The implications of a rise in the minimum wage on the Mexican labour market

by

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Abstract

This thesis details a comprehensive empirical evaluation of the implications of a minimum wage increase in the Mexican labour market, estimating the impact on real wages, the distribution of earnings, employment, and informal employment. It uses, as a natural experiment the 2012 partial harmonization of Mexico's regional minimum wages, in which one out of the three minimum wage zones experienced an unexpected minimum wage rise. Using Difference in Differences regressions, we find no evidence of adverse employment effects in the labour market. Instead, the estimates suggest positive effects on real hourly wages, employment, and occupation in the formal sector. These results can be taken as evidence for the existence of monopsonistic labour markets in Mexico. Synthetic Control Method procedures demonstrate that the employment findings are robust to the choice of estimation method and to the level of aggregation in the data, corroborating non-negative effects on employment. In addition, Unconditional Quantile Regressions for the distributional wage effects suggest a small improvement in wages for the targeted lowest income workers, although, due to positive spillover effects, the relative increase in wages for the upper percentiles is even greater. This has the net effect of actually widening dispersion of wages.

To Paulina

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CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION: TOPICS COMMON TO THE EMPIRICAL ANALYSIS [1]

Up until November 2012, Mexico was divided into three wage zones, A, B, and C for the purposes of setting minimum wages. On the 27th of November 2012 the minimum wage in Zone B was unexpectedly brought into line with that in Zone A. This intervention on Zone B, which covers around 10% of Mexico's workforce, represented a 2.9 percent nominal increase in its minimum wage level. Throughout this dissertation, we analyse the effect of this increment in Mexico's minimum wage for Zone B relative to zones A and C. Using various econometric approaches, this study provides a comprehensive evaluation of the impact of this legislative change on: wage rates, the distribution of earnings, labour status, and informal employment.

By the implementation of a rich set of econometric methods —including Difference in Differences estimation, Sample Selection Correction, Unconditional Quantile Regressions and Synthetic Control Method— this doctoral dissertation provides evidence that the minimum wage increase did not have adverse effects on various aspects of the labour market.

Our Difference in Differences estimates suggest that real wages increased, the level of employment did not diminish (in fact evidence is found in support of a marginal increase in employment, which is corroborated by Synthetic Control Method estimates) and participation in the informal sector decreased. Nevertheless, an unconditional quantile re-

[1] A former version of this chapter was submitted as part of the doctoral research proposal for the Advanced Research Methods module in March 2015 (see *The effect of minimum wages on employment. The case for Mexico,* by Jorge Alfredo Bouchot Viveros.) Some of the analysis contained in pages 6 to 9, and 12 to 41 in this chapter was taken from the aforementioned research proposal.

gression analysis of the impact on the earnings distribution shows important minimum wage *spillover effects*. These spillovers indicate that low-paid workers benefited less than high-paid workers, which increased the wage dispersion.

In the economics literature there has been a long and controversial debate on the effects of changes in minimum wages on the labour market. Until now, no consensus of the impact of the increase in minimum wages on employment has been reached. Furthermore, although the existence of minimum wage spillovers on the earnings distribution has been demonstrated, it is not clear how strong these spillovers can be.

With respect to the income effect of the policy change, a real terms increase in the minimum wage[2] does not guarantee a rise the in real earnings of the targeted low-paid workers. There exists the possibility, for example, that minimum wage regulations are not actually accomplished, or, that inflation nullifies the nominal rise. Even assuming that the minimum wage is in force, cases may occur in which a higher minimum wage may increase the labour supply from previously inactive middle class workers. For productivity reasons, employers might prefer to hire these middle class workers instead of the lowest paid workers. As a consequence, the minimum wage increase would have the opposite effect to that expected on the targeted low-paid workers.

Regarding the impact on employment, the standard competitive labour market model predicts that firms optimize profits given the wage determined by the market, and there exists an inverse relationship between wages and employment. Nevertheless, there are alternative approaches that consider some market imperfections, mainly some level of market power held by firms. Card and Krueger (1995) asserted that although the standard economic theory is quite powerful in explaining labour markets, it is incomplete for specific contexts where firms are not necessarily price (wage) takers. Thus, models of monopsonistic labour market competition have been widely used as the theoretical approach to support findings of non-negative effects of minimum wage increases on employment (Dickens et al., 1999; Manning, 2004; Bhaskar et al., 2002). The basic idea

[2]Throughout this document, when we refer to minimum wage, we make reference to the real minimum wage unless something different is specified.

behind monopsonistic labour market is that, as equilibrium wages may be higher than the marginal costs of firms, increases in minimum wages do not necessarily reduce the level of employment.

Talking specifically about our detailed case of study, the minimum wage legislation in Mexico has been atypical with respect other policies implemented in Latin America. There have been, for instance, aggressive minimum wage interventions in Brazil, Uruguay and Argentina to recover the purchasing power of the minimum wage after periods of high inflation. In contrast, during the last thirty years, the Mexican minimum wage policy has been characterized by the absence of mechanisms to adjust for the loss of the real value of wages. The result of this have been that the Mexican minimum wage has lost more than 70% of its real value since the mid-80s. Between 1970 and 1988 the Mexican economy suffered deep recessions and hyperinflation periods. Within the set of economic policies implemented to achieve macroeconomic stabilization, the mechanisms for setting the minimum wage were reformed to make it an instrument for price stabilization. But, since 1994 the Mexican economy has experienced more than twenty years of macroeconomic and financial stability with moderate and controlled inflation rates, but the (real) minimum wage level has remained stagnant. As a consequence of this decline, the minimum wage is not enough to reach the monetary value of the extreme poverty line.

Numerous voices have expressed the need to increase the minimum wage level,[3] but the idea that an increase in wages can generate disequilibrium in the labour market, causing unemployment and/or inflation, has prevailed. For instance, the Central Bank's Governor expressed the view that an increment in the minimum wage could have only three possible (adverse) consequences: inflation, dismissals, or growth of the informal sector.[4]

Given the trend observed in the real minimum wage, the population share under

[3] In August 2014 the Mexico City Governor proposed a scheme to increase gradually the minimum wage levels during the following three years until the value of the basic food basket is reached. The project was not approved for years 2015, 2016, and 2017 although the discussion remains active in the Congress.

[4] Conference press of the presentation of the quarterly report on inflation (13 August 2018). Source: *El Financiero*, Accessed on 11 February 2015. `http://www.elfinanciero.com.mx/economia/alza-al-salario-provocaria-resultados-indeseables-banxico.html`.

poverty conditions, as well as the size of the workforce potentially affected by minimum wage changes, it is fundamental to formally assess the impact of the minimum wage on the labour market.

The main challenge to carry out an econometric evaluation for the Mexican labour market is the lack of variation in the minimum wage. It is set by a single institution at the federal level, the National Commission on Minimum Wage (CONASAMI). Even though there were three different wage zones, the variation was proportional and practically constant since the definition of the three minimum wage zones in 1986. In addition, in contrast to United States policy, local governments in Mexico do not have the prerogative to set their own minimum wages, which makes it difficult to use geographical variations for identification. To overcome these difficulties with identification, we use the 2012 minimum wage increase observed in only one out of the three minimum wages zones to identify the impact of a minimum wage increase on the Mexican labour market.

The main objective of this research is therefore to measure the impact of the 2012' minimum wage increase on real wages, earnings distribution, employment levels, and informal employment.

In the minimum wage literature, empirical research for developing countries is relatively scarce. Different studies have indicated the need to explore these impacts beyond developed countries (Neumark and Wascher, 2006; Lemos, 2009). Particular attention must be put on the repercussions on the informal sector of the labour market. As Neumark and Wascher (2006) asserted, given the difficulties related to enforcement, there is an important gap on the analysis in the spillovers to the informal workers.

This dissertation contributes to the literature in different ways. First, making use of a public database, it incorporates the informal labour market into the analysis, providing a comprehensive evaluation of the minimum wage on the labour market. Second, it presents evidence in favour of the existence of monopsonistic labour markets in Mexico. Minimum wages can therefore have positive effects on employment and, particularly, on formal employment. Third, in contrast to the traditional minimum wage literature, this dissertation puts special emphasis on the effects for different age subgroups, finding important effects on the oldest workers of the labour force. Fourth, it demonstrates that given the context of the minimum wage setting in Mexico, there are income-increasing spillover effects on the earnings distribution.

The basic model for the econometric specifications implemented in Chapters 2, 3 and 4 is Difference in Differences estimation, using as a source of identification the 2012 harmonization of Zone B's minimum wage . The econometric models rely on two empirical tools. On the one hand, the conditional mean effects on real earnings, employment and informality are tested and corrected for sample selection bias using the procedure introduced by Heckman (1979). This procedure allows us to estimate the effects on the whole labour market, without restricting the sample to active labour market individuals or waged workers. The implementation of this technique differentiates our analysis from that of Campos et al. (2017). They used the same source of variation, the 2012' minimum wage harmonization, but their evaluation restricted the sample to the segment of the labour force actually working, generating the possibility of biased estimates. On the other hand, in order to estimate the wage effects across the earnings distribution, unconditional quantile regressions are implemented. We use this novel procedure developed by Firpo et al. (2009), which offers the analytical advantage of estimating directly marginal treatment effects at different points of the distribution. The objective is twofold: to evaluate if there is actually an impact on the lowest segment of the earnings distribution, and to verify the existence of spillover effects on segments of the earnings distribution above the minimum wage value.

Chapter 5 tests the robustness of the employment findings by using another estimation approach, namely the Synthetic Control Method pioneered by (Abadie et al., 2010). It exploits the difference between treated and untreated regions, but in contrast to Difference in Differences, it does not assign the same weight to every untreated region. The Synthetic Control Method generates a weighted average for the pretreatment period of the unaffected regions that matches the trend followed by treated regions. Afterwards, post-treatment observations are projected using the same weights of the weighted average. Treatment effects are just the difference between treated and synthetic control groups in every post-intervention period. Recent evaluations on minimum wage interventions have used this data-driven approach (Dube and Zipperer, 2015; Reich et al., 2017; Jardim et al., 2017), so that this method is useful for corroborating the findings made using Difference in Differences regressions.

The dataset employed for the econometric analysis is the National Survey on Employment and Occupation (ENOE). The period of analysis from Chapters 2 to 4 is 2012Q1-2013Q4, although some robustness exercises extend (or modify) the time span. In Chapter 5, given that Synthetic Control Method requires the use of a larger pretreatment period to construct a valid counterfactual, the analysis is extended to the period 2005Q1-2014Q4.

The objective of this introductory chapter is to describe the common ground upon which the four subsequent empirical chapters are based. Thus, the chapter is organised as follows. Section 1.1 provides a description of the theoretical models on minimum wage effects. Section 1.2 describes the database and the 2012 minimum wage intervention used as a source of identification. The current features of the policy on minimum wages are discussed in Section 1.3, as well as some of the main socio-demographic characteristics of the workforce in Mexico. Finally, Section 1.4 provides some final remarks.

Finally, in order to comply with the Code of Practice on Academic Integrity of the University of Birmingham, it is important to mention that some of the analysis in the rest of the chapter corresponds to an earlier work as part of the research proposal of this thesis project. The research proposal was submitted with the following title: *The effect of minimum wages on employment. The case for Mexico.*

1.1 Theoretical approaches on minimum wage effects

The theoretical and empirical research on minimum wages developed during the last seventy years has been extensive. In order to understand the mechanisms of how minimum wage can affect the labour market, this section aims at summarizing the main theoretical approaches on the effects of an introduction, or a rise, of the minimum wage on the labour market. Subsection 1.1.1 describes the standard competitive labour market model on minimum wages, while Subsection 1.1.2 details an extension of the standard model allowing for an uncovered sector. Subsection 1.1.3 analyses the monopsonistic competition labour market model. Depending on the specific research question, the respective revision of the previous impact evaluation studies of minimum wage on wages, earnings distribution, and employment, is included in the corresponding chapter below.

1.1.1 The standard competitive labour market model

The simplest version of the standard competitive model assumes that the labour force is homogeneous and the skill level and effort put into the labour activities are identical across workers and given exogenously. In consequence, the wage rate is also the same for all workers due to output (y) depends exclusively on the quantities of inputs used, not on the productivity of workers. In addition, there is no room for non-compliance with the minimum wage regulations.

Following the notation employed by Card and Krueger (1995), the factors used by firms to produce output (y) can be classified into labour (L), and non-labour (K) inputs:

$$y = f(L, K) \tag{1.1}$$

The critical assumption of the classic model is that the wage rate (w), and the price of non-labour inputs (r) is set exogenously by the market, that is, firms are price-takers in the input market. Thus, Card and Krueger (1995) asserted that the optimal choice for labour input, conditional on the output choice is determined by the following function:

$$L = h(y, w, r) \tag{1.2}$$

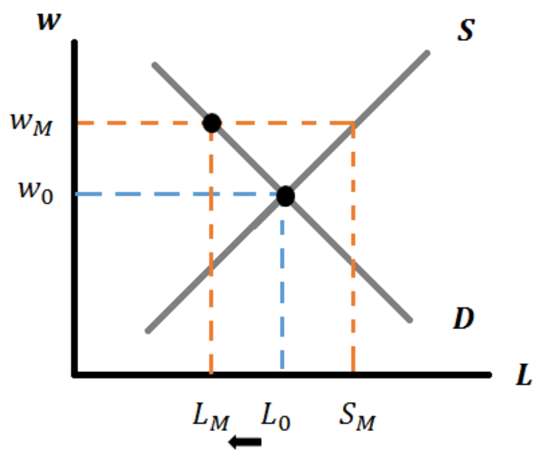
Hence, Card and Krueger (1995) state that under the assumption of constant returns to scale, the elasticity of conditional labour demand with respect to wage (η) is related to the elasticity of substitution implicit in the production function (σ) and labour's share of total cost (α), by the following function:

$$\eta = -(1 - \alpha)\sigma \tag{1.3}$$

Equation (1.3) describes how labour demand changes as a consequence of variation of wages. This function expresses elasticity for a representative firm, but it ignores heterogeneous labour force and the lack of full compliance with the minimum wage regulations.

To simplify the analysis, Figure 1.1 summarizes the effect of the introduction of a minimum wage regulation for a representative firm. The initial levels of wage (w_0) and employment (L_0) are determined by the equilibrium of the labour demand and supply. After the introduction of the minimum wage, employment falls to L_M at the compulsory wage rate w_M.

Figure 1.1
Increase of minimum wage under the standard competitive model



Source: Adapted from Brown et al. (1982).

Therefore, as stated in Brown et al. (1982), the proportional contraction in employment ($\ln L_M - \ln L_0$) is equal to the proportional wage increment ($\ln w_M - \ln w_0$) multiplied by the elasticity of labour demand η.

Notice that the difference $(S_M - L_M)$ corresponds to the excess of labour supply after the introduction of a minimum wage. But, this difference does not necessarily constitute a measure of unemployment, because there may be workers willing to work at the minimum wage level but not necessarily looking actively for a job. It expresses the number of workers (or working hours) willing to work at the minimum wage level.

There are several extensions for the basic model. The most common of them incorporates some kind of heterogeneity to the model. For instance, the *Welch-Gramlich-Mincer Two Sector Model*, which is described in the following subsection, differentiates a segment of the workforce paid below the minimum wage from those workers fully covered by the law regulations. This model predicts that the level of employment is reduced in the covered sector, while the impact on the uncovered sector might be positive or negative. Other theoretical perspectives consider different levels of skills among the labour force. Independently of discrete or continuous characterizations of the skill distribution, these models predict that workers with lower wage (or sectors with a higher proportion of minimum wage workers) will suffer a deeper unemployment effect (Brown et al., 1982). According to Card and Krueger (1995) the logic behind this conclusion is that the minimum wage generates a rise in the price of skills in affected industries, leading to changes in the wage distribution, causing workers with the lowest wage to lose their jobs.

In summary, the classic model in their different versions unambiguously anticipate employment reductions as a result of minimum wages increases, at least for the directly affected workers.

1.1.2 The two sector labour market model

Recognizing the existence of a partial coverage of the minimum wage regulations in the labour market (which corresponds to the presence of *sub-minimum wage* workers), Welch (1974) developed a two sector model integrating the fact that not all firms are covered under the minimum wage provisions (or not all of them fulfill it). Mincer (1976) and Gramlich et al. (1976) expanded the model putting special emphasis on the unemployment effects. They argued that, given a minimum wage introduction, transitions are not restricted to the covered-uncovered sector, but also to the unemployment or even out of the labour market.

This model is particularly relevant for our analysis because currently it is the only minimum wage theoretical framework in which an informal labour market can be considered. Although there are differences between a Latin American informal labour market and an uncovered sector in US, the model depicts the effects in both covered and uncovered sectors after a minimum wage increase. To illustrate how the uncovered sector is distinguished in the *two sector model*, Card and Krueger (1995), described that during 1992 in US, 3.3% of all workers and 10.2% of all teenagers reported earnings below the respective hourly minimum wage. In contrast, the informal sector in developing countries is not restricted to wage rates below the minimum wage, it is characterised by the lack of recognition of the labour relationship from the employer, which implies that the legal regulations are not necessarily fulfilled, including for instance, the minimum wage, access to social security and other benefits by law.

To describe the model, we start by assuming that all workers are identical in both markets. Following the notation by Card and Krueger (1995) to define the labour demand functions in the covered and uncovered sector:

$$\log L_c = \eta_c \, w_c + \text{constant} \tag{1.4}$$

$$\log L_u = \eta_u \, w_u + \text{constant} \tag{1.5}$$

where L_c and L_u are the level of employment respectively in the covered and uncovered sectors, w_c and w_u are their corresponding wage rates, and η_c and η_u are the elasticities of employment demand in each sector.

Given equation (1.3), a minimum wage setting would reduce the employment level in the covered sector, but the effect on the uncovered sector depends on the specific assumptions of the model. In the benchmark model, total labour market supply depends on the weighted average wage of the two sectors, while the labour supply in the uncovered sector is the residual of the labour supply in the covered sector. In this case, if wage rates are similar in both sectors, the wage variation in the uncovered sector is expressed by the following equation:

$$\mathrm{d}\log w_u = -\frac{c}{1-c} \times \frac{\zeta - \eta_u}{\zeta - \eta_c} \times \log w_c \tag{1.6}$$

where c is the fraction of workers employed in the covered sector before the minimum wage introduction, and ζ is the elasticity of supply of the overall labour market.

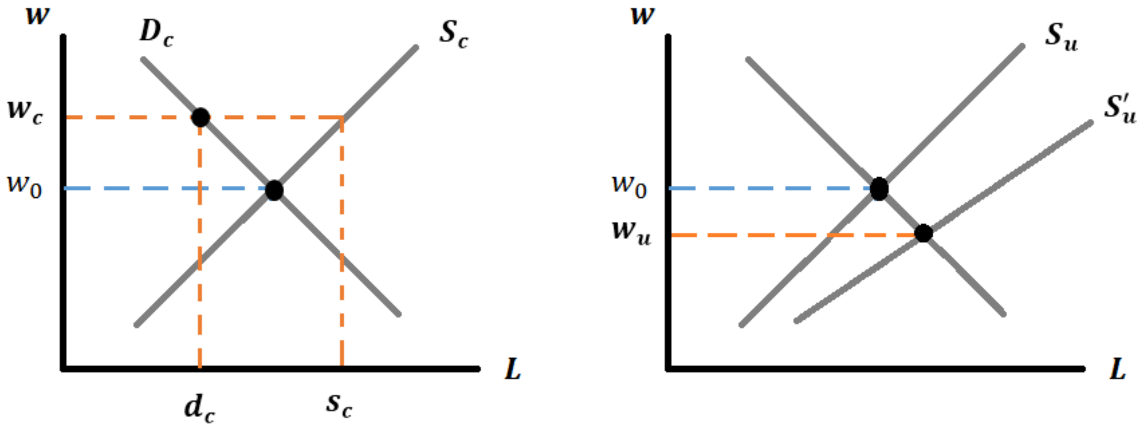
Given that η_c and η_u are negative, equation (1.6) predicts that a minimum wage increase will impact negatively the wage rate of the uncovered sector. As a consequence, by equation 1.5, the employment level in the covered sector is increased. Moreover, if the covered sector is relatively larger, then the reduction in wages in the covered sector would be significant.

Following Card and Krueger (1995), the intuition behind this effect is the following: if the share of workers in the covered sector is bigger, a given percentage employment reduction in this sector, L_c, will generate a larger percentage increment in labour supply to the uncovered sector, which can be only absorbed by a deeper wage cut.

Gramlich et al. (1976) summarizes very clearly the impact of the minimum wage increase under this framework. In Figure 1.2 we can observe that setting the minimum wage at w_c (from the original w_0) generates an excess of labour supply similar to that discussed in Figure 1.1. But, allowing for an uncovered sector, this excess of supply is transfered to this sector. It creates a decline of wages in the uncovered sector, and an increase in its level of employment.

Mincer (1976) asserted that these predictions are not necessarily robust to the presence of unemployment. So, the residual of workers not employed in the covered sector after the minimum wage introduction are not automatically absorbed by the uncovered sector. They effectively can move to the uncovered sector, or they can opt for unemployment queuing up for covered sector jobs, or even opt out of the labour market. This depends on the gap between covered sector wages and the monetary value of non-participation, and on the elasticity of employment demand. Card and Krueger (1995) asserted that if employment demand in the covered sector is relatively inelastic, then the minimum wage introduction creates a rise in w_u and a loss in employment in both sectors.

Figure 1.2
Minimum wages under competitive labour market allowing for an uncovered sector



Source: Adapted from Gramlich et al. (1976).

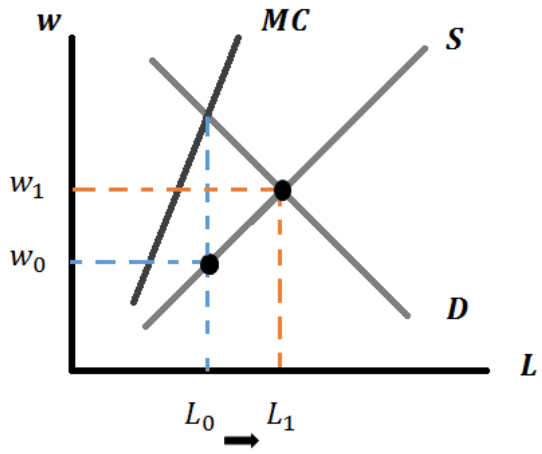
(a) Covered Sector **(b)** Uncovered Sector

Independently of the effect on the uncovered sector, this model predicts a reduction of the level of employment in the covered sector.

1.1.3 The monopsonistic competition labour market model

The fundamental concept behind the monopsonistically competitive labour market model is that firms have some level of discretion to determine wages. In this framework, and according to the general description in Brown et al. (1982), in the absence of minimum wage settings, the marginal cost of the labor factor always exceeds the supply price. Thus, as illustrated in Figure 1.3, labour is hired until marginal cost and labour demand are equal, at employment level L_0 and wage rate w_0. If the minimum wage is set below the competitive wage w_1, employment would increase due to the fact that firms have enough space to absorb the cost of the additional labour hired. Increases to the minimum wage beyond w_1 would reduce employment by even a higher magnitude than in the standard model.

Figure 1.3
Increase of minimum wage under monopsony



Source: Adapted from Brown et al. (1982).

Monopsony has been conceptualized as an extreme case in the labour market, commonly illustrated in textbooks by the example where a single company in a small town hires all the labour force having total discretion in setting wages. Even though in this context monopsony could look implausible for the current labour market configurations, the idea of monopsony goes beyond this basic example. Dickens et al. (1999) argued that the extreme outcome is indeed the perfect competition labour market model, in which the labour supply curve is perfectly elastic. It is not credible that when employers diminish the wage rate offered, even in marginal amounts, they will immediately lose all their workers.

In order to differentiate this case of a single employer firm from a more general framework, some studies have used the term *dynamic* monopsonistic model (Hirsch et al., 2015; Schmitt et al., 2013). In these models the source of firms' discretion to set wages is originated from frictions in the labour market, such as hiring costs, spatial location of the firms, and search costs, among others. Under this framework, minimum wage increases lead to a reduction of the turnover costs for workers with lowest wages, so employment is not negatively affected. For the purposes of this study, as we do not explore the origins of the employers market power, the term monopsonistic model is used to denote both dynamic and baseline models. But we keep its basic conclusion: minimum wage increases do not necessarily cause a decline in the employment level.

Dickens et al. (1999) developed a more detailed model based on the Dixit-Stiglitz monopolistic competition model, but applied to the labour market, which allows them to describe the impact of minimum wage on the different kinds of firms in the same labour market.

In this model, the marginal product revenue of the labour factor ($MPRL$) faced by each firm i in a given industry, is given by the following function:

$$MPRL_i = M(L_i, A_i); \tag{1.7}$$

M is a decreasing function of L_i, the employment level, and an increasing function of A_i, which represents productivity shocks. The labour supply curve, on the other hand, is described by the expression:

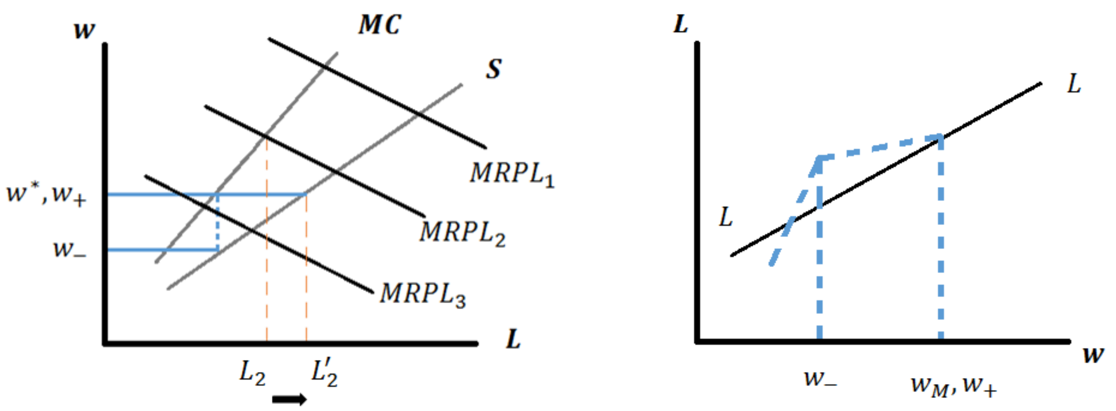
$$L_i = f(B_i, w_i/w) \cdot L(w); \tag{1.8}$$

B_i are supply shocks for firm i, that according to Dickens et al. (1999) could be different kinds of non-monetary differences in the quality of the jobs across firms. The term w_i/w represents the relative wage offered by firm i, and finally L is the aggregated labour supply for the specific industry which is positively related to the average wage w. It is important to emphasize that under perfect competition, labour supply is perfectly elastic with respect to variations in the relative wage, but if this is not the case, there exists some extent of monopsony.

Dickens et al. (1999) asserted that, in absence of minimum wage regulations, firms determine the wage offered to maximize profits, so each firm chooses the level of employment where the $MRPL$ is equal to the marginal cost of labour (MC). Thus, the wage paid by each firm in the labour market is heterogeneous given by the specific productivity and supply shocks faced. Figure 1.4 describes the different kind of impacts of minimum wages on employment depending on the level of the initial wage offered (in absence of a minimum wage), w_{0i}.

Following Dickens et al. (1999) notation, for analytical ease to rank initial level of wages, we denote initial wage greater than the minimum wage as w_+, while initial wages sufficiently lower than w_M correspond to w_-. Thus, Panel (a) describes the three different cases once minimum wage (w_M) is introduced:

Figure 1.4
Minimum wages under monopsonistic labour markets



Source: Adapted from Dickens et al. (1999).

(a) Three possible regimes

(b) The effect on employment

1. $w_{0i} > w_+$: even though the wage rate does not have to be modified for those firms that initially paid wages higher than the minimum wage setting (curve $MRPL_1$), the average wage in the industry has changed. Although for modelling purposes, it can be assumed that the average wage does not affect the ranking of firms in terms of wages, the set of firms above the minimum wage (in this case w_+) is not the same. Anyway, the effect on employment is ambiguous as we can observe in equation (1.5). Average wage appears in the denominator in the relative wage term, but also affects positively the industry employment, $L(w)$.

2. $w_{0i} < w_M$: if the marginal revenue of product of labour leads to initial wages moderately below the minimum wage level (curve $MRPL_2$), it is optimal for firms to pay the minimum wage accepting all workers attracted by this increase. Thus, employment is going to be higher due to the minimum wage introduction. In the

figure, the increase is illustrated with the change in employment from L_2 to L_2'. Again, the key point is that market power allows firms to raise wages but for a level still below the competitive wage.

3. $w_{0i} < w_-$: for firms whose marginal revenue of product of labour corresponds to $MRPL_3$, the initial wage rate offered is considerably lower than the minimum wage level (less than some w_-), so that it is not profitable to hire all workers attracted by minimum wage w_M. These firms have to fulfill the minimum wage requirements, setting the employment (constrained by the labour demand side) at $MPRL = w_M$, which is below their original levels. The reduction in employment is going to be lower as w_- approaches to w_M, even showing increases as we discussed in the previous case.

Following the assumption in Dickens et al. (1999), those firms which $w_{0i} > w_+$ are unaffected. Panel (b) of Figure 1.4 summarizes the effect on employment depending on the initial wages paid by firms. Line LL expresses the relationship between the initial wage w_{0i} and employment before the minimum wage setting. The new level of employment is represented by the dotted line, where only for the lowest levels of w_{0i} a reduction is going to be observed. As productivity increases and w_{0i} is closer to w_M, the change in employment is less negative until certain cutoff where it becomes positive. The total impact on employment is obtained aggregating the effects for each firm.

In conclusion, under monopsonistic labour markets, employment increases as a consequence of the introduction or raising of minimum wages are theoretically supported. Nevertheless, it is necessary to restate that the effect is not uniform, it depends on the marginal revenue product that each firm faces. For the purposes of the dissertation, it is important to remark that given that the 2012' minimum wage increase took place at the national scale without differencing economic sectors, the evaluation of the effects of the minimum wage is going to be developed on the whole labour market, not only on specific affected sectors where the conclusions can be biased.

1.2 Data and source of identification

1.2.1 Data source: the National Survey on Employment and Occupation (ENOE)

Every empirical chapter addresses its own research question, which implies the use of different methodological approaches. As a consequence, the dependent variables used, the period of analysis, and the aggregation of the data also change depending on the specific objective of the chapters. In spite of this, the data source is the same throughout this research: the National Survey on Employment and Occupation. This section describes the broad features of the data.

ENOE is a publicly available database, which is published on a quarterly basis by the National Institute of Statistics and Geography (INEGI). This survey constitutes the source for the official information in Mexico on unemployment, informality and participation rates.[5]

ENOE's sample is representative at national and state level by the use of expansion factors adjusted by the population estimates of each year, developed by the National Council on Population (CONAPO), based on the National Census of 2010.

The information is collected continuously over the year, and the survey is conducted at a household level using a sample size fixed at 120,060 dwellings every quarter, disaggregated by households and individuals. Thus, although the number of dwellings remains constant, the total number of individual observations by quarter may change. Each dwelling in the sample is interviewed during five consecutive quarters, and there is a rotation sample system such that every quarter one fifth of the sample is replaced by a new

[5]Even though the micro-data information is available since 2005, ENOE is the result of the fusion of two former surveys: the National Survey on Urban Employment (ENEU), with coverage from 1983 to 2004, and the National Survey on Employment (ENE), covering the period 1994 to 2004. The integration of these surveys was carried on with the purpose of providing the main features of the Mexican labour market in a single source for both urban and rural settings. Although the questionnaires changed between the surveys, there are available long time-series data for some variables, specifically for unemployment and participation rates.

subsample of the same size.[6] The number of observations fluctuates around 2.4 million every quarter.

ENOE collects data on all individuals in the household older than 11 years old. But, as the legal minimum age for performing labour activities is 15 years old,[7] the calculation of the official figures on active labour market and employed population does not consider individuals aged less than 15. Since one of the central objectives of this study is to incorporate the informal sector to the minimum wage evaluation, we consider all those individuals included in the sample independently of their age, and independently also of the contractual relationship with the employer.

From Chapters 2 to 4, we use data at the individual level. Given that it is possible to observe the same individual at most five consecutive quarters, panel data models are not used. All the Difference in Differences specifications in these chapters use pooled OLS models. The period of analysis for the main specifications is 2012Q1 to 2013Q4. In contrast, Synthetic Control Method procedure in Chapter 5 requires the use of regional aggregated data. So, we make use of the delimitation of metropolitan areas by CONAPO to aggregate all the information by metropolitan areas (see Figure 5.1 and Appendix 5.A for the geographical location and a listing of the metropolitan areas, respectively). The period of analysis in this case is 2005Q1 to 2014Q4.

Concerning the dependent variables used, for the analysis of the effects on wages (Chapter 2) the outcome variable is the real hourly wage. To analyse the impact on the earnings distribution (Chapter 3), the dependent variable corresponds to the recentered influence function of real hourly wages,[8] although for some robustness tests, the recentered influence function is estimated using real monthly wages. ENOE reports nominal wages in current pesos. Real wages are obtained deflating them using the National Consumer Price Index, obtained also from INEGI (Appendix 2.A describes all the process of data generation process).

[6] New entries are randomly selected with unequal probabilities from stratified sampling frame (Carriquiry and Majmundar, 2013).

[7] Until December 2014 the minimum age for working was 14.

[8] The details of the recentered influence function are explained in Section 3.5.1.

In Chapter 4 we estimate the effect on the probability of being under different labour status. Following the ILO recommendation, ENOE classifies individuals into active and inactive labour market population. Active population refers to individuals that, during the week of interview are currently working, or in the previous two weeks developed specific activities to find a job. Inactive individuals are those people not working and not looking for a job. Within the active labour market population, there are employed and unemployed workers. These two different categories are going to be used for the effect on labour status. Moreover, employed workers are also classified into formal and informal workers. In the same way, following the ILO conceptual framework, ENOE uses the Hussmanns' matrix to identify and sub-categorise informal workers into waged, unwaged, and self-employed. Separate effects for each category are also estimated as well as the overall effect on informal workers.

Chapter 5 tests the robustness and validity of the employment effects estimated in Chapter 4 by the use of Synthetic Control Method at the metropolitan area level. After the aggregation of the data in ENOE, instead of evaluating the effect on the probability of having certain labour status at the individual level, we use as dependent variables labour market rates by metropolitan areas: active labour market rate, employment rate and informal employment rate (considering also the subcategories for informal workers).

The set of control variables also depend on the econometric approach used, but in general terms they do not change. We control for age, educational attainment, gender, rural municipalities, and in Chapter 5 we also control for economic sector.

All the econometric models implemented in this dissertation have in common the use of the regional variation in 2012 as a source of identification, which is detailed in the following subsection.

1.2.2 Description of the intervention

From 1986 to 2012, minimum wage setting in Mexico was based on the classification of three minimum wages zones: A, B and C. This classification was based on the economic development of each municipality. On November 26, 2012 the Council of Representatives of CONASAMI agreed to change the configuration of the minimum wage zones, incorporating Zone B into Zone A.[9]

The main argument for this decision was that since 1988 the municipalities that belonged to Zone B had experienced a development process that had led them to similar economic conditions to those observed in Zone A.[10] In addition, this overhaul represented an important step towards reaching a unique minimum wage level in Mexico.[11]

This intervention in the minimum wage zones for the Mexican labour market is used as the source of identification to evaluate the minimum wage impact on wages, the distribution of earnings, employment and informality. Using the term of Angrist and Pischke (2008), these observational data (not generated by a randomized trial) are going to be utilized to "approximate a real experiment".

A fundamental characteristic of the intervention is that it was implemented without any anticipation from the labour market, so it is not necessary to model any anticipated responses. The meetings between Federal Government, CONASAMI, employers organisations, and workers representatives were just covered in press as the usual meetings to agree the nominal increase for 2013 (which usually is in accordance to the observed inflation rate). One day after the announcement, the legislation it came into force (27 November 2012).

Figure 1.5 describes the pattern of the monthly minimum wages for the three different zones. In monetary terms, the increase observed in the former Zone B was $53.00 MXN, which represents a rise of 2.9% in nominal terms. According to ENOE and with data for 2012Q3, which is the immediate quarter before the policy change, 55 municipalities with

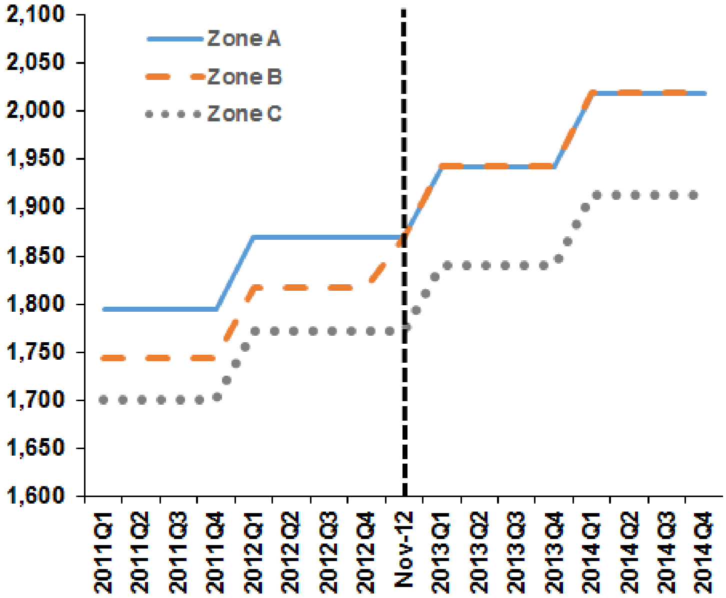
[9]Appendix 1.A lists the states and the municipalities included in each wage zone.

[10]Source: National Official Bulletin (*Diario Oficial de la Federaciǿn*). November 26 2012. Accessed on March 3, 2015.
`http://www.conasami.gob.mx/pdf/resoluciones/CNSM11261.pdf`

[11]In fact, a subsequent minimum wage increase took place on 20 March 2015. The Ministry of Labour announced that an agreement was reached among Federal Government, CONASAMI, employers associations and workers representatives to have a unique national minimum wage value. The increase for Zone B was divided into two parts; a half of the increment was put into effect in April and the other half in October 2015. Source: Ministry of Labour.

approximately 11.54 million inhabitants (9.7% of the total population in Mexico) were potentially affected by this intervention.

Figure 1.5
Monthly minimum wage by zones
(current Mexican pesos, 2010-2014)



Source: own calculations with data retrieved from ENOE.

Panel (a) of Figure 1.6 shows the geographical distribution of the minimum wage zones valid until November 27, 2012. It makes evident that the zones' classification was not done in a regional basis. For example, all the municipalities in 21 out of 32 states belonged to Zone C. But, there are also cases where one single state can have municipalities classified in the three different wages zones, as Sonora in the northwest, and Tamaulipas and Veracruz in the west of Mexico. Panel (b) describes the distribution of the active labour market population among the three wage zones for 2012Q3, which corresponds to the last period under this three zones classification. More than 5.3 million of individuals of the former Zone B (10.2% of the labour force), were incorporated into Zone A. Zone C remained unchanged.

With respect to the treated Zone B, it is important to mention that a considerable proportion of its total population, 71.1%, was concentrated in two cities. Approximately 4.4 million of inhabitants lived in the Metropolitan Zone of Guadalajara and 3.5 million of inhabitants lived in the Metropolitan Zone of Monterrey, these two metropolitan areas account for 13 of the 55 municipalities in the zone. The rest of Zone B includes municipalities in the states of Sonora, Jalisco and Veracruz.[12]

Figure 1.6
Minimum wage zones (1986-2012)

(a) Geographical Distribution

MW Zone	Population	%
Zone A	11,811,875	22.75
Zone B	5,300,422	10.21
Zone C	34,814,753	67.05
TOTAL	51,927,050	

(b) Active Labour Market Population by wage zones (2012Q3)

Source: Own elaboration with data retrieved from CONASAMI and ENOE. See Apeendix 1.A for the full list of states and municipalities by wage zone.
Expansion factors used for population statistics.

With respect to the distribution of the *minimum wage segment* of the workforce — understood as those waged workers with earnings equal or lower than the minimum wage value— across the wage zones, around 426,000 workers were employed in the former Zone B in 2012Q3, which represents 6.1% of the minimum wage workers. Meanwhile, 13.9% and 78.0% of the minimum wage workers were employed in Zone A and Zone C, respectively. The fact that the former Zone C had a bigger proportion of the minimum wage workers is explained by the own design of the wage zones. This zone covers those municipalities with lower levels of economic development, including all the rural areas.

[12]The data for the population in each metropolitan area was obtained from CONAPO. Every five years CONAPO publishes an inform of the urban ambit in Mexico, including the population for each metropolitan area. The last available report corresponds to 2010. In order to make the information comparable, the data used for the total population in the wage zone B from ENOE correspond to the last quarter of 2010.
`http://www.conapo.gob.mx/es/CONAPO/Zonas_metropolitanas_2010`. Accessed on March 3, 2015.

1.3 The Mexican labour market context

1.3.1 Minimum wage policy in Mexico

According to the Minimum Wage Fixing Recommendation (R135, 1970) of the International Labour Organization (ILO), the fundamental objective of minimum wage setting is to give workers the most elemental social protection. It should constitute an element designed to overcome poverty and to ensure the satisfaction of the needs of all workers and their families. In addition, the document establishes that minimum wage rates should be revisited and adjusted continuously to take account of changes in the cost of living and other economic conditions.[13]

The concept of the minimum wage was considered for the first time in Mexico in the Federal Constitution of 1917, establishing that it must be enough to satisfy the normal needs of a head of household in material, social and cultural terms, and to promote the compulsory education of children. Furthermore, it was specified that the minimum wage must be exempted from any kind of deduction by employers, including social security fees.[14]

In the first stage of the minimum wage setting framework in Mexico, the minimum wage level was set by special commissions at the municipality level, subordinated to the Conciliation Committees installed in every state. The heterogeneity in both, the magnitude and the methodology of the minimum wage setting, led to the creation in 1963 of the National Commission on Minimum Wages, as well as 111 Regional Commissions. The purpose was to standardize the setting mechanism and to consider the specific features of economic development at the regional level. This system remained active until 1986[15] when the Federal Congress approved a reform establishing that a single commission

[13] Source: ILO website. Accessed on February 27, 2015. http://www.ilo.org/dyn/normlex/en/f?p=NORMLEXPUB:12100:0::NO:12100:P12100_INSTRUMENT_ID:312473:NO

[14] Article 123 of the Political Constitution of the Mexican United States. Accessed on February 15, 2015 from the Mexican Congress website.
http://www.diputados.gob.mx/LeyesBiblio/pdf/1_150917.pdf

[15] Although with several modifications throughout 23 year of functioning. At the end of its application there were only 67 regional Commissions.

(CONASAMI) would set the minimum wage level for only three different wage zones: A, B and C. This system was operating under this framework until November 2012, when the policy change of our interest took place in which Zone B was incorporated with Zone A. Then, from 27 November 2012 there were only two minimum wage zones defined as A (former zones A and B), and B (former Zone C).[16] [17]

The 1986' classification of the minimum wage zones was not geographical, it depended on the level of economic development of each municipality. Although in terms of surface area, zones A and B seem to have much lower coverage than Zone C, the biggest cities in the country were included in these zones. Thus, inter alia the Metropolitan Zone of Mexico City, with one fifth of the total population in the country, was included in Zone A, while Guadalajara and Monterrey (the second and third major cities, respectively) were contained in Zone B. In turn, Zone C included all the rural area and smaller urban concentrations with lower levels of economic development.

A key feature of the minimum wage policy in Mexico is the fact that minimum wage has suffered a constant loss of its purchasing power during the last 40 years. Figure 1.7 shows the evolution of the value of the daily minimum wage in real terms.[18] Recurrent hyperinflation periods, as well as the lack of mechanisms to recover the real value of the minimum wage have reduced by more than two thirds its purchasing power.

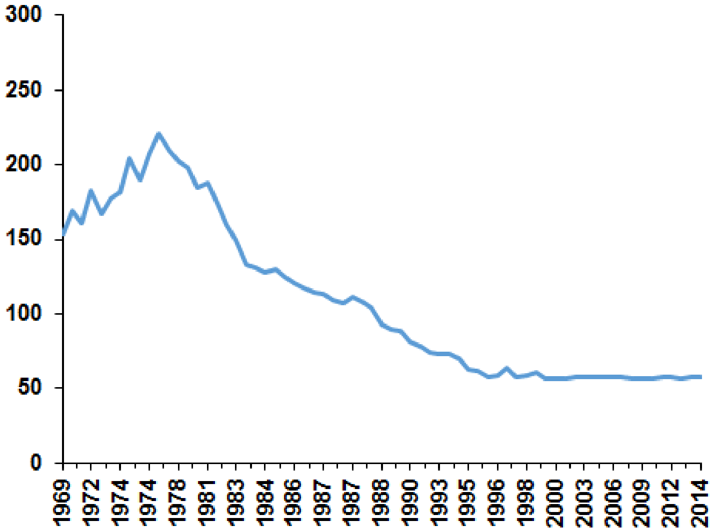
The minimum wage reform of 1986 took place after recurrent episodes of economic crises where the public finances, the exchange rate and especially the level of prices were severely affected (according to INEGI, the average annual inflation rates for the decades of the 70's, 80's and 90's, respectively were 15.3%, 69.7% and 20.2%). Thus, at the end of the 1980's, the Mexican government designed a set of public policies —the so-called *Economic Solidarity Pacts* and *Incomes policies*— with the aim of achieving macroeconomic

[16]Afterwards, two subsequent increments were applied to Zone B in 2015 in order to reach the value of Zone A. Thus, form October 2015 there is a single minimum wage in Mexico

[17]Source: CONASAMI. Accessed on February 19, 2015.
http://www.conasami.gob.mx/fig_salario.html

[18]Minimum wage in Mexico is set in daily terms, not hourly as in the United States or the United Kingdom.

Figure 1.7
Real daily minimum wage
(Mexican pesos 1F December 2010,1969-2014)



Source: Own calculations with data from CONASAMI and INEGI.

stabilization, but specially to contain hyperinflation. Under this framework, minimum wage was also used as an mechanism to constrain the escalation of prices by controlling wage increases (Woodruff, 1999). Section 3.3 in Chapter 3 describes in a more detailed way how the minimum wage in Mexico became a reference rate for wage and price setting.

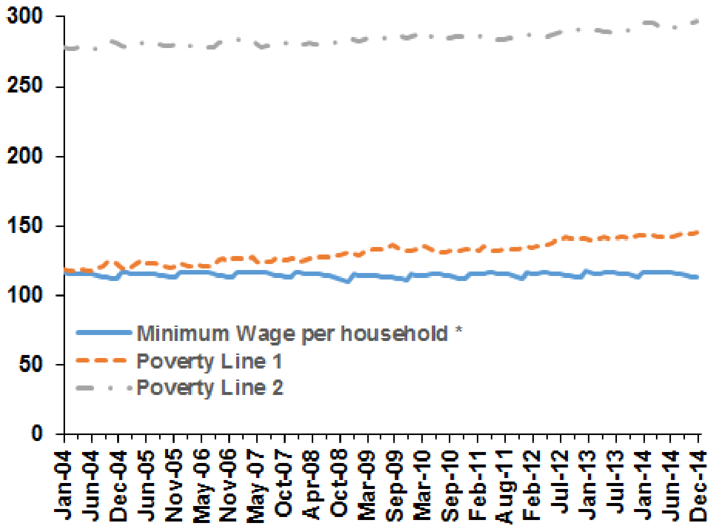
This set of macroeconomic policies can be considered as successful due to the price stability achieved during the last 20 years: for the decade of 2000's, the average annual inflation rate was 4.9%, while for the period 2010-2016 it was 3.6%.[19] In spite of this, the policy of using the minimum wage as a price container has remained unchanged despite the evolving macroeconomic conditions. The minimum wage has been set annually by considering mainly the expected inflation for the next year, but adjustments as a results of mistakes in expectations have not been considered barring special occasions.[20] In consequence, from 1974 to 2014 the purchasing power of the minimum wage in Mexico decreased by 73.8%.

[19] Annual inflation rates calculated with data from INEGI.

[20] Since 1990, there have been seventeen occurrences in which the real value of the minimum wage has decreased with respect to the previous year, but only 3 times out of those 17 there have been adjustments in response to the loss of purchasing power of the minimum wage. The most recent adjustment took place in 1996.

In addition to the erosion of the real minimum wage, a greater concern is the fact that minimum wage is not even enough to satisfy the most fundamental requirements of the households. To illustrate this point, Figure 1.8 describes the differences between the income of a household with earnings equal to the minimum wage and the monetary value of the national poverty lines defined by the National Council for Evaluation of Social Development Policy (CONEVAL).[21] Poverty Line 1 corresponds to the Minimum Welfare Line that considers exclusively the monetary value of the food products needed for the basic caloric intake for a human being. It is also referred as the *Extreme Poverty Line*. Poverty Line 2 *Standard Poverty Line* includes also the monetary value of basic services such as education, transport, housing and clothing.

Figure 1.8
Real daily minimum wage and poverty lines
(Mexican pesos 1F December 2010, 2004-2014)



* Characteristic household assuming four integrants, for which two are working and two are economic dependants.
Source: Own calculations with data from CONASAMI and CONEVAL.

In order to match the poverty lines per household and the monthly minimum wage, we follow previous calculations in which the minimum wage per household is constructed considering a representative household of four members: two of them working with a salary

[21]Poverty lines are calculated in a monthly basis by CONEVAL, which is an autonomous institution responsible for providing the official measures for poverty in Mexico and for evaluating public policies on social development.

that corresponds to the minimum wage, and the remaining two members are economic dependents (Gob.Distrito-Federal, 2014). Under this conservative scenario,[22] household earnings were 22% below the *Extreme Poverty Line*, and 62% from the *Standard Poverty Line*.

So, even assuming full compliance of the minimum wage regulations, two minimum wage workers do not have enough earnings to satisfy the basic needs of a household. In fact, for the representative household in Figure 1.8, it is necessary to earn 2.5 times the current value of the minimum wage in order to reach Poverty Line 2.[23]

Thus, this subsection provides a general description of the minimum wage policy in Mexico, including two important remarks. First, as a consequence of the use of the minimum wage as an instrument for inflation container, minimum wage has decreased more than 70% in real terms during the last four decades. And second, the current value of the minimum wage is not enough to escape from poverty.

1.3.2 International comparison

In order to put into perspective the minimum wage policy followed in Mexico, this subsection compares the value of the minimum wage in Mexico with respect to different country samples. In addition, it also contrasts the trends observed in productivity of the labour factor across Latin American countries.

Figure 1.9 shows the value of the annual minimum wage in 2013 for the country members of the Organisation for Economic Co-operation and Development (OECD). Minimum wages are expressed in US Dollars Purchase Parity Power (PPP). Mexico not only has the lowest minimum wage within OECD members ($1,750 USD), its minimum wages furthermore represents only 13% of the average minimum wage of the organisation ($13,190 USD). Moreover, if we look at the relative value of the minimum wage in relation to the median income within every country, Mexico exhibits the second lowest relative minimum

[22] According to the ENOE, the average number per children for the employed population is 2.1, while for those households with earnings equivalent to the minimum wage, the average is 2.8. (See Table 1.1)

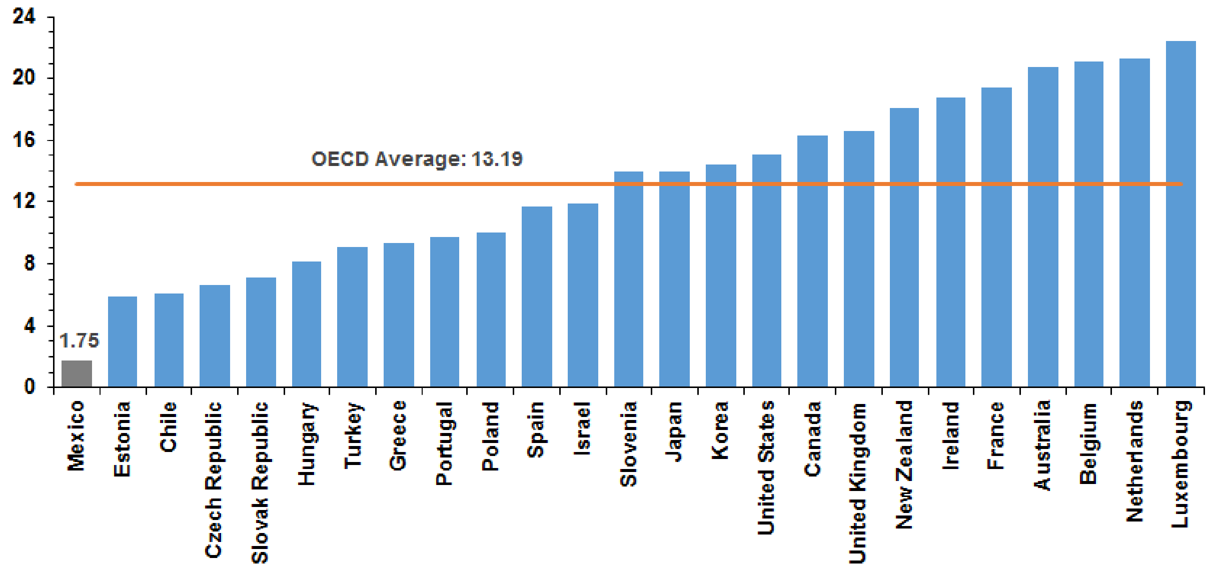
[23] Indeed, according to the proposal by the Governor of Mexico City (Gob.Distrito-Federal, 2014), gradual increases to the minimum wage should be implemented until Poverty Line 2 is achieved.

wage, only higher than Czech Republic. Minimum wage in Mexico represents 36.8% of the median income, while the OECD average is 50.0%.[24]

Figure 1.9

Real annual minimum wage, OECD country members

(Thousand PPP US dollars, 2013)



Source: OECD

Even if the value of the Mexican minimum wage is compared with countries with similar geographical features and level of development, according to the United Nations Economic Commission for Latin America and the Caribbean (ECLAC), the minimum wage in Mexico in 2013 was one of the lowest in the region, only above Venezuela.

More relevant is the fact that practically all the countries in the region have suffered strong episodes of crises and hyperinflation (even deeper than in Mexico), but in general there have been efforts to implement public policies oriented to recover the purchasing power of minimum wage. As we can observe in Figure 1.10, only Venezuela, Mexico and Paraguay exhibit decreasing levels for the three periods showed in the graph (1990, 2005 and 2013).[25] On the other hand, there are countries that exhibit important trends of growth in the real value of the minimum wages, as Brazil, Honduras, Uruguay and

[24]Source: OECD. Accessed on March 28, 2016. `http://stats.oecd.org/`

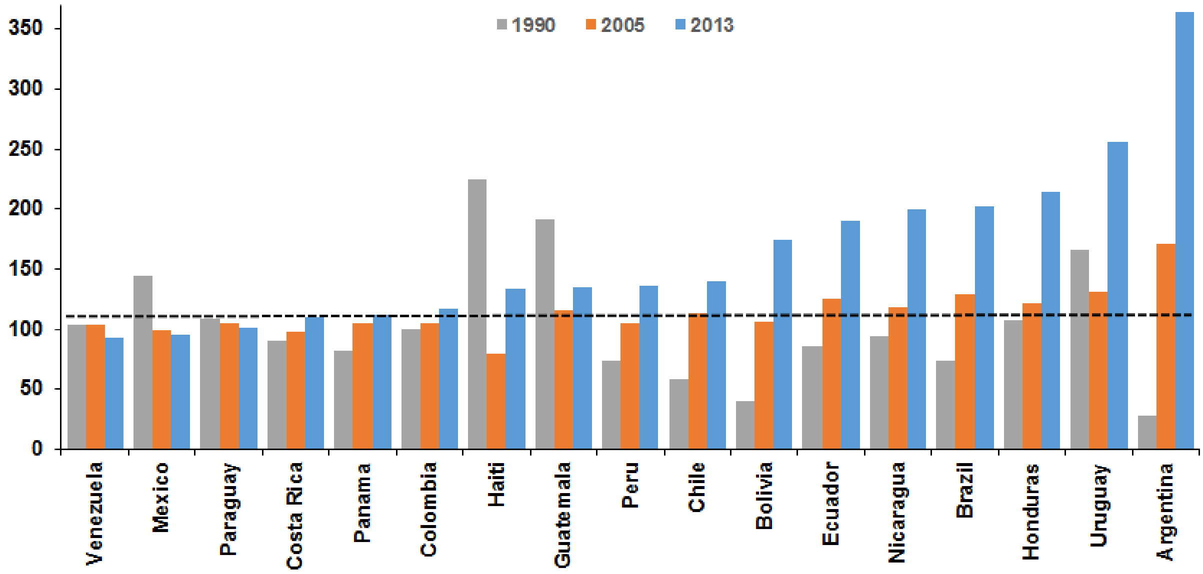
[25]The United States suffered a similar episode. From 1980 to 1990 there were no changes in the federal minimum wage, occasioning a loss of more than 30% in its real value.

Argentina.

Figure 1.10

Real annual minimum wage, selected Latin American countries

(Average annual index, 2000=100)



Source: ECLAC.

Maurizio (2014) describes that in Argentina, for example, after a decade of declining minimum wages in the 1990's, between 2003 and 2012 the minimum wage increased 200% in real terms. Similarly, in Brazil the recovery started in the 1990's, although with a more accelerated rate during the 2000's when the purchasing power of the minimum wage increased by 90%. Uruguay represents other case of an important recovery; in 2004 the minimum wage was 25% of the real value in 1969, but between 2005 and 2012 it rose by 180%.

One common argument against raising the minimum wage is that changes in wage levels must be justified by increases in productivity, not by decree, a position unambiguously supported by economic theory. Nevertheless, minimum wage defenders argue that minimum wage itself does not constitute a market price; it is created as a market regulation with the aim of protecting a specific segment of the labour force (Gob.Distrito-Federal, 2014). In addition, there are efficiency reasons that lead workers to increase the productivity as a result of rises in wage. The fair wage-effort hypothesis by Akerlof and Yellen

(1986, 1990) asserts that workers are going to contribute full effort to their jobs only if they receive the perceived fair wage, otherwise the effort depends on the distance from the fair wage.[26]

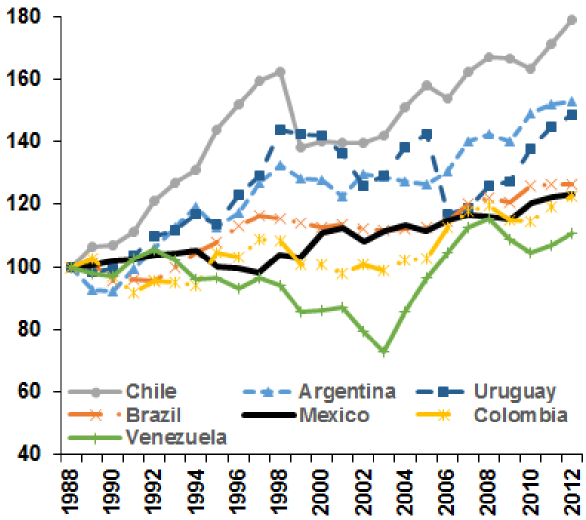
In order to explore the changes in the labour productivity level in some selected Latin American countries, Panel (a) of Figure 1.11 compares the worker productivity trends in Mexico and some other countries in the region. Mexico does not exhibit the same dynamism of Uruguay and Argentina, but it has a very similar trend to Brazil and Colombia, countries with an active policy for recovering the purchasing power of the minimum wage. Furthermore, Mexico keeps some distance with Venezuela, a country with a comparable trend in the minimum wage (as Figure 1.10 shows).

Moreover, Panel (b) of Figure 1.11 compare the trends followed by the minimum wage in Mexico and the productivity per worker measured as the GDP per worker. It is clear that there exists an important gap between the evolution of productivity and minimum wage. While the minimum wage in Mexico has decreased in real terms, the productivity of the whole economy has experienced a growth that, although modest, has a positive trend.

It is clear that the performance of the whole labour market does not necessarily correspond to the productivity for the workers who earn the minimum wage. Unfortunately, there is no available data on productivity for the specific segment of minimum wage workers, either in Mexico or for other Latin American countries. Nevertheless, we can compare the gap between minimum wage and productivity for similar countries to Mexico. Taking as a reference Brazil and Colombia, the trend followed by their levels of minimum wage is totally different to that observed in Mexico. For the case of Brazil, Panel (c) shows that during the last two decades the minimum wage growth is even higher than the growth in productivity. For Colombia, Panel (d), we can observe that the minimum wage trend is smoother and closer to the pattern followed by the productivity per worker.

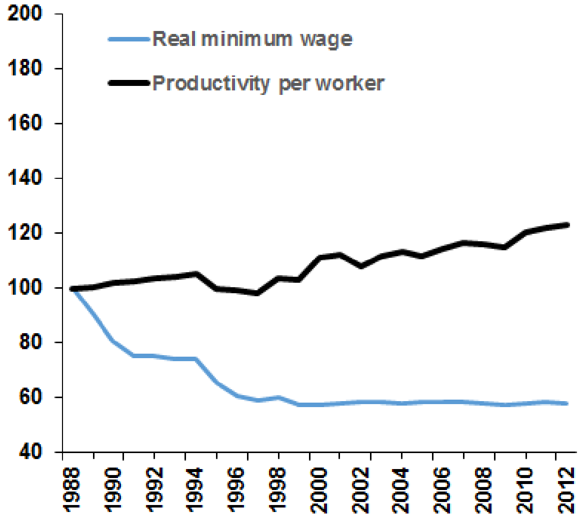
[26]The fair wage hypothesis establishes that $e = min(w/w*, 1)$, where e denotes effort supplied, w the actual wage, and $w*$ the fair wage, and effort is denoted in units such that 1 is the normal effort. Moreover, unemployment arises when $w*$ exceeds the clearing market wage.

Figure 1.11
Evolution of the productivity by worker and minimum wages
(Index of GDP per hour worked 1988=100, 1988-2012)



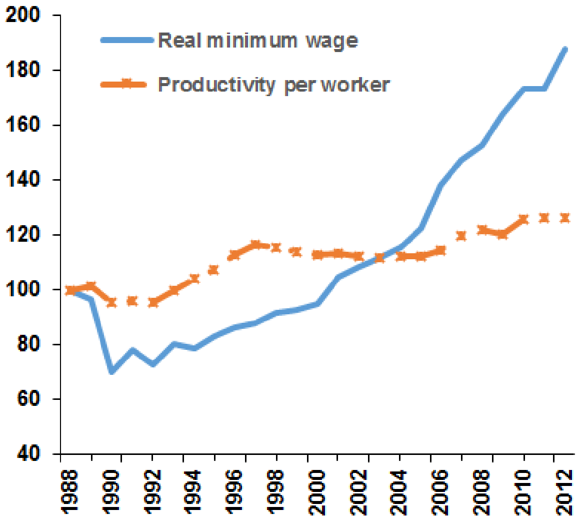
Source: Key Indicators of the Labour Market, ILO.

(a) Comparative in Latin America



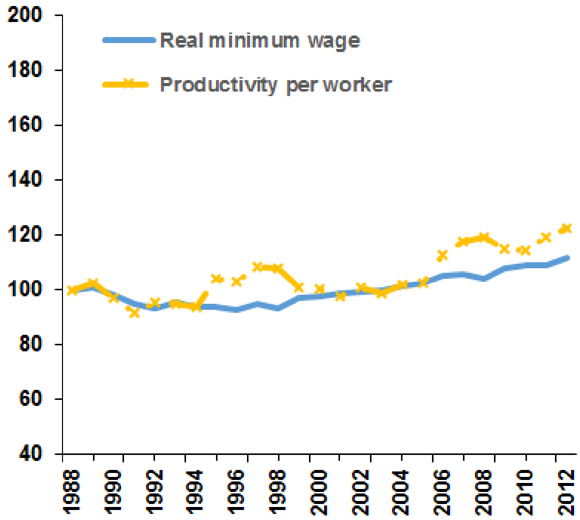
Source: Own calculations with data from CONASAMI and ILO.

(b) Mexico. Productivity vs minimum wage



Source: Own calculations with data from ECLAC and ILO.

(c) Brazil. Productivity vs minimum wage



Source: Own calculations with data from ECLAC and ILO.

(d) Colombia. Productivity vs minimum wage

Thus, the real minimum wage in Mexico seems to be atypical not only compared with respect to the OECD country members, but also in relation to Latin American labour markets. Furthermore, the trend followed by the productivity of the labour factor does not seem to support the loss of the minimum wage purchasing power.

1.3.3 Minimum wage segment of the labour force

We have explained that the real value of the minimum wage in Mexico has declined during the last forty years, but we have not said anything about its repercussions on the configuration of the Mexican labour market. This subsection describes the economic and socio-demographic characteristics of those workers earning a remuneration equivalent to the value of the minimum wage. The objective is to understand the size of the proportion of the workforce affected by minimum wage policies, as well as their main features in terms of schooling, age, formality condition and size of the firms in which they perform their labour activities.

It is necessary to start with a couple of remarks regarding the sample used. First, all the statistical and econometric analyses presented in the doctoral dissertation include workers aged 12 or older. Even though the legal minimum age for working prevailing in 2012 was 14 years old,[27] if we want to consider the informal labour market, it is necessary to include all those individuals active in the labour market, including workers aged below the legal restrictions.

Second, in order to present information compatible with the representative official figures at the national level presented by the INEGI, expansion factors are employed to present statistics at the population level, at least when something else it is not specified. It is important to specify that expansion factors are used only for the descriptive analysis in this chapter. The data for the econometric analysis in Chapters 2, 3, 4 and 5 do not use expansion factors to avoid any kind of biases in the estimates.

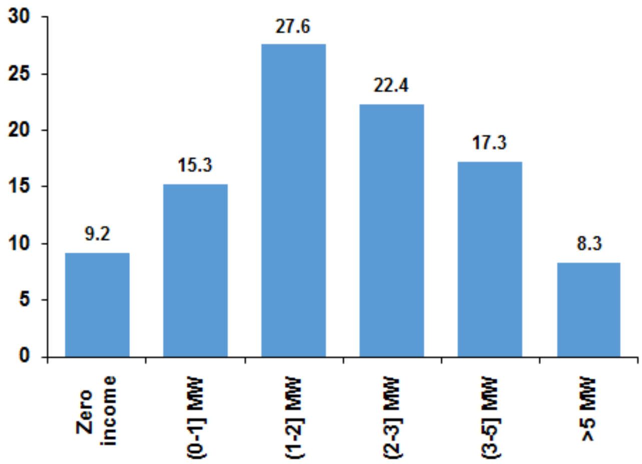
It is next necessary to consider the actual value of the minimum wage in Mexico. After the intervention, on November 27 2012, the nominal monthly minimum wage corresponded to $1,870 and $1,772 Mexican current pesos (MXN), respectively for wage zones A and B. To give a reference point, the equivalence in current US dollars was $145 USD for Zone A and $137 USD for Zone B.[28]

[27] In December 2014, Mexican Congress approved a Constitutional reform in which the minimum compulsory age for employment activities increased from 14 to 15 years old.

[28] The exchange rate used was $12.94 MXN per dollar, which corresponds to the daily average exchange

It is also essential to describe the number of workers potentially affected by the minimum wage policy change. In Mexico there exists the common belief that the minimum wage is so low, that there are actually no workers who earn it (see for example, Calva and Picard (2007) for a discussion concerning this matter). Nevertheless, according to the ENOE, for the third quarter of 2012 (just before the intervention) there were 6.79 million of workers earning at most the salary equivalent to the minimum wage (this figure excludes unpaid workers). This represents 15.3% of the employed population,[29] and 8.0% of the total working age population, which for our purposes corresponds to all those individuals aged 12 or older.

Figure 1.12
Wage distribution by multiples of minimum wages
(% of employed population, 2013 Q2)



Source: Own calculations with data from ENOE, INEGI.
Observations with non-specificated income are excluded.

Figure 1.12 describes the earnings distribution in terms of multiples of minimum wage of the workforce in Mexico. Around 9.2% of the workers perform some kind of labour activities without a payment. These workers are mainly employed in small family firms and in the agricultural sector in self-consumption activities. As it was stated above, more than 15% of the population earns at most one minimum wage. But, it is relevant the fact

rate for the fourth quarter of 2012. Source: Mexican Central Bank. Accessed on March 19, 2015. http://www.banxico.org.mx/portal-mercado-cambiario/index.html

[29] According to INEGI, the employed population corresponds to all those individuals who had labour activities (with or without remuneration) during the week when the survey took place, or individuals temporally absent from work but without interrupting their employment relationship.

that more than a half of the working population earns between one and three minimum wages. This implies that changes in the setting of minimum wage could affect a significant segment of the labour force. On the other hand, the proportion of workers earning more than five minimum wages represents less than 10% of the employed population.

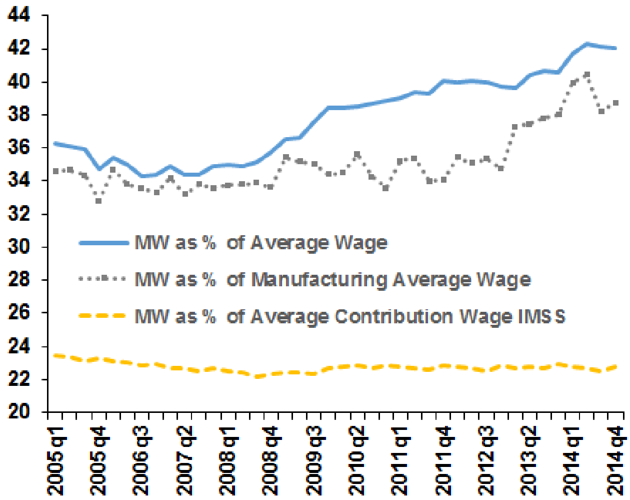
Therefore, the aspects to highlight are the following. First, the proportion of minimum wage workers is not negligible; second, changes to the minimum wage could have considerable spillovers, due to the proportion of workers in the neighborhood of the minimum wage is high (almost 28% of the workers earn between one and two minimum wages). On this regard, the distributional effects of the 2012 minimum wage increase in Zone B are analysed in Chapter 3.

Figure 1.13
Income distribution by deciles and relative minimum wage

Decile	Mean wage
1	0.00
2	681.53
3	1,756.40
4	2,663.04
5	3,257.41
6	4,042.43
7	4,958.97
8	6,050.53
9	7,771.43
10	15,309.96
Total	**4,429.18**

Source: Own calculations with data from ENOE.

(a) Mean wages by income deciles (current Mexican pesos, 2012 3Q)



Source: INEGI, and own calculations with data from ENOE.
Observations with non-specificated income are excluded.

(b) Relative measures of the minimum wage (2005-2014)

Panel (a) of Figure 1.13 provides a more detailed description of the earnings distribution showing the mean wage by income deciles. As we can observe, the average wage for the employed population is about $4,429 MXN ($342 USD). Thus, the minimum wage represents around 40% of the mean wage. In addition, given that zero-income workers are considered, wage levels higher than the minimum wage are beyond the third decile. It is also worth highlighting the fact that the mean income for the top decile of the distribution is \$15,310, which just corresponds to \$1,183 USD. This implies that the sample in ENOE does not include the actual top income earners of the Mexican labour market. Section 3.4 covers in a more detailed these issues of the sample.

To illustrate the relative value of the minimum wage in Mexico, Panel (b) of Figure 1.13 shows the trend of the minimum wage expressed as proportion of different measures of the mean wage: the national average wage, the manufacturing sector average wage, and the average wage reported to the Mexican Institute for the Social Security (IMSS), which constitutes a reference of the remunerations in the formal labour market.

Starting for the first two series, it is possible to appreciate that minimum wage has increased as a proportion of the national average wage. However, this effect is entirely caused by the reduction of general level of real earnings. From the second quarter of 2008 to the last quarter of 2014 the mean wage for the working population has decreased by 15.5% in real terms. Thus, the average level of earnings has not reached the levels observed previous the financial crises in 2008 an 2009. A very similar pattern is exhibited by the mean wage in the manufacturing sector, losing 11.4% of its purchasing power for the same period.

The minimum wage expressed as proportion of the average contribution wage in the IMSS[30] in Panel (b) of Figure 1.13 deserves a separate explanation because it was not obtained from the ENOE. Each month, IMSS publishes the average wage paid to the workers reported by the employers. As we can see, this measure of the minimum wage exhibits a very different performance respect to the manufacturing and total average wages. The reasons for the observed difference is that the IMSS wage includes the payment of some benefits like holidays and Christmas bonus. But more importantly, IMSS wage reflects the wages paid by the formal sector, while the ENOE calculations include also

[30]This institution is in charge of the provision of social security for private sector workers, and among other services it includes health care services. Although by law every worker in the country must have access to social security, many firms do not register their workers in order to reduce labour costs. Thus, the access to Social Security provided by the IMSS is a common measure of formality.

the informal sector. As a consequence, we can observe that not only wages are higher in the formal sector, but also that it responds in a different way to macroeconomic shocks. Moreover, it is also worth emphasizing that minimum wage has decreased in relative terms with respect to the average wage paid in the formal sector.

In order to explore the characteristics of the minimum wage workers, it is necessary to provide some descriptive statistics in terms of their socio-demographic features of the Mexican workforce. Table 1.1 summarizes the main differences between the labour force in general, and the minimum wage workers, understanding this category as the threshold of the workforce earning at most one minimum wage. A surprising feature is the mean age of the minimum wage workers. In contrast to developed countries like the United States or the United Kingdom, where the minimum wage population is concentrated on youth segments, for the Mexican labour market the average age for the minimum wage segment is higher (40.6 years) than the mean for the employed population (38.2 years).

Table 1.1
Sociodemogrphic differences between the workforce and minimum wage workers (2012 3Q)

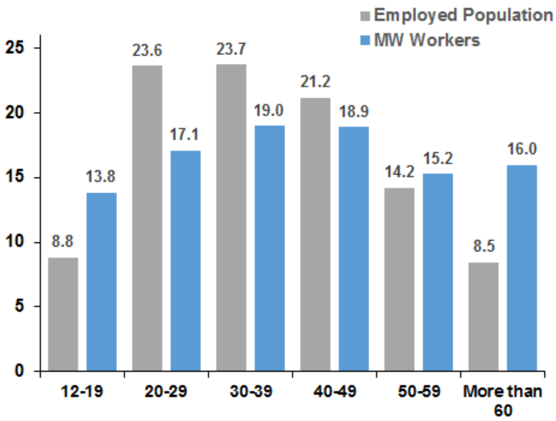
Variable of Interest	Employed Population	MW Workers
Age (mean)	38.19	40.64
Schooling years (mean)	9.35	6.71
Proportion of female workers (%)	38.07	51.74
Head of household (%)	47.87	41.55
Number of children (mean)	2.10	2.84
Financial support* (%)	7.00	23.23
Access to social security benefits (%)	34.83	3.47

Source: Own calculations with data from ENOE. Observations with non-specified answers are excluded.
* Figures corresponding to 2013Q1.

Figure 1.14 separates the population by age groups; even more shocking is the fact that more than 31% of the minimum wage workers is older than 50 years old, while for the employed population this age segment represents only 23%. This is relevant because of the vulnerability of this specific sector of the labour force. First, it is very unlikely that the oldest workers could aspire to earn a higher salary; there are not many options for an improvement of their qualifications, skills, or experience that could lead to increases in their productivity, and as a consequence, to raises in their wages. Second, they are characterized by the lack of social security access and important levels of poverty conditions. Then, the impact of minimum wages policies can be stronger than the effect on youth population. Chapters 2 and 4 analyse in a detailed way the minimum wage impact on earnings, employment and informality at different age thresholds.

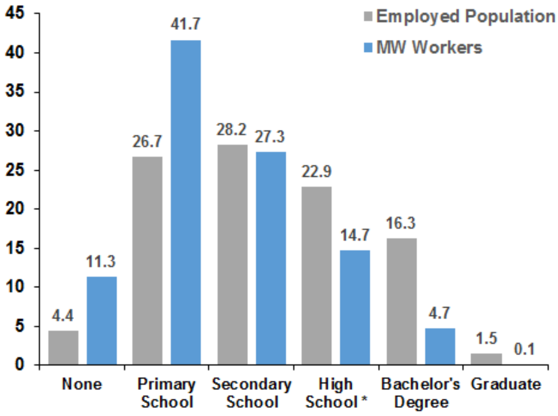
With respect to the educational attainments, as expected, less skilled workers belong to the minimum wage sector. The average schooling years for minimum wage workers is 6.7, while for the employed population in general the corresponding figure is 9.4 years. Besides, as we can observe in Figure 1.15, 11.3% of the minimum wage workers did not receive education, and 41.7% have only basic schooling (4.4% and 25.2%, respectively for the general labour force).

Figure 1.14
Labour force age distribution
(% of working population, 2012 3Q)



Source: Own calculations with data from ENOE, INEGI.
Observations with non-specificated age are excluded.

Figure 1.15
Labour force schooling distribution
(% of working population, 2012 3Q)



* This category included technician degree and teaching degree.
Non-specificated answers are excluded. Preschool is not considered.

Additionally and in accordance to previous literature, the proportion of women workers is considerably higher for the minimum wage segment (51.8% versus 38.1% for the employed population), which is explained by the concentration of female workers in the housing-care services sector.

With respect to the vulnerability of the minimum wage sector, 41.6% of minimum wage workers are head of the household, which implies that they are the main source of income in the household. So, unlike US minimum wage workers, in Mexico these workers are economically in charge of the households, which in addition tend to have more children than the labour force in general (on average 2.8 and 2.1 children, respectively), exacerbating the poverty conditions discussed in the previous subsection. Moreover, 23.2% of minimum wage workers receive some kind of financial support (from government of private agents) to afford the needs in the household. Finally, only 3.5% of the minimum wage workers have access to social security services.

Table 1.2
Distribution of the labour force by job features
(%, 2012 3Q)

	Employed population	**MW workers**
Panel (a). Number of workers in the firm		
1	20.62	47.01
2 - 5	36.74	41.79
6 - 10	7.50	4.62
11 - 15	3.40	1.21
16 - 50	10.48	2.53
More than 51	21.25	2.84
Panel (b). Position in the job		
Waged workers	65.42	47.31
Employers	4.77	2.47
Self-employed	22.74	50.22
Non-waged workers	7.08	-

Source: Own calculations with data from ENOE.
Observations with non-specified answers are excluded.

Concerning the general features of the job performed, Panel (a) of Table 1.2 shows that, according to the expected, most of the minimum wage workforce are employed in very small firms; 89% of this segment works in business entities with at most 5 employees. Nonetheless, 3% of the minimum wage workers are employed by big companies with more than 51 workers. Moreover, in Panel (b) we can observe that the minimum wage sector can be divided by position into the job in two groups practically of the same size: waged workers and self-employed workers.

One of the main features of the labour market in developing countries is the presence of high levels of informal employment. Mexico is not an exception as more than a half of the labour force is employed by the informal sector.[31] Table 1.3 summarizes the main categories of the Hussmanns' Matrix, which is the standard classification for measuring informal employment, adopted for example by the ILO. As we can observe, for the third quarter of 2013 more than 60% of the working population worked in the informal sector, while only 6.8% of the minimum wage workers are hired under formality conditions.

Table 1.3
Distribution of the employed population by formality condition
(% of working population, 2012 3Q)

	Informal Sector		Formal Sector	
Hussmanns's Matrix Clasification	**Employed population**	**MW workers**	**Employed population**	**MW workers**
Waged workers	27.33	39.29	33.82	3.35
Waged workers (plus non-cash)	3.84	4.60	0.43	0.08
Employers	1.98	0.73	2.78	1.74
Self-employed	20.10	48.56	2.63	1.66
Non-waged workers	7.08	0.00	0.00	0.00
Total*	**60.34**	**93.18**	**39.66**	**6.82**

Source: Own calculations with data from ENOE. Observations with non-specified answers are excluded.
* The official figure for workers under informality conditions is 59.8%. The difference is explained by the inclusion of workers younger than 15 years old.

In previous research on the effects of minimum wage in Latin America, informality has represented a challenge in the empirical estimations. The lack of accurate data in a sector that, by definition, is out of the legal framework makes it difficult to justify credible estimates. But, precisely one of the main advantages of the data collected by ENOE is the inclusion of the analysis of informal workers. The interviews are conducted directly to the individuals in their households, not in the firms nor to the employers. In addition, in theoretical models, informal workers are assumed as *uncovered* by the minimum wage

[31]For the period 2005-2014 the average for the labour informality rate was 59.2%.

regulations, but it does not imply that the informal labour market is not going to respond to changes to the minimum wage level. The subsequent chapters demonstrate that there are actually important effects on the informal labour market and sometimes in higher proportions than in the formal labour market.

Finally, to close this subsection, the economic sector distribution of the minimum wage workers is described in Table 1.4. Agricultural, Retail Trade and "Other Services" (which includes primarily mechanical repair services for automobiles, household and personal services) are the sectors with a higher number of minimum wage workers in relative terms. Jointly, these three sectors account for two thirds of the minimum wage workers, but there is no single sector capturing the minimum wage working force. The distribution is very different to the reported by Card and Krueger (1995) for the United States workforce, in which according to the Current Population Survey, one half of the minimum wage workers belong to the Retail Trade sector, while Services employs another 30% of this segment.

As a consequence, unlike the United States or Great Britain, where studies on fast-food restaurants or housing-care services are representative of minimum wage workers, for the Mexican labour market evaluations of minimum wages effects on these specific sectors are not really informative.

Panel (b) of Table 1.4 describes the distribution of the working force by institutional sector. As we can observe, the Household Sector in the informal labour market comprises almost 50% of the minimum wage workers, which in appearance contradicts the information on Panel (a), but the sector here refers to small family businesses engaged in different kinds of economic activities, not necessarily housing care. In addition, most of these workers receive no pecuniary payment for their work, which makes this sector difficult to analyse as the workers may not respond in the same way to labour market policies.

Then, the classification of the labour force by economic and institutional sector does not seem to be relevant to characterise the minimum wage segment. Our preliminary wage and employment analyses confirmed this obtaining statistically insignificant parameters on the economic sector variables (not reported in the text). So, we decided not to include it in our final econometric specifications in Chapters 2, 3 and 4, although in Chapter 5 economic sector is included as a covariate to construct the synthetic control group in order to control for the economic composition of the metropolitan areas in Mexico.

Table 1.4
Classification of the labour force by economic sector
(% of working population, 2012 3Q)

	Employed population	**MW workers**
(a) Economic sector		
Agricultural	14.07	26.12
Industry		
Extractive and electricity	0.91	0.16
Construction	7.46	2.83
Manufacturing	15.28	12.62
Trade		
Wholesale trade	2.32	0.85
Retail trade	17.79	23.74
Services		
Transports/ Communication/ Storage	4.67	1.69
Professional, financial and corporative	7.02	3.80
Restaurants and accommodation	6.87	8.08
Health, education and social assistance	8.09	1.99
Other	10.74	17.52
Government and international organisations	4.77	0.61
(b) Institutional sector		
Financial institutions	1.05	0.11
Firms and non-financial societies	21.81	3.94
Non-incorporated formal firms (agricultural)	9.69	26.12
Non-incorporated formal firms (non-agricultural)	15.69	9.14
Government	4.76	0.61
Private non-profit institutions	1.79	0.56
Public non-profit institutions	6.84	1.18
Households. Informal sector	29.45	47.53
Waged housing care	4.54	10.80
Self-consumption agricultural	4.38	0.00

Source: Own calculations with data from ENOE. Observations with non-specified answers are excluded.

This subsection has provided a general characterization of the structure of the labour market differentiating the minimum wage working force. Some of the most important socio-demographic facts are the following. There are workers actually earning less than the established minimum wage, and the proportion of workers potentially affected by minimum wage changes is large. Moreover, the descriptive analysis reveals that minimum wage workers have in general less years of schooling, they tend to work under informal labour market conditions, in very small firms (or in family business), and more importantly, without access to social security services. However, contrary to expected wisdom, a high proportion of the minimum wage workers is older than 50 years, which represents a specially vulnerable sector.

The above descriptive discussion of the Mexican labour market has influenced the econometric modelling in Chapters 2, 3, 4 and 5. First, given the large size of the informal sector, it is important to analyse the minimum wage effects on the subtypes of informal workers (waged, self-employed and non-waged). This disaggregation of the informal sector is present in all the subsequent empirical chapters. Second, as the minimum wage sector is not concentrated in the youth segment of the labour market, we include all age segments in our analysis. Furthermore, in Chapters 2 and 4 we separately evaluate the minimum wage effects by age threshold. Third, a wage distribution in which most of the labour force is compressed relatively close to the minimum wage level suggests potential minimum wage spillover effects. The main objective of Chapter 3 is therefore to determine the magnitude of these spillover effects on real wages at every percentile of the earnings wage distribution.

1.4 Summarizing remarks

The central research question for the doctoral dissertation is to determine how an increase in the minimum wage affected real earnings and employment in the Mexican labour market. To answer this question it is also necessary to look at the impact on the earnings distribution, and also to consider the simultaneous effect on the informal labour market.

Even though several empirical studies have explored the impact of minimum wage regulations in Mexico, there is a shortage of unambiguous conclusions. At the theoretical level, there are also discrepancies depending on the assumptions made; on the one hand, standard competitive models predict a decline in employment, while monopsonistic models predict potential increases as a consequence of the introduction, or an increase, of the minimum wage.

In addition, there are specific features of the Mexican labour market that make a formal assessment of minimum wages important for informing future policy prescriptions. First, minimum wage has lost more than two thirds of its purchasing power during the last thirty years, which has resulted in a failure to satisfy the most basic needs of the households. Second, the reduction in the real value of the minimum wage does not seem to be supported by the trend observed in labour productivity. The international experience in the Latin American region suggests that it is possible to recover successfully the real value of the minimum wage. Third, the wage distribution suggests that minimum wage variations could affect a large proportion of the labour force. Fourth, it is important to measure the impact on the most vulnerable sections of the population which consist not only of young unskilled workers, but also older employees, and informal workers who constitutes more than half the workforce.

The doctoral dissertation is organised as follows. Chapter 2 presents the treatment effects of the 2012 minimum wage increase on mean real hourly wages. The impact is disaggregated by the formality of employment and by age groups. In order to evaluate the magnitude of the wage effects at different points of the earnings distribution, Chapter 3 implements unconditional quantile regressions. To complete the evaluation of the policy intervention, Chapter 4 reports estimates of the effect on the labour status of the individuals and on the probability of working in the informal labour market. Finally, Chapter 5 tests the validity of the employment findings in Chapter 4 by the use of the Synthetic Control Method, whose estimation requires aggregation of the data and the use of a longer period of analysis.

Appendix 1.A The three minimum wages zones (1986-2012)

Table 1.A.1

List of states by minimum wage zone

Zone A		Zone B		Zone C
Baja California State	**Chihuahua State:**	**Jalisco State**	**Sonora State**	**Aguascalientes State**
Baja California Sur State	Guadalupe	Guadalajara	Altar	**Campeche State**
Mexico City	Juárez	El Salto	Atil	**Coahuila de Zaragoza State**
Tamaulipas State	Praxedis G. Guerrero	Tlajomulco de Zúñiga	Bácum	**Colima State**
Camargo	**Guerrero State**	Tlaquepaque	Benjamín Hill	**Chiapas State**
Guerrero	Acapulco de Juárez	Tonalá	Caborca	**Durango State**
Gustavo Díaz Ordaz	**State of Mexico**	Zapopan	Cajeme	**Guanajuato State**
Matamoros	Atizapán de Zaragoza	**Nuevo León State**	Carbó	**Hidalgo State**
Mier	Coacalco de Berriozábal	Apodaca	La Colorada	**Michoacán State**
Miguel Alemán	Cuautitlán	San Pedro Garza García	Cucurpe	**Nayarit State**
Nuevo Laredo	Ecatepec de Morelos	General Escobedo	Empalme	**Morelos State**
Reynosa	Naucalpan de Juárez	Guadalupe	Etchojoa	**Puebla State**
Río Bravo	Tlalnepantla de Baz	Monterrey	Guaymas	**Oaxaca State**
San Fernando	Tultitlán	San Nicolás de los Garza	Hermosillo	**Querétaro State**
Valle Hermoso	Cuautitlán Izcalli	Santa Catarina	Huatabampo	**Quintana Roo State**
Veracruz State	**Sonora State**	**Tamaulipas State**	Imuris	**San Luis Potosí State**
Coatzacoalcos	Agua Prieta	Aldama	Magdalena	**Sinaloa State**
Cosoleacaque	Cananea	Altamira	Navojoa	**Tabasco State**
Las Choapas	Naco	Antiguo Morelos	Opodepe	**Tlaxcala State**
Ixhuatlán del Sureste	Nogales	Ciudad Madero	Oquitoa	**Yucatán State**
Minatitlán	Puerto Peñasco	Gómez Farías	Pitiquito	**Zacatecas State**
Moloacán	San Luis Río Colorado	González	San Miguel de Horcasitas	**Chihuahua State***
Agua Dulce	Santa Cruz	El Mante	Santa Ana	**Guerrero State***
Nanchital de Lázaro Cárdenas	General Plutarco Elías Calles	Nuevo Morelos	Sáric	**Jalisco State***
		Ocampo	Suaqui Grande	**State of México***
		Tampico	Trincheras	**Nuevo León State***
		Xicoténcatl	Tubutama	**Sonora State***
		Veracruz State	Benito Juárez	**Tamaulipas State***
		Coatzintla	San Ignacio Río Muerto	**Veracruz State***
		Poza Rica de Hidalgo		
		Tuxpan		

Notes: there are states with more than one minimum wage zone, so some states may be listed more than once. An asterisk indicates that the remaining municipalities not listed in Zones A and B belong to Zone C. If there are no municipalities listed below a state, it indicates that all the municipalities in that state belong to the respective wage zone. To distinguish between states and municipalities, states are highlighted in bold.

Source: CONASAMI.

CHAPTER 2

THE EFFECT ON REAL WAGES

2.1 Introduction

This chapter implements Difference in Differences (DiD) regressions, corrected for sample selection bias, to estimate the effect on real wages of the Mexico's 2012 Zone B minimum wage intervention. On 27 November 2012, the minimum wage was unexpectedly raised in only one out of the three wage zones. Using this policy change as a natural experiment to quantify the impact on real wages, we found evidence of an increase in average real wages by 3.6%. This implies an elasticity of 1.2 on real earnings, so the effect is on average more than proportional to the minimum wage increase, which may suggest the existence of spillover effects. Furthermore, by exploiting the information on the informal labour market contained in the National Survey on Employment and Occupation (ENOE), we find a positive and significant impact on the informal labour market. This indicates that minimum wage variations can also affect incentives in the informal sector, which by definition is not covered by the minimum wage regulations. Exploring the minimum wage effects by socio-demographic features of the labour force, our results also suggest that the wage effect was stronger for female and middle age workers.

Although the controversy surrounding the minimum wage is focused on the employment effects, before discussing its impact on employment and informality, it is essential to verify whether there is actually an effect on real wage. On the one hand, in terms of the implementation of the public policy, we cannot take for granted that a minimum wage regulation is truly in force in a labour market. The presence of an informal labour market, and even a lack of full enforcement in the formal sector, can make the practical implementation of minimum wage changes difficult. If minimum wage regulations are not accomplished in the labour market, we cannot expect to find employment effects. Machin et al. (2003), for instance, argued that verifying whether a minimum wage is really affecting wages in the expected direction is a prerequisite before evaluating its impact on employment.

On the other hand, and related to the social implications of the minimum wage policies, it is necessary to evaluate the effect on earnings discounting inflation. Even assuming a full compliance of the minimum wage regulations, it is not possible to be certain that minimum wage increases are going to enhance the purchasing power of earnings. Thus, the main purpose of this chapter is to evaluate the implications of the 2012 minimum wage increase on real wages. Furthermore, given that the responses and incentives may not be the same on different segments of the labour force, we consider by separately: formality condition, gender, and age groups.

The earnings effects of the minimum wage policies are usually presented in empirical studies complementing the main findings on employment, or analysing the effects on inequality and the wage distribution. We decide to examine these minimum wage implications in depth, and in a separate chapter, because of the heterogeneity found in the Mexican labour market.

Previous literature on the wage effects of the 2012 minimum wage increase found positive effects on real wages (Campos et al., 2017). Nevertheless, the fact that sample selection issues were ignored in their models could imply biased estimators. The most common examples of sample selection bias in labour economics are precisely for models on earnings. This is because often the sample for the econometric analysis is limited to the waged population, and therefore estimates can be biased by the sampling process. Therefore, the estimates presented in this chapter (and also in Chapter 4) implement procedures to test and correct for sample selection. Our estimates in this chapter suggest that the findings in Campos et al. (2017) were actually underestimating the minimum wage effect.

Thus, this chapter provides evidence of minimum wage effects on earnings for the whole labour market, not only on one single specific low-wage sector nor restricting the sample to the waged population. And, given the complexities of the Mexican labour market we also analyse the minimum wage implications on some specific segments of the workforce. For instance, on the informal labour market, elderly people and female workers.

Our empirical estimates by DiD regressions, and with data from the ENOE, suggest that the 2012 minimum wage intervention increased real earnings by 3.6%. As minimum wage was increased by 2.9%, the earnings elasticity corresponds, on average, to 1.2. This implies that minimum wage policies may have important repercussions on wage setting in the Mexican labour market. The model is robust to the control group used, to different periods of analysis, and to the exclusion of self-employed workers.

Separating the wage effect by formality condition, estimates suggest that there was an increase in real wages for both formal and informal sectors. This means that the minimum wage legislation is also changing the incentives in the informal labour market. To retain their workers, informal employers increase the remuneration that they pay even by a greater magnitude than the formal market. Finally, we also found evidence that the most affected segment of the labour force, in terms of age, were those workers aged between 30 and 49, while by gender the effect was stronger for female.

The plan for the rest of the chapter is as follows. Section 2.2 describes the main empirical findings in the literature of the minimum wage effects on wages. Section 2.3 presents the data, some descriptive statistics, as well as a graphical inspection of the trends followed by the dependent variables before the policy intervention. Sample selection procedures, and the DiD specifications are described Section 2.4. Section 2.5 presents the results of the empirical analysis including some robustness tests. Section 2.6 concludes the chapter.

2.2 Literature Review

This section describes the main empirical findings in the previous literature with respect to the impact minimum wage on earnings. First, we review studies analysing the effect on the UK and US labour market. Next, given the features of the labour markets in developing countries, specifically the presence of a large informal sector, we describe some of the previous minimum wage findings for Latin America and Mexico.

In one of the first papers suggesting that minimum wages may not have adverse effects on employment, Katz and Krueger (1992) collected data from fast-food restaurants in Texas to analyse the effect of the federal minimum wage increases in 1990 and 1991. They found that, as a consequence of the increases, there was a positive impact on real wages by even a greater proportion than the minimum wage rises, which implies an elasticity greater than one. Following Akerlof and Yellen (1986) and Grossman (1983), Katz and Krueger argued that relative wages could be the reason for this "overreaction". That is, changes to relative wages within or between firms can affect work effort. So, firms may decide to adjust wages above the minimum wage level to avoid a decrease in the level of effort by workers not originally affected by the minimum wage change.

Card (1992a) evaluated the 1988 minimum wage increase in California from $3.35 to $4.25. By DiD models, and using as a control group workers in Arizona, Florida, Georgia, New Mexico and Texas, he estimated an average increase in real earnings of between 5% and 10% on teenagers (workers aged between 16 and 24). Subsequently, Card (1992b) examined the impact of the 1990 federal minimum wage rise in the US on teenagers. Even though the minimum wage increase was uniform, he exploited the regional differences on the fraction of workers affected by the policy change, defined as the segment of workers initially earning less than the "new" minimum wage. Their results suggested that the rise from $3.35 to $3.80 increased real earnings of teenagers by around 6%.

In the case of the UK, there were no minimum wages in force between 1993 and 1999 (except for the agricultural sector). The discussion about its re-introduction at the end of the 90's brought about some relevant studies in the field. Dickens et al. (1999) analysed the effects of minimum wages under the Wage Councils scheme, in which every economic sector discussed and negotiated its own minimum wage setting. With data from the New Earnings Survey for the period 1975-1992, they found that the existence of the minimum wage regulations had a positive and significant effect on the average wage.

Machin et al. (2003) investigated the impact of the National Minimum Wage introduction on the UK residential home care sector, which is characterized for being a non-unionized low wage sector. Collecting their own data by postal surveys before and after the intervention, their results suggest that the minimum wage introduction increased real earnings of workers at the bottom of the distribution, affecting the wage setting structure of the sector.

In subsequent studies, Richard Dickens and Alan Manning concluded that although the introduction of the UK National Minimum Wage was widely implemented, it had a limited impact on wage setting. This was because the minimum wage was set at a very low level (£3.60 in April 1999) so that only a limited proportion of workers were affected. With data from the Labour Force Survey, and implementing reweighting methods for the hourly wage rate, Dickens and Manning (2004a) found detectable effects of the minimum wage only at the bottom five percent of the wage distribution but not at the bottom ten percent. Afterwards, with information obtained from a postal survey of workers in residential homes for the elderly, Dickens and Manning (2004b) showed that the New Minimum Wage affected 40% of the workers in the sample. They found evidence of very high compliance with minimum wage regulations, but no evidence of spillover effects. This chapter is focused on the average wage effects, while Chapter 3 analyses the spillover effects and presents the impact on the earnings distribution.

More recently, in an influential paper for the US labour market, Dube et al. (2010) compared all the contiguous border county pairs in the US. They evaluated the impact of the differentiated minimum wage policies at the state level on earnings and employment for low-wage sectors. Independently of the econometric specification used, their results suggested positive and statistically significant effects on earnings, with elasticities ranging between 0.15 and 0.23.

With respect to the impact of minimum wage policies in Latin American countries, there are some studies analysing the effect on formal and informal labour markets. Exploiting temporal variation of the minimum wage in Brazil, Fajnzylber (2001) estimated the impact on monthly income at different levels of earnings (using multiples of minimum wages). For formal workers, he estimated elasticities between 0.39 and 1.43, while for informal workers they were slightly lower but still significant, between 0.21 and 1.18. Nevertheless, Lemos (2004b) argued that Fajnzylber focused his analysis on a period characterized by high inflation, which may generate an overestimation of the wage effects. Indeed, Lemos (2004b) tried to deal with these problems by expanding the period of analysis and including labour demand and supply controls, but pooling together formal and informal labour markets. The size of the estimated impact is lower than in Fajnzylber, depending on the specific point in the distribution where the effect is evaluated, but it is positive and statistically significant.

For the Argentinian labour market, Khamis (2013) analysed the impact of the 1993 federal minimum wage increase. Using a similar specification to Card (1992a), she argued that minimum wage "bites" to different degrees in an area's wage distribution to identify the minimum wage impact. By DiD models, Khamis found significant effects in the informal labour market, but no effects in the formal sector. She argued that employment under informal conditions does not imply noncompliance of the minimum wage. This is, informal employers may compensate their workers with raises similar to that minimum wage increase observed in the formal labour market. Nevertheless, there could be noncompliance to other regulations as social security contributions.

Bell (1997) implemented an evaluation of the minimum wage effects in Colombia and Mexico. For the period 1962-1990 in Colombia, she found positive effects on average wages. In contrast, for the period 1972-1990 in Mexico, her estimates on average wages for the manufacturing sector resulted non statistically different from zero. She contended that the reason for this difference was that minimum wages in Mexico were not an effective wage, that is, minimum wages were not actually in use. However, the fact that the analysis was limited to the formal manufacturing sector, which was characterized for a relatively higher level of remuneration, might explain these conclusions.

Using the National Survey on Urban Employment in Mexico for the period 1982-2001, Bosch and Manacorda (2010) found positive effects of the minimum wage on wages at different points of the earnings distribution. Their estimates, for instance, suggest an elasticity of 0.3 at the median of the distribution. In separate regressions by gender, they found similar impacts although higher standard errors for the female earnings distribution. Finally, they failed to find a significant effect on informal workers, although it is important to emphasize that the data used was restricted to urban employment. Moreover, the criteria used for identifying informal workers was the lack of social security contributions, which generated an under-representation of the informal sector, having only 22% of informal workers in the sample.

In a closely related paper to our investigation, Campos et al. (2017) used the same database, the ENOE, as well as the 2012 minimum wage increase in Zone B to identify the minimum wage effect. They implemented cross-sectional and panel data DiD regressions, finding significant effects on average hourly wages. In the cross-sectional models, they estimated an impact of between 1.6% and 2.0% on Zone B's hourly wages (corresponding to elasticities between 0.55 and 0.69), although they reported negative coefficients on the untreated Zone A by similar proportions of around -1.6%. In the panel data analysis, depending on the time span (ENOE allows the same individual up to 5 consecutive quarters), the effect on hourly wage was of around 3.4%. The monthly wage estimates are only significant for the panel data models, but they are highly sensitive to the time span, ranging from 0.04% to 7.7%. So, the elasticities computed ranged between 0.14 and 2.66. Nevertheless, Campos et al. (2017) did not consider the fact that restricting the sample to waged workers might bias the estimates due to sample selection.

The main difference between this chapter and Campos et al. (2017) is precisely that we also consider all those unwaged and inactive labour market individuals when we estimate the wage effects. In addition, we carefully explore the impact on different social strata by considering the population under vulnerable conditions. Finally as a remark, we do not implement panel data models in order to use the same specification throughout this and the following two chapters. The estimation of the unconditional quantile regressions in Chapter 3 becomes computationally expensive, while for the probit models in Chapter 4 we would lose a large number of observations if we had used fixed effects models.

2.3 The data

As explained in the previous chapter, to implement DiD regressions we use data from ENOE. This is a public database provided by the National Institute of Geography and Statistics in a quarterly basis. The survey is conducted a the individual level directly in the households in order to allow workers to speak anonymously about their job conditions and collect information on the informal labour market.

Subsection 2.3.1 describes the variables included in the specifications, as well as some descriptive statistics. Subsection 2.3.2 presents some graphical inspection respect to the pretreatment trends of the dependent variables.

2.3.1 Variables description

The dependent variable used to quantify the minimum wage effect on real earnings is the logarithm of real hourly wages. ENOE reports nominal earnings in current pesos, so we use the National Consumer Price Index (the base period corresponds to December 2010) to calculate real earnings. Appendix 2.A describes in detail the definition and generation process of all the variables included in the regression models.

Although the minimum wage in Mexico is set on a daily basis, our preferred specification uses hourly wages as a dependent variable because of the following reasons. First, if the purpose is to reveal the minimum wage effects on real wages, we need to focus the evaluation on wages and isolate it from the decision on the quantity of hours worked. The spotlight is the level of earnings, not the time allocated to work or the accumulated income affected by this decision. Second, minimum wage changes may affect employment beyond reducing employment positions. Employers can decide, for instance, to cut working hours or to replace full time with part time positions. In consequence, this would affect total earnings and more importantly, it may bias the real wages findings. Moreover, aiming for consistency in the estimates, in Chapter 3 we evaluate the minimum wage impact at different points of the earnings distribution using hourly wages. Of course, earnings percentiles are different if we estimate hourly or monthly earnings' distributions, which can also alter the conclusions reached. So, we prefer to leave the decision on the number of hours worked as a separate issue.

Table 4.3.1 presents some descriptive statistics for the variables included in the econometric specification. To follow the DiD model, the sample is divided by wage zones and by two periods, before and after the minimum wage intervention.

The first aspect to highlight is the number of observations for the dependent variable. As we can observe, from 2.45 million working-age individuals in the eight quarters of analysis, only 0.96 million are identified as waged workers. The rest of them are unemployed or inactive in the labour market. This implies that to estimate the effect only on this segment of the workforce means to leave out of the analysis more than 60% of the sample. In contrast, by implementing sample selection bias correction procedures, we can carry out our analysis on the full working-age sample.

Regarding the number of observations by wage zones, treated Zone B has systematically fewer observations than the other two zones. As discussed in Section 1.2.2, Zone B is the smallest in terms of the number of municipalities and population covered (around 10% Mexican population). For our DiD estimates, it implies that we have available a robust number of observations in the control group.

Table 2.1
Sample descriptive statistics (2012Q1-2013Q4)

	Pretreatment period			Post-treatment period			National
	Zone A	Zone B	Zone C	Zone A	Zone B	Zone C	
Dependent Variables							
Hourly real wage (Mexican pesos)							
Mean	34.45	34.72	29.62	33.72	35.64	29.23	30.52
Std. Deviation	45.99	44.19	65.04	95.94	45.61	43.47	56.95
Observations	53,599	42,188	348,085	62,598	47,951	406,747	961,168
Monthly real wage (Mexican pesos)							
Mean	5,545.35	5,572.03	4,755.33	5,446.71	5,668.47	4,734.89	4,917.16
Std. Deviation	5,369.97	5,463.97	5,448.21	7,514.70	5,170.70	5,431.49	5,592.36
Observations	53,599	42,188	348,085	62,598	47,951	406,747	961,168
Control Variables							
Age							
Mean	37.52	37.84	37.23	37.64	38.12	37.27	37.36
Std. Deviation	17.87	18.14	18.32	17.86	18.18	18.26	18.23
Observations	135,567	107,501	879,645	163,602	126,481	1,044,201	2,456,997
Female							
Mean	0.5155	0.5154	0.5248	0.5201	0.5163	0.5249	0.5232
Std. Deviation	0.4998	0.4998	0.4994	0.4996	0.4997	0.4994	0.4995
Observations	135,589	107,607	879,955	163,630	126,651	1,044,621	2,458,053
Rural							
Mean	0.0820	0.0625	0.2039	0.0624	0.0458	0.1937	0.1691
Std. Deviation	0.2744	0.2421	0.4029	0.2420	0.2090	0.3952	0.3748
Observations	135,589	107,607	879,955	163,630	126,651	1,044,621	2,458,053
School_level2 (7th - 9th year)							
Mean	0.2398	0.2188	0.2435	0.2365	0.2199	0.2375	0.2380
Std. Deviation	0.4270	0.4134	0.4292	0.4249	0.4142	0.4255	0.4258
Observations	135,500	107,554	879,523	163,536	126,578	1,044,070	2,456,761
School_level3 (10th - 12th year)							
Mean	0.3167	0.3624	0.3096	0.3197	0.3615	0.3156	0.3182
Std. Deviation	0.4652	0.4807	0.4623	0.4664	0.4804	0.4648	0.4658
Observations	135,500	107,554	879,523	163,536	126,578	1,044,070	2,456,761
School_level4 (University)							
Mean	0.3047	0.2976	0.2655	0.3174	0.3054	0.2728	0.2777
Std. Deviation	0.4603	0.4572	0.4416	0.4655	0.4606	0.4454	0.4478
Observations	135,500	107,554	879,523	163,536	126,578	1,044,070	2,456,761
Head of the Household							
Mean	0.3511	0.3402	0.3375	0.3504	0.3417	0.3383	0.3398
Std. Deviation	0.4773	0.4738	0.4729	0.4771	0.4743	0.4731	0.4736
Observations	135,589	107,607	879,955	163,630	126,651	1,044,621	2,458,053

Note: sample restricted to individuals aged between 12 and 97. For wage variables, observations with non-reported values for hourly wage are excluded. For socio-demographic controls, observations with non-specified responses are also omitted. Appendix 2.A described in detail the variables generation procedure.

With respect to real wages, some important points emerge. First, zones A and B exhibit a greater level of mean wages than Zone C. Although zone C is the largest in terms of population and surface area, it contains the municipalities with the lowest economic development. Second, Zone B is the only wage zone that experienced an increase in real wages after the intervention. The other two zones exhibit a decrease. It suggests that, without controlling for other covariates, the minimum wage intervention could have a positive effect on real earnings, in the treated Zone B.

The control variables included in the model are the following: *age* of the individuals (in years at the moment of conducting the survey), indicator variables for $female$ workers and $rural$ municipalities, and a set of dummy variables for completed *schooling* level (basic school=1,[1] secondary school=2, high school=3, university and post grad studies=4). As we can observe in Table 4.3.1, there are no substantial differences on the gender and age composition by wage zones. Indeed, the means for these two variables among zones are not statistically different.

Nevertheless, if we look at the schooling level of the individuals, schooling level in zones A and B is greater on average than Zone C. This reflects the classification itself of the wage zones based on its economic development. Thus, given that by definition wage zones are different among them, specifically with respect to Zone C, the main identification assumption is that outcome variables follow the same trend before the intervention. Pretreatment trends are analysed in the following subsection.

Taking into account these sample dissimilarities with respect to Zone C, all the DiD models in this Chapter are run using two specifications. In the first of them, all the untreated units (zones A and C) are part of the control group. In the second version of the model, only observations from Zone A are included within the control group. The magnitude of the estimated treatment effects do not vary significantly.

Finally, the control variable $Head$ of the household, which is a dummy variable indicating the individual in the household who is the main responsible of the earnings of

[1]Excluded from the regression models to avoid multicollinearity

the household, is included only in the first stage of the sample selection correction bias procedures as the exclusion restriction variable.[2] Subsection 2.4.2 describes in detail the procedures implemented to correct for sample selection bias.

2.3.2 Pretreatment trends on real earnings

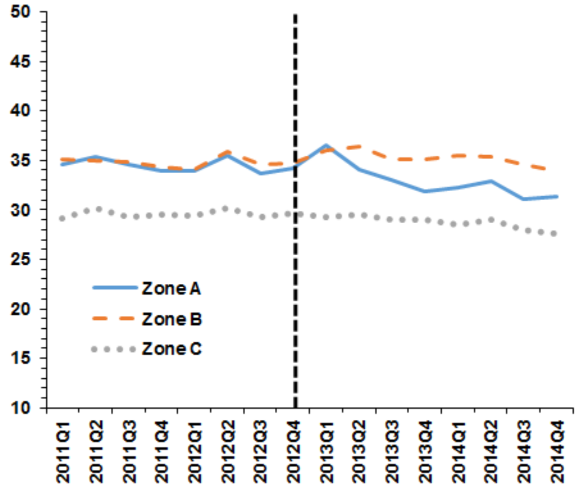
The legislation change on 27 November 2012, which is used to identify the effect on real wages, raised the minimum wage for Zone B and left unaffected zones A and C. So, these untreated zones, A and C, constitute the natural control group for the DiD regressions. But, given that the intervention was not performed in a randomized way, a common concern in this kind of observational studies is precisely the validity of the control group.

By construction, minimum wages zones in Mexico are different. Their classification was not carried out by regional differences, but by the level of economic development across municipalities. Under this circumstances, in which control and treatment were not randomized and they are not identical in their observable characteristics, the key identifying assumption is that, in absence of the intervention, control and treatment groups follow the same trend in their outcome variables before the policy change. To verify this assumption, we implement a graphical inspection of the trends on real wages by each zone.

Figure 3.1 shows the outcome trend variable (real hourly wage) for the period 2011Q1-2014Q4. Before the intervention — the dotted vertical line denotes the period in which the legislation change took place — the trends followed by all three zones are and parallel. That is, we can argue that the three minimum wage zones exhibit the same trend on real wages as the distance between the mean wage in Zone B with respect zones A and C remains basically constant. This implies that in absence of treatment, real wages in all three zones respond in the same way to exogenous shocks, or in other words, there is no evidence of differences on real earnings behaviour among wages zones. As a consequence,

[2]The model on the estimation of the probability of being active in the labour market variable, in Chapter 4 (see Table 4.2) is not corrected for sample selection bias. It includes the variable *Head* of household directly as a regressor.

Figure 2.1
Real hourly wage trends by wage zone
(Mexican pesos of 1F December 2010)



Source: own calculations with data retreived from ENOE.

treatment and control groups are valid for implementing DiD regressions.

With respect to the post-treatment period, although all three zones exhibit decreasing trends in real wages, it is possible to notice that the gap between Zone B and the other two zones increases after 2012Q4. Visually, the difference between Zone B and Zone A is more compelling. This, because Zone A suffered an important reduction in the real earnings level.[3] But, it is also possible to appreciate that the distance between zones B and C was constant before the intervention, and after that, the gap increases. This means that Zone B's relative wages increased after the policy change so that the minimum wage effect should be positive. However, of course it is necessary to implement a formal causality analysis to talk about treatment effects.

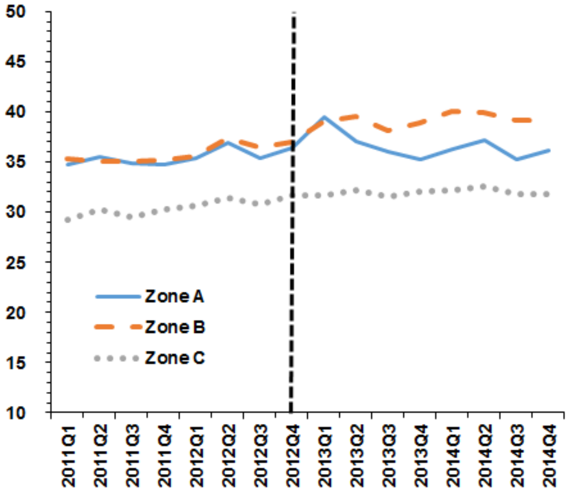
A legitimate concern may be that the trend for the level of prices can be different among zones. As specified in Appendix 2.A, real wages are calculated deflating nominal wages by using the National Consumers Price Index (INPC). So, a single price index is used for the three zones. The reason is that there are no price indices at the municipality

[3]Literature on Mexican labour market has no explored the causes of this decrease in wages in Zone A. Figure 2.2 shows that the decline is also observed in nominal wages. Appendix 2.C implements some descriptive analysis to explore some different explanations that could have lead to this reduction. But, it is important to highlight that in our econometric specifications we introduce a DiD parameter on Zone A — equation (2.1b) —to check this decline is consequence of the intervention. In all cases, the corresponding parameter is not statistically significant.

level. In fact, to construct the national price index, INEGI collects data only from 46 representative urban cities. As minimum wage zones are classified at the municipality level, it is not possible to construct a precise price index by wage zones.

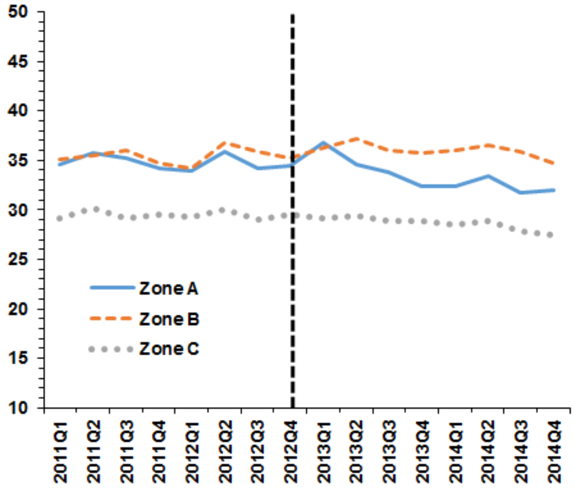
Therefore, to confirm that the pretreatment trends are actually the same, and this is not a consequence of the use of a single price index for the three zones, we implement the following analysis. First, Figure 2.2 shows trends by nominal wages by zones. The trends are positive because the lack of consideration of the inflationary process, but the conclusion remains: before the intervention there exists a parallel trend of the nominal wages by zones, but after the policy change in 2012Q4, the gap increased.

Figure 2.2
Nominal wage trends by wage zone
(Current Mexican pesos)



Source: own calculations with data retreived from ENOE.

Figure 2.3
Real wage trends by wage zone, separate CPI
(Mexican pesos of 1F December 2010)



Source: own calculations with data retreived from ENOE.

Second, although there is no information on price indices at the municipality level, we construct an approximation calculating a simple average of the available cities by zones (see Appendix 2.B for a listing of the cities included in the INEGI' INPC calculation by minimum wage zone). Of course, there can be an important bias on these exercise because there may be an underrepresentation of municipalities by zones. But, the purpose is only to show that there are no fundamental differences generated by the dynamics of prices in the wages zones. We use these new zones' Consumer Price Indices (CPI) to deflate nominal wages in order to replicate the graphical inspection on real earnings. Figure 2.3

shows that zones A, B, and C exhibit parallel trends before the intervention even if we use their respective price index to deflate nominal earnings.

In summary, this subsection presents descriptive evidence to show that average real wages in zones A and C follow parallel trends with respect to Zone B. This, independently of the level of prices at the national and at the wage zone level. Therefore, zones A and C constitute a valid control group to Zone C.

2.4 Strategy of identification

2.4.1 Differences in Differences (DiD) specifications

Given that the survey allows us to observe the labour market before and after the policy intervention, and based on the assumption that all three zones exhibit the same trends in the pretreatment period, it is possible to implement DiD estimates. This section describes the econometric specifications used to evaluate the minimum wage effect on real earnings.

Regarding the econometric specifications, the control group represents the counterfactual of the treated observations, but in terms of the econometric estimation of the treatment effect, it also corresponds to the reference group used to measure the relative difference generated by the intervention. In other words, for invalid control groups, the choice of the reference group can alter significantly the magnitude of the estimated impact. Then, using the fact that there are two untreated zones, and with the aim at verifying the robustness of the model, we use two different specifications for all the subsequent estimations. In the first of these specifications only individuals in Zone C are included in the control group. In this case, observations from Zone A are not dropped from the analysis; instead, a dummy variable for this zone is included as a regressor. For the second specification, the control group is created using all the untreated individuals in the sample, so we combine control zones A and C.

Although Zones A and B are more similar in terms of economic development, Zone C is the preferred control group because of its size. In the sample, 80% of the observations correspond to Zone C.

So, in the first specification, equation (2.1a), we have the traditional DiD equation, in which are included binary variables for identifying the treated zone ($ZoneB$) and the post-treatment period ($Period2$), as well as the interaction of these two dummy variables, which corresponds to the DiD variable ($ZoneB * Period2$). For the second specification, (2.1b), we include as independent variables the dummy variable $ZoneA$ and — for completeness— its interaction with the post-treatment period dummy, $Period2$. Thus, the DiD specifications are the following:

$$\begin{aligned}\ln(w_i) = {} & \beta_0 + \delta_1 ZoneB_i * Period2_i + \delta_2 Period2_i + \delta_3 TrendB + \delta_5 TrendA\&C \\ & + \delta_4 EmpRate + \beta_1 ZoneB_i + \sum_{k=2}^{k} \beta_k X_{ki} + e_i \end{aligned} \tag{2.1a}$$

$$\begin{aligned}\ln(w_i) = {} & \beta_0 + \delta_1 ZoneB_i * Period2_i + \delta_2 Period2_i + \delta_3 TrendB + \delta_4 TrendA + \delta_5 TrendC \\ & + \delta_6 EmpRate + \delta_7 ZoneA_i * Period2_i + \beta_1 ZoneB_i + \beta_2 ZoneA_i + \sum_{k=3}^{k} \beta_k X_{ki} + e_i \end{aligned} \tag{2.1b}$$

where the dependent variable $\ln(w_i)$ corresponds to the natural log of real hourly wages. δ_1 is the parameter of interest in both equations. In equation (2.1a), it corresponds to the estimated impact of the minimum wage increase on Zone B with respect to individuals in both, zones A and C. On the other hand, in (2.1b) δ_1 is the estimated effect of the intervention with respect only to individuals in Zone C. If the control groups are valid, δ_1 from equations (2.1a) and (2.1b) should not be different.

It is important to highlight that the coefficient δ_2 in equation (2.1b) is not a treatment effect, the purpose is not trying to measure the impact on the untreated Zone A. It is included only for completeness in the model in order to avoid losing all the observations from Zone A when the control group is only Zone C.

For the set of independent variables, $Period2_i$ is an indicator variable that takes the value of 1 if the observation corresponds to the post-treatment period,[4] and 0 otherwise. $ZoneB_i$ and and $ZoneA_i$ are dummy variables that identify the observations that belong to Zone B or A, respectively.[5]

$TrendB$ is a simple linear quarterly trend for Zone B to control, to some extent, for the macroeconomic time trend in the treated zone that, by the nature of the survey, is not possible to include variables at the macroeconomic level in the model. Depending on the control group used, equation (2.1a) includes a common linear trend for zones A and C ($TrendA\&C$), while equation (2.1b) controls separately for each zone' linear trend including $TrendA$ and $TrendC$ by separately.

To control for the labour market conditions at the regional level, we include quarterly employment rates by state (*EmpRate*), defined as the proportion of individuals with working activities with respect to the active labour market population. Regarding potential endogeneity problems by the inclusion of this variable, Appendix 2.D presents some analytical arguments, as well as the Durbin-Hu-Hausman test to demonstrate the exogeneity of this covariate in the wage equation.

X_k corresponds to the set of socio-demographic variables at the individual level. It is composed of variables for age, squared age, a binary variable for gender, an educational variable (schooling level), and an indicator of rural residence. Interactions of schooling level with rural residence and gender are also included. Finally, e_i corresponds to the error term.

In addition to the full sample specification, each model is also estimated restricting the sample to the following age thresholds: individuals between 12 and 29 years old,

[4]The intervention was announced on Monday, 26 November 2012 and it was in force on Tuesday, November 27. ENOE allows to identify the week when the interview took place for urban municipalities and the month of interview for rural observations. Thus, $Period2_i = 1$ for those urban observations interviewed at least on the ninth week of the fourth quarter of 2012, and for rural observations interviewed after December 2012; $Period2_i = 0$ otherwise. See Appendix 2.A for a more detailed explanation on the variables construction.

[5]Although ENOE contains a variable for identifying the minimum wage zones, we use directly the official classification from CONASAMI. See Appendix 2.A for the codes of the municipalities included in each zone.

between 30 and 49 years old, and finally, individuals aged equal or older than 50. We also investigate the difference of the impact by gender. To check the robustness of the model, we also estimate the effect excluding self-employed workers.

Furthermore, in order to evaluate how the estimated effect is changing over time, a second set of specifications are estimated in Subsection 2.5.2, where the post-treatment period variable, $Period2_i$, is decomposed into four quarterly dummy variables: 2013_Q1, 2013_Q2, 2013_Q3 and, 2013_Q4. These four time-dummy variables are included in the models with their respective DiD regressors to explore the dynamics of the effect.

$$\begin{aligned}\ln(w_i) = \beta_0 + \sum_{j=1}^{4} \delta_j ZoneB_i * 2013\_Q_{ji} + \sum_{j=1}^{4} \delta_{j+4} 2013\_Q_{ji} \\ + \delta_9 TrendB + \delta_{10} TrendA\&C + \beta_1 ZoneB_i + \sum_{k=2}^{k} \beta_k X_{ki} + e_i \end{aligned} \tag{2.2a}$$

$$\begin{aligned}\ln(w_i) = \beta_0 + \sum_{j=1}^{4} \delta_j ZoneB_i * 2013\_Q_{ji} + \sum_{j=1}^{4} \delta_{j+4} ZoneA_i * 2013\_Q_{ji} + \sum_{j=1}^{4} \delta_{j+8} 2013\_Q_{ji} \\ + \delta_{13} TrendB + \delta_{14} TrendA + \delta_{15} TrendC + \beta_1 ZoneB_i + \beta_2 ZoneA_i + \sum_{k=3}^{k} \beta_k X_{ki} + e_i \end{aligned} \tag{2.2b}$$

Restricting the sample to waged individuals implies the systematic exclusion of the unemployed and inactive labour market population. Then, we implement sample correction procedures in all the regressions presented in the chapter. A general description of this procedure is developed in the following subsection. Appendix 2.F presents the pooled OLS estimates for the main specifications without sample selection bias correction.

2.4.2 Sample selection bias correction.

Heckman (1979) developed an estimation method to test and correct for selection bias. Following Wooldridge (2010), sample selection bias correction is implemented in two stages:

1. The selection equation is estimated. Using the full sample, the probability of selection in the sample is estimated by a probit model. In our case, the so-called selection equation estimates the probability of participating actively in the labour market. Subsequently, the fitted values for the inverse Mills ratio are calculated, which correspond to the ratio between the density and cumulative probability predicted functions: $\hat{\lambda}(\cdot) \equiv \phi(\cdot)/\Phi(\cdot)$.

2. To obtain the unbiased estimators, $\hat{\lambda}$ is included as a regressor in the selected sample. In order to test the null hypothesis of no selection bias, it is enough to implement a standard t test on the $\hat{\lambda}$ coefficient.

Wooldridge (2010) states that technically, the set of regressors for the two stages do not have to be different. However, collinearity between $\hat{\lambda}$ and the set of explanatory variables can lead to large standard errors of the parameters. To avoid this, the binary variable $Head$ is used as an exclusion restriction in the selection equation, equations (2.3) and (2.4). This indicator variable is equal to one if the individual is the head of the household, and zero otherwise.

As with any instrument, this needs to satisfy two conditions. It must be *relevant* in the reduced form, which in our case means that the parameter on $Head$ in the selection equation (labour force participation equation) has to be statistically different from zero. And, it must be *exogenous* in the equation of interest, which in our analysis corresponds to specifications (2.1a) and (2.1b). That is, the covariance between $Head$ and the respective errors e has to be zero.

We can justify the fulfillment of both conditions by the following argument: the fact that an agent is the head of a household affects directly the decision to participate in the labour market for being the one mainly responsible to satisfy the household's needs (*relevance* condition). But, the role within the household does not affect the dependent variable, it does not determine the wage rate (*exogeneity* condition).

This is an additional advantage of the use of hourly wage as a dependent variable. The wage rate should not be affected by the variable $Head$, but it can have an influence on the decision on the number of hours worked. Under this scenario, being the head of a household could potentially affect monthly earnings, so the *exogeneity* condition would be violated. In that case, the Heckman correction procedure would be valid, but the standard errors may be overestimated, so that the statistical significance of our estimates would be underestimated.

The reduced form equations for the selection equation on labour active market are expressed by these specifications:

$$\begin{aligned} Y_i =& \theta_0 + \gamma_1 Period2_i + \theta_1 Head_i + \theta_2 TrendB + \theta_3 TrendA\&C \\ &+ \theta_4 Female_i + \theta_5 Age_i + \theta_6 Age_i^2 + \theta_7 Rural_i + \sum_{j=8}^{10} \theta_j SchLevel_{ki} \\ &+ \sum_{j=11}^{13} \theta_j SchLevel_{ki} * Rural_i + \sum_{j=14}^{16} \theta_j SchLevel_{ki} * Female_i + r_i \end{aligned} \tag{2.3a}$$

$$\begin{aligned} Y_i =& \theta_0 + \gamma_1 Period2_i + \theta_1 Head_i + \theta_2 TrendB + \theta_3 TrendA + \theta_4 TrendC \\ &+ \theta_5 Female_i + \theta_6 Age_i + \theta_7 Age_i^2 + \theta_8 Rural_i + \sum_{j=9}^{11} \theta_j SchLevel_{ki} \\ &+ \sum_{j=12}^{14} \theta_j SchLevel_{ki} * Rural_i + \sum_{j=15}^{17} \theta_j SchLevel_{ki} * Female_i + r_i \end{aligned} \tag{2.3b}$$

for $k = 2, 3, 4$

And for the models on the dynamics of the effects, the selection equations are:

$$\begin{aligned} Y_i =& \theta_0 + \sum_{l=1}^{4} \gamma_l 2013\_Q_{li} + \theta_1 Head_i + \theta_2 TrendB + \theta_3 TrendA\&C \\ &+ \theta_4 Female_i + \theta_5 Age_i + \theta_6 Age_i^2 + \theta_7 Rural_i + \sum_{j=8}^{10} \theta_j SchLevel_{ki} \\ &+ \sum_{j=11}^{13} \theta_j SchLevel_{ki} * Rural_i + \sum_{j=14}^{16} \theta_j SchLevel_{ki} * Female_i + r_i \end{aligned} \tag{2.4a}$$

$$
\begin{aligned}
Y_i = &\theta_0 + \sum_{l=1}^{4} \gamma_l 2013\_Q_{li} + \theta_1 Head_i + \theta_2 TrendB + \theta_3 TrendA + \theta_4 TrendC \\
&+ \theta_5 Female_i + \theta_6 Age_i + \theta_7 Age_i^2 + \theta_8 Rural_i + \sum_{j=9}^{11} \theta_j SchLevel_{ki} \\
&+ \sum_{j=12}^{14} \theta_j SchLevel_{ki} * Rural_i + \sum_{j=15}^{17} \theta_j SchLevel_{ki} * Female_i + r_i \qquad (2.4b)
\end{aligned}
$$

for $k = 2, 3, 4$

Unlike equations (2.1) and (2.2), this specification does not include the variables $ZoneB$, $ZoneA$, $ZoneB * Period2$ and $ZoneA * Period2$. These interaction terms are excluded because the purpose of the selection equation is not to estimate a treatment effect. Besides, they are not relevant in the model. Testing the individual and joint significance of these variables in the model on the probability of being active in the labour market, all of them are not statistically different from zero.[6] Beyond the variable $Head$, the rest of the control variables are the same as in equation (2.1).

2.5 Results

The first step to implement a comprehensive evaluation of the minimum wage increase is to analyse if the policy change is truly affecting real earnings. This section presents an analysis that corrects for sample selection on the entire sample of waged and unwaged Mexican workers. In addition, we explore the impact on sectors not covered by the minimum wage policies, specifically on the informal labour market. To do so, we exploit the official data from ENOE to analyse the impact on the informal labour market, in which by definition, there is no full enforcement of the legal labour market framework.

This section is organised in the following way. The results for our main specifications

[6] Testing the joint significance of parameters of $ZoneB * Period2$, and $ZoneB$ on dependent variable *Active Labour Market*, for equation (2.1a) we cannot reject the null hypothesis that these variables are jointly insignificant (with a p-value of 0.91). For equation (2.1b), the null hypothesis that the parameters of $ZoneB * Period2$, $ZoneB$, $ZoneA * Period2$, and $ZoneA$ are jointly equal to zero cannot be rejected (p-value of 0.67).

(2.1a) and (2.1b) are presented in Subsection 2.5.1, including regressions by age threshold, by formality condition and by gender. The dynamics of the effect, modelled equations (2.2a) and (2.2b) are analysed in Subsection 2.5.2. For robustness, and following the previous literature on earnings effects, we also estimate the treatment effect excluding self-employed workers from the sample in Subsection 2.5.3. Finally, using an extension to equation (2.2), we implement some additional robustness checks to verify the validity of our DiD estimates.

Some complementary estimates on the effect on real monthly wages are presented in Appendix 2.E, while Appendix 2.G shows the full list of coefficients of the main DiD models discussed in the following subsection.

2.5.1 Main results: the average effect on hourly real wages

This subsection presents our main estimates of the 2012 minimum wage intervention on real hourly wages. In all the cases, we test and correct for sample selection bias. We report only the parameters of interest, δ_1, of the second stage Heckman procedure, as well as the Inverse Mills ratio. The coefficients for the rest of the control variables for the second stage and the parameters of the first stage for the main specifications are presented in Appendix 2.G. Moreover, Pooled OLS without sample selection bias correction results are reported in Appendix 2.F.

With respect to the inference of our estimators, it is important to make a clarifying remark on the standard errors presented. Given that the sample selection procedure is explicitly estimated in two stages, robust or clustered standard errors are not feasible. So, standard errors are obtained by the two-step variance estimator derived by Heckman (1979). In this paper, Heckman actually states that in the presence of sample selection bias, the usual procedure for estimating standard errors can lead to an overestimation of significance levels.

Thus, Table 2.2 presents the minimum wage effects on real wages correcting for sample selection bias, while considering both formal and informal workers. It shows that independently of the specification used, the impact for the full sample is positive and statistically significant. The minimum wage rise in Zone B increased real hourly wages, on average, by 3.6% in that zone. The associated elasticity (ϵ) is 1.24, which is economically significant, particularly considering the decreasing purchasing power of earnings (Figure 3.1). The legislation, with a nominal increase of only 2.9%, broke the negative trend in real earnings which is still observed in the two untreated zones A and C.

Table 2.2

The impact on hourly wages

Heckman second stage for sample selection bias.

Dependent variable:	ln(*hourly_wage*)			
Equation:	(2.1a)		(2.1b)	
Full age threshold: 12 ≤ Age ≤ 97				
ZoneB*Period2	0.0359***	(0.00942)	0.0363***	(0.00948)
$\hat{\lambda}$ (IMR)	-0.1588***	(0.00541)	-0.1580***	(0.00541)
Total observations	2,112,508		2,112,508	
Uncensored observations	960,550		960,550	
Age threshold: 12 ≤ Age ≤ 29				
ZoneB*Period2	0.0399***	(0.01418)	0.0384***	(0.01426)
$\hat{\lambda}$ (IMR)	-0.2616***	(0.00961)	-0.2564***	(0.00958)
Total observations	886,481		886,481	
Uncensored observations	309,008		309,008	
Age threshold: 30 ≤ Age ≤ 49				
ZoneB*Period2	0.0473***	(0.01374)	0.0492***	(0.01383)
$\hat{\lambda}$ (IMR)	-0.1553***	(0.00841)	-0.1554***	(0.00840)
Total observations	687,799		687,799	
Uncensored observations	450,695		450,695	
Age threshold: 50 ≤ Age ≤ 97				
ZoneB*Period2	-0.0075	(0.02411)	-0.0075	(0.02426)
$\hat{\lambda}$ (IMR)	-0.1033***	(0.01455)	-0.1052***	(0.01454)
Total observations	538,228		538,228	
Uncensored observations	337,381		337,381	

Note: the covariates included are state employment rate, gender, age, squared age, rural, schooling level, and interactions of schooling level with rural and gender.
Observations with non-reported wages are excluded from the analysis.
Standard errors in parentheses, by two-step variance estimator Heckman (1979).
Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

To test the presence of sample selection bias, it is enough to test the significance of the inverse Mills ratios (λ) in the second stage estimation. As we can see, for all the specifications $\hat{\lambda}$ results as statistically significant. So, the null hypothesis of no selection bias is rejected, which implies that OLS is indeed producing biased estimators. Therefore, the sample selection bias correction procedure needs to be implemented, and more importantly, pooled OLS models without sample selection correction are biased (reported in Appendix 2.F). With regard to the first stage, Table 2.G.2 in the appendix reports the results for the selection equation for the income specification. It is worth highlighting that for the exclusion restriction, the parameter on $Head$ is positive and highly significant.[7]

Regarding previous findings in the literature for the 2012 Mexican minimum wage harmonization, Campos et al. (2017) is the only reference. Using a similar pooled OLS specifications, but without correcting for sample selection bias, they estimated an impact in the range of 1.67% and 1.98% (to the 2.9% change in the minimum wage). This confirms that the lack of sample selection bias procedures underestimates the impact of the minimum wage raise.[8]

Table 2.2 also presents the analyses of the subsamples by age thresholds. The effect is present only for subsamples of individuals aged less than 50; for the youngest sector of the workforce the impact is a little bit lower than 4% ($\epsilon \approx 1.33$), while for workers aged 30 to 49 the effect is estimated to be between 4.7% and 4.9% ($\epsilon \approx 1.65$). In contrast to the traditional minimum wage literature, our analysis suggests that the wage effect is present not only on young workers. This is explained by the age distribution of the minimum wage workforce: 69% of workers on or below the minimum wage are older than 29 (see Figure 1.14).

Our analysis focuses the main estimates on hourly wages because it also addresses the impact on employment. That is, it absorbs the minimum wage effect on the number of

[7] It is important to remark that for these models, all those individuals with non-valid response for wage are omitted from the analyses. Around one fourth of the employed individuals in the sample (343,889 observations) did not specify or did not answer correctly their wages. Although these observations could have been included in the first stage of the Heckman sample correction procedure (estimating the probability of being active in the labour market, joint to the probability of reporting valid income), this model would have a lack of economic interpretation. In addition it would be necessary the strong assumption of homogeneous distribution of wages across the non-respondents. On this regard, a common concern in the literature with respect to the use of the ENOE survey, is the fact that the number of non-reported income observations has increased over time, and the distribution of these missing observations are not homogeneously distributed among the working population. Rodríguez-Oreggia and López-Videla (2015) found that the probability of non-reporting the income is highly correlated with the factors that determine it. Thus, more educated and formal workers exhibit a higher probability to non-report wages.

[8] They also implemented panel data models estimating stronger effects (although not robust to different time-spans): up to 3.5% for hourly wages.

hours worked. In contrast, regressions on monthly wages only indicate the impact on the earnings that workers are taking home given that they kept their jobs. For completeness, monthly real wages estimates are presented in Appendix 2.E. Table 2.E.1 shows that the estimated effect is statistically significant only in the analysis of the full age sample, with an effect between 1.6% and 1.9% for the 2.9% minimum wage increase. Nevertheless, there is no evidence of negative effects on real monthly wage in any of the estimated models.[9]

Tables 2.G.1 (second stage) and 2.G.2 (first stage) in Appendix 2.G presents the full list of variable coefficients for the four models presented in Table 2.2, . There are a couple of aspects to highlight.

First, for the interaction $ZoneA * Period2$ in equation (2.1b), all the parameters are statistically insignificant independently of the age threshold under analysis. As stated before, these parameters do not correspond to a treatment effect; they are only reflecting the relative difference in real wages between Zone A and Zone C during 2013. This interaction term was included in the model only for completeness, but it also implies that there are no spillover effects to the untreated zones.

Second, with respect to other included control variables (also in Table 2.G.1), the simple linear trend for each zone is negative and statistically significant for all the specifications. This confirms the pattern observed in Figure 3.1, in which all the zones exhibited a negative trend in real wages for the period 2012-2013.

Comparing our results with those obtained without correcting for sample selection bias (Table 2.F.1), the magnitudes of the estimated parameters are very similar, but the standard errors of the estimators become smaller allowing for a higher statistical significance. Related to this, it is important to make a quick remark about the estimates on the inverse Mills ratio, although negative coefficients for $\hat{\lambda}$ denote underestimated coefficients by pooled OLS. The fact that the parameters are very similar before and after the Heckman correction, could lead to conclude that sample size, by the inclusion of more

[9]Campos et al. (2017) found no evidence of significant effects on monthly wages by pooled OLS regressions. By panel date models they estimated an increase on monthly wages by 7.7%, but their results are not robust to different time-spans.

observations is in fact causing the inverse Mills ratio to be significant. But, the analyses by age threshold allows to test this inference. Once that sample size is systematically reduced by age restrictions, the coefficient on $\hat{\lambda}$ remains statistically different from zero (the p-value is close to zero in all the specifications), thus we can conclude that sample selection bias actually exists.

The minimum wage effect by formality condition

Now, given the magnitude of the estimates and the size of the informal labour market, it is necessary to explore the impact by the formality of the employment condition. On the one hand, we analyse if minimum wage regulations are actually in force in the formal labour market. On the other hand, it is interesting to check if the minimum wage is also affecting wage setting in the *uncovered* informal sector. The Standard *Welch–Gramlich–Mincer Two Sector Model* (Welch, 1974; Mincer, 1976; Gramlich et al., 1976) is used to explain the differences between workers actually affected by the minimum wage regulations and workers (see Subsection 1.1.2), that for some reason, are outside of the umbrella of the minimum wage legislation (Lemos, 2009). According to this model, workers not covered by the minimum wage ruling — in our case these workers correspond to the informal sector — should suffer a decrease in their real wages. However, our estimates demonstrate the opposite.

Table 2.3 shows the analysis of the wage effects by formality condition. First, there is a statistically significant impact on wages in the formal sector, which means that the legislation is actually being enforced. The estimated effect on hourly wages for the full age threshold is 3.2%, with an implied elasticity of 1.1. Unlike previous estimates on the sample pooling formal and informal workers, the effect is stronger on workers younger than 30 years old (between 4.6% and 4.7%, $\epsilon \approx 1.6$), although the impact is still present on middle age workers (3.5%, $\epsilon \approx 1.2$).

Second, for the informal sector, there is also evidence of a positive impact on real hourly wages of around 3.1% ($\epsilon \approx 1.07$). This confirms that the intervention is having spillover effects to this specific *uncoverded* sector. It is important to point out that the effect comes from the impact on workers aged 30 to 49, which is estimated to be between 5.8% and 6.0%, reaching an associated elasticity of 1.7. The fact that it is taking place in the informal labour market implies that the minimum wage legislation is substantially affecting the wage incentives in this sector. A possible explanation is the importance of relative remunerations[10] on wage setting: given that the minimum wage rise is making more attractive the formal sector, in response, informal employers also increase the wage rates offered in order to retain their workers and might need an even freater porportionate increase to compensate for other missing aspects.

Table 2.3
The impact on hourly wages by formality condition
Heckman second stage for sample selection bias.

	Formal workers				**Informal workers**			
Dependent variable:	ln(*hourly_wage*)				ln(*hourly_wage*)			
Equation:	(2.1a)		(2.1b)		(2.1a)		(2.1b)	
Full age threshold: 12 ≤ Age ≤ 97								
ZoneB*Period2	0.0319***	(0.01137)	0.0316***	(0.01149)	0.0316**	(0.01458)	0.0309**	(0.01464)
$\hat{\lambda}$ (IMR)	-0.1121***	(0.00560)	-0.1124***	(0.00560)	-0.1482***	(0.00685)	-0.1474***	(0.00684)
Total observations	1,567,202		1,567,202		1,664,940		1,664,940	
Uncensored observations	428,783		428,783		531,767		531,767	
Age threshold: 12 ≤ Age ≤ 29								
ZoneB*Period2	0.0470***	(0.01673)	0.0456***	(0.01690)	0.0281	(0.02240)	0.0263	(0.02247)
$\hat{\lambda}$ (IMR)	-0.1763***	(0.00912)	-0.1750***	(0.00912)	-0.2056***	(0.01232)	-0.1990***	(0.01226)
Total observations	704,294		704,294		751,993		751,993	
Uncensored observations	130,639		130,639		178,369		178,369	
Age threshold: 30 ≤ Age ≤ 49								
ZoneB*Period2	0.0351**	(0.01620)	0.0347**	(0.01636)	0.0576**	(0.02241)	0.0599***	(0.02250)
$\hat{\lambda}$ (IMR)	-0.1148***	(0.00867)	-0.1153***	(0.00867)	-0.1182***	(0.01003)	-0.1187***	(0.01001)
Total observations	452,579		452,579		455,842		455,842	
Uncensored observations	221,419		221,419		229,276		229,276	
Age threshold: 50 ≤ Age ≤ 97								
ZoneB*Period2	-0.0033	(0.03185)	-0.0011	(0.03213)	-0.0167	(0.03358)	-0.0203	(0.03374)
$\hat{\lambda}$ (IMR)	-0.0805***	(0.01930)	-0.0826***	(0.01929)	-0.0841***	(0.01828)	-0.0866***	(0.01826)
Total observations	410,329		410,329		457,105		457,105	
Uncensored observations	76,725		76,725		124,122		124,122	

Note: the covariates included are state employment rate, gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender. Observations with non-reported wages are excluded from the analysis.
Standard errors in parentheses, by two-step variance estimator Heckman (1979). Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

These set of results challenge the *Welch–Gramlich–Mincer Two Sector Model*: the

[10]See Grossman (1983) for a detailed analysis on the relevance of relative wages on wage setting.

minimum wage increase of 2012 did not affect negatively the level of real wages of informal workers. These estimates are in line with previous findings in the literature (Lemos, 2009; Khamis, 2013), in which there exists a real wage increase in both formal and informal workers as a consequence of a minimum wage rise. The main argument in favour to these findings is that the *Welch–Gramlich–Mincer Two Sector Model* was actually designed for independent sectors. But, there exists evidence that in Latin America formal and informal labour markets are actually integrated in a single competitive labour market. See Pratap and Quintin (2006) for the Argentinian labour market, and Maloney (1999) for the Mexican case.

This finding is also relevant in terms of its social implications. Given the size of the informal labour market in Mexico, it is an important concern the fact that a minimum wage increase may benefit only workers in the formal labour market at cost of reducing the purchasing power of — the vulnerable *per se* — informal workers. Our result demonstrate that it is not the case. Chapter 3 analyses also the effect on the distribution of earnings of informal workers, while chapters 4 and 5 evaluate if there is an increase in the activities performed under informal conditions.

Finally, when we evaluate the effect on real monthly earnings, the impact is smaller, and in practically all cases, not statistically different from zero. The impact is significant — just at the 10% level — for the full age threshold, and for workers aged below 29 (1.7% ans 2.7%, respectively). In both cases, the statistically significant effects are obtained only by specification (2.1b) (estimates presented in Table 2.E.2).[11]

The minimum wage effect by gender

Given the differences in the level of remuneration by gender, we cannot assume that minimum wage policies are going to have the same implications on male and female workers. There are structural differences in the labour market that affects wage setting asymmetrically, starting from the fact that only 38% of the workforce are women, but

[11]The full list of coefficients, for the second stage and for the selection equation are presented from Table 2.G.3 to Table 2.G.6.

51% of workers below the minimum wage are female workers (see Table 1.1).

Recognizing these facts, it is common to find these kind of gender analysis on wage equations. Previous studies on the effects of minimum wages on the earnings distribution have also implemented these regressions by gender. See for example Lee (1999), Aeberhardt et al. (2016) and Autor et al. (2016).

Thus, this subsection seeks an answer to the question on how the minimum wage increase affected real earnings but splitting the sample by gender.

Table 2.4

The impact on hourly wages by gender excluding self-employed workers
Heckman second stage for sample selection bias.

	Female workers				Male workers			
Dependent variable:	ln(*hourly_wage*)				ln(*hourly_wage*)			
Equation:	(2.1a)		(2.1b)		(2.1a)		(2.1b)	
Full age threshold: 12 ≤ Age ≤ 97								
ZoneB*Period2	0.0487***	(0.01538)	0.0469***	(0.01548)	0.0275**	(0.01187)	0.0294**	(0.01195)
$\hat{\lambda}$ (IMR)	-0.0220***	(0.00798)	-0.0182**	(0.00798)	-0.3741***	(0.00915)	-0.3759***	(0.00915)
Total observations	1,149,201		1,149,201		963,307		963,307	
Uncensored observations	376,687		376,687		583,863		583,863	
Age threshold: 12 ≤ Age ≤ 29								
ZoneB*Period2	0.0296	(0.02418)	0.0284	(0.02433)	0.0461***	(0.01736)	0.0445**	(0.01746)
$\hat{\lambda}$ (IMR)	-0.2165***	(0.02696)	-0.2066***	(0.02687)	-0.4119***	(0.01214)	-0.4064***	(0.01209)
Total observations	457,849		457,849		428,632		428,632	
Uncensored observations	115,364		115,364		193,644		193,644	
Age threshold: 30 ≤ Age ≤ 49								
ZoneB*Period2	0.0630***	(0.02199)	0.0617***	(0.02214)	0.0365**	(0.01747)	0.0411**	(0.01758)
$\hat{\lambda}$ (IMR)	-0.0061	(0.00982)	-0.0022	(0.00983)	-0.6247***	(0.01859)	-0.6360***	(0.01867)
Total observations	440,618		440,618		305,290		305,290	
Uncensored observations	185,875		185,875		264,820		264,820	
Age threshold: 50 ≤ Age ≤ 97								
ZoneB*Period2	0.0301	(0.03938)	0.0263	(0.03965)	-0.0310	(0.03042)	-0.0286	(0.03060)
$\hat{\lambda}$ (IMR)	0.0355**	(0.01649)	-0.0339**	(0.01649)	-0.3346***	(0.04306)	-0.3488***	(0.04333)
Total observations	308,843		308,843		229,385		229,385	
Uncensored observations	75,448		75,448		125,399		125,399	

Note: the covariates included are state employment rate, gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender. Observations with non-reported wages are excluded from the analysis.
Standard errors in parentheses, by two-step variance estimator Heckman (1979). Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

There are some interesting findings. For the female labour force the impact is on average stronger (by around 4.8%), but only statistically significant for middle age workers. Actually the strongest effect throughout this chapter is precisely estimated on these segment, with an impact of between 6.2% and 6.3%, which implies an elasticity of 2.1.

The coefficients for the youngest and oldest segments of the female workforce are similar, around 3% but all of them resulted statistically insignificant.

With respect to the effect on the male labour force, the effect for the full age threshold is between 2.8% and 2.9%, having a stronger impact on the youngest segment (by around 4.5%) than on middle age workers (around 4%).

As in all the previous cases, we do not find evidence of significant effects on the eldest workers.

Table 2.E.3 shows that the large significant effects on hourly wages for female workers aged 30 to 49 practically vanishes when it is analysed the impact on monthly wages. For the rest of the age thresholds, the effect remains positive (between 0.8% and 3.8%) but not statistically significant. For male workers, the effect is positive and statistically significant for the full age threshold sample (2.3%), but we fail to find significant effects on workers older than 29 years old.[12]

So, in spite of the gender composition of the segment of the labour force with the lowest level of remunerations, in general we do not find evidence of stronger effects on female workers. The effect on the male workforce follows a similar pattern with respect to previous estimates, in which the impact is found statistically significant for workers younger than 50 years old. In contrast, for women, the 2012 minimum wage intervention had an effect only on the middle age workers.

2.5.2 Dynamics of the impact on real earnings

This subsection uses specification (2.2) to estimate the persistence of the minimum wage effects on earnings, and to test the robustness of the model. Instead of including a single DiD estimator, this models captures the treatment effect for each quarter after the intervention. Following the same structure of previous results, equation (2.2a) uses as a control group zones A and C, while specification (2.2b) includes only wage zone C in the reference group.

[12]Tables 2.G.7 to Table 2.G.10 present the coefficients for all the variables included in the model, for both second stage and for selection equation.

Table 2.5 shows, as expected, smaller coefficients but still positive and statistically significant. The impact on earnings is present three quarters after the intervention. The strongest effect is observed in the second quarter of 2013, with estimated impacts in the range of 2.2% and 2.6%. Subsequently, the effect becomes lower and statistically not different from zero. For the dynamics of monthly earnings, the impact persists up to the second quarter after the intervention with coefficients around 2% (see Table 2.E.4).

These results imply that the Mexican labour market is able to response immediately to the minimum wage intervention. Although the policy change was not anticipated by employers, we can observe significant effects in the next quarter after the intervention. Furthermore, there is no evidence of a subsequent decline in real hourly wages. One of the hazards of the minimum wage increases is that they can generate an erosion to the purchasing power of wages via inflation.

Table 2.5

The dynamics for the impact on hourly wages

Second stage for Heckman correction for sample selection bias.

Dependent variable:	ln(*hourly_wage*)			
Equation:	(2.2a)		(2.2a)	
ZoneB*D2013_Q1	0.022***	(0.0078)	0.023***	(0.0077)
ZoneB*D2013_Q2	0.022***	(0.0078)	0.026***	(0.0077)
ZoneB*D2013_Q3	0.019**	(0.0079)	0.021***	(0.0079)
ZoneB*D2013_Q4	0.006	(0.0077)	0.011	(0.0077)
$\hat{\lambda}$ (IMR)	-0.161***	(0.0054)	-0.162***	(0.0054)
Total observations	2,112,508		2,112,508	
Uncensored observations	960,550		960,550	

* Observations with non-reported wages are excluded from the analysis.

Note: the covariates included are state employment rate, gender, age, squared age, rural, schooling level, and interactions of schooling level with rural and gender.

Standard errors in parentheses, by two-step variance estimator Heckman (1979).

Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

With respect to the sample selection bias, this model corroborates the bias found in previous estimates. The inverse Mills ratio has a similar magnitude to that presented in Table 2.2 for the full age threshold regression.

Campos et al. (2017) estimate a similar regression on the dynamics of the impact on wages, by pooled OLS models. According to their results, the effect on hourly wages also vanishes after the second quarter, but they found no effects on monthly wages in any quarter after the minimum wage legislation.

2.5.3 Robustness checks

The effect excluding self-employed workers

Following previous literature on the minimum wage effects on earnings (Lee, 1999; Autor et al., 2016), we replicate the previous econometric analysis, equation (2.1), but excluding self-employed workers. The argument is that these workers may not be affected by minimum wage changes, or in a lesser extent than waged workers.

The drawback of this exercise is that it implies the systematic restriction of a segment of the labour force, which is precisely what we have avoided implementing by the Heckman two stage procedure. Nevertheless, the objective is not to obtain a better estimator of the minimum wage effect, but to demonstrate that our conclusions are not led by this group of *uncovered* workers.

So, the exclusion of self-employed workers reduces the sample to 767,006 observations, which means that this segment of the labour force represents a bit more than 20% of the workforce. Only 12% of the self-employed workers performed their labour activities in the formal labour market.

Thus, Table 2.6 presents the estimates for this robustness checks. For the full age sample, the effect is 0.2% stronger (3.8%) with respect to our baseline specification presented in Table 2.2. This is according to the expected; focusing on waged workers, the magnitude of the impact increases. But, if we observe the estimates for workers aged 12 to 29 years old, the effect remains significant but it is now smaller, by more than one percentage point (between 2.7% and 2.8%), and with greater standard errors . With respect to the middle age workers, the effect does not change importantly, estimating an impact by around 4.6%. The impact for the oldest workers remains statistically not different from zero.

Given that the composition of the self-employed workers is not homogeneous in terms of their formality condition, we replicate the analysis separating the sample by formal and informal workers.

Table 2.6
The impact on hourly wages excluding self-employed workers
Heckman second stage for sample selection bias.

Dependent variable:	ln(*hourly_wage*)			
Equation:	(2.1a)		(2.1b)	
Full age threshold: 12 ≤ Age ≤ 97				
ZoneB*Period2	0.0383***	(0.00899)	0.0384***	(0.00905)
$\hat{\lambda}$ (IMR)	-0.1437***	(0.00492)	-0.1436***	(0.00491)
Total observations	1,913,207		1,913,207	
Uncensored observations	767,006		767,006	
Age threshold: 12 ≤ Age ≤ 29				
ZoneB*Period2	0.0284**	(0.01424)	0.0269*	(0.01432)
$\hat{\lambda}$ (IMR)	-0.4960***	(0.01025)	-0.4910***	(0.01022)
Total observations	858,102		858,102	
Uncensored observations	281,420		281,420	
Age threshold: 30 ≤ Age ≤ 49				
ZoneB*Period2	0.0457***	(0.01333)	0.0463***	(0.01342)
$\hat{\lambda}$ (IMR)	-0.1361***	(0.00748)	-0.1366***	(0.00748)
Total observations	593,419		593,419	
Uncensored observations	358,930		358,930	
Age threshold: 50 ≤ Age ≤ 97				
ZoneB*Period2	0.0066	(0.02391)	0.0099	(0.02411)
$\hat{\lambda}$ (IMR)	-0.0661***	(0.01415)	-0.0688***	(0.01415)
Total observations	461,686		461,686	
Uncensored observations	126,656		126,656	

Note: the covariates included are state employment rate, gender, age, squared age, rural, schooling level, and interactions of schooling level with rural and gender.
Observations with non-reported wages are excluded from the analysis.
Standard errors in parentheses, by two-step variance estimator Heckman (1979).
Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.7 shows that the effect on the formal labour market does not change importantly. The minimum wage effect is estimated at 3.4%, 4.6% and 3.8%, for the full age threshold, youngest segment and middle age workers, respectively. But, as expected th impact on informal workers is lower, having a statistically significant effect only on workers aged 30 to 49 (around 4.9%). Yet, for these workers, the effect is still strongest than the observed on formal workers.

But, the fundamental message of this exercise is that none of the conclusions changes. On average, the impact on the full age threshold has an elasticity around 1.3. The effect is present only in workers younger than 50 years old. And, the model corroborates the presence of sample selection bias by the exclusion of the inactive labour force.

Table 2.7

The impact on hourly wages by formality condition excluding self-employed workers
Heckman second stage for sample selection bias.

	Formal workers				**Informal workers**			
Dependent variable:	ln(*hourly_wage*)				ln(*hourly_wage*)			
Equation:	(2.1a)		(2.1b)		(2.1a)		(2.1b)	
Full age threshold: 12 ≤ Age ≤ 97								
ZoneB*Period2	0.0343***	(0.01125)	0.0336***	(0.01137)	0.0299**	(0.01411)	0.0297**	(0.01416)
$\hat{\lambda}$ (IMR)	-0.0976***	(0.00550)	-0.0979***	(0.00549)	-0.1373***	(0.00618)	-0.1373***	(0.00617)
Total observations	1,543,225		1,543,225		1,489,616		1,489,616	
Uncensored observations	405,217		405,217		361,789		361,789	
Age threshold: 12 ≤ Age ≤ 29								
ZoneB*Period2	0.0457***	(0.01656)	0.0441***	(0.01674)	0.0220	(0.02134)	0.0202	(0.02141)
$\hat{\lambda}$ (IMR)	-0.1719***	(0.00904)	-0.1707***	(0.00904)	-0.2260***	(0.01172)	-0.2199***	(0.01166)
Total observations	701,821		701,821		726,087		726,087	
Uncensored observations	128,198		128,198		153,222		153,222	
Age threshold: 30 ≤ Age ≤ 49								
ZoneB*Period2	0.0384**	(0.01613)	0.0374**	(0.01629)	0.0484**	(0.02238)	0.0496**	(0.02247)
$\hat{\lambda}$ (IMR)	-0.1034***	(0.00853)	-0.1039***	(0.00852)	-0.1069***	(0.00875)	-0.1077***	(0.00874)
Total observations	440,618		440,618		373,423		373,423	
Uncensored observations	209,643		209,643		149,287		149,287	
Age threshold: 50 ≤ Age ≤ 97								
ZoneB*Period2	0.0042	(0.03180)	0.0062	(0.03211)	-0.0012	(0.03423)	0.0007	(0.03446)
$\hat{\lambda}$ (IMR)	-0.0357*	(0.01901)	-0.0381**	(0.01901)	-0.0580***	(0.01865)	-0.0622***	(0.01865)
Total observations	400,786		400,786		390,106		390,106	
Uncensored observations	67,376		67,376		59,280		59,280	

Note: the covariates included are state employment rate, gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender. Observations with non-reported wages are excluded from the analysis.
Standard errors in parentheses, by two-step variance estimator Heckman (1979). Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Falsification test: pretreatment parameters

As a final robustness check, we run a similar regression to the specification on the dynamics of the effect, equation (2.2), but we now extend the period of analysis from 2011 to 2014. In addition, using a specification similar to Autor (2003), we include DiD estimators for every quarter in the sample even before the intervention. The logic behind the falsification test is that the only difference between control and treatment groups is precisely the policy intervention, so for legitimate control groups all those parameters before the intervention should be insignificant. That is, in absence of the policy reform control and treatment groups are identical, so there should be no effect.

Furthermore, taking advantage of specification (2.5a), we also analyse graphically the DiD parameters on Zone A to contrast with our parameters of interest.

$$\begin{aligned}\ln(w_i) = \beta_0 &+ \sum_{j=1}^{7} \tau_j ZoneB_i * Q_{-ji} + \sum_{j=1}^{8} \delta_j ZoneB_i * Q_{ji} \\ &+ \sum_{j=1}^{7} \phi_j Q_{-ji} + \sum_{j=1}^{8} \eta_j Q_{ji} + \beta_1 ZoneB_i + \sum_{k=2}^{k} \beta_k X_{ki} + e_i \end{aligned} \tag{2.5a}$$

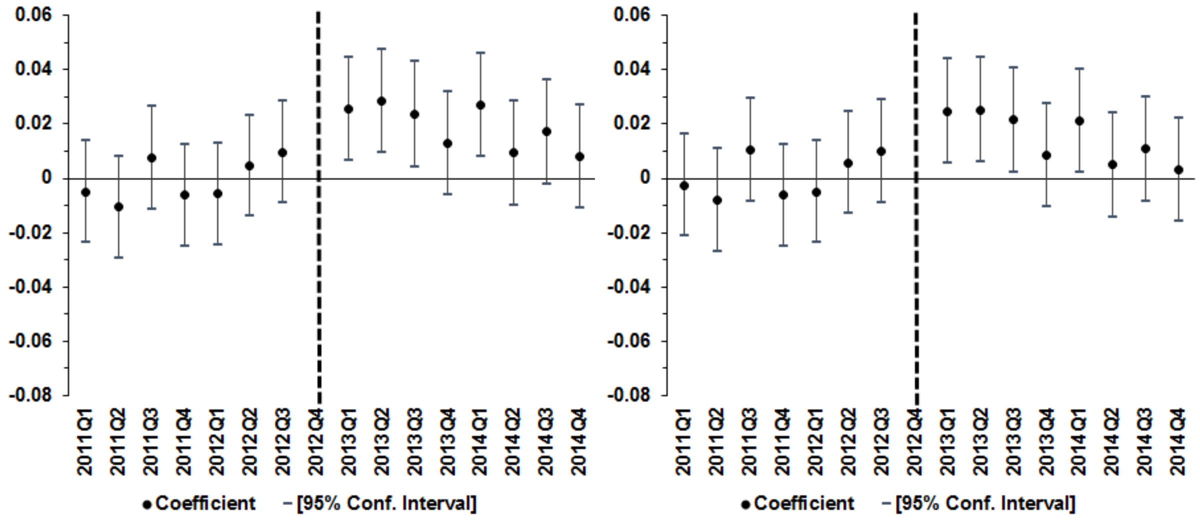
$$\begin{aligned}\ln(w_i) = \beta_0 &+ \sum_{j=1}^{7} \tau_j ZoneB_i * Q_{-ji} + \sum_{j=1}^{8} \delta_j ZoneB_i * Q_{ji} \\ &+ \sum_{j=1}^{7} \phi_j Q_{-ji} + \sum_{j=1}^{8} \eta_j Q_{ji} + \sum_{j=1}^{7} \varphi_j ZoneA_i * Q_{-ji} + \sum_{j=1}^{8} \psi_j ZoneA_i * Q_{ji} \\ &+ \beta_1 ZoneB_i + \beta_2 ZoneA_i + \sum_{k=3}^{k} \beta_k X_{ki} + e_i \end{aligned} \tag{2.5b}$$

where Q_j correspond to binary variables that identify the number of quarters j before and after the intervention. τ_j and φ_j are the pretreatment parameters, corresponding to the period from 2011Q1 to 2013Q3. Our parameters of interest are δ_j, while ψ_j are the post-intervention parameters for Zone A. The quarter where the legislation came into force (20124Q) is omitted, so this period constitutes the basis for comparison. With exception of the variable for the simple linear trend, which is contained in the quarterly dummy variables Q_{ji}, the set of control variables is the same to that used in Subsection 2.5.1, including the state employment rate.

Figure 2.4 shows the value of the wage coefficients, as well as the 95% confidence intervals of the DiD estimators for the treated Zone B. For both specifications, the pre-treatment coefficients are statistically non-different from zero, which implies that there

Figure 2.4

Falsification test for the effect on hourly wages. DiD coefficients for Zone B



(a) Equation (2.5b) **(b)** Equation (2.5a)

are no differences between control and treatment group in absence of the policy change. That is, control groups are valid to evaluate the minimum wage increase on Zone B.

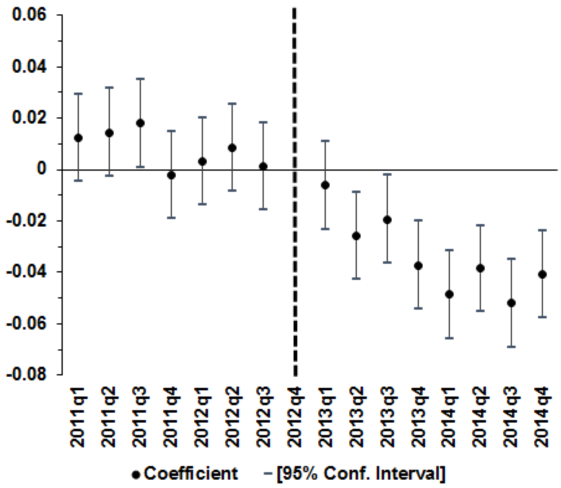
On the other hand, for the first three quarters after the intervention the parameters become positive and statistically significant. In line with our previous results in subsection 2.5.2, this analysis confirm that Mexican labour responds immediately to the minimum wage change and there is no evidence of a decline in real earnings even in a longer period.

Exploiting the design of this specification, as well as the larger period of observation, as a complementary analysis we also explore the real hourly wage trend followed by Zone A. We can observe that for the parameters corresponding to the interaction between Zone A and the respective dummy quarters, the pattern of the estimators is completely different. Figure 2.5 shows clearly the negative trend on real wages for Zone A. There are significant estimators before and after the intervention, being positive in the pretreatment period and subsequently the coefficients become negative. This implies that minimum wage legislation is not the source of the decreasing levels of wages for Zone A.

Then, this analyses confirms that the evaluation of the increase of minimum wages in Zone B using as a control groups zones A and C generates valid and successful estimators by DiD procedures.

Figure 2.5

Falsification test for the effect on hourly wages. DiD coefficients for Zone A



(a) Equation (2.5a)

2.6 Conclusions

The empirical estimates in this chapter suggest that the 2012 Zone B's minimum wage increased real earnings by an important magnitude. On average, real hourly wages increased by 3.6%, which means that the effect is stronger than the minimum wage rise by itself (2.9%).

There are multiple and important repercussions of these findings. First, minimum wages are actually biting in the Mexican labour market. Even though it has suffered an erosion of more than 70% in real terms, it is still in force. Changes to the minimum wage level actually affect the wage setting.

Second, the minimum wage effect is not restricted to the formal labour market. Minimum wage variations affect also incentives and wage setting in the labour market. For some segments of the informal workforce is even stronger than in the informal labour market. This means that minimum wage works as a reference for fair remuneration in the informal sector.

Third, elasticities higher than one imply spillover or *lighthouse* effects. That is, the impact of minimum wage regulations goes beyond workers with earnings originally below the minimum wage value. If the purpose itself of this kind of policies is to improve the purchasing power of the workers, we can consider the 2012 intervention achieved that objective. The problem is that the expansion on real earnings may not be limited to the poorest segment of the labour force, implying for instance an increase on inequality.

Precisely, the objective of the following chapter is to evaluate the effects at different points of the earnings distribution in order to determine whose workers actually experienced changes on their real wages.

Appendix 2.A Variables construction

This appendix describes in a detailed way the process of variable generation procedure. The variables used are contained in the database *sociodem*, from ENOE, for all the quarters from 2011 to 2014.

Dependent Variables

- **Real wages**

  ENOE provides two variables for earnings. On the one hand, *ingocup* reports the nominal monthly wage by worker, while ing_x_hrs presents hourly earnings.

  Both variables are used for the analyses of the impact on wages, but in real terms. Nominal wages are deflated using the National Consumer Price Index (INPC), which is not contained in ENOE but it is also obtained from INEGI, and whose base period corresponds to the second fortnight of December 2010.

  Price indices at the municipality level are not available. INEGI considers only 46 cities to construct the INPC. As a consequence, a large number of the municipalities in ENOE are not included for the INPC calculation. We considered some options to generate approximations of price indices by state or wage zone, but important biases can be produced specially in rural areas (affecting mainly our prefered control Zone C). Then, in order to avoid subjective decisions for constructing regional price indices, we use the national price index —the INPC— to deflate wages.

  It is also relevant to mention that there is a discrepancy in the number of valid observations between monthly and hourly expressions. Hourly wages are obtained simply from the division of monthly wages over the number of hours worked (*hrsocup*, in ENOE). When the hours worked are not reported or wrongly answered, hourly wage is a missing value. Aiming to have a consistent sample size, observations with missing values for hourly wage are not considered in the regressions. These dropped observations represent 3.25% of the valid income sample. Estimates for the whole set of observations for monthly income are not reported, but its exclusion does not affect significantly.

Thus, the logarithm of wage variables are generated by the following expressions:

$\ln(monthly\_wage_i)$ $=\ln[(ingocup_i/INPC) * 100] \iff ing\_x\_hrs_i > 0$

$\ln(hourly\_wage_i)$ $=\ln[(ing\_x\_hrs_i/INPC) * 100]$

- **Labour status**

  To identify the labour status for each individual, the survey provides variables $clase1$ and $clase2$. In the first of them, it is possible to distinguish active labour market individuals ($clase1 = 1$), from those inactive ($clase1 = 2$). $clase2$ classifies active and inactive population in employed ($clase2 = 1$), unemployed ($clase2 = 2$), labour available ($clase2 = 3$), and labour unavailable individuals ($clase2 = 4$). The dichotomous variables on labour status are constructed by the following way:

  $labour\_market\_active_i = 1 \; \forall \; i \; clase1_i = 1$; $labour\_market\_active_i = 0$ otherwise.

  $employed_i = 1 \; \forall \; i \; clase2_i = 1$; $employed_i = 0 \; \forall \; i \; clase2_i = 2$.

  The definition of these variables implies that *employed* is restricted to active labour market population.

- **Informality status.**

  ENOE follows the Hussmanns' Matrix criteria to identify formal and informal workers. For our purpose we use the variable *mh_col*, which reports the columns of the Hussmanns' matrix. Values ($mh\_col = 2, 4, 6, 8$) correspond to formal workers. So, for the analysys on the sub-categories of informality (waged, self-employed and non-waged), we are comparing them with respect to all formal workers. Transition to unemployment or to inactive status are not considered.

  $informal_i = 1 \; \forall \; i \; mh\_col_i = 1, 3, 5, 7, 9$; $informal_i = 0$ otherwise

  $waged\_informal_i = 1 \, \forall \, i \; mh\_col_i = 1, 3$; $waged\_informal_i = 0 \, \forall \, mh\_col_i = 2, 4, 6, 8$

$self\_emp\_informal_i = 1 \; \forall \; i \; mh\_col_i = 5,7$; $self\_emp\_informal_i = 0 \; \forall \; mh\_col_i = 2,4,6,8$

$non\_waged\_informal_i = 1 \; \forall \; i \; mh\_col_i = 9$; $non\_waged\_informal_i = 0 \; \forall \; mh\_col_i = 2,4,6,8$

Minimum wage zones and post-treatment period dummies

- **Minimum wages zones**

  ENOE contains a variable to identify the minimum wage zone for each observation (*zona*). Nevertheless, using this variable is not possible to follow individuals in Zone B after the intervention; by construction these individuals belong to Zone A after November 2012. In addition, there are some mistakes detected in the classification by INEGI; three municipalities are classified in Zone B, but according to CONASAMI[13] they belong to Zone A (Apodaca, Zapopan, and Tlajomulco, all of them in the state of Jalisco), while four municipalities from Zone C are wrongly included in Zone B (Panuco and Pueblo Viejo, in the state of Veracruz, and Salinas Victoria and Juarez, in the state of Nuevo Leon).

  In consequence, it was necessary to generate a variable that allows to identify minimum wage zones for all the period of analyses. We obtain from CONASAMI the minimum wage zones classification, and using the codes by states and municipalities, it is possible to identify the municipalities in ENOE database.

  First, we generate a variable that allows to identify the municipality, by concatenating the state code (variable *ent*, two digits) and the municipality code (variable *mun*, three digits):

  $id\_mun = "ent" + "mun"$

  Then, it is possible to construct the variables $ZoneB$, $ZoneA$ and $ZoneC$:

[13] `http://www.conasami.gob.mx/pdf/estructura%20municipal/Estructura_municipal.pdf` Last accessed, 17 March 2016.

$ZoneB_i = 1 \; \forall \; i \; id\_mun_i = 14039, 14070, 14097, 14098, 14101, 14120, 19006,$
$19019, 19021, 19026, 19039, 19046, 19048, 26004, 26007, 26012, 26016, 26017, 26018,$
$26020, 26021, 26022, 26025, 26026, 26029, 26030, 26033, 26035, 26036, 26042, 26045,$
$26046, 26047, 26056, 26058, 26060, 26062, 26064, 26065, 26071, 26072, 28002, 28003,$
$28004, 28009, 28011, 28012, 28021, 28028, 28029, 28038, 28043, 30040, 30131, 30189;$
$ZoneB_i = 0$ otherwise.

$ZoneA_i = 1 \; \forall \; i \; ent_i = 02, 03, 09$ or $id\_mun_i = 08028, 08037, 08053, 12001,$
$15013, 15020, 15024, 15033, 15057, 15104, 15109, 15121, 26002, 26019, 26039, 26043,$
$26048, 26055, 26059, 26070, 30039, 30048, 30061, 30082, 30108, 30111, 30204, 30206,$
$28007, 28014, 28015, 28022, 28024, 28025, 28027, 28032, 28033, 28035, 28040;$
$ZoneA_i = 0$ otherwise.

$ZoneC_i = 1 \iff ZoneA = 0 \text{and} ZoneB = 0$; $ZoneC_i = 0$ otherwise.

- **Post-treatment period**

  The intervention came into force on 27 November 2012. Given that the survey presents the information in a quarterly basis, for the 2012Q4 it is necessary to differentiate individuals interviewed before and after the legislation. To do that, we use the variable *d_sem*, whose last two digits shows the number of the week when the interview took place for urban households (taking values from 01 to 13), or the month of the interview for rural households (taking values from 01 to 03).

  $Period2_i = 1 \; \forall \; i \; t_i \geq 2013Q1$, or ($d\_sem_i \geq 09 \; \forall \; i \; rural_i = 1$ and $t_i = 2012Q4$) or ($d\_sem_i \geq 03 \; \forall \; i \; rural_i = 0$ and $t_i = 2012Q4$); $Period2_i = 0$ otherwise.

Control Variables

- **Head of the household.**

  Variable *par_c* identifies the family relationship of each member of the household with respect to the head: $head_i = 1 \; \forall \; i \; par\_c_i = 101$; $head_i = 0$ otherwise.

- **Female individuals.**

  $female_i = 1 \ \forall \ i \ sex_i = 2$; $female = 0$ otherwise.

- **Age.**[14]

  $age_i = eda_i \ \forall \ i \ eda_i \leq 97$

  $age_i^2 = eda_i^2 \ \forall \ i \ eda_i \leq 97$

  Observations with non-specified age are excluded. $eda = 99$ denotes non-specified age for workers older or equal to 12 years old. $eda = 98$ denotes non-specified age for workers younger than 12 years old.

- **Rural municipalities.**

  Variable t_loc describes the population size in the village or municipality. In this case we follow the definition by INEGI, where rural municipalities are those with a population lower than 2,500 inhabitants.

  $rural_i = 1 \forall \ i \ t\_loc_i = 4$; $rural = 0$ otherwise.

- **School Level**

  Primary basic school completed (from first to sixth year of education):
  $school\_level_i = 1 \ \forall \ i \ niv\_ins_i = 1$

  Secondary basic school completed (from seventh to sixth year of education):
  $school\_level_i = 2 \ \forall \ i \ niv\_ins_i = 2$;

  High school completed (from ninth to twelfth year of education):
  $school\_level_i = 3 \ \forall \ i \ niv\_ins_i = 3$;

  Undergraduate and Post-graduate degree:
  $school\_level_i = 4 \ \forall \ i \ niv\_ins_i = 4$;

  Observations with non-specified level of education are excluded from the sample.

[14] It is important to specify the age delimitation of the sample. ENOE applies the questionnaire on occupation and employment to individuals from 12 years old, but given that the minimum legal working age since 2014 is 15 years old, official figures are delimited to population aged at least 15. But, given that our analyses is highly focused on the informal labour market, the sample includes all individuals interviewed. Table 4.1 describes the number of observations by labour status.

Appendix 2.B List of cities included in the calculation of the INPC by INEGI

Table 2.B.1
Cities considered in the calculation of the INPC by minimum wage zone

Minimum wage zone	**City**	**State(s)**
B	Guadalajara	Jaliso
B	Hermosillo	Sonora
B	Huatabampo	Sonora
B	Monterrey	Nuevo León
B	Tampico	Tamaulipas
A	Mexico City	Mexico City-Mexico State
A	Acapulco	Guerrero
A	Ciudad Juárez	Chihuahua
A	La Paz	Baja California Sur
A	Matamoros	Tamaulipas
A	Mexicali	Baja California
A	Tijuana	Baja California
C	Aguascalientes	Aguascalientes
C	Campeche	Campeche
C	Ciudad Acuña	Coahuila
C	Ciudad Jiménez	Chihuahua
C	Colima	Colima
C	Córdoba	Veracruz
C	Cortazar	Guanajuato
C	Cuernavaca	Morelos
C	Culiacán	Sinaloa
C	Chetumal	Quintana Roo
C	Chihuahua	Chihuahua
C	Durango	Durango
C	Fresnillo	Zacatecas
C	Iguala	Guerrero
C	Jacona	Michoacán
C	León	Guanajuato
C	Mérida	Yucatán
C	Monclova	Coahuila
C	Morelia	Michoacán
C	Oaxaca	Oaxaca
C	Puebla	Puebla
C	Querétaro	Queretaro
C	San Andrés Tuxtla	Veracruz
C	San Luis Potosí	San Luis Potosí
C	Tapachula	Chiapas
C	Tehuantepec	Oaxaca
C	Tepatitlán	Jaliso
C	Tepic	Nayarit
C	Tlaxcala	Tlaxcala
C	Toluca	Mexico State
C	Torreón	Coahuila
C	Tulancingo	Hidalgo
C	Veracruz	Veracruz
C	Villahermosa	Tabasco

Source: INEGI and CONASAMI.

Appendix 2.C The declining trend on Zone's A real wages

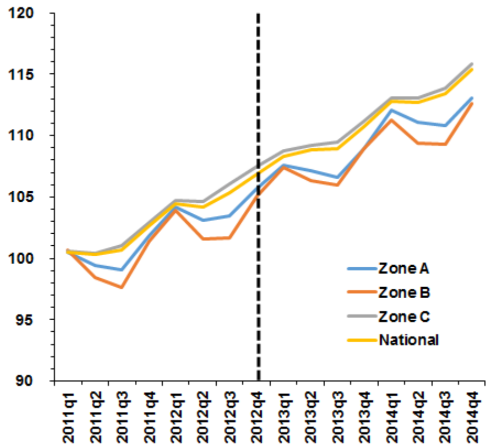
Although this issue is out of the scope of the thesis, this appendix explores some options to explain the drop in wage levels for Zone A. First of all, it is important to emphasize that Zone A includes Mexico City, the states of Baja California, Baja California Sur, and some municipalities in Sonora, Guerrero, Veracruz and Tamaulipas. But, 80.2% of the active population of Zone A are resident of Mexico City, which implies that changes in the labour market for Zone A, are mostly explained by changes in Mexico City.

Given that the models estimate the effects on real income, the most straightforward explanation is difference in the level of prices. In order to explore the pattern in nominal terms, exactly as ENOE reports income, Figure 2.2 describes nominal wages expressed in monthly and hourly terms, respectively. Although nominal wages exhibit a small increasing trend, for the case of Zone A that increment is smaller with respect to the other two zones, and even close to zero if we observe hourly wages. So, the inference is basically the same, nominal wages in Zone A are not growing at the same level of zones B and C.

For all the econometric specifications, real wages are constructed deflating wages using the National Consumer Price Index. As explained previously. there are no price indices by wage zone, and its construction is not plausible because not all the municipalities are considered in the INPC calculation. Nevertheless, with the aim of corroborating if there exist differences in price levels trends among wage zones for period 2013-2014, we construct a proxy of the price index by zones by a simple average of the available cities included in the INPC. Figure 2.C.1 shows that the price level trend in Zone A does not exhibit a different behaviour with respect to the other zones. In addition, there are no atypical increases in its price index for the post-treatment period. Then, the reduction in real wages for Zone A should not be occasioned by a price level increase.

An option beyond inflation is the sampling process in the survey. Even though ENOE

Figure 2.C.1
Consumer price indices by minimum wage zone
(100=1F December 2010)



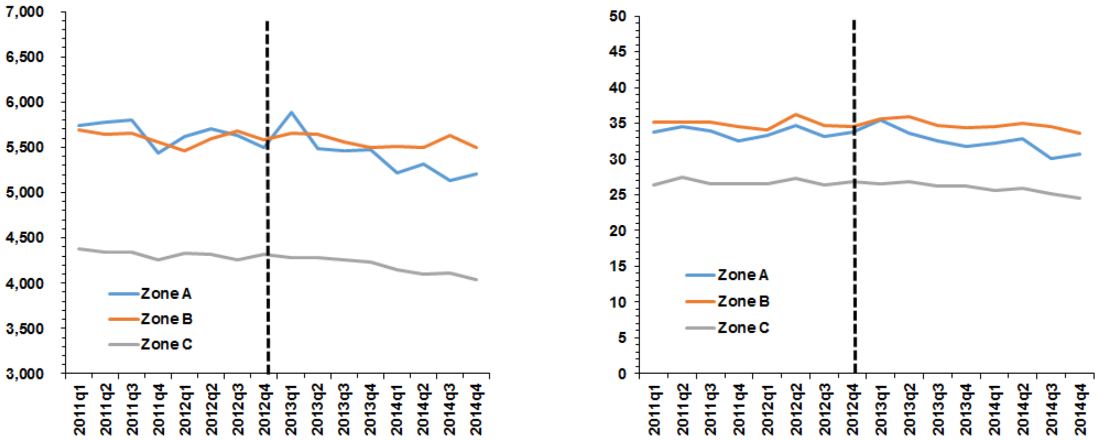
is representative at the national and at the state level, we are not using expansion factors in the econometric regressions, nor in the pretreatment trend analysis. Thus, it is possible that the sample chosen is biasing mean wages for Zone A. In the sample, active population in Mexico City represents only 31.9% of the active population in Zone A. Figure 2.C.2 shows the trends observed in wages, but weighted by the expansion factors included in ENOE. As we can observe, the gap between Zone A and Zone B is smaller, and the decreasing trend is smoother. DiD procedures are implemented using expansion factors. Nevertheless the result does not change significantly (not reported).

In terms of the minimum wage intervention, there is no reason to believe that minimum wages legislation change could affect wages in the untreated Zone A. There is no evidence of labour force migration across zones as a consequence of the intervention. So, an increase in the labour supply can be dismissed.

Nevertheless, s plausible hypothesis that may lead to the reduction observed in Zone A, or in Mexico City, is the Federal Labour Reform in 2012. One feature that could be closely related to the reduction in average wages in Mexico City was the reform to the Article 15 of the Labour Federal Law, which defines the figure of subcontracting arrangement or outsourcing.[15] This regime is characterized by temporary contracts, and

[15]Source: Official Journal of the Federation. November 30 2012. Accessed on February 5, 2016. http://www.dof.gob.mx/nota_detalle.php?codigo=5280815&fecha=30/11/2012

Figure 2.C.2
Real wage trends by wage zone
(Sample weighted by expansion factors. Mexican pesos of 1F December 2010)



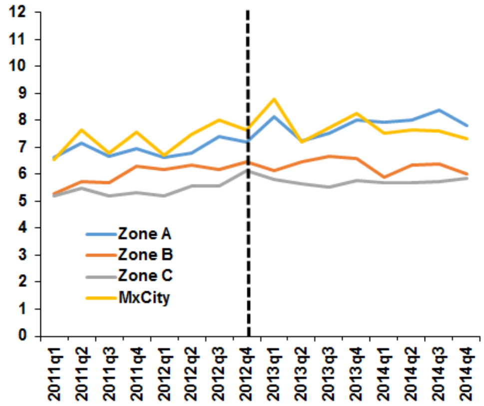
(a) Real Mean Monthly Wage **(b)** Real Mean Hourly Wage

lower wages without benefits. It allows the employer to hire a subcontractor for a specific task, which for its specialisation requires external workers. Outsourcing is not allowed when it implies to perform the total labour activities done in the job centre, and when tasks are the same that those carried out by the rest of workers.

Even though this reform came into force at the national level, by the composition of the labour markets in urban areas, it is likely to have higher impact in bigger cities. Unfortunately, ENOE is not designed to identify this kind of labour arrangements. But, in order to explore the validity of this hypotheses Panel (a) of Figure 2.C.3 shows the weighted percentage of temporary labour arrangements with respect to employed population, by wages zones (Mexico City is also included separately for the purposes of the analyses).

Some important facts arise. First, Zone A exhibits the higher proportion of temporary arrangements (between 6.5% and 8.4%). Second, the trend for the three wage zones is slightly positive, although a structural change in the trend is not identified, especially in Zones B and C. And third, in contrast to zones B and C, Zone A shows an increase in the relative number of temporary contracts in 2013, which could support the hypothesis that this kind of labour arrangements is generating a decrease in mean wages. Panel (b) shows

Figure 2.C.3
Rate of temporary contracts
(% with respect to employed population)



Source: Own calculations with data from ENOE, INEGI.

the sample values for the same series; the trends are similar but once again, the sampling process increases the proportion of temporary arrangements for Zone A, especially for 2014.

Appendix 2.D Potential endogeinity problems of the state employment rate

A valid concern with respect to the inclusion of employment rate as a regressor in the wage equation is its potential endogeinity with respect to the disturbance term e_i. In this case, the source of endogeinity is simultaneity because employment is the dependent variable in other structural equation that we are also estimating: the causal effect on labour status.

Nevertheless, our argument is that given that the database provides information at the individual level, the state employment rate can be taken as given in the wage equation. First, we are not trying to estimate the equilibrium wage at the national scale, nor the employment rate in equilibrium. Second, employment level by states is not our dependent variable when we measure the effect of the Zone B minimum wage increase; we are evaluating the effect on the individual labour status. And third, although we include as regressors zone dummies and separate linear trends by zones, it is not enough to control for the structural economic activity at a more local level. Given the size of the labour market in Mexico we exploit the differences of the labour force participation by states (32 states). Municipalities belonging to the same wage zone can have very different characteristics in terms of development, employment, and even geographical location.

Then, employment rate at the state level is not necessarily correlated with the unexplained factors in the wage equation at the individual level. A relevant example of the inclusion of regional employment rates in the wage equation is Mroz (1987).[16] In this paper, aiming to correct previous misspecification on female labour supply, Mroz performs an exhaustive analysis on the exogeinity assumptions of the woman's labour supply equation with respect to her wage rate. By the use of instrumental variables, he found that the use of experience variables as an instrument in the wage equation fails to be exogenous.

[16]With respect to minimum wage literature, Autor et al. (2016) also use sate-level employment rate as a control variable in the model to estimate the effect of minimum wage on inequality.

To correct this endogeinity problem, several sets of instruments are used in the reduced form of the wage equation (family and regional background, children variables, husband's age and education, among others). County unemployment rate is always part of the set of instruments used in the baseline model, that is, the exogeinity of the regional employment rate in the wage equation is never subject to discussion.

In addition, we implement a simple Durbin-Hu-Hausman test to verify the exogeinity of employment rate in the wage equation (Wooldridge, 2010). The instruments used for the employment rate at the sate level are the following:

First, a categorical variable to control for the industrial and institutional composition of the firms, allowing to distinguish among governmental, agricultural formal and informal, and household units; second, a variable to control for the size of the economic units within the states; and finally, to control for the geographical differences among the municipalities we use the minimum wage zones variable. In addition we also include a dummy variable to identify the rural municipalities, and a simple linear trend variable.

To test the null hypothesis that employment rate is not correlated with the error term of the wage equation, the test adds the fitted values of the residuals of the employment rate equation as a regressor in the wage equation. For the baseline model,in spite of the number of observations, the coefficient of the residuals is statistically equal to zero (-0.0009 with a p-value of 0.785). Therefore, we cannot reject the null hypothesis of the exogeinity of employment rate in the wage equation.

Table 2.D.1 shows the parameters of both equations of the Durbin-Hu-Hausman test. We also carried on the test including in the employment rate equation the DiD parameters, as well as the post-treatment period dummy. This specification does not alter the results of the test: employment rate is not endogenous in the wage equation.

Table 2.D.1

Durbin-Hu-Hausman test.

Employment rate' Exogeinity in the wage equation

(a) Reduced form. Employment

Dependent Variable:	*EmpRate*	
Institutional sector of the firm		
Non-financial firms	-0.0841***	(0.01172)
Formal non-agricultural	-0.0482***	(0.01201)
Governmental	0.8056***	(0.09688)
Private non-profit org	-0.0156	(0.01364)
Public non-profit org	0.1333***	(0.01224)
Household informal	-0.0447***	(0.01245)
Waged household work	0.4072*	(0.21127)
Size of the establishment		
No establishmenTrend	-0.0905***	(0.00424)
Small establishmenTrend	-0.1198***	(0.00563)
Medium establishmenTrend	-0.1680***	(0.00665)
Large establishmenTrend	-0.3531***	(0.00672)
Governmental	-0.8565***	(0.09618)
Other	-0.4715**	(0.21090)
Rural	-0.1110***	(0.00370)
Trend	-0.0234***	(0.00049)
Zone B	-0.0714***	(0.00397)
Zone C	0.6051***	(0.00371)
Total observations	851,475	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1.

(b) Durbin-Hu-Hausman test.

Dependent Variable:	ln(*hourly_wage*)	
Residuals EmpRate	-0.0009	(0.00313)
ZoneB*Period2	0.0369***	(0.00908)
ZoneB	0.6686	(0.41462)
Period2	0.0061**	(0.00302)
TrendB	-0.0095***	(0.00187)
TrendA&C	-0.0069***	(0.00065)
EmpRate	-0.0410***	(0.00304)
Female	-0.3117***	(0.00490)
Age	0.0451***	(0.00030)
Age^2	-0.0004***	(0.00000)
Rural	-0.1879***	(0.00671)
School_level2 (7th-9th year)	0.0929***	(0.00379)
School_level3 (10th-12th year)	0.1948***	(0.00359)
School_level4 (University)	0.5829***	(0.00375)
School_level2*Rural	0.0705***	(0.00840)
School_level3*Rural	0.0549***	(0.00771)
School_level4*Rural	0.0121	(0.00905)
School_level2*Female	0.0838***	(0.00591)
School_level3*Female	0.1832***	(0.00542)
School_level4*Female	0.2808***	(0.00560)
Total observations	850,933	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1.

Appendix 2.E The impact on real monthly wages

Table 2.E.1

The impact on monthly real wages

Heckman second stage for sample selection bias.

Dependent variable:	ln(*monthly_wage*)			
Equation:	(2.1a)		(2.1b)	
Full age threshold: 12 ≤ Age ≤ 97				
ZoneB*Period2	0.0195**	(0.00967)	0.0161*	(0.00974)
$\hat{\lambda}$ (IMR)	-0.3667***	(0.00569)	-0.3667***	(0.00569)
Total observations	2,112,508		2,112,508	
Uncensored observations	960,550		960,550	
Age threshold: 12 ≤ Age ≤ 29				
ZoneB*Period2	0.0199	(0.01497)	0.0136	(0.01508)
$\hat{\lambda}$ (IMR)	-0.4832***	(0.01073)	-0.4833***	(0.01073)
Total observations	886,481		886,481	
Uncensored observations	309,008		309,008	
Age threshold: 30 ≤ Age ≤ 49				
ZoneB*Period2	0.0211	(0.01386)	0.0203	(0.01396)
$\hat{\lambda}$ (IMR)	-0.4240***	(0.00880)	-0.4239***	(0.00880)
Total observations	687,799		687,799	
Uncensored observations	450,695		450,695	
Age threshold: 50 ≤ Age ≤ 97				
ZoneB*Period2	-0.0019	(0.02443)	-0.0053	(0.02460)
$\hat{\lambda}$ (IMR)	-0.2110***	(0.01485)	-0.2111***	(0.01485)
Total observations	538,228		538,228	
Uncensored observations	337,381		337,381	

Note: the covariates included are state employment rate, gender, age, squared age, schooling level, and interactions of schooling level with rural and gender.

Observations with non-reported wages are excluded from the analysis.

Standard errors in parentheses, by two-step variance estimator Heckman (1979).

Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.E.2

The impact on real monthly wages by formality condition

Heckman second stage for sample selection bias.

	Formal workers				Informal workers			
Dependent variable:	ln(*monthly_wage*)				ln(*monthly_wage*)			
Equation:	(2.1a)		(2.1b)		(2.1a)		(2.1b)	
Full age threshold: 12 ≤ Age ≤ 97								
ZoneB*Period2	0.0170*	(0.01010)	0.0161	(0.01020)	0.0213	(0.01499)	0.0166	(0.01507)
$\hat{\lambda}$ (IMR)	-0.1762***	(0.00501)	-0.1763***	(0.00501)	(0.00724)	-0.3738***	(0.00724)	-0.3738***
Total observations	1,567,202		1,567,202		1,664,940		1,664,940	
Uncensored observations	428,783		428,783		531,767		531,767	
Age threshold: 12 ≤ Age ≤ 29								
ZoneB*Period2	0.0268*	(0.01495)	0.0241	(0.01511)	0.0225	(0.02354)	0.0159	(0.02366)
$\hat{\lambda}$ (IMR)	-0.2554***	(0.00839)	-0.2555***	(0.00839)	-0.4464***	(0.01366)	-0.4464***	(0.01366)
Total observations	704,294		704,294		751,993		751,993	
Uncensored observations	130,639		130,639		178,369		178,369	
Age threshold: 30 ≤ Age ≤ 49								
ZoneB*Period2	0.0199	(0.01432)	0.0193	(0.01446)	0.0201	(0.02263)	0.0190	(0.02275)
$\hat{\lambda}$ (IMR)	-0.1872***	(0.00773)	-0.1871***	(0.00773)	-0.4015***	(0.01051)	-0.4014***	(0.01050)
Total observations	452,579		452,579		455,842		455,842	
Uncensored observations	221,419		221,419		229,276		229,276	
Age threshold: 50 ≤ Age ≤ 97								
ZoneB*Period2	-0.0110	(0.02845)	-0.0103	(0.02871)	0.0002	(0.03370)	-0.0072	(0.03389)
$\hat{\lambda}$ (IMR)	-0.0890***	(0.01726)	-0.0894***	(0.01726)	-0.1776***	(0.01847)	-0.1774***	(0.01847)
Total observations	410,329		457,105		457,105		457,105	
Uncensored observations	76,725		76,725		124,122		124,122	

Note: the covariates included are state employment rate, gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender. Observations with non-reported wages are excluded from the analysis.

Standard errors in parentheses, by two-step variance estimator Heckman (1979).

Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.E.3

The impact on real monthly wages by gender

Heckman second stage for sample selection bias.

	Female workers				Male workers			
Dependent variable:	ln(*monthly_wage*)				ln(*monthly_wage*)			
Equation:	(2.1a)		(2.1b)		(2.1a)		(2.1b)	
Full age threshold: 12 ≤ Age ≤ 97								
ZoneB*Period2	0.0292*	(0.01652)	0.0249	(0.01663)	0.0233**	(0.01168)	0.0233**	(0.01175)
$\hat{\lambda}$ (IMR)	-0.2504***	(0.00873)	-0.2455***	(0.00872)	-0.6811***	(0.00947)	-0.6831***	(0.00948)
Total observations		1,149,201		1,149,201		963,307		963,307
Uncensored observations		772,514		379,444				
Age threshold: 12 ≤ Age ≤ 29								
ZoneB*Period2	0.0158	(0.02612)	0.0083	(0.02627)	0.0328*	(0.01774)	0.0300*	(0.01785)
$\hat{\lambda}$ (IMR)	-0.3941***	(0.03022)	-0.3824***	(0.03007)	-0.8155***	(0.01451)	-0.8109***	(0.01445)
Total observations		457,849		457,849		428,632		428,632
Uncensored observations		342,485		342,485		234,988		234,988
Age threshold: 30 ≤ Age ≤ 49								
ZoneB*Period2	0.0269	(0.02354)	0.0271	(0.02369)	0.0274	(0.01776)	0.0291	(0.01814)
$\hat{\lambda}$ (IMR)	-0.2929***	(0.01081)	-0.2877***	(0.01080)	-0.8290***	(0.01985)	-0.8401***	(0.02017)
Total observations		382,509		382,509		305,290		305,290
Uncensored observations		196,634		196,634		40,470		40,470
Age threshold: 50 ≤ Age ≤ 97								
ZoneB*Period2	0.0385	(0.04223)	0.0296	(0.04251)	-0.0145	(0.02956)	-0.0121	(0.02974)
$\hat{\lambda}$ (IMR)	-0.1748***	(0.01778)	-0.1730***	(0.01777)	-0.4338***	(0.04235)	-0.4454***	(0.04262)
Total observations		308,843		308,843		229,385		229,385
Uncensored observations		233,395		233,395		103,986		103,986

Note: the covariates included are state employment rate, age, squared age, schooling level, rural, and interactions of schooling level with rural.
Observations with non-reported wages are excluded from the analysis.
Standard errors in parentheses, by two-step variance estimator Heckman (1979).
Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.E.4

The dynamics for the impact on real monthly wages

Second stage for Heckman correction for sample selection bias.

Dependent variable:	ln(*hourly_wage*)			
Equation:	(2.2a)		(2.2b)	
ZoneB*D2013Q1	0.017**	(0.0080)	0.019**	(0.0079)
ZoneB*D2013Q2	0.018**	(0.0080)	0.022***	(0.0079)
ZoneB*D2013Q3	0.007	(0.0081)	0.011	(0.0081)
ZoneB*D2013Q4	0.002	(0.0079)	0.005	(0.0079)
$\hat{\lambda}$ (IMR)	-0.368***	(0.0057)	-0.368***	(0.0057)
Total observations	2,112,508		2,112,508	
Uncensored observations	960,550		960,550	

Note: the covariates included are state employment rate, gender, age, squared age, rural, schooling level, and interactions of schooling level with rural and gender.
Observations with non-reported wages are excluded from the analysis.
Standard errors in parentheses, by two-step variance estimator Heckman (1979).
Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Appendix 2.F POLS estimates without sample selection correction

Table 2.F.1

Pooled OLS for the impact on real hourly wages.

Dependent variable:	ln(*monthly_wage*)			
Equation:	(2.1a)		(2.1b)	
Full age threshold: 12 ≤ Age ≤ 97				
ZoneB*Period2	0.0359***	(0.00942)	0.0362***	(0.00948)
Observations	960,550		960,550	
Age threshold: 12 ≤ Age ≤ 29				
ZoneB*Period2	0.0405***	(0.01419)	0.0389***	(0.01427)
Observations	309,008		309,008	
Age threshold: 30 ≤ Age ≤ 49				
ZoneB*Period2	0.0472***	(0.01375)	0.0491***	(0.01384)
Observations	450,695		450,695	
Age threshold: 50 ≤ Age ≤ 97				
ZoneB*Period2	-0.0076	(0.02411)	-0.0076	(0.02427)
Observations	337,381		337,381	

Note: the covariates included are state employment rate, gender, age, squared age, schooling level, and interactions of schooling level with rural and gender.

Observations with non-reported wages are excluded from the analysis.

Standard errors in parentheses, by two-step variance estimator Heckman (1979).

Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.F.2

Pooled OLS for impact on real hourly wages by formality condition

	Formal workers				Informal workers			
Dependent variable:	ln(*monthly_wage*)				ln(*monthly_wage*)			
Equation:	(2.1a)		(2.1b)		(2.1a)		(2.1b)	
Full age threshold: 12 ≤ Age ≤ 97								
ZoneB*Period2	0.0321***	(0.01138)	0.0319***	(0.01149)	0.0311**	(0.01460)	0.0304**	(0.01465)
Observations	428,783		428,783		531,767		531,767	
Age threshold: 12 ≤ Age ≤ 29								
ZoneB*Period2	0.0484***	(0.01673)	0.0470***	(0.01690)	0.0272	(0.02245)	0.0252	(0.02251)
Observations	130,639		130,639		178,369		178,369	
Age threshold: 30 ≤ Age ≤ 49								
ZoneB*Period2	0.0351**	(0.01620)	0.0347**	(0.01636)	0.0572**	(0.02243)	0.0594***	(0.02252)
Observations	221,419		221,419		229,276		229,276	
Age threshold: 50 ≤ Age ≤ 97								
ZoneB*Period2	-0.0035	(0.03185)	-0.0012	(0.03214)	-0.0168	(0.03359)	-0.0204	(0.03375)
Observations	76,725		76,725		124,122		124,122	

Note: the covariates included are state employment rate, gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender. Observations with non-reported wages are excluded from the analysis.
Standard errors in parentheses, by two-step variance estimator Heckman (1979).
Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.F.3

Pooled OLS for the impact on real hourly wages by gender

	Female workers				Male workers			
Dependent variable:	ln(*monthly_wage*)				ln(*monthly_wage*)			
Equation:	(2.1a)		(2.1b)		(2.1a)		(2.1b)	
Full age threshold: 12 ≤ Age ≤ 97								
ZoneB*Period2	0.0487***	(0.01538)	0.0469***	(0.01548)	0.0275**	(0.01191)	0.0292**	(0.01198)
Observations		376,687		583,863				
Age threshold: 12 ≤ Age ≤ 29								
ZoneB*Period2	0.0303	(0.02417)	0.0289	(0.02432)	0.0471***	(0.01745)	0.0453***	(0.01754)
Observations		115,364		115,364		193,644		193,644
Age threshold: 30 ≤ Age ≤ 49								
ZoneB*Period2	0.0630***	(0.02199)	0.0617***	(0.02214)	0.0350**	(0.01758)	0.0393**	(0.01769)
Observations		185,875		185,875		264,820		264,820
Age threshold: 50 ≤ Age ≤ 97								
ZoneB*Period2	0.0298	(0.03939)	0.0260	(0.03966)	-0.0306	(0.03048)	-0.0284	(0.03067)
Observations		75,448		75,448		125,399		125,399

Note: the covariates included are state employment rate, age, squared age, schooling level, rural, and interactions of schooling level with rural.
Observations with non-reported wages are excluded from the analysis.
Standard errors in parentheses, by two-step variance estimator Heckman (1979).
Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Appendix 2.G Full list of coefficients. Heckman sample selection

Table 2.G.1
The impact on real hourly wages
Heckman second stage for sample selection bias

Dependent variable:	ln(*hourly_wage*)							
Age threshold:	$12 \leq$ Age ≤ 97		$12 \leq$ Age ≤ 29		$30 \leq$ Age ≤ 49		Age ≥ 50	
Equation:	(2.1a)	(2.1b)	(2.1a)	(2.1b)	(2.1a)	(2.1b)	(2.1a)	(2.1b)
ZoneB*Period2	0.0359***	0.0363***	0.0399***	0.0384***	0.0473***	0.0492***	-0.0075	-0.0075
	(0.00942)	(0.00948)	(0.01418)	(0.01426)	(0.01374)	(0.01383)	(0.02411)	(0.02426)
ZoneB	0.4638	0.6425	1.2472*	1.3332**	0.1722	0.4052	-0.4228	-0.2739
	(0.42814)	(0.43087)	(0.64410)	(0.64785)	(0.62333)	(0.62747)	(1.10185)	(1.10887)
Period2	0.0155***	0.0139***	0.0113**	0.0113**	0.0137***	0.0108**	0.0320***	0.0307***
	(0.00292)	(0.00313)	(0.00455)	(0.00484)	(0.00421)	(0.00453)	(0.00742)	(0.00795)
ZoneA*Period2		0.0086		-0.0053		0.0187		0.0076
		(0.00855)		(0.01337)		(0.01211)		(0.02199)
ZoneA		1.3691***		0.7154		1.7094***		1.1307
		(0.38574)		(0.60350)		(0.54576)		(0.99687)
TrendB	-0.0104***	-0.0101***	-0.0120***	-0.0117***	-0.0091***	-0.0089***	-0.0104**	-0.0101**
	(0.00195)	(0.00195)	(0.00293)	(0.00293)	(0.00284)	(0.00284)	(0.00502)	(0.00501)
TrendA&C	-0.0087***		-0.0066***		-0.0088***		-0.0130***	
	(0.00063)		(0.00098)		(0.00091)		(0.00161)	
TrendA		-0.0137***		-0.0088***		-0.0153***		-0.0171***
		(0.00172)		(0.00270)		(0.00242)		(0.00444)
TrendC		-0.0077***		-0.0059***		-0.0076***		-0.0121***
		(0.00068)		(0.00105)		(0.00098)		(0.00172)
EmpRate	-0.0583***	-0.0529***	-0.0549***	-0.0491***	-0.0567***	-0.0517***	-0.0684***	-0.0633***
	(0.00068)	(0.00070)	(0.00106)	(0.00108)	(0.00099)	(0.00101)	(0.00178)	(0.00181)
Female	-0.0499***	-0.0519***	0.0607***	0.0532***	-0.0652***	-0.0660***	-0.0545***	-0.0546***
	(0.00545)	(0.00544)	(0.01387)	(0.01385)	(0.00888)	(0.00888)	(0.01133)	(0.01133)
Age	0.0259***	0.0259***	-0.1205***	-0.1186***	0.0149***	0.0146***	0.0350***	0.0350***
	(0.00063)	(0.00063)	(0.00555)	(0.00553)	(0.00277)	(0.00277)	(0.00309)	(0.00309)
Age^2	-0.0002***	-0.0002***	0.0029***	0.0028***	-0.0001***	-0.0001**	-0.0003***	-0.0003***
	(0.00001)	(0.00001)	(0.00011)	(0.00011)	(0.00004)	(0.00004)	(0.00002)	(0.00002)
Rural	-0.3585***	-0.3529***	-0.1845***	-0.1846***	-0.3207***	-0.3157***	-0.4247***	-0.4178***
	(0.00431)	(0.00431)	(0.01112)	(0.01110)	(0.00704)	(0.00704)	(0.00703)	(0.00704)
School_level2	0.1553***	0.1541***	0.0783***	0.0770***	0.0908***	0.0896***	0.1798***	0.1789***
	(0.00375)	(0.00374)	(0.00794)	(0.00793)	(0.00599)	(0.00599)	(0.00697)	(0.00697)
School_level3	0.2536***	0.2529***	0.1583***	0.1566***	0.2000***	0.1997***	0.3358***	0.3348***
	(0.00353)	(0.00353)	(0.00751)	(0.00749)	(0.00555)	(0.00554)	(0.00756)	(0.00756)
School_level4	0.6632***	0.6617***	0.4612***	0.4581***	0.6520***	0.6505***	0.9233***	0.9218***
	(0.00353)	(0.00353)	(0.00809)	(0.00808)	(0.00554)	(0.00554)	(0.00728)	(0.00728)
School_level2*Rural	0.1225***	0.1237***	0.0220*	0.0279**	0.0753***	0.0773***	0.0807***	0.0806***
	(0.00586)	(0.00585)	(0.01284)	(0.01281)	(0.00896)	(0.00895)	(0.01237)	(0.01237)
School_level3*Rural	0.1493***	0.1508***	0.0238**	0.0317***	0.0905***	0.0919***	0.1012***	0.1018***
	(0.00551)	(0.00550)	(0.01201)	(0.01199)	(0.00856)	(0.00855)	(0.01590)	(0.01589)
School_level4*Rural	0.0962***	0.0972***	-0.0604***	-0.0528***	0.0986***	0.0994***	0.2171***	0.2165***
	(0.00667)	(0.00667)	(0.01289)	(0.01286)	(0.01037)	(0.01036)	(0.02134)	(0.02133)
School_level2*Female	-0.0191***	-0.0184***	-0.0223*	-0.0186	0.0036	0.0043	-0.0380***	-0.0380***
	(0.00535)	(0.00534)	(0.01339)	(0.01336)	(0.00837)	(0.00836)	(0.00984)	(0.00983)
School_level3*Female	0.0433***	0.0445***	-0.0227*	-0.0179	0.0552***	0.0558***	0.0877***	0.0885***
	(0.00487)	(0.00487)	(0.01255)	(0.01253)	(0.00769)	(0.00768)	(0.01052)	(0.01052)
School_level4*Female	0.0878***	0.0900***	-0.0019	0.0045	0.1447***	0.1462***	0.0958***	0.0974***
	(0.00515)	(0.00515)	(0.01321)	(0.01318)	(0.00803)	(0.00803)	(0.01136)	(0.01135)
λ (IMR)	-0.1588***	-0.1580***	-0.2616***	-0.2564***	-0.1553***	-0.1554***	-0.1033***	-0.1052***
	(0.00541)	(0.00541)	(0.00961)	(0.00958)	(0.00841)	(0.00840)	(0.01455)	(0.01454)
Total observations	2,112,508		886,481		687,799		538,228	
Censored observations	1,151,958		577,473		237,104		337,381	

* Observations with non-reported wages are excluded from the analysis.
Standard errors in parentheses, by two-step variance estimator Heckman (1979). Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.G.2

Selection equation on real wages estimates

Heckman first stage for sample selection bias.

Dependent variable:	ln(*hourly_wage*)							
Age threshold:	$12 \leq$ Age ≤ 97		$12 \leq$ Age ≤ 29		$30 \leq$ Age ≤ 49		Age ≥ 50	
Equation:	(2.3a)	(2.3b)	(2.3a)	(2.3b)	(2.3a)	(2.3b)	(2.3a)	(2.3b)
Period2	-0.0489***	-0.0488***	-0.0573***	-0.0572***	-0.0448***	-0.0448***	-0.0427***	-0.0426***
	(0.00379)	(0.00379)	(0.00613)	(0.00613)	(0.00660)	(0.00660)	(0.00749)	(0.00749)
Head	0.5845***	0.5846***	0.6322***	0.6327***	0.5961***	0.5961***	0.4720***	0.4720***
	(0.00261)	(0.00261)	(0.00587)	(0.00587)	(0.00413)	(0.00413)	(0.00464)	(0.00464)
TrendB	0.0073***	0.0073***	0.0093***	0.0092***	0.0070***	0.0070***	0.0080***	0.0079***
	(0.00082)	(0.00082)	(0.00133)	(0.00133)	(0.00143)	(0.00143)	(0.00163)	(0.00163)
TrendA&C	0.0073***		0.0089***		0.0071***		0.0082***	
	(0.00082)		(0.00133)		(0.00143)		(0.00163)	
TrendA		0.0072***		0.0087***		0.0071***		0.0080***
		(0.00082)		(0.00133)		(0.00143)		(0.00163)
TrendC		0.0073***		0.0089***		0.0071***		0.0081***
		(0.00082)		(0.00133)		(0.00143)		(0.00163)
EmpRate	0.0409***	0.0397***	0.0118***	0.0094***	0.0528***	0.0530***	0.0658***	0.0647***
	(0.00093)	(0.00094)	(0.00151)	(0.00153)	(0.00162)	(0.00165)	(0.00183)	(0.00187)
Female	-0.8352***	-0.8353***	-1.0773***	-1.0771***	-0.9482***	-0.9481***	-0.7867***	-0.7867***
	(0.00513)	(0.00513)	(0.01483)	(0.01483)	(0.01021)	(0.01021)	(0.00684)	(0.00684)
Age	0.1479***	0.1479***	0.6636***	0.6636***	0.0624***	0.0624***	-0.0653***	-0.0653***
	(0.00030)	(0.00030)	(0.00373)	(0.00373)	(0.00450)	(0.00450)	(0.00271)	(0.00271)
Age^2	-0.0018***	-0.0018***	-0.0124***	-0.0124***	-0.0009***	-0.0009***	0.0000	0.0000
	(0.00000)	(0.00000)	(0.00009)	(0.00009)	(0.00006)	(0.00006)	(0.00002)	(0.00002)
Rural	-0.0764***	-0.0781***	-0.0211	-0.0229	-0.2374***	-0.2372***	-0.0263***	-0.0281***
	(0.00539)	(0.00539)	(0.01536)	(0.01536)	(0.01012)	(0.01013)	(0.00708)	(0.00710)
School_level2	-0.0498***	-0.0495***	0.0105	0.0110	0.1876***	0.1876***	-0.1118***	-0.1115***
	(0.00514)	(0.00514)	(0.01103)	(0.01103)	(0.01112)	(0.01112)	(0.00791)	(0.00791)
School_level3	0.1686***	0.1688***	-0.0727***	-0.0723***	0.2725***	0.2725***	-0.1901***	-0.1898***
	(0.00501)	(0.00501)	(0.01088)	(0.01088)	(0.01025)	(0.01025)	(0.00879)	(0.00879)
School_level4	0.0180***	0.0182***	-0.5109***	-0.5110***	0.1972***	0.1971***	-0.2212***	-0.2209***
	(0.00507)	(0.00507)	(0.01126)	(0.01127)	(0.01030)	(0.01030)	(0.00836)	(0.00836)
School_level2*Rural	0.0046	0.0044	-0.0176	-0.0195	-0.0474***	-0.0474***	0.0392***	0.0393***
	(0.00740)	(0.00740)	(0.01759)	(0.01759)	(0.01325)	(0.01325)	(0.01330)	(0.01330)
School_level3*Rural	0.0102	0.0099	-0.0315*	-0.0337**	-0.0192	-0.0192	0.0723***	0.0724***
	(0.00716)	(0.00716)	(0.01668)	(0.01668)	(0.01277)	(0.01277)	(0.01783)	(0.01783)
School_level4*Rural	0.1024***	0.1024***	0.0601***	0.0585***	0.1536***	0.1536***	0.0785***	0.0792***
	(0.00907)	(0.00907)	(0.01801)	(0.01801)	(0.01659)	(0.01659)	(0.02599)	(0.02599)
School_level2*Female	0.0611***	0.0610***	0.1668***	0.1664***	-0.0316**	-0.0316**	0.0800***	0.0799***
	(0.00643)	(0.00643)	(0.01639)	(0.01639)	(0.01271)	(0.01271)	(0.00989)	(0.00989)
School_level3*Female	0.0232***	0.0230***	0.2750***	0.2745***	0.0145	0.0145	0.1212***	0.1209***
	(0.00605)	(0.00605)	(0.01556)	(0.01556)	(0.01171)	(0.01171)	(0.01089)	(0.01089)
School_level4*Female	0.4015***	0.4015***	0.7381***	0.7380***	0.3348***	0.3348***	0.2387***	0.2385***
	(0.00622)	(0.00622)	(0.01571)	(0.01571)	(0.01197)	(0.01197)	(0.01151)	(0.01151)
Total observations	2,112,508		886,481		687,799		538,228	

* Observations with non-reported wages are excluded from the analysis.

Standard errors in parentheses, by two-step variance estimator Heckman (1979). Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.G.3

The impact on hourly wages of formal workers
Heckman second stage for sample selection bias.

Dependent variable:	$\ln(hourly\_wage)$							
Age threshold:	$12 \leq$ Age ≤ 97		$12 \leq$ Age ≤ 29		$30 \leq$ Age ≤ 49		Age ≥ 50	
Equation:	(2.1a)	(2.1b)	(2.1a)	(2.1b)	(2.1a)	(2.1b)	(2.1a)	(2.1b)
ZoneB*Period2	0.0319***	0.0316***	0.0470***	0.0456***	0.0351**	0.0347**	-0.0033	-0.0011
	(0.01137)	(0.01149)	(0.01673)	(0.01690)	(0.01620)	(0.01636)	(0.03185)	(0.03213)
ZoneB	0.4360	0.6305	1.0038	1.1180	0.3530	0.4965	-0.1205	0.2817
	(0.51604)	(0.52109)	(0.75744)	(0.76551)	(0.73389)	(0.74099)	(1.45784)	(1.47050)
Period2	0.0147***	0.0141***	0.0065	0.0072	0.0173***	0.0170***	0.0241**	0.0209*
	(0.00389)	(0.00421)	(0.00600)	(0.00649)	(0.00543)	(0.00589)	(0.01069)	(0.01154)
ZoneA*Period2		0.0024		-0.0037		-0.0003		0.0204
		(0.01081)		(0.01657)		(0.01496)		(0.03046)
ZoneA		1.3121***		0.8545		0.9396		2.7634**
		(0.48577)		(0.74585)		(0.66968)		(1.38280)
TrendB	-0.0112***	-0.0110***	-0.0114***	-0.0113***	-0.0112***	-0.0111***	-0.0127*	-0.0125*
	(0.00232)	(0.00232)	(0.00339)	(0.00339)	(0.00331)	(0.00331)	(0.00657)	(0.00657)
TrendA&C	-0.0094***		-0.0069***		-0.0099***		-0.0135***	
	(0.00084)		(0.00130)		(0.00117)		(0.00232)	
TrendA		-0.0143***		-0.0101***		-0.0133***		-0.0243***
		(0.00214)		(0.00329)		(0.00294)		(0.00612)
TrendC		-0.0083***		-0.0063***		-0.0091***		-0.0115***
		(0.00091)		(0.00141)		(0.00127)		(0.00250)
EmpRate	-0.0235***	-0.0195***	-0.0261***	-0.0227***	-0.0219***	-0.0183***	-0.0249***	-0.0203***
	(0.00091)	(0.00094)	(0.00147)	(0.00150)	(0.00126)	(0.00129)	(0.00252)	(0.00259)
Female	-0.0747***	-0.0769***	0.0703**	0.0625**	-0.0999***	-0.1017***	-0.0989***	-0.0987***
	(0.01152)	(0.01151)	(0.03000)	(0.02999)	(0.01860)	(0.01859)	(0.02443)	(0.02442)
Age	0.0290***	0.0289***	-0.1220***	-0.1207***	0.0091***	0.0087**	0.0203***	0.0202***
	(0.00093)	(0.00093)	(0.00925)	(0.00924)	(0.00352)	(0.00352)	(0.00540)	(0.00539)
Age^2	-0.0002***	-0.0002***	0.0030***	0.0030***	0.0000	0.0001	-0.0001***	-0.0001***
	(0.00001)	(0.00001)	(0.00018)	(0.00018)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Rural	-0.1592***	-0.1578***	-0.1068***	-0.1138***	-0.1525***	-0.1500***	-0.2047***	-0.2017***
	(0.01032)	(0.01032)	(0.02750)	(0.02748)	(0.01690)	(0.01689)	(0.01702)	(0.01702)
School_level2	0.1545***	0.1536***	-0.0068	-0.0073	0.0428***	0.0422***	0.1783***	0.1774***
	(0.00689)	(0.00689)	(0.01726)	(0.01725)	(0.01129)	(0.01129)	(0.01205)	(0.01204)
School_level3	0.2856***	0.2859***	0.0297*	0.0304*	0.1568***	0.1576***	0.3438***	0.3433***
	(0.00660)	(0.00660)	(0.01638)	(0.01637)	(0.01086)	(0.01086)	(0.01218)	(0.01217)
School_level4	0.7201***	0.7199***	0.3245***	0.3247***	0.6366***	0.6368***	0.9689***	0.9675***
	(0.00652)	(0.00652)	(0.01597)	(0.01596)	(0.01084)	(0.01083)	(0.01208)	(0.01208)
School_level2*Rural	0.1087***	0.1105***	0.0657**	0.0740**	0.0927***	0.0940***	0.0963***	0.0961***
	(0.01312)	(0.01312)	(0.03108)	(0.03107)	(0.02022)	(0.02021)	(0.02582)	(0.02581)
School_level3*Rural	0.0844***	0.0867***	0.0558*	0.0662**	0.0566***	0.0572***	0.1784***	0.1786***
	(0.01167)	(0.01167)	(0.02858)	(0.02857)	(0.01845)	(0.01844)	(0.02731)	(0.02731)
School_level4*Rural	0.0591***	0.0614***	-0.0233	-0.0128	0.0885***	0.0891***	0.1938***	0.1941***
	(0.01203)	(0.01203)	(0.02880)	(0.02879)	(0.01898)	(0.01897)	(0.02818)	(0.02817)
School_level2*Female	-0.0445***	-0.0432***	-0.0582*	-0.0530*	-0.0135	-0.0123	-0.0238	-0.0236
	(0.01162)	(0.01161)	(0.03087)	(0.03085)	(0.01825)	(0.01825)	(0.02031)	(0.02030)
School_level3*Female	0.0793***	0.0813***	-0.0584**	-0.0518*	0.1080***	0.1097***	0.2270***	0.2280***
	(0.01062)	(0.01062)	(0.02899)	(0.02897)	(0.01693)	(0.01693)	(0.01986)	(0.01986)
School_level4*Female	0.1358***	0.1385***	0.0007	0.0082	0.1923***	0.1948***	0.1561***	0.1571***
	(0.01090)	(0.01089)	(0.02946)	(0.02944)	(0.01736)	(0.01735)	(0.02050)	(0.02049)
λ (IMR)	-0.1121***	-0.1124***	-0.1763***	-0.1750***	-0.1148***	-0.1153***	-0.0805***	-0.0826***
	(0.00560)	(0.00560)	(0.00912)	(0.00912)	(0.00867)	(0.00867)	(0.01930)	(0.01929)
Total observations	1,567,202		704,294		452,579		410,329	
Censored observations	1,138,419		573,655		231,160		333,604	

* Observations with non-reported wages are excluded from the analysis.

Standard errors in parentheses, by two-step variance estimator Heckman (1979). Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.G.4

Selection equation on real hourly wage estimates for formal workers

Heckman first stage for sample selection bias

Dependent variable:	ln(*hourly_wage*)							
Age threshold:	12 ≤ Age ≤ 97		12 ≤ Age ≤ 29		30 ≤ Age ≤ 49		Age ≥ 50	
Equation:	(2.3a)	(2.3b)	(2.3a)	(2.3b)	(2.3a)	(2.3b)	(2.3a)	(2.3b)
Period2	-0.0351***	-0.0352***	-0.0368***	-0.0368***	-0.0378***	-0.0380***	-0.0347***	-0.0346***
	(0.00506)	(0.00506)	(0.00851)	(0.00851)	(0.00828)	(0.00828)	(0.01052)	(0.01052)
Head	0.6779***	0.6778***	0.7011***	0.7007***	0.6675***	0.6675***	0.5010***	0.5010***
	(0.00344)	(0.00344)	(0.00715)	(0.00716)	(0.00520)	(0.00520)	(0.00683)	(0.00683)
TrendB	0.0031***	0.0031***	0.0057***	0.0057***	0.0035*	0.0035**	0.0012	0.0011
	(0.00110)	(0.00110)	(0.00185)	(0.00185)	(0.00179)	(0.00179)	(0.00229)	(0.00229)
TrendA&C	0.0027**		0.0048***		0.0033*		0.0013	
	(0.00110)		(0.00185)		(0.00179)		(0.00229)	
TrendA		0.0029***		0.0050***		0.0035*		0.0012
		(0.00110)		(0.00185)		(0.00179)		(0.00229)
TrendC		0.0027**		0.0048***		0.0034*		0.0013
		(0.00110)		(0.00185)		(0.00179)		(0.00229)
EmpRate	-0.0042***	-0.0024*	-0.0473***	-0.0442***	0.0164***	0.0183***	0.0322***	0.0312***
	(0.00126)	(0.00129)	(0.00214)	(0.00218)	(0.00206)	(0.00210)	(0.00263)	(0.00268)
Female	-1.0894***	-1.0893***	-1.1407***	-1.1410***	-1.1074***	-1.1072***	-1.0218***	-1.0218***
	(0.00950)	(0.00950)	(0.03145)	(0.03147)	(0.01691)	(0.01691)	(0.01251)	(0.01251)
Age	0.1890***	0.1890***	0.9712***	0.9712***	0.0614***	0.0613***	-0.1127***	-0.1127***
	(0.00049)	(0.00049)	(0.00737)	(0.00737)	(0.00563)	(0.00563)	(0.00452)	(0.00452)
Age^2	-0.0023***	-0.0023***	-0.0180***	-0.0180***	-0.0008***	-0.0008***	0.0003***	0.0003***
	(0.00001)	(0.00001)	(0.00016)	(0.00016)	(0.00007)	(0.00007)	(0.00004)	(0.00004)
Rural	-0.2624***	-0.2602***	-0.1063***	-0.1054***	-0.3934***	-0.3911***	-0.1921***	-0.1933***
	(0.01050)	(0.01051)	(0.03400)	(0.03403)	(0.01842)	(0.01843)	(0.01365)	(0.01367)
School_level2	0.1747***	0.1743***	0.5702***	0.5693***	0.4997***	0.4992***	0.1690***	0.1691***
	(0.00825)	(0.00825)	(0.02460)	(0.02460)	(0.01613)	(0.01613)	(0.01163)	(0.01163)
School_level3	0.5874***	0.5873***	0.7239***	0.7238***	0.8647***	0.8648***	0.2896***	0.2897***
	(0.00773)	(0.00773)	(0.02285)	(0.02285)	(0.01470)	(0.01470)	(0.01203)	(0.01203)
School_level4	0.6045***	0.6046***	0.3248***	0.3253***	0.9389***	0.9389***	0.4351***	0.4353***
	(0.00765)	(0.00765)	(0.02271)	(0.02271)	(0.01454)	(0.01455)	(0.01118)	(0.01118)
School_level2*Rural	-0.1088***	-0.1085***	-0.2454***	-0.2418***	-0.1471***	-0.1466***	-0.0567**	-0.0566**
	(0.01377)	(0.01377)	(0.03878)	(0.03882)	(0.02298)	(0.02299)	(0.02271)	(0.02270)
School_level3*Rural	-0.1121***	-0.1117***	-0.2881***	-0.2842***	-0.1353***	-0.1351***	-0.0318	-0.0316
	(0.01253)	(0.01253)	(0.03553)	(0.03556)	(0.02128)	(0.02129)	(0.02623)	(0.02623)
School_level4*Rural	0.1044***	0.1044***	-0.0744**	-0.0713**	0.2134***	0.2133***	0.1455***	0.1461***
	(0.01374)	(0.01374)	(0.03613)	(0.03616)	(0.02373)	(0.02373)	(0.03158)	(0.03158)
School_level2*Female	0.1586***	0.1588***	-0.1077***	-0.1068***	-0.0526***	-0.0523***	0.1311***	0.1311***
	(0.01131)	(0.01131)	(0.03483)	(0.03485)	(0.02006)	(0.02006)	(0.01617)	(0.01617)
School_level3*Female	0.2007***	0.2009***	0.2107***	0.2115***	0.0390**	0.0391**	0.2827***	0.2825***
	(0.01032)	(0.01032)	(0.03219)	(0.03220)	(0.01831)	(0.01831)	(0.01620)	(0.01620)
School_level4*Female	0.6483***	0.6482***	0.8030***	0.8031***	0.4957***	0.4956***	0.4663***	0.4663***
	(0.01026)	(0.01026)	(0.03202)	(0.03204)	(0.01823)	(0.01823)	(0.01599)	(0.01599)
Total observations	1,567,202		704,294		452,579		410,329	

* Observations with non-reported wages are excluded from the analysis.

Standard errors in parentheses, by two-step variance estimator Heckman (1979). Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.G.5

The impact on hourly wages of informal workers

Heckman second stage for sample selection bias.

Dependent variable:	ln(*hourly_wage*)							
Age threshold:	$12 \leq$ Age ≤ 97		$12 \leq$ Age ≤ 29		$30 \leq$ Age ≤ 49		Age ≥ 50	
Equation:	(2.1a)	(2.1b)	(2.1a)	(2.1b)	(2.1a)	(2.1b)	(2.1a)	(2.1b)
ZoneB*Period2	0.0207	0.0198	0.0057	0.0039	0.0479	0.0500	-0.0191	-0.0228
	(0.14078)	(0.14057)	(0.50782)	(0.50145)	(0.21055)	(0.21237)	(0.16279)	(0.16384)
ZoneB	-0.5725	-0.4955	-0.2243	-0.1934	-0.8249	-0.5885	-1.1131	-1.2152
	(6.41957)	(6.41001)	(23.20315)	(22.91157)	(9.57821)	(9.66068)	(7.43457)	(7.48250)
Period2	-0.0354	-0.0358	-0.1496	-0.1465	-0.0365	-0.0403	0.0246	0.0267
	(0.04627)	(0.04809)	(0.25755)	(0.25754)	(0.06708)	(0.07072)	(0.05072)	(0.05375)
ZoneA*Period2		0.0014		-0.0141		0.0270		-0.0186
		(0.12210)		(0.45036)		(0.17782)		(0.14533)
ZoneA		0.6380		-0.0486		2.0030		-0.7207
		(5.53800)		(20.39147)		(8.07897)		(6.58395)
TrendB	0.0126	0.0129	0.0405	0.0401	0.0134	0.0138	0.0012	0.0015
	(0.03076)	(0.03054)	(0.12671)	(0.12453)	(0.04579)	(0.04593)	(0.03459)	(0.03459)
TrendA&C	0.0098		0.0394		0.0095		-0.0045	
	(0.01153)		(0.06895)		(0.01674)		(0.01174)	
TrendA		0.0078		0.0398		0.0019		-0.0009
		(0.02603)		(0.11047)		(0.03782)		(0.02999)
TrendC		0.0103		0.0390		0.0109		-0.0047
		(0.01184)		(0.06853)		(0.01742)		(0.01233)
EmpRate	-0.0730***	-0.0679***	-0.0444	-0.0393	-0.0808***	-0.0753***	-0.0862***	-0.0821***
	(0.00963)	(0.00975)	(0.03962)	(0.03902)	(0.01477)	(0.01511)	(0.01162)	(0.01203)
Female	0.0132	0.0110	0.0372	0.0310	0.0033	0.0029	-0.0112	-0.0123
	(0.07592)	(0.07542)	(0.39781)	(0.39125)	(0.12303)	(0.12338)	(0.06881)	(0.06879)
Age	0.0223***	0.0222***	0.0835	0.0824	0.0147	0.0144	0.0115	0.0116
	(0.00552)	(0.00547)	(0.10954)	(0.10772)	(0.04081)	(0.04095)	(0.02418)	(0.02415)
Age^2	-0.0003***	-0.0003***	-0.0018	-0.0018	-0.0002	-0.0002	-0.0002	-0.0002
	(0.00005)	(0.00005)	(0.00283)	(0.00278)	(0.00052)	(0.00052)	(0.00019)	(0.00019)
Rural	-0.2776***	-0.2713***	-0.1697	-0.1692	-0.2643***	-0.2574***	-0.3649***	-0.3580***
	(0.06679)	(0.06600)	(0.30033)	(0.29513)	(0.09714)	(0.09725)	(0.06825)	(0.06672)
School_level2	0.1708***	0.1690***	0.1255	0.1235	0.1508*	0.1494*	0.1799***	0.1787***
	(0.05519)	(0.05484)	(0.23137)	(0.22743)	(0.08231)	(0.08259)	(0.05469)	(0.05477)
School_level3	0.2631***	0.2609***	0.2343	0.2306	0.2542***	0.2533***	0.2476***	0.2454***
	(0.06352)	(0.06309)	(0.25969)	(0.25538)	(0.09634)	(0.09661)	(0.05672)	(0.05684)
School_level4	0.4944***	0.4911***	0.3582	0.3555	0.5182***	0.5153***	0.5781***	0.5748***
	(0.06715)	(0.06675)	(0.23408)	(0.23012)	(0.11016)	(0.11054)	(0.07129)	(0.07158)
School_level2*Rural	0.0245	0.0261	-0.0083	-0.0023	-0.0001	0.0022	0.0056	0.0060
	(0.07889)	(0.07835)	(0.34931)	(0.34338)	(0.11076)	(0.11114)	(0.08768)	(0.08762)
School_level3*Rural	0.0277	0.0303	-0.1221	-0.1122	0.0147	0.0174	-0.0293	-0.0270
	(0.08638)	(0.08580)	(0.37952)	(0.37355)	(0.11387)	(0.11427)	(0.12093)	(0.12082)
School_level4*Rural	-0.0359	-0.0338	-0.0714	-0.0644	-0.1253	-0.1231	0.0407	0.0433
	(0.10916)	(0.10841)	(0.37088)	(0.36460)	(0.18113)	(0.18171)	(0.18545)	(0.18557)
School_level2*Female	-0.0623	-0.0611	-0.1417	-0.1364	-0.0390	-0.0383	-0.0479	-0.0475
	(0.06926)	(0.06879)	(0.42664)	(0.41952)	(0.10433)	(0.10467)	(0.06293)	(0.06292)
School_level3*Female	-0.0785	-0.0764	-0.1038	-0.0979	-0.0742	-0.0738	-0.0134	-0.0122
	(0.07620)	(0.07569)	(0.39479)	(0.38822)	(0.12217)	(0.12252)	(0.07518)	(0.07524)
School_level4*Female	-0.2045	-0.2007	-0.3792	-0.3675	-0.1721	-0.1714	-0.1180	-0.1154
	(0.13464)	(0.13369)	(0.72963)	(0.71785)	(0.20583)	(0.20633)	(0.13582)	(0.13578)
λ (IMR)	7.5805**	7.5289**	15.6186	15.3487	7.3318	7.3553	4.4242	4.4259
	(3.33280)	(3.30517)	(21.81930)	(21.46139)	(4.79040)	(4.79944)	(3.16668)	(3.14632)
Total observations	545,306		182,187		235,220		127,899	
Censored observations	13,539		3,818		5,944		3,777	

* Observations with non-reported wages are excluded from the analysis.

Standard errors in parentheses, by two-step variance estimator Heckman (1979). Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.G.6

Selection equation on real hourly wages estimates for informal workers

Heckman first stage for sample selection bias.

Dependent variable:	ln(*hourly_wage*)							
Age threshold:	$12 \leq$ Age ≤ 97		$12 \leq$ Age ≤ 29		$30 \leq$ Age ≤ 49		Age ≥ 50	
Equation:	(2.3a)	(2.3b)	(2.3a)	(2.3b)	(2.3a)	(2.3b)	(2.3a)	(2.3b)
Period2	-0.0511***	-0.0511***	-0.0915***	-0.0915***	-0.0474**	-0.0474**	-0.0133	-0.0132
	(0.01427)	(0.01427)	(0.02622)	(0.02622)	(0.02154)	(0.02154)	(0.02777)	(0.02777)
Head	-0.0597***	-0.0597***	-0.0383**	-0.0382**	-0.0598***	-0.0599***	-0.0728***	-0.0732***
	(0.00900)	(0.00900)	(0.01855)	(0.01855)	(0.01297)	(0.01297)	(0.01811)	(0.01811)
TrendB	0.0176***	0.0175***	0.0261***	0.0261***	0.0171***	0.0170***	0.0091	0.0090
	(0.00311)	(0.00311)	(0.00573)	(0.00573)	(0.00470)	(0.00470)	(0.00605)	(0.00605)
TrendA&C	0.0182***		0.0265***		0.0177***		0.0099	
	(0.00311)		(0.00573)		(0.00470)		(0.00605)	
TrendA		0.0180***		0.0265***		0.0177***		0.0096
		(0.00311)		(0.00573)		(0.00470)		(0.00605)
TrendC		0.0181***		0.0265***		0.0177***		0.0099
		(0.00311)		(0.00573)		(0.00470)		(0.00605)
EmpRate	-0.0021	-0.0031	0.0086	0.0084	-0.0073	-0.0078	-0.0048	-0.0074
	(0.00339)	(0.00344)	(0.00630)	(0.00639)	(0.00511)	(0.00518)	(0.00654)	(0.00663)
Female	0.1163***	0.1165***	0.0946	0.0947	0.1367***	0.1368***	0.1077***	0.1084***
	(0.01751)	(0.01751)	(0.06204)	(0.06204)	(0.02985)	(0.02985)	(0.02364)	(0.02364)
Age	-0.0093***	-0.0093***	0.0232	0.0233	-0.0010	-0.0010	-0.0320***	-0.0321***
	(0.00127)	(0.00127)	(0.01662)	(0.01662)	(0.01480)	(0.01480)	(0.01184)	(0.01184)
Age^2	0.0001***	0.0001***	-0.0007*	-0.0007*	-0.0000	-0.0000	0.0003***	0.0003***
	(0.00001)	(0.00001)	(0.00037)	(0.00037)	(0.00019)	(0.00019)	(0.00009)	(0.00009)
Rural	0.1071***	0.1057***	0.0115	0.0114	0.0964***	0.0957***	0.1321***	0.1280***
	(0.01758)	(0.01760)	(0.05479)	(0.05479)	(0.02916)	(0.02918)	(0.02414)	(0.02422)
School_level2	0.0669***	0.0671***	0.0316	0.0316	0.0630**	0.0631**	0.0735***	0.0742***
	(0.01551)	(0.01551)	(0.03960)	(0.03960)	(0.02493)	(0.02493)	(0.02423)	(0.02423)
School_level3	0.1027***	0.1029***	0.0666*	0.0667*	0.1109***	0.1110***	0.0532*	0.0542*
	(0.01530)	(0.01530)	(0.03788)	(0.03788)	(0.02383)	(0.02383)	(0.02841)	(0.02841)
School_level4	0.1017***	0.1021***	0.0295	0.0296	0.1305***	0.1307***	0.0950***	0.0967***
	(0.01694)	(0.01694)	(0.03971)	(0.03971)	(0.02679)	(0.02679)	(0.03253)	(0.03254)
School_level2*Rural	-0.0881***	-0.0882***	-0.0153	-0.0155	-0.0632*	-0.0634*	-0.1116**	-0.1119**
	(0.02460)	(0.02460)	(0.06375)	(0.06375)	(0.03820)	(0.03821)	(0.04353)	(0.04354)
School_level3*Rural	-0.1314***	-0.1316***	-0.0840	-0.0843	-0.0824**	-0.0826**	-0.1503**	-0.1506**
	(0.02398)	(0.02398)	(0.06007)	(0.06008)	(0.03784)	(0.03784)	(0.05859)	(0.05862)
School_level4*Rural	-0.1368***	-0.1369***	-0.0153	-0.0155	-0.1661***	-0.1663***	-0.0699	-0.0710
	(0.03254)	(0.03254)	(0.06635)	(0.06636)	(0.05260)	(0.05260)	(0.10844)	(0.10848)
School_level2*Female	-0.0593***	-0.0595***	-0.0964	-0.0965	-0.0599	-0.0599	-0.0440	-0.0440
	(0.02273)	(0.02274)	(0.06961)	(0.06961)	(0.03658)	(0.03658)	(0.03512)	(0.03512)
School_level3*Female	-0.1088***	-0.1090***	-0.0851	-0.0852	-0.1398***	-0.1399***	-0.0592	-0.0599
	(0.02150)	(0.02150)	(0.06570)	(0.06570)	(0.03451)	(0.03451)	(0.04107)	(0.04107)
School_level4*Female	-0.2739***	-0.2742***	-0.2556***	-0.2557***	-0.2967***	-0.2967***	-0.2188***	-0.2200***
	(0.02363)	(0.02363)	(0.06643)	(0.06644)	(0.03850)	(0.03850)	(0.05426)	(0.05426)
Total observations	545,306		182,187		235,220		127,899	

* Observations with non-reported wages are excluded from the analysis.

Standard errors in parentheses, by two-step variance estimator Heckman (1979). Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.G.7

The impact on hourly wages of female workers
Heckman second stage for sample selection bias.

Dependent variable:	ln(*hourly_wage*)							
Age threshold:	12 ≤ Age ≤ 97		12 ≤ Age ≤ 29		30 ≤ Age ≤ 49		Age ≥ 50	
Equation:	(2.1a)	(2.1b)	(2.1a)	(2.1b)	(2.1a)	(2.1b)	(2.1a)	(2.1b)
ZoneB*Period2	0.0487***	0.0469***	0.0296	0.0284	0.0630***	0.0617***	0.0301	0.0263
	(0.01538)	(0.01548)	(0.02418)	(0.02433)	(0.02199)	(0.02214)	(0.03938)	(0.03965)
ZoneB	0.8569	0.9441	1.1410	1.2175	0.2725	0.4445	1.5139	1.3347
	(0.69798)	(0.70263)	(1.09862)	(1.10531)	(0.99597)	(1.00273)	(1.79513)	(1.80745)
Period2	0.0082*	0.0087*	0.0063	0.0056	0.0083	0.0083	0.0247**	0.0271**
	(0.00474)	(0.00510)	(0.00784)	(0.00835)	(0.00667)	(0.00720)	(0.01203)	(0.01294)
ZoneA*Period2		-0.0064		-0.0015		-0.0046		-0.0166
		(0.01380)		(0.02293)		(0.01914)		(0.03497)
ZoneA		0.7079		0.8019		1.1863		-1.0960
		(0.62265)		(1.03426)		(0.86323)		(1.58134)
TrendB	-0.0117***	-0.0114***	-0.0108**	-0.0104**	-0.0101**	-0.0099**	-0.0174**	-0.0171**
	(0.00317)	(0.00317)	(0.00499)	(0.00498)	(0.00454)	(0.00453)	(0.00817)	(0.00817)
TrendA&C	-0.0081***		-0.0059***		-0.0092***		-0.0107***	
	(0.00103)		(0.00169)		(0.00144)		(0.00261)	
TrendA		-0.0103***		-0.0085*		-0.0134***		-0.0057
		(0.00276)		(0.00462)		(0.00382)		(0.00701)
TrendC		-0.0074***		-0.0052***		-0.0082***		-0.0114***
		(0.00110)		(0.00181)		(0.00155)		(0.00281)
EmpRate	-0.0532***	-0.0475***	-0.0611***	-0.0547***	-0.0476***	-0.0424***	-0.0580***	-0.0527***
	(0.00111)	(0.00114)	(0.00182)	(0.00185)	(0.00157)	(0.00160)	(0.00286)	(0.00292)
Age	0.0437***	0.0439***	-0.1284***	-0.1252***	0.0183***	0.0182***	0.0464***	0.0466***
	(0.00088)	(0.00088)	(0.01209)	(0.01205)	(0.00442)	(0.00441)	(0.00520)	(0.00520)
Age^2	-0.0004***	-0.0004***	0.0032***	0.0032***	-0.0001**	-0.0001**	-0.0004***	-0.0004***
	(0.00001)	(0.00001)	(0.00023)	(0.00023)	(0.00006)	(0.00006)	(0.00004)	(0.00004)
Rural	-0.2789***	-0.2758***	-0.1773***	-0.1880***	-0.2676***	-0.2661***	-0.3183***	-0.3120***
	(0.00824)	(0.00824)	(0.02433)	(0.02429)	(0.01305)	(0.01303)	(0.01319)	(0.01319)
School_level2	0.1586***	0.1577***	0.0730***	0.0733***	0.1221***	0.1215***	0.1535***	0.1525***
	(0.00499)	(0.00498)	(0.01441)	(0.01438)	(0.00770)	(0.00769)	(0.00844)	(0.00844)
School_level3	0.3478***	0.3484***	0.1467***	0.1486***	0.3019***	0.3024***	0.4446***	0.4444***
	(0.00476)	(0.00476)	(0.01389)	(0.01385)	(0.00716)	(0.00715)	(0.00905)	(0.00905)
School_level4	0.8225***	0.8234***	0.4686***	0.4707***	0.8639***	0.8646***	1.0432***	1.0436***
	(0.00508)	(0.00507)	(0.01422)	(0.01418)	(0.00751)	(0.00751)	(0.00996)	(0.00996)
School_level2*Rural	0.0898***	0.0923***	0.0169	0.0311	0.0534***	0.0569***	0.0921***	0.0927***
	(0.01087)	(0.01087)	(0.02715)	(0.02711)	(0.01615)	(0.01614)	(0.02249)	(0.02248)
School_level3*Rural	0.0852***	0.0877***	0.0571**	0.0725***	0.0545***	0.0580***	0.0124	0.0118
	(0.01004)	(0.01003)	(0.02520)	(0.02516)	(0.01526)	(0.01525)	(0.02751)	(0.02749)
School_level4*Rural	0.0805***	0.0826***	-0.0135	0.0021	0.1343***	0.1376***	0.2057***	0.2045***
	(0.01166)	(0.01165)	(0.02610)	(0.02606)	(0.01796)	(0.01795)	(0.04338)	(0.04335)
λ (IMR)	-0.0220***	-0.0182**	-0.2165***	-0.2066***	-0.0061	-0.0022	-0.0355**	-0.0339**
	(0.00798)	(0.00798)	(0.02696)	(0.02687)	(0.00982)	(0.00983)	(0.01649)	(0.01649)
Total observations	1,149,201		457,849		382,509		308,843	
Censored observations	772,514	342,485	196,634	233,395				

* Observations with non-reported wages are excluded from the analysis.

Standard errors in parentheses, by two-step variance estimator Heckman (1979). Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.G.8

Selection equation on real hourly wages estimates for female workers
Heckman first stage for sample selection bias.

Dependent variable:	ln(*hourly_wage*)							
Age threshold:	$12 \leq$ Age ≤ 97		$12 \leq$ Age ≤ 29		$30 \leq$ Age ≤ 49		Age ≥ 50	
Equation:	(2.3a)	(2.3b)	(2.3a)	(2.3b)	(2.3a)	(2.3b)	(2.3a)	(2.3b)
Period2	-0.0421***	-0.0421***	-0.0521***	-0.0521***	-0.0347***	-0.0348***	-0.0385***	-0.0385***
	(0.00506)	(0.00506)	(0.00859)	(0.00859)	(0.00811)	(0.00811)	(0.01018)	(0.01018)
Head	0.5551***	0.5549***	0.4020***	0.4022***	0.6469***	0.6464***	0.5060***	0.5058***
	(0.00363)	(0.00363)	(0.01004)	(0.01004)	(0.00548)	(0.00549)	(0.00549)	(0.00549)
TrendB	0.0063***	0.0063***	0.0073***	0.0073***	0.0050***	0.0051***	0.0082***	0.0083***
	(0.00110)	(0.00110)	(0.00186)	(0.00186)	(0.00176)	(0.00176)	(0.00222)	(0.00222)
TrendA&C	0.0063***		0.0068***		0.0052***		0.0084***	
	(0.00110)		(0.00186)		(0.00176)		(0.00222)	
TrendA		0.0063***		0.0068***		0.0053***		0.0085***
		(0.00110)		(0.00186)		(0.00176)		(0.00222)
TrendC		0.0063***		0.0068***		0.0052***		0.0085***
		(0.00110)		(0.00186)		(0.00176)		(0.00222)
EmpRate	0.0409***	0.0415***	0.0070***	0.0066***	0.0525***	0.0539***	0.0679***	0.0688***
	(0.00123)	(0.00126)	(0.00210)	(0.00214)	(0.00198)	(0.00202)	(0.00249)	(0.00253)
Age	0.1239***	0.1239***	0.4858***	0.4858***	0.0683***	0.0683***	-0.0456***	-0.0456***
	(0.00041)	(0.00041)	(0.00532)	(0.00532)	(0.00555)	(0.00555)	(0.00388)	(0.00388)
Age^2	-0.0015***	-0.0015***	-0.0089***	-0.0089***	-0.0009***	-0.0009***	-0.0001**	-0.0001**
	(0.00000)	(0.00000)	(0.00012)	(0.00012)	(0.00007)	(0.00007)	(0.00003)	(0.00003)
Rural	-0.3366***	-0.3358***	-0.2583***	-0.2585***	-0.4585***	-0.4569***	-0.2683***	-0.2668***
	(0.00756)	(0.00757)	(0.02341)	(0.02341)	(0.01316)	(0.01317)	(0.01009)	(0.01012)
School_level2	-0.0253***	-0.0254***	0.0890***	0.0891***	0.1111***	0.1108***	-0.0452***	-0.0454***
	(0.00516)	(0.00516)	(0.01454)	(0.01454)	(0.00927)	(0.00927)	(0.00736)	(0.00736)
School_level3	0.1566***	0.1565***	0.1929***	0.1930***	0.2336***	0.2334***	-0.0801***	-0.0801***
	(0.00494)	(0.00494)	(0.01390)	(0.01390)	(0.00855)	(0.00855)	(0.00797)	(0.00797)
School_level4	0.3723***	0.3722***	0.2647***	0.2647***	0.4695***	0.4689***	0.0129	0.0127
	(0.00510)	(0.00510)	(0.01407)	(0.01407)	(0.00873)	(0.00873)	(0.00924)	(0.00924)
School_level2*Rural	0.0747***	0.0748***	0.0315	0.0311	0.0535***	0.0541***	0.1043***	0.1043***
	(0.01038)	(0.01038)	(0.02667)	(0.02667)	(0.01706)	(0.01706)	(0.01878)	(0.01878)
School_level3*Rural	0.0875***	0.0876***	-0.0112	-0.0116	0.0956***	0.0962***	0.2569***	0.2566***
	(0.00981)	(0.00981)	(0.02507)	(0.02508)	(0.01630)	(0.01631)	(0.02441)	(0.02441)
School_level4*Rural	0.2213***	0.2213***	0.0907***	0.0904***	0.3328***	0.3331***	0.2995***	0.2992***
	(0.01233)	(0.01233)	(0.02660)	(0.02660)	(0.02124)	(0.02124)	(0.04295)	(0.04295)
Total observations	1,149,201		457,849		382,509		308,843	

* Observations with non-reported wages are excluded from the analysis.

Standard errors in parentheses, by two-step variance estimator Heckman (1979). Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.G.9

The impact on hourly wages of male workers

Heckman second stage for sample selection bias.

Dependent variable:	ln(*hourly_wage*)							
Age threshold:	$12 \leq$ Age ≤ 97		$12 \leq$ Age ≤ 29		$30 \leq$ Age ≤ 49		Age ≥ 50	
Equation:	(2.1a)	(2.1b)	(2.1a)	(2.1b)	(2.1a)	(2.1b)	(2.1a)	(2.1b)
ZoneB*Period2	0.0275**	0.0294**	0.0461***	0.0445**	0.0365**	0.0411**	-0.0310	-0.0286
	(0.01187)	(0.01195)	(0.01736)	(0.01746)	(0.01747)	(0.01758)	(0.03042)	(0.03060)
ZoneB	0.1816	0.4237	1.3081*	1.3984*	0.1457	0.4381	-1.7118	-1.3713
	(0.54021)	(0.54355)	(0.78847)	(0.79302)	(0.79388)	(0.79904)	(1.39250)	(1.40074)
Period2	0.0236***	0.0205***	0.0185***	0.0188***	0.0256***	0.0203***	0.0415***	0.0380***
	(0.00378)	(0.00403)	(0.00570)	(0.00604)	(0.00583)	(0.00621)	(0.00964)	(0.01028)
ZoneA*Period2		0.0200*		-0.0076		0.0385**		0.0241
		(0.01084)		(0.01630)		(0.01546)		(0.02821)
ZoneA		1.8518***		0.6709		2.2089***		2.5757**
		(0.48959)		(0.73611)		(0.69702)		(1.28156)
TrendB	-0.0100***	-0.0098***	-0.0135***	-0.0132***	-0.0101***	-0.0099***	-0.0063	-0.0061
	(0.00247)	(0.00246)	(0.00360)	(0.00360)	(0.00365)	(0.00365)	(0.00635)	(0.00635)
TrendA		-0.0168***		-0.0098***		-0.0186***		-0.0251***
		(0.00219)		(0.00331)		(0.00314)		(0.00575)
TrendC		-0.0084***		-0.0072***		-0.0085***		-0.0134***
		(0.00087)		(0.00131)		(0.00134)		(0.00222)
EmpRate	-0.0635***	-0.0578***	-0.0531***	-0.0472***	-0.0682***	-0.0627***	-0.0808***	-0.0754***
	(0.00089)	(0.00090)	(0.00134)	(0.00136)	(0.00139)	(0.00142)	(0.00261)	(0.00260)
Age	-0.0014	-0.0018	-0.1828***	-0.1804***	0.0033	0.0025	0.0304***	0.0303***
	(0.00108)	(0.00108)	(0.00728)	(0.00725)	(0.00385)	(0.00386)	(0.00388)	(0.00388)
Age^2	0.0001***	0.0001***	0.0039***	0.0038***	0.0001	0.0001	-0.0002***	-0.0002***
	(0.00001)	(0.00001)	(0.00014)	(0.00014)	(0.00005)	(0.00005)	(0.00003)	(0.00003)
Rural	-0.4434***	-0.4365***	-0.2094***	-0.2060***	-0.4115***	-0.4052***	-0.5190***	-0.5128***
	(0.00533)	(0.00532)	(0.01279)	(0.01275)	(0.00903)	(0.00905)	(0.01063)	(0.01058)
School_level2	0.1366***	0.1355***	0.0687***	0.0681***	0.0300***	0.0277***	0.1776***	0.1769***
	(0.00397)	(0.00397)	(0.00820)	(0.00818)	(0.00694)	(0.00695)	(0.00757)	(0.00758)
School_level3	0.2112***	0.2104***	0.1709***	0.1697***	0.1143***	0.1127***	0.3339***	0.3336***
	(0.00386)	(0.00386)	(0.00780)	(0.00778)	(0.00668)	(0.00670)	(0.00856)	(0.00857)
School_level4	0.6370***	0.6355***	0.5199***	0.5173***	0.5726***	0.5698***	0.9247***	0.9239***
	(0.00378)	(0.00377)	(0.00881)	(0.00879)	(0.00659)	(0.00661)	(0.00840)	(0.00840)
School_level2*Rural	0.1553***	0.1562***	0.0230	0.0268*	0.1264***	0.1288***	0.0900***	0.0900***
	(0.00710)	(0.00709)	(0.01475)	(0.01471)	(0.01160)	(0.01163)	(0.01522)	(0.01524)
School_level3*Rural	0.1890***	0.1904***	-0.0023	0.0039	0.1462***	0.1477***	0.1685***	0.1710***
	(0.00675)	(0.00674)	(0.01388)	(0.01385)	(0.01116)	(0.01119)	(0.02028)	(0.02032)
School_level4*Rural	0.1130***	0.1138***	-0.1106***	-0.1045***	0.1228***	0.1235***	0.2753***	0.2765***
	(0.00840)	(0.00839)	(0.01532)	(0.01529)	(0.01378)	(0.01381)	(0.02561)	(0.02564)
TrendA&C	-0.0098***		-0.0079***		-0.0101***		-0.0152***	
	(0.00082)		(0.00124)		(0.00126)		(0.00208)	
λ (IMR)	-0.3741***	-0.3759***	-0.4119***	-0.4064***	-0.6247***	-0.6360***	-0.3346***	-0.3488***
	(0.00915)	(0.00915)	(0.01214)	(0.01209)	(0.01859)	(0.01867)	(0.04306)	(0.04333)
Total observations	963,307		428,632		305,290		229,385	
Censored observations	379,444		234,988		40,470		103,986	

* Observations with non-reported wages are excluded from the analysis.

Standard errors in parentheses, by two-step variance estimator Heckman (1979). Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.G.10

Selection equation on real hourly wages estimates for male workers
Heckman first stage for sample selection bias.

Dependent variable:	ln(*hourly_wage*)							
Age threshold:	$12 \leq$ Age ≤ 97		$12 \leq$ Age ≤ 29		$30 \leq$ Age ≤ 49		Age ≥ 50	
Equation:	(2.3a)	(2.3b)	(2.3a)	(2.3b)	(2.3a)	(2.3b)	(2.3a)	(2.3b)
Period2	-0.0597***	-0.0595***	-0.0659***	-0.0657***	-0.0658***	-0.0658***	-0.0489***	-0.0484***
	(0.00574)	(0.00574)	(0.00883)	(0.00883)	(0.01140)	(0.01140)	(0.01109)	(0.01109)
Head	0.4806***	0.4797***	0.6366***	0.6370***	0.5152***	0.5141***	0.2944***	0.2922***
	(0.00410)	(0.00410)	(0.00770)	(0.00770)	(0.00643)	(0.00643)	(0.00874)	(0.00874)
TrendB	0.0094***	0.0093***	0.0122***	0.0120***	0.0113***	0.0112***	0.0079***	0.0076***
	(0.00125)	(0.00125)	(0.00192)	(0.00192)	(0.00248)	(0.00248)	(0.00242)	(0.00242)
TrendA&C	0.0094***		0.0119***		0.0113***		0.0081***	
	(0.00125)		(0.00192)		(0.00248)		(0.00242)	
TrendA		0.0090***		0.0114***		0.0111***		0.0076***
		(0.00125)		(0.00192)		(0.00248)		(0.00242)
TrendC		0.0093***		0.0118***		0.0113***		0.0079***
		(0.00125)		(0.00192)		(0.00248)		(0.00242)
EmpRate	0.0429***	0.0391***	0.0195***	0.0151***	0.0556***	0.0531***	0.0648***	0.0607***
	(0.00141)	(0.00144)	(0.00218)	(0.00221)	(0.00282)	(0.00287)	(0.00272)	(0.00277)
Age	0.1771***	0.1773***	0.7477***	0.7478***	0.0586***	0.0590***	-0.1089***	-0.1086***
	(0.00047)	(0.00047)	(0.00526)	(0.00526)	(0.00769)	(0.00769)	(0.00382)	(0.00382)
Age^2	-0.0021***	-0.0021***	-0.0136***	-0.0136***	-0.0009***	-0.0009***	0.0003***	0.0003***
	(0.00001)	(0.00001)	(0.00012)	(0.00012)	(0.00010)	(0.00010)	(0.00003)	(0.00003)
Rural	0.2318***	0.2266***	0.1823***	0.1780***	0.1305***	0.1273***	0.2546***	0.2484***
	(0.00806)	(0.00806)	(0.02122)	(0.02122)	(0.01659)	(0.01660)	(0.01033)	(0.01036)
School_level2	0.0012	0.0020	0.0414***	0.0421***	0.2596***	0.2603***	-0.0824***	-0.0815***
	(0.00572)	(0.00572)	(0.01258)	(0.01259)	(0.01223)	(0.01224)	(0.00855)	(0.00855)
School_level3	0.1957***	0.1963***	-0.1580***	-0.1575***	0.3654***	0.3657***	-0.1658***	-0.1645***
	(0.00559)	(0.00559)	(0.01243)	(0.01244)	(0.01123)	(0.01123)	(0.00946)	(0.00947)
School_level4	0.0417***	0.0421***	-0.6731***	-0.6735***	0.3183***	0.3190***	-0.1889***	-0.1874***
	(0.00562)	(0.00562)	(0.01286)	(0.01287)	(0.01120)	(0.01120)	(0.00897)	(0.00898)
School_level2*Rural	-0.0946***	-0.0949***	-0.0418*	-0.0446*	-0.1872***	-0.1878***	-0.0342*	-0.0335*
	(0.01103)	(0.01103)	(0.02430)	(0.02430)	(0.02199)	(0.02199)	(0.01974)	(0.01974)
School_level3*Rural	-0.0444***	-0.0452***	0.0305	0.0271	-0.1589***	-0.1594***	-0.1272***	-0.1274***
	(0.01101)	(0.01101)	(0.02340)	(0.02340)	(0.02173)	(0.02173)	(0.02684)	(0.02684)
School_level4*Rural	-0.0323**	-0.0321**	0.1248***	0.1228***	-0.1331***	-0.1331***	-0.2013***	-0.1987***
	(0.01388)	(0.01388)	(0.02579)	(0.02579)	(0.02739)	(0.02739)	(0.03315)	(0.03317)
Total observations	963,307		428,632		305,290		229,385	

* Observations with non-reported wages are excluded from the analysis.
Standard errors in parentheses, by two-step variance estimator Heckman (1979). Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

CHAPTER 3

THE DISTRIBUTIONAL CONSEQUENCES OF THE MINIMUM WAGE INCREASE

3.1 Introduction

In this chapter we use the 2012' regional minimum wage increase in Mexico as a natural experiment to analyse the effect of minimum wage legislation on the distribution of real earnings. We evaluate the effect of the policy change on different points of the earnings distribution by implementing unconditional quantile regressions. We find evidence of positive and significant effects at the bottom of the earnings distribution, which suggests a small improvement in wages for the targeted lowest income workers. Interestingly, the model also shows the existence of income-increasing *spillover* effects on formal and informal labour markets, which widens the dispersion of wages.

Even though the discussion surrounding the impact of minimum wages is often focused on employment effects, the goal of any minimum wage policy is not to affect the level of employment, but to set an earnings floor for workers, and possibly, to reduce inequality. The objective of this chapter is twofold: to evaluate if as a consequence of a minimum wage increase in Mexico there is actually an impact on the lowest segment of the earnings distribution, and to verify the existence of spillover effects on higher income workers and spillover effects on the informal labour market. To estimate the effect at different points of the earnings distribution we implement unconditional quantile regressions, developed by Firpo et al. (2009), exploiting as a natural experiment setting the 2012' minimum wage intervention in Mexico (see Section 1.2.2).

Thus, this chapter beyond intending to answer what impact minimum wage has on the earnings' conditional mean, aims to estimate each of the treatment effects along the distribution of real wages. The previous chapter showed that the rise of the minimum wage in Zone B truly had an impact on real wages. As a consequence of the intervention, wage rates increased on average by 3.6% (an implied elasticity of 1.24). But this analysis did not provide any information on how the intervention impacted earnings across different points of its distribution, especially on the targeted poorest segment of the labour force. Given the nature of the minimum wage policy purposes and the potential spillover effects, it is fundamental to evaluate the impact of the minimum wage increase at different levels of real earnings.

This chapter investigates precisely this, the effects of the minimum wage policies, both directly and via spillover effects, on the level of wages at all points of the earnings distribution. But, it also considers the specific characteristics of labour market in a developing country as Mexico. These include an important share of the labour force under informality conditions (60% of the labour force), and a particular wage setting in which a set of earnings and benefits are tied to the value of the minimum wage. This empirical evaluation extends the minimum wage literature by demonstrating the existence of income-increasing spillover effects in the Mexican labour market.

We find evidence of positive wage effects on the whole earnings distribution. For the percentiles at the bottom of the distribution the impact is small, but still statistically significant with an elasticity by around 0.34. Yet, unconditional quantile regressions reveal income-increasing spillover effects (with elasticities up to 1.9), which increases wage dispersion. To our knowledge, this is the first study documenting spillover effects at the top of the earnings distribution. We argue that this is explained by the fact that the Mexican labour market constitutes a unique case in which wages and prices are legally tied to the value of the minimum wage (Fairris et al., 2008; Woodruff, 1999),[1] which generates

[1]Until 2016, many forms of benefits and remunerations in the formal and informal labour markets were tied to multiples of the minimum wages including, for instance, pensions, productivity bonuses, grants for graduate students, among others.

the outcome that minimum wage interventions affect not only to the lowest-paid workers.

Our estimates on the earnings distribution for informal workers suggest no effects on centiles below the median, although there is a strong positive effect in the rest of the earnings distribution. These findings are in line with previous empirical studies (Lemos, 2009; Khamis, 2013), but not with the only theoretical model that embodies both the formal and informal sectors: the *Welch–Gramlich–Mincer Two Sector Model* described in Subsection 1.1.2 (Welch, 1974; Mincer, 1976; Gramlich et al., 1976).

This model, in the presence of an uncovered sector —in our case corresponds to workers under informal conditions— predicts opposite effects in both sectors. The model predicts a positive effect on wages and a negative impact on employment in the formal sector. In contrast, in the informal sector the wage effect is predicted to be negative (Gramlich et al., 1976), and positive on the level of employment. In this chapter we find no evidence of negative effects on any point of the wage distribution, on any of the labour markets.[2]

The econometric model relies on unconditional quantile regressions. This novel and useful procedure developed by Firpo et al. (2009), is estimated using a recentered influence function that offers the analytical advantage of estimating directly marginal effects at any point of the dependent variable's distribution, in our case, hourly wages. Therefore, it also allows us to test straightforwardly the existence of minimum wage spillover effects. Before the development of this technique, previous studies —exploiting differentiated minimum wage settings at the state level in the US— had to use alternative specifications to estimate the minimum wage effect on the state' log-difference of real earnings between percentiles ($w_{p50} - w_{p10}$, for instance) (Lee, 1999). So, the minimum wage effect estimated in Lee (1999) was on the wage gap between two specific centiles. In contrast, unconditional quantile regression allows us to estimate the effect on any quantile of the distribution. In addition, the importance of unconditional quantile regressions for our analysis for Mexico is that the lack of changes to the minimum wage at the state level did not allow the use

[2]Our results in Chapter 4, using also the 2012 minimum wage intervention, suggest that the effect of raising minimum wages is to raise employment in the formal sector and lower it in the informal sector. Thus, formal and informal labour markets are interdependent, they constitute complementary markets where a non-homogeneous labour force chooses and competes for positions.

of the state' earnings differential between percentiles as a dependent variable.[3]

By pooled Difference in Differences (DiD) specifications and with data from the National Survey on Employment and Occupation (ENOE), for the period 2012Q1-2013Q4, our results suggest that the minimum wage harmonization in 2012 had the weakest wage effects on the lowest percentiles of the distribution, while the institutional setting framework led to spillover effects that increased wage dispersion. The econometric specifications are consistent with those used in Chapter 2. The results are robust to different econometric specifications, particularly to the period of analysis, to the control group used and to the exact specification of the DiD estimator. This corroborates the existence of income-increasing spillover effects in the formal and informal labour market.

The following section presents the literature review on the distributional effects of minimum wages. Section 3 discusses the institutional framework of the minimum wage regulations in Mexico. Section 4 presents the data source and some descriptive statistics on wage distribution. Section 5 describes the estimation method and the econometric specifications. The main results, some falsification tests, and the discussion of the estimates are presented in Section 6. The last section concludes the chapter.

3.2 Literature Review

Although the discussion on the implications of minimum wages has focused mainly on employment effects, there is also much research on the distributional impacts of minimum wages arguing the case for the existence of wage spillover effects. Empirical research during the decade of the 90's demonstrated that the loss of purchasing power of the real minimum wage in the United States was largely responsible of the rise in wage inequality (DiNardo et al., 1996; Lee, 1999). Wage dispersion increased, but not only in relation to the bottom of the distribution, also in percentiles beyond the minimum wage

[3]Minimum wages zones in Mexico are set at the municipality level depending on their economic development, not their geographic location (see Panel (b) of Figure 1.6). Thus, one state can have all the three wage zones, which restricts the use of states for the construction of control and treatment groups.

threshold, which revealed the existence of spillover effects. More recently, Autor et al. (2016) reassessed Lee's estimates concluding that although the effect of minimum wage on inequality is significant, and it is not possible to deny the presence of wage spillover effects, its magnitude is lower than estimates in the decade of the 90's (at most up to the fourth decile of the distribution).

The structure of labour markets in developing countries is however different.[4] Previous empirical studies for Latin America found stronger minimum wage spillover effects,[5] so it has been necessary to extend theoretical models to characterize the informal sector.

The *Welch–Gramlich–Mincer Two Sector Model* has been used to characterize a sector outside the covered sector, in this case formal and informal labour markets (for instance, in Lemos, 2004a, 2009; Mora and Muro, 2017). Assuming homogeneous labour and perfect competition, this model predicts that the introduction (or an increase) of the minimum wage reduces the level of employment in the covered sector. A fraction of those workers not hired in the covered sector can find a job in the uncovered sector, but the existence of the uncovered sector only partially offsets the employment loss. The wage in the uncovered sector may rise (Mincer, 1976; Gramlich et al., 1976) or fall (Welch, 1974) depending on the assumptions with respect to the possibility of the workers of choosing between covered or uncovered sectors.[6]

Lemos (2009) showed that there were positive minimum wage spillover effects in both sectors for the Brazilian labour market. She argued that opposite results to the *Welch–Gramlich–Mincer Two Sector Model* are explained by the lack of segmented labour markets. Formal and informal sectors could be integrated offering different kind of jobs, which heterogeneous workers can choose from. These results are in line with previous estimates

[4]Appendix 3.A describes in a more detailed way previous studies evaluating minimum wage spillover effects on the US labour market.

[5]See for example, Maloney and Mendez (2004) and Maurizio (2014) for comparative studies evaluating the implemented policies in the region aiming at the recovery of the real value of the minimum wages.

[6]Informal markets in Latin America are more complex than the defined 'uncovered sector'. It is not only about the non-compliance of the minimum wage regulations, there are other factors not considered in this model, like the differences on the skills distribution and the incentives for working in the informal labour market. Unfortunately, the *Welch–Gramlich–Mincer Two Sector Model* constitutes so far the only theoretical reference to explain the minimum wage effects given changes to minimum wages.

that concluded that minimum wage in Brazil compressed the earnings distribution for both, formal and informal sectors (Lemos, 2004a; Fajnzylber, 2001; Carneiro, 2000). For Argentina, Khamis (2013) found that wages in the informal labour market were affected by a greater proportion than the formal sector after the minimum wage increase of 1993. This reinforces the idea that minimum wage constitutes a reference rate for remunerations even in non-compliant sectors.

Nevertheless, not all the studies in Latin America find significant effects in the informal sector. Using a similar specification to Lee (1999), Borraz and Gonzlez-Pampillón (2017) found evidence that the minimum wage hikes in Uruguay during the decade of the 2000's (which more than doubled the real minimum wage) increased real monthly wages up to the seventh decile of the earnings distribution, but only in the formal labour market.[7]

Similarly, Bosch and Manacorda (2010) demonstrated that real minimum wage reduction in Mexico explained most of the growth of earnings inequality for the period 1989-2001, finding also evidence that minimum wage can affect earnings up to the sixth decile of the earnings distribution, but they failed to find a significant effect on informal workers. However, the main caveat of their analysis is that in the absence of a structural change in the minimum wage for that period, they instrumented the so-called 'effective minimum wages' using social security data. Thus, they took the erosion of the real minimum wage as exogenous, which is not necessarily true. Moreover, the database used was restricted to urban areas, impeding to observe a significant segment of the informal labour market.

Thus, while the previous literature for Latin America recognizes the existence of spillover effects even larger than those estimated in industrialized countries (in some cases, also in the informal labour market), in all cases these spillover effects are decreasing in earnings. By the implementation of unconditional quantile regressions, we show that the

[7]Nevertheless, their results are not consistent to the choice of the reference decile and to the econometric specification. For example, for the IV estimates using the 80th percentile as a reference, they could find positive and significant effects up to the seventh decile, while if they use the 70th percentile as a reference, they estimate significant effects at most up to the fourth decile. Moreover, in contrast to OLS estimates, IV regressions yield insignificant parameters below the 25th percentile of the distribution.

2012 minimum wage increase in Mexico affected earnings along the entire distribution. Moreover, the strongest impacts are observed at the top of the earnings distribution in the formal and informal labour markets.

Related to the use of unconditional quantile regressions to evaluate the distributional effects of minimum wage policies, there are two previous studies. Hallward-Driemeier et al. (2017) found evidence of spillover effects in an evaluation of the minimum wage impact on gender gap in Indonesia. Minimum wage increased female earnings up the fifth decile, but no effects were found on the male earnings distribution. Controlling for educational attainment, they found positive effects on workers with at least a high school degree, up to the seventh decile for woman and up to the ninth decile for men. Aeberhardt et al. (2016) exploited the coexistence of several minimum wages in France between 2003 and 2005. They found that the minimum wage increase had positive impacts over a large part of the distribution: up to the seventh decile for men and up to the fifth decile for women, but the effect was decreasing in earnings.

Although our estimation method is the same, the identification strategy and the context of wages' setting are not. On the one hand, we use regional differences in the minimum wage setting, while their strategy relies on temporal differences in the adoption of new minimum wage regulations. On the other, to our knowledge there were no regulations in Indonesia or France about the use of the minimum wage as a *numeraire* to set wages and earnings. The following section describes precisely how the minimum wage was used in Mexico as a reference rate for these purposes.

3.3 Policy context: minimum wages as a reference rate

Fairris et al. (2008) explored the relation between minimum wages and the wage structure in Mexico for the period of 1988-1992. The analysis suggests that minimum wages had a *normative* role in the whole process of wage setting in Mexico. Minimum wage in Mexico was used as a reference rate, in which earnings were tied to multiples of minimum wages in both labour markets, formal and informal.

This section describes the institutional framework in Mexico that gave rise to the use of the minimum wage as a reference rate, and as consequence potentially affected the wage setting for workers with remunerations above the minimum wage.

The role of the minimum wage as a reference rate was not spontaneous; specific policies were designed to give minimum wages the function of controlling wages. The decade of the 1980's in Mexico was characterized by macroeconomic crises. The fall in the oil price at the beginnings of that decade, as well as the increase of the government expenditure on bureaucracy led to Mexico's default in 1982, followed by devaluation and hyperinflation episodes. There was a slow recovery impulsed by fiscal discipline, but in 1987 the annual inflation rate reached the highest level ever recorded: 159.17%. As a response, the government implemented a set of stabilization policies, among them the *Economic Solidarity Pact* and the so-called *Incomes policies*, having as a central objective to stop the raising inflation, by restraining wages and prices. The recently created National Commission on Minimum Wages (CONASAMI) was the responsible of the task of minimum wage setting.

The Pact was signed on 15 December 1987 by the government, unions, employers, and agricultural producers. The main characteristics of the agreement were fiscal cuts, tighter monetary policy, trade liberalization, and a comprehensive income policy (Lustig, 2000). It was essential to control wage increases as a mechanism to suppress further rises in the prices of commodities and services as an instrument also to stop increases in government payroll expenses (Fairris et al., 2008). The target of the wage policies was focused directly on minimum wages.

Even though the agreements on wages increases included in the *The Pact* were applied only to minimum wages, the variations were proposed as a general "guide to salary negotiation" (Woodruff, 1999). For instance, the document of the first renewal of the agreements in February 1988 by the Mexican Presidency explicitly states "The business sector will raise contractual salaries to the same extent that minimum wages are increased" (as cited in Woodruff, 1999).

According to the goals set, the stabilization policies were successful. In December 1988 the annual inflation rate was 51.66% and one year later was 19.70%. These agreements were renewed and maintained until 1995, in which annual inflation rate was 7.05%. Even though the key objectives evolved towards strengthening the macroeconomic stability and boosting the economic growth, inflation containment remained as a priority. As a consequence, the use of minimum wages also remained as an instrument of wage setting.[8]

Although episodes of hyperinflation had been overcome, the policy on minimum wages for wage control did not change. In contrast, the use of the minimum wage as a reference rate was taken to different ways of remunerations and prices, not only wages. This include the setting of social security fees, pensions, scholarships for graduate students, productivity bonuses and retirement benefits for teachers, eligibility for housing credits, income tax brackets, and even traffic fines.

By the end of 2015, there were 216 legal regulations, only at the federal level that considered the prevailing value of the minimum wage as a reference rate. Under this framework in which minimum wages are used as an index or *numeraire* to determine other remunerations and other prices, changes to the minimum wage level can have repercussions on workers earning beyond the minimum wage level.

Thus, the referencing of the minimum wage in Mexico came about from a need to impose discipline on wage negotiations at different levels and occupations. So that the role of minimum wages as a reference rate, while it may have helped to moderate prices may also heave contributed to exacerbate difficulties in the public policies implementation.

This legal framework remained in force until January 2016 when it was reformed. As part of the discussion on the importance of the implementation public policies to recover the value of the real minimum wage level (Gob.Distrito-Federal, 2014), it was recognized that the first stage before increasing the minimum wage value, was to 'de-index' it from

[8]Inflation figures calculated with data from the National Institute of Geography and Statistics.

any other form of remunerations, earnings or prices. Thus the National Congress passed the 'Decree on the de-indexation of the minimum wage' on 27 January 2016.

Given that the Zone B's minimum wage increase under evaluation took place in 2012, before the 'de-indexation reform', it is expected that its impact on the wage earnings have significant effects on workers above the minimum wage level, as our results demonstrate in Section 3.6.

3.4 Data and descriptive statistics

3.4.1 Database description and limitations

As in the previous chapter, the data used for the econometric analysis were obtained from the National Survey on Employment and Occupation (ENOE), which has been previously described (see Section 1.2.1). We focus on the period 2012Q1-2013Q4, although in Section 3.6.2 we implement some falsification tests for the period 2011Q1-2012Q4.

We exploit this information to explore the spillover effects of the minimum wage increase not only on workers above the minimum wage level, but also on the 'uncovered' informal sector, in which by definition minimum wage regulations are not enforced.

Aiming for consistency on the period of analysis among the models used previously to evaluate the effects of the 2012 minimum wage intervention on mean wages, employment and informality, the period covered for the main estimates does not change.

The dependent variable is the recentered influence function of the logarithm of the hourly real wage.[9] All the details of the estimation of the recentered influence function are explained in Section 3.5.1. Given that the estimates are focused on the impact at different points of the earnings distribution, we only consider individuals reporting non-zero earnings. The set of the socio-demographic control variables included in the regressions are also the same with respect to the specifications used in Chapters 2 and 4: gender, age, squared age, schooling level, state employment rate, rural municipalities, and interactions

[9]Nominal wages in ENOE are deflated using the National Price Index, also obtained from INEGI.

of schooling level with rural and gender.

Nevertheless, there are two important differences with respect to the restriction imposed on the sample. First, following previous research on wage distribution effects of minimum wage changes, self-employed workers are excluded (Lee, 1999; Autor et al., 2016) independently of their formality condition. Second, in line with the procedure by Autor et al. (2016), to reduce the influence of the outliers, the data *winsorizes* the extreme 0.2 percentiles of the wage distribution by assigning the 0.02 and 99.8 percentile value to the respective extreme quantiles. These modifications do not alter significantly the estimates obtained, nor the conclusions of the analysis.

It is important to discuss a crucial limitation of the data. Workers with the highest level of earnings are not properly captured in the survey. One of the major disadvantages of surveys at the household level is that top income households are sub-represented, so aggregate earnings tend to be underestimated. ENOE has the particular problem that non-response observations on wages have increased, going from 14% in 2005 to 25% in 2013 (Rodríguez-Oreggia and López-Videla, 2015). And more importantly, non-responses are not independent of socio-demographic features. More educated workers are precisely those who do not respond to earnings questions. (Campos-Vázquez, 2013; Rodríguez-Oreggia and López-Videla, 2015). For our analysis, this implies that we by and large do not observe top-income earners.

Table 3.1 illustrates this, by detailing the average wage by monthly earnings deciles. The mean monthly minimum wage corresponds to \$1,866 MXN,[10] hence median earnings (\$4,019.04 MXN, \$246.10 USD for comparison purposes) are just 2.15 times the minimum wage. If we look at the top of the distribution, the mean wage of the 9$^{\text{th}}$ decile (\$9,238.34 MXN) corresponds to 4.94 times the minimum wage.

So, when we talk about top-income individuals, we are not referring to the richest in Mexico, nor to white-collar workers. We refer to workers at the top of this specific ENOE's earnings distribution, which in addition is underestimated. To put this earnings

[10]Weighted average by the labour force in the three minimum wage zones

underestimation into perspective, INEGI also publishes the National Accounts' aggregated level of earnings for waged workers. Dividing this figure by the total number of waged workers reported by the ENOE (also published by INEGI), average monthly earnings for waged workers correspond to $11,170 MXN. So, with aggregated data form national accounts in Mexico, mean monthly wages are equivalent to those by the 94th earnings percentile in ENOE.

Table 3.1
Mean earnings by deciles, 2012-2013
(constant MXN pesos of 2010)

Earnings deciles by ln(monthly wage)	ln(hourly wage)	Monthly wage (MXN)	(USD*)
1	2.5871	1,714.67	105.00
2	2.6642	2,459.47	150.60
3	2.8179	3,057.13	187.20
4	2.8876	3,565.07	218.30
5	3.0081	4,019.04	246.10
6	3.1288	4,742.20	290.38
7	3.3441	5,540.70	339.28
8	3.6135	6,702.81	410.44
9	3.9228	9,238.34	565.69
Mean	3.1021	5,038.46	308.52

Source: own computations with data from ENOE. Self employed workers are excluded. Earning population values were computed using expansion factors.
*Computed using the average exchange rate for 2012-2013 (13.004 USD/MXN).

In spite of the earnings underestimation and not observing those individuals actually at the top of the earnings distribution, we are able to accomplish the two objectives of the chapter: to evaluate the impact at the bottom of the distribution and to investigate the presence of spillover effects. Moreover, ENOE has the fundamental advantage of including the informal labour market. There exist other databases that may capture in a better way the top-paid workers, for instance, the Mexican Institute of Social Security collects monthly information on wages for workers registered for social security services, which by definition implies formal workers. But in addition to other important limitations, restricting the analysis to formal workers would provide an incomplete and possibly biased analysis of the Mexican labour market opposed to the one of the basic objectives of this thesis, which is to evaluate the impact on informal workers.

3.4.2 Pre-treatment trends

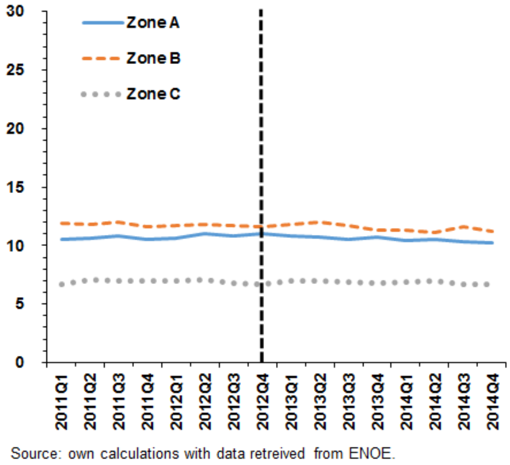
In absence of a randomized treatment allocation, an essential assumption to implement DiD estimations is that control and treatment groups have the same behaviour before the intervention. That is, it is necessary to show the existence of parallel trends of the dependent variables in the pretreatment period.

For our distributional analysis, in which the impact of the minimum wage intervention is evaluated at different points of the distribution, graphical inspection of wages at the means is not enough, so Figure 3.1 displays the graphical analysis of real hourly wage trends for a set of selected earnings deciles. Graphs show that there are no considerable differences in the preintervention period for any of the quantiles analysed. The distance between Zone B and control zones A and C remains practically constant for the period before the minimum wage increase (illustrated by the vertical dotted line).

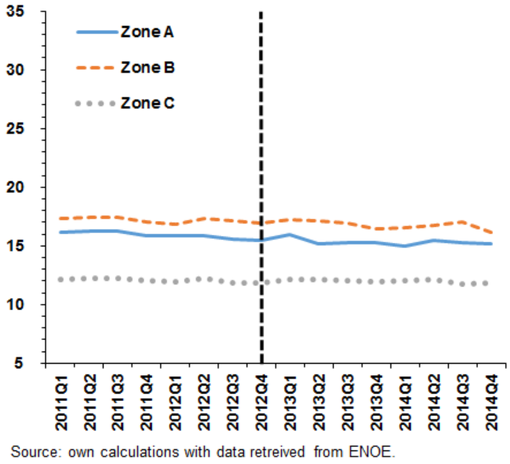
If we analyse the post-intervention period, it is possible to appreciate differences in wage trends only for percentiles 75$^{\text{th}}$ and 90$^{\text{th}}$. For the rest of percentiles it is not possible to recognize differences in wages, which suggest that the treatment effects in the bottom part of the distribution should be small. The results presented in Section 3.6.1 corroborates this.

This descriptive analysis suggests that the implementation of DiD procedures is valid. Robustness exercises in Section 3.6.2 formally demonstrate that there are no differences between minimum wage zones before the intervention, which corroborates this descriptive visual inspection.

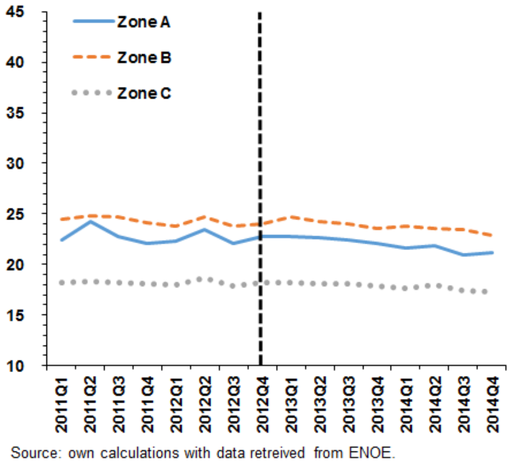
Figure 3.1
Real hourly wage trends by percentile and wage zones
(Mexican pesos of 1F December 2010)



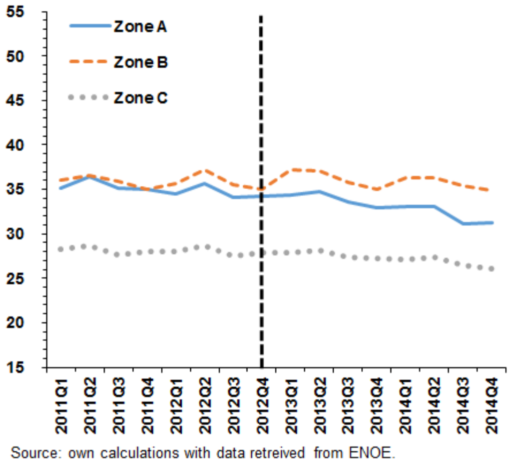
(a) 10^{th} percentile



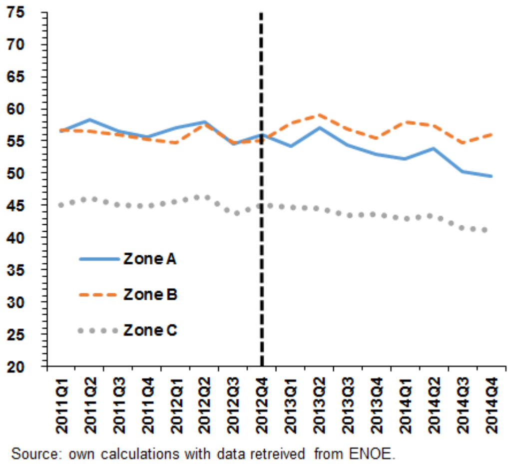
(b) 25^{th} percentile



(c) 50^{th} percentile



(d) 75^{th} percentile



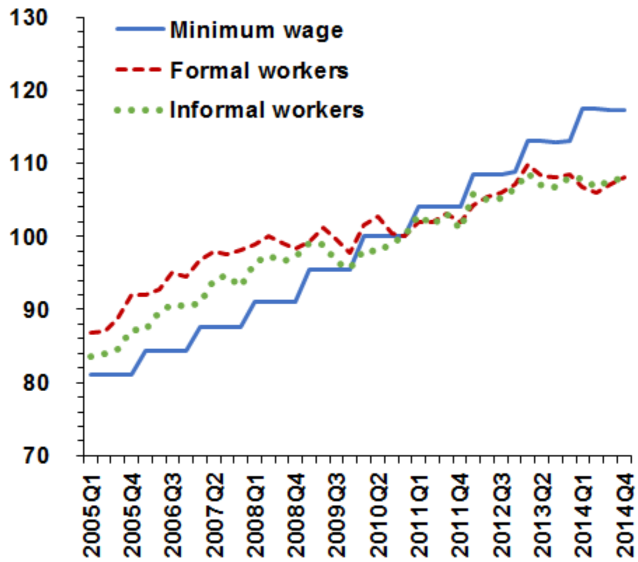
(e) 90^{th} percentile

3.4.3 Descriptive statistics on real earnings and wage dispersion

In addition to the descriptive statistics presented in previous chapters, in this subsection we analyse graphically the trend followed by mean earnings, its dispersion, as well as the evolution by some selected wage percentiles. The objective is to provide a general description of the earnings distribution in the Mexican labour market before presenting the model to evaluate the minimum wage effects at different quantiles of the distribution.

Following the argument in Section 3.3, if the minimum wage has the role of a reference rate or *numeraire*, it should be an important determinant of the whole wage setting process in the Mexican labour market. Figure 3.2 presents the path followed by the minimum wage and average earnings in nominal terms. The solid blue line corresponds to the average minimum wage weighted by the active labour market population by zone, while the dotted lines show the mean earnings by formality condition. We graph nominal instead of real earnings in order to capture more closely the wage-setting dynamics. The reference period for the index number is 2010Q4, which corresponds to the base period for the construction of the National Price Index by INEGI.

Figure 3.2
Nominal minimum wage and mean earnings by formality condition
(Index 2010Q4=100 , 2005Q1-2014Q4)



Notes: Nominal minimum wage is an average weighting by the active labour market population by zone. Earnings population values using expansion factors in ENOE.

Although nominal minimum wage exhibits a higher growth rate, the annual increases to the minimum wage (at the beginning of every year) are usually accompanied by similar raises in the average level of earnings. The graph illustrates that there is a common variation between average earnings and minimum wage, and more importantly, not only in the formal labour market. Indeed, the correlation index of the mean earnings in the formal and informal sectors, with respect to the minimum wage level are 0.94 and 0.96, respectively. It is also interesting the fact that there is some kind of convergence in the variation (although not in absolute wage levels) between average earnings in the formal and informal sectors.

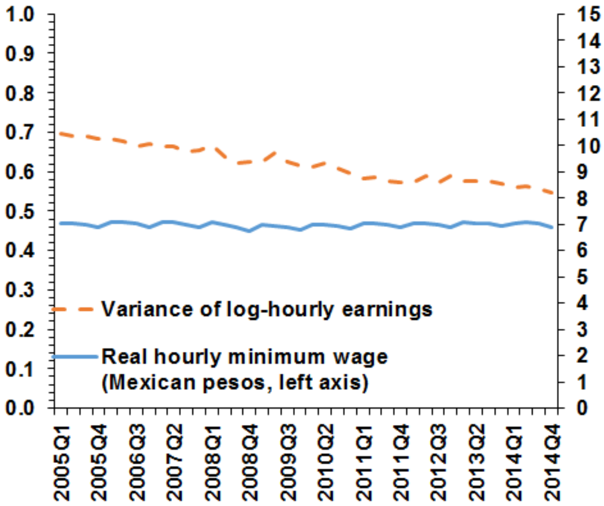
If we look at the relationship between wage dispersion and the real minimum wage, panel (a) of Figure 3.3 shows that from 2005 to 2014, the variance of log-hourly earnings has decreased by 0.15 log points. In contrast, the real hourly minimum wage (considering an 8-hour workday) has remained unchanged for the same period. This is intuitively sensible since the annual increases to the nominal minimum wage are aimed precisely at adjusting the loss by inflation in the previous year to keep constant its purchasing power. Thus, the observed decline in the earnings dispersion does not seem to be related to the minimum wage policy.

Panel (b) of Figure 3.3 analyses separately the wage dispersion for the formal and informal labour markets. As expected, the log-hourly variance for informal workers is higher (by around 0.1 log points), but it is interesting that both labour markets respond in a similar way to exogenous shocks.

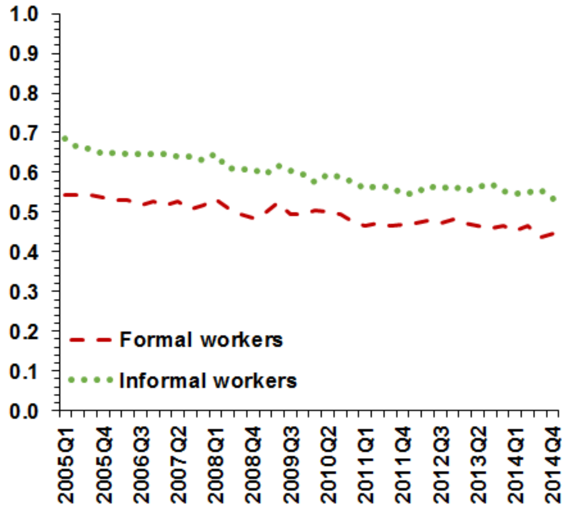
Thus, figures 3.2 and 3.3 suggest that there is a close relationship between minimum wages and wage setting in the formal and informal labour market, but minimum wage is not responsible for the reduction in the wage dispersion between 2005 and 2014.

In order to analyse in depth the earnings distribution for the same period, panel (a) of Figure 3.4 describes the evolution of the mean earnings quantiles for some selected percentiles. Following a similar analysis in Engbom and Moser (2017), real log-hourly wage percentiles are normalised to zero in the initial period, which in our case corresponds

Figure 3.3
Wage dispersion and real minimum wage
(2005Q1-2014Q4)



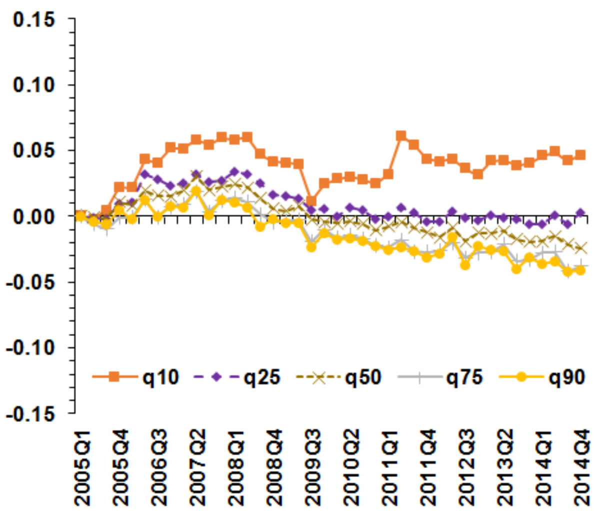
(a) Variance of log-hourly earnings and real minimum wage



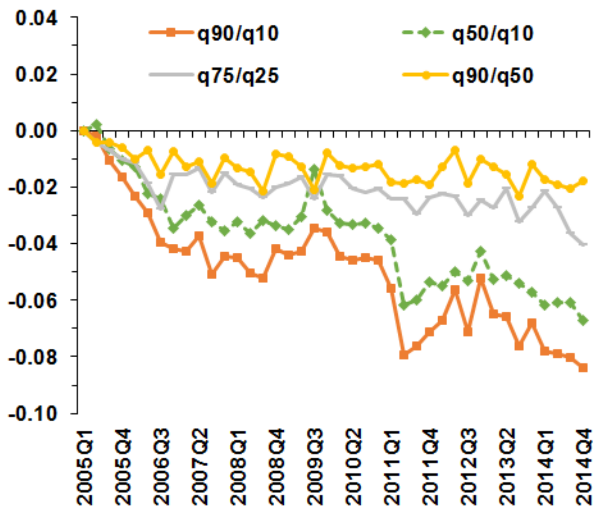
(b) Variance of log-hourly earnings by formality condition

Notes: Nominal minimum wage is an average weighting by the active labour market population by zone. Earnings population values using expansion factors in ENOE.

Figure 3.4
Real earnings by percentiles
(2005Q1-2014Q4)



(a) Normalised real log-hourly wage percentiles (2005Q1=0)



(b) Normalised percentile ratios (2005Q1=0)

Notes: earnings population values using expansion factors in ENOE.

to 2005Q1. From 2005 to 2008 there is a generalized increase in real wages, but after the financial crises in 2008 there is a negative trend for which only the 10th percentile was able to recover. The 25th percentile exhibits practically the same level in 2014Q4 to that observed 2005Q1, but the rest of the percentiles had an important decrease, including the median of the distribution.

With the objective of having an additional measure of wage dispersion, but at different points of the distribution, panel (b) of Figure 3.4 depicts percentile ratios —also normalised to zero in 2005Q1. In all cases, the wage gap within percentiles decreased. But, there was a more important decline for the ratio q50/q10. In absolute terms, it decreased by 0.1 log points, while for the interquartile range (q75/q25) the decline observed was by 0.05 log points, and 0.02 points for the ratio q90/q50.

Finally, with respect to the real earnings distribution for our specific period of analysis, Figure 3.5 plots the kernel density estimates[11] of the real log-hourly wages for treated Zone B (self-employed workers are not included). The earnings distribution is also decomposed into the weighted sum of the densities of formal and informal workers.

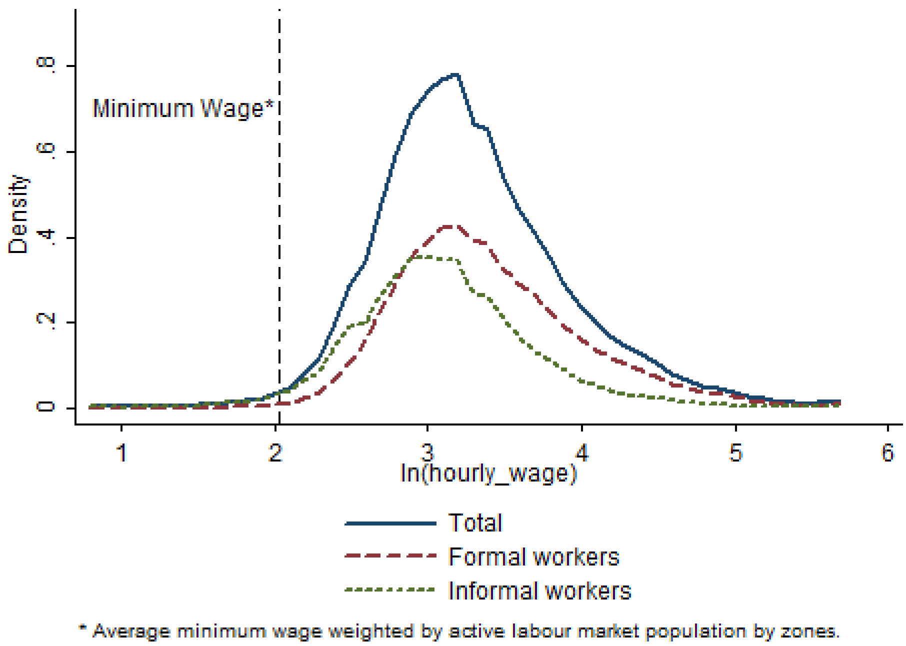
The dotted vertical line expresses the minimum wage considering a workday of 8 hours. So, the first issue to emphasize is that in the Mexican labour market there are actually workers with earnings below the minimum wage, in both formal and informal labour markets. Secondly, as expected, informal workers are grouped in lower levels of remunerations in comparison to the formal counterpart.

This section has provided a general characterization of the ENOE's Mexican wage distribution. Some interesting points emerged. First, in ENOE's sample, wage distribution is compressed relatively close to the value of the minimum wage, which suggests potential minimum wage spillover effects. Second, there exists a correlation of the minimum wage level with the overall wage setting, but not with the dispersion of wages. Third, during

[11]Epanechnikov kernel using the optimal cross validation bandwidth (Silverman, 1986) computed by the following calculation: $h = 0.9 \min(\sigma, IQR/1.349)n^{-1/5}$. Where σ is the standard deviation of the log hourly real wages and IQR denotes the interquartile range. Self-employed workers are not included in the analysis, and the data *winsorizes* the extreme 0.2 percentiles of the wage distribution by assigning the 0.02 and 99.8 percentile value to the respective quantiles.

the last ten tears there has been a decline in the relative distance in wages between top and bottom percentiles, but this has been a consequence of a reduction in real earnings for workers beyond the 25th percentile. Next section describes the UQR procedure that will allows us to estimate the minimum wage marginal effects at every percentile of the real wages distribution.

Figure 3.5
Wage distribution density estimates by formality condition, Zone B
(pooled sample, 2012-2013)



3.5 Methodology

3.5.1 Unconditional quantile regression

Conditional quantile regression (CQR), developed by Koenker and Bassett (1978), became a useful empirical tool to characterize the full distribution of a certain outcome conditioned on a set of covariates. Nevertheless, the interpretation of the estimated parameters in an evaluation program setting is complicated; the coefficients do not translate to the relevant policy questions that are linked to the covariates, they do not summarize the causal effect of a treatment (Borah and Basu, 2013; Frolich et al., 2010).[12] This subsection describes the method recently proposed by Firpo et al. (2009), unconditional quantile regression, which allows us to evaluate how a marginal change in one variable —in this case, the minimum wage variation in Zone B— affects the entire wage distribution, keeping the distribution of the rest of covariates constant.

Formally, the aim is to estimate the effect of the minimum wage rise, denoted as mw,[13] on the τ^{th} quantile of the earnings unconditional distribution, $F_Y(y)$. In the OLS regression framework, the parameter δ is interpreted as the impact on the conditional mean: $\delta = d\mu(\text{mw})/d\text{mw} = \text{E}(Y|\text{mw} = 1) - \text{E}(Y|\text{mw} = 0)$. In contrast, the coefficient δ_τ^{CQR} from conditional quantile regression analysis is generally different from the partial effect: $\delta_\tau^{CQR} = F_Y^{-1}(\tau|D = 1) - F_Y^{-1}(\tau|D = 0) \neq dq_\tau(\text{mw})/d\text{mw}$.

The reason of the inequality is simple, conditional and unconditional distributions are not necessarily the same. Following an example in Borah and Basu (2013), the set of workers at the 5$^{\text{th}}$ percentile of the unconditional earnings distribution of Y may not be the same as the workers at the 5$^{\text{th}}$ percentile of the conditional distribution of $Y|\text{mw}$.[14]

Under this context, Firpo et al. (2009) developed a procedure to obtain directly the marginal effects in quantile regression. They showed that the *unconditional quantile partial effect* can be obtained by running an OLS regression of the recentered influence function (RIF) of the unconditional quantile on the explanatory variables.

The influence function, $\text{IF}(Y; v; F_Y)$, of a distributional statistic $v(F_Y)$ represents the influence of a single observation on that distributional statistic, for instance, variance, quantiles, or the Gini coefficient. For the τ^{th} quantile, the influence function corresponds to: $\text{IF}(Y; q_\tau, F_Y) = \tau - \mathbb{1}\{Y \leq q_\tau\})/f_Y(q_\tau)$. The RIF is obtained just by adding back the

[12]Differences in differences estimates using Conditional Quantile Regressions are reported in Appendix 3.B. Even though it is not possible to interpret the coefficients as a marginal treatment effects, it is worth emphasizing that the general conclusions of our results in terms of the magnitude of the effects at different points of the distribution do not change.

[13]mw = 1 denotes treatment, that is, it identifies those workers performing labour activities in some municipality of Zone B after 26 November 2012; mw = 0 indicates absence of treatment.

[14]The coefficients of a covariate on a specific quantile outcome are the same by conditional or unconditional quantile regressions only in the following cases: if there are no other covariates influencing the data generating process, or if the effect is constant across levels of other covariates (Borah and Basu, 2013).

statistic $v(F_Y)$ to the influence function, in this case the τ^{th} quantile: $\text{RIF}(Y; q_\tau, F_Y) = q_\tau + IF(Y; q_\tau, F_Y)$.

Firpo, Fortin and Lemieux demonstrated that the average derivative of the conditional expectation of the RIF, $\text{E}[\text{RIF}(Y; q_\tau, F_Y)|X] = m_v(X)$, corresponds to the marginal effect on the unconditional quantile of a small location shift in the distribution of covariates, holding everything else constant. Therefore, the RIF-regression model can be viewed as an unconditional quantile regression.

Hence, to implement the unconditional quantile regression the first step is to estimate the RIF, which is used as dependent variable:

$$\text{RIF}(Y; q_\tau, F_Y) = q_\tau + \tau - \mathbb{1}\{Y \leq q_\tau\})/f_Y(q_\tau) \tag{3.1}$$

To do so, it is necessary to compute each of its components: the sample quantile q_τ, a dummy variable $\mathbb{1}\{Y \leq q_\tau\}$ indicating whether the outcome variable is below q_τ, and the density $f_Y(q_\tau)$ at the point q_τ by Kernel procedures, or other non-parametric methods. Finally, this new dependent variable is regressed on the set of covariates.

Thus, a RIF-regression is similar to a standard regression, with the only difference that the dependent variable is replaced by its recentered influence function of the quantile of interest τ. The main advantage of the method is that the distribution function is *locally* inverted (Fortin et al., 2011); the binary variable $\mathbb{1}\{Y \leq q_\tau\}$ is actually divided by the density of the marginal distribution $f_Y(q_\tau)$. This allows us to estimate locally what is the minimum wage effect at any specific point τ of the distribution.

The following subsection details the DiD specifications to estimate the effect of the 2012 minimum wage increase at different percentiles of the earnings distribution.

3.5.2 The model. Difference in Differences specification

To estimate the effect of an increase in minimum wage zone B on real hourly earnings $\ln(w_i)$ at different percentiles of the distribution, we follow the structure of the econometric specifications used to evaluate the conditional mean effect in Chapter 2. Thus, we use two

DiD equations, which change depending on the zone used as a control group. In equation (3.2a) the control group consists of the untreated zones A and C. For equation (3.2b) only Zone C is part of the control group; to avoid losing all the observations from Zone A, the dummy variable $ZoneA$ is included as a regressor.

$$\begin{aligned}\text{RIF}(Y;q_\tau, F_Y) = {} & \beta_{0,\tau} + \delta_{1,\tau} ZoneB_i * Period2_i + \delta_{2,\tau} Period2_i + \delta_{3,\tau} t + \delta_{4,\tau} ER \\ & + \beta_{1,\tau} ZoneB_i + \sum_{k=2}^{k} \beta_{k,\tau} X_{ki} + e_{i,\tau} \end{aligned} \tag{3.2a}$$

$$\begin{aligned}\text{RIF}(Y;q_\tau, F_Y) = {} & \beta_{0,\tau} + \delta_{1,\tau} ZoneB_i * Period2_i + \delta_{2,\tau} Period2_i + \delta_{3,\tau} t + \delta_{4,\tau} ER \\ & + \delta_{5,\tau} ZoneA_i * Period2_i + \beta_{1,\tau} ZoneB_i + \beta_{2,\tau} ZoneA_i + \sum_{k=3}^{k} \beta_{k,\tau} X_{ki} + e_{i,\tau} \end{aligned} \tag{3.2b}$$

$$\text{where } \tau = (0.10, 0.11, ..., 0.90)$$

$\delta_{1,\tau}$ is our parameter of interest. It expresses the marginal effect of the minimum wage increase in Zone B on the real hourly wage for the centile τ. $Period2$ is a dummy variable for identifying the post-treatment period to capture the 'shift effect' of the intervention. $ZoneB$ and $ZoneA$ are also indicator variables to differentiate from wages zones. By the inclusion of the interaction $ZoneA_i * Period2_i$ in equation (3.2b), the purpose is not to estimate the effect on Zone A; it is only included for completeness given that $ZoneA$ is added as an independent variable in the model.[15]

The specifications also include a quarterly common linear trend (t) in order to capture the macroeconomic factors not considered in the model at the individual level. To control for the labour market conditions at the state level, state employment rate (ER) is also added in the equations (constructed as the percentage of employed workers over the active population by state). For a discussion on the potential endogeneity problems of the variable state employment rate ER, see Appendix 2.D.[16]

[15] In all cases, the parameter $\delta_{5,\tau}$ for equation (3.2b) is not statistically different from zero.

[16] We cannot reject the null hypothesis of the exogeneity of employment rate in the wage equation after the implementation of the Durbin-Hu-Hausman test. Examples of the use of aggregate employment rates as a control variable in wage equations in previous literature are found in Mroz (1987) and Autor

Finally, X_{ki} is a vector of socio-demographic variables, including age, squared age, gender, schooling level, an indicator variable of rural municipalities, and interactions of schooling level with rurality and gender. An indicator variable for identifying informal workers is also included for the pooled sample analysis (Figure 3.6 and Panel (a) of Table 3.2).

For the quantile regression analysis is not necessary to implement sample section bias correction. Since the purpose is to estimate the effect on the earnings distribution, there is no reason to consider the inactive labour market population in the analysis. By definition this sector does not have labour activities and therefore does not perceive earnings, so it is not possible to estimate treatment effects for this segment of the workforce outside the wage distribution.

3.6 Results. The impact on earnings distribution

This section describes the estimates of the implementation of the innovative method developed by Firpo et al. (2009), which by the use of the recentered influence function estimates directly the marginal treatment effects on the unconditional quantiles of the distribution. The objective is to evaluate if the minimum wage intervention on Zone B is actually affecting positively earnings on the lowest segment of the earnings distribution, and to test if as a consequence of the institutional framework of wage setting in Mexico, there exist minimum wage spillover effects.

The first subsection presents our core results for equations (3.2a) and (3.2b), analysing separately the effect on formal and informal workers. Subsection 3.6.2 presents some falsification tests. For this exercise, we use a different period of time (2011Q1-2012Q4) in which there were no changes to the real minimum wage, but we introduce an artificial treatment in 2012 to check the robustness of the model, as well as the validity of the use of the intervention as a natural experiment. The last subsection discusses the main policy

et al. (2016).

implications of our results, emphasizing the inequality effects.

3.6.1 Main results

Throughout this subsection and the following one, for both equations (3.2a) and (3.2b) we present graphically the unconditional partial effects of the parameter of interest, $\delta_{1,\tau}$ (including its 95% confidence interval), for each of the 10^{th} to the 90^{th} percentile of the real hourly wage distribution. Table 3.2 presents the estimated parameters of interest, as well as their associated standard errors across different percentiles. In all cases, standard errors were obtained by bootstrap methods.

Figure 3.6 shows the RIF-regression DiD coefficients for the pooled sample including formal and informal waged workers. The first aspect to highlight is that the intervention has a positive, although weak effect on the lowest deciles of the distribution. For centiles 10^{th}, 11^{th}, 14^{th}, 15^{th}, and 16^{th} the effect is not statistically significant, at least at the 5% level. For those below the 20^{th} centile, the effect on earnings is significant with a magnitude by around 1%. Even though the impact is small, there exists evidence of significant and positive effects at the bottom of the distribution. This implies that a 2.9% rise in the minimum wage for Zone B is enough to increase real wages by 1% for workers at the bottom of the distribution, which means an elasticity $\epsilon \approx 0.34$.

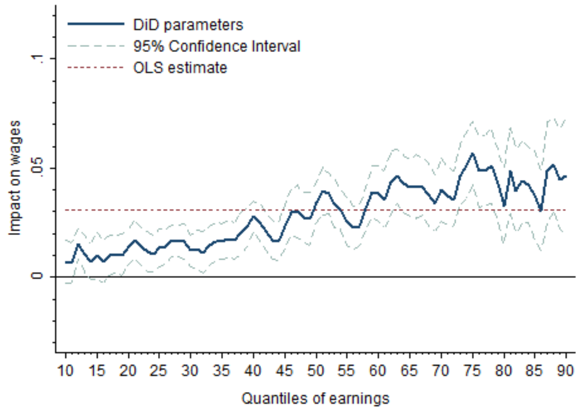
Secondly, it is worth emphasizing that the intervention increased wages on the entire distribution of earnings. This implies that the 2012 minimum wage change affected the whole labour market earnings distribution, not only the lowest centiles. The shortcoming of this policy intervention is that the effect is stronger for the upper percentiles of the distribution. For the median of the distribution, the impact is 3.4% ($\epsilon \approx 1.13$), while for the top quartile the treatment effect reaches the highest level, increasing real hourly wages by around 5.6% —see Table 3.2, Panel (a). Its implied elasticity is 1.93, which means that for every 1% minimum wage increase, real wages for the 75^{th} percentile increased by almost twice the minimum wage change, by 1.93%.

Moreover, considering that the absolute level of wages for workers at the top of the

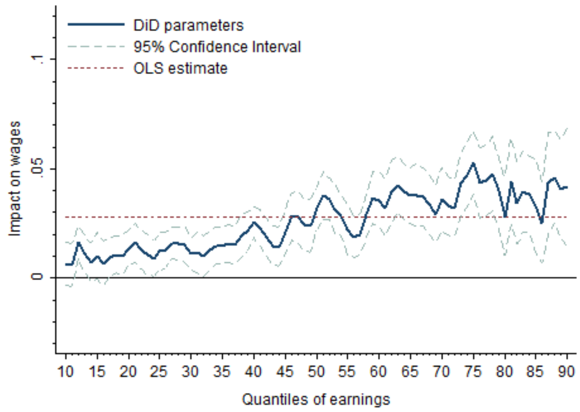
Figure 3.6

Unconditional quantile regressions on earnings distribution

Pooled sample, formal and informal workers



(a) Equation (3.2a)



(b) Equation (3.2b)

Notes: Self employed workers and observations with non-reported wages are excluded from the analysis. The set of covariates included are informal workers, state employment rate, gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender. Standard errors are obtained by bootstrapping, 100 repetitions.

earnings distribution are by definition higher, the increase in wages for the wealthiest workers is many times greater than the impact on workers at the bottom of the distribution. As a consequence of the Zone B's minimum wage increase wage dispersion increased.

Thus, even though the intervention fulfills the primary goal of any minimum wage legislation, which is to improve the wage conditions for the lowest waged workers, it does not seem to be a successful policy in terms of reducing inequality. Section 3.6.3 discusses in more detail the policy implications of the intervention.

In order to investigate the different impact of between formal and informal labour markets, our subsequent analyses separate workers by formality condition.

For the formal workers' earnings distribution, Figure 3.7 (and Panel (b) of Table 3.2) shows that the impact along the distribution is similar to that for the pooled sample. There is evidence of a positive impact on the workers with the lowest level of earnings, but minimum wage effects are stronger on the top of the earnings distribution.

Table 3.2

The impact on the hourly earnings distribution for selected percentiles (τ)

Dependent variable:	RIF[ln($hourly\_wage$); q_τ, F_Y]											
	Pooled OLS		τ =0.1		τ =0.25		τ =0.50		τ =0.75		τ =0.90	
(a) Pooled sample, formal and informal workers *												
Equation (3.2a)												
ZoneB*Period2	0.0305***	(0.00439)	0.0070	(0.00443)	0.0135***	(0.00417)	0.0339***	(0.00573)	0.0562***	(0.00844)	0.0459***	(0.01200)
Equation (3.2b)												
ZoneB*Period2	0.0277***	(0.00443)	0.0062	(0.00451)	0.0121***	(0.00423)	0.0317***	(0.00577)	0.0521***	(0.00849)	0.0412***	(0.01207)
Total observations	767,006		767,006		767,006		767,006		767,006		767,006	
(b) Formal workers												
Equation (3.2a)												
ZoneB*Period2	0.0291***	(0.00543)	0.0128**	(0.00643)	0.0184***	(0.00564)	0.0346***	(0.00758)	0.0338***	(0.00955)	0.0566***	(0.01272)
Equation (3.2b)												
ZoneB*Period2	0.0251***	(0.00550)	0.0132**	(0.00655)	0.0154***	(0.00571)	0.0289***	(0.00765)	0.0297***	(0.00965)	0.0516***	(0.01285)
Total observations	405,217		405,217		405,217		405,217		405,217		405,217	
(c) Informal workers												
Equation (3.2a)												
ZoneB*Period2	0.0268***	(0.00728)	0.0292***	(0.00781)	0.0043	(0.00781)	0.0150**	(0.00694)	0.0341***	(0.01155)	0.0413**	(0.01842)
Equation (3.2b)												
ZoneB*Period2	0.0256***	(0.00731)	0.0294***	(0.00789)	0.0032	(0.00788)	0.0141**	(0.00698)	0.0339***	(0.01159)	0.0386**	(0.01846)
Total observations	361,789		361,789		361,789		361,789		361,789		361,789	

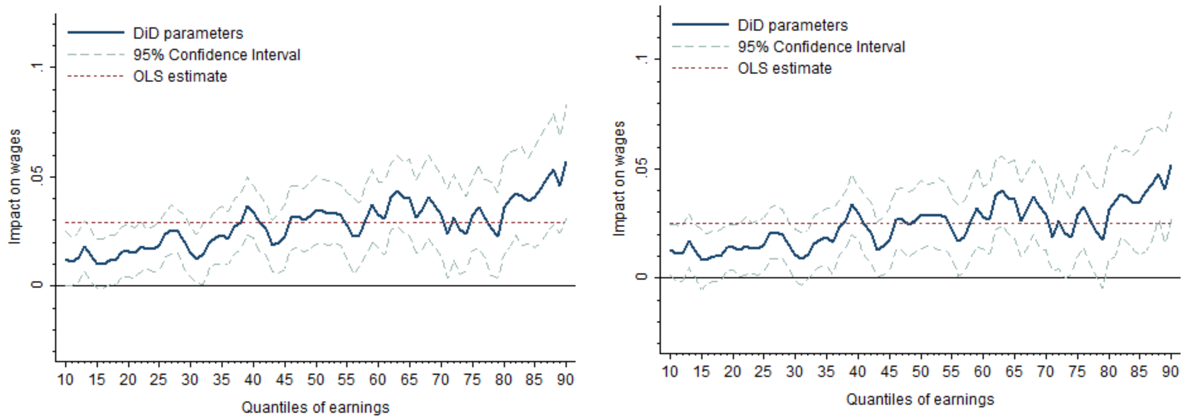
Notes: Self employed workers and observations with non-reported wages are excluded from the analysis. The set of covariates included are: state employment rate, gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender.

Bootstrapped standard errors in parentheses, 100 repetitions. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

* An indicator variable for identifying informal workers is also included for the pooled sample regression.

Figure 3.7

Unconditional quantile regressions on formal workers earnings distribution



(a) Equation (3.2a) **(b)** Equation (3.2b)

Notes: Self employed workers and observations with non-reported wages are excluded from the analysis. The set of covariates included are state employment rate, gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender. Standard errors are obtained by bootstrapping, 100 repetitions.

The impact for the lowest centiles of the distribution are slightly higher with respect to the pooled sample: for the bottom decile the estimated effect is 1.3% ($\epsilon \approx 0.45$), while for the 25$^{\text{th}}$ percentile is around 1.6% ($\epsilon \approx 0.58$). The sizes of the coefficients become higher as we move to the right of the distribution; the impact on the 50$^{\text{th}}$ distribution is around 3.2% ($\epsilon \approx 1.09$), and the strongest effect is observed at the 90$^{\text{th}}$ percentile with an estimated impact greater than 5% ($\epsilon \approx 1.87$). This corroborates that the wage dispersion in the formal labour market is also increased by the minimum wage intervention.

It is important to highlight that these estimates confirm that minimum wages are truly in force in the formal labour market. A common argument against minimum wage increases in Mexico is that the target group (lowest-income workers) performs the labour activities out of the formal labour market. If minimum wages are not enforced in the informal sector, and the segment potentially affected in the formal labour market by minimum wage policies is small, then minimum wage policies could not affect the lowest income workers. Our results demonstrate that there is a positive, although small, impact on the lowest quantiles of the earnings distribution of formal workers.

The magnitude of the estimated impacts reveals the relevance of the institutional wage setting. The fact that the Zone B's intervention took place before the 'de-indexation reform' of 2016 can explain the size of the effect beyond the 20th percentile, in which minimum wages were an important determinant of wage setting in the whole labour market, not only for the lowest earnings sector.

Unfortunately, it is not possible to construct a counterfactual to estimate the distributional effects of the minimum wage reform in the presence of the 'de-indexation reform' to distinguish between the 'pure' minimum wage effect on the lowest deciles, and the spillover effects at the top of the distribution.

Nonetheless, our results corroborate the findings in previous literature in two ways. They confirm that minimum wage affects several occupational wages, not only the lower end of the distribution (Grossman, 1983; Lee, 1999; Lemos, 2009; Autor et al., 2016). And also that minimum wage in Mexico has a role of a reference rate for wage and price setting (Fairris et al., 2008; Bosch and Manacorda, 2010; Castellanos et al., 2004; Kaplan and Pérez-Arce, 2006) that gives rise to the minimum wage spillover effects.

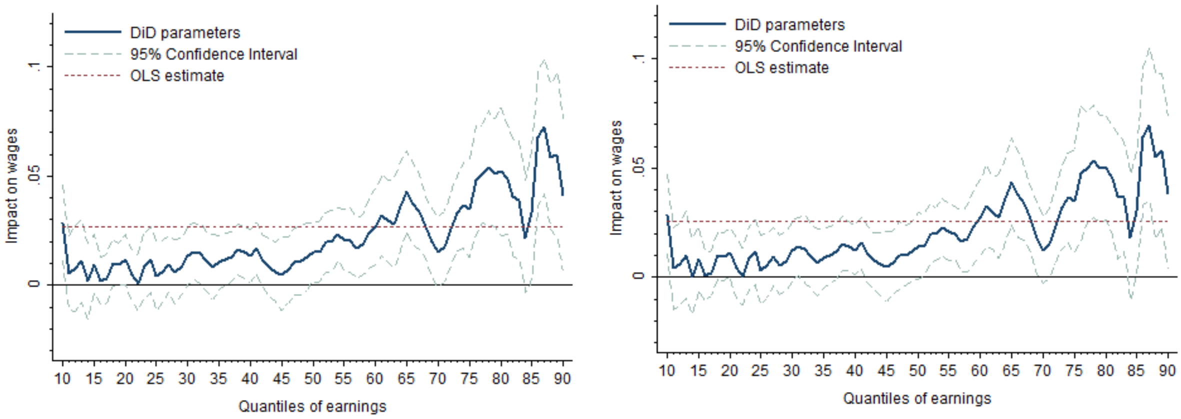
Even though the previous literature recognizes the existence of the minimum wage spillover effects, there is no prior evidence of minimum wage effects on the top percentiles of the earnings distribution. But, neither is there previous international experience on indexing prices and remunerations to the value of the minimum wage.

With respect to the distribution of earnings in the informal labour market, the pattern of the effect is different. Figure 3.8 shows that there are only some isolated significant effects below the 50th percentile, but the RIF regression shows that the intervention increased real wages in the informal sector for workers with earnings above the median, even more strongly than in the formal sector. The impact, for example, for the 86th percentile is around 7%, which implies an elasticity of 2.4.

It is not surprising that our model does not find a significant impact at the bottom of the distribution in the informal labour market. The activities performed by this specific segment of the labour force are related to household activities and small family business. So, there is no a formal labour market for these informal jobs. That is, the lack of statistically significant effects for the lowest percentiles of the distribution is explained by the absence of a reference rate of remunerations in that segment of the formal market.

Figure 3.8

Unconditional quantile regressions on informal workers earnings distribution



(a) Equation (3.2a) **(b)** Equation (3.2b)

Notes: Self employed workers and observations with non-reported wages are excluded from the analysis. The set of covariates included are state employment rate, gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender. Standard errors are obtained by bootstrapping, 100 repetitions.

In contrast, for higher levels of remuneration, heterogeneous workers —in terms of skills and qualifications— are able to choose between formal and informal markets. On this issue, Maloney and Mendez (2004) state that although minimum wage is not enforced by law in this sector, it appears to operate as a benchmark for 'fair' remuneration.[17] There is pressure from informal workers to obtain the same increases than those observed in the formal labour market. Therefore, the incentives on the highest quantiles are different; the results can confirm the hypotheses that an increase of wages in the formal labour market affects the opportunity cost for high waged informal workers of remaining employed under informal conditions. In response, informal employers increase wages for these workers to retain them even by stronger magnitudes than in the formal labour market counterpart.

Our results also corroborate previous findings by Khamis (2013), who argues that minimum wages may have stronger wage effects on the informal labour market. The mechanism behind this phenomena could be a compensation for the lack of formal benefits.

[17]Other studies argue that informal employers may comply the minimum wage regulations even though they do not comply other formal labour market arrangements as social security contributions (Marshall, 2004; Kristensen and Cunningham, 2006).

That is, increases to the minimum wage would also generate (under formality conditions) an increase of the labour costs for the employers, as higher social security contributions. Given that informal employers are not paying for these extra costs, they may tend to compensate directly the monetary remunerations of their workers.

In all cases, there are no significant differences between the estimates generated by equations (3.2a) and (3.2b). This implies that the use of Zone A and Zone C, or only Zone C as a control group does not affect the conclusions reached. Therefore, it also confirms the validity to the difference and differences procedures.

Thus, the unconditional quantile regression analysis proves that the minimum wage rise actually improved real wages for the targeted workers, even if the increase was only 2.9% in nominal terms. Simultaneously, it corroborates the presence of income-increasing spillover effects suggesting that the institutional setting of the minimum wage as a reference price can have negative repercussions on the labour market, specifically on the increase of earnings dispersion.

3.6.2 Robustness checks

In this section we report tests on whether the Zone B minimum wage increase in 2012 was a valid natural experiment for identifying the effects of minimum wages on the earnings distribution. By the use of a simulated intervention, the central objective is to validate the DiD specifications, as well as the control groups used.

Joined to that purpose, this exercise also provides clarification regarding the estimated spillover effects for the percentiles at the upper end of the wage distribution. Given that minimum wages policies are by definition focused on improving earnings for workers at the lower end of the wage distribution, a valid concern with respect to the estimates presented in the previous section is the magnitude of the DiD parameters for the upper end of the wage distribution. Earnings inequality has increased during the last three decades (OECD, 2015). So, the possibility exists that macroeconomic factors, not included in the model, are actually driving the increase in wages for the top earners, and not necessarily the 2012 minimum wage intervention.

If this is the case, we would observe positive and significant effects even in the absence of the intervention. We use a specification similar to Autor (2003), in which a placebo treatment is introduced in the DiD model. To do so, we restrict the sample to 2011 and 2012, and a treatment is artificially defined for Zone B in the period 2012Q1-2012Q4 when no policy change actually took place. All the individuals interviewed after the actual intervention on 26 November 2012 are therefore excluded from the sample in this simulated intervention. We use exactly the same specifications described by equation (3.2) to estimate the marginal treatment effects (by the re-centered influence function) on the percentiles from the 10^{th} to the 90^{th} centile of the real hourly wage distribution.

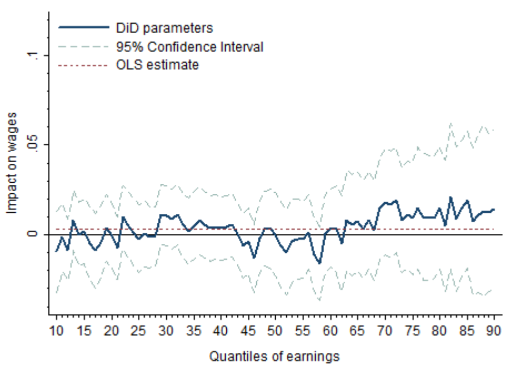
Figure 3.9 shows the unconditional quantile regressions for the falsification test. Following the structure of our main results, we replicate the model for the pooled sample, for formal workers and, finally, for informal workers. These results are reported in panels (a), (b) and (c), respectively. The results are compelling. In all cases, the simulated intervention shows that the DiD parameters are not statistically different from zero.

It is reassuring that there were no significant effects when there was no actual intervention. This corroborates the finding that the 2012 Zone B minimum wage intervention can be effectively used as a natural experiment to evaluate the impact on the real earnings distribution. With respect to the model, it also confirms that the implementation of DiD models allows us to identify the treatment effect.

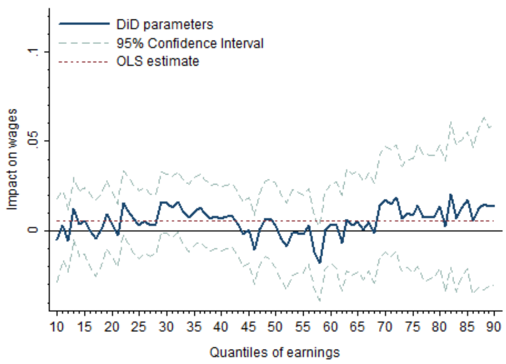
Moreover, the simulated intervention shows no evidence of differentiated parameters throughout the earnings distribution. This implies that the estimated effects for workers at the top of the distribution, for the actual intervention, are purely a consequence of the 2012 minimum wage change. Even though the magnitude of the effect at the top end of the wage distribution is greater than the 2.9% change in the Zone B minimum wage, we argue that it is a result of the *reference* role of the minimum wage in the Mexican labour market. Therefore, the analysis in this subsection also allows us to conclude that the findings for the top earning centiles do not constitute spurious effects.

Figure 3.9
Falsification Test

(a) Pooled sample, formal and informal workers *

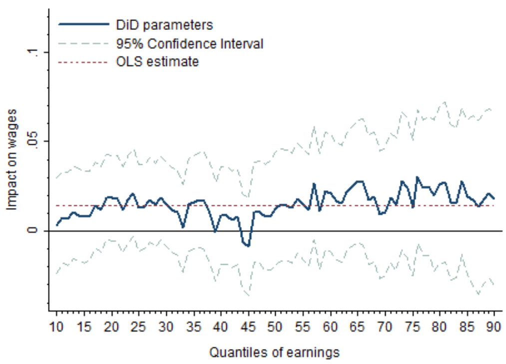


Equation (3.2a)

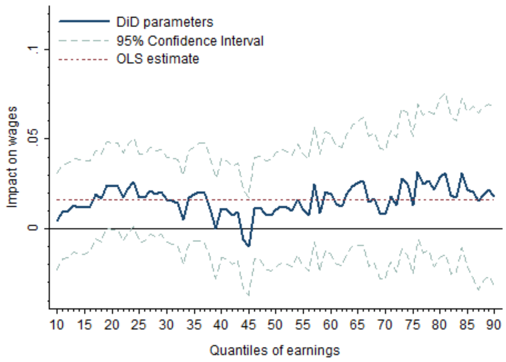


Equation (3.2b)

(b) Formal workers

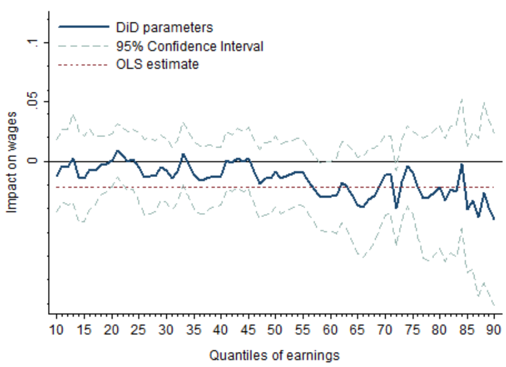


Equation (3.2a)

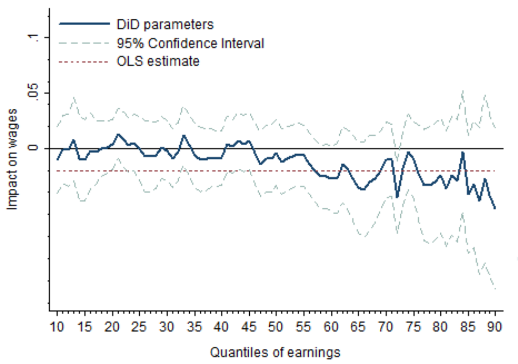


Equation (3.2b)

(c) Informal workers



Equation (3.2a)



Equation (3.2b)

Notes: Self employed workers and observations with non-reported wages are excluded from the analysis. The set of covariates included are state employment rate, gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender. Standard errors are obtained by bootstrapping, 100 repetitions.
* An indicator variable for identifying informal workers is also included for the pooled sample regression.

Some additional robustness checks, with some changes to the econometric specification are reported in Appendix 3.C. On the one hand, given that the minimum wage reform came into force in November 2012 and the period of analysis from goes from 2012Q1 to 2013Q4, it implies that December 2012 and December 2013 are included in the post-treatment period. If there are seasonal fluctuations on earnings, which is possible, this can affect our estimates. Figure 3.C.1 reports the DiD regressions excluding December in both years. The coefficients are not statistically different from those reported in figures 3.6 to 3.8 and Table 3.2.

On the other hand, with respect to the socio-demographic control variables included in the model, *age* is commonly included in wage equations, but in our case it could introduce an undesired shift effect. As ENOE follows the same individual up to five quarters, it is possible that some individuals —not all of them— have a shift by one or even two years in age. This depends on the specific date of the interviews (if individuals completed the five quarterly waves) generating an artificial shift effect on the age of some workers, which potentially can affect our estimates. To check this, we run two additional specifications. First, we simply omit *age* from the unconditional quantile regressions (parameters reported in Figure 3.C.2). And second, we keep constant the initial age of all the individuals in the sample to avoid missing this important variable (parameters reported in Figure 3.C.3). In all cases, including also the analysis for the formal and informal labour markets, the results and the conclusions are not affected significantly.[18]

3.6.3 Policy implications

It is important to emphasize that reducing poverty or inequality was not an explicit purpose of the Zone B's 2012 minimum wage increase. This policy intervention was implemented as an administrative change, aiming to adjust the level of remunerations in two out of three zones according to their convergence in terms of economic development.

[18]Some other robustness exercises, not reported in the text were: real monthly earnings as a dependent variable, the inclusion of self-employed workers an extension of the period of analysis from 2011Q1 to 2014Q4, and the inclusion of the economic sector as a regressor. In any case our general conclusions were affected significantly.

Furthermore, the magnitude of the increase seems insufficient for a public policy oriented at combating poverty. For this reason, the purpose of our analysis is not to evaluate the impact on poverty or inequality measures.

Nevertheless, the use of the intervention as a natural experiment provides fundamental information on how the Mexican labour market responds to minimum wage changes. The evaluation of the wage effects on the poorest workers, as well as the recognition of spillover effects on jobs with levels of remuneration already above the minimum wage, represent a guideline for further reforms with the explicit objective of increasing the living standards of the lowest income workers.

The estimates presented in this chapter demonstrate that the 2012 minimum wage rise increased real wages on the whole earnings distribution. For the lowest percentiles of the distribution, the impact is only present for formal workers, but the minimum wage reform is still accomplishing its central objective: to increase real remunerations for those workers with the lowest level of earnings in the formal, covered sector. The shortcoming of the policy intervention is that the increase in real earnings is stronger on the segment of the workforce with the highest level of remunerations potentially generated by the use of the minimum wage as a reference rate for wage setting.

We can implement a simple exercise to illustrate the likely inequality implications of the income-increasing spillover effects: if we apply the estimated coefficients to every log-earning percentile mean, the interquartile range would have increased by 0.014 log points. This means that the wage differential between percentiles 75^{th} and 25^{th} increased by around 1.4% as a consequence of the intervention.[19]

Thus, if the purpose of the minimum wage increase was only to raise real wages for the poorest sector of the labour market, the 2012 intervention may be considered successful. But if reducing inequality is part of the objectives of the policy makers, the message from our research is clear, given the conditions of the Mexican labour market in 2012, the policy change benefited top-income workers to a greater extent, thus increasing wage dispersion.

[19] Exercise restricted to the earnings distribution of the treated Zone B for 2012Q3, just before the policy change.

We cannot forget that the legal context of the labour market has also changed. The 2016 'de-indexation' reform was not a coincidence. Indeed, it was a result of the recognition of the likely consequences of the use of the minimum wage as a reference rate. It represented the first step towards a stronger minimum wage reform. So far, it is not possible to determine if the 'de-indexation' reform is enough to avoid the spillover effects on workers earning above the minimum wage.

3.7 Conclusions

The implementation of Unconditional Quantile Regressions in this chapter shows that Zone B minimum wage increase had a positive impact on the lowest deciles of the real earnings distribution. It suggests that the minimum wage regulations are actually binding, specifically on the formal labour market, and moreover, that increases to the minimum wage have a positive effect on the poorest workers.

Exploring the impact on workers with earnings above the minimum wage, we find strong statistical evidence of important spillover effects on the whole distribution of earnings. Nevertheless, the effect exhibits the lowest magnitudes precisely at the bottom percentiles of the distribution. Therefore, the policy intervention can be considered successful in terms of increasing real earnings for workers with the lowest level of wages, but not in terms of the distributional effects.

Independently of whether the workers are formally or informally employed, the model suggests that real wages increased by a higher proportion at the top percentiles. This implies that the 2012 minimum wage intervention increased the dispersion of wages. Previous empirical studies have recognized the existence of minimum wage spillover effects, but not in the magnitude of our estimates, nor at the top of the distribution. There are two important differences with respect to these prior estimates. On the one hand, the data source does not include richest people in the labour market, so we do not observe actual top-income workers. And more importantly, to our knowledge there is no previous international experience in a wage setting in which the minimum wage is used as a reference rate to determine other remunerations.

Related to this, the previous literature has contended that the institutional wage setting in Mexico, specifically the role of the minimum wage as a reference rate, could be responsible for this spillover effects. Even though this institutional setting has been legally modified by the 'de-indexation' reform of 2016, so far we do not have enough data to evaluate if the spillover effects are entirely generated by the *numeraire* role of minimum wages. Meanwhile, it is essential to consider the likely distributional repercussions in the implementation of future labour market policies.

New legislation, with stronger changes on the minimum wage is expected to be passed before December 2018. This would represent a suitable source of variation to test the minimum wage effects on the labour market once the 'de-indexation reform' has been implemented. Moreover it would also represent an opportunity to test for the robustness of the estimates presented in this chapter, but in the presence of deeper variations in the minimum wage level.

Appendix 3.A Literature review on minimum wage spillover effects in the United States

The first paper advocated exclusively to investigate the impact of minimum wages on earnings for non-minimum wage workers is Grossman (1983). He developed a theoretical model of the wage compression effect of minimum wages, based on the importance of relative wages on the effort supplied by workers, and therefore, on their productivity. According to Grossman, the impact of a minimum wage variation has two different effects on wages for skilled workers.

First, an increase of the minimum wage makes the wage rate paid to workers above the minimum wage (more skilled and with higher productivity levels) relatively cheaper, which increases the demand for this type of labour, and it raises in consequence the skilled labour wage. This effect corresponds to the well-known substitution effect in neoclassical models, which in addition implies an employment decline of unskilled workers. The second effect depends on interpersonal wage comparisons. Labour force legally unaffected by minimum wage legislation can be discontented by the increase observed on wages for the group of workers below them in the wage hierarchy. As a response, the effort supplied diminishes. Thus, in order to keep constant the productivity of skilled workers, firms have incentives to increase their wages. Of course, the magnitude of the effects depends on the elasticities of supply and demand for alternative types of labor, but also on the sensibility of workers to wage comparisons. His empirical results support these theoretical predictions, although workers earning much more than the minimum wage are not affected. Grossman thereby showed that it can be optimal for firms to increase wages beyond the minimum wage boundaries, giving place to redistributive effects of minimum wage policies.

Although the analysis is not focused on the distributional effects of the minimum wage, Katz and Krueger (1992) provided evidence on the existence of spillover effects in low-wage sectors. They collected their own data surveying fast food restaurants in Texas to evaluate the effects of the increases to the US federal minimum wage in April 1990 (raised from \$3.35 to \$3.80) and April 1991 (raised to \$4.25). They found that those firms paying the minimum wage before the 1991 increase (\$3.80) experienced an increase in wages by 12.0%, but firms that initially were paying above the new minimum wage (\$4.25) there was also an effect by 4.6%. They argue that these spillover effects can be generated precisely by the importance of the relative wages as Grossman (1983) and Akerlof and Yellen (1986) contended.

Similarly, recognizing that the important increase of wage inequality in the United States during the decade of the 80's coincided with the lack of adjustments to the federal minimum wages, Lee (1999) analysed the impact of the real minimum wage erosion on earnings dispersion. By the use of state variation in the relative level of minimum wages for the period 1979-1991, Lee found that a considerable part of the wage gap between the tenth and fiftieth percentiles was explained by the fall of the real value of minimum wages, although the effect is stronger and more convincing for the female wage distribution (between 70 and 100 percent for women, and around 70 percent for men).

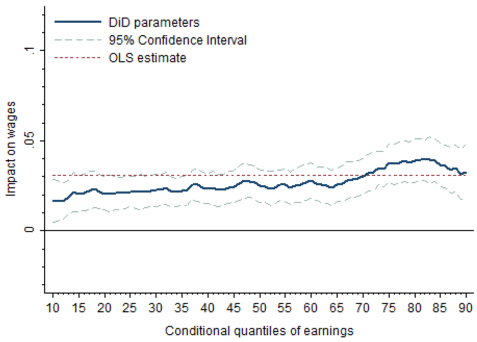
In a reassessment of the significance of the minimum wage on earnings inequality in the United States, Autor et al. (2016) enlarged the analyses by Lee (1999) in two senses. They extended the period of analysis to 2012, and also tested the minimum wage spillover effects for workers earning above the minimum, pointing out that spillovers effects are potentially important, but scarcely understood in minimum wage legislation. They concluded that the significant impacts for higher percentiles estimated in previous literature were upward biased by errors of measurement. Once that the bias is purged by instrumenting effective minimum wage with legislated minimum wage, their results suggest that minimum wage effectively affects the wage dispersion, but only in the lower tail of the distribution: up to the 25h percentile for woman and up to the 10$^{\text{th}}$ percentile for men.

Appendix 3.B Conditional Quantile Regressions

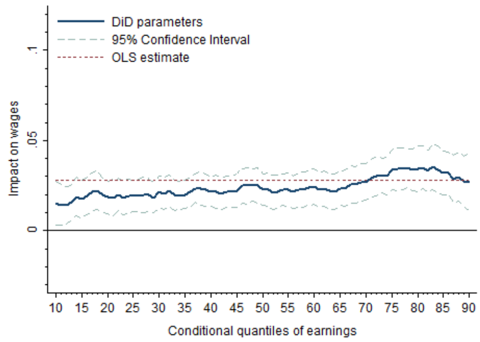
Figure 3.B.1

Conditional Quantile Regressions

(a) Pooled sample, formal and informal workers *

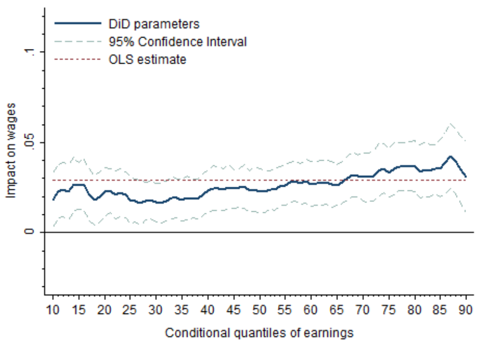


Equation (3.2a)

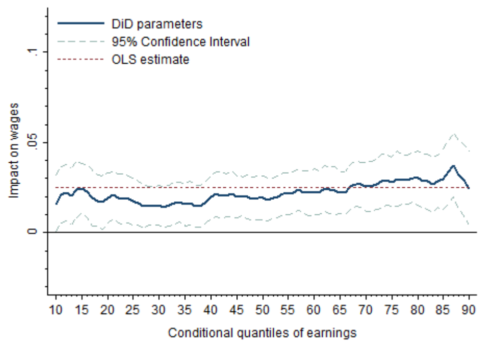


Equation (3.2b)

(b) Formal workers

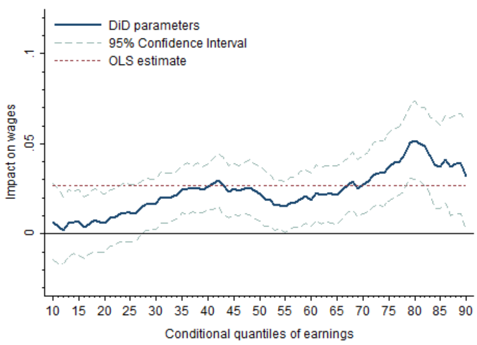


Equation (3.2a)

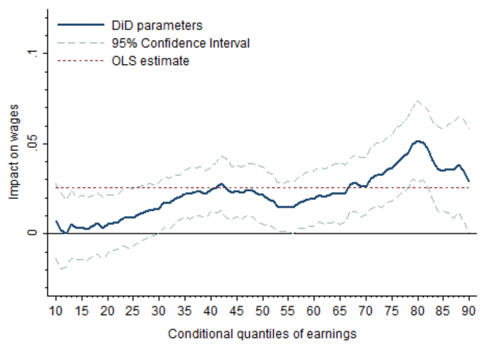


Equation (3.2b)

(c) Informal workers



Equation (3.2a)



Equation (3.2b)

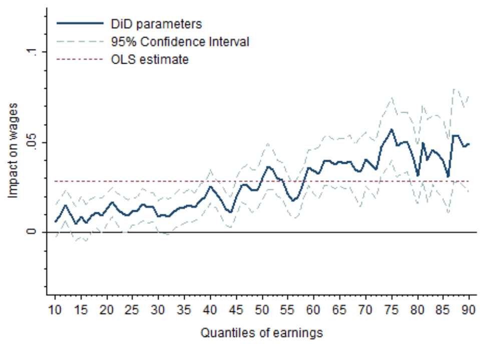
Notes: Self employed workers and observations with non-reported wages are excluded from the analysis. The set of covariates included are state employment rate, gender, schooling level, rural, and interactions of schooling level with rural and gender. Standard errors are obtained by bootstrapping, 100 repetitions.
* An indicator variable for identifying informal workers is also included for the pooled sample regression.

Appendix 3.C Additional robustness checks

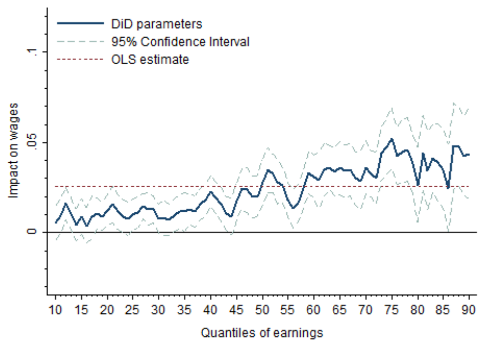
Figure 3.C.1

Excluding observations from December 2012 and 2013

(a) Pooled sample, formal and informal workers *

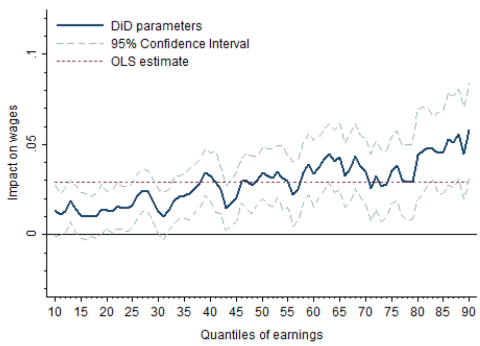


Equation (3.2a)

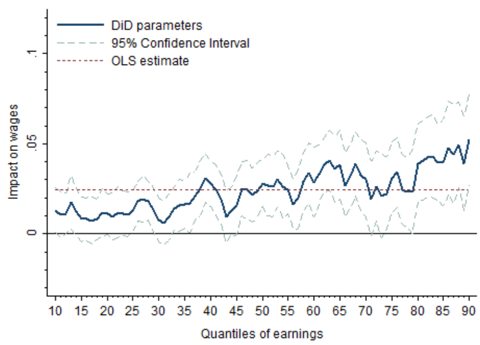


Equation (3.2b)

(b) Formal workers

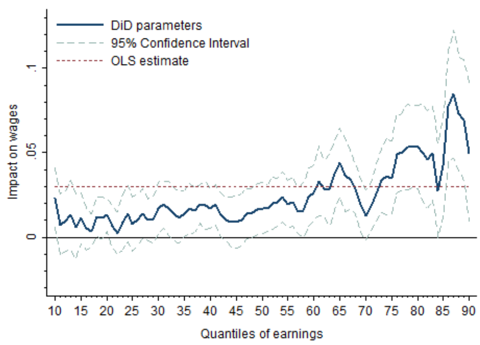


Equation (3.2a)

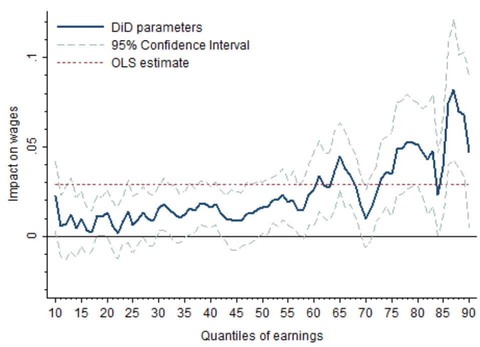


Equation (3.2b)

(c) Informal workers



Equation (3.2a)



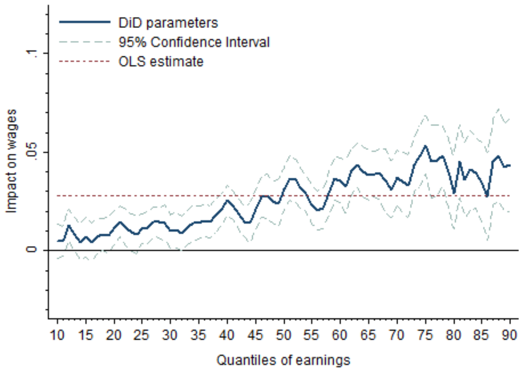
Equation (3.2b)

Notes: Self employed workers and observations with non-reported wages are excluded from the analysis. The set of covariates included are state employment rate, gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender. Standard errors are obtained by bootstrapping, 100 repetitions.
* An indicator variable for identifying informal workers is also included for the pooled sample regression.

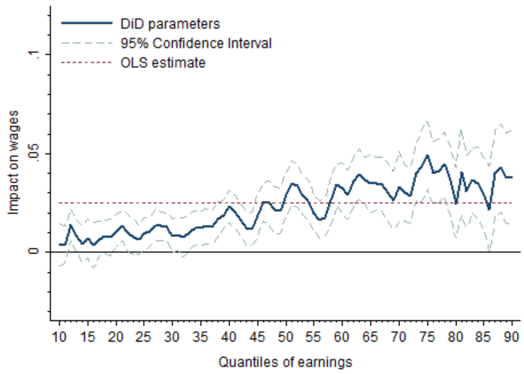
Figure 3.C.2

Excluding *Age* as a control variable

(a) Pooled sample, formal and informal workers *

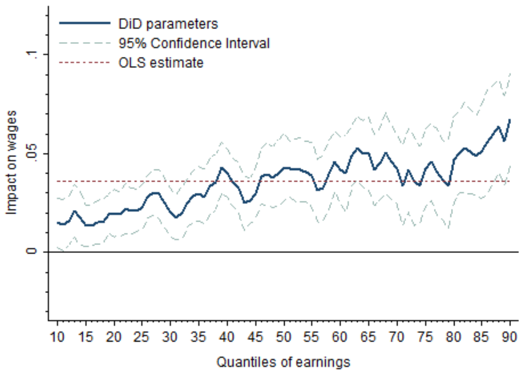


Equation (3.2a)

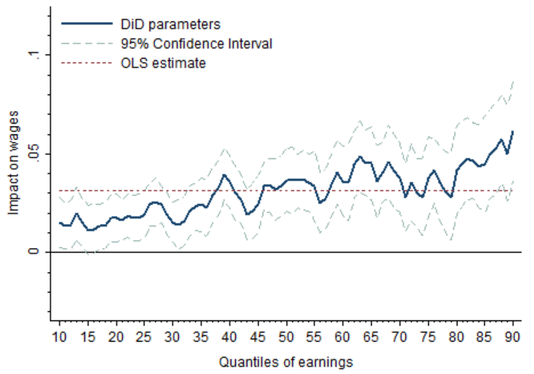


Equation (3.2b)

(b) Formal workers

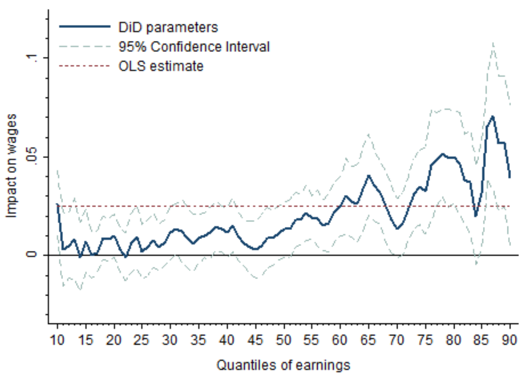


Equation (3.2a)

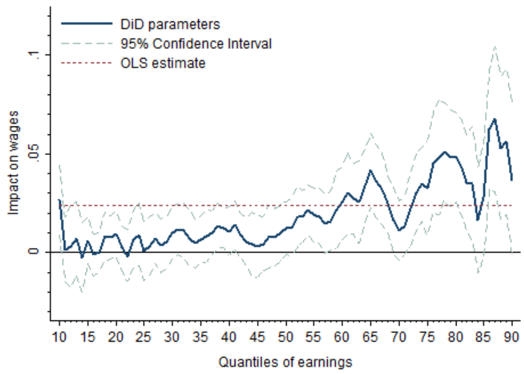


Equation (3.2b)

(c) Informal workers



Equation (3.2a)

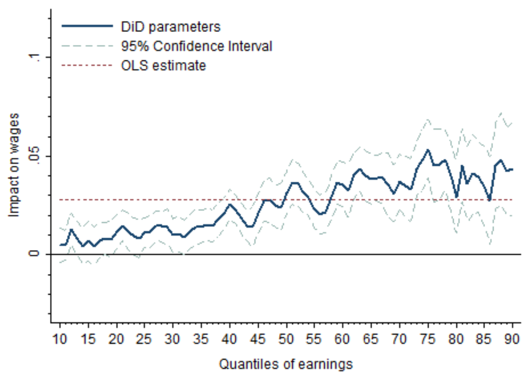


Equation (3.2b)

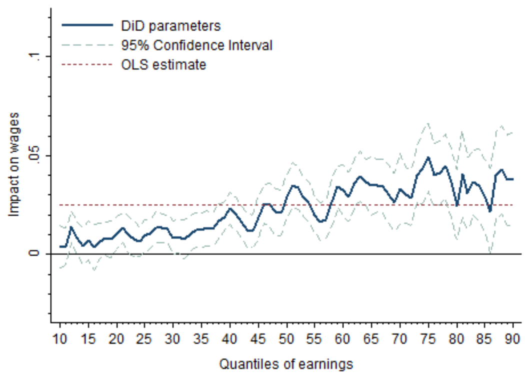
Notes: Self employed workers and observations with non-reported wages are excluded from the analysis. The set of covariates included are state employment rate, gender, schooling level, rural, and interactions of schooling level with rural and gender. Standard errors are obtained by bootstrapping, 100 repetitions.
* An indicator variable for identifying informal workers is also included for the pooled sample regression.

Figure 3.C.3
Keeping *Age* constant in time

(a) Pooled sample, formal and informal workers *

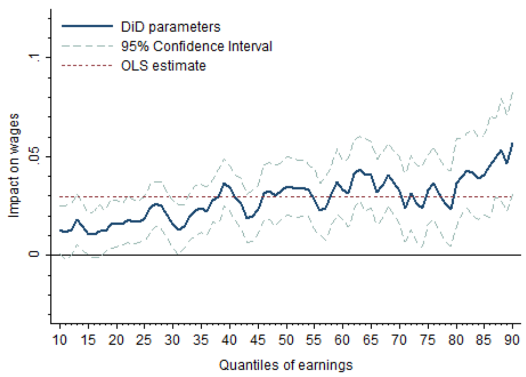


Equation (3.2a)

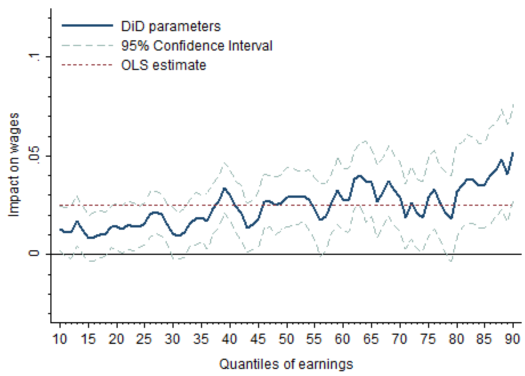


Equation (3.2b)

(b) Formal workers

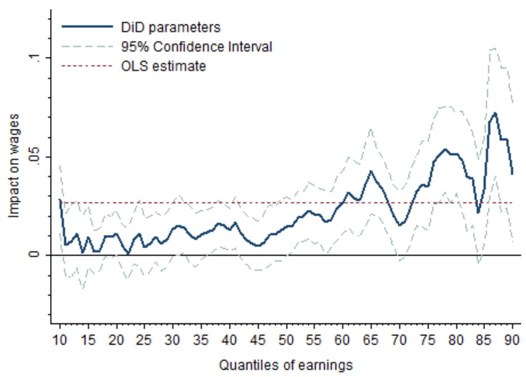


Equation (3.2a)

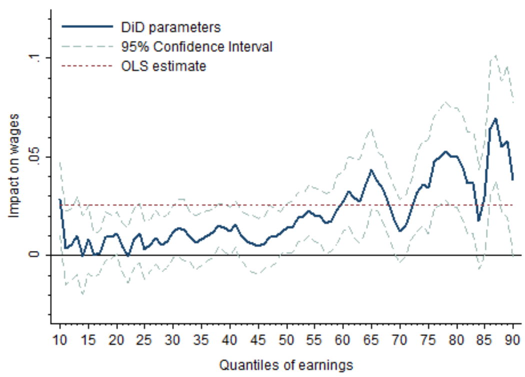


Equation (3.2b)

(c) Informal workers



Equation (3.2a)



Equation (3.2b)

Notes: Self employed workers and observations with non-reported wages are excluded from the analysis. The set of covariates included are state employment rate, gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender. Standard errors are obtained by bootstrapping, 100 repetitions.
* An indicator variable for identifying informal workers is also included for the pooled sample regression.

CHAPTER 4

THE EFFECT ON LABOUR STATUS

4.1 Introduction

This chapter evaluates the impact of the 2012 partial harmonization in regional minimum wage levels on the labour market status of the individuals. Correcting for sample selection bias, we do not find significant effects on the probability of being active in the labour market, but there is statistical evidence of an increase in the probability of being employed. We found also evidence of a decline on the occupation in the informal labour market.[1] Together, the results support the existence of monopsonistic labour markets in the Mexican economy.

The Difference in Differences (DiD) regressions (correcting for sample selection bias) exploit the previously described natural experiment setting, in which one out of the three wages zones in Mexico experienced an increase of its minimum wage level. In November 2012 the minimum wage in Zone B was brought into line with that in Zone A, while that in Zone C remained the same (see Figure 1.5).

Regarding the specific characteristics of the Mexican labour market, it is essential to consider its large informal labour market. In 2012, one quarter before the intervention, almost 60% of the labour force in Mexico worked under informal conditions (see Table 1.3). This implies that minimum wage regulations do not have full compliance in the labour market. In consequence, the effects of policy changes are not generalizable to all workers, and it is necessary to assess the effect on both formal and informal sectors.

[1]Subsection 4.3.1 details the definitions of the different labour status under analysis. In general terms, active labour market individuals are those working or looking for a job. Employed workers refers to individuals currently in a job. Informal workers are those working, but without the recognition of the labour relationship from the employer.

As we showed in Chapter 2, the 2012 minimum wage legislation affected wages of all workers independently of their age (although significant effects are observed in a greater extent on workers younger than 50 years old). This is unlike the US, where the minimum wage effect is observed only at the youngest segment of the workforce. In addition, minimum wage workers in United States do not tend to live in poverty and their wages do not represent the main source of income for the household. In the case of Mexico this is very different; as noted also in Section 1.3.3, for most of the minimum wage workers their earnings are the main source of household income, and an important share of them has no access social security services. In this setting, minimum wage legislation has important social implications for the effects on this vulnerable segment of the population.

All these features of the Mexican labour market are considered in the empirical strategy design to evaluate the minimum wage harmonization. Following the structure of Chapter 2, the impact is estimated on the whole population, and it is also disaggregated into different age groups by different types of labour status and formality condition.

Campos et al. (2017) used the same source of variation, the 2012 minimum wage intervention, finding no evidence of negative effects on employment, while some positive effects on the formal sector are estimated. Nevertheless, as discussed in Chapter 2, these results can be biased by sample selection. Their evaluation restricted the sample to the segment of the labour force actually working, generating the possibility of biased estimates.

The typical example of sample selection bias is precisely that related to a labour market analysis restricted to paid workers when the dependent variable is earnings. Nevertheless, sample selection in empirical labour studies is not restricted to wage regressions, nor to continuous variables. Exclusion of some subsets of the workforce can also emerge in limited dependent variable models. For example, when the probability of being employed is estimated, it is very common to delimit the sample to only employed and unemployed workers, while the inactive population is not considered in the analysis. This kind of exclusion can affect the magnitude and the statistical significance of the estimators.

Thus, this chapter tests and corrects for sample selection bias to estimate the minimum wage effect on active labour market participation, employment and informality. Using data from ENOE for the period 2012Q1-2013Q4, DiD estimates from pooled probit models, suggest that the minimum wage harmonization in 2012 had no effect on the probability to participate actively in the labour market, but the probability of being employed increased. To complete the analysis on the labour market, it is also estimated the effect on the probability of being working in the informal labour market. We find that the minimum wage legislation reduced the probability of being employed in the informal labour market. Jointly, these results allows us to conclude that there exists a presence of monopsonistic labour markets in Mexico.

Moreover, evaluating the impact by age thresholds, the empirical estimation shows that the most affected segment of the workforce are those workers older than 50 years old. This result is relevant in terms of the design of public policy design, since the oldest cohort of the population in Mexico is considered particularly vulnerable due to the high prevalence of poverty and lack of access to social security services. As in Chapter 2, we also analyse the dynamics of the impact. By introducing quarterly DiD estimators in the model, the treatment effect is found to be mainly transitory, being present at most two quarters after the intervention.

The estimates are robust to the control group used and to the period of analyses. Furthermore, the econometric specifications are consistent with those used in Chapters 2 and 3. In order to provide reliability to our results, the set of dependent variables in the preferred model is exactly the same to the one used in previous chapters.

The rest of the chapter is organised as follows. The literature review on the employment effects of the minimum wage is described in the following section . The data, some descriptive statistics, and the pretreatment trends of the outcome variables are presented in Section 4.3.1. Section 4.4 describes the econometric specifications, as well as the sample selection correction process when the model includes binary dependent variables. The DiD estimates are presented in Section 4.5, describing the results for the impact on active labour market population, employment and informality for different age groups. Besides, the dynamics of the impact, and some robustness exercises are presented at the end of the section. Finally, Section 4.6 concludes the chapter.

4.2 Literature review

In the economics literature there has been a long and controversial debate on the effects of changes in minimum wages on the labour market. Until now, a consensus of the impact of the increase in minimum wages on employment has not been reached.

As detailed in Chapter 1, at the theoretical level, the standard competitive labour market model (in its simplest version) assumes that labour force is homogeneous in terms of workers' skills. Given that output depends exclusively on the quantities of inputs used, not on the workers productivity, wage rate is the same for all workers. Firms optimize profits given the wage determined by the market. In consequence, there must be an inverse relationship between wages and employment (see figure 1.1).

There are several extensions to the basic model incorporating some kind of heterogeneity, for example, the degree of compliance with the minimum wage regulations (Welch, 1974), the effect on the unemployed sector (Mincer, 1976; Gramlich et al., 1976), and different levels of skills among the labour force (Brown et al., 1982). In all of these versions, the model unambiguously anticipates employment reductions as a result of minimum wages increases, at least for the directly affected workers.

One of the main critiques to the standard labour market model is the assumption that firms do not affect wage setting. In fact, it seems logical to assume that firms have some kind of market power on this regard. If this is the case, employers may pay wage rates below the equilibrium wage of the market. This implies that in the presence of a minimum wage introduction, firms can have some space to increase wages without reducing the level of employment (see figures 1.3 and 1.4).

In dynamic monopsonic models (Manning, 2004; Flinn, 2006; Hirsch et al., 2015), the source of the discretionary wage setting by the firms can be originated by several kinds of frictions in the labour market. For instance, hiring costs, spatial location of the firms, bargaining search, among others. Thus, minimum wage raises lead to a decline in the turnover costs for the lowest-paid workers, so employment level is not unambiguously reduced. Given that our analysis does not aim at investigating the source of the discretionary setting, the term *monopsony* is used indistinctly from *dynamic mononopsony.*

The empirical minimum wage literature is extensive, especially for the US. Between 1961 and 1981, seventeen nominal increases to the federal minimum wage were recorded. Exploiting this variation, time-series studies achieved an apparent consensus: an increase of 10% in the federal minimum wage reduces employment by between 1% and 3% (Brown et al., 1982).

But in the decade of the 90's, as a result of differentiated labour policies at the state level in the US, a new wave of cross-section studies started to challenge the previous findings, claiming that the effect on the employment level was not negative and could be even positive. Thus, Card (1992a,b) and Card and Krueger (1994, 1995) represented the turning point in the literature. Afterwards, the discussion on the changes in the minimum wage policy in the United Kingdom brought new cross-sectional evaluations that supported the findings by Card and Krueger (Machin and Manning, 1994; Dickens et al., 1999; Stewart, 2002).

However, there is still the opposite position that asserts that, those cross-sectional and panel-data analyses fail to capture the whole long-term effect on employment, arguing also that those results are only applicable for some specific sectors. To mention just some of the most relevant studies, Brown et al. (1995), Neumark (2001) and Sabia (2009) found negative and significant effects on employment.

In a new wave of studies, Dube et al. (2010) (which in the words of Schmitt et al. (2013) is probably the 'most important and influential paper in minimum wages' during the last decade) developed a different way to construct control groups. They identified all the contiguous counties in the US with different minimum wage settings at the state level from 1990 to 2006, estimating no adverse effects on employment.[2]

Regarding the empirical analyses implemented in Mexico and Latin America, it is necessary to separate them from the minimum wage literature in developed countries; the particular features of Latin American labour markets make it even more difficult to obtain generalised results of the effects of minimum wages. Neumark and Wascher (2006) argued that the main complications to implement these evaluations are the high presence of informal labour markets and the lack of full enforcement of the minimum wage regulations.

There is also a high degree of heterogeneity in the estimates. For the Brazilian case, for instance, Lemos (2009) found no adverse effects on employment, while for the Colombian labour market, both Bell (1997) and Maloney and Mendez (2004) estimated strongly negative impacts. There are also cases of mixed results within the same country; Montenegro and Pages (2004) concluded that minimum wages reforms in Chile reduced the employment level for youth and unskilled workers, but generated a positive impact among women.

For the specific case of Mexico, there are three relevant studies. In the first of them, Bell (1997) used both, time series and panel data models (data from 1972 to 1990 and 1985 to 1990, respectively), finding no effect on employment for manufacturing firms. Bell argued the results are explained by the fact that minimum wage was not an effective wage, at least on the manufacturing sector.

For a similar period, and using the reductions in real minimum wage levels as a source of variation, Feliciano (1998) found employment increases for women workers between 15 and 64 years of age, but adverse effects for men between 55 and 64 years old. Feliciano asserted that unlike Bell (1997), she found significant effects on employment because her analyses explored the impact on the whole labour market, and not only on one specific sector.

Using also the regional variation observed in November 2012, Campos et al. (2017)

[2]See Apeendix 4.A for a more extensive revision of previous studies analysing the minimum wage effects on employment in the US and in the UK.

estimated cross-sectional and panel-data regressions concluding that there is no empirical evidence of adverse employment effects generated by the minimum wage increase. Nevertheless, there are important methodological issues to be analysed, especially to consider the presence of sample selection bias.

Therefore, it is practically impossible to be able to generate conclusions. Although novel research has made use of different data sets and new strategies of identification have emerged, the debate remains active. In this chapter we use the traditional DiD specifications, but correcting for sample selections bias to estimate the effect of the 2012 minimum wage intervention on various labour status.

4.3 The data

4.3.1 Description of the dependent variables

The data for the empirical estimation are also obtained from ENOE. The period covered for the analyses is from 2012Q1 to 2013Q4. Some robustness exercises include data from 2011Q1 to 2014Q4 to implement falsification tests.

As in the previous chapters, the sample include individuals aged 12 to 97.[3] Although the minimum legal age for working in 2012 was 14 years old, ENOE collects information on individuals from 12 years old that perform labour market activities. By definition, workers aged between 12 and 14 work under informal conditions, so for the objectives of our analysis they are included in the sample. The total number of observations for the eight quarters analysed in the main specification (2012Q1-2013Q4), as in Chapter 2, is 2,458,053.

We use the same set of control variables with respect to that included in Chapters 2 and 3 (see Table for their sample descriptive statistics). But, instead of having one single dependent variable (the log of real hourly wage and its RIF), in this chapter the outcome

[3]In the survey, observations with age equal to 98 or 99 denotes non-specified age. See Appendix 2.A for more details.

variables change depending on the labour status under examination. The model estimates the effect on active population and employed workers. Following the ILO recommendation for workforce classification, ENOE categorises the population in active and inactive labour market population. Active population refers to individuals that, during the week of interview were currently working, or in the previous two weeks developed specific activities to find a job. Inactive individuals are those people not working and not looking for a job. Within active labour market population, ENOE classifies individuals in employed and unemployed workers.

Employed workers are also classified into formal and informal workers. In the same way, following the ILO conceptual framework, the key feature to distinguish between formal and informal workers is the lack of recognition of the job relationship from the employer, which generates a vulnerable condition on the worker. ENOE uses the Hussmanns' matrix to identify and classify informal workers into waged, and self-employed and non-waged (see Table 1.3). Separate effects for each category are estimated in next section, as well as the overall effect on informal workers.

Table 4.1 shows the sample descriptive statistics for the dependent variables included in the econometric model. Given that all the outcome variables correspond to binary variables, the sample means are between 0 and 1. The sample is disaggregated by wage zones and also by the pretreatment and post-treatment periods.

The first feature to emphasize is the composition of the workforce in Mexico. The last column in Table 4.1 presents the sample means by labour status at the national level. On average, 57.2% of the total population is active in the labour market. Among these, 95.1% were employed at the moment of the conduction of the interview, and 55.6% of these employed workers performed their labour activities in the informal sector.[4]

For the sub-classification of informal workers into waged, self-employed and non-waged, the definition of each binary variable excludes the other two categories of informal workers.

[4]The difference of these figures with respect to those presented in Table 1.3 is explained by the use of expansion factor in the descriptive statistics of Chapter 1. Given that we are not using expansion factors in the econometric analysis, we present the sample descriptive statistics of the dependent variables included in the econometric models.

For example, for the analysis on the probability of working as an informal waged worker, this variable takes the value of one if the worker works under informal conditions and receives a monetary payment by his work; and takes the value of zero if the worker performs his labour activities in the formal market. This explains the values reported in Table 4.1. It means that, at the national level, excluding self-employed and non-paid informal workers, 40.5% are informal, and the remaining 59.5% works in the formal labour market. In the same way, self-employed informal workers represent 30.6% with respect to formal workers, and non-paid informal workers 11.5%.

Regarding the classification within the informal sector by type of worker (not reported in Table 4.1), 54.4% receive a monetary remuneration, 35.2% are self-employed, and 10.4% do not receive any kind of monetary wage.[5]

With respect to the differences among wage zones, Table 4.1 also shows, without controlling for any other variables, that all the three zones experienced on average a decrease on the active labour market population rate. But, the employment rate increased in zones A and B by around 0.3%, while in Zone C there was a reduction by almost 0.1%.

Regarding the occupation in the informal labour market, the three zones experienced an important reduction of the informality rate. On average, the informality rate decreased by 1.7%, 1.8% and 0.8%, respectively for zones A , B and C. Although the decline in the number of workers in the informal sector was present in all the three sub-categories, the reduction was stronger for waged informal workers.

As in the previous chapters, the set of socio-demographic control variables included in the model are: age, age squared, indicator variables for head of household, female individuals, and rural municipalities, level of studies. The descriptive statistics of these control variables were presented in Table 4.3.1.

[5]Chapter 1 details that non-waged workers are mainly employed in small family business and in the agricultural sector.

Table 4.1
Sample descriptive statistics, employment dependent variables (2012Q1-2012Q4)

	Pretreatment period			Post-treatment period			National
	Zone A	Zone B	Zone C	Zone A	Zone B	Zone C	
Labour Status							
Active labour market population among these aged 12 to 97							
Mean	0.5827	0.5864	0.5704	0.5821	0.5821	0.5683	0.5723
Std. Deviation	0.4931	0.4925	0.4950	0.4932	0.4932	0.4953	0.4947
Total observations	135,589	107,607	879,955	163,630	126,651	1,044,621	2,458,053
Employed population among these aged 12 to 97							
Mean	0.9399	0.9436	0.9534	0.9431	0.9460	0.9525	0.9507
Std. Deviation	0.2377	0.2306	0.2108	0.2316	0.2261	0.2128	0.2165
Total observations	79,014	63,097	501,951	95,253	73,723	593,703	1,406,741
Informal Sector							
Informal workers among employed population							
Mean	0.5005	0.4498	0.5849	0.4835	0.4319	0.5772	0.5561
Std. Deviation	0.5000	0.4975	0.4927	0.4997	0.4953	0.4940	0.4968
Total observations	74,263	59,540	478,544	89,836	69,740	565,486	1,337,409
Waged informal among formal workers							
Mean	0.3735	0.3179	0.4292	0.3577	0.2992	0.4224	0.4052
Std. Deviation	0.4837	0.4657	0.4950	0.4793	0.4579	0.4939	0.4909
Total observations	59,208	48,028	348,022	72,238	56,535	413,991	998,022
Self-employed informal among formal workers							
Mean	0.2518	0.2268	0.3314	0.2427	0.2185	0.3260	0.3063
Std. Deviation	0.4340	0.4188	0.4707	0.4287	0.4133	0.4688	0.4610
Total observations	49,572	42,368	297,108	61,262	50,697	354,788	855,795
Non-waged informal among formal workers							
Mean	0.0649	0.0549	0.1390	0.0556	0.0509	0.1303	0.1151
Std. Deviation	0.2464	0.2278	0.3459	0.2292	0.2199	0.3366	0.3192
Total observations	39,667	34,664	230,724	49,128	41,744	274,931	670,858

Note: sample restricted to individuals aged between 12 and 97.

4.3.2 Pretreatment trends on labour status

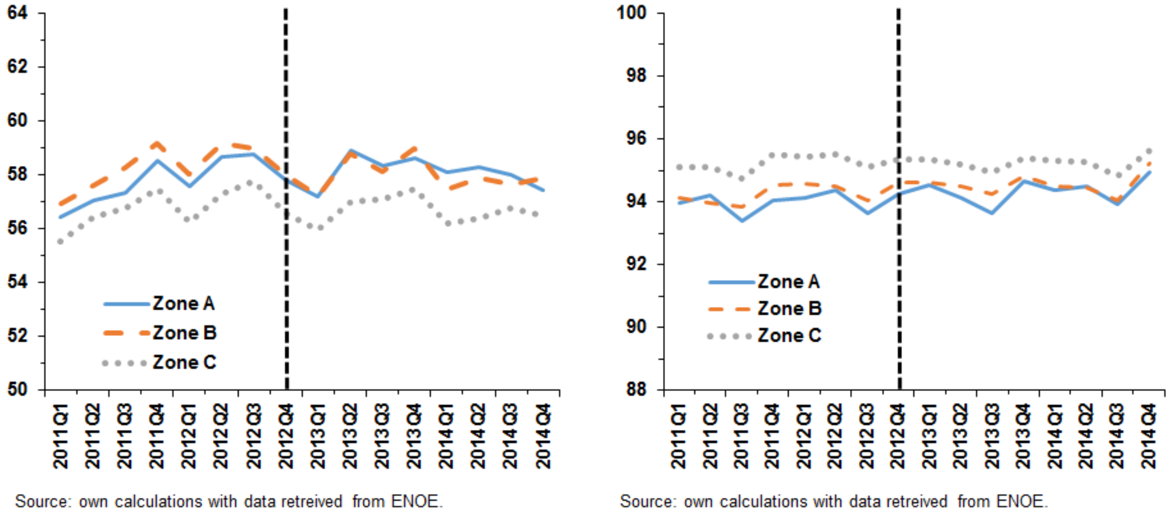
Following the pretreatment analysis implemented in Chapters 2 and 3, this subsection examines the trend followed by the labour status dependent variables before the intervention. As explained in Section 2.3.2, in absence of randomized treatments, the basic assumption for identifying treatment effects by DiD models is that the outcome variables exhibited the same performance previous to the change in the minimum wage policy.

This subsection implements a graphical inspection of the trends followed by every outcome variable employed in the econometric regressions. We show the trends followed from 2011Q1 to 2014Q4 in order to cover the period of all the econometric regressions estimated in this chapter. In all cases, the orange dotted line correspond to the treated

Zone B. The vertical dotted line denotes the period of the intervention.

For the analyses of labour status, Panel (a) of Figure 4.1 shows the active labour market rate by wage zones, that is, the proportion of individuals with labour activities or looking for a job with respect to the total population. Panel (b) describes the employment rate, which is the percentage of working population relative to active labour market population. In both cases the pretreatment trend is similar among zones, but there is not a clear pattern after the intervention, so the treatment effect is not distinguishable.

Figure 4.1
Participation rates by wage zone
(%)

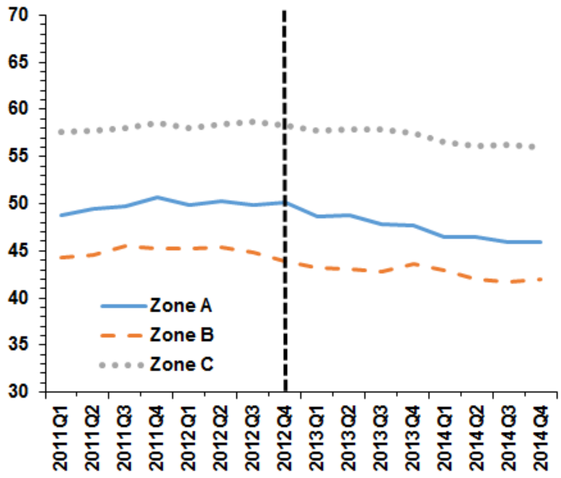


(a) Active labour market rate **(b)** Employment rate

Figure 4.2 shows the trends on the informal labour market participation, constructed as the percentage of individuals working under informal conditions with respect to the total working population. The difference observed in the informality rates across the zones is practically constant before the intervention. In contrast, after the treatment Zones B and C experimented a higher decrease in comparison to Zone A, but it is not possible determine the magnitude, nor the sign of the impact.

Finally, Figure 4.3 separates the informal labour market by type of worker to complete the graphical inspection on the whole set of dependent variables used in this chapter. Each graph describes the trend followed by the proportion of each type of informal workers with

Figure 4.2
Proportion of informal workers by minimum wage zone
(% with respect to the employed population)



Source: own calculations with data retreived from ENOE.

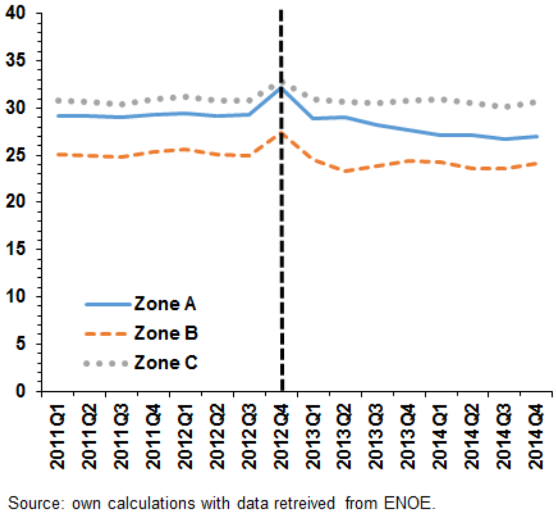
respect to the employed population in each wage zone.

The graphs are compelling in all cases. The trends before the intervention are parallel, which means that the macroeconomic shocks are affecting uniformly the wage zones. But, after the policy intervention of 2012 the corresponding trend for Zone B exhibits a change. For waged informal workers in Panel (a), there is a reduction in its proportion with respect to the employed workers, while the trend of the other two zones remain parallel. Similarly, regarding self-employed informal workers in Panel (b), we can observe that during the pretreatment period the pattern followed in the three wages zones is the same, but after the intervention it seem to be a relative increase in Zone B with respect to zones A and C. Finally, Panel (c) describes the trends for non-waged informal workers. It is not possible to distinguish a change in Zone B after the intervention, but the important issue is that there exists parallel trends among wage zones.

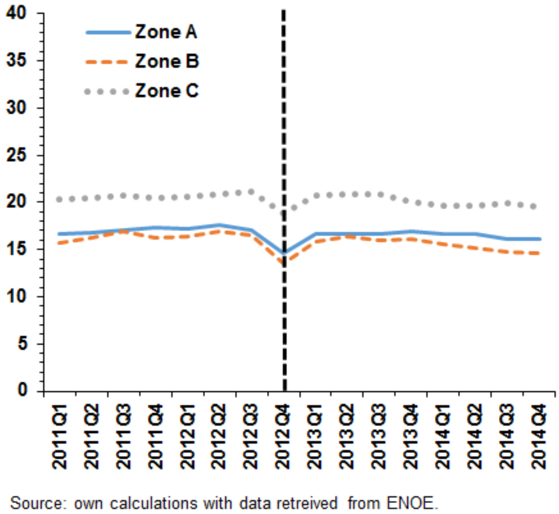
Hence, treatment (Zone B) and control groups (zones A and C) show similar trends in the outcome variables before the intervention, which means that it is possible to implement DiD procedures to estimate the respective treatment effects.[6] So far it is not possible to determine if the effects — if there are any — are positive or negative.

[6]Section 4.5.2 presents some formal falsification tests to validate control and treatment groups.

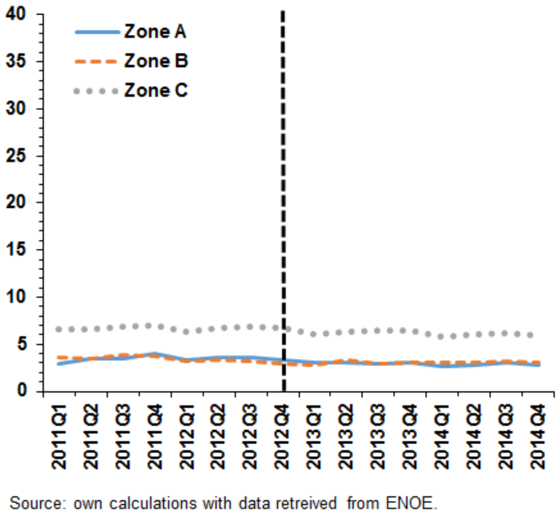
Figure 4.3
Proportion of informal workers by category and minimum wage zone
(% with respect to the employed population)



(a) Informal waged workers



(b) Self-employed informal workers



(c) Non-waged informal workers

4.4 Strategy of identification

4.4.1 Econometric specification

The econometric model estimates the impact of the 2012 minimum wage harmonization on the probability of being under certain labour status. Using the ENOE classification of the labour force, we use the following dependent variables (Y_i): *labour market active*, *employed*, *informal*, *waged informal*, *self-employed informal*, and *non-waged informal*.[7]

Aiming at the consistency of the estimates with respect to the previous two chapters, we use exactly the same set of control variables in our specifications. Furthermore, the composition of the DiD regressions does not change. As in the chapters above, we use two equations, in which the difference between them is the wage zones included in the control group. In the first of them, equation (4.1a), zones A and C are together included in the comparison group. To check the robustness the model, as well as the validity of the of the strategy of identification, equation (4.1b) includes only Zone C in the control group, while Zone A is included as a control variable.

Thus the pooled probit DiD specifications are the following:

$$\begin{aligned} Y_i = \beta_0 + \delta_1 ZoneB_i {*} Period2_i + \delta_2 Period2_i \\ + \delta_3 Trend + \beta_1 ZoneB_i + \sum_{k=2}^{k} \beta_k X_{ki} + e_i \end{aligned} \tag{4.1a}$$

$$\begin{aligned} Y_i = \beta_0 + \delta_1 ZoneB_i {*} Period2_i + \delta_2 ZoneA_i * Period2_i + \delta_3 Period2_i \\ + \delta_4 Trend + \beta_1 ZoneB_i + \beta_2 ZoneA_i + \sum_{k=3}^{k} \beta_k X_{ki} + e_i \end{aligned} \tag{4.1b}$$

As in previous chapters, the parameter of interest is δ_1. This DiD parameter expresses the marginal effect on treated individuals, with respect to untreated individuals in zones A and C, equation (4.1a), or with respect to individuals in Zone C, equation (4.1b).

For the rest of independent variables in the model, we include a dummy variable for the post-treatment period ($Period2$), a simple linear time-trend for each of the eight quarters of the analysis ($Trend$), and a dummy variable for identifying the treated zone ($ZoneB$). In equation (4.1b), in order to avoid dropping the observations for the untreated Zone A, we included it as a regressor in the model, as well as its respective DiD regressor. It is important to remark that the parameter δ_2 is not a treatment effect, it is included only for

[7] Appendix 2.A describes in a detailed way the construction and the definition of the variables employed in the model.

purposes of completeness. The socio-demographic variables in the vector X_k are age, age squared, schooling level, dummy variables for female workers and rural municipalities, and interactions of female and rural with schooling level. *Head of Household* is included as a control variable only in the model of *labour market active*. In the rest of the econometric specifications, it is included in the selection equation for the sample selection correction.

Given the composition of the workforce in Mexico, every model is also estimated by age groups. The descriptive statistics in Chapter 1 showed that there exists an important proportion of minimum wage workers beyond the youth segment of the labour force, specially workers aged older then 50.[8] So, the sample is disaggregated in three different age groups: younger than 30 years old, aged between 30 and 49, and older than 49.

Following the structure of the estimates in Chapter 2, we also include a set of specifications to analyse the dynamics of the effect. Instead of pooling together the four corresponding quarters before and after the intervention, we introduce quarterly DiD variables. The purpose is to verify how long the labour market takes to respond to the minimum wage changes and to verify the persistence of the estimated impacts.

$$\begin{aligned} Y_i = \beta_0 + \sum_{j=1}^{4} \delta_j ZoneB_i * 2013\_Q_{ji} + \sum_{j=1}^{4} \delta_{j+4} 2013\_Q_{ji} \\ + \delta_9 Trend + \beta_1 ZoneB_i + \sum_{k=2}^{k} \beta_k X_{ki} + e_i \end{aligned} \tag{4.2a}$$

$$\begin{aligned} Y_i = \beta_0 + \sum_{j=1}^{4} \delta_j ZoneB_i * 2013\_Q_{ji} + \sum_{j=1}^{4} \delta_{j+4} ZoneA_i * 2013\_Q_{ji} + \sum_{j=1}^{4} \delta_{j+8} 2013\_Q_{ji} \\ + \delta_{13} Trend + \beta_1 ZoneB_i + \beta_2 ZoneA_i + \sum_{k=3}^{k} \beta_k X_{ki} + e_i \end{aligned} \tag{4.2b}$$

The set of variables included in the model do not change with respect to equation (4.1). The only difference is that, instead including one single dummy variable for the post-treatment period for identifying the shift effect, equation (4.2) includes one dummy

[8] Table 1.14 shows that 31% of the workers earning at most the minimum wage are older than 49 years old. Indeed, this is the only range of age for which the number of workers under informality conditions is greater than those under formality.

for each of the four quarters after in the post-treatment period.

4.4.2 Sample selection bias correction for binary dependent variable models

Given the classification of the labour force, in which some labour status correspond to subgroups of other status, the use of binary dependent variables necessarily excludes some individuals from the analysis. For example, when we use probit models to estimate the minimum wage impact on the probability of being *employed*, inactive labour market individuals are not considered in the model. Similarly, if the analysis is focused on the probability of being an *informal* worker, both unemployed workers and inactive individuals are excluded of the analysis. As explained in Chapter 2, the systematic exclusion of a segment of the population could lead to biased estimators. So, it is necessary to test the presence of sample selection bias in the probit models and in case of statistical evidence of its existence, to correct it.

For binary dependent variable models, the Heckman two-stage procedure is not valid, but Van de Ven and Van Praag (1981) introduced a maximum likelihood probit estimator to correct sample selection models. The method is similar to the Heckman procedure. It is implemented in two stages, and the first of them corresponds to a selection equation. But, the main difference is that the first stage is estimated by fitted maximum likelihood estimators, not by probit models. Besides, to test the selection bias it is necessary to estimate the correlation between the fitted errors of the sample selection equation and the equation of interest, ρ. Actually, ρ is not estimated directly, but the transformation $\text{atanh}(\rho)$[9]. If ρ is statistically different from zero, it means that there exists correlation between the errors of the two equations and the estimates from probit models are biased.

In this chapter, the only model that does not require sample selection correction is the one corresponding to the estimation of the effect of being *labour market active*. In this case, there is no exclusion of any segment of the sample. We use all the observations

[9] $\text{atanh}(x) = 1/2 \cdot log((1 + x)/(1 - x))$

in the sample because all the individuals are classified either into labour market active ($Y_i = 1$), or inactive ($Y_i = 0$). But, for the rest of the five dependent variables models we test and correct for sample selection, in which inactive labour market individuals are systematically excluded from the sample (and also unemployed workers when the effect is estimated on informal workers).

The first stage equation is the same to the selection equation used in Chapter 2. For the exclusion restriction variable, we include the variable *Head of household.* As discussed in Section 2.4.2, we argue that being the main responsible of the earnings of a household affects the decision of participating actively in the labour market, but it does not affect their current labour status in terms of being employed, or to perform their labour activities in the formal or informal labour market.

$$\begin{aligned} Y_i = \theta_0 &+ \delta_1 Period2_i + \delta_2 t + \theta_1 Head_i + \theta_2 Trend + \theta_3 Female_i + \theta_4 Age_i \\ &+ \theta_5 Age_i^2 + \theta_6 Rural_i + \sum_{j=7}^{9} \theta_j SchLevel_{ki} + \sum_{j=10}^{12} \theta_j SchLevel_{ki} * Rural_i \\ &+ \sum_{j=13}^{15} \theta_j SchLevel_{ki} * Female_i + r_i \end{aligned} \tag{4.3}$$

The corresponding equation for the models on the dynamics of the effects is the following:

$$\begin{aligned} Y_i = \theta_0 &+ \sum_{l=1}^{4} \delta_l 2013\_Q_{li} + \delta_5 t + \theta_1 Head_i + \theta_2 Trend + \theta_3 Female_i + \theta_4 Age_i \\ &+ \theta_5 Age_i^2 + \theta_6 Rural_i + \sum_{j=7}^{9} \theta_j SchLevel_{ki} + \sum_{j=10}^{12} \theta_j SchLevel_{ki} * Rural_i \\ &+ \sum_{j=13}^{15} \theta_j SchLevel_{ki} * Female_i + r_i \end{aligned} \tag{4.4}$$

for $k = 2, 3, 4$

As a final remark, the total sample size in every model does not change by the use of different dependent variables. This is precisely because of the implementation of sample selection correction methods. For instance, when we estimate the impact on the probability of being *employed*, Y_i takes the value of one for all those individuals currently employed, and zero for all those unemployed, leaving aside inactive labour market individuals. These inactive individuals are included into the analysis as a censored observations. Similarly, for the estimation of being working under informal conditions, Y_i takes the value of one if the worker is classified as informal and zero if he is classified as informal. In this case, inactive labour market individuals, as well as unemployed workers correspond to the censored observations.

4.5 Results

All the DiD specifications in this section were estimated in two versions: by pooled probit, and correcting for sample selection bias. This section reports only second stage marginal effects. Pooled probit estimates of the main results (corresponding to Subsection 4.5.1) are reported in Appendix 4.B, while the full set of parameters for the first stage of sample selection correction, as well as the second stage are reported in Appendix 4.C. The following subsection describes the results of the impact of the 2012 minimum wage increase on the six different labour status previously described. The effect is also analysed by age groups. Subsection 4.5.2 presents the dynamics of the effects running the econometric model corresponding to equation (4.2). Finally, some robustness test to check the validity of our estimates are presented in Subsection 4.5.3.

4.5.1 Main results: the effect on employment and informality

In a very general framework, a higher wage rate makes more attractive the labour market in terms of remuneration, so it increases the labour supply. But, as discussed in Section 1.1, the effect on labour demand is ambiguous: given the higher labour costs generated by the legislation change, employers can reduce the level of employment (under the standard competitive labour model), or to hire more workers (under the monopsonistic labour model). Thus, this subsection estimates the impact of the minimum wage raise on the probability of being active on the labour market (with respect to be inactive), the probability of being employed (with respect to be unemployed), and the probability of performing the labour activity in the informal labour market (with respect to be formally employed).

The impact on employment

The model on active labour market population does not need selection bias correction procedures. This is the only specification where the full sample is considered in the econometric analyses. So, it constitutes an unrestricted regression. Indeed, for the rest of the models presented, censored observations in the selection equation correspond to inactive individuals in the sample.

Second and third columns in Table 4.2 show that there is no effect of the minimum wage increase in Zone B on the probability of being active in the labour market. All the parameters of interest, independently of the age group and the control group used, are not statistically different to zero. This result makes sense: if individuals are initially out of the labour market, an increment of 2.9% in the nominal minimum wage seems to be an insufficient incentive to encourage them to participate actively in the labour market looking for a job.

For the case of effect on the employment rate, pooled OLS models systematically restrict the sample to employed and unemployed individuals excluding inactive population. Therefore, sample selection procedures are implemented to test and correct the potential bias. According to the fourth and fifth columns in Table 4.2, the impact is positive and statistically significant independently of the specification estimated. For specification (4.1a) the marginal effect at the mean (MEM) is estimated at 0.19%, while for specification (4.1b) the effect is 0.24%. The implicit elasticities are small, but still positive: 0.07 and 0.08, respectively.

This result is economically significant: the minimum wage rise in Zone B did not reduce the overall employment level. In contrast, the employment rate increased by around 0.2%. Without differentiating between formal and informal workers, the model suggests that labour demand is increasing.

Table 4.2
MEM's probit for the impact on labour status.
Second stage for sample selection bias correction.

Dependent variable:	*Labour market active*		*Employed*	
Specification:	(4.1a)	(4.1b)	(4.1a)	(4.1b)
Full age threshold: 12 ≤ Age ≤ 97				
ZoneB*Period2	-0.0010	-0.0007	0.0019***	0.0024***
	(0.00258)	(0.00271)	(0.00068)	(0.00073)
atanh(ρ)	—	—	-0.1236***	-0.1251***
			(0.01566)	(0.01562)
Total observations	2,455,814		2,455,814	
Uncensored observations	—		1,405,478	
Age threshold: 12 ≤ Age ≤ 29				
ZoneB*Period2	0.0032	0.0031	0.0009	0.0014
	(0.00577)	(0.00566)	(0.00169)	(0.00171)
atanh(ρ)	—	—	-0.3526***	-0.3570***
			(0.02859)	(0.02865)
Total observations	995,920		995,920	
Uncensored observations	—		531,322	
Age threshold: 30 ≤ Age ≤ 49				
ZoneB*Period2	-0.0054	-0.0046	0.0019	0.0025
	(0.00505)	(0.00510)	(0.00153)	(0.00153)
atanh(ρ)	—	—	-0.1259***	-0.1279***
			(0.02901)	(0.02939)
Total observations	833,501		833,501	
Uncensored observations	—		635,977	
Age threshold: 50 ≤ Age ≤ 97				
ZoneB*Period2	-0.0007	-0.0088	0.0043***	0.0048***
	(0.00499)	(0.00517)	(0.00096)	(0.00106)
atanh(ρ)	—	—	0.2038***	0.2117***
			(0.05072)	(0.05017)
Total observations	626,393		626,393	
Uncensored observations	—		305,081	

Note: the parameter of atanh(ρ) corresponds to the correlation between the errors of the two equations, not to a marginal effect. The covariates included are gender, age, squared age, rural, schooling level, and interactions of schooling level with rural and gender. The model on active labour market population, in consistency with equation (4.2), also includes $Head$ as a regressor.
Clustered standard errors at the state level in parentheses.
Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Regarding the subsamples by groups of age, for the youngest and middle age workers, the estimated effects are positive but insignificant. So, changes in minimum wages does not seem to affect the probability of being employed for workers younger than 50 years old. In contrast, for the oldest segment of the labour force the effect is stronger, between 0.43% and 0.48% (implicit elasticities equal to 0.15 and 0.17, respectively), depending on the specification composition of the control group. Actually, the significant marginal effects estimated for the full sample specification are actually driven by the impact on this age threshold.

The atanh(ρ) parameter to test the null hypothesis of no selection bias, is statistically significant for all the regressions, which implies that there exists evidence of a correlation between the errors of the two equations. Therefore, the pooled OLS parameters are biased. Table 4.B.1 in columns (1) and (2) corroborates that original pooled OLS marginal effects are indeed different with respect to those obtained by sample selection bias correction procedures.

Comparing our findings with previous studies, Campos et al. (2017) evaluated the impact of the same intervention on three different labour status: *workers* (which in our case would correspond to the variable *employed*), *unemployed individuals*, and *workers out of the labour force* (corresponding to *inactive* individuals). By pooled and panel data models, they do not find statistical evidence of the effect of the minimum wage legislation on any of the dependent variables used.[10]

Our analysis indicates that after implementing the sample selection bias procedure, there is no statistical evidence of adverse effects on employment generated by the minimum wage rise. In contrast, for the oldest workers the effect on employment is positive and strongly significant: the employment rate is augmenting by almost half a percentage point

[10]However, their estimates do not look consistent. The effect on the probability of being working, as well as the probability of being unemployed exhibit negative coefficients (although insignificant), while one should expect coefficients with opposite signs. By the number of observations included in the models, the problem could be that the dummy variables are not correctly restricted. For example, for the *unemployed* dummy variable, it seems that it takes the value of zero for both, *employed* and *out of the labour force* individuals, which has a lack of interpretation. Appendix 2.A explains in a detailed way how the dependent variables are defined in our sample.

after the 2.9% minimum wage increase. Although it is necessary to complete the analysis evaluating the impact on the informal sector of the labour market, these results suggest the existence of monopsonistic labour markets.

The impact on informality

The analysis of the effect of the minimum wage legislation on the levels of employment in the Mexican labour market is incomplete if the analysis does not incorporate an evaluation on the informal sector. The previous subsection estimated the impact on the probability of being working by 0.2%, but the models do not differentiate between individuals performing their labour activities under formal or informal conditions. So, it is possible that the increase in the employment rate was generated by a higher level of occupation in the informal sector, which by definition is not covered by the minimum wage regulations. In consequence, the conclusion regarding the presence of monopsonistic labour markets may not be valid.

As a remark, sample selection correction for the impact on informality takes the usual concept of active labour market participation, but it restricts the sample to the informality category under examination. For example, in the model for waged informal workers, the first stage excludes from the analyses those informal workers classified as self-employed or non-waged. The presence of sample selection bias is confirmed. atanh(ρ) is statistically significant, which indicates that there exists correlation between the errors in the selection and outcome equation.

For the full age threshold analysis, Table 4.3 shows that the effect on the overall category of informal workers is negative, but not statistically significant. Yet, for the subgroup of waged informal workers, the marginal effect results statistically significant at the 10% level, with a magnitude of -0.009, which implies an elasticity of -0.38. Then, the 2012 minimum wage intervention is reducing the probability of participating in the informal sector by around 0.9%.[11]

[11] Table 4.B.1, in columns 3 and 4, shows the estimates by pooled OLS, which confirms that in absence of sample selection correction, the impact of the increase in minimum wage on informality reduction is

Table 4.3

MEM's probit for the impact on informality
Second stage for sample selection bias correction.

Dependent variable:	*informal*		*waged_informal*		*self_emp_informal*		*non_waged_informal*	
Specification:	(4.1a)	(4.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)
Full age threshold: 12 ≤ Age ≤ 97								
ZoneB*Period2	-0.0068	-0.0076	-0.0088*	-0.0094**	-0.0045	-0.0053	0.0009	0.0008
	(0.00557)	(0.00538)	(0.00486)	(0.00445)	(0.00440)	(0.00438)	(0.00168)	(0.00167)
atanh(ρ)	0.4180***	0.4229***	0.4832***	0.4860***	0.4269***	0.4317***	0.5372***	0.5407***
	(0.02132)	(0.02261)	(0.04024)	(0.04118)	(0.03444)	(0.03781)	(0.03383)	(0.03501)
Total observations	2,386,516		2,386,516		2,386,516		2,386,516	
Uncensored observations	1,336,180		997,073		855,037		670,300	
Age threshold: 12 ≤ Age ≤ 29								
ZoneB*Period2	0.0053	0.0064	0.0012	0.0013	0.0150	0.0158	0.0039	0.0038
	(0.00833)	(0.00800)	(0.01058)	(0.01022)	(0.01010)	(0.00990)	(0.00647)	(0.00624)
Total observations	957,436		957,436		957,436		957,436	
Uncensored observations	426,114		344,527		204,813		214,954	
Age threshold: 30 ≤ Age ≤ 49								
ZoneB*Period2	-0.0134***	-0.0155***	-0.0144***	-0.0125***	-0.0097**	-0.0083**	0.0007	0.0010
	(0.00466)	(0.00505)	(0.00406)	(0.00341	(0.00413)	(0.00418)	(0.00131)	(0.00124)
Total observations	810,581		810,581		810,581		810,581	
Uncensored observations	612,879		471,838		429,611		326,846	
Age threshold: 50 ≤ Age ≤ 97								
ZoneB*Period2	-0.0128**	-0.0140**	-0.0158***	-0.0143***	-0.0123*	-0.0118*	-0.0003	-0.0002
	(0.00522)	(0.00559)	(0.00322)	(0.00356)	(0.00660)	(0.00675)	(0.00153)	(0.00156)
Total observations	618,499		618,499		618,499		618,499	
Uncensored observations	297,187		180,708		220,613		128,500	

Note: the parameter of atanh(ρ) corresponds to the correlation between the errors of the two equations, not to a marginal effect.
The covariates included are gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender.
Clustered standard errors at the state level in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Indeed, if minimum wage regulations can affect wage setting in the informal labour market, the natural group of potentially affected workers correspond to waged informal workers. As discussed in Chapter 3, minimum wage in the Mexican labour market works as a guide of fair remuneration not only in the formal sector, but also in the informal labour market. So, it is precisely the segment of waged workers where we expect to observe a response in terms of their labour status.

Results in Chapters 2 and 3 suggest that as a consequence of the 2012 intervention, real earnings in the informal labour market experienced an increase even in stronger proportions than in the formal sector. The fact that the policy intervention also generated

over-estimated between 0.01 and 0.02%.

a decline in the probability of working under informal conditions, implies that the wage rise by informal employers was not enough to retain their workers. Formal jobs are more attractive, and not only by the higher monetary remunerations. Social benefits also improve. Given the *numeraire* use of the minimum wage in Mexico discussed in Section 3.3, benefits like pensions and housing credits were tied to the value of the minimum wage, which enhance the conditions of working in the formal sector.

Comparing these estimates with the findings in Campos et al. (2017), they found no significant effects on informality by pooled probit regressions. By panel data models, they estimated that the probability of remaining as a formal worker increases by 5.3%, while the probability of remain as a waged informal worker diminishes by up to 9.8%. But, the fact of ignoring sample selection bias, as well as the low number of observations included in their sample (only those workers that exhibited transition in the formal/informal status are included) generates skepticism about the magnitude of the parameters. For this reason our analyses implement only pooled DiD regressions, aiming to keep all the observations in the sample.

With respect to the age threshold subsamples, there is no effect on the youngest sector of the employed population, but important effects emerge for older workers. First, for workers aged 30 to 49, there is evidence of significant marginal effects on the whole classification of informal workers. The effect is estimated to be between -1.3% and -1.5%, depending on the control group used. On waged informal workers, our model suggests an impact by between -1.3% and -1.4%, while on the self-employed informal workers was between 0.8% and 1%. The associated elasticities for this age threshold fluctuate between -0.29 and -0.53.

For the oldest segment of the working population the estimated effects are even stronger: the probability of working under informal conditions was reduced by between -1.3% and -1.4% (elasticities equal to 0.48 and 0.44), while for waged informal workers the effect is stronger in absolute terms, of around -1.5% (elasticities around -0.50). Finally, for self-employed workers the impact is also higher, -1.2% in both specifications (elasticity equal to 0.42).

It is worth to reiterate that given the construction of the binary dependent variables, these set of negative treatment effects do not imply an absolute loss of employment in the informal sector. It implies a relative decline in employment with respect to the formal labour market, not with respect to unemployment.

In terms of the impact of the minimum wage rise as a public policy, the result is highly relevant, specially for the vulnerable group of the eldest workers in the workforce. According to CONEVAL, 45.9% of individuals older than 64 years old live in poverty conditions. In addition, it is very unlikely that these workers could aspire to earn a higher salary, or to transit to formality. There are not many options for an increase in their productivity by the improvement of their skills, experience or qualifications. Our results show that one of the main implications of the 2012 minimum wage legislation was that formal employment increased for workers older than 50 years old.

On the other hand, for non-waged informal workers, there is no evidence of any effect generated by the policy intervention. This result is to be expected; this sector consists mainly on workers with labour activities in small family business, usually within the household, whose incentives are different from the rest of the labour market.

It is relevant to emphasize that none of the specifications show evidence of an increase of the informal labour market size. Neither by age groups, nor by the type of worker. In contrast, the DiD regressions demonstrate that the probability of working under formal conditions increases for some age cohorts. This result implies that, although the minimum wage intervention is not biting the informal sector in terms of a compulsory wage rate, a higher minimum wage in the formal market may change the incentives to work under informal conditions.

In summary, our estimates challenge classic economic theory regarding the implications of a rise in the minimum wage level. The employment elasticities are close to zero, but still statistically significant: around 0.08 for the whole labour force. With respect to the informality rate, the results suggest an elasticity of -0.31 for waged informal workers, also using the full age sample.

Given the increase of the employment rate and the reduction of the informality rate, it is possible to confirm the existence of monopsonistic labour markets in Mexico: as a result of the minimum wage increase, labour demand in the formal market absorbs more workers in spite of higher wages rates.

4.5.2 Dynamics of the impact on labour status

Following the structure of the econometric models estimated in Chapter 2, this subsection presents also an evaluation of the dynamics of the employment effects of the 2012 minimum wage increase. Subsection 4.5.1 presents the parameters of interest (δ_1) for equation (4.1), in which the four quarters after the intervention are pooled in the defined post-treatment period ($Period2$). With the objective of verifying the robustness of our results, we now introduce one DiD estimator for each quarter after the intervention as showed in equation (4.2). Beyond verifying the validity of the parameters, this specification also allows us to analyse the timing of the responses by the labour market to the minimum wage increase.

Table 4.4 confirms that there is no impact on the probability of being active in the labour market. In every post-treatment quarter, the DiD parameters are not statistically different to zero. These results corroborate that the minimum wage increase by 2.9% is insufficient for attracting workers out of the labour force.

With respect to the evaluation of dynamics of the effect on employment status, the treatment effect is only present in the second quarter of 2013. So, in terms of employment decisions, Mexican labour market takes two quarters to respond to the minimum wage variation, and afterwards there is no statistical evidence of subsequent changes on the employment level. The magnitude of the significant marginal effects are similar to those observed in Table 4.2, between 0.17% and 0.20%, with a corresponding elasticity between 0.06 and 0.07, depending on the minimum wages zones included the control group. Even though the magnitude of the impact is small, the robustness exercise demonstrates that there is actually a positive effect of the minimum wage increase on employment rate.

Table 4.4
MEM's probit for the dynamics of the impact on labour status
Second stage for sample selection bias correction

Dependent variable:	*Labour market active*		*Employed*	
Specification:	(4.2a)	(4.2b)	(4.2a)	(4.2b)
ZoneB*D2013Q1	-0.0034	-0.0035	0.0009	0.0014
	(0.00454)	(0.00459)	(0.00215)	(0.00210)
ZoneB*D2013Q2	0.0018	0.0027	0.0017**	0.0020**
	(0.00478)	(0.00406)	(0.00085)	(0.00088)
ZoneB*D2013Q3	-0.0044	-0.0043	0.0019	0.0019
	(0.00393)	(0.00271)	(0.00155)	(0.00160)
ZoneB*D2013Q4	0.0015	0.0015	0.0019	0.0024
	(0.00659)	(0.00672)	(0.00167)	(0.00168)
atanh(ρ)	—	—	-0.1248***	-0.1263***
			(0.01571)	(0.01568)
Total observations	2,455,814		2,455,814	
Uncensored observations	—		1,405,478	

Note: the parameter of atanh(ρ) corresponds to the correlation between the errors of the two equations, not to a marginal effect. The covariates included are gender, age, squared age, rural, schooling level, and interactions of schooling level with rural and gender.
Clustered standard errors at the state level in parentheses.
Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

There are two points to highlight. First, in spite of the more than 2.4 million of observations, and independently of the composition of the control group and the definition of the differences of differences variable, the fact of failing to find significant effects on active labour market population is really informative in terms of the minimum wage policies repercussions. Second, in contrast to the labour market responses on earnings (see Table 2.5), for the case of the employment decisions the effect is present only two quarters after the intervention.

Finally, for the dynamics of the impact on the informal labour market, we observe a similar pattern to that in the employment estimates. At least for the full age sample analyses, the effect is statistically significant only for the second quarter of 2013, and afterwards the impact is not present anymore.

Table 4.5 shows that the effect is observed on the entire classification of informal workers, whose estimated impact is -0.9%, and also for the waged informal workers, where the effect is between -1.6% and -1.7%.

The magnitude of the marginal effects presented in tables 4.4 and 4.5 do not change with respect to the main estimates in Section 4.5.1, which corroborates the robustness of our econometric models.

Table 4.5
MEM's for the dynamics of the impact on informality
Second stage MEM's for sample selection bias correction.

Dependent variable:	*informal*		*waged_informal*		*self_emp_informal*		*non_waged_informal*	
Specification:	(4.2a)	(4.2b)	(4.2a)	(4.2b)	(4.2a)	(4.2b)	(4.2a)	(4.2b)
ZoneB*D2013Q1	-0.0072	-0.0076	-0.0057	-0.0060	-0.0093	-0.0095	0.0011	0.0011
	(0.00955)	(0.00957)	(0.00772)	(0.00772)	(0.00758)	(0.00761)	(0.00265)	(0.00262)
ZoneB*D2013Q2	-0.0084***	-0.0090***	-0.0161***	-0.0160***	-0.0025	-0.0038	0.0030	0.0028
	(0.00248)	(0.00276)	(0.00331)	(0.00311)	(0.00500)	(0.00533)	(0.00189)	(0.00187)
ZoneB*D2013Q3	-0.0077	-0.0094	-0.0099	-0.0113	-0.0054	-0.0071	-0.0001	-0.0004
	(0.00965)	(0.00943)	(0.00989)	(0.00953)	(0.00685)	(0.00680)	(0.00227)	(0.00223)
ZoneB*D2013Q4	0.0025	0.0013	-0.0008	-0.0028	0.0048	0.0053	0.0004	0.0003
	(0.00763)	(0.00698)	(0.00845)	(0.00764)	(0.00646)	(0.00625)	(0.00168)	(0.00163)
atanh(ρ)	0.4679***	0.4739***	0.3394***	0.3446***	0.1146***	0.1179***	0.1387***	0.1376***
	(0.02241)	(0.02404)	(0.02963)	(0.03141)	(0.04122)	(0.04255)	(0.04895)	(0.04917)
Total observations	2,386,516		2,386,516		2,386,516		2,386,516	
Uncensored observations	1,336,180		997,073		855,037		670,300	

Note: the parameter of atanh(ρ) corresponds to the correlation between the errors of the two equations, not to a marginal effect.
The covariates included are gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender.
Clustered standard errors at the state level in parentheses.Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

4.5.3 Falsification Tests

The previous subsection demonstrated that the definition of the DiD regressor does not affect the magnitude of the estimates. Using either four quarterly variables or a variable pooling the four quarters after the treatment does not change any of the conclusions reached. To complete our set of econometric estimates, in this subsection we test if the use of the Zone B's 2012 minimum wage increase is valid as a treatment for the DiD specifications.

To do so, we implement a falsification test similar to the one used in Section 3.6.2. The sample is restricted to the period 2011Q1-2012Q4 just before the intervention so that all the post-treatment period is dropped out. To run the DiD models, we use a similar specification to Autor (2003), in which an artificial treatment is introduced in the model.

We define the period 2012Q1 to 2012Q4 as the *placebo* post-treatment period. In case that the intervention is not valid as a treatment we would observe significant parameters even in the absence of the actual policy change.

Table 4.6 reports the estimates for the falsification tests on active labour market population and employed workers for equation (4.1). The results are totally convincing. In all the models, independently of the age threshold and the composition of the control group, all the parameters of interest are statistically not different from zero. This could seem trivial: if there is no treatment, there is no effect. But, it demonstrates that our model is truly able to identify the treatment effect of the 2012 minimum wage increase.

Table 4.6

Falsification test, the impact on labour status (2011Q1-2012Q4)

Second stage MEM's for sample selection bias correction

Dependent variable:	*Labour market active*		*Employed*	
Specification:	(4.1a)	(4.1b)	(4.1a)	(4.1b)
Full age threshold: 12 $\leq$ Age $\leq$ 97				
ZoneB*Period2	-0.0003	0.0000	0.0002	-0.0000
	(0.00525)	(0.00531)	(0.00194)	(0.00204)
Total observations	2,355,457		2,355,457	
Uncensored observations	—		1,343,874	
Age threshold: 12 $\leq$ Age $\leq$ 29				
ZoneB*Period2	-0.0018	-0.0018	0.0021	0.0019
	(0.00708)	(0.00699)	(0.00250)	(0.00268)
Total observations	966,915		966,915	
Uncensored observations	—		453,970	
Age threshold: 30 $\leq$ Age $\leq$ 49				
ZoneB*Period2	-0.0004	-0.0004	-0.0014	-0.0016
	(0.00775)	(0.00774)	(0.00240)	(0.00248)
Total observations	794,551		794,551	
Uncensored observations	—		602,506	
Age threshold: 50 $\leq$ Age $\leq$ 97				
ZoneB*Period2	0.0035	0.0018	0.0002	-0.0003
	(0.00545)	(0.00537)	(0.00283)	(0.00296)
Total observations	593,991		593,991	
Uncensored observations	—		287,398	

Note: the covariates included are gender, age, squared age, rural, schooling level, and interactions of schooling level with rural and gender. The model on active labour market population, in consistency with equation (4.2), also includes *Head* as a regressor.
Clustered standard errors at the state level in parentheses.
Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Finally, Table 4.7 shows the parameters of interest for the falsification test on the

Table 4.7
Falsification test, impact on informal employment (2011Q1-2012Q4)
Second stage MEM's for sample selection bias correction

Dependent variable:	*informal*		*waged_informal*		*self_emp_informal*		*non_waged_informal*	
Specification:	(4.1a)	(4.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)
Full age threshold: 12 ≤ Age ≤ 97								
ZoneB*Period2	-0.0018	-0.0017	0.0005	0.0008	-0.0001	-0.0001	-0.0028***	-0.0027***
	(0.00409)	(0.00417)	(0.00524)	(0.00535)	(0.00377)	(0.00383)	(0.00097)	(0.00096)
Total observations	2,355,457		2,355,457		2,355,457		2,355,457	
Uncensored observations	1,276,149		948,185		813,577		639,497	
Age threshold: 12 ≤ Age ≤ 29								
ZoneB*Period2	0.0014	0.0030	0.0057	0.0073	0.0051	0.0055	-0.0091*	-0.0071
	(0.00915)	(0.00921)	(0.01274)	(0.01281)	(0.01226)	(0.01251)	(0.00527)	(0.00497)
Total observations	966,915		966,915		966,915		966,915	
Uncensored observations	415,820		334,106		197,299		208,911	
Age threshold: 30 ≤ Age ≤ 49								
	-0.0033	-0.0040	-0.0036	-0.0043	0.0024	0.0026	-0.0031***	-0.0032***
	(0.00493)	(0.00517)	(0.00486)	(0.00504)	(0.00327)	(0.00345)	(0.00088)	(0.00087)
Total observations	794,551		794,551		794,551		794,551	
Uncensored observations	580,460		444,791		407,770		309,465	
Age threshold: 50 ≤ Age ≤ 97								
ZoneB*Period2	-0.0059	-0.0065	-0.0009	-0.0005	-0.0092	-0.0103	-0.0006	-0.0007
	(0.00617)	(0.00627)	(0.00434)	(0.00442)	(0.00836)	(0.00851)	(0.00129)	(0.00129)
Total observations	593,991		593,991		593,991		593,991	
Uncensored observations	279,869		169,288		208,508		121,121	

Note: the covariates included are gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender. Clustered standard errors at the state level in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

impact on the probability of being an informal worker. The three categories in which we previously found significant impacts, that is the whole set of informal workers, waged informal workers, and self-employed informal workers, for the falsification test there are no statistically significant effects. This implies that our results on informality using the 2012 intervention are valid and robust. Yet, interestingly we found a significant *placebo* effect for non-waged informal workers, which is basically driven by middle age workers. These parameters do not modify any of the results obtained. In any case it means that we are failing to characterize correctly this particular set of workers,[12] but given their characteristics we are not focused on the impact on this segment of the workforce. As we

[12]Given that these group of workers are generally teenagers, some of the control variables included in the model may not be relevant for the labour market decisions of these individuals, as age or schooling level.

have explained before, we do not expect that non-waged informal workers respond in the same way with respect to the rest of the labour market.

It is relevant to remark the use of exactly the same specifications in Chapters 2, 3 and 4. All the control variables are exactly the same among the entire dissertation, which corroborates the consistency and robustness of our estimates.

Summarizing, the robustness checks in tables 4.6 and 4.7 demonstrate that our empirical analysis is robust to the definition of the DiD variable, to the period of analysis and to the composition of the control group.

4.6 Conclusions

This chapter contributes to the discussion on the impact of minimum wages on the labour market providing strong empirical evidence on the existence of monopsonistic labour markets in Mexico. One of the main arguments against minimum wage increases in Mexico is that it could led minimum wage workers to a worst position: without their jobs. Our analysis suggest that the 2012 intervention had no negative effects on occupation and employment.

Previous evaluations of the effects on minimum wages on the Mexican labour market have omitted the fact that restricting the analysis to active labour market population generates a problem of sample selection bias. Our empirical analyses proves that there is evidence of sample selection in the analyses. Once that the bias is corrected, DiD models do not find statistical evidence of adverse effects on the labour force. Robust to different specifications, our estimates show that the 2012 Zone B's minimum wage increase did not damage the level of occupation. Our results also suggest that there was no effect on the active labour market population, but the employment rate increased —specifically on the oldest sector of the population— and occupation in the informal labour market decreased.

The central finding of this chapter is the existence of monopsonistic labour markets in Mexico, which implies that minimum wage increases (in real terms) do not necessarily mean negative impacts on employment, specially for the most vulnerable workers.

And precisely the effect on workers aged over 50 is one of the most relevant findings of this chapter. These workers are particularly vulnerable not only for the necessity of access to social security services, but also for of the high levels of poverty and informality that aggravate their conditions. Results in Chapter 2 suggest that there was no impact on the real earnings of this group, but the probability of being employed augmented (with an estimated elasticity of 0.17), and more importantly, the probability of working in the informal sector, with respect to the formal counterpart, was reduced by the intervention (elasticity around -0.50).

Finally, there are some analytical issues pending for future research. First, for the informal employment models, the labour status of the workers is restricted to formal and informal employment, but there are other possibilities. The legislation change could have led them to unemployment or even to being inactive in the labour market. To evaluate the complete set of choices faced by informal workers multinomial logit regressions can be implemented, but sample selection correction represents the main challenge.

Second, the nature of the database allows for panel data analyses, at least for five consecutive quarters, but it implies to lose an important number of observations. It is necessary to explore the validity of the results in order to incorporate fixed effects specifications.

Appendix 4.A Extended literature review of minimum wages effects on employment in the US and in the UK [13]

Given the extensive literature on empirical evaluations of the minimum wage effects on employment in the US and in the UK, we we divide this appendix in two sections considering the theoretical models in which are based on, the methodology employed, and the results found. On the one hand, time series studies during the decades of the 1960's 1970's and 1980's reached an apparent consensus on the negative effects on employment, supporting the predictions of the classical standard model in perfect competition. On the other, the so-called *new minimum wage research* based mainly on the monopsonistic labour market model. By the use of panel-data regressions, these studies have argued that minimum wage effects are not necessarily negative.

4.A.1 Time-series studies

The decades of 1960's and 1970's in the US were characterized by important efforts by the Congress to broaden the coverage of the minimum wage. From 1961 to 1981, the percentage of workers covered by minimum wage legislation increased from 63% to 90% (Brown, 1999). These increases on the minimum wage level, as well as its workforce coverage attracted the attention of labour economists.

Brown et al. (1982) described the methodology and the main results of a compendium of time-series evaluations in the previous decade regarding the impact of the minimum wage on employment and unemployment levels. Even though the objective is not to replicate their description, this subsection is mainly based on that survey.

Most of the research of time-series studies was focused on the effect on youth and

[13] A former version of this section was submitted as part of the doctoral research proposal for the Advanced Research Methods module in March 2015. See *The effect of minimum wages on employment. The case for Mexico*, by Jorge Alfredo Bouchot Viveros.

teenagers for a period commonly between 1950 and 1980. According to Brown et al. (1982), a common characteristic was to estimate single equation models of the following form: $Y = f(MW, D, X_i)$; where Y represents the labour status (employed/unemployed), D an aggregate demand variable to account for changes in the economic activity or business cycle and, X_i is a set exogenous explanatory variables that included, among others, labour supply, school enrollment rates and participation in the armed forces.

Regarding the dependent variable Y, at the beginning of the decade of the 1970's, the earliest time-series studies used unemployment variables to measure the *employment effect* (Adie, 1971, 1973; Lovell, 1972, 1973). Nevertheless, in the following decade some studies started to use employment to population ratios (Abowd and Killingsworth, 1981; Boschen and Grossman, 1981; Betsey and Dunson, 1981; Hamermesh, 1982). Brown et al. (1982) argued that this was due to the fact that the concept of unemployment could be imprecise because job-search periods could bias the real status of the workers. In addition, measuring the impact on employment also allowed the consideration of potential affectations to job opportunities as a consequence of minimum wage increases.

The minimum wage variable, MW, was commonly expressed as the ratio of the nominal minimum wage to the average hourly earnings, weighted by the proportion of workers covered by the minimum wage regulations. For the business cycle variable D, the most common variables used were the Industrial Production Index, the gap between the actual and potential GNP, the adult employment rate, among others.

According to Brown et al. (1982), all the studies analyzed found negative employment effects for workers between 16 and 19 years of age (although not all the estimations were statistically significant). In general, they concluded that an increase of 10% in the federal minimum wage reduced employment by between 1% and 3%. Yet, there were mixed results regarding the impact on less skilled workers. For the earlier studies women and black workers were more affected, but when the data for the decade of 1970's was incorporated, white men were the most damaged sector.

The impact on young adults was also found to be negative, but in smaller magnitudes (in general by less than 1%) and with an important variability across the sectors. Wachter and Kim (1982), for instance reported a relatively stronger impact on black men (compared to white men), but for black women they found large positive effects.

With respect to the specification of the employment variable, an important remark is that when the effect on unemployment is measured, the results had a higher variability. Adie (1971), for example found large and positive effects, while Moore (1971) reported a negative impact.

After the decade of the 1980's, there were some other time series studies that basically used the same specifications, but extending the period of analysis, as well as the variations observed at the state level. This is the case for Wellington (1991) who analysed the period 1954-1986, finding lower elasticities than the range estimated by Brown et al. (1982) (between -0.05 and -0.09 for teenagers and from -0.02 to zero for young adults). Moreover, Bernstein and Schmitt (2000) using different methods for seasonality, and incorporating data until 2000, estimated negative elasticities but closer to zero (at most of -0.05) and mostly statistically non-significant.

4.A.2 New minimum wage research

According to the US Department of Labor, from 1961 to 1981 seventeen nominal increases to the federal minimum wage in United States were recorded.[14] In contrast, between 1981 and 1990 there were no adjustments which generated pressure on the purchasing power of minimum wages. As a response, some state congresses started to set the minimum wage level above the federal setting. In terms of the econometric evaluations, these differences across states provided new statistical variation, but more importantly, the opportunity to test the impact of minimum wages by the use of different methodological approaches.

California was the first state to raise the minimum wage above the federal level. In 1988, it was increased from \$3.35 to \$4.25 USD. Card (1992a) compared the changes observed in employment with respect to the variations of a control group sample (in-

[14]Source: US Department of Labor. `https://www.dol.gov/whd/minwage/chart.htm`

cluding workers from Arizona, Florida, Georgia, New Mexico, and Dallas-Fort Worth, Texas). Using data from the Current Population Survey and DiD estimators, Card found no empirical support for the conventional competitive model predictions that minimum wage increases affect negatively employment. Indeed, he concludes that employment for teenagers rose more rapidly in California than in the control group areas.

Likewise, Katz and Krueger (1992) evaluated the impact of the federal minimum wage increase in April 1990 (from $3.35 to $3.80 USD) on the fast-food sector in Texas. To measure the effect on employment, two rounds of surveys were conducted. One before the increase, in December 1990, and the other one in July and August 1991. They measure the effect of the minimum wage gap, defined as the difference between the initial wage paid and the new federal minimum wage, by instrumental variables regressions. The study found that employment increased for those firms relatively more affected by the minimum wage raise, estimating positive elasticities between 1.7 and 2.7.

Considered by Neumark and Wascher (2006) as "by far the best known and most influential study of a specific minimum wage increase", Card and Krueger (1994) measured the impact on employment and prices of the 1992 in New Jersey's minimum wage (from $4.25 to $5.05 USD). As in Katz and Krueger (1992), this paper is based in a survey of fast food restaurants conducted two months before and seven months after the minimum wage increase. But in contrast to the earlier study, Card and Krueger used as a control group a sample of fast food stores in eastern Pennsylvania supported by the similarities in the seasonal patterns on employment. Thus, by using DiD estimations they found no evidence of employment reductions in New Jersey due to the minimum wage increase.

Given the relevance of the results, these studies generated a lot of controversy and reactions from different positions in the field. According to Neumark and Wascher (2006), the main criticisms are focused on the following areas: the use of valid control groups, the very short term of the period of analysis (not considering the whole effect of the increases), and the reliability of data obtained from own-conducted surveys.

There are some papers that sought to re-evaluate the Card and Krueger estimations, getting opposite conclusions. Kim and Taylor (1995) by instrumental variables estimations and using data for the retail trade sector, found elasticities ranging from -0.9 to -0.7 for the California minimum wage increase in 1988. In the same way, Neumark and Wascher (2000) replicated the DiD estimations of Card and Krueger (1994) for the fast-food industry in New Jersey. The main difference with respect to the evaluation by Card and Krueger was that the information of employment and wages of the restaurants was obtained from administrative payroll records. This study found elasticities between -0.2 and -0.1 (although not all of them statistically significant).

Nevertheless, further research in the UK supported the previous findings by Card, Krueger and Katz. As in the case of the US, in Great Britain there was an active political debate on minimum wages during the decade of the 1990's. In 1993 the Wage Councils were abolished, which constituted the minimum wage system that had operated since 1909. Under this scheme, workers, employers representatives, and independent members appointed by the government, set the minimum wage floors for the different sectors of the industry. According to Machin et al. (2003) at the moment of their abolition, there were 26 councils covering around 12% of the working population. From 1993 to 1999 there were no minimum wage regulations, but in 1999 the National Minimum Wage (NMW) was introduced.

Dickens et al. (1994) developed a theoretical model of monopsonistic labour market competition to subsequently evaluate empirically the impact of the Wage Councils between 1975 and 1990. For the minimum wage variable they used a measure of *toughness*, which is the ratio between the minimum wage level and the average wage for each specific industry. Their estimations suggest positive and large effects of the Wage Council settings on employment.

In a further study, Dickens et al. (1999) analyzed the impact on the different sectors covered by the Wage Councils for the period 1975-1992. In order to measure beyond the short-term impact, they included some lags to the minimum wage specification, finding positive and significant effects on employment, and even higher than their static specifications. An important remark is the fact that for higher levels of toughness (understood as a higher increase of the minimum wages in relative terms) the impact became lower and not statistically significant, although the impact remained positive.

In the same way, Machin et al. (2003) conducted a survey in the residential care homes industry to evaluate the impact of the introduction of the NMW on this sector, which is considered specially vulnerable to minimum wage policies. According to their findings, minimum wage reduced employment and hours worked but in a small magnitude considering the increase relative to the wage increase generated. Depending on the dependent variable used —number of workers or hours worked— the elasticities estimated were between -0.35 to -0.55 (not all of them were statistically significant).

Stewart (2002) also evaluated the impact of the introduction NMW but exploiting the geographical variation in wages, that is, considering the differences in the wage distribution across the United Kingdom. Even though the estimations vary depending on the proportion of low-wage workers in the sample, Stewart found that there was not enough empirical evidence to suggest a systematic adverse effect on employment.

Subsequently, using individual-level data Stewart (2004) estimated the effects of the NMW, but from a different perspective, namely the probability of remaining in employment. The analysis was carried out comparing those workers that initially were paid below the minimum wage, with respect to the workers that originally were paid just above the minimum wage. By using DiD regressions, Stewart found that the impact on the probability of remaining in employment was not statistically different from zero for all the demographic groups analyzed, concluding that there was not statistical evidence of the existence of a minimum wage effect on employment.

From a firm perspective, Galindo-Rueda and Pereira (2004) estimated DiD regressions to compare the effects between the most affected firms and the least affected in terms of the share of low-paid workers. Matching data from the Annual Business Inquiry and the New Earnings Survey they found that the NMW introduction had no significant unemployment effects.

Nevertheless, there exists an opposite view arguing that there is enough empirical evidence to assert that minimum wages have negative effects on employment. Sabia (2009) for example, following the discussion in Card and Krueger (1995), Burkhauser et al. (2000) and Neumark and Wascher (2006) with respect to the inclusion of year effects in employment models, used alternative macroeconomic controls and included more recent data (from 1979 to 2004 for the United States) finding evidence of negative employment effects, with elasticities estimated around -0.5. In a recent survey Sabia (2014) asserted that the empirical evidence has shown that "policymakers should abandon higher minimum wages as an antiquated anti-poverty tool. Minimum wages deter employment and are poorly targeted to those in need".

On the other hand, Dube et al. (2010), developed a different approach to improve the construction of control groups more similar to treated zones. They used, as an identification strategy policy discontinuities at the county level in state borders with different settings of minimum wage in United States form 1990 to 2006. Comparing all contiguous border-county pairs in the United States they found no adverse employment effects. Neumark et al. (2014) asserted that there were serious problems with the empirical design of Dube et al. (2010), noting that some of the excluded non-border counties had important similarities with the treatment group, and also that the matched pairs exhibited differences across the observable features. Thus, once that these are corrected for to construct valid control groups, negative employment effects emerge. Nevertheless, Allegretto et al. (2017) refuted the critique by Neumark et al. (2014), arguing that they failed to generate good matches for the treated counties finding the highest employment reductions where the relative minimum wage fell.

Meer and West (2013) focused on job growth in United States rather than in employment levels. By the use of a state panel difference-in-differences approach, and employing the Business Dynamics Statistics, the Quarterly Census of Employment and Wages, and the Quarterly Workforce Indicators found that job growth declined significantly as a consequence of raises in the minimum wage. In response, Dube (2013) argued that the different minimum wage policies across states were not randomly distributed, and together with the timing of the minimum wage increases (which are more likely to occur during the latter part of economic expansions) lead to biased econometric inferences. Hence, using bordering counties to construct more credible control groups, Dube found non-negative correlation between minimum wages and employment growth.

From a different perspective, Hirsch et al. (2015) evaluated the 2007-2009 federal minimum wages increases in the United States by analyzing the different potential minimum wage adjustment channels in addition to employment. Using a sample of quick-service restaurants in Georgia and Alabama, they concluded that there were no employment effects, and that the firm costs increases were absorbed by different channels of adjustment, like inflation, wage compression, and higher performance standards.

Appendix 4.B Pooled probit estimates without sample selection correction

Table 4.B.1

Pooled probit MEM's of the effect on labour status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:	*Employed*		*informal*		*waged_informal*		*self_emp_informal*		*non_waged_informal*	
Specification:	(4.1a)	(4.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)
Full age threshold: 12 ≤ Age ≤ 97										
ZoneB*Period2	0.0026***	0.0021***	-0.0078	-0.0069	-0.0096**	-0.0090*	-0.0051	-0.0043	0.0015	0.0018
	(0.00080)	(0.00075)	(0.00557)	(0.00575)	(0.00454)	(0.00495)	(0.00417)	(0.00420)	(0.00285)	(0.00289)
Total observations	1,405,478		1,336,180		997,073		855,037		670,300	
Age threshold: 12 ≤ Age ≤ 29										
ZoneB*Period2	0.0020	0.0013	0.0069	0.0058	0.0013	-0.0003	0.0097	0.0092	0.0061	0.0062
(0.00231)	(0.00227)	(0.00848)	(0.00883)	(0.01085)	(0.01121)	(0.00620)	(0.00631)	(0.00879)	(0.00888)	
Total observations	635,799		426,114		344,527		204,813		214,954	
Age threshold: 30 ≤ Age ≤ 49										
ZoneB*Period2	0.0027	0.0021	-0.0156***	-0.0135***	-0.0158***	-0.0137***	-0.0101**	-0.0085**	0.0010	0.0015
	(0.00167)	(0.00166)	(0.00478)	(0.00517)	(0.00393)	(0.00457)	(0.00439)	(0.00432)	(0.00237)	(0.00255)
Total observations	635,799		612,879		471,838		429,611		326,846	
Age threshold: 50 ≤ Age ≤ 97										
ZoneB*Period2	0.0041***	0.0037***	-0.0145**	-0.0132**	-0.0174***	-0.0158***	-0.0133*	-0.0126*	-0.0021	-0.0011
	(0.00081)	(0.00071)	(0.00567)	(0.00527)	(0.00381)	(0.00339)	(0.00725)	(0.00706)	(0.00624)	(0.00619)
Total observations	305,081		297,187		180,708		220,613		128,500	

Note: the covariates included are gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender.
Clustered standard errors at the state level in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 4.B.2

Pooled probit MEM's of the dynamics of the effect on labour status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:	*Employed*		*informal*		*waged_informal*		*self_emp_informal*		*non_waged_informal*	
Specification:	(4.1a)	(4.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)
ZoneB*D2013_Q1	0.0121	0.0183	-0.0199	-0.0210	-0.0162	-0.0169	-0.0268	-0.0275	0.0227	0.0219
	(0.02802)	(0.02772)	(0.02466)	(0.02475)	(0.02128)	(0.02134)	(0.02199)	(0.02215)	(0.05410)	(0.05411)
ZoneB*D2013_Q2	0.0226**	0.0266**	-0.0219***	-0.0232***	-0.0450***	-0.0446***	-0.0070	-0.0109	0.0652*	0.0618
	(0.01137)	(0.01190)	(0.00676)	(0.00756)	(0.00920)	(0.00873)	(0.01422)	(0.01520)	(0.03715)	(0.03769)
ZoneB*D2013_Q3	0.0244	0.0249	-0.0203	-0.0248	-0.0280	-0.0320	-0.0154	-0.0202	0.0008	-0.0054
	(0.02087)	(0.02154)	(0.02555)	(0.02501)	(0.02808)	(0.02718)	(0.01971)	(0.01957)	(0.05046)	(0.05059)
ZoneB*D2013_Q4	0.0244	0.0320	0.0071	0.0041	-0.0017	-0.0072	0.0139	0.0153	0.0147	0.0107
	(0.02241)	(0.02300)	(0.01986)	(0.01812)	(0.02340)	(0.02121)	(0.01838)	(0.01779)	(0.03610)	(0.03543)
Total observations	1,405,478		1,336,180		997,073		855,037		670,300	

Note: the covariates included are gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender.
Clustered standard errors at the state level in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Appendix 4.C Full list of coefficients of the sample selection bias procedure

Table 4.C.1

Pooled probit coefficients on employment

Second stage for sample selection bias correction

Dependent variable:	*employed*							
Age threshold:	$12 \leq$ Age ≤ 97		$12 \leq$ Age ≤ 29		$30 \leq$ Age ≤ 49		Age ≥ 50	
Equation:	(2.1a)	(2.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)
ZoneB*Period2	0.0247***	0.0307***	0.0073	0.0115	0.0290	0.0372	0.0616***	0.0692***
	(0.00931)	(0.01008)	(0.01353)	(0.01386)	(0.02345)	(0.02392)	(0.01273)	(0.01460)
ZoneB	-0.0540**	-0.0738***	-0.0420	-0.0579*	-0.0485**	-0.0700***	-0.0793***	-0.1102***
	(0.02180)	(0.02228)	(0.03095)	(0.03151)	(0.02432)	(0.02444)	(0.02702)	(0.02628)
Period2	0.0233**	0.0169*	0.0473***	0.0429***	0.0051	-0.0035	0.0221	0.0140
	(0.00712)	(0.00963)	(0.01209)	(0.01245)	(0.01526)	(0.01524)	(0.01984)	(0.01880)
ZoneA*Period2		0.0399***		0.0311**		0.0503*		0.0428
		(0.01524)		(0.01529)		(0.02836)		(0.02967)
ZoneA		-0.1265***		-0.1095***		-0.1291***		-0.1788***
		(0.03204)		(0.03856)		(0.02834)		(0.04828)
Trend	0.0105***	-0.0072***	-0.0093***	-0.0093***	-0.0064**	-0.0063**	-0.0096**	-0.0096**
	(0.00191)	(0.00312)	(0.00340)	(0.00340)	(0.00241)	(0.00241)	(0.00445)	(0.00438)
Female	0.3232***	0.3254***	0.2481***	0.2517***	0.2579***	0.2599***	0.3076***	0.3047***
	(0.03868)	(0.03466)	(0.03571)	(0.03627)	(0.04409)	(0.04375)	(0.06359)	(0.06362)
Age	0.0270***	0.0272***	-0.2888***	-0.2891***	0.0713***	0.0718***	-0.0850***	-0.0846***
	(0.00209)	(0.00210)	(0.01618)	(0.01638)	(0.01123)	(0.01123)	(0.01153)	(0.01157)
Age^2	-0.0001***	-0.0001***	0.0066***	0.0066***	-0.0007***	-0.0007***	0.0007***	0.0007***
	(0.00002)	(0.00002)	(0.00031)	(0.00031)	(0.00014)	(0.00014)	(0.00010)	(0.00010)
Rural	0.2925***	0.2854***	0.2390***	0.2356***	0.2619***	0.2536***	0.3299***	0.3148***
	(0.04750)	(0.04677)	(0.06298)	(0.06307)	(0.05165)	(0.05123)	(0.04490)	(0.04335)
School_level2	0.0774***	0.0801***	-0.1032***	-0.1011***	0.0596**	-0.0625**	0.0717***	0.0749***
	(0.01749)	(0.01678)	(0.02986)	(0.02971)	(0.02613)	(0.02535)	(0.02249)	(0.02192)
School_level3	0.0855***	0.0883***	-0.1482***	-0.1457***	0.1457***	0.1537***	0.1476***	-0.1518***
	(0.02143)	(0.02052)	(0.03321)	(0.03323)	(0.02439)	(0.02344)	(0.02675)	(0.02607)
School_level4	0.0729**	0.0760**	-0.1296***	-0.1269***	0.1801***	0.1834***	0.1645***	0.1699***
	(0.03438)	(0.03378)	(0.04212)	(0.04248)	(0.03505	(0.03436)	(0.03755)	(0.03674)
School_level2*Rural	-0.0306	-0.0320	0.0790	0.0745	-0.0978**	-0.0999**	-0.1508***	-0.1699***
	(0.02670)	(0.02654)	(0.04518)	(0.04554)	(0.03951)	(0.03931)	(0.05783)	(0.03574)
School_level3*Rural	-0.0947***	-0.0964***	-0.0221	0.0169	-0.1503***	0.1515***	-0.2456***	-0.2453***
	(0.03221)	(0.03189)	(0.04771)	(0.04803)	(0.04906)	(0.04881)	(0.05414)	(0.05383)
School_level4*Rural	-0.2362***	-0.2365***	-0.1632***	-0.1673***	-0.1503**	-0.1562**	-0.2964***	-0.2896***
	(0.04288)	(0.04241)	(0.05633)	(0.04906)	(0.05463)	(0.06065)	(0.08469)	(0.07953)
School_level2*Female	-0.1616***	-0.1623***	-0.0924***	-0.0937***	-0.0959***	-0.0964***	-0.0839**	-0.0831***
	(0.02071)	(0.02051)	(0.02961)	(0.02984)	(0.03393)	(0.03337)	(0.03684)	(0.03594)
School_level3*Female	-0.2776***	-0.2791***	-0.1517***	-0.1536***	-0.2160***	-0.2173***	-0.1927***	-0.1933***
	(0.02425)	(0.02402)	(0.02958)	(0.03004)	(0.03694)	(0.03634)	(0.03683)	(0.03801)
School_level4*Female	-0.3019***	-0.3042***	-0.2320***	-0.2052***	-0.2084***	-0.2107***	-0.1493***	-0.1481***
	(0.02881)	(0.02850)	(0.03140)	(0.03176)	(0.04205)	(0.04146)	(0.04843)	(0.04839)
atanh(ρ)	-0.1236***	-0.1251***	-0.3526***	-0.3570***	-0.1259***	-0.1279***	0.2038***	0.2117***
	(0.01566)	(0.01562)	(0.02859)	(0.02865)	(0.02901)	(0.02939)	(0.05072)	(0.05017)
Total observations	2,455,814		995,920		833,501		626,393	
Uncensored observations	1,405,478		531,322		635,977		305,081	

Clustered standard errors at the state level in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 4.C.2

Pooled probit coefficients on selection equation for *employment*

First stage for sample selection bias correction

Dependent variable:		*employed*		
Equation:		(4.3)		
Age threshold:	$12 \leq$ Age ≤ 97	$12 \leq$ Age ≤ 29	$30 \leq$ Age ≤ 49	Age ≥ 50
Period2	-0.0588***	-0.0857***	-0.0411***	-0.0439***
	(0.00712)	(0.00787)	(0.00953)	(0.00966)
Head	0.5722***	0.6086***	0.6382***	0.4189***
	(0.01439)	(0.02847)	(0.01675)	(0.01281)
Trend	0.0105***	0.0154***	0.0078***	0.0100***
	(0.00191)	(0.00211)	(0.00241)	(0.00238)
Female	-0.9946***	-1.0935***	-1.1491***	-0.9510***
	(0.03868)	(0.06355)	(0.04607)	(0.03235)
Age	0.1517***	0.5806***	0.0559***	-0.0781***
	(0.00264)	(0.01967)	(0.00749)	(0.00738)
Age^2	-0.0018***	-0.0104***	-0.0008***	0.0001*
	(0.00003)	(0.00042)	(0.00009)	(0.00005)
Rural	0.0246	0.2019***	-0.2245***	0.0666**
	(0.03297)	(0.05735)	(0.04072)	(0.02680)
School_level2	-0.0550**	0.0198	0.2994***	-0.1152***
	(0.02320)	(0.02471)	(0.02811)	(0.02458)
School_level3	0.2405***	0.0274	0.4726***	-0.1626***
	(0.02855)	(0.03374)	(0.03556)	(0.02876)
School_level4	0.1825***	-0.3513***	0.5701***	-0.0631*
	(0.03191)	(0.04212)	(0.03478)	(0.03414)
School_level2*Rural	-0.0079	-0.0652*	-0.0940***	-0.0181
	(0.02815)	(0.03880)	(0.03398)	(0.02591)
School_level3*Rural	-0.0818**	-0.2148***	-0.1248***	-0.0319
	(0.03458)	(0.04968)	(0.04372)	(0.03493)
School_level4*Rural	-0.0437	-0.1906***	0.0316	-0.0792
	(0.03727)	(0.06184)	(0.05463)	(0.05760)
School_level2*Female	0.1076***	0.1672***	-0.1207***	0.1083***
	(0.02678)	(0.04549)	(0.02810)	(0.02703)
School_level3*Female	0.0401	0.1904***	-0.1146***	0.1715***
	(0.03204)	(0.05534)	(0.03932)	(0.03113)
School_level4*Female	0.4571***	0.7083***	0.1809***	0.2571***
	(0.04090)	(0.06469)	(0.04184)	(0.03941)
Total observations	2,455,814	995,920	833,501	626,393

Clustered standard errors at the state level in parentheses.

Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 4.C.3

Pooled probit coefficients on informal employment
Second stage for sample selection bias correction

Dependent variable:	*informal*							
Age threshold:	$12 \leq$ Age ≤ 97		$12 \leq$ Age ≤ 29		$30 \leq$ Age ≤ 49		Age ≥ 50	
Equation:	(2.1a)	(2.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)
ZoneB*Period2	-0.0170	-0.0190	0.0138	0.0166	-0.0338***	-0.0390***	-0.0321**	-0.0351**
	(0.01397)	(0.01350)	(0.02163)	(0.02077)	(0.01267)	(0.01170)	(0.01310)	(0.01402)
ZoneB	-0.2097***	-0.2266***	-0.3203***	-0.3496***	-0.1919***	-0.2041***	-0.0923***	-0.0982***
	(0.05586)	(0.05639)	(0.07994)	(0.08039)	(0.05122)	(0.05218)	(0.03424)	(0.03585)
Period2	-0.0180***	-0.0165**	-0.0251**	-0.0808***	-0.0130	-0.0083	-0.013	-0.0103
	(0.00672)	(0.00650)	(0.01105)	(0.00782)	(0.00820)	(0.00751)	(0.00859)	(0.00892)
ZoneA*Period2		-0.0111		0.0262		-0.0330		-0.0199
		(0.02498)		(0.03044)		(0.03243)		(0.02090)
ZoneA		-0.1154		-0.2134**		-0.0804		-0.0386
		(0.08820)		(0.10615)		(0.08397)		(0.07635)
Trend	0.0036**	0.0037**	0.0015	0.0016	0.0022	0.0023	0.0095***	0.0095***
	(0.00163)	(0.00164)	(0.00060)	(0.00061)	(0.00203)	(0.00203)	(0.00201)	(0.00201)
Female	0.0640**	0.0620**	-0.2001**	-0.193***	-0.0040	-0.0074	0.0123	0.1039
	(0.02701)	(0.02811)	(0.08717)	(0.08077)	(0.04566)	(0.04792)	(0.03141)	(0.03237)
Age	-0.0339***	-0.0322***	-0.3299***	-0.3280***	0.0013	0.0018	0.0246***	0.0246***
	(0.00311)	(0.00331)	(0.02531)	(0.02577)	(0.00717)	(0.00726)	(0.00667)	(0.00660)
Age^2	0.0003***	0.0003***	0.0061***	0.0061***	-0.0001	-0.0001	-0.0002***	-0.0002***
	(0.00003)	(0.00003)	(0.00050)	(0.00051)	(0.00008)	(0.00009)	(0.00005)	(0.00005)
Rural	0.3927***	0.3839***	0.3050**	0.3061**	0.3716***	0.3638***	0.4067***	0.4025***
	(0.05100)	(0.05223)	(0.13998)	(0.13081)	(0.06111)	(0.06282)	(0.03921)	(0.04139)
School_level2	0.3446**	-0.3417***	-0.3614***	-0.3564***	-0.3369***	-0.3341***	-0.3965***	-0.3953***
	(0.02437)	(0.02376)	(0.03778)	(0.03623)	(0.02610)	(0.02544)	(0.02939)	(0.02950)
School_level3	-0.8106***	-0.8072***	-0.8612***	-0.8562***	-0.8392***	-0.8372***	-0.7931***	-0.7914***
	(0.03477)	(0.03521)	(0.05018)	(0.04996)	(0.03553)	(0.03592)	(0.03299)	(0.03341)
School_level4	-1.2648***	-1.2605***	-1.1684***	-1.1641***	-1.3523***	-1.3491***	-1.2615***	-1.2589***
	(0.04229)	(0.04243)	(0.05028)	(0.04876)	(0.04441)	(0.04471)	(0.04253)	(0.04276)
School_level2*Rural	0.0958	0.0944***	0.1701*	0.1559**	0.0831**	0.0810**	0.0884**	0.0884**
	(0.02361)	(0.02499)	(0.09541)	(0.08706)	(0.03692)	(0.03606)	(0.03565)	(0.03546)
School_level3*Rural	0.1580***	0.1563***	0.2843**	0.2665**	0.1418***	-0.1410***	0.1052**	0.1045**
	(0.04323)	(0.04285)	(0.12640)	(0.11525)	(0.04851)	(0.04844)	(0.04086)	(0.04079)
School_level4*Rural	0.0387	0.0381	0.1761	0.1601	-0.0272	-0.0271	-0.1155	-0.1151
	(0.05047)	(0.05062)	(0.13085)	(0.12061)	(0.06375)	(0.06432)	(0.07097)	(0.07122)
School_level2*Female	-0.0496***	-0.0496**	0.0558	0.0489	-0.0234	-0.0233	0.0038	-0.0032
	(0.02373)	(0.02379)	(0.07584)	(0.07089)	(0.03200)	(0.03211)	(0.02588)	(0.02626)
School_level3*Female	-0.0943***	-0.0947***	0.0818	0.0735	-0.0143	-0.0134	-0.1098***	-0.1091***
	(0.02669)	(0.02664)	(0.07567)	(0.07049)	(0.03993)	(0.03995)	(0.03379)	(0.03398)
School_level4*Female	-0.1610***	-0.1609***	0.1006	0.0925	-0.1037**	-0.1023**	-0.1859***	-0.1851***
	(0.02757)	(0.02772)	(0.08226)	(0.07622)	(0.04517)	(0.04594)	(0.03240)	(0.03302)
atanh(ρ)	0.4180***	0.4229***	0.4832***	0.4860***	0.4269***	0.4317***	0.5372***	0.5407***
	(0.02132)	(0.02261)	(0.04024)	(0.04118)	(0.03444)	(0.03781)	(0.03383)	(0.03501)
Total observations	2,386,516		957,436		810,581		618,499	
Uncensored observations	1,336,180		426,114		612,879		326,846	

Clustered standard errors at the state level in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 4.C.4

Pooled probit coefficients on selection equation for informal employment

First stage for sample selection bias correction

Dependent variable:	*informal*			
Equation:	(4.3)			
Age threshold:	$12 \leq$ Age ≤ 97	$12 \leq$ Age ≤ 29	$30 \leq$ Age ≤ 49	Age ≥ 50
Period2	-0.0554***	-0.0808***	-0.0391***	-0.0420***
	(0.00715)	(0.00782)	(0.00957)	(0.00944)
Head	0.5846***	0.6307***	0.6457***	0.4243***
	(0.01428)	(0.02862)	(0.01666)	(0.01263)
Trend	0.0096***	0.0143***	0.0069***	0.0095***
	(0.00196)	(0.00217)	(0.00243)	(0.00235)
Female	-0.9877***	-1.0964***	-1.1383***	-0.9349***
	(0.03904)	(0.06358)	(0.04626)	(0.03277)
Age	0.1530***	0.5606***	0.0566***	-0.0787***
	(0.00269)	(0.01942)	(0.00769)	(0.00749)
Age^2	-0.0018***	-0.0099***	-0.0008***	0.0001**
	(0.00003)	(0.00042)	(0.00009)	(0.00005)
Rural	0.0340	0.2206***	-0.2124***	0.0755***
	(0.03360)	(0.05863)	(0.04065)	(0.02705)
School_level2	-0.0562**	0.0125	0.3009***	-0.1141***
	(0.02341)	(0.02499)	(0.02896)	(0.02508)
School_level3	0.2298***	0.0098	0.4761***	-0.1618***
	(0.02870)	(0.03379)	(0.03637)	(0.02919)
School_level4	0.1678***	-0.3749***	0.5733***	-0.0596*
	(0.03311)	(0.04339)	(0.03582)	(0.03508)
School_level2*Rural	-0.0001	-0.0575	-0.0927***	-0.0179
	(0.02833)	(0.04002)	(0.03426)	(0.02621)
School_level3*Rural	-0.0748**	-0.2038***	-0.1292***	-0.0355
	(0.03475)	(0.05092)	(0.04369)	(0.03406)
School_level4*Rural	-0.0513	-0.1996***	0.0334	-0.0847
	(0.03796)	(0.06351)	(0.05539)	(0.05726)
School_level2*Female	0.1056***	0.1630***	-0.1233***	0.1088***
	(0.02688)	(0.04583)	(0.02850)	(0.02734)
School_level3*Female	0.0374	0.1831***	-0.1184***	0.1717***
	(0.03219)	(0.05546)	(0.03993)	(0.03120)
School_level4*Female	0.4559***	0.7078***	0.1803***	0.2550***
	(0.04123)	(0.06526)	(0.04185)	(0.04013)
Total observations	2,386,516	957,436	810,581	618,499

Clustered standard errors at the state level in parentheses.

Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 4.C.5

Pooled probit coefficients of the dynamics of the effect on labour status

Second stage for sample selection bias correction

Dependent variable:	*Employed*		*informal*		*waged_informal*		*self_emp_informal*	
Specification:	(4.1a)	(4.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)	(4.1a)	(4.1b)
ZoneB*D2013_Q1	0.0120	0.0182	-0.0181	-0.0192	-0.0156	-0.0162	-0.0267	-0.0274
	(0.02784)	(0.02755)	(0.02394)	(0.02400)	(0.02104)	(0.02108)	(0.02186)	(0.02201)
ZoneB*D2013_Q2	0.0225**	0.0264**	-0.0211***	-0.0225***	-0.0441***	-0.0437***	-0.0070	-0.0109
	(0.01136)	(0.01188)	(0.00622)	(0.00692)	(0.00883)	(0.00833)	(0.01423)	(0.01519)
ZoneB*D2013_Q3	0.0245	0.0249	-0.0194	-0.0236	-0.0271	-0.0309	-0.0155	-0.0202
	(0.02070)	(0.02137)	(0.02420)	(0.02365)	(0.02710)	(0.02619)	(0.01960)	(0.01947)
ZoneB*D2013_Q4	0.0245	0.0320	0.0063	0.0034	-0.0023	-0.0076	0.0137	0.0151
	(0.02239)	(0.02298)	(0.01914)	(0.01750)	(0.02291)	(0.02079)	(0.01827)	(0.01768)
ZoneB	-0.0511**	-0.0699***	-0.2102***	-0.2268***	-0.2232***	-0.2353***	-0.1475***	-0.1664***
	(0.02113)	(0.02162)	(0.05537)	(0.05588)	(0.05693)	(0.05759)	(0.05410)	(0.05539)
D2013_Q1	0.0193	0.0132	-0.0159***	-0.0151***	-0.0581***	-0.0524***	0.0566***	0.0576***
	(0.01227)	(0.01130)	(0.00635)	(0.00564)	(0.00701)	(0.00660)	(0.00809)	(0.00776)
D2013_Q2	0.0052	0.0015	-0.0069	-0.0056	-0.0649***	-0.0656***	0.0884***	0.0926***
	(0.01135)	(0.01149)	(0.00753)	(0.00792)	(0.00844)	(0.00844)	(0.01135)	(0.01263)
D2013_Q3	-0.0120	-0.0123	-0.0098	-0.0059	-0.0829***	-0.0796***	0.1075***	0.1125***
	(0.01471)	(0.01530)	(0.01041)	(0.01005)	(0.01168)	(0.01098)	(0.01295)	(0.01350)
D2013_Q4	0.0480***	0.0407**	-0.0175	-0.0147	-0.0987***	-0.0939***	0.1035***	0.1026***
	(0.01595)	(0.01618)	(0.01171)	(0.01106)	(0.01212)	(0.01102)	(0.01843)	(0.01825)
ZoneA*D2013_Q1		0.0399		-0.0065		-0.0037		-0.0043
		(0.03212)		(0.01939)		(0.02391)		(0.01862)
ZoneA*D2013_Q2		0.0275		-0.0057		0.0058		-0.0242
		(0.02428)		(0.01560)		(0.02141)		(0.01726)
ZoneA*D2013_Q3		0.0056		-0.0253		-0.0226		-0.0289
		(0.01955)		(0.03147)		(0.03855)		(0.02621)
ZoneA*D2013_Q4		0.0506**		-0.0157		-0.0331		0.0163
		(0.02177)		(0.03564)		(0.04034)		(0.03152)
ZoneA		-0.1201***		-0.1136		-0.0815		-0.1271
		(0.03185)		(0.08837)		(0.08835)		(0.09239)
Trend	-0.0067**	-0.0067**	0.0016	0.0025	0.0162***	0.0162***	-0.0177***	-0.0179***
	(0.0033)	(0.00331)	(0.00182)	(0.00183)	(0.00172)	(0.00171)	(0.00307)	(0.00309)
Female	0.3239***	0.3261***	0.0393	0.0366	0.1310***	0.1295***	0.2469***	0.2466***
	(0.03489)	(0.03468)	(0.02716)	(0.02857)	(0.02976)	(0.03070)	(0.04800)	(0.04878)
Age	0.0269***	0.0271***	-0.0285***	-0.0286***	-0.0476***	-0.0469***	0.0236***	0.0240***
	(0.00209)	(0.00211)	(0.00309)	(0.00333)	(0.00394)	(0.00412)	(0.00440)	(0.00455)
Age^2	-0.0001***	-0.0001***	0.0003***	0.0002***	0.0003***	0.0003***	-0.0001***	-0.0001***
	(0.00002)	(0.00002)	(0.00003)	(0.00003)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Rural	0.2935***	0.2854***	0.3929***	0.3841***	0.1603***	0.1545***	0.5608***	0.5508***
	(0.04750)	(0.04677)	(0.05072)	(0.05190)	(0.05880)	(0.05810)	(0.06330)	(0.06330)
School_level2	0.0775***	0.0803***	-0.3415***	-0.3384***	-0.3447***	-0.3421***	-0.3953***	0.0116
	(0.02141)	(0.01679)	(0.02489)	(0.02324)	(0.02041)	(0.01969)	(0.06331)	(0.06510)
School_level3	0.0856***	0.0883***	-0.8005***	-0.7969***	-0.8200***	-0.8167***	-0.8412***	-0.8378***
	(0.02141)	(0.02050)	(0.03541)	(0.03589)	(0.03267)	(0.03353)	(0.05010)	(0.05010)
School_level4	0.0730**	0.0761**	-1.2521***	-1.2475***	-1.2271***	-1.2225***	-1.2676***	-1.2631***
	(0.03436)	(0.03376)	(0.04378)	(0.04399)	(0.04328)	(0.04391)	(0.06678)	(0.06724)
School_level2*Rural	-0.0305	-0.0320	0.0944***	0.0929***	0.1513***	0.1497***	0.0772**	0.0753**
	(0.02668)	(0.02653)	(0.02569)	(0.02506)	(0.02940)	(0.02905)	(0.03359)	(0.03318)
School_level3*Rural	-0.0945**	-0.0961***	0.1550***	0.1532***	0.2606***	0.2585***	0.0439	0.0426
	(0.03217)	(0.03184)	(0.04278)	(0.04235)	(0.04892)	(0.04892)	(0.04361)	(0.04342)
School_level4*Rural	-0.2361**	-0.2363***	0.0357	0.0351	0.2606***	0.1528***	0.1382***	0.1379***
	(0.04287)	(0.04241)	(0.04984)	(0.04997)	(0.04934)	(0.05473)	(0.05760)	(0.05835)
School_level2*Female	-0.1618***	-0.1624***	-0.0440*	-0.0440*	0.1544***	-0.0968***	-0.0631***	0.0634***
	(0.02068)	(0.02049)	(0.02378)	(0.02390)	(0.05498)	(0.05498)	(0.02684)	(0.02677)
School_level3*Female	-0.2778***	-0.2793***	-0.0830**	-0.0831**	-0.1897***	-0.1904	-0.0849***	-0.0860***
	(0.02421)	(0.02399)	(0.02690)	(0.02693)	(0.02627)	(0.02589)	(0.03903)	(0.03912)
School_level4*Female	-0.3023***	-0.3047***	-0.1398***	-0.1391***	-0.2600***	-0.2600***	-0.2565***	-0.2579***
	(0.02880)	(0.02848)	(0.02804)	(0.02841)	(0.02678)	(0.02667)	(0.04477)	(0.04490)
atanh(ρ)	-0.1248***	-0.1263***	0.4679***	0.4739***	0.3394***	0.3446***	0.1146***	0.1179***
	(0.01571)	(0.01568)	(0.02241)	(0.02404)	(0.02963)	(0.03141)	(0.04122)	(0.04255)
Total observations	2,455,814		995,920		833,501		626,393	
Uncensored observations	1,405,478		531,322		635,977		305,081	

Note: the covariates included are gender, age, squared age, schooling level, rural, and interactions of schooling level with rural and gender.
Clustered standard errors at the state level in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 4.C.6

Pooled probit coefficients on selection equation for the dynamics of the effect on labour status
First stage for sample selection bias correction

Dependent variable:	*Employed*	*informal*	*waged_informal*	*self_emp_informal*
Specification:	(4.1b)	(4.1b)	(4.1b)	(4.1b)
D2013_Q1	-0.0478***	-0.0394***	-0.0489***	0.0208***
	(0.00683)	(0.00712)	(0.00583)	(0.00358)
D2013_Q2	-0.0145*	-0.0122	-0.0472***	0.0523***
	(0.00776)	(0.00777)	(0.00696)	(0.00587)
D2013_Q3	-0.0228***	-0.0239***	-0.0681***	0.0572***
	(0.00714)	(0.00756)	(0.00690)	(0.00667)
D2013_Q4	-0.0118	-0.0024	-0.0548***	0.0769***
	(0.00994)	(0.00985)	(0.01047)	(0.00822)
Head	0.5722***	0.5440***	0.3939***	0.4385***
	(0.01439)	(0.01251)	(0.01075)	(0.00904)
Trend	0.0030	0.0016	0.0096***	-0.0119***
	(0.00214)	(0.00228)	(0.00194)	(0.00149)
Female	-0.9946***	-0.9187***	-0.6599***	-0.6602***
	(0.03868)	(0.03799)	(0.01658)	(0.02906)
Age	0.1517***	0.1448***	0.1252***	0.1337***
	(0.00264)	(0.00242)	(0.00195)	(0.00156)
Age^2	-0.0018***	-0.0017***	-0.0016***	-0.0014***
	(0.00003)	(0.00003)	(0.00002)	(0.00002)
Rural	0.0250	0.0510	-0.3182***	0.0730**
	(0.03297)	(0.03224)	(0.05133)	(0.03241)
School_level2	-0.0550**	-0.0501**	0.0872***	0.0116
	(0.02321)	(0.02324)	(0.01346)	(0.02042)
School_level3	0.2405***	0.1924***	0.3848***	0.3755***
	(0.02855)	(0.02713)	(0.01765)	(0.02971)
School_level4	0.1825***	0.1315***	0.5105***	0.6057***
	(0.03193)	(0.03365)	(0.02063)	(0.02258)
School_level2*Rural	-0.0079	-0.0020	0.0415*	-0.1861***
	(0.02819)	(0.02728)	(0.02267)	(0.02218)
School_level3*Rural	-0.0820**	-0.0688**	0.0403	0.-0.3668***
	(0.03459)	(0.03273)	(0.03578)	(0.03456)
School_level4*Rural	-0.0438	-0.0570	0.1055**	-0.3016***
	(0.03729)	(0.03651)	(0.04153)	(0.03641)
School_level2*Female	0.1076***	0.1058***	0.0162	0.1355***
	(0.02677)	(0.02390)	(0.01479)	(0.01944)
School_level3*Female	0.0401	0.1057***	-0.0186	0.1557***
	(0.03204)	(0.02604)	(0.01616)	(0.02772)
School_level4*Female	0.4571***	0.4700***	0.2790***	0.3980***
	(0.04090)	(0.04013)	(0.01672)	(0.03063)
Total observations	2,455,814	995,920	833,501	626,393

Clustered standard errors at the state level in parentheses.
Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

CHAPTER 5

USING A SYNTHETIC CONTROL METHOD TO VERIFY THE EMPLOYMENT EFFECTS OF THE 2012 MEXICAN MINIMUM WAGE INCREASE

5.1 Introduction

This chapter re-evaluates the employment effects of the 2012 minimum wage increase in Mexico by the implementation of the Synthetic Control Method (SCM) procedure. The objective of the chapter is to test the robustness of our previous Difference in Differences estimates by implementing the data-driven SCM introduced by Abadie et al. (2010). In the minimum wage literature, the SCM has gained attention, especially after Jardim et al. (2017) and Reich et al. (2017). These studies found opposite employment effects when analysing exactly the same 2015/2016 minimum wage hikes in Seattle. Adopting their methodological procedure in this chapter, we corroborate our previous results in this thesis. Our estimates suggest that the change in Zone B's minimum wage had an insignificant impact on the active labour market participation, but show evidence of a small and significant positive effect on the employment rate. Regarding employment under informal conditions, we do not find any statistical evidence of significant effects on the informal employment rate.

Like the Differences in Differences estimator, the SCM exploits the dissimilarities between treated and untreated regions. But, the most attractive feature of the synthetic control approach is that, instead of giving the same weight to all the untreated units that are part of the control group, it constructs a weighted average control that matches the treated regions in the preintervention period. Subsequently, it projects the outcome of the synthetic group to the post-treatment period to estimate the treatment effect. In other words, it just generates the counterfactual — by using the actual observations of the untreated region — that replicates the outcome trend of the treated group. After this, the treatment effect is estimated by simply measuring the difference in the outcome variable between the treated group and its synthetic counterpart.

By its simplicity and transparency, the SCM has become very popular in the impact evaluation literature. It has been widely used in areas not related to minimum wages. The two most seminal examples of its implementation looked at the economic effects of conflict in the Basque Country (Abadie and Gardeazabal, 2003) and the impact of California's tobacco program in 1988 (Abadie et al., 2010). In both studies, there was one single treated region (Basque Country and California, respectively), and the rest of regions in Spain and in the United States, respectively, constituted potential donor regions to construct the synthetic counterfactual.

The SCM offers several methodological advantages. Possibly the most important is that it does not require the same rigid assumptions for estimating treatment effects as Difference in Differences (McClelland and Gault, 2017); parallel pretreatment trends are not necessary if it is actually possible to replicate the treated outcome itself. Moreover, the SCM is transparent as it evinces how well the matching process works by making explicit the similarities —or lack thereof— between these groups (Abadie et al., 2010).

In the field of minimum wages, some papers have also implemented this technique (Jardim et al., 2017; Reich et al., 2017; Powell, 2017; Dube and Zipperer, 2015; Sabia et al., 2012) finding mixed results on the direction of the employment effects. The following section describes in detail the context and the main findings of these evaluations.

The objective of this chapter is to test the robustness of our Difference in Differences findings by changing the estimation method, and also the data used by the requirements of the SCM. These requirements are related to the use of aggregate-level data and to the need for many pretreatment periods to construct the weighted average from the potential donor regions. We therefore, use of 57 metropolitan areas instead of individual-level data, and extend the pretreatment start period from 2005Q1 to 2012Q3.

The reason for data aggregation at the metropolitan area level is two-fold. The first is that analysing in excess of ten million individuals by the SCM is computationally prohibitive. Most past studies have contained just one treated area and no more than forty control areas. In our analysis we use five treated areas and 52 control areas. The second reason is that individuals are only observed five times in a 12 month interval so aggregating the data into regions allows us to extend the data further back in time.

Alternative levels of aggregation we considered but proved unfeasible. Aggregation by minimum wages zones created only two donor zones (A and C), making it difficult to construct a weighted average that performed well as a synthetic control group for Zone B. Aggregation at the state level was not an option either given that Mexico's minimum wage zones classification are at municipal level and these do not coincide with the state boundaries. Thus, we aggregated the data from ENOE at the metropolitan area level following the classification by the Mexican National Council on Population (CONAPO). As a result of this process, we have the five treated metropolitan areas and 52 untreated potential donor areas discussed above.

This classification is particularly attractive for our impact evaluation purposes. As minimum wage zones are classified by the level of economic development of the municipalities, a metropolitan area delimitation actually considers the economic development features of each municipality. As a consequence, this aggregation leaves out rural municipalities that are more likely to be different to the treated units thus improving the quality of the synthetic control groups.

So, this chapter evaluates the same 2012 minimum wage policy change, but using a SCM approach. Data are aggregated at the metropolitan area level and the analysis period corresponds to 2005Q1-2012Q4. In general, the SCM results corroborate our earlier findings that zone's B minimum wage intervention did not have adverse effects on employment.

The rest of the chapter is organised as follows. The next section reviews the literature by focusing on previous studies that have evaluated minimum wage interventions using the SCM. The model proposed by Abadie et al. (2010) is discussed in Section 5.3. The data, including aggregation to the metropolitan level, as well as the outcome variables, are described in Section 5.4. Section 5.5 presents the results and some robustness checks. Section 5.6 concludes the chapter.

5.2 Literature review

In the first four chapters of this thesis we have discussed theoretical and empirical contributions in the literature on the employment effects of minimum wage increases, this section reviews exclusively those studies using as method of estimation the SCM. We start by describing the two papers evaluating the minimum wage increases in Seattle that motivated the idea of this chapter.

In June 2014, the City of Seattle passed a Minimum Wage Ordinance, which gradually increased the minimum wage within Seattle City boundaries. In the first stage (on April 1, 2015) the minimum wage rose from the state's $9.47 minimum to $11.00. In the second stage, it reached $13.00 (on January 1, 2016).[1] As mentioned before, Jardim et al. (2017) and Reich et al. (2017) released separate evaluations of this minimum wage intervention finding opposite results even though they used the same methodological approach: the SCM.

The main difference between these two papers is the data source and the potential donor counties for the synthetic control group. Jardim et al. (2017) used quarterly administrative employment data from Washington State for the period 2005-2016, collected by the Washington's Employment Security Department.[2] The authors argued that one of the

[1] In a third stage, minimum wage will reach $15.00 in 2021 in all sectors.

[2] It is relevant to highlight that one important limitation of the analysis is that it is restricted to firms reporting employment at specific locations. They cannot properly locate employment for multi-location firms that do not report employment separately by location (to construct the synthetic control group). Single-site businesses comprise 89% of firms and employ 62% of the entire workforce in Washington State.

advantages of the dataset is that it contained information on earnings and hours worked, which allowed them to estimate directly a threshold for the low-wage workers affected by minimum wage changes. They focused on jobs with calculated hourly wages below a fixed threshold. The main argument was that including in the analysis those workers not affected by minimum wage regulations (at the top of the distribution) underestimated the effects. But, a very low threshold could overstate employment reductions if there are workers with actual wage increases above it. To identify a fixed point, above which there does not appear to be any impact, a series of Difference in Differences and synthetic control models are estimated at average wages in bins of width $1, up to the $39-40/hour level. The threshold of low-wage positions was set at $19. Thus, constructing a synthetic control group using potential donor counties only within the State of Washington, their core finding is that minimum wage rises reduced hours worked in low-wage jobs by around 9%.[3] The effect on the number of jobs is weaker. Synthetic control estimates fail to find significant effects for the first minimum wage increase.

On the other hand, Reich et al. (2017) focused the analysis on the Seattle food services industry using county and city-level data from 2009 to 2016 on all employees counted in the Quarterly Census of Employment and Wages (QCEW). In contrast to Jardim et al. (2017), to generate the synthetic control group Reich, Allegretto and Godoey used more similar counties to Seattle (in terms of population size and minimum wage institutions) from all the states in the US, not only from Washington State. They did not find statistical evidence of any adverse effects on employment in food services industry. Authors emphasized that employment was not affected even among the limited-service restaurants (many of them franchisees), for whom the policy was most binding.

Reich et al. (2017) emphasized that this policy brief is part of the evaluation process of the minimum wage policy change in Seattle. So, future reports are expected as the city's $15 policy continues to phase in.

These are not the only studies that have used the SCM to estimate the minimum

[3] A zero effect is estimated when analyzing employment only in the restaurant industry at all wage levels, comparable to prior studies, including Reich et al. (2017)

wage employment effects. Sabia et al. (2012) evaluated the minimum wage increase in the state of New York, which set the minimum wage from \$5.15 in 2014, to \$6.00 in 2005 and to \$6.75 in 2006. This constitutes the first attempt to implement synthetic control method into the minimum wage literature. From a pool of 25 donor states, they estimated an atypically large 7.9% reduction in employment for individuals between 16 and 29 years old. Nevertheless, it is important to emphasize that they failed to construct a valid synthetic control group, for the preintervention period. They explicitly said that the pretreatment trend for the synthetic control state is remarkably similar to that observed for the geographically proximate comparison states, but it is actually different from the treated New York state, which is the key objective of this procedure. One plausible reason of this discrepancy with respect to the treated group is the non inclusion of employment lags within the set of predictor variables. As Dube and Zipperer (2015) stated, some combination of preintervention outcomes should be included. Indeed, more recent discussion in the literature is about the pertinence of not including all the set of outcome lags (Kaul et al., 2015), taking for granted the inclusion of some of them.

Dube and Zipperer (2015) also carried out synthetic control procedures to evaluate the effect of 29 cases of state minimum wage increases over the period 1979-2013 in the United States. They found a persistent small effect, not statistically different from zero, on teen employment. They report that the mean effect of the 29 interventions was equal to -0.051, for which 17 out of the 29 cases had a negative effect. Since the SCM requires a set of untreated donor states for every intervention, to maximise the number of treated events and their respective potential donor units, Dube and Zipperer (2015) restricted their analysis to only 29 minimum wage state variations (out of 215 in that period) including only states with no minimum wage changes two years prior to treatment and with data available at least 1 year after the minimum wage change. Regarding the details of the construction of their pooled estimator, given that the magnitude of the minimum wage interventions is not constant, they converted estimates to elasticities considering the size of the minimum wage variation. They subsequently pooled these elasticities and used their ranks to construct the confidence interval to state the statistical significance of the one single aggregated estimator. Their results are not affected when they limit the case studies to those with better pretreatment fit.

Finally, Powell (2017) proposed a generalisation of the synthetic control method to estimate treatment effects for multiple treatment events. Implementing this procedure for a similar period used by Dube and Zipperer (2015) (1979-2014), but considering all the observed minimum wage changes at the state level, he found negative employment effects (for workers aged between 16 and 19) with an elasticity around -0.44. A motive of concern in this study is the fact that preintervention and post-intervention periods may be overlapping.

In summary, like in the minimum wage effects field in general, the use of the SCM does not offer a consensus on the employment impact of minimum wage increases. On the one hand, Dube and Zipperer (2015) and Reich et al. (2017) found nonnegative effects on employment, while Jardim et al. (2017), Powell (2017), and Sabia et al. (2012) estimated a reduction in the level of employment. This chapter presents an evaluation of a minimum wage increase out of the US labour market, but finding coincidences with Dube and Zipperer (2015) and Reich et al. (2017) regarding the lack of statistical evidence on a reduction in the level of employment as a consequence of a minimum wage increase.

5.3 Methodology: Synthetic Control Method

5.3.1 The model

The SCM is a data-driven procedure used in small-sample comparative case studies to estimate treatment effects (Galiani and Quistorff, 2017). If there exists a policy change in which only some specific regions or zones are affected by the intervention, this approach simulates the outcome path of the treated region under the counterfactual scenario in which it did not experience the policy intervention. This counterfactual is generated by the calculation of a weighted average of the unaffected regions (pool of donors) in the pretreatment period. If the synthetic control group is able to match closely the trend in the treated region, the treatment effect is just estimated by the difference in outcomes between treated region and its hypothetical counterfactual.

The key assumptions for implementing the SCM approach are similar to any method aiming at evaluating comparative case studies. First, the policy intervention is unable to affect the outcome in the non-treated regions. Second, there must not be any other similar interventions in the set of unaffected regions affecting the outcome variables. And third, the intervention has no anticipated effects. Moreover, an effective use of the SCM approach requires an additional assumption to hold. The treated regions' counterfactual outcome can be approximated by a fixed combination of donor regions (McClelland and Gault, 2017).

The general motivation of the model, and even the nomenclature of its components, seem similar to that found in statistical matching literature. For instance, both approaches use a pool of donor regions to construct the counterfactuals. Although the goal is to construct an adequate control group to estimate treatment effects, there is a fundamental difference. The Propensity Score Method matches units in control and treatment groups, while the SCM creates a match for the aggregated treated group. That is, the synthetic control counterpart is constructed at the aggregate level following a factor model, instead of generating a propensity score index to match units at the individual level.

To describe the model, we will follow the notation by Abadie et al. (2010), but incorporate as the unit of analysis metropolitan areas instead of the generic 'regions'. We start by assuming that there are $J + 1$ observed metropolitan areas. Without loss of generality, suppose also that only the first metropolitan area is exposed to the minimum wage intervention, so that we have J remaining metropolitan areas as potential controls.

Let Y_{it}^{N} be the employment outcome (which in our specific case corresponds to the active labour market rate, employment rate or informality rate) that would be observed for metropolitan area i at time t in the absence of the intervention for units $i = 1, ..., J+1$, in time periods $t = 1, ..., T$.

To identify the period in which the policy change takes place, we denote T_0 as the number of preintervention periods, with $1 \leq T_0 < T$.

Let Y_{it}^I be the employment outcome that would be observed for metropolitan area i at time t if this area i is exposed to the policy change in periods from $T_0 + 1$ to T. Following the assumption explained above, the minimum wage increase has no effect before the implementation period. Then, for $t \in \{1, ..., T_0\}$ and all $i \in \{1, ..., N\}$, we have that $Y_{it}^N = Y_{it}^I$

Let α_{it} be the effect of the policy change for metropolitan area i at time t. And let D_{it} be an indicator variable, which takes the value of one if metropolitan area i receives treatment at time t, and zero otherwise.

The observed outcome for unit i at time t is:

$$Y_{it} = Y_{it}^N + \alpha_{it} D_{it}$$

Regarding the indicator variable D_{it}, we have assumed that the only metropolitan area subject to treatment is the metropolitan area 1, so D_{it} will be equal to one for this metropolitan area and only after period T_0. Formally,

$$D_{it} = \begin{cases} 1 & \text{if } i = 1 \text{ and } t > T_0 \\ 0 & \text{otherwise} \end{cases}$$

Thus, the target is to estimate $(\alpha_{1T_0+1}, ..., \alpha_{1T})$. For $t > T_0$,

$$\alpha_{1t} = Y_{1t}^I - Y_{1t}^N$$

Given that the outcome for the treated metropolitan area 1 is actually observed, to estimate the treatment effect, α_{1t}, we just have to estimate Y_{1t}^N. To do so, suppose that Y_{it}^N is given by a factor model:

$$Y_{it}^N = \delta_t + \theta_t \mathbf{Z}_i + \lambda_t \mu_i + \epsilon it, \tag{5.1}$$

where δ_t is an unknown common time factor with constant factor loadings across units, $\mathbf{Z}_i$ is a $(r \times 1)$ vector of observed covariates unaffected by treatment, and θ_t corresponds to its associate $(1 \times r)$ vector of unknown parameters. λ_t is a $(1 \times F)$ vector of unobserved common factors, μ_i is an $(F \times 1)$ vector of unknown factor loadings, and ϵ_{it} are unobserved transitory shocks at the metropolitan area level with zero mean.

If we were able to observe the true factor loadings, μ_i, we could generate an unbiased control for μ_1 by using the untreated metropolitan areas whose factor loadings' weighted average is equal to μ_1. Since μ_1 is unobserved, the SCM generates a vector of weights $\mathbf{W}$ over J donor areas, such that the weighted combination of donor metropolitan areas closely matches the outcome trend of the treated area in preintervention units (Dube and Zipperer, 2015).

As Abadie et al. (2010) highlight, notice that equation (5.1) generalises the traditional fixed-effects Difference in Differences model, which imposes that λ_t is constant for all t.

5.3.2 Implementation of the Synthetic Control Method

To implement this model, let $\mathbf{W}$ be $(J \times 1)$ a vector of positive weights that sum to one. That is, $\mathbf{W} = [w_2, ..., w_{J+1}]'$, with $w_J \geq 0$ for each of the untreated metropolitan areas $j = 2, ..., j + 1$ and $w_2 + ... + w_{J+1} = 1$. Each weighted average of the available control metropolitan areas, $\mathbf{W}$, constitutes a synthetic control group.

To generate a synthetic group as similar as possible to the treated group, it is also necessary to incorporate the $(r \times 1)$ vector of preintervention characteristics unaffected by the policy change $\mathbf{Z}_i$, and a $(T_0 \times 1)$ vector $\mathbf{K} = [k_1, ..., k_{T_0}]'$, which defines a linear combination of preintervention outcomes: $\bar{Y}_i^{\mathbf{K}} = \sum_{s=1}^{T_0} k_s Y_{is}$. Vector $\mathbf{K}$ just weights the relevance of any pretreatment outcome variables. For example, if it is considered that the only preintervention period relevant to the employment outcome is the period immediately before the policy change, then $0 = k_1 = k_2 = ... = k_{T_0-1}$ and $k_{T_0} = 1$, so $\bar{Y}^{\mathbf{K}} = k_{T_0}$. Consider M of such linear combinations defined by the vectors $\mathbf{K}_1, ..., \mathbf{K}_M$.

For the treated metropolitan area, let $\mathbf{X}_1 = [\mathbf{Z}_1', \bar{Y}_1^{\mathbf{K}}, ..., \bar{Y}_{T_0}^{\mathbf{K}}]'$ be a $(r \times 1)$ vector of preintervention characteristics, for which $k = r+M$. In the same way, we define the $(k \times J)$ matrix $\mathbf{X}_0$ that contains the same variables for the J donor metropolitan areas. The SCM chooses donor weights $\mathbf{W}$ to minimize the distance between pretreatment characteristics $\mathbf{X}_1$ and $\mathbf{X}_0$ of the treated and untreated metropolitan areas. Given the optimal weights $\mathbf{w}_j^*$ for each of the $j = 2, ..., J+1$ donors, the synthetic control at period t is just the weighted combination of the respective employment outcome variable $\sum_{j=2}^{J+1} \mathbf{w}_j^* Y_{jt}$ (Dube and Zipperer, 2015).

Therefore, the estimation of the impact of the minimum wage increase is the difference between the outcome variable in the treated metropolitan area Y_{1t} and the synthetic area $\sum_{j=2}^{J+1} \mathbf{w}_j^* Y_{jt}$ at every post-treatment period $t > T_0$:

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} \mathbf{w}_j^* Y_{jt}$$

Regarding the decisions that the researcher has to make to accurately implement the SCM, it is worth to mention that so far there is no much information in the literature about how to choose the variables to include in the vector of preintervention characteristics, $\mathbf{Z}$, neither on the linear combination of preintervention outcomes, $\mathbf{K}$. McClelland and Gault (2017) wrote an interesting research report on the practical details of implementating the SCM. They recommended that the covariates of characteristics must exhibit similar values for the treated group and for the pool of donors, while the values for the treated region cannot be outside any linear combination of the values for the donor pool. Also, these covariates and the outcome must have at least an approximate linear relationship. Following this set of suggestions, we include the following covariates: the proportion of workers aged between 30 and 49 by metropolitan area, the proportion of workers who completed the second level of education in Mexico (9th year), as well as the proportion of workers in the industrial and services sector (see Table5.2 in Section 5.3).

The inclusion of pretreatment outcome variables is also relevant in the model. Using lagged outcome variables as a predictors may help to avoid the problem of omitting important covariates in the **Z** vector. For this reason, researchers may be tempted to include the full set of pretreatment outcome variables in vector **K**. In that case, $k_1 = k_2 = ... = k_{T_0} = 1/T_0$ then, $\bar{Y}^{\mathbf{K}}$ is just the simple average of the outcome variable in the pretreatment period, $\bar{Y}^{\mathbf{K}} = k_{T_0}^{-1} \sum_{s=1}^{T_0} k_s Y_{is}$ (Abadie et al., 2010). Nevertheless, as Abadie et al. (2010) and Kaul et al. (2015) have pointed out, if all the available lagged outcome variables are included in the model, it makes irrelevant to the analysis the inclusion of the set of covariates **Z**. We examined how the synthetic control group behaved when including different sets of pretreatment outcome variables allowing up to 10 lagged dependent variables. In our preferred specification, we include the lag values corresponding to 2012Q3 (the quarter immediately before the minimum wage increase) and the lag values corresponding to 2007Q3.

Given that there are different decisions in hands of the researchers on how to implement the method, it is important to highlight that in order to provide consistency to our implementation of the model, vectors **K** and **Z** are exactly the same independently of the outcome variable under examination.

5.3.3 Inference and multiple treated metropolitan areas

An additional challenge of the SCM is to determine if the estimated treatment effects are statistically significant. Usual inferential techniques for large sample studies with individual data are not applicable for small sample aggregated data. Abadie et al. (2010) proposed some inferential techniques, similar to permutation tests in order to carry out the inferential analysis.

Permutation tests are actually performed as placebo tests. The process is the following. The same model is estimated on each metropolitan area of the pool of donors, taking each of them as an 'artificial' treated unit. After a permutation of all the potential control metropolitan areas, it is possible to obtain a distribution of the placebo effects. Then, it is possible to compare the magnitude of the treatment effect with respect to the estimated effect on a random metropolitan area. In other words, we are able to know the exact location of the estimate in the distribution of the placebo effects. Following Galiani and Quistorff (2017), if the distribution of placebo effects yields many effects as large as the actual estimate of interest, then it is likely that the estimated effect was observed by chance.

This test offers several advantages. Abadie et al. (2010) argued that it is exact in the sense that, it is always possible to construct the distribution of the placebo effects independently of the number of potential donors, periods of analysis, and the use of individual or aggregated data. Moreover, the test does not impose any particular distribution on the errors.

Finally, to relax the assumption that only one metropolitan area is exposed to the treatment, we follow the extension by Cavallo et al. (2013), which allowed the implementation of the SCM approach for more than one treated region (not necessarily simultaneously). If we index treated metropolitan areas $g \in 1, ..., G$, then treatment effect $\hat{\alpha}_{gt}$ corresponds to the average effect at specific period t:

$$\bar{\alpha}_t = G^{-1} \sum_{g=1}^{G} \hat{\alpha}_{gt}$$

In the particular case of the 2012 minimum wage increase, all municipalities in Zone B experienced the minimum wage increase at the same time, so the set of potential donors remains the same for $t > T_0$. There were 5 metropolitan areas affected by the 2012 intervention $g = 1, ..., 5$.

To obtain the p-values for the treatment effect estimator, we follow the same placebo test described above. For each treatment g, it is possible to estimate a corresponding set of placebo effects where each untreated metropolitan area receives the 'artificial' treatment at the same time as each of the five g areas in 2012Q4.

5.4 Data

5.4.1 Aggregation of data to metropolitan areas

As in the rest of the dissertation, the data source is Mexico's National Survey on Employment and Occupation (ENOE). This database provides a quarterly rotating panel at the individual level on employment and informal employment in Mexico. In contrast to our previous chapters, there are two crucial differences in our method of analysis: the time period covered and the level of data aggregation.

First, to have a relatively high number of pretreatment periods, we use all the preintervention available quarters in ENOE starting in 2005Q1. As Zone B's minimum wage increase took place in 2014Q4, we have 31 pretreatment periods (T_0).

Second, the SCM requires aggregate level data, so ENOE data is aggregated at the metropolitan area level. To proceed with this aggregation, we use make use of the *Demarcation of Metropolitan Zones* by CONAPO.[4] CONAPO identifies 59 metropolitan areas in Mexico according to the following criteria:

(a) Municipalities with a population greater than one million of inhabitants.

(b) The set of two or more municipalities with at least 50 thousand inhabitants, which urban area and economic activities have spread beyond the geographical limit of the central municipality.

(c) Municipalities in the northern border sharing a process of conurbation with cities of United States with at least 250 thousand inhabitants.

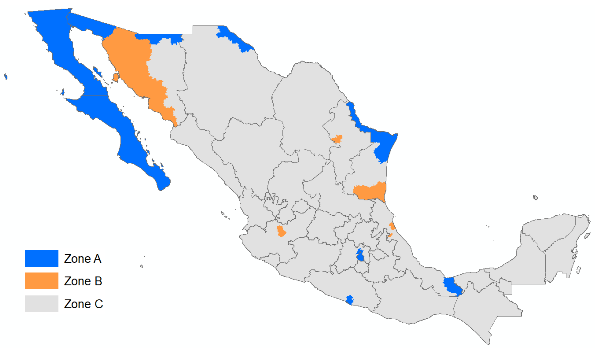
The ENOE survey contains consistent data for the period 2005Q1-2014Q4 for 57 out of the 59 metropolitan areas. Five of them belong to the treated Zone B (G), ten to Zone A and the rest to Zone C. Thus, 52 potential donor metropolitan areas (J) are available to construct the synthetic control group described in the previous section. Table 5.A.1 in

[4]Source: `http://www.conapo.gob.mx/en/CONAPO/Delimitacion_de_Zonas_Metropolitanas`. Accessed on 15 March 2018.

Appendix lists all the 59 metropolitan areas defined by CONAPO, describing the number of municipalities in each metropolitan area, as well as their total population.

Figure 5.1 shows the geographical location of the metropolitan areas distinguishing the minimum wage zones. In Panel (a) this figure illustrates the classification by wage zones for all the municipalities in Mexico, which is compared in Panel (b) to the classification only considering municipalities that are part of a metropolitan area.

Figure 5.1
Minimum wage zones in Mexico considering metropolitan areas



(a) By municipalities **(b)** By metropolitan area

Source: Own elaboration with data retrieved from CONASAMI and CONAPO.

From this figure we can see that most of the municipalities not included in our analysis at the metropolitan area level are those in the minimum wage zone C. This is explained by the fact that the minimum wage zone classification was designed in terms of the economic development of each municipality. As a consequence, many municipalities in zones B and A are actually part of a metropolitan area.

Table 5.1 compares the size of the labour force in all the municipalities in Mexico with respect to the workforce in the metropolitan areas. According to data corresponding to the quarter before the intervention (2012Q3), by excluding from the analysis all those municipalities not catalogued as a metropolitan area, we lose almost half of the labour market. From those 25 million excluded active labour individuals excluded, almost 23 million performed their labour activities in Zone C.

So, focusing the analysis on metropolitan areas is particularly attractive for our treatment evaluation purposes. It may provide the conditions to improve the quality of the control group, by only including in the control group those municipalities that are more similar to those found in Zone B.

Table 5.1
Active labour market population
(2012Q3)

MW Zone	All municipalities Population	%	Metropolitan areas Population	%
Zone A	11,891,299	22.59	10,721,022	39.00
Zone B	5,343,727	10.15	4,284,431	15.59
Zone C	35,415,741	67.27	12,482,300	45.41
TOTAL	52,650,767		27,487,753	

Source: Own calculations with data from ENOE.

5.4.2 Outcome variables and vector of covariates

In order to be able to compare these results with those in Chapter 4, we use the same set of outcome variables, but at the aggregate level:

- Active labour market rate: this is the proportion of individuals active in the labour market, with respect to the working age population by metropolitan area.
- Employment rate: proportion of individuals performing a job, with respect to the working age population by metropolitan area.
- Informal employment rate: the proportion of individuals performing labour market activities under informal conditions, with respect to the employed population by metropolitan area.
- Informal employment rate (paid workers): the proportion of informal workers receiving a monetary payment, with respect to the employed population by metropolitan area.
- Informal employment rate (self-employed workers): the proportion of self-employed informal workers, with respect to the employed population by metropolitan area.

- Informal employment rate (non-paid workers): the proportion of informal workers with no salary, or receiving a non-monetary payment, with respect to the employed population by metropolitan area.

Table 5.2 provides some descriptive statistics distinguishing treated from untreated metropolitan areas, as well as the difference at the mean between them.

As our purpose is to generate a weighted average from the donor pool of untreated metropolitan areas that is as similar as possible to the treated group, it is important that the outcome variables for the treated region should not be outside any linear combination of the values for the donor pool (McClelland and Gault, 2017). The summary statistics for the dependent variables in Table 5.2 show that the means for informal employment rate are not statistically the same between the control and treated groups (column 10). But this does not imply that it is not possible to construct and accurate synthetic control group. Indeed, a more important cause for concern is the fact that for the informal employment rate variables (paid workers and self-employed workers, figures highlighted in bold), there are cases in which the minimum informal employment rate is actually observed in a metropolitan area from the treated Zone B. This issue may complicate the generation of a valid synthetic control group, although it does not limit it because we are averaging the five treated metropolitan areas. The respective mean for the treated metropolitan areas, reported in column (1), can be potentially matched from a linear combination of the pool of donor areas.

Regarding the set of potential covariates to construct the weights for the synthetic group (vector **Z**), we generate the following variables at the metropolitan area level: mean age, proportion of rural municipalities, proportion of female individuals, proportion of individuals with the respective maximum level of education completed, proportion of individuals by age range, and proportion of workers performing labour activities in the agricultural, industrial and services sector, respectively. McClelland and Gault (2017) argue that, to avoid possible interpolation bias, the variables used to generate the weights in the donor pool regions must have similar values to those observed for the treated

Table 5.2
Pretreatment descriptive statistics by treated group
(2005Q1 - 2012Q3)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Treated metropolitan areas				Potential donor metropolitan areas				Difference at mean	
	Mean	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Diff.**	**p-value**
(a) Dependent variables										
Active labour market rate	0.5619	0.0390	0.4556	0.6254	0.5645	0.0410	0.4042	0.7248	0.0026	0.4486
Employment rate	0.5357	0.0359	0.4278	0.6037	0.5386	0.0402	0.3583	0.6771	0.0029	0.3755
Informal employment rate	0.4314	0.0595	0.2674	0.6154	0.5321	0.1194	0.2566	0.8755	0.1007	0.0000
Paid workers	0.2388	0.0601	**0.0928**	0.4667	0.3021	0.0742	0.1260	0.5758	0.0633	0.0000
Self-employed workers	0.1536	0.0283	**0.0349**	0.2529	0.1763	0.0484	0.0732	0.4364	0.0227	0.0000
Non-paid workers	0.0390	0.0193	0.0052	0.1111	0.0537	0.0308	0.0000	0.2966	0.0147	0.0000
(b) Covariates										
Age	38.0114	1.6331	35.2163	**42.7013**	36.5084	1.5137	31.0472	41.8333	-1.5030	0.0000
Rural Municipalities	0.1115	0.2144	0.0000	**0.6817**	0.1132	0.1349	0.0000	0.6690	0.0017	0.8834
Female	0.5220	0.0189	**0.4740**	0.5976	0.5293	0.0194	0.4788	0.5976	0.0073	0.0000
School level 1 (1st-6th year)	0.1409	0.0403	**0.0637**	0.2627	0.1870	0.0684	0.0851	0.4667	0.0461	0.0000
School level 2 (7th-9th year)	0.2428	0.0304	0.1646	0.3368	0.2622	0.0440	0.1766	0.4654	0.0194	0.0000
School level 3 (10th-12th year)	0.3314	0.0642	0.1694	0.4632	0.3021	0.0464	0.1609	0.4688	-0.0293	0.0000
School level 4 (University)	0.2849	0.0688	0.1554	**0.4777**	0.2487	0.0785	0.0465	0.4406	-0.0362	0.0000
Aged between 12 and 29	0.3883	0.0343	**0.2727**	0.4500	0.4189	0.0315	0.3151	0.5963	0.0306	0.0000
Aged between 30 and 49	0.3453	0.0208	0.2784	0.4033	0.3448	0.0249	0.2258	0.4450	-0.0005	0.8106
Older than 50 years old	0.2664	0.0346	0.2044	0.3511	0.2363	0.0351	0.1208	0.3694	-0.0301	0.0000
Agricultural sector	0.0615	0.1102	0.0000	**0.4257**	0.0653	0.0819	0.0000	0.4074	0.0038	0.5872
Industrial sector	0.2775	0.0364	0.1728	0.3768	0.2749	0.0961	0.0833	0.6619	-0.0026	0.7330
Services sector	0.6610	0.1002	0.3789	0.8148	0.6598	0.1130	0.2843	0.8645	-0.0012	0.8971
Observations	160				1664					

Source: Own calculations with data from ENOE.

metropolitan areas.

The summary statistics for the explanatory variables in Table 5.2, Panel (b), show that after the aggregation of the data, some of the covariates that we used in previous chapters (*age, female*) are not statistically the same by group of treatment. Furthermore, some covariates for the treated metropolitan areas cannot be a linear combination of the pool of potential donor areas (maximums and minimums highlighted in bold), as it is the case of the variable *rural*. To deal with this, an additional set of covariates are generated. To control for the age composition at the metropolitan area level, we use the proportion by the age thresholds used in Chapters 2 and 4. As we can observe, the proportion of workers aged between 30 and 49 is potentially a good covariate to control for the age composition in each metropolitan area. To control for the educational attainment composition of the workforce, we use schooling level variables used in previous chapters. We include in the **Z** vector the second level of schooling in Mexico (which is finished after completing the 9th year) in the set of covariates as these are the most similar between the treated and untreated groups. Finally, we incorporate into the analysis the proportion of workers by economic sector. On this regard, the proportion of workers in the industrial and services sector, respectively, can be also used to construct the weights for the synthetic control group.

5.5 Results

5.5.1 Main results

This section presents estimates for the employment effects of the 2012 minimum wage increase on the metropolitan areas that belong to the treated Zone B by the implementation of the SCM. We evaluate its impact on: the active labour market rate, the employment rate, and the informal employment rate (including the subgroups of informal employment). Each of these variables may follow different and independent trends in the preintervention period, which implies that the vector of relevant pretreatment characteristics, $\mathbf{Z}$, as well as the vector of lagged dependent variables, $\mathbf{K}$, can be different for each of them. To avoid any potential subjective decision on every model, the set of covariates and lagged outcome variables remain unchanged among the models presented below.

In addition to the set of estimators for the treatment effects and their respective p-values (Table 5.3), to highlight the transparency of this estimation approach, we also present the outcome trend followed for the pool of potential donors compared to the treated group and, of course, for the estimated synthetic control group.

We start by analysing the broadest employment category: the active labour market population. Figure 5.2 presents the path of this outcome variable for the whole analysis period. The dotted line in the left-hand side graph corresponds to the average active labour market rate for the 52 untreated metropolitan areas. If we compare this to the treated metropolitan areas, it is worth emphasizing the differences between these two groups in the quarters just before the intervention (represented by the red vertical line). As we can observe, there exists a gap between treated (solid line) and potential donors

Table 5.3
Effect of the 2012 minimum wage increase on the labour market
SCM estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Active Labour	**Employment**	**Informal Employment Rate**			
	Market Rate	**Rate**	**All informal**	**Paid**	**Self-employed**	**Non-paid**
2013 Q1	-0.0070	-0.0030	0.0049	-0.0024	**0.0231****	**-0.0142****
	(0.3115)	(0.6540)	(0.7345)	(0.8130)	**(0.0276)**	**(0.0131)**
2013 Q2	-0.0004	0.0008	-0.0093	-0.0070	0.0057	-0.0065
	(0.9582)	(0.9306)	(0.6035)	(0.5106)	(0.4769)	(0.1873)
2013 Q3	-0.0076	-0.0053	0.0122	0.0010	0.0081	-0.0040
	(0.3926)	(0.5010)	(0.5479)	(0.9407)	(0.4958)	(0.4343)
2013 Q4	0.0164	**0.0196***	0.0131	-0.0103	0.0197	-0.0084
	(0.1479)	**(0.0692)**	(0.5868)	(0.4665)	(0.1144)	(0.1116)
2014 Q1	-0.0065	-0.0108	-0.0036	-0.0050	-0.0099	**-0.0119****
	(0.5527)	(0.3544)	(0.8573)	(0.6831)	(0.4580)	**(0.0308)**
2014 Q2	-0.0126	-0.0106	-0.0146	-0.0039	0.0071	**-0.0142*****
	(0.2256)	(0.3932)	(0.52554)	(0.6931)	(0.5602)	**(0.0064)**
2014 Q3	0.0090	0.0099	-0.0061	0.0070	0.0048	**-0.0148*****
	(0.5049)	(0.5504)	(0.7171)	(0.6295)	(0.6633)	**(0.0058)**
2014 Q4	0.0035	0.0048	0.0112	0.0217	-0.0072	-0.0036
	(0.8090)	(0.6992)	(0.5985)	(0.2581)	(0.4813)	(0.4693)

Note: the covariates included are proportion of individuals between 30 and 49 years old, proportion of individuals with the second level of education completed (9th year), and proportion of workers in the industrial and services sector.
The lagged outcome variables correspond to 2007Q3 and 2012Q3.
P-values in parentheses. Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

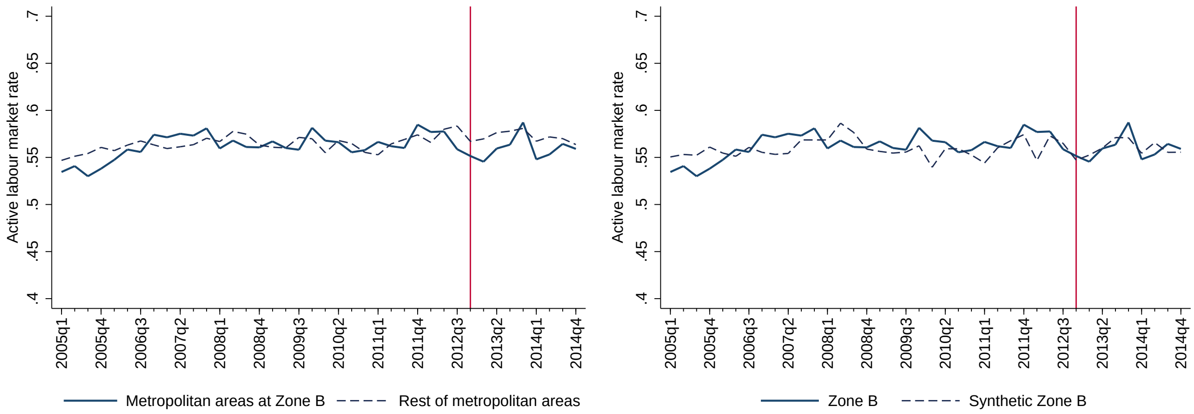
(dotted line) starting two periods before the policy change, which does not allow for an accurate estimation of the treatment effect.

In the right-hand side graph of Figure 5.2 we introduce our estimate of the synthetic control group represented by the dotted line. The effect of the policy change is just the difference between the treated and synthetic control groups after the minimum wage increase, which is close to zero in each of the eight post-intervention periods. Column (1) in Table 5.3 shows that the policy impact does not statistically differ from zero for all quarters between 2012Q1 and 2014Q1. In 2012Q4, for example, we observe the biggest treatment effect, 0.0164, but it is still insignificant having a p-value of 0.1479.

Without constructing a valid counterfactual, the difference in the active labour market rate between treated and untreated groups is negative, and probably statistically significant, as we can observe in Panel (a) of Figure 5.2. In contrast, our estimates suggest no

Figure 5.2

Trends in active labour market rate



(a) Zone B vs rest of metropolitan areas **(b)** Zone B vs synthetic Zone B

Note: the covariates included are proportion of individuals between 30 and 49 years old, proportion of individuals with the second level of education completed (9th year), and proportion of workers in the industrial and services sector. The lagged outcome variables correspond to 2007Q3 and 2012Q3.

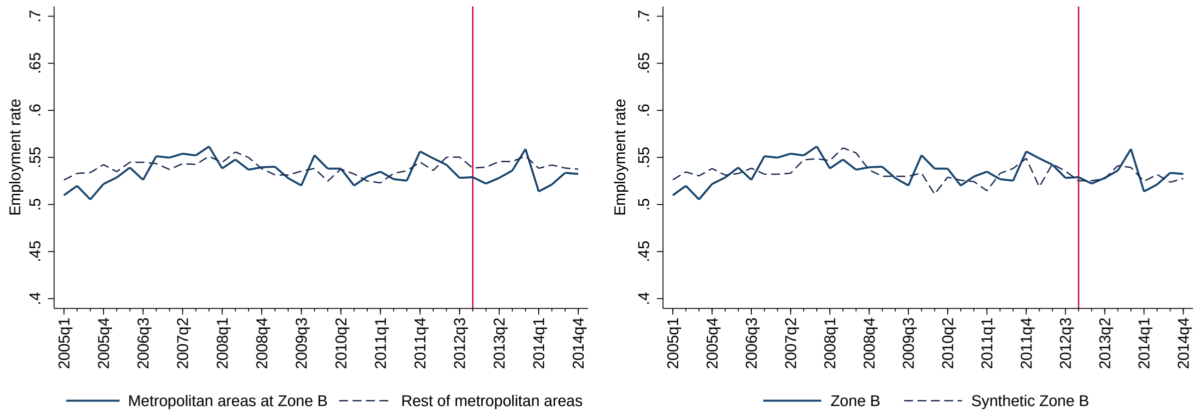
effect on the size of the labour market after Zone B's minimum wage increase.

These results are consistent with the Difference in Differences findings in Chapter 4 (Table 4.1). So, we can assert that there is no statistical evidence that the 2012 minimum wage increase affected the incentives to participate actively in the labour market.

Figure 5.3 shows the trends in the employment rate. Given that employed individuals correspond to a subgroup within the active labour market population, the observed path is very similar to that presented in Figure 5.2. Nevertheless, after the construction of the synthetic control group, there is a positive and significant treatment effect in the fourth quarter after the intervention (2012Q4) with a magnitude of 0.0196% (see Table 5.3).

The size of treatment effect is very similar to that obtained in Chapter 4 by Difference in Differences, which is between 0.017% and 0.024% (see Tables 4.1 and 4.3), depending on the control group used. Unlike that estimation, this positive impact is found four quarters after the intervention, while in Chapter 4 we found it two quarters after the minimum wage increase. The elasticity associated with this impact is 0.07. This corroborates that the minimum wage increase did not affect employment, and at some point later on there exists evidence of a significant employment increase. This finding is relevant because it implies that Mexican labour market is monopsonistic, which explains why the employment

Figure 5.3
Trends in employment rate



(a) Zone B vs rest of metropolitan areas **(b)** Zone B vs synthetic Zone B

Note: the covariates included are proportion of individuals between 30 and 49 years old, proportion of individuals with the second level of education completed (9th year), and proportion of workers in the industrial and services sector. The lagged outcome variables correspond to 2007Q3 and 2012Q3.

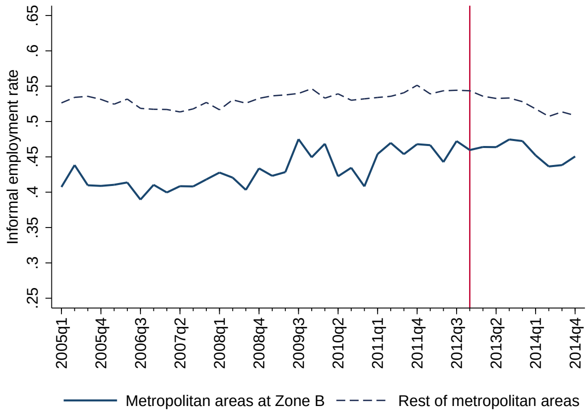
rate increased in spite of a minimum wage increase.

Regarding informal employment illustrated in Figure 5.4, Panel (a) shows a greater difference between untreated metropolitan areas and the pool of donors areas, so it is more evident the need of the implementation of the SCM to estimate a treatment effect. After the aggregation of the data, it would not be possible to argue that the two series are evolving in parallel during the. As a consequence, Difference in Differences would not be valid under this framework of data aggregation at the metropolitan area level.

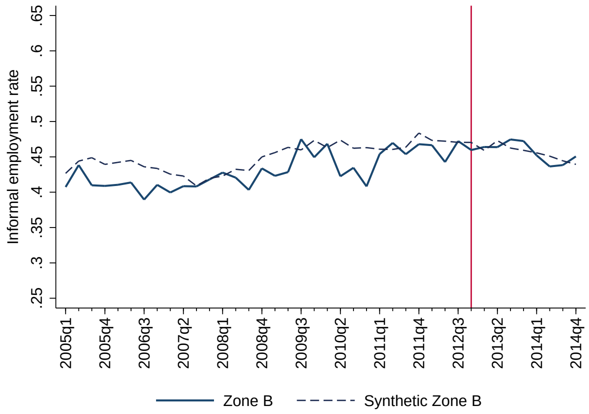
Once we constructed a valid counterfactual using the SCM, we found a zero effect of the minimum wage rise on the informal employment rate. This result suggests that the increase in overall employment was not a consequence of an increase in informal employment. To be clearer, for the analysis on the employment rate in Figure 5.3 we do not distinguish between formal or informal workers. The employment rate corresponds to the proportion of all workers who have a job relative to the working age population. So, it could be possible that the increase in employment was a consequence of an increase in informal labour activities, which was not the case according to the evidence above.

These set of results clearly indicate that the increase in overall employment must have been due to an increase in employment in the formal sector following the policy

Figure 5.4
Trends in informal employment rate



(a) Zone B vs rest of metropolitan areas



(b) Zone B vs synthetic Zone B

Note: the covariates included are proportion of individuals between 30 and 49 years old, proportion of individuals with the second level of education completed (9th year), and proportion of workers in the industrial and services sector. The lagged outcome variables correspond to 2007Q3 and 2012Q3.

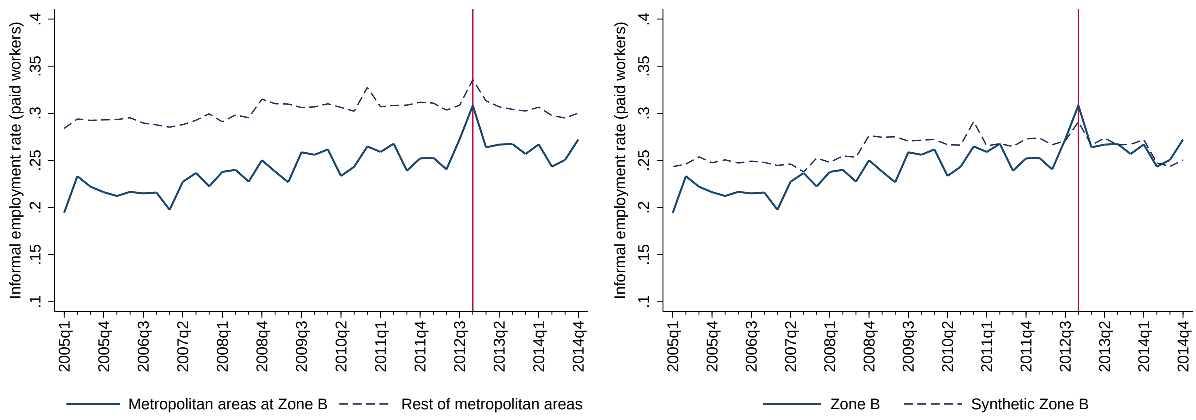
intervention. Moreover, joined to the fact that we do not find any effect on the size of active labour market (i.e. the sum of workers plus the unemployed), it is possible to dismiss the possibility that the positive impact on employment is a consequence of the macroeconomic cycle in the Mexican economy. It has often been argued that minimum wages are raised when there exists a positive trend on macroeconomic activity. If this is the case, wages and employment increase but not necessarily as a consequence of the policy change. However, this does not correspond to our findings described above. Our estimates demonstrate that neither the size of the labour force nor the size of the informal labour market change, so increases in employment werw purely a consequence of the minimum wage intervention.

Following the analysis developed in Chapter 4, we disaggregate informal employment into three separate sub-groups: informal paid workers, self-employed informal workers, and non-waged informal workers.

For the subgroup of informal paid workers, it is particularly difficult to construct the synthetic control group. As we discussed in Section 5.4.2, if we separately analyse metropolitan areas, there are treated units for which this outcome variable is not a convex combination of the unaffected treated areas. As we estimate an average o effect f the treated metropolitan areas, it makes easier to implement the SCM. The outcome trends presented in Figure 5.5 show that the SCM performs very well to equalize the trend of the treated group with the synthetic counterfactual.

Figure 5.5

Trends in informal employment (paid workers)



(a) Zone B vs rest of metropolitan areas **(b)** Zone B vs synthetic Zone B

Note: the covariates included are proportion of individuals between 30 and 49 years old, proportion of individuals with the second level of education completed (9th year), and proportion of workers in the industrial and services sector. The lagged outcome variables correspond to 2007Q3 and 2012Q3.

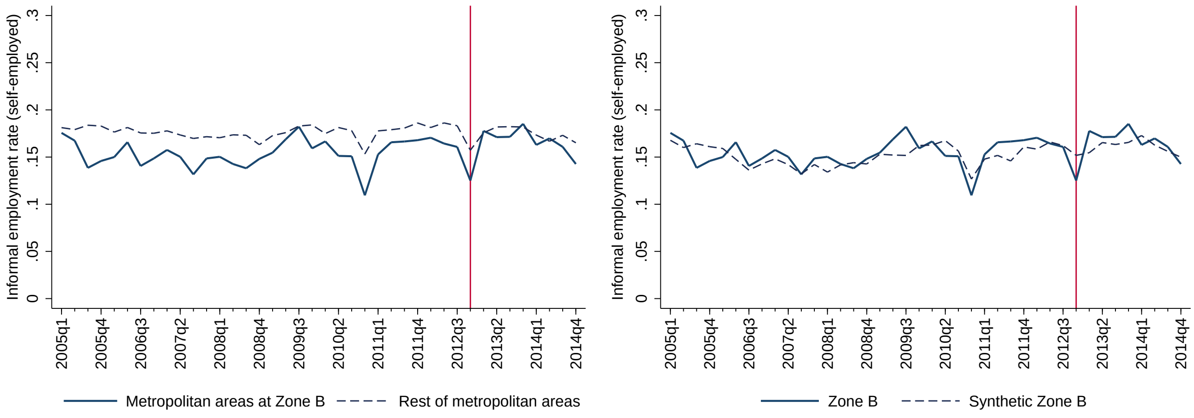
Panel (b) in Figure 5.5 shows that after the policy change there is no difference between the treated and the synthetic control groups. The effect is not statistically significant for any of the post-intervention periods (see Column 4 in Table 5.3). This contrasts with our findings in Chapter 4, in which we find a statistically significant reduction by around 0.9% (Table 4.2) on the informality rate for informal paid workers.

We can see from Figure 1.6 that in the case of self-employed informal workers, the difference between treated metropolitan areas and the pool of donors is not as complex as in the previous case, but synthetic control method generates a better counterfactual. Surprisingly, our estimates suggest a positive and statistically significant effect in the immediate quarter after the intervention of around 0.023%.

So, our estimates suggest that there was an increase of the informal employment

Figure 5.6

Trends in informal employment (self-employed workers)



(a) Zone B vs rest of metropolitan areas **(b)** Zone B vs synthetic Zone B

Note: the covariates included are proportion of individuals between 30 and 49 years old, proportion of individuals with the second level of education completed (9th year), and proportion of workers in the industrial and services sector. The lagged outcome variables correspond to 2007Q3 and 2012Q3.

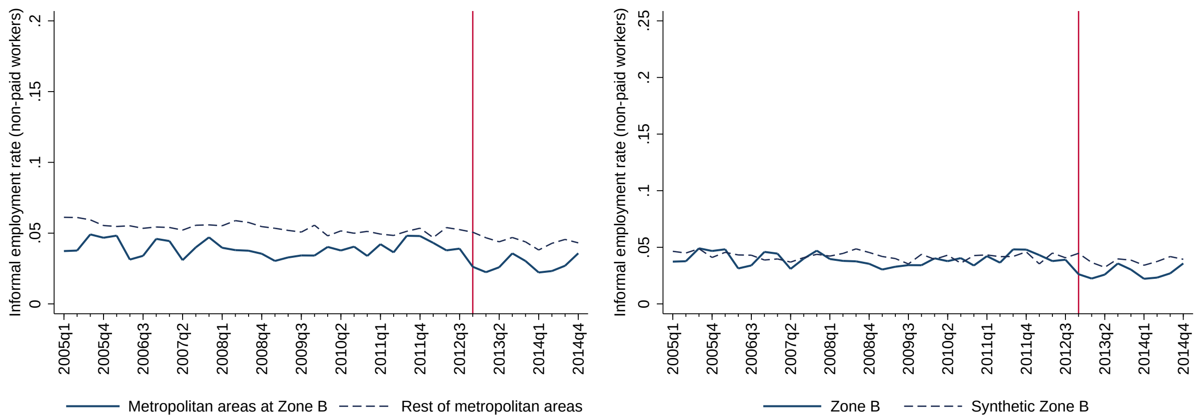
rate for this specific category of workers. The estimated effect remains positive for the subsequent three quarters, although not statistically different from zero (see Column 5 in Table 5.3). In Chapter 4, by Difference in Differences estimates, we did not find any effect for self-employed workers, at least for the full age threshold.

To complete the analysis on informal workers, Panel (b) in Figure 5.7 shows that as a consequence of the minimum wage intervention, metropolitan areas in Zone B exhibited a consistent decline in the proportion on non-paid informal workers with respect to its synthetic counterpart. So, the effect on the informality rate is negative and statistically significant in 2012Q1, and from 2013Q1 to 2013Q3. The size of the impact is estimated to be between -0.012% and -0.015%.

Among the previous chapters, we have not found any significant effect on this specific group of workers, which mainly consists of individuals in small family businesses in the agricultural sector. As we estimated an increase in the informal rate for self-employed workers and a decline for non-paid workers, a likely explanation for these findings is that there was just a transition of informal workers between these two categories, but still under informal employment conditions. To verify this proposition, we run an additional model pooling together self-employed and non-paid informal workers. Almost all the effects become statistically insignificant, although there is still a positive impact of 0.025% in the fourth quarter after the intervention which is just significant at the 10% level with a p-value of 0.095 (not reported).

Figure 5.7

Trends in informal employment (non-paid workers)



(a) Zone B vs rest of metropolitan areas　　**(b)** Zone B vs synthetic Zone B

Note: the covariates included are proportion of individuals between 30 and 49 years old, proportion of individuals with the second level of education completed (9th year), and proportion of workers in the industrial and services sector. The lagged outcome variables correspond to 2007Q3 and 2012Q3.

Thus, by the implementation of the synthetic control approach, we find no evidence of a harm on employment as a consequence of the minimum wage increase. The estimates suggest no effect on the size of the workforce, no long-term effect on the overall employment rate (though there is a significant temporary increase in the overall employment rate in 2013Q1) and no overall impact on informal employment.

5.5.2 Robustness Checks

In order to demonstrate the consistency of the estimates, we run some additional models. As we mentioned before, there are several decisions that a researcher needs to make to implement this data-driven approach. Within the set of robustness checks, we run the SCM restricting the number of metropolitan areas in the pool of donors, changing the set of covariates, and also modifying the period of analysis. In all these cases our results are unaffected.

One likely concern about our estimates is that within the set of potential metropolitan area donors there exists an important diversity in terms of geographical location, population size and labour market characteristics. We have 52 potential donors, including for example the metropolitan area of Mexico City with a population of more than 20 million inhabitants in 2010, which contrasts with the metropolitan area of Acayucan, in the state of Veracruz, with a population of 112 thousand inhabitants.[5] The SCM just picks some metropolitan areas to construct a weighted average that most closely matches the outcome trend observed by the treated areas. But, the metropolitan areas included in the vector of weights, $\mathbf{w}$, are not necessarily the most similar to the set of treated areas.

We make two different restrictions to the set of potential donors with the objective of verifying how sensitive is our estimates are to changes in the composition of the group of metropolitan areas unaffected by the intervention. In the first of them, we exclude Mexico City from the model on the basis that it is not comparable to any other metropolitan area in Mexico In the second exercise, we do not include nine areas form Zone C that we consider dissimilar to the treated areas in Zone B. The criteria followed was to exclude the smallest areas that are not geographically close to the treated units (see in Table 5.A.1 in Appendix the metropolitan areas excluded).

Table 5.4 shows that not including Mexico City changes slightly the magnitude of the treatment effects, but it does not affect our overall findings (Figure 5.B.1 shows the outcome variable trends). This implies that the weight given to Mexico City to construct the synthetic control group is relatively small. Column (1) shows that we are not able to find any effect on the active labour market rate. Regarding the impact on the overall employment rate, the corresponding treatment effect in 2012Q4 is smaller (0.188%), but still statistically significant. As in our main specification, we find no impact on informal employment, although persists the estimate of a positive effect on self-employed informal

[5]Data from CONAPO. See Table 5.A.1 in Appendix for the full list of metropolitan areas my minimum wage zone and population.

Table 5.4
Robustness checks: restricting pool of donors excluding Mexico City

	(1)	(2)	(3)	(4)	(5)	(6)
	Active Labour Market Rate	Employment Rate	Informal Employment Rate			
			All informal	Paid	Self-employed	Non-paid
2013 Q1	-0.0068	-0.0033	0.0051	-0.0024	**0.0231****	**-0.0142****
	(0.3382)	(0.6225)	(0.7318)	(0.8352)	**(0.0251)**	**(0.0141)**
2013 Q2	-0.0019	0.0001	-0.0090	-0.0069	0.0058	-0.0064
	(0.9825)	(0.9932)	(0.6171)	(0.5150)	(0.4757)	(0.1903)
2013 Q3	-0.0073	-0.0055	0.0125	0.0011	0.0081	-0.0040
	(0.4103)	(0.4717)	(0.5490)	(0.9298)	(0.4853)	(0.4497)
2013 Q4	0.0167	**0.0188***	0.0133	-0.0101	0.0198	-0.0084
	(0.1447)	**(0.0781)**	(0.5853)	(0.4551)	(0.1302)	(0.1158)
2014 Q1	-0.0062	-0.0117	-0.0032	-0.0049	-0.0098	**-0.0119****
	(0.5771)	(0.3018)	(0.8734)	(0.6860)	(0.4980)	**(0.0330)**
2014 Q2	-0.0124	-0.0112	-0.0143	-0.0037	0.0072	**-0.0142*****
	(0.2402)	(0.3545)	(0.5434)	(0.6998)	(0.5520)	**(0.0064)**
2014 Q3	0.0093	0.0092	-0.0057	0.0071	0.0049	**-0.0149*****
	(0.4951)	(0.5596)	(0.7279)	(0.5708)	(0.7092)	**(0.0060)**
2014 Q4	0.0038	0.0038	0.0115	0.0219	-0.0071	-0.0036
	(0.7987)	(0.8528)	(0.5811)	(0.1830)	(0.4605)	(0.4808)

Note: the covariates included are proportion of individuals between 30 and 49 years old, proportion of individuals with the second level of education completed (9th year), and proportion of workers in the industrial and services sector.
The lagged outcome variables correspond to 2007Q3 and 2012Q3.
P-values in parentheses. Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

workers and a negative effect on non-paid informal workers.

Table 5.5 shows the estimates after ommiting from the analysis nine small metropolitan areas part of minimum wage zone C that are geographically distant from the treated areas (see Figure 5.B.2 for the outcome variable trends). Again, there is no impact on the size of workforce, but the positive effect on the overall employment rate for 2012Q4 is not statistically significant. Nevertheless, it is relevant to highlight that the central finding about no evidence of a reduction in the employment rate does not change. The results on informal employment, and its respective sub-categories are basically the same.

Thus, these two exercises show that the SCM is actually performing well in the choice of the area weights, w, for constructing the synthetic control group. The weights assigned in our favourite specification to these specific metropolitan areas that we consider (subjectively) less similar to the treated areas are indeed small. As a consequence, their exclusion does not affect the overall estimates.

Table 5.5
Robustness checks: restricting pool of donors excluding nine metropolitan areas

	(1)	(2)	(3)	(4)	(5)	(6)
	Active Labour Market Rate	**Employment Rate**	**Informal Employment Rate**			
			All informal	**Paid**	**Self-employed**	**Non-paid**
2013 Q1	-0.0072	-0.0046	0.0053	-0.0110	**0.0278*** **	**-0.0078***
	(0.2683)	(0.5025)	(0.6911)	(0.2285)	**(0.0014)**	**(0.0909)**
2013 Q2	-0.0017	-0.0114	-0.0087	-0.0101	0.0080	-0.0008
	(0.8133)	(0.9452)	(0.5447)	(0.3881)	(0.3715)	(0.8522)
2013 Q3	-0.0069	0.0033	0.0134	0.0001	0.0120	-0.0051
	(0.4222)	(0.6152)	(0.5093)	(0.9925)	(0.3109)	(0.2850)
2013 Q4	0.0149	0.0170	0.1952	-0.0056	**0.0244***	-0.0023
	(0.2210)	(0.1114)	(0.4514)	(0.7085)	**(0.0903)**	(0.6493)
2014 Q1	-0.0081	-0.0094	0.0032	-0.0095	-0.0076	**-0.0111***
	(0.4354)	(0.3763)	(0.8662)	(0.4752)	(0.5935)	**(0.0704)**
2014 Q2	-0.0162	-0.0140	-0.0079	0.0015	0.0073	**-0.0134*** **
	(0.1509)	(0.2716)	(0.6966)	(0.8906)	(0.6140)	**(0.0014)**
2014 Q3	0.0104	0.2008	-0.0028	-0.0062	0.0083	**-0.0167*** **
	(0.4802)	(0.2090)	(0.9874)	(0.6846)	(0.4706)	**(0.0010)**
2014 Q4	0.0023	0.0027	0.0179	0.0252	-0.0065	-0.0055
	(0.8740)	(0.8528)	(0.3928)	(0.1830)	(0.5722)	(0.2195)

Note: the covariates included are proportion of individuals between 30 and 49 years old, proportion of individuals with the second level of education completed (9th year), and proportion of workers in the industrial and services sector.
The lagged outcome variables correspond to 2007Q3 and 2012Q3.
P-values in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1

To check the robustness of our model to the choice of covariates, **Z**, we consider it relevant to keep controlling for the three factors used in our main specification in Section 5.5.1: age composition, education, and economic sector. Regarding age composition, we now include the proportion of workers aged between 12 and 29 to include the group of young workers traditionally used in minimum wage evaluations. With respect to the economic sector we include only services sector, which accounts for 66% of the economic activity in the metropolitan areas, independently of the treatment group. Results are reported in Table 5.6 (and outcome variable trends in Figure 5.B.3) showing that our main findings are not affected by these changes. Remarkably, the policy impact on the employment rate in 2012Q4 results statistically significant with a size of 0.185%.

As a final robustness exercise, we limit our analysis period to 2007Q1-2014Q4. Even though we lose eight periods of analysis, it is likely that these omitted quarters are not very relevant to the labour market conditions at the time of the policy change. As we can observe in Table 5.7 and in Figure 5.B.4, our estimates of the treatment effects are practically the same: the size of the labour force is not affected by the minimum wage increase, there is no harm in terms of employment and there is evidence of a positive and significant effect four quarters after the intervention, and there is no impact on the level of informal employment.

Table 5.6
Robustness checks: changing the vector of covariates

(individuals between 12 and 29 years old and and of workers in services sector)

	(1)	(2)	(3)	(4)	(5)	(6)
	Active Labour	**Employment**	**Informal Employment Rate**			
	Market Rate	**Rate**	**All informal**	**Paid**	**Self-employed**	**Non-paid**
2013 Q1	-0.0048	-0.0032	0.0057	-0.0051	**0.0285*****	**-0.0082***
	(0.5932)	(0.6527)	(0.6402)	(0.5317)	**(0.0004)**	**(0.0731)**
2013 Q2	0.0064	0.0022	-0.0087	0.0024	**0.0192****	-0.0006
	(0.4467)	(0.8008)	(0.6021)	(0.8352)	**(0.0277)**	(0.8950)
2013 Q3	-0.0071	-0.0087	0.0128	-0.0009	**0.0207***	-0.0020
	(0.4795)	(0.4795)	(0.4709)	(0.9467)	**(0.0887)**	(0.7091)
2013 Q4	0.0259	**0.0185***	0.0112	-0.0211	**0.0389****	-0.0021
	(0.1199)	**(0.0644)**	(0.6062)	(0.2126)	**(0.0144)**	(0.6985)
2014 Q1	0.0076	-0.0074	0.0042	0.0020	0.0070	**-0.0089***
	(0.5273)	(0.4817)	(0.8678)	(0.8856)	(0.5699)	**(0.0976)**
2014 Q2	-0.0113	-0.0127	-0.0058	-0.0212	0.0141	**-0.0091***
	(0.3378)	(0.2495)	(0.7966)	(0.1418)	(0.21423)	**(0.0665)**
2014 Q3	0.0134	0.0017	-0.0023	-0.0062	0.0054	**-0.0112****
	(0.4209)	(0.9059)	(0.8948)	(0.5852)	(0.5912)	**(0.0301)**
2014 Q4	0.0293	0.0068	0.0173	0.0178	0.0009	0.0009
	(0.1330)	(0.6180)	(0.4379)	(0.2401)	(0.9217)	(0.8204)

Note: the covariates included are proportion of individuals between 30 and 49 years old, proportion of individuals with the second level of education completed (9th year), and proportion of workers in the industrial and services sector.
The lagged outcome variables correspond to 2007Q3 and 2012Q3.
P-values in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1

5.6 Conclusions

In this chapter we tested the robustness of our employment findings from Chapter 4 by implementing a different empirical evaluation. We used the increasingly popular SCM, whose simplicity and transparency makes it a powerful tool to evaluate minimum wage policy interventions.

Table 5.7
Robustness checks: changing the period of analysis
2007Q1 to 2014Q4

	(1)	(2)	(3)	(4)	(5)	(6)
	Active Labour Market Rate	**Employment Rate**	**Informal Employment Rate**			
			All informal	**Paid**	**Self-employed**	**Non-paid**
2013 Q1	-0.0043	-0.0021	0.0103	0.0009	**0.0218****	**-0.0136****
	(0.5619)	(0.7166)	(0.4886)	(0.9191)	**(0.0287)**	**(0.0282)**
2013 Q2	0.0029	0.0075	0.0019	-0.0054	0.0071	-0.0060
	(0.7391)	(0.3751)	(0.9190)	(0.6165)	(0.5030)	(0.2283)
2013 Q3	-0.0059	-0.0049	0.0154	0.0003	0.0098	-0.0033
	(0.6217)	(0.5648)	(0.4225)	(0.9751)	(0.5072)	(0.5294)
2013 Q4	0.0180	**0.0172***	0.2558	-0.0104	0.0201	-0.0072
	(0.1590)	**(0.0765)**	(0.2634)	(0.4557)	(0.1120)	(0.1550)
2014 Q1	-0.0045	-0.0112	0.0109	-0.0012	-0.0059	**-0.0111****
	(0.7352)	(0.2949)	(0.6079)	(0.9143)	(0.7101)	**(0.0390)**
2014 Q2	-0.0085	-0.0151	-0.0041	-0.0082	0.0082	**-0.0139****
	(0.4144)	(0.2394)	(0.8593)	(0.4653)	(0.5036)	**(0.0138)**
2014 Q3	0.0094	0.0021	-0.0011	0.0037	0.0039	**-0.0131****
	(0.5059)	(0.8921)	(0.9454)	(0.7887)	(0.7404)	**(0.0204)**
2014 Q4	0.0057	0.0072	0.0251	0.0198	-0.0071	-0.0016
	(0.6919)	(0.5278)	(0.2348)	(0.2401)	(0.4842)	(0.7287)

Note: the covariates included are proportion of individuals between 30 and 49 years old, proportion of individuals with the second level of education completed (9th year), and proportion of workers in the industrial and services sector.
The lagged outcome variables correspond to 2007Q3 and 2012Q3.
P-values in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1

The data-driven SCM constitutes a generalisation of fixed-effects Difference in Differences models, but its implementation demands different data. It requires aggregation of the data to a regional level so we lose all the information at the individual level used in the previous chapters. We handled this by aggregating the labour market data at the metropolitan area level using the delimitation of metropolitan areas suggested by CONAPO. In addition, the SCM needs a relatively high number of preintervention time periods, so we extend the period of analysis to cover the period 2005Q1 to 2014Q4. As a consequence, the data and methodological setting in this chapter is entirely different with respect to the rest of the dissertation. However, our findings remain essentially the same: the 2012 Zones B minimum wage increase did not have adverse employment effects, which suggests the existence of monopsonistic labour markets in Mexico.

First, our estimates suggest that the 2012 minimum wage increase did not affect the size of the active labour market population. In other words, it did not find that more individuals were looking for a job as a consequence of a higher statutory wage. Second, employment positions were not reduced. On the contrary, there is statistical evidence that there was a small increase by around 0.02% four quarters after the intervention. And third, there is no evidence of an increase of informal labour market employment.

These findings are robust to: the selection of a sub-set of metropolitan areas used as donors to construct the synthetic control group, to the choice of covariates affecting the outcome variables, and to the period of analysis.

Therefore, this chapter demonstrates that our main conclusions that the minimum wage increase did not affect employment is robust to the estimation method and to the choice of data aggregation.

Appendix 5.A Metropolitan areas by CONAPO

Table 5.A.1

Metropolitan Areas (MA) by wage zone, population and municipalities

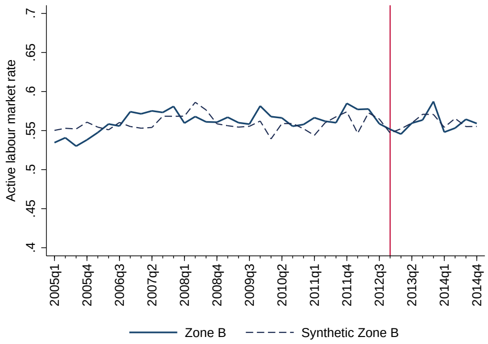
Minimum wage zone	Metropolitan area	State(s)	Population (2010)	Number of municipalities
B	MA of Guadalajara	Jalisco	4,434,878	8
B	MA of Monterrey	Nuevo León	4,106,054	13
B	MA of Guaymas	Sonora	203,430	2
B	MA of Tampico	Tamaulipas-Veracruz	859,419	5
B	MA of Poza Rica	Veracruz	513,518	5
A	MA ofl Valle de México	Mexico City-Hidalgo-México	20,116,842	76
A	MA of Tijuana	Baja California	1,751,430	3
A	MA of Mexicali	Baja California	936,826	1
A	MA of Juárez	Chihuahua	1,332,131	1
A	MA of Acapulco	Guerrero	863,431	2
A	MA of Reynosa-Río Bravo	Tamaulipas	727,150	2
A	MA of Matamoros	Tamaulipas	489,193	1
A	MA of Nuevo Laredo	Tamaulipas	384,033	1
A	MA of Minatitlán	Veracruz	356,137	6
A	MA of Coatzacoalcos	Veracruz	347,257	3
C	MA of Aguascalientes	Aguascalientes	932,369	3
C	MA of Chihuahua	Chihuahua	852,533	3
C	MA of La Laguna	Coahuila-Durango	1,215,817	4
C	MA of Saltillo	Coahuila	823,128	3
C	MA of Monclova-Frontera	Coahuila	317,313	3
C	MA of Piedras Negras	Coahuila	180,734	2
C	MA of Colima-Villa de Álvarez *	Colima	334,240	5
C	MA of Tecomán *	Colima	141,421	2
C	MA of Tuxtla Gutiérrez	Chiapas	684,156	3
C	MA of León	Guanajuato	1,609,504	2
C	MA of San Francisco del Rincón	Guanajuato	182,365	2
C	MA of Moroleón-Uriangato	Guanajuato	108,669	2
C	MA of Pachuca	Hidalgo	512,196	7
C	MA of Tulancingo *	Hidalgo	239,579	3
C	MA of Tula *	Hidalgo	205,812	5
C	MA of Puerto Vallarta	Jalisco-NayariTrend	379,886	2
C	MA of Ocotlán	Jalisco	141,375	2
C	MA of Toluca	México	1,936,126	15
C	MA of Morelia	Michoacán	829,625	3
C	MA of Zamora-Jacona	Michoacán	250,113	2
C	MA of La Piedad-Pénjamo	Guanajuato-Michoacán	249,512	2
C	MA of Cuernavaca	Morelos	924,964	8
C	MA of Cuautla *	Morelos	434,147	6
C	MA of Tepic	NayariTrend	429,351	2
C	MA of Oaxaca	Oaxaca	607,963	22
C	MA of Tehuantepec	Oaxaca	161,337	3
C	MA of Puebla-Tlaxcala	Puebla-Tlaxcala	2,728,790	39
C	MA of Tehuacán *	Puebla	296,899	2
C	MA of Querétaro *	Querétaro	1,097,025	4
C	MA of Cancún	Quintana Roo	677,379	2
C	MA of San Luis Potosí	San Luis Potosí	1,040,443	2
C	MA of Ríoverde-Ciudad Fernández *	San Luis Potosí	135,452	2
C	MA of Villahermosa *	Tabasco	755,425	2
C	MA of Tlaxcala-Apizaco	Tlaxcala	499,567	19
C	MA of Veracruz	Veracruz	811,671	5
C	MA of Xalapa	Veracruz	666,535	7
C	MA of Orizaba	Veracruz	427,406	12
C	MA of Córdoba	Veracruz	316,032	4
C	MA of Acayucan	Veracruz	112,996	3
C	MA of Mérida	Yucatán	973,046	5
C	MA of Zacatecas-Guadalupe	Zacatecas	309,660	3
C	MA of Celaya *	Guanajuato	602,045	3
C	MA of Tianguistenco	México	157,944	6
C	MA of Teziutlán *	Puebla	122,500	2

Source: National Council on Population (CONAPO).

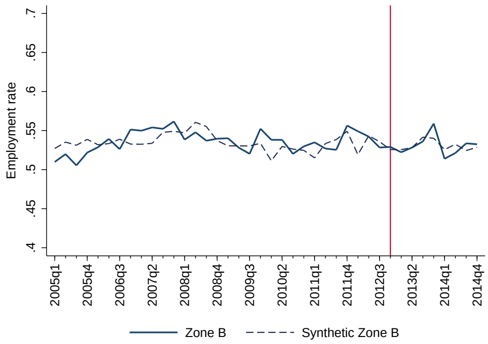
*Metropolitan areas excluded from the robustness check analysis reported in Table 5.5

Appendix 5.B Robustness checks

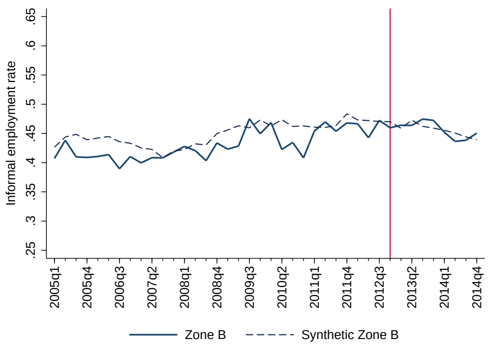
Figure 5.B.1
SCM excluding Mexico City



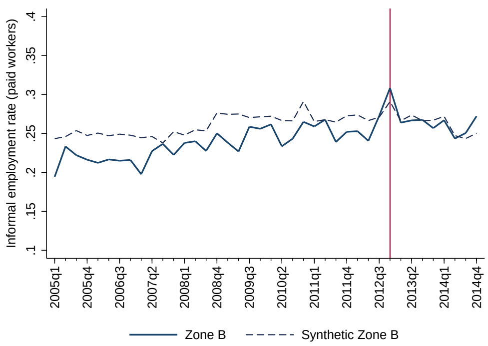
(a) Active labour market rate
Zone B vs synthetic Zone B



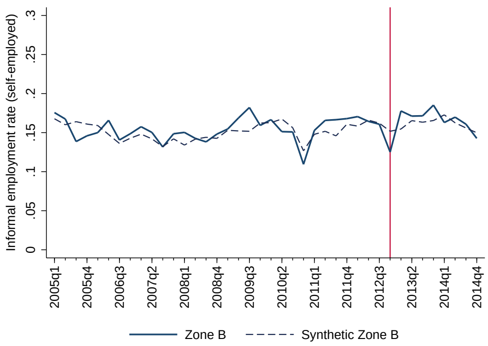
(b) Employment rate
Zone B vs synthetic Zone B



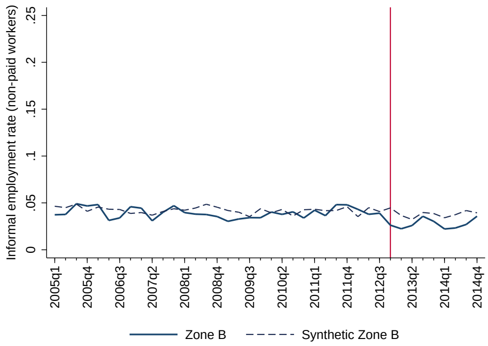
(c) Informal employment rate
Zone B vs synthetic Zone B



(d) Informal emp. rate (paid)
Zone B vs synthetic Zone B



(e) Informal emp. rate (self-employed)
Zone B vs synthetic Zone B

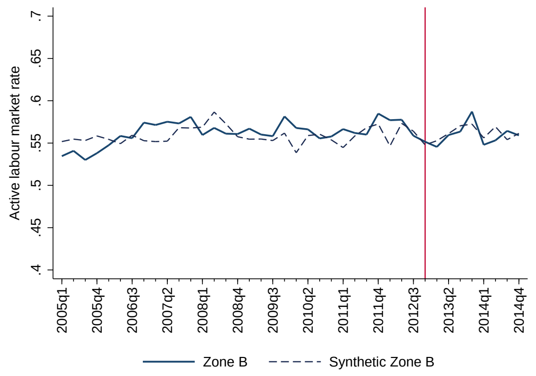


(f) Informal emp. rate (non-paid)
Zone B vs synthetic Zone B

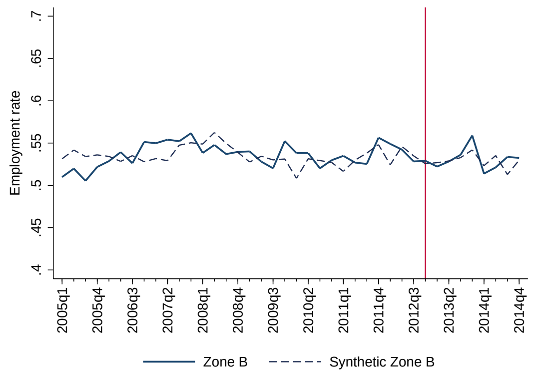
Note: the covariates included are proportion of individuals between 30 and 49 years old, proportion of individuals with the second level of education completed (9th year), and proportion of workers in the industrial and services sector. The lagged outcome variables correspond to 2007Q3 and 2012Q3.

Figure 5.B.2

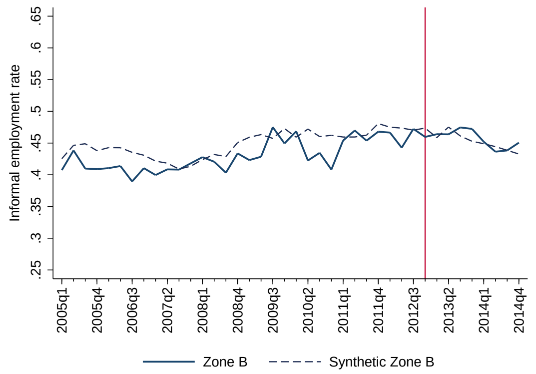
SCM restricting pool of donors excluding nine metropolitan areas



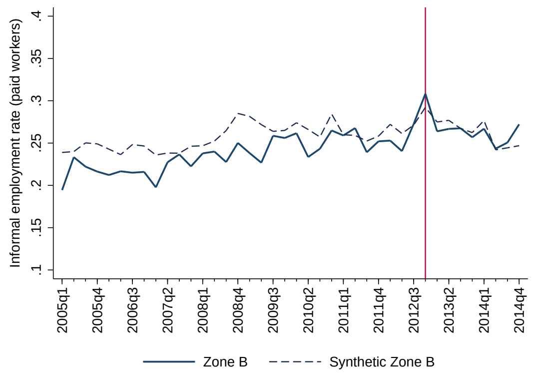
(a) Active labour market rate
Zone B vs synthetic Zone B



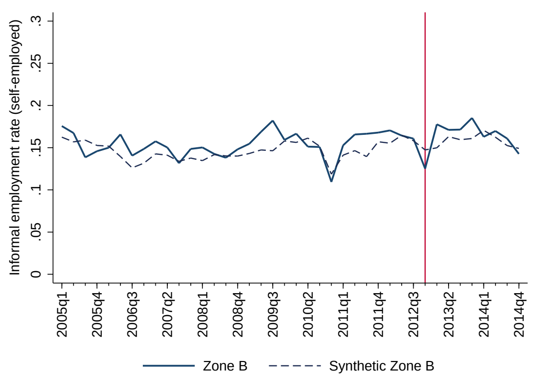
(b) Employment rate
Zone B vs synthetic Zone B



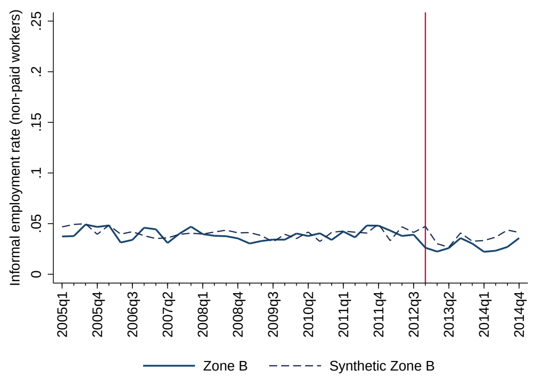
(c) Informal employment rate
Zone B vs synthetic Zone B



(d) Informal emp. rate (paid)
Zone B vs synthetic Zone B



(e) Informal emp. rate (self-employed)
Zone B vs synthetic Zone B



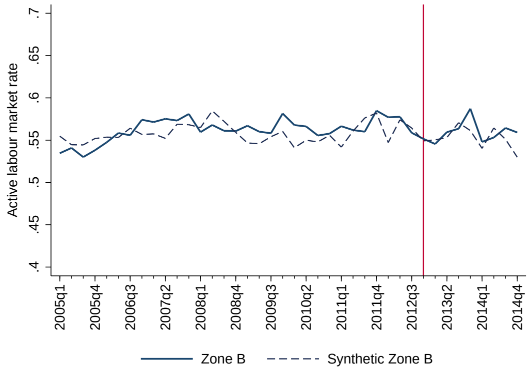
(f) Informal emp. rate (non-paid)
Zone B vs synthetic Zone B

Note: the covariates included are proportion of individuals between 30 and 49 years old, proportion of individuals with the second level of education completed (9th year), and proportion of workers in the industrial and services sector. The lagged outcome variables correspond to 2007Q3 and 2012Q3.

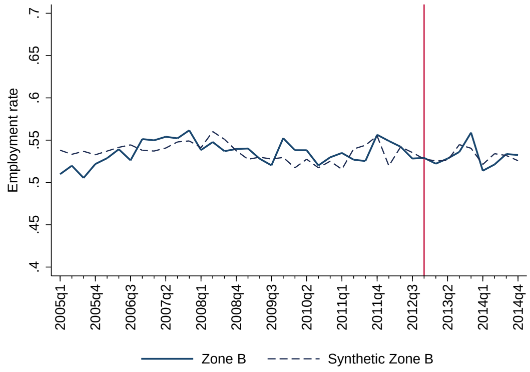
Figure 5.B.3

SCM changing the vector of covariates

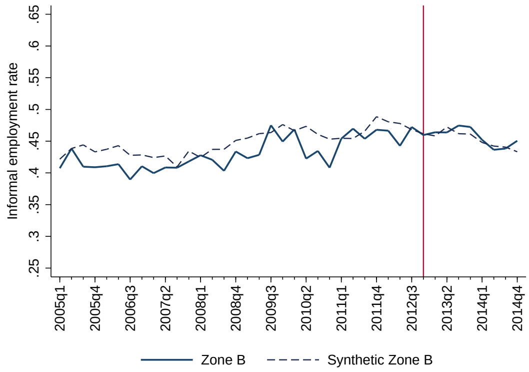
(individuals between 12 and 29 years old and and of workers in services sector)



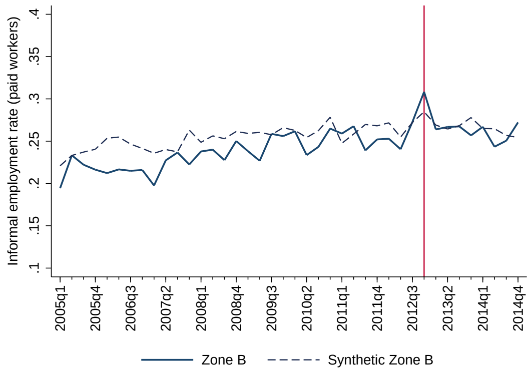
(a) Active labour market rate
Zone B vs synthetic Zone B



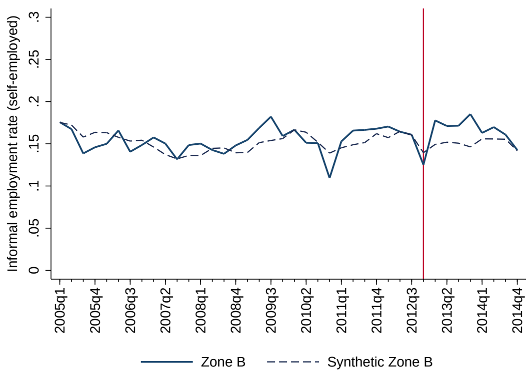
(b) Employment rate
Zone B vs synthetic Zone B



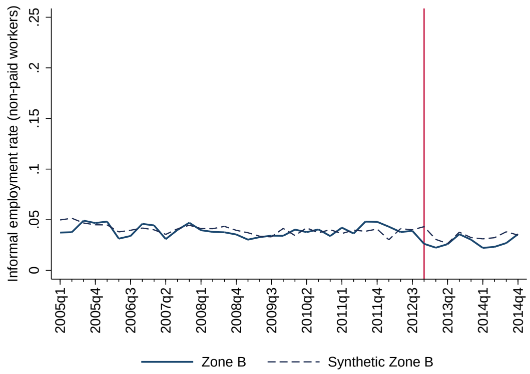
(c) Informal employment rate
Zone B vs synthetic Zone B



(d) Informal emp. rate (paid)
Zone B vs synthetic Zone B



(e) Informal emp. rate (self-employed)
Zone B vs synthetic Zone B

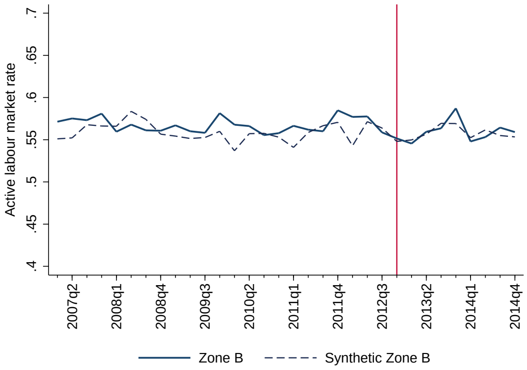


(f) Informal emp. rate (non-paid)
Zone B vs synthetic Zone B

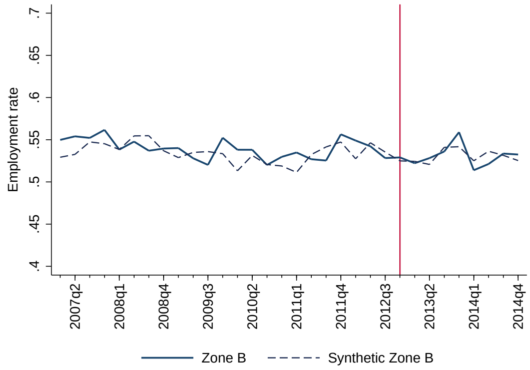
Note: the covariates included are proportion of individuals between 12 and 29 years old, proportion of individuals with the second level of education completed (9th year), and proportion of workers in services sector. The lagged outcome variables correspond to 2007Q3 and 2012Q3.

Figure 5.B.4

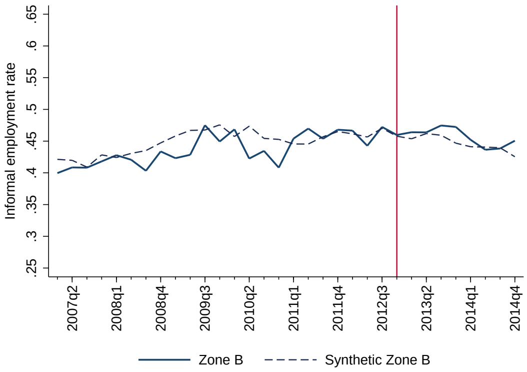
SCM changing the period of analyisis: 2007Q1 to 2014Q4



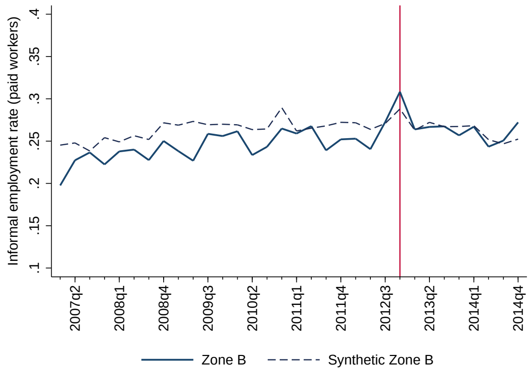
(a) Active labour market rate
Zone B vs synthetic Zone B



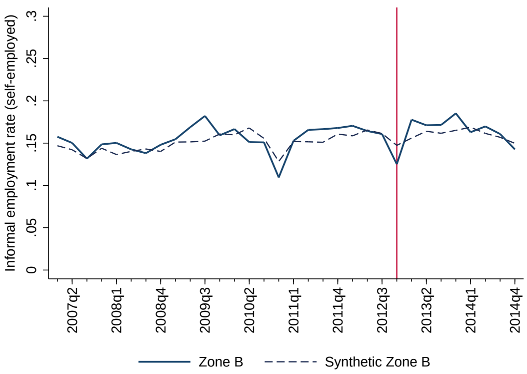
(b) Employment rate
Zone B vs synthetic Zone B



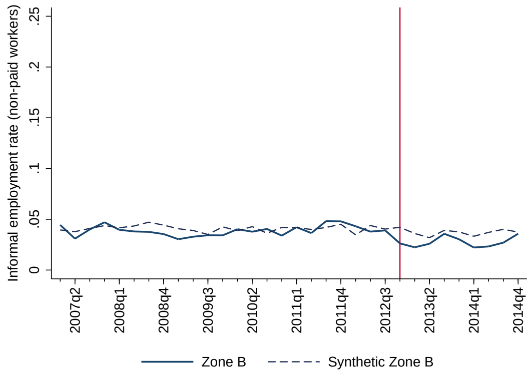
(c) Informal employment rate
Zone B vs synthetic Zone B



(d) Informal emp. rate (paid)
Zone B vs synthetic Zone B



(e) Informal emp. rate (self-employed)
Zone B vs synthetic Zone B



(f) Informal emp. rate (non-paid)
Zone B vs synthetic Zone B

Note: in model (1), the covariates included are proportion of individuals between 30 and 49 years old, proportion of individuals with the second level of education completed, and proportion of workers in the industrial and services sector. In model (2) the covariates are proportion of workers between 12 and 29 years old and the proportion of workers in the services sector.

CHAPTER 6

CONCLUSIONS

The aim of this thesis has been to evaluate the labour market implications of a minimum wage increase in Mexico, using as a natural experiment the 2012 minimum wage intervention. This minimum wage rise took place in only one out of the three minimum wage zones, which allowed us to implement various techniques developed in the field of causal treatment effects, including Difference in Differences regressions and the Synthetic Control Method approach. We have evaluated the effects of this policy change on: real wages, the distribution of real wages, overall employment and informal employment.

The identification strategy in every chapter changed depending on the particular technical requirements needed to answer each research question. Nevertheless, there were several methodological aspects in common throughout the dissertation. First, the use of Zone B's minimum wage rise as the source of identification. Second, the Mexican National Survey on Employment and Occupation (ENOE) as data source. Third, the systematic estimation of the respective treatment effects on the informal employed workers. Moreover, to provide consistency to our estimates, in Chapters 2 to 4 we used exactly the same set of control variables in our econometric specifications.

Synthesizing our findings in Chapter 2, our Difference in Differences regressions, which also made corrections for sample selection bias, suggested that there was an important positive effect of the minimum wage intervention on real wages. The resulting increase in real wages was found in both the formal and informal labour markets. This represented a general improvement of workers' real earnings, although the effect was stronger on workers aged 30 to 49. Moreover, the overall elasticity of the treatment effect was found to be greater than unitary, which meant a real wage expansion that was more than proportional to the minimum wage rise. Given these findings, the next step in Chapter 3 was to implement Unconditional Quantile Regressions to estimate a treatment effect on every percentile of the real earnings distribution. At the bottom of the real earnings distribution, there was a modest increase in real wages, which implies that the targeted low-wage segment of the labour force actually benefited from the minimum wage change. But, analysing the impact on the rest of the wage percentiles, the estimated effect was greater at the top of the real wages distribution, suggesting the existence of income-increasing spillover effects at the upper end of the wage distribution possibly due to wage-indexing effects. Regarding the employment effects, in Chapter 4 we did not find any statistical evidence of negative minimum wage effects neither on the size of the workforce nor on the level of employment, suggesting a monopsonistic labour market in Mexico. By Difference in Differences regressions we estimated small and temporary positive effects on the employment rate and a decline in the share of informal workers. Remarkably, these effects had a higher magnitude on workers aged over 50. Finally, Chapter 5 tested if the employment effects found in Chapter 4 were robust to the estimation method and to the level of aggregation in the data. By the implementation of the Synthetic Control Method, and aggregating the data at the metropolitan area level, we corroborated most of our previous results finding no adverse effects on the employment rate, and even a temporary improvement two quarters after the intervention. However, the reduction in the overall informal employment was found to be no longer significant.

Therefore, the central findings of the econometric evaluation carried out in this dissertation suggest that the 2012 minimum wage rise in Mexico had a positive impact on real wages and no adverse effects on employment, revealing the existence of a monopsonistic labour market. But in terms of the distributional effects, the income-increasing spillover effects suggest an expansion of the dispersion of wages.

Our employment findings are in line with the *new minimum wage research* wave. Its empirical findings, theoretically supported by monopsonistic labour market model, contend that minimum wage rises do not necessarily imply a decline in the level of employment

(Card and Krueger, 1994; Dickens et al., 1999; Dube and Zipperer, 2015), even in countries with an important share of informal employment (Lemos, 2009; Campos et al., 2017). With respect to the distributional effects, our results also suggest common findings with respect to previous literature. On the one hand, wage spillover effects beyond the minimum wage threshold are well documented in the field (Lee, 1999; Autor et al., 2016). On the other hand, there exist previous evaluations challenging the *Welch-Gramlich-Mincer Two Sector Model* regarding positive wage effects on the *uncovered* informal labour market (Lemos, 2009; Khamis, 2013). Nevertheless, to our knowledge this is the first study that finds more-than-proportional income-increasing spillover effects on the upper end of the wage distribution. We argue that the institutional wage setting in Mexico, specifically the role of the minimum wage as a reference rate to set wages and other forms of remunerations, was responsible for these strong minimum wage spillover effects.

On this regard, it is important to make two remarks. First, a central limitation of the data employed is that the ENOE survey does not properly cover those workers with the highest level of earnings. As a consequence, the estimated effects at the top of the earnings distribution, do not correspond to the actual share of top earners in the Mexican labour market.

Second, this institutional wage setting, in which wages were tied to the value of the minimum wage, was legally modified by the 2016 'de-indexation of the minimum wage reform'. In terms of our policy evaluation purposes, it implies that in case of a further minimum wage intervention after this legal amendment, it should be possible to test whether the income-increasing spillover effects were actually generated by the institutional framework, or in contrast, by the existence of pure minimum wage *lighthouse effects*. A more aggressive increase to the minimum wage has been discussed in Mexico in the last four years. Nevertheless, political conditions have not been favourable to its implementation. Right now, as part of the renegotiations process of the *North American Free Trade Agreement* (NAFTA) with US and Canada, the relatively low wage level in Mexico has been part of the agenda. So, these conditions, together with the domestic economic context, have generated expectations with respect to an important minimum wage rise before December 2018. Under this scenario, we could verify the validity of our findings, and not only those related to the income-increasing spillover effects, but also our conclusions on employment and informal employment effects.

Also related to our future research agenda, it is important to recognize the lack of a theoretical model in the field of minimum wages that fully characterises the informal labour market. The *Welch-Gramlich-Mincer Two Sector Model* represents the only theoretical framework currently available to analyse minimum wage in dual labour markets. However, it was not designed to define an actual informal labour market, but just to identify to those workers earning less than the minimum wage (legally or illegally). Informal employment is not only about non-compliance with the minimum wage legislation. It also constitutes a complementary labour market, with its own incentives to attract workers with different skills. It is essential to extend the theoretical model by adjusting its assumptions regarding a heterogeneous skills distribution and the capacity of workers to choose the labour market in which they decide to perform their labour activities. The development of this model can contribute to understand and also to support the recent empirical findings about the effects of minimum wage increases in developing countries with an important share of informal employment.

As a final consideration, given the current context of the Mexican labour market, in which the real value of the minimum wage has decreased almost 70% in the last 30 years, more than a half of the population lives in poverty, and 60% of the labour force is employed in the informal labour market, the implementation of public policies to adjust the real value of minimum wage seems unavoidable. Nevertheless, the purpose of this dissertation has not been to encourage indiscriminate increases to the minimum wage. The elasticities found in this study apply only for the specific context of the 2012 Zone's B minimum wage intervention. The estimated treatment effects are not proportional to stronger changes to the minimum wage level, and an optimal minimum wage setting is beyond the scope of this research. In contrast, this thesis provides a formal evaluation of the labour market implications of a minimum wage rise serving as a guideline to understand the responses of the Mexican labour market to changes in the minimum wage level, which in turn must be considered in the process of designing larger interventions in the minimum wage legislation.

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