ESSAYS ON MINIMUM WAGES AND DECLINING WAGE INEQUALITY IN LATIN AMERICA

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Abstract

This thesis studies the factors behind the declining wage inequality in Latin America, focusing on minimum wage policies.

Chapter 1 studies potential explanations of the declining wage inequality in Brazil such as changes in demographic/skill composition, wage structure, occupations/sectors and minimum wage. I perform a decomposition of wage inequality to quantify composition and price effects, and use a CES production function to estimate the effects of skill supply on relative wages. I find that the fall in upper-tail inequality is given by changes in the returns to education and experience, while the fall in lower-tail inequality is also explained by those to minimum wage and female workers.

Chapter 2 documents the effectiveness of the minimum wage on compressing lower-tail inequality without harming employment significantly. The study complements empirical literature on the subject by identifying the effects of the minimum wage through its level of bindingness on the wage distribution across regions. I find that 35 percent of the decline in lower-tail inequality is attributed to the minimum wage, while its effects on upper-tail inequality are negligible. Prior studies find significant effects throughout the wage distribution, I argue that these are likely to suffer from misspecification and sample selection issues.

Chapter 3 is motivated by the findings from previous chapters. I develop a two-region economy in which one region employs labour more efficiently than the other and unemployed workers search for jobs in both regions. I study the effects of setting a minimum wage which is particularly binding in the low-productivity region. Under a common market of unemployed workers, a binding minimum wage changes the value of unemployed search affecting wage-setting rules and employment in both regions. I illustrate the use of the model by performing counterfactual and policy experiments motivated by the desire of providing potential explanations of intraregional inequalities.

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Chapter 1

Skill Prices and Compositional Effects on the Declining Wage Inequality in Latin America: Evidence from Brazil

1.1 Introduction

The decline in income inequality in Latin America over the 2000s has motivated an extensive literature investigating the driving factors behind this trend. Social transfers in favour of the poorest, redistribution through progressive taxation and changes in the skill and demographic composition of the labour market are commonly mentioned in the literature (López-Calva and Lustig 2010; Cornia 2014; Fritz and Lavinas 2016; Bértola and Williamson 2017). The empirical consensus suggests that most of the decline in income inequality has been driven by the fall in wage inequality (Barros et al. 2010; Gasparini et al. 2011; Cruces et al. 2014). Although labour earnings depend on several workers' individual characteristics, changes in the price of skills seem to play a significant role in shaping wage inequality. Traditional literature has linked changes in the price of skills to the interaction between the labour supply of and demand for skills. In fact, there is empirical evidence of the effects of skill demand shifts on the increase in income inequality that the region experienced in the 1990s (Robertson 2004; Behrman et al. 2007; Goldberg and Pavcnik 2007; Kahhat 2010). The favourable trade conditions in the 1990s such as a reduction in tariffs on imports of capital goods shifted the labour demand in favour of high-skilled workers because capital is assumed to be skill-biased, thus trade liberalization increased the skill premium and income inequality in this period (Green et al. 2001; Sánchez-Páramo and Schady 2003; Parro 2013).[1]

As the region experienced a turning point in income inequality over the early 2000s, traditional factors that shaped wage inequality in the 1990s are unlikely to explain the long-lasting decline in income inequality over the last decade. In Brazil, income inequality reversed its trend in the late 1980s and has been falling since then in spite of the trade liberalization process that the country experienced over the 1990s. As Brazil accounts for approximately 34 percent of total GDP in Latin America and 33 percent of its entire population, it is not surprising that most of the literature has focused on this country to understand the declining income inequality in the region. However, income inequality has also fallen among 15 other Latin American economies, particularly in the 2000s. Figure 1.1 depicts the evolution of income inequality in Brazil and Latin America measured by the Gini coefficient.

Income inequality in Brazil increased sharply from 1985 to 1989, this was a period characterized by economic instability and four-digits inflation rates. Currency depreciation led to the abolition of several local currencies which lasted less than two years on average. Finally, the adoption of the "Brazilian Real"

[1] Literature on the subject for Latin American economies follows the pioneering work of Tinbergen (1974). The increase in the skill premium is explained by the relative increase in the demand for skills which is linked to the development of skill-biased technology (Acemoglu 1998; Autor et al. 1998; Berman et al. 1998; Caselli 1999; Acemoglu 2007). This technology is embodied in capital goods which are more complementary with high-skilled workers. Moreover, globalization has enabled the transmission of the capital-skill complementary effect from industrialized countries to developing ones (Goldberg and Pavcnik 2007).

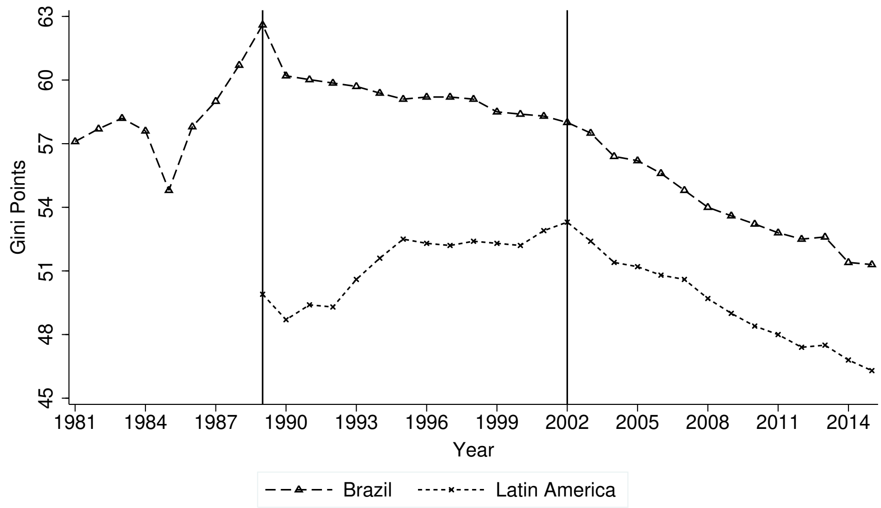


Figure 1.1: GINI Coefficient in Brazil and Latin America

Source: Socio-Economic Database for Latin America and the Caribbean (CEDLAS and The World Bank). Version: May 2018. Gini coefficient for the distribution of household per capita income excluding zero income. The average Gini coefficient for Latin America is an arithmetic average of 18 Latin American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay and Venezuela) from 1989 to 2015. Data became available only after 1989 for most countries and there are missing observations in specific countries and years, thus around 25 percent of the observations were obtained by interpolation.

in 1994 stopped the rampant inflation that the country experienced in previous years. Income inequality decreased at a slow pace but steadily over the 1990s in Brazil unlike average income inequality in Latin America.[2] In the early 2000s, income inequality decreased faster not only for Brazil but also for most Latin American economies, following the boom in the commodity prices in this period. The Gini coefficient fell on average 0.5 points per year during the period 2001-2014, reaching its lowest point recorded in more than three decades in the last year of the sample.[3] The reduction in income inequality mirrors the decrease in the income

[2]Although most of the literature attributes the increase in income inequality in the 1990s to trade liberalization, Dix-Carneiro and Kovak (2015) find that this had a small but significant equalizing effect in Brazil.

[3]Despite the remarkable decline in income inequality over the 2000s, Latin America is still the region with the highest Gini coefficient in the world. According to data from the World Bank and United Nations Development Programme (UNDP) for 2013, the Gini coefficient for the region is 3 points higher than in Sub-Saharan Africa —the second region with the highest income inequality— and 16 points higher than in North America and the European Union —the region with the lowest income inequality—.

gap between the richest and the poorest in Brazil.[4]

The long-lasting decline in income inequality in Brazil as well as in other Latin American economies is an opportunity to understand how labour market forces and other factors interact with income inequality in the region. As an extensive literature predicted that wage inequality in Latin America would follow the same pattern as in more developed regions because Latin American countries are still highly dependent on capital goods import which are essentially skill-biased, some questions arise on this matter. Is capital less skill-biased than it was in previous decades? Has the supply of skills outweighed the effects of skill demand shifts on the skill premium? or Are labour market institutions responsible for this pattern?

Some of these questions and others are addressed by studying changes in the skill and demographic composition of the labour market and their respective prices, changes in occupational and sectoral structure and minimum wage policies in Brazil from 1981 to 2015. I perform a counterfactual exercise following Firpo et al. (2018) to estimate composition and price effects on wage inequality. As the validity of this counterfactual exercise relies on the assumption that changes in quantities do not affect prices, I complement the study by estimating the effects of changes in the labour supply of skills on relative wages among educational groups following the supply-demand framework proposed by Katz and Murphy (1992). This framework has been used in previous studies for a panel of Latin American countries such as Manacorda et al. (2010) and Gasparini et al. (2011). Given the heterogeneity among Latin American economies in terms of labour market composition and minimum wage policies, it is worthwhile to perform an analysis at a country level. This study also uses the traditional Katz and Murphy framework to estimate elasticities of substitution for more than the two traditional educational groups (college and high-school graduates). The reasons are merely

[4]According to data from the World Bank, the income share held by the poorest 10 percent grew at an annual average of 2.6 percent from 2001 to 2013, while that held by the richest 10 percent decreased by approximately 1 percent over the same period. Moreover, the decline in income inequality has been accompanied by a reduction in the proportion of people living in extreme and moderate poverty, both indicators fell by an annual average rate of 8.2 and 8.4 percent, respectively.

obvious; the skill composition in the Brazilian labour market is substantially different from that in developed countries. High-school graduates and high-school dropouts constitute the bulk of the labour force in Brazil, thus these might not necessarily be perfect substitutes in the eyes of the employers.[5] I further use this specification to examine whether workers with different years of experience are perfect substitutes within the same educational group and whether changes in the real minimum wage, net of the effects of labour market forces, has contributed to the evolution of the skill premium in Brazil, something that has been overlooked in previous specifications.

I use cross-sectional data from the Brazilian National Household Survey (PNAD, Pesquisa Nacional por Amostra de Domicílios) which is the most disaggregate source of microdata in the country after the Census. I find that changes in the wage structure explain the entire decline in both upper and lower-tail inequality. The former is explained by changes in the returns to education and age/experience, while the latter is also explained by those to minimum wage and female workers. The empirical evidence also suggests that wage structure is driven by changes in the skill composition of the labour market which is reflected in the decline of the skill premium. In agreement with previous literature, the increase in the relative supply of skills has played a significant role in the decline of the tertiary/non-tertiary wage gap. On the other hand, the fall in the skill premium between secondary and primary educated workers is driven by the increase in the real minimum wage rather than by changes in their relative labour supply. This last finding seems to be opposed to what has been found previously in the literature on the subject. The disagreement may arise for both the inclusion of additional years of data in which the minimum wage increases rapidly and the heterogeneity among Latin American labour markets in panel data studies. Furthermore, the increase in the labour earnings among workers

[5]The skill composition of these educational groups has changed significantly in the last decades. For instance, the share of individuals with high-school diplomas has quadrupled from 1981 to 2015, whereas the share of individuals with less than a high-school diploma has decreased around 40 percent over this period.

who perform low-skill occupations such as personal services and agriculture, in spite of the decline in their employment participation, along with the sharp decrease in the skill premium, particularly among young workers, reinforces the idea that the minimum wage plays a significant role in the compression of wage inequality. There is also evidence of a significant effect of labour demand shifts on the skill premium, however, this effect is relatively small compared to other potential explanations.

The remainder of the paper is organized as follows. Section 2 describes data sources and provides non-causal information on changes in wages and labour supplies by educational and demographic groups. Section 3 sheds light on changes in occupational/sectoral structure and their interaction with labour earnings. Section 4 estimates the causal relationship between the minimum wage and wage inequality, presents a counterfactual exercise to decompose wage inequality into composition and price effects and outlines the supply-demand framework to estimate the effects of changes in the skill supply and minimum wage on relative wages. Section 5 concludes.

1.2 Overview of the Labour Market

1.2.1 Data Sources

Studies in income inequality for Latin American economies are relatively new compared to those from more developed countries because household surveys were not available until the late 1970s. Moreover, it was not until the early 1980s that Latin American countries reconciled data collection strategies and provided more reliable data. Undoubtedly, Brazil takes the lead with respect to its counterparts when it comes to the availability of microdata sources. I draw on the National Brazilian household survey (PNAD, in its Portuguese acronym) which is carried out by the Brazilian Institute of Geography and Statistics (IBGE, in its Portuguese acronym). This annual household survey provides socio-economic information from 26 regions in Brazil with national coverage. I use 31 household surveys that cover the period 1981-2015.[6]

I construct two different samples, one for labour earnings and one for labour supply, by following Katz and Murphy (1992) to account for composition-adjusted labour earnings and efficiency units of labour supply. The "wage sample" provides a reasonable constant composition of workers' characteristics through time. This comprises labour earnings in the main occupation of full-time workers —those who worked at least 35 hours or more per week—, aged 18 to 65 years old. Workers who do not report labour earnings in the month prior to the PNAD survey reference week are excluded from the sample as well as those who declare to be self-employed, volunteer or produce for self-consumption. Labour earnings from 1981 to 1993 are converted to Brazilian Reals —the official currency in Brazil since 1994—, and deflated using the Consumer Price Index deflator for PNAD (INPC base year 2012, in its Portuguese acronym) which is obtained from the Institute for Applied Economic Research (IPEA, in its Portuguese acronym).[7] The measure of labour earnings is the logarithm of the hourly real wage —real monthly wages divided by 4.3 and the number of working hours per week for each worker—.

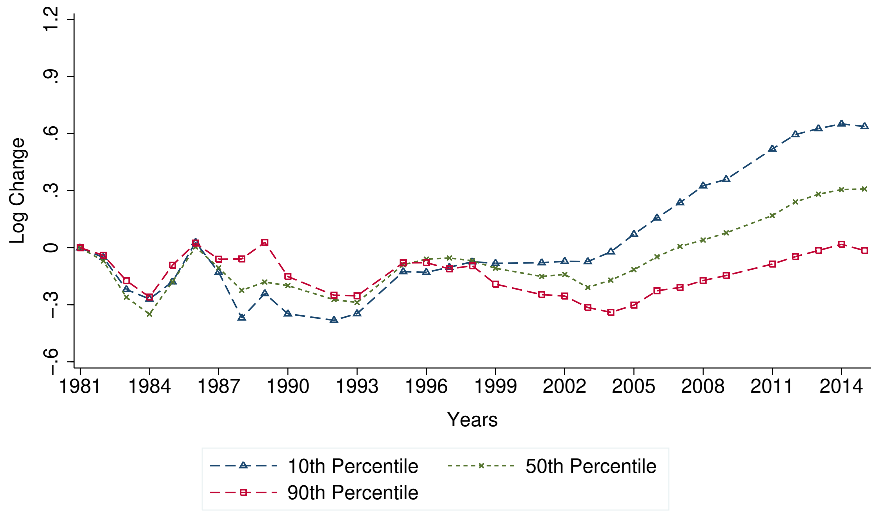
The "supply sample" comprises all individuals that worked in the reference week or were employed in the year prior to the reference week regardless of whether they are salary or wage workers, self-employed or otherwise. The measure of labour supply is simply the number of individuals adjusted to the sample weights provided by PNAD. Additional information on sampling can be found in the notes of each figure and table.

[6] There are no data available for 1991, 1994, 2000 and 2010 because the National Census was carried out instead of PNAD in those years.

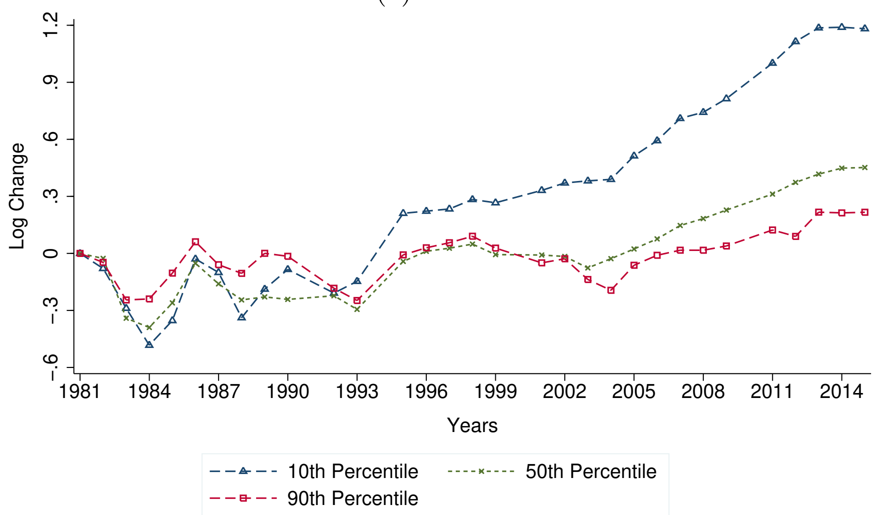
[7] The following exchange rates are used according to the period: 1 Brazilian Real= 2750 billion Cruzeiros from 1981 to 1985, 1 Brazilian Real= 2750 million Cruzados from 1986 to 1988, 1 Brazilian Real= 2.75 million Cruzeiros/Cruzado Novos from 1989 to 1992, and 1 Brazilian Real = 2750 Cruzeiro Real for 1993.

1.2.2 Overall Wage Inequality

I begin this discussion by studying the changes in the wage distribution over the sample period 1981-2015. Figure 1.2 illustrates the evolution of the log real hourly wage at the 10th, 50th and 90th percentiles by gender.



(a) Males



(b) Females

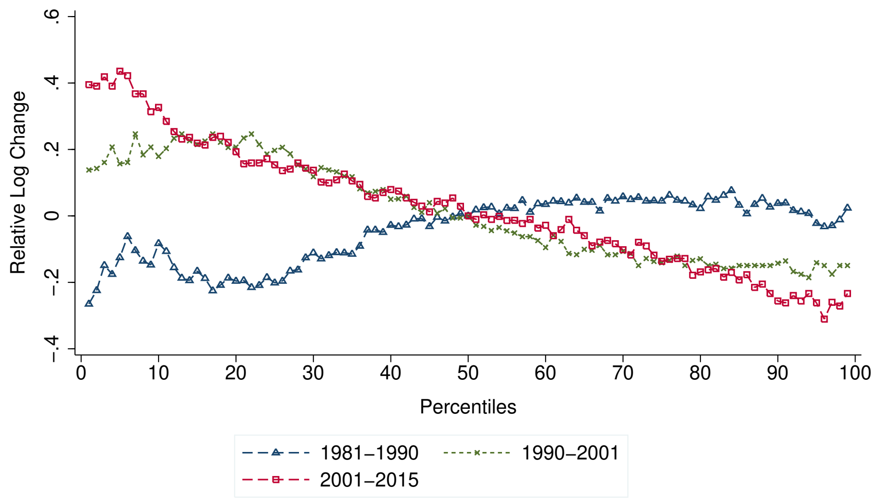
Figure 1.2: Log Change in Wage Percentiles by Gender

Source: PNAD data from 1981 to 2015. Log changes in hourly wages at the 10th, 50th and 90th percentiles from the "wage sample" are normalized to zero in 1981.

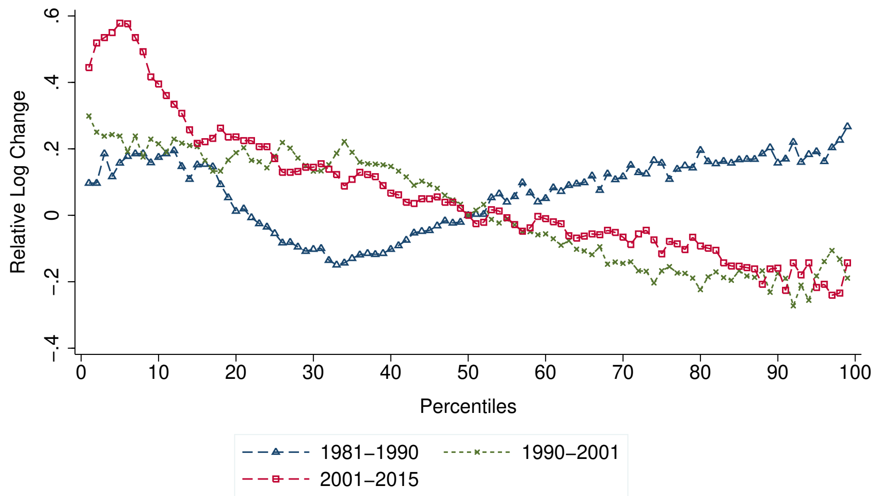
The spikes in the evolution of real wages over the 1980s and the early 1990s reflect the economic and political turbulence that the country experienced over this period. Monetary financing of budget deficits and frequent devaluations led

Brazil to experience three-to-four-digit annual inflation rates. The attempts to control hyperinflation failed, and the country changed currencies several times. As expected, the 90th percentile had a better evolution over the inflationary period, as price volatility was more detrimental to the poor. The launch of the "Plano Real" in 1994 which involved the adoption of a new currency the "Brazilian Real" with a crawling peg against the dollar, austerity policies and de-indexation of the economy were successful in controlling inflation rates. Currency stabilization did not imply the end of the macroeconomic instability, thus the recovery of real wages in 1994 was followed by a stagnation of the 10th percentile and a fall of the 50th and 90th percentiles over the late 1990 and early 2000s. It was not until the mid-2000s that real wages rose rapidly throughout the wage distribution as the economy benefited from increases in commodity prices. Notice that there is a deceleration in real wages growth in the last years of the sample as inflation has increased above the targets.

In terms of wage inequality, the 90th/10th wage gap increased in the 1980s as the 90th percentile was less affected than the 10th percentile over the inflationary period. Wage inequality decreased in the 1990s as the 10th percentile grows faster, particularly among women. Further decreases in wage inequality can be observed in the 2000s as the 10th percentile pulls away from the other percentiles. Notice that both lower and upper-tail inequality measured by the 50th/10th and 90th/50th, respectively, fall over the 2000s. Both inequality measures shrink continuously and symmetrically among males, while the 50th/10th shrinks more rapidly than the 90th/50th among females. The evolution of wage inequality seems to track remarkably well the evolution of the GINI coefficient in Figure 1.1 over the 1980s, 1990s and 2000s. The contrast among these periods is shown in Figure 1.3 which plots the change in log hourly wage percentiles relative to the median wage for 1981-1990, 1990-2001 and 2001-2015.



(a) Males



(b) Females

Figure 1.3: Relative Log Change in Wage Percentiles by Gender and Periods

Source: PNAD data for 1981, 1990, 2001 and 2015. Relative changes in log hourly wages from the "wage sample" between two years. The change in the log hourly wage at the median is normalized to zero for each period.

The 1980s were characterized by a non-monotone change throughout the wage distribution. The negative change in percentiles below the median implies an increase in lower-tail inequality throughout all percentiles in the bottom half of the wage distribution among males and those between the 22nd and 50th percentiles among females. Upper-tail inequality remains relatively constant among males, whereas there is a sizeable increase among females. These patterns change dramatically in the 1990s and both lower and upper-tail inequality fall for both genders. Further decreases in wage inequality can be observed in the 2000s mostly driven by the rise in the lowest percentiles of the wage distribution. Notice that wage inequality shrinks further for percentiles below the 15th and above the 80th among males and below the 25th percentile among females. These results suggest that the further compression in wage inequality in the 2000s is driven by the faster growth of the lowest percentiles of the wage distribution with respect to the median.

To put this information in context, I use the 10th and the 90th percentiles relative to the median wage as measures of lower and upper-tail inequality. Lower-tail inequality among males fell by 18 log points in the 1990s and 33 log points in the 2000s, while upper-tail inequality decreased by 14 and 26 log points in each period, respectively. Among females, the fall in lower-tail inequality is even more significant around 22 log points in the 1990s and 40 log points in the 2000s, while upper-tail inequality fell more modestly around 16 log points in each period. The empirical evidence on the subject for more developed countries suggests that changes in wage inequality are mainly driven by changes in the upper half of the wage distribution. This is clearly not the case in the Brazilian labour market as most of the recent decline in wage inequality is given by the compression of the bottom half of the wage distribution. The remarkable increase in the lowest wage percentiles might echo the unprecedented rise in the real value of the minimum wage over the 2000s. According to data from the Brazilian Ministry of Labour (MTE, in its Portuguese acronym), the real minimum wage increased by approximately 80 percent from 2001 to 2015. There is not a straightforward explanation for the slower growth in the highest wage percentiles with respect to the median, but we can intuit that the same factors that shape wage inequality in developed countries might have played a role in this phenomenon such as wage growth polarization and changes in the return to skills.

1.2.3 Skill Premium and Relative Labour Supply

The effects of labour market forces such as supply of and demand for skills on the return to education and inequality have been well documented in the literature, particularly for more developed countries. These empirical studies reach two conclusions that explain the widening of wage inequality, particularly in the U.S. First, wage inequality echoes the rise in the labour earnings of more educated workers which is linked to the development of computer-based technologies and the corresponding labour demand shifts in favour of this skill type (Autor et al. 1998; Berman et al. 1998; Caselli 1999; Krusell et al. 2000; Acemoglu 2007). The idea that capital is more complementary with high-skilled workers was initially introduced by Griliches (1969) and this is still widely popular in the literature to explain increases in wage inequality. In fact, the literature for Latin America suggests that the increase in inequality over the 1990s was driven by a capital-skill complementarity effect which was spread from the developed world towards the region through capital acquisition (Green et al. 2001; Sánchez-Páramo and Schady 2003; Parro 2013). Second, a rising wage inequality requires that the secular increase in the labour supply of more educated workers does not outweigh the skill-biased technological effect on the returns to skills.

As most of the Latin American countries experienced a decrease in wage inequality over the 2000s, a question arises: How do labour market forces affect the return to skills in the region over that period? A decrease in the return to skills requires that the labour supply of skills outweigh the labour demand for them. The remarkable educational upgrading of the labour force in the region is the most straightforward explanation of the decrease in the price of skills and the corresponding decrease in wage inequality (Barros et al. 2010; Gasparini et al. 2011; Cruces et al. 2014). Thus, a natural starting point is to study the evolution of the labour supply of skills and its effects on the skill premium.

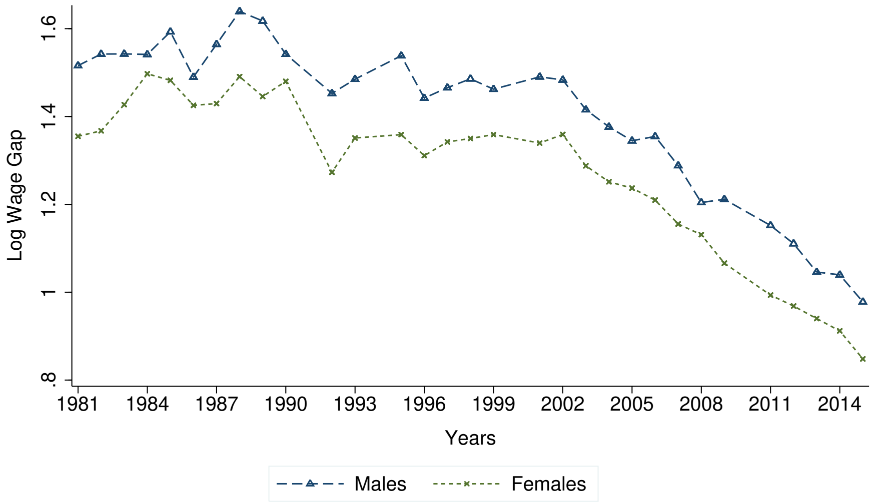
Motivated by the labour supply-demand framework of Katz and Murphy (1992) and, Acemoglu and Autor (2011), I estimate measures of relative wages and labour supplies between educational groups. The samples described in the Data section are split into different cells that comprise homogeneous workers in order to estimate changes in labour earnings driven by factors others than changes in the demographic composition of the workforce. Workers are sorted into two genders (males and females), five groups of education (illiterate, less than 11 years of schooling, 11 years of schooling, 12 to 14 years of schooling, and 15+ years of schooling)[8] and 49 groups of experience (corresponding to single-year categories from 0 to 48 years of potential experience).[9] Consequently, workers are sorted into 490 gender-education-experience categories by year.

The "wage sample" is used to estimate the composition-adjusted log hourly wages which are the weighted average of the predicted log wage from a regression of log hourly wages on education and race dummies, a quartic in experience, and interactions between education and experience in each one of the 490 gender-education-experience groups. I use a set of fixed weights equal to the participation in employment of each cell to aggregate through demographic groups.

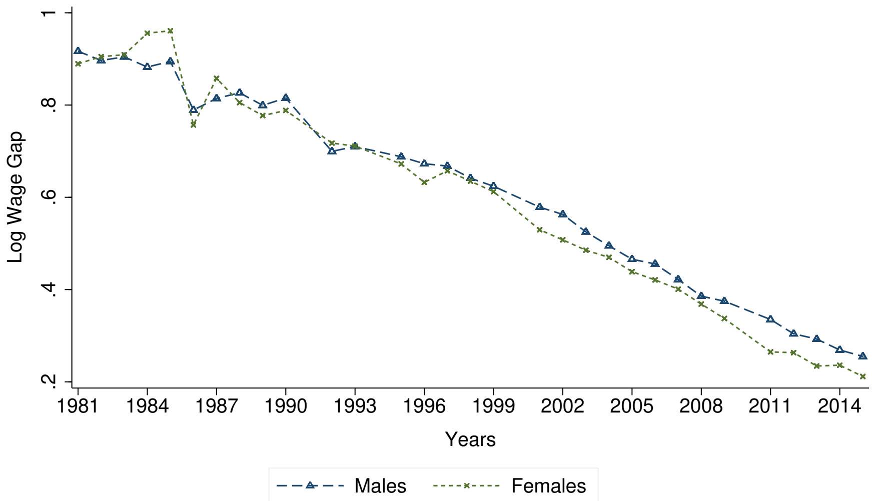
Figure 1.4 plots the wage gap between tertiary/non-tertiary and secondary/primary educated workers. Although the former is the standard measure of the skill premium, the latter provides a clearer picture of the effects of the educational upgrading on the price of skills because the increase in the average years of education has been mostly attributed to the expansion of secondary education in Brazil.

[8]The required years of schooling to complete an educational category have changed over time, particularly for primary education. For example, primary education was completed after 4 years of schooling in the 1960s, 6 years in the 1970s, 8 years in the 1980s and 9 years from the 1990s to the present. To obtain consistent sample cells in terms of education over time, I consider primary-educated workers as those who are literate and have less than 11 years of schooling, secondary-educated workers as those with 11 years of schooling, and complete-tertiary-educated/postgraduate workers as those with 15 or more years of schooling, thus incomplete-tertiary-educated workers report years of schooling between the two previous categories.

[9]Years of potential experience are estimated as max(min(age-years of schooling-6, age-17), 0). This ensures either zero or a positive number of years of experience and that no individual has started working before 18 years of age.



(a) Tertiary/Non-Tertiary



(b) Secondary/Primary

Figure 1.4: Skill Premium by Gender

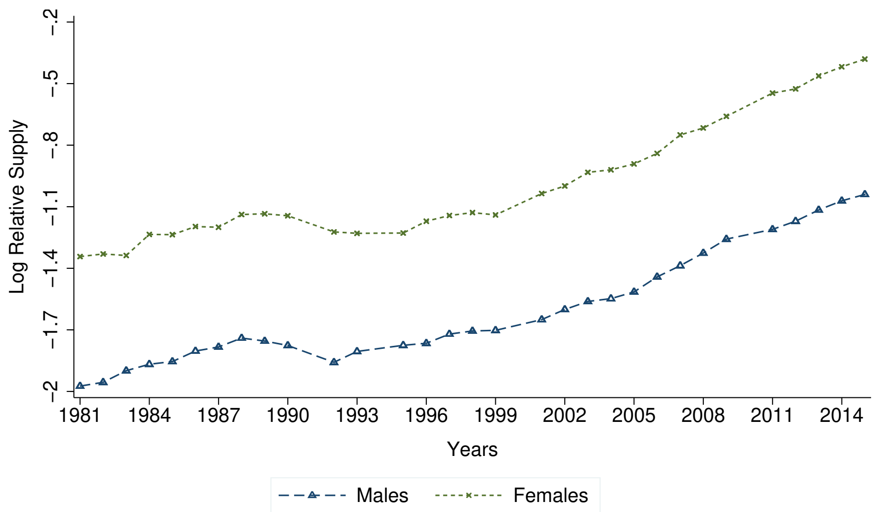
Source: PNAD data from 1981 to 2015. Log hourly wages for full-time salary workers are regressed by gender in each year on four education dummy variables (less than 11, 11, 12 to 14, and 15 or more years of schooling), a quartic in experience, two race dummies (black/indigenous and others non-white/non-mix-race) and the corresponding interactions between education and experience. I calculate a set of fixed weights equal to the participation in employment of each one of the 490 gender-education-experience groups. The composition-adjusted log wage for each educational group is the weighted average of the predicted log wage of white/mix-race workers evaluated at each demographic group. The skill premiums are the weighted average of the composition-adjusted log wages between the corresponding educational categories. Tertiary and non-tertiary educated workers are aggregate categories. The former comprises workers with at least some tertiary education and the latter comprises illiterate, primary and secondary educated workers.

The irregular pattern of the skill premium between tertiary/non-tertiary educated workers over the 1980s and the early 1990s mirrors the struggle for a stable currency and macroeconomic stability. After the adoption of the Brazilian Real in 1994, the skill premium seems to plateau for several years until 2002. On average, the skill premium was approximately 142 log points in this year which implies that the labour earnings of tertiary-educated workers were three times higher than those of non-tertiary-educated ones (i.e. exp(1.42)-1). The skill premium falls sharply thereafter, which is consistent with the decline in the GINI coefficient that we observed in Figure 1.1. Following a decade of decrease, the tertiary/non-tertiary skill premium reaches its lowest point on average in 2015 at 92 log points which implies that the wage gap shrank by 163 percent (i.e. exp(1.42)-exp(0.92)) over this period.

The decrease in the skill premium between secondary and primary-educated workers has been falling instead for more than three decades. Notice that this is only 25 log points in 2015, which implies a remarkable decrease of 118 percent (i.e. exp(0.90)-exp(0.25)) from 1981 to 2015. Interesting, there are no significant differences in the secondary/primary skill premium between genders, unlike the tertiary/non-tertiary skill premium which is larger for males than for females over the entire sample period. Figure 1.A.1 in the Appendix section provides additional information on the respective skill premiums by two groups of experience (0-9 and 20-29 years of potential experience). The tertiary/non-tertiary skill premium falls sharper among workers with 0-9 years of experience between 2002 and 2015, particularly among females. On the other hand, the decline in the secondary/primary skill premium over the sample period seems to be mostly driven by the decline in the wage gap of workers with 20-29 years of experience. In fact, Figure 1.A.1 shows that the secondary/primary wage gap of the most experienced workers converges almost to the same level as that of the least experienced ones in 2015.

The remarkable decrease in the skill premium in Brazil as well as in most of the Latin American economies has been linked to the secular growth in the supply of skills in the region over the 2000s. In fact, Gasparini et al. (2011) argue that the increase in the supply of skills, particularly among high-school graduates, might explain the entire decrease in the skill premium for this educational group leaving a modest role for labour demand factors and labour market institutions.

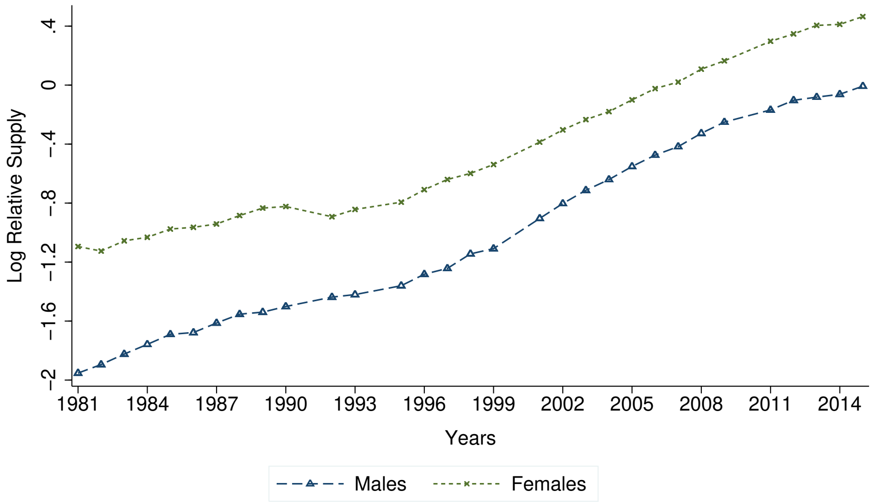
I use the "supply sample" to estimate efficiency units of labour supply among skill groups by following Katz and Murphy (1992) and, Acemoglu and Autor (2011) as follows. Individual labour supplies are given by the employment share of the 490 gender-education-experience groups. Labour supplies are weighted by using a set of fixed weights equal to the mean wage in each cell normalized to the wage of a base group over the sample period. Efficiency units of labour supply are then given by the weighted average of the individual labour supplies. Figure 1.5 plots the log efficiency units of labour supply between workers with tertiary/non-tertiary and secondary/primary education.



(a) Tertiary/Non-Tertiary

Figure 1.5: Relative Labour Supply by Gender

Source: PNAD data from 1981 to 2015. Employment participation of the 490 gender-education-experience groups from the "supply sample" is weighted by using a set of fixed weights equal to the mean wage in each cell normalized to the wage of male workers with secondary education and 10 years of potential experience (base group) over the sample period. Efficiency units of labour supply are given by the weighted average of labour supplies in each demographic group. Relative supply of tertiary/non-tertiary and secondary/primary educated workers is the logarithm of the ratio between efficiency units of labour supply of the corresponding skill group.



(b) Secondary/Primary
Figure 1.5 (continued)

There is a clear educational upgrading of the labour force over the last decades which reflects the efforts of the Brazilian government to invest in education, particularly in primary and secondary education.[10] Barros et al. (2010) state that the access to education grew twice faster in the 1990s and 2000s than this did in previous decades which explains the rapid increase particularly in the secondary/primary relative supply since the mid-1990s. College enrolment has also grown in the last decades, though at a much slower pace. In fact, Figure 1.5 shows a deceleration in the tertiary/non-tertiary relative supply over the early and mid-1990s which is given by the stagnation in the relative supply of young workers (those with 0-9 years of potential experience) as can be seen in Figure 1.A.2 in the Appendix section. Figure 1.A.2 shows that the tertiary/non-tertiary supply among the least experienced workers grows faster since the early 2000s which agrees with the sharper decline in their corresponding skill premium as was mentioned previously.

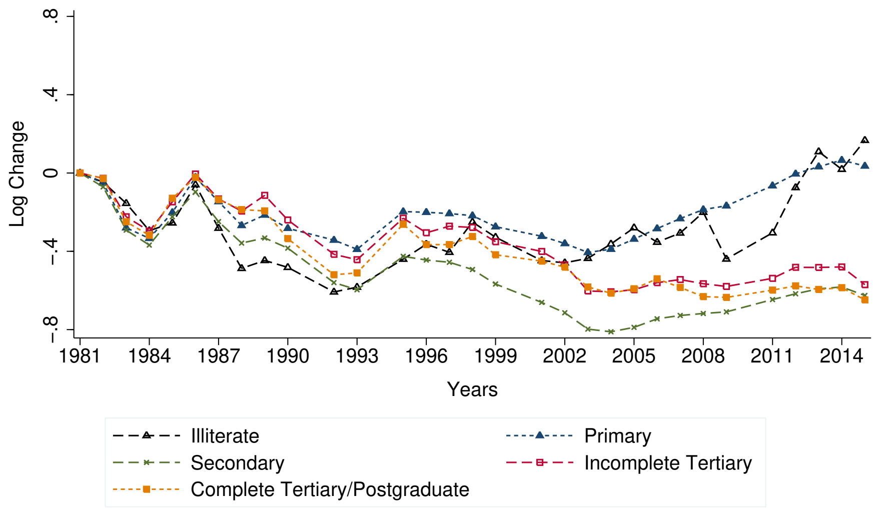
There are some additional features we can draw from Figure 1.5. First, the relative supply among females is larger than among males, implying that female workforce has a higher proportion of more educated workers than the male workforce. Second, despite the remarkable increase in the relative supply

[10]Data from ECLAC (Economic Commission for Latin America and the Caribbean) show that public spending on education in Brazil has grown 5 percent per year over the past two decades.

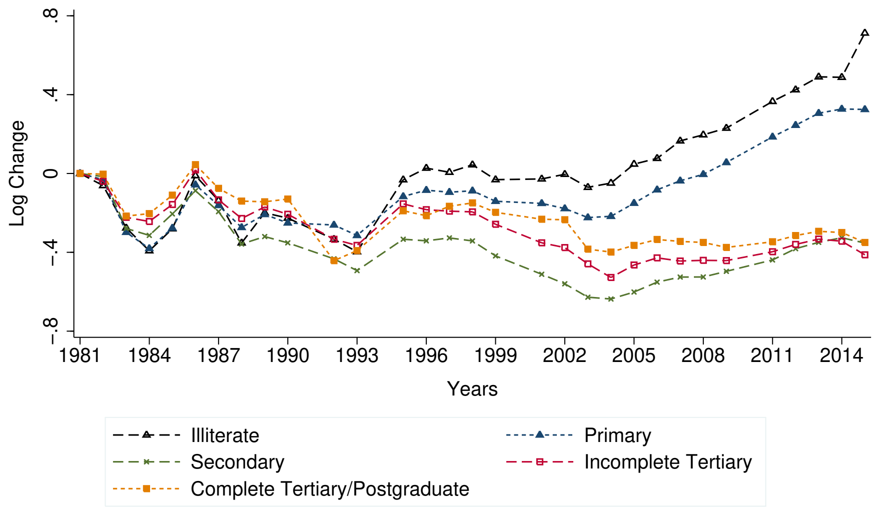
of skills, the Brazilian labour market is still intensive in low-skilled workers. The negative log tertiary/non-tertiary relative supply suggests that the proportion of tertiary-educated workers is still lower than that of non-tertiary-educated ones for both genders. In fact, the proportion of secondary-educated workers is also smaller than that of primary-educated ones among males, while the former overcomes the latter among females, but only after 2006.

At first glance, there is a strong correlation between relative supplies in Figure 1.5 and the corresponding skill premiums in Figure 1.4 which suggests that changes in the skill composition of the labour market might explain most of the variation in the price of skills. An obvious limitation of Figures 1.4 and 1.5 is that both omit information on individual skill groups. For example, the tertiary/non-tertiary skill premium might have decreased because of a fall in the market value of tertiary-educated workers, an increase in that of the non-tertiary-educated ones or both. Labour demand and supply models predict that a decrease in the skill premium must be driven by an increase in the relative supply of skills which is consistent with the findings so far. This does not necessarily imply that the labour earnings of the most educated workers must fall to be consistent with the decline in the skill premium. In fact, there is no reason to believe that labour demand is no longer skill-biased, or that capital is less skill complementary in Brazil. Figures 1.6 and 1.7 show the changes in the composition-adjusted log hourly wages and the participation of labour supplies by educational groups, respectively.

The effects of the macroeconomic instability in Brazil over the 1980s and the early 1990s are reflected in the erosion of the real labour earnings of all educational groups. Notice that the rising prices appear to have a more negative effect on the wages of illiterate and secondary educated males and secondary educated females in the late 1980s and early 1990s which explains why the tertiary/non-tertiary skill premium did not decrease over these periods. The patterns of the labour earnings are more dispersed after the adoption of the Brazilian Real in 1994. Although this proved to be a more stable currency than its predecessors, real



(a) Males



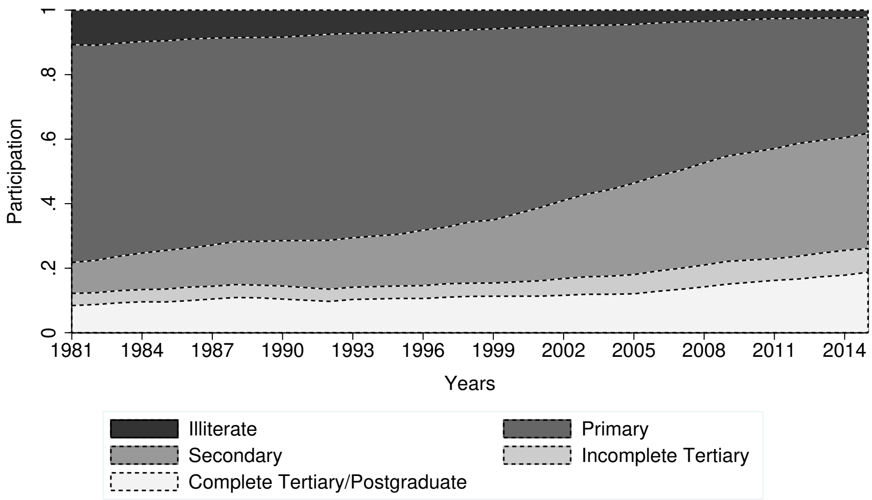
(b) Females

Figure 1.6: Composition-Adjusted Log Hourly Wages by Educational Groups

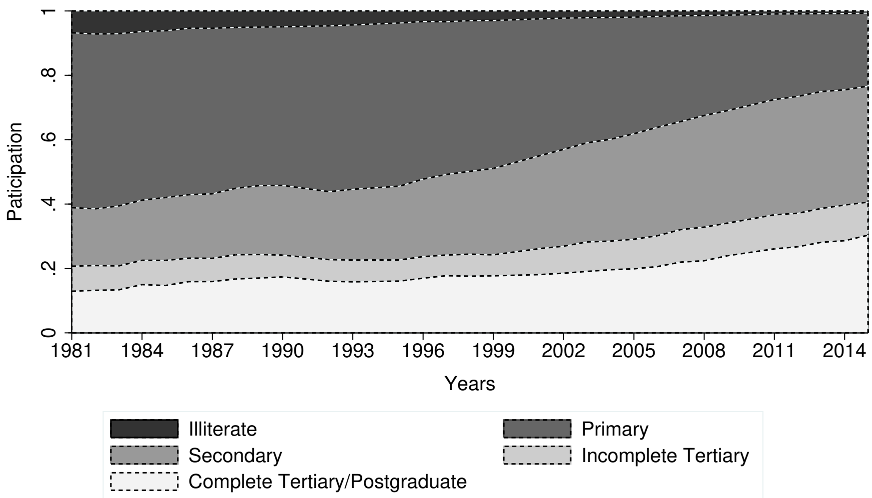
Source: PNAD data from 1981 to 2015. Composition-adjusted log hourly wages for full-time workers are the weighted average of the predicted log wage in each of the 490 gender-education-experience groups. Each series is normalized at zero in 1981. See Figure 1.4 notes for more details.

wages remained falling until the early 2000s. The recovery of labour earnings over the 2000s is evident among primary and illiterate workers, these also recovered among secondary educated ones though at a much slower pace. In contrast, labour earnings for more educated workers seem to stagnate in this period.

Figure 1.7 suggests that labour earnings trends across educational groups might be linked to the evolution of their corresponding participation in the labour supply, particularly among the least-educated workers. To put this information



(a) Males



(b) Females

Figure 1.7: Efficiency Units of Labour Supply by Educational Groups

Source: PNAD data from 1981 to 2015. Efficiency units of labour supply are the weighted average of the employment participation of 490 gender-education-experience groups. See Figure 1.5 notes for more details.

in context, log wages among primary-educated workers grew by 36 log points among males and by 48 log points among females, while their participation in the labour supply falls by 20 percent for both genders from 2001 to 2015. The increase in the labour earnings of illiterate workers is even larger, however, their participation in the labour supply has been falling over the sample period and these only represent less than 2 percent of the total labour supply in 2015. On the other hand, the labour earnings of high-school graduates grew over the 2000s in spite of the increase in their labour supply participation. The increase in the labour supply of more educated workers seems not to have adverse effects on their labour earnings either, which is consistent with a skill-biased labour demand.

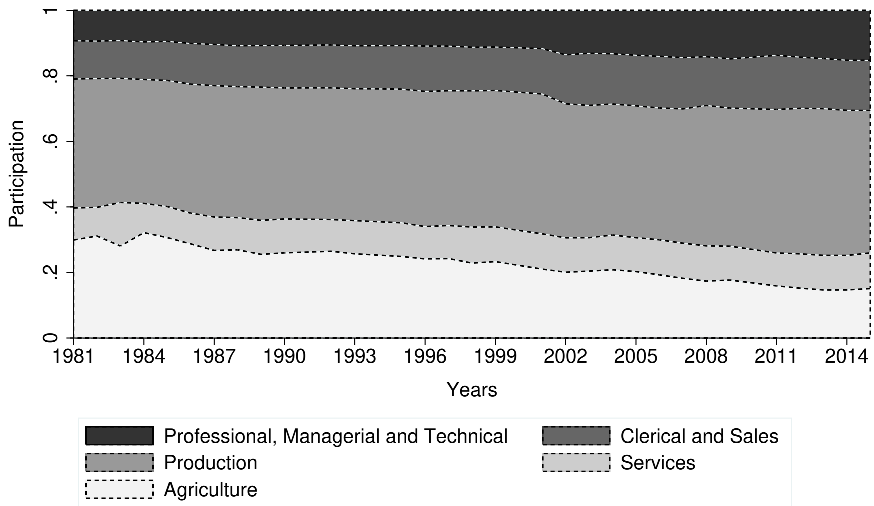
Figure 1.A.3 and 1.A.4 in the Appendix section provide additional information on changes in the composition-adjusted log wages and labour supply participation of each educational group by years of potential experience, respectively. Four important conclusions can be drawn from this analysis. First, the labour earnings of the least educated workers (illiterate and primary educated) increase over the 2000s within each experience group. Second, their labour market participations decrease irrespectively of the experience group, however, these patterns are more significant among the least experienced workers (those with 0-9 and 10-19 years of experience). In fact, the labour force participation of young-illiterate workers almost vanishes over this period. Third, the recovery in the labour earnings of secondary-educated workers that we observed in Figure 1.6 is given by the rise in real wages of young high-school graduates despite the growth in their labour supply. Finally, the increase in the labour supply of college-educated workers is mostly given by a higher participation of young college graduates.

In summary, the decline in the tertiary/non-tertiary skill premium over the 2000s is given by the increase in the labour earnings of primary and illiterate workers, whereas the fall in the secondary/primary skill premium is given by the sharp decrease in the labour earnings of high-school graduates in the 1990s and their relatively slow recovery in the 2000s. Apparently, years of potential experience play a modest role in the evolution of real wages except among the youngest workers in the sample. These trends might reflect the desire of the labour market for younger and cheaper labour force. Although we cannot claim causality between wages and labour supplies at this stage, it seems that changes in the skill composition of the labour force might have determined the changes in the price of skills. However, another question arises regarding the increase in the labour earnings of the least educated and youngest workers over the 2000s. Given the characteristics of these workers, it is straightforward to believe that factors such as labour market institutions might have contributed to this phenomenon, I will come back to this latter. We cannot rule out the possibility that this polarization of wage growth has been induced by a change in the share of low-skill occupations either. Gasparini et al. (2008) state that the improvement in the terms of trade given by the boom in the price of commodities and devaluations benefit low-skill intensive sectors in the 1990s and 2000s, thus changes in occupational and sectoral structure might explain the evolution of the skill premium in the last decades.

1.3 Occupational and Sectoral Structure

It is well known that wage inequality may arise by labour demand shifts in favour of workers with specific skills. Changes in technological progress and capital acquisition have been studied in the literature for developed countries as potential sources of wage and job polarization (Levy and Murnane 2005; Autor et al. 2008; Autor and Dorn 2013). Acemoglu and Autor (2011) show that the simultaneous growth in low and high-wage occupations in detriment of middle-wage ones in the U.S is driven by job polarization in favour of non-routine-task jobs. This is because low-wage occupations such as personal services involve non-routine-manual tasks which are difficult to substitute with capital, unlike middle-wage occupations such as clerical jobs which involve routine-manual tasks. Figure 1.3 showed that the lowest percentiles in the wage distribution had a better evolution than the median wage in the 1990s and 2000s, while the opposite is true for the highest percentiles. If the hypothesis of job polarization also applies to the Brazilian labour market, we certainly might rule out that this has benefited high-wage occupations, but this might explain the gains in low-wage ones.

Even in the absence of wage and job polarization in the Brazilian labour market, it is important to understand how changes in the occupational and sectoral structure have affected the evolution of the labour earnings in the country. There is limited empirical work on this matter, perhaps for the lack of a data source that provides consistent occupational categories over the sample period. PNAD provides information on individual and aggregate occupational categories that are only consistent within two periods (1981-2001 and 2002-2015). I use the definition of each individual occupation to reconcile categories throughout the sample period and construct five broad occupational categories: (i) managers, professionals and technicians, (ii) office/administration and sales, (iii) production and repair, (iv) personal services and (v) agricultural occupations.[11] Figure 1.8 shows the participation of employment among occupational categories by gender.

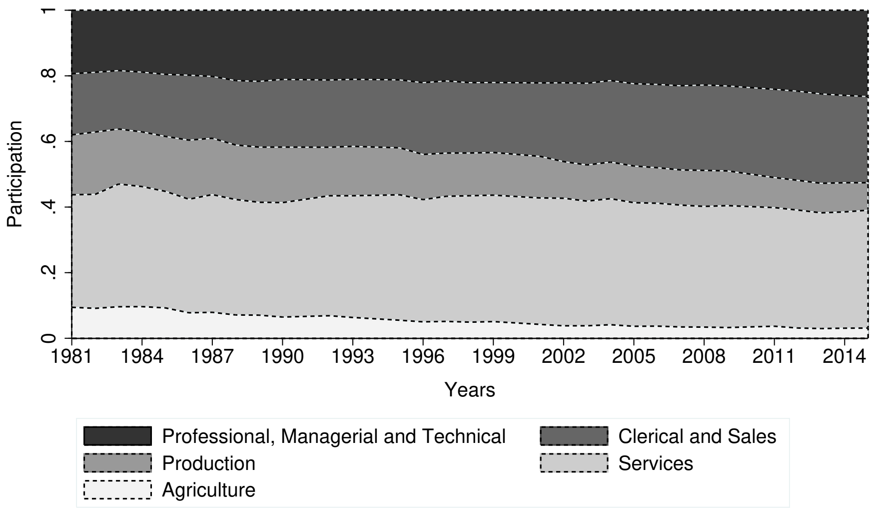


(a) Males

Figure 1.8: Employment Shares by Occupations

Source: PNAD data from 1981 to 2015. Sample comprises salary/wage workers and self-employed, aged 18-65 years old. Workers employed in the military are excluded from the sample. PNAD provides information on individual occupations and eight aggregate categories (Managers, Professionals, Technicians, Office and administration, Sales, Production and repair, Personal services and Agricultural occupations) from 2002 to 2015. This categorisation is not consistent with that in prior years. I sort around 380 occupations from 1981 to 2001 into the previous eight occupational categories by matching the definitions of individual occupations between the two periods. Occupations that are not assigned to any category are excluded from the sample (around 7 percent). Figure 1.8 plots five aggregate occupations: Professional, managerial and technical, Clerical (office and administration) and sales, Production (Production and repair), Services (personal services) and Agriculture (agricultural occupations).

[11] Acemoglu and Autor (2011) following the U.S. Department of Labour's Dictionary of Occupational Titles (DOT) classify these categories as non-routine cognitive, routine-cognitive, routine-manual and non-routine manual tasks, respectively. There is no agreement in the literature about the type of tasks performed in agricultural occupations. However, we can assume that these are more likely to comprise routine and non-routine manual tasks.



(b) Females
Figure 1.8 (continued)

The employment share in professional, managerial and technical occupations grew from 9 to 15 percent among males and from 19 to 26 percent among females from 1981 to 2015. We can also observe a growth in the participation of clerical and sales occupations, particularly among women. This is consistent with the educational upgrading of the workforce as most of the employees in these occupational categories have at least a secondary education. Figure 1.A.5 in the Appendix section shows that the participation of workers with at least some tertiary education in professional, managerial and technical occupations grew from 40 percent for both genders in 1981 to 55 percent among males and 68 percent among females in 2015. The educational upgrading in clerical and sales occupations, in turn, was mostly driven by the increase in the participation of high-school graduates in detriment of less-educated ones. The participation of workers with at least a high school diploma in clerical and sales occupations grew approximately 40 percentage points among males and 33 percentage points among females from 1981 to 2015.

Production occupations have been traditionally held by males, we can see that a large proportion of male workers are employed in these occupations and their participation in male employment has remained relatively constant over the sample period. This is not the case among females, their participation in production occupations fell in 10 percentage points from 1981 to 2015. The decrease in the participation of female workers in production occupations might be related to changes in automation in labour-intensive industries. However, the participation of women in production remained relatively steady during the trade liberalization reforms in the 1980s and 1990s as the market demanded more labour force, thus the posterior fall over the 2000s might be the result of changes in trade policies. The educational upgrading of the labour force is also evident in production occupations as can be seen in Figure 1.A.5 in the Appendix section. Workers with at least a high-school diploma represented less than 5 percent of the workforce in 1981 for both genders, whereas these represent half of the female workforce and one-third of the male one in 2015.

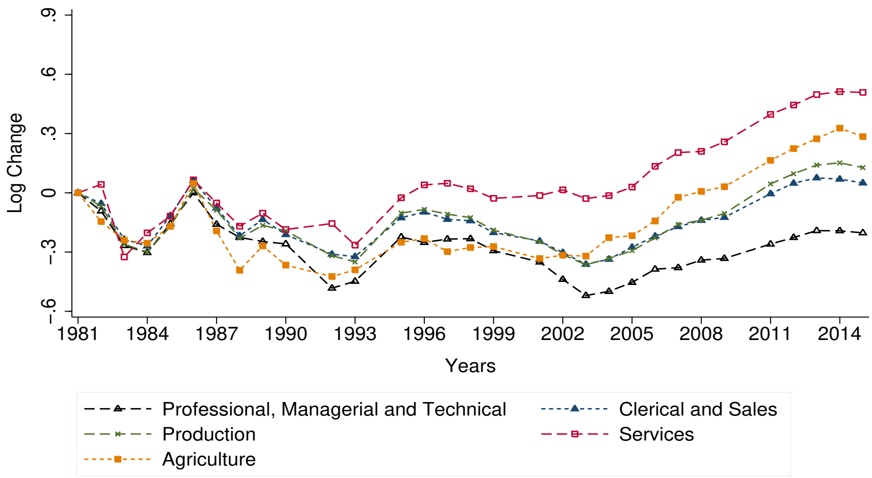
Personal services, unlike production occupations, have been traditionally held by females, these represent one-third of the total employment among females and only 10 percent among males. The employment share of personal services has remained relatively constant through time for both genders. As the previous occupational categories, there has been a remarkable educational upgrading of the labour force given by the higher participation of high-school graduates, however personal services are still mostly performed by primary educated workers.

The most important feature in Figure 1.8 is the sharp decrease in the employment share of agricultural occupations for both genders. The fall in 15 percentage points among males and 6 percentage points among females over the sample period responds to the development of labour-saving agricultural technologies and genetically modified crops (Bustos et al. 2016).[12] The bulk of the labour force in agricultural occupations is comprised of illiterate and primary educated workers, however, the latter ones have been gaining ground over the sample period as can be seen in Figure 1.A.5.

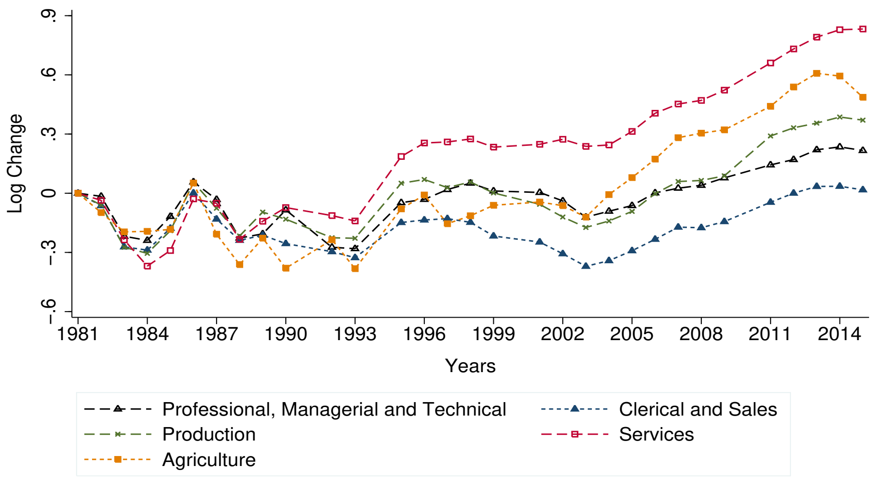
There are two conclusions that we can draw from the previous analysis.

[12] It is important to mention that the low participation of agricultural occupations in total employment is given by the exclusion of individuals that work for self-consumption who are basically the bulk of the agricultural sector.

First, the educational upgrading of the workforce is present in each occupational category and this is more significant among females than among males. This difference responds to the remarkable increase in the labour force participation of more educated women relative to that of more educated men in the last decade. Second, whether technical changes have been labour saving, these have only affected agricultural occupations for both genders and production occupations among females. In that sense, it is expected that changes in employment shares of these occupations have significant effects on the labour earnings of the workers who perform them. Figure 1.9 provides information on this matter.



(a) Males



(b) Females

Figure 1.9: Log Hourly Wages by Occupations

Source: PNAD data from 1981 to 2015. Log hourly wages of salary/wage workers and self-employed excluding those in the military, aged 18-65 years old. Each series is normalized at zero in 1981. See Figure 1.8 notes for more details on occupational categories.

Figure 1.9 keeps certain similarities with the changes in wage percentiles in Figure 1.2 and changes in real wages by educational groups in Figure 1.6. High inflation rates over the 1980s and the early 1990s harmed the labour earnings in all occupational categories and these seem to recover only after the early 2000s. Although professional, managerial and technical occupations have been gaining ground in employment, the labour earnings of the workers performing these occupations seem to have a slower recovery than those of their counterparts. Moreover, the mild growth of the labour earnings among these occupations in the 2000s is mostly driven by the growth of wages among the least educated workers as can be seen in Figure 1.A.6 in the Appendix section. In fact, real wages in other occupations with a high percentage of workers with at least secondary education such as clerical and sales, and production occupations have a slower recovery than those intensive in primary educated workers such as personal services and agriculture. Notice the remarkable recovery of the labour earnings in personal services that unlike other occupations, reached the same level of 1981 immediately after the adoption of the Brazilian Real in 1994. After a period of stagnation, real wages in personal services increase rapidly over the 2000s. This positive trend can also be observed across all educational groups performing these occupations in Figure 1.A.6. Although the sharp decrease in the participation of agricultural occupations in employment, there is a substantial increase in the labour earnings of workers employed in agriculture over the 2000s, irrespectively of their educational attainment.

The decrease in the employment of agricultural occupations for both genders and production occupations among females might signal a change in the demand for routine-manual tasks. However, it is expected that a labour-saving technical change harms the labour earnings of workers performing these tasks which is not the case in Brazil. Moreover, the employment in clerical and sales occupations that are also assumed to involve routine-manual tasks has grown over the sample period along with the labour earnings of their workers. Nevertheless, this is not proof of a non-existent job polarization as there are different factors that might have affected the evolution of the labour earnings among these workers. For instance, the unprecedented increase in the real minimum wage could have masked the adverse effects of the technical change on wages, particularly among workers employed in agriculture and production. In order to understand the nature of the changes in the employment across occupations, I perform a between and within decomposition of changes in national employment of occupation i during time interval t, following Acemoglu and Autor (2011). Formally:

$$\Delta E_{it} = \sum_{j} \Delta E_{jt} E_{ijt} + \sum_{i} \Delta E_{ijt} E_{jt}$$

Where ΔE_{jt} is the change in employment share of industry j in period t, E_{ijt} is the average employment share of occupation i in industry j during t, ΔE_{ijt} is the change in employment share of occupation i in industry j during t, and E_{jt} is the average employment share of industry j in period t. Table 1.1 shows the results of this exercise.[13]

There is a relatively small growth in managerial, professional and technical occupations among males compared to that among females over the 1980s and the 1990s. Over the 2000s, the employment share of these occupations increased significantly for both genders and seems to be mostly driven by within-industry shifts among males, while among females both between and within-industry shifts play a role in this change. Similarly, the increase in employment of clerical and sales occupations is more significant for females than for males, and this is driven by both between and within-industry changes, particularly over the 1990s and 2000s. The decrease in the employment of production occupations among females over the last two periods is driven by within-industry shifts and this behaviour can also be observed among males over the 2000s. The within-industry shifts against production occupations which involve routine-manual tasks and favouring

[13] Table 1.1 provides information on changes in total employment (males and females) across occupations, these estimates are not directly comparable to those in Figure 1.8 which provides information on changes in employment within each gender.

Table 1.1: Decomposition of Changes in Employment of Occupational Categories

	Males			Females		
	1981-1990	**1990-2001**	**2001-2015**	**1981-1990**	**1990-2001**	**2001-2015**
Professional, Manag. and Technical						
Between-Industry	0.01	0.11	-0.17	1.47	0.58	1.28
Within-Industry	0.37	0.06	1.87	0.24	0.67	1.14
Total	0.38	0.17	1.69	1.70	1.26	2.41
Clerical and Sales						
Between-Industry	0.54	0.31	0.13	1.68	0.67	1.16
Within-Industry	-0.35	-0.31	0.33	0.08	0.85	1.15
Total	0.19	0.00	0.46	1.76	1.52	2.31
Production						
Between-Industry	-2.64	-0.62	1.10	1.11	0.10	0.61
Within-Industry	0.86	0.68	-1.86	-0.59	-1.15	-2.11
Total	-1.79	0.05	-0.76	0.52	-1.05	-1.50
Services						
Between-Industry	0.28	0.56	0.10	1.78	3.24	0.10
Within-Industry	-0.46	-0.71	-0.34	0.33	-0.40	-0.14
Total	-0.18	-0.15	-0.25	2.11	2.84	-0.04
Agriculture						
Between-Industry	-3.74	-4.27	-3.97	-0.50	-0.68	-0.33
Within-Industry	-0.42	0.28	0.00	-0.06	0.03	-0.03
Total	-4.15	-3.99	-3.96	-0.56	-0.65	-0.36

Source: PNAD data for 1981, 1990, 2001 and 2015. Sample comprises salary/wage workers and self-employed, aged 18-65 years old. Workers employed in the military are excluded from the sample. PNAD provides information on individual industries and 11 aggregate categories (Agriculture, Industry, Manufacturing, Construction, Wholesale and retail trade, Business service, Transportation and communication, Public administration, Professional services, Domestic services, Personal services and entertainment) over the period 2002-2015. This categorisation is not consistent with that in prior years. I sort around 170 industries from 1981 to 2001 into the previous 11 industrial categories by matching the definitions of individual industries between these two periods. Industries that are not assigned to any of these categories or those which are wrong defined are excluded from the sample (around 6 percent). See Figure 1.8 notes for more details on occupational categories.

high-skill occupations which involve non-routine cognitive tasks might signal some polarization of employment across occupations. However, the employment in other occupations that involve non-routine tasks such as personal services follows a decreasing pattern among males. Moreover, the increase in employment of personal services among women, in decades previous to the 2000s, is dominated by between-industry shifts, that is, these were primarily driven by employment shifts towards industries intensive in personal services rather than shifts in favour of non-routine tasks. Finally, the decline in the employment of agricultural occupations is entirely driven by changes in industrial composition.[14]

[14]As the agricultural occupations are mostly employed in agriculture, the change in their employment is given by changes in the participation of the agriculture sector in the economy.

To sum up, there are three important findings that can be drawn from this analysis: i) within-industry shifts are responsible for the decline in employment of production occupations over the 2000s, ii) within and between-industry shifts have favoured high-skill occupations, particularly among females, iii) changes in employment of personal services are mostly driven by changes in industry structure and are only significant among females over the 1980s and 1990s. The first two might suggest some degree of job polarization in the Brazilian labour market against routine-manual task and favouring non-routine cognitive tasks. However, it is only logical to think that as workers become more educated, these move from low-paid occupations to high-paid ones. This seems to be a more reasonable explanation given that the labour earnings in production occupations grew at a faster pace than those in higher-wage occupations. Finally, there is no evidence that the increase in the labour earnings of low-wage occupations such as personal services and agricultural occupations is the result of a shift in the demand for the task performed in these occupations. Once again, the increase in the real value of the minimum wage seems to provide a more reasonable explanation for these patterns.

1.4 The Sources of Declining Wage Inequality

1.4.1 The Role of the Minimum Wage

Labour market institutions and their effects on wage inequality have been extensively studied, particularly in developed countries. The literature on the subject suggests that changes in minimum wage policies might shape wage inequality as much as labour market forces, particularly in the lower half of the wage distribution (DiNardo et al. 1996; Lee 1999; Card and DiNardo 2002). Minimum wage effects on wage inequality go beyond the direct impact on the labour earnings of minimum wage workers and might affect wages way above the minimum level through changes in the returns to human capital (Teulings 2003).

These effects are known in the literature as spillover effects of the minimum wage which are beyond the scope of this paper, but these might offer a reasonable explanation on the compression of the upper half of the wage distribution that is not accounted for by changes in labour market forces.

Minimum wages might play a more significant role in shaping wage inequality in Latin American countries than in more developed ones given the larger proportion of workers earning at the minimum wage level in the region. Cunningham (2007) states that up to 20 percent of the labour force earns the minimum wage in Latin American economies. Of course, this proportion varies across countries, demographic and occupational groups. Figure 1.10 shows the ratio of the proportion of minimum wage workers in each demographic and occupational group to the proportion of minimum wage workers in the economy. Thus, a ratio above 1 suggests that the demographic/occupational group is overrepresented among minimum wage workers.

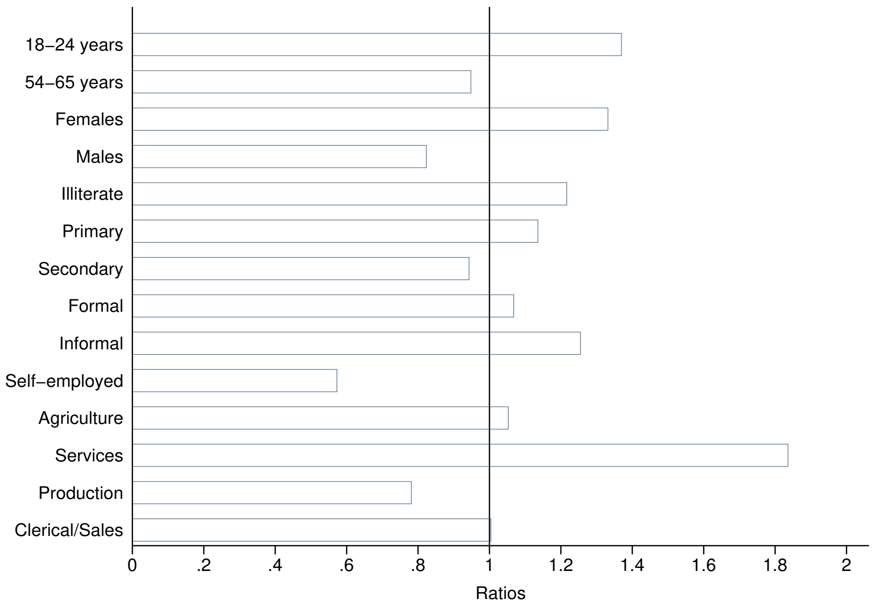


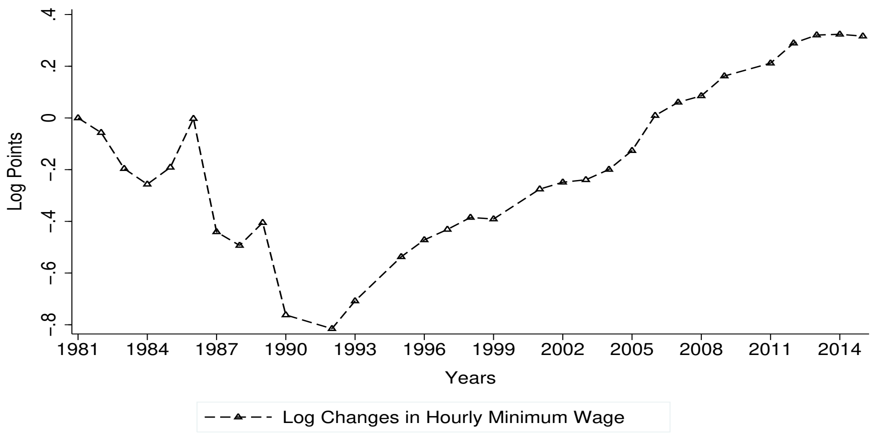
Figure 1.10: Ratio of the Proportion of Minimum Wage Workers in each Group relative to that in the Workforce

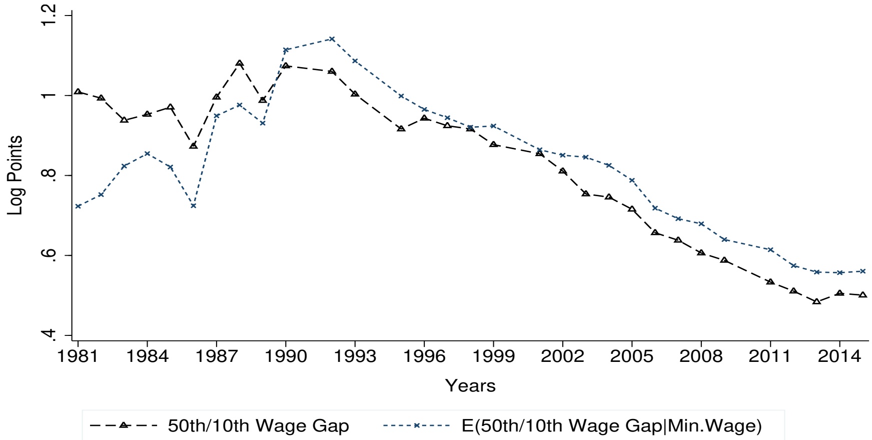
Source: PNAD and MTE data from 1981 to 2015. Sample comprises salary/wage workers and self-employed, aged 18-65 years old. The ratio is the proportion of minimum wage workers in each demographic/occupational group to the proportion of minimum wage workers in the workforce. Minimum wage workers are defined as those who earn +/- 5 percent the nominal minimum wage in each year.

Young, females, illiterate or primary educated workers are overrepresented among the minimum wage population. Regarding occupational groups, personal services and agriculture have a large proportion of minimum wage workers than the other occupational groups. Minimum wage workers are also overrepresented in the formal and informal sectors. It is not surprising the over-representation in the formal sector given the large proportion of workers earning at the minimum wage level in Brazil. What it is striking is the over-representation of minimum wage workers in the informal sector who are not typically covered by minimum wage policies. This suggests that the minimum wage might act as a benchmark for wage setting in the informal sector. Given the demographic and occupational characteristics of the groups with a large proportion of minimum wage workers is straightforward to think that minimum wage policies play a significant role in the declining wage inequality.

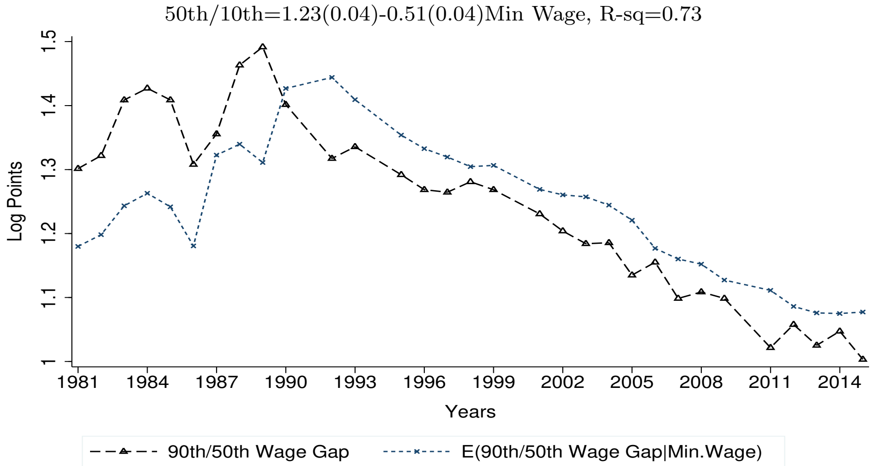
The real value of the minimum wage increased in 14 out of 18 Latin American countries in the 2000s (Keifman and Maurizio 2014). Brazil is not the exception, the real value of the minimum wage decreased more than 50 percent over the inflationary period in the 1980s, recovered around 45 percent in the 1990s and increased approximately 80 percent from 2001 to 2015. Figure 1.11 shows that there is a strong time-series relationship between the real minimum wage and wage inequality.

A simple regression between lower-tail inequality measured by the 50th/10th wage gap on the real value of the minimum wage yields a coefficient of -0.51 and R-squared of 0.73. The tight correspondence between the observed 50th/10th, and the predicted 50th/10th suggests that the decline in lower-tail inequality might be attributed to the secular increase in the real minimum wage. As most of the decline in overall wage inequality in the 2000s is given by the compression in the lower half of the wage distribution, the minimum wage could have played a much more significant role that it is believed in the most recent decline in wage inequality. However, somewhat the real minimum wage is also correlated with





50th/10th=1.23(0.04)-0.51(0.04)Min Wage, R-sq=0.73



90th/50th=1.5(0.05)-0.32(0.04)Min Wage, R-sq=0.56

Figure 1.11: Log Hourly Wage Gaps and Real Minimum Wage

Source: PNAD and MTE data from 1981 to 2015. Figure on the top shows changes in log real hourly minimum wage normalized at zero in 1981. The remaining figures show the observed and predicted wage gap between 50th/10th and 90th/50th percentiles for full-time salary/wage workers aged 18-65 years old. Predicted values are obtained from separate OLS regressions of wage gaps on a constant term and the log real minimum wage. Coefficients, robust standard deviations in parentheses, and R-squared are reported.

upper-tail inequality. In fact, the coefficient of this relationship suggests that an increase in 1 log point in the real value of the minimum wage is associated with a decrease of 0.32 log points in upper-tail inequality.

This strong relationship is highly robust even when other explanatory variables such as a time trend and the relative supply between tertiary/non-tertiary educated workers are included in the regressions. The coefficients suggest that an increase in 1 percentage point in the real minimum wage compresses the 50th/10th wage gap in 0.30 log points and the 90th/50th wage gap in 0.21 log points both significant at 1 percent level. Of course, one could argue that the robustness of the results regarding the significant association between the real minimum wage and upper-tail inequality might indicate a potential spurious relationship between them. However, several explanations come to mind that could suggest that this is a legitimate relationship. The minimum wage is significantly binding in Brazil even above the 50th percentile in some demographic and occupational groups, which could explain the compression in upper-tail inequality. Moreover, the compression in the upper half of the wage distribution might also be the result of spillover effects of the minimum wage on the median wage.

1.4.2 Compositional and Wage Structure Effects on Wage Inequality

To explicitly quantify the effects of changes in the skill and demographic composition of the labour market and the prices of these characteristics (wage structure) on wage inequality, I use a decomposition approach based on recentered influence function (RIF) regressions by Firpo et al. (2018). Let $IF(w, q_p)$ denotes the influence function corresponding to an observed wage, w, for the quantile, q_p.[15] To obtain the recentered influence function (RIF), we simply add the quantile, q_p,

[15] The influence function basically quantifies changes in the quantile, q_p, in response to small changes in the data and takes the form: $IF(w, q_p) = \frac{p - \mathbf{1}[w \leq q_p]}{f_w(q_p)}$, where $\mathbf{1}[w \leq q_p]$ is an indicator function and $f_w(q_p)$ is the pdf which is estimated by using non-parametric kernel densities.

to the influence function such as:

$$RIF(w, q_p) = q_p + IF(w, q_p) \tag{1.1}$$

RIF regressions are performed in the same way as standard regressions in Oaxaca-Blinder decompositions, except that RIF is used as the dependent variable. RIF regressions allow us to perform a detailed decomposition for any statistic that admits an influence function.[16] The decomposition exercise consists of two steps. First, I use a reweighting procedure as in DiNardo et al. (1996). I use a probit model to estimate the probability of observing a worker with certain demographic characteristics, X, in period 1. I reweight period 0 to have the same distribution of X as in period 1 in order to recover the counterfactual wage distribution. Second, I run Oaxaca-Blinder decompositions using RIF regressions on the reweighted data to decompose compositional and wage structure effects into the contribution of individual explanatory variables to changes in wage inequality. Formally:

$$\hat{\Delta}^{q_p} = \underbrace{(\overline{X}_0^c - \overline{X}_0)'\hat{\beta}_0 + \overline{X}_0^{c\prime}(\hat{\beta}_c - \hat{\beta}_0)}_{\hat{\Delta}_x^{q_p}} + \underbrace{\overline{X}_1'(\hat{\beta}_1 - \hat{\beta}_c) + (\overline{X}_1 - \overline{X}_0^c)'\hat{\beta}_c}_{\hat{\Delta}_s^{q_p}} \tag{1.2}$$

Where $\overline{X}_t$ and $\hat{\beta}_t$ denote the average of demographic characteristics and the estimated vector of parameters from RIF regressions on the corresponding X_t in period t, with t=0, 1 and, $\overline{X}_0^c$ and $\hat{\beta}_c$ those from the reweighted period 0 that mimics period 1. The composition effect, $\hat{\Delta}_x^{q_p}$, reflects the part of the change in q_p that is explained by changes in the distribution of demographic characteristics, X and is given by the first two terms in equation (1.2) which correspond to the pure composition effect and specification error, respectively. The wage structure effect,

[16] As the expectation of RIF is the quantile, q_p, Firpo et al. (2018) demonstrate that $E[RIF(w, q_p)|X_t] = X_t'\beta_t$. The expression relates the effects of changes in the expected value of X_t on q_p.

$\hat{\Delta}_s^{q_p}$, reflects the part of the change in q_p that is explained by changes in the return to demographic characteristics and is given by the last two terms in equation (1.2) which correspond to the pure wage structure effect and the reweighting error which goes to zero in large samples.

In the present analysis, the vector of $X's$ comprises education, age and their corresponding squared terms, and dummy variables for female workers, low-skill occupations, and minimum wage workers. Table 1.2 shows the compositional and wage structure effects on changes in wage inequality between 1995 and 2015 (post-inflationary period) for the 90th/10th, 50th/10th and 90th/50th wage gaps.

Table 1.2: Compositional and Wage Structure Effects on Wage Inequality, 1995-2015

	90th/10th	**50th/10th**	**90th/50th**
Overall Change	-0.723***	-0.425***	-0.298***
	(0.012)	(0.002)	(0.013)
Composition Effects	0.084***	-0.012	0.095***
	(0.023)	(0.028)	(0.012)
Education	0.076***	0.002*	0.073***
	(0.005)	(0.001)	(0.004)
Age	0.014	-0.001	0.015***
	(0.014)	(0.014)	(0.001)
Female	-0.007**	-0.006***	-0.002**
	(0.003)	(0.001)	(0.001)
Low-Skill Occupations	-0.011	-0.012***	0.001
	(0.008)	(0.004)	(0.002)
Minimum Wage Workers	0.012***	0.004	0.008
	(0.003)	(0.007)	(0.006)
Wage Structure Effects	-0.808***	-0.413***	-0.393***
	(0.028)	(0.029)	(0.023)
Education	-0.579***	-0.075***	-0.503***
	(0.073)	(0.008)	(0.072)
Age	-1.767***	-0.001	-1.765***
	(0.315)	(0.040)	(0.283)
Female	0.161***	-0.023***	0.184***
	(0.036)	(0.004)	(0.034)
Low-Skill Occupations	0.080**	0.025*	0.055*
	(0.039)	(0.014)	(0.030)
Minimum Wage Workers	-0.014***	-0.018**	0.003
	(0.004)	(0.007)	(0.004)
Constant	1.310***	-0.321***	1.631***
	(0.303)	(0.031)	(0.273)

Source: PNAD and MTE data from 1995 to 2015. Sample comprises full-time salary workers. I perform two Oaxaca-Blinder decompositions using RIF regressions. In the first decomposition, I use the sample in period 0 and the counterfactual sample in period 0 that mimics period 1 to obtain composition effects. In the second decomposition, I use the sample in period 1 and the counterfactual sample to obtain wage structure effects. Standard errors in parentheses are obtained by bootstrapping with 100 replications. Significant at 1 percent ***, at 5 percent ** and at 10 percent *.

The results in Table 1.2 are in line with the observed decline in wage inequality over the post-inflationary period, 1995-2015. Overall wage inequality measured by the wage gap 90th/10th decreases by 72 log points from 1995 to 2015, approximately 60 percent of this decline was driven by the fall in the 50th/10th. The estimates in Table 1.2 suggest that the decline in both upper and lower-tail inequality was entirely driven by wage structure effects, that is, the residual part that cannot be explained by group differences. In fact, wage structure effects counteracted the composition effects that were increasing wage inequality, particularly in the upper half of the wage distribution. In that sense, upper-tail inequality measured by the 90th/50th wage gap would have decreased by 39 log points, instead of the observed 30 log points, between 1995 and 2015 under a constant demographic composition of the labour market.

Table 1.2 decomposes further the compositional and wage structure effects on wage inequality measures accounting for the contribution of education, age as a measure for experience, female participation, low-skill occupations including production, personal services and agricultural occupations and whether a worker is a minimum wage earner, that is, earns a wage +/- 5 percent the nominal minimum wage. Among the compositional effects, changes in the participation of females and the employment of low-skill occupations have an equalizing effect on lower-tail inequality, while changes in the years of schooling and age/experience have an unequalizing effect in upper-tail inequality. The counterfactual estimates suggest that compositional effects driven by changes in education would have increased the 90th/10th in 7.6 log points between 1995 and 2015 under constant price of demographic characteristics.

Among wage structure effects, education and age/experience have a large equalizing effect, particularly in upper-tail inequality, which offsets the unequalizing composition effect and others that counteracted the decline in wage inequality. The counterfactual estimates suggest that changes in the return to education would have contributed to a decline of 58 log points in the 90th/10th wage gap which represents 80 percent of the actual decline. Notice that changes in the return to education are more significant to explain the decline in the 90th/50th than in the 50th/10th. In fact, the estimates for the 50th/10th suggests that changes in the schooling premium would have decreased this gap in 7.5 log points which represents only 18 percent of the actual decline in lower-tail inequality.

Other factors besides education and age/experience seem to have less significant effects on the declining wage inequality. We can see that a higher participation of females in the labour market has an equalizing compositional and wage structure effect on the 50th/10th, whereas the equalizing compositional effect is offset by the unequalizing wage structure effect on the 90th/50th. Changes in low-skill occupations seem to have an equalizing compositional effect only in the 50th/10th and this is relatively small. Finally, changes in the proportion of minimum wage workers appear to affect neither lower nor upper-tail inequality, however, the return to minimum wage workers has a significant equalizing effect on the 50th/10th. These results should be seen in the light of changes in the proportion of minimum wage workers and the minimum wage. In that sense, this variable does not account for spillover effects of the minimum wage neither above nor below the minimum wage level which have been proved to drive most of the compression of lower-tail inequality in developed countries. [17]

In conclusion, changes in the skill and demographic composition of the labour market cannot explain the changes in wage inequality over the last two decades in Brazil by themselves. In fact, the changes in the price of skills and the price of other demographic characteristics seem to explain the entire declining pattern in wage inequality over this period. Of course, the validity of this counterfactual exercise relies on the partial equilibrium assumption that changes in quantities and prices are independent of each other. As Autor et al. (2008) mention that

[17] The small effect of the minimum wage on wage inequality might also be the result of the sample choice. As the sample comprises salary workers both formal and informal, the 50th/10th might be not necessarily affected by changes in the minimum wage as the 10th percentile mostly comprises the labour earnings of informal workers who are not covered by minimum wage policies.

although this assumption is analytical convenient to perform decompositions of wage inequality, this is opposite to what is observed in labour market studies. In Section 1.2, we observed a significant correlation between labour earnings and employment participation among educational groups which suggests that changes in the wage structure might be driven by changes in the composition of the labour market and not necessarily in spite of them. For instance, if workers are not perfect substitutes in production, then a change in the skill composition would affect relative wages. In the next section, I provide an analysis of this mechanism to rationalize the observed patterns so far.

1.4.3 The Effects of the Skill Supply on Relative Wages

The following analysis employs a supply-demand framework based on the ideas of Tinbergen (1974), Katz and Murphy (1992), Katz and Autor (1999), Goldin and Katz (2007), Autor et al. (2008), Acemoglu and Autor (2011) among many others to analyse the effects of shifts in labour supply of and demand for skills on the skill premium.[18] The model traditionally involves two types of workers who are imperfect substitutes in production under a competitive labour market. The substitution between these two types of workers is captured by a constant elasticity production function CES of the form:

$$Q_t = [\alpha_t(a_t H_t)^{\frac{\eta-1}{\eta}} + (1-\alpha_t)(b_t L_t)^{\frac{\eta-1}{\eta}}]^{\frac{\eta}{\eta-1}} \tag{1.3}$$

Where H_t and L_t are the quantities employed of high and low-skilled workers in period t, a_t and b_t are their respective factor-augmenting technology terms, α_t is a time-varying technological parameter, for example, the share of activities allocated to each skill group, and $\eta \in [0, \infty)$ is the elasticity of substitution between high and low-skill labour. Both skill groups are gross substitutes if $\eta > 1$

[18] Building on the ideas in these papers, Manacorda et al. (2010) and Gasparini et al. (2011) study the evolution of the skill premium by pooling data from Latin American economies. The present analysis extends this earlier work allowing for different educational groups and drawing on additional years of data for Brazil.

and are gross complements if $\eta < 1$. A skill-neutral technological change raises a_t and b_t by the same proportion, whereas a skill-biased technological change increases either, $\frac{a_t}{b_t}$, or α_t. Under the assumption that both skill groups are paid their marginal products, the wage of high-skilled workers w_t^H and low-skilled ones w_t^L can be obtained by differentiating (1.3).

$$w_t^H = \frac{dQ_t}{dH_t} = \alpha_t a_t^{\frac{\eta-1}{\eta}} \left[\alpha_t a_t^{\frac{\eta-1}{\eta}} + (1-\alpha_t) b_t^{\frac{\eta-1}{\eta}} \left(\frac{H_t}{L_t} \right)^{-\frac{\eta-1}{\eta}} \right]^{\frac{1}{\eta-1}} \tag{1.4}$$

$$w_t^L = \frac{dQ_t}{dL_t} = (1-\alpha_t) b_t^{\frac{\eta-1}{\eta}} \left[(1-\alpha_t) b_t^{\frac{\eta-1}{\eta}} + \alpha_t a_t^{\frac{\eta-1}{\eta}} \left(\frac{H_t}{L_t} \right)^{\frac{\eta-1}{\eta}} \right]^{\frac{1}{\eta-1}} \tag{1.5}$$

There are two important implications of equation (1.4) and (1.5). First, $\frac{\delta w_t^H}{\delta \frac{H_t}{L_t}} < 0$, that is, an increase in the relative labour supply of high-skilled workers pushes down the wages of this skill group as these become relatively more abundant in the labour market. Analogously, $\frac{\delta w_t^L}{\delta \frac{H_t}{L_t}} > 0$, an increase in the relative labour supply of high-skilled workers increases the wages of low-skilled ones as a consequence of the imperfect elasticity of substitution between skill types. Second, $\frac{\delta w_t^H}{\delta a_t} > 0$, $\frac{\delta w_t^H}{\delta b_t} > 0$ and $\frac{\delta w_t^L}{\delta a_t} > 0$, $\frac{\delta w_t^L}{\delta b_t} > 0$, that is, a technological change increases the labour earnings of both skill types. Combining equations (1.4) and (1.5), we obtain the relative wage between high and low-skilled workers as a function of their corresponding relative labour supply at time t.

$$\frac{w_t^H}{w_t^L} = \frac{\alpha_t}{1-\alpha_t} \left[\frac{a_t}{b_t} \right]^{\frac{\eta-1}{\eta}} \left[\frac{H_t}{L_t} \right]^{-\frac{1}{\eta}} \tag{1.6}$$

Taking logs of (1.6).

$$ln \left(\frac{w_t^H}{w_t^L} \right) = ln \left(\frac{\alpha_t}{1-\alpha_t} \right) + \left(\frac{\eta-1}{\eta} \right) ln \left[\frac{a_t}{b_t} \right] - \frac{1}{\eta} ln \left[\frac{H_t}{L_t} \right] \tag{1.7}$$

Rewriting (1.7).

$$ln\left(\frac{w_t^H}{w_t^L}\right) = \frac{1}{\eta}\left[D_t - ln\left(\frac{H_t}{L_t}\right)\right] \tag{1.8}$$

Where $D_t = \eta ln\left(\frac{\alpha_t}{1-\alpha_t}\right) + (\eta - 1)ln\left(\frac{a_t}{b_t}\right)$ indexes shifts in the relative labour demand for high-skilled workers. The term in brackets in equation (1.8) shows that the relative wage or skill premium depends on the magnitude of changes in the relative labour demand for and the supply of skills. The aggregate elasticity of substitution between skill types, η, determines the magnitude of a change in the skill premium given a change in the relative supply of skills. An increase in the log relative labour supply decreases the log skill premium by $\frac{1}{\eta}$. Thus, the larger η is, the smaller the effect of a change in the relative supply of skills on the skill premium will be and vice versa. The effect of the relative labour demand on the skill premium also depends on the elasticity of substitution between skill types and is given by $\frac{\eta-1}{\eta}$. If $\eta > 1$, then an increase in the relative skill-biased augmenting technology, a_t/b_t, leads to an increase in the skill premium because a higher demand for skills always pays off when technology is skill-biased. If $\eta < 1$, a rise in a_t/b_t lowers the skill premium because it increases both the relative productivity of high-skilled workers and the relative demand for low-skilled ones as these are complementary in production.

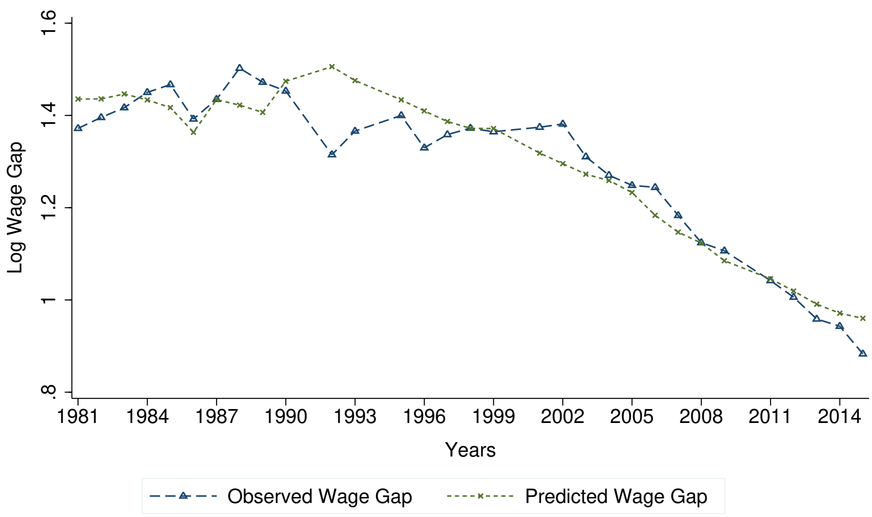
As the ratio a_t/b_t in the labour demand term is not directly observable, most of the literature assumes that this can be captured by a linear time trend of the form: $ln\left(\frac{a_t}{b_t}\right) = \beta_0 + \beta_1 t$. Setting $\alpha_t = \frac{1}{2}$ as in Acemoglu and Autor (2011), equation (1.8) can be rewritten as:

$$ln\left(\frac{w_t^H}{w_t^L}\right) = \left(\frac{\eta - 1}{\eta}\right)\beta_0 + \left(\frac{\eta - 1}{\eta}\right)\beta_1 t - \frac{1}{\eta}ln\left(\frac{H_t}{L_t}\right) \tag{1.9}$$

Equation (1.9) allows us to explain how changes in labour market factors affect the skill premium. We can estimate the model by using specification (1.10) which includes the log of the real minimum wage, $\tilde{m}$, as an explanatory variable:

$$ln\left(\frac{w_t^H}{w_t^L}\right) = \beta_0 + \beta_1 t + \beta_2 ln\left(\frac{H_t}{L_t}\right) + \beta_3 \tilde{m}_t + \epsilon_t \tag{1.10}$$

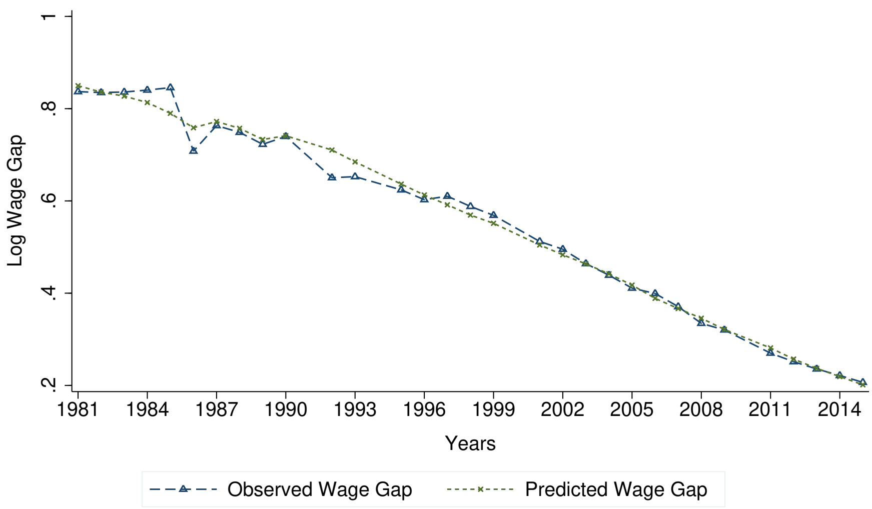
The coefficient β_1 provides information on the trend growth in the skill premium per year and β_2 provides an estimate for the elasticity of substitution between skill types, η. Empirical literature on the subject for more developed countries suggests that η ranges between 1 and 2.5. Manacorda et al. (2010) find an elasticity of substitution between high-school graduates and primary educated workers of 2.3 by using data from the largest economies in Latin America, while Gasparini et al. (2011) find elasticities of substitution within tertiary and non-tertiary educated workers for 16 Latin American economies that range between 4 and 6. Figure 1.12 shows the observed Tertiary/Non-Tertiary and Secondary/Primary wage gap and the corresponding predicted wage gaps obtained from specification (1.10).



(a) Tertiary/Non-Tertiary

Figure 1.12: Observed Vs. Predicted Skill Premium

Source: PNAD and MTE data from 1981 to 2015. The predicted skill premium is obtained by regressing the log of the composition-adjusted wage gap between skill types on a constant, linear time trend, the corresponding log relative supply in efficiency units and the log of the real minimum wage (equation 1.10). See Figure 1.4 and 1.5 notes on how to obtain composition-adjusted wages and efficiency units of labour supply.



(b) Secondary/Primary
Figure 1.12 (continued)

The model does a good job capturing the evolution of the wage gap for different skill types except for the tertiary/non-tertiary wage gap in the early 1990s. As the growth in the relative supply between these skill types slowed down in the early 1990s, the model over-predicts the skill premium in this period. This can be easily observed in Figure 1.A.7 in the Appendix section which plots wage gaps and relative labour supplies deviated from a linear time trend. After the inflationary period, deviations in relative labour supplies from linear time trends explain well those of the corresponding detrended skill premiums, particularly over the 2000s. Figure 1.A.7 underscores the relationship between skill premiums and relative supplies of skills as this depicts the remarkable growth in the relative supply between tertiary/non-tertiary educated workers along with the sharp fall in their wage gap over the 2000s. Similar behaviour can be observed between the secondary/primary relative supply and the corresponding skill premium in the 2000s, however, there is a deceleration in their respective patterns in the last years of the sample. Table 1.3 shows the estimates obtained from regression models for different skill premiums by using specification (1.10).

The first, third and fifth columns in Table 1.3 show the coefficients of a basic specification that accounts for a constant, a linear time trend and the corresponding measure of relative supply for all, males and females, respectively.

Table 1.3: OLS Estimates for Skill Premiums

	All		**Males**		**Females**	
Tertiary/Non-Tertiary						
Relative Supply	-0.699***	-0.371**	-0.718***	-0.412**	-0.561***	-0.265**
	(0.112)	(0.155)	(0.116)	(0.183)	(0.097)	(0.121)
Log Real Minimum Wage		-0.177***		-0.164**		-0.185***
		(0.062)		(0.070)		(0.065)
Time	0.004	-0.001	0.002	-0.002	-0.001	-0.005**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Constant	0.262	0.956***	0.215	0.922**	0.743***	1.266***
	(0.219)	(0.311)	(0.252)	(0.410)	(0.157)	(0.194)
R-squared	0.892	0.925	0.903	0.928	0.892	0.921
Secondary/Primary						
Relative Supply	-0.185***	-0.023	-0.179***	-0.030	-0.149**	0.015
	(0.043)	(0.059)	(0.031)	(0.040)	(0.056)	(0.096)
Log Real Minimum Wage		-0.072***		-0.074***		-0.083*
		(0.024)		(0.018)		(0.048)
Time	-0.009***	-0.017***	-0.009***	-0.017***	-0.014***	-0.021***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)
Constant	0.568***	0.899***	0.600***	0.949***	0.794***	1.053***
	(0.086)	(0.114)	(0.070)	(0.090)	(0.088)	(0.146)
R-squared	0.989	0.992	0.992	0.995	0.982	0.984
Tertiary/Secondary						
Relative Supply	-0.677***	-0.538***	-0.625***	-0.511***	-0.667***	-0.480***
	(0.063)	(0.083)	(0.057)	(0.077)	(0.085)	(0.113)
Log Real Minimum Wage		-0.091**		-0.085**		-0.120**
		(0.042)		(0.040)		(0.058)
Time	-0.008***	-0.005***	-0.012***	-0.008***	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.939***	0.962***	0.994***	1.014***	0.919***	0.958***
	(0.016)	(0.019)	(0.015)	(0.020)	(0.024)	(0.025)
R-squared	0.693	0.765	0.680	0.753	0.558	0.663

Source: PNAD and MTE data from 1981 to 2015. Columns one, three and five show the coefficients obtained from regressing the log of the composition-adjusted wage gap on the corresponding log relative supply in efficiency units, a constant term and a linear time trend for all, males and females, respectively. The remaining columns show the coefficients obtained from using equation (1.10). Robust standard errors in parentheses. Significant at 1 percent ***, at 5 percent ** and at 10 percent *.

The overall elasticity of substitution between workers with tertiary/non-tertiary education, η^T_{NT}, is 1.43 ($\eta^T_{NT} = 1/0.699$) which is similar to that among males, while among females this is much larger approximate 1.8. These values are significantly smaller than those found from a pooled sample of Latin American economies in Gasparini et al. (2011). The difference in the estimates may arise for the heterogeneity of Latin American labour markets and the inclusion of additional years of data.

Low elasticities of substitution imply a significant effect of the relative labour supply on the skill premium. The inclusion of the log real minimum wage in the model lowers the explanatory power of the relative supply and increases η^T_{NT} to 2.4 among males and 3.8 among females. The negative coefficient of the log real minimum wage suggests that an increase in 1 percent in the real minimum wage decreases the tertiary/non-tertiary wage gap in approximately 0.18 percent.

The other panels repeat the same exercise for skill types that are closer substitutes for each other. As expected, the elasticity of substitution between secondary and primary educated workers, η^S_P, is high, approximately 5.4 ($\eta^S_P = 1/0.185$). The coefficient suggests that an increase in 1 percent in the secondary/primary labour supply decreases the corresponding skill premium in 0.19 percent. Manacorda et al. (2010) found a much smaller elasticity of substitution for these workers, approximately 2.3 implying that secondary/primary relative supply plays a significant role in the determination of the skill premium. However, Manacorda et al. (2010) use a sample that excludes the 2000s in which the relative supply between these skill types grew rapidly, as can be seen in Figure 1.5. The inclusion of the log real minimum wage in the model diminishes the effects of the relative supply on the skill premium. In fact, this is no longer significant, as can be seen in Table 1.3. Conditional on the inclusion of the real minimum wage, primary and secondary educated workers are basically perfect substitutes, thus changes in the relative supply between these skill types do not affect their wage gap. On the other side, the coefficient for the time trend seems to play a more significant role in the compression of this skill premium which falls 1.7 percent among males and 2.1 percent among females per year.

Finally, the bottom panel in Table 1.3 shows the skill premium between tertiary and secondary educated workers which has been used as a measure of the skill premium for developed countries. The elasticity of substitution for these skill types, η^T_S, is around 1.48 ($\eta^T_S = 1/0.677$) which is similar to the one estimated for tertiary and non-tertiary educated workers. Notice that the inclusion of the log real minimum wage seems to have a smaller effect on η^T_S in this specification than in previous ones. This suggests that the minimum wage plays a more significant role in the evolution of the labour earnings of workers with less than a high-school diploma. The trend decline in the skill premium per year is smaller than that of the secondary/primary skill premium. Thus, most of the decline in the tertiary/secondary skill premium is driven by changes in their relative labour supply and the real minimum wage.

Up to now, we have assumed that workers with different years of potential experience are perfect substitutes within each educational group. Figure 1.A.1 in the Appendix section showed that most of the decline in the skill premium is concentrated among the youngest workers, those with 0-9 years of potential experience. Following Autor et al. (2008), I extend the basic specification in (1.10) to account for experience-group relative supplies within each educational group. Formally:

$$\begin{aligned} ln\left(\frac{w_{et}^{H}}{w_{et}^{L}}\right) =& \beta_0 + \beta_1 \left[ln\left(\frac{H_{et}}{L_{et}}\right) - ln\left(\frac{H_t}{L_t}\right)\right] + \beta_2 ln\left(\frac{H_t}{L_t}\right) + \beta_3 \tilde{m}_t \\ & + \gamma_e + \gamma_e \times t + \upsilon_t \end{aligned} \tag{1.11}$$

Where e indexes experience groups, γ_e and $\gamma_e \times t$ are experience-group fixed effects and specific time trends. Equation (1.11) arises from an aggregate CES production function as in equation (1.3), where educational groups are themselves CES sub-aggregates of the corresponding skill type. Under this specification, β_1 provides information on the elasticity of substitution between workers with different years of potential experience within the same educational group. Table 1.4 shows the estimates from this specification for the tertiary/non-tertiary skill premium which unlike the secondary/primary skill premium seems to be affected by the increase in the relative labour supply even when the real minimum wage is included in the model.

The first two columns in Table 1.4 show the estimates from specification (1.11)

Table 1.4: OLS Estimates for Tertiary/Non-Tertiary Skill Premium by Experience Groups

			Years of Potential Experience			
	Pooled		0-9	10-19	20-29	30-39
All						
Exp. Group minus Agg. Supply	-0.088***	-0.084***	-0.108***	-0.029	0.013	0.068**
	(0.028)	(0.028)	(0.026)	(0.027)	(0.029)	(0.032)
Aggregate Supply	-0.663***	-0.338***	-0.473***	-0.397***	-0.332***	0.022
	(0.034)	(0.027)	(0.055)	(0.045)	(0.054)	(0.073)
Log Real Min. Wage		-0.175***	-0.127***	-0.170***	-0.222***	-0.182***
		(0.007)	(0.020)	(0.016)	(0.019)	(0.025)
Time	0.003***	-0.002**	0.000	0.000	-0.000	-0.011***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	0.180**	0.867***	0.461***	0.842***	1.133***	1.914***
	(0.071)	(0.056)	(0.108)	(0.094)	(0.107)	(0.154)
R-squared	0.879	0.895	0.918	0.916	0.891	0.805
Males						
Exp. Group minus Agg. Supply	-0.001	0.001	-0.080***	0.006	-0.012	0.067**
	(0.035)	(0.035)	(0.022)	(0.026)	(0.025)	(0.028)
Aggregate Supply	-0.708***	-0.397***	-0.367***	-0.496***	-0.544***	-0.091
	(0.027)	(0.027)	(0.060)	(0.050)	(0.054)	(0.076)
Log Real Min. Wage		-0.167***	-0.144***	-0.125***	-0.187***	-0.204***
		(0.006)	(0.022)	(0.017)	(0.019)	(0.026)
Time	0.001	-0.003***	-0.003***	-0.0001	0.003**	-0.006***
	-0.001	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.048	0.768***	0.630***	0.649***	0.727***	1.756***
	(0.065)	(0.061)	(0.131)	(0.112)	(0.116)	(0.171)
R-squared	0.873	0.887	0.916	0.916	0.898	0.769
Females						
Exp. Group minus Agg. Supply	-0.083***	-0.082***	-0.098***	-0.040	0.042	0.018
	(0.015)	(0.015)	(0.030)	(0.025)	(0.027)	(0.024)
Aggregate Supply	-0.484***	-0.191***	-0.479***	-0.266***	-0.060	0.167**
	(0.044)	(0.036)	(0.053)	(0.040)	(0.055)	(0.078)
Log Real Min. Wage		-0.183***	-0.116***	-0.209***	-0.259***	-0.131***
		(0.013)	(0.023)	(0.018)	(0.024)	(0.034)
Time	-0.002**	-0.007***	-0.001	-0.003***	-0.009***	-0.019***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)
Constant	0.726***	1.244***	0.719***	1.217***	1.722***	2.110***
	(0.064)	(0.054)	(0.087)	(0.068)	(0.091)	(0.138)
R-squared	0.862	0.878	0.901	0.919	0.871	0.779

Source: PNAD and MTE data from 1981 to 2015. Coefficients in the first two columns are obtained by using equation (1.11) with 1240 observations (corresponding to 40 single-year experience groups and 31 years). Workers with more than 40 years of experience were excluded from the specification, as these seem to be not affected by changes in the relative labour supply. The remaining columns show the estimates from separate regressions by individual experience groups. Standard errors in parentheses are clustered by experience group (Pooled sample). Significant at 1 percent ***, at 5 percent ** and at 10 percent *.

for the pooled sample of experience groups and the remaining columns, those from separate regressions by experience group. The coefficients reveal a small, but significant effect of the experience-group relative supply on the evolution of the skill premium, particularly among women. For instance, as seen in Figure 1.A.1 in the Appendix section, the tertiary/non-tertiary wage gap among females with 0-9 and 20-29 years of experience fell by 58 and 44 log points from 1981 to 2015, respectively. Over the same period, the relative supply for these experience groups, as seen in Figure 1.A.2 in the Appendix section, grew by 90 log points for the former and 138 log points for the latter. Thus, using the coefficient for the experience-group relative supply among females from Table 1.4, approximately one-third of the larger decrease in the skill premium for the least experienced females ($0.083 \times 48 \approx 4$ log points out of 14 log points) is explained by the relatively slower growth in their relative supply.

Among males, the estimates for the pooled specification suggest that experience groups are perfect substitutes within the same educational group. However, a closer inspection to the data reveals that this is not the case among the least experienced males, as can be seen in the third column of Table 1.4. Trend demand changes have a small effect on the skill premium, except for the most experienced workers. Thus, most of the variation in the tertiary/non-tertiary skill premium is given by changes in the relative supply of skills and the real minimum wage.

1.5 Conclusions

The decline in income inequality has been a recent phenomenon in the history of Latin America, which has been considered one of the most unequal regions of the world. Brazil reached a turning point in its income inequality trend in the late 1980s after years of four-digit inflation rates and economic instability. Following the economic growth triggered by the boom in the commodity prices in the 1990s and the early 2000s, the improvement in trade conditions and the adoption of a steadier currency in the mid-1990s, the country experienced a long-lasting decline in income inequality which accelerated over the 2000s reaching its lowest point in more than 30 years in 2015. This paper provides a detailed account of the factors behind the evolution of wage inequality from 1981 to 2015 in Brazil.

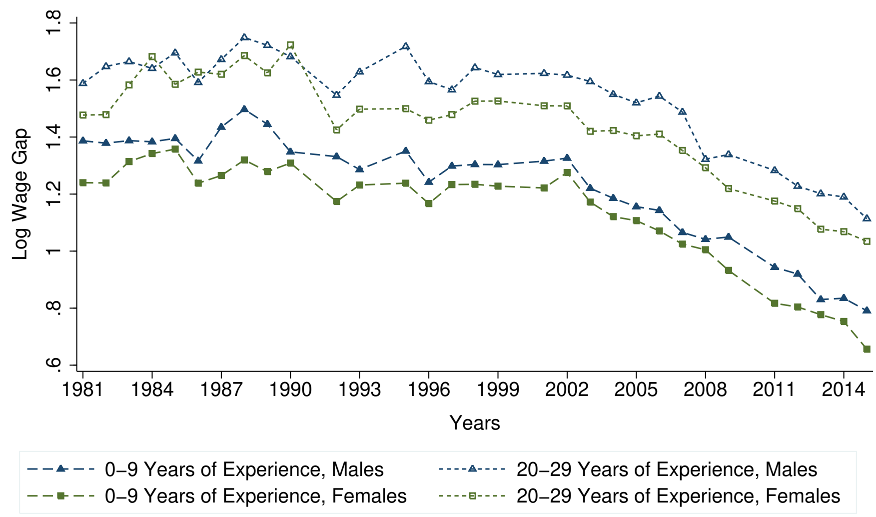
I use a counterfactual wage distribution to estimate the effects of changes in the demographic composition and the wage structure on wage inequality. The results suggest that changes in the composition of skills and demographic characteristics have unequalizing effects on the wage distribution, thus most of the decline in wage inequality is driven by changes in the returns to those characteristics. Changes in the prices of education and age/experience explain the decline in upper-tail inequality, while the fall in lower-tail inequality is also attributed to changes in the returns to minimum wage workers and female labour market participants.

To link changes in wage structure to the observed changes in the skill composition of the labour market, I use a two-factor CES production function with imperfect substitution among different educational and experience groups. I found that the secular increase in the relative supply of skills is key to explaining changes in the tertiary/non-tertiary skill premium. I also find a small but significant effect of the relative supply of workers with different years of experience within the same educational group on their respective skill premium, particularly among the youngest. This implies that these workers are not necessarily perfect substitutes within their educational category. Skill demand shifts have small but significant effects on the declining pattern of the skill premium, which may be related to trade liberalization policies over the 1990s, which according to the literature on the subject has contributed to the growth of low-skill-intensive sectors and thus, the labour opportunities of low-skilled workers. However, a closer inspection of the changes in occupations and sectoral structure shows that the labour earnings of workers employed in low-skill occupations grew in spite of their declining employment participation, particularly in agriculture.

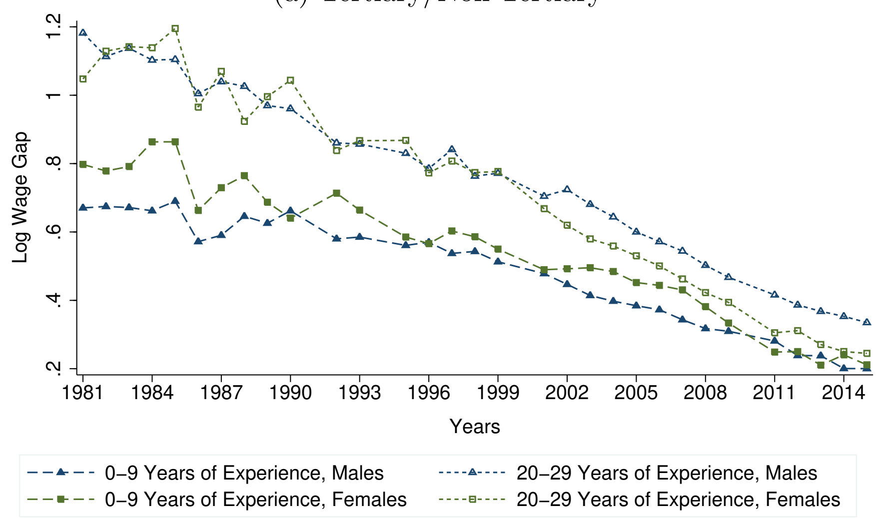
The decrease in the return to skills among young workers and the remarkable increase in the labour earnings of workers employed in low-skill occupations, personal services and agriculture, which are mostly performed by high-school graduates and dropouts suggest that minimum wage policies might have played a significant role in the decline of the skill premium and wage inequality. The increase in the relative supply of skills seems to lose explanatory power when controlling for changes in the minimum wage. In fact, the estimates for the secondary/primary skill premium suggest that the relative labour supply between these skill types is not responsible for its decline. In other words, these workers are assumed to be perfect substitutes in production, thus the decline in the secondary/primary skill premium is mostly attributable to changes in the minimum wage. This finding seems to be opposed to most of the literature on the subject for Latin American economies as most of the empirical work available uses cross-sectional data from several Latin American economies and despite the obvious advantages of accounting for individual effects, there is also a substantial heterogeneity among Latin American countries as far as minimum wage policies are concerned. The estimates of the minimum wage on wage inequality also suggest a significant effect on the compression of both lower and upper-tail inequality. Although we can argue that the latter is likely to be the result of a spurious relationship, this may also be a legit relationship given by spillover effects of the minimum wage which are not accounted for by wage inequality decompositions as the one performed in this study.

Appendices

1.A Figures



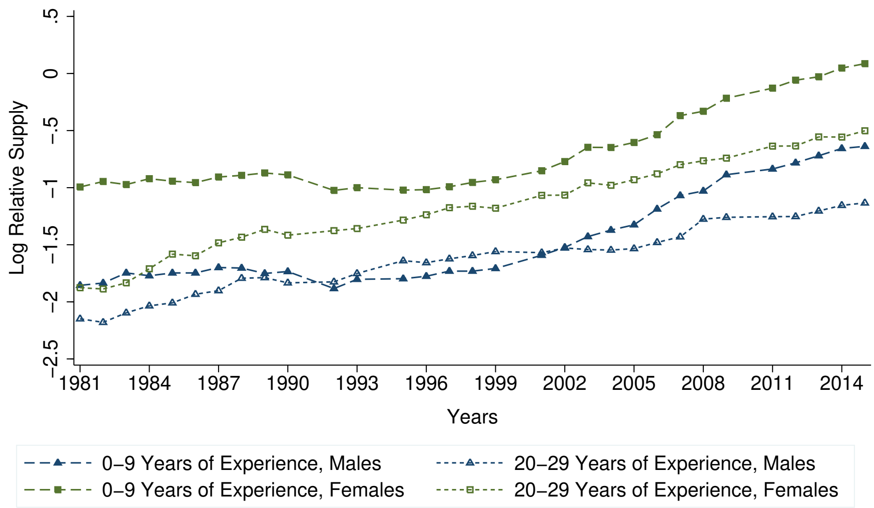
(a) Tertiary/Non-Tertiary



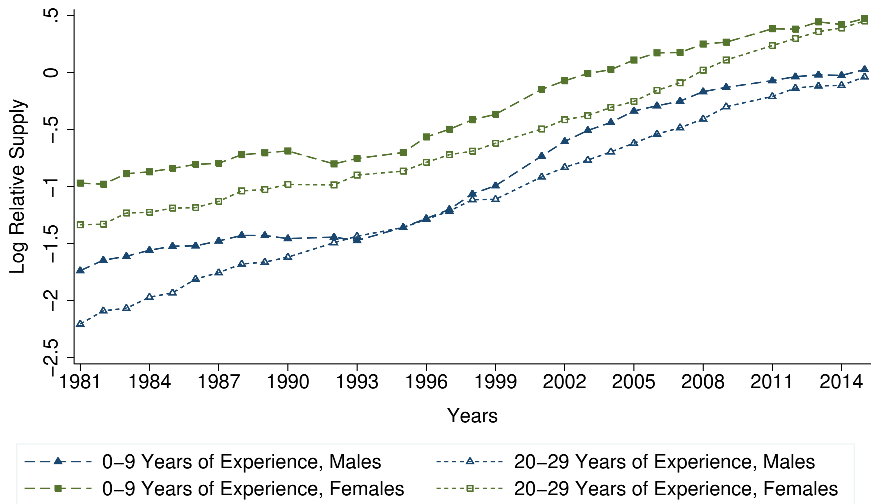
(b) Secondary/Primary

Figure 1.A.1: Skill Premium by Gender and Years of Potential Experience

Source: PNAD data from 1981 to 2015. Tertiary/non-tertiary and secondary/primary wage gaps are given by the ratio between the weighted average of the composition-adjusted log wages of the corresponding education and experience categories. See Figure 1.4 notes for more details.



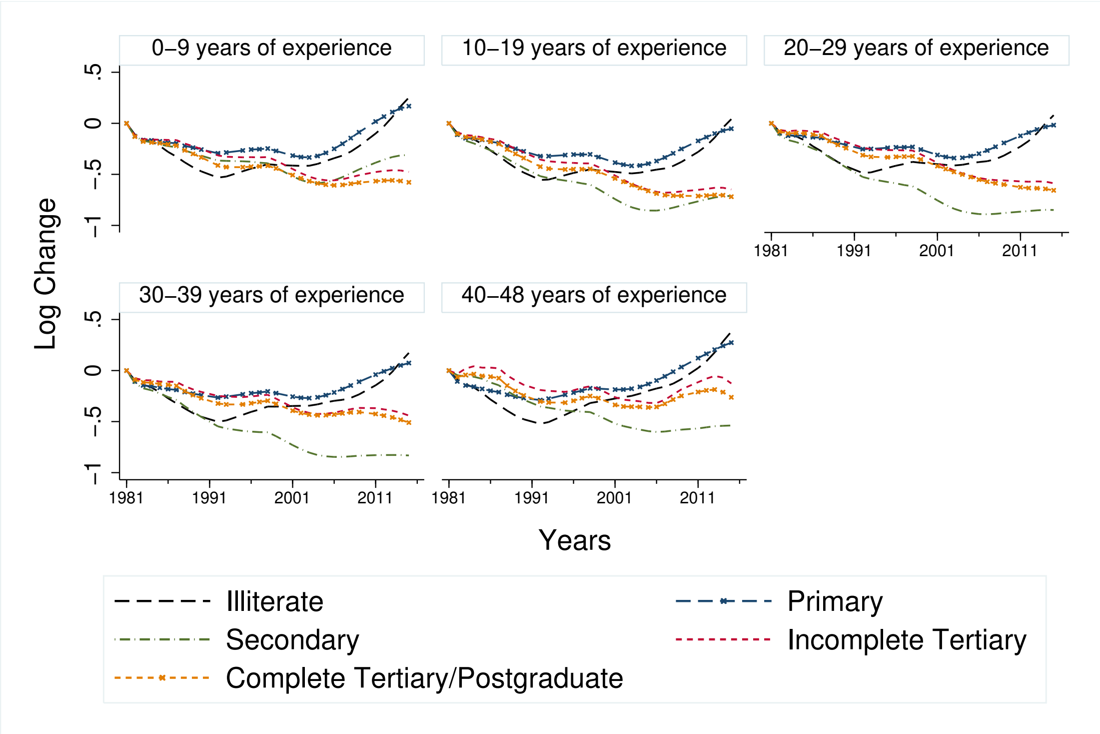
(a) Tertiary/Non-Tertiary



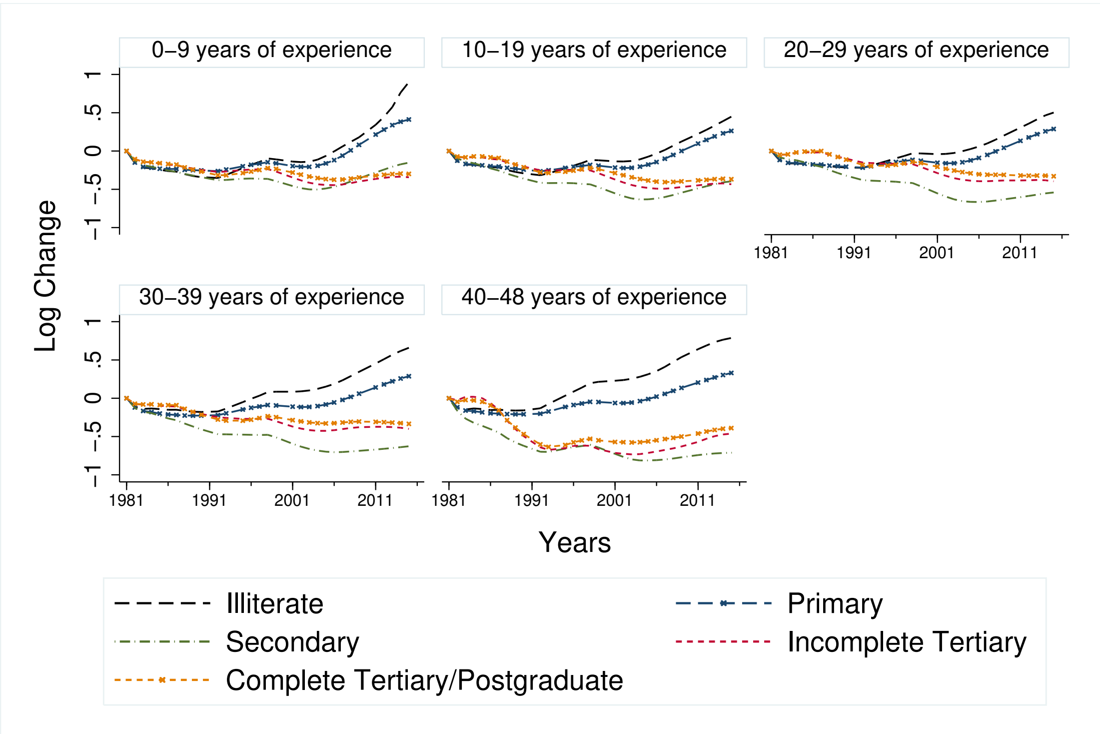
(b) Secondary/Primary

Figure 1.A.2: Relative Labour Supply by Gender and Years of Potential Experience

Source: PNAD data from 1981 to 2015. Log tertiary/non-tertiary and secondary/primary labour supplies are given by the ratio between the weighted average of efficiency units of labour supply of the corresponding education and experience categories. See Figure 1.5 notes for more details.



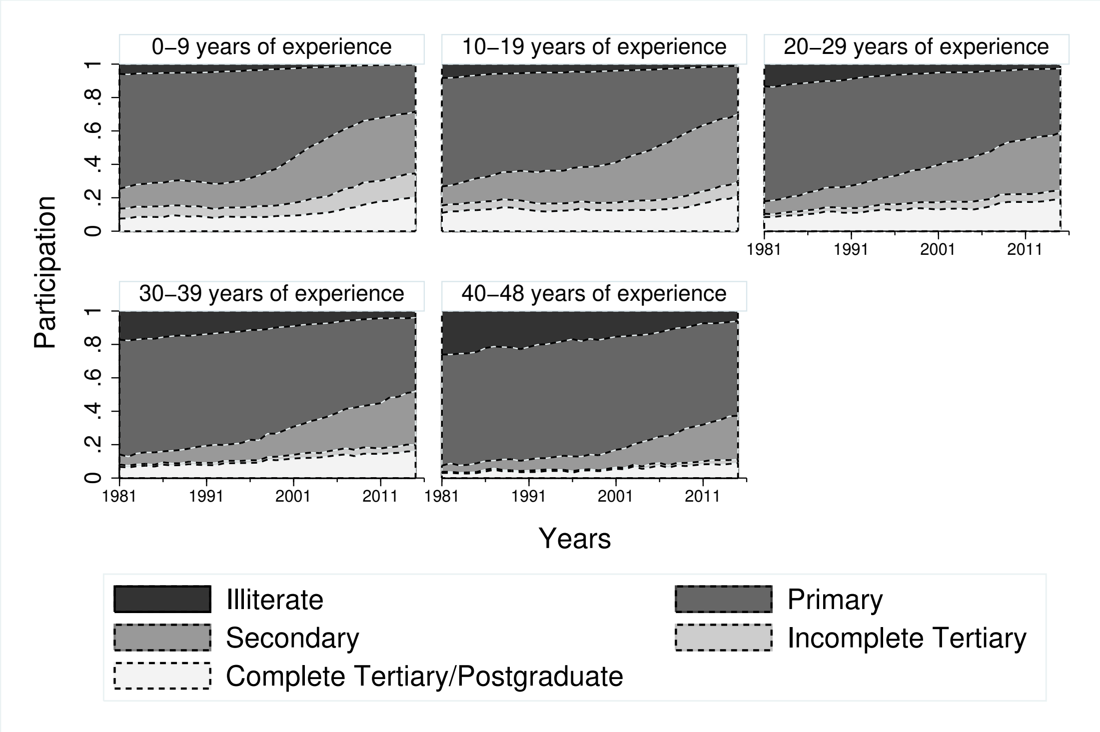
(a) Males



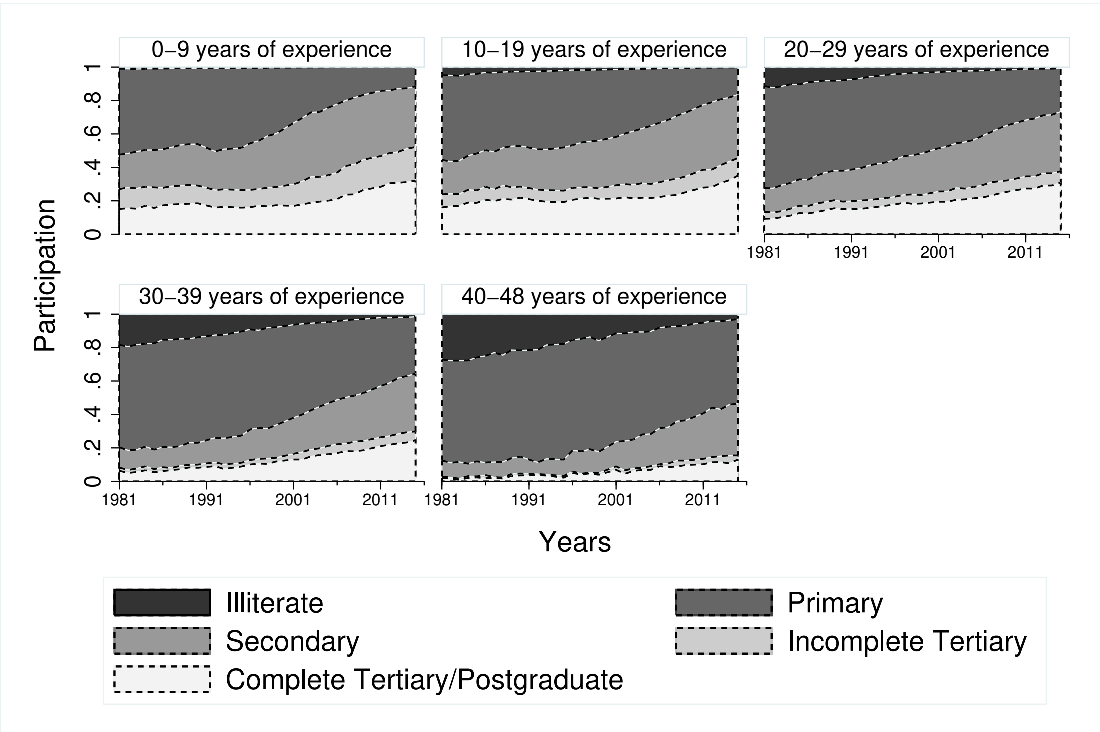
(b) Females

Figure 1.A.3: Composition-Adjusted Log Hourly Wages by Educational and Experience Groups

Source: PNAD data from 1981 to 2015. Composition-adjusted log hourly wages for full-time workers are the weighted average of the predicted log wages in each one of the 490 gender-education-experience groups. Each series is normalized at zero in 1981. Figure 1.A.3 plots changes in composition-adjusted log hourly wages using a weighted smoothing regression with a bandwidth of 0.4. See Figure 1.4 notes for more details.



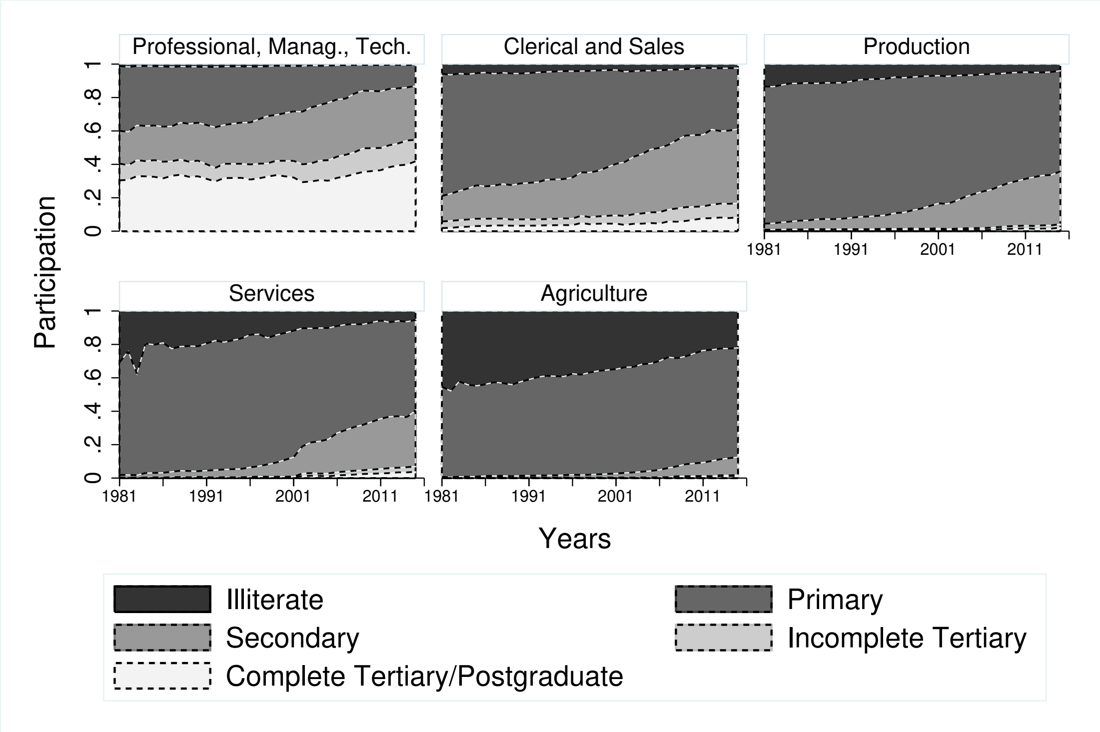
(a) Males



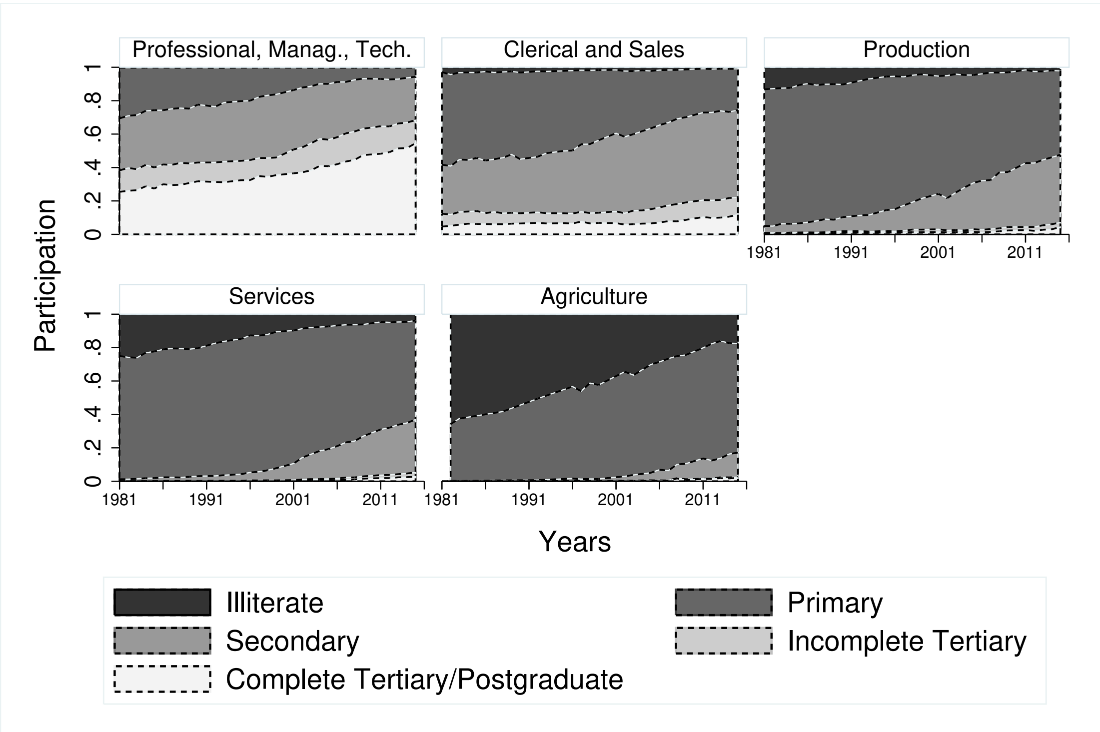
(b) Females

Figure 1.A.4: Efficiency Units of Labour Supply by Educational and Experience Groups

Source: PNAD data from 1981 to 2015. Efficiency units of labour supply are given by the weighted average of the employment participation of 490 gender-education-experience groups. See Figure 1.5 notes for more details.



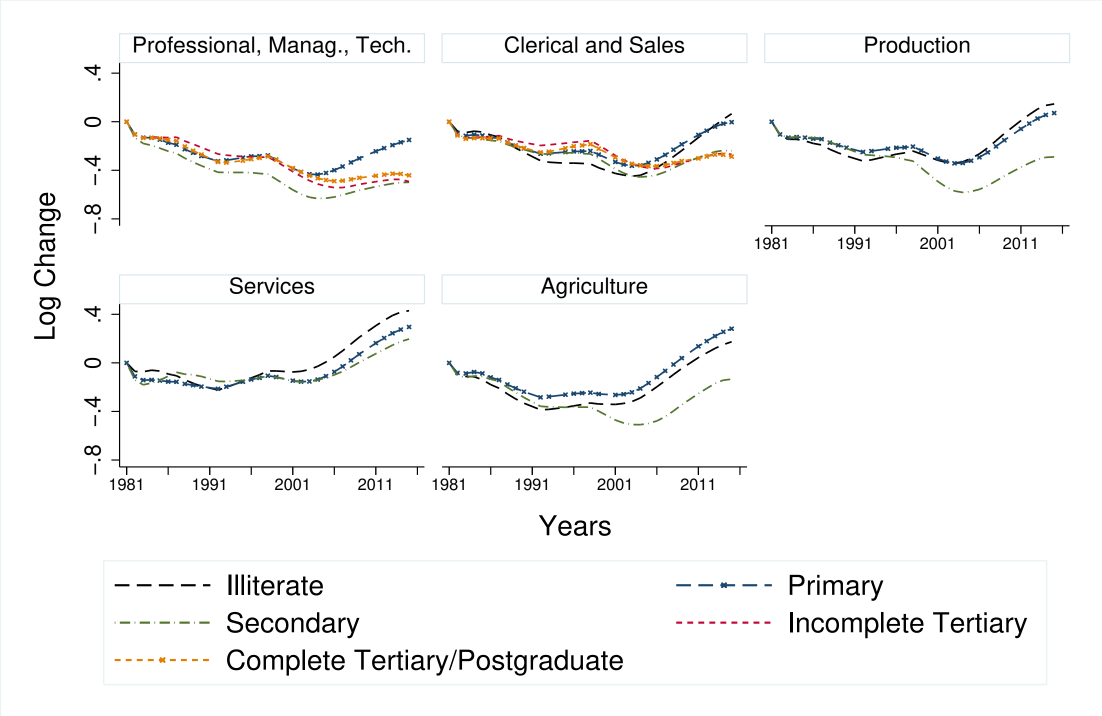
(a) Males



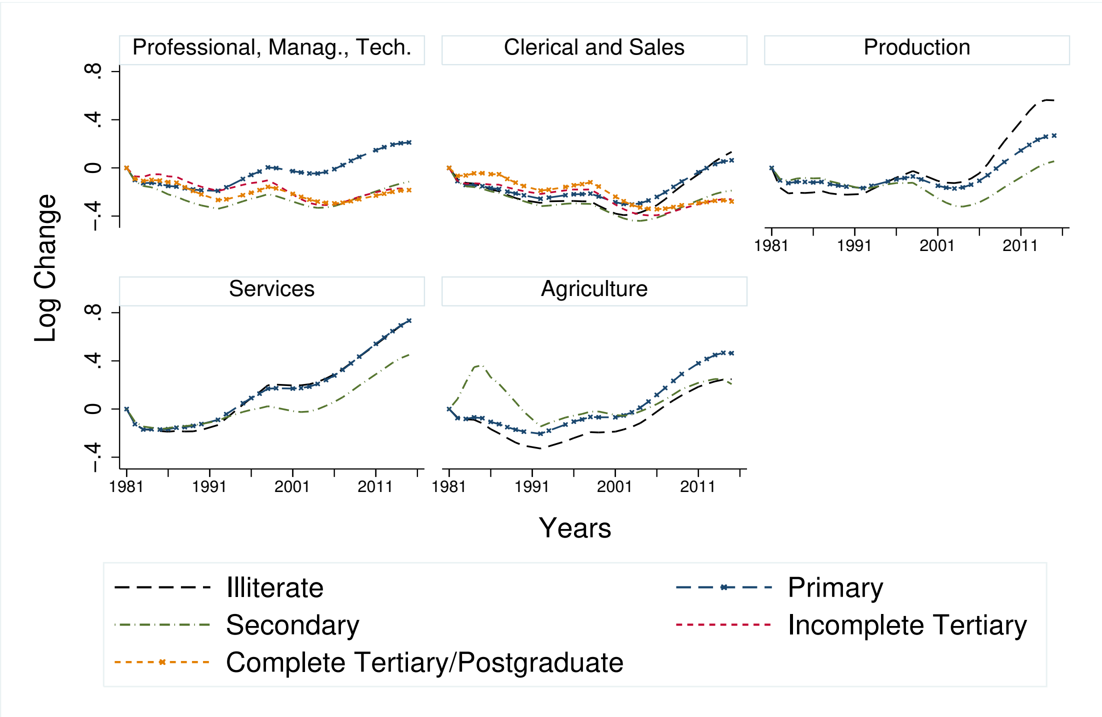
(b) Females

Figure 1.A.5: Employment Shares in Occupational Categories by Educational Groups

Source: PNAD data from 1981 to 2015. Sample comprises salary/wage workers and self-employed, aged 18-65 years old. Workers employed in the military are excluded from the sample. See Figure 1.8 notes for more details on occupational categories.



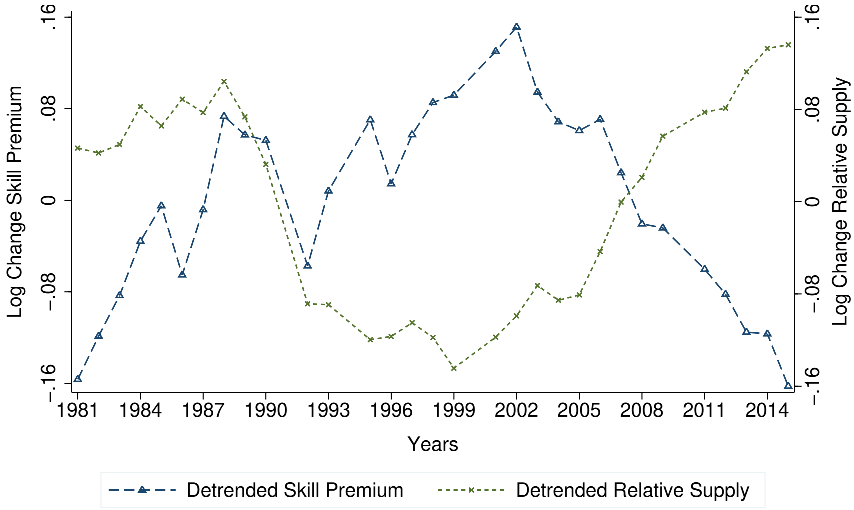
(a) Males



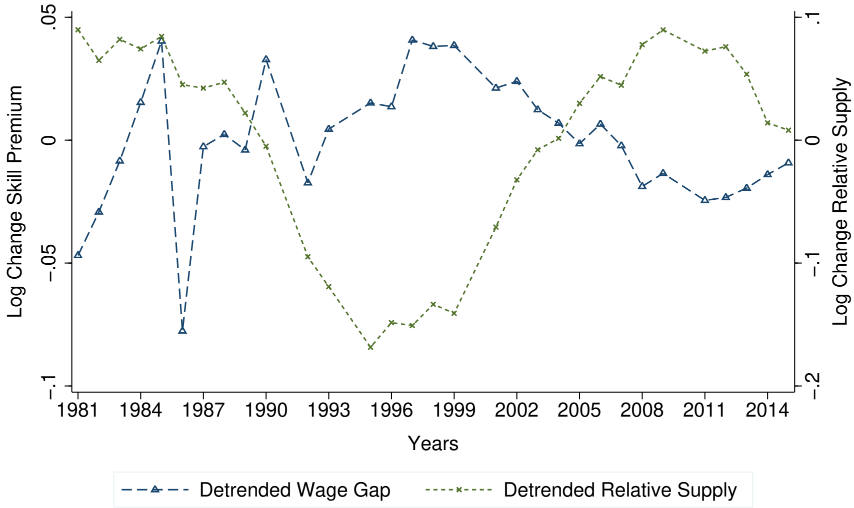
(b) Females

Figure 1.A.6: Log Hourly Wages in Occupational Categories by Educational Groups

Source: PNAD data from 1981 to 2015. Log hourly wages of salary/wage workers and self-employed excluding those in the military, aged 18-65 years old. Each series is normalized at zero in 1981. Figure 1.A.6 plots changes in log hourly wages using a weighted smoothing regression with a bandwidth of 0.4. Educational groups with less than 1 percent of employment participation within each occupational category are not plotted. See Figure 1.8 notes for more details on occupational categories.



(a) Males



(b) Females

Figure 1.A.7: Detrended Changes in Skill Premium and Relative Labour Supply

Source: PNAD data from 1981 to 2015. Detrended skill premiums and relative labour supplies are the residuals obtained from separate regressions of the composition-adjusted wage gap and the relative labour supply in efficiency units on a constant and a time trend term. See Figure 1.4 and 1.5 notes on how to obtain the composition-adjusted wages and efficiency units of labour supplies, respectively.

Chapter 2

The Role of the Minimum Wage on the Declining Wage Inequality in Latin America: Evidence from Brazil

2.1 Introduction

Over the last decade, income inequality has decreased in most Latin American countries, and an extensive debate has taken place on the causes of this phenomenon. There are several factors behind this downward trend and these differ across countries.[1] In Brazil, the decline in income inequality began during the 1990s with the adoption of the Brazilian Real in 1994 which stopped the rampant inflation that Brazil had experienced during the 1980s and the early 1990s. Most of the literature on the subject for Brazil, as well as for other Latin American economies, points out that labour market forces and public policies in favour of the poorest are the driving factors of the declining income inequality.[2]

[1]A compilation of literature on this subject can be found in López-Calva and Lustig (2010); Cornia (2014); Fritz and Lavinas (2016) and Bértola and Williamson (2017).

[2]See Barros et al. (2010) for evidence on the effects of social policies on income inequality in Brazil and Gasparini et al. (2011) for a study of the effects of labour market forces on income

Less attention has been paid to the role played by institutional factors such as minimum wages and labour unions despite the extensive literature on this subject for more developed regions.

Do institutional factors shape wage inequality in Latin American countries? There are two reasons why the minimum wage could have played a more significant role in shaping wage inequality and employment in Latin America than in more developed regions, particularly in Brazil. First, the Brazilian labour market is characterized by a large wage dispersion and a significant binding minimum wage (Maloney and Nunez 2004), thus the effects of the minimum wage on wage setting may be far beyond those contemplated in developed economies. Second, minimum wage earners are more evenly distributed across the workforce in Latin American countries than in more industrialized economies (Kristensen and Cunningham 2006), thus a change in the minimum wage might affect wage inequality throughout the wage distribution.

Most of the empirical work on institutional factors in Latin America has focused on the effects of the minimum wage on average wages and employment rather than its distributional effects on wage inequality. In contrast to the view that the minimum wage is an ineffective tool to reduce inequality in developing economies, this appears to explain a significant part of the variation in wage inequality (Lemos 2009 for Brazil; Bosch and Manacorda 2010 for Mexico; Maurizio and Vazquez 2016 for several Latin American economies). The literature is more ambiguous with respect to the effects of the minimum wage on employment, particularly in Brazil. Lemos (2004a, 2004b) state that the minimum wage has small adverse effects on employment, while Fajnzylber (2002) and; Maloney and Nunez (2004) find a significant decline in employment following an increase in the minimum wage. The latter findings are in line with those of Neumark et al. (2006) who find that an increase in the minimum wage decreases employment among household heads. The potential adverse effect of the minimum

inequality for 16 Latin American economies including Brazil.

wage on employment is perhaps the main reason why the literature has overlooked its distributional effects on wage inequality because any potential benefit of the minimum wage on the labour earnings of those workers who remain employed may be offset by disemployment effects. Another plausible reason is that changes in the minimum wage affect a relatively small proportion of workers directly, thus a significant change in wage inequality relies on spillover effects —effects on the part of the wage distribution in which the minimum wage is non-binding— which are more difficult to quantify because of their indirect nature.

Another issue arises from an identification perspective. For example, Brazil has experienced dramatic changes in the skill composition of the labour force, the return to education, trade liberalization policies and commodity prices that could have also contributed to a greater or lesser extent to shape inequality. Regarding the lack of empirical work on the subject and the disagreement in findings of the available one, I estimate the effects of the minimum wage on wage inequality from a regional-level panel data set.[3] It is important to point out that the minimum wage in Brazil is set nationally, thus this only varies across time, but not across regions. With that in mind, I follow Lee (1999), who identifies the effects of the minimum wage on wage inequality in the U.S. over the 1980s —a period with little cross-statutory variation in the minimum wage—. This approach uses a well-known economic indicator the "Kaitz index" or the "effective minimum wage" (Kaitz 1970), which is measured by the difference between the minimum wage and a regional centrality measure —typically the regional median wage—. The design of this index enables the identification of the effects of the minimum wage on the wage distribution across regions through its level of bindingness.

This paper contributes to the existing literature as follows: First, I quantify the effects of the minimum wage on the declining wage inequality and employment in Brazil over the post-inflationary period (1995-2015). This is important because most of the literature on inequality in Brazil (Foguel 1998; Foguel et al. 2001;

[3] I use the term "wage inequality" even when referring to changes in income inequality of non-wage workers to be consistent throughout the paper.

Fajnzylber 2002; Lemos, 2004a, 2004b) uses microdata from the period of hyperinflation in which the minimum wage was adjusted to the rampant increase in prices, thus these estimates are likely to be biased from an identification perspective. Although there are a few papers that provide information on the subject for the first years of the post-inflationary period (1994-2002), such as Neumark et al. (2006) and Lemos (2009), these in turn do not use data from the middle and the end of the 2000s in which wage inequality fell sharply along with unprecedented increases in the minimum wage. Second, I compare estimates from two of the most important microdata sources available in Brazil, PNAD (Pesquisa Nacional por Amostra de Domicilios) which provides cross-sectional data from 26 regions and PME (Pesquisa Mensal de Emprego) which provides data from 6 major metropolitan areas in Brazil. The latter data source has been extensively used in the literature such as Neumark et al. (2006) and Lemos (2009); however, estimates from PME are likely to be affected by the exclusion of non-metropolitan areas in which the minimum wage is potentially more binding. Consequently, the estimates from PNAD will provide additional information on the relative importance of the inclusion of non-metropolitan regions in the sample. Finally, I construct instrumental variables to tackle plausible endogeneity issues, motivated by the desire to provide reliable estimates of the effects of the minimum wage on wage inequality and employment.

I uncover three main results. First, around 35 percent of the decline in lower-tail inequality among all workers is attributable to minimum wage increases from 2002 to 2015. This effect is even larger, approximately 50 percent, when only formal employees were accounted for. Second, the equalizing effect of the minimum wage extends to high percentiles in the wage distribution, which implies significant spillover effects; however, its effects on upper-tail inequality appear to be the result of a spurious relationship. Finally, the estimates suggest adverse effects of the minimum wage on formal employment though these are relatively small. Thus, it is not expected that small disemployment effects outweigh the large equalizing effect of the minimum wage on income inequality.

The rest of the paper is structured as follows. Section 2 provides a literature review on the subject. Section 3 provides non-conditional evidence of the effects of the minimum wage on wage inequality in Brazil. Section 4 describes the methodology to assess the conditional effects of the minimum wage on both wage inequality and employment. Section 5 provides estimates of these conditional effects over the post-inflationary period and Section 6 concludes.

2.2 Literature Review

Institutional factors, such as minimum wages and labour unions, have become widely accepted in the literature as plausible causes of the changes in wage inequality that cannot be entirely explained by labour market forces. A clear example is the influential literature published during the 1990s about the effects of the decline in the real minimum wage on the widening of lower-tail inequality in the U.S. (DiNardo et al. 1996; Fortin and Lemieux 1997; Lee 1999). Despite differences in methodology, these studies suggest that institutional factors contribute as much as labour market forces to shaping wage inequality. These findings, along with an extensive literature on small adverse effects of the minimum wage on employment (Card et al. 1994; Freeman 1996; Card and Krueger 2015), suggest that the minimum wage is an effective tool to compress wage inequality without harming employment significantly.

There is also an extensive literature that fails to reconcile findings on this matter and suggests that an increase in the minimum wage may not always benefit those it is intended to help. The intuition behind this is that an increase in the minimum wage leads firms to reduce working hours or the number of jobs as an attempt to realign the marginal productivity of their workers with the new minimum (Neumark et al. 2004; Neumark et al. 2014; Neumark and Wascher 2008). The disagreement about the effects of the minimum wage on wages and employment in the literature arises from the exclusion of long-run minimum wage effects because contemporaneous effects of the minimum wage overstate wage gains and understate adverse effects on employment. Furthermore, identification issues are commonly mentioned in the literature. For example, Autor et al. (2016) state that Lee's approach overestimates the effects of the minimum wage on wage inequality because of endogeneity issues in his specification.

The literature for Latin America is more extensive on the effects of the minimum wage on average wages and employment rather than on its distributional effects on wage inequality. In Brazil, Foguel et al. (2000) find positive effects of the minimum wage on average wages of both formal and informal workers in the short run. Fajnzylber (2002) also finds positive effects on average wages, even of those workers who are not covered by the minimum wage legislation, such as informal workers and self-employed. The most striking findings in these papers are the significant spillover effects, not only above the minimum wage level but also below it. Moreover, these spillover effects are also present in the labour earnings of uncovered workers who are not supposed to be affected by changes in the minimum wage. Cunningham (2007) finds that the minimum wage is a benchmark for fair wages in several Latin American countries, thus employers voluntarily offer this fair wage not only to attract labour but also to minimize labour turnover.

Regarding the effects of the minimum wage on employment, Fajnzylber (2002) finds negative elasticities of employment with respect to the minimum wage, particularly among informal workers. Maloney and Nunez (2004) observe significant estimates of the probability of becoming unemployed following an increase in the minimum wage by using data from several Latin American economies, including Brazil. Neumark et al. (2006) find that increases in the minimum wage decrease employment of minimum wage earners, particularly among household heads. On the other hand, Lemos (2004a) points out that increases in the minimum wage do not cause significant adverse effects on Brazilian employment because firms pass this increased cost on through prices. Lemos

(2004b) uses political variables as instruments for the minimum wage to tackle endogeneity issues in previous studies and concludes that an increase in the minimum wage has small adverse effects on employment. It is important to mention that Fajnzylber (2002) and Lemos (2004a, 2004b) use PME data from the 1980s and the 1990s which include the hyperinflation period, unlike Neumark et al. (2006) who use the same dataset but only from the first years of the post-inflationary period (1996-2001). Consequently, the disagreement between findings can be generated not only from the use of different sample periods but also from an identification perspective over two periods that differ significantly in terms of price volatility.

Most of the literature on the distributional effects of the minimum wage on wage inequality in Latin America has been released over the last decade. Barros et al. (2010) and Gasparini et al. (2011) state that the effects of the minimum wage on income inequality are small in comparison to the effects of labour market forces and public policies. Undoubtedly, labour market forces such as changes in the labour demand and the supply of skills are the most straightforward explanation for changes in wage inequality because of their quantifiable nature. However, there is still much disagreement about whether these changes are driven by demand or supply-side factors.[4] Moreover, labour market forces cannot account for the entire decline in wage inequality. On the contrary, Lemos (2009) find significant effects of the minimum wage on the compression of wage inequality and suggests that the minimum wage could be an effective policy tool against poverty in Brazil. Bosch and Manacorda (2010) find that the minimum wage played an important role in shaping lower-tail inequality in Mexico during the 1990s. Maurizio and Vazquez (2016), following the semi-parametric analysis performed by DiNardo et al. (1996), find significant effects of the minimum wage on the compression of the lower-tail

[4]Gasparini et al. (2011) state that most of the decline in wage inequality was driven by changes in demand-side factors such as changes in the labour demand for skills. Barros et al. (2010) instead argue that the decline in wage inequality is driven by the rapid increase in the supply of skills and the subsequent decrease in the returns to education. The authors also mentioned other plausible factors that contribute to the decline in income inequality in Brazil such as government transfers to the poorest.

inequality in some Latin American countries, particularly in Argentina, Brazil, and Uruguay.

2.3 Trends in Wage Inequality and the Minimum Wage

2.3.1 Data

I use two of the most relevant data sources in Brazil to provide evidence of the potential "bite" of the minimum wage on the wage distribution: the Brazilian national household sample survey (PNAD) and the Brazilian monthly employment survey (PME).[5] PNAD is the largest national household survey that provides annual cross-sectional data for 26 regions. I analyse 31 annual household surveys that cover the period 1981-2015.[6] PME is a data source with a longitudinal format and covers 6 metropolitan regions: Recife, Salvador, Belo Horizonte, Rio de Janeiro, Sao Paulo and Porto Alegre. Households are visited for two periods of four consecutive months, with a span of eight months between periods. I use all monthly household surveys available from March 2002 to February 2016 as a sequence of cross-sectional data.[7] The data for the minimum wage are obtained from the Brazilian Ministry of Labour (MTE).

I construct the following three samples to assess the effects of the minimum wage on wage inequality: i) the "formal workers" sample comprises workers who have signed a legal employment contract and thus are more likely to be covered by minimum wage laws, ii) the "salary workers" sample includes both formal and informal workers, iii) "all workers" sample comprises both salaried workers and self-employed. Although informal workers and self-employed are not legally

[5]Both microdata sources are available on the Brazilian Institute of Geography and Statistics (IBGE, in its Portuguese acronym) website.

[6]There are no data available for 1991, 1994, 2000 and 2010 which are the years in which the Census took place in Brazil.

[7]PME has been available since the early 1980s, however, this underwent a major change in the questionnaire design and the rotation scheme in the early 2000s. The new PME replaced the original PME which was close down in 2002, thus it is not possible to compare them.

covered by the minimum wage legislation, it has been well established in the literature that the minimum wage acts as a benchmark for their labour earnings. The unconditional effects of the minimum wage on wage inequality in the next section are obtained by using mainly the “salary workers” sample, whereas, the conditional effects in the “Results” section are estimated for the three samples. All samples comprise workers aged 16 to 64 years old who worked at least 35 hours in the reference week.[8] The number of individual observations per region-year in PNAD and per region-month in PME varies according to the sample studied (Table 2.B.1 in the Appendix section). Detailed information of each sample can be found in the notes of each graph and table.

PNAD and PME only provide data on monthly labour earnings, thus I construct a measure for hourly labour earnings by using monthly income from all jobs and the number of weekly working hours per individual. I also use the number of working hours and the sample weights provided by PNAD and PME to calculate adequate weights for different samples. Analogously, the hourly minimum wage is constructed by using the national minimum wage and the number of working hours per week for a full-time worker which is established by Brazilian legislation. All nominal labour earnings and the nominal minimum wage are deflated by using the corresponding CPI index provided by IBGE.

2.3.2 Stylized Facts

Brazil has one of the highest Gini coefficients in the world which has fluctuated significantly over the last 30 years. Data from SEDLAC (Socio-Economic Database for Latin America and the Caribbean, May 2018) show that income inequality measured by the Gini coefficient fell around 4 points during the 1990s and 7 points from 2001 to 2015. This sharp decline in income inequality has been

[8]The samples are less restrictive in terms of age and education than those in the traditional literature on the subject because minimum wage earners in Brazil are more evenly distributed throughout the age and education distribution than in more developed regions. In fact, there are no obvious restrictions to obtain a reliable sample of minimum wage workers, thus I only restrict the sample to full-time workers because these are more likely to generate labour earnings above or near the minimum wage than their counterparts.

accompanied by an unprecedented increase in the real minimum wage, particularly over the 2000s. This section is devoted to providing evidence on the relationship between the minimum wage and the declining wage inequality in Brazil. Although the present study focuses on the post-inflationary period (1995-2015), this section also provides an analysis of this relationship during the 1980s and the early 1990s by using PNAD data. This data set allows us to compare the inflationary and the post-inflationary period in which both minimum wage and wage inequality patterns changed.

The minimum wage in Brazil is national and covers all workers in the formal sector. Initially, the minimum wage was region-specific; however, the inflationary crisis that took place in the 1980s and the early 1990s led to the setting up of a national minimum wage which was adjusted whenever the inflation rate was higher than 20 percent. Over the inflationary-period, both the real minimum wage and labour earnings dropped sharply, and not surprisingly, wage inequality increased. The four-digit inflation rates came to an end after the adoption of the Brazilian Real in 1994 as an attempt to stabilize the Brazilian currency. The minimum wage has been adjusted yearly since then.

Following monetary stabilization, wage inequality began its downward trend along with a remarkable recovery in the real value of the minimum wage. According to data from MTE, the real minimum wage grew by approximately 155 percent between 1994 and 2015. To put this information in context, Figure 2.1 shows the evolution of the real minimum wage along with lower and upper-tail wage inequality measured by the ratio between the $log(10th/50th)$ and the $log(90th/50th)$ wage percentiles, respectively.

Figure 2.1 shows that the real minimum wage fell around 82 log points from 1981 to 1992. The spikes in the minimum wage are the result of changes in the Brazilian currency in 1986 and 1989 in order to control the rampant inflation rate and currency depreciation over this period. The erosion of the minimum wage was accompanied by an increase in lower-tail inequality, particularly among

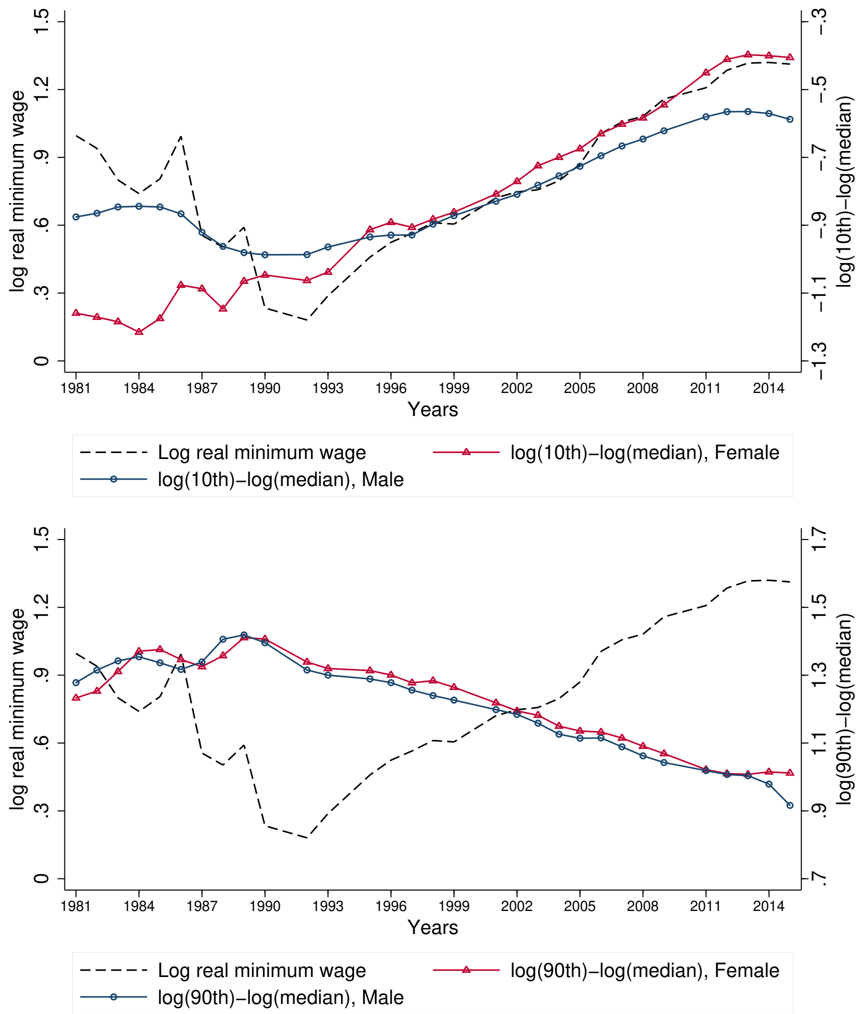


Figure 2.1: Trends in National Real Minimum Wage and Lower and Upper-Tail Inequality, PNAD 1981-2015

Source: PNAD and MTE data from 1981 to 2015. The sample comprises full-time salary workers. The top and the bottom figures depict the evolution of the gap between the $10th/50th$ and the $90th/50th$ percentiles of the log wage distribution along with the log of the real minimum wage, respectively.

males. Upper-tail inequality also increased during the 1980s for both genders. Lower and upper-tail inequality fell sharply after the adoption of the Brazilian Real in 1994 and the subsequent price stabilization led to the rapid recovery of the real minimum wage. The real minimum wage increased by approximately 85 log points from 1995 to 2015 along with a decline in lower-tail inequality. The positive trend of lower-tail inequality in Figure 2.1 implies that the $10th$ percentile grew at a faster rate than the $50th$ percentile over this period. It is worth noticing the reversal of this positive trend over the last years in the sample which may be explained by the increase in the inflation rate. It appears that lower-tail inequality decreased more significantly among females than among males, by approximately 50 versus 35 log points, respectively. The negative pattern of upper-tail inequality instead implies that the $50th$ percentile grew faster than the $90th$ percentile over the post-inflationary period. Upper-tail, unlike lower-tail inequality, seems to fall in a similar proportion for both genders.

The high correlation between lower-tail inequality and the minimum wage is not surprising. The intuition behind this is that the minimum wage truncates the lower-tail of the wage distribution, affecting wages of workers earning at or below the minimum wage. We can also observe a strong negative correlation between the minimum wage and upper-tail inequality. Perhaps the simplest explanation is that there is a spurious relationship between them; however, this might also be a genuine relationship caused by the presence of spillover effects of the minimum wage. For example, an increase in the minimum wage may affect the individuals' education decisions through a change in their expected labour earnings and the price of skills.[9] In such a scenario, a change in the minimum wage would affect the skill composition in the labour market and thus the entire wage distribution. The general equilibrium effects of the minimum wage are beyond the scope of this study, but it is important to mention that the role played by the minimum wage on the declining wage inequality may be over- or underestimated without taking them into account.

Although it is tempting to assign the decline in wage inequality to the increase in the minimum wage, there are other factors that could also have contributed to this behaviour as was mentioned previously. Thus, it is important to use a well-suited strategy to identify the nature of this relationship. Most of the empirical work on the effects of the minimum wage on wage inequality uses the minimum wage as the shock variable for a time series or panel data analysis. The standard approach regresses the variation in labour earnings on changes

[9]See Bárány (2016) for an analysis of the spillover effects of the minimum wage on the wage distribution, generated by changes in educational decisions and the price of skills.

in the minimum wage, inflation rate, unemployment rate, individual observable characteristics and fixed-effect controls. However, the sample period in the case of Brazil is not long enough to obtained reliable estimates from a time series specification. A panel data analysis instead would require that the minimum wage varied across regions but the minimum wage in Brazil is set nationally. With regard to these issues, I use the Kaitz index or the effective minimum wage, which is measured by the gap between the log of the minimum wage and the log of a centrality measure of the wage distribution, $log(min.wage) - log(median\ wage)$. This measure has been used in the literature to identify the effects of the minimum wage on the wage distribution over periods with little variation in statutory minimum wages in more developed economies. Figure 2.2 provides a first insight into the relationship between this measure and the wage distribution in Brazil for selected periods of time.

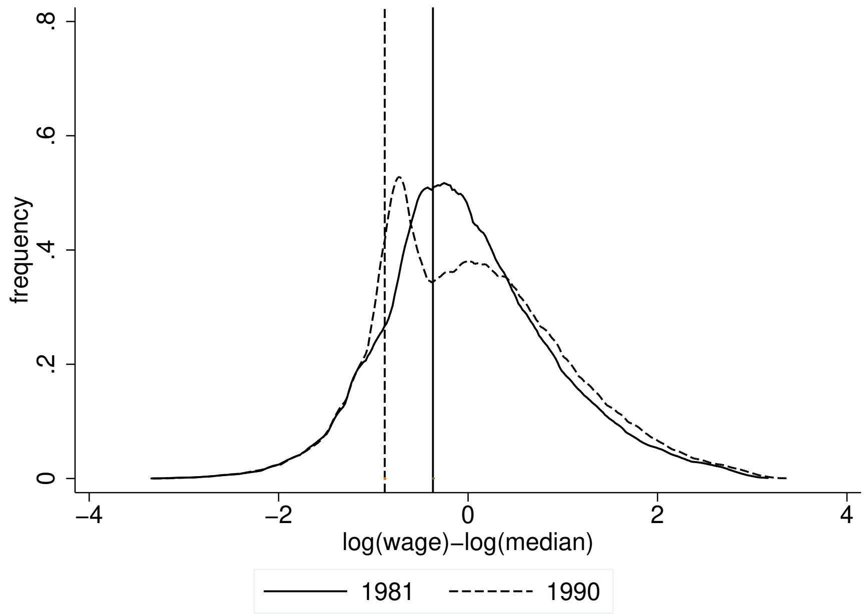
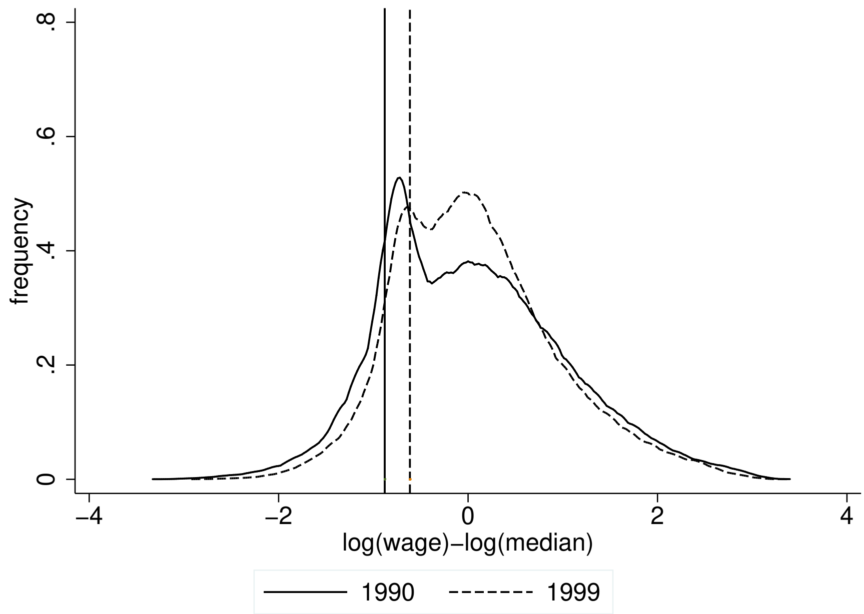


Figure 2.2: Changes in Inequality and the Effective Minimum Wage by Selected Years, PNAD

Source: PNAD and MTE data for 1981, 1990, 1995, 1999 and 2015. The sample comprises full-time salary workers. The figures compare kernel density estimates of the log wage distribution between two years. All series are standardized to the contemporaneous median wage. The vertical lines report the effective minimum wage, $log(min.wage) - log(median\ wage)$, for each year.



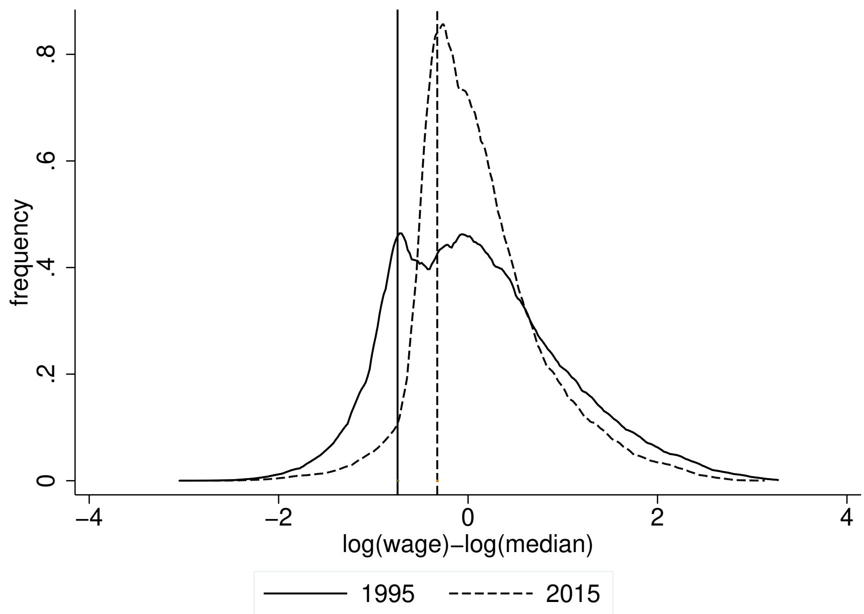


Figure 2.2 (continued)

A large proportion of wage observations below the effective minimum wage in Figure 2.2 belongs to workers in the informal sector who are not covered by the legal minimum wage. Observations below the minimum wage were also recorded among formal workers which can be interpreted as measurement error or non-compliance with the minimum wage law. The figure at the top shows the inflationary period over the 1980s. Notice the spike in the wage distribution in 1990. This appears to be driven by the erosion of the effective minimum wage which is represented by the leftward shift of the vertical line. The next figure instead shows how the wage distribution begins to shrink during the 1990s along with the recovery of the real minimum wage after the adoption of the Brazilian Real. The same behaviour can be observed in the figure at the bottom which represents the entire post-inflationary period (1995-2015).

There are two important features of these graphic representations. First, the effective minimum wage offers some support to the wage distribution, particularly from 1990 onwards. Second, there are evident spillover effects on the wages of those earning just above the minimum wage, while the upper-tail of the wage distribution appears not to be significantly affected.[10]

The relative support of the minimum wage, the spikes of the wage distribution around the minimum and its spillover effects can also be observed when we split the sample into groups of workers who are, or are not, covered by minimum wage laws (See Figure 2.A.2 in the Appendix section). It appears that the minimum wage has significant effects on the labour earnings of both informal workers and the self-employed. It has been well established in the literature for Latin America countries that the minimum wage acts as a benchmark for setting wages, particularly in the informal sector. What is striking is the effect of the minimum wage on the labour earnings of the self-employed. There is no theoretical explanation for why the distribution of these workers is affected by the minimum wage. Lemos (2009) suggests that the minimum wage acts as a signal when the self-employed set their labour earnings because these are willing to work for an income near to or above it.

Although Figure 2.2 provides more reliable information about the relationship between the minimum wage and wage inequality over time, this is not informative about the effects of the minimum wage on wage inequality across regions. It is expected that a binding minimum wage has more significant effects on the wage distribution of low-wage regions. Figure 2.3 provides information on this matter

[10] Analogous figures on the "bite" of the minimum wage on the wage distribution of metropolitan regions for PME data can be found in Figure 2.A.1 in the Appendix section.

by comparing the effective minimum wage and wage inequality across regions for two years, 1992 and 2015, which are the years with the lowest and the highest real minimum wage in the sample, respectively. For this analysis, I restrict the sample to formal workers because these are affected directly by changes in the minimum wage and provide a less ambiguous representation of the "bite" of the minimum wage on the wage distribution.

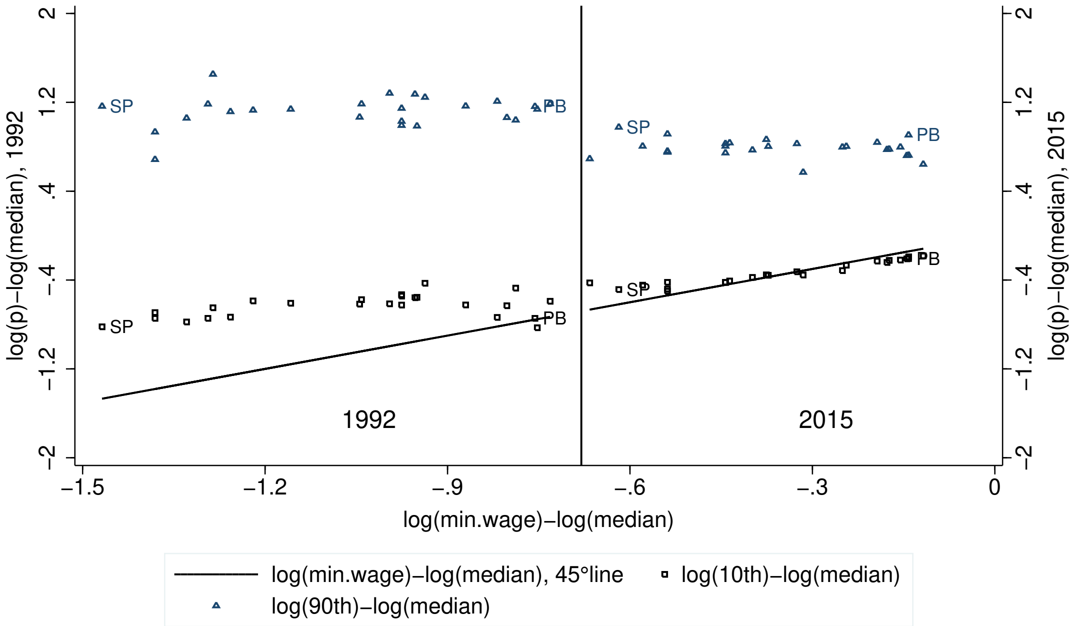


Figure 2.3: Changes in Inequality and the Effective Minimum Wage across Regions, PNAD 1992 and 2015

Source: PNAD and MTE data for 1992 and 2015. The sample comprises full-time salary workers who have a legal employment contract. The plots depict the gaps between the $10th/50th$ and $90th/50th$ percentiles of the log wage distribution across regions for 1992 and 2015. The 45-degree line represents the effective minimum wage in each year. The Federal District was eliminated from the sample for being an atypical value. SP and PB are abbreviations for regions: Sao Paulo and Paraíba, respectively.

Figure 2.3 shows the relationship between the effective minimum wage, which is represented by the 45-degree line with both lower and upper-tail inequality, in 1992 (on the left-hand side of the vertical line) and 2015 (on the right-hand side of the vertical line). Notice that most of the observations lie above the 45-degree line in 1992 which implies that the minimum wage lost its "bite" on the wage distribution across regions in that year. This behaviour agrees with the substantial decline in the real value of the minimum wage that reached its lowest point in the early 1990s. On the other hand, the effective minimum wage tracks the dispersion of lower-tail inequality across regions remarkably well in 2015. There is a significant correlation between lower-tail inequality and the effective minimum wage across regions, particularly among those with low median wages —those with a less negative effective minimum wage—.

There are three general conclusions that can be drawn by comparing these two years. First, the effective minimum wage (horizontal axis) becomes less negative and less dispersed in 2015 which implies that the minimum wage grew at a faster pace than the median wage, particularly across high-median-wage regions. Second, the gap between upper- and lower-tail inequality (vertical axis) shrinks in 2015 which implies that the $10th$ percentile grew faster than the $90th$ percentile within regions. Finally, the positive trend of lower-tail inequality in 2015 suggests that the minimum wage is more likely to affect wage inequality in low-wage regions. To see this, consider two regions with a high and a low median wage in Figure 2.3: Sao Paulo, SP, and Paraíba, PB, respectively. The horizontal axis in Figure 2.3 shows that the gap in the effective minimum wage, $log(min.wage) - log(median\ wage)$, between SP and PB was 71 log points in 1992, while this falls to 48 log points in 2015. Since the minimum wage is the same across regions, the decline in the effective minimum wage gap suggests that the median wage in PB grew at a faster pace than the median wage in SP. Although the growth in median wages can be driven by several factors, the minimum wage could have played a significant role in the growth of median wages, particularly among low-wage regions because this is more binding on their wage distributions.

The gap between lower and upper-tail inequality, which is basically the gap between the $90th$ and the $10th$ percentile, decreases for both regions. The vertical axis in Figure 2.3 shows that this gap is practically the same for PB and SP in 1992, which is consistent with a non-binding minimum wage, while the same gap is evidently smaller in PB than in SP in 2015. In fact, the $90th/10th$ gap decreases by 80 log points in PB and by only 52 log points in SP from 1992 to

2015. These results are consistent with the previous statement that the minimum wage is more likely to affect wage dispersion in low-wage regions.[11] These results are also consistent with those obtained from PME data for metropolitan regions. By comparing the first and last year available in this sample (2002 and 2016), the $90th/10th$ gap in low-wage regions such as Recife and Salvador decreases by approximately 65 log points, whereas the same gap in high-wage regions such as Sao Paulo and Rio de Janeiro decreases by approximately 40 log points.[12]

Finally, Figure 2.3 shows that there is a weak correlation between the effective minimum wage and upper-tail inequality which is something expected and desirable for identification. Notice that upper-tail inequality across regions also decreases from 1992 to 2015 which suggests that the median wage grew faster than the $90th$ percentile. The literature for more developed countries finds that median wages are not affected by changes in the minimum wage. For instance, Lee (1999) and Autor et al. (2016) find that the minimum wage binds up to the $10th$ percentile of the wage distribution in the U.S., thus most of the effect of the minimum wage on wage inequality in the U.S. comes from spillover effects which do not extend through the median. In the case of Brazil, the minimum wage is much more binding, particularly when informal workers are included in the sample. Perhaps this is the reason why upper-tail inequality also decreases. Figure 2.4 shows that the minimum wage binds above the median wage in some regions, particularly during the 1980s.

The sample comprises regions in which the minimum wage barely binds the wage distribution and others in which the minimum wage binds above the median wage.[13] The large variation in the bindingness of the minimum wage on the wage distributions across regions is the result of differences in their

[11] The average decrease in the $90th/10th$ gap of the five regions with the lowest median wage and the five regions with the highest median wage from 1992 to 2015 is 81 and 53 log points, respectively.

[12] A graphic representation of the changes in wage inequality across regions for PME data can be found in Figure 2.A.3 in the Appendix section.

[13] See Figure 2.A.4 in the Appendix section for information on the bindingness of the minimum wage on the wage distribution across metropolitan regions by using PME data.

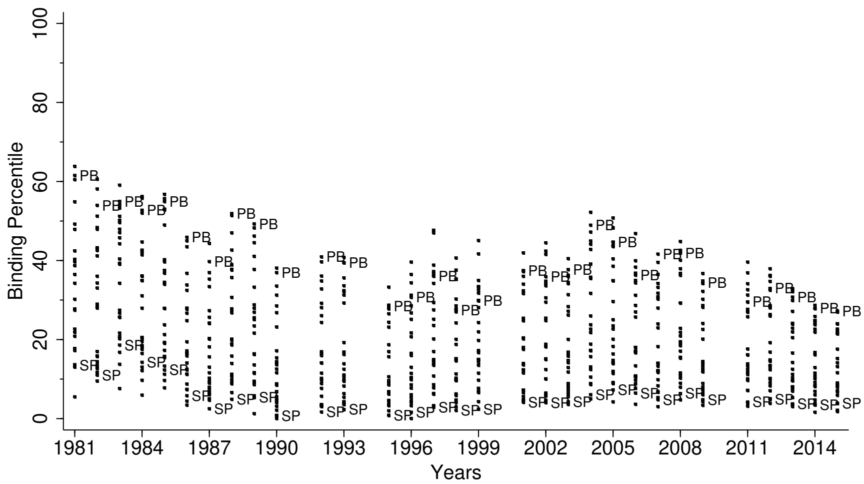


Figure 2.4: Bindingness of the Minimum Wage on the Wage Distribution across Regions, PNAD 1981-2015

Source: PNAD and MTE data from 1981 to 2015. The sample comprises full-time salary workers. The figure shows the lowest and the highest percentile at which the minimum wage binds across 26 regions per year. SP and PB are abbreviations for regions: Sao Paulo and Paraíba, respectively.

wage levels which is a desirable condition for identification. However, it is also desirable that the centrality measure (median wage) is not affected by changes in the minimum since this is used to construct wage inequality measures and the effective minimum wage. To see why this is an issue, consider an increase in the minimum wage that increases both the $10th$ percentile and the median wage in the same proportions, other variables *ceteris paribus*. In this extreme case, lower-tail inequality, $log(10th) - log(median\ wage)$, would not be affected, while upper-tail inequality, $log(90th) - log(median\ wage)$, would decrease, implying that the minimum wage is only effective in compressing upper-tail inequality even when this did increase wages below the median. Consequently, I use a centrality measure above the median wage, which is less likely to be affected directly by changes in the minimum wage, I will come back to this in the following section.

2.4 Methodology

This section is divided into three parts. The first part describes the general specification for this study, the remaining two propose the strategy to obtain robust estimates of the effects of the minimum wage on wage inequality and employment.

2.4.1 General Specification

I follow Lee (1999) who proposes an empirical model to identify the effects of the minimum wage on the wage distribution through its level of bindingness. The intuition behind the model is that in absence of a minimum wage, the structure of the wage distribution would have evolved identically across regions, hence any deviation from this pattern is attributed to changes in the minimum wage. Formally:

$$\begin{cases} w_{rt}^{p} - w_{rt}^{\mu} = w_{rt}^{p*} - w_{rt}^{\mu*} & \text{if} \quad min.wage_t - w_{rt}^{\mu} < w_{rt}^{p*} - w_{rt}^{\mu*} \\ \\ w_{rt}^{p} - w_{rt}^{\mu} = min.wage_t - w_{rt}^{\mu} & \text{otherwise} \end{cases} \tag{2.1}$$

Where w_{rt}^{p} and w_{rt}^{μ} are the p-th percentile and the centrality measure of the actual log wage distribution in region r at time t, respectively. The start denotes latent log wage percentiles, those which would have been observed in the absence of a binding minimum wage. Consequently, actual wage inequality equals latent wage inequality whenever the effective minimum wage, $min.wage_t - w_{rt}^{\mu}$, is below the latent wage differential, $w_{rt}^{p*} - w_{rt}^{\mu*}$. On the other hand, actual wage differential equals the effective minimum wage whenever the latter is larger or equal than the latent wage gap.

Lee's model relies on several assumptions that allow us to separate the average growth in latent wage inequality from the effects of the minimum wage on actual wage inequality. First, the centrality measure and the percentiles above are not affected by changes in the minimum wage, thus $w_{rt}^{p} - w_{rt}^{\mu} = w_{rt}^{p*} - w_{rt}^{\mu*}\ \forall p,\ p \geq \mu$. Second, latent wage inequality is the same across regions such as $w_{rt}^{p*} - w_{rt}^{\mu*} = w_{st}^{p*} -$

$w_{st}^{\mu *}$ $\forall r, s$. Finally, the regional centrality measure is systematically uncorrelated with latent wage dispersion such as $cov[w_{rt}^{p*} - w_{rt}^{\mu}, min.wage_t - w_{rt}^{\mu}|t] = 0$. Consequently, a significant association between the effective minimum wage and lower-tail inequality is only possible because of a change in the minimum wage, whereas a significant association between the effective minimum wage and upper-tail inequality implies a violation of the main assumptions of the model. However, Lee's approach allows for the possibility of spillover effects such as, $w_{rt}^{p} - w_{rt}^{\mu} = f(min.wage_t - w_{rt}^{\mu})$, that is, the wage inequality measure is an increasing function of the effective minimum wage as long as spillover effects diminish monotonically higher up in the wage distribution. Lee (1999) suggests the following specification to estimate the effects of the minimum wage throughout the wage distribution.

$$w_{rt}^{p} - w_{rt}^{\mu} = \beta_1 mw_{rt} + \beta_2 mw_{rt}^2 + \alpha_t + \epsilon_{rt} \tag{2.2}$$

Equation (2.2) suggests that the change in the differential between the log wage percentile, w_{rt}^{p}, and the log of the centrality measure, w_{rt}^{μ}, depends on the log of the effective minimum wage, $mw_{rt} = log(min.wage_t) - log(w_{r,t}^{\mu})$, its square, mw_{rt}^2, and time fixed effects, α_t. The latter captures the latent wage differential, which is indexed only across time because it is assumed to be the same across regions. Equation (2.2) also relies on the assumption that, ϵ_{rt}, is orthogonal to the effective minimum wage and its square. The quadratic term captures the idea that the minimum wage has a larger effect on the wage distribution of low-wage regions in which this is more binding. Notice that the marginal effect of the effective minimum wage is given by, $\beta_1 + 2\beta_2 mw_{rt}$, which is obtained by differentiating equation (2.2) with respect to mw_{rt}.

This simple specification is restrictive because it assumes that latent wage inequality is identical across regions, which is certainly false in practice. Moreover, Autor et al. (2016) point out that the violation of the assumption of zero correlation between the centrality measure and other latent wage percentiles would imply that estimates from equation (2.2) are likely to be biased from the exclusion of region-fixed effects. This assumption can be tested by using a measure of wage inequality which is not likely to be affected by the minimum wage as a plausible proxy for latent wage inequality. I regress the mean $log(90th) - log(70th)$ across years as a measure for latent wage inequality on two potential centrality measures, the mean $log(50th)$, and the mean $log(60th)$ by region, separately. I also perform an analogous analysis by regressing instead the trend of $log(90th) - log(70th)$ across years on the trends of their respective centrality measures by regions. The results of these tests show a significant negative correlation between the latent log wage inequality with both centrality measures, though this is less significant when I use the $60th$ percentile as a centrality measure.[14] Following Autor et al. (2016) recommendation, the specification below allows for differences in latent wage dispersion across regions and within regions over time. Formally:

$$w^p_{rt} - w^\mu_{rt} = \beta_1 mw_{rt} + \beta_2 mw^2_{rt} + \alpha_t + \alpha_r + \alpha_r \times t + \upsilon_{rt} \tag{2.3}$$

Where α_r and $\alpha_r \times t$ are time-invariant region effects and region-specific trends, respectively. Regarding the previous findings from the data, I consider this specification to be more appropriate to estimate the effects of the effective minimum wage on wage inequality in Brazil. I also use the $60th$ percentile as a centrality measure because this seems to be a more suitable centrality measure than the median wage for this specification.

Although it is expected that the inclusion of regional dummies and region-specific trends tackle any spurious relationship between the effective minimum wage and wage inequality, there is still a potential endogeneity problem in Lee's specification given by the mechanical nature of the relationship between the dependent and independent variables. Notice that the centrality measure is

[14] A graphical representation of these tests and their respective OLS estimates can be found in Figure 2.A.5 in the Appendix section.

used to construct both the wage inequality measure (left-hand side of equation (2.3)) and the effective minimum wage (right-hand side of equation (2.3)), thus if sampling error is an important part of the variability in the centrality measure, then a spurious relationship between the dependent and the independent variables is expected. Although this is a valid concern, the sample sizes for PNAD and PME are large, in average 4000 and 5000 observations for each unit of time and region, respectively. The estimated sampling error for the centrality measure is around 1 percent, which implies that 1 percent of the variation in the effective minimum wage is attributable to sampling error. However, this becomes important when the sample is split into genders or smaller groups of workers. In addition, regional centrality measures are also functions of transitory effects, υ^{μ}_{rt}, and if $cov(\upsilon^{\mu}_{rt},\ \upsilon_{rt}) \neq 0$, that is, the correlation between the transitory fluctuations of regional centrality measures and the gap between these and other percentiles is different of zero, then OLS estimates are likely to be biased.[15]

Autor et al. (2016) deal with these issues by instrumenting the effective minimum wage with the statutory minimum wage which is assumed to be exogenous. This instrument is not available for Brazil because minimum wages are set nationally. In fact, the identification of the effects of the minimum wage on regional wage inequality relies entirely on the variation of the centrality measure across regions. However, we can mitigate transitory fluctuations of the contemporaneous centrality measure by using a wage distribution from s periods prior to the increase in the minimum wage in hope that $cov(\upsilon^{\mu}_{r,t-s},\ \upsilon^{\mu}_{r,t}) = 0$. I discuss this in more detail in the following subsection.

2.4.2 Identification

Full identification of the effects of the minimum wage on wage inequality requires addressing the endogeneity issue that arises from the use of a contemporaneous

[15]According to Autor et al. (2016), transitory fluctuations are expected to dissipate as we move to further percentiles from the centrality measure, thus $cov(\upsilon^{\mu}_{rt},\ \upsilon_{rt}) < 0$ which leads to upward biased OLS estimates in both lower and upper-tail inequality.

centrality measure in both sides of equation (2.3). It is of interest to obtain an effective minimum wage that is driven by the contemporaneous fluctuations of the minimum wage and not by changes in the contemporaneous wage levels. I propose to instrument the contemporaneous effective minimum wage by using instrumental variables which are constructed with wage distributions from previous periods, in hope that the span of time tackles any possible correlation between the error components in both sides of equation (2.3).

The first instrument uses a centrality measure of, $t - s$, periods prior to the contemporaneous minimum wage, thus the effective minimum wage and its square in equation (2.3) are instrumented by using the difference between the log of the contemporaneous minimum wage and the log of the centrality measure of, s, months earlier, $log(min.wage_t) - log(w^{\mu}_{r,t-s})$, and its square, respectively. The second instrument uses the percentile at which the minimum wage binds the wage distribution across regions at time, $t - s$, to estimate the probability of earning at or below the contemporaneous minimum wage. I define this instrument as the fraction of hourly wages at or below this percentile, formally: $F_{rt} = Pr(w_{r,t-s} \leq min.wage_t)$.[16] To instrument the two endogenous variables in equation (2.3), I propose a set of three instruments: F_{rt}, its square and the interaction between, F_{rt}, and the average log of the centrality measure per region across time, w^{μ}_{r}. The identification of mw_{rt} comes from F_{rt}, while the identification of $mw^2_{rt} = (min.wage - w^{\mu}_{rt})^2$ comes from both the square F_{rt} and the interaction term, $F_{rt}w^{\mu}_{r}$, because the quadratic structure of mw^2_{rt}, yields three terms, one of which is the interaction between the minimum wage and the centrality measure.[17]

The span of time, s, must be short enough to ensure a significant correlation

[16] Different measures for the probability of being affected by changes in the minimum wage have been used in the literature mainly to identify the effects of the minimum wage on employment. Some examples include Card (1992) ("fraction affected" defined as the fraction of workers between the old and the new minimum wage); Neumark et al. (2006) ("fraction below" defined as the fraction of workers earning strictly below the minimum wage) and Card and Krueger (2015) ("fraction at" defined as the fraction of workers earning at the minimum wage).

[17] Although the average log of the centrality measure, w^{μ}_{r}, is not completely exogenous with respect to the factors that affect the effective minimum wage, it is expected that the endogenous component between the instrument and the instrumented variable is small enough to not bias the estimates significantly.

between the effective minimum wage and the instrument, but not too short to ensure its exogeneity. Unfortunately, PNAD data are collected annually, thus, the span of time is not suitable to construct such instruments. Consequently, I only use data from PME because its monthly structure allows us to do so. The correlation between the effective minimum wage and the instruments decreases with the number of lags up to the four-quarter lag of the wage distribution which is highly correlated with the contemporaneous minimum wage as this often increases in the same month in each year. Although we can use one-month lag of the wage distribution, this instead raises concerns of endogeneity bias. Thus, the instruments are based on the wage distribution one quarter earlier, this span of time seems to perform well as the instruments are jointly significant and pass standard diagnostic tests.

The OLS estimates for PNAD and PME along with the 2SLS estimates for PME will be discussed in the "Results" section. To conclude this section, I present the strategy to estimate the effects of the minimum wage on employment below.

2.4.3 The Effects of the Minimum Wage on Employment

There is an extensive literature on the adverse effects of the minimum wage on the employment of workers who were intended to benefit. In this case, the equalizing effect of the minimum wage on the wage distribution of those who remain employed may be outweighed by negative effects on the labour earnings of those who become unemployed. A loss in the sample following an increase in the minimum wage would lead to a mechanical change in the observed percentiles of the wage distribution. We are not able to observe the lost part of the wage distribution because the samples are only comprised of employed workers.

To shed light on the possible adverse effects of the minimum wage on employment, I include in the PME data samples, unemployed workers who are actively looking for jobs in the reference week. I use three different measures of employment as dependent variables: i) employment rate, E_{rt}: number of employed workers divided by the number of individuals in the labour force in region r at time t, ii) working hours, T_{rt}: total working hours per week divided by the number of individuals in the labour force in region r at time t, and iii) working hours if employed, H_{rt}: total working hours per week divided by the number of employed workers in region r at time t. I use the fraction of hourly wages at or below the minimum wage, $F_{r,t}$, as was defined previously, as the explanatory variable along with time-fixed effects, region-fixed effects and region-specific trends. Following Neumark et al. (2006), I include lags of the shock variable in order to capture the long-run effects of the minimum wage on employment. Formally:

$$E_{rt}, T_{rt}, H_{rt} = \sum_{s=0}^{S} \beta_s F_{r,t-s} + \alpha_t + \alpha_r + \alpha_r \times t + \upsilon_{rt} \tag{2.4}$$

2.5 Results

In this section, I report OLS and 2SLS estimates of the relationship between the minimum wage and wage inequality in Brazil by using both PNAD and PME data for different groups of workers. I also perform a counterfactual exercise to quantify the decline in wage inequality that is driven by changes in the minimum wage over the post-inflationary period (1995-2015). Finally, I estimate the effects of the minimum wage on employment by using PME data and propose an exercise for robustness check.

I begin this section by presenting the estimates for three groups of workers: "all workers" comprises both salary workers and self-employed, "salary workers" comprises both formal and informal workers and "formal workers" comprises workers who have a legal employment contract in the reference week. Table 2.1 reports estimates for the sample period 2002-2016 to make PNAD and PME comparable.

Table 2.1: OLS and 2SLS Estimates between Log(pth)-Log(60th) and Log(min.wage)-Log(60th) for Selected Percentiles

Percentiles	**10th**	**20th**	**30th**	**40th**	**50th**	**70th**	**80th**	**90th**
All workers								
OLS (PNAD)	0.53***	0.49**	0.46***	0.28***	0.32***	0.17***	0.28**	0.23**
	(0.19)	(0.23)	(0.14)	(0.08)	(0.08)	(0.06)	(0.11)	(0.10)
OLS (PME)	0.43***	0.42***	0.27***	0.24***	0.12***	-0.001	0.11*	0.16**
	(0.08)	(0.06)	(0.02)	(0.03)	(0.01)	(0.03)	(0.05)	(0.05)
2SLS* (PME)	0.42***	0.40***	0.24***	0.20***	0.08***	-0.03	0.07	0.11
	(0.09)	(0.07)	(0.02)	(0.04)	(0.02)	(0.04)	(0.07)	(0.06)
2SLS** (PME)	0.55***	0.49***	0.25***	0.13	0.06**	-0.01	0.11	0.12
	(0.08)	(0.06)	(0.05)	(0.08)	(0.02)	(0.04)	(0.08)	(0.08)
Salary workers								
OLS (PNAD)	0.76***	0.72***	0.63***	0.44***	0.43***	0.25***	0.32***	0.19*
	(0.16)	(0.14)	(0.08)	(0.07)	(0.09)	(0.05)	(0.07)	(0.10)
OLS (PME)	0.55***	0.44***	0.28***	0.20***	0.12***	-0.01	0.05	0.12*
	(0.05)	(0.04)	(0.03)	(0.03)	(0.01)	(0.03)	(0.08)	(0.06)
2SLS* (PME)	0.53***	0.41***	0.24***	0.14***	0.06***	-0.05	-0.01	0.04
	(0.05)	(0.04)	(0.03)	(0.03)	(0.01)	(0.03)	(0.10)	(0.06)
2SLS** (PME)	0.65***	0.49***	0.21***	0.10**	0.03	-0.07	-0.003	-0.002
	(0.05)	(0.06)	(0.05)	(0.04)	(0.03)	(0.06)	(0.10)	(0.12)
Formal workers								
OLS (PNAD)	0.51***	0.34***	0.43***	0.45***	0.30***	0.14*	0.04	-0.20
	(0.06)	(0.10)	(0.10)	(0.13)	(0.07)	(0.08)	(0.08)	(0.17)
OLS (PME)	0.52***	0.38***	0.31***	0.20***	0.15***	0.01	0.10	0.13*
	(0.02)	(0.03)	(0.05)	(0.02)	(0.01)	(0.02)	(0.07)	(0.06)
2SLS* (PME)	0.49***	0.33***	0.25***	0.12***	0.08***	-0.02	0.05	0.07
	(0.02)	(0.04)	(0.05)	(0.04)	(0.02)	(0.04)	(0.07)	(0.08)
2SLS** (PME)	0.44***	0.24***	0.15***	0.05	-0.01	-0.03	0.04	0.02
	(0.03)	(0.03)	(0.06)	(0.04)	(0.06)	(0.02)	(0.06)	(0.07)

Source: PNAD, PME and MTE data from 2002 to 2016. The coefficients are the marginal effects of $log(min.wage) - log(60th)$. Regressions are weighted by the product between weekly working hours and PNAD/PME sample weights. The number of observations for OLS estimation is 338 (26 regions and 13 years) for PNAD, and 1008 (6 regions and 168 months) for PME per each percentile. The span used for both 2SLS estimation is 3 months ($s = 3$). 2SLS* and 2SLS** estimates use the, $log(min.wage) - log(w^{\mu}_{r,t-3})$, and the, F_{rt}, as instruments, respectively. The first stage of the 2SLS procedures can be found in Table 2.B.2 in the Appendix section. Standard errors in parentheses. Significant at 1 percent ***, at 5 percent ** and at 10 percent * using bootstrap inference.

The OLS estimates for PNAD in Table 2.1 suggest significant effects of the minimum wage throughout the wage distribution; however, these are relatively smaller in the upper half of the wage distribution. Notice there is no evidence of significant effects of the minimum wage on upper-tail inequality when only formal workers are considered. The significant estimates above the centrality measure, $60th$, for the other groups of workers, may in principle suggest very significant spillover effects. According to the model specification, spillover effects are expected to decrease monotonically higher up in the wage distribution;

however, this is not the case for these groups of workers, thus we have to be suspicious of the significant OLS estimates, particularly in the upper tail of the distribution. Recall that OLS estimates are likely to be biased because of the mechanical dependence of both sides of equation (2.3).

The OLS estimates from PME data show similar behaviour to those from PNAD; however, these are relatively smaller. Recall that PME data, unlike PNAD data, do not provide information on non-metropolitan areas in which the minimum wage may be potentially more binding, this is perhaps why PME estimates are smaller. Endogeneity is also an issue for OLS estimates from PME data, thus I perform 2SLS procedures by using the instrumental variables as were described in the previous section. The 2SLS* in Table 2.1, instruments the effective minimum wage by using the difference between the log of the minimum wage and the log of the centrality measure from a three-month-earlier wage distribution, $log(min.wage_t) - log(60_{r,t-3})$. The 2SLS** instead uses the fraction of hourly wages at or below the contemporaneous minimum wage from a three-month-earlier wage distribution, F_{rt}, as an instrument for the effective minimum wage.

Both 2SLS specifications appear to eliminate the significant effects of the minimum wage above the centrality measure which supports the suspicion of a spurious relationship between the minimum wage and the compression of upper-tail inequality.[18] Notice that 2SLS* specification provides more conservative estimates of the effects of the minimum wage on lower-tail inequality (except for formal workers); however, these suggest significant spillover effects higher up in the wage distribution. For example, 2SLS* estimates suggest significant spillover effects of the minimum wage up to the median wage for all groups of workers, whereas 2SLS** estimates suggest significant spillover effects as follows: up to median wage when all workers are considered in the sample,

[18]The validity of the IV estimates relies on the assumption that the specification of the instruments purges issues of measurement error and transitory shocks. As was mentioned previously, the former is not a concern given the large number of observations, particularly in pooled samples and the latter seems to be mitigated as 2SLS procedure seems to correct the expected upward bias in the OLS estimates of percentiles further from the centrality measure.

up to the $40th$ percentile when self-employed are excluded and up to the $30th$ percentile when both informal workers and self-employed are excluded from the sample. These results imply that the minimum wage has positive effects on the labour earnings of uncovered workers, otherwise, the lowest percentiles would not be affected when we account for this type of workers. In fact, both 2SLS estimates suggest a larger equalizing effect of the minimum wage on lower-tail inequality when we pool formal and informal workers in the sample than when we account only for formal workers.

I do not split the sample into smaller groups such as informal workers and self-employed because the estimates from these samples might be seriously biased for two reasons. First, each group of these workers represents around 20 percent of the sample, thus the mean cell size is not large enough and sampling error is a serious source of concern. Second, the minimum wage is significantly more binding in the labour earnings distribution of these workers. In fact, this binds above the $60th$ percentile in some regions, therefore, the selected centrality measure would not yield reliable estimates.

The expected positive sign of the 2SLS estimates suggests that the minimum wage is effective to compress lower-tail inequality. For example, the 2SLS* estimate for "all workers" suggest that an increase in 1 percent of the effective minimum wage, shrinks the gap between the $10th/60th$ —becomes less negative— by 0.42 percent. This positive effect decreases monotonically up to the median as expected. Separate estimates for males and females are reported in Table 2.B.3 and 2.B.4 in the Appendix section, respectively. There are three important features that we can observe from the analysis by gender. First, the 2SLS estimates are larger for females than for males which suggest that the minimum wage plays a more significant role in the decline of wage inequality among women. Second, the spillover effects of the minimum wage are more significant among males, particularly when formal workers are considered. Finally, 2SLS** estimates suggest that there is no evidence of significant effects of the minimum wage on upper-tail inequality at 5 percent level of significance for both genders. However, we have to be cautious when interpreting estimates by gender groups because sampling error is an important part of the variability in the centrality measure for small samples, thus our preferred estimates are those obtained from pooled samples.

The estimates in Table 2.1 suggest that the minimum wage plays an important role in the compression of lower-tail inequality, whereas the effects of the minimum wage on upper-tail inequality are negligible. In order to provide a more concise picture of the effects of the minimum wage on the declining wage inequality in Brazil over the post-inflationary period, I perform a reduced form of counterfactual estimates of the change in latent wage inequality by following Lee (1999) and Autor et al. (2016). I essentially simulate what would be the labour earnings of individuals at the p-th percentile in region r at time t_1, if the minimum wage had remained at its level at time t_0, by adding or subtracting the following amount to the log wage of each worker.

$$\Delta w^p_{rt} = \beta_1(mw_{r,t_0} - mw_{r,t_1}) + \beta_2(mw^2_{r,t_0} - mw^2_{r,t_1}) \tag{2.5}$$

Where mw_{r,t_0} is the observed effective minimum wage at time t_0, mw_{r,t_1} is the observed effective minimum wage at time t_1, and β_1 and β_2 are OLS and 2SLS estimates from Table 2.1. The idea behind this procedure is to construct a counterfactual wage distribution absent the increase in the minimum wage by adjusting each wage observation in the data by the quantity in equation (2.5).[19] Table 2.2 compares observed changes in lower-tail inequality with those from the simulated distribution.

The observed and the counterfactual change in lower-tail inequality in Table 2.2 are measured by the change in the gap $10th/60th$ from the observed and

[19]For example, to simulate what a worker would earn in 2016 if the minimum wage had remained at its 2002 level. I add the following quantity to the hourly wage of that individual in 2016: $w^*_{r,2016} = w_{r,2016} + \beta_1 mw_{r,2002} - \beta_1 mw_{r,2016} + \beta_2(mw_{r,2002})^2 - \beta_2(mw_{r,2016})^2$.

Table 2.2: Observed and Counterfactual Changes in Wage Inequality over the Post-Inflationary Period, PNAD and PME

	PME (2002-2016)				**PNAD (1995-2015)**			
	Observed Change	**Counterfactual Change OLS**	**2SLS***	**2SLS****	**Observed Change**	**Counterfactual Change OLS**	**2SLS***	**2SLS****
All workers								
Pooled	-34.6	-22.3***	-22.3***	-23.4***	-45.6	-26.9**	-28.6***	-27.7***
		(3.32)	(3.56)	(1.76)		(10.02)	(10.12)	(4.34)
Males	-32.9	-20.1***	-19.7***	-13.6***	-43.2	-19.0**	-21.2**	-11.8
		(2.45)	(2.95)	(2.96)		(4.90)	(6.55)	(8.54)
Females	-38.5	-22.8**	-23.0**	-16.6**	-53.8	-37.4**	-37.4**	-30.2***
		(7.89)	(8.17)	(4.24)		(11.22)	(12.01)	(6.15)
Salary workers								
Pooled	-31.7	-18.5***	-18.1***	-15.1***	-49.1	-31***	-31.5***	-26.5***
		(1.73)	(1.94)	(2.05)		(4.13)	(4.38)	(2.66)
Males	-29.2	-17.8***	-17.9***	-12.8***	-44.8	-26.1***	-28.3***	-22.8***
		(1.49)	(1.58)	(2.92)		(3.03)	(4.35)	(5.21)
Females	-33.4	-19.6***	-18.9**	-14.4***	-56.0	-39.5***	-39.3***	-31.6***
		(4.41)	(5.00)	(3.36)		(7.52)	(8.03)	(5.03)
Formal workers								
Pooled	-29.2	-15***	-15.2***	-14.4**	-45.4	-27.7***	-28.3***	-26.3***
		(1.20)	(1.03)	(4.94)		(3.59)	(3.51)	(4.25)
Males	-24.3	-8.4***	-9.1***	-10.0**	-48.7	-30.8***	-32.1***	-32.7***
		(1.64)	(2.18)	(3.37)		(2.74)	(3.50)	(6.75)
Females	-31.5	-16.6***	-15.6***	-13.7**	-48.7	-22.4***	-21.7***	-16.8**
		(2.16)	(2.14)	(4.73)		(4.52)	(4.40)	(6.11)

Source: PNAD data from 1995 to 2015 and PME data from March 2002 to February 2016. Actual and counterfactual changes are measured by the gap between the $60th$ and $10th$ percentiles from the observed and the counterfactual wage distributions, respectively. The reported marginal effects and standard errors in parentheses are obtained by bootstrapping with replacement taking regions as the sampling unit as follows: I run regressions by using equation (2.3) and obtain OLS, 2SLS* and 2SLS** estimates from PME data (Table 2.1), then I use these coefficients to simulate a wage distribution for PME and PNAD by adding or subtracting the amount specified in equation (2.5) to the hourly wages in the last year of each respective sample. I perform 1000 replications of this counterfactual exercise to improve accuracy. Significant at 1 percent ***, at 5 percent ** and at 10 percent *.

the counterfactual wage distributions, respectively. Although OLS estimates are reported in Table 2.2, the favourite specification is given by 2SLS estimates as was mentioned previously. There is a slight difference between 2SLS* and 2SLS** counterfactual estimates when we pooled males and females in the sample; however, it appears that 2SLS** estimates give extra weight to the effect of the minimum wage on the declining wage inequality when we split the sample into genders. As was previously mentioned, we have to be cautious when interpreting estimates from smaller samples as sampling error might bias the results. Thus, I provide an interpretation of the results in Table 2.2 by using the 2SLS* estimates for the pooled sample which are the most conservative estimates of the effects of the minimum wage on lower-tail inequality.

PME estimates for "all workers" sample show that lower-tail inequality decreases by 35 log points from 2002 to 2016. The respective estimated counterfactual from the pooled sample suggests that 35 percent of this decrease is attributed to the increase in the minimum wage. To see this, consider the 2SLS* estimate for this group of workers, this suggests that lower-tail inequality would decrease by 22.3 log points if the real value of the minimum wage had remained at its level in 2002. Thus, the difference between the observed change in inequality and the change in latent inequality, (34.6-22.3) is attributed to the increase in the minimum wage, around 12 log points which represent 35 percent of the decline in lower-tail inequality. The effect of the minimum wage on the decline of lower-tail inequality is larger when self-employed are excluded from the sample, around 43 percent, and this is even larger when we exclude both informal workers and self-employed, around 48 percent. The estimates by gender also suggest that the effects of the minimum wage on the compression of lower-tail inequality are more significant when we account only for formal workers.

PNAD data allow us to repeat this exercise by taking into account non-metropolitan regions and the entire post-inflationary period (1995-2015). The change in lower-tail inequality from 1995 to 2015 is approximately 45 log points. The 2SLS* estimates from the pooled sample suggest that approximately 37 percent of this decline is driven by the increase in the minimum wage and this effect is similar among different groups of workers. PNAD estimates by gender suggest that the equalizing effect of the minimum wage on lower-tail inequality is more significant among males when uncovered workers are included in the sample. In turn, this effect is significantly larger among females when only formal workers are considered.

In summary, the results so far show that the increase in the minimum wage is responsible for slightly less than 40 percent of the decline in lower-tail inequality in Brazil after the adoption of the Brazilian Real. Of course, this analysis only accounts for the effects of the minimum wage on the labour earnings of those who remain employed. In that sense, these results provide information on the compression of labour earnings inequality, but nothing can be said about changes in income inequality that accounts for non-labour income and changes in employment. Regarding the latter, Table 2.3 provides information on the effects of the minimum wage on employment by estimating equation (2.4) for PME data.

Table 2.3: OLS Estimates of the Minimum Wage Effects on Employment, Working Hours and Working Hours if Employed, PME 2002-2016

Effects	**Total Employment**			**Formal Employment**		
	Employment	**Working Hours**	**Hours if Employed**	**Employment**	**Working Hours**	**Hours if Employed**
Contemporaneous						
F_{rt}	0.0058	0.0018	-0.0007**	-0.0020	-0.0006	-0.0018
	(0.0038)	(0.0016)	(0.0003)	(0.0046)	(0.0022)	(0.0017)
L. one quarter						
F_{rt}	0.0059	0.0019	-0.0006*	-0.0031	-0.0009	-0.0022
	(0.0042)	(0.0019)	(0.0003)	(0.0050)	(0.0024)	(0.0023)
Summed effect	-0.002	-0.001	-0.001	-0.010**	-0.004*	-0.003**
	(0.0037)	(0.001)	(0.0004)	(0.004)	(0.002)	(0.001)
L. two quarters						
F_{rt}	0.0061	0.0022	-0.0004	-0.0021	-0.0005	-0.0015
	(0.0041)	(0.0019)	(0.0003)	(0.0048)	(0.0023)	(0.0022)
Summed effect	-0.007	-0.002	0.001	-0.019***	-0.009***	-0.004***
	(0.005)	(0.003)	(0.001)	(0.005)	(0.002)	(0.001)
L. three quarters						
F_{rt}	0.0070	0.0024	-0.0006	-0.0002	0.0001	-0.0007
	(0.0044)	(0.0020)	(0.0004)	(0.0048)	(0.0023)	(0.0019)
Summed effect	-0.017*	-0.006	0.001	-0.030***	-0.014***	-0.006*
	(0.009)	(0.005)	(0.002)	(0.005)	(0.003)	(0.003)

Source: PME data from March 2002 to February 2016. The sample comprises all economically active individuals aged 16-64. The first row in the table reports estimates from regressions of three employment measures on the fraction below or at the minimum wage, F_{rt}, fixed time and region effects, and region-specific trends for total employment and formal employment. Lags of F_{rt} are added to the basic specification in the remaining panels, thus the summed effect is the sum of the contemporaneous effect and the lag effects. Regressions are weighted by the product between weekly working hours and PME sample weights. Standard errors in parentheses. Significant at 1 percent ***, at 5 percent ** and at 10 percent * using bootstrap inference.

Table 2.3 provides information on the contemporaneous and the long-run effects of the minimum wage on the number of jobs and the number of working hours for both total and formal employment. The only contemporaneous adverse effect of the minimum wage on total employment is observed in the decline of "working hours if employed" which is the most sensitive measure of employment because this is normalized only to the number of workers who remain employed following the increase in the minimum wage. We can observe; however, that this adverse effect vanishes after two quarters. In the long run, it appears that the only adverse effect of the minimum wage is on the number of jobs after three quarters; however, this is only significant at 10 percent level. It is important to highlight that these estimates provide information on total employment including informal employment and self-employment which have a highly volatile nature, thus identification issues are a matter of concern.

The adverse effects of the minimum wage on employment become more evident when we account only for formal jobs. Although there is no evidence of significant contemporaneous effects, these become significant after the first quarter for all employment measures. Although the adverse effects of the minimum wage on formal employment are significant in the long run, these are relatively small. Consider the last row in Table 2.3, the summed effect of the minimum wage on formal employment suggests that an increase in the minimum wage that binds an additional 10 percent of the wage distribution, decreases formal employment by 0.30 percentage points and working hours by 0.14 after three quarters. These findings differ from those of Neumark et al. (2006) who find that the adverse effect of the minimum wage on employment is as large as 1.6 percentage points among household heads; however, their sample only comprises the first 6 years after the adoption of the Brazilian Real (1996-2001).[20] The previous findings also differ from those of Lemos (2009) who does not find statistically significant effects of the minimum wage on formal employment. Perhaps the difference in these results

[20]Aside from the differences in the sample choice, Neumark et al. (2006) omit regional-specific trends in their specification which may lead to obtaining biased estimates as was demonstrated previously.

is because of the sample choice that in case of Lemos includes the inflationary period and excludes the mid-2000s in which the minimum wage increased sharply. There are also findings that fall between the previous ones, such as Foguel (1998), Foguel et al. (2001) and Fajnzylber (2002) who find small but significant adverse effects of the minimum wage on employment. The findings in this paper are in line with the latter ones.

Table 2.B.5 and 2.B.6 in the Appendix section show the estimates of the effects of the minimum wage on employment by gender. The contemporaneous effects of the minimum wage on formal employment are only significant among females; however, these vanish in the long run. The adverse effects of the minimum wage on employment in the long run are more significant when we account for informal employment and self-employment for both genders. The summed effects after three quarters suggest that an increase in the minimum wage that binds an additional 10 percent of the labour earnings distribution decreases total employment by 0.37 percentage points among males and by 0.27 percentage points among females.

In summary, the significant but small adverse effects of the minimum wage on employment suggest that the minimum wage is an effective tool to compress wage inequality without harming employment significantly. It is important to keep in mind that the effects of the minimum wage on wage inequality and employment in the present study are estimated at the individual level. In that sense, further study must be done to determine if minimum wage workers belong to poor households and claim that the minimum wage might be a potential welfare-improving instrument.

2.5.1 Robustness Checks

A potential limitation in the specification of equation (2.3) is that this does not account for worker mobility across regions. Although it is expected that worker mobility would be generated by sources others than changes in the minimum wage, because the minimum wage is set nationally in Brazil, the effects of the minimum wage on inequality and employment may be estimated with bias without taking it into account. Previous literature on worker mobility in Brazil has pointed out that most of the internal migration is generated from non-metropolitan areas to metropolitan ones (Fiess and Verner 2003; Hering and Paillacar 2015). In such a scenario, estimates from PNAD data are more vulnerable to be biased than those from PME data which only comprises geographically separated metropolitan regions. Moreover, Ferreira-Filho and Horridge (2016) state that internal migration has decreased dramatically during the 2000s in Brazil. Thus, the estimates in Tables 2.1 and 2.3 for 2002-2016 using PME data are not likely to be significantly affected by regular worker mobility across regions.

Although PME data do not provide information on worker mobility and PNAD data provides limited information on this matter, it is still possible to control for changes in the labour market composition in each region generated by either within-region changes or migration across regions. I propose to perform this exercise by adding labour supply controls in the specification of equation (2.3) in order to check the robustness of the estimates in Table 2.1. The labour supply controls are estimated by region and unit of time and these are the proportion of the total population who are between 16 and 24 years of age, between 55 and 64 years of age, illiterate, living in urban areas, out of the labour force, informal workers, self-employed; and the mean years of education.

The results can be found in Table 2.B.7 in the Appendix section. Neither the OLS nor the 2SLS estimates are significantly affected in the lower tail of the wage distribution. However, it appears that the inclusion of labour supply controls ascribes some variation in upper-tail inequality to changes in the minimum wage, particularly for the OLS specifications. The 2SLS estimates instead suggest that this relationship is likely to be spurious as before. The 2SLS estimates are qualitatively similar to those in Table 2.1, thus the main conclusion from before is basically the same. I also perform this analysis for the estimates of the effects of the minimum wage on employment by adding the labour supply controls to equation (2.4). The results can be found in Table 2.B.8 in the Appendix section. These estimates lead to the same conclusions, small but significant adverse effects of the minimum wage on employment.

Finally, it is important to mention that the identification of the effects of the minimum wage on wage inequality in equation (2.3) and on employment in equation (2.4), relies only on within regional variation. Thus, we have to be cautious with the inclusion of additional controls to avoid reducing identifying variation resulting from eliminating permanent regional effects. Perhaps this is the reason why estimates from the robust specification suggest slightly smaller effects of the minimum wage on both wage inequality and employment.

2.6 Conclusion

This paper estimates the effects of the minimum wage on wage inequality and employment in Brazil over the post-inflationary period (1995–2015), by using two of the most important microdata sources available in the country: PNAD and PME. Following Lee (1999) and Autor et al. (2016), I use an empirical approach that identifies the effects of the minimum wage on wage inequality through its "bite" on the wage distribution at the regional level. I construct instrumental variables from wage distributions prior to the increase in the minimum wage in order to tackle endogeneity issues in the model specification. This allows us to ascribe changes in wage inequality to changes in the minimum wage.

The OLS estimates obtained from PNAD data suggest that the equalizing effect of the minimum wage is present throughout the wage distribution, whereas 2SLS estimates from PME data, which provides information only on metropolitan regions, suggest that these effects are only significant up to the median wage. These results imply that the significant spillover effects of the minimum wage on upper-tail inequality for PNAD are the result of either the inclusion of non-metropolitan regions in the sample or a spurious relationship between the minimum wage and the decline in upper-tail inequality; it seems that the latter is a more plausible explanation.

I use the OLS and the 2SLS estimates to simulate a latent wage distribution —wage distribution in absence of a minimum wage—for different groups of workers. The change in lower-tail inequality from the observed and the latent wage distributions suggests that around 35 percent of the decline in lower-tail inequality is attributable to the increase in the minimum wage from 2002 to 2016 when all workers are considered in the sample. This decline becomes more significant when only formal workers are considered, approximately 50 percent. These results are consistent with those obtained from PNAD data for the entire post-inflationary period (1995-2015). It is important to mention that, unlike previous studies for other Latin American economies, the decline in lower-tail inequality in Brazil is not entirely explained by changes in the minimum wage. In fact, around two-thirds of this decline may be attributed to other factors.

I also find evidence of small but significant adverse effects of the minimum wage on employment, particularly on formal employment. The estimates from the pooled sample (males and females) suggest that the minimum wage must bind an additional 30 percent of the workforce to decrease formal employment by approximately 1 percent.

In conclusion, these findings suggest that the minimum wage is an effective tool to compress wage inequality in Brazil without harming employment significantly. However, the increase in the minimum wage is not the only contributing factor to the decline in lower-tail inequality, there is still a significant proportion of this decline that was certainly driven by other factors. Moreover, these findings only provide information on the effects of the minimum wage on wage inequality and employment at the individual level. Thus, further examination is required of the welfare-improving effects of the minimum wage on family income and employment at the household level.

Appendices

2.A Figures

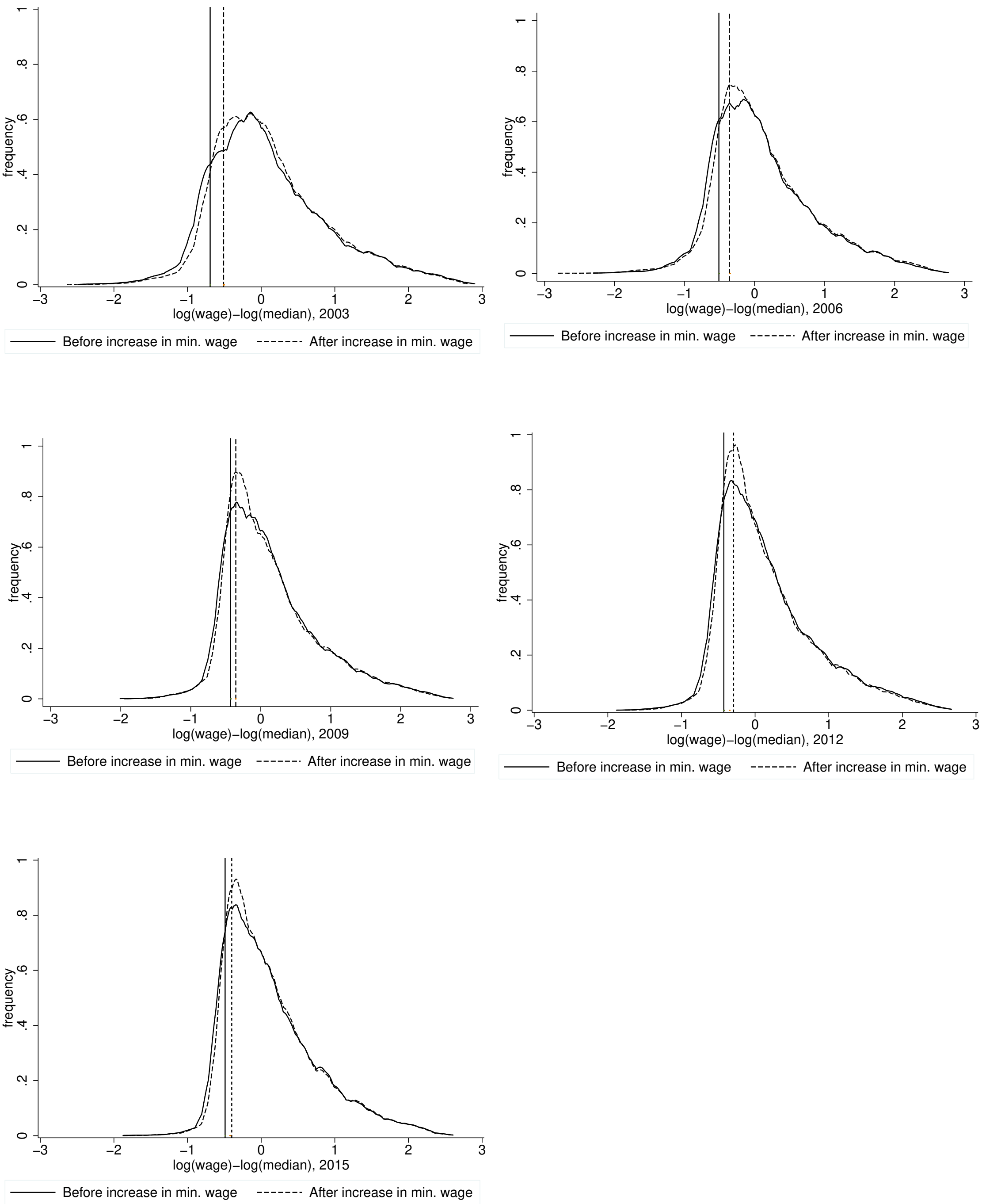
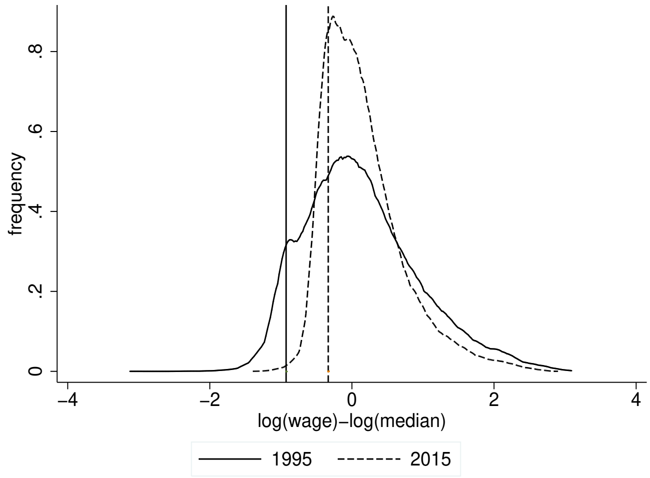
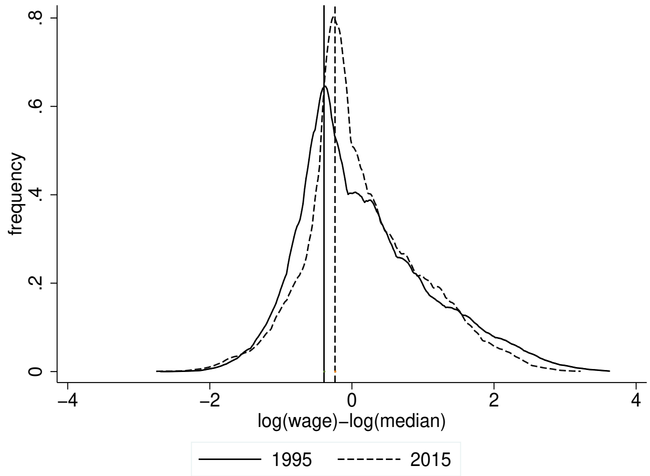


Figure 2.A.1: Changes in Inequality and the Effective Minimum Wage by Selected Years, PME

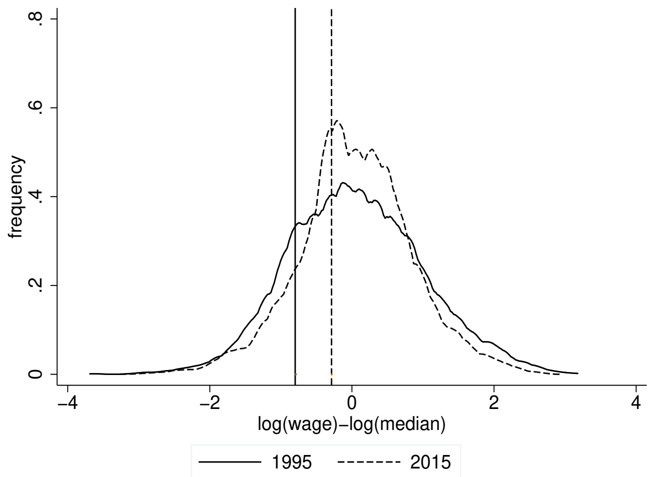
Source: PME and MTE data for 2003, 2006, 2009, 2012 and 2015. The sample comprises full-time salary workers. The figure compares kernel density estimates of the log wage distribution between two months: before and after the increase in the minimum wage. All series are standardized to the contemporaneous monthly median wage. The vertical lines report the effective minimum wage, $log(min.wage) - log(median\ wage)$, for each month.



Formal workers



Informal workers



Self-employed

Figure 2.A.2: Changes in Inequality and the Effective Minimum Wage By Groups of Workers, PNAD 1995 and 2015

Source: PNAD and MTE data for 1995 and 2015. Figures compare kernel density estimates of the log wage distribution between two years. All series are standardized to the contemporaneous median wage. The vertical lines report the effective min. wage, $log(min.wage) - log(median)$, for each year.

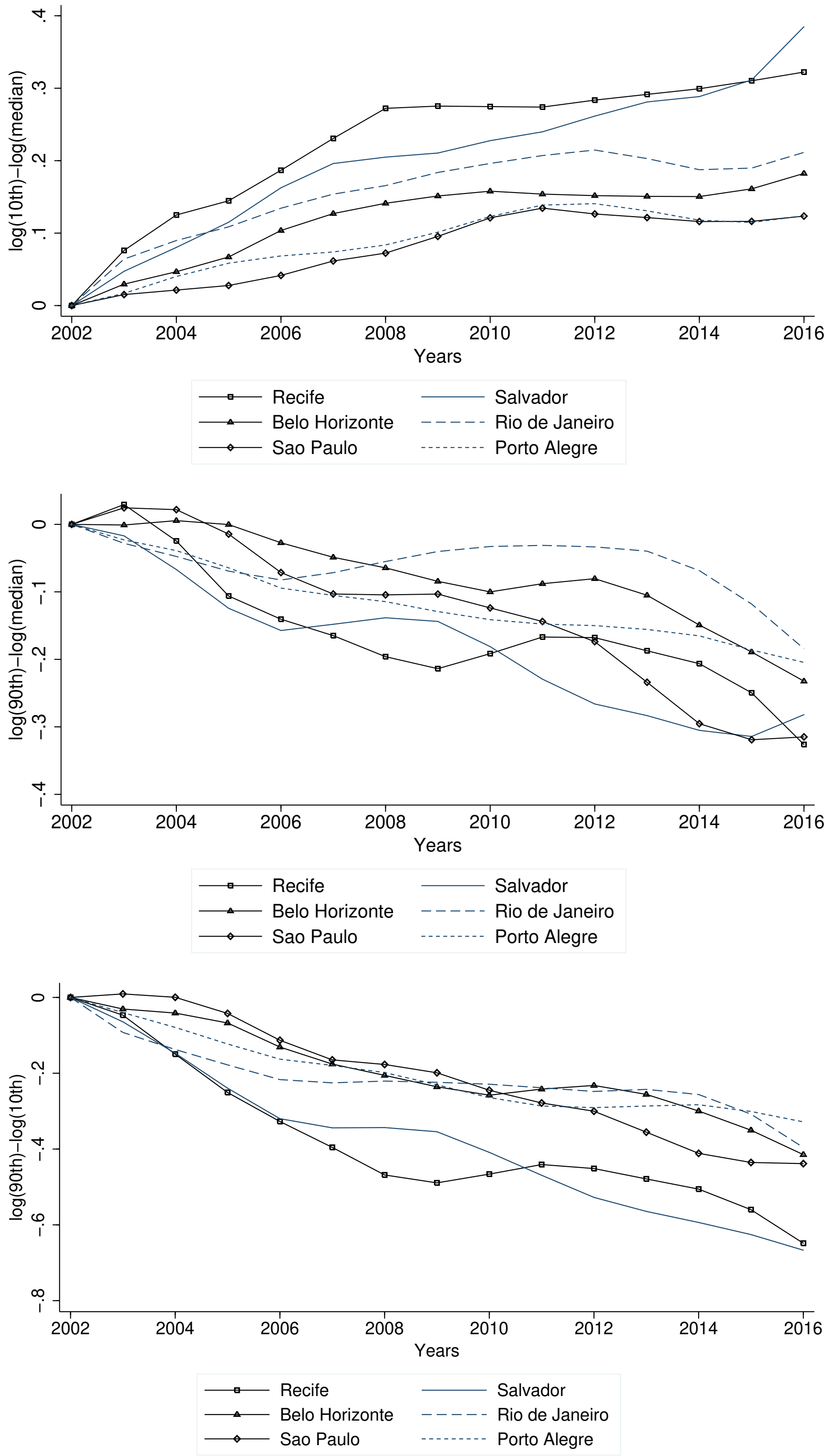


Figure 2.A.3: Changes in Inequality and the Effective Minimum Wage across Regions, PME 2002-2016

Source: PME and MTE data from March 2002 to February 2016. The sample comprises full-time salary workers who have a legal employment contract. Figures from the top to the bottom depict the change in the 10th/50th, 90th/50th and 90th/10th wage inequality, respectively. All inequality measures are normalized at 2002.

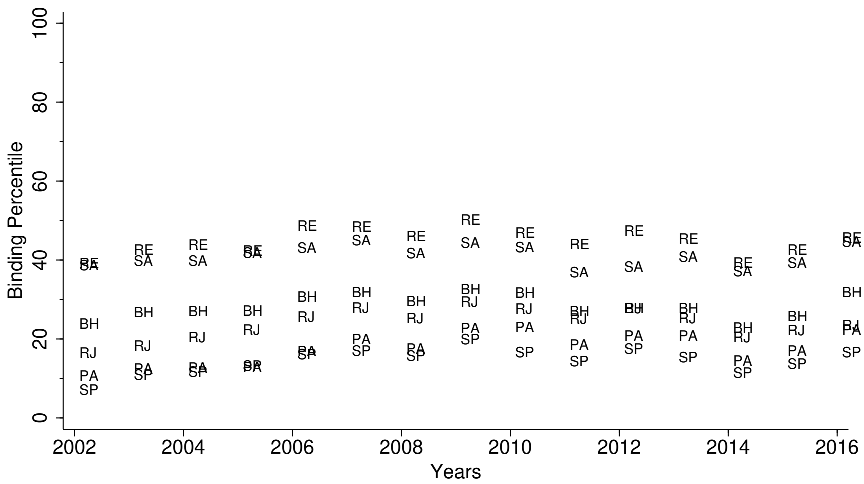
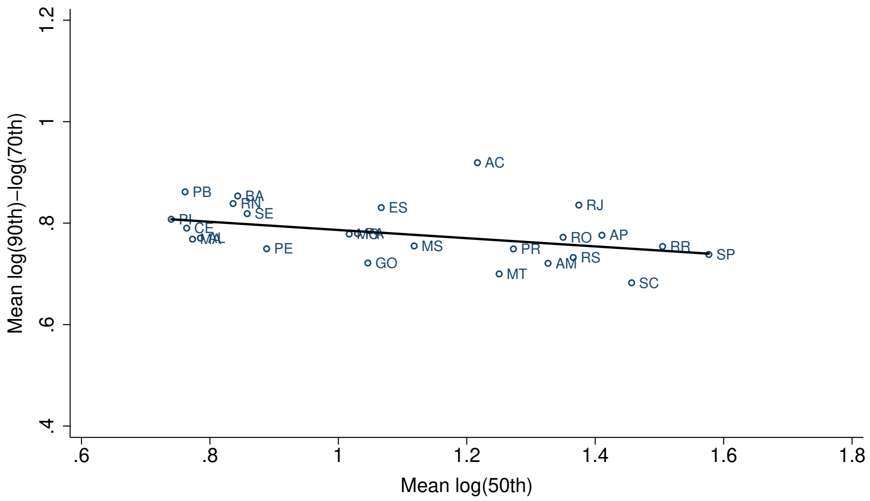


Figure 2.A.4: Bindingness of the Minimum Wage on the Wage Distribution across Regions, PME 2002-2016

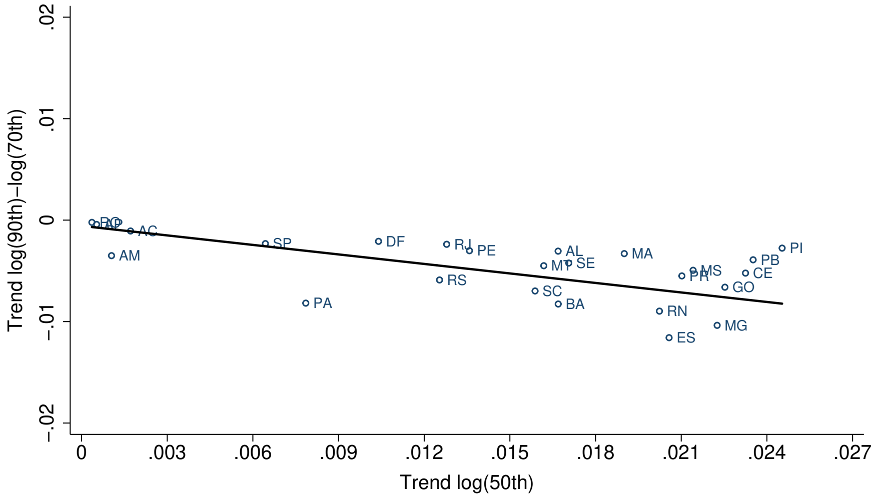
Source: PME and MTE data from 2002 to 2016. The sample comprises full-time salary workers. The figure shows the lowest and the highest percentile at which the minimum wage binds across 6 metropolitan regions. See Table 2.B.1 for information on the respective abbreviation of each region's name.



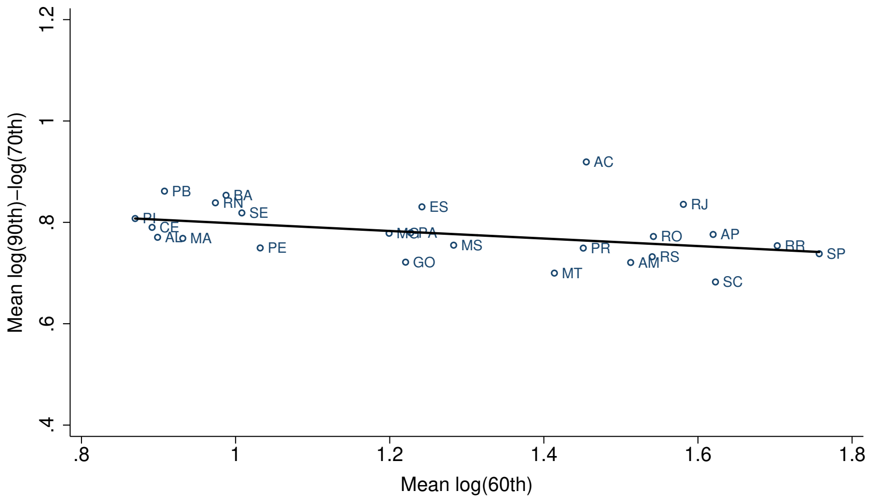
$$mean\ log(90th/70th) = \underset{(0.05)}{0.87} - \underset{(0.03)}{0.09} \times mean\ log(50th)$$

Figure 2.A.5: OLS Estimates of the Relationship between Latent Wage Inequality and the Centrality Measure

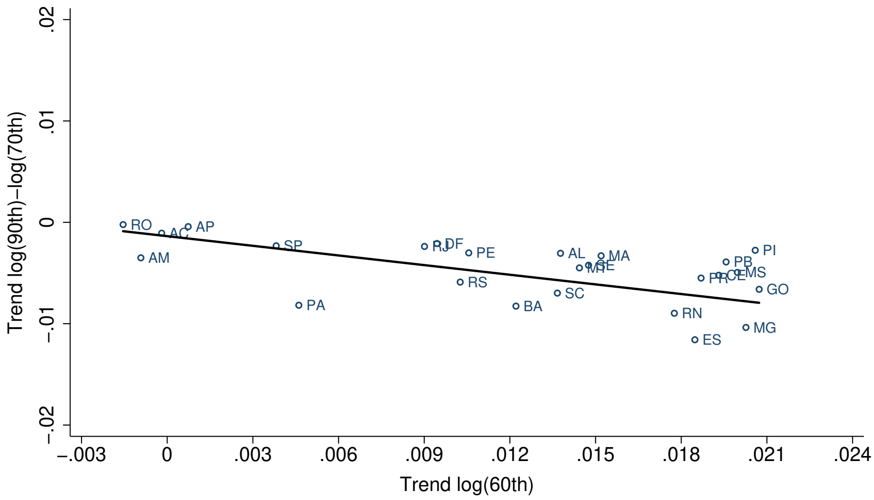
Source: PNAD and MTE data from 1981 to 2015. The sample comprises full-time salary workers. Figures show the OLS estimates of the relationship between the mean $log(90th) - log(70th)$ with two centrality measures, the mean $log(50th)$ and the mean $log(60th)$ and between the trend of $log(90th) - log(70th)$ and the respective trends of the centrality measures. The Federal District, DF, and Roraima, RR, were eliminated from figures for being atypical values. See Table 2.B.1 for information on the respective abbreviation of each region's name.



$$trend\ log(90th/70th) = \underset{(0.001)}{-0.002} - \underset{(0.07)}{0.21} \times trend\ log(50th)$$



$$mean\ log(90th/70th) = \underset{(0.05)}{0.87} - \underset{(0.04)}{0.07} \times mean\ log(60th)$$



$$trend\ log(90th/70th) = \underset{(0.001)}{-0.002} - \underset{(0.07)}{0.22} \times trend\ log(60th)$$

Figure 2.A.5 (continued)

2.B Tables

Table 2.B.1: Regions and Mean Cell Sizes for All, Salary and Formal Workers, PNAD and PME

Regions	**Abbreviation**	**All Workers**	**Salary Workers**	**Formal Workers**
PNAD				
Rondônia	RO	1880	1489	768
Acre	AC	995	744	324
Amazonas	AM	2653	1986	1078
Roraima	RR	604	468	171
Pará	PA	5600	4238	2016
Amapá	AP	766	586	251
Maranhão	MA	1681	1121	441
Piauí	PI	1227	875	356
Ceará	CE	5952	4769	2472
Rio Grande do Norte	RN	1452	1166	585
Paraíba	PB	1607	1248	553
Pernambuco	PE	5895	4809	2885
Alagoas	AL	1220	966	505
Sergipe	SE	1466	1157	617
Bahia	BA	8680	6943	3677
Minas Gerais	MG	11054	9444	6129
Espírito Santo	ES	2173	1837	1162
Rio de Janeiro	RJ	7846	6657	4391
São Paulo	SP	14661	12941	9323
Paraná	PR	6464	5433	3766
Santa Catarina	SC	3436	2873	2140
Rio Grande do Sul	RS	9562	8019	5617
Mato Grosso do Sul	MS	2237	1881	1133
Mato Grosso	MT	2499	2036	1175
Goiás	GO	6831	5653	2959
Distrito Federal	DF	3447	3134	1866
PME				
Recife	RE	3889	3163	2125
Salvador	SA	3941	3214	2241
Belo Horizonte	BH	6939	5850	4365
Rio de Janeiro	RJ	6151	4922	3347
São Paulo	SP	8053	6857	5004
Porto Alegre	PA	5408	4526	3369

Source: PNAD data from 2002 to 2015 and PME data from March 2002 to February 2016. Mean cells are simple average across years for PNAD and across months for PME by region. The observations in each cell are used to estimate the percentiles that comprise the region-level panel data set. "All workers" sample comprises formal workers, informal workers and self-employed, "salary workers" sample excludes self-employed. Formal workers are defined as workers who have a legal employment contract in the reference week.

Table 2.B.2: First Stage Estimates for 2SLS Specifications, PME

Specification	**All Workers**		**Salary Workers**		**Formal Workers**	
	mw_{rt}	mw^2_{rt}	mw_{rt}	mw^2_{rt}	mw_{rt}	mw^2_{rt}
2SLS*						
$log(min.wage_t) - log(w^{60}_{r,t-3})$	0.73***	-0.04	0.74***	-0.02	0.81***	-0.07
	(0.09)	(0.06)	(0.08)	(0.06)	(0.10)	(0.07)
$[log(min.wage_t) - log(w^{60}_{r,t-3})]^2$	0.10	0.88***	0.10	0.86***	0.05	0.87***
	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)
F statistic	101.0***	57.7***	91.9***	61.4***	198.7***	109.8***
p value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SW Chi sq Underid. test	210.8***	162.2***	169.4***	149.5***	548.1***	465.4***
p value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SW F Weak id. test	171.43***	131.91***	137.8***	121.6***	445.8***	378.5***
p value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2SLS**						
F_{rt}	-0.30	0.95**	-0.25	0.90**	-0.45**	1.18***
	(0.22)	(0.38)	(0.24)	(0.37)	(0.18)	(0.30)
F^2_{rt}	-0.26	0.19	-0.21	0.12	0.15	-0.39
	(0.30)	(0.47)	(0.36)	(0.58)	(0.29)	(0.51)
$F_{rt} \times mean\ log(w^{60}_r)$	0.30***	-0.64***	0.26***	-0.58***	0.26***	-0.60***
	(0.04)	(0.10)	(0.05)	(0.07)	(0.06)	(0.09)
F statistic	1080.7***	463.4***	1615.2***	901.6***	192.6***	196.9***
p value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SW Chi sq Underid. test	139.0***	91.8***	47.1***	34.2***	47.6***	33.2***
p value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SW F Weak id. test	56.5***	37.3***	19.1***	13.9***	19.3***	13.5***
p value	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)

Source: PME and MTE data from March 2002 to February 2016. The dependent variables are the log of the effective minimum wage, $mw = log(min.wage) - log(60th)$, and its square. All regressions include time and region fixed effects, and region-specific trends. Regressions are weighted by the product between weekly working hours and PME sample weights. F-statistics and SW (Sanderson and Windmeijer (2015)) tests for underidentification and weak identification along with their associated p-values are reported. Standard errors in parentheses. Significant at 1 percent ***, at 5 percent ** and at 10 percent * using bootstrap inference.

Table 2.B.3: OLS and 2SLS Estimates between Log(pth)-Log(60th) and Log(min.wage)-Log(60th) for Males

Percentiles	**10th**	**20th**	**30th**	**40th**	**50th**	**70th**	**80th**	**90th**
All workers								
OLS (PNAD)	0.30*	0.36**	0.49***	0.31***	0.30***	0.19***	0.26***	0.27**
	(0.17)	(0.16)	(0.11)	(0.09)	(0.05)	(0.04)	(0.06)	(0.11)
OLS (PME)	0.42***	0.33***	0.25***	0.16***	0.09***	-0.002	0.07	0.09*
	(0.06)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.06)	(0.04)
2SLS* (PME)	0.38***	0.28***	0.19***	0.10***	0.02	-0.03	0.02	0.03
	(0.07)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.07)	(0.05)
2SLS** (PME)	0.49***	0.39***	0.30***	0.16***	0.07	0.02	-0.08	0.04
	(0.03)	(0.05)	(0.04)	(0.02)	(0.04)	(0.05)	(0.07)	(0.15)
Salary workers								
OLS (PNAD)	0.57***	0.54***	0.52***	0.42***	0.27***	0.13**	0.23***	0.22*
	(0.10)	(0.08)	(0.05)	(0.08)	(0.04)	(0.06)	(0.05)	(0.13)
OLS (PME)	0.46***	0.33***	0.26***	0.17***	0.09***	0.02	0.07	0.06
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.07)	(0.05)
2SLS* (PME)	0.42***	0.27***	0.20***	0.09***	0.03*	-0.01	0.004	0.01
	(0.04)	(0.03)	(0.04)	(0.02)	(0.02)	(0.02)	(0.07)	(0.05)
2SLS** (PME)	0.62***	0.37***	0.27**	0.08*	-0.01	-0.04	-0.07	-0.03
	(0.04)	(0.05)	(0.08)	(0.04)	(0.03)	(0.06)	(0.08)	(0.12)
Formal workers								
OLS (PNAD)	0.33***	0.45***	0.42***	0.38***	0.20***	0.15***	0.14**	0.10
	(0.08)	(0.09)	(0.08)	(0.10)	(0.05)	(0.05)	(0.06)	(0.11)
OLS (PME)	0.50***	0.33***	0.27***	0.19***	0.12***	0.002	0.04	0.113
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)	(0.10)
2SLS* (PME)	0.46***	0.26***	0.19***	0.10***	0.04*	-0.06**	-0.04**	0.06
	(0.02)	(0.04)	(0.05)	(0.02)	(0.02)	(0.02)	(0.01)	(0.10)
2SLS** (PME)	0.53***	0.43***	0.25*	0.26***	0.10**	-0.03	-0.10	0.03
	(0.06)	(0.11)	(0.11)	(0.06)	(0.03)	(0.05)	(0.09)	(0.07)

Source: PNAD, PME and MTE data from 2002 to 2016. Detailed information on the procedure to obtain these estimates can be found in the footnote of Table 2.1. For all samples, the instruments are jointly significant and pass standard test for weak instruments and underidentification. Standard errors in parentheses. Significant at 1 percent ***, at 5 percent ** and at 10 percent * using bootstrap inference.

Table 2.B.4: OLS and 2SLS Estimates between Log(pth)-Log(60th) and Log(min.wage)-Log(60th) for Females

Percentiles	**10th**	**20th**	**30th**	**40th**	**50th**	**70th**	**80th**	**90th**
All workers								
OLS (PNAD)	0.87***	0.80***	0.55***	0.37***	0.26***	0.27***	0.12	0.27**
	(0.17)	(0.21)	(0.12)	(0.11)	(0.07)	(0.08)	(0.11)	(0.11)
OLS (PME)	0.48***	0.44***	0.36***	0.26***	0.16***	-0.01	0.06	0.13**
	(0.10)	(0.06)	(0.04)	(0.04)	(0.04)	(0.01)	(0.05)	(0.05)
2SLS* (PME)	0.48***	0.41***	0.32***	0.21***	0.10*	-0.04**	0.02	0.10
	(0.12)	(0.06)	(0.04)	(0.05)	(0.05)	(0.02)	(0.04)	(0.06)
2SLS** (PME)	0.51***	0.52***	0.38***	0.22***	0.13	-0.01	0.10	0.14
	(0.10)	(0.09)	(0.05)	(0.05)	(0.07)	(0.03)	(0.06)	(0.08)
Salary workers								
OLS (PNAD)	1.19***	1.04***	0.53***	0.38***	0.32***	0.32***	0.23**	0.38***
	(0.24)	(0.20)	(0.15)	(0.14)	(0.08)	(0.09)	(0.11)	(0.14)
OLS (PME)	0.56***	0.50***	0.37***	0.30***	0.14***	-0.04*	0.07	0.21**
	(0.04)	(0.09)	(0.03)	(0.05)	(0.03)	(0.02)	(0.05)	(0.07)
2SLS* (PME)	0.54***	0.47***	0.32***	0.24**	0.07	-0.09**	0.01	0.13
	(0.04)	(0.10)	(0.05)	(0.07)	(0.04)	(0.03)	(0.05)	(0.09)
2SLS** (PME)	0.61***	0.45***	0.31***	0.22***	0.06	-0.08	0.03	0.18
	(0.02)	(0.08)	(0.05)	(0.05)	(0.04)	(0.06)	(0.09)	(0.10)
Formal workers								
OLS (PNAD)	0.50***	0.40***	0.39***	0.29***	0.23***	-0.08	-0.06	-0.17
	(0.08)	(0.08)	(0.08)	(0.05)	(0.06)	(0.09)	(0.13)	(0.15)
OLS (PME)	0.62***	0.50***	0.37***	0.30***	0.17***	0.02	0.10	0.14**
	(0.05)	(0.05)	(0.03)	(0.05)	(0.03)	(0.04)	(0.09)	(0.06)
2SLS* (PME)	0.58***	0.44***	0.29***	0.20***	0.08***	-0.06	0.02	0.02
	(0.05)	(0.05)	(0.05)	(0.06)	(0.03)	(0.04)	(0.11)	(0.07)
2SLS** (PME)	0.60***	0.43***	0.37***	0.14	0.07	0.02	0.15	0.16*
	(0.09)	(0.11)	(0.03)	(0.08)	(0.05)	(0.08)	(0.08)	(0.08)

Source: PNAD, PME and MTE data from 2002 to 2016. Detailed information on the procedure to obtain these estimates can be found in the footnote of Table 2.1. For all samples, the instruments are jointly significant and pass standard test for weak instruments and underidentification. Standard errors in parentheses. Significant at 1 percent ***, at 5 percent ** and at 10 percent * using bootstrap inference.

Table 2.B.5: OLS Estimates of the Minimum Wage Effects on Employment, Working Hours and Working Hours if Employed, Males

Effects	**Total Employment**			**Formal Employment**		
	Employment	**Working Hours**	**Hours if Employed**	**Employment**	**Working Hours**	**Hours if Employed**
Contemporaneous						
F_{rt}	0.0090**	0.0025	-0.0017	-0.0028	-0.0002	-0.0015
	(0.0035)	(0.0022)	(0.0010)	(0.0122)	(0.0052)	(0.0049)
L. one quarter						
F_{rt}	0.0090*	0.0024	-0.0018**	-0.0017	0.0001	-0.0008
	(0.0043)	(0.0023)	(0.0007)	(0.0114)	(0.0050)	(0.0047)
Summed effect	-0.006***	-0.004***	-0.002**	-0.0002	-0.0001	0.0001
	(0.001)	(0.001)	(0.001)	(0.004)	(0.002)	(0.001)
L. two quarters						
F_{rt}	0.0085*	0.0022	-0.0017**	-0.0007	0.0005	-0.0004
	(0.0037)	(0.0019)	(0.0007)	(0.0111)	(0.0049)	(0.0045)
Summed effect	-0.022**	-0.012**	-0.003**	-0.010	-0.005	-0.003
	(0.007)	(0.004)	(0.001)	(0.010)	(0.005)	(0.004)
L. three quarters						
F_{rt}	0.0090*	0.0025	-0.0016***	0.0023	0.0017	0.0008
	(0.0042)	(0.0020)	(0.0004)	(0.0110)	(0.0049)	(0.0044)
Summed effect	-0.037***	-0.021***	-0.005***	-0.024	-0.011	-0.007
	(0.010)	(0.005)	(0.001)	(0.016)	(0.007)	(0.006)

Source: PME data from March 2002 to February 2016. Detailed information on the procedure to obtain these estimates can be found in the footnote of Table 2.3. Standard errors in parentheses. Significant at 1 percent ***, at 5 percent ** and at 10 percent * using bootstrap inference.

Table 2.B.6: OLS Estimates of the Minimum Wage Effects on Employment, Working Hours and Working Hours if Employed, Females

Effects	**Total Employment**			**Formal Employment**		
	Employment	**Working Hours**	**Hours if Employed**	**Employment**	**Working Hours**	**Hours if Employed**
Contemporaneous						
F_{rt}	0.0046	0.0005	-0.0014*	-0.0097***	-0.0040***	-0.0054***
	(0.0026)	(0.0014)	(0.0007)	(0.0025)	(0.0012)	(0.0010)
L. one quarter						
F_{rt}	0.0051*	0.0005	-0.0016***	-0.0078***	-0.0029***	-0.0045***
	(0.0026)	(0.0012)	(0.0004)	(0.0017)	(0.0006)	(0.0005)
Summed effect	-0.007**	-0.004***	-0.001**	-0.001	-0.0001	-0.0001
	(0.003)	(0.001)	(0.0004)	(0.007)	(0.003)	(0.003)
L. two quarters						
F_{rt}	0.0061**	0.0010	-0.0015***	-0.0038	-0.0014**	-0.0031***
	(0.0025)	(0.0010)	(0.0004)	(0.0025)	(0.0005)	(0.0007)
Summed effect	-0.015***	-0.006***	-0.0003	0.002	0.0004	0.003
	(0.004)	(0.002)	(0.001)	(0.013)	(0.005)	(0.006)
L. three quarters						
F_{rt}	0.0058*	0.0013	-0.0011**	-0.0043*	-0.0017	-0.0037***
	(0.0029)	(0.0011)	(0.0004)	(0.0020)	(0.0011)	(0.0012)
Summed effect	-0.027***	-0.008***	0.003**	0.001	-0.0004	0.003
	(0.005)	(0.002)	(0.001)	(0.009)	(0.004)	(0.004)

Source: PME data from March 2002 to February 2016. Detailed information on the procedure to obtain these estimates can be found in the footnote of Table 2.3. Standard errors in parentheses. Significant at 1 percent ***, at 5 percent ** and at 10 percent * using bootstrap inference.

Table 2.B.7: Robustness Checks: OLS and 2SLS Estimates between Log(pth)-Log(60th) and Log(min.wage)-Log(60th) for Selected Percentiles

Percentiles	**10th**	**20th**	**30th**	**40th**	**50th**	**70th**	**80th**	**90th**
All workers								
OLS (PNAD)	0.63***	0.54**	0.50***	0.35***	0.39***	0.23***	0.34***	0.40***
	(0.16)	(0.21)	(0.10)	(0.06)	(0.07)	(0.06)	(0.10)	(0.09)
OLS (PME)	0.47***	0.42***	0.25***	0.24***	0.15***	0.04***	0.17***	0.21***
	(0.05)	(0.04)	(0.03)	(0.02)	(0.02)	(0.01)	(0.03)	(0.03)
2SLS* (PME)	0.42***	0.39***	0.20***	0.15***	0.09***	-0.01	0.08	0.05
	(0.05)	(0.06)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)
2SLS** (PME)	0.49***	0.47***	0.24**	0.11	0.07	0.02	0.12	0.08
	(0.08)	(0.06)	(0.07)	(0.09)	(0.05)	(0.08)	(0.09)	(0.07)
Salary workers								
OLS (PNAD)	0.81***	0.75***	0.66***	0.45***	0.43***	0.28***	0.41***	0.33***
	(0.15)	(0.14)	(0.06)	(0.06)	(0.08)	(0.06)	(0.07)	(0.10)
OLS (PME)	0.55***	0.43***	0.28***	0.20***	0.15***	0.02*	0.11**	0.14***
	(0.06)	(0.04)	(0.03)	(0.02)	(0.02)	(0.01)	(0.04)	(0.03)
2SLS* (PME)	0.50***	0.36***	0.22***	0.10***	0.07***	-0.01	0.01	-0.01
	(0.06)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)
2SLS** (PME)	0.62***	0.48***	0.18*	0.08	0.04	-0.08	-0.02	-0.08
	(0.08)	(0.07)	(0.09)	(0.06)	(0.05)	(0.10)	(0.06)	(0.13)
Formal workers								
OLS (PNAD)	0.50***	0.28***	0.34***	0.44***	0.30***	0.24***	0.12	0.07
	(0.07)	(0.09)	(0.09)	(0.12)	(0.06)	(0.07)	(0.09)	(0.16)
OLS (PME)	0.50***	0.36***	0.30***	0.22***	0.18***	0.03**	0.11***	0.15**
	(0.01)	(0.03)	(0.05)	(0.02)	(0.01)	(0.01)	(0.02)	(0.06)
2SLS* (PME)	0.43***	0.27***	0.20***	0.10**	0.09**	-0.07	0.02	0.04
	(0.01)	(0.03)	(0.05)	(0.04)	(0.03)	(0.04)	(0.04)	(0.08)
2SLS** (PME)	0.40***	0.17**	0.10	0.01	-0.03	-0.05	-0.05	-0.09
	(0.04)	(0.07)	(0.08)	(0.05)	(0.09)	(0.05)	(0.05)	(0.14)

Source: PNAD, PME and MTE data from 2002 to 2016. The estimates in the table are obtained by adding labour supply controls to the specification in equation (2.3). Detailed information on the procedure to obtain these estimates can be found in the footnote of Table 2.1. For all samples, the instruments are jointly significant and pass standard test for weak instruments and underidentification. Standard errors in parentheses. Significant at 1 percent ***, at 5 percent ** and at 10 percent * using bootstrap inference.

Table 2.B.8: Robustness Checks: OLS Estimates of the Minimum Wage Effects on Employment, Working Hours and Working Hours if Employed, PME 2002-2016

Effects	**Total Employment**			**Formal Employment**		
	Employment	**Working Hours**	**Hours if Employed**	**Employment**	**Working Hours**	**Hours if Employed**
Contemporaneous						
F_{rt}	0.0030	0.0007	-0.0006	-0.0003	-0.0006	-0.0007
	(0.0031)	(0.0011)	(0.0008)	(0.0010)	(0.0005)	(0.0005)
L. one quarter						
F_{rt}	0.0029	0.0004	-0.0009	-0.0001	-0.0004	-0.0006
	(0.0035)	(0.0013)	(0.0008)	(0.0010)	(0.0004)	(0.0005)
Summed effect	0.0003	0.0001	-0.0001	-0.003*	-0.001*	-0.0001
	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
L. two quarters						
F_{rt}	0.0030	0.0005	-0.0008	0.0006	-0.0000	-0.0004
	(0.0035)	(0.0014)	(0.0009)	(0.0013)	(0.0005)	(0.0004)
Summed effect	-0.008***	-0.004***	-0.001	-0.009***	-0.003***	0.0001
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
L. three quarters						
F_{rt}	0.0039	0.0010	-0.0006	0.0006	-0.0001	-0.0004
	(0.0034)	(0.0014)	(0.0009)	(0.0012)	(0.0005)	(0.0005)
Summed effect	-0.012***	-0.006***	-0.001	-0.014**	-0.005**	0.0004
	(0.003)	(0.002)	(0.001)	(0.005)	(0.002)	(0.001)

Source: PME data from March 2002 to February 2016. The estimates in the table are obtained by adding labour supply controls to the specification in equation (2.4). Detailed information on the procedure to obtain these estimates can be found in the footnote of Table 2.3. Standard errors in parentheses. Significant at 1 percent ***, at 5 percent ** and at 10 percent * using bootstrap inference.

Chapter 3

Intraregional Labour Market Outcomes and Minimum Wages: A Search and Matching Approach

3.1 Introduction

In economies with large differences in regional wage levels, the imposition of a national minimum wage is expected to play a more significant role in the determination of wages and employment in low-wage regions than in high-wage ones. Understanding the interaction between regional labour market outcomes and minimum wage policies is essential for a social planner who faces a trade-off between redistribution of income and unemployment across regions. Although this interaction can be observed in a variety of labour markets, Latin American economies are of particular interest because minimum wage policies have drawn significant attention from researchers following the remarkable decrease in inequality in the region over the 2000s.[1] Brazil constitutes a clear example of this phenomenon as income inequality started its downward trend after the adoption of the Brazilian Real in 1994 which stopped the rampant inflation rate that the

[1] A compilation of literature on this subject can be found in López-Calva and Lustig (2010); Cornia (2014); Fritz and Lavinas (2016); Bértola and Williamson (2017).

country experienced over the 1980s and the early 1990s. An interesting fact of the post-inflationary Brazilian labour market is that within and between regional inequality fell sharply along with an unprecedented increase in the real value of the minimum wage.[2]

Empirical literature finds that the minimum wage plays a significant role in the compression of wage inequality across regions in Brazil (Neumark et al. 2006; Lemos 2009; Maurizio and Vazquez 2016; Garcia 2019). This phenomenon can be explained by the large proportion of workers earning at the minimum wage level in low-wage regions. However, high-wage regions seem also to encounter spillover effects —effects on percentiles of the wage distribution in which the minimum wage is not binding—. Spillover effects are difficult to quantify because of their indirect nature. The empirical literature on the subject, mostly for developed countries, agrees about the significant role that spillover effects of the minimum wage play in the compression of wage inequality but do not explain how these are generated (Lee 1999; Autor et al. 2016). Most of these approaches also rely on the assumption of separate regional labour markets which is clearly not the case in many economies including the Latin American ones which are characterized by high labour mobility.[3] If an increase in the minimum wage leads workers to search for jobs in other regions because, for instance, these are unable to find a local job or have a higher probability of finding it in another region, then minimum wage policies would affect labour market outcomes even in regions in which this is not binding or barely binds the wage distribution. Thus, the interaction between regional labour markets and the minimum wage might explain differentials in wages and employment across regions. The present study assesses this interaction by using a search model based on empirical facts from the Brazilian labour market.

[2]The fall in within regional inequality has been explained by the substantial income growth among low-income households, particularly in the most unequal regions, while the income convergence across regions has been the result of fast income growth among the poorest regions in Brazil (Góes and Karpowicz 2017).

[3]In Brazil, Brito and Carvalho (2006) find that 75 percent of migrants from north-east regions move to Sao Paulo and this migration flow is also significant in the opposite direction around 70 percent of migrants move from Sao Paulo to a north-east region.

I construct a two-region “matching and bargaining” model with an endogenous labour force participation in which regions differ in their productivity levels and firms search randomly for workers who are heterogeneous in human capital. The model in this paper builds upon the Diamond-Mortensen-Pissarides model of equilibrium unemployment (Pissarides 2000) and follows a similar structure of the two-sector search model of Albrecht et al. (2017). I follow Flinn (2006) to introduce a binding minimum wage that generates focal points in the wage distribution at the minimum wage level. The intuition behind the model is that changes in the minimum wage affect the value of the worker’s outside option or the value of unemployed search which determines wage-setting rules and employment in both regions. Thus, a binding minimum wage in the wage distribution of at least one region is enough to affect wages and employment in the other one. Most of the labour market studies that involve a binding minimum wage show that this lowers employment unambiguously as the minimum wage constrains the set of feasible matches. However, there is an empirical consensus about the small adverse effects of the minimum wage on employment in Latin America.[4] To be coherent with these findings, I use an endogenous labour force participation function to changes in the value of unemployed search in the spirit of Flinn (2006), Flinn and Mabli (2008), and Ahn et al. (2011). An endogenous labour force participation ensures that a change in the minimum wage has more ambiguous effects on employment.

The model is calibrated by using microdata for Sao Paulo (high-wage region) and Minas Gerais (low-wage region) from the Brazilian National Household Survey PNAD, 2015 (Pesquisa Nacional por Amostra de Domicilios). I use the calibrated model to perform a variety of counterfactuals and policy experiments. Counterfactual exercises involve changing the parameters that determine wage-setting rules and labour market transitions between regions and

[4]Lemos (2004a, 2004b) and Garcia (2019) for Brazil and Cunningham (2007) for other Latin American countries find small adverse effects of the minimum wage on employment. These findings are in line with the literature on the subject for more developed regions such as Card et al. (1994), Freeman (1996) and Card and Krueger (2015).

are motivated by the desire of providing potential explanations, others than the minimum wage, to regional inequalities. Policy experiments study the effects of an increase in the minimum wage on labour market outcomes and assess its efficiency as a welfare-improving instrument between regions.

I find that changes in the value of unemployed search that are driven by changes in the minimum wage or the parameters that characterized the labour market equilibrium in one region have important implications on the labour market outcomes of the other one. Specifically, an increase in the hourly minimum wage from $R\$$ 4.925 (baseline value) to $R\$$ 5.5 raises the value of unemployed search across skill types which encourages participation and thus, aggregate employment is not adversely affected. The increase in the minimum wage has both a positive direct and an indirect effect (spillover effects) on regional wages. The hourly wage gap between regions decreases by approximately 28 cents as the proportion of minimum wage workers is larger in the low-wage region. The previous findings are sensitive to the assumptions on the exogeneity of the contact rates to changes in the minimum wage. Under endogenous contact rates, an increase in the minimum wage implies higher labour costs which deter firms from creating vacancies and thus, aggregate employment falls. This feeds back to lower the value of unemployed search which counteracts the positive direct effect of the minimum wage on wages. As the findings under exogenous contact rates seem to be most in line with the empirical evidence on the small adverse effects of the minimum wage on employment, welfare analysis is conducted under this assumption. The results suggest an optimal minimum wage of $R\$$ 8.67 which in spite of decreasing employment in 1.2 percentage points in the low-wage region, increases welfare for participants from both sides of the labour market.

The literature on regional inequalities in Brazil is mostly empirical. De Oliveira and Carvalho (2016) find that the regional wage gap arises not only because of differences in the distribution of human capital across regions but also because of differences in regional labour market frictions. On this subject, Azzoni and Servo (2002) find that regional wage gaps cannot be entirely explained by observable individual characteristics even when they control for differences in the cost of living across regions. Freguglia and Menezes-Filho (2012) track workers before and after a migration process takes place between two regions and find that a significant proportion of the regional wage gap is given by individual unobservable heterogeneity across workers. Góes and Karpowicz (2017) point out that income growth, formalization, educational attainment and distributive policies are driving factors of the decline in inequality across regions. However, the empirical consensus points out that differentials in labour market outcomes across regions are not entirely accounted for by the previous factors.

The literature that employs search models to explain inequalities across labour markets in Latin America is scarce. The available one is devoted to assessing the effectiveness of labour market policies to either reinforce formality or penalize informality (Albrecht et al. 2009 for the largest Latin American economies; Ulyssea 2010; Bosch and Esteban-Pretel 2012 and Meghir et al. 2015 for Brazil; Bobba et al. 2017 for Mexico). Albrecht et al. (2017) build a two-sector search and matching model to assess the interaction between public and private sector in Colombia. The setup of this model is particularly interesting because this captures the mechanism through which changes in the value of the workers' outside option in one sector affects labour market outcomes in another one. However, the authors forgo minimum wages policies and instead perform counterfactual analysis by changing the parameters that determine the equilibrium of unemployment. Few papers assess spillover effects of the minimum wage on wages and employment in Latin America. Navarro and Tejada (2017) assess the interaction between minimum wages and public-sector employment and find that minimum wage policies change the skill composition in the Chilean labour market. Engbom and Moser (2018) assess the spillover effects of the minimum wage in a wage posting model à la Burdett and Mortensen (1998) which is calibrated by using Brazilian administrative data. The spillover effects of the minimum wage in Engbom and

Moser model are generated by decreases in both the productivity-pay gradient across firms and the returns to ability across workers. Haanwinckel (2018) uses a task-based production function with imperfect substitution between skill types and generates spillover effects of the minimum wage based on distance-dependent complementarity which lowers wage gaps irrespectively of the worker's skill type. Unlike Engbom and Moser; and Haanwinckel models, the spillover effects of the minimum wage in this study are generated by changes in the value of unemployed search and these are not unambiguously equalizing. Moreover, neither of these papers assess the minimum wage as a welfare-improving instrument.

The rest of the paper is structured as follows. Section 2 characterizes the unemployment equilibrium for a two-region economy with and without a binding minimum wage, and presents the welfare maximising function. Section 3 discusses the estimation procedure and evaluates the fit of the model to the data. Section 4 discusses the results of policy/counterfactual experiments and assesses the minimum wage from a welfare-maximising perspective. Section 5 concludes.

3.2 The Model

3.2.1 Search Bargaining Model without a Minimum Wage

In this section, I extend the Diamond-Mortensen-Pissarides (Pissarides 2000) model to introduce a two-region economy with a non-binding minimum wage to understand the interaction between regional labour markets in the first place. This also allows us to introduce a binding minimum wage into the model in a more straightforward way in the next section. In line with the literature for a two-sector economy (Albrecht et al. 2009, 2017), firms in the high-productivity region H and low-productivity region L create vacancies and share the same pool of unemployed workers to fill those vacancies. The model departs from Albrecht's specification by assuming that wages differ across regions because of differences in workers' productivities conditional on being employed in either region L or H

and no by a pure regional wage premium.[5]

The model is set in continuous time and stationary environment. Workers are heterogeneous with respect to human capital, y, and productivity, x. In terms of human capital, workers can be either low-skilled (type-l) or high-skilled (type-h). The match productivity between a type-y worker and an employer in region j, is a draw from the productivity distribution $G_j^y(x)$, with $j = L,\ H$ and $y = l,\ h$. Only unemployed workers search for jobs and this process is random. The rate at which employers and workers contact each other depends on labour market tightness, $\theta = (v_L + v_H)/u$, where u is the unemployment rate and, v_L and v_H are measures of vacancies posted in region L and H, respectively. An unemployed worker meets a potential employer at a Poisson rate $m(\theta)$, while an employer meets an unemployed worker at a rate $m(\theta)/\theta$. Conditional on meeting a potential employer, the probability that the job is in region L is given by $\phi = v_L/(v_L + v_H)$.[6] A match takes place if and only if $x \geq R_j^y$, where, R_j^y, is a type-y reservation productivity in region j. Finally, employment matches can be exogenously terminated at a Poisson rate, λ_j^y. Figure 3.1 summarizes workers' transitions for three possible labour market states: unemployed U, employed in region L and employed in region H.

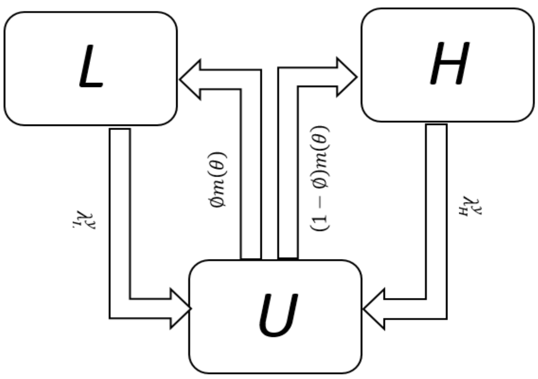


Figure 3.1: Labour Market Transition

[5]Productivity differences between labour markets can be generated by structural differences within an economy. It is well-established in the literature that labour markets with homogenous workers in term of productivities might exhibit productivity differentials because one employs labour more efficiently than the others (Bontemps et al. 2000; Moser and Stahler 2009).

[6]Neither $m(\theta)$ nor ϕ depends on y, thus transition rates out of unemployment are driven by differences in the probability of finding an acceptable job offer between regions rather than by differences in the contact rates at which worker types meet a potential employer.

Value Functions

All agents are subject to a common discount rate ρ. Let, ρU^y, be the type-specific value of unemployed search and, $\rho W_j^y(x)$, be the type-specific value of employment in region j. Formally:

$$\rho U^y = z^y + \gamma_L E\ max\left[W_L^y(x) - U^y, 0\right] + \gamma_H E\ max\left[W_H^y(x) - U^y, 0\right] \tag{3.1}$$

$$\rho W_j^y(x) = w_j^y(x) + \lambda_j^y[U^y - W_j^y(x)] \tag{3.2}$$

Equation (3.1) states that a type-y worker receives a type-specific utility (or disutility) flow z^y while unemployed, meets vacancies at rate $\gamma_L = \phi m(\theta)$ in region L and $\gamma_H = (1-\phi)m(\theta)$ in region H, and obtains surplus from accepting a job offer whenever $[W_j^y(x) - U^y]$ is positive, zero otherwise. Equation (3.2) states that the employment value for a type-y worker in region j is given by the wage payment, $w_j^y(x)$, which is a function of the worker's match-specific productivity x, and the capital loss $[U^y - W_j^y(x)]$ when the employment match is exogenously terminated at rate, λ_j^y.

Firms create vacancies and search for workers. Let $\rho J_j^y(x)$ be the present discounted value of a vacancy filled by a type-y worker in region j, and ρV_j that of an unfilled vacancy such as:

$$\rho J_j^y(x) = (1+\delta_j^y)x - w_j^y(x) + \lambda_j^y[V_j - J_j^y(x)] \tag{3.3}$$

$$\rho V_j = -c_j + \frac{m(\theta)}{\theta} E\ max[J_j^y(x) - V_j, 0] \tag{3.4}$$

Equation (3.3) shows that the value of a filled vacancy is given by the difference between the type-specific match with productivity $(1+\delta_j^y)x$, with $\delta_H^y > 0$ (productivity premium of being employed in region H) and $\delta_L^y = 0\ \forall y$, and the type-specific wage payment, $w_j^y(x)$, plus the capital loss $[V_j - J_j^y(x)]$ if the job is destroyed at rate λ_j^y. In equation (3.4), the flow cost of keeping a vacancy open is denoted by c_j, employers meet potential employees at rate $m(\theta)/\theta$ and obtain surplus if the job is filled by a type-y worker whenever $[J_j^y(x) - V_j]$ is positive, zero otherwise.

Wage Determination

Wages are determined via Nash bargaining with an exogenous parameter, β_j (worker's bargaining power). The maximization problem for a type-specific worker in region j is given by:

$$w_j^y(x) = arg \underset{w}{max} \quad \left[W_j^y(x) - U^y\right]^{\beta_j} \left[J_j^y(x) - V_j\right]^{1-\beta_j} \tag{3.5}$$

In steady-state, the value of posting a vacancy in region j is zero, $V_j = 0$, because of the free market entry assumption. The Nash-bargaining solution for equation (3.5) is then given by:

$$w_j^y(x) = \beta_j(1 + \delta_j^y)x + (1 - \beta_j)\rho U^y \tag{3.6}$$

Equation (3.6) states that a type-specific worker receives his outside option ρU^y plus a fraction β_j of the net surplus from the productivity match $[(1+\delta_j^y)x - \rho U^y]$, with $\delta_H^y > 0$ and $\delta_L^y = 0 \ \forall y$.[7]

Equilibrium

Substituting (3.6) into (3.2) and defining $W_L^y(R_L^y) = U^y$ implies that $R_L^y = \rho U^y$, that is, the reservation productivity for a type-y worker in region L equals the value of unemployed search, thus the net surplus for this match-specific productivity equals zero. Given the wage equation for region H is without loss

[7] In absence of a minimum wage, wages are an affine mapping from the left-truncated match-productivity distribution $G_j^y(x|x \geq R_j^y)$ into $F_j^y(w_j^y|w_j^y \geq R_j^y)$.

of generality to assume that $W_H^y(R_H^y) > U^y$ which implies, $R_H^y > R_L^y\ \forall y$, that is, the reservation productivity for a type-y worker in region H is larger than that in region L. We can now rewrite equation (3.1), the value of unemployed search, by using equations (3.2) and (3.6) as follows:

$$\rho U^y = z^y + \gamma_L \beta_L \int_{\rho U^y}^{\infty} \frac{x - \rho U^y}{\rho + \lambda_L^y} dG_L^y(x) + \gamma_H \beta_H \int_{R_H^y}^{\infty} \frac{(1+\delta_H^y)x - \rho U^y}{\rho + \lambda_H^y} dG_H^y(x) \tag{3.7}$$

The next step is to characterize the optimal entry condition in region j (equation (3.3) and (3.4)) by using (3.6) with $V_j = 0$ and $R_L^y = \rho U^y$ as follows:

$$J_j^y(x) = \frac{(1+\delta_j^y)x - w_j^y(x)}{\rho + \lambda_j^y} = (1-\beta_j)\frac{(1+\delta_j^y)x - \rho U^y}{\rho + \lambda_j^y}$$

$$0 = -c_j + (1-\beta_j)\frac{m(\theta)}{\theta}\left\{\alpha_U^l \int_{R_j^l}^{\infty} \frac{(1+\delta_j^l)x - \rho U^l}{\rho + \lambda_j^l} dG_j^l(x) + \alpha_U^h \int_{R_j^h}^{\infty} \frac{(1+\delta_j^h)x - \rho U^h}{\rho + \lambda_j^h} dG_j^h(x)\right\} \tag{3.8}$$

Where α_U^y is the proportion of type-y unemployed workers with $y = l,\ h$.

Steady-State Conditions

In steady-state, the unemployment rate of type-y workers, u^y, and, the fraction of type-y workers in region L, n_L^y, and H, n_H^y, must satisfy the following equations:

$$\begin{aligned} \lambda_L^y n_L^y &= \gamma_L \widetilde{G}_L^y(\rho U^y) u^y \\ \lambda_H^y n_H^y &= \gamma_H \widetilde{G}_H^y(R_H^y) u^y \end{aligned} \tag{3.9}$$

Where $\widetilde{G}_L^y(\rho U^y) = 1 - G_L^y(\rho U^y)$ and $\widetilde{G}_H^y(R_H^y) = 1 - G_H^y(R_H^y)$. Equation (3.9) states that outflows from employment to unemployment (left-hand side) equal inflows from unemployment to employment (right-hand side). Using (3.9) and

$u^y + n^y_L + n^y_H = 1 \ \forall y$, we obtain:[8]

$$
\begin{aligned}
u^y &= \frac{\lambda^y_L \lambda^y_H}{\lambda^y_L \lambda^y_H + \lambda^y_H \gamma_L \widetilde{G}^y_L(\rho U^y) + \lambda^y_L \gamma_H \widetilde{G}^y_H(R^y_H)} \\
n^y_L &= \frac{\lambda^y_H \gamma_L \widetilde{G}^y_L(\rho U^y)}{\lambda^y_L \lambda^y_H + \lambda^y_H \gamma_L \widetilde{G}^y_L(\rho U^y) + \lambda^y_L \gamma_H \widetilde{G}^y_H(R^y_H)} \\
n^y_H &= \frac{\lambda^y_L \gamma_H \widetilde{G}^y_H(R^y_H)}{\lambda^y_L \lambda^y_H + \lambda^y_H \gamma_L \widetilde{G}^y_L(\rho U^y) + \lambda^y_L \gamma_H \widetilde{G}^y_H(R^y_H)}
\end{aligned}
\tag{3.10}
$$

3.2.2 Search Bargaining Model with a Minimum Wage and an Endogenous Labour Market Participation

The labour market environment is assumed to be exactly as described in the previous section. The minimum wage applies to all potential matches, thus employment contracts must yield a payment of at least the value of the minimum wage, $\tilde{m}$. Recall that the reservation productivity for a type-y worker is, $R^y_L = \rho U^y$, if employed in region L and R^y_H, if employed in region H, with $R^y_H > \rho U^y \ \forall y$. In the model without a minimum wage, a match forms if and only if $x \geq R^y_j \ \forall j, y$. Consequently, the setup of the model depends on whether $\tilde{m}$ is large enough to bind the reservation match productivities across skill types. It is clear that a non-binding minimum wage, $\tilde{m} \leq \rho U^y \ \forall y$, affects neither the wage-setting rule nor job creation, thus the model could be solved by using the specification without a minimum wage.

Now let's consider the specific case of imposing a binding minimum wage such as $\tilde{m} > R^l_L$. In principle, it is expected that none but type-l workers in region L are directly affected by $\tilde{m}$. However, as $R^l_L = \rho U^l$ and given that ρU^l determines the wage-setting rule for type-l workers in both regions, type-l workers in region H are also affected by $\tilde{m}$. A more general case assumes that the minimum wage binds the reservation match productivities of both workers' types. This assumption

[8] It is assumed at this stage that the labour force participation of type-y workers equals 1 for simplicity. I will relax this assumption when we consider an endogenous labour force participation to changes in the minimum wage in the next subsection.

is not arbitrary and will become clearer with the inspection of the data in the calibration section.

Wage Determination

The bargaining problem is identical to the one given in equation (3.5) except that the set of feasible wages is now restricted to the interval $[\tilde{m}, \infty)$. Formally:

$$w_j^y(x, \tilde{m}) = \underset{w > \tilde{m}}{arg\ max} \quad \left[W_j^y(x, \tilde{m}) - U^y(\tilde{m})\right]^{\beta_j} \left[J_j^y(x, \tilde{m}) - V_j\right]^{1-\beta_j} \tag{3.11}$$

The equilibrium wage equation under a binding minimum wage for type-y workers in region j is given by:

$$w_j^y(x, \rho U^y(\tilde{m})) = \beta_j(1 + \delta_j^y)x + (1 - \beta_j)\rho U^y(\tilde{m}) \tag{3.12}$$

Following Flinn (2006), we can determine the match productivity, x, at which a type-y worker will receive a wage payment equals to $\tilde{m}$ by using equation (3.12):

$$\tilde{x}_j^y(\tilde{m}, \rho U^y(\tilde{m})) = \frac{\tilde{m} - (1 - \beta_j)\rho U^y(\tilde{m})}{\beta_j(1 + \delta_j^y)} \tag{3.13}$$

If $x < \tilde{m}$, there are no feasible matches because the firm cannot hire without making a loss. If $x \in [m, \tilde{x}_j^y)$ the resulting bargaining wage would be less than $\tilde{m}$ according to equation (3.12); however, we assumed that no employment contracts yield wage payments below the mandatory minimum wage, thus firms choose to pay $\tilde{m}$ and give up some surplus. If $x \geq \tilde{x}_j^y$, the wage offer is determined by equation (3.12). Notice that $\tilde{x}_H^y = \tilde{x}_L^y/(1 + \delta_H^y)$, thus $\tilde{x}_H^y < \tilde{x}_L^y$ given $\delta_H^y > 0\ \forall y$. Figure 3.2 shows the cut-off point wage determination under a binding minimum wage for type-y workers in region j.

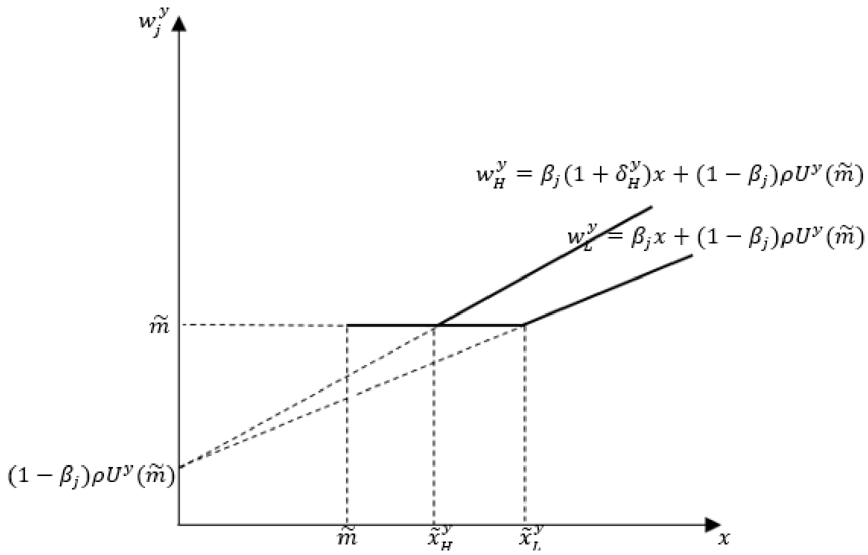


Figure 3.2: Cut-off Productivities for Type-y Workers

Figure 3.2 shows the case of a binding minimum wage for all type-y workers in both regions. Firms offer a wage payment of $\tilde{m}$ for all match productivities $x \in [\tilde{m}, \tilde{x}_L^y)$ in region L and $x \in [\tilde{m}, \tilde{x}_H^y)$ in region H, $\forall y$.[9] Wages are determined via bargaining for $x \geq \tilde{x}_L^y$ in region L and for $x \geq \tilde{x}_H^y$ in region H, $\forall y$.

Equilibrium

We can now consider the worker's search problem given a binding minimum wage for all type-y workers in both regions. Analogously to equation (3.7), the value of unemployed search reads:

$$\rho U^y(\tilde{m}) = z^y + \tfrac{\gamma_L}{\rho+\lambda_L^y}\left\{\int_{\tilde{m}}^{\tilde{x}_L^y}[\tilde{m} - \rho U^y(\tilde{m})]dG_L^y(x) + \beta_L\int_{\tilde{x}_L^y}^{\infty}[x - \rho U^y(\tilde{m})]dG_L^y(x)\right\}$$
$$+\tfrac{\gamma_H}{\rho+\lambda_H^y}\left\{\int_{\tilde{m}}^{\tilde{x}_H^y}[\tilde{m} - \rho U^y(\tilde{m})]dG_H^y(x) + \beta_H\int_{\tilde{x}_H^y}^{\infty}[(1+\delta_H^y)x - \rho U^y(\tilde{m})]dG_H^y(x)\right\} \tag{3.14}$$

The first and third integrals in equation (3.14) show the capital gain

[9]This specification assumes that there are no feasible matches in region H for $x < \tilde{m}$ even though firms will be willing to pay $\tilde{m}$ to workers with productivities as low as $\tilde{m}/(1+\delta_H^y)$. The reason for this restriction is to have a continuous of workers with positive probabilities of finding a job in both regions. The imposition of this restriction is not likely to affect the estimates in the model due to the small proportion of type-y workers in region H with productivities in the interval $x \in [\tilde{m}/(1+\delta_H^y), \tilde{m})$.

associated with an acceptable match productivity x, with $x \in [\tilde{m}, \tilde{x}_j^y)$, which generates a wage payment, $\tilde{m}$, for a type-y worker in region L and H, respectively. The second and fourth integrals show in turn the capital gain of an acceptable match productivity x, with $x \geq \tilde{x}_j^y$, which generates a wage payment determined by bargaining. We can now rewrite the free entry condition equation (3.8) under a binding minimum wage for all type-y workers in both regions.

$$0 = -c_j + \frac{m(\theta)}{\theta}\Bigg\{\alpha_U^l\left[\int_{\tilde{m}}^{\tilde{x}_j^l}\frac{(1+\delta_j^l)x-\tilde{m}}{\rho+\lambda_j^l}dG_j^l(x) + (1-\beta_j)\int_{\tilde{x}_j^l}^{\infty}\frac{(1+\delta_j^l)x-\rho U^l(\tilde{m})}{\rho+\lambda_j^l}dG_j^l(x)\right]$$

$$+\alpha_U^h\left[\int_{\tilde{m}}^{\tilde{x}_j^h}\frac{(1+\delta_j^h)x-\tilde{m}}{\rho+\lambda_j^h}dG_j^h(x) + (1-\beta_j)\int_{\tilde{x}_j^h}^{\infty}\frac{(1+\delta_j^h)x-\rho U^h(\tilde{m})}{\rho+\lambda_j^h}dG_j^h(x)\right]\Bigg\} \tag{3.15}$$

Analogous to equation (3.14), the first and third integrals in equation (3.15) show the net surplus associated with a match productivity, x, with $x \in [\tilde{m}, \tilde{x}_j^y)$, while the second and fourth integrals show the net surplus associated with a match productivity, x, with $x \geq \tilde{x}_j^y$.

The steady-state conditions under a binding minimum wage read:

$$\begin{aligned} \lambda_L^y n_L^y &= \gamma_L \widetilde{G}_L^y[\max\{\tilde{m}, \rho U^y(\tilde{m})\}]u^y \\ \lambda_H^y n_H^y &= \gamma_H \widetilde{G}_H^y[\max\{\tilde{m}, R_H^y(\tilde{m})\}]u^y \end{aligned} \tag{3.16}$$

Note that the effect of imposing a left-side constraint is that fewer encounters between unemployed workers and firms will result in employment contracts and under a fixed labour force participation, an increase in the unemployment rate implies a decrease in the employment rate. In order to allow for more ambiguous effects of the minimum wage on employment, I specify an endogenous labour force participation function to changes in the value of unemployed search as in Flinn (2006) and Ahn et al. (2011).

Individuals decide whether to participate in the labour market or not. Let $\rho O^y(\tilde{m})$ be the value of a type-specific individual out of the labour market under a minimum wage and assume this random variable follows a parametric distribution

$Q[\rho O^y(\tilde{m}),\ \zeta^y]$, where ζ^y is a type-specific finite-dimensional parameter vector. All type-y individuals who decide to participate in the labour market start in the unemployment state. Individuals choose to participate in the labour market if $\rho O^y(\tilde{m}) < \rho U^y(\tilde{m})$, that is, if the value of unemployed search is larger than that of being out of the labour force. It follows that the labour force participation rate of type-y workers, n_T^y, is determined within the model by $Q[\rho U^y(\tilde{m}),\ \zeta^y]$. Thus, a change in the minimum wage affects labour force participation only through changes in the value of unemployed search.

Given the set of labour market participants, n_T^y, the probabilities of labour market states under a binding minimum wage are given by:

$$\begin{aligned}
u^y &= \frac{n_T^y \lambda_L^y \lambda_H^y}{\lambda_L^y \lambda_H^y + \lambda_H^y \gamma_L \widetilde{G}_L^y[\max\{\tilde{m}, \rho U^y(\tilde{m})\}] + \lambda_L^y \gamma_H \widetilde{G}_H^y[\max\{\tilde{m}, R_H^y(\tilde{m})\}]} \\
n_L^y &= \frac{n_T^y \lambda_H^y \gamma_L \widetilde{G}_L^y[\max\{\tilde{m}, \rho U^y(\tilde{m})\}]}{\lambda_L^y \lambda_H^y + \lambda_H^y \gamma_L \widetilde{G}_L^y[\max\{\tilde{m}, \rho U^y(\tilde{m})\}] + \lambda_L^y \gamma_H \widetilde{G}_H^y[\max\{\tilde{m}, R_H^y(\tilde{m})\}]} \\
n_H^y &= \frac{n_T^y \lambda_L^y \gamma_H \widetilde{G}_H^y[\max\{\tilde{m}, R_H^y(\tilde{m})\}]}{\lambda_L^y \lambda_H^y + \lambda_H^y \gamma_L \widetilde{G}_L^y[\max\{\tilde{m}, \rho U^y(\tilde{m})\}] + \lambda_L^y \gamma_H \widetilde{G}_H^y[\max\{\tilde{m}, R_H^y(\tilde{m})\}]}
\end{aligned} \tag{3.17}$$

To close the model, the fraction of vacancies posted in L, ϕ, can be written as a function of the unemployment rate, u, labour market tightness, θ, and the fraction of vacancies posted in region H, v_H, as follows:

$$\phi = 1 - \frac{v_H}{\theta u} \tag{3.18}$$

Definition. A steady-state equilibrium in a two-region economy under the presence of a binding minimum wage is characterized by the vector (n_T^y, θ, ϕ, $\rho U^y(\tilde{m})$) which is a function of a vector of parameters (ρ, β_j, $\tilde{m}$, z^y, ζ^y, λ_j^y, δ_j^y, c_j), a matching function $m(\theta)$ and a probability distribution function of match productivities $G_j^y(x)$ with $j = L,\ H$ and $y = l,\ h$.

An equilibrium, if one exists, can be constructed as follows: Given θ and ϕ, $\rho U^y(\tilde{m})$ solves equation (3.14). The participation rate is determined as $n_T^y = Q[\rho U^y(\tilde{m}),\ \zeta^y]$. For a given value ϕ, equation (3.15) provides at least one solution for θ. Given $\rho U^y(\tilde{m})$, θ, and steady-state conditions (equation (3.17)), equation (3.18) provides at least one solution for ϕ. Given $\rho U^y(\tilde{m})$, θ, ϕ and n_T^y, we can solve numerically for the equilibrium distribution of wages and employment between regions.

3.2.3 The Welfare Function

I estimate the effect of minimum wage increases on labour market states and welfare measures for the supply and demand side of the labour market following Flinn (2006). Labour market participants have four possible states on the supply side of the labour market: employed in region L, employed in region H, unemployed and out of the labour force. On the demand side, firms have filled, unfilled and no vacancies. The minimum wage, $\tilde{m}$, is the only instrument available to maximize a utilitarian welfare function for type-y labour market participants defined as follows:

$$\begin{aligned} W_T^y(\tilde{m}) &= u^y(\tilde{m})\bar{U}^y(\tilde{m}) + n_L^y(\tilde{m})\bar{W}_L^y(\tilde{m}) + n_H^y(\tilde{m})\bar{W}_H^y(\tilde{m}) \\ &+ s_L^y(\tilde{m})\bar{J_L}^y(\tilde{m}) + s_H^y(\tilde{m})\bar{J_H}^y(\tilde{m}) \end{aligned} \tag{3.19}$$

Where $\bar{U}^y(\tilde{m}) = U^y(\tilde{m})$ is the average welfare level of a type-y unemployed worker under a minimum wage which equals the individual welfare level because this is the same for all unemployed workers; $\bar{W}_L^y(\tilde{m})$ and $\bar{W}_H^y(\tilde{m})$ are the average welfare levels of a type-y worker under a minimum wage who is employed in region L and H, respectively. On the demand side of the labour market, $s_L^y(\tilde{m})$ and $s_H^y(\tilde{m})$ are the share of firms with a vacancy filled by a type-y worker under a minimum wage in region L and H, respectively and, $\bar{J_L}^y(\tilde{m})$ and $\bar{J_H}^y(\tilde{m})$ are the corresponding average welfare levels of their owners. Only the welfare level of firms' owners with filled vacancies is considered in this analysis because the welfare of firms' owners with unfilled vacancies and no vacancies is zero under the free entry condition. Thus, the share of firms with vacancies filled by type-y workers must be equal to the share of type-y employed workers such as $s^y_L(\tilde{m}) = n^y_L(\tilde{m})$ and $s^y_H(\tilde{m}) = n^y_H(\tilde{m})$ for region L and H, respectively.

3.3 Calibration

3.3.1 Data

The model is calibrated by using microdata from the National Brazilian household survey (PNAD, 2015). I use data from two Brazilian regions: Minas Gerais and Sao Paulo, which differ significantly in their wage levels in spite of their geographical proximity. Moreover, it has been well established in the Brazilian literature on migration that inflows and outflows of workers between these regions are among the largest in the country. I use data from Minas Gerais to construct a sample for the low-productivity region, L, and from Sao Paulo to construct a sample for the high-productivity region, H. The samples comprise full-time formal workers —those who worked at least 35 hours in the reference week and signed a job contract—. The sample for type-l workers comprises individuals with at least completed primary education (8 years of schooling) and no more than a high-school diploma (12 years of schooling), while the sample for type-h workers comprises individuals with incomplete and completed tertiary education (13 years of schooling or more). The samples are further restricted to workers aged 18 to 30 to account only for workers in the early stage of their labour market history. The previous restrictions generate samples with workers who are more likely to be affected by changes in the minimum wage.[10]

PNAD data provide information on the distribution of type-y workers across four labour market states: out of the labour force, unemployed, employed in Minas Gerais and employed in Sao Paulo. Monthly wages from the main occupation and employment durations for each worker type across regions are also reported. Since employees in Brazil are not typically paid on an hourly basis, I calculate an hourly

[10]Information on demographic characteristics of minimum wage workers in the labour market and their distribution across regions in Brazil can be found in Appendix 3.A.

wage by dividing the monthly wage from the main occupation for 4 weeks and 40 working hours per week which are established as the number of working hours for a full-time job.[11] I do the same to calculate the hourly minimum wage by using data from the Brazilian Ministry of Labour (MTE).

Table 3.1 shows descriptive statistics from Minas Gerais (region L) and Sao Paulo (region H) in 2015. It is assumed that the labour market was in steady-state equilibrium at the nominal minimum wage of $R\$$ 788 or the hourly minimum wage of $R\$$ 4.925 which was due to expire at the end of 2015.

Table 3.1: Descriptive Statistics, PNAD 2015

Characteristics	**Pooled**	**Low-Skilled Workers (Type-l Workers)**	**High-Skilled Workers (Type-h Workers)**
Sample Composition			
Sample Size	9,345	6,997	2,348
Population	8,430,868	6,278,986	2,151,882
OLF Rate	0.340	0.336	0.354
Unemployment Rate	0.110	0.128	0.055
Employment Rate in L	0.148	0.156	0.121
Employment Rate in H	0.402	0.380	0.470
Total	1	1	1
Descriptive Statistics for Employed Population			
Skill Composition			
Employment Rate in L	1	0.790	0.210
Employment Rate in H	1	0.703	0.297
Employment Durations			
Mean Duration in L	28.670	27.927	31.467
SD Duration	(24.161)	(24.028)	(24.482)
Mean Duration in H	29.420	27.262	34.519
SD Duration	(23.678)	(22.776)	(24.966)
Mean Hourly Wage			
Mean Hourly Wage in L	8.002	7.122	11.313
SD Hourly Wage	(5.117)	(2.884)	(8.927)
Mean Hourly Wage in H	10.162	8.130	14.961
SD Hourly Wage	(7.585)	(2.920)	(11.858)
Proportion of Minimum Wage Workers			
$w_L = \tilde{m}$	0.183	0.208	0.091
$w_H = \tilde{m}$	0.057	0.071	0.024

Source: PNAD, 2015. Sample comprises full-time formal workers, unemployed and individuals out of the labour force, aged 18-30 years, between 8 and 12 years of schooling (type-l), and more than 13 years of schooling (type-h), from Minas Gerais (region L) and Sao Paulo (region H). Statistics are adjusted by using sampling weights.

[11] Although PNAD provides information on the number of working hours per week, I do not use this information to calculate the hourly wage because this may underestimate the proportion of minimum wage workers in the sample. Data show that around 50 percent of workers earning at the minimum wage level claim to work more than 40 hours per week which would lead to an imputed hourly wage smaller than the hourly minimum wage.

It is important to mention a few restrictions that were imposed on the samples in order to obtain the statistics in Table 3.1. First, all individuals who claim to be unemployed, but attend school are considered as individuals out of the labour force. This restriction is important because the proportion of unemployed workers might be overestimated due to the aforementioned restrictions that were imposed on the sample of employed workers. Second, wages below the mandatory minimum wage are eliminated from the sample. These observations might be interpreted as measurement error or non-compliance with minimum wage laws. The model does not allow for observations below the minimum wage, thus we can deal with this issue by either rounding up wages to the minimum wage level or dropping observations below it. I choose the latter because rounding up wages to the minimum wage level may bias the estimates of the parameters in the model since the proportion of the minimum wage workers is relevant for identification. Around 51 observations were deleted which represent around 1 percent of the sample for employed workers.

The first column in Table 3.1 shows descriptive statistics for the pooled sample (low and high-skilled workers combined) and the next two columns show those by skill group. It is not surprising the large proportion of the population out of the labour force (OLF) for both skill types given that the samples comprise young individuals. As expected, the proportion of type-l unemployed workers is larger than that of type-h ones within each educational group. Regarding employment, most of this is generated in region H for both skill types. When we account only for employed workers, we can see that region H has a larger proportion of type-h workers than region L. Employment durations are similar between regions at least for type-l workers, however, these are longer in region H for type-h ones, this is surprising given its more dynamic nature.

The most interesting feature in Table 3.1 is the gap in regional wage levels and their interaction with the minimum wage. The minimum wage in Brazil is set nationally, thus its bindingness across regions and skill groups varies according to their wage distributions. Notice the large mass of observations at the minimum wage in region L, particularly among low-skilled workers. Although the minimum wage is also binding in region H, the proportion of minimum wage workers in this region is significantly smaller. In fact, there is not an obvious focal point in the wage distribution of type-h workers at the minimum wage level in region H.

In principle, the regional wage gap could be explained by the difference in the skill composition between regions. A simple Oaxaca-Blinder decomposition can shed light on this matter by estimating regional and educational premiums between regions. Formally: $\bar{w}_H - \bar{w}_L = \sum_y \alpha_H^y(\bar{w}_H^y - \bar{w}_L^y) + \sum_y \bar{w}_L^y(\alpha_H^y - \alpha_L^y)$, where $\bar{w}_j^y$ and α_j^y, are mean wages and employment shares of type-y workers in region j, respectively. The first term accounts for the wage gap within skill groups given by returns to employment in region L and H, and the second one accounts for the wage gap given by the skill composition between regions. By using the information from Table 3.1, the difference in regional mean wages is approximately 2.2. The Oaxaca-Blinder decomposition suggests that this differential is given by a regional premium of 1.8 and an educational premium of 0.4. Thus, less than 20 percent of the difference in regional mean wages is attributed to the educational composition between regions.

3.3.2 Estimation and Identification of the Parameters

As was mentioned previously, the setup of the model relies on the assumptions about the bindingness of the minimum wage among skill types and regions. According to Table 3.1, there is a significant proportion of type-l workers earning at the minimum wage in both regions and even though there is not an obvious focal point at the minimum wage for type-h workers, particularly in region H, the minimum wage is still binding in their wage distribution. Thus, I estimate a model in which the minimum wage binds the wage distribution of both skill types in both regions. The model can be solved numerically for the equilibrium distribution of wages and productivities across skills and regions by either simulating the model or analytically. However, the simulation approach is computationally less demanding to perform policy and counterfactual experiments. The calibration strategy of the model involves the following steps:

1. I initially estimate the location and scale of the type-specific productivity distribution, $G^y_j(x)$, and the reservation productivity, R^y_j, with $j = L,\ H$ and $y = l,\ h$. For this purpose, I use the observed wage distribution of type-y workers in region j, the percentage of type-y workers earning at the minimum wage in region j, and the minimum wage, $\tilde{m}$. The observed distribution of wages provides information on the location and scale parameters of the productivity distribution, $G^y_j(x)$, which is assumed to be log-normal distributed with parameters μ^y_j and σ^y_j. Wages are mapped to productivities in region j by using equation (3.12) as follows:

$$ln(x) = ln\left[\frac{w^y_j - (1-\beta_j)\rho U^y(\tilde{m})}{\beta_j(1+\delta^y_j)}\right]$$

Recall that workers with productivities in the interval $[\tilde{m}, \tilde{x}^y_j)$ in region j are paid $\tilde{m}$, while workers with productivity larger or equal than $\tilde{x}^y_j$ (equation (3.13)) are paid a wage that results from a bargaining process which is given by equation (3.12). Thus, wages for a type-y worker in region j are drawn from the following conditional density.

$$f_j(w^y_j|w^y_j \geq \tilde{m}) = \begin{cases} \frac{[\beta_j(1+\delta^y_j)]^{-1} g^y_j(x(w^y_j,\, \rho U^y(\tilde{m})))}{1-G^y_j(\tilde{m})}, & w^y_j > \tilde{m} \\ \frac{G^y_j(\tilde{x}^y_j(\tilde{m},\, \rho U^y(\tilde{m}))) - G^y_j(\tilde{m})}{1-G^y_j(\tilde{m})}, & w^y_j = \tilde{m} \\ 0, & w^y_j < \tilde{m} \end{cases}$$

Where $g^y_j(.)$ and $G^y_j(.)$ are the log-normal density and cumulative distributions of type-y productivities in region j, respectively.

The percentage of type-y workers earning at the minimum wage in region L and $\tilde{m}$ provide information on the cut-off productivity point, $\tilde{x}^y_L$. Given an assumed value of β_L and expressions for the mean and the variance of a log-normal distribution truncated at $\tilde{m}$, we are able to back out estimates for μ_L^y, σ_L^y and $R_L^y = \rho U^y(\tilde{m})$.

In region H, the reservation productivity, R_H^y, can be expressed as a function of $\rho U^y(\tilde{m})$ by evaluating R_H^y in the wage equation (3.12) and setting $R_H^y = w_H^y(R_H^y,\ \rho U^y(\tilde{m}))$ as follows:

$$R_H^y = \frac{1-\beta}{1-\beta(1+\delta_H^y)}\rho U^y(\tilde{m})$$

The productivity premium, δ_H^y, can be estimated by using the proportion of minimum wage workers in region H and $\tilde{m}$ following the same procedure that was used to identify $\rho U^y(\tilde{m})$. Analogously, we are able to back out estimates for μ_H^y, σ_H^y and R_H^y given an assumed value of β_H and expressions for the mean and the variance of a log-normal distribution truncated at $\tilde{m}$.

2. Labour force participation rate in the model is determined by $n_T^y = Q[\rho U^y(\tilde{m}),\ \zeta^y]$. Given consistent estimates for $\rho U^y(\tilde{m})$ and one equilibrium value of the labour force participation rate, n_T^y, we can invert the outside option distribution $Q[\rho U^y(\tilde{m}),\ \zeta^y]$ to obtain an estimate for the parameter ζ^y, as follows $\hat{\zeta}^y = Q^{-1}[\widehat{\rho U^y(\tilde{m})},\ \widehat{n_T^y}]$.[12]

3. To estimate $m(\theta)$ and ϕ, I use expressions for the expected average duration of employment in region L and H. First, the expected duration of employment for a type-specific worker in region j is given by $1/\lambda_j^y$ because the model assumes exponential durations. Second, the expected average duration of employment in region j is given by $E(T_j) = \sum_y \alpha_j^y(1/\lambda_j^y)$, where α_j^y is the employment share of a type-y worker in region j. Third, the expected average duration of employment can be expressed as a function of $m(\theta)$ and ϕ. I obtain a system of two equations with two unknowns, $\gamma_L = \phi m(\theta)$ and $\gamma_H = (1-\phi)m(\theta)$, by using equation (3.16) as follows:

[12]Both Q and Q^{-1} are assumed to be continuously differentiable in both arguments.

$$
\begin{aligned}
E(T_L) &= \sum_y \frac{\alpha_L^y n_L^y}{\gamma_L \widetilde{G}_L^y[\max\{\tilde{m}, \rho U^y(\tilde{m})\}]u^y} \\
E(T_H) &= \sum_y \frac{\alpha_H^y n_H^y}{\gamma_H \widetilde{G}_H^y[\max\{\tilde{m}, R_H^y\}]u^y}
\end{aligned}
$$

4. It is not possible to identify any additional parameter in the matching function, $m(\theta)$, without information on vacancies. Thus, I use the following Cobb-Douglass matching function $m(u, v) = Au^{1-\eta}v^{\eta}$ as in Albrecht et al. (2017). Given an assumed value for A and an estimate for $m(\theta)$, we can estimate the labour market tightness parameter $\theta = v/u$, with $v = v_L + v_H$.

5. The previous estimates altogether allow us to estimate both the cost of search for workers, c_j, by using equation (3.15) and the type-specific unemployment flow utility, z^y, by using equation (3.14).

6. Finally, I use equation (3.18) along with the estimates for ϕ and θ to provide an estimate of posted vacancies in region j, v_j.

7. I iterate over ϕ and θ. The algorithm solution can be found in Appendix 3.B.

3.3.3 Estimation Results

The results of the calibration are shown in Table 3.2. Fixed parameters are not estimated in the model and are assumed to be the same between regions. Nash-bargaining power parameter in region j, β_j, is set at 0.4 following the estimates from Flinn (2006) who uses a similar sample of workers to the one in this study.[13] The elasticity of the matching function with respect to unemployment, η, is set at 0.5 which is the standard value in the literature on the subject. Following Albrecht et al. (2017), I set the scale parameter of the matching function, A, at

[13] I set $\beta_L = \beta_H$ for the baseline calibration, however, I allow β_j to differ between regions when performing counterfactual exercises.

Table 3.2: Estimated Parameters

Parameters	Description	Value	
Fixed			
ρ	Discount rate	0.006	
$\beta_L = \beta_H$	Nash-bargaining power parameter	0.4	
A	Scale factor-matching function	0.25	
η	Elasticity-matching function	0.5	
$\tilde{m}$	Hourly minimum wage-2015	4.925	
Demand Side			
$m(\theta)$	Contact rate	0.219	
θ	Market tightness	0.767	
ϕ	Fraction of vacancies in L	0.252	
c	Vacancy posting cost	24.043	
Supply Side		Low-Skilled (Type-l)	High-Skilled (Type-h)
μ_L	Mean log-normal distribution of productivities in region L	2.360	2.621
σ_L	SD log-normal distribution of productivities in region L	0.552	0.879
μ_H	Mean log-normal distribution of productivities in region H	2.460	2.946
σ_H	SD log-normal distribution of productivities in region H	0.460	0.816
δ_H	Productivity premium	0.176	0.142
λ_L	Destruction rate in region L	0.041	0.022
λ_H	Destruction rate in region H	0.053	0.018
$\rho U(\tilde{m})$	Value of unemployed search	3.143	3.817
z	Value of leisure	-9.516	-12.179

0.25 which produces a reasonable value of θ in the calibration. The discount rate, ρ, is consistent with the annual average return of a diversified portfolio of 8 percent following Heckman and Pagés (2000) who uses this value for calibration of Latin American labour markets. Finally, the hourly minimum wage, $\tilde{m}$, of $R\$$ 4.925 is consistent with the monthly minimum wage of $R\$$ 788 in 2015.

The remaining parameters are estimated in the model by using the sample moments from Table 3.1 and following the identification procedure from the previous section. The estimated contact rate $m(\theta)$, 0.219, implies that job offers arrive approximately every 4.5 months on average. Given the values for A, η, and the estimate for $m(\theta)$, the implied estimate for θ is 0.77, that is, there are approximately 1.3 workers looking to fill the same vacancy. The estimate for ϕ indicates that around 25 percent of the unfilled vacancies are generated in region L and the remaining 75 percent in region H. In steady-state, the previous estimates allow us to determine the rates of vacancies, v_j, which are 6.3 and 2.1 vacancies posted per 100 workers in region H and L, respectively.[14] The estimated flow

[14]In the calibration procedure v_L is determined by a standard free entry condition, while v_H is endogenously determined by the rest of the equilibrium objects in the model.

cost of a vacancy, c, is relatively high with respect to the estimates of mean productivities in both regions.[15] This might suggest that employers are deterred from posting vacancies due to their high costs per period, even though vacancies are filled on average in less than 4 months.

I turn now to the supply-side parameters in Table 3.2. The first four estimates are location and scale parameters of the match productivity distributions. Given the log-normality assumption, the expected value of a match-specific productivity, x, in region j is given by $\exp[\mu_j^y + (\sigma_j^y)^2/2]$, and the corresponding variance is given by $[\exp((\sigma_j^y)^2) - 1]\exp[2\mu_j^y + (\sigma_j^y)^2]$, with $j = L,\ H$ and $y = l,\ h$. Using the estimates in Table 3.2, the expected match-specific productivity is slightly lower in region L than in H for type-l workers, approximately 12.3 versus 13. These results reinforce the idea that type-l workers earn a higher wage in H not because more productive workers are employed in H, but rather because workers with similar productivities are more productive if they are employed in this region. In turn, type-h workers in region L have a much smaller match-specific productivity than their counterparts in H, approximately 20.2 versus 26.6 which suggests that the wage gap between these workers, unlike type-l ones, is also driven by a skill component.[16] As expected, the dispersion in productivities is higher among type-h than among type-l workers for both regions.

The productivity premium parameter, δ_H, suggests that type-l and type-h workers are approximately 18 and 14 percent more productive if these are employed in region H, respectively. The estimates for the dismissal rates, λ_L and λ_H, suggest that the expected duration of a job among type-l workers is shorter in region H than in L, while the opposite is true among type-h workers. Notice that the expected duration of a job is shorter for type-l workers on average around 21 months, while this is significantly longer for type-h ones around 50 months. We

[15] This estimate represents the flow cost faced by a firm's owner in region L whose value of an unfilled vacancy, unlike that in region H, is not affected by the productivity premium, δ_H.

[16] The results are in line with the estimates obtained from the Oaxaca-Blinder decomposition. The regional wage gap is not only driven by differences in the skill composition between regions but also because workers conditional on education are more productive in region H.

should bear in mind that these estimates apply to workers aged 18 to 30 years old, thus the relative brevity of a job is not surprising. As expected, the value of the unemployed search or the implicit reservation wage as Flinn (2006) refers to, $\rho U(\tilde{m})$, is larger for the highest educated workers.[17] Finally, the estimates for the flow value while a worker is unemployed, z, are negative for both skill types which suggest that workers face disutility of unemployment.[18]

Table 3.3 compares moments predicted by the model with those obtained from the data in Table 3.1 at an aggregate level, that is, aggregating across skill types within each region.

Table 3.3: Descriptive Statistics, Model Vs. Data

	Data	**Model**
OLF Rate	0.340	0.340
Unemployment Rate	0.110	0.110
Employment Rate in L	0.148	0.148
Employment Rate in H	0.402	0.402
Mean Duration in L	28.670	28.670
Mean Duration in H	29.420	29.420
Mean Hourly Wage in L	8.002	8.061
SD Hourly Wage	(5.117)	(5.049)
Mean Hourly Wage in H	10.162	10.149
SD Hourly Wage	(7.585)	(7.557)
Mean Wage Diff. ($\bar{w}_H - \bar{w}_L$)	2.16	2.09
Regional Diff.	1.79	1.73
Educational Diff.	0.37	0.36
$\Pr(w_L = \tilde{m})$	0.183	0.184
$\Pr(w_H = \tilde{m})$	0.057	0.056

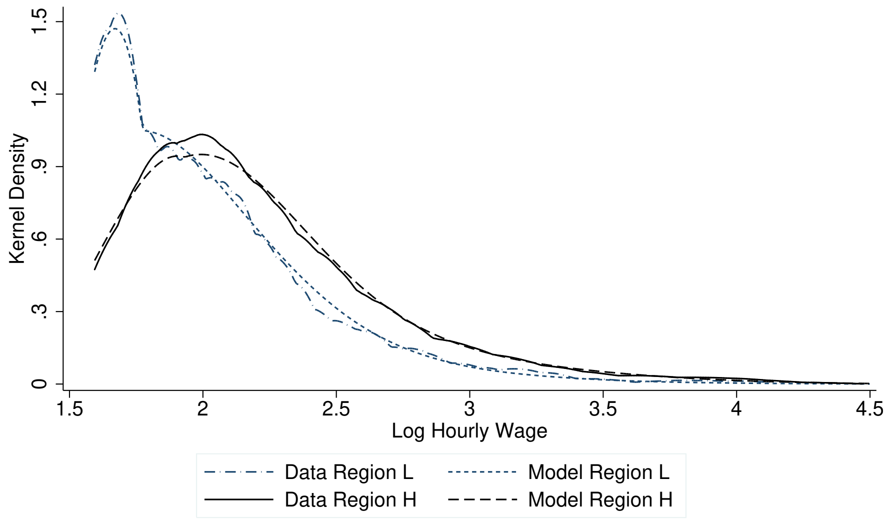
Source: PNAD, 2015. Sample comprises full-time formal workers, unemployed and individuals out of the labour force, aged 18-30 years from Minas Gerais (region L) and Sao Paulo (region H).

The calibrated model does a good job of matching the data. Model predictions for labour market states, employment durations and the proportion of minimum wage workers fit the data perfectly. Regarding mean hourly wages, the fit is not perfect since wages are generated by pseudo-random draws, thus the mean hourly wage and its standard deviation differ with a few cents from those observed in the data, particularly in region L in which the proportion of minimum

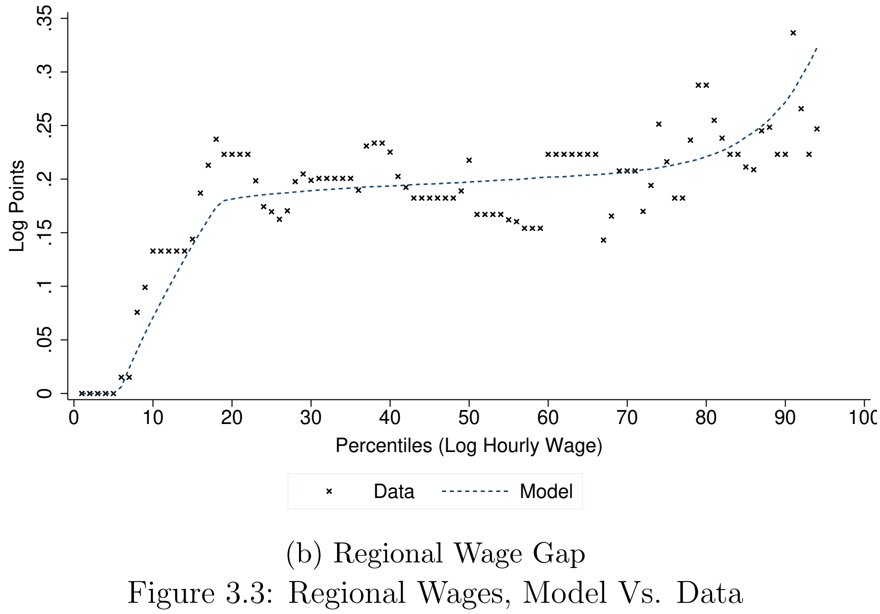
[17] Although this is not a parameter per se, it is useful to treat it as such for estimation purposes.

[18] Hornstein et al. (2011) point out that sizeable frictional dispersion relies on large negative values of z, particularly in search models that do not account for job to job transitions.

wage workers is large. Nevertheless, wage distributions generated by the model do a reasonable job of matching those from the data, particularly capturing the focal point at the minimum wage level in region L as we can see in the top panel of Figure 3.3 which compares the kernel density of log hourly wages predicted by the model with those from the data by region. Finally, the bottom panel of Figure 3.3 shows the wage percentile gap between regions as predicted by the model to the corresponding observed from the data. The model does a good job of matching the regional wage gap which is zero up to the 5th percentile because workers are minimum wage earners in both regions, increases rapidly up to the 20th, remains somehow stable thereafter and increases again in the last decile.



(a) Kernel Densities of Regional Wages



(b) Regional Wage Gap

Figure 3.3: Regional Wages, Model Vs. Data

3.4 Results

3.4.1 Counterfactual and Policy Experiments

I use the estimated parameters of the model from Table 3.2 to perform counterfactual and policy experiments. The former illustrates the use of the model and provides several explanations of regional inequalities, others than minimum wage policies, and the latter is motivated by the desire to understand the direct and indirect effects of the minimum wage on regional labour market outcomes. I perform four counterfactual experiments by changing the parameters that determine wage-setting rules (β_j and δ_j^y) and labour market transitions (λ_j^y and v_j) between regions.[19] A change in these parameters not only affects wages and employment directly but also indirectly through changes in the value of unemployment share, $\rho U^y(\tilde{m})$. In partial equilibrium, $\rho U^y(\tilde{m})$ affects the proportion of labour market participants and determines wages in both regions. In general equilibrium, $\rho U^y(\tilde{m})$ also affects labour market tightness, θ, the contact rate, $m(\theta)$ and the probability of finding a job in region L, ϕ as this constrains the number of feasible matches. A detailed general equilibrium analysis can be found in Appendix 3.C.

In this section, I focus the analysis on the effects of the minimum wage on labour market states and wages. I start by studying the effects of a small increase in the hourly minimum wage from $R\$$ 4.925, which was due to expire at the end of 2015, to $R\$$ 5.5, which was the hourly minimum wage in 2016 on labour market outcomes. I estimate these effects under two specifications. In the first specification, all primitive parameters and contact rates are fixed except for the value of unemployed search, $\rho U^y(\tilde{m})$, which is endogenous to changes in the minimum wage, $\tilde{m}$. In the second specification, not only $\rho U^y(\tilde{m})$ but also the contact rates are endogenous to changes in $\tilde{m}$, while holding the other

[19] I change these parameters one at a time while holding the minimum wage and all the other primitive parameters in their point estimates and use the model equations to solve for the endogenous variables in the model.

parameters in their estimate points. Tables 3.4 and 3.5 show the results of this policy experiment at an aggregate and a skill-group level, respectively.

Table 3.4: Small Increase in the Minimum Wage

	Baseline	**Exogenous Contact Rates**	**Endogenous Contact Rates**
m(θ)	0.219	0.219	0.213
θ	0.767	0.767	0.725
ϕ	0.252	0.252	0.232
OLF Rate	0.340	0.337	0.351
Unemployment Rate	0.110	0.113	0.113
Employment Rate in L	0.148	0.146	0.131
Employment Rate in H	0.402	0.405	0.405
Mean Duration in L	28.670	28.568	28.563
Mean Duration in H	29.420	29.184	29.175
Mean Hourly Wage in L	8.061	8.298	8.242
SD Hourly Wage	(5.049)	(4.990)	(4.976)
Mean Hourly Wage in H	10.149	10.265	10.197
SD Hourly Wage	(7.557)	(7.487)	(7.480)
Mean Wage Gap ($\bar{w}_H - \bar{w}_L$)	2.09	1.97	1.95
Regional Gap	1.73	1.61	1.60
Educational Gap	0.36	0.35	0.35
Pr($w_L = \tilde{m}$)	0.184	0.267	0.283
Pr($w_H = \tilde{m}$)	0.056	0.109	0.119

Table 3.5: Small Increase in the Minimum Wage by Skill Groups

	Region L			**Region H**		
	Baseline	**Exogenous Contact Rates**	**Endogenous Contact Rates**	**Baseline**	**Exogenous Contact Rates**	**Endogenous Contact Rates**
Employment						
Type-l	0.795	0.795	0.795	0.708	0.710	0.710
Type-h	0.205	0.205	0.205	0.292	0.290	0.290
R_j^l	3.143	3.184	3.056	3.560	3.606	3.462
R_j^h	3.817	3.826	3.701	4.217	4.228	4.089
Mean Wage						
Type-l	7.233	7.479	7.426	8.157	8.299	8.234
	(2.792)	(2.704)	(2.687)	(2.900)	(2.840)	(2.829)
Type-h	11.314	11.588	11.524	14.956	15.139	15.069
	(8.885)	(8.925)	(8.916)	(11.818)	(11.826)	(11.825)
Wage Gaps						
Type-l						
50th/10th	0.258	0.169	0.157	0.375	0.320	0.310
90th/50th	0.520	0.511	0.516	0.462	0.456	0.460
90th/10th	0.778	0.680	0.673	0.837	0.777	0.770
Type-h						
50th/10th	0.541	0.466	0.457	0.655	0.636	0.642
90th/50th	0.864	0.855	0.860	0.880	0.875	0.878
90th/10th	1.405	1.321	1.317	1.535	1.511	1.520

The first column in Table 3.4 shows the estimates from the baseline calibration, while the second and third columns show the estimates for the policy experiment. Under exogenous contact rates to changes in $\tilde{m}$, the size of unemployment increases in 0.3 percentage points, however, aggregate employment is not adversely affected as the minimum wage has a positive effect on the value of unemployed search, $R_L^y = \rho U^y(\tilde{m})$, with $y = l,\ h$, (See Table 3.5) which raises the labour force participation rate. Mean hourly wages increase by 24 cents in region L and 12 cents in H, while wage dispersions decrease because the minimum wage is more binding in the wage distribution of both regions. In fact, the proportion of minimum wage workers increases by 8.3 and 5.3 percentage points in region L and H, respectively. The increase in mean wages has a direct and indirect component. The latter is given by the increase in $\rho U^y(\tilde{m})$ which raises mean wages by approximately 3.5 cents in each region. This indirect effect can be seen as a spillover effect of the minimum wage as $\rho U^y(\tilde{m})$ determines wages throughout the wage distribution. As expected the regional wage gap falls mostly because of the direct effect of the minimum wage on wages. It is important to point out that the previous results can be seen as partial equilibrium effects of changes in the minimum wage as contact rates are invariant to them.

Under endogenous contact rates to changes in $\tilde{m}$, unemployment rate increases in the same proportion as before and aggregate employment falls in 1.4 percentage points. The intuition is that an increase in $\tilde{m}$ deters firms from creating vacancies because of the expected increase in labour costs, thus θ decreases and so does $m(\theta)$. There are also equilibrium effects that are driven by the decrease in $\rho U^y(\tilde{m})$ which deters workers from participating in the labour market and counteracts the positive direct effect of the minimum wage on wages. The regional wage gap decreases further under endogenous contact rates because the minimum wage has both an increasing direct and a decreasing spillover effect on wages. The former is relatively more significant in region L and the latter in H given the proportion of minimum wage workers in each region.

The first two rows in Table 3.5 show the skill composition in each region.

Notice that there is a small increase in the fraction of type-l workers employed in H following the increase in $\tilde{m}$ under both specifications. Under exogenous contact rates, the increase in $R_L^l = \rho U^l(\tilde{m})$ is higher than that in $R_L^h = \rho U^h(\tilde{m})$, thus the relative labour force participation of type-l workers increases. Under endogenous contact rates, the fall in the value of unemployed search seems to have a more adverse effect on the participation rate among type-h workers. Table 3.5 also provides information on wage inequality within each region and skill group. Lower-tail inequality given by the wage gap 50th/10th decreases within each educational group in region L and among type-l workers in region H. Notice that the decline in the 50th/10th gap is more significant when we account for endogenous contact rates to changes in $\tilde{m}$. Recall that $\rho U^y(\tilde{m})$ falls under this specification which lowers the 50th percentile while the net direct effect of the minimum wage on the 10th is still positive. Upper-tail inequality seems not to be affected as the $50th$ and $90th$ percentiles are only indirectly affected by the minimum wage through changes in $\rho U^y(\tilde{m})$. In fact, under the model specification, any change in upper-tail inequality would be merely the result of a truncation effect of $\tilde{m}$ on the wage distribution.

Although the minimum wage in Brazil is set nationally, we could intuit that a policymaker might use the minimum wage as a tool to reduce the wage gap between regions. I repeat the previous exercise by assuming that the increase in the minimum wage only takes place in region L while holding the minimum wage in its baseline value of $R\$$ 4.925 in region H. The results of this experiment at an aggregate and a skill-group level can be found in Tables 3.6 and 3.7, respectively.

Some important features can be drawn from this experiment. The increase in the minimum wage affects labour market outcomes in region L directly and indirectly, while labour market outcomes in region H are only affected indirectly through changes in the value of unemployed search, $\rho U^y(\tilde{m})$. Notice that the size of employment in region H increases with respect to the previous experiment which is driven by the larger decrease in the size of employment in region-L. As

Table 3.6: Small Increase in the Minimum Wage only in Region L

	Baseline	**Exogenous Contact Rates**	**Endogenous Contact Rates**
m(θ)	0.219	0.219	0.213
θ	0.767	0.767	0.726
ϕ	0.252	0.252	0.222
OLF Rate	0.340	0.338	0.352
Unemployment Rate	0.110	0.111	0.111
Employment Rate in L	0.148	0.144	0.124
Employment Rate in H	0.402	0.407	0.413
Mean Duration in L	28.670	28.579	28.569
Mean Duration in H	29.420	29.172	29.150
Mean Hourly Wage in L	8.061	8.296	8.241
SD Hourly Wage	(5.049)	(4.995)	(4.980)
Mean Hourly Wage in H	10.149	10.115	10.043
SD Hourly Wage	(7.557)	(7.486)	(7.480)
Mean Wage Gap ($\bar{w}_H - \bar{w}_L$)	2.09	1.82	1.80
Regional Gap	1.73	1.48	1.46
Educational Gap	0.36	0.35	0.35
Pr($w_L = \tilde{m}$)	0.184	0.269	0.283
Pr($w_H = \tilde{m}$)	0.056	0.055	0.063

Table 3.7: Small Increase in the Minimum Wage only in Region L by Skill Groups

	Region L			**Region H**		
	Baseline	**Exogenous Contact Rates**	**Endogenous Contact Rates**	**Baseline**	**Exogenous Contact Rates**	**Endogenous Contact Rates**
Employment						
Type-l	0.795	0.794	0.795	0.708	0.709	0.710
Type-h	0.205	0.206	0.205	0.292	0.291	0.290
R_j^l	3.143	3.170	3.045	3.560	3.590	3.449
R_j^h	3.817	3.830	3.719	4.217	4.232	4.109
Mean Wage						
Type-l	7.233	7.473	7.422	8.157	8.172	8.102
	(2.792)	(2.703)	(2.689)	(2.900)	(2.901)	(2.895)
Type-h	11.314	11.589	11.533	14.956	14.963	14.899
	(8.885)	(8.925)	(8.918)	(11.818)	(11.816)	(11.818)
Wage Gaps						
Type-l						
50th/10th	0.258	0.168	0.156	0.375	0.374	0.378
90th/50th	0.520	0.511	0.516	0.462	0.461	0.465
90th/10th	0.778	0.679	0.672	0.837	0.835	0.843
Type-h						
50th/10th	0.541	0.466	0.459	0.655	0.654	0.660
90th/50th	0.864	0.855	0.859	0.880	0.879	0.883
90th/10th	1.405	1.321	1.318	1.535	1.534	1.542

match productivities are not restricted by the new minimum wage in region H, the skill composition of the workforce in this region changes in favour of type-l workers as can be seen in Table 3.7. This is why the mean wage in region H decreases even when the minimum wage has a positive spillover effect on wages under exogenous contact rates. Consequently, the regional wage gap falls further as the mean wage increases in L and decreases in H irrespectively of the model specification. Finally, the 50th/10th wage gaps decreases only in region L, while these are not affected in H as spillover effects of the minimum wage affect the entire wage distribution across skill types.

The bottom line from the previous policy experiment is that changes in minimum wage policies that target one region have relevant indirect (spillover effects) on the labour market outcomes of the other one. The associated spillover effects of the minimum wage on regional labour market outcomes are relatively small compared to those from the counterfactual exercises in the Appendix section, particularly when contact rates are assumed to be exogenous. This is the result of the small change in the minimum wage that was assumed for these policy experiments. In the next section, I explore the effects of further increases in the minimum wage on labour market states and welfare measures.

3.4.2 Welfare Impact of the Minimum Wage

The results in this section rely on the assumptions we make regarding the model structure. I consider the effects of the minimum wage on labour market states and welfare under the assumption that contact rates are exogenous to changes in the minimum wage. From the results in Table 3.4, we concluded that a small change in the minimum wage increases the value of unemployed search which encourages participation, and this counteracts the adverse effects of the minimum wage on employment. These results seem to agree with most of the empirical evidence on the small adverse effects of the minimum wage on employment in Brazil.

Figure 3.4 depicts the proportion of workers in four labour market states: out of the labour force, unemployed, employed in L and employed in H aggregating across skill types and Figure 3.5 depicts their corresponding welfare measures as functions of the hourly minimum wage while holding all the other parameters that characterize the model equilibrium fixed to their estimated values in Table 3.2.

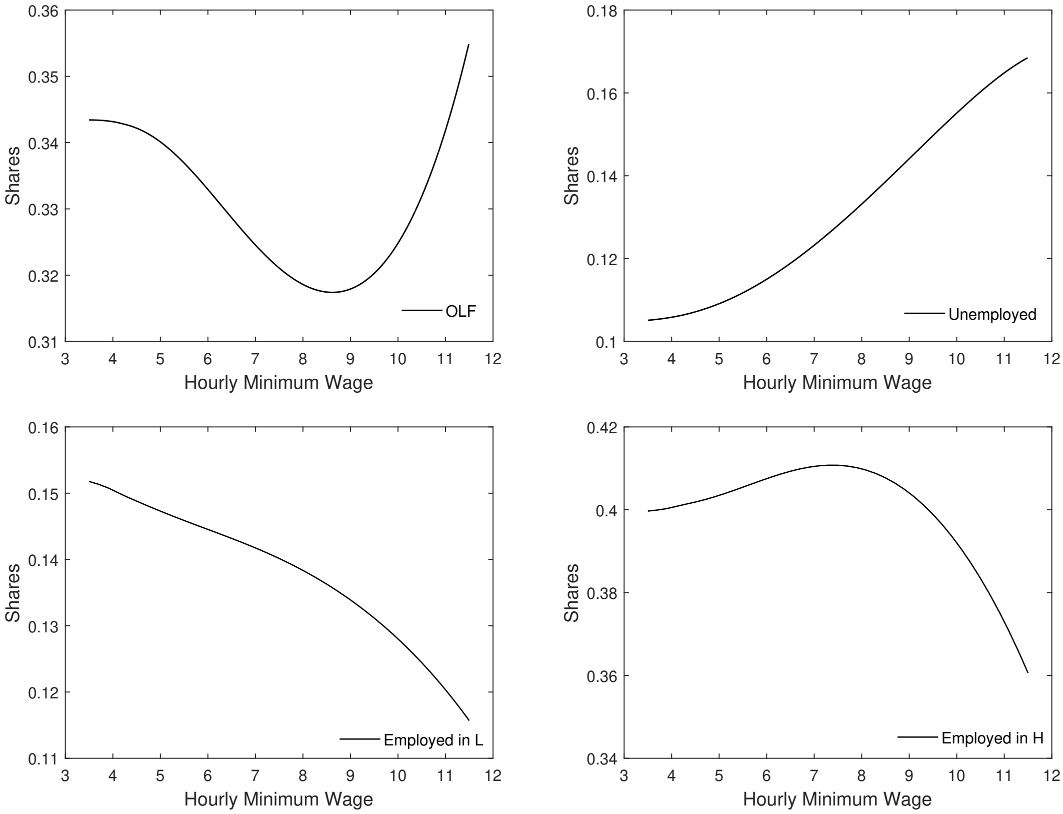


Figure 3.4: Shares of Labour Market States

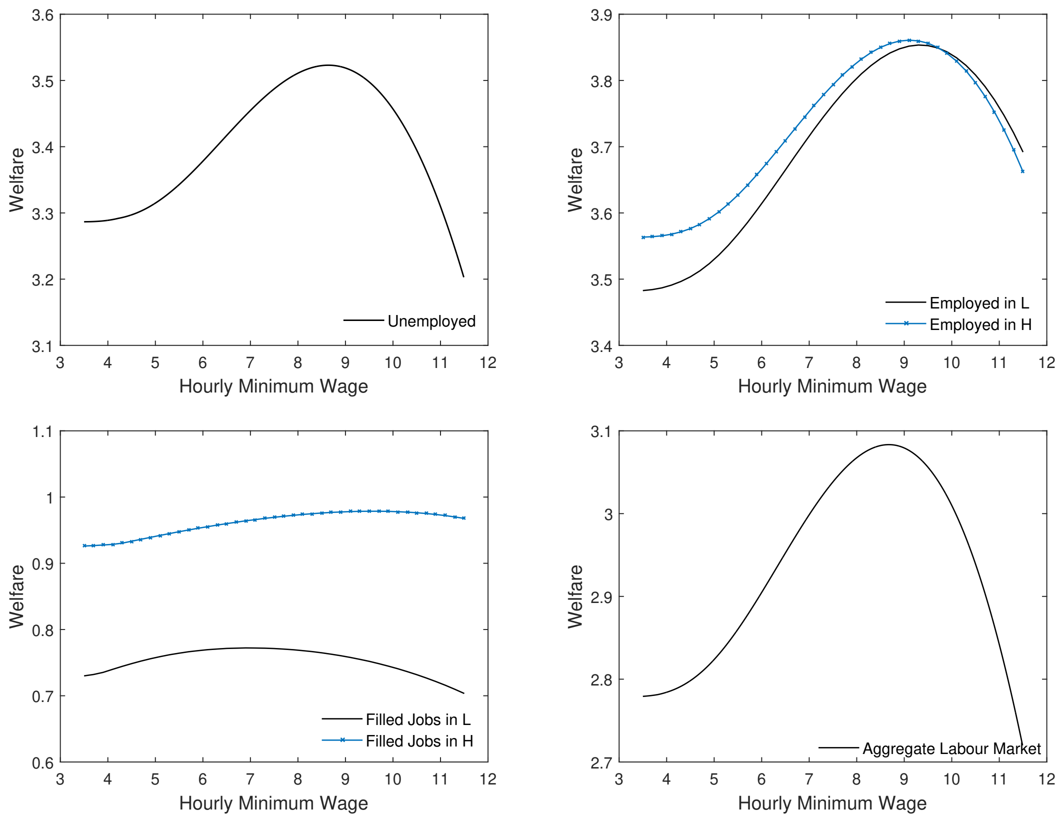


Figure 3.5: Welfare Measures

Figure 3.4 shows that the share of individuals out of the labour force has a negative relationship with the value of unemployed search or unemployment welfare in Figure 3.5. Unemployment rate grows steadily in the minimum wage and only changes its pattern with very high values of the minimum wage as workers would rather leave the labour market than remain unemployed. Notice that the size of employment in region L decreases monotonically with new increases in the minimum wage, while employment in region H increases up to approximately $R\$$ 7.4 per hour and decreases thereafter.

Unemployment welfare reaches its maximum at an hourly minimum wage of approximately $R\$$ 8.6 as can be seen in Figure 3.5. The implied value of unemployed search at this point is approximately $R\$$ 3.52. As expected, employed workers are the most benefit from increases in the minimum wage as their welfare increases faster in the minimum than any other welfare measure in the labour market. Employment welfare is larger for workers in region H than in L, particularly for low values of the minimum wage. This is the result of the difference in the productivity premium between regions. However, employment welfare seems to converge between them with large values of the minimum wage. On the demand side, the aggregate welfare of firms' owners with filled vacancies reaches its maximum at $R\$$ 6.85 in region L and $R\$$ 9.74 in H. The fall in the welfare of firms' owners after reaching its maximum in each region implies that the positive selection effect of the increase in the minimum wage is not large enough to offset the higher labour costs. Finally, the aggregate labour force welfare reaches its maximum at an hourly minimum wage of $R\$$ 8.67.

Analogous figures for labour market states and welfare measures as functions of the hourly minimum wage by skill groups can be found in Figures 3.D.1 and 3.D.2 in the Appendix section, respectively. As expected, labour market states and welfare measures are more sensitive to changes in the hourly minimum wage among type-l workers. Thus, maximums and minimums are reached at a lower value of the hourly minimum wage among this skill type. For instance, the value of the hourly minimum wage that minimizes the proportion of individuals out of the labour force, which is also the value that maximizes the value of unemployed search, is $R\$$ 8.46 among type-l workers and $R\$$ 11 among type-h ones. Table 3.8 compares labour market states and welfare measures at the baseline hourly minimum wage of $R\$$ 4.925 with those at the optimal minimum wage, that is, the hourly minimum wage that maximizes the aggregate labour market welfare.

Table 3.8: Results of Welfare Analysis

	Pooled		**Low-Skilled Workers (Type-l Workers)**		**High-Skilled Workers (Type-h Workers)**	
	Baseline	**Optimum**	**Baseline**	**Optimum**	**Baseline**	**Optimum**
$\tilde{m}$	4.925	8.67	4.925	8.53	4.925	10.86
OLF Rate	0.340	0.317	0.336	0.309	0.354	0.336
Unemployment Rate	0.110	0.140	0.128	0.164	0.055	0.071
Employment Rate in L	0.148	0.136	0.156	0.144	0.121	0.108
Employment Rate in H	0.402	0.407	0.380	0.382	0.470	0.485
Unemployment Welfare	551.88	587.17	523.88	563.60	636.17	667.67
Employment Welfare in L	587.46	640.05	560.32	618.49	669.29	718.93
Employment Welfare in H	598.73	642.49	570.71	619.44	683.13	716.02
Filled Jobs Welfare in L	126.05	127.18	100.33	97.43	203.21	217.48
Filled Jobs Welfare in H	156.58	162.80	109.36	112.47	298.26	313.27
Aggregate Welfare	469.82	513.89	428.73	476.19	602.14	647.55

Under the optimal minimum wage, the share of individuals out of the labour force decreases in 2.7 percentage points among type-l workers and 1.8 percentage points among type-h ones because of the increase in their corresponding values of unemployed search. The implied value of unemployed search, $\rho U(\tilde{m})^y$, at the optimal minimum wage is $R\$$ 3.38 among type-l workers and $R\$$ 4 among type-h ones, that is, an increase of 24 cents per hour for the former and 18 cents per hour for the latter with respect to their corresponding baseline values in Table 3.2. Unemployment rate increases at the optimum for both skill types; however, this is larger among type-l workers as the minimum wage is more binding for this skill group. The size of employed workers in region L decreases for both skill types, while employment in region H increases at the optimal minimum wage, particularly among type-h workers. Notice that all welfare measures are larger at the optimal minimum wage, except for the welfare of the firms' owners with vacancies filled by type-l workers in region L as the positive selection effect at the optimum is not large enough to offset the higher labour costs. Finally, the aggregate labour force welfare (equation (3.19)) reaches its maximum at an hourly minimum wage of $R\$$ 8.53 among type-l workers and at $R\$$ 10.86 among type-h ones. Thus, the aggregate welfare at the optimum is approximately 11 percent for the former and 8 percent for the latter larger than their corresponding welfares at the baseline value.

As the minimum wage increases in both regions, it is difficult to distinguish between direct and spillover effects of the minimum wage on labour market states and welfare measures. In order to provide a clearer picture of how spillover effects of the minimum wage are generated between regions, I allow for the minimum wage to change in region L, while this is held constant at its baseline calibration value of $R\$$ 4.925, in region H. Figure 3.6 and 3.7 compare labour market states and welfare measures from this experiment with those from the previous one (baseline), in which the minimum wage changes in both regions at the same time.

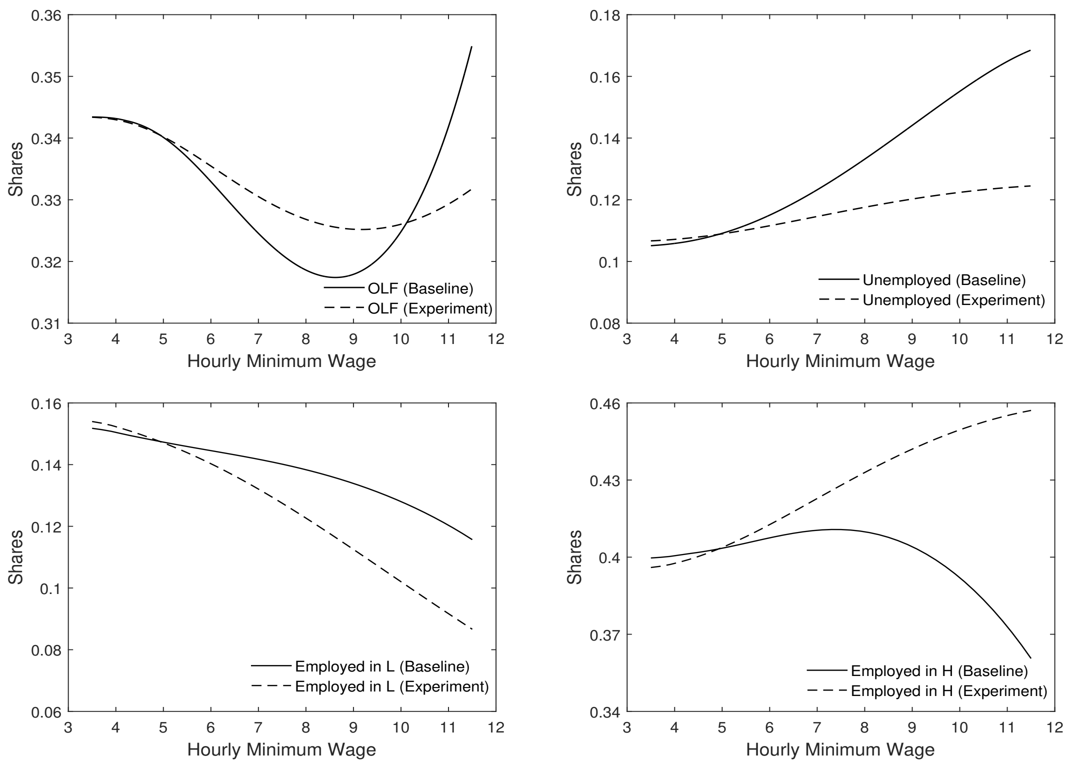


Figure 3.6: Shares of Labour Market States of an Increase in $\tilde{m}$ only in L

Baseline figures show labour market states when the hourly minimum wage increases in both regions (See Figure 3.4), while experiment figures show those when the hourly minimum wage increases only in region L and remains at its baseline value of $R\$$ 4.925 in region H.

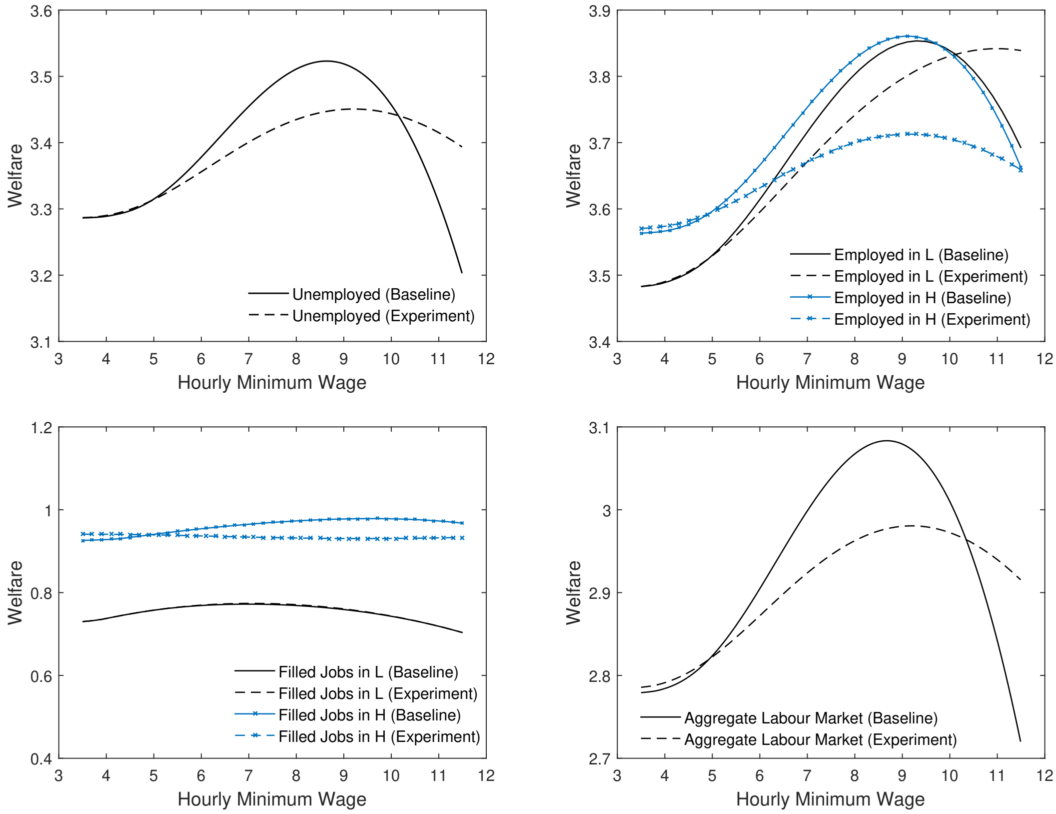


Figure 3.7: Welfare Measures of an Increase in $\tilde{m}$ only in L

Baseline figures show welfare measures when the hourly minimum wage increases in both regions (See Figure 3.5), while experiment figures show those when the hourly minimum wage increases only in region L and remains at its baseline value of $R\$$ 4.925 in region H.

Figure 3.6 shows that the decrease in the population out of the labour force is less significant under this experiment as the minimum wage has a smaller effect on the value of unemployed search because this only affects employment perspectives in region L. As expected, the growth in unemployment is less steep as new increases in the minimum wage only constrain feasible matches in region L. Employment falls sharper in region L, while this increases rapidly in region H. The latter is a clear example of a spillover effect of the minimum wage on employment which is driven by the fall in the employment share of region L and the increase in the participation of individuals out of the labour force.

Figure 3.7 provides information on the spillover effects of the minimum wage on welfare measures between regions. As the value of unemployed search grows, employment welfare increases in both regions. This increase is more noticeable in region L as the minimum wage has both a direct and an indirect effect on the value of employment, while the minimum wage only affects indirectly the value of being employed in region H. In regard to the demand side of the labour market, firm owners' welfare in region H initially falls with respect to the baseline experiment as firms in region H faces higher values of unemployed search and relatively constant productivities per worker and only recovers when the former decreases. In region L, there is a positive selection effect as before because the increases in the minimum wage lead more productive workers to fill vacancies in this region. Although aggregate welfare is smaller, this reaches its maximum at a higher value of the hourly minimum wage approximately $R\$$ 9.2.

To sum up at the optimal value of the minimum wage of $R\$$ 9.2, the population out of the labour force falls in 1.5 while unemployment increases in 1.1 percentage points from its baseline value. Employment in region L decreases in 3.7 whereas employment in region H increases in 4.1 percentage points as an indirect effect of the increase in the minimum wage in L, thus aggregate employment increases. As the value of unemployed search increases at the optimum, mean wages are positively affected in both regions. The estimated spillover effect of the minimum wage in the mean wage of region H is an increase of approximately 14 cents per hour.

Finally, I would like to discuss informally the implications of the interaction between regional labour markets. Specifically, how the results would be affected if workers have access to jobs in only one of the two regions. Table 3.9 shows the results of this analysis at the baseline hourly minimum wage of $R\$$ 4.925.

Columns 2 and 5 in Table 3.9 show the estimates from a model in which there are no vacancies available in region H, that is, the probability of finding a job in H, $(1-\phi)$, is zero. Thus, a type-y worker, with $y = l,\ h$, is restricted to search for jobs only in region L. Recall that the destruction rate for type-l workers in region H, λ_H^l, is larger than that in L, λ_H^l while the opposite is true among type-h ones (See Table 3.2). This implies that more type-l workers and less type-h ones will be available to fill vacancies in region L, thus employment grows for the former

Table 3.9: Welfare Analysis by Restricting Employment to only one Region

	Low-Skilled Workers (Type-l Workers)			**High-Skilled Workers (Type-h Workers)**		
	Baseline	**Region L**	**Region H**	**Baseline**	**Region L**	**Region H**
$\tilde{m}$	4.925	4.925	4.925	4.925	4.925	4.925
OLF Rate	0.336	0.336	0.336	0.354	0.354	0.354
Unemployment Rate	0.128	0.113	0.133	0.055	0.066	0.051
Employment Rate in L	0.156	0.551	-	0.121	0.580	-
Employment Rate in H	0.380	-	0.531	0.470	-	0.595
Unemployment Welfare	523.88	523.95	523.85	636.17	636.22	636.16
Employment Welfare in L	560.32	560.38	-	669.29	669.32	-
Employment Welfare in H	570.71	-	570.69	683.13	-	683.11
Filled Jobs Welfare in L	100.33	100.34	-	203.21	203.28	-
Filled Jobs Welfare in H	109.36	-	109.37	298.26	-	298.32
Aggregate Welfare	428.73	423.37	430.86	602.14	548.05	616.26

Table 3.9 shows labour market states and welfare measures at the value of the minimum wage in the baseline calibration (Table 3.8). Columns 2 and 5 show the estimates for a model in which a type-y worker is restricted to search for jobs only in region L and, columns 3 and 6 show analogous estimates when employment is restricted to region H.

and falls for the latter. Notice that welfare measures are not affected significantly. However, as workers do not have access to region H, in which welfare is higher because of the productivity premium, aggregate welfares decrease for both skill types with respect to their baseline estimates. Columns 3 and 6 in Table 3.9 show instead analogous estimates when employment is restricted to region H. This experiment has pretty much the opposite effect, a decrease in the employment of type-l workers and an increase in that of type-h ones. Aggregate welfares increase because employed workers are benefited from the high productivity premium in this region, particularly the most educated ones. In conclusion, these results suggest that workers might benefit from regional mobility conditional on the productivity of the region that they have access to and their corresponding skill type.

We must keep in mind that the validity of the previous results relies on the assumption of exogenous contact rates to changes in the minimum wage. In practice, the contact rate, $m(\theta)$, the probability of finding a job in either region L or H, which is given by the parameter ϕ, as well as other primitive parameters that determine the steady-state equilibrium may vary with changes in the minimum wage as was seen in Table 3.4. Nevertheless, the results of the welfare analysis under exogenous contact rates seem to be more in line with the empirical evidence on the small adverse effects of the minimum wage on employment in Brazil.

An obvious extension of the current framework is to allow for on-the-job search as labour market transitions among young participants might call into questions the previous results. For instance, Flinn and Mabli (2008) show that allowing for on-the-job search produces a higher value of the optimal minimum wage because workers have a much lower bargaining power parameter, β_j, which determines match productivities in their model. In fact, the match productivity, x, in this study is an inverse function of β_j and δ_H^y. Thus, the larger these parameters are, the lower the minimum wage that maximizes aggregate welfare will be (See Figure 3.D.3 in the Appendix section). In this sense, the present study might also benefit from the use of administrative data to estimate additional parameters of the matching function and others that determine match productivities and thus, the minimum wage that maximizes welfare.

3.5 Conclusion

This paper develops a simple two-region model of wage determination and labour market dynamics under a binding minimum wage. Regions differ in terms of productivity and firms share the same pool of unemployed workers. In such a scenario, a change in the parameters that determine wage and employment-setting rules in one region affects labour market outcomes in the other one through changes in the value of unemployed search (worker's outside option). The model is further used to assess the interaction between regional labour market outcomes and the minimum wage motivated by the desire of providing potential explanations of regional inequalities as well as assessing the efficiency of the minimum wage as a welfare-improving instrument.

The model is calibrated by using Brazilian microdata on wages and employment durations from PNAD, 2015. In the baseline calibration of the model, an increase in the hourly minimum wage from $R\$$ 4.925 to $R\$$ 5.5 increases the value of unemployed search for both low and high-skilled workers which raises labour force participation rate and thus, aggregate employment is not adversely affected. These results rely on invariant contact rates to changes in the minimum wage. When this assumption is relaxed, the increase in the minimum wage lowers aggregate employment as firms are deterred from creating new vacancies because of the higher labour costs. Mean wages unlike employment increase unambiguously in the minimum wage irrespectively of the worker's skill type or region. The increase is larger when contact rates are exogenous because the minimum wage has both a positive direct and an indirect effect —through the increase in the value of unemployed search—on wages. In turn, when we allow for endogenous contact rates, the positive direct effect of the minimum wage is counteracted by a negative spillover effect on wages; however, the latter is not large enough to outweigh the former. The hourly wage gap between regions falls by approximately 28 cents and lower-tail inequality within skill groups falls in region L, particularly under endogenous contact rates as minimum wage workers face both effects of the minimum wage, while workers earning above the minimum are only affected by its spillover effects.

The results obtained under the assumption of exogenous contact rates to changes in the minimum wage seem to be more consistent with the empirical evidence on the small adverse effects of the minimum wage on Brazilian employment. Thus, I allow for further increases in the minimum wage under this assumption to determine the optimal minimum wage that maximizes aggregate labour market welfare. This analysis suggests a welfare-maximizing minimum wage of $R\$$ 8.53 among low-skilled workers and $R\$$ 10.86 among high-skilled ones. At the respective optimums, the value of unemployment share increases in 24 cents per hour for the former and 18 cents per hour for the latter which can be interpreted as a positive spillover effect of the minimum wage on their corresponding wages. The increase in the value of unemployed search also lowers the proportion of individuals out of the labour force for both skill types which counteracts the adverse effect of the minimum wage on employment at least in the most productive region. However, aggregate employment is adversely affected among low-skilled workers given their relatively smaller productivities. As expected, the aggregate labour market welfare is mainly driven by the increase in the welfare of employed workers; however, welfare measures of other agents in the economy also increase at the optimum. Finally, the specification of the model suggests that welfare is larger when unemployed workers have access to the most productive region than when these are restricted to searching for jobs in the least productive one.

Of course, the assumption of exogenous contact rates may be questionable. In practice, it is expected that the contact rates, as well as other primitive parameters, change with increases in the minimum wage. This study provided information on the effects of a small increase in the minimum wage on labour market outcomes under endogenous contact rates. However, we have no way to estimate credible contact rates or other primitive parameters for large values of the minimum wage such as the optimal values. Finally, an obvious extension of the current framework is to introduce on-the-job search which may have important implications on the determination of labour market outcomes, particularly for young labour market participants whose information characterized the set of parameters in this study.

Appendices

3.A Who are the Minimum Wage Workers in Brazil?

It has been well established in the literature that minimum wage workers are overrepresented in certain occupations, tasks and demographic groups, particularly in developed countries. This literature defines minimum wage workers as young individuals with short job histories, with less than a bachelor's degree, typically performing low-skill tasks. In Brazil, minimum wage workers seem to be overrepresented in broader demographic and occupational groups. This section provides information on who the minimum wage workers are in Brazil which is useful to generate an adequate sample for the calibration of the model in this paper. I use a variety of household surveys from Brazil namely PNAD (National household survey, 2002-2015), PNADC (National continuous household survey, 2015 and 2016), and Censo (Census, 2010). Detailed information on the sample composition can be found in the footnote of each table and figure. Table 3.A.1 starts this discussion by providing information on the proportion of workers at and below the minimum wage level by occupation.

Table 3.A.1: Proportion of Workers Earning at/below the Minimum Wage by Occupation, PNAD 2002-2015

Occupation	Pr(wage=min.wage)	Pr(wage<min.wage)	Pr(wage≤min.wage)
Management, Professional and Technical Services	0.053	0.012	0.064
Office and Administration	0.126	0.020	0.146
Sales	0.178	0.064	0.243
Production and Transportation	0.115	0.040	0.155
Construction	0.132	0.111	0.244
Installation and Repair	0.096	0.071	0.167
Cleaning and Maintenance	0.308	0.144	0.453
Personal Care	0.180	0.160	0.340
Protective and Other Services	0.174	0.051	0.224
Farming, Fishing and Forestry	0.217	0.304	0.521

Source: PNAD data from 2002 to 2015. The sample comprises salary workers (excluding those from the military), aged 16-64 years old, from 26 regions in Brazil. PNAD provides information on aggregate and individual occupation categories. I use this information to sort 492 occupations per year into ten occupation categories. Occupations which are not assigned to any category in Table 3.A.1 are excluded from the sample, these represent less than 1 percent of the sample.

Table 3.A.1 shows that management, professional and technical occupations are the only category with a relatively small proportion of minimum wage workers around 5 percent. Minimum wage workers represent a significant proportion of the working force in medium-skill occupations such as clerical and sales unlike these do in more developed countries. Low-skill services and agricultural occupations are for far the categories with the highest proportion of minimum wage workers. It is not surprising that these occupations also have a large proportion of workers earning below the minimum wage level. In fact, the proportion of workers earning below the minimum wage in agricultural occupations exceeds that of the minimum wage workers. The reason why a large proportion of these workers earn below the minimum wage is that most of them are employed in the informal sector which is not covered by the minimum wage legislation. Of course, there is also an educational composition effect because workers with fewer years of education are more likely to work in low-skill occupations or low-skill intensive sectors.

I turn now to the analysis of the distribution of minimum wage workers by age and educational attainment. The top and bottom panel in Figure 3.A.1 show the proportion of workers earning at and below the minimum wage by age and years of schooling, respectively.

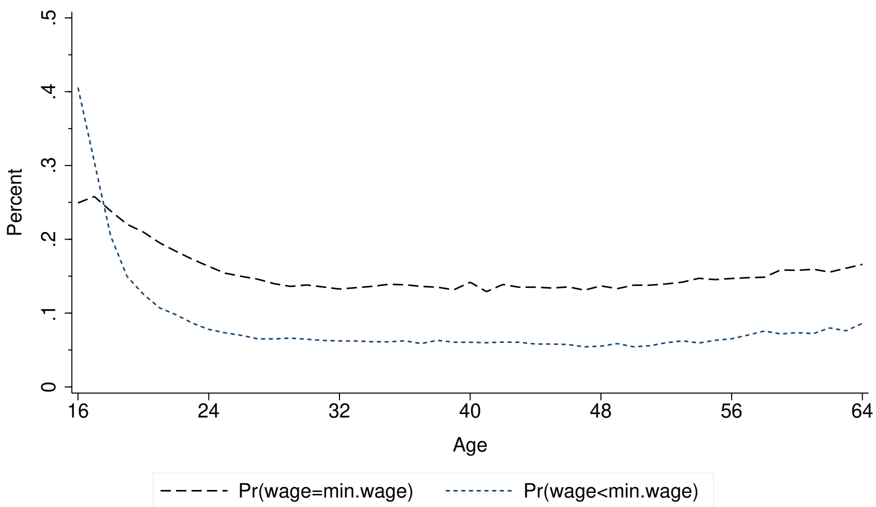


Figure 3.A.1: Proportion of Workers Earning at and below the Minimum Wage by Age and Years of Schooling, PNAD 2002-2015

Source: PNAD data from 2002 to 2015. The sample comprises salary workers (excluding those from the military), aged 16-64 years old, from 26 regions.

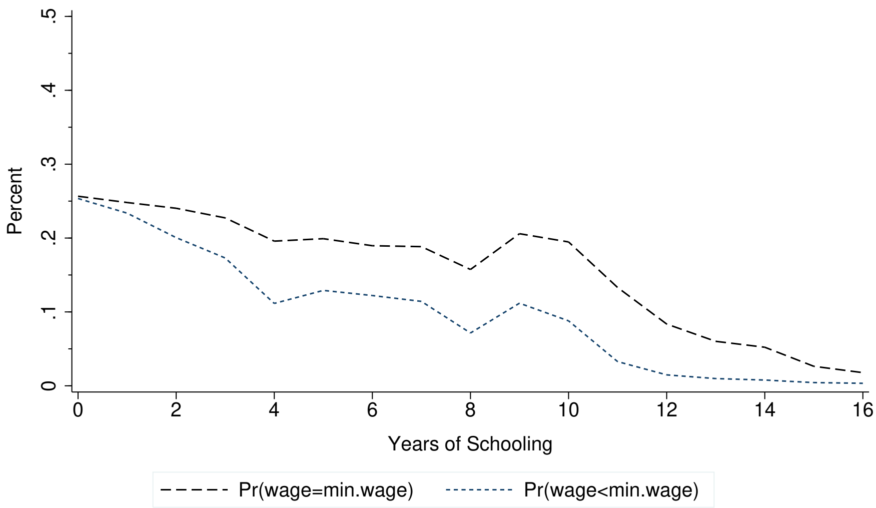
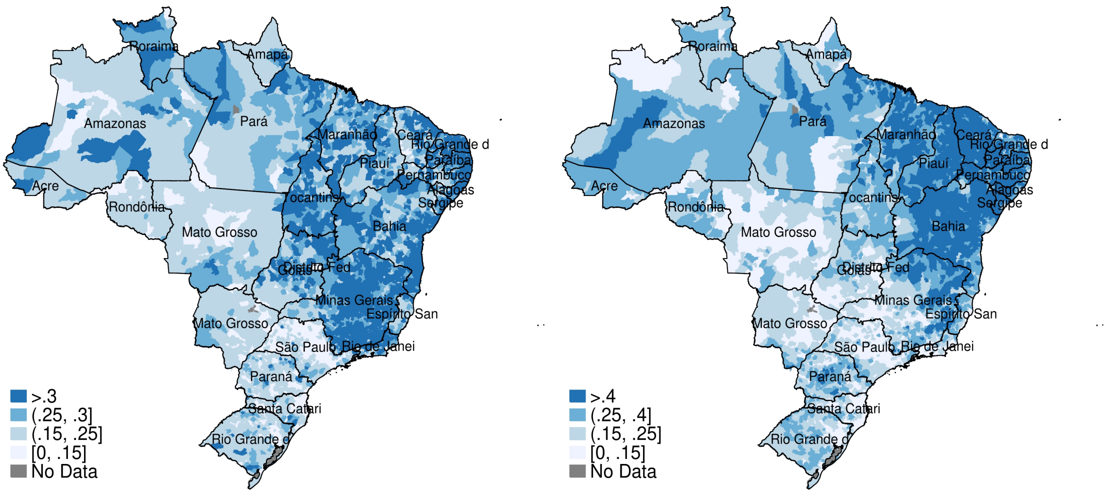


Figure 3.A.1 (continued)

Notice that there is a large proportion of workers earning below the minimum among the youngest workers in the sample. Under-age workers are more likely to be employed in the informal sector and may not receive the same labour protection as their counterparts do. We can see that from the age of 18, the proportion of minimum wage workers overcomes that of workers earning below the minimum wage. After the age of 24, both the proportion of minimum wage workers and that of workers earning below it remain relatively stable with respect to age. Minimum wage workers in Brazil appear to be more uniformly distributed with respect to age than in more developed countries.

As expected, there is a negative relationship between the proportion of workers earning at or below the minimum wage and the years of schooling. Notice that the proportion of workers with jobs that pay less than the minimum wage decreases rapidly over the first 4 years of education. Thereafter, remains somehow steady and only decreases again after workers attain a complete primary education. The proportion of workers earning at the minimum wage decreases at a slower pace with the first 4 years of schooling, then this behaves similar to the former.

From the previous analysis, we can infer that minimum wage workers are evenly distributed across ages (after the age of 24), are employed in middle or low-skill occupations, and have less than secondary education (11 years of schooling). We can also infer that workers located in the left-tail of the age distribution, with just a few years of schooling and employed in agricultural occupations are more likely to end up getting a job that pays less than the minimum wage. There are two important differences in the characteristics of minimum wage workers between Brazil and more developed countries. First, these workers are not overrepresented in small demographic and occupational groups in Brazil. Second, the proportion of workers earning at and below the minimum wage is considerably large in Brazil, exceeding 50 percent in some demographic groups. In a labour market with such a large proportion of minimum wage workers, a change in the minimum wage is expected to have significant effects on wages and employment. However, Brazil is a country with large differentials in regional wage levels, thus the imposition of a national minimum wage may not have the same effect on labour market outcomes across regions. Figure 3.A.2 provides information on the proportion of workers earning at and below the minimum wage across Brazilian regions. This analysis uses information from the Brazilian Census which is the most disaggregate data source available in the country.

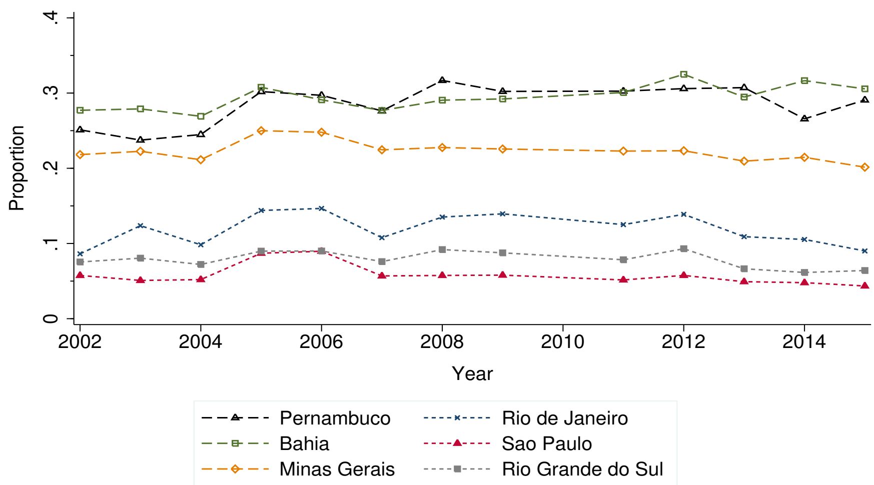


(a) Pr(wage=min.wage) (b) Pr(wage<min.wage)

Figure 3.A.2: Proportion of Workers Earning at and below the Minimum Wage by Microregions, Census 2010

Source: Census, 2010. The samples comprise salary workers, aged 16-64 years old, from 5565 microregions in Brazil.

Panel (a) and (b) of Figure 3.A.2 show the proportion of workers earning at and below the minimum wage in Brazilian microregions (regions outlined in black), respectively. Note that the vast majority of workers that earn at and below the minimum wage live in the north-east regions. The proportion of minimum wage workers range from less than 2 percent in south-east microregions to more than 60 percent in north-east microregions. An interesting exception of a south-east region with a high proportion of minimum wage workers is Minas Gerais which connects the north-east regions with the south-east ones. Notice that microregions in Minas Gerais with a large proportion of workers earning below the minimum wage are closer to Bahia (a north-east region), while those with a small proportion of these workers are closer to Sao Paulo (a south-east region), perhaps the significant worker mobility from Minas Gerais to north-east regions and Sao Paulo is related to this phenomenon[20]. In fact, the proportion of workers earning below the minimum wage in Minas Gerais has converged to the levels of south-east regions such as Sao Paulo and Rio de Janeiro in the last years. Figure 3.A.3 provides information on this matter for Minas Gerais and other highly populated regions in Brazil from 2002 to 2015.

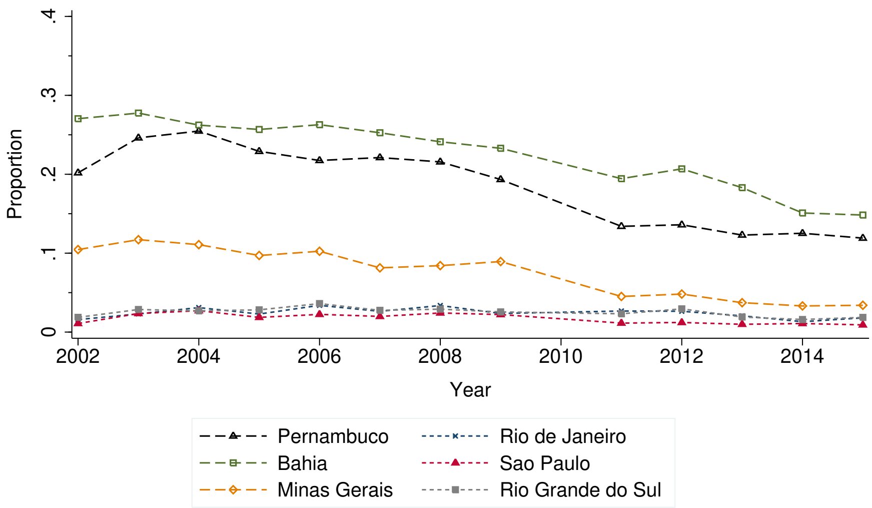


(a) Proportion of Workers Earning at the Minimum Wage

Figure 3.A.3: Proportion of Workers Earning at and below the Minimum Wage by Regions and Years, PNAD 2002-2015

Source: PNAD data from 2002 to 2015. The sample comprises salary workers, aged 16-64 years old.

[20]See Brito and Carvalho (2006) for a study on migration across regions in Brazil



(b) Proportion of Workers Earning below the Minimum Wage

Figure 3.A.3 (continued)

The top panel of Figure 3.A.3 shows that the proportion of workers earning at the minimum wage exceeds 20 percent in regions such as Pernambuco, Bahia and Minas Gerais, while this is around 10 percent in Rio de Janeiro and barely exceeds 5 percent in Sao Paulo. This disparity can also be observed among workers earning below the minimum wage, particularly over the 2000s. However, the number of workers with jobs that pay less than the minimum wage has been decreasing over the last years in the sample. Notice that the participation of these workers in Minas Gerais has converged almost to the same levels as Sao Paulo. However, this proportion is still high in north-east regions such as Pernambuco and Bahia.

The disparity in the proportion of minimum wage workers across regions would suggest that the effects of minimum wage policies on wages and employment may also differ across them. I do not present evidence of causality between the minimum wage and labour market outcomes in this study because the literature is extensive on this subject.[21] However, I perform a before and after comparison of labour market transitions that follow an increase in the minimum wage which has not been assessed in previous studies. For this exercise, I use a relatively new household survey, PNADC data which has a panel data structure which allows

[21]See Neumark et al. (2006), Lemos (2009), Engbom and Moser (2018) and Garcia (2019).

us to follow individuals up to 5 consecutive quarters. I pool data from regions in which the minimum wage is highly binding (Pernambuco, Bahia and Minas Gerais) and from those in which this is not (Sao Paulo, Rio de Janeiro and Rio Grande do Sul). Table 3.A.2 shows the results of this exercise.

Table 3.A.2: Transition Probabilities of a Change in the Minimum Wage, PNADC 2015-2016

	Final State, $\tilde{m}_1 = 880$				
Initial State, $\tilde{m}_0 = 788$	*Unemp*	$\Pr(w_1 < \tilde{m}_1)$	$\Pr(w_1 = \tilde{m}_1)$	$\Pr(w_1 > \tilde{m}_1)$	N
Pernambuco, Bahia and Minas Gerais					
$\Pr(w_0 < \tilde{m}_0)$	0.121	0.689	0.117	0.072	1523
$\Pr(w_0 = \tilde{m}_0)$	0.051	0.080	0.655	0.214	2047
$\Pr(\tilde{m}_0 < w_0 \leq \tilde{m}_1)$	0.082	0.135	0.375	0.408	802
$\Pr(w_0 > \tilde{m}_1)$	0.041	0.020	0.077	0.862	5282
Total	0.059	0.148	0.231	0.563	9654
Sao Paulo, Rio de Janeiro and Rio Grande do Sul					
$\Pr(w_0 < \tilde{m}_0)$	0.144	0.566	0.097	0.193	910
$\Pr(w_0 = \tilde{m}_0)$	0.067	0.083	0.532	0.317	936
$\Pr(\tilde{m}_0 < w_0 \leq \tilde{m}_1)$	0.077	0.164	0.266	0.493	801
$\Pr(w_0 > \tilde{m}_1)$	0.039	0.014	0.024	0.923	12565
Total	0.049	0.059	0.073	0.819	15212

Source: PNADC data 2015 and 2016. The sample comprises salary workers who are employed at time 0 (third quarter of 2015) and remain employed in the same job or become unemployed at time 1 (second quarter of 2016), aged 16-64 years old from Pernambuco, Bahia and Minas Gerais (low-wage regions) and, Sao Paulo, Rio de Janeiro and Rio Grande do Sul (high-wage regions). To calculate transitions, I identify the initial status of an individual by using the labour earnings of the main occupation, w_0, and the minimum wage, $\tilde{m}_0$. I track these individuals after one quarter and identify their labour market status by using their labour earnings of the main occupation, w_1, and the minimum wage, $\tilde{m}_1$.

Table 3.A.2 compares the employment status of workers at their first interview over the third quarter of 2015 (time 0) in which the monthly nominal minimum wage, $\tilde{m}_0$, was $R\$$ 788, with the status of the same worker over the second quarter of 2016 (time 1), in which the monthly nominal minimum wage, $\tilde{m}_1$, was $R\$$ 880. The sample is further constrained to workers who remained employed in the same job or become unemployed following the increase in the minimum wage.[22] It is important to point out that there is a large proportion of workers earning

[22] The high attrition in the data source does not allow us to obtain larger samples of matched workers. We can in principle follow workers right after the increase in the minimum wage which would provide larger samples of matched workers. However, I allow for a span of time (one quarter) to avoid capturing transitional dynamics from the first months that follow the increase in the minimum wage.

below the minimum wage at the initial state for both regional groups. As was explained previously, Brazil has a large informal sector, thus observations below the minimum wage are not the result of measurement error as these have been considered in the traditional literature for more developed countries. We can see that the probability of entering unemployment after a change in the minimum wage is high for this type of workers. If holding a job not covered by minimum wage laws is why $w_0 < \tilde{m}_0$, then a change in the minimum wage must not be the reason for which a worker is unemployed at time 1. The same is true for workers who already had labour earnings above the new minimum wage, $w_0 > \tilde{m}_1$. Although it has been well established in the literature that increases in the lowest wages may translate to wages higher up in the wage distribution in order to preserve the wage structure. Nevertheless, the probability of becoming unemployed following an increase in the minimum wage is the lowest among workers with $w_0 > \tilde{m}_1$.

The group of interest is comprised of workers earning at the minimum wage, $w_0 = \tilde{m}_0$, or between the old and the new minimum wage, $\tilde{m}_0 < w_0 \leq \tilde{m}_1$. Notice that the former ones have a higher probability of being paid the new minimum wage in time 1, while the latter ones are more likely to be paid above $\tilde{m}_1$. Notice that changes in the minimum wage have large effects on the labour market states of both regional groups even though the proportion of minimum wage workers is around 10 percent of the working force in the sample for Sao Paulo, Rio de Janeiro and Rio Grande do Sul. It is important to bear in mind that these regions have also a more dynamic labour market, thus transitions, particularly to unemployment, might be caused by reasons others than changes in the minimum wage.

3.B Algorithm

The solution algorithm involves the following steps.

1. Guess a value for ϕ and θ.

2. Calculate $m(\theta)$ by using a Cobb-Douglas matching function namely $m(\theta) = A\theta^{\eta}$, given assumed values for A and η.

3. Find the value of unemployment $\rho U^{y}(\tilde{m})$ by using equation (3.14).

4. Estimate the labour force participation rate, n_T^y and the steady-state conditions by using equation (3.17).

5. Find ϕ given the estimated value of u, θ and v_H, equation (3.18).

6. Find θ by using job creation equation (3.15).

7. Iterate over ϕ and θ.

3.C Counterfactual Experiments

Table 3.C.1: Counterfactual Experiments

	Baseline	$\beta_H = 0.45$	$\delta^y_H = 0$	$\lambda^y_L = \lambda^y_H$	$v_H = 0.073$
m(θ)	0.219	0.212	0.229	0.209	0.218
θ	0.767	0.720	0.838	0.702	0.761
ϕ	0.252	0.258	0.225	0.191	0.145
OLF Rate	0.340	0.309	0.396	0.377	0.334
Unemployment Rate	0.110	0.118	0.097	0.111	0.112
Employment Rate in L	0.148	0.158	0.122	0.093	0.087
Employment Rate in H	0.402	0.416	0.385	0.419	0.467
Mean Duration in L	28.670	28.598	28.576	28.896	28.479
Mean Duration in H	29.420	29.265	29.218	29.069	29.011
Mean Hourly Wage in L	8.061	8.198	7.825	8.227	8.054
SD Hourly Wage	(5.049)	(5.050)	(4.983)	(5.615)	(4.993)
Mean Hourly Wage in H	10.149	11.119	8.789	9.928	10.109
SD Hourly Wage	(7.557)	(8.452)	(6.535)	(7.492)	(7.451)
Mean Wage Gap ($\bar{w}_H - \bar{w}_L$)	2.09	2.92	0.96	1.70	2.06
Regional Gap	1.73	2.57	0.61	1.68	1.71
Educational Gap	0.36	0.36	0.35	0.02	0.36
Pr($w_L = \tilde{m}$)	0.184	0.149	0.240	0.211	0.179
Pr($w_H = \tilde{m}$)	0.056	0.024	0.165	0.079	0.054

Table 3.C.2: Counterfactual Experiments by Skill Groups

	Region L					**Region H**				
	Baseline	$\beta_H = 0.45$	$\delta^y_H = 0$	$\lambda^y_L = \lambda^y_H$	$v_H = 0.073$	**Baseline**	$\beta_H = 0.45$	$\delta^y_H = 0$	$\lambda^y_L = \lambda^y_H$	$v_H = 0.073$
Employment										
Type-l	0.795	0.794	0.795	0.717	0.799	0.708	0.707	0.708	0.712	0.714
Type-h	0.205	0.206	0.205	0.283	0.201	0.292	0.293	0.292	0.288	0.286
R^l_j	3.143	3.431	2.679	2.763	3.178	3.560	4.036	2.679	3.130	3.600
R^h_j	3.817	4.160	3.352	3.782	3.956	4.217	4.776	3.352	4.179	4.371
Mean Wage										
Type-l	7.233	7.372	7.020	7.057	7.249	8.157	8.923	7.039	7.948	8.176
	(2.792)	(2.819)	(2.739)	(2.748)	(2.795)	(2.900)	(3.285)	(2.371)	(2.879)	(2.902)
Type-h	11.314	11.508	11.072	11.321	11.396	14.956	16.530	13.126	14.940	15.039
	(8.885)	(8.910)	(8.879)	(8.904)	(8.903)	(11.818)	(13.295)	(10.319)	(11.823)	(11.810)
Wage Gaps										
Type-l										
50th/10th	0.258	0.285	0.214	0.222	0.262	0.375	0.388	0.257	0.388	0.374
90th/50th	0.520	0.509	0.538	0.534	0.518	0.462	0.472	0.462	0.473	0.461
90th/10th	0.778	0.794	0.752	0.756	0.780	0.837	0.860	0.719	0.861	0.834
Type-h										
50th/10th	0.541	0.524	0.520	0.543	0.534	0.655	0.676	0.654	0.656	0.648
90th/50th	0.864	0.851	0.884	0.868	0.859	0.880	0.893	0.880	0.881	0.876
90th/10th	1.405	1.375	1.404	1.411	1.393	1.535	1.569	1.534	1.538	1.524

Increase in the Nash-bargaining power parameter of region H, β_H: The intuition behind this experiment is based on the assumption that workers are more productive if they are employed in region H, thus make sense that firms put extra weight on performance in this region. The direct effect of an increase in

β_H from its baseline value 0.4 to 0.45 is a substantial rise in wages and standard deviations in region H as workers obtain a larger proportion of their respective productivities as wage payments. The value of unemployed search, $R_L^y = \rho U^y(\tilde{m})$, with $y = l,\ h$, increases as can be seen in Table 3.C.2. The increase in $\rho U^y(\tilde{m})$ raises labour force participation but also restricts the number of feasible matches, thus θ and $m(\theta)$ fall. Both the size of unemployment and aggregate employment increase. The regional wage gap increases as wages in region L are only affected indirectly through changes in $\rho U^y(\tilde{m})$. As β_H affects both skill groups, there are no significant changes in the skill composition between regions. Notice that $\rho U^h(\tilde{m})$ increases more than $\rho U^l(\tilde{m})$, thus the rise in mean wages is significantly larger among type-h workers. Table 3.C.2 also provides information on wage inequality within each educational group. Although the proportion of minimum wage workers decreases in both regions, the minimum wage still binds the 10th percentile in region L, thus wage inequality is not significantly affected.

Eliminating the productivity premium, δ_H^y: In other words, reservations productivities conditional on education are assumed to be equal between regions. The expected direct effect of this experiment is a decrease in wages of region H, particularly among workers with high productivities because δ_H^y enters into the wage equation of region H as a multiplicative of worker's productivity. It is also expected that δ_H^y affects wages in region L indirectly through changes in $\rho U^y(\tilde{m})$. Setting δ_H^y to zero lowers $\rho U^y(\tilde{m})$ which decreases labour force participation but also forms productivity matches that were not feasible before, thus θ and $m(\theta)$ increase. The former effect seems to be significantly larger, thus employment falls. The wage gap between regions also falls because wages are more adversely affected in H than in L. The fall in $\rho U^y(\tilde{m})$ increases the proportion of minimum wage workers, thus the 50th/10th wage gap decreases within each educational group, except for type-h workers in region H as the minimum wage still binds below the 10th percentile of their wage distribution.

Equal separation rates between regions, $\lambda_L^y = \lambda_H^y$: Specifically, I set the separation rate in region L, λ_L^y, to be equal to the separation rate in region H, λ_H^y, with $y = l,\ h$. Although average employment durations are not substantially different between regions, there are significant effects of changing the separation rates in region L. According to the baseline estimates of the separation rates in Table 3.2, type-l workers have shorter employment durations in region H than in L, while the opposite is true for type-h ones. This implies that more type-l and less type-h workers are now available to be hired by employers in region H and these respond by creating more vacancies for the former and less for the latter. On the other hand, the smaller separation rate among type-h workers in region L implies an increase in the relative employment of this skill type. Table 3.C.2 shows that there is a significant change in the skill composition of region L in favour of type-h workers, while the opposite effect, though much less significant, takes place in region H. There are also equilibrium effects on wages and employment that are driven by the decline in the value of unemployed search, $\rho U^y(\tilde{m})$. Although wages are adversely affected by $\rho U^y(\tilde{m})$, the mean wage in region L increases because of the change in the skill composition in this region and thus, the regional wage premium falls. Notice that the decline in the regional wage gap is mainly driven by the fall in the educational differential as the skill composition between regions is almost the same following the experiment.

Increase in the measure of posted vacancies in region H, v_H: The immediate effect is an increase in the employment of region H and the probability of finding a job in this region, $(1-\phi)$. Overall employment rate increases, because the increase in the value of unemployed search, $\rho U^y(\tilde{m})$, raises the labour force participation rate. Although $\rho U^y(\tilde{m})$ has an increasing effect on wages, regional mean wages fall because of the increase in the participation of type-l workers in both regions as can be seen in Table 3.C.2. This is explained by the larger increase in the value of unemployed search among the most educated workers, which restricts the number of feasible matches among this skill type.

3.D Figures

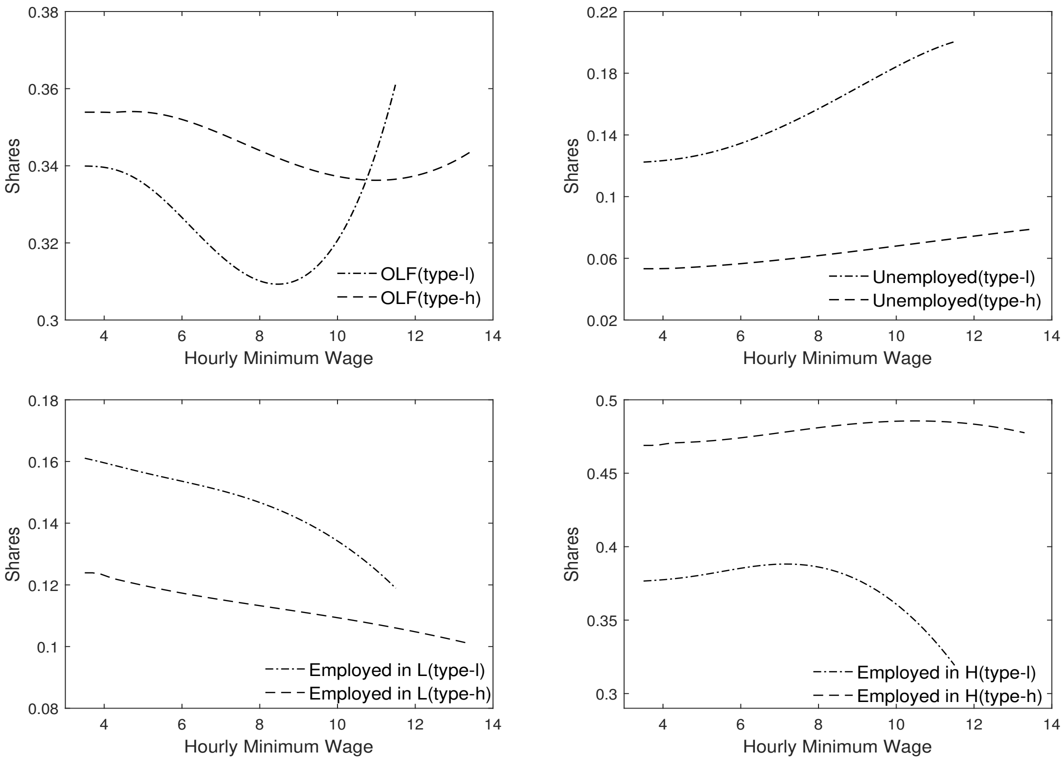


Figure 3.D.1: Shares of Labour Market States by Skill Types

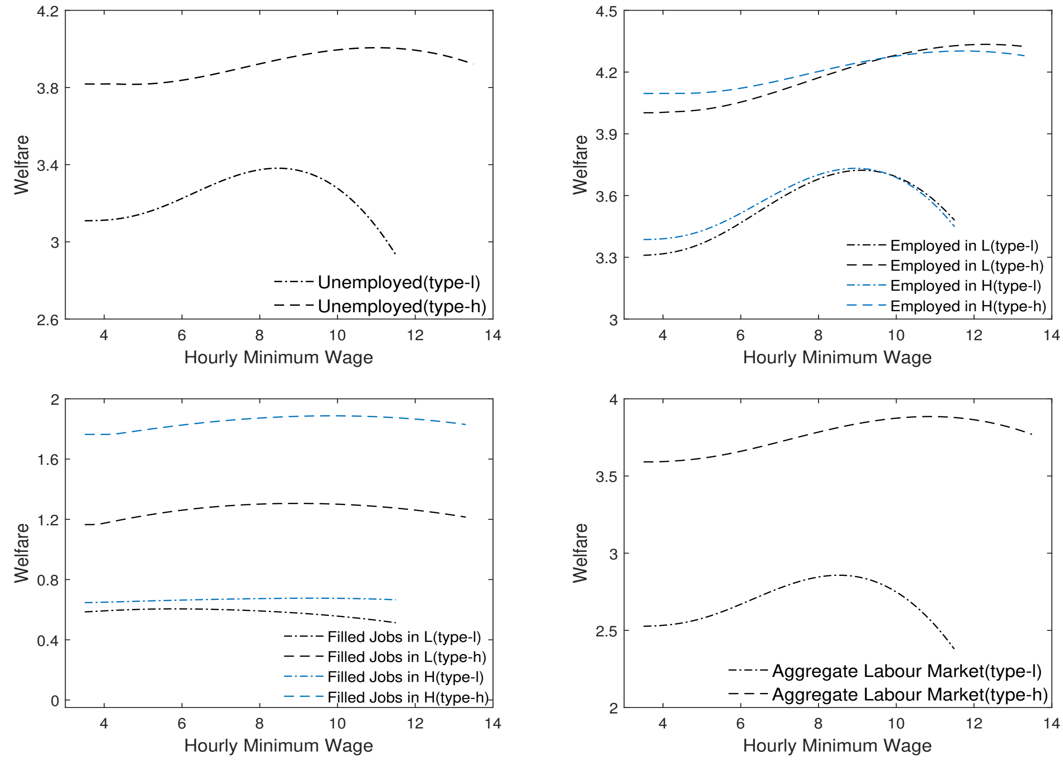
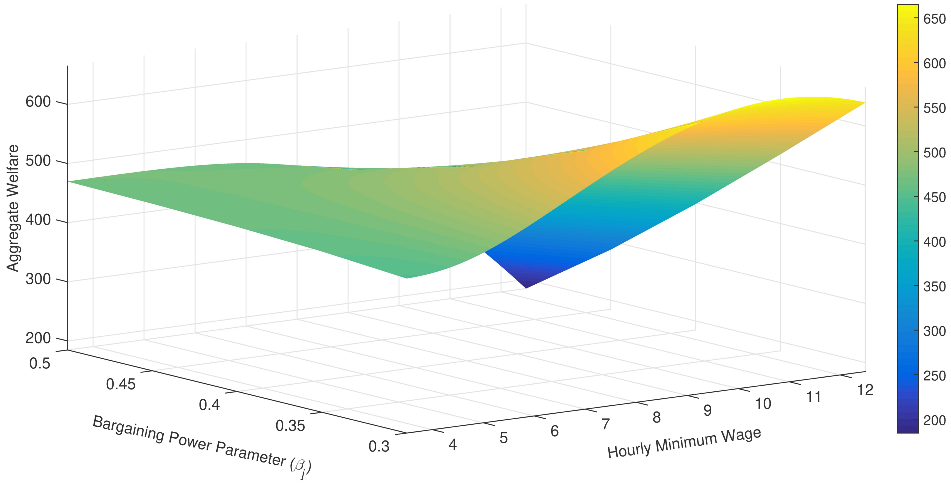


Figure 3.D.2: Welfare Measures by Skill Types



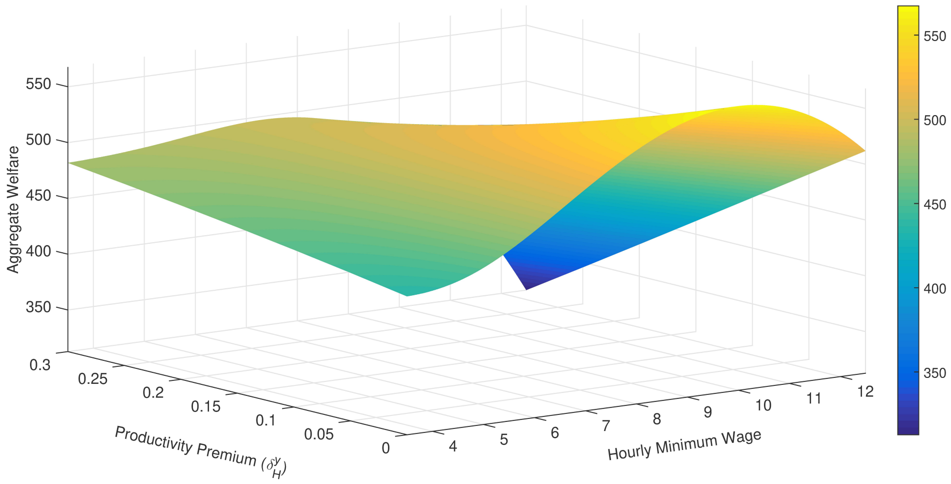


Figure 3.D.3: Changes in Aggregate Welfare to Changes in β_j and δ_H

Figure on the top and the bottom show the value of the hourly minimum wage that maximizes aggregate welfare for different values of the Nash-bargaining power parameter, β_j, and the productivity premium, δ_H, respectively.

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