 'asked employer' and 'advertisement' yield significant effects for a transition to a formal job. In addition, 'asked employer' and 'asked friends and family' also seem to be highly significant in influencing the odds of getting an informal job against 'searching'.

Not all the empirical evidence supports the fact that increasing search intensity leads to a greater probability of job offer arrival and hence a shorter unemployment spell. One of the main reasons for this is that a worker must devote the time and resources to this process, hence it becomes costly. In this sense, Keeley and Robins (1985) findings for the US suggest that the most productive forms of job search are those that are directly associated with direct employer contacts. Search intensity and search channels used can also vary depending on personal characteristics and the type of job a worker is looking for. For example, Weber and Mahringer (2002) for the case of Austria find that, on average, unemployed individuals use two methods of job search. They report that search effort decreases with age and that more educated individuals search harder compared to lower educated ones. Going directly to the workplace accounts for more than half of the jobs found. Women and persons with higher level of career motivation have a higher probability of getting a job through the public employment office. Moreover, they find no significant effect of increasing search effort on higher wages.

As can be observed throughout the literature review, different methodologies for different countries have been used to analyse labour market transitions and the duration of unemployment for unemployed workers. The review of what has been done becomes important to provide a framework in which to place this study, given that the same methodology can be applied to the case of Mexico in order to shed light on how different search channels affect the transition of unemployed job searchers to different labour force states in the Mexican context. The aim of this research is to analyse a two episode transition over ten years (i.e., transition from quarter one to quarter two for the period 2005-2015), given the information provided by the Mexican Employment Survey (ENOE). We now turn to a description of the Mexican labour market and the data used.

1.3 The Mexican Labour Market and Data

In Mexico there is no national unemployment insurance program.[3] However, the government provides training scholarships, and advice for finding a job through the National Employment Service (SNE in Spanish to unemployed individuals). Individuals that become unemployed, and were previously formal workers, have the right by law (Federal Labour Law for dismissals) to a severance payment that will vary with the type of worker contract they possessed. If the contract was for less than a year, the payment consists of an amount that equals the monthly wage of half the time for which the employee was hired. If the contract was for more than a year the amount consists of six months of wages for the first year and 20 days for each of the years the worker was employed. If the contract was for an indefinite time, the payment consists of 20 days for each of the years worked.

Quitting a job affords no right to a worker in terms of severance payment. Workers in the formal sector have access to fringe benefits that are partly financed by payroll taxes. These benefits (provided mainly by the two major health institutions IMSS and ISSSTE) consist of health care, life insurance, housing loans, retirement pension and severance payment.[4] In contrast, workers in informal jobs do not have a legal right to any of these fringe benefits. Their work conditions and wages are a matter of personal agreement between the employer and employee.

A formal worker in Mexico is defined as a wage earning person that is registered and

[3] The only Mexican state that has an unemployment insurance scheme is Mexico City. This was implemented in 2010 as a state policy by the Local Labour Office. It consists of financial aid for up to six months to finance job search and enhance the transition to formality.

[4] IMSS provides social security and health services to workers employed in the private sector whilst ISSSTE provides these services to workers in the public sector.

has access to public social security and health services provided by the government. A person that owns a small business with employees has to formally register his business to provide these services to all his workers to be considered as formal. In this way, using the self-reported information from the survey, workers are classified as formal, if at the time of the interview, they report being employed and are entitled to access health service from the government. They are defined as informal workers otherwise. It is worth noting that a worker can be hired by a formally constituted firm but have informal worker status.

In this paper, the Mexican National Employment Survey (ENOE in Spanish) is used from 2005 to 2015. This survey constitutes a nationally representative random sample of individuals. The National Statistical Office in Mexico (INEGI) asks individuals in this survey about different socio-economic characteristics and their current employment status. This survey is designed to be a rotating panel where the interviewed individuals remain in the sample for five periods and then exit. Two types of questionnaires are used in this survey: the basic and the extended version. The basic version is used in the second to fourth quarters of each year and the extended version is only used in the first quarter of each year.

The extended version contains questions on financial and other types of support. The objective of this set of questions is to capture if a person receives any form of financial aid from the government or from friends and relatives regardless of their employment status. As the sample represents only unemployed job searchers, it is of interest to determine if this aid (pecuniary or not) assists a person in exiting unemployment. Since this information is only available on the extended versions of the questionnaire, the analysis is limited to the first and second quarter of each year from 2005 to 2015. In this way, given the limitations of the data, the panel dimension of the data is not exploited but only the cross-section is used.

The survey includes questions regarding the job search channel used by individuals. These questions are asked in both surveys (basic and extended) and they capture the alternative search methods used by job searchers. Responses are divided into 11 categories and these are not mutually exclusive. The categories comprise: directly, private placement agency, government placement agency, job government program, formalities to start a new business, on-line job advertisement, published or answered a newspaper or other printed source advertisement, went to a union or guild, asked relatives to recommend or inform about a job, check advertisements on newspapers and others. Due to the similarity between categories, the responses were merged into six broader categories in the following way: Ask for job directly, on-line job advertisement, advertisement (printed, newspaper, radio, and television), social networks, allocation services (public and private allocation service, went to union or guild) and other (arrangements to start a new business and other).

The identification of sources of income to finance job search are also included in the survey. According to the questions, income is from three main sources: financial aid from friends and relatives, financial aid from a government program and income after employment (e.g., severance payment). Financial aid from friends can come from: someone abroad, someone in another Mexican state or someone in the same state. In the same way, aid from government may come from the following sources: fellowship, financial aid to start a new business, financial aid from any other government program. Finally, income after employment can come from either a severance payment, sale of a former business, a retirement pension, unemployment insurance or private unemployment insurance.

As the number of people that did not have access to any of the three sources of income to finance job search is relatively small, the categories are merged to create three binary variables that capture whether they had access to income or not. Hence, a zero captures if a person did not have access (to aid from government, friends or income from a previous job) and one captures if the person did have access to any of the above.

The survey is a rotating panel of five interviews and for the purpose of the analysis I only considered those individuals that by the first quarter of each year were in their first to fourth interview. This allows tracking them to the next quarter of the survey and identify which channels they used to find a job in the first quarter and their labour market status in the second quarter. All these individuals state that by the first quarter they were unemployed and actively looking for a job. I also drop all those that appear only in one quarter of the sample and only retain those cases that had previous job experience.[5]

Having no unemployment insurance in place at the national level makes the informal sector the ideal 'scape mechanism" for workers who are in need of a steady source of income whilst they find a suitable job. This complementarity is also possible for two reasons, there is a lack of infrastructure to ensure that workers secure a formal well paid

[5]These individuals only comprise 7.0% of the total sample of job searchers.

job. The current public allocation service is often not used by workers. If we observe in table 1.1 most of the job searchers either go directly to the workplace or rely on friends and relatives to secure a job. So this means that the current system is failing to bring down matching costs for both employers and employees. The effectiveness of some channels over others reflects how the labour market is composed. For example, public funds are devoted to government placement agencies and if job searchers are not using these channels or the type of jobs found through these channels are temporary or low paid. Then these public funds can be more efficiently spent in other public programs such as training or scholarships for unemployed individuals

The second reason for the complementarity between the formal and informal sectors is that informality in Mexico is not an illegal activity, so there is no restriction to enter this sector. There is a large debate on the segmentation of the Mexican labour market. Some argue that individuals have to work in informal jobs because the formal sector cannot offer sufficient jobs and thus individuals have to engage in informal activities to secure an income. This in part can be observed in graph 3.1, which plots the unemployment and informality participation rate for the period 2005-2015. There are marked periods of increasing trends in both the unemployment and informality rate. The period after the great recession in the late 2008 is the more clear example of this. Whenever there are periods of rising unemployment, this will spillover into the informal sector. When the unemployment rate is going down as in the period after 2010, the participation rate in the informal sector also goes down.

There is another argument about informality in developing countries, and is that workers choose freely in which sector to work and the choice only depends on the wage and other factors that are preferred by them. Whether the Mexican labour market is segmented or perfectly integrated and the result of personal choice, it is important to shed light on the job search returns to the use of different search channels by individuals and whether this channels are also the ones helping them secure a high paid job.

Table 1.1 reports the summary statistics for the variables of interest in the selected sample for the first quarter of each year. It can be observed that 70% of the sample is comprised of male job searchers, 65% are heads of household and the proportion that has access to any type of income to finance job search is relatively small. The sample is evenly distributed among educational categories, although it is worth reporting that, on average, secondary schooling has the highest proportion of job searchers (30%). Approximately 6%

of the sample has access to income after work or financial aid from friends and relatives and only 2% to aid from government. When looking at the stated reasons for job loss, it can be seen that being dismissed or finishing a job accounts for 60%, whereas 31% of job searchers reported that dissatisfaction with the previous job was the main reason for exiting their job. Regarding the search channels, three are worth highlighting: going directly to the workplace (74%), social networks (14%) and advertisements (13%). For the case of the five Mexican regions, the north and center comprise approximately 59% of the sample and the east, west and south regions the remaining 41%.

It is important to acknowledge that the search channels used by job searchers are endogenous to personal characteristics of the individual and previous work experience in a given sector. Moreover, an unemployed individual will use the channels that are more likely to help secure a job. For this reason, the results presented here in section 1.3 should be interpreted with care as I am not claiming causality. Instead, this exercise aims at looking how one search channel increases the probability of securing a job relative to others. Looking at how different search channels affect the probability of securing a job is by itself an interesting exercise that enables us to draw conclusions on the dynamics of a labour market that is characterized by being segmented along two dimensions (i.e. formal and informal).

1.4 Econometric Methodology

For the case where more than two destinations in the dependent variable are possible, the ordering among the destinations is irrelevant and regressors do not vary over alternatives, the multinomial logit model is more appropriate.

Let $y_{ij} = 1$ if the i^{th} individual in t experiences a transition in $t+1$ into one of the four labour market states (unemployed, formal job, informal job, out of the labour force) and $y_{ij} = 0$ otherwise, and where $j = 1, 2, 3, 4$.

$Prob[y_{ij} = 1] = \pi_{ij}$ and since the individual probabilities sum one we have:

$$\pi_{i1} + \pi_{i2} + \pi_{i3} + \pi_{i4} = 1$$

The multinomial logit can be re-expressed in a general form as:

$$\pi_{ij} = \frac{exp[x_i'\beta_j]}{\sum_j^k exp[x_i'\beta_j]} \tag{1.1}$$

Where k is the number of outcomes being modelled which are four in this case. This equation expresses the probability that an individual with characteristics x_i experiences a transition into the j^{th} labour force state. However, a normalization is required for identification and this is achieved by arbitrarily setting the elements of the β_1 vector to zero. This is referred to as *Theil normalization.*

For this four-outcome model of labour force transitions described by equations (1) to (4), the restriction implies that the probabilities are re-expressed as:

$$\pi_{i1} = \frac{1}{1 + exp[x_i'\beta_2] + exp[x_i'\beta_3] + exp[x_i'\beta_4]} \tag{1.2}$$

$$\pi_{i2} = \frac{exp[x_i'\beta_2]}{1 + exp[x_i'\beta_2] + exp[x_i'\beta_3] + exp[x_i'\beta_4]} \tag{1.3}$$

$$\pi_{i3} = \frac{exp[x_i'\beta_3]}{1 + exp[x_i'\beta_2] + exp[x_i'\beta_3] + exp[x_i'\beta_4]} \tag{1.4}$$

$$\pi_{i4} = \frac{exp[x_i'\beta_4]}{1 + exp[x_i'\beta_2] + exp[x_i'\beta_3] + exp[x_i'\beta_4]} \tag{1.5}$$

The parameters of the multinomial logit model are estimated by specifying the following log likelihood function after substituting for π_{ij}.

$$L = \sum_{i}^{n} \sum_{j}^{k} y_{ij} log(\pi_{ij})$$

Finally, for this multinomial logit model there is no single conditional mean of the dependent variable, y. Instead one has to model the probabilities of the different outcomes, because we have an interest in how these probabilities change as regressors change. In other words, if a change in x increases the probability of attachment to one category, it must reduce the probability in one or more of the other categories to ensure the underlying probabilities sum to one. In the case of having discrete binary variables as regressors, as in this case, one would estimate impact effects rather than marginal effects.[6]

1.5 Empirical results

1.5.1 Transitions out of unemployment

The effects of personal characteristics, search channels and financial aid on the probability of transitioning from unemployment in the first quarter of the survey to either a formal or informal job or even out of the labour force is estimated. It is acknowledged that the results presented here can be influenced by seasonality in the Mexican labour market, because we are specifically working on a transition from the first quarter of the year to the second over a period of 10 years. However, due to the limitations of the data this is the best that can be done in terms of explaining the sectoral choice unemployed individuals prefer to work in.

As described before, the categories of analysis are: unemployed, employed in a formal job, employed in an informal job and out of the labour force. All of the individuals of this sample are unemployed in the first quarter. Therefore they transition to these four different labour market states. The multinomial logit model controls for age[7], gender, marital status, position in the household (i.e., being the head), regional dummies (north, south, east, west, center), educational categories (elementary school, secondary school, high school and more than high school) if the previous job was formal, reason for job loss (dismissed, dissatisfaction, left previous business and others).

[6] See chapter 15 of Cameron and Trivedi (2005) for details on the estimation of impact effects.

[7] The age categories include 5 year cohorts. These are only used as controls so are not reported in the main estimation. The same criteria is also used for the estimation of the multinomial logit by gender.

Additionally, three variables to capture if a person is in receipt of any sort of financial aid (i.e., financial aid from friends and relatives, financial aid from government or any sort of income after work which can be considered as a “financial cushion”) are introduced. The different search channels used by workers to find a job are also included (i.e., directly to the workplace, job offer on line, advertisement in newspaper or classifieds, friends and relatives, used public or private allocation service and others).

As part of the econometric analysis of the model, the Independence of Irrelevant Alternatives (IIA) proposition is tested for the four outcomes of the model. The result of the Small-Hsiao test supports the null hypothesis. This means that the alternatives are independent of each other vindicating the use of the multinomial logit model.

The results of the multinomial logit estimation are presented in table 1.2 with robust standard errors reported in parenthesis. The coefficient for the gender variable indicates that being male increases the probability of experiencing a transition to employment for both formal and informal sectors. This is not surprising, given that the majority of the sample is comprised of male job searchers and traditionally in Mexican households the head is often male and the main provider for the family. This is consistent with the negative coefficient of the out of the labour force category, male job searchers are more likely to continue actively searching for a job rather than not working at all compared to women, even if this means remaining unemployed for an additional period. This is supported by the positive coefficient of the unemployed category.

Regarding marital status or being a head of household, the results yield a a strong positive effect on the probability of transitioning to employment for both formal and informal jobs. As mentioned previously, regardless of the gender, the head of household is often the main provider even more so if this means that they have to support a family in the case when they are married. Moving on to the educational categories, introducing this variable with multiple options entails using one of these categories as base for the comparison. In this case, “more than high school” was used as base. Two aspects are worth noting here, lower educational levels such as elementary and secondary school have a strong and positive impact on the probability of securing a formal or informal job but the effect is opposite for the case of formal jobs. High school on the other hand, does not appear to have an impact on the probability of securing either a formal or informal job. It actually increases the probability of going out of the labour force. This might indicate that highly educated individuals would have higher reservation wages relative to less educated workers and hence would experience higher levels of "wait unemployment", whereas less educated are willing to take informal jobs.[8] This result is consistent with Calderón-Madrid (2008) in the sense that those with low levels of education become informal employees faster than more educated employed workers and these same job searchers require longer job search spells to secure formal jobs.[9]

Being previously employed in the formal labour market has a positive impact on the probability of transitioning into employment in a formal job and has a negative impact on the probability of transitioning into an informal job. The fact that the effect is the opposite for those that transition into informal jobs is a signal that there are certain characteristics in the formal sector that are desired by formal workers. There are a number fringe benefits that come with a formal job such as housing loans, daycare, paid holidays and health care. The effect is such that unemployed individuals in this setting would prefer to remain unemployed for an additional period. This is confirmed from the positive and strong coefficient for the unemployed category.

Looking at the reasons for being unemployed, relative to the base category "dissatisfaction with previous job", it is more likely for individuals to choose an informal job in $t+1$ regardless of the reason for being unemployed. The effect is opposite for the case of those that secure a formal job. One can imagine a scenario where the informal sector is more dynamic and re-employment is easier than in the formal sector. Hence, the coefficients are actually reflecting this fact.

Regarding the variables that capture the effect of a"financial cushion" or aid to finance job search either through friends and relatives or from the government, the estimates reveal that, as expected, individuals that received a severance payment from a previous

[8]The model was calculated changing the schooling base category to elementary, results show that having more than high school, on average, increases the probability of remaining unemployed by 8.4 percentage points, which means that they are still actively looking for a job as opposed to going out of the labour force, where job hunting ceases.

[9]"Wait unemployment" among highly skilled individuals is common as their reservation wage is higher compared to non skilled individuals. This is more common if job searchers have a preference for the sector they wish to access. For an analysis of wait unemployment in public sector jobs for highly skilled workers see Reilly and Hyder (2006).

job are more likely to secure a formal job. Considering that one of the many benefits of a formal job is receiving this payment, the estimates are consistent. This does not mean that informal workers do not receive this benefit, but the quantity presumably would be much lower than a formal job. Other forms of financing job search such as friends and relatives decrease the probability of transitioning to employment in the formal sector and at the same time increases the probability of going out of the labour force. Similar results are registered for the case when individuals receive financial support from the government via scholarships, training or any other government program that is not unemployment insurance. The results presented here, are in line with Calderón-Madrid (2008) findings on the effect of a financial cushion on the duration of unemployment, which suggests that those who are without this income would transit to employment faster. This implies that those with access to a "financial cushion" will be able to finance a longer job search.

It is important to briefly comment about the results presented above. Despite the small number of those having access to the three types of financial help. It is not surprising to have statistically significant results for those that had access to a severance payment and end up finding a formal job. As previously explained, by law, previous formal workers have access to this benefit. Regarding those that had access to government aid and considering the lack of an unemployment insurance program in Mexico during the years of analysis here it can be concluded that the effect is coming from government training programs instead. The evidence from Caldern-Madrid and Trejo (2002) highlights the effectiveness of programs such as PROBECAT (Labour training scholarship program, in Spanish) in the successful re-employment of individuals in more long term jobs. However, these individuals also take longer to get a job compared to non-participants in the program. This because those that have access to training are not allowed to have a job until the training is completed. And this will have a positive impact on the probability of them going out of the labour force. Finally, it is not uncommon to receive financial help from relatives in times of economic hardship, so even with a small sample these statistically significant results are also not surprising. [10]

[10] The number of workers per state is even across the whole sample. So one state being over-represented is not what it is driving the statistical significance of the results. The explanation just presented above, also applies to the results found in the second chapter. As the dataset for the analysis is the same and results are expected to be consistent. The duration component introduced in chapter 2 will give us a deeper understanding of unemployment transitions in this market.

It is common in the literature to assign a base category to interpret the coefficients of independent binary variables when estimating a multinomial logit model. However, in this setting the unemployed individuals used many search channels to secure a job. Creating a variable to differentiate between the channels using one base category could lead to the incorrect estimation of the true effect of the channels independently. However, to avoid the issue known as the dummy variable trap, the estimation is done dropping the constant or intercept variable in this estimation and the following ones, including chapter 2.

In this study, the descriptive statistics suggest that going directly to the workplace and the 'friends and relatives' channels were the most used by job searchers. The results of the estimation suggest that going directly to the workplace, searching for a job on-line, looking for a job in the newspaper and using allocation services, increases the probability of securing formal jobs but has the opposite effect for informal jobs. For the case of asking friends, broadly interpreted as a network effect, the results yield a positive effect on the probability of securing an informal job but has no effect on securing a formal job. This effect might be different for male and female workers and that is discussed below. In contrast, Calderón-Madrid (2008) finds that those that rely on newspaper, radio and the internet escape faster from unemployment compared to those relying on social networks.

1.5.2 Gender differences in transitions out of unemployment

To test whether there are gender effects in the model. I conducted a Chow form of the likelihood ratio test to see if there are systematic differences between the fit of the full model against the model with only male workers and the model with only female workers. The null hypothesis is that there are no systematic gender differences. The result of the test rejects the null hypothesis with $Prob > chi2 = 0.0001$. Following the result of the test, I estimate the model with sub-samples for male and female job searchers. It is of interest to see if there are different results between the job search methods used by men and women.

Table B.2 presents the results of the estimation for the male sample. Alternatively, the same procedure is followed for the sample of female workers, and the results are displayed in table B.3. The results for the male sample reveal that receiving financial aid from friends and relatives has a negative impact on the probability of transitioning to a formal job and at the same time it increases the probability of going out of the labour force. This result is consistent with the discussion in subsection 1.5.1 and traditionally in Mexico, family support in monetary terms is not unusual in times of economic hardship.[11] This result sheds light on a particular aspect of the family support as a way to finance job search. Specifically, for male job searchers, such support is enabling them to finance unemployment and stop searching for jobs. In contrast, family support does not seem to have any impact on the employment outcomes of female job searchers.

Having access to a severance payment for males has the same effect for the full sample discussed in subsection 1.5.1. For female workers, on the other hand, the means to finance job search do not seem to be benefiting them in securing a job in either the formal and informal sectors. There is evidence to conclude that for the case of both female and male job searchers, receiving support from the government increases the probability of experiencing a transition out of the labour force. Given that this support can come through many of the governmental programs in Mexico, out of which many of them are cash transfers, the result presented here is not surprising.[12]

Moving on to search channels, the results reveal that going directly to the workplace increases the probability of transition to a formal job for both male and female job searchers. However, this also has a negative impact on the probability of males securing an informal job. Given that this channel is the most widely used by job searchers the negative coefficient for males is somewhat surprising. An explanation for this may be that there are some characteristics associated with informal jobs that hinder the probability of securing a job if males go directly to the workplace to hand in a resume or job application. Such characteristics have to be very specific to the informal sector as this is not reflected for the case of formal jobs.

Searching for a job on-line increases the probability of females securing formal jobs but not so for informal jobs. For males, the effect of using this search channel is not different from zero. This result is not surprising because formal firms are usually big and these are the ones that in an effort to target a larger population, advertise jobs on-line. Moreover, it

[11] It is specifically called family support as we can think of an situation where a person, who does not possess any way to earn an income, receives a cash transfer from a family member on a regular basis compared to receiving it from a friend, which would most likely be a one time loan.

[12] One example of a Mexican government cash transfer program is what is currently known as "Prospera". This program targets low income households and is available throughout the country.

is possible that a large percentage of the vacancies on-line are targeting women, explaining why this might help females more to leave unemployment. Alternatively, when a person replies to a job offer found in the newspaper, the probability of securing a formal job increases for both males and females. The opposite effect is found for the case of informal jobs for males, which is not surprising given that informal job vacancies are not often advertised in the newspaper.

The second most used way to search for a job is via friends and networks. The results demonstrate that this channel is effective when used by male job searchers to secure informal jobs. The effect is also positive for females, although is weak. Comparing these results with those in table (1.2) it can be concluded that in Mexico, when an unemployed individual uses networks to search for a job, this channel proves to be more effective for the case of informal jobs, this effect is stronger for male job searchers. Alternatively, this channel has a negative effect when used to secure a formal job for the case of males but no effect for females.

In the case of using employment allocation services, this channel seems to benefit female jobs searchers in securing formal jobs. For male job searchers the effect of using such channels is not different from zero. This channel, despite being one of the least used by job searchers, seems to be of benefit when trying to access a formal job. This effect is also found to be stronger for females. It has the opposite effect for informal jobs, which is expected, as allocation services do not advertise informal jobs.

The results discussed above reveal that both male and female job searchers benefit more from a different number of channels[13] if trying to access formal jobs. Male job searchers on the other hand, seem to benefit more from networks to access informal jobs. The fact that most channels have a negative effect on the probability of being employed as informal can indicate a possible preference to be employed in the formal sector. If this is true, and is reflected by unobservables the issue of selection bias is likely to beset the estimation of wage equation.

[13]These channels are: going directly to the workplace, searching for a job on-line, newspaper ads and allocation offices.

1.5.3 Wage returns from search channels and selection bias

Until now the focus of the analysis has been on the returns to job search by different channels used by unemployed individuals. However, given that the ENOE includes information on wages, it is used to determine to what extent search channels have an effect on the wage of individuals. Furthermore, the wage equation is estimated introducing the six categories of search channels to disentangle their effect on wages for both formal and informal jobs.

The occupational choice of individuals in this setting, entails a selection process to either remaining unemployed, the formal or informal sector conditional on personal characteristics and search channels used to secure jobs. The choice of the sector can bias the estimation of the wage for individuals if not accounted for.

Moreover, one can argue that the wage of a workers is higher just because they chose a job that matches precisely his personal characteristics and offers certain conditions that are more appealing and this could be reflected when estimating the wage equation. For example, Some workers might prefer to be formal as often the wages and benefits associated are higher compared to informal jobs. On the other hand, individuals might prefer informal jobs due to the flexibility of working hours, the proximity to their homes even if this means sacrificing income. In the sample used here, unemployed individuals get to choose in which sector they are to be employed in from one period to the other. In this way, personal, household characteristics and preference for a certain sector determine this choice.

For this exercise the variable that captures labour market states is recoded to reflect if a person is unemployed formal or informal.[14] Following the specification detailed in Reilly (1991), an individual chooses between three mutually exclusive options, the probability of a given occupational attachment is captured in a vector X that can be expressed in terms of a reduced form model that is estimated with a multinomial logit model as follows:

$$p_{ij} = \frac{exp(X\gamma_j)}{1 + \sum_{j=1}^{k-1}(X\gamma_j)} \tag{1.6}$$

[14] As opposed to having four categories like in subsection (1.5.1), to estimate the wages for formal and informal workers the information of active job search by an individual becomes irrelevant as they would not report income that is used to estimate difference between sectors.

where p_{ij} is the probability of attachment of the individual i to the option j, X_i is the vector containing the variables that determine the attachment and γ is a vector of unknown occupational coefficients. The parameters of $k-1$ of the k employment choices can be identified imposing the normalization $\sum \gamma_k = 0$.

In the second stage the information resulting from the estimation of the reduced form model in equation 1.6 is used to correct for the potential effects of selection bias. The wage equation conditional on the jth category being chosen can be detailed as follows:

$$W_j = Z_j\beta_j - \sigma_j\rho_j\frac{\phi(J(X_j\gamma_j))}{F(X_j\gamma_j)} + \zeta_j \tag{1.7}$$

where ϕ is the standard normal density function, J is a monotonic increasing transformation of the random variable associated with the occupational attachment equation into a standard normal variable where $J = \Phi^{-1}F$, Φ is the standard normal distribution function and F is the probability distribution function. σ_j is the standard error of the disturbance term in the wage equation in the wage equation and ρ_j the correlation between both the error terms of the wage equation and the occupational attachment equation.

The coefficient vector $\hat{\gamma}$ obtained after estimating the reduced form equation through maximum likelihood in equation 1.6 are inserted in equation 1.7. This equation can be re-written as:

$$W_j = Z_j\beta j + \theta_j\hat{\lambda}_j + \zeta j \tag{1.8}$$

where $\theta_j = \sigma_j\rho_j$ and $\hat{\lambda}_j = \frac{\phi(J(X_i\hat{\gamma}_j))}{F(X_i\hat{\gamma}_j)}$ and ζ is an error term.

The term $\hat{\lambda}$ in the equation controls for the effects of selectivity bias in the wage equation. Equation 1.8 yields consistent estimates for the jth sector's wage equation after applying an OLS procedure.

1.5.4 Empirical specification to correct for selection bias

The estimation of equations (1.6) and (1.8) are specified here. In the first stage, a similar multinomial logit model to the one presented in table 1.2 is estimated to predict employment outcomes to either remain unemployed the formal or informal sectors and is specified as follow:

$$\begin{aligned}P_j = & f(\text{Age}, \text{Gender}, \text{Schooling level}, \text{Marital status}, \\ & \text{previous job}, \text{reason for unemployment}, \\ & \text{Option to finance job search}), j = 1, 2, 3,\end{aligned} \tag{1.9}$$

$$\begin{aligned}ln(wages) = & f(\text{Age}, \text{Age squared}, \text{Gender}, \\ & \text{Schooling level}, \text{Regional controls}, \\ & \text{Search channels}, \text{Correction term}), \text{iff} j = 3,\end{aligned} \tag{1.10}$$

Equation (1.9) represents the first stage of the estimation and is the employment selection function. This is a slightly different specification to the one reported in table 1.2[15]. This specification contains variables that are commonly used in the literature to predict employment decisions. Additionally, the identifying instruments for the selection effects used are marital status, if previous job was formal, options to finance job search and reasons for unemployment in period t. The ways to finance job search determine the type of job a worker secures, if the worker has access to a severance payment then it is more likely to secure a formal job, receiving financial aid from relatives increases the likelihood of remaining unemployed. In the same way, the reasons for unemployment impact differently the employment decision of individuals.

The results for the first stage will not be discussed as this has already been done in subsection 1.5.1 but the results are reported in table A.1 of the appendix. Equation (1.10) is the wage equation, this specification includes the correction term from the first stage, personal characteristics controls and the search channels for the purpose of determining if search channels have any influence on the wages of individuals. Those that work without pay are dropped from the analysis.[16]

[15] The specification is different from the first multinomial presented because here the interest lies on estimating the wage returns to the use of different search channels. The search channels then are omitted from the first stage equation and instead the reasons for being unemployed and personal characteristics are used as identifying instruments in the first stage.

[16] These individuals constitute 10% of the total sample. It is a common feature of the Mexican labor market to have individuals working in a family business without a pay. The motivation of these individuals to work under such circumstances is different from a common worker.

One aspect worth noting here, the reason why the information for unemployed was used to correct for selection bias is that the information for whether the unemployed individual chose to remained unemployed is also important and influences the employment outcome in $t+1$. More specifically, given that to correct for selection bias in one outcome, the wage of the remaining options are assumed as zero, the information for unemployed has a potential effect on the magnitude of the bias. Additionally, there is evidence that some individuals choose to remain unemployed as noted when the effects of "wait unemployment" were discussed.

Some results after correcting for selection bias are presented in table 1.5 are important to highlight. On average, compared to females, being male increases the worker's wage by 17.8% and 36.5% for formal and informal sectors respectively. A more detailed gender analysis is presented in table 1.6. Compared to just having elementary school, those with higher levels of education earn more. In specific, having more than high school, increases the wage by 30.0% and 28.4% for formal and informal workers, respectively. Compared to those in the center region of the country, those in the south working informally earn less, but the opposite effect on wages appears if working with a formal contract.

Regarding the search channels, the results yield that those searching on-line for a job, on average, earn 12.3% more in the case for formal jobs and 7.0% more for the case of informal jobs. This can be attributed to the type of jobs advertised through the web, which presumably would be better paid jobs targeting more skilled workers. A similar finding is presented by Kuhn and Skuterud (2004) who conclude that searching on-line for a job is associated with being highly skilled. On the other hand, those using newspaper adds as a channel to search for a job experience a wage penalty. It is common knowledge, the type of jobs advertised in the newspaper are often low paid and for non-skilled workers.

Finally, looking at the results for the selection term and its interpretation it can be used to ascertain evidence of non-randomness if workers to either the formal or informal sector. The coefficient at the bottom of the table reports the selectivity bias. It is statistically significant and negative for both the formal and informal sectors of the labour market (imr2 and imr3).[17]

[17] The interpretation of this coefficient follows Gyourko and Tracy (1988) and Reilly (1991) and it refers to the effect of the selection variable on the wage. The effect is obtained multiplying minus the selection variable coefficient by the mean value of the selection variable.

For the case of formal jobs, the calculation suggests that those self-selecting into the formal sector earn, on average, 16.0% higher wages that an individual drawn at random from the labour force with identical observable characteristics would be expected to earn. For the case of informal workers that self-select into this sector earn, on average, 8.2% higher wages than an average informal workers drawn at random would earn. Evidence is provided that workers are non randomly selected into either formal or informal jobs. Instead, they decide in which sector they prefer to work and this process eventually means higher earnings for them.

In table 1.6 the results are presented by gender. The results suggest that compared to only having elementary school, men employed as formal and that have more than high school on average earn 27.4% higher wages. The other schooling levels are not statistically significant, which suggests that there is not difference in earnings for those with up to high school when employed in the formal sector. In contrast, those with more than high school experience a wage premium.[18] Compared to living in the centre region, workers in the South earn 6.1% higher wages as formal workers. Men that search for jobs on-line earn 16.2% higher wages but experience a wage penalty of 4.9% when using the newspaper to find a job.

This result confirms the findings in table 1.5 that the wage premium from searching for jobs on-line and the penalty from searching via newspapers is explained by the type of jobs that are advertised through these means. Regarding the selection term, there is evidence of selection of male formal workers. Specifically, those that select into formal jobs earn on average 14.4% wages than an average worker drawn at random would earn.This result is slightly higher in magnitude but consistent with the results for the pooled sample in table 1.5.

For the case of male informal job searchers, there is difference in the earnings of workers by schooling level. Having elementary school as the base, those with secondary, high school and more than high school earn 6.6%, 7.97% and 28.4% higher wages, respectively. Moreover, there are also notable differences in earnings depending on the region of residence. Compared to living in the centre region, workers that live in the north and west

[18]This category is composed of those with bachelor, master and PhD degree.

earn 3.7% and 4.2% higher wages and those living in the east and south earn 1.2% and 4.4% lower wages. These regional wage differences can be explained by the prevalence of manufacturing industries in the north and access to the many of the Mexican ports in the west. On the other hand, according to the National Comission for the Minimum Wage (Conasami) which reports wages by geographic area in Mexico, the south and east part of the country are characterized by having the lowest wage levels in the country.[19]

Regarding search channels for male informal workers, there is only one channel that remains statistically significant. More specifically, those using allocation services experience a wage penalty of 9.2% and this result is consistent with the one presented for the pooled sample. Finally, in terms of the selection effect it can be concluded that there is presence of selection bias, those that select into informal jobs earn on average 12.5% higher wages than a worker with similar characteristics drawn at random.

We now turn to the interpretation for female workers. It can be observed that in general terms the effect of some of the variables on the wage is not different from zero and this can be explained by the sample size that is reduced significantly when only the women are analyzed. Compared to having only elementary school, formal female workers earn 7.5% and 35% more if they have high school or more than high school, respectively. This result suggest that in a similar way to male, female workers earn more with a higher degree of education. However, magnitude of the premium is higher for females (35.4% vs. 27.4%). It is important to remember that women in Mexico still bear the traditional role of housewives and their motivations to work are different from men. In this sample, of the total of workers only 30% are women so this means that their marginal returns are higher when they enter the labour market.

The results on the regional wage differences yield a wage penalty of 6.5% for formal female workers living in the East compared to living in the centre. Women in formal jobs also earn 5.0% lower wages when they use newspapers to get a job, which is consistent with the effect for men and the pooled sample. The coefficient for the selection bias is significant which suggest that women also self-select into formal jobs and earn 20.8% higher wages that an identical women drawn at random.

[19] Although the informal sector does not adjust its wages following the national minimum wage standards, it serves as a reference to this sector.

Finally, for informal women the coefficient for more than high school suggests that women earn 21.0% higher wages compared to only having elementary school. Looking at the coefficient for the selection bias it can be concluded that women that select into informal jobs experience a wage penalty of 19.1% compared to those drawn at random. This result is consistent with the argument that female workers would sacrifice income for other benefits offered by informal jobs.

1.6 Conclusions

The aim of this study was twofold: to disentangle the effects of a set of personal characteristics and different search channels on the probability of an individual experiencing a transition to different labour market states and to analyse the effect of these search channels on the wages of formal and informal workers by gender.

Some interesting findings arise from the analysis of labour market transitions. The results of the estimation reveal that there is a strong and positive correlation between being formally employed and transitioning to employment in the formal sector in period $t+1$. There is"wait unemployment" by highly skilled individuals given their higher reservation wage and this makes them wait for an offer in the formal sector and discard those offers from the informal sector. In comparison, less skilled individuals experience more transitions to informal jobs. This result is confirmed by the positive impact of the variable which captures if a person was previously a formal worker on two outcomes: remaining unemployed and experiencing a transition into a formal job.

There are also gender differences when using the search channels. Women appear to benefit more when using various types of search channels such as uploading or replying to a job offer on-line, using newspaper or classified ads and allocation offices (public and private). On the contrary, asking friends for recommendations seems to help male job searchers more in securing informal jobs.

After correcting for the presence of selection bias in the estimation of the wages for those that reported a transition into employment in $t+1$. The results reveal that those searching on-line for a job, experience a wage premium of 12.3% and 7.0% for formal and informal jobs, respectively. On the other hand, those that secured a job via advertisements in newspapers experience a wage penalty of 5.24%. The wage premium of searching on-line for jobs can be partly explained by the type of jobs that are advertised through the web and that presumably are better paid. Alternatively, jobs advertised through the newspaper are often low paid with temporary contracts so the wage penalty is a reflection of the working conditions offered by these type of jobs.

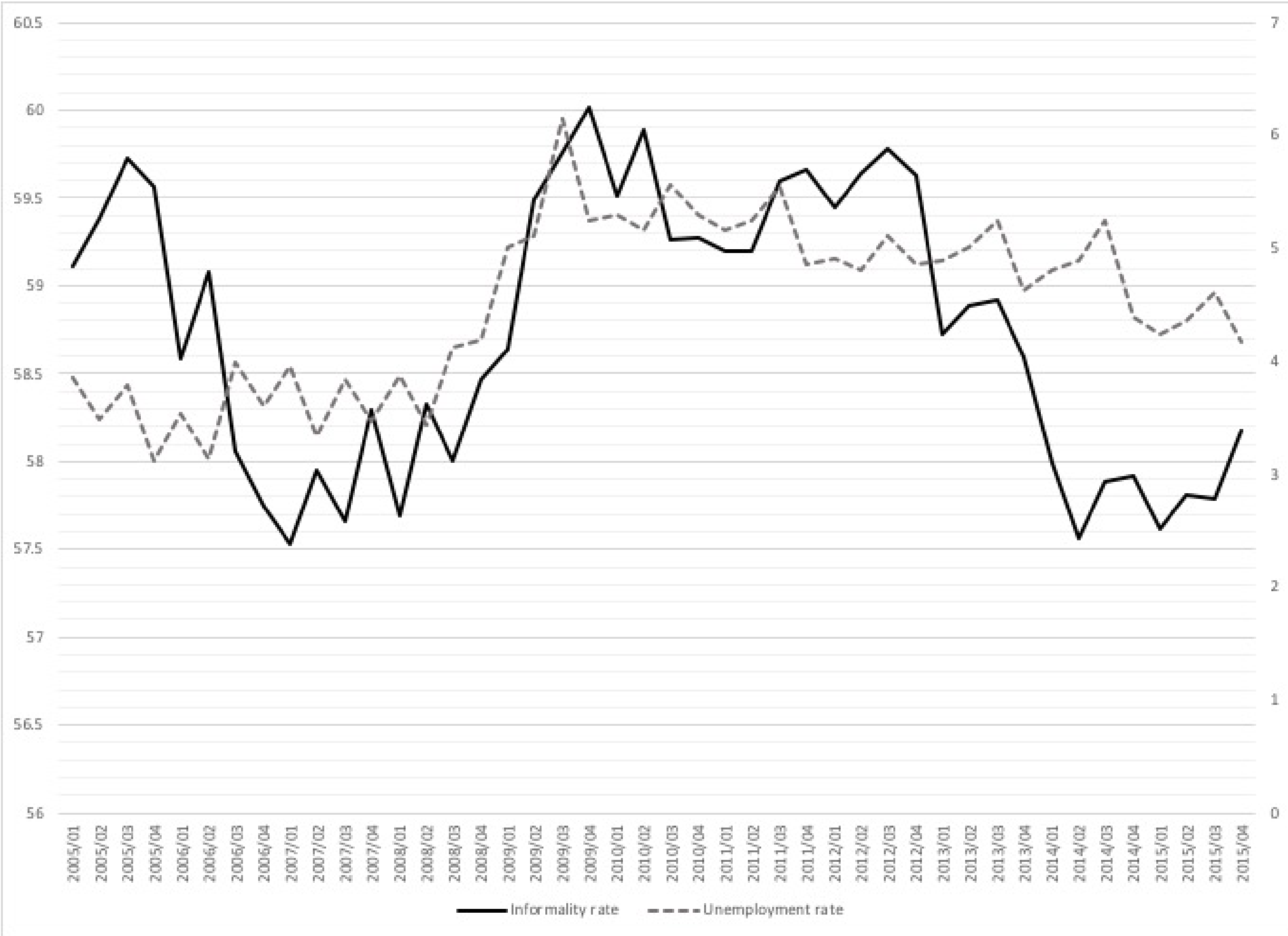
Furthermore, the results are presented by gender. Male that search for formal jobs on-line earn 16.2% higher wages but 4.9% and 9.2% lower wages, respectively, when using newspaper or allocation services. On the other hand, formal female workers also earn 5.0% lower wages when using the newspaper to search for jobs.

The results presented here shed light on the returns to job search used by workers who exit into formal and informal jobs in Mexico. Moreover, there are differences in the returns to job search by gender and not always the most used channels are the ones that are helping unemployed workers secure high paid jobs. Higher paid jobs instead are secured via the channels that correlate positively to the schooling level of the worker.

Although the informal sector employs approximately 60% of the total workforce and contributes to almost 24% of the Gross Domestic Product, it is also well known that the prevalence of the informal sector harms the tax base and this implies less government income via taxes. The informal sector is characterized by low levels of productivity and no innovation. Moreover, it is a subsistence level that emerged as a consequence of the inability of the formal sector to cope with the demand of employment from Mexican workers, the difficulty for small firms to register as formal, the skill mismatch and in last instance the preference of individuals. In this sense, reducing the informal sector has to be a result of the combination of various policies that address all the factors that help to its proliferation. There are already some programs in place such as the formalization program from the International Labor Organization (ILO) but its effectiveness its heterogeneous and depends on the structure already in place in every Mexican State.

Tables and figures

Figure 1.1: Quarterly informality and unemployment rate 2005-2015



Source: Elaborated using data from INEGI

Table 1.1: Descriptive Statistics for independent variables

Head of Household	0.65
Married or free union	0.56
Male	0.70
No financial cushion	0.94
No government aid	0.98
No Financial aid from friends or relatives	0.95
Previous job formal	0.45
Education	
Elementary school	0.21
Secondary School	0.30
High School	0.22
More than high school	0.27
Reason for job loss	
Dismissed of finished previous job	0.60
Dissatisfaction with previous job	0.31
Left or closed previous business	0.06
Other	0.03
Search Channel	
Directly	0.74
On-line job advertisement	0.08
Advertisement	0.13
Social networks	0.14
Allocation service	0.04
Other forms of job search	0.04
Number of observations	30320

Table 1.2: Multinomial Logit Estimation-Marginal and Impact Effects

	Outcome employment status			
	(1)	(2)	(3)	(4)
	Unemployed	Formal	Informal	Out of labour force
Gender	0.0578***	0.0406***	0.102***	-0.201***
	(0.00511)	(0.00483)	(0.00624)	(0.00591)
Married	-0.0704***	0.0173***	0.0268***	0.0263***
	(0.00576)	(0.00547)	(0.00683)	(0.00514)
Head of household	-0.00757	0.0247***	0.0617***	-0.0788***
	(0.00672)	(0.00651)	(0.00785)	(0.00561)
Elementary school	-0.0845***	-0.0908***	0.141***	0.0343***
	(0.00659)	(0.00629)	(0.00944)	(0.00767)
Secondary school	-0.0632***	-0.0180***	0.0878***	-0.00657
	(0.00614)	(0.00604)	(0.00831)	(0.00638)
High School	-0.0413***	0.0109*	0.0115	0.0190***
	(0.00648)	(0.00657)	(0.00888)	(0.00686)
Previous job formal	0.0388***	0.158***	-0.163***	-0.0342***
	(0.00513)	(0.00508)	(0.00583)	(0.00460)
Dismissed or finished previous job	0.0229***	0.00234	0.0149**	-0.0401***
	(0.00538)	(0.00497)	(0.00644)	(0.00499)
Left or closed previous business	-0.00927	-0.0529***	0.0789***	-0.0167*
	(0.0121)	(0.0115)	(0.0138)	(0.00960)
Other reasons for unemployment	-0.00792	-0.0464***	0.0432**	0.0111
	(0.0153)	(0.0131)	(0.0173)	(0.0133)
Financial cushion	0.00884	0.0304***	-0.0247**	-0.0145
	(0.00985)	(0.00907)	(0.0121)	(0.00948)
Financial aid from government	-0.0472***	-0.0332**	-0.0181	0.0985***
	(0.0158)	(0.0150)	(0.0189)	(0.0163)
Financial aid from relatives	0.00791	-0.0249**	-0.0197	0.0366***
	(0.0113)	(0.0101)	(0.0129)	(0.0106)
Went directly to the workplace	0.0105	0.0338***	-0.0210**	-0.0233***
	(0.00731)	(0.00668)	(0.00924)	(0.00731)
Uploaded or replied to a job offer online	0.0122	0.0225**	-0.0262**	-0.00847
	(0.00961)	(0.00944)	(0.0121)	(0.00904)
Used advertisement in newspaper	0.0335***	0.0364***	-0.0423***	-0.0276***
	(0.00790)	(0.00768)	(0.00906)	(0.00661)
Asked friends or relatives to recommend a job	-0.0251***	-0.0121	0.0311***	0.00608
	(0.00781)	(0.00761)	(0.00965)	(0.00762)
Allocation services to get job (public of private)	0.0550***	0.0368***	-0.0623***	-0.0295***
	(0.0129)	(0.0124)	(0.0143)	(0.0104)
Used other channels to find a job	0.00213	-0.0151	0.0284	-0.0154
	(0.0145)	(0.0137)	(0.0173)	(0.0122)
Region controls	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
Observations	30320	30320	30320	30320
Pseudo R-squared	0.078	0.078	0.078	0.078

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.3: Multinomial Logit Estimation Male sample

	outcome employment status			
	Unemployed	Formal	Informal	Out of labour force
Married	-0.0549***	0.0557***	0.0677***	-0.0684***
	(0.00809)	(0.00740)	(0.00958)	(0.00623)
Head of household	-0.0301***	0.00579	0.0361***	-0.0118*
	(0.00880)	(0.00812)	(0.0104)	(0.00693)
Elementary school	-0.0899***	-0.0923***	0.176***	0.00563
	(0.00802)	(0.00768)	(0.0112)	(0.00710)
Secondary school	-0.0674***	-0.0122	0.114***	-0.0342***
	(0.00771)	(0.00762)	(0.0105)	(0.00643)
High school	-0.0434***	0.0204**	0.0243**	-0.00122
	(0.00818)	(0.00845)	(0.0114)	(0.00701)
Previous job formal	0.0485***	0.167***	-0.181***	-0.0354***
	(0.00632)	(0.00627)	(0.00721)	(0.00477)
Dismissed or finished previous job	0.0178***	-0.00692	0.0226***	-0.0335***
	(0.00682)	(0.00623)	(0.00823)	(0.00542)
Left or closed previous business	-0.00459	-0.0516***	0.0842***	-0.0280***
	(0.0146)	(0.0134)	(0.0168)	(0.00884)
Other reasons for unemployment	-0.00679	-0.0456***	0.0467**	0.00570
	(0.0185)	(0.0154)	(0.0210)	(0.0131)
Financial cushion	0.00984	0.0301***	-0.0397***	-0.000236
	(0.0116)	(0.0105)	(0.0145)	(0.00988)
Financial aid from government	-0.0686***	0.0163	-0.0395	0.0918***
	(0.0229)	(0.0255)	(0.0302)	(0.0238)
Financial aid from relatives	0.0103	-0.0377***	-0.00785	0.0352***
	(0.0163)	(0.0136)	(0.0189)	(0.0132)
Went directly to the work place	0.0115	0.0258***	-0.0306***	-0.00674
	(0.00910)	(0.00840)	(0.0115)	(0.00731)
Uploaded or replied to a job offer online	0.00711	0.0137	-0.0286*	0.00785
	(0.0125)	(0.0119)	(0.0160)	(0.0105)
Used advertisement in newspaper	0.0460***	0.0347***	-0.0660***	-0.0148**
	(0.0101)	(0.00946)	(0.0115)	(0.00722)
Asked to relatives and friends to recommend job	-0.0218**	-0.0186**	0.0309***	0.00951
	(0.00949)	(0.00895)	(0.0117)	(0.00759)
Allocation services to get job (public of private)	0.0496***	0.0246	-0.0538***	-0.0204*
	(0.0167)	(0.0155)	(0.0192)	(0.0117)
Used other channels to find a job	0.00700	-0.0202	0.0324	-0.0192
	(0.0186)	(0.0169)	(0.0223)	(0.0128)
Regional controls	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes
Observations	20648	20648	20648	20648
Pseudo R^2	0.070	0.070	0.070	0.070

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.4: Multinomial Logit Estimation Female sample

	outcome employment status			
	Unemployed	Formal	Informal	Our of labour force
1 if married or free union	-0.0912***	-0.0510***	-0.0375***	0.180***
	(0.00868)	(0.00840)	(0.0101)	(0.0115)
Head of household	0.0116	-0.00358	0.0547***	-0.0627***
	(0.0128)	(0.0123)	(0.0143)	(0.0144)
Elementary school	-0.0688***	-0.0691***	0.0474***	0.0904***
	(0.0120)	(0.0118)	(0.0164)	(0.0180)
Secondary school	-0.0521***	-0.0276***	0.0316**	0.0480***
	(0.00984)	(0.00961)	(0.0125)	(0.0135)
High School	-0.0368***	-0.00684	-0.00716	0.0508***
	(0.00996)	(0.0101)	(0.0125)	(0.0138)
Previous job formal	0.0200**	0.131***	-0.110***	-0.0418***
	(0.00832)	(0.00835)	(0.00938)	(0.0102)
Dismissed or finished previous job	0.0295***	0.0158**	-0.00660	-0.0387***
	(0.00840)	(0.00793)	(0.00949)	(0.0101)
Left or closed previous business	-0.0279	-0.0565***	0.0721***	0.0123
	(0.0203)	(0.0206)	(0.0227)	(0.0233)
Other reasons	-0.0106	-0.0518**	0.0311	0.0314
	(0.0260)	(0.0226)	(0.0272)	(0.0304)
Financial cushion	0.00309	0.0205	0.0160	-0.0396*
	(0.0177)	(0.0169)	(0.0216)	(0.0215)
Financial aid from government	-0.0334*	-0.0657***	0.00876	0.0904***
	(0.0194)	(0.0171)	(0.0212)	(0.0241)
Financial aid from relatives	0.00492	-0.00686	-0.0287*	0.0306*
	(0.0146)	(0.0144)	(0.0153)	(0.0184)
Went directly to the work place	0.00838	0.0425***	-0.00210	-0.0488***
	(0.0117)	(0.0106)	(0.0140)	(0.0157)
Uploaded or replied to a job offer online	0.0193	0.0375**	-0.0181	-0.0386**
	(0.0143)	(0.0148)	(0.0166)	(0.0178)
Used advertisement in newspaper	0.0140	0.0388***	0.00403	-0.0568***
	(0.0121)	(0.0124)	(0.0137)	(0.0141)
Asked relatives and friends to recommend job	-0.0338**	0.00120	0.0293*	0.00333
	(0.0133)	(0.0141)	(0.0167)	(0.0175)
Allocation services to get job (public of private)	0.0608***	0.0531***	-0.0619***	-0.0520**
	(0.0193)	(0.0197)	(0.0190)	(0.0221)
Used other channels to find a job	-0.00371	-0.00279	0.0299	-0.0234
	(0.0220)	(0.0225)	(0.0250)	(0.0259)
Region Controls	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes
Observations	9672	9672	9672	9672
Pseudo R^2	0.052	0.052	0.052	0.052

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: Effect on wages correcting for selection bias

	(1) Formal OLS	(2) Informal OLS	(3) Formal Corrected	(4) Informal Corrected
Age	0.0313***	0.0365***	0.0299***	0.0355***
	(0.00368)	(0.00349)	(0.00370)	(0.00352)
Age squared	-0.000311***	-0.000451***	-0.000282***	-0.000441***
	(0.0000543)	(0.0000479)	(0.0000548)	(0.0000480)
Gender	0.194***	0.385***	0.177***	0.365***
	(0.0126)	(0.0168)	(0.0131)	(0.0195)
Secondary School	-0.00155	0.0365**	-0.0296	0.0467***
	(0.0185)	(0.0151)	(0.0196)	(0.0159)
High School	0.0722***	0.0533***	0.0402*	0.0791***
	(0.0202)	(0.0192)	(0.0215)	(0.0229)
More than High school	0.326***	0.253***	0.300***	0.284***
	(0.0219)	(0.0227)	(0.0226)	(0.0275)
North region	0.0207	0.0268	-0.00442	0.0320*
	(0.0144)	(0.0172)	(0.0156)	(0.0173)
West region	0.0109	0.0404*	0.00672	0.0355*
	(0.0202)	(0.0209)	(0.0202)	(0.0210)
East region	-0.0253	-0.105***	-0.0196	-0.117***
	(0.0233)	(0.0196)	(0.0234)	(0.0204)
South region	0.0435**	-0.0456**	0.0421**	-0.0566***
	(0.0209)	(0.0181)	(0.0208)	(0.0190)
Went directly to the work place	-0.00474	-0.0300	-0.00593	-0.0297
	(0.0176)	(0.0214)	(0.0176)	(0.0214)
Uploaded or replied to a job offer online	0.127***	0.0685*	0.124***	0.0709*
	(0.0261)	(0.0411)	(0.0261)	(0.0411)
Used advertisement in newspaper or classifieds to get job	-0.0506***	-0.0105	-0.0524***	-0.00759
	(0.0168)	(0.0216)	(0.0168)	(0.0216)
Asked to relatives and friends to recommend his job	0.0218	-0.0253	0.0269	-0.0281
	(0.0198)	(0.0212)	(0.0198)	(0.0213)
Used allocation services to get job (public of private)	0.0116	-0.0505	0.00817	-0.0474
	(0.0282)	(0.0404)	(0.0280)	(0.0405)
Used other channels to find a job	-0.00996	0.0141	-0.0120	0.0123
	(0.0409)	(0.0433)	(0.0409)	(0.0432)
imr2			-0.109***	
			(0.0249)	
imr3				-0.0732**
				(0.0360)
Constant	7.540***	7.131***	7.743***	7.227***
	(0.0633)	(0.0644)	(0.0791)	(0.0801)
Observations	5956	10269	5956	10269
R^2	0.168	0.085	0.170	0.086

Standard errors in parentheses and bootstrapped with 500 replications

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.6: Effect on wages controlling for selection bias by gender

	(1) Formal Male	(2) Informal Male	(3) Formal Female	(4) Informal Female
Age	0.0380***	0.0394***	0.0219***	0.0373***
	(0.00420)	(0.00377)	(0.00835)	(0.0101)
Age squared	-0.000368***	-0.000473***	-0.000274**	-0.000578***
	(0.0000612)	(0.0000509)	(0.000133)	(0.000146)
Secondary school	-0.0219	0.0662***	-0.0311	-0.0214
	(0.0228)	(0.0168)	(0.0355)	(0.0463)
High school	0.0282	0.0797***	0.0756**	0.0314
	(0.0254)	(0.0249)	(0.0382)	(0.0590)
More than high school	0.274***	0.284***	0.354***	0.210***
	(0.0276)	(0.0312)	(0.0400)	(0.0637)
North region	-0.00599	0.0374**	-0.00175	0.00918
	(0.0183)	(0.0188)	(0.0303)	(0.0426)
West region	0.0337	0.0421*	-0.0471	0.0186
	(0.0249)	(0.0231)	(0.0342)	(0.0494)
East region	-0.00283	-0.120***	-0.0656*	-0.0790
	(0.0291)	(0.0224)	(0.0381)	(0.0491)
South region	0.0616**	-0.0445**	-0.0170	-0.0631
	(0.0247)	(0.0206)	(0.0377)	(0.0470)
Went directly to the work place	-0.00230	-0.0361	-0.0106	-0.0258
	(0.0222)	(0.0241)	(0.0286)	(0.0463)
Uploaded or replied to a job offer online	0.162***	0.0424	0.0585	0.102
	(0.0361)	(0.0525)	(0.0357)	(0.0659)
Used advertisement in newspaper or classifieds to get job	-0.0494**	-0.0136	-0.0506*	0.00637
	(0.0213)	(0.0245)	(0.0263)	(0.0450)
Asked to relatives and friends to recommend his job	0.0341	-0.0362	0.00275	-0.0328
	(0.0240)	(0.0237)	(0.0342)	(0.0498)
Used allocation services to get job (public of private)	-0.00273	-0.0921*	0.0302	0.0658
	(0.0376)	(0.0475)	(0.0388)	(0.0768)
Used other channels to find a job	-0.0223	0.0135	0.0158	0.0278
	(0.0527)	(0.0497)	(0.0632)	(0.0843)
imr2	-0.0978***		-0.141***	
	(0.0289)		(0.0497)	
imr3		-0.112***		0.170*
		(0.0393)		(0.0900)
Constant	7.742***	7.535***	8.005***	7.050***
	(0.0890)	(0.0808)	(0.154)	(0.199)
Observations	4214	8018	1742	2251
R^2	0.164	0.043	0.161	0.057

Standard errors in parentheses and bootstrapped with 500 replications

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Chapter 2

Duration of unemployment and transitions into formal and informal jobs in Mexico

2.1 Introduction

Compared to other OECD countries, Mexico's unemployment rate is low (3.74% on average since year 2000). This can be explained by the presence of a large informal sector. Having low rates of unemployment means that individuals do not remain unemployed for long, as the alternatives to choose from within a dual labour market are plenty.

The duality of the Mexican labour market provides an interesting framework to analyze the channels through which individuals exit unemployment into formal or informal jobs, and to what extent these channels, in conjunction with personal characteristics, affect the duration of unemployment. This type of analysis provides a greater understanding of the dynamics of labour supply and how workers manage to secure jobs that presumably match their personal characteristics and preferences. The literature has analyzed how different search channels impact on exits out of unemployment, duration and the type of job secured and have detected mixed results (Addison and Portugal, 2002; Woltermann, 2002; Márquez and Ruiz-Tagle, 2004; Calderón-Madrid, 2008; Meliciani and Radicchia, 2011; Iriarte, 2017). This study contributes to this literature by examining the overall effects of a set of personal characteristics, search channels and financial variables on the duration of unemployment. Moreover, this analysis is undertaken for Mexico, a country where the majority of workers are employed as informal, and hence do not have access to lump-sum payments to finance long periods of job search.

Using micro-level labour market data for Mexico the overall effects of a set of personal characteristics, search channels and financial variables[1] on the duration of unemployment are analyzed. The analysis is then enriched to account for individual-level heterogeneity in the estimation because its omission may lead to biased estimates (Jenkins, 2005). Moreover, given the dual nature of the labour market in Mexico, where individuals exit into formal or informal jobs, a multiple destination or a competing risks model is also estimated.

Given the self-reported information of the survey I am able to address the following research questions: What is the impact of different channels to find a job, as well as the means by which a person finances job search, on the duration of unemployment? In particular, what is the impact on unemployment duration of a person that exits into a formal or informal job?

Studies of similar nature, conclude that two of the most used search channels are going directly to the workplace and asking friends or relatives to recommend a job. Frequently, these are also the most effective channels for securing a job (Addison and Portugal, 2002; Woltermann, 2002; Márquez and Ruiz-Tagle, 2004; Calderón-Madrid, 2008; Meliciani and Radicchia, 2011). However, the type of jobs that are secured through these channels do not always match workers' personal characteristics and lead to low paid jobs given their temporary nature and that the jobs are targeted to low skilled workers (Addison and Portugal, 2002; Iriarte, 2017). Also, there is negative duration dependence which might be interpreted by employers as a "scarring effect". The concept of a "scarring effect" or "unlearning by not doing" can be interpreted as the longer an individual remains unemployed, the less likely is a hire. This to some extent indicates that the individual's skills depreciate with time (Lockwood, 1991; Serneels, 2008).

Some interesting facts arise from the estimation of the duration of unemployment in Mexico. Using a discrete duration model and controlling for unobserved heterogeneity,

[1]The financial variables as already noted in chapter 1 of this thesis, refer to having access to income via government assistance (via training scholarships, aid from a government program and financial aid to start a new business), receiving cash transfer from relatives either in Mexico or abroad and a lump sum payment from a previous job.

the duration of unemployment is found to be lower for those that were previously informal workers compared to formal ones. Interpreting the result from a different perspective, it can be concluded that there is presence of "wait unemployment"[2] for those that are formal workers.

The coefficients for the variables measuring the presence of a financial cushion yield mixed results. On the one hand, those that had access to a lump sum payment from a previous job, experience shorter unemployment durations. On the other, those receiving support from a government program and support from friends and relatives experience longer unemployment periods. The results of the multiple destination model allow us to further understand that the shorter durations for those in possession of a lump sum payment happens when they exit into formal jobs. Also that government programs, via cash transfers and training programs, reduce the time until job searchers exit the labour force, this means that it increases the likelihood of this individual stopping active job search. Similarly, the Mexican household structure permits longer period of job search.

Regarding the search channels, going directly to the workplace and searching for jobs via newspaper reduce the unemployment duration for those exiting into a formal job. Asking friends and relatives helps job searchers to reduce the time unemployed before securing an informal job for both male and female. The use of other channels rather than reducing the time unemployed, seem to prolong it. Both the single and multiple destination model permit us to conclude that search channels do not seem to be important determinants of unemployment durations for analyzed sample. Duration of unemployment is determined largely by personal characteristics and previous working experience. The results presented here are robust after controlling for unobserved heterogeneity.

The structure of the chapter is as follows. In section 2.2 the existing literature on search channels, job outcomes in developed and developing countries, and unemployment duration is reviewed. In section 2.3, the data are described and summary statistics presented. In section 2.4 the econometric methodology is detailed and in section 2.5 the empirical results are presented. Section 2.6 provides some conclusions.

[2]This is that formal workers decide to remain unemployed until a job considered by them as "good" arrives, instead of taking an informal job. For a detailed discussion of this in the context of a job market, where preference by highly skilled workers is given to jobs in the public sector in Pakistan, see Reilly and Hyder (2006).

2.2 Literature Review

Unemployment duration has been studied extensively in the labour economics literature, efforts have been put in trying to understand the factors that allow an unemployed individual to escape unemployment faster and to what extent there is a "scarring effect". The more the worker remains unemployed the less likely it is to find a job.[3] Long periods of unemployment may indicate low productivity due to the depreciation of skills that unemployment spells bring about. Hence, the searcher is less likely to be hired by firms. Employers often use this information to sort "good" from "bad" workers (Lockwood, 1991; Arulampalam, 2001).

The conjunction of personal characteristics and the different channels and ways to finance job search and intensity have an effect on the time unemployed. Using data from the Panel Study of Income Dynamics (PSID) from 1969 to 1976, Bong Joon (1981) analyse the duration of unemployment in the US and how the cost of job search impacts this. The results of the estimation, confirm that increasing unit costs of search intensity leads to longer unemployment duration. Although this study provides insights on the importance of the intensity and costs of job search, it does not shed light on the type of search channels used by unemployed individuals.

The nature of the job search process is endogenous, as a given person would choose the best strategies or means to find a job in the least possible time and also without incurring high costs. We can think of a situation where it is cheaper to send cv's on-line than to pay travel costs to deliver the document directly to the firm. Kuhn and Skuterud (2004) test for the incidence and diffusion of internet job search by investigating who searches for jobs online and the outcomes of looking for a job through this channel. The authors use a probit model to control for observable characteristics in the outcome of job search and with internet option as a search variable, they conclude that Internet job search is more common among workers with observed characteristics that are usually associated with more rapid re-employment (i.e., occupations with low unemployment rates, young and well educated workers and persons that became unemployed after finishing school or had previous job experience). They also use duration analysis to investigate whether internet job search has an impact on diminishing the unemployment duration and find that it does

[3] See Narendranathan and Elias (1993) and Arulampalam et al. (2000) for a detailed analysis of the "scarring effect" for the UK labour market.

not appear to decrease search time. In fact, it appears to prolong the time of job search.

Addison and Portugal (2002) using Portugal's Labour Force Survey, assess the effects of different job search strategies on the escape rates from unemployment, and measure the effectiveness of the job search strategies on obtaining a job. They find evidence indicating that the most successful methods in finding a job are approaching directly the employer and informal methods (i.e., friends and family networks). The authors use a discrete time duration model where a discrete hazard function describes the conditional probability of an individual exiting unemployment at interval t, given that a person remained unemployed until time t. They find that direct applications to employers, taking examinations and self employment decreases the time unemployed, compared to other channels used.

The channels used for job search can be further subdivided into formal and informal ones. Presumably there are certain channels that would be more effective in ensuring a job offer given a worker's characteristics and the desire to access these type of jobs and this is associated with shorter duration of unemployment. Márquez and Ruiz-Tagle (2004) suggest that workers who come from formal jobs are more likely to use more formal methods relative to those originating from jobs in non-regulated segments of the labour market. Using a logit model and the Venezuelan Household Survey, they analyze the impact of a set of different search strategies in determining whether a worker will experience a transition into employment. They conclude that previous job status (being employed or unemployed) has a dominant impact on transitions into employment.

The study by Meliciani and Radicchia (2011) investigate if being recruited through informal channels in the Italian labour market has both a wage penalty for job searchers and affects the duration spells of unemployment, thus reducing search costs. They divide these search channels into friends and relatives and professional ties. Estimating a Mincerian wage equation and controlling for observable characteristics, they find there is a wage penalty for those hired through the friends and family channels and a wage premium for those hired through professional ties. They use duration analysis to address search cost reductions and find that the use of these search channels reduce the average spell of unemployment.

For Mexico, the paper by Calderón-Madrid (2008) investigates the unemployment duration of job searchers in the Mexican labour market and also analyses the effectiveness of different search channels. Using survival models, Calderón finds that those that relied on social and family networks were more effective in reducing the time until a worker secures an informal job and the searching for a job via newspapers and the internet reduce the time of unemployment for those securing a formal job. However, this paper does not account for unobserved heterogeneity in the estimation and imposes a Cox baseline hazard which is a general way of modelling the unemployment duration of individuals.

The use of a combination of different search methods does not always result in shorter unemployment spells. The main reason for this is that a worker must devote the time and resources to this process, hence it becomes costly. In this sense, Keeley and Robins (1985) findings for the US suggest that the most productive forms of job search are those associated with direct employer contacts, as these measures are most strongly associated with unemployment durations. But the more methods individuals use, the longer their duration of unemployment. The latter suggests that unemployed individuals using few channels of job search intensively have shorter durations of unemployment compared to those who use many methods in a less intensive way.

The search intensity and search channels used can also vary depending on personal characteristics and the type of job a worker is looking for. For example, Weber and Mahringer (2002), find that, on average, unemployed individuals use two methods of job search for case of Austria. They find that search effort decreases with age and that more educated individuals search harder compared to lower educated ones. Going directly to the workplace accounts for more than half of the jobs found. Moreover, they find no significant effect on the hazard of leaving unemployment of increasing search effort and higher wages offers.

The probability of securing a job and the duration of unemployment is also affected by social and economic policy. In this way, unemployment insurance is the most common of these programs but is not exclusive. However, it has been found that this prolongs job search as individuals wait for better employment opportunities compared to not having any sort of financial help. (see Meyer, 1990; Addison and Portugal, 2002; Caliendo et al., 2013). However, unemployment insurance or any other type of government program must be properly implemented to avoid creating a scarring effect. There is evidence that some programs might have a negative effect on employment and there might be gender effects when these programs target women only Iturriza et al. (2011).

The empirical evidence to date of the duration of unemployment for formal and informal job searchers is scarce. It is important to address this phenomena to understand the dynamics and interaction between these two sectors. There is evidence for the case of Bolivia a labour market which is characterized by having a larger share of informal workers compared to Mexico. Canavire and Casazola (2006) suggests that informal workers with higher schooling levels experience longer unemployment durations given their higher reservation wages. On the contrary, indigenous workers with lower schooling levels experience shorter unemployment durations because their reservation wage is lower.

For the case of Argentina Canavire and Lima (2009) presents empirical evidence that the duration of unemployment for formal and informal workers is determined by the schooling level. More schooling level implies longer duration of unemployment. Moreover, the lack of access to schools and universities explains the restriction to the mobility from informal to formal jobs.

It is important to highlight that in developing countries often informal labour markets are used as a transitory state to finance job search and ensure a better job match in the formal labour market. Presumably duration of unemployment before entering this sector is shorter compared to the formal sector given that, as explained above, reservation wages are lower for informal jobs. This can contribute to the understanding of another dimension to the segmentation or dualism of the labour market that has been discussed in the literature. Moreover, there is empirical evidence that the proportion of workers that have preferences for informal jobs is not trivial (Alcaraz et al., 2012). Simultaneously, there is a proportion of workers wanting to enter formal jobs and who use informal jobs to finance a longer job search. It is hoped the empirical analysis presented here will shed light on these issues.

2.3 Mexican Labour market and Data

As noted in the previous chapter, the Mexican labour market is comprised of formal and informal jobs. It is important in this context to differentiate between these two sectors. A worker is formal if it has access to public social security and health services provided by the government. Otherwise, it is considered informal, even if it works for a formally registered firm.

Being a formal worker in Mexico comes with fringe benefits that are partly financed by payroll taxes. These are provided mainly by the two major health institutions IMSS and ISSSTE and consist of health care, life insurance, housing loans, retirement pension and severance payment.[4] In contrast, workers in informal jobs do not have a legal right to any of these fringe benefits. Their work conditions and wages are a matter of personal agreement between the employer and employee in this case.

Although the benefits that come with being formally employed surpass those of being informal, the majority of Mexican workers are informal. This topic is debatable and there are many competing hypothesis of why this is the case. On the one hand, some ague that being informal is simply a personal choice and reflects preference for the characteristics of informal jobs. These are flexibility of working hours, proximity to the place of residence or avoiding paying taxes (Maloney, 1999, 2004; Bargain and Kwenda, 2010; Alcaraz et al., 2012; Günther and Launov, 2012). On the other hand, it is argued that the segmentation of the labour market or the restrictions to access formal jobs, fuels the informal sector and that this is a result of market inefficiencies (Serneels, 2008; Mondragón-Veléz et al., 2010). However, this analysis focuses only on the duration of unemployment before transition into formal and informal jobs and contributes to this debate only in the sense that it provides additional insights on the determinants of duration across these two sectors.

During the period of analysis here (2005-2015), there is no unemployment insurance in Mexico at the national level. The lack of a way of financing job search creates the conditions for the rapid transitions out of unemployment or into the informal sector to secure an income whilst finding a suitable job. In this sense, figure 2.1 plots the duration of unemployment for this period. The majority of job searchers do not spend more than three months searching for a job and this holds true even during times of economic downturn. This can be observed in the graph for the period of the great recession in the late 2008, the proportion shrinks but it is still larger compared to workers who spend more time searching for jobs.

[4]IMSS provides social security and health services to workers employed in the private sector whilst ISSSTE provides these services to workers in the public sector.

The fact that transitions into employment are relatively fast makes it worth analyzing what are the factors contributing to these rapid transitions. The contribution of this chapter then is to analyze the different factors that contribute to these quick transitions between the unemployment pool and the formal and informal sectors.

To perform the analysis in this paper, a period of ten years (2005-2015) of the Mexican National Employment Survey (ENOE in Spanish) is used. This survey constitutes a nationally representative random sample of individuals. The National Institute of Statistics and Geography (INEGI) asks respondents in this survey about different socio-economic characteristics and their current and past employment status. Two types of questionnaires are used in this survey: the basic and the extended version. The basic version is used in the second to fourth quarters of each year and the extended version is only used in the first quarter of each year. The questions reflect worker's previous activity including job search and the duration of their unemployment, which is central to the analysis here.

The extended version contains the duration of job search indicator, which reflects the time the individual spent searching for a job prior to interview and is divided into 5 categories: up to one month, more than one but less than three months, more than three but less than six months, more than six months but less than a year and more than a year searching. Given that the duration variable categorizes the duration by months, the variable is instead recoded to reflect weeks of job search. [5] The duration variable then has a minimum of 4 weeks and a maximum of 53 weeks. It also contains questions on issues such as financial and other types of support. The objective of this is to capture if a person receives any form of financial aid from the government or from friends and relatives regardless of their employment status. As the sample represents only unemployed job searchers, it is of interest to determine if this aid (pecuniary or not) assist a person in exiting unemployment. Given that both the unemployment duration and the information on financial aid is only given in the first quarter of each year, the analysis is restricted to the first two quarters of the period (2005-2015).

The survey includes questions regarding the job search channel used by individuals prior to the interview.[6] These questions are asked in both surveys (basic and extended) and they capture the alternative search methods used by job searchers. Answers

[5]This was done simply multiplying the month times four weeks.

[6]For the case of those that are in their second interview onwards this period becomes a quarter.

are divided into 11 categories and are not mutually exclusive. The categories comprise: directly, private placement agency, government placement agency, temporal job government program, formalities to start a new business, on-line job advertisement, published or answered a newspaper or other printed source advertisement, went to a union or guild, asked relatives to recommend or inform about a job, check advertisements on newspapers and others. Due to the broad similarity between categories the responses were merged into six categories in the following way: Ask for job directly, on-line job advertisement, Advertisement (printed, newspaper, radio, television), Friends and relatives, Allocation service (public and private allocation service, went to union or guild), Other (temporal job, arrangements to start a new business and other).

The survey contains questions that permits the identification of sources of income to finance job search. According to the questions, income comes from three main sources: financial aid from friends and relatives, financial aid from a government program and income after employment (e.g. severance payment). Financial aid from friends can come from: someone abroad, someone in another Mexican state or someone in the same state. In the same way, aid from government may come from the following sources: fellowship, financial aid to start a new business, financial aid from any other government program. Finally, income after employment can come from, either a severance payment, sale of a former business, a retirement pension, unemployment insurance[7] or private unemployment insurance.

As the number of people that did not have access to any of the three sources of income to finance job search is relatively low, the categories are merged to create three binary variables that capture whether they had access to the income or not. Hence, a zero captures if a person did not have access and a 1 if the person did.

Finally, the survey is a rotating panel of five interviews and for the purpose of the analysis I only considered those individuals that by the first quarter of 2011 were in their first to fourth interviews, as this allows tracking them to the next quarter of the survey. These individuals state that by the first quarter they were unemployed and actively looking for a job. In this way I also exclude all those that appear only in one quarter of the sample to get a balanced sample and only retain those cases that had previous job experience.[8]

[7] This applies to those living in Mexico City and that have access to this benefit.

[8] As in the previous chapter, I dropped those that stated that they did not have job experience because

Table 2.1 reports the summary statistics for the sample. It has been divided by gender, because it is of interest to view duration of unemployment separately and to compare differences. From the table, the proportion of male job searchers that are head of household is more than twice the proportion of woman. Half of the job searchers are married but only 31% of the females are.

The sample is evenly distributed among educational categories, although it is worth mentioning that on average the proportion of females with higher degrees is larger than males. The proportion of job searchers receiving any form of financial support to finance job search is quite low among all the categories. Those that were previously employed as formal workers account for 43% of males and 49% of females.

Regarding the search channels, the most used channel for both male and female is going directly to the workplace. However, for the rest there are some differences. Females search more via the advertisements in newspapers and on-line. Males, on the other hand, search more via friends and also via newspaper ads.

The indicator of duration of job search is also included in the table. Half of the job searchers have been looking for a job for less than a month by the time of the first interview and if we consider the second category, almost 90% of the job searchers have been looking for a job for less than 3 months.

In this paper the dynamics of labour market transitions in the Mexican context are explored. This analysis is necessarily descriptive as there is a lack of a exogenous variation that impacts unemployment spells. Despite this drawback, understanding the dynamics of Mexican worker's transitions is useful to inform policy makers if the policies implemented to promote certain types of search channels is reaching the target individuals and in what magnitude this is helping them to secure jobs efficiently (and in a relative short period of time). These results are further subdivided to analyse how the set of policies differ between male and female job searchers.

I could not distinguish between those having no work experience and those that did not report whether they had experience or not, this only constitutes 7% of the total sample.

2.4 Econometric Methodology

2.4.1 Failure time distribution

Under the failure time data setting, T is always a nonnegative random variable that represents the failure of an individual taken from an homogeneous population. Following Kalbfleisch and Prentice (2002), the probability distribution is specified in three ways that apply to the survival setting: the survivor function, the probability density function and the hazard function. The survivor function is defined by the probability that T exceeds a value t and can be expressed as:

$$F(t) = P(T > t), \qquad 0 < t < \infty$$

In order to analyze the transitions from unemployment into employment in the Mexican labour market, and given that the information regarding job search is recorded in weeks, a discrete time duration model is specified. Discrete duration modelling is particularly useful in this context, as the responses from workers are grouped in a certain number of weeks but the exact time of the week is unknown. With T being a discrete random variable that takes the values $a_1 < a_2 < ...$ and that has an associated probability function.

$$f(a_i) = P(T = a_i), \qquad i = 1, 2, ...,$$

The survivor function is

$$F(t) = \sum_{j|a_j > t} f(a_j)$$

The hazard is defined as the conditional probability of failing at point a_i conditioned on the job searcher surviving until a_i and can be expressed as:

$$\lambda_i = P(T = a_i | T \geq a_i) = \frac{f(a_i)}{F(a_i^-)}, \qquad i = 1, 2, ...,$$

Where $F(a^-) = lim_{t \to a^-} F(t)$. Hence, the survivor function and the probability density function are given by

$$F(t) = \prod_{j|a_j \leq t} (1 - \lambda_j) \tag{2.1}$$

and

$$f(a_i) = \lambda_i \prod_{j=1}^{i-1}(1-\lambda_j) \tag{2.2}$$

The discrete hazard function ($\lambda_i = 1, 2, ...$) uniquely determines the distribution of the failure time variable T. Given that the interest of this analysis is to calculate the duration of unemployment conditioned on remaining unemployed up to time t but also on covariates x, following Cameron and Trivedi (2005), a proportional hazards model (ph) is specified.

$$\lambda(t|x) = \lambda_0(t, \alpha)\phi(x, \beta) \tag{2.3}$$

The expression $\lambda_0(t, \alpha)$ is commonly known as the baseline hazard which is a function of t. And $\phi(x, \beta)$ is a function of x. Equation (2.3) implies that the hazard rate can be factored into separate functions of that same type. Hazard functions $\lambda(t|x)$ similar to equation (2.3) are proportional to the baseline hazard with a scale factor $\phi(x, \beta)$ that is not an explicit function of t.

2.4.2 Discrete-time Proportional Hazards Model

In this setting the hazard within the interval is assumed to be constant. For discrete time data[9] with grouping points t_a, $a = 1, ..., A$, the discrete-time hazard function is defined by

$$\lambda^d(t_a|x) = Pr[t_{a-1} \leq T < t_a | T \geq t_{a-1}, x(t_{a-1})],\ a = 1, ..., A. \tag{2.4}$$

And the associated discrete-time survivor function is

$$S^d(t_a|x) = Pr[T \geq t_{a-1}|x] = \prod_{s=1}^{a-1}(1 - \lambda^d(t_s|x(t_s))) \tag{2.5}$$

The discrete-time hazard is the probability of failure in $[t_{a-1}, t_a)$ divided by the probability of surviving to at least time t_{a-1} and this can be written as

$$\lambda^d(t_a|x) = \frac{S(t_{a-1}|x) - S(t_a|x)}{S(t_{a-1}|x)} \tag{2.6}$$

[9]For a detailed development of the discrete time duration model see Lunde et al. (1999) and Prentice and Gloeckler (1978)

Where $S(t|x)$ is the survivor function. The (instantaneous) hazard rate function is assumed to take the proportional hazards form

$$\lambda(t) = \lambda_0(t)exp(x(t_{a-1})'\beta) \tag{2.7}$$

For t in $[t_{a-1}, t_a)$. Finally, the associated discrete-time survivor function is

$$S^d(t_a|x) = \prod_{s=1}^{a-1} exp(-exp(ln\lambda_{0s} + x(t_{s-1})'\beta)) \tag{2.8}$$

The density for the ith job searcher is a result of the product of the survivor function in each week that the individual remains unemployed times the hazard at the time of failure. The likelihood then is written as

$$\begin{aligned} L(\beta, \lambda_{01}, ..., \lambda_{0A}) = \prod_{i=1}^{N} & \left[\prod_{s=1}^{a_i-1} exp(-exp(ln\lambda_{0s} + x_i(t_{s-1})'\beta)) \right] \\ & \times (1 - exp(-exp(ln\lambda_{0a_i} + x_i(t_{a-1})'\beta))), \end{aligned} \tag{2.9}$$

In equation (2.9) transition out of unemployment is assumed to happen at time t_{ai} for the ith worker. And at least one failure is assumed to occur in each interval of time $[t_{a-1}, t_a)$.

2.4.3 Unobserved Heterogeneity

In the analysis of the duration of unemployment spells, one has to take into account the presence of unobserved heterogeneity. More specifically, observed heterogeneity refers to differences between job searchers that are measured by regressors and unobserved heterogeneity refers to factors that are not accounted for in the regression (Cameron and Trivedi, 2005). Ignoring this problem in duration analysis can lead to several issues: the non-frailty model can over-estimate the negative duration dependence in the (true) baseline hazard and underestimate positive duration dependence. According to Jenkins (2005) this is a selection effect because, *ceteris paribus*, for the case of negative duration dependence, individuals with high values of unobserved differences fail faster, so the survivors are increasingly composed of observations with relative low values of unobserved differences and thence, lower hazard rates.

Another issue that can arise from ignoring unobserved heterogeneity in the regression is that the proportionate effect of a given regressor on the hazard rate is no longer constant nor independent of survival time. Finally, having unobserved heterogeneity attenuates the proportionate response of the hazard to variation in each regressor at any survival time. This is that the estimate of a positive (negative) β_k derived from an incorrect non-frailty model will under-estimate (over-estimate) the 'true' estimate. Following Rodrıguez (2005) unobserved heterogeneity is introduced in the hazard via a random variable θ. This model in its general form is called proportional hazards model with a frailty term as follows:

$$\lambda(t, x, \theta) = \theta\lambda_0(t)e^{x'\beta}$$

Where θ is the random effect with mean zero and a distribution that is independent of the observed covariates x. t is the hazard at the time for an given individual. The estimation of this model is done following Heckman and Singer (1984) which assumes a non-parametric maximum likelihood estimator (NPMLE) of the distribution of frailty θ. The model takes values $\theta_1, \theta_2, ..., \theta_k$ with probabilities $\pi_1, \pi_2, ...\pi_k$ for some value of k. In this case with $k = 2$ and a non-parametric distribution of the baseline hazard.

2.4.4 Competing risk specification

Given the structure of the Mexican labour market, where individuals that experience a transition into employment exit to either formal or informal jobs or simply exit the labour force. It is of interest to expand the single risk analysis into a competing risk setting. Measuring the different durations of unemployment before exiting into each of these labour market states will shed light on the dynamics of the Mexican labour market and the factors contributing to their hazard. Moreover, it is important not just to include the unemployed but also the category "out of the labour force" because the motivations to stop searching for a job completely that are implied here, are different from just remaining unemployed. Often the motivation to choose one category over the other come from the way the household is structured. For example, it is common to have more than one family with its respective head of household living under the same roof and sharing the same living expenses. Under this circumstance, if a member of the household becomes unemployed the economic burden for the household becomes less given that other member of his family and the other family sharing the house can help finance a longer job search or might even stop completely for the case of female workers.

The competing risk setting is of particular use in this context as job searchers either remain unemployed or exit into three different labour market states: formal job, informal job or out of the labour force. In this way, each destination-specific hazard rate is considered independent, because this follows the assumption that transition to other labour market states is not possible. In this sense, hazard rates of every labour market state are 'latent' rather than actually observed (Jenkins, 2005). Under this scenario, the discrete hazard rate for exit at time j to any of the destinations, would be the sum of the destination-specific discrete hazard rates.[10]

$$h(j) = h_F(j) + h_I(j) + h_O(j)$$

Due to the nature of the weekly duration data (being intrinsically discrete), when an individual experiences a transition into any of the labour market states in the second quarter of 2011, the individual cannot experience a transition into another labour market state in the same quarter. Following Jenkins (2005), the likelihood contributions for the discrete time model in this particular setting, are of four types, each one corresponding to every labour market state and those considered as censored (unemployed):

$$\begin{aligned} L^F &= h_F(j)S(j-1) \\ &= \Big[\frac{h_F(j)}{1-h(j)}\Big]S(j) \\ &= \Big[\frac{h_F(j)}{1-h_F(j)-h_I(j)-h_O(j)}\Big]S(j) \end{aligned}$$

[10] The subindices in the equation indicate if an individual experiences a transition into a Formal (F), Informal (I) job or Out of the labour force (O).

Similarly,

$$
\begin{aligned}
L^I &= h_I(j)S(j-1) \\
&= \Big[\frac{h_I(j)}{1-h(j)}\Big]S(j) \\
&= \Big[\frac{h_F(j)}{1-h_F(j)-h_I(j)-h_O(j)}\Big]S(j)
\end{aligned}
$$

$$
\begin{aligned}
L^O &= h_O(j)S(j-1) \\
&= \Big[\frac{h_O(j)}{1-h(j)}\Big]S(j) \\
&= \Big[\frac{h_F(j)}{1-h_F(j)-h_I(j)-h_O(j)}\Big]S(j)
\end{aligned}
$$

and finally,

$$L^U = S(j)$$

Given that the common term among each of the likelihood contributions is $S_i(j)$. The expressions can grouped in the following way:

$$S(j) = \prod_{k=1}^{j}[1-h(k)] = \prod_{k=1}^{j}[1-h_F(k)-h_I(k)-h_O(k)]$$

This likelihood has the same form as the likelihood for a standard multinomial logit model with re-organized data (Jenkins, 2005).

2.5 Empirical results

2.5.1 Non-parametric duration analysis

The dataset has to be arranged to facilitate the analysis of discrete time duration, following Jenkins (2005). For each person there are as many rows as there are time intervals at risk of becoming employed per individual. If a person has been searching for a job for 4 weeks, the contribution to the dataset will be of 4 rows of data observations. Additionally a spell week identifier has to be created, which is equal to zero for the weeks unemployed and will be equal to one in the last week to indicate that the person exited unemployment. If the person is still unemployed then the variable will be equal to zero in all the rows.

The failure estimates are now calculated with the discrete time duration dataset and plotted to get a visual representation and compare between different subsamples. These represent the probability of becoming employed conditional on the time unemployed from

t to $t + 1$, without specifying any particular functional form or including any covariates in the estimation (Dendir, 2006; Marcenaro-Gutierrez and Vignoles, 2010). This is to get an idea of how the failure rates "behave" for the sample of job searchers analysed. It is confirmed graphically in figure 2.2 that almost 50% of the initial sample of unemployed becomes employed after 12 weeks and almost 74% just after 26 weeks of job search.[11]

The differences in failure rates dividing by groups of the subsample are now compared. Figure 2.3a provides graphic evidence of the failure rates by gender. It can be observed that a larger proportion of males become employed quicker than their female counterparts. During the first four weeks of job search almost 30% of males become employed, whereas just 24% of females become employed. During 26 weeks of job search, more than 75% of males exit unemployment and approximately 60% of females have secured a job.

Figure 2.3b provides the estimates separated by formal and informal jobs. A majority of unemployed individuals exit faster into informal compared to formal jobs.[12] After four weeks of job search, more than 50% exit into informal jobs but less than 20% secure a formal job. Additionally after 12 weeks of job search of those unemployed more than 80% transition into an informal job and less than 20% get a formal job. In figure 2.4a the failure rates for females is plotted by type of job. The pattern shown now again is of a larger proportion of unemployed exiting into informal jobs. Figure 2.4b plots the failure rates for males and more males exit into informal jobs than formal ones. These graphs show clearly that there are differences in the failure rates by gender and that these differences are larger when dividing the sample by the type of job. Evidence is provided here of a lower reservation wage for informal workers compared to those aspiring to secure a formal job. Whether this is the result of barriers to entry to formal jobs or simply a choice of the individual, cannot be identified from the results presented here.

The visual representation of the difference in failure rates can be confirmed formally with a test of equality of survivor functions. Table 2.2 displays the Log rank test, the Wilcoxon-Breslow and the Tarone-Ware tests. As the table shows, all three tests re-

[11] I use the term job search indistinctly to refer to unemployment in period t because respondents of the survey were explicitly asked their duration of unemployment without job search interruption.

[12] This result is consistent with other studies for countries with a large presence of an informal sector and which suggest that the lower reservation wage of informal workers reduces their duration of unemployment see Canavire and Casazola (2006) and Canavire and Lima (2009).

ject the null hypothesis of equality between the different groups tested.[13] The difference between average duration of unemployment by gender and the choice of sector motivates our interest to estimate the discrete duration proportional hazards model dividing the sample by gender and sector.

2.5.2 Non-parametric analysis under a discrete time framework

To undertake the econometric analysis of unemployment duration, a single spell, discrete time proportional hazard (ph) model with non-parametric baseline hazard is used. The model estimated is due to Prentice and Gloeckler (1978) and uses a maximum likelihood methodology following the method proposed by Heckman and Singer (1984). The non-parametric baseline hazard is used as this is data coherent and widely used when estimating discrete time models. It takes into account (weekly) duration and personal characteristics such as age, head of household status, marital status and schooling.[14]

Specifically for our analysis, the model includes other factors that might influence duration dependence, such as the person having access to a lump sum payment that acts as a financial cushion for job search, government aid to find a job, financial support from friends or relatives, if the previous job was informal or not, reasons for quitting a former job and regional controls.[15] Finally, controls for search channels used during job search have been included.[16] The model yields the hazard probability of finding a job in time $t + 1$, conditional on remaining unemployed until time t.

Table 2.3 presents the results for the pooled sample and gender, and table 2.4 presents the results by gender and sector of employment. Being married and being head of household increases the hazard of exiting unemployment. The result is consistent when dividing the sample between formal and informal workers and gender in both tables 2.3 and 2.4.

[13] Given that the survivor function is the mirror of the failure function, the tests are conducted interchangeably on the survivor function.

[14] According to Jenkins (2008), given that there is no specific routine in stata to estimate the discrete time proportional hazards model, the estimation is done rearranging the dataset and creating variables to define the baseline hazard function and the estimation is done with a logit model. However, the interpretation is in terms of a discrete time proportional hazards model.

[15] Five Mexican regions are taken into account here: North, West, East, Center and South.

[16] Such as Going directly to the workplace, On-line job advertisement, Advertisement in newspapers, Social networks, public or private allocation services and other forms of job search

It is common for the head of households to bear the responsibility of providers, and the results suggest that this holds true even when they are married. Even when experiencing episodes of unemployment, these individuals will try to find a job as quick as possible to fulfil their role as main provider for the household.

Relative to the centre, workers living in a different region experience shorter unemployment spells, this result is consistent for both men and women but for the case of formal and informal workers the results are mixed. In the north region, male and female workers have shorter unemployment spells when exiting into formal jobs but longer unemployment duration when exiting into informal jobs. The opposite effect takes place in the south region where workers have shorter unemployment spells when exiting into informal jobs. According to INEGI, if we look at the proportion of formal and informal workers per region, in Nuevo Leon (in the north), informality accounts for approximately 40% of the total workforce, this can explain why individuals experience shorter unemployment spells when exiting into formal jobs. In contrast, in Oaxaca (in the south), informality accounts for almost 80% of the total workforce, so it is expected that informal workers take less time to get a job.

For the schooling category, relative to those that had completed elementary school, the results suggest that schooling has a positive impact on the hazard of formal workers but not for informal workers, where the more schooling the longer their duration of unemployment before exiting into informal jobs. The formal sector attracts more skilled workers compared to the informal one, this means that the more qualified the less an individual will wait until securing a job as formal. In contrast, higher schooling levels represent longer duration of unemployment for workers when they exit into informal jobs. Highly skilled workers have higher reservation wages, so they experience longer unemployment spells before entering the informal sector, this result might also be signaling that highly skilled workers prefer to be employed as formal so they will be hesitant to take informal jobs and wait for a formal job offer instead. Empirical evidence for this selection bias was presented in the previous chapter. It was found that workers do have a preference for the formal and informal sector.

The indicator of being previously employed as a formal worker allows us to capture the impact of previous experience in the formal sector on re-employment. The results of the estimation presented in table 2.4. Being previously employed as a formal worker reduces the time unemployed before securing a formal job. However, it increases the time unemployed for those exiting into informal jobs.

The remaining part of the table contains the variables of interest for our key analysis. The financial variables that presumably act as a cushion for job searchers are divided into three alternatives. Having a lump sum payment from a previous job, receiving aid from the government and receiving financial aid from relatives either in Mexico or from abroad.

The results in table 2.3 and 2.4 reveal that receiving a lump sum payment reduces the time unemployed for the whole sample and by gender. However, the effect is not statistically significant for formal workers and it increases the time unemployed for those exiting to informal jobs. It was anticipated that the effect would be uncertain as financing job search can both prolong the time unemployed or can intensify job search. For the case of this analysis, having access to this type of financial support permits a more intensive job search, making them exit the unemployment state faster compared to those that do not possess it. Other studies have found a similar effect on the hazard rate of job searchers for the case of Sri Lanka and Ethiopia (Dickens and Lang, 1991; Serneels, 2008).

On the other hand, having financial aid from relatives and aid from government prolongs the time unemployed and the effect persists after dividing the analysis by gender. Those that receive money from relatives are financing longer periods of job search compared to non-recipients. It is common in Mexico to have two households under the same roof sharing living costs, it is also common for relatives to support each other in times of financial hardship. These situations can impact differently the willingness of unemployed individuals to actively engage in the job search process.

Receiving government support is also prolonging the time for job search. Even though, the unemployment insurance program in Mexico at the national level was introduced in Mexico in 2016, many other government cash transfer programs have comprehensive coverage. Such is the case of the program "prospera", which is a cash transfer program that was originally designed to reduce poverty, but nowadays it covers more aspects such as health and education and this does have an impact on the household income.

Regarding the search channels, the results suggest that going directly to the workplace and searching for jobs in the newspaper reduce the unemployment spell for formal workers. Searching for jobs in the newspaper prolongs the time unemployed for those exiting into informal jobs (for both male and female). On the other hand, asking friends and relatives, helps workers reduce their time unemployed before exiting into informal jobs. Using allocation services prolongs time of unemployment for informal workers when used by men, but has no effect for women. Search channels might be effective in helping unemployed individuals escape unemployment as previously found in the literature Addison and Portugal (2002); Keeley and Robins (1985) and more specific for the case of Mexico see the previous chapter. But some are not as effective to reduce the time unemployed. This result is consistent with the findings by Calderón-Madrid (2008) in terms of the hazard. There seem to be other factors that are more effective in reducing the time unemployed for job searchers, such as personal characteristics or the means to finance job search.

Finally, time of job search was included in the model to measure the duration dependence and if individuals are experiencing a scarring effect. The results suggest a negative duration dependence, this is that the more time an individual remains unemployed, the less likely it is to find a job. The signs of the dummies capturing different weeks of job search suggest a that the negative duration dependence is monotonic. This effect is consistent after dividing the sample for male and female workers both in the formal and informal sector.

As a robustness check, the model was estimated using a continuous time setting. Assuming different distributions for the baseline hazard. The distributions assumed are *Exponential*, *Weibull*, *Gompertz*, and *Cox*. The results are presented in table B.1. For males by type of job in table B.2 and for females by type of job in table B.3 of the Appendix. The results presented assuming different distributions of the hazard for a continuous time setting are similar in magnitude and sign of the coefficient to the discrete setting. The negative effect of the search channels on the hazard of unemployed individuals also holds. The positive effect of the lump sum payment on the hazard rate of individuals is also similar.

2.5.3 Non-parametric analysis under a discrete time framework controlling for unobserved heterogeneity

Survival models assume that individuals share the same risk of failing. This if course can be a very strict assumption to make as there are factors affecting the hazard of some individuals that do not affect others in the same way. Introducing covariates into the estimation of the hazard rate controls for a source of heterogeneity that can be observed. However, there is still a source of unobserved heterogeneity that we are not accounting for. The model proposed by Heckman and Singer (1984) accounts for unobserved sources of heterogeneity that can bias the results by assuming a non-parametric distribution of the heterogeneity which is more flexible compared to imposing a distribution of the heterogeneity that can bias the results.[17] In this subsection, as a robustness check, the model just presented is re-estimated incorporating unobserved heterogeneity into the regression model.

The results are reported in table 2.5 for the pooled sample and gender. In table 2.6 the results are presented by gender and sector of employment. The results reveal some differences in magnitude and in some cases in sign compared to the previous results but these effects are not statistically significant. The coefficients for the educational category show a change in sign for the case of males that experience a transition to informal jobs, compared to having elementary school, a higher educational level, prolongs the time unemployed rather than decreasing it as shown in the model without the effects of unobserved heterogeneity.

The impact of the means to finance job search remains the same in the sign of the coefficient but not the magnitude. The magnitude is higher after incorporating unobserved heterogeneity. Regarding search channels, the magnitude is also higher and the sign of the effect remains. Not all channels are effective in helping workers secure jobs faster, thus confirming the finding in the previous subsection.

Finally, time was included in the model in the same way it was included in the model without unobserved heterogeneity. The dummy variables presented in tables 2.3 and 2.4 are computed but not presented here, at the bottom of the table the variable m2 reflects

[17](Van den Berg, 2001) argues that estimates might be biased if the distributional assumption is incorrectly specified.

the duration dependence, which in this case is negative, confirming the results in the previous section.

2.5.4 Competing risk specification

Until now, the focus of this research has been on the transition from unemployment to employment. However, unemployed individuals in this context have at least three paths out of unemployment, these are: exiting into a formal job, into an informal job and out of the labour force. Analyzing these transitions is important because it provides a deeper understanding of Mexican labour market dynamics in the presence of a formal and informal sectors, conditional on time unemployed and personal characteristics of job searchers. The analysis of a single spell model does not allow to capture the specific destination of a worker, instead a competing risk destination model is used.

To perform this analysis an important assumption is made and it comes from the specification in the paper by Marcenaro-Gutierrez and Vignoles (2010). The factors that make a person choose one employment state impact differently the choice of another sector. This assumption is not unrealistic as often workers choose the informal sector to avoid paying taxes, the flexibility of working schedule or not having to respond to a boss when they are informally self-employed. A person can also choose to remain unemployed and wait for a better job or stop searching for jobs because there are household circumstances that allow this, specially for women. All of these factors, in conjunction with personal characteristics, are not affecting equally the employment decision. In this sense, the model is set to be run as separate logit equations to analyze the different options rather than to perform a multinomial logit analysis. In this way, the Independence of Irrelevant Alternatives (IIA) test that is implicit in the multinomial logit setting is also avoided.

Table 2.7 presents the results of the competing risk specification. Being male reduces the time unemployed compared to females. This implies that female job searcher are more likely to experience a transition out of the labour force, which is not surprising, given the traditional role of females in Mexican households, and even though this is changing it is still common.[18] The results presented here are also estimated dividing the sample by gender in table 2.8. In the results by gender, conditional on time unemployed, being

[18]The percentage of women participating in the labour force has drastically increased in Mexico, from 19.4% in 1970 up to 42.3% in 2010 (Orraca et al., 2016).

married increases the hazard of going out of the labour force for females as reported in column (4).

The results in table 2.7 yield a positive effect of all schooling levels (taking elementary school as the base category) on the hazard of formal jobs but it decreases the hazard for those exiting into informal jobs, remaining unemployed or going out of the labour force. Dividing this result by gender in table 2.8 it is clear that the effects hold, although for females the impact is weaker than for males. In the same way, looking at the coefficients of the variable that captures if a worker was previously employed as formal, the results are consistent with those in the single destination model and the coefficients by gender. This reduces the hazard of going out of the labour force or remaining unemployed.

The remaining part of the table contains the variables that capture if the worker had access to financial cushion and the variables that capture the search channels used by job searchers. Having access to a lump sum payment from a previous job increases the hazard of those exiting into a formal job, this is consistent for both male and female. This can be explained by the fact that those having access to this type of support, are those that were previously employed as formal workers and the likelihood of those securing a formal job is high, compared to the informal ones. Receiving aid from government increases the hazard of those going out of the labour force for both male and female as can be confirmed in table 2.8. The support provided by the government, additional to cash transfer programs, is mainly training to enhance worker's skills and increase job opportunities.

From the results in the estimation, it seems that the training is stopping active job search, perhaps unemployed individuals decide to stop and focus on their training instead to enhance their employability and skills. Finally, receiving financial aid from relatives reduces the hazard of those that exit into formal jobs, specially for males, for females it is not statistically significant. It is possible that those receiving help from relatives might relax the intensity of job search and thus remain searching for longer until an adequate offer arrives, as previously discussed.

The last part of the table reports the variables that relate to the search channels used. The results presented here are consistent with the ones presented in previous subsections. The use of some of the search channels seems to lessen the hazard of individuals. This implies that rather than helping escape unemployment faster is prolonging it. Instead there are other factors that are helping workers to secure a job, like personal characteristics, schooling, age, and if the worker had access to any type of financial help to secure a job. The results of the impact of duration of the hazard is similar to the models under a single spell model, there is negative duration dependence in the model.

As a robustness check, the competing risk model is now estimated again including unobserved heterogeneity in the estimation with the methodology proposed by Heckman and Singer (1984). The results for the full sample are presented in table 2.9 and by gender in table 2.10. The results reveal that similar to the model with a single destination, not including unobserved heterogeneity leads to underestimate the impact of the different covariates and the time on the hazard of job searchers. However, some if the effects for females are not statistically significant after controlling for unobserved heterogeneity. The positive effect of government aid on the hazard of going out of the labour force is still strong here.

2.6 Conclusions

The analysis undertaken here aimed to answer two main questions. First, it attempted to explain what the impact of different search channels and the means by which a person finances job search affects unemployment duration. Second, what is the impact of these attributes on the duration of unemployment for workers obtaining a formal or informal job?

To address the questions of this analysis a discrete duration model was used. The model also accounts for unobserved heterogeneity using the methodology proposed by Heckman and Singer (1984). Furthermore, the model was also estimated assuming a multiple destination or competing risk set up. This allows us to understand the different characteristics that have an impact on the duration of those workers exiting each of the labour market states.

Some interesting findings arise from the analysis. The results provide evidence for regional differences for workers when exiting into formal and informal jobs. In the north, those that exit into formal jobs experience shorter unemployment spells. In contrast, in the south those that exit into informal jobs have shorter duration of unemployment. Higher schooling levels lessen the time unemployed when exiting into formal jobs but the effect is the opposite if exiting into informal jobs. The formal sector attracts a larger number of formal workers and those highly skilled are willing prolong the time unemployed before securing an informal job.

Regarding the financial variables, different ways of financing job search have different implications for unemployment duration. For example, those that were receiving financial support from the government and support from friends and relatives experience longer unemployment periods. It is concluded that the structure of the Mexican household allows workers to engage in longer job searches. It is common to have multiple families living under the same roof and sharing living costs, this situation leads to workers to wait for a more suitable job offer. Similarly, those receiving support from the government via cash transfer programs or training, are spending more time unemployed before securing a job. In contrast, those that had access to a lump sum payment from a previous job, experience shorter unemployment durations.

Regarding the search channels and the impact they exert on unemployment duration, the results suggest that going directly to the workplace and searching for jobs via newspaper reduce the unemployment duration for those exiting into a formal job. Asking friends and relatives helps job searchers to reduce the time unemployed before securing an informal job for both male and female. Only a few channels are effective in reducing the time unemployed, instead, there are other factors that are determinant in lowering (or increasing) the period of unemployment. These determinants have to do more with personal characteristics like age, schooling and previous working experience in a given sector. All the results presented here are robust after controlling for the effects of unobserved heterogeneity in the estimation.

The results of the multiple destination model allows us to understand further that the shorter duration for those in possession of a lump sum payment occurs when workers exit into formal jobs for both males and females. This effect holds and it is larger after controlling for unobserved heterogeneity in the regression. This is anticipated because in the Mexican context, formal workers have access by law to a lump sum payment after finishing a labour contract relation. Hence, as the results show, previous formal workers experience shorter duration of unemployment when the exit destination is to a formal job.

2.7 Tables and figures

Table 2.1: Descriptive Statistics for independent variables

Variable	Male	Female
Head	0.43	0.17
Married	0.50	0.31
Education		
Elementary school	0.25	0.12
Secondary School	0.32	0.26
High School	0.21	0.24
More than high school	0.22	0.36
Financial cushion	0.07	0.05
Aid from government	0.01	0.05
Aid from friends or relatives	0.03	0.09
Previous job formal	0.43	0.49
Reason for job loss		
Dismissed of finished previous job	0.65	0.49
Dissatisfaction with previous job	0.26	0.43
Left or closed previous business	0.06	0.05
other	0.03	0.02
Search Channel		
Directly	0.75	0.72
On-line job advertisement	0.07	0.11
Advertisement	0.11	0.16
Social networks	0.15	0.10
Allocation service	0.04	0.06
Other forms of job search	0.03	0.04
Duration of job search		
Up to 1 month	0.51	0.50
More than 1 but less than 3 months	0.36	0.37
More than 3 but less than 6 months	0.08	0.09
More than 6 months but less than 1 year	0.03	0.03
More than a year	0.01	0.01
Number of observations	23,190	10,591

Table 2.2: Test for equality of Survivor Functions

Log-rank	**Wilcoxon-Breslow**	**Tarone-Ware**
$\chi^2 = 537.30$	$\chi^2 = 461.86$	$\chi^2 = 513.05$
$Prob. > \chi^2 = 0.0000$	$Prob. > \chi^2 = 0.0000$	$Prob. > \chi^2 = 0.0000$
	Formal-Informal	
$\chi^2 = 8836.62$	$\chi^2 = 6880.14$	$\chi^2 = 7894.17$
$Prob. > \chi^2 = 0.0000$	$Prob. > \chi^2 = 0.0000$	$Prob. > \chi^2 = 0.0000$
	Female and type of job	
$\chi^2 = 3012.35$	$\chi^2 = 3012.35$	$\chi^2 = 2635.00$
$Prob. > \chi^2 = 0.0000$	$Prob. > \chi^2 = 0.0000$	$Prob. > \chi^2 = 0.0000$
	Male and type of job	
$\chi^2 = 5544.17$	$\chi^2 = 4358.40$	$\chi^2 = 4990.50$
$Prob. > \chi^2 = 0.0000$	$Prob. > \chi^2 = 0.0000$	$Prob. > \chi^2 = 0.0000$

Table 2.3: Estimates for logit hazard single risk model

	(1)	(2)	(3)
	Pooled sample	Male	Female
Gender	0.308***		
	(0.0219)		
Married	0.196***	0.212***	0.211***
	(0.0226)	(0.0224)	(0.0224)
Head of household	0.327***	0.391***	0.392***
	(0.0260)	(0.0255)	(0.0255)
Age	-0.0181***	-0.0186***	-0.0186***
	(0.00107)	(0.00107)	(0.00107)
North region	0.142***	0.138***	0.136***
	(0.0239)	(0.0238)	(0.0238)
West region	0.145***	0.134***	0.131***
	(0.0321)	(0.0321)	(0.0321)
East region	0.156***	0.146***	0.145***
	(0.0302)	(0.0301)	(0.0301)
South region	0.245***	0.241***	0.241***
	(0.0283)	(0.0283)	(0.0282)
Secondary school	-0.0750***	-0.0821***	-0.0809***
	(0.0273)	(0.0273)	(0.0273)
High school	-0.270***	-0.286***	-0.285***
	(0.0302)	(0.0302)	(0.0302)
More than high school	-0.456***	-0.500***	-0.499***
	(0.0295)	(0.0293)	(0.0293)
Previous job formal	-0.0661***	-0.0706***	-0.0713***
	(0.0199)	(0.0198)	(0.0198)
Dismissed or finished previous job	-0.00697	0.0287	0.0289
	(0.0211)	(0.0210)	(0.0210)
Left or closed previous business	-0.0317	-0.0129	-0.0126
	(0.0437)	(0.0436)	(0.0436)
Other reason	0.0217	0.0481	0.0485

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	(1) Pooled sample	(2) Male	(3) Female
	(0.0586)	(0.0586)	(0.0586)
Financial cushion	0.0923**	0.101***	0.0993**
	(0.0389)	(0.0388)	(0.0388)
Financial aid from government	-0.147**	-0.241***	-0.240***
	(0.0640)	(0.0641)	(0.0641)
Financial aid from relatives	-0.183***	-0.252***	-0.251***
	(0.0431)	(0.0426)	(0.0426)
Went directly to the work place	-0.126***	-0.123***	-0.124***
	(0.0283)	(0.0282)	(0.0282)
Uploaded or replied to a job offer online	-0.193***	-0.195***	-0.194***
	(0.0369)	(0.0367)	(0.0367)
Asked to relatives and friends to recommend his job	-0.00338	0.0124	0.0117
	(0.0297)	(0.0296)	(0.0296)
Used allocation services to get job (public of private)	-0.228***	-0.241***	-0.240***
	(0.0465)	(0.0463)	(0.0463)
Used advertisement in newspaper or classifieds to get job	-0.126***	-0.137***	-0.138***
	(0.0288)	(0.0286)	(0.0286)
Used other channels to find a job	-0.126**	-0.136**	-0.137**
	(0.0553)	(0.0552)	(0.0555)
Weeks of job search 4	-0.517***	-0.311***	-0.310***
	(0.0538)	(0.0517)	(0.0517)
Weeks of job search 8	-3.333***	-3.124***	-3.122***
	(0.0741)	(0.0724)	(0.0724)
Weeks of job search 12	-0.0406	0.164***	0.165***
	(0.0557)	(0.0537)	(0.0537)
Weeks of job search 16	-1.820***	-1.611***	-1.610***
	(0.0710)	(0.0692)	(0.0693)
Weeks of job search 20	-4.953***	-4.741***	-4.739***
	(0.230)	(0.230)	(0.230)

continued . . .

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	(1) Pooled sample	(2) Male	(3) Female
Weeks of job search 24	-2.700***	-2.489***	-2.488***
	(0.0926)	(0.0913)	(0.0913)
Weeks of job search 26	-0.363***	-0.156**	-0.155**
	(0.0644)	(0.0625)	(0.0626)
Weeks of job search 28	-4.077***	-3.864***	-3.863***
	(0.238)	(0.237)	(0.237)
Weeks of job search 30	-2.292***	-2.079***	-2.078***
	(0.115)	(0.114)	(0.114)
Weeks of job search 34	-5.779***	-5.564***	
	(0.580)	(0.580)	
Weeks of job search 36	-6.180***	-5.967***	-5.965***
	(0.709)	(0.709)	(0.708)
Weeks of job search 38	-2.523***	-2.310***	-2.308***
	(0.132)	(0.131)	(0.131)
Weeks of job search 40	-6.770***	-6.554***	
	(1.002)	(1.002)	
Weeks of job search 42	-4.814***	-4.601***	-4.600***
	(0.383)	(0.383)	(0.383)
Weeks of job search 50	-6.066***	-5.851***	
	(0.710)	(0.710)	
Weeks of job search 52	-0.431***	-0.219***	-0.218***
	(0.0834)	(0.0819)	(0.0819)
Weeks of job search 53	-0.0801	0.127	0.128
	(0.101)	(0.0997)	(0.0997)
Weeks of job search 56	-1.315***	-1.086***	-1.084***
	(0.198)	(0.197)	(0.197)
Weeks of job search 57	-1.321***	-1.104***	-1.103***
	(0.228)	(0.228)	(0.228)
Weeks of job search 60	-3.202***	-2.972***	-2.971***
	(0.591)	(0.591)	(0.591)

continued ...

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	(1) Pooled sample	(2) Male	(3) Female
Weeks of job search 62	-4.283***		-4.058***
	(1.011)		(1.009)
Weeks of job search 64	-0.743***	-0.519**	-0.517**
	(0.239)	(0.236)	(0.236)
Weeks of job search 65	-0.917***	-0.668**	-0.667**
	(0.313)	(0.313)	(0.313)
Weeks of job search 68	-1.687***	-1.423***	
	(0.528)	(0.530)	
Weeks of job search 72	-2.791***	-2.557**	
	(1.019)	(1.023)	
Weeks of job search 76	-2.835***	-2.602**	
	(1.028)	(1.031)	
Weeks of job search 77	-2.612***	-2.383**	
	(1.001)	(1.004)	
Weeks of job search 78	-1.009*	-0.802	-0.802
	(0.570)	(0.576)	(0.576)
Weeks of job search 79	-0.844	-0.643	-0.643
	(0.640)	(0.642)	(0.642)
Weeks of job search 90	-0.165		1.275
	(0.943)		(1.421)
Weeks of job search 105	0.796	1.137	
	(1.336)	(1.313)	
Observations	98010	97882	93435
Log pseudolikelihood	-37678.532	-37772.353	-37709.031

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4: Estimates for logit hazard single risk model by gender and sector

	(1) Male Formal	(2) Male Informal	(3) Female Formal	(4) Female Informal
Married	0.144***	0.137***	0.146***	0.142**
	(0.0501)	(0.0393)	(0.0459)	(0.0601)
Head of household	0.273***	0.396***	0.271***	0.368***
	(0.0584)	(0.0446)	(0.0535)	(0.0686)
Age	-0.0270***	-0.00403**	-0.0264***	-0.00470*
	(0.00257)	(0.00186)	(0.00234)	(0.00282)
North region	0.338***	-0.175***	0.330***	-0.197***
	(0.0536)	(0.0440)	(0.0492)	(0.0660)
West region	0.0225	0.0145	0.0225	-0.0527
	(0.0760)	(0.0586)	(0.0697)	(0.0894)
East region	-0.134*	0.276***	-0.149**	0.286***
	(0.0761)	(0.0547)	(0.0700)	(0.0805)
South region	-0.122*	0.246***	-0.118*	0.242***
	(0.0662)	(0.0505)	(0.0608)	(0.0773)
Secondary school	0.413***	-0.236***	0.431***	-0.238***
	(0.0704)	(0.0470)	(0.0644)	(0.0744)
High school	0.558***	-0.561***	0.571***	-0.528***
	(0.0763)	(0.0540)	(0.0697)	(0.0832)
More than high school	0.497***	-0.623***	0.513***	-0.609***
	(0.0745)	(0.0521)	(0.0682)	(0.0777)
Previous job formal	0.855***	-0.598***	0.864***	-0.524***
	(0.0473)	(0.0365)	(0.0432)	(0.0546)
Dismissed or finished previous job	0.102**	0.143***	0.0988**	0.155***
	(0.0461)	(0.0380)	(0.0422)	(0.0579)
Left or closed previous business	-0.307**	0.338***	-0.287**	0.377***
	(0.125)	(0.0759)	(0.116)	(0.111)
Other reason	-0.132	0.190*	-0.161	0.221
	(0.156)	(0.104)	(0.142)	(0.168)
Financial cushion	0.0952	-0.199***	0.116	-0.287**
	(0.0784)	(0.0740)	(0.0717)	(0.114)
Financial aid from government	-0.384**	-0.166	-0.363**	0.0453
	(0.155)	(0.117)	(0.143)	(0.174)
Financial aid from relatives	-0.0328	-0.280***	-0.0767	-0.321***
	(0.107)	(0.0774)	(0.0977)	(0.114)
Went directly to the work place	0.214***	-0.0954*	0.210***	-0.0845
	(0.0663)	(0.0530)	(0.0608)	(0.0753)
Uploaded or replied to a job offer online	0.116	-0.145**	0.115	-0.162*
	(0.0800)	(0.0709)	(0.0738)	(0.0960)
Asked to relatives and friends to recommend his job	-0.0751	0.159***	-0.0702	0.180**
	(0.0714)	(0.0548)	(0.0658)	(0.0790)

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	(1) Male Formal	(2) Male Informal	(3) Female Formal	(4) Female Informal
Used allocation services to get job (public of private)	0.0927	-0.203**	0.107	-0.126
	(0.102)	(0.0899)	(0.0937)	(0.124)
Used advertisement in newspaper or classifieds to get job	0.233***	-0.201***	0.220***	-0.192**
	(0.0653)	(0.0539)	(0.0599)	(0.0769)
Used other channels to find a job	0.0111	-0.0724	-0.00847	-0.178
	(0.133)	(0.103)	(0.122)	(0.149)
Weeks of job search 4	-1.795***	-0.0250	-1.821***	
	(0.121)	(0.0923)	(0.111)	
Weeks of job search 8	-1.830***	-0.0655	-1.857***	
	(0.123)	(0.0941)	(0.113)	
Weeks of job search 12	-1.839***	-0.0778	-1.866***	-0.0955
	(0.123)	(0.0942)	(0.114)	(0.138)
Weeks of job search 16	-1.875***	-0.154	-1.902***	-0.173
	(0.128)	(0.0974)	(0.118)	(0.141)
Weeks of job search 20	-1.934***			-0.138
	(0.129)			(0.142)
Weeks of job search 24	-1.915***	-0.117	-1.943***	-0.136
	(0.129)	(0.0985)	(0.120)	(0.142)
Weeks of job search 26	-1.926***	-0.142	-1.954***	-0.161
	(0.130)	(0.0990)	(0.120)	(0.143)
Weeks of job search 28	-2.055***	-0.0988	-2.083***	-0.118
	(0.139)	(0.105)	(0.129)	(0.146)
Weeks of job search 30	-2.055***	-0.0852	-2.083***	-0.104
	(0.139)	(0.106)	(0.130)	(0.147)
Weeks of job search 34	-2.042***	-0.0475		
	(0.141)	(0.107)		
Weeks of job search 36	-1.991***		-2.019***	
	(0.142)		(0.133)	
Weeks of job search 38	-2.059***	-0.0708	-2.087***	-0.0904
	(0.142)	(0.108)	(0.133)	(0.149)
Weeks of job search 40	-2.038***			
	(0.143)			
Weeks of job search 42	-2.057***	-0.0464	-2.086***	
	(0.143)	(0.109)	(0.134)	
Weeks of job search 50	-2.084***			
	(0.144)			
Weeks of job search 52	-2.077***	-0.0418	-2.105***	-0.0614
	(0.144)	(0.109)	(0.135)	(0.149)
Weeks of job search 53	-2.007***	0.00659	-2.034***	-0.0118
	(0.168)	(0.127)	(0.160)	(0.162)

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	(1) Male Formal	(2) Male Informal	(3) Female Formal	(4) Female Informal
Weeks of job search 56	-1.716***	-0.362**	-1.745***	-0.375*
	(0.205)	(0.174)	(0.200)	(0.200)
Weeks of job search 57	-1.987***	-0.244	-2.015***	-0.259
	(0.242)	(0.193)	(0.238)	(0.216)
Weeks of job search 60	-1.957***	-0.0528		-0.0730
	(0.261)	(0.213)		(0.234)
Weeks of job search 62				-0.0824
				(0.236)
Weeks of job search 64	-2.170***	-0.0853	-2.201***	-0.0974
	(0.282)	(0.223)	(0.279)	(0.243)
Weeks of job search 65	-2.057***	-0.195		-0.223
	(0.337)	(0.288)		(0.303)
Weeks of job search 68	-2.387***	-0.174		
	(0.491)	(0.348)		
Weeks of job search 72	-1.662***			
	(0.465)			
Weeks of job search 76		-0.166		
		(0.446)		
Weeks of job search 77		0.459		
		(0.449)		
Weeks of job search 78	-2.189***	-0.268		-0.290
	(0.586)	(0.490)		(0.495)
Weeks of job search 79	-1.687**			-0.840
	(0.679)			(0.682)
Weeks of job search 90			-1.083	
			(1.887)	
Observations	97820	88837	88521	44219
Log pseudolikelihood	-46367.982	-54223.886	-42115.254	-26704.242

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: Duration controlling for unobserved heterogeneity by gender

	(1) Pooled	(2) Male	(3) Female
Gender	0.270***		
	(0.0247)		
Married	0.181***	0.319***	-0.0501
	(0.0245)	(0.0320)	(0.0496)
Head of household	0.260***	0.187***	0.207***
	(0.0276)	(0.0342)	(0.0630)
Age	-0.0178***	-0.0193***	-0.0116***
	(0.00115)	(0.00128)	(0.00271)
Secondary school	0.528***	0.598***	0.285***
	(0.0327)	(0.0383)	(0.0746)
High school	-0.137***	0.443***	0.307***
	(0.0282)	(0.0356)	(0.0555)
More than high school	-0.280***	0.309***	0.130**
	(0.0323)	(0.0384)	(0.0563)
Previous job formal	-0.0921***	-0.161***	0.0987**
	(0.0217)	(0.0255)	(0.0439)
Dismissed or finished previous job	-0.0307	-0.0232	-0.0696
	(0.0229)	(0.0274)	(0.0442)
Left or closed previous business	-0.108**	-0.103*	-0.0802
	(0.0470)	(0.0540)	(0.104)
Other	0.0527	0.0245	0.170
	(0.0602)	(0.0686)	(0.126)
Financial cushion	0.127***	0.116**	0.177**
	(0.0404)	(0.0462)	(0.0851)
Financial aid from government	-0.0363	-0.0563	0.0870
	(0.0748)	(0.110)	(0.108)
Financial aid from relatives	-0.173***	-0.236***	-0.0905
	(0.0480)	(0.0668)	(0.0767)
Went directly to the work place	-0.190***	-0.224***	-0.116*
	(0.0321)	(0.0379)	(0.0648)
Uploaded or replied to a job offer online	-0.289***	-0.328***	-0.235***
	(0.0449)	(0.0559)	(0.0777)
Asked to relatives and friends to recommend his job	-0.0696**	-0.0899**	-0.0695
	(0.0340)	(0.0390)	(0.0744)
Used allocation services to get job (public of private)	-0.293***	-0.251***	-0.365***
	(0.0554)	(0.0681)	(0.104)
Used advertisement in newspaper or classifieds to get job	-0.174***	-0.223***	-0.0559
	(0.0333)	(0.0401)	(0.0644)
Used other channels to find a job	-0.109*	-0.118	-0.0512
	(0.0609)	(0.0748)	(0.114)
Constant	-5.755***	-5.946***	-6.401***
	(0.0787)	(0.0889)	(0.158)
m2 constant	-2.742***	-2.643***	-2.938***
	(0.0346)	(0.0404)	(0.0771)
Regional controls	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
Observations	98010	97882	93435

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: Duration controlling for unobserved heterogeneity by gender and sector

	(1) Male Formal	(2) Female Formal	(3) Male Informal	(4) Female Informal
Married	0.568***	-0.146*	0.0812**	0.214***
	(0.0566)	(0.0780)	(0.0370)	(0.0602)
Head of household	0.283***	0.0968	0.0909**	0.0958
	(0.0609)	(0.106)	(0.0396)	(0.0743)
Age	-0.0401***	-0.0224***	-0.00981***	-0.00833***
	(0.00244)	(0.00441)	(0.00145)	(0.00322)
Secondary school	0.164**	-0.143	0.368***	0.274***
	(0.0708)	(0.132)	(0.0463)	(0.0849)
High school	0.356***	0.167**	0.243***	0.360***
	(0.0566)	(0.0837)	(0.0451)	(0.0716)
More than high school	0.330***	0.0792	0.212***	0.213***
	(0.0577)	(0.0815)	(0.0496)	(0.0742)
Previous job formal	0.496***	0.774***	-0.203***	-0.126**
	(0.0443)	(0.0704)	(0.0321)	(0.0564)
Dismissed or finished previous job	-0.0489	-0.0643	-0.0374	-0.0979*
	(0.0454)	(0.0656)	(0.0332)	(0.0557)
Left or closed previous business	-0.377***	-0.712***	-0.173***	-0.133
	(0.124)	(0.244)	(0.0582)	(0.111)
Other	-0.301**	-0.150	0.0426	0.253*
	(0.144)	(0.241)	(0.0730)	(0.136)
Financial cushion	0.242***	0.228*	0.0909	0.264**
	(0.0705)	(0.122)	(0.0625)	(0.122)
Financial aid from government	-0.201	-0.260	0.145	0.170
	(0.184)	(0.201)	(0.128)	(0.115)
Financial aid from relatives	-0.469***	0.0150	-0.0828	-0.0252
	(0.117)	(0.120)	(0.0747)	(0.0920)
Went directly to the work place	-0.109*	0.0839	-0.193***	-0.352***
	(0.0641)	(0.0937)	(0.0451)	(0.0864)
Uploaded or replied to a job offer online	-0.194**	-0.0496	-0.373***	-0.244**
	(0.0860)	(0.104)	(0.0767)	(0.111)
Asked to relatives and friends to recommend his job	-0.117	-0.0636	0.107**	0.301***
	(0.0712)	(0.114)	(0.0451)	(0.0967)
Used allocation services to get job (public of private)	-0.165	-0.0797	-0.241***	-0.556***
	(0.104)	(0.131)	(0.0849)	(0.143)
Used advertisement in newspaper or classifieds to get job	-0.0617	0.0626	-0.157***	-0.197**
	(0.0620)	(0.0921)	(0.0518)	(0.0893)
Used other channels to find a job	-0.458***	-0.0913	-0.0516	-0.214
	(0.148)	(0.190)	(0.0828)	(0.138)
Constant	-6.048***	-7.119***	-5.332***	-5.078***
	(0.155)	(0.241)	(0.107)	(0.202)
m2 constant	-2.669***	-3.291***	-2.348***	-2.137***
	(0.0748)	(0.121)	(0.0494)	(0.0925)
Regional Controls	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Observations	97820	88837	88521	44219

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: Competing risk specification

	(1) Unemployment	(2) Formal	(3) Informal	(4) Out of the labour force.
Gender	0.220***	0.148***	0.260***	-0.881***
	(0.0204)	(0.0304)	(0.0256)	(0.0299)
Married	0.170***	0.202***	0.148***	0.122***
	(0.0209)	(0.0322)	(0.0258)	(0.0311)
Head of household	0.271***	0.223***	0.289***	-0.373***
	(0.0240)	(0.0379)	(0.0291)	(0.0380)
Age	-0.0165***	-0.0289***	-0.0103***	0.00377**
	(0.000994)	(0.00164)	(0.00116)	(0.00162)
Secondary school	-0.0761***	0.318***	-0.174***	-0.214***
	(0.0246)	(0.0450)	(0.0283)	(0.0410)
High school	-0.245***	0.354***	-0.486***	-0.150***
	(0.0276)	(0.0478)	(0.0333)	(0.0440)
More than high school	-0.457***	0.161***	-0.683***	-0.517***
	(0.0274)	(0.0476)	(0.0330)	(0.0443)
Previous job formal	-0.0787***	0.687***	-0.556***	-0.292***
	(0.0184)	(0.0296)	(0.0234)	(0.0298)
Dissatisfaction with prevoius job	0.0233	0.0444	0.000755	0.273***
	(0.0195)	(0.0291)	(0.0245)	(0.0298)
Left or closed previous business	-0.0339	-0.357***	0.0218	0.0217
	(0.0377)	(0.0843)	(0.0413)	(0.0595)
Other reason for unemployment	0.0381	-0.281***	0.138**	0.379***
	(0.0506)	(0.0957)	(0.0570)	(0.0725)
Financial cushion	0.105***	0.233***	-0.00391	0.00276
	(0.0357)	(0.0466)	(0.0498)	(0.0633)
Financial aid from government	-0.0853	-0.218**	-0.0221	0.350***
	(0.0597)	(0.104)	(0.0708)	(0.0749)
Financial aid from relatives	-0.154***	-0.156**	-0.155***	0.117**
	(0.0404)	(0.0635)	(0.0496)	(0.0568)
Went directly to the work place	-0.135***	0.0134	-0.206***	-0.265***
	(0.0264)	(0.0399)	(0.0333)	(0.0429)
Uploaded or replied to a job offer online	-0.221***	-0.115**	-0.291***	-0.317***
	(0.0353)	(0.0501)	(0.0470)	(0.0566)
Asked to relatives and friends to recommend his job	-0.0257	-0.118***	-0.0171	-0.0817*
	(0.0272)	(0.0445)	(0.0333)	(0.0460)
Used allocation services to get job (public of private)	-0.231***	-0.0457	-0.355***	-0.329***
	(0.0440)	(0.0638)	(0.0583)	(0.0727)
Used advertisement to get job	-0.121***	0.0371	-0.209***	-0.211***
	(0.0267)	(0.0394)	(0.0348)	(0.0441)
Used other channels to find a job	-0.153***	-0.238***	-0.103*	-0.287***
	(0.0516)	(0.0830)	(0.0624)	(0.0799)
Constant	-2.598***	-3.991***	-3.068***	-3.355***
	(0.0502)	(0.0805)	(0.0612)	(0.0817)
Regional controls	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Observations	363620	363620	363620	363620
Pseudo R^2	0.014	0.031	0.032	0.034

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: Competing risk specification by gender

	(1) Unemployment Male	(2) Formal Male	(3) Informal Male	(4) Out of the labour force Male	(5) Unemployment Female	(6) Formal Female	(7) Informal Female	(8) Out of the labour force Female
1 if married or free union	0.279***	0.346***	0.241***	-0.587***	-0.0248	-0.0566	0.00472	0.564***
	(0.0279)	(0.0440)	(0.0339)	(0.0546)	(0.0389)	(0.0578)	(0.0497)	(0.0416)
Head of household	0.208***	0.166***	0.224***	-0.0569	0.217***	0.0795	0.298***	-0.107*
	(0.0301)	(0.0478)	(0.0363)	(0.0606)	(0.0511)	(0.0807)	(0.0625)	(0.0611)
Age	-0.0176***	-0.0313***	-0.0112***	0.0147***	-0.0118***	-0.0213***	-0.00549**	-0.0128***
	(0.00113)	(0.00191)	(0.00130)	(0.00215)	(0.00215)	(0.00329)	(0.00263)	(0.00246)
Secondary school	-0.0828***	0.332***	-0.186***	-0.318***	0.0297	0.243**	-0.0263	-0.0977
	(0.0274)	(0.0504)	(0.0313)	(0.0560)	(0.0590)	(0.102)	(0.0701)	(0.0648)
High school	-0.245***	0.396***	-0.503***	-0.104*	-0.139**	0.223**	-0.295***	-0.158**
	(0.0315)	(0.0543)	(0.0380)	(0.0584)	(0.0617)	(0.104)	(0.0754)	(0.0690)
More than high school	-0.515***	0.134**	-0.743***	-0.433***	-0.246***	0.150	-0.418***	-0.541***
	(0.0323)	(0.0556)	(0.0391)	(0.0608)	(0.0582)	(0.0996)	(0.0707)	(0.0673)
Previous job formal	-0.130***	0.675***	-0.603***	-0.437***	0.0693**	0.706***	-0.405***	-0.155***
	(0.0218)	(0.0356)	(0.0275)	(0.0449)	(0.0348)	(0.0538)	(0.0453)	(0.0407)
Dissatisfaction with prevoius job	0.0271	0.0827**	-0.0175	0.327***	0.0545	-0.00697	0.0961**	0.176***
	(0.0237)	(0.0356)	(0.0295)	(0.0441)	(0.0348)	(0.0504)	(0.0448)	(0.0404)
Left or closed previous business	-0.0498	-0.305***	-0.00546	-0.0958	0.0636	-0.509***	0.175**	0.122
	(0.0436)	(0.0962)	(0.0471)	(0.0827)	(0.0769)	(0.177)	(0.0874)	(0.0842)
Other reason for unemployment	0.0363	-0.248**	0.114*	0.397***	0.0462	-0.359*	0.236**	0.340***
	(0.0578)	(0.111)	(0.0650)	(0.0986)	(0.109)	(0.195)	(0.120)	(0.104)
Financial cushion	0.105***	0.252***	-0.0220	0.0818	0.143*	0.193**	0.0960	-0.0590
	(0.0406)	(0.0532)	(0.0566)	(0.0842)	(0.0758)	(0.0959)	(0.107)	(0.0935)
Financial aid from government	-0.0260	0.0624	-0.0718	0.685***	-0.0636	-0.463***	0.0932	0.203**
	(0.0869)	(0.135)	(0.107)	(0.129)	(0.0851)	(0.162)	(0.0963)	(0.0866)
Financial aid from relatives	-0.232***	-0.313***	-0.201***	0.158*	-0.0468	0.0362	-0.110	0.0581
	(0.0553)	(0.0906)	(0.0667)	(0.0957)	(0.0606)	(0.0917)	(0.0769)	(0.0717)
Went directly to the work place	-0.151***	-0.0245	-0.205***	-0.178***	-0.0864*	0.0745	-0.195***	-0.307***
	(0.0317)	(0.0485)	(0.0391)	(0.0605)	(0.0480)	(0.0716)	(0.0634)	(0.0609)
Uploaded or replied to a job offer online	-0.236***	-0.156**	-0.278***	-0.292***	-0.187***	-0.0322	-0.321***	-0.354***
	(0.0440)	(0.0640)	(0.0576)	(0.0877)	(0.0590)	(0.0808)	(0.0814)	(0.0741)
Asked to relatives and friends to recommend his job	-0.0330	-0.134**	-0.0187	-0.0223	-0.0430	-0.118	-0.0260	-0.135**
	(0.0318)	(0.0526)	(0.0381)	(0.0617)	(0.0552)	(0.0867)	(0.0709)	(0.0682)
Used allocation services to get job (public of private)	-0.217***	-0.0935	-0.290***	-0.280**	-0.239***	0.0224	-0.464***	-0.364***
	(0.0543)	(0.0816)	(0.0700)	(0.114)	(0.0738)	(0.102)	(0.104)	(0.0973)
Used advertisement in newspaper or classifieds to get job	-0.171***	0.0108	-0.272***	-0.229***	0.0138	0.0916	-0.0394	-0.207***
	(0.0324)	(0.0481)	(0.0421)	(0.0664)	(0.0469)	(0.0696)	(0.0621)	(0.0598)
Used other channels to find a job	-0.167***	-0.297***	-0.0900	-0.285**	-0.0940	-0.132	-0.102	-0.286***
	(0.0638)	(0.104)	(0.0763)	(0.126)	(0.0874)	(0.137)	(0.108)	(0.103)
Constant	-2.313***	-3.799***	-2.738***	-4.482***	-2.975***	-4.095***	-3.557***	-3.076***
	(0.0545)	(0.0899)	(0.0652)	(0.109)	(0.101)	(0.158)	(0.129)	(0.121)
Regional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	247485	247485	247485	247485	116135	116135	116135	116135
Pseudo R^2	0.014	0.035	0.032	0.021	0.006	0.023	0.018	0.022

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: Competing risk specification adding Unobserved heterogeneity

	(1) Unemployment	(2) Formal	(3) Informal	(4) Out of the labour force
Male	0.255***	0.173***	0.311***	-1.072***
	(0.0246)	(0.0389)	(0.0317)	(0.0379)
Married	0.195***	0.253***	0.201***	0.0818**
	(0.0244)	(0.0419)	(0.0313)	(0.0406)
Head of household	0.262***	0.243***	0.317***	-0.478***
	(0.0277)	(0.0485)	(0.0353)	(0.0500)
Age	-0.0178***	-0.0354***	-0.0129***	0.00680***
	(0.00115)	(0.00215)	(0.00144)	(0.00199)
Secondary School	-0.111***	0.370***	-0.227***	-0.306***
	(0.0282)	(0.0570)	(0.0355)	(0.0537)
High School	-0.260***	0.428***	-0.549***	-0.229***
	(0.0324)	(0.0606)	(0.0417)	(0.0579)
More than high school	-0.518***	0.208***	-0.791***	-0.649***
	(0.0328)	(0.0603)	(0.0414)	(0.0574)
Previous job formal	-0.0977***	0.855***	-0.676***	-0.343***
	(0.0217)	(0.0372)	(0.0290)	(0.0380)
Dissatisfaction with previous job	-0.0336	-0.0449	0.00183	-0.353***
	(0.0229)	(0.0373)	(0.0301)	(0.0384)
Left or closed previous business	-0.106**	-0.562***	0.000134	-0.376***
	(0.0471)	(0.107)	(0.0561)	(0.0822)
Other reasons for unemployment	0.0573	-0.307**	0.176**	0.143
	(0.0598)	(0.121)	(0.0792)	(0.102)
Financial cushion	0.105***	0.301***	0.00108	-0.0352
	(0.0405)	(0.0630)	(0.0576)	(0.0812)
Financial aid from government	-0.0148	-0.272**	0.0685	0.493***
	(0.0745)	(0.128)	(0.0889)	(0.0962)
Financial aid from relatives	-0.189***	-0.184**	-0.175***	0.176**
	(0.0479)	(0.0836)	(0.0613)	(0.0741)
Went directly to the work place	-0.201***	-0.0117	-0.310***	-0.373***
	(0.0322)	(0.0528)	(0.0420)	(0.0571)
Uploaded or replied to a job offer online	-0.281***	-0.0931	-0.420***	-0.452***
	(0.0448)	(0.0661)	(0.0614)	(0.0749)
Asked to relatives and friends to recommend his job	-0.0750**	-0.172***	-0.0664	-0.119**
	(0.0341)	(0.0595)	(0.0433)	(0.0604)
Used allocation services to get job (public of private)	-0.304***	-0.0991	-0.511***	-0.445***
	(0.0554)	(0.0807)	(0.0759)	(0.0916)
Used advertisement in newspaper or classifieds to get job	-0.201***	0.0325	-0.317***	-0.269***
	(0.0334)	(0.0514)	(0.0440)	(0.0586)
Used other channels to find a job	-0.105*	-0.385***	-0.0462	-0.437***
	(0.0609)	(0.112)	(0.0762)	(0.108)
Constant	-5.731***	-7.269***	-5.833***	-5.663***
	(0.0785)	(0.139)	(0.0982)	(0.139)
m2				
Constant	-2.727***	-3.205***	-2.845***	-3.086***
	(0.0345)	(0.0626)	(0.0457)	(0.0679)
Regional controls	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Observations	363620	363620	363620	363620

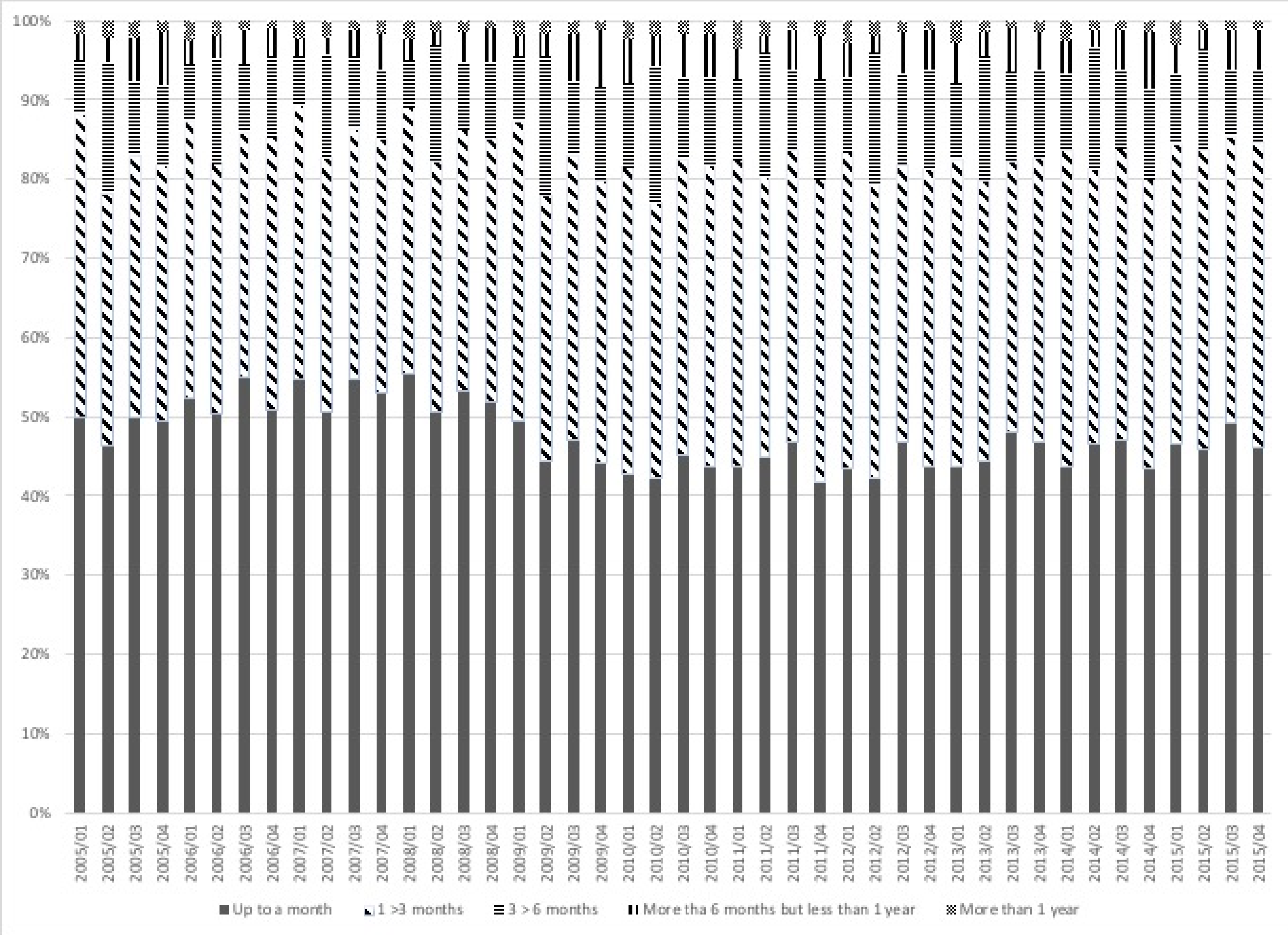
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10: Competing risk specification controlling for Unobserved heterogeneity by gender

	(1) Unemployment Male	(2) Formal Male	(3) Informal Male	(4) Out of the labour force Male	(5) Unemployment Female	(6) Formal Female	(7) Informal Female	(8) Out of the labour force Female
Married	0.320***	0.413***	0.313***	-0.705***	-0.0315	-0.0550	0.0130	0.690***
	(0.0319)	(0.0569)	(0.0405)	(0.0751)	(0.0496)	(0.0782)	(0.0635)	(0.0536)
Head of household	0.195***	0.201***	0.241***	-0.127	0.219***	0.0591	0.311***	-0.142*
	(0.0342)	(0.0612)	(0.0432)	(0.0824)	(0.0632)	(0.105)	(0.0811)	(0.0771)
Age	-0.0192***	-0.0384***	-0.0146***	0.0177***	-0.0124***	-0.0254***	-0.00292	-0.0148***
	(0.00128)	(0.00245)	(0.00157)	(0.00264)	(0.00273)	(0.00440)	(0.00347)	(0.00312)
Secondary school	-0.147***	0.362***	-0.262***	-0.380***	0.0341	0.314**	0.00207	-0.108
	(0.0310)	(0.0631)	(0.0383)	(0.0725)	(0.0730)	(0.130)	(0.0918)	(0.0792)
High school	-0.285***	0.470***	-0.584***	-0.181**	-0.133*	0.290**	-0.303***	-0.189**
	(0.0364)	(0.0678)	(0.0467)	(0.0803)	(0.0777)	(0.135)	(0.0997)	(0.0845)
More than high school	-0.607***	0.167**	-0.884***	-0.501***	-0.265***	0.205	-0.446***	-0.591***
	(0.0386)	(0.0698)	(0.0486)	(0.0821)	(0.0749)	(0.130)	(0.0935)	(0.0810)
Previous job formal	-0.169***	0.833***	-0.747***	-0.533***	0.0875**	0.901***	-0.528***	-0.204***
	(0.0256)	(0.0441)	(0.0340)	(0.0578)	(0.0439)	(0.0700)	(0.0587)	(0.0508)
Dissatisfaction with previous job	-0.0211	-0.0722	0.0286	-0.351***	-0.0874**	-0.0596	-0.129**	-0.263***
	(0.0275)	(0.0458)	(0.0357)	(0.0601)	(0.0441)	(0.0656)	(0.0587)	(0.0505)
Left or closed previous business	-0.0887	-0.466***	0.00838	-0.528***	-0.0944	-0.823***	0.109	-0.120
	(0.0541)	(0.121)	(0.0638)	(0.123)	(0.104)	(0.228)	(0.121)	(0.107)
Other reason for unemployment	0.0269	-0.340**	0.108	0.0218	0.155	-0.240	0.353**	0.232
	(0.0684)	(0.140)	(0.0856)	(0.136)	(0.128)	(0.259)	(0.168)	(0.157)
Financial cushion	0.111**	0.333***	-0.0158	0.0183	0.154*	0.220*	0.163	-0.0441
	(0.0464)	(0.0739)	(0.0652)	(0.116)	(0.0862)	(0.128)	(0.127)	(0.119)
Financial aid from government	-0.0444	-0.140	-0.00971	0.704***	0.108	-0.385**	0.284**	0.299***
	(0.107)	(0.182)	(0.129)	(0.205)	(0.107)	(0.195)	(0.127)	(0.106)
Financial aid from relatives	-0.245***	-0.371***	-0.227***	0.214*	-0.0809	0.0797	-0.187*	0.0825
	(0.0674)	(0.120)	(0.0838)	(0.123)	(0.0766)	(0.119)	(0.0983)	(0.0854)
Went directly to the work place	-0.218***	-0.0477	-0.309***	-0.279***	-0.113*	0.111	-0.338***	-0.397***
	(0.0381)	(0.0643)	(0.0486)	(0.0849)	(0.0648)	(0.0923)	(0.0868)	(0.0774)
Uploaded or replied to a job offer online	-0.323***	-0.192**	-0.440***	-0.368***	-0.262***	-0.0182	-0.446***	-0.457***
	(0.0564)	(0.0872)	(0.0761)	(0.118)	(0.0790)	(0.104)	(0.108)	(0.0948)
Asked to relatives and friends to recommend his job	-0.0827**	-0.167**	-0.0787	-0.0486	-0.0620	-0.152	-0.0652	-0.243***
	(0.0391)	(0.0704)	(0.0483)	(0.0866)	(0.0744)	(0.115)	(0.0986)	(0.0886)
Used allocation services to get job (public of private)	-0.240***	-0.104	-0.365***	-0.364**	-0.345***	0.0272	-0.805***	-0.441***
	(0.0687)	(0.103)	(0.0917)	(0.154)	(0.103)	(0.129)	(0.147)	(0.115)
Used advertisement in newspaper or classifieds to get job	-0.232***	0.0239	-0.361***	-0.282***	-0.0608	0.0567	-0.165*	-0.286***
	(0.0402)	(0.0626)	(0.0527)	(0.0895)	(0.0647)	(0.0919)	(0.0864)	(0.0773)
Used other channels to find a job	-0.0976	-0.435***	-0.0154	-0.452***	-0.0369	-0.162	-0.140	-0.343***
	(0.0749)	(0.141)	(0.0927)	(0.167)	(0.114)	(0.192)	(0.150)	(0.132)
Constant	-5.354***	-6.847***	-5.401***	-7.106***	-6.187***	-7.670***	-6.420***	-5.366***
	(0.0878)	(0.159)	(0.108)	(0.198)	(0.172)	(0.269)	(0.218)	(0.194)
m2	-2.641***	-3.001***	-2.739***	-3.593***	-2.990***	-3.528***	-3.218***	-2.642***
	(0.0404)	(0.0769)	(0.0531)	(0.103)	(0.0763)	(0.123)	(0.0978)	(0.0931)
Regional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	247485	247485	247485	247485	116135	116135	116135	116135

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 2.1: Unemployed by duration of unemployment quarterly 2005-2015



Source: Elaborated using data from INEGI

Figure 2.2: Kaplan-Meier failure estimates

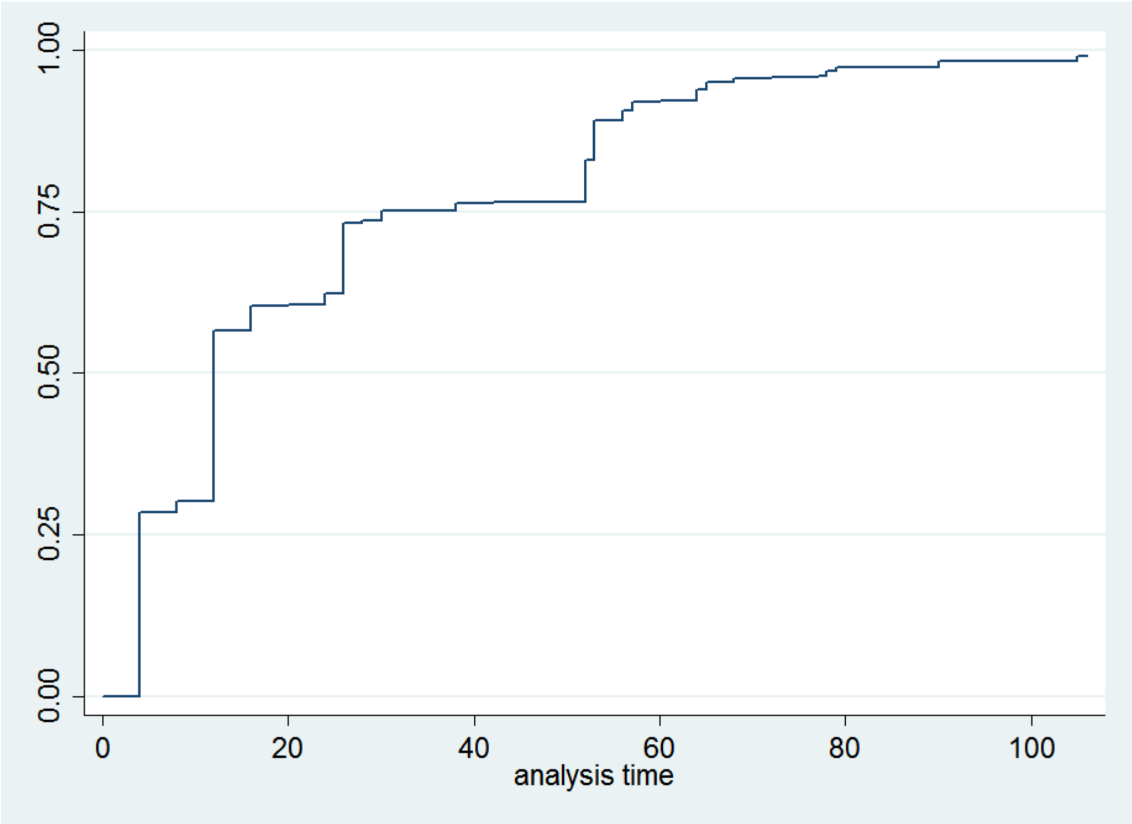
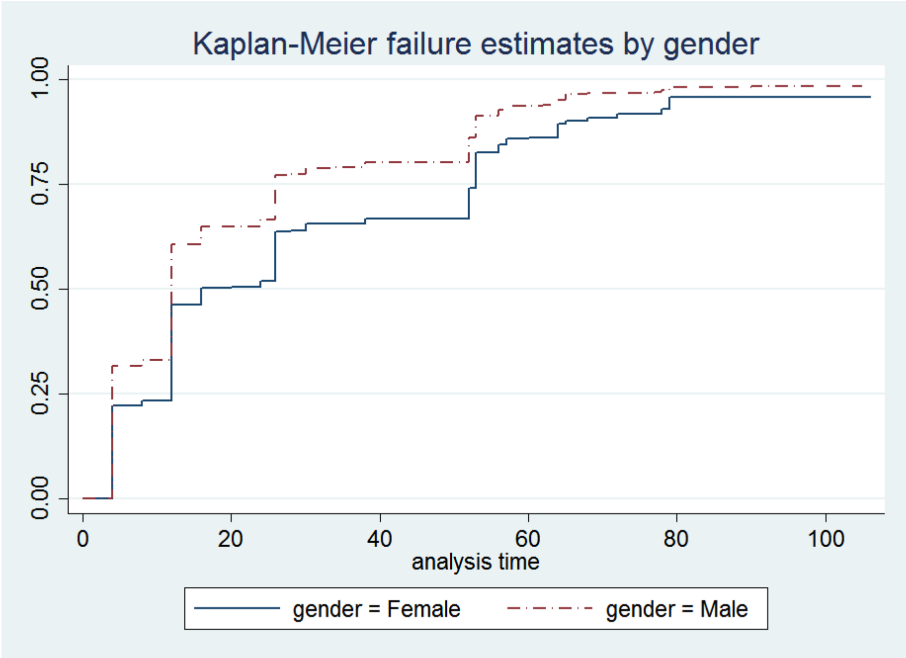
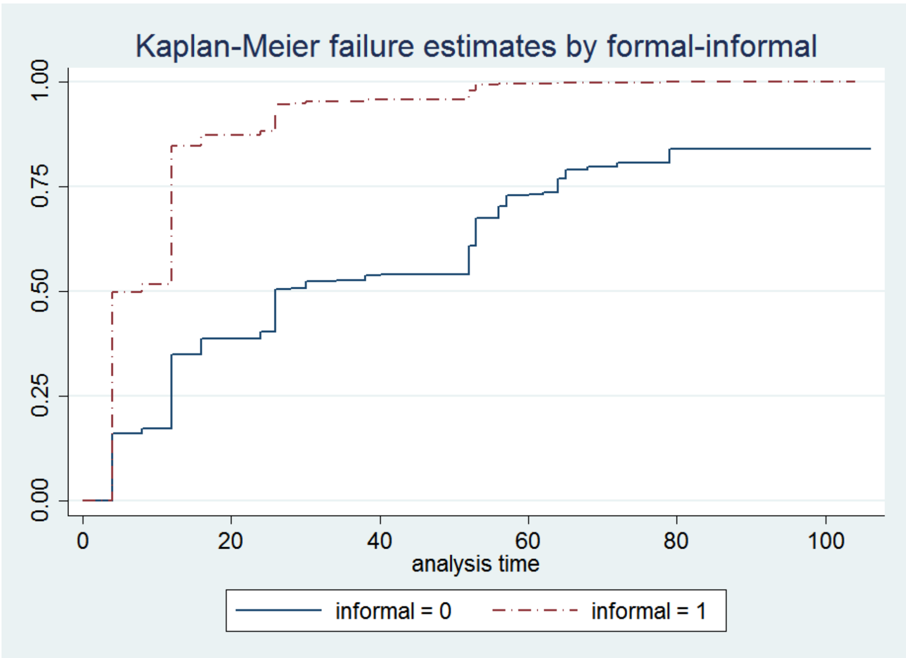


Figure 2.3: Kaplan-Meier failure estimates by gender and job

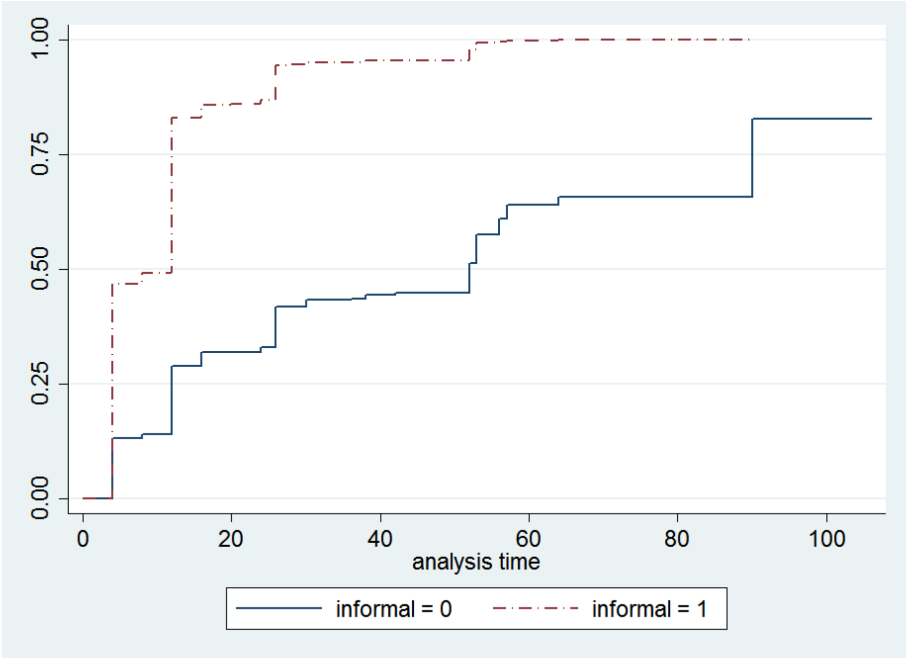


(a) Failure estimates by gender

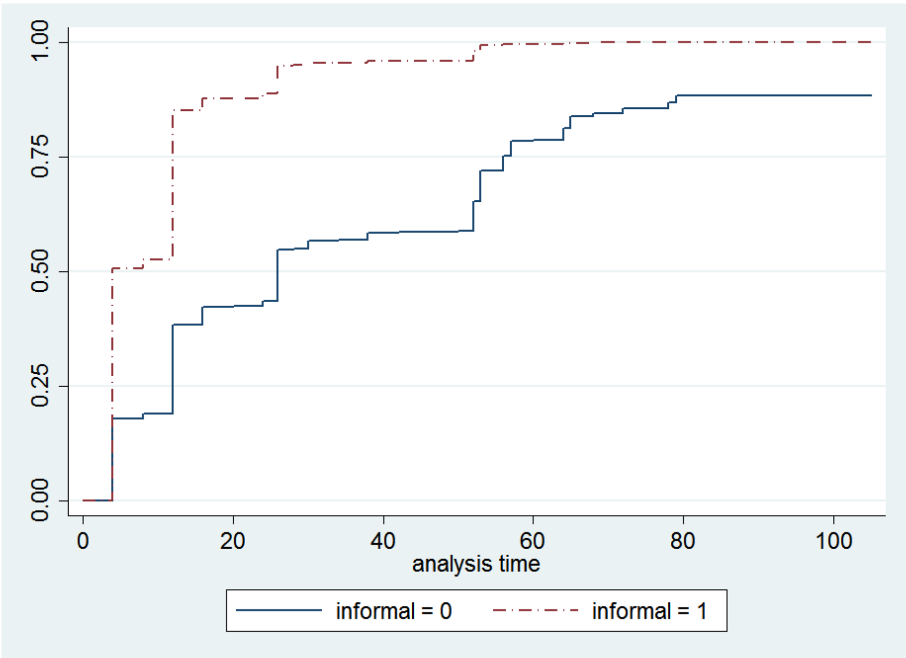


(b) Failure by type of job

Figure 2.4: Kaplan-Meier failure estimates separate by gender and job



(a) For female



(b) For male

Chapter 3

The impact of the criminal presence and violence on wages: Evidence from Mexico

3.1 Introduction

In 2006, after Felipe Calderon became president, the government of Mexico launched an offensive to tackle organized crime in what was the beginning of the so called 'War on Drugs in Mexico'. The government pursued an intensive policy of containment of Drug Trafficking Organizations (DTOs) and this led to a dramatic increase in violence and the presence of criminial organizations in Mexican municipalities measured by homicide rates and the presence of DTOs respectively. Violence in a country, if persistent, has costly and profound negative effects on economic and social outcomes, promotes illegality and discourages investment in infrastructure.

The literature on conflict has pointed out that crime "taxes" the economy and increases the cost of doing business (Abadie and Gardeazabal, 2003; Gaibulloev and Sandler, 2008; Detotto and Otranto, 2010; Enamorado et al., 2014) not just in the formal but in the informal sector as well(Camacho and Rodriguez, 2013; BenYishay and Pearlman, 2014). The impacts of crime go beyond factor accumulation and also have negative effects on economic diversification, increasing sector concentration and diminishing economic complexity (Ríos, 2015).

On the other hand, the effects of violence on socioeconomic aspects range from inequality (Fajnzlber et al., 2002; Enamorado et al., 2016) to migration (Kondylis, 2010; Calderón et al., 2011; Gómez, 2012; Lozano and Aleman, 2013; Ríos, 2014; Atuesta and Paredes, 2015; Calderón-Mejía and Ibáñez, 2015), human capital accumulation and school performance (Barrera et al., 2004; Shemyakina, 2011; Rodriguez and Sanchez, 2012; Leon, 2012; Justino et al., 2013; Brown and Velásquez, 2015; Orraca, 2015), labour productivity and other labour outcomes (Bozzoli et al., 2013; Robles et al., 2013; BenYishay and Pearlman, 2013; Fernández et al., 2014; Velásquez, 2014; Cabral et al., 2016). However, the literature has generally neglected the effect on wages in a developing economy setting. The only two studies that analyse the effect on the wage of high levels of crime are Smith Kelly (2011) and Braakmann (2009) but within a developed country setting. The contribution of this paper to the literature is twofold. First, it offers an explanation of the impact that the presence of DTOs in Mexican municipalities and violence have on the wages of individuals. Second, it offers an explanation of the impact for both formal and informal workers as this sector functions differently to the formal sector. To my knowledge, these are issues in the literature that remain unexplored to date.

Given the availability of individual information from the Mexican Family Life Survey (2005-2010), data on municipal homicide rates and a unique dataset that reflects the presence of drug cartels in Mexican Municipalities (see Coscia and Ríos (2012)), I am able to address how the violence associated with the 'War on Drugs' and the presence of DTOs in Mexican municipalities impacts wages. The effect is unknown ex ante as the impact of violence and criminal presence on labour markets is multidimensional and can vary depending on the sector the worker is employed (i.e. formal or informal). For example, the presence of such groups can signal the absence of the rule of law in Municipalities pushing firms to re-locate to avoid the risk of attacks, extortion or theft, thus pushing wages down. It can also mean that because these groups inject illegal money into the local economy, this could create employment opportunities and thus push wages up.

The estimation results of the preferred specification after instrumenting violence and the presence of DTOs to address reverse causality, yields a positive effect of the presence of DTOs, but no effect of violence. More specifically, an additional DTO per municipality increases wages by 5.7%. On further dissagregation, wages are found to increase by 4.9% and 3.4% for informal and formal workers, respectively. This chapter is divided as follows: In section 3.2 the context behind the war on drugs in Mexico is detailed, section 3.3 reviews the current literature on the causes and effects of the increase in violence, and section 3.4 details the data used and the empirical strategy. Results are discussed in section 3.5 and some conclusions are detailed in section 3.6.

3.2 The Mexican context: Drug trafficking, violence and the War on drugs

Mexico's geographic location is crucial for terrestrial smuggling of drugs to the US. Ensuring the safe passage of drugs and its commercialization is the *raison d'etre* of Drug Trafficking Organizations (DTO) in Mexico and their existence goes a long way back in Mexican history.[1] It is argued that these criminal organizations are so deeply

[1] An example of how long this trafficking has existed in Mexican Society is that after the period of opium Prohibition in 1914, the U.S. customs officials recorded that the Governor of Baja California (1916-1920)

rooted in society that they entered into pacts with the Mexican Government. Arrangements between Officials and DTOs were possible because there was official complicity with some corrupt officials of the Institutional Revolutionary Party (PRI), an hegemonic party that ruled the country for a protracted period after the Mexican Revolution of 1910. The PRI used its "great patronage machine" to establish a patron-client relationship with the DTOs (O'Neil, 2009).

The PRI allowed these organizations to operate following a strict code of conduct and enforced its compliance using "extra-official mechanisms", as explained by Ricardo Monreal, former Governor of the State of Zacatecas and ex-PRI official. The most important rule to follow was respect for DTO territories. The size and borders were granted by the ruling party and all DTOs had to respect them(Ríos, 2010).[2] All this control over such groups was possible because the PRI had a strict centralized control over state and municipal governments. The outcome was a win-win situation in which the government received a "tax" via bribes, information about dealings, associates and competition (specially from those that traffic without permission)[3] and, as a quid pro quo the DTO would be permitted to operate without being systematically prosecuted (Ríos, 2010).

In the 1980s and 1990s, Mexico underwent a process of political opening at the state level. This slowly weakened the PRI's compacts with DTOs. Electoral competition ended understandings and pushed the DTOs drug lords to negotiate with parties at different levels of government (O'Neil, 2009; Ríos, 2010). This encouraged rival traffickers to bid for new market opportunities. Mexico's drug related violence rose first in states where the opposition ruled,[4] because the incoming political parties had relatively less ruling experience and this created information asymmetries, hence increasing the cost of negotiations. The increased violence in states governed by the opposition was capitalised on politically by the party in the Federal Government. Governors that didn't belonged to the PRI had almost no support from the President relative to those that did. (Astorga, 2001)

The weakening of the DTOs-government agreement was coincidental with two other important aspects: First, the increase demand for marijuana which became quite popular among U.S. consumers in the 1970s and then shifted to cocaine in the 1980s. Second, an increasing involvement of the Mexican DTOs with their Colombian counter-

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was implicated as being responsible for the control of opium trafficking (Astorga, 2001).

[2]There were other rules that had to be strictly followed by the DTOs. Such rules included keeping the visibility of DTO operations to a minimum (from media scandals to dead people in the streets), periodic seizure of illegal drugs and imprisonment of lower level traffickers, generation of economic revenues for small, poor communities, among others. To see the full details of the rules see Ríos (2010).

[3]This helped officials in the Government in gaining credit, praise and promotion(Snyder and Duran-Martinez, 2009).

[4]For example, after the PRI lost its first governorship in Baja California in 1989, drug-related violence surged there. The same happened in 1992 in Chihuahua. For a full discussion see O'Neil (2009).

parts. Colombian DTOs moved cocaine into Miami, via the Gulf of Mexico and the Caribbean. Later, with the disintegration of the major Colombian DTOs in the late 1980s and early 1990s, their Mexican counterparts gained entire control over smuggling routes into the US. By 1991, Mexico reportedly accounted for an estimate 300-350 tons of cocaine and roughly 30 percent of all heroin and marijuana that entered into the US (Astorga, 2001; Astorga and Shirk, 2010).

In the 2000 presidential elections, Vicente Fox, the right wing opposition candidate was elected President. This event resulted in the termination of the arrangements between the PRI and DTOs. The DTOs strategy then shifted towards gaining autonomy and ending their subordination to the government. This was accomplished by buying off or intimidating local authorities to secure the safe passage of drugs to the US (O'Neil, 2009; Ríos, 2010). Given that the number of border crossings and ports of entry are limited, the competition between DTOs became fierce and violent. Gaining control over such ports of entry ensures a more profitable business for drug trafficking (Robles et al., 2013).[5]

Despite the fact that agreements between government and DTOs were weakening, violence (as measured by homicide rates) remained relatively stable over time as shown in figure 3.1. However, there is a period when the violence increased at levels never seen before.[6] Soon after taking office in 2006, President Felipe Calderon changed the strategy towards DTOs. Calderon's government pursued an intensive policy of containment of DTO, this involved the use of security forces at all three levels of government, including the Army and Navy. The War against drugs, which involved the deployment of over 45,000, troops officially began in December 2006, when the Army was sent to Michoacan. This was the launch of the first "Joint Operation".[7] Soon after, the Army also arrived in Nuevo Leon, Guerrero and Tijuana(O'Neil, 2009; Dıaz-Cayeros et al., 2011; Robles et al., 2013).

The increasing competition among Mexican DTOs created an atmosphere of violence. The use of violence became the way these groups demonstrated they were in control (Castillo et al., 2014). This implied operations to create fear, such as recruiting members in the streets, leaving messages in the open that could be widely broadcast on the media (Dıaz-Cayeros et al., 2011). Bodies were left mutilated in the streets with messages directed at

[5]Skaperdas (2002) defines this as localized competition, where geography, transportation difficulties and communication costs makes warlords use violence to establish control over a limited area.

[6]There are alternative hypothesis as to why the homicides increased so dramatically, which are worth mentioning here. Dube et al. (2013) argues that the expiration of the U.S. Federal Assault Weapon Ban in 2004 exerted a spillover of gun supply in Mexico, thus fueling the violence between groups and against the Government. Castillo et al. (2014), on the other hand, argue that violence increased as a consequence of cocaine supply shortages as a result of a change in the Colombian Government strategy towards DTOs, which focused more on the interdiction of drug shipments rather than targeting coca crops.

[7]In total, nine "Joint Operations" have been enacted (Dıaz-Cayeros et al., 2011).

politicians, citizens and fellow criminals. Heads were thrown into the doors of primary schools and mass executions replaced targeted murders (Ríos, 2014).

The government military strategy targeted the drug hierarchy in a non-selective way in what is commonly known as the "Kingpin Strategy".[8] It is reported that after the offensive began, approximately 23 criminal leaders were arrested or shot. Lindo and Padilla-Romo (2015) find that the capture of a DTO leader in a municipality increases its homicide rate by 80% and that this effect holds in the short-run for up to a period of 12 months.[9] In this operation, major DTOs such as *Beltran-Leyva*, *La Familia Michoacana*, and the *Cartel del Golfo* were weakened. The fragmentation of DTO created conditions for second and third generations of criminal leaders to compete for territory, control and power. Soon, other groups emerged such as *Cartel de Jalisco Nueva Generacion* and *Caballeros Templarios*. Violence emerged because many of their aspiring leaders worked as 'hitmen' for the major DTOs and were accustomed to using violence (O'Neil, 2009; Dıaz-Cayeros et al., 2011). One group recruited former military officials and became widely known as *Los Zetas*, characterized by the use of extreme, high profile violence (Astorga and Shirk, 2010).

Figure 3.1 shows the national homicide and drug-related homicide rates per 100,000 inhabitants from the period of 2000 until 2013.[10] The homicide rate had remained broadly constant prior to Calderon's period, then it increased dramatically from around 9 per 100,000 in 2006 up to almost 24 per 100,000 in 2011. It is clear that the sudden increase in homicides after 2006 is largely attributed to drug-related homicides. Furthermore, figure 3.2 shows the rate per 100,000 by municipalities for different years before and after 2006.[11] Violence is concentrated in areas that are close to the border and where marijuana is planted and grown. Finally, it can be visually confirmed in figure 3.3 that the presence of one DTO or more in a municipality is highly correlated with the homicide rate in figure 3.2 for a set of selected years.

The proliferation of new groups created the conditions for the foray into other illegal activities such as kidnappings, human trafficking, petroleum theft, money laundering and arms trafficking. Perhaps, extortion was the most widespread of these activities. It first targeted illegal business such as prostitution and casinos, in which the

[8] It has been documented that municipalities where elections were closely contested and where eventually the PAN won, violence increased, as these mayors were more likely to support the President's strategy to combat crime in a direct way (Dell, 2015).

[9] This study confirms that the strategy caused destabilization within organizations after the capture.

[10] This is based on data from the National Institute of Statistics and Geography (INEGI) and data from the National Security Commission (CNS). Data for drug-related homicides is only available after 2006, when the government officially launched its operation against DTO.

[11] In Mexico, there are three different levels of government. National level, state level and Municipality level.

probability of being denounced by the owners to the authorities was low. Soon, extortions also extended into the legal setting, creating an atmosphere of fear that affected local businesses. High protection fees and intimidation forced many to close (Ríos, 2014). Violence increased more in municipalities with DTO presence and especially in those that had more than one DTO (as shown in figure 3.3) as there is no monopoly of violence and such groups engage in competition to win power (see Castillo et al. (2014)). In addition, violence and DTOs proliferated more where illegal crops are grown and where there was trading and the transit of drugs, money laundering and potential markets for consumption (O'Neil, 2009).

3.3 Literature review

The analysis of how violence affects economic and social aspects is not new. There are a number of studies which have found that crime has negative effects on economic performance. The presence of crime acts like a tax on the whole economy, as it increases the cost of doing business and creates uncertainty (Abadie and Gardeazabal, 2003; Gaibulloev and Sandler, 2008; Detotto and Otranto, 2010; Enamorado et al., 2014). It also affects firms, harming their competitiveness and pushing them to close in locations that lack the institutions to enforce the Rule of Law and property rights.[12] The incentives to invest or to expand operations of a firm are thus low. This negative effect is stronger in areas where the fear of victimization is high. Operational costs increase due to the additional costs on security infrastructure incurred by the firms. This affects both formal and informal sector, manufacturing or services (Camacho and Rodriguez, 2013; BenYishay and Pearlman, 2014). The impacts of crime go beyond factor accumulation and also exert negative effects on economic diversification, increasing sector concentration and diminishing economic complexity (Ríos, 2015).

Alternatively, there are studies analyzing the effect of crime on foreign and direct investment. Results are mixed and depend on the context and more specifically, the industry. Ashby and Ramos (2013) find that in Mexico crime deters foreign direct investment in financial services, commerce and agriculture but not in oil and mining sectors, for which they found the opposite. The latter is consistent with the findings for Colombia by Maher (2015), which is that the presence of crime in certain industries such as oil creates conditions that facilitate foreign direct investment flows. This could occur because, according to Driffield et al. (2013), countries with weaker institutions and less concern about corporate social responsibility are more likely to invest in conflict regions.

The literature on the impact of crime on socioeconomic aspects range from inequality to migration, human

[12] Firms that are exposed to violence may not always close, but instead shrink and go through a process of "forgetting by not doing", which has negative effects on productivity. This process has important implications in the long run as the post conflict economic recovery of countries is slow and in some cases stagnates (Collier and Duponchel, 2013).

capital accumulation, labour productivity and labour outcomes. A number of studies have pointed out that high inequality creates the conditions for the proliferation of violence and illegal activities (Fajnzlber et al., 2002; Enamorado et al., 2016). To some extent, the population in a given locality normalizes violence and learns to live with it.[13] However, when violence becomes extreme, it disrupts the life of the population and changes their behaviour. The first natural response to the presence of high levels of violent crime on the place of residence (and one which has been widely documented) is displacement. Both internal and external due to the fear of victimization or threats by the groups causing the violence (Kondylis, 2010; Calderón et al., 2011; Gómez, 2012; Lozano and Aleman, 2013; Ríos, 2014; Atuesta and Paredes, 2015; Calderón-Mejía and Ibáñez, 2015).

One of the aspects that has received particular attention is the investment in education. A number of studies have found that in the short run, exposure to high levels of violent crime, reduces school attendance and increases dropout rates (Barrera et al., 2004; Shemyakina, 2011; Rodriguez and Sanchez, 2012). This affects negatively child performance in school and increases failure rates (Orraca, 2015). The effects are largely visible in the long run, where it has been found that individuals exposed to violence have, on average, less years of schooling (Leon, 2012; Justino et al., 2013; Brown and Velásquez, 2015).

Violence can also alter the equilibrium in labour markets. The literature has documented that in areas affected by high levels of violence, productivity, the proportion of employed and working hours fall (Robles et al., 2013; Cabral et al., 2016). This reduction in working hours is largely attributed to the self employed as the flexible nature of their jobs allows them to devote less time to work and minimize their exposure to risk. This effect is stronger for women, as they not only cut the number of hours worked but they also leave the labour market and devote more time to household chores and caring for their family. This results in a loss in hourly and total earnings (BenYishay and Pearlman, 2013; Fernández et al., 2014; Velásquez, 2014). Men, on the other side, spend more time on other types of activities, which are often informal, to mitigate significant loss of income, increasing the share of self employed and informal individuals in the labour market (Bozzoli et al., 2013).

Another way of measuring how violence affects the labour market is looking at how it influences wages and earnings. The effect here can be either positive or negative depending on the context. The impact can be positive in violent areas if the displacement of individuals to non-violent areas results in a reduction in labour supply, thus pushing wages up. This is commonly known in the literature as a compensating wage differential effect, where firms

[13] It has been documented that individuals change their behavior when their perception of risk is high. They stop using public transport services, change commuting routes, stop going to restaurants and coffee shops. In more extreme cases they arm themselves and even suffer from sleep deprivation (Becker et al., 2004; Braakmann, 2012).

offer a pay premium for risk to attract workers (Rosen, 1986).[14] Smith Kelly (2011) analysed the compensating wage differential effect of crime in Miami and found that a rise in crime rates led to high-crime-risk workers earning a higher per hour relative wage than high-crime-risk workers in other cities. But often the effect cannot be identified clearly as there might be unobservables that affect wages which make it difficult to isolate the impact. For example, Braakmann (2009) using three way component estimators to control for individual and regional heterogeneity found that wages are not affected by changes in both violent and non-violent crime rates. Alternatively, high levels of violence can have a negative effect on wages and earnings in non-violent areas as a result of displacement of individuals from violent ones, which creates an oversupply of labour (Atuesta and Paredes, 2015; Calderón-Mejía and Ibáñez, 2015).

Mexico is a country that has a dual labour market, with almost 60% of workers employed in the informal sector of the economy, according to most recent statistics from the National Institute of Statistics (INEGI).[15] Analysing if violence and the presence of criminal groups affects these sectors differently is an interesting question. One can think that given the flexible nature of informal jobs, this sector would be more responsive to any external influence, workers would simply reduce working hours to reduce exposure. This mechanism is clear in the case of self-employed individuals (see Fernández et al. (2014); Velásquez (2014)), but not for wage earners. On the other hand, formal wage earners would not be able to reduce working hours as formal firms are less likely to respond to episodes of violence in this way, but rather increasing wages when the supply of labour decreases.

Finally, an alternative way of thinking about the impact of the presence of Drug Trafficking Organizations is that these groups hire from the local labour force. According to Ríos (2010) two of the main DTOs in Mexico, Sinaloa and Golf, opened their recruitment process to outsiders in the early 2000s.[16] Such groups transmitted radio adds and posted messages in the main border cities of Mexico, encouraging "brave men" to join their organization. This could have a positive spillover effect on wages that would most likely be reflected in the informal sector of the labour market.[17]

The contribution of this chapter then is to measure and explain the differential impact of violence and the presence of Drug Trafficking Organizations on wages within both the formal and informal labour market and to what extent the presence of criminal groups affect the wages and working hours of individuals.

[14] According to Rosen (1986) the actual wage under these conditions can be also considered a negative price for the job paid by the firms to workers.

[15] Informal workers possess no social security or any of the fringe benefits that come with being formally employed.

[16] Before this, DTOs membership was reserved only for family and close friends of the leaders.

[17] This can be possible even if this is not directly expressed in the self-reported information of wages in the household survey.

3.4 Data and empirical strategy

3.4.1 Homicides, Drug Trafficking Organizations and the Mexican Family Life Survey

Data for the empirical analysis was obtained from three sources: First, individual level information is taken from the three waves of the Mexican Family Life Survey (MxFLS). Second, the number of monthly deaths by intentional homicides at the municipal level available from 1990 to 2013 are provided by the National Institute of Statistics and Geography (INEGI). Third, the number of drug trafficking organizations by year per municipality is obtained directly from Coscia and Ríos (2012).

The MxFLS is a longitudinal panel survey that covers different aspects of household activity and is representative at the municipal level and conducted for the years 2002, 2005 and 2009.[18] It includes information for 8,400 households and almost 35,600 individuals for 16 states throughout Mexico.[19] The survey contains individual and household information, the type of job, monthly wages, position in the job, industry, number of co-workers and if the person has access to social security. It also contains information on personal characteristics such as if the person is the head of household,their schooling level, age, gender and marital status. Information at the household level is also collected such as household size, number of children under 14 years and number of elderly in the household. It also to this it contains information on community size and location which makes it possible to construct the identifier to merge with the dataset on homicides and number of DTOs.

The timing of the MxFLS survey is particularly apposite for the purpose of this analysis as the first and second waves were conducted in 2002 and 2005, well before President Calderon took office, which is also a period of relative stability in terms of violence. The third wave was conducted between 2009 and 2010, the period where the homicide rates reached its highest point as observed in figure 3.4. The analysis is carried out on the extensive margin rather than the intensive one (i.e. focusing on both formal and informal wage earners). Excluding non-paid workers, the self-employed, owners or employers, retired or those working on agricultural activities for self-consumption. Table 3.1 contains the descriptive statistics for the years of analysis. It is worth pointing out several things from this table. On average, 65% of the sample is comprised of male workers, with elementary or secondary schooling. The

[18]Some of the topics being covered are health, education, migration, labour, income and access to government programs. One of the main characteristics of this survey is the low attrition rate from one wave to the next. Almost 89% of individuals were re-contacted from 2002 to 2005 and 85% of individuals from 2005 to 2009. This was possible because the design of the survey allowed interviewers to track individuals if they moved out of their original place of residence after the first wave in 2002.

[19]The total number of States is 31 plus Mexico City or Federal District.

share of informal workers is large compared to their formal counterparts, although decreasing over time.

The information for homicides is taken from INEGI sources. This is based on a detailed monthly report of intentional homicides for all 2,457 Mexican municipalities from 1990 to 2015. The rate per 100,000 is calculated using yearly population figures from the Mexican Census. This information is used to measure the presence of violent crime in the place of residence as it has less issues of under-reporting compared to other types of crime. The total number of homicides is not just a result of the war on drugs and this information might not be providing the most accurate effect of violence related to this phenomena, but given that this information has been used in other studies, it is also used here as it is disaggregated at the municipal level. Given that this information spans 1990 to 2010, an average has been constructed covering 1990 to 2001, and this would be used as an instrument for current levels of homicides. More details of this are reported in subsection 3.4.3.

The information regarding illegal activities carried out by Drug Trafficking Organizations is either non-existent, restricted by the authorities or unreliable. For this reason, often researchers rely on the homicide rates as a proxy for the violence caused by the confrontations between different criminal groups and as a way to measure the impact that these groups have on several aspects of interest. However, the media reports the activities of such groups when this implies a violent event. This reporting of activities has led some researchers to quantify the presence of DTOs, based on the content found on the web. This is the case of Coscia and Ríos (2012). This unique dataset is the result of a text analysis algorithm designed to obtain information from the web to identify where criminal groups operate. It is possible as it extracts information reading digitalized news, blogs and Google-News indexed content. Google is used as it organizes reliable sources of information such as newspapers and blogs that belong to the media. This database is entirely extracted from digital sites that belong to local and national newspapers.

The objective is to identify a number of hits or mentions per actor. The actors are municipalities and DTOs, so the algorithm yields different combinations of hits of the actors (i.e. when a local newspaper reports the presence of a DTO in a given municipality). The outcome of the rigorous analysis is a dataset containing information for 13 DTOs in Mexico for the period 1990-2010, disaggregated down to the municipal level. According to Coscia and Ríos (2012) DTOs only operate in 713 of 2,441 municipalities in Mexico. Leaving large areas of the country practically without the presence of these criminal groups. There is temporal variation in the data, as some DTOs appear in municipalities for most of the years in the period analyzed which is the case for the large DTOs and others only appear until recently and these groups were created when the fragmentation of the DTOs occurred. In addition, according to Coscia and Ríos (2012) there appears to be a clustering of the areas of operation for DTOs and as a result, many municipalities of the country remain untouched by the DTOs throughout the period of analysis. Another important aspect of the data is that it is precisely after 2006 that a growth in the number of mentions takes place, approximately 10,000 articles to 100,000 articles in just four years (until 2010), which is consistent with the sudden increase in homicide rates in Mexico over the same period.

Another aspect that is worth highlighting in this data is that as of 2010, 62% of the municipalities that have a presence of DTOs, have more than one group operating simultaneously. Information on the number of DTOs per municipality allows us to draw conclusions on the effect of the presence of these criminal organizations on the labour market. The effects are not limited to the violence brought about by these organizations but more about the presence of more than one group per municipality, compared to the presence of just one or indeed none. In addition, an indicator of the average presence of DTOs per municipality is constructed covering the period 1990-2001, and it is used to control for the current presence of these criminal organizations per municipality. This will be discussed in more detail in section 3.4.3.

3.4.2 Understanding how the fragmentation of DTOs spreads violence

It is important to highlight that the presence of DTOs does not necessarily mean violence. In fact, a municipality that has the presence of only one DTO tends to have relatively less homicides compared to those that have more than one.[20] One of the main assumptions made in this analysis relates to the way DTOs behave before 2006 and after. According to Robles et al. (2013), DTO can behave as stationary or roving bandits. The stationary bandits' main characteristic is to retain control over a certain area in the long term. The rationale behind this is that such groups pursue long term goals that favour the growth and expansion of the criminal organization. In the Mexican context, these groups are commonly those that are large in membership and have an important presence throughout the country. These are groups that have made historical pacts with the government and were abiding by the rules establisehd from the beginning.[21]

Roving bandits on the other hand, have just a temporary domain. They extort, kidnap and murder to enhance short term gains.[22] They behave this way because they are interested in gaining immediate territorial power and

[20]See Castillo et al. (2013) for a detailed analysis of the increase in homicide rates in Mexican municipalities when comparing the presence of one DTO against more than one. In fact, they conclude that the presence of one DTO does not predict homicide rates whereas for more than one the effect is strong and positive.

[21]These are major DTOs such as *Cartel de Sinaloa*, *Cartel del Golfo*, *Cartel Beltran-Leyva*. Also defined by Castillo et al. (2013) as the traditional groups.

[22]These are commonly new groups such as *Cartel de Jalisco Nueva Generación*, *Los Caballeros Templarios* and *Los Zetas*, to mention a few. Also defined as Castillo et al. (2013) as the competitive and expansionary groups.

violence is their tool to acquire this (O'Neil, 2009; Dıaz-Cayeros et al., 2011).[23]

In this analysis it is assumed that until 2006 before the army's deployment on the streets, DTOs behave like stationary bandits as the equilibrium of power is kept by those involved in the traffic of drugs to the United States. However, after the year 2006, they behave like roving bandits, as the confrontation against the government and the consequent fragmentation of major DTOs brought about a sharp increase in violence. There is empirical evidence by Osorio (2015) arguing that the government's strategy weakened major DTOs and motivated the invasion of neighboring ones. This effect is particularly strong in areas with a high density of these groups. More specifically, both the intensification of the government strategy and the increasing number of DTOs are positively associated with the severity of violence between groups. This evidence is consistent with findings by Lindo and Padilla-Romo (2015) who suggests that the capture of a DTO leader increases the homicide rate in a municipality by 80%. However, the presence of many groups per municipality also implies that these groups are in need of labour and these communities can supply it.

3.4.3 Identification Strategy

The empirical analysis starts by estimating an OLS regression to measure the impact of homicides and the presence of DTOs on wages in a given municipality. This is specified in equation (3.1).

$$LnW_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 S_{it} + u_{it} \tag{3.1}$$

Where LnW_{it} is the log of the real wage in municipality i in period t[24] and it is regressed on X_{it} which contains personal characteristics such as age, schooling level, gender, the industry classification of the worker and S_{it} is a control for five Mexican regions in Mexico.[25] u_{it} is the error term.

The main concern when identifying the impact of violence and the presence of DTOs on wages as specified in equation (3.1) is reverse causality. It can be argued that the presence of criminal groups is not exogenous to a

[23]In their study, Robles et al. (2013) argue that there is evidence that DTOs behave one way or the other, citing the case of the *Cartel de Tijuana* in 2010 which split into two factions. One faction was led by Teodoro García Simental (aka *El Teo*), who favoured kidnappings in Tijuana. The other faction was led by Luis Fernando Sánchez Arellano (aka *The Engineer*) who wanted to focus more on the traffic of drugs fearing that other types of crime such as kidnapping local businessmen would attract too much attention from the government. After the arrest of *El Teo*, the faction led by Arellano, regained control of the group and peace was reestablished in Tijuana after multiple confrontations between the two factions.

[24]The wage is deflated using the Mexican consumer price index for 2010.

[25]The regions were classified based on the INEGI's classification: north, south, centre, east and west.

municipality. The location of DTOs is potentially correlated with unobservables that also affect wages. Instead, DTOs locate in municipalities with better economic performance as this would allow for more extraction of rents. These conditions would then attract more criminal groups. On the other hand, homicide rates would increase only in those municipalities where DTOs are located which are also the municipalities with better economic performance.

However, homicides and the presence of DTO remained relatively stable throughout the years at the national level (as can be observed in figure 3.1). Moreover, the location of DTOs rather than being determined by the economic prosperity of a municipality is determined by access to entry points to the United States.[26] Additionally, after the Mexican government launched its offensive to tackle such criminal groups in 2006, the confrontations between the government and criminal groups, on the one hand, and the fragmentation of the large DTOs and the consequent fight to gain territorial power, on the other, brought about a sharp increase in violence and in the number of DTOs trying to access power and control drug trafficking routes. As a result, many groups engaged in other activities such as kidnapping and extortion, affecting the local population.

To overcome this potential issue of reverse causality, the instrumental variable adopted originally by Ríos (2015) is used here. This is estimated by a Two-Stage Least Squares estimation strategy (2SLS). The presence of DTO and the log homicide rate in a municipality i is instrumented using the average presence of DTOs and average homicide rate per municipality; both instruments are for the period of 1990-2001.[27] The logic behind these instruments is that criminal groups historically locate in municipalities that are important in terms of the traffic of drug regardless of economic conditions. To access such positions, the new groups that flourished as a consequence of the war on drugs in 2006, had to fight and violence subsequently increased. The exclusion restriction holds if the historical location of DTO correlates with the current presence of more than one criminal group per municipality i, but it is uncorrelated with unobserved factors affecting wages in the current period t. The same criteria applies to the homicide rates, as the average homicide rates in a municipality would be correlated with the current rate in a municipality, but is not with the current level of wages for an individual or unobserved factors affecting it.

Additionally, the instrument proposed by Castillo et al. (2013) is also used in this exercise, which is the result of the interaction between two variables: negative supply shocks of cocaine (which provides the temporal variation) and distance to the nearest point of entry of cocaine to Mexico or point of exit to the US (which provides the spatial variation), the major consumer of this product. Cocaine supply shocks are measured by the amount of cocaine seized by the Colombian Government, which shifted its drug interdiction strategy from 2006 as already noted, and this affected the value of the amount of cocaine supplied to the intermediaries or the DTOs in Mexico. According to

[26]See Castillo et al. (2013) for a detailed explanation of location of DTOs in Mexican municipalities.

[27]The average is taken from 1990 until 2001, as this is a year before the first wave of the MxFLS was conducted.

Castillo et al. (2013) the Colombian government shift in strategy targeted less the eradication of coca crops, which are considered low value added, but instead focused on the interdiction of drug shipments and destruction of coca processing labs. Under the assumption that the demand for drugs is inelastic,[28] a contraction of supply derives in an increase in drug trafficking activities because the DTOs will try to access the product even if it is scarce and costs more. This ultimately affects the levels of violence. In figure 3.5 the homicide rate in Mexico is plotted against cocaine seizures in Colombia, it can be observed that there is a positive correlation between cocaine seizures and homicide rates, specially after 2006.

The increase in drug trafficking activities and levels of violence as a result of the reduction of supply of cocaine, happens only in localities that are valuable for the smuggling of cocaine into Mexico and to the United States. These localities are the ones close to the northern and southern border and ports in the Pacific Ocean and Gulf of Mexico. These localities provide a comparative advantage for the trade of drugs, so these locations are valuable for the DTOs. Figure 3.6 shows the geographic coordinates of such points of entry in the southern border, ports in the Pacific Ocean and Gulf of Mexico and the exit points to the United States. Comparing this map with the location of DTOs in figure 3.3 specially in the year 2010 and the homicide rates shown in figure 3.2 it can be observed that there is a correlation between the location of these points and the location of DTOs and homicide rates. Identification of the effect of supply shocks on the number of DTOs and homicide rates comes from the interaction of these two variables.

The first stage reduced form regression is then specified in equation (3.2).

$$V_{it} = \pi_0 + \pi_1 Z_{1990-2001} + \pi_2 g_i \times s_t + \pi_3 X_{it} + \varepsilon_{it} \tag{3.2}$$

where Vit is the variable of primary interest and represents either the log of homicide rates per 100,000 inhabitants, (as used commonly in the literature) plus one or the number of DTOs, both at the municipality level.[29] The historical average of violence is measured by $Z_{1990-2001}$, g_i is the distance of a municipality to the entry and exit points in the borders and ports and s_t is the cocaine seizure rate in Colombia. Finally ε_{it} is the error term.

[28] As detailed in Castillo et al. (2014) there is enough evidence to support the claim that demand for drugs is inelastic, this assumption is central to the use of this instrumental variable.

[29] Rios (2015) also uses the log of homicide rates and details that because the many zeros in this variable are important in the estimation to compare between municipalities where there is high presence of violence versus those that have almost none, a transformation is made; where the measure is calculated as the log of homicide rate plus one.

The second stage then is estimated via equation (3.3).

$$LnW_{it} = \delta_0 + \delta_1 \widehat{V_{it}} + \delta_2 X_{it} + \upsilon_{it} \tag{3.3}$$

where LnW_{it} is the log of the wage and it is regressed on the predicted values of $\widehat{V_{it}}$ from the first stage and X_{it} which contains personal characteristics such as age, schooling level, gender and the industry classification. υ_{it} represents the error term.

Instrumenting current levels of violence with historical average and the interaction variable described above, should yield non-biased estimates of the violence and presence of Drug Cartels on wage levels. All of the regressions are clustered at the municipal level.

3.5 Empirical Results

When analyzing the impact of violence on local wages, our primary interest lies in the the impact on those that remain in a municipality and absorb the violence shock by adapting to the new circumstances. In a way it can be perceived as a supply and demand problem. This would be true if the movement of workers out of the municipalities with high levels of violence is enough to push wages up for those that remain. Since the survey is successful in following individuals from the first to the last wave, those that move to a different municipality from one wave to the next are dropped from the sample, which only accounts for 1.4% of the total sample. In this way it is ensured that the analysis is done on the stayers. It is also acknowledged that limiting the analysis to the three waves of the MxFLS (2002, 2005 and 2009) rather than having yearly information posses a limitation to the analysis done here as we might not be capturing enough variation to analyze the impact of the increase in homicide rates and the presence of DTOs from year to year.

3.5.1 Instrumentation of violence and presence of Drug Trafficking Organizations

Following equation (3.2), violence is instrumented combining the historic average from 1990-2001 and the instrument from Castillo et al. (2013) which interacts the supply shock with the location of entry points in the south border and for the entry ports in the Pacific Ocean and adding controls for state income per capita and region. It is expected that the negative shock to the supply of cocaine after 2006 will affect those municipalities that are closer to the entry points more compared to those that are further away. Also, given that crime and the location of DTOs is not random, the historic average is used to predict current levels of these two variables.

The results of the first stage are presented in table 3.2. Columns (1) and (4) present the results for the pooled sample, columns (2) and (5) for formal workers and columns (3) and (6) for informal workers. The results show that instruments are strong predictors of the presence of DTOs but not when the log of homicide rates is used as a dependent variable. The log of state income per capita does not seem to be have any effect on the log of homicides, but it affects negatively the presence of DTOs. Holding everything else constant, an increase of 10 percent of state income per capita decreases the number of DTOs by 1.7 percent for the pooled sample. States with larger income per capita are less likely to have presence of DTOs at least in this context. This might be possible because better economic performing states have better functioning institutions and more effective enforcement of the rule of law.

Moreover, these results are consistent with the literature on the relationship between crime and economic performance which has found that this relationship is negative. Detotto and Otranto (2010) suggest that the effect is stronger during recessions. Enamorado et al. (2016) show that this effect might be larger when analyzing drug-related crimes compared to more 'common' types of crime.

The results of the second stage of the 2SLS regression are presented in table 3.3. Columns (1) to (3) show that, after the instrumentation of the average homicides per municipality, the effect of homicides on wages is not statistically significant. There is no evidence at least under this setting that high levels of homicides have any significant effect on individual wages. Comparing this result with the literature, Braakmann (2009) finds no significant impact of crime on wages for Germany for both violent and non violent types of crime. In contrast, Velásquez (2014) has found that the effect of homicide rates is heterogeneous among individuals and it depends factors such as the sector of employment, if the person is self-employed or wage earner and the gender. Moreover, she finds weak evidence that self-employed females living in municipalities with high levels of homicide rates experience a reward in their hourly earnings but this effect is not significant for wage earners. On the other hand, males' hourly earnings are affected negatively by this variable.

After the instrumentation, the effect of the presence of DTOs remains robust to the specification. Holding everything else constant, an additional DTO per municipality increases the monthly wages of workers by 5.7%. A word of caution must be inserted here and it relates to the interpretation of this coefficient. This variable does not explicitly measure violence related to DTOs, it is merely representing a count of the number of these organizations per municipality. However, it can be assumed that it is only after 2006 when these groups engaged in confrontation with the government and with other groups and other external factors mentioned before. The proliferation of DTOs in Mexican municipalities can have spillover effects on the local economy as an expanding organization needs to hire a labour force or simply exert an influence on the economy via consumption. For this reason, the interpretation of the effect of this variable must be undertaken with caution.

Further dividing the sample between formal and informal workers, columns (5) and (6) of table 3.3 present the results for this specification, it can be observed that an additional DTO per municipality increases wages of formal workers by 3.4% and the wage of informal workers by 4.9%. The estimated coefficient is larger for informal workers. However, the statistical difference between the mean of the coefficients between formal and informal workers is formally tested. The χ^2 test for the difference is computed and the result yields a value of $prob > \chi^2 = 0.1694$, which means that we fail to reject the null of equality between the effect of DTOs on formal an informal workers. Moreover, this implies that even though the point estimate is larger in magnitude for informal workers, the effects are not statistically different.

Contrary to what was expected, there is no differential impact of the presence of DTOs on the wages of informal workers compared to formal. If we believed that the effect is indeed true, both sectors benefited to a similar magnitude from the presence of DTOs in a municipality. This can be attributed to the fact that we are only analyzing wage earners rather than self-employed workers, which have shown to respond to external shocks differently compared to other sectors as found in Velásquez (2014). The positive effect of DTOs on wages can be attributed to the economic effect these groups introduce when they take control over a certain municipality. It is possible that the groups, that are well known for handling large amounts of cash, manage to have spillover effects on the local economy via consumption and even hiring from the local labour force. This would eventually push wages up assuming supply remains constant (or even falls).

Values for the F-statistic are displayed at the bottom of the table and all are well above 10, for the model using DTOs as a dependent variable, confirming that the instruments have relevance. The test for underidentification and overidentification are presented at the bottom of the table. All the values for the Kleibergen-Paap test suggest that the models are not underidentified. In addition, the values for the Hansen-J statistic and its respective p-value, suggest that the identifying instruments are orthogonal to the to the error term in the log wage equation. Results are also presented for the full sample, and for both formal and informal workers.

Additionally, the results of the OLS are presented in table C.1 of the appendix. The results yield a positive impact of DTOs of 3.7% on wages for the case of the pooled sample, which is similar in magnitude and sign to the 5.7% found in the 2SLS estimation. Not correcting for reverse causality leads to a slight underestimation of the effect of DTOs presence on the log of wages.

3.5.2 Robustness check

We can argue that the decision of individuals to participate in the formal or informal sector can impact on the estimated effect on the log wage equation. If we do not account for the unobservables that influence the decision of individuals to choose the sector of employment we are leaving out factors that can have a potential effect on their earnings. Some workers might prefer to be formal as often the wages and benefits associated are higher compared to informal jobs. This also implies having access to health services provided by the state. On the other hand, individuals might prefer informal jobs due to the flexibility of working hours, the proximity to their homes even if this means sacrificing income or simply to avoid paying taxes. Finally, individuals might simply choose to remain unemployed, which is not uncommon in Mexico, given that often many families live in the same house and share living expenses.

To correct for the selection bias a two step procedure will be estimated. In the first step, a multinomial logit will be estimated to calculate the probability of attachment to a given labour market state. In the second step, the estimated probabilities will be introduced in the wage equation in the way proposed by Lee (1983). We can specify the first stage equation as follows:

$$\begin{aligned} P_j =& f(\text{Age, Gender, Schooling level, Marital status,} \\ & \text{Number of children under 14 years in the HH, HH size,} \\ & \text{Number of older that 65 in the HH}), j = 1, 2, 3 \end{aligned} \tag{3.4}$$

The second stage is then:

$$\begin{aligned} ln(wages) =& g(\text{Age, Gender, Schooling,} \\ & \text{Violence corrected, regional controls, occupational controls,} \\ & \text{Correction terms), iffj} = 3, \end{aligned} \tag{3.5}$$

Where equation (3.4) represents the first stage of the estimation and is the employment selection function. It contains variables that are commonly used in the literature to predict employment decisions such as the number of children under 14 years of age in the household, the household size, the number of adults over 65 years of age that are unemployed, the marital status, age, and gender. Equation (3.5) is the wage equation, this specification includes the variable violence instrumented from equation (3.1) and the correction term from the first stage and personal characteristics. The use of a multinomal logit model implies the testing of the Independence of Irrelevant Alternatives (IIA) assumption. The result of the Small-Hsiao supports the use of the multinomial logit model.

Results for the first stage of the estimation are presented in table 3.4. It can be observed, that age and schooling all have the expected sign. From the controls used, only being married and living in a household with elderly people have a negative impact on the probability of being informal. The coefficients for age indicate that the probability of being informal is negative for younger individuals at early stages of their working career and then becomes positive with age. Being married, head of household and the household size have a positive effect on the probability of occupational attachment.

The results for the wage equation after controlling for selection bias into either formal or informal jobs are presented in table 3.5. The coefficient of the selection terms at the bottom of the table (imr2 and imr3) yield a negative effect of selection of individuals into informal jobs. The interpretation of this coefficient follows Gyourko and Tracy (1988) and Reilly (1991) and it refers to the effect of the selection variable on the wage. This is obtained multiplying minus the selection variable coefficient by the mean value of the selection variable. For the case of informal jobs, the calculation suggests that those self-selecting into the informal sector earn on average 18.0% higher wages that an individual drawn at random from the labour force with identical observable characteristics would be expected to earn.

Given that the focus of this section was to see if selection leads to a biased estimation of the effect of DTOs on wages, we now focus on the coefficient of the number of DTOs. The sign of the coefficient of the impact of the presence of DTOs holds. The magnitude of the coefficient, on the other hand, is marginally higher after correcting for selection bias, meaning that if we do not account for this we are underestimating the effect of the impact of DTOs on the wages of individuals. *Ceteris paribus*, an additional DTO in a municipality, increases the wages of individuals by 8.7% for the pooled sample.

For the case of formal workers, the presence of DTOs increase their wages by 6.1% and for informal workers, their wage increase 9.5% We again test for the statistical difference for the mean impact for both sectors and the result with a value of $prob > \chi^2 = 0.2317$ suggest that the effect is not statistically different for both sectors.

The results just presented here must be interpreted with caution. Even though the analysis of the available data was done in a rigorous way to try to establish a causal relationship between the presence of both the DTOs and the violence that they bring about. The concern about the causality of the DTOs on wages still persists. Given that the homicides were not statistically significant leads to conclude that DTO's location is correlated with wages. Here the analysis has been conducted as rigorous as possible to try to identify the true effect of DTOs presence and wages.

3.6 Conclusions

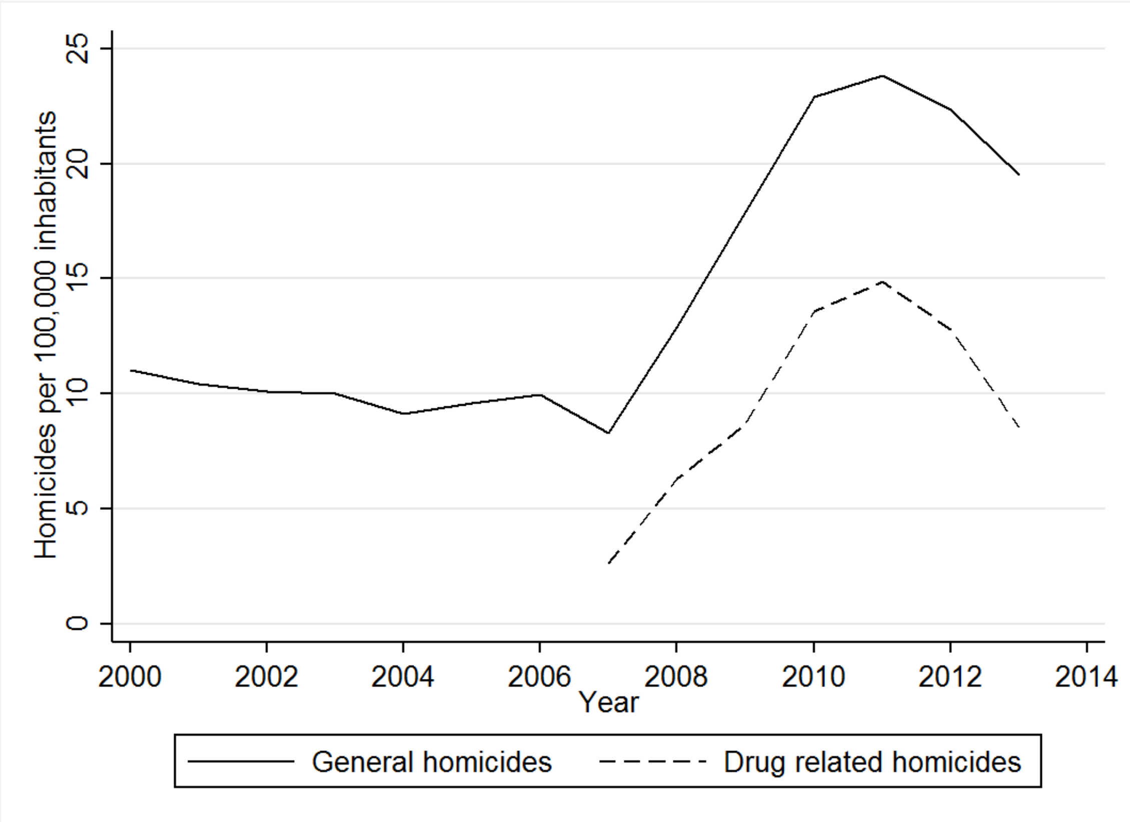
It has been the aim of this analysis to measure to what extent episodes of high levels of violence and the presence of Drug Trafficking Organizations (DTOs) affect the wages of individuals in Mexican municipalities. Studying this effect became specially important after 2006 when the homicide rates increased at unprecedented levels. It has been argued that two factors influenced this increase. On the one hand, the government deployed the army into the streets to combat DTOs. On the other hand, a shift in the drug interdiction strategy by the Colombian government created a shortage of cocaine in the market which led to confrontations between DTOs to gain access to the product.

After instrumenting the presence of Drug Trafficking Organizations (DTOs), the effect is to raise wages of workers by 5.7% Further dividing the sample between formal and informal workers The results yield an increase of 4.9% for informal workers and 3.4% percentage points for formal workers. However, after testing we find that the effect for both formal and informal workers is not statistically different. If we believe that the effect is true, both sectors are benefited from the presence of DTOs in a municipality in a similar magnitude. This can be attributed to the fact that we are only analyzing wage earners rather than self-employed workers, which have shown to respond to external shocks differently compared to other sectors. The positive effect of DTOs on wages can be attributed to the economic effect these groups introduce when they take control over a certain municipality. It is possible that these groups, that are well known for handling large amounts of cash, manage to have spillover effects on the local economy via consumption and even hiring from the local labour force. This would eventually push wages up.

On the other hand, after correcting the model for the presence of self-selection that results from the occupational choice of individuals using a Lee (1983) two step procedure, the results show that there is evidence of selection into informal jobs. However, the sign of the coefficient presented after instrumenting DTOs presence holds after the correction. Hence the results presented here are robust to the selection of individuals into formal and informal jobs. The statistical difference for the effect of DTOs on the log of wages for formal and informal workers is also tested and the result yields that the effects are not statistically different. The labour market for salaried employees reacts in the same way regardless of the sector of employment contrary to other types of employment, such as self-employment, that have shown to be more affected by high levels of violence Velásquez (2014).

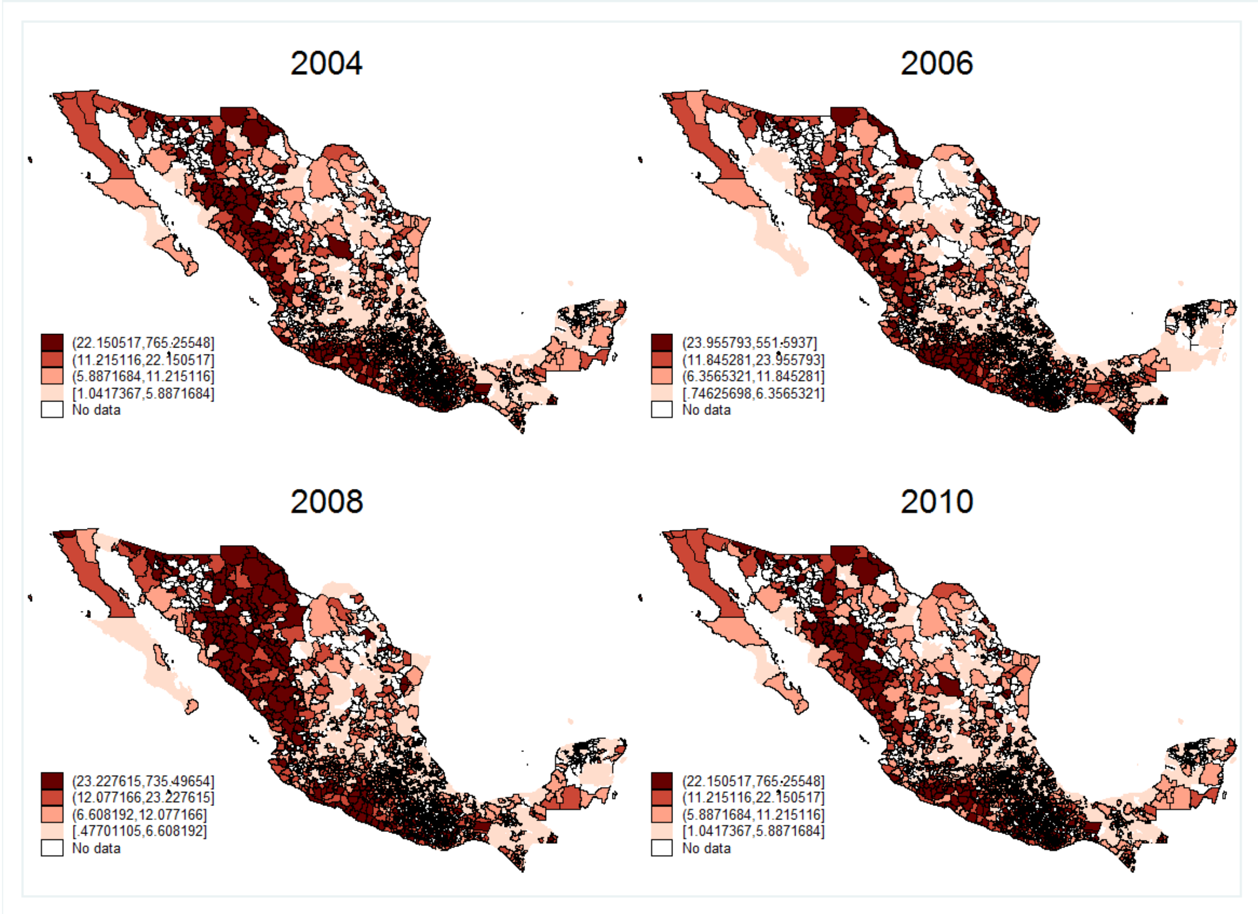
3.7 Tables and figures

Figure 3.1: National Homicide rate per 100,000 (2000-2013)



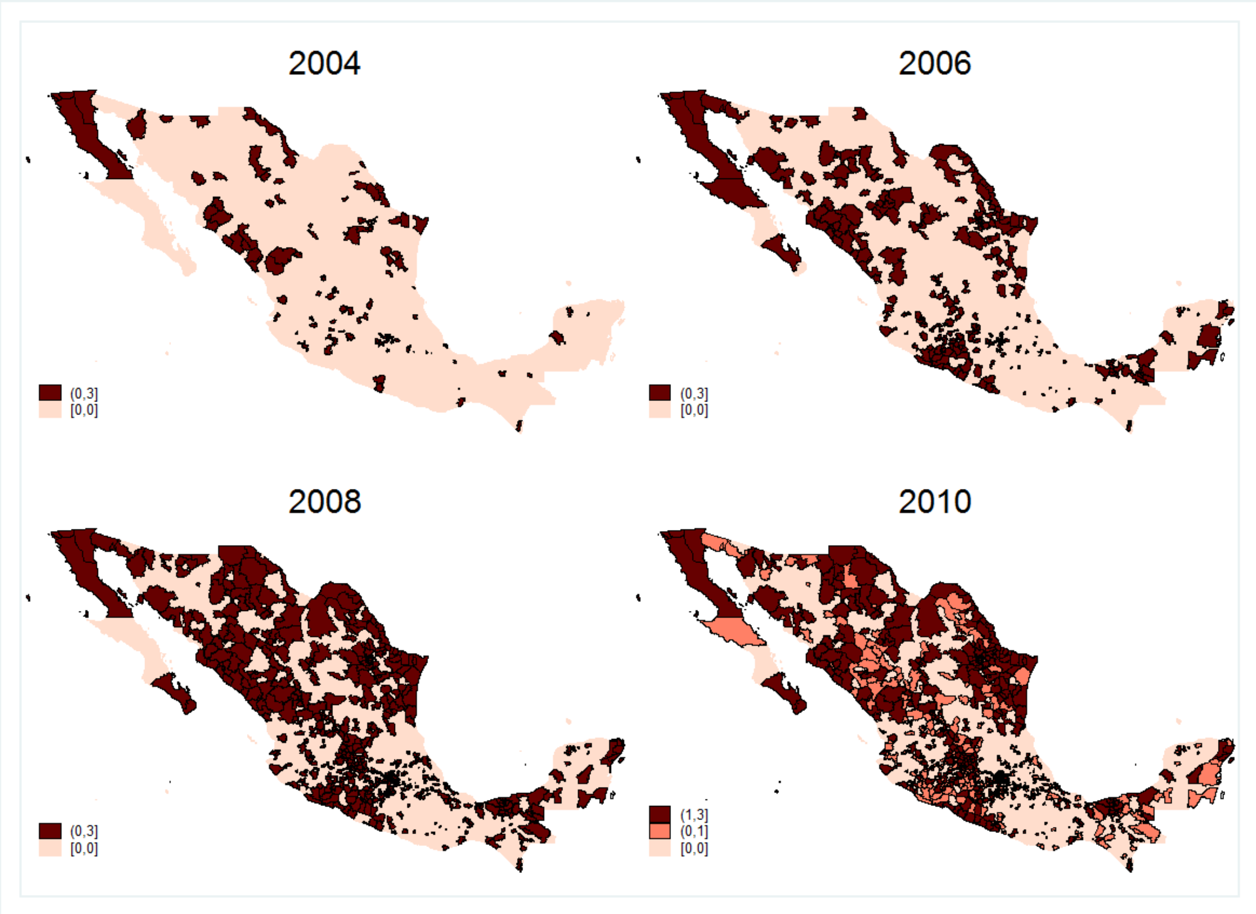
Source: Elaborated using data from INEGI and CNS

Figure 3.2: Homicide rate per 100,000 inhabitants by municipality



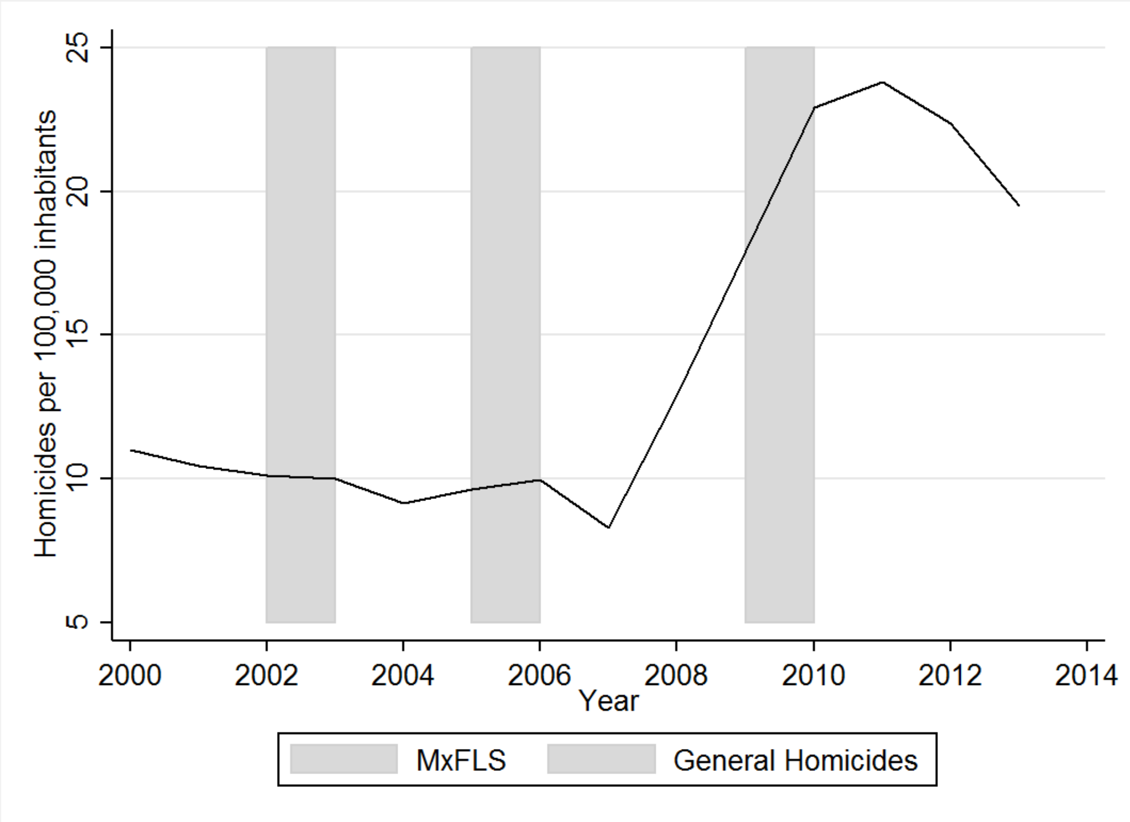
Source: Elaborated using data from INEGI

Figure 3.3: Number of Drug Trade Organizations per municipality 2004-2010



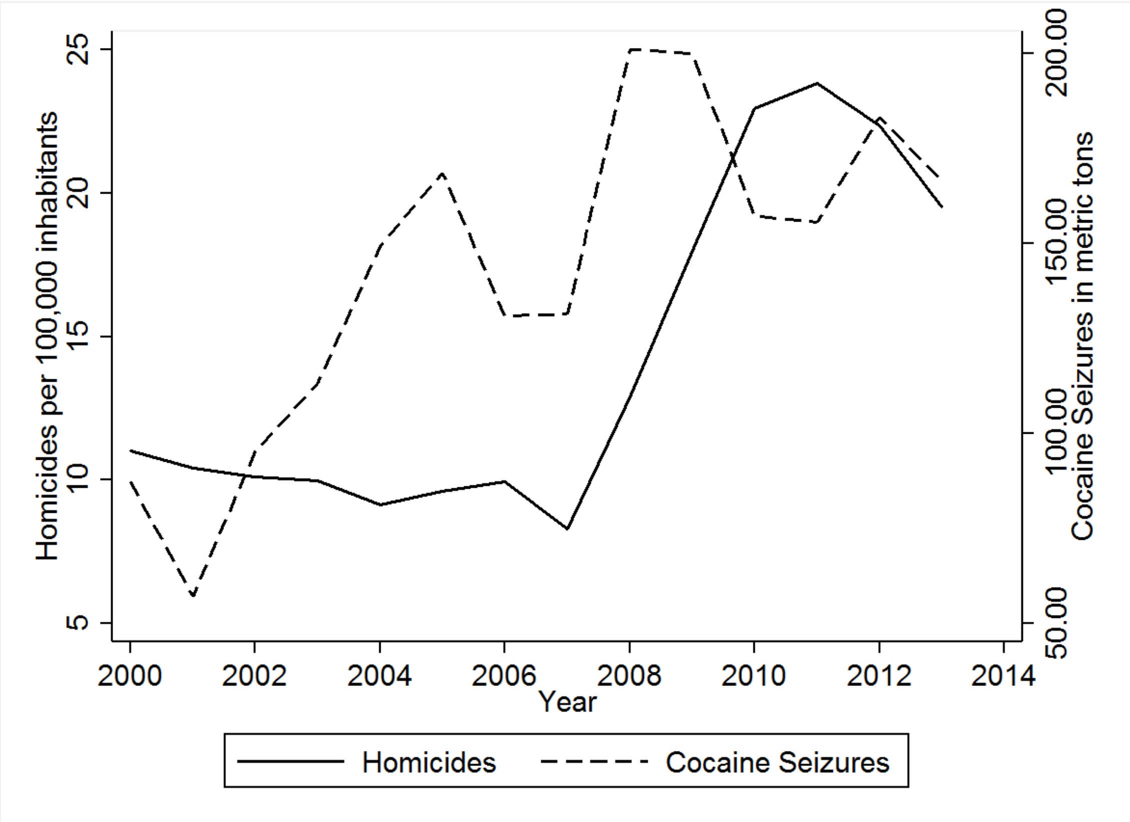
Source: Author's elaboration with data from Coscia and Ríos (2012)

Figure 3.4: National Homicide rate per 100,000 and MxFLS (2000-2013)



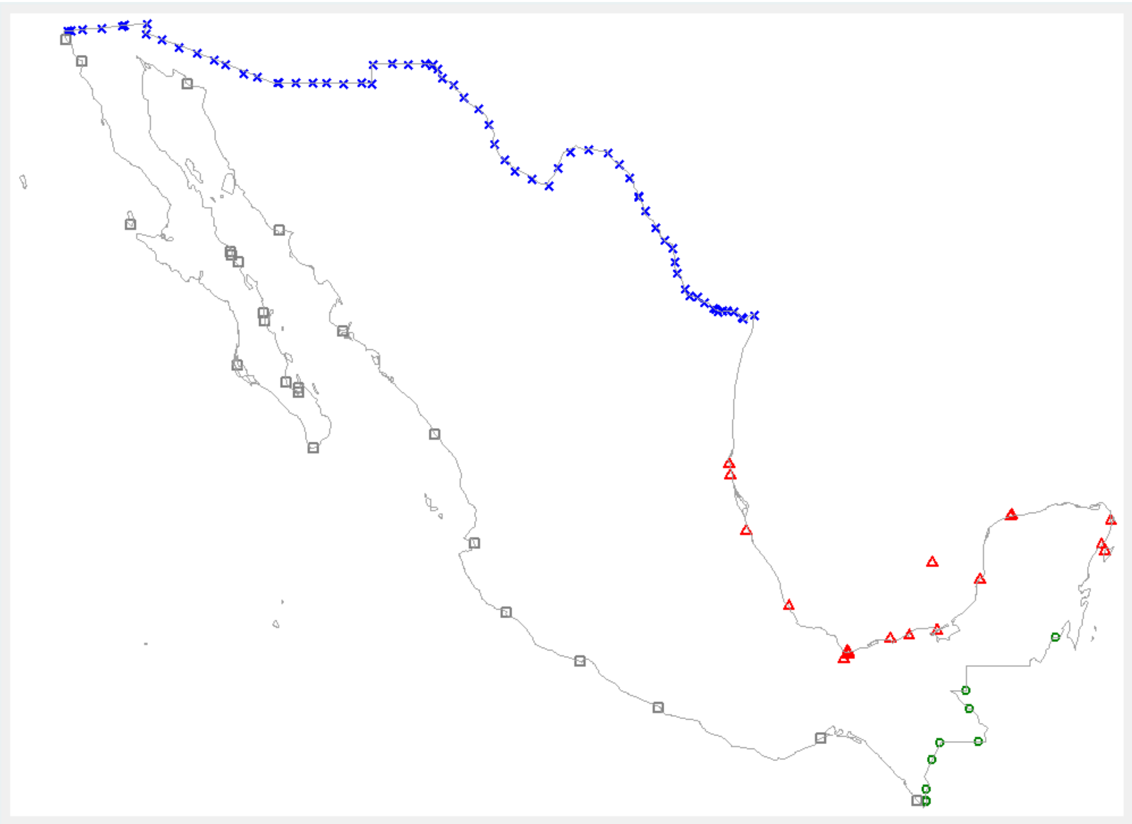
Source: Elaborated using data from INEGI and MxFLS

Figure 3.5: Homicide rate in Mexico and cocaine seizures in Colombia



Source: Elaborated using data from INEGI and ODC

Figure 3.6: Geographic coordinates of entry and exit points in the Mexican borders



Source: Elaborated using data from INEGI and World Port Source

Table 3.1: Descriptive statistics for the sample of workers by year (means)

Variable	2002	2005	2009
Log of monthly wages	8.11	8.25	8.25
	(0.85)	(0.78)	(0.76)
Age	34.0	36.0	36.0
	(13.04)	(13.47)	(13.41)
Male*	0.66	0.66	0.62
No education*	0.06	0.06	0.05
Elementary school	0.34	0.32	0.30
Secondary school	0.32	0.32	0.33
High school	0.13	0.15	0.17
More than high school	0.16	0.15	0.16
Share of informal*	0.72	0.65	0.58
Number of DTOs	0.15	0.97	2.28
	(0.41)	(1.13)	(1.78)
Homicide rate per 100,000	8.34	9.45	19.19
	(7.56)	(10.96)	(26.46)
Cocaine seizures (mt)	95.27	162.66	186.09
Observations	3,103	4,925	5,361
Additional Variables			
Mean homicide rate (1990-2001)	14.58		
	(13.51)		
Mean DTOs (1990-2001)	0.093		
	(0.17)		
Distance to the US (km)	630.83		
	(252.97)		
Distance to South (km)	1,254.07		
	(602.47)		
Distance to Atlantic (km)	523.80		
	(454.56)		
Distance to Pacific (km)	309.62		
	(201.62)		

*These values refer to shares of the total. Standard deviations in parenthesis.

Table 3.2: First stage reduced form regression for IV

	Log of Homicide rates			Number of DTOs		
First stage:	(1)	(2)	(3)	(4)	(5)	(6)
Violence on instruments	Pooled	Informal	Formal	Pooled	Informal	Formal
Average homicides 1990-2001	0.0338***	0.0293***	0.0578***			
	(0.0080)	(0.0070)	(0.0093)			
Average number of DTO p/municipality 1990-2001				2.8139***	2.8701***	2.8143***
				(0.6832)	(0.6651)	(0.7459)
Cocaine seizures and south border	4.61e-06 ***	4.73e-06***	4.84e-06***	0.0000105***	0.000011***	9.78e-06***
	(1.44e-06)	(1.56e-06)	(1.48e-06)	(2.00e-06)	(1.94e-06)	(2.29e-06)
Cocaine seizures and pacific border	-1.37e-06	-2.43e-06	2.04e-06	0.0000158***	0.0000145***	0.0000168***
	(2.19e-06)	(2.34e-06)	(2.73e-06)	(2.82e-06)	(2.64e-06)	(3.57e-06)
Log of state income per capita	-0.0073**	-0.0042	0.0011	-0.1780***	-0.1566***	-0.2271***
	(0 .0179)	(0.0177)	(0.00210)	(0.0266)	(0.0230)	(0.03844)
Constant	1.0400***	1.1592***	1.211***	-1.4225***	-1.4104	-1.1600**
	(0.4224)	(0.4110)	(0.349)	(0.2875)	(0.2364)	(0.5140)
Regional controls	yes	yes	yes	yes	yes	yes
F-statistic	9.12	9.51	18.64	23.75	25.39	17.06
Observations	13269	8550	4717	13269	8550	4717

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3: Impact of Violence on Wages (2SLS Estimation)

	Log of Homicide rates			Number of DTOs		
	(1)	(2)	(3)	(4)	(5)	(6)
Second Stage	Pooled	Formal	Informal	Pooled	Formal	Informal
Male	0.314***	0.211***	0.380***	0.318***	0.214***	0.381***
	(0.0181)	(0.0230)	(0.0213)	(0.0190)	(0.0233)	(0.0221)
Elementary School	0.149***	0.102	0.129***	0.154***	0.114*	0.129***
	(0.0301)	(0.0629)	(0.0348)	(0.0290)	(0.0660)	(0.0344)
Secondary School	0.354***	0.317***	0.285***	0.351***	0.329***	0.279***
	(0.0367)	(0.0639)	(0.0413)	(0.0341)	(0.0665)	(0.0406)
High School	0.466***	0.437***	0.323***	0.460***	0.447***	0.316***
	(0.0417)	(0.0695)	(0.0464)	(0.0405)	(0.0725)	(0.0460)
More than High School	0.835***	0.736***	0.737***	0.842***	0.752***	0.744***
	(0.0492)	(0.0688)	(0.0568)	(0.0459)	(0.0717)	(0.0552)
Directors & Chiefs	0.938***	0.767***	0.951***	0.913***	0.754***	0.932***
	(0.0530)	(0.0817)	(0.0697)	(0.0517)	(0.0818)	(0.0690)
Manufacture &Industry	0.401***	0.259***	0.385***	0.386***	0.248***	0.375***
	(0.0319)	(0.0533)	(0.0327)	(0.0301)	(0.0515)	(0.0315)
Commerce & Sales	0.338***	0.267***	0.303***	0.284***	0.227***	0.264***
	(0.0376)	(0.0599)	(0.0417)	(0.0377)	(0.0582)	(0.0433)
Services	0.342***	0.295***	0.307***	0.316***	0.285***	0.282***
	(0.0350)	(0.0554)	(0.0366)	(0.0346)	(0.0521)	(0.0374)
Professional Services	0.666***	0.543***	0.619***	0.612***	0.512***	0.574***
	(0.0318)	(0.0502)	(0.0404)	(0.0329)	(0.0509)	(0.0425)
Log of homicide rates	-0.0122	-0.0117	0.00105			
	(0.0239)	(0.0195)	(0.0254)			
Number of DTOs				0.0573***	0.0347**	0.0496***
				(0.0141)	(0.0137)	(0.0173)
Constant	6.223***	6.968***	6.217***	6.166***	6.904***	6.194***
	(0.0912)	(0.121)	(0.0961)	(0.0796)	(0.0998)	(0.0906)
Regional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.317	0.304	0.257	0.314	0.299	0.256
F-statistic	9.12	9.51	18.64	23.75	25.39	17.06
Kleibergen-Paap	16.753	10.839	17.299	19.178	19.697	21.531
Hansen J statistic	1.894	0.98	1.503	2.036	1.964	3.713
p-value	0.388	0.6128	0.4716	0.3614	0.3747	0.1562
Observations	13269	4717	8550	13269	4717	8550

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4: Multinomial Logit Estimation to predict selection of individuals

	Employment Status		
	Unemployed	Informal	Formal
Age	0.00242***	-0.00256***	0.000138
	(0.000329)	(0.000250)	(0.000200)
Male	-0.355***	0.274***	0.0802***
	(0.00974)	(0.0111)	(0.00814)
Elementary school	-0.184***	0.0686***	0.115***
	(0.0198)	(0.0105)	(0.0195)
Secondary School	-0.320***	0.0469***	0.273***
	(0.0296)	(0.0129)	(0.0331)
High School	-0.335***	-0.0540***	0.389***
	(0.0397)	(0.0134)	(0.0468)
More than High school	-0.528***	-0.0442**	0.572***
	(0.0314)	(0.0183)	(0.0441)
North Region	0.0310*	-0.0461***	0.0151
	(0.0179)	(0.0101)	(0.0127)
West Region	0.0252	-0.0211*	-0.00407
	(0.0205)	(0.0127)	(0.0167)
East Region	0.0168	0.0110	-0.0278**
	(0.0234)	(0.0150)	(0.0131)
South Region	0.0605**	-0.0551***	-0.00542
	(0.0249)	(0.0139)	(0.0204)
Married	-0.0405***	0.000207	0.0403***
	(0.00658)	(0.00517)	(0.00529)
Head or household	-0.335***	0.207***	0.127***
	(0.0143)	(0.0107)	(0.0112)
Children under 14 years in the HH	0.0152***	-0.00930***	-0.00588***
	(0.00391)	(0.00301)	(0.00225)
Household size	-0.0187***	0.0135***	0.00512***
	(0.00200)	(0.00148)	(0.00147)
Elderly in the HH	0.0139***	-0.0127***	-0.00127
	(0.00438)	(0.00326)	(0.00265)
Observations	26211	8550	4717
Pseudo R^2	0.191	0.191	0.191

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5: Effect on wages of violence and DTOs on wages correcting for self-selection

	(1) log of homicides Pooled	(2) log of homicides Formal	(3) log of homicides Informal	(4) DTO Pooled	(5) DTO Formal	(6) DTO Informal
Age	0.0484***	0.0314***	0.0512***	0.0464***	0.0303***	0.0495***
	(0.00317)	(0.00392)	(0.00300)	(0.00311)	(0.00382)	(0.00299)
Age squared	-0.000548***	-0.000295***	-0.000576***	-0.000531***	-0.000286***	-0.000561***
	(0.0000342)	(0.0000467)	(0.0000361)	(0.0000334)	(0.0000453)	(0.0000361)
Male	0.244***	0.160***	0.285***	0.253***	0.162***	0.289***
	(0.0397)	(0.0426)	(0.0426)	(0.0396)	(0.0426)	(0.0417)
Elementary School	0.0656	0.0609	0.106***	0.0708*	0.0685	0.113***
	(0.0402)	(0.0667)	(0.0368)	(0.0383)	(0.0681)	(0.0358)
Secondary School	0.186***	0.244***	0.270***	0.171***	0.240***	0.265***
	(0.0639)	(0.0785)	(0.0418)	(0.0623)	(0.0789)	(0.0416)
High School	0.258***	0.354***	0.340***	0.229***	0.344***	0.328***
	(0.0855)	(0.0928)	(0.0470)	(0.0854)	(0.0938)	(0.0476)
More than High School	0.578***	0.627***	0.738***	0.566***	0.627***	0.752***
	(0.0970)	(0.105)	(0.0575)	(0.0932)	(0.102)	(0.0563)
Directors & Chiefs	0.920***	0.758***	0.953***	0.886***	0.744***	0.906***
	(0.0533)	(0.0832)	(0.0699)	(0.0507)	(0.0809)	(0.0654)
Manufacturer & Industry	0.391***	0.252***	0.381***	0.372***	0.248***	0.355***
	(0.0317)	(0.0552)	(0.0324)	(0.0312)	(0.0522)	(0.0331)
Commerce & Sales	0.333***	0.267***	0.305***	0.249***	0.209***	0.219***
	(0.0375)	(0.0606)	(0.0425)	(0.0417)	(0.0565)	(0.0519)
Services	0.333***	0.292***	0.307***	0.296***	0.273***	0.264***
	(0.0348)	(0.0561)	(0.0369)	(0.0353)	(0.0525)	(0.0405)
Professional Services	0.664***	0.546***	0.621***	0.578***	0.492***	0.528***
	(0.0319)	(0.0505)	(0.0408)	(0.0379)	(0.0505)	(0.0533)
Norrth Region	0.0698*	-0.0133	0.130***	0.0350	-0.0367	0.0979**
	(0.0384)	(0.0350)	(0.0408)	(0.0415)	(0.0359)	(0.0423)
West Region	0.0862**	0.00218	0.110**	0.0813**	-0.00656	0.114***
	(0.0421)	(0.0455)	(0.0460)	(0.0383)	(0.0433)	(0.0429)
East Region	-0.186***	-0.122**	-0.216***	-0.0958*	-0.0621	-0.135**
	(0.0528)	(0.0530)	(0.0515)	(0.0508)	(0.0475)	(0.0519)
South Region	-0.208***	-0.179**	-0.204***	-0.133**	-0.116*	-0.139**
	(0.0582)	(0.0785)	(0.0618)	(0.0570)	(0.0657)	(0.0643)
imr2	0.0491		-0.122**	0.0657		-0.122**
	(0.0639)		(0.0499)	(0.0645)		(0.0491)
imr3	-0.200***	-0.0887		-0.218***	-0.0946	
	(0.0574)	(0.0630)		(0.0579)	(0.0632)	
Log of homicides	-0.0426*	-0.0425	-0.0189			
	(0.0243)	(0.0401)	(0.0235)			
Numbert of DTOs				0.0907***	0.0618***	0.0953***
				(0.0217)	(0.0156)	(0.0300)
Constant	6.901***	7.342***	6.476***	6.786***	7.222***	6.388***
	(0.160)	(0.246)	(0.130)	(0.149)	(0.209)	(0.118)
Observations	13269	4717	8550	13269	4717	8550
R^2	0.319	0.305	0.258	0.322	0.307	0.261

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

General Conclusions

The aim of this thesis was to contribute to the understanding of a labour market that is characterized by having two sectors out of unemployment (i.e. formal vs. informal). In specific, the difference between the decision of individuals to engage in formal vs informal jobs and their duration of unemployment was disentangled. It was also analysed how the labour market adjusts wages under the presence of high levels of violence in Mexican municipalities and if the magnitude of the adjustment differs for formal vs. informal jobs.

In general, the findings lead to conclude that the decision of individuals to engage in formal and informal jobs in Mexico do not differ substantially. However, there are some difference in the personal characteristics of workers that are worth mentioning. On average, formal workers are more educated and earn higher wages than informal workers, when the sample is further divided by gender, it is clear that a male worker earns higher wages in formal jobs compared to informal jobs. This is also true when we compare female workers. However, the magnitude of the adjustment for both sectors when experiencing high levels of violence is not statistically different.

In particular, in the first chapter it is found that more educated individuals have a lower probability of securing a job compared to those with less education. The relevant literature has defined this as "wait unemployment" and this is explained by the fact that more educated workers have higher reservation wages, this means that they would experience longer unemployment spells before securing a job that matches their personal characteristics and preferences. On the other hand, less educated workers have a higher probability of exiting unemployment given that their reservation wages are lower compared to highly educated individuals.

Additionally, there are gender differences in the use of search channels. In specific, although both male and female women have higher returns from search channels when searching for formal jobs but they do not benefit from search channels when accessing informal ones. Male job searchers have higher returns to job search for informal jobs when asking friends and relatives for recommendations.

Empirical evidence was found of selection bias in this sample of analysis. Specifically, women that self-select into informal jobs experience a wage penalty, which is consistent with the hypothesis that informal jobs offer characteristics that are valuable even if this implies sacrificing income. This fact is not surprising because the traditional role of Mexican women as housewives is still valid nowadays and spread throughout the country. If such characteristics (i.e. proximity to home or flexibility of working schedule) enables them to continue with the household chores, then the loss in earnings is justified. On the other hand, there is a clear preference for the sector of employment from workers in both the formal and informal sectors and this preference leads them to earn higher wages compared to those randomly allocated. This applies to both male and female workers in the formal sector but only for males in the informal sector.

Regarding the wage returns to the use of different search channels, the results suggest that those searching online for jobs experience a wage premium and those searching for jobs in the newspaper exhibit a wage penalty. These results can be explained by the type of jobs that are secured via these channels. On the one hand, jobs advertised online correlate positively with the schooling of the individual and thus are better paid. On the other hand, jobs advertised through the newspaper are temporary and low paid.

From the results of the second chapter, we can conclude that highly skilled formal workers have longer unemployment duration. This is reflected by the positive coefficients of the variable indicating if a worker was previously formal in conjunction with the schooling level. Workers with higher educational levels have a higher reservation wage, they are willing to prolong the time unemployed until a suitable job comes along. Regarding the means to finance job search, the evidence is mixed. Those that receive financial support from the government and from friends and relatives, experience longer unemployment periods. On the other hand, those that had access to a lump sum payment from a previous job, experience shorter duration of unemployment.

With regards to the impact of search channels on unemployment duration, the results suggest that going directly to the workplace and searching for jobs via newspaper reduce the unemployment duration of formal workers. Asking friends and relatives help reduce the job search time for informal workers. The use of other channels rather than helping workers reduce their time unemployed, seems to prolong it, instead there are other factors that decrease the unemployment spell of job searchers. These factors relate to personal characteristics like age, schooling level and previous working experience in a given sector.

In order to understand unemployment duration of individuals that have more than one exit out of unemployment, a multiple destination model was estimated. The results of the competing model helps to understand that the shorter duration for those in receipt of a lump sum payment occurs when workers exit into formal jobs for both male and female workers. This effect is robust to the inclusion of unobserved heterogeneity in the estimation.

Finally, the results presented in the third chapter suggest that there is no effect of high levels of violence on wages for the period 2002-2009. Alternatively, the presence of DTOs in a given municipality increase wages of workers by 5.7%. After dividing the sample to differentiate the impact for formal and informal workers the results yield a positive impact of 4.9% for informal workers and 3.4% for formal workers. As one of the main interests of this chapter was to analyze if formal and informal sectors react differently to the presence of DTOs, the statistical difference for both formal and informal wage earners was tested and it is concluded that the wages in both sectors increase in the same magnitude. There is no evidence suggesting that the wage for informal workers adjusts differently to formal ones.

The non-differential impact for both formal and informal sectors to the presence of DTOs can be partly explained by the fact that the focus of this analysis is wage earners, leaving the self-employed, employers and workers for self-consumption out of the analysis. In specific, self-employed have shown to respond to external shocks differently compared to other sectors as shown in other studies (Fernández et al., 2014; Velásquez, 2014).

On the other hand, the positive effect of DTOs on wages can be attributed to the economic effect introduced by such groups when they take control over a municipality. It is well known that such groups handle large amounts of cash and this could potentially have spillover effects on the local economy via consumption and perhaps even through the hiring of the local labour force. This spillover effect would eventually push wages up. The effects presented in the third chapter are robust after correcting for the problem of selection bias that arises when individuals explicitly choose their sector of employment.

Even if the decision to engage in one sector vs. the other does not vary among individuals, there are large differences in the type of firms they are employed in. According to McKinsey Global Institute (MGI), although the informal sector employs an important number of workers in Mexico, most firms are small in size, with no more than 10 employees and these are the ones creating the most jobs. These firms are often characterized by having low levels of productivity, lack of access to credit, low technology and under-reporting of income to avoid paying taxes. Moreover, in the period 1999-2009 their productivity fell by 6.5%. In contrast, large modern corporations, which are often formal, increased productivity by 5.8% in the same period. This is an indicator of the large productivity gap in Mexico's labour market and has important repercussions in the economy as both type of firms grow in the opposite direction.

The disparity in the productivity growth of both types of firms ultimately has an impact on economic growth. Efforts must be oriented to reconcile both sectors and promote the integration of small firms into the more competitive sector by facilitating their access to credit and technology. Moreover, this integration must be done in conjunction with a wide formalization strategy to tackle informal practices, particularly in states where informality is high. According to the International Labor Organization (ILO) although the national average proportion of informal workers is important in magnitude, within states, the situation is heterogeneous and in some cases, worse. In Oaxaca, in the south of the country, this accounts for around 80% of the total workforce, whereas in Nuevo Leon, in the north, it is 40% of the total workforce, which is below the national average. Achieving the formalization the large proportion of informal workers and firms would benefit the economy by increasing productivity and the tax income base.

There are some programs already in place which promote formalization of firms and jobs, such as the one promoted by the ILO in several states such as Mexico City, Querétaro, Hidalgo and Chihuahua. The effectiveness of programs such as this one is very heterogeneous and depends on the quality of local institutions and the infrastructure in each state. Perhaps a coordinated effort from all levels of government would be more effective in achieving a large formalization of jobs and firms.

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Appendix A

Appendix First chapter

Table A.1: Multinomial Logit Estimation, first stage

	Outcome Employment status		
	(1)	(2)	(3)
	Unemployed	Formal	Informal
Married	-0.0681***	0.0261***	0.0420***
	(0.00706)	(0.00543)	(0.00693)
Head of household	-0.139***	0.0438***	0.0952***
	(0.00812)	(0.00668)	(0.00809)
Age	0.00588***	-0.00420***	-0.00168***
	(0.000347)	(0.000271)	(0.000319)
Gender	-0.132***	0.0308***	0.101***
	(0.00670)	(0.00489)	(0.00633)
Secondary school	-0.0132	0.0701***	-0.0569***
	(0.00899)	(0.00805)	(0.00760)
High school	0.0540***	0.0846***	-0.139***
	(0.0100)	(0.00926)	(0.00776)
More than high school	0.0927***	0.0724***	-0.165***
	(0.00957)	(0.00871)	(0.00735)
Previous job formal	0.00581	0.151***	-0.157***
	(0.00646)	(0.00513)	(0.00588)
Dismissed or finished previous business	-0.0253***	0.00286	0.0225***
	(0.00674)	(0.00494)	(0.00655)
Left or closed previous business	-0.0207	-0.0456***	0.0663***
	(0.0149)	(0.0117)	(0.0142)
Other reasons for unemployment	-0.00851	-0.0449***	0.0534***
	(0.0183)	(0.0127)	(0.0176)
Financial cushion	0.00215	0.0227**	-0.0248**
	(0.0129)	(0.00905)	(0.0125)
Financial aid from government	0.0483**	-0.0325**	-0.0158
	(0.0190)	(0.0140)	(0.0183)
Financial aid from relatives	0.0395***	-0.0255***	-0.0140
	(0.0137)	(0.00969)	(0.0129)
Region controls	Yes	Yes	Yes
Observations	30320	30320	30320
Pseudo R^2	0.078	0.078	0.078

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix B

Appendix Second chapter

Table B.1: Continuous survival model

	(1) Full Exponential	(2) Full Weibull	(3) full Gompertz	(4) full Cox	(5) Male Exponential	(6) Male Weibull	(7) Male Gompertz	(8) Male Cox	(9) Female Exponential	(10) Female Weibull	(11) Female Gompertz	(12) Female Cox
Male	0.228***	0.224***	0.228***	0.237***								
	(0.0187)	(0.0215)	(0.0185)	(0.0153)								
Married	0.149***	0.167***	0.148***	0.121***	0.257***	0.271***	0.256***	0.234***	-0.0442	-0.0200	-0.0463	-0.0893***
	(0.0187)	(0.0220)	(0.0186)	(0.0149)	(0.0243)	(0.0293)	(0.0242)	(0.0187)	(0.0362)	(0.0406)	(0.0359)	(0.0307)
Head of household	0.247***	0.266***	0.246***	0.214***	0.185***	0.208***	0.185***	0.149***	0.187***	0.201***	0.186***	0.156***
	(0.0212)	(0.0252)	(0.0210)	(0.0166)	(0.0260)	(0.0315)	(0.0259)	(0.0197)	(0.0468)	(0.0529)	(0.0462)	(0.0388)
Previous job formal	-0.0640***	-0.0796***	-0.0633***	-0.0360***	-0.107***	-0.130***	-0.107***	-0.0701***	0.0620*	0.0631*	0.0619*	0.0657**
	(0.0165)	(0.0195)	(0.0164)	(0.0130)	(0.0194)	(0.0232)	(0.0193)	(0.0149)	(0.0323)	(0.0363)	(0.0319)	(0.0269)
Age	-0.0150***	-0.0169***	-0.0149***	-0.0116***	-0.0161***	-0.0180***	-0.0161***	-0.0129***	-0.0100***	-0.0122***	-0.00984***	-0.00574***
	(0.000885)	(0.00106)	(0.000880)	(0.000687)	(0.000996)	(0.00121)	(0.000993)	(0.000755)	(0.00198)	(0.00223)	(0.00196)	(0.00165)
Secondary school	-0.0562***	-0.0642**	-0.0559***	-0.0407**	-0.0589**	-0.0667**	-0.0587**	-0.0455**	0.0233	0.0188	0.0237	0.0396
	(0.0217)	(0.0261)	(0.0215)	(0.0166)	(0.0238)	(0.0291)	(0.0237)	(0.0178)	(0.0545)	(0.0616)	(0.0539)	(0.0460)
High school	-0.207***	-0.235***	-0.206***	-0.159***	-0.211***	-0.239***	-0.210***	-0.164***	-0.105*	-0.133**	-0.103*	-0.0539
	(0.0246)	(0.0292)	(0.0244)	(0.0191)	(0.0277)	(0.0333)	(0.0275)	(0.0211)	(0.0569)	(0.0642)	(0.0563)	(0.0482)
More than high school	-0.386***	-0.448***	-0.383***	-0.274***	-0.434***	-0.498***	-0.432***	-0.323***	-0.211***	-0.267***	-0.206***	-0.0965**
	(0.0245)	(0.0290)	(0.0245)	(0.0193)	(0.0286)	(0.0341)	(0.0286)	(0.0222)	(0.0540)	(0.0609)	(0.0536)	(0.0457)
Dismissed or finished previous job	-0.0278	-0.0386*	-0.0274	-0.0114	-0.0302	-0.0421*	-0.0299	-0.0144	-0.0581*	-0.0678*	-0.0576*	-0.0389
	(0.0175)	(0.0206)	(0.0173)	(0.0138)	(0.0209)	(0.0251)	(0.0208)	(0.0160)	(0.0321)	(0.0361)	(0.0317)	(0.0268)
Left or closed previous business	-0.0305	-0.0466	-0.0300	-0.00806	-0.0323	-0.0533	-0.0319	-0.00341	-0.0242	-0.0315	-0.0239	-0.0190
	(0.0355)	(0.0416)	(0.0352)	(0.0279)	(0.0409)	(0.0488)	(0.0407)	(0.0313)	(0.0737)	(0.0825)	(0.0729)	(0.0625)
Other	0.0237	0.0314	0.0233	0.00876	0.0203	0.0300	0.0199	0.000174	-0.0153	-0.0219	-0.0140	0.000137
	(0.0468)	(0.0550)	(0.0464)	(0.0375)	(0.0533)	(0.0639)	(0.0530)	(0.0420)	(0.101)	(0.114)	(0.100)	(0.0841)
Financial cushion	0.109***	0.127***	0.108***	0.0758***	0.101***	0.124***	0.101***	0.0640**	0.172**	0.181**	0.172**	0.144***
	(0.0315)	(0.0372)	(0.0312)	(0.0245)	(0.0354)	(0.0423)	(0.0352)	(0.0272)	(0.0686)	(0.0790)	(0.0676)	(0.0543)
Financial aid from government	-0.0849	-0.0781	-0.0852	-0.102**	-0.0368	-0.0243	-0.0374	-0.0639	-0.0610	-0.0616	-0.0604	-0.0630
	(0.0530)	(0.0618)	(0.0526)	(0.0438)	(0.0749)	(0.0900)	(0.0744)	(0.0587)	(0.0772)	(0.0873)	(0.0764)	(0.0658)
Financial aid from relatives	-0.143***	-0.155***	-0.143***	-0.120***	-0.201***	-0.221***	-0.200***	-0.161***	-0.0559	-0.0525	-0.0565	-0.0601
	(0.0365)	(0.0422)	(0.0362)	(0.0295)	(0.0491)	(0.0578)	(0.0488)	(0.0385)	(0.0557)	(0.0625)	(0.0551)	(0.0469)
Went directly to the work place	-0.122***	-0.144***	-0.121***	-0.0800***	-0.136***	-0.153***	-0.135***	-0.101***	-0.0802*	-0.108**	-0.0778*	-0.0270
	(0.0238)	(0.0278)	(0.0236)	(0.0188)	(0.0282)	(0.0335)	(0.0280)	(0.0217)	(0.0444)	(0.0496)	(0.0440)	(0.0374)
Uploaded or replied to a job offer online	-0.213***	-0.252***	-0.210***	-0.136***	-0.230***	-0.270***	-0.229***	-0.154***	-0.180***	-0.218***	-0.176***	-0.104**
	(0.0324)	(0.0368)	(0.0322)	(0.0262)	(0.0399)	(0.0459)	(0.0398)	(0.0318)	(0.0550)	(0.0611)	(0.0544)	(0.0458)
Asked to relatives and friends to recommend his job	-0.0322	-0.0404	-0.0319	-0.0132	-0.0393	-0.0435	-0.0391	-0.0258	-0.0458	-0.0647	-0.0442	-0.0106
	(0.0245)	(0.0287)	(0.0243)	(0.0193)	(0.0283)	(0.0336)	(0.0281)	(0.0218)	(0.0510)	(0.0571)	(0.0505)	(0.0428)
Used allocation services to get job (public of private)	-0.217***	-0.247***	-0.216***	-0.160***	-0.196***	-0.224***	-0.195***	-0.142***	-0.243***	-0.272***	-0.241***	-0.186***
	(0.0405)	(0.0463)	(0.0402)	(0.0330)	(0.0494)	(0.0574)	(0.0491)	(0.0391)	(0.0699)	(0.0770)	(0.0692)	(0.0597)
Used advertisement in newspaper or classifieds to get job	-0.107***	-0.118***	-0.107***	-0.0855***	-0.146***	-0.159***	-0.145***	-0.120***	0.00368	0.00217	0.00341	0.0122
	(0.0241)	(0.0278)	(0.0239)	(0.0194)	(0.0288)	(0.0337)	(0.0286)	(0.0228)	(0.0438)	(0.0487)	(0.0433)	(0.0369)
Used other channels to find a job	-0.108**	-0.135**	-0.107**	-0.0504	-0.101*	-0.120*	-0.101*	-0.0529	-0.0919	-0.128	-0.0881	-0.0219
	(0.0459)	(0.0529)	(0.0455)	(0.0366)	(0.0557)	(0.0652)	(0.0554)	(0.0432)	(0.0805)	(0.0903)	(0.0796)	(0.0672)
Constant	-2.468***	-2.948***	-2.461***		-2.196***	-2.699***	-2.191***		-2.739***	-3.179***	-2.729***	
	(0.0445)	(0.0520)	(0.0439)		(0.0487)	(0.0578)	(0.0481)		(0.0921)	(0.103)	(0.0911)	
ln_p constant		- 0.190***				- 0.195***				-0.179***		
		(0.00479)				(0.00573)				(0.00879)		
Gamma constant			-0.00116*				-0.000790				-0.00190	
			(0.000594)				(0.000694)				(0.00118)	
Observations	30651	30651	30651	30651	21059	21059	21059	21059	9592	9592	9592	9592

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Duration model for males

	(1) Male-Formal Exponential	(2) Male-Formal Weibull	(3) Male-Formal Gompertz	(4) Male-Formal Cox	(5) Male-Informal Exponential	(6) Male-Informal Weibull	(7) Male-Informal Gompertz	(8) Male-Informal Cox
Married	0.454***	0.472***	0.454***	0.425***	0.0325	0.0403	0.0327	0.0218
	(0.0419)	(0.0476)	(0.0417)	(0.0354)	(0.0285)	(0.0384)	(0.0288)	(0.0169)
Head of household	0.210***	0.228***	0.209***	0.181***	0.110***	0.140***	0.111***	0.0678***
	(0.0460)	(0.0526)	(0.0458)	(0.0383)	(0.0303)	(0.0411)	(0.0307)	(0.0181)
Previous job formal	0.415***	0.404***	0.415***	0.433***	-0.156***	-0.195***	-0.157***	-0.0996***
	(0.0339)	(0.0376)	(0.0337)	(0.0298)	(0.0253)	(0.0338)	(0.0257)	(0.0153)
Age	-0.0310***	-0.0334***	-0.0309***	-0.0270***	-0.00714***	-0.00882***	-0.00718***	-0.00466***
	(0.00182)	(0.00206)	(0.00182)	(0.00156)	(0.00115)	(0.00157)	(0.00117)	(0.000686)
Secondary school	0.210***	0.207***	0.210***	0.218***	-0.0715***	-0.0869**	-0.0720***	-0.0514***
	(0.0496)	(0.0553)	(0.0493)	(0.0435)	(0.0271)	(0.0367)	(0.0274)	(0.0163)
High school	0.159***	0.139**	0.160***	0.196***	-0.133***	-0.168***	-0.134***	-0.0827***
	(0.0529)	(0.0590)	(0.0526)	(0.0462)	(0.0333)	(0.0446)	(0.0337)	(0.0201)
More than high school	-0.0770	-0.131**	-0.0745	0.0227	-0.298***	-0.372***	-0.300***	-0.191***
	(0.0537)	(0.0596)	(0.0535)	(0.0471)	(0.0341)	(0.0452)	(0.0348)	(0.0205)
Dismissed or finished previous job	-0.0595*	-0.0726*	-0.0590*	-0.0383	-0.0491*	-0.0625*	-0.0495*	-0.0393**
	(0.0337)	(0.0382)	(0.0335)	(0.0286)	(0.0266)	(0.0358)	(0.0269)	(0.0157)
Left or closed previous business	-0.215**	-0.237**	-0.215**	-0.180**	-0.0962**	-0.120**	-0.0966**	-0.0735***
	(0.0972)	(0.105)	(0.0969)	(0.0881)	(0.0449)	(0.0601)	(0.0454)	(0.0267)
Other	-0.271**	-0.283**	-0.270**	-0.267***	0.0953*	0.131*	0.0962*	0.0525
	(0.110)	(0.122)	(0.109)	(0.0984)	(0.0562)	(0.0757)	(0.0567)	(0.0335)
Financial cushion	0.188***	0.212***	0.187***	0.150***	0.127***	0.166***	0.128***	0.0678**
	(0.0488)	(0.0555)	(0.0486)	(0.0407)	(0.0474)	(0.0642)	(0.0480)	(0.0287)
Financial aid from government	0.0000293	0.0281	-0.00181	-0.0528	-0.00704	-0.0150	-0.00736	0.00622
	(0.117)	(0.129)	(0.117)	(0.104)	(0.101)	(0.133)	(0.102)	(0.0605)
Financial aid from relatives	-0.389***	-0.427***	-0.388***	-0.321***	-0.0553	-0.0601	-0.0552	-0.0431
	(0.0876)	(0.0975)	(0.0873)	(0.0763)	(0.0558)	(0.0739)	(0.0564)	(0.0339)
Went directly to the work place	-0.0964**	-0.122**	-0.0953**	-0.0453	-0.0928**	-0.104**	-0.0930**	-0.0783***
	(0.0457)	(0.0508)	(0.0455)	(0.0397)	(0.0361)	(0.0480)	(0.0364)	(0.0213)
Uploaded or replied to a job offer online	-0.194***	-0.235***	-0.191***	-0.110**	-0.208***	-0.246***	-0.209***	-0.149***
	(0.0608)	(0.0675)	(0.0605)	(0.0520)	(0.0520)	(0.0668)	(0.0526)	(0.0317)
Asked to relatives and friends to recommend his job	-0.115**	-0.123**	-0.115**	-0.0918**	-0.0325	-0.0289	-0.0323	-0.0376*
	(0.0498)	(0.0550)	(0.0495)	(0.0437)	(0.0347)	(0.0459)	(0.0351)	(0.0210)
Used allocation services to get job (public of private)	-0.134*	-0.161*	-0.133*	-0.0839	-0.178***	-0.222**	-0.179***	-0.106***
	(0.0764)	(0.0848)	(0.0761)	(0.0660)	(0.0675)	(0.0878)	(0.0683)	(0.0391)
Used advertisement in newspaper or classifieds to get job	-0.0458	-0.0599	-0.0450	-0.0187	-0.104***	-0.122**	-0.104***	-0.0772***
	(0.0446)	(0.0496)	(0.0444)	(0.0386)	(0.0377)	(0.0495)	(0.0380)	(0.0226)
Used other channels to find a job	-0.259***	-0.297***	-0.258***	-0.183**	-0.0185	-0.0192	-0.0185	-0.00554
	(0.0964)	(0.105)	(0.0960)	(0.0847)	(0.0693)	(0.0927)	(0.0700)	(0.0387)
Constant	-2.980***	-3.453***	-2.974***		-1.893***	-2.456***	-1.898***	
	(0.0864)	(0.0965)	(0.0860)		(0.0614)	(0.0807)	(0.0613)	
ln_p constant		-0.190***				-0.212***		
		(0.00874)				(0.00826)		
Gamma constant			-0.000985				0.000730	
			(0.00119)				(0.000852)	
Observations	12220	12220	12220	12220	8839	8839	8839	8839

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Duration model female

	(1) Female-Formal Exponential	(2) Female-Formal Weibull	(3) Female-Formal Gompertz	(4) Female-Formal Cox	(5) Female-Informal Exponential	(6) Female-Informal Weibull	(7) Female-Informal Gompertz	(8) Female-Informal Cox
Married	-0.154***	-0.139**	-0.159***	-0.190***	0.209***	0.274***	0.218***	0.128***
	(0.0569)	(0.0606)	(0.0558)	(0.0511)	(0.0429)	(0.0583)	(0.0455)	(0.0282)
Head of household	0.108	0.119	0.103	0.0831	0.0948*	0.112	0.0959*	0.0612*
	(0.0800)	(0.0854)	(0.0783)	(0.0705)	(0.0546)	(0.0731)	(0.0573)	(0.0357)
Previous job formal	0.594***	0.603***	0.591***	0.578***	-0.117***	-0.143***	-0.121***	-0.0811***
	(0.0529)	(0.0561)	(0.0520)	(0.0479)	(0.0416)	(0.0549)	(0.0436)	(0.0270)
Age	-0.0175***	-0.0198***	-0.0167***	-0.0118***	-0.00816***	-0.0101***	-0.00839***	-0.00548***
	(0.00323)	(0.00348)	(0.00317)	(0.00284)	(0.00236)	(0.00314)	(0.00249)	(0.00154)
Secondary school	0.210**	0.199*	0.214**	0.240***	0.0805	0.112	0.0848	0.0541
	(0.101)	(0.107)	(0.0991)	(0.0924)	(0.0623)	(0.0840)	(0.0652)	(0.0411)
High school	0.191*	0.170	0.198*	0.240**	-0.127*	-0.177*	-0.134*	-0.0666
	(0.103)	(0.109)	(0.101)	(0.0943)	(0.0697)	(0.0934)	(0.0731)	(0.0459)
More than high school	0.108	0.0546	0.125	0.235***	-0.210***	-0.269***	-0.218***	-0.118***
	(0.0983)	(0.104)	(0.0968)	(0.0902)	(0.0636)	(0.0852)	(0.0670)	(0.0417)
Dismissed or finished previous job	0.00403	0.000569	0.00375	0.0134	-0.104**	-0.135**	-0.109**	-0.0614**
	(0.0488)	(0.0524)	(0.0477)	(0.0430)	(0.0408)	(0.0542)	(0.0428)	(0.0264)
Left or closed previous business	-0.450**	-0.457**	-0.449**	-0.446***	-0.0759	-0.0894	-0.0781	-0.0617
	(0.178)	(0.184)	(0.177)	(0.170)	(0.0779)	(0.104)	(0.0816)	(0.0514)
Other	-0.357*	-0.375*	-0.351*	-0.309*	0.0264	0.0177	0.0214	0.0456
	(0.197)	(0.207)	(0.193)	(0.177)	(0.113)	(0.148)	(0.118)	(0.0756)
Financial cushion	0.194**	0.197*	0.194**	0.177**	0.254***	0.337***	0.265***	0.148***
	(0.0926)	(0.101)	(0.0898)	(0.0781)	(0.0845)	(0.111)	(0.0880)	(0.0574)
Financial aid from government	-0.259*	-0.238	-0.265*	-0.291**	-0.0588	-0.107	-0.0675	-0.00585
	(0.151)	(0.157)	(0.149)	(0.141)	(0.0984)	(0.130)	(0.103)	(0.0654)
Financial aid from relatives	-0.0599	-0.0550	-0.0617	-0.0660	0.0436	0.0644	0.0476	0.0237
	(0.0906)	(0.0963)	(0.0889)	(0.0811)	(0.0636)	(0.0846)	(0.0664)	(0.0413)
Went directly to the work place	0.0363	0.0110	0.0458	0.0874	-0.193***	-0.221***	-0.195***	-0.135***
	(0.0694)	(0.0740)	(0.0680)	(0.0613)	(0.0573)	(0.0748)	(0.0599)	(0.0373)
Uploaded or replied to a job offer online	-0.0626	-0.0962	-0.0497	0.0175	-0.186***	-0.217**	-0.188**	-0.140***
	(0.0776)	(0.0831)	(0.0760)	(0.0679)	(0.0715)	(0.0925)	(0.0747)	(0.0458)
Asked to relatives and friends to recommend his job	-0.0308	-0.0326	-0.0309	-0.0256	-0.251***	-0.329***	-0.261***	-0.155***
	(0.0835)	(0.0886)	(0.0819)	(0.0749)	(0.0661)	(0.0869)	(0.0693)	(0.0421)
Used allocation services to get job (public of private)	-0.0735	-0.0971	-0.0659	-0.0238	-0.249**	-0.297**	-0.254**	-0.166***
	(0.100)	(0.107)	(0.0982)	(0.0883)	(0.0972)	(0.129)	(0.102)	(0.0618)
Used advertisement in newspaper or classifieds to get job	0.0654	0.0591	0.0671	0.0790	-0.0511	-0.0415	-0.0475	-0.0434
	(0.0672)	(0.0717)	(0.0657)	(0.0593)	(0.0557)	(0.0725)	(0.0578)	(0.0361)
Used other channels to find a job	-0.150	-0.188	-0.135	-0.0684	-0.131	-0.160	-0.133	-0.0654
	(0.132)	(0.141)	(0.130)	(0.118)	(0.102)	(0.136)	(0.107)	(0.0628)
Constant	-3.729***	-4.100***	-3.702***		-1.870***	-2.459***	-1.895***	
	(0.157)	(0.168)	(0.154)		(0.110)	(0.141)	(0.113)	
ln_p constant		-0.158***				-0.222***		
		(0.0125)				(0.0141)		
Gamma constant			-0.00604***				-0.00340**	
			(0.00189)				(0.00144)	
Observations	7036	7036	7036	7036	2556	2556	2556	2556

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix C

Appendix Third chapter

Table C.1: OLS regression for the effect of violence and DTOs presence on wages

	(1) Log of Homicides Pooled	(2) Log of hom Formal	(3) Log of Hom Informal	(4) DTO Pooled	(5) DTO Formal	(6) DTO Informal
Male	0.311***	0.210***	0.375***	0.313***	0.210***	0.376***
	(0.0184)	(0.0230)	(0.0223)	(0.0187)	(0.0231)	(0.0225)
Elementary school	0.163***	0.101	0.146***	0.160***	0.0981	0.142***
	(0.0321)	(0.0655)	(0.0382)	(0.0325)	(0.0655)	(0.0384)
Secondary school	0.383***	0.320***	0.318***	0.375***	0.316***	0.309***
	(0.0399)	(0.0663)	(0.0453)	(0.0397)	(0.0659)	(0.0453)
High school	0.483***	0.433***	0.342***	0.474***	0.429***	0.335***
	(0.0443)	(0.0722)	(0.0503)	(0.0448)	(0.0718)	(0.0504)
More than high school	0.852***	0.732***	0.757***	0.851***	0.730***	0.760***
	(0.0507)	(0.0715)	(0.0592)	(0.0501)	(0.0716)	(0.0582)
Log of homicide rates	0.0317**	0.0193	0.0353**			
	(0.0134)	(0.0141)	(0.0166)			
Number of DTOs				0.0375***	0.0101	0.0426***
				(0.00871)	(0.00722)	(0.0127)
Constant	6.111***	6.899***	6.133***	6.174***	6.940***	6.199***
	(0.0833)	(0.117)	(0.0936)	(0.0800)	(0.0966)	(0.0905)
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
Regional Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.297	0.299	0.232	0.301	0.299	0.236
Observations	13269	4717	8550	13269	4717	8550

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$