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Redistributive policies and returns to schooling.

The case of Uruguay during 2005-2015

Mijail Yapor García

Montevideo – Uruguay
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Directores:
D.Ec. Prof. Graciela Sanroman García
Ec. Prof. Rodrigo Arim Ihlenfeld

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Graciela Sanroman García

Rodrigo Arim Ihlenfeld

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INTEGRANTES DEL TRIBUNAL DE DEFENSA DE TESIS

Ph.D. Prof. Verónica Amarante

Ph.D.. Prof. Fernando Borráz

Ph.D. Prof. Martín Leites

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RESUMEN

Durante la década pasada, nuevas políticas redistributivas y una caída pronunciada de la desigualdad salarial tuvieron lugar en Uruguay. En particular, durante esos años se implementaron dos fuertes reformas en el mercado laboral: incrementos sustanciales del salario mínimo y una reforma tributaria progresiva. El presente trabajo aborda la forma en que estas políticas afectaron los retornos a la educación y analiza sus posibles impactos en la desigualdad salarial. En primer lugar, mediante la aplicación de técnicas de bootstrapping se analiza la diferencia entre los retornos educativos sobre los salarios antes y después de impuestos. En segundo término, se utilizan métodos de descomposición basados en el enfoque de regresiones RIF para estudiar los determinantes de la evolución salarial. Los resultados muestran que los retornos a la educación sobre salarios líquidos y nominales evolucionaron de manera paralela. Además, la evidencia indica que los trabajadores más educados pudieron, al menos parcialmente, mitigar el efecto redistributivo de la reforma tributaria.

Palabras claves:
desigualdad salarial, retornos a la educación, regresiones RIF, políticas redistributivas, .

ABSTRACT

During the past decade, new redistribution policies and a substantial reduction of wage inequality took place in Uruguay. In particular, two important labor market reforms were implemented during those years: substantial increases of minimum wages and a progressive tax reform. This work addresses how these policies affected returns to schooling and analyzes their potential impacts on wage inequality. Firstly, we use bootstrapping techniques to test the difference between before- and after-tax returns. Secondly, we apply decomposition methods based on the RIF-regression approach to study the determinants of the evolution of wages. We find evidence that before- and after-tax returns to schooling evolved in a parallel manner. Also, we find that the most educated workers were able to, at least partially, mitigate the redistributive effect of the tax reform.

Keywords:
wage inequality, returns to schooling, RIF-regressions, redistributing policies.

Contents

Chapter 1

Introduction

The Uruguayan economy showed a significant dynamism between 2005 and 2015, characterized by sustained economic growth, an important decline in wage inequality and a large reduction in poverty levels. During this years, the annual average growth rate was 5%, the overall informality[1] rate fell from 37% to 23%, and the unemployment rate reduced from 12.2% to 7.8%. While in 2006 over the 24% of household were below the poverty line, in 2015 only 6% were in that condition. Besides, the Gini coefficient fell from 0.46 to 0.38 in those years. This behavior, which followed one of the worst economic crises in the country, was similar to that observed in other Latin American countries during the same period.

Regarding wages, the significant reduction observed during the crisis began to revert, slowly and did not reached its pre-crisis levels until 2010. Between 2005 and 2015 the average real salary grew 49%. However, this evolution was not invariant throughout the wage distribution, with grater increases in the left tail respect to the top earnings, leading to a strong decline of the labor income inequality (see Figure 1). As can be seen in Table 3, this evolution is robust to the different measures of inequality considered. At this point, it is clear that the Uruguayan economy experienced during this years a relative good performance of its economic activity together with an improvement of the levels of inequality and social conditions.

To find the determinants behind the evolution of earnings inequality has become a main concern over the last fifty years, occupying a central role in the

[1]Measured as the share of workers who do not contribute to the social security system.

labor economics literature. In particular, the key economic question regarding which factors account for changes (or differences) in distributions has become easier to approach thanks to recent methodological developments like those of DiNardo et al. (1996) or Firpo et al. (2007), that will be discussed in depth later. Uruguay is not an exception on this field, and a wide numbers of applied works has addressed the distributional issue. Those authors that implement a decomposition approach agree on pointing out that the narrowing of the wage gap by educational level has been the driving force of the inequality decline. This is also the case for other countries in the region (see Amarante et al. 2014; Alves et al. 2012, among others).

But less attention has been paid to the potential impacts of institutional features of the labor market over inequality. This becomes particularly important since Uruguay has undergone a series of far-reaching institutional reforms in the last fifteen years, and its potential impact on inequality has not been addressed in depth. The most recent effort to take into account that kind of features is the work of Amarante et al. (2016), who focus on the relationship between formality and inequality. They found significant evidence that labor market formalization (together with returns to education) played a significant role in the reduction of inequality. However, as the authors point out, this may be due to the close link between the institutional reforms and the labor formalization process. In particular, a large increase in the national minimum wage (NMW, starting on 2005) and a progressive tax reform (since 2007) have been implemented and there are no studies which take into account its potential effects on inequality. In this context, the contribution of this paper is to empirically address the role of the minimum wage policy and the tax reform into inequality and wages evolution.

It is expected that these policies will affect in a non-homogeneous way the wage distribution. While an increase in minimum wage may have impact at the bottom of the distribution, a tax reform that taxes wages progressively is expected to change the upper tail (see Chapter 2). Thus, by pushing up the bottom tail and pushing down the upper tail, those polices acts in the same direction of reducing wages inequality. Increments on low wages given by the enforcement of minimum wage policy can be increasing the wages usually associated with less educated people. While at the top of the distribution, higher tax burden on the highest income -where are the most educated workers-can lead to reductions in the wage premium because of years of education. This is the central hypotheses to be under question in this work. Our primary results are quiet surprising and indicate that the most educated sectors managed to reversed (at least partially) the aforementioned negative effects on the returns to education derived from a greater tax burden. Thus, this kind of workers could be cushioning the equalizing effects of the tax reform.

This work uses data of Encuesta Continua de Hogares (ECH) for the period 2005–2015. Given that wage information are collected after taxes, it was necessary to reconstruct the pre-tax salaries[2]. The procedure to gross-up the incomes is detailed later in this work, and represents a subsidiary but not less important contribution of the present research, since there are no other precedent on recovery the nominal wages for such a long period.

To disentangle the evolution of the returns to education, in this work we proceed to estimate four different specifications of the classical mincerian wage equations. We compute the empirical distributions of the returns to schooling via bootstrapping and perform a variety of hypothesis testing. Afterword, we go further and disentangle the determinants of the changes of returns to schooling by using decomposition methods. We use the Firpo et al. (2007, 2009, 2011*a*) approach and includes covariates that capture policy reforms. This method allow us to decompose the total change of a distributional statistic into the so called composition and wage structure effects, and therefore enables us to evaluate the contribution of several covariates to each effect. Applying this procedure over pre and post taxes wage allows us to identify if there where differential impacts of the tax reform on returns to education, and its link with the evolution of wage inequality.

The remaining of this work is organized as follows. In the next chapter discusses more deeply the relationship between inequality and minimum wage policy and tax reform (Chapter 2). After that, Chapter 3 summarize the literature related to the scope of this work, focusing on the relationship between inequality, returns to education and pre and post taxes wages. Chapter 4 describes the data used and present the gross-up procedure necessary to obtain pre-tax wages. We then presents a short exposition of the methodology used (Chapter 5). The ensuing results are presented in Chapter 6 and we conclude

[2]Throughout the text we will refer indistinctly to nominal, pre-taxes or before-taxes wages, as well as to liquid, post-taxes or after-taxes wages.

in Chapter 7.

Chapter 2

Main facts

The past fifteen year of the Uruguayan economy were characterized by a combination of economic dynamism and reduction on inequality. According to previous studies, the evolution of inequality was mostly due to the reduction of the returns to educations. In what follows we argue that this reduction can be explained by the combination of a large increase in the minimum wage and a tax reform that substantially increase the tributary pressure on higher wages. We will also show that probably the reduction of inequality would have been greater if market mechanisms linked to the bargaining power of the more educated workers (those potentially most affected by the tax reform) had not operated.

At the beginning of the analyzed period the NMW were in a very low level. For private workers, the 2005 average hourly wage was 52 Uruguayan pesos, while the minimum wage barely reached $U 10 an hour (close to 30 cents of US dollar)[1]. Since then to 2015 the minimum wage grew over 200% in real terms, while the average wage for private sector increased by 60%. The extremely low level of minimum wage in 2005 can be at least partially explained by the fact that it was used as an indexer of a wide variety of fiscal variables and adjustments to social benefits like conditional cash transfers[2]. Thus, the government had no incentive to improve it, even less in times of crisis like it was the beginning of the century. In 2004, an alternative unit of measure[3] was created as a substitute of the NMW, modifying all references in the current legal system to the last one as a basis of contribution to social security or as a

[1] All values at constant December 2006 prices.

[2] For a detailed list of this variables indexed by NMW see Mazzuchi 2011.

[3] The law N°17.856 created the unit called Base de Prestaciones y Contribuciones (BCP).

unit of account or indexation. This modifications allowed to considered again the NMW as a policy variable, performing as a minimum wage reference in the labor market.

To see the potential impacts on the wage distribution of the large increase of the NMW, we perform a simple counterfactual exercise. Figure 3 shows the observed 2005 wage distribution and the one that would have prevailed if the lowest salaries were at 2015 NMW levels. As can be seen, a large part of wages at the bottom of the wage distribution would be affected by the minimum wage policy (potential treaties). So taking this fact into account seems important in distributive terms (see Table 5 for descriptive statistics of this exercise).

This result is also verified if the same exercise is computed over experience categories and education levels. The results showed in Table 4 reinforce the previous idea and illustrate the potential effects of the increase of NMW: workers with primary incomplete or complete are those who were potentially treated by the policy, with highest expected impact in women with respect to men[4].

In 2007 the Uruguayan government implemented a tax reform which introduced, among other features, a new progressive labour income tax (replacing the so called Impuesto a las Retribuciones Personales (IRP) for the Impuesto a las Renta de las Personas Físicas (IRPF)). In terms of wage taxes, the reform established scales of tax rates in which the rate charged increases in steps as the income level rise.[5] Table 6 shows that, as a result of the tax reform, the tax effective rate was reduced for 74% of formal workers. On the other side, workers at the very top tail of wage distribution faced an increase of effective rate from 6% to 20%.

A similar counterfactual exercise to that applied to minimum wages shows that if the wage structure were like 2005 but with 2015 tax structure, a reduction in post-taxes wage would have took place for more educated workers. Figure 6 shows that the impact of the tax reform on wages was small for those with less than complete secondary school; but for the most educated salaries

[4]Table 2 presents the distribution of workers by education levels and quartiles of the wage distribution. It can be seen that at the bottom of the distribution the proportion of less skilled workers is higher.

[5]See Chapter 4 and Decrete 254/012 of 08/08/2012 for a detailed information of tax rates structure and income levels.

decreased up to 5%. The previous analysis leads us to the idea that tax reform contributed to reduce the schooling premium for highest levels of wages. If this mechanism had been fully operational, a sharper decline on the returns to education in the post-tax specification have been observe. However, this is not the case between 2005 and 2015, so the underlying hypothesis regarding the more educated workers premium becomes relevant. Even more if we consider the fact that during the period of analysis there was an increase in the educational level of the labor force (see Table 1). Chapter 6 is dedicated to this issue via performing several test of the distribution of pre and post returns to education over time and decomposition exercises of inequality measures for pre and post tax wages.

Chapter 3

Literature review

Wage inequality is a well-documented economic topic, both regionally and internationally. In particular, distributive issues have played a central role in the Latin American economic literature, given that this region is one of the most unequal of the entire world. As were mentioned before, it is usual to find that returns to education play a central role to explain the evolution on wage inequality over the past decades. Also, other possible determinants have been gained ground, as tasks or job characteristics, structural reforms or affirmative policies on certain groups of workers. The link between inequality and returns to education with others factors as tax reforms or minimum wage policies has been less explored.

Several strands of evidence show that wage inequality has increased over the past decades in developed countries (Lemieux, 2007; Atkinson, 2015). For the 2000s this trend is usually associated with skill-biased technological progress that results in higher wage premium for education and experience (see Autor et al., 2008; Autor and Dorn, 2013; Firpo et al., 2011*b*; Autor, 2014, among many others). Also, the role of education has been extensively analyzed in the wage inequality literature. Lemieux (2006) argue that the increase of return to post-secondary education was a key determinant of the rise of US wage inequality over the past three decades. For a similar period, Lindley and Machin (2016) find evidence that the increase in the demand for postgraduates is a key factor behind rising the US wage inequality. However, some recent evidence indicate a slightly different evolution of the returns to education for the United States over the past five years. On an interesting article, Valletta (2016) suggest that polarization and skill downgrading have contributed to the recent flattening of higher education wage premiums, questioning its unequalizer effect.

Wage inequality has been increasing also in the majority of the European countries for the past decades (see, for example, Biewen and Juhasz 2012 for the Germany, Centeno and Novo 2014 for Portugal and Voitchovsky et al. 2012 for Ireland). In contrast, there is evidence of a fall in wage inequality in some other European countries during the same period. For instance, driven by the fall in the returns to education, Verdugo (2014) for France and Naticchioni and Ricci (2008) for Italy, find a reduction of the wage inequality over the past thirty years.

But in some cases not everything is a matter of premium. Brunello et al. (2009) studied 12 European countries and found evidence that compulsory school reforms significantly affect educational attainment and that additional education reduces conditional wage inequality. Fournier and Koske (2012) estimates RIF and conditional quantile regressions for 32 countries of the OECD. The authors shows that the reduction of wage inequality is due to a rise in the share of workers with an uppersecondary or post-secondary non-tertiary degree and a rise in the share of workers on permanent contracts. On the same direction, Breen and Chung (2015) investigate the extent to which increasing the educational attainment of the US population might ameliorate inequality.

Carrasco et al. (2015) analyze the particular case of Spain, where the trend of inequality was different of the rest of European countries. Using RIF regressions and decomposition methods for the period 1995-2010, they found that the initial reduction of the wage dispersion is largely explained by a decrease in the returns to education. In contrast, the later widening of the wage distribution is explained by an increase in the relative demand for high-skilled workers.

Also other possible complementary explanations has been recently developed for industrialized economies. Blundell et al. (2018) explore household income inequality in both Great Britain and the United States from 1979 to 2015. They analyze the interplay between labor market earnings and the tax system. While both countries have witnessed secular increases in 90/10 male earnings inequality, this measure of inequality in net family has declined in Britain and risen in the US. Authors found evidence that the welfare system in Britain played a key role in equalizing net income growth across the wage distribution. For the US, the relatively weak safety net played a central role in the observed wage inequality increase.

There are also some evidence linking the evolution of wage inequality and minimum wage. Aeberhart et al. (2016) analyze the impact of the minimum wage on the earnings distribution in France over the period 2003-2005. Using the Firpo et al. (2009) RIF-regression method, they found a small but significant effect of the changes in the minimum wage level up to the seventh decile for full-time full-year employees. Stewart (2012) investigates spillover effects of the UK minimum wage for the period 1997 to 2008, finding evidence of a significant effect of this policy at the bottom-end of the wage distribution. Fortin and Lemieux (2015) arrived at the same conclusion for Canada covering the period 1997-2013, by estimating RIF regressions and constructing counterfactual wage distributions at the provincial level. Finally, Dube (2017) apply RIF-regression method for US between 1990 and 2012, finding evidence that higher minimum wages moderately reduce the share of individuals with incomes below 50, 75 and 100 percent of the federal poverty line.

With regard to the relationship between returns to schooling and taxes, Heckman et al. (2006) and Heckman et al. (2008) deeply explore the Mincer equation and rates of return, modeling different types of tax structure. They fund a significant reduction of the rates of returns when taxes are into account. On the other hand, Abramitzky and Lavy (2014) use an unusual pay reform produced in Israel beginning in 1998, to test the responsiveness of investment in schooling to changes in redistribution schemes that increase the rate of return to education. The authors find strong evidence that education investment is highly responsive to changes in the redistribution policy.

Trends on wage inequality that characterizes developed countries differs substantially from that observed for developing countries in the past few decades. First we will mention some evidence for BRIC group (Brazil, Russia, India and China) and other developing countries in and outside Latin America. Finally, we go further in the analysis of Uruguay.

Carnoy (2011) for a large number of developing countries and Carnoy et al. (2012) for BRIC group, shows that mass expansion of higher education can contribute to greater income inequality under the conditions of i) rising returns to university education relative to secondary and primary education, ii) decreasing public spending differences between higher and lower levels of education, and iii) increasing spending differences between elite and mass universities. Sakellariou and Fang (2010) analyze the Vietnam economy. Applying decomposition methods they found that the increase in wage inequality over the period 1998-2008 could be attributed to changes in wage structure and composition of education and experience for men, and returns to experience for women.

Performing a decomposition technique, Bakis and Polat (2015) investigates wage inequality in Turkey over 2002-10. The authors suggests that skill-biased technical change and minimum wage variations were the main determinants of the wage inequality decrease, and that the wage structure effect dominates the composition effect. Popli and Yilmaz (2017) found different causes for the same facts at the same period in Turkey. They suggest that decreasing inequality in the bottom half of the distribution was largely due to decreasing returns to education and experience. However both papers agree in attributing the moderate decline in inequality in the upper tail of the wage distribution to a fall in returns to the 'routine' occupational tasks.

As mentioned before, Latin America has experienced a huge reduction of the inequality levels that prevailed until the beginning of the century (see Alvaredo and Gasparini, 2015; Cornia, 2014; Lustig et al., 2016). One of the components that driven this decline was the decrease of wage inequality, generally explained by the educational upgrading of its labor force and the fall of the secondary and tertiary education (Galiani et al., 2017). The following papers explore the evolution of wage inequality for different countries, all of them applying the RIF regression-based decomposition approach proposed by Firpo et al. (2007).

Beccaria et al. (2015) explore recent changes in wage inequality in Argentina (2003-2012). They shows that the declining returns to education have been a major factor explaining the improvement in the distribution, but the process of labor formalization also had an equalizing effect. The possible effects of formalization is explored deeply by Casanova and Alejo (2015). They found that collective bargaining had a significant effect to reduce labor income inequality, mainly by lowering dispersion of wages among covered workers and by narrowing the gap of labor incomes between not covered workers belonging to high-income groups and covered workers.

Campos et al. (2014) study the rise and fall of income inequality in Mexico over 1989-2010. They found that the main driver is changes in returns, and also government transfers contributed to the decline in inequality, especially after 2000. The case of Bolivia is studied by Canavire-Bacarreza and Rios-Avila (2017). From 2002 to 2012, their results indicate that the decline in wage inequality was driven by the faster wage growth of usually low-paid jobs, and that structural factors associated with productivity, such as workers' level of education, explain only a small portion of these wage changes. Ferreira et al. (2017) analyze the decline in earnings inequality in Brazil over 1995-2012. Their results suggests that the decline in returns to experience was the main factor behind lower wage disparities, combined with a substantial reductions in the gender, race, informality and urban-rural wage gaps conditional on human capital and institutional variables. In this case the effect of minimum wages on inequality was muted.

Using a conditional quantile regression approach, Posso (2010) analyze the increase of wage inequality of Colombia until 2005. He found that the characteristic or composition effect and the returns to tertiary education was the main factors to explain this trend. Battistón et al. (2014) make focus on the relationship between education attainment and income inequality, by carrying out microsimulations for most Latin American countries. Due to the convexities in returns to education, the authors found that the direct effect of the increase in years of education in the region in the 1990s and 2000s was unequalizing. However, during the 2000s this pattern is less marked and do not apply for Uruguay, regardless of whether years of education or educational levels are used in order to measure changes in education.

The evidence of the recent evolution of the returns to skills or schooling for Latin America is much less extensive. Using data for Argentina, Brazil, Chile, Colombia, and Mexico, Manacorda et al. (2010) document the rising trends in men's returns to education during the 1980s and the 1990s and estimate the role of supply and demand factors over the changes in skill premium. Galiani et al. (2017) studies the evolution of wage differentials and the skill premium for sixteen Latin American countries between 1991 and 2013. According to them, the fall in the trend of returns to more skilled workers observed in the 2000s can be partially attributed to demand-side effects, such as the boom in commodity prices that could favor the unskilled, and a skill mismatches that may reduce the labor productivity of highly-educated workers. García-Suaza et al. (2014) present estimations of before and after taxes earning for Colombia, representing the only one antecedent of that kind for Latin America.

At last, in the next paragraphs we briefly present a review of the recent studies concerning inequality and its possible determinants for Uruguay. The past thirty year have been characterized by three different stages in reference to the evolution of wage inequality: relative stable trend over 1986 and 1994, an increase between 1994 and 2005, and a sustained fall in the last ten years. Alves et al. (2013) analyze the evolution of wage inequality over 1986-2007 by computing a decomposition method based on conditional quantile regressions proposed by Melly (2005). They found that the main drive of the inequality changes was the change in the composition of workers by educational level. Alves et al. (2012) extend the temporal analysis to 2012 and found evidence that for the period 2005-2012 the returns to educations leads the already mentioned decrease of wage inequality.

Going beyond an overall interpretation of the trends in wage inequality, some articles investigate the potential contributions of other factors than the usual like education or experience. Thus, Borraz and Robano (2010) apply a Machado and Mata (2005) decomposition method to analyze the gender wage gap with selection correction in Uruguay. Considering data of 2007, they found that the wage gap is increasing at the top of the distribution so there will be evidence that support a glass ceiling. Applying a traditional Oaxaca-Blinder decomposition for 2005, Bucheli and Sanromán (2005) arrive to similar conclusions. Borraz and Gonzáles (2011) consider the effects of the already mentioned large increase in minimum wage since 2005. The authors find no impact of the minimum wage increases on wage inequality and argue that this could be explained by its low starting level or the lack of compliance with it.

On an interesting perspective, Amarante et al. (2014) explore the relationship between income inequality and political regimes during 1981-2010. They found that inequality have been a better performance over democracy governments, but this is not exogenous to the orientation of the country's economic policies. In times of liberal policies the inequality increased and the trend partially reversed with progressive governments. Amarante et al. (2016) apply the Firpo et al. (2007, 2009) decomposition method to explore the role of formalization in the labor market over the evolution of wages for 2001-2013. They found significant evidence that formalization (together with a large impact of the returns to education) contribute to reduce wage inequality.

Martorano (2014) investigate the possible impact of the 2007 tax reform on wage inequality and equity efficiency. Using a Difference-in-Differences technique, this work shows that the new tax system lowered inequality by 2 Gini points without producing any discernible disincentive effect. Rodriguez (2014) apply the Firpo et al. (2007, 2009) decomposition method to study the contribution of technology content of tasks to the distribution of men wages in Uruguay, during 1990s and the first decade of the 2000s. Their estimates suggest that technological task content of occupations contributes to explain changes in men wages distribution, but she do not found evidence of a polarization process of the labor market.

The evolution and determinants of wage inequality has been deeply explored, both local and internationally. It is notorious the key role playing for the returns to education on the inequality rise. In developed countries, these fact are mostly attributed to a skill-biased technological progress that increase the returns to post-secondary education. Also another possible explanations has been developed, like institutional factors such as minimum wage policy. However, there is no much evidence focusing on the link between tax structure and returns to education.

For Uruguay and other countries in Latin America, there are evidence that the evolution of wage inequality has a different pattern in the upper and the lower ends of wage distribution. Again, returns to education is the main drive explanation for the upper tail changes, supporting the skilled biased technology hypothesis. Formalization explain the most part of the wage recovery at the bottom end of the distribution. In the case of Uruguay, while tax reform emerge as an important factor to explain reductions in the Gini coefficient, there are no evidence that explore possible impacts of this policy over the schooling premiums and its consequences over wage inequality.

Chapter 4

Data

The empirical analysis of this paper is based on data from the Current Household Survey (Encuesta Continua de Hogares, ECH), collected by the National Statistics Institute (Instituto Nacional de Estadística, INE) and corresponding to the period 2005-2015. The ECH consists of a random sample of households, and collect data on socio-demographic characteristics of households and their members. In particular, the survey includes data on gender, age, place residence and educational attainment; job characteristics including sector of activity, occupation type and working hours; and income variables including wages and utilities.

The coverage of the survey has increased over time. Until 2006 the ECH was representative of localities up to 5000 inhabitants, and from there it is representative of the whole country. Thus, for comparability reasons we compute only regions over 5000 inhabitants.

Other important changes of the data has been occurred in this period. From 2005 to 2011, the classification of occupations correspond to the third revision of the International Standard Industrial Classification of All Economic Activities (Clasificación Internacional Industrial Uniforme, CIIU). Until March 2005 the CIIU was two digits, and four digits thereafter. From 2012 to 2015 the classification is the fourth revision of the CIIU, at four digits too. The same change periods occurs for the International Standard Classification of Occupations (Clasificación Internacional Uniforme de Ocupaciones, CIUO). From 2005 to 2011 the ECH apply the revision 88, while from 2012 revision 08 is used.

In order to obtain an homogeneous sample over time, the study considers women and men workers from private sector, aged 18 to 60 and work between 10 and 60 hours a week[1]. We compute workers' real hourly wage by taking the ratio of the monthly salary to the number of hours worked. All values are in real terms, expressed into December 2006 Uruguayan pesos.

One of the main contribution of this work refers to the recovery of the gross labor income from the information of the ECH, and doing so for a long period including pre an post tax reform years [2]. Thus, the present work contribute to complement and expand previous efforts such as OPP (2017) and Burdín et al. (2014).

The gross-up procedure used to obtain the pre-tax wages are detailed in Appendix 1. Briefly, four steps must be computed: i) define the universe of potential tax informants and construct the net labor income taxed by social security declared in the ECH; ii) define and apply to the liquid wages obtained in (i) the rates of social security and health insurance in order to obtain the first 'nominal wage'; iii) apply the direct taxes rates (IRP or IRPF), obtain a first estimate of direct taxes amount and define a second 'nominal wage' as the sum of the first 'nominal wage' and taxes; iv) iterate the procedure from steps (i) to (iii), considering from each iteration the last estimated nominal income as 'liquid' income.

In order to measure the impact of minimum wage we follow (Firpo et al., 2011*b*, pg. 27). Authors suggestion is to construct a counterfactual variable that indicate those who in the base period could have been affected by the policy if it had been implemented in that period. That is, potential treated are workers whose 2005 salaries was between the minimum wage of that year and the minimum wage of 2015, deflated at base year prices. More precisely, the process of construction of is the following: first, create a dummy variable who take value 1 when the individual has a wage higher than the minimum wage in 2005 and lower than the deflated 2015 minimum wage; second, build a grid where each cell correspond to workers grouped by sex, age and education segments; third, construct the policy variable as the percentage of people with

[1]It is restricted to people 18 years of age and over in order to work with a more stable labor market participation. Only people under 60 year are included because it represents the retirement age in most sectors of activity.

[2]The entire procedure, do files and data bases necessary to reconstruct the pre-tax labor incomes can be consulted in the website Thesis Documentation

the characteristic (i.e. the average of the dummies), for each cell of the grid.

Taking the above into account, two different specification of a RIF regression are used for the empirical strategy. The first can be called the *Mincer extended specification*, including variables of sex, six groups of education levels, nine gropus of potential experience, eight groups of industries, geographical region and dummy for informality. The second specification adds the one that captures the effects of minimum wage policy (we call this specification as the *Mincer extended including minimum wage policy*). In all cases the explained variables are the pre and post-tax real hourly wage (in logs).

Chapter 5

Methodology

The main goal of this work is to analyze the effects of the 2007 Uruguayan tax reform on returns to schooling and over wage inequality. First, a bootstrapping technique is used for this purpose. It is also necessary to perform a strategy that allow us to measure the impact of covariates on the changes of distribution of wages. To this end, a decomposition method based in RIF-regression is applied.

5.1 Bootstrapping and Hypothesis testing

In first place, to analyze the returns to education we use a bootstrap method to construct the sample distribution of the regressions coefficient. Afterwards, we use the empirical distribution of the parameters of interest to formally test several hypotheses.

Following Cameron and Trivedi (2005, Chap. 11), a general bootstrap algorithm is as follow:

1. Given data $w_1, w_2, \ldots, w_N$ where usually $w_i = (y_i, x_i)$, it is possible to draw a bootstrap sample of size N, obtaining a new sample $w_1^*, \ldots, w_N^*$
2. Calculate an appropriate statistics using the bootstrapped sample. In our case this include the vector $\hat{\beta}^*$ of β, an estimator of the parameters of the regressions of y over x.
3. Repeat steps 1 and 2 B independent times (B is a large number) and obtain B bootstrapped replications of the statistic, i.e. $\hat{\beta}^*{}_1, \ldots, \hat{\beta}^*{}_B$.

4. Use these B bootstrapped replications to obtain a bootstrapped version of the statistic.

The method chosen in this work to generate the bootstrapped sample $w_1^*, \dots, w_N^*$ is the so called empirical distribution function (EDF) or paired bootstrap, since both y_i and x_i of w_i are resampled. Concerning to the number of bootstraps, Cameron and Trivedi (2005, pg. 361) suggest to carry out at least 200 replications. Thus, in this work we perform between 200 and 1000 replications of the entire procedure depending the objective of the bootstrap.

Applying the described procedure, it is possible to compute the bootstrap estimate of variance of β, applied to the B bootstrap replications, $\hat{\beta}^*{}_1, \dots, \hat{\beta}^*{}_B$:

$$s^2_{\hat{\beta},Boot} = \frac{1}{B-1}\sum_{b=1}^{B}(\hat{\beta}^*_b - \bar{\hat{\beta}}^*)^2, \tag{5.1}$$

where

$$\bar{\hat{\beta}}^* = B^{-1}\sum_{b=1}^{B}\hat{\beta}^*_b, \tag{5.2}$$

As usually, taking square root the bootstrapped estimate of the standard error, $s_{\hat{\beta},Boot}$, is obtained. This bootstrap estimate is consistent, so it can be used to perform hypothesis tests that are asymptotically valid.

Consider tests on an individual coefficient, β, that may be either an upper one-tailed alternative or a two-sided test. The approach used in this work consist in computing the statistic $t = (\hat{\beta} - \beta_0)/s_{\hat{\beta},Boot})$, where $s_{\hat{\beta},Boot}$ is obtained from equation (5.1), β_0 is the value included in the null hypothesis. Then we compare this test statistic to critical values from the standard normal distribution.

Testing the difference of two coefficients from different regressions (in our case the education coefficients from regressions of pre and post taxes wages), require to compute the statistic:

$$t = \frac{(\hat{\beta}_1 - \hat{\beta}_2)) - (\beta_{01} - \beta_{02)}}{\sqrt{(s^2_{\hat{\beta}_1,Boot} + s^2_{\hat{\beta}_2,Boot})/B}} \tag{5.3}$$

Finally we compare this test statistic to critical values from the t-distribution with B degrees of freedom.

5.2 Decomposition methods and RIF regressions

5.2.1 Methodology

For the analysis of the evolution of wage inequality, we apply the microeconometric decomposition method proposed by Firpo et al. (2007, 2009, 2011*a*). The goal here is to compute the effects of different covariates (e.g. education, gender) across the wage distribution between two time periods, and to disentangle the contribution of each covariate. This method extends the traditional Oaxaca-Blinder decomposition of mean earnings to other features of the distribution. More precisely, it is possible to decompose the total change of a distributional statistic of interest (Δ_O^v) into two effects: a composition or characteristics effect (Δ_X^v), which captures the impact of changing the distribution of the covariates (X); and a wage structure (Δ_S^v), or return or price effect, which reflects how the conditional distribution of wage ($F(w|x)$) changes over time.

Thus, considering two time period (T=0 and T=1), the overall change of a distributional statistic v of variable wage (w), between 0 and 1, can be written as:

$$\Delta_O^v = v(F_{w1|T=1}) - v(F_{w0|T=0}) = v_1 - v_0 \tag{5.4}$$

In order to decompose the overall change into composition and wage structure effects, it is necessary to compute a counterfactual statistical, $v_C = v(F_{w0|T=1})$. This counterfactual can be interpreted as the distributional statistic that would have prevailed if individuals observed in base period ($T = 1$) had been paid under the wage structure of $T = 0$. Adding and subtracting v_C in (5.4), we have:

$$\Delta_O^v = (v_1 - v_C) + (v_C - v_0) = \Delta_S^v + \Delta_X^v \tag{5.5}$$

Now the interpretation of the decomposition becomes clearer. The wage structure effect term corresponds to the effect on v of a change from price structure keeping the distribution of X in period 1 constant. On the other hand, the composition effect's term will correspond to changes in distribution from the one of $X|T = 1$ to that of $X|T = 0$.

As previously explained, one of the main goals of this work is to explain changes on wage inequality, especially focus on the effects of deep institutional reforms (tax structure reform and minimum wage policy) and their link with education premiums. And as also was pointed out before, it is expected that they will have different impacts throughout the wage distribution. Therefore, going beyond the mean (and also the variance) will help to better understand and enrich the analysis of changes in wages inequality. The RIF-regression decomposition method, proposed by Firpo et al. (2007, 2011*a*), is the method chosen here to carry out this exercise.

The first step of the method is to estimate the re-centered influence function regression (RIF-regression), proposed by Firpo et al. (2009). The influence function (IF) is a measure of robustness of a general functional $v = v(F)$ in the presence of outliers (Hirano et al., 2003). Therefore, the IF can be interpreted as a function that captures the influence of each observation on $v = v(F)$:

$$IF(w; v, F) = \lim_{\epsilon \to \infty} \frac{v(F_\epsilon) - v(F)}{\epsilon}, \tag{5.6}$$

where $F\epsilon(w) = (1 - \epsilon)F + \epsilon\delta_w$, $0 \leq \epsilon \leq 1$ and δ_w is a distribution that only puts mass at the value w of wage distribution.

It can be shown that $\int_{-\infty}^{\infty} IF(w; v, F)dF(w) = 0$. Define the RIF as $RIF(w, v) = v(F) + IF(w; v)$, it is immediate to see that $\int_{-\infty}^{\infty} RIF(w; v)dF(w) = \int_{-\infty}^{\infty} (v(F) + IF(w; v))dF(w) = v(F)$

Assuming that the earnings w of individual i in period T are generated from a function h, it is straightforward to define $w_i = h_T(X_i)$. By the law of iterated expectations, the unconditional expectation of $v(F)$ is given by:

$$v(F) = \int_{-\infty}^{\infty} E[RIF(w; v)|X = x]dF_X(w), \tag{5.7}$$

and the RIF regression is defined as:

$$\begin{aligned} &h^v_{T=0,1} = E[RIF(w; v)|X, T = t], \quad t = 0, 1 \\ &h^v_C = E[RIF(w0; v_C)|X, T = 1] \end{aligned} \tag{5.8}$$

And therefore:

$$v_t = E[h_t^v(X)|T = t], \texttt{ and } v_C = E[h_C^v(X)|T = 1] \tag{5.9}$$

Thus, it is possible to rewrite Δ_S^v and Δ_X^v in the following way:

$$\begin{aligned} \Delta_S^v &= E[h_1^v(X)|T = 1] - E[h_C^v(X)|T = 1] \\ \Delta_X^v &= E[h_C^v(X)|T = 1] - E[h_0^v(X)|T = 0] \end{aligned} \tag{5.10}$$

Even if there is no reason to suppose linearity of $h_t^v(X)$, for the comparability of the Oaxaca-Blinder decompositions it is nonetheless useful to consider the case of the linear specification. Indeed, consider the linear projections $h_T = x'\gamma_t$, the equations in (5.10) can be rewritten as:

$$\Delta_S^v = E[X|T = 1]'(\gamma_1^v - \gamma_C^v) \tag{5.11}$$

$$\Delta_X^v = E[X|T = 1]'\gamma_C^v - E[X|T = 0]'\gamma_0^v \tag{5.12}$$

As Firpo et al. (2007) point out, the linear specification used in the regression is only a local approximation that may not hold for larger changes in the covariates. As a result, the estimations of both effects might be biased. Firpo et al. (2007, 2011*a*) propose a solution that combine both reweighting and RIF-regressions. The basic idea is to consider the fact that a regression is the best linear approximation for a given distribution of X, and to apply a weighting function that corrects for misspecification, generating a counterfactual observation that makes the distributions of X's in period 0 similar to that of period 1. This reweighing function[1] is:

$$\omega(X) = \frac{Pr(T = 1|X)}{Pr(T = 1)} \frac{Pr(T = 0|X)}{Pr(T = 0)} \tag{5.13}$$

Now it is possible to compute the RIF regressions on the reweighted covariates in order to obtain γ_1^v, γ_0^v and γ_C^v, and proceed to compute the decomposition analysis. Additionally, it is possible to rewrite the composition effect and divided it into two components: a pure composition effect, $(\Delta_{X,p}^v)$ and a specification error,$(\Delta_{X,e}^v)$. Adding and subtracting $E[X|T = 1]'\gamma_0^v$ in (5.12), the composition effect can be rewritten as:

[1] In practice, the reweighing function is computed based on estimating a logit or probit model on the probability of being observed in period 1, including a large set of interaction between the explanatory variables

$$\Delta_X^v = \underbrace{\left(E[X|T=1] - E[X|T=0]\right)' \gamma_0^v}_{\Delta_{X,p}^v} + \underbrace{E[X|T=1]' \left(\gamma_C^v - \gamma_0^v\right)}_{\Delta_{X,e}^v} \tag{5.14}$$

While the first term refers to the 'true policy effect' of changing the distribution of covariates from $T = 0$ to $T = 1$, the second term indicates the lineal projection error associated at the fact that the RIF regression-based procedure only provides a first-order approximation to the composition effect Δ_X^v. Hence, the magnitude of the specification error provides a specification test of FFL's regression model-based procedure[2].

Finally, the RIF regression approach admit to compute a detailed decomposition:

$$\Delta_S^v = E[X|T=1]'(\gamma_1^v - \gamma_C^v) = \sum_{k=1}^{K} E[X_k|T=1](\gamma_{1,k}^v - \gamma_{C,k}^v) \tag{5.15}$$

$$\Delta_X^v = E[X|T=1]'\gamma_C^v - E[X|T=0]'\gamma_0^v = \sum_{k=1}^{K} \left(E[X_k|T=1] - E[X_k|T=0]\right)' \gamma_{0,k}^v + \Delta_{X,e}^v \tag{5.16}$$

Thus, it is possible to calculate the contribution of each covariate to the wage structure and composition effect.

5.2.2 Advantages and limitations

In comparison with other methods, like DiNardo et al. (1996), Machado and Mata (2005) and Chernozhukov et al. (2013), one important advantage of the RIF regression decomposition method is that it is path independent. That is, the decomposition results do not depend on the order in which the decomposition is performed. This condition of independence obeys to the linearity of the RIF regression, because it is possible to locally invert the proportion of interest by dividing by the density. Hence, monotonicity is not a problem. In

[2]Empirically, this error can be computed as the difference between the overall composition effect and the reweighted estimate of the composition effect.

addition, the results are a simple regression and therefore are easy to interpret (Firpo et al., 2011*a*).

A methodological advantage is the efficiency of the method, established by Hampel (1974) and Firpo and Pinto (2016). To compute the standard errors of the parameters of interest the bootstrap method is used.

Another advantage of the method is its simplicity. The reweighting approach allows us to run, for any distributional statistic, an aggregate and detailed decomposition without intensive computational requirements and using standard statistical packages.

On the other hand, this decomposition method presents some limitations. First, RIF regressions (such as decomposition methods in general) assume that there are no general equilibrium effects. Second, the method does not solve the omitted group problem, present in the standard decompositions. This problem refer to the sensitivity of the detailed decomposition of the wage structure effect with respect to the choice of omitted category. To see this, following Firpo et al. (2007) let us rewrite the equation (5.15) as follow:

$$\Delta_S^v = \sum_{k=2}^{K} E[X_k - x_{k,B}|T=1](\gamma_{1,k}^v - \gamma_{C,k}^v) + \left[\gamma_{1,1}^v - \gamma_{C,1}^v + \sum_{k=2}^{K} x_{k,B}[\gamma_{1,k}^v - \gamma_{C,k}^v]\right] \quad (5.17)$$

Here, $x_{k,B}$ is the base group. Thus, the first term on the right hand side of the equation is the wage structure effect associated to a given covariate k, while the second term can be interpreted as the residual difference[3]. As can be noted, both component of this expression depend on the choice of the base group. If the RIF-regression method provides a good approximation, the residual term should be close to the actual change in the distributional statistic observed in the base group $(v_{B1} - v_{B0})$. As (Firpo et al., 2007, pg. 18) indicates, these two effects can be estimated separately. Thus, the difference between those, called reweighting error, provides another specification test of FFL's approach.

[3] $\gamma_{1,1}^v - \gamma_{C,1}^v$ is the difference in the intercepts of the model and $x_{k,B}[\gamma_{1,k}^v - \gamma_{C,k}^v]$ is the wage structure effect of the base group

Chapter 6

Results

The main results of our work are presented in this section, organized into two parts. First, we characterize the behavior of the returns to education before and after taxes. The focus is on the evolution of schooling premium: we formally address for disparities between pre and post taxes returns by applying mean difference tests, using bootstrapped empirical distributions. Second, based on RIF regressions, we estimate aggregate and detailed decomposition of changes in inequality, analyzing the role of the wage structure effect of education.

The covariates included in the regressions were detailed in Chapter 4 and reflects the different determinants that would explain the changes in the wage distribution over the considered period. This is the case of relevant variables like experience or gender, as well as job characteristics and minimum wage policy. We also include controls for region and sector of activity in all the estimated models.

6.1 Pre and Post Taxes Returns to Education

Workforce has improve his levels of education over the analyzed period. Additionally, returns to education, both before and after taxes, falls systematically in those years (see Figure 7). Table 8 shows the returns to education for selected years, estimated from OLS-regressions with pre-tax and post-tax wage as dependent variable, and the two sets of co-variables detailed in Chapter 4. The reference group of education attainment is workers with 6 years of formal education, corresponding to primary complete. As expected, and in line with the international evidence, returns computed from pre-tax wages are higher than those that come from post-taxes salaries (see, for example, Heckman et al. 2006 for estimations for US, Abramitzky and Lavy 2014 for Israel, Booth and Coles 2010 for OECD or García-Suaza et al. 2014 for Colombia). Another interesting finding is that the returns to education are lower once controlling for minimum wage policy. This pattern is observed along the period of analysis, consistent with the fact that the minimum wage continue growing at a persistent rate.

In this context of decreasing returns to education, it were expected that the tax reform initiated in 2007 would have a differentiated effect on the returns to pre and post taxes across the education levels: given the progressive nature of the reform and that more educated perceive higher wages, the post-taxes returns of more educated will show a more pronounced fall. However, as can be seen in Figures 8, the jump occurred between 2007 and 2008 is homogeneous for all education levels from secondary incomplete to tertiary complete and more. Thus, more educated workers do not suffer a higher penalization due to the increasing marginal tax rates.

Complementing this regression analysis we simulate the empirical distribution of the returns to education and perform statistical test over the differences in the coefficients. To do so, we perform a bootstrap technique consisting of 1000 replications of the entire procedure. Figures 11 and 12 present the distribution of each coefficient of education level for the years 2005 and 2015[1]. Table 14 present the mean difference test for pre and post taxes coefficients by education levels for selected years, and it is concluded that the difference between before and after taxes education returns is significant, except for those with incomplete primary education. This find are consistent with the fact that workers with very low education attainment are located at the bottom of the wage distribution, were the wage taxes are virtually zero and do not change over the period considered.

Two additional test are performed in order to analyze the changes of the returns to education over time. These tests are presented in Table 15. The first one (see the two first columns) shows that the fall in both pre and post taxes coefficients are statistically significant, confirming the evolution observed in

[1]The results for bootstrap procedure over the hole period are available under request, like other results for year within the period covered that are not reported in this work.

Figure 9. The second, presented in the last column, is the test of the difference between the two first columns, and represents a measure of the difference between the rate of variation of both before and after tax coefficients. As can be seen, we reject that the rate of variation between before and after taxes coefficients is similar for each education level. Moreover, in all cases the difference (pre-tax minus pos-tax) is positive, indicating that the fall in the former returns are less than the last one. Also it can be seen that the rate of variation increases according the education level increase (the diff in diff for secondary incomplete is 0.002, while for university complete an more is 0.041).

Therefore, these results confirm the idea that there was a widening of the gap between pre and post returns for the different educational levels compared to primary complete, but said gap varied in a similar way in both wage measures without a greater differentiation in the case of the higher educational levels.

The analysis of the returns to education of RIF-regressions goes in the same direction and complement the previous findings. Notice that an important feature of RIF-regressions is that they allow to capture non-monotonic effects. As Firpo et al. (2011*a*) establish, in the case of quantiles this property means that the regression coefficients capture the effect of covariates on both between and within group components of wage dispersion.

In that sense, Figure 10 shows that the returns increases with the percentile and its slope are more pronounced according the education level increases, both in pre and post tax specification. This feature can be observed for the 4 years considered, with the particularity that it is downward as the years pass[2]. This feature is notorious for the low educational levels, and, for example, for secondary incomplete in 2015 the coefficients are practically flat along quantiles. These findings are in line, for a long period, with those presented by Alves et al. (2013) and Rodriguez (2014).

But this analysis is enriched by comparing the estimation of returns before and after taxes, allowing to analyze the role of the tax regime. In fact Figure 10 shows that, while for the returns of secondary incomplete to tertiary incomplete presents a more pronounced decrease at the top of the distribution, for the returns to tertiary complete and more these fall is less marked. So,

[2]Estimation for other years of the period are available under request.

the reduction on the return to education for highest level must be explained mostly by what happens in the lower part of the wage distribution. Thus, these findings enforces the idea that the most educated and richest workers were able to cushion the impact of the tax reform with rise of their pre-tax salaries.

It is interesting to analyze the RIF-coefficients related to other characteristics than education. For example, the effect of the formalization is highly decreasing across quantiles and becoming more pronounced at the end of the period, both pre and post taxes. In the case of pre-tax wages, while in 2005/06 the effect of been registered were around 0.9 at the 10^{th} quantile and go down up to 0.156 at 90^{th}, in 2014/15 this values were 1.5 and 0.087 respectively (Tables 10 and 12). This indicates that formality decrease inequality both in the lower end and in the higher end of the distribution. This result is consistent with Amarante et al. (2016) who investigate the role of formality in the reduction of wage inequality for Uruguay.

The case of gender is also interesting. The OLS-regressions presented in Table 9 show that the gender gap is relatively stable, with a very slight fall in ten years. However the result is not homogeneous along the distribution of wages. While for the lower end the gap remains practically unchanged, the male premium increases at the top. Also, it is in that part of the distribution where the coefficient varies, so the small reduction on the average gender gap is explained for a small reduction in the gap for highest wages. These results confirm the 'glass ceiling' hypothesis for women (Borraz and Robano, 2010; Bucheli and Sanromán, 2005), and although indicate a slight decrease in wage differences.

6.2 Decomposition Results

The results of the aggregate and detailed decomposition for pre and post tax wages are presented in Figures 13, 14 and 15. Tables 17, 18 and 19 summarize the results for the standard measures of 90-10 gap, top-end (90-50 gap) and low-end (50-10) wage inequality, as well as for the variance of log hourly wages and the Gini coefficient. The base group used in the RIF-regression models consists of men who lives out of Montevideo, with primary complete, 15 to 19 years of potential experience, not registered in social security, working on agriculture and mining sector. Following Firpo et al. (2007) the reweighting factor is estimated with logit models that include a richer specification with additional interaction terms.

As can be seen in Table 17, wage inequality substantially falled between 2005 and 2015, for all considered inequality measures[3]. This evolution is mainly driven by the wage structure effect. For example, the 90-10 gap fall around 0.5 points in the decade for both pre and post tax wages, where almost 80% are explained by the wage structure effect in the pre-tax case and 88% in the post-tax case. In terms of the wage changes over the entire distribution, it can be seen that the reduction of inequality is due to changes of similar magnitude at the low-end and top-end of the wage distribution. However, this result is not homogeneous between wage structure and composition effects. For the former, almost two thirds of the change are explained by changes in the top of the distribution [4]. Therefore, the pattern of the evolution of inequality is characterized mostly by a price effect at the top-end of wage distribution.

Table 17 also report the specification error, which corresponds to the difference between the total composition effect obtained by re-weighting and the RIF-Regression method without reweighing (see equation (5.14) in Chapter 5). As Firpo et al. (2007, 2011*a*) establish, the magnitude of this term provides a specification test of RIF-regression model-based procedure. In our case the specification error is always very small and not significant.

Figure 13 show the decomposition results at each percentile. The negative slope curve indicating the fall in the inequality is clear, and it is also clear that this pattern is driven by the wage structure effect. This pattern apply for both pre and post taxes wages, but its similarity hides a difference associated to the contribution of each characteristic to wage inequality.

In this sense, the detailed decomposition give us the possibility of apportion the composition and wage structure effects to the contribution of each set of covariates. For pre-tax wages the results are shown in Table 18 and Panel A of

[3]Table 16 present the values of the inequality measures for the pooled years 2005/06 and 2014/15 and its variation over the period.

[4]in the case of Gini and variance all values are different from zero at 1% of significance. For the 90-10, 90-50 and 50-10 gaps of pre-tax wages, all values are different from zero at 1% of significance except of 90-50 gap for composition effect, which is significant at 5%. For post-tax wages the gaps also are significant at 1%, except for the 90-10 of composition effect which it is at 5% and 90-50 of composition effect which is not significant.

Figures 14 and 15. Table 19 and Panel B of Figures 14 and 15 does the same for post-tax wages. The presentation of the results are reported for seven set of explanatory factors: minimum wage, education, experience, industry, gender, region and formality.

Concerning the composition effect, education, minimum wage policy and formalization are significant to explain wages gaps. Here the concentrating effect of education is highlighted, which may be due to the increase of the percentage of workers with highest educational levels, as can be seen in Table 1. As expected, the impact happens mostly at the top-end of the distribution (90-50 gap). The equalizing effect of the formality compensate this effect, resulting in the overall small contribution of the composition effect to the reduction of inequality. In the case of formality, the contribution to reduce inequality is in equal parts in the lower and upper part of the distribution. These results apply both to pre and post taxes wages.

In the case of the wage structure effect, the covariates industry, gender and formality result significant for pre-tax wages in all inequality measures. For post-tax wages also minimum wage becomes significant. While formality and minimum wage have a positive contribution to reduce inequality, industry and the gender gap do not.

The case of returns to education is not the same under pre-tax and post-tax equations. In the first case is not significant. In the case of pos-tax wage, the contribution is significant and goes in direction of reduce inequality. In fact, together with minimum wage policy and formality, drive the reduction of inequality for all indicators.

If the more educated workers had not been able to reverse, at least partially, the effects of the tax reform, it should be noted that the contribution of the returns to education to the reduction of inequality are at least equally significant in the specification with and without taxes. However, the previous evidence indicate that in the case of pre-tax wages the education's wage structure effect vanished.

In sum, from the analysis of the evolution of returns to education (both pre- and post-tax) on average and over different quantiles, and the results of decomposition for several measures of inequality, it seems possible to affirm that, controlling for a set of variables, the more educated workers managed to partially reverse the equalizing effects of the tax reform. This in a context in which other policies with direct impact on the labor market were processed, together with regional and international conditions that favored the performance of strongly primarized economy such as Uruguay.

Chapter 7

Concluding remarks

In this paper we look at the role played by two of the major institutional policies applying during the past decade in Uruguay, to changes in the wage distribution through the returns to education. These policies were a progressive tax reform and a strong increase of the minimum wages. Also, these policies were implemented in a context of good performance of economic activity and the improvement of social conditions prevailing in previous years.

We first characterize the evolution of returns to education comparing the results of estimations of extended mincerian equations, including a covariable capturing the impact of minimum wage, over pre and post-tax wages. We do so by using a bootstrap technique to construct the empirical distribution of the returns, and then perform hypothesis tests to compare the level and evolution of said coefficients over time. Then we apply a microeconometric decomposition method based on RIF-regression proposed by Firpo et al. (2007, 2009), to quantify the contribution of education in wage inequality considering two alternative specification of the dependent variable (pre and post taxes wages), in order to capture the potential effects of the tax policy.

The entire work are based on data from the Uruguayan household survey for the period 2005–2015, were the wage inequality experiment a sharp decrease. Given that the income information are in after-tax terms, it was necessary to reconstruct the before tax-income. This process represents per-se an important contribution of the present work, since there are no other precedent on recovery the pre-tax wages for such a long period.

Previous studies (Amarante et al., 2016; Rodriguez, 2014, among others) find evidence that the the decrease of wage inequality is mostly due to a reduction of the returns to educations and institutional factors like formality. We confirm in general these results, but a deeply analysis of the behavior of the returns to education and potential effects of the main institutional reforms produce some additional interesting discovers.

Performing a simple counterfactual exercise show that the observed large increase in the minimum wage should have an important effect at the low-end of the wage distribution, indicating that workers with primary incomplete or complete are those who were potentially treated by the policy. On the other hand, a similar counterfactual exercise considering the changes of tax structure, indicate that a reduction in post-taxes wage would have take place for more educated workers.

However the estimates of the mincerian OLS regressions indicates that returns to education for both before and after taxes, decreases systematically in those years in a similar magnitude. These findings are complemented with mean difference tests of the education parameters, performed from the empirical distributions obtained via bootstrapping. In all cases we do not reject that the rate of variation between before and after taxes coefficients would be similar. Thus, more educated workers does not suffer a higher penalization due to the biggest marginal tax rate.

Complementary, RIF-regression for the earning equations were performed. The estimations shows that the return to education profiles increases with the percentile and becomes more steeply according the education level increase, both in pre and post tax specification. Comparing the estimation of the returns of before and after tax wages, we found that for lower educational levels exist a pronounced decrease at the top of the distribution. But for the returns to tertiary complete and more this fall is less marked. So, this evidence reinforce the OLS results, in the sense that the most educated and richest workers could be cushioned the fall on his schooling premmia due to the tax reform.

The results of the aggregate decomposition confirms previous findings that the wage inequality falls whatever been the measure considered. All measures fall at least a quarter of their value at the beginning of the period, and this happen both pre and post taxes wages. This evolution is in all cases mainly driven by the wage structure effect, and considering both the 90-10 gap and the Gini index and the variance, this effect explains at least 75% of the total change of the indicator.

In the case of the gaps, the total change is explained in equal parts by what happens at low-end and top-end of the distribution of wages. However this behavior is not invariant within composition and wage structure effect. 60% of the wage structure effect is explained by what happens at the top-end of the wage distribution, while in the case of composition effect the major changes occur at the bottom (65%). Finally, in all measures the specification error is always very small and not significant.

Detailed decomposition allow us to quantify the contribution of each covariate to wage structure and composition effects. In the case of our main goal, we center the attention on the difference of contribution of education to the wage structure effect under the two alternative wage specifications. Considering pre-tax wages, we found no significant effect of the education. In the case of pos-tax wage, the contribution is significant and goes in direction of reduce inequality. This difference on the impact of the education over the two alternatives, goes in the direction that the more educated workers had the capacity of reverse, at least partially, the equalizer power of the tax reform.

Summing up, our results seems to indicate that the large reduction of the inequality were characterized by a overall reduction of the wage dispersion, dominated by a wage structure effect mostly explained by reforms with impact on labor market institutions (tax reform, formality and minimum wage increase) and changes in education premiums. In this context, the more educated workers seems to managed to partially reverse the equalizing effects of the tax reform.

It is worth to notice that this conclusion should be analyzed carefully. The regional and international context, high demand for commodities with its strongly impact on prices and the productive structure of the national economy, and other institutional change that took place over this years, may be conditioning the evolution of the economic activity and therefore influence the inequality indicators considered.

Regarding further research, it would also be interesting to extend this work in at least three directions. First, it would be convenient to extend the period of analysis. Consider years in which inequality increased and deregulation of the labor market was the norm, such as the 1990s, or a period of modest improvement in inequality but with a lower degree of institutional reforms such as the late 1980s, they would enrich the analysis by providing comparability between different institutional and economic regimes.

A second appealing extension refer to modeling on a more stylized way the influence of collective bargaining on the wage dispersion. In this work we only consider the potential impacts of the national minimum wage level, but the installation of wage councils with participation of the state, workers and companies, has involved a series of changes in labor conditions that far exceed the effect of the minimum wage.

Last but not least, a third possible extension are related to a methodological issue. Given that sample selection is a major issue in empirical work and it is not yet well solved for RIF-regressions, a possibility is to perform a different estimation strategy, based on the method proposed by Arellano and Bonhomme (2017). Apply this technique and compare the results with the RIF-regression approach could be an interesting exercise to calibrate methods on a particular case.

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Tables

Table 1: Descriptive statistics

Variables	2005/2006 Means	2005/2006 Standard Deviation	2014/2015 Means	2014/2015 Standard Deviation	Difference in Means
Pre-tax wages	5,158	0,816	5,897	0,659	0,739***
Post-tax wages	5,001	0,763	5,697	0,593	0,696***
Primary incomplete	0,057	0,232	0,032	0,177	-0,025***
Primary complete	0,202	0,401	0,164	0,370	-0,038***
Secondary incomplete	0,457	0,498	0,414	0,493	-0,043***
Secondary complete	0,108	0,311	0,188	0,391	0,080***
Tertiary incomplete	0,087	0,282	0,100	0,300	0,012***
Tertiary complete and more	0,089	0,284	0,102	0,302	0,013***
Experience<5	0,014	0,116	0,015	0,121	0,001
5<Experience<10	0,070	0,256	0,084	0,277	0,014***
10<Experience<15	0,167	0,373	0,146	0,353	-0,021***
15<Experience<20	0,163	0,370	0,147	0,354	-0,017***
20<Experience<25	0,135	0,341	0,148	0,355	0,013***
25<Experience<30	0,126	0,332	0,129	0,335	0,003
30<Experience<35	0,109	0,312	0,110	0,313	0,001
35<Experience<40	0,090	0,286	0,100	0,299	0,010**
Experience>40	0,126	0,332	0,123	0,328	-0,003
Agriculture and Mining	0,048	0,213	0,042	0,201	-0,005*
Manufacturing	0,195	0,396	0,156	0,363	-0,039***
Electricity, gas and water	0,002	0,048	0,007	0,082	0,004**
Construction	0,066	0,248	0,084	0,277	0,018***
Commerce, Rest. and Hot.	0,223	0,416	0,239	0,426	0,016***
Transp. and Communic.	0,065	0,247	0,096	0,294	0,030***
Company Services	0,087	0,281	0,092	0,289	0,005
Comm., soc. and pers. svcs.	0,313	0,464	0,285	0,452	-0,028***
Women	0,460	0,498	0,466	0,499	0,006
Montevideo	0,536	0,499	0,530	0,499	-0,006
Registered	0,763	0,426	0,904	0,295	0,142***
N	34.707		41.757		

Source: Author's own calculation based on ECH data.

Note: * p<0.05, ** p<0.01, *** p<0.001

Table 2: Workers characteristics by quartiles of the wage distribution

2005	**0-25**	**25-50**	**50-75**	**75-100**
Education levels				
Primary incomplete	12,1	7,2	5,4	2,3
Primary complete	30,6	24,8	20,6	9,3
Secondary incomplete	47,2	51,8	48,7	34,9
Secundary complete	6,0	9,3	11,0	14,9
Tertiary incomplete	2,7	4,6	8,7	16,4
Tertiary complete and more	1,3	2,3	5,6	22,2
Potential Experience				
Experience<5	0,3	0,6	1,4	1,9
5<Experience<10	3,7	5,8	6,9	8,0
10<Experience<15	15,7	17,2	14,6	12,5
15<Experience<20	15,6	16,1	14,9	14,5
20<Experience<25	12,8	12,4	13,4	14,2
25<Experience<30	12,5	12,4	12,8	14,6
30<Experience<35	11,4	11,2	12,0	13,0
35<Experience<40	10,7	9,7	9,9	10,2
Experience>40	17,3	14,6	14,1	11,2
Industry				
Agriculture and Mining	8,3	6,0	3,9	2,6
Manufacturing	15,7	20,4	21,2	19,4
Electricity, gas and water	0,2	0,2	0,2	0,5
Construction	5,2	5,7	9,4	6,1
Commerce, Rest. and Hot.	22,5	27,4	21,0	15,4
Transp. and Communic.	3,6	4,9	6,8	10,5
Company Services	4,8	5,5	6,6	13,3
Community, social and personal services	39,7	29,9	30,9	32,2
Gender				
Men	42,4	48,5	55,9	60,2
Women	57,6	51,5	44,1	39,8
Region				

Interior	60,9	45,6	38,8	29,1
Montevideo	39,1	54,4	61,2	70,9
Formality				
Not registered	58,4	21,5	9,4	3,2
Registered	41,6	78,5	90,6	96,8
2015	**0-25**	**25-50**	**50-75**	**75-100**
Education levels				
Primary incomplete	6,7	3,2	2,4	1,1
Primary complete	27,0	18,6	14,0	7,1
Secondary incomplete	48,8	49,7	41,9	24,9
Secundary complete	12,2	18,3	23,0	21,8
Tertiary incomplete	3,5	7,1	11,5	16,9
Tertiary complete and more	1,8	3,2	7,2	28,2
Potential Experience				
Experience<5	0,5	0,9	1,7	2,3
5<Experience<10	5,1	7,8	8,8	8,9
10<Experience<15	13,7	14,7	13,7	12,2
15<Experience<20	13,3	14,2	15,0	14,3
20<Experience<25	13,2	14,3	15,5	15,9
25<Experience<30	12,2	12,4	13,2	14,4
30<Experience<35	11,2	10,7	10,6	12,7
35<Experience<40	11,1	10,6	10,3	10,5
Experience>40	19,8	14,3	11,2	8,9
Industry				
Agriculture and Mining	6,2	4,6	4,2	2,6
Manufacturing	13,9	15,4	16,2	15,7
Electricity, gas and water	0,6	0,6	0,7	0,8
Construction	5,0	5,1	10,4	12,4
Commerce, Rest. and Hot.	27,3	30,0	21,2	15,4
Transp. and Communic.	5,1	7,7	11,1	13,5
Company Services	5,9	9,2	8,4	12,7
Comm., soc. and pers. svcs.	36,0	27,3	27,8	26,9
Gender				

Men	38,7	48,2	56,9	61,9
Women	61,3	51,8	43,1	38,1
Region				
Interior	62,1	51,7	48,3	38,4
Montevideo	37,9	48,3	51,7	61,6
Formality				
Not registered	32,8	3,8	1,5	0,9
Registered	67,2	96,2	98,5	99,1

Source: Author's own calculation based on ECH data.

Table 3: Inequality Measures on Pre and Post Taxes Hourly Wages

	Measure:	Gini		90-10		Theil	
Years	Specification:	pre-tax	post-tax	pre-tax	post-tax	pre-tax	post-tax
2005		0,458	0,435	7,390	6,287	0,397	0,365
2006		0,449	0,430	7,283	6,271	0,380	0,354
2007		0,451	0,428	7,456	6,341	0,384	0,349
2008		0,430	0,394	7,043	5,642	0,349	0,291
2009		0,426	0,391	6,732	5,450	0,344	0,289
2010		0,411	0,376	6,177	5,071	0,317	0,262
2011		0,388	0,358	5,650	4,660	0,274	0,238
2012		0,364	0,330	5,019	4,226	0,238	0,195
2013		0,362	0,327	4,666	3,957	0,240	0,197
2014		0,356	0,321	4,533	3,835	0,233	0,189
2015		0,357	0,322	4,467	3,822	0,237	0,192

Source: Author's own calculation based on ECH data.

Table 4: Workers potentially affected by the minimum wage policy 2005

	Education levels					
	Primary incomplete	Primary complete	Second. incomplete	Second. complete	Tertiary incomplete	Tertiary complete and more
Women						
Potential Experience						
Experience<5					0,049	0,044
5<Experience<10			0,226	0,144	0,060	0,030
10<Experience<15	0,500	0,203	0,177	0,120	0,062	0,030
15<Experience<20	0,276	0,183	0,169	0,120	0,062	0,030
20<Experience<25	0,239	0,183	0,169	0,120	0,062	0,029
25<Experience<30	0,239	0,183	0,169	0,110	0,054	0,029
30<Experience<35	0,239	0,173	0,155	0,097	0,051	0,029
35<Experience<40	0,173	0,139	0,150	0,097	0,051	0,029
Experience>40	0,155	0,139	0,150	0,097	0,051	0,029
Men						
Potential Experience						
Experience<5					0,123	0,043
5<Experience<10			0,129	0,077	0,047	0,033
10<Experience<15	0,167	0,150	0,100	0,052	0,034	0,033
15<Experience<20	0,150	0,113	0,093	0,052	0,034	0,033
20<Experience<25	0,148	0,113	0,093	0,052	0,034	0,036
25<Experience<30	0,148	0,113	0,093	0,054	0,032	0,041
30<Experience<35	0,148	0,111	0,074	0,060	0,032	0,041
35<Experience<40	0,132	0,103	0,067	0,060	0,032	0,041
Experience>40	0,127	0,103	0,067	0,060	0,032	0,041

Source: Author's own calculation based on ECH data. Note: Empty cells because there are no observation to compute. This is because potential experience are constructed as $age - educ - 6$, and the universe of workers include people over 24 years old. Thus, for example, workers with primary complete would have at least thirteen years of potential experience. On the other hand, a youngest worker (with 25 years old) and secondary complete never could achieve less than seven years of potential experience.

Table 5: 2005 Pre-Tax Hourly Wages

Counterfactual exercise with minimum wages		
Percentiles	Observed	NMW Contrafact
10	66	76
50	167	167
90	497	497
Mean	249	251
Variance	80920	80046

Source: Author's own calculation based on ECH data. Note: Wages include registered and not registered payments.

Table 6: Effective tax rate wit IRP and IRPF - Year 2007

	Effective tax rate		
Income intervals according to BPC	IPR	IRPF	Informant (%)
Less than or equal to 5	0,1%	0,0%	37%
Between 5 and 10	1,3%	0,7%	37%
Between 10 and 15	3,4%	4,2%	14%
Between 15 and 50	5,4%	9,8%	12%
Between 50 and 100	5,7%	16,2%	1%
More than 100	6,0%	19,9%	0%
Total	1,6%	2,4%	

Source: Author's own calculation based on ECH data.

Table 7: 2005 Post-Tax Hourly Wages

Counterfactual exercise with IRP and IRPF		
Percentiles	Observed	IRPF Contrafact
10	78	78
50	164	167
90	435	435
95	622	598
99	1248	1127
Mean	233	230
Variance	61515	50334

Source: Author's own calculation based on ECH data. Note: Only taxable payments are considered to compute wages.

Table 8: Returns to education of pre and post taxes wage

	Primary in-comp.	Second. in-comp.	Second. comp.	Tertiary in-comp.	Tertiary comp. and more
2005:					
pre-tax wages					
Mincer extended specification	-0,028	0,247	0,552	0,869	1,267
	(0,030)	(0,019)	(0,027)	(0,033)	(0,034)
Including minimum wage policy	-0,028	0,216	0,481	0,762	1,147
	(0,030)	(0,022)	(0,036)	(0,050)	(0,055)
post-tax wages					
Mincer extended specification	-0,028	0,239	0,533	0,842	1,232
	(0,030)	(0,019)	(0,027)	(0,032)	(0,034)
Including minimum wage policy	-0,028	0,209	0,465	0,739	1,115
	(0,030)	(0,022)	(0,036)	(0,049)	(0,054)
2008:					
pre-tax wages					
Mincer extended specification	-0,128	0,182	0,492	0,776	1,190
	(0,021)	(0,012)	(0,016)	(0,021)	(0,023)
Including minimum wage policy	-0,144	0,187	0,519	0,815	1,234
	(0,023)	(0,013)	(0,025)	(0,033)	(0,037)
post-tax wages					
Mincer extended specification	-0,125	0,170	0,454	0,717	1,095
	(0,020)	(0,012)	(0,015)	(0,020)	(0,022)
Including minimum wage policy	-0,139	0,175	0,477	0,750	1,132
	(0,022)	(0,013)	(0,022)	(0,030)	(0,033)
2011:					
pre-tax wages					
Mincer extended specification	-0,108	0,144	0,428	0,686	1,090
	(0,022)	(0,011)	(0,014)	(0,018)	(0,021)
Including minimum wage policy	-0,096	0,133	0,407	0,653	1,066
	(0,023)	(0,013)	(0,020)	(0,028)	(0,027)
post-tax wages					

Mincer extended specification	-0,099	0,132	0,394	0,634	1,005
	(0,022)	(0,011)	(0,013)	(0,017)	(0,021)
Including minimum wage policy	-0,087	0,120	0,373	0,601	0,981
	(0,022)	(0,013)	(0,019)	(0,027)	(0,026)
2015:					
pre-tax wages					
Mincer extended specification	-0,083	0,133	0,406	0,629	1,047
	(0,023)	(0,010)	(0,012)	(0,016)	(0,018)
Including minimum wage policy	-0,051	0,135	0,390	0,620	1,027
	(0,027)	(0,010)	(0,014)	(0,017)	(0,019)
post-tax wages					
Mincer extended specification	-0,075	0,120	0,366	0,570	0,946
	(0,023)	(0,010)	(0,012)	(0,015)	(0,017)
Including minimum wage policy	-0,043	0,122	0,349	0,561	0,926
	(0,026)	(0,010)	(0,013)	(0,015)	(0,018)

Source: Author's own calculation based on ECH data.

Note 1: The returns to education corresponds to the estimated coefficients in the OLS-regressions associated to the dummies of six levels of education. Dependent variable is real hourly wage (in logs) for pre-tax and post-tax wages. The two sets of covariates include (besides the six groups of education levels) variables of sex, three gropus of age, eight groups of industries, geographical region and dummy for informality. The difference between their are the covariate capturing the minimum wage policy.

Note 2: Robust standard errors in parentheses

Table 9: OLS-Regression Coefficients on Log (pre and post taxes) Wages - Including minimum wage policy

Explanatory variables	Years:	2005/06		2014/15	
	Dep. Var.:	pre-tax	post-tax	pre-tax	post-tax
Education (Primary complete omitted)					
Primary incomplete		-0,062	-0,061	-0,101	-0,093
		(0,019)	(0,019)	(0,016)	(0,016)
Secondary incomplete		0,211	0,204	0,128	0,115
		(0,012)	(0,012)	(0,007)	(0,007)
Secondary complete		0,514	0,499	0,386	0,347
		(0,022)	(0,022)	(0,012)	(0,011)
Tertiary incomplete		0,788	0,767	0,620	0,560
		(0,031)	(0,031)	(0,019)	(0,018)
Tertiary complete and		1,176	1,149	1,026	0,925
more		(0,037)	(0,036)	(0,022)	(0,021)
Potential Experience (15< Experience < 20 omitted)					
Experience<5		-0,483	-0,475	-0,433	-0,393
		(0,038)	(0,038)	(0,025)	(0,023)
5<Experience<10		-0,285	-0,276	-0,236	-0,217
		(0,021)	(0,021)	(0,011)	(0,011)
10<Experience<15		-0,106	-0,102	-0,092	-0,087
		(0,015)	(0,014)	(0,009)	(0,009)
20<Experience<25		0,089	0,086	0,066	0,061
		(0,016)	(0,016)	(0,009)	(0,008)
25<Experience<30		0,138	0,134	0,080	0,071
		(0,016)	(0,015)	(0,009)	(0,009)
30<Experience<35		0,152	0,148	0,092	0,079
		(0,017)	(0,016)	(0,010)	(0,009)
35<Experience<40		0,154	0,150	0,082	0,069
		(0,018)	(0,018)	(0,011)	(0,010)

Experience>40	0,186	0,181	0,062	0,048
	(0,018)	(0,017)	(0,011)	(0,010)
Industry (Agriculture and Mining omitted)				
Manufacturing	0,192	0,178	0,105	0,087
	(0,021)	(0,021)	(0,014)	(0,013)
Electricity, gas and water	0,509	0,487	0,111	0,095
	(0,071)	(0,069)	(0,035)	(0,033)
Construction	0,276	0,218	0,309	0,210
	(0,024)	(0,023)	(0,015)	(0,014)
Commerce, Restaurants and Hotels	0,093	0,083	0,007	-0,004
	(0,021)	(0,021)	(0,014)	(0,013)
Transport and Communications	0,324	0,306	0,165	0,141
	(0,026)	(0,025)	(0,015)	(0,015)
Company Services	0,315	0,293	0,118	0,099
	(0,027)	(0,027)	(0,016)	(0,015)
Community, social and personal services	0,228	0,219	0,067	0,062
	(0,022)	(0,021)	(0,014)	(0,013)
Other characteristics				
Gender	-0,248	-0,241	-0,228	-0,204
	(0,016)	(0,016)	(0,010)	(0,009)
Region	0,191	0,189	0,059	0,054
	(0,009)	(0,009)	(0,005)	(0,005)
Registered	0,708	0,509	0,828	0,626
	(0,011)	(0,011)	(0,010)	(0,010)
Minimum Wage	-0,342	-0,298	-0,068	-0,081
	(0,218)	(0,215)	(0,137)	(0,128)
Constant	4,110	4,121	4,845	4,872
	(0,035)	(0,035)	(0,023)	(0,022)
Observations	34487	34487	41757	41757

Source: Author's own calculation based on ECH data.

Note: Robust standard errors in parentheses.

Table 10: Unconditional Quantile Regression Coefficients on Log Pre-taxes Wages - Including minimum wage policy

Explanatory variables	Years:	2005/06			2014/15		
	Quantiles:	10	50	90	10	50	90
Education (Primary complete omitted)							
Primary incomplete		-0,050	-0,017	-0,231	-0,127	0,012	-0,190
		(0,053)	(0,027)	(0,029)	(0,041)	(0,017)	(0,021)
Secondary incomplete		0,153	0,170	0,331	0,096	0,091	0,220
		(0,033)	(0,016)	(0,023)	(0,018)	(0,010)	(0,014)
Secondary complete		0,159	0,389	1,120	0,177	0,295	0,752
		(0,044)	(0,029)	(0,064)	(0,024)	(0,015)	(0,032)
Tertiary incomplete		0,045	0,557	1,988	0,146	0,419	1,464
		(0,059)	(0,038)	(0,103)	(0,034)	(0,022)	(0,061)
Tertiary complete and		-0,021	0,693	3,238	0,176	0,587	2,624
more		(0,065)	(0,040)	(0,143)	(0,038)	(0,024)	(0,083)
Potential Experience (15<Exp<20 omitted)							
Experience<5		0,175	-0,071	-1,893	0,026	-0,173	-1,368
		(0,047)	(0,048)	(0,139)	(0,032)	(0,029)	(0,074)
5<Experience<10		0,059	-0,133	-0,906	-0,022	-0,153	-0,608
		(0,032)	(0,026)	(0,067)	(0,018)	(0,015)	(0,032)
10<Experience<15		-0,033	-0,094	-0,204	-0,045	-0,085	-0,154
		(0,034)	(0,021)	(0,035)	(0,017)	(0,011)	(0,018)
20<Experience<25		0,032	0,091	0,136	0,046	0,057	0,118
		(0,033)	(0,020)	(0,033)	(0,019)	(0,012)	(0,021)
25<Experience<30		0,068	0,131	0,220	0,028	0,057	0,162
		(0,032)	(0,021)	(0,042)	(0,018)	(0,012)	(0,021)
30<Experience<35		0,087	0,141	0,295	0,016	0,033	0,259
		(0,038)	(0,022)	(0,040)	(0,021)	(0,012)	(0,023)
35<Experience<40		0,068	0,129	0,352	-0,008	0,015	0,287
		(0,036)	(0,024)	(0,046)	(0,020)	(0,014)	(0,024)

Experience>40	0,071	0,149	0,410	-0,048	-0,021	0,298
	(0,040)	(0,022)	(0,041)	(0,023)	(0,014)	(0,023)
Industry (Agriculture and Mining omitted)						
Manufacturing	0,211	0,238	0,062	0,096	0,084	0,125
	(0,054)	(0,026)	(0,039)	(0,032)	(0,017)	(0,025)
Electricity, gas and	0,321	0,499	0,609	0,137	0,065	0,168
water	(0,081)	(0,100)	(0,298)	(0,061)	(0,042)	(0,074)
Construction	0,401	0,432	-0,108	0,278	0,359	0,187
	(0,066)	(0,034)	(0,042)	(0,036)	(0,020)	(0,029)
Commerce, Restaurants	0,254	0,082	-0,075	0,102	-0,066	-0,008
and Hotels	(0,055)	(0,026)	(0,041)	(0,033)	(0,016)	(0,024)
Transport and	0,264	0,429	0,210	0,141	0,172	0,192
Communications	(0,060)	(0,033)	(0,062)	(0,032)	(0,018)	(0,033)
Company Services	0,165	0,248	0,632	0,119	0,026	0,221
	(0,062)	(0,031)	(0,065)	(0,033)	(0,018)	(0,032)
Community, social and	0,251	0,322	0,020	0,070	0,078	0,003
personal services	(0,054)	(0,027)	(0,042)	(0,032)	(0,016)	(0,025)
Other characteristics						
Gender	-0,024	-0,138	-0,661	-0,094	-0,113	-0,529
	(0,027)	(0,019)	(0,045)	(0,017)	(0,010)	(0,029)
Region	0,239	0,178	0,211	0,088	0,045	0,068
	(0,019)	(0,015)	(0,020)	(0,010)	(0,006)	(0,011)
Registered	1,234	0,715	0,223	2,361	0,506	0,134
	(0,046)	(0,020)	(0,015)	(0,077)	(0,009)	(0,010)
Minimum Wage	-2,877	-2,269	4,865	-1,555	-2,076	4,686
	(0,440)	(0,296)	(0,565)	(0,262)	(0,144)	(0,353)
Constant	3,091	4,267	4,880	2,992	5,401	5,550
	(0,087)	(0,050)	(0,082)	(0,087)	(0,026)	(0,050)
Observations	34487	34487	34487	41757	41757	41757

Source: Author's own calculation based on ECH data.

Note: Bootstrapped standard errors are in parentheses (200 replications of the entire procedure).

Table 11: RIF-Regression Coefficients of Inequality Measures on Log Pre-taxes Wages - Including minimum wage policy

Explanatory variables	Years:	2005/06		2014/15	
	Ineq. Meas.:	Gini	Variance	Gini	Variance
Education (Primary complete omitted)					
Primary incomplete		-0,009	-0,175	0,001	0,020
		(0,002)	(0,032)	(0,002)	(0,033)
Secondary incomplete		0,003	0,092	0,003	0,063
		(0,001)	(0,020)	(0,001)	(0,014)
Secondary complete		0,028	0,527	0,018	0,305
		(0,002)	(0,035)	(0,001)	(0,023)
Tertiary incomplete		0,061	1,096	0,043	0,661
		(0,004)	(0,056)	(0,002)	(0,035)
Tertiary complete and more		0,110	1,948	0,082	1,260
		(0,004)	(0,075)	(0,003)	(0,046)
Potential Experience (15< Experience < 20 omitted)					
Experience<5		-0,071	-1,214	-0,046	-0,682
		(0,004)	(0,062)	(0,002)	(0,044)
5<Experience<10		-0,032	-0,539	-0,020	-0,307
		(0,002)	(0,037)	(0,001)	(0,016)
10<Experience<15		-0,005	-0,102	-0,003	-0,048
		(0,002)	(0,025)	(0,001)	(0,016)
20<Experience<25		0,004	0,078	0,001	0,020
		(0,002)	(0,029)	(0,001)	(0,015)
25<Experience<30		0,005	0,104	0,004	0,054
		(0,002)	(0,028)	(0,001)	(0,015)
30<Experience<35		0,007	0,141	0,008	0,115
		(0,002)	(0,028)	(0,001)	(0,017)
35<Experience<40		0,010	0,190	0,011	0,169
		(0,002)	(0,031)	(0,001)	(0,018)

Experience>40	0,013	0,237	0,012	0,184
	(0,002)	(0,031)	(0,001)	(0,020)
Industry (Agriculture and Mining omitted)				
Manufacturing	-0,009	-0,087	-0,001	-0,012
	(0,003)	(0,047)	(0,002)	(0,029)
Electricity, gas and	0,013	0,279	0,000	-0,005
water	(0,008)	(0,159)	(0,003)	(0,050)
Construction	-0,023	-0,277	-0,007	-0,086
	(0,003)	(0,053)	(0,002)	(0,028)
Commerce, Restaurants	-0,013	-0,171	-0,004	-0,073
and Hotels	(0,003)	(0,047)	(0,002)	(0,028)
Transport and	-0,007	-0,076	-0,000	0,005
Communications	(0,003)	(0,052)	(0,002)	(0,029)
Company Services	0,012	0,236	0,003	0,048
	(0,003)	(0,055)	(0,002)	(0,029)
Community, social and	-0,011	-0,133	-0,003	-0,049
personal services	(0,003)	(0,046)	(0,002)	(0,028)
Other characteristics				
Gender	-0,021	-0,398	-0,015	-0,244
	(0,002)	(0,028)	(0,001)	(0,019)
Region	-0,005	-0,030	-0,001	-0,009
	(0,001)	(0,011)	(0,001)	(0,008)
Registered	-0,051	-0,550	-0,081	-0,967
	(0,001)	(0,018)	(0,001)	(0,022)
Minimum Wage	0,324	5,149	0,257	3,786
	(0,027)	(0,393)	(0,016)	(0,279)
Constant	0,094	0,452	0,098	0,782
	(0,005)	(0,067)	(0,003)	(0,045)
Observations	34487	34487	41757	41757

Source: Author's own calculation based on ECH data.

Note: Bootstrapped standard errors are in parentheses (200 replications of the entire procedure).

Table 12: Unconditional Quantile Regression Coefficients on Log Post-taxes Wages - Including minimum wage policy

Explanatory variables	Years:	2005/06			2014/15		
	Quantiles:	10	50	90	10	50	90
Education (Primary complete omitted)							
Primary incomplete		-0,025	-0,013	-0,202	-0,093	0,012	-0,131
		(0,045)	(0,024)	(0,029)	(0,036)	(0,016)	(0,019)
Secondary incomplete		0,153	0,151	0,313	0,080	0,086	0,180
		(0,029)	(0,015)	(0,020)	(0,017)	(0,009)	(0,012)
Secondary complete		0,199	0,358	1,035	0,145	0,271	0,629
		(0,038)	(0,026)	(0,058)	(0,021)	(0,014)	(0,029)
Tertiary incomplete		0,107	0,523	1,807	0,107	0,383	1,228
		(0,055)	(0,034)	(0,098)	(0,028)	(0,020)	(0,052)
Tertiary complete and		0,051	0,651	3,036	0,132	0,537	2,239
more		(0,062)	(0,038)	(0,128)	(0,032)	(0,022)	(0,071)
Potential Experience (15< Exp < 20 omitted)							
Experience<5		0,120	-0,060	-1,816	0,015	-0,160	-1,193
		(0,046)	(0,045)	(0,122)	(0,027)	(0,023)	(0,064)
5<Experience<10		0,046	-0,123	-0,800	-0,024	-0,142	-0,534
		(0,027)	(0,027)	(0,062)	(0,018)	(0,013)	(0,030)
10<Experience<15		-0,048	-0,090	-0,176	-0,029	-0,077	-0,134
		(0,030)	(0,021)	(0,032)	(0,016)	(0,011)	(0,019)
20<Experience<25		0,025	0,092	0,147	0,050	0,054	0,100
		(0,031)	(0,022)	(0,032)	(0,016)	(0,011)	(0,018)
25<Experience<30		0,046	0,120	0,228	0,030	0,054	0,132
		(0,030)	(0,020)	(0,036)	(0,015)	(0,011)	(0,017)
30<Experience<35		0,051	0,124	0,279	0,001	0,029	0,212
		(0,031)	(0,020)	(0,038)	(0,016)	(0,011)	(0,021)
35<Experience<40		0,063	0,113	0,333	-0,009	0,008	0,229
		(0,035)	(0,022)	(0,039)	(0,018)	(0,012)	(0,022)

Experience>40	0,050	0,132	0,389	-0,047	-0,024	0,229
	(0,039)	(0,024)	(0,040)	(0,019)	(0,012)	(0,020)
Industry (Agriculture and Mining omitted)						
Manufacturing	0,169	0,225	0,053	0,074	0,068	0,110
	(0,053)	(0,023)	(0,039)	(0,027)	(0,016)	(0,024)
Electricity, gas and	0,141	0,474	0,636	0,142	0,046	0,181
water	(0,102)	(0,092)	(0,241)	(0,047)	(0,042)	(0,069)
Construction	0,293	0,376	-0,121	0,231	0,249	0,056
	(0,059)	(0,029)	(0,044)	(0,030)	(0,016)	(0,026)
Commerce, Restaurants	0,173	0,077	-0,063	0,081	-0,069	-0,003
and Hotels	(0,056)	(0,026)	(0,039)	(0,027)	(0,015)	(0,022)
Transport and	0,199	0,407	0,230	0,124	0,147	0,160
Communications	(0,058)	(0,029)	(0,053)	(0,028)	(0,018)	(0,025)
Company Services	0,078	0,239	0,588	0,098	0,016	0,207
	(0,054)	(0,029)	(0,061)	(0,029)	(0,016)	(0,033)
Community, social and	0,183	0,312	0,038	0,061	0,067	0,033
personal services	(0,051)	(0,025)	(0,040)	(0,028)	(0,015)	(0,022)
Other characteristics						
Gender	-0,048	-0,123	-0,585	-0,081	-0,100	-0,425
	(0,026)	(0,017)	(0,047)	(0,014)	(0,009)	(0,026)
Region	0,224	0,176	0,196	0,076	0,042	0,058
	(0,017)	(0,013)	(0,019)	(0,009)	(0,006)	(0,010)
Registered	0,875	0,505	0,156	1,510	0,400	0,087
	(0,042)	(0,016)	(0,015)	(0,046)	(0,009)	(0,010)
Minimum Wage	-2,487	-2,144	4,180	-1,649	-1,817	3,606
	(0,449)	(0,229)	(0,545)	(0,239)	(0,139)	(0,317)
Constant	3,328	4,285	4,774	3,682	5,308	5,490
	(0,085)	(0,041)	(0,077)	(0,060)	(0,025)	(0,046)
Observations	34487	34487	34487	41757	41757	41757

Source: Author's own calculation based on ECH data.

Note: Bootstrapped standard errors are in parentheses (200 replications of the entire procedure).

Table 13: RIF-Regression Coefficients of Inequality Measures on Log Pre-taxes Wages - Including minimum wage policy

Explanatory variables	Years:	2005/06		2014/15	
	Ineq. Meas.:	Gini	Variance	Gini	Variance
Education (Primary complete omitted)					
Primary incomplete		-0,009	-0,169	0,001	0,020
		(0,002)	(0,028)	(0,002)	(0,030)
Secondary incomplete		0,003	0,087	0,003	0,050
		(0,001)	(0,019)	(0,001)	(0,012)
Secondary complete		0,028	0,485	0,017	0,246
		(0,002)	(0,032)	(0,001)	(0,018)
Tertiary incomplete		0,061	1,003	0,040	0,537
		(0,003)	(0,053)	(0,002)	(0,028)
Tertiary complete and		0,111	1,804	0,077	1,031
more		(0,004)	(0,078)	(0,002)	(0,034)
Potential Experience (15< Experience < 20 omitted)					
Experience<5		-0,071	-1,124	-0,043	-0,559
		(0,004)	(0,052)	(0,002)	(0,035)
5<Experience<10		-0,032	-0,494	-0,019	-0,252
		(0,002)	(0,033)	(0,001)	(0,013)
10<Experience<15		-0,005	-0,093	-0,003	-0,038
		(0,002)	(0,022)	(0,001)	(0,013)
20<Experience<25		0,004	0,072	0,001	0,013
		(0,002)	(0,025)	(0,001)	(0,012)
25<Experience<30		0,005	0,092	0,003	0,040
		(0,002)	(0,024)	(0,001)	(0,013)
30<Experience<35		0,007	0,128	0,007	0,089
		(0,002)	(0,025)	(0,001)	(0,013)
35<Experience<40		0,010	0,170	0,010	0,138
		(0,002)	(0,026)	(0,001)	(0,015)

Experience>40	0,012	0,214	0,012	0,153
	(0,002)	(0,025)	(0,001)	(0,016)
Industry (Agriculture and Mining omitted)				
Manufacturing	-0,009	-0,087	-0,001	-0,015
	(0,003)	(0,039)	(0,002)	(0,025)
Electricity, gas and water	0,013	0,268	0,001	0,001
	(0,009)	(0,159)	(0,003)	(0,040)
Construction	-0,024	-0,282	-0,009	-0,110
	(0,003)	(0,043)	(0,002)	(0,024)
Commerce, Restaurants and Hotels	-0,013	-0,150	-0,004	-0,064
	(0,003)	(0,039)	(0,002)	(0,024)
Transport and Communications	-0,008	-0,079	-0,000	-0,000
	(0,003)	(0,045)	(0,002)	(0,028)
Company Services	0,013	0,215	0,003	0,037
	(0,003)	(0,047)	(0,002)	(0,025)
Community, social and personal services	-0,011	-0,124	-0,003	-0,041
	(0,003)	(0,041)	(0,002)	(0,025)
Other characteristics				
Gender	-0,022	-0,374	-0,014	-0,197
	(0,002)	(0,028)	(0,001)	(0,015)
Region	-0,005	-0,019	-0,001	-0,006
	(0,001)	(0,012)	(0,000)	(0,007)
Registered	-0,038	-0,387	-0,063	-0,681
	(0,001)	(0,016)	(0,001)	(0,020)
Minimum Wage	0,330	4,881	0,246	3,181
	(0,025)	(0,398)	(0,014)	(0,213)
Constant	0,080	0,281	0,080	0,535
	(0,004)	(0,066)	(0,003)	(0,042)
Observations	34487	34487	41757	41757

Source: Author's own calculation based on ECH data.

Note: Bootstrapped standard errors are in parentheses (200 replications of the entire procedure).

Table 14: Testing the Difference of Pre and Post Taxes Education Coefficients by Education Levels - Selected Years

	H0) $\beta_{pre} - \beta_{post} = 0$			
	2005	2008	2011	2015
Primary incomplete	-0,000	-0,006	-0,008	-0,008
	(0,114)	(0,000)	(0,000)	(0,000)
Secondary incomplete	0,007	0,013	0,012	0,013
	(0,000)	(0,000)	(0,000)	(0,000)
Secondary complete	0,016	0,043	0,034	0,041
	(0,000)	(0,000)	(0,000)	(0,000)
Tertiary incomplete	0,023	0,067	0,053	0,059
	(0,000)	(0,000)	(0,000)	(0,000)
Tertiary complete and more	0,032	0,104	0,086	0,101
	(0,000)	(0,000)	(0,000)	(0,000)

Source: Author's own calculation based on ECH data.

Note: Empirical distribution of parameters were estimated computing 1000 bootstrap replications of the entire procedure. p-values in parentheses.

Table 15: Testing the Difference 2005-2015 of Education Coefficients by Education levels - Pre and post taxes coefficients separately and the difference between

	Pre-tax difference	Post-tax difference	Diff.
	$(\beta_{pre}^{2015} - \beta_{pre}^{2005})$	$(\beta_{post}^{2015} - \beta_{post}^{2005})$	in diff.
Primary incomplete	-0,082	-0,078	-0,004
	(0,000)	(0,000)	(0,000)
Secondary incomplete	-0,064	-0,066	0,002
	(0,000)	(0,000)	(0,000)
Secondary complete	-0,083	-0,095	0,011
	(0,000)	(0,000)	(0,000)
Tertiary incomplete	-0,191	-0,205	0,014
	(0,000)	(0,000)	(0,000)
Tertiary complete and more	-0,124	-0,164	0,041
	(0,000)	(0,000)	(0,000)

Source: Author's own calculation based on ECH data.

Note: Empirical distribution of parameters were estimate computing 1000 bootstrap replications of the entire procedure. p-values in parentheses.

Table 16: Inequality Measures on Pre and Post Taxes Log Hourly Wages 2005/06 and 2014/15

Inequality Measure:	90-10	90-50	50-10	Gini	Variance
A: Pre-Tax Log Hourly Wages					
2005	2,007	1,032	0,975	0,085	0,658
2015	1,504	0,799	0,705	0,059	0,422
Difference	-0,504	-0,234	-0,270	-0,026	-0,236
%	-25%	-23%	-28%	-30%	-36%
B: Post-Tax Log Hourly Wages					
2005	1,845	0,966	0,878	0,082	0,576
2015	1,355	0,706	0,649	0,055	0,342
Difference	-0,489	-0,260	-0,229	-0,027	-0,234
%	-27%	-27%	-26%	-33%	-41%

Source: Author's own calculation based on ECH data.

Table 17: Aggregate Decomposition Results 2005/06-2014/15

Inequality Measure:	90-10	90-50	50-10	Gini	Variance
A: Pre-Tax Log Hourly Wages					
Total change	-0,5033	-0,2765	-0,2268	-0,0270	-0,2286
	(0,0164)	(0,0133)	(0,0111)	(0,0006)	(0,0093)
Composition	-0,0708	-0,0254	-0,0454	-0,0058	-0,0450
	(0,0156)	(0,0115)	(0,0098)	(0,0005)	(0,0082)
Wage Structure	-0,3967	-0,2344	-0,1623	-0,0208	-0,1745
	(0,0148)	(0,0131)	(0,0102)	(0,0005)	(0,0081)
Specification Error	-0,0010	0,0002	-0,0011	-0,0001	-0,0031
	(0,0081)	(0,0060)	(0,0027)	(0,0003)	(0,0046)
B: Post-Tax Log Hourly Wages					
Total change	-0,5077	-0,2951	-0,2126	-0,0278	-0,2278
	(0,0154)	(0,0128)	(0,0097)	(0,0006)	(0,0083)
Composition	-0,0327	-0,0053	-0,0275	-0,0040	-0,0265
	(0,0141)	(0,0108)	(0,0078)	(0,0005)	(0,0074)
Wage Structure	-0,4487	-0,2729	-0,1758	-0,0238	-0,1985
	(0,0140)	(0,0127)	(0,0084)	(0,0005)	(0,0075)
Specification Error	-0,0008	0,0002	-0,0010	-0,0001	-0,0031
	(0,0075)	(0,0057)	(0,0024)	(0,0003)	(0,0042)

Source: Author's own calculation based on ECH data.

Note: Bootstrapped standard errors are in parentheses (500 replications of the entire procedure).

Table 18: Detailed Decomposition Results of Pre-Tax Log Hourly Wages 2005/06-2014/15

Inequality Measure:	90-10	90-50	50-10	Gini	Variance
A: Detailed Composition Effects					
Minimum Wage	-0,0550	-0,0507	-0,0043	-0,0021	-0,0331
	(0,0079)	(0,0070)	(0,0035)	(0,0003)	(0,0051)
Education	0,1357	0,1043	0,0315	0,0040	0,0718
	(0,0187)	(0,0150)	(0,0058)	(0,0006)	(0,0108)
Experience	-0,0050	-0,0053	0,0004	-0,0001	-0,0008
	(0,0076)	(0,0062)	(0,0018)	(0,0003)	(0,0046)
Industry	-0,0001	-0,0008	0,0007	-0,0001	-0,0006
	(0,0051)	(0,0043)	(0,0026)	(0,0002)	(0,0027)
Gender	-0,0041	-0,0034	-0,0007	-0,0002	-0,0041
	(0,0054)	(0,0044)	(0,0010)	(0,0002)	(0,0034)
Region	0,0001	-0,0001	0,0002	0,0000	-0,0001
	(0,0004)	(0,0003)	(0,0006)	(0,0000)	(0,0003)
Registered	-0,1425	-0,0694	-0,0731	-0,0072	-0,0781
	(0,0084)	(0,0041)	(0,0075)	(0,0003)	(0,0036)
Total	-0,0708	-0,0254	-0,0454	-0,0058	-0,0450
	(0,0156)	(0,0115)	(0,0098)	(0,0005)	(0,0082)
B: Detailed Wage Structure Effects					
Minimum Wage	-0,0946	-0,0653	-0,0293	-0,0061	-0,1187
	(0,0860)	(0,0835)	(0,0513)	(0,0030)	(0,0511)
Education	-0,0752	-0,0238	-0,0513	-0,0028	-0,1013
	(0,0561)	(0,0506)	(0,0336)	(0,0018)	(0,0299)
Experience	-0,0173	0,0187	-0,0361	-0,0005	-0,0125
	(0,0358)	(0,0289)	(0,0246)	(0,0011)	(0,0178)
Industry	0,1446	0,2416	-0,0970	0,0120	0,1461
	(0,0715)	(0,0483)	(0,0620)	(0,0026)	(0,0459)
Gender	0,0591	0,0321	0,0270	0,0029	0,0682
	(0,0298)	(0,0293)	(0,0140)	(0,0009)	(0,0164)
Region	-0,0237	-0,0113	-0,0124	0,0004	-0,0043
	(0,0191)	(0,0141)	(0,0131)	(0,0006)	(0,0089)
Registered	-0,7614	0,1114	-0,8728	-0,0131	-0,1561
	(0,0835)	(0,0177)	(0,0805)	(0,0019)	(0,0282)
Constant	0,3718	-0,5378	0,9096	-0,0136	0,0041
	(0,1735)	(0,1117)	(0,1367)	(0,0051)	(0,0850)
Total	-0,3967	-0,2344	-0,1623	-0,0208	-0,1745
	(0,0148)	(0,0131)	(0,0102)	(0,0005)	(0,0081)

Source: Author's own calculation based on ECH data.

Note: Bootstrapped standard errors are in parentheses (500 replications of the entire procedure).

Table 19: Detailed Decomposition Results of Post-Tax Log Hourly Wages 2005/06-2014/15

Inequality Measure:	90-10	90-50	50-10	Gini	Variance
A: Detailed Composition Effects					
Minimum Wage	-0,0473	-0,0449	-0,0024	-0,0021	-0,0315
	(0,0071)	(0,0064)	(0,0032)	(0,0003)	(0,0048)
Education	0,1203	0,0957	0,0246	0,0040	0,0662
	(0,0172)	(0,0142)	(0,0050)	(0,0006)	(0,0100)
Experience	-0,0042	-0,0045	0,0003	-0,0001	-0,0007
	(0,0070)	(0,0058)	(0,0016)	(0,0003)	(0,0042)
Industry	0,0032	0,0006	0,0025	-0,0001	-0,0010
	(0,0047)	(0,0039)	(0,0000)	(0,0002)	(0,0026)
Gender	-0,0035	-0,0030	-0,0005	-0,0002	-0,0039
	(0,0046)	(0,0040)	(0,0007)	(0,0002)	(0,0032)
Region	0,0001	-0,0001	0,0002	0,0000	0,0000
	(0,0003)	(0,0003)	(0,0004)	(0,0000)	(0,0002)
Registered	-0,1013	-0,0491	-0,0522	-0,0054	-0,0555
	(0,0070)	(0,0033)	(0,0061)	(0,0003)	(0,0030)
Total	-0,0327	-0,0053	-0,0275	-0,0040	-0,0265
	(0,0141)	(0,0108)	(0,0078)	(0,0005)	(0,0074)
B: Detailed Wage Structure Effects					
Minimum Wage	-0,1494	-0,1305	-0,0189	-0,0087	-0,1727
	(0,0819)	(0,0768)	(0,0466)	(0,0031)	(0,0486)
Education	-0,1134	-0,0709	-0,0425	-0,0045	-0,1368
	(0,0537)	(0,0479)	(0,0338)	(0,0019)	(0,0282)
Experience	-0,0094	0,0072	-0,0165	-0,0006	-0,0131
	(0,0326)	(0,0259)	(0,0219)	(0,0012)	(0,0169)
Industry	0,1648	0,2154	-0,0506	0,0118	0,1322
	(0,0647)	(0,0456)	(0,0545)	(0,0027)	(0,0427)
Gender	0,0802	0,0606	0,0196	0,0039	0,0852
	(0,0282)	(0,0273)	(0,0130)	(0,0010)	(0,0157)
Region	-0,0214	-0,0087	-0,0126	0,0003	-0,0056
	(0,0175)	(0,0132)	(0,0116)	(0,0006)	(0,0083)
Registered	-0,4467	0,0509	-0,4977	-0,0143	-0,1347
	(0,0564)	(0,0188)	(0,0536)	(0,0018)	(0,0242)
Constant	0,0466	-0,3969	0,4435	-0,0118	0,0471
	(0,1398)	(0,1015)	(0,1065)	(0,0051)	(0,0780)
Total	-0,4487	-0,2729	-0,1758	-0,0238	-0,1985
	(0,0140)	(0,0127)	(0,0084)	(0,0005)	(0,0075)

Source: Author's own calculation based on ECH data.

Note: Bootstrapped standard errors are in parentheses (500 replications of the entire procedure).

Graphics

Figure 1: Inequality Measures on Pre and Post Taxes Hourly Wages

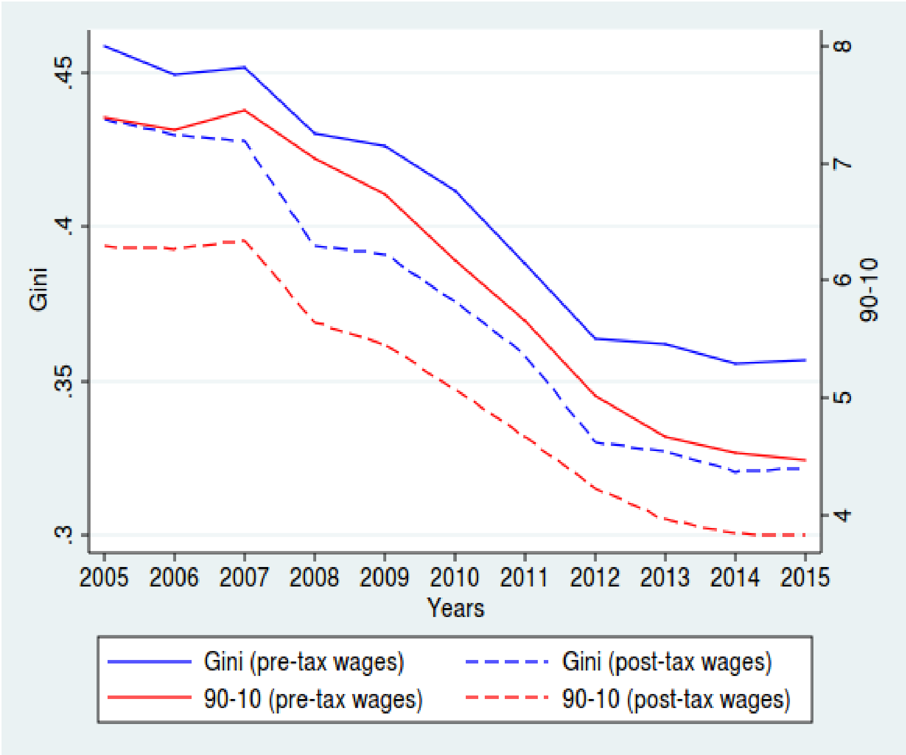


Figure 2: Densities of Log Hourly Wages Pre and Post Taxes

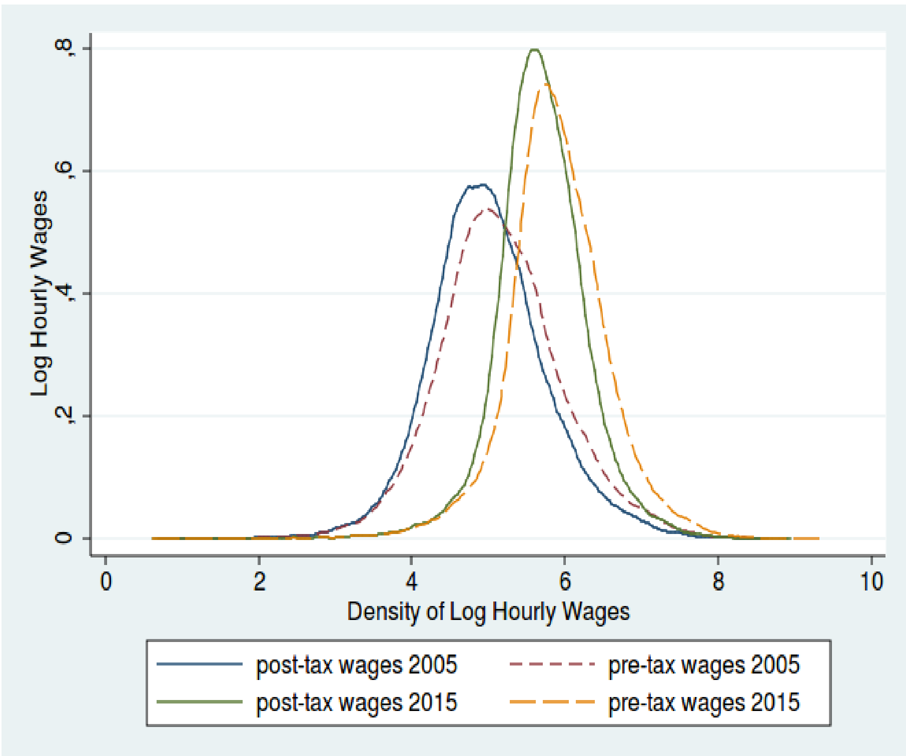


Figure 3: Observed and Counterfactual 2005 Hourly Wages
Change in Minimum Wage

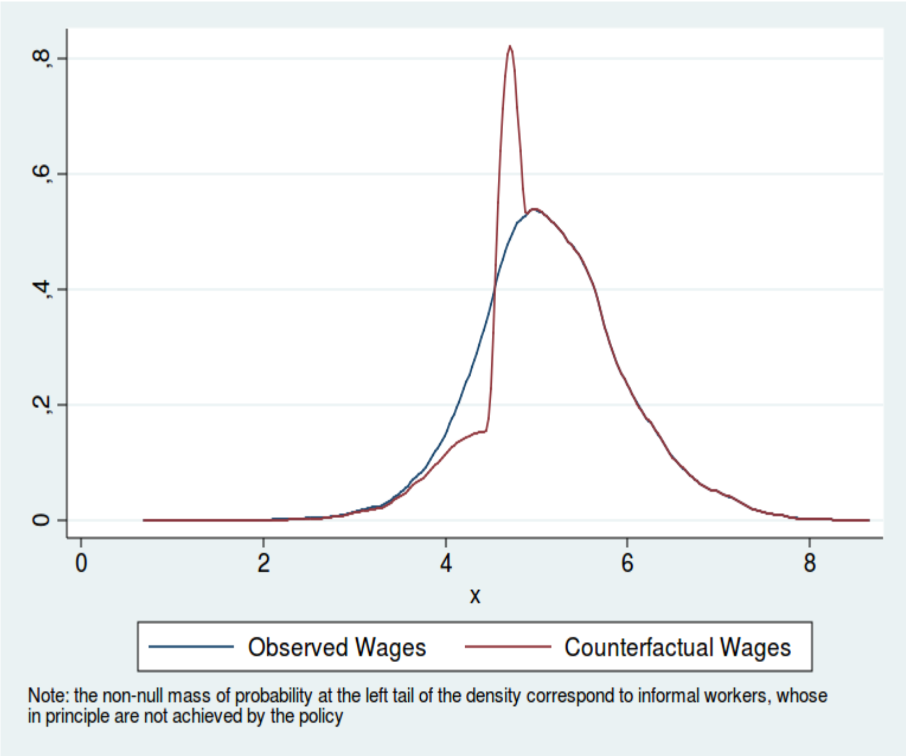


Figure 4: Ratio of Pre and Post Taxes Wages by Percentile

Figure 5: Ratio of 2005 and 2015 Wages by Percentile

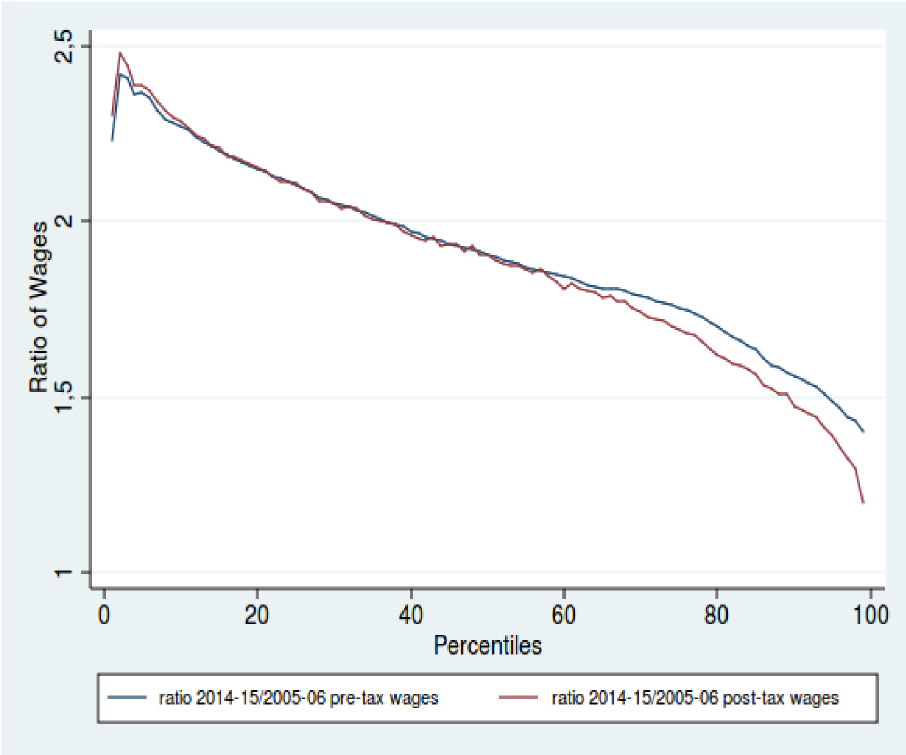


Figure 6: Observed (after IRP) and Counterfactual (after IRPF) 2005 Hourly Wages

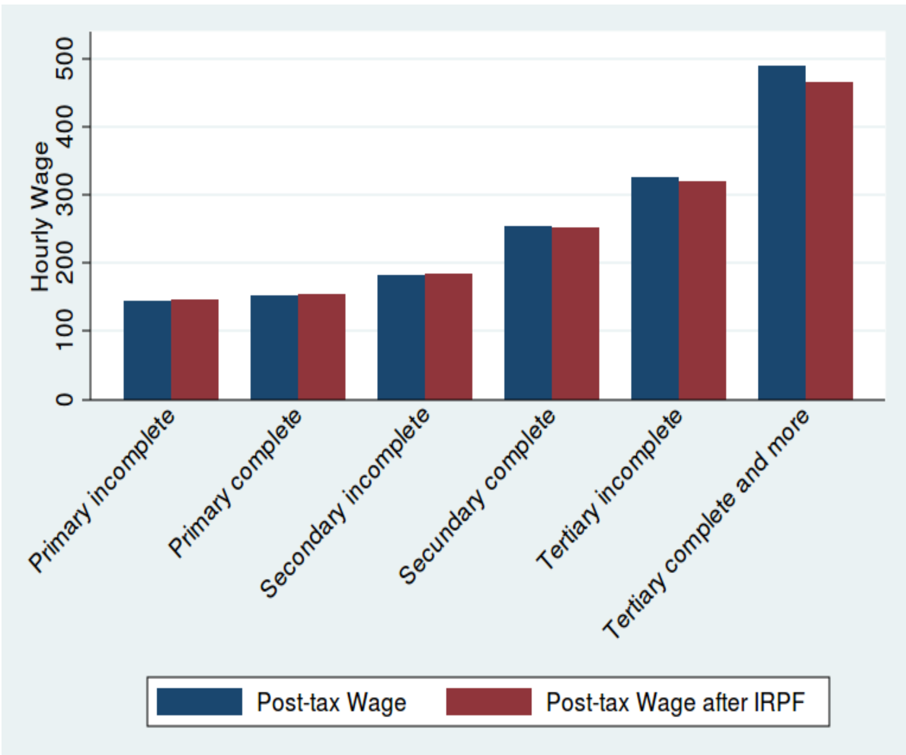


Figure 7: Returns to Education of Pre and Post Taxes Log Hourly Wages
Mincer extended including minimum wage policy specification

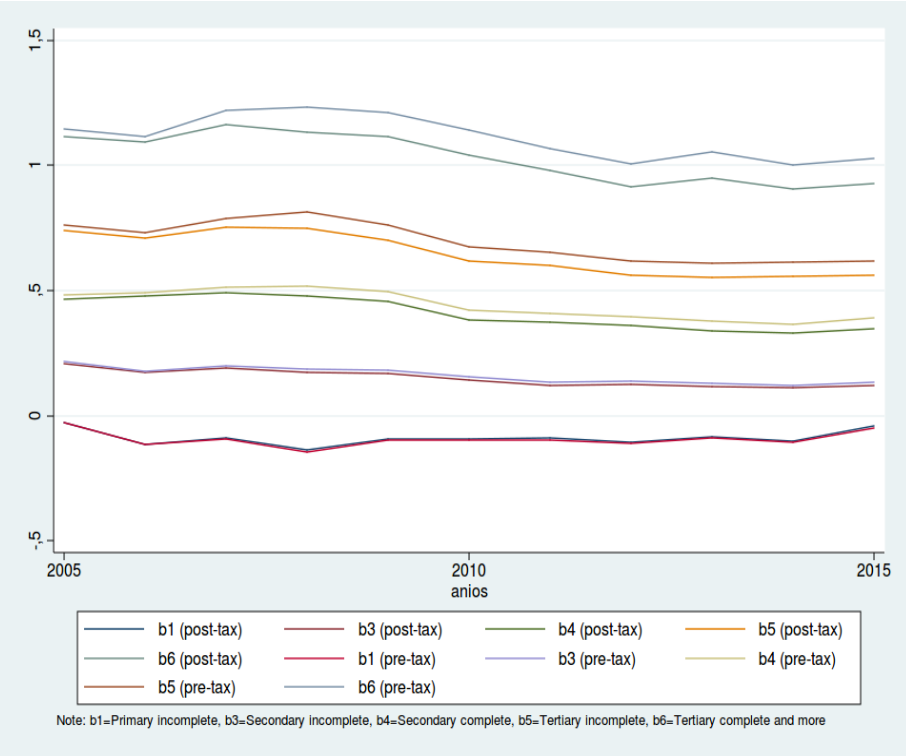


Figure 8: Ratio of Returns to Education of Pre and Post Taxes Log Hourly Wages

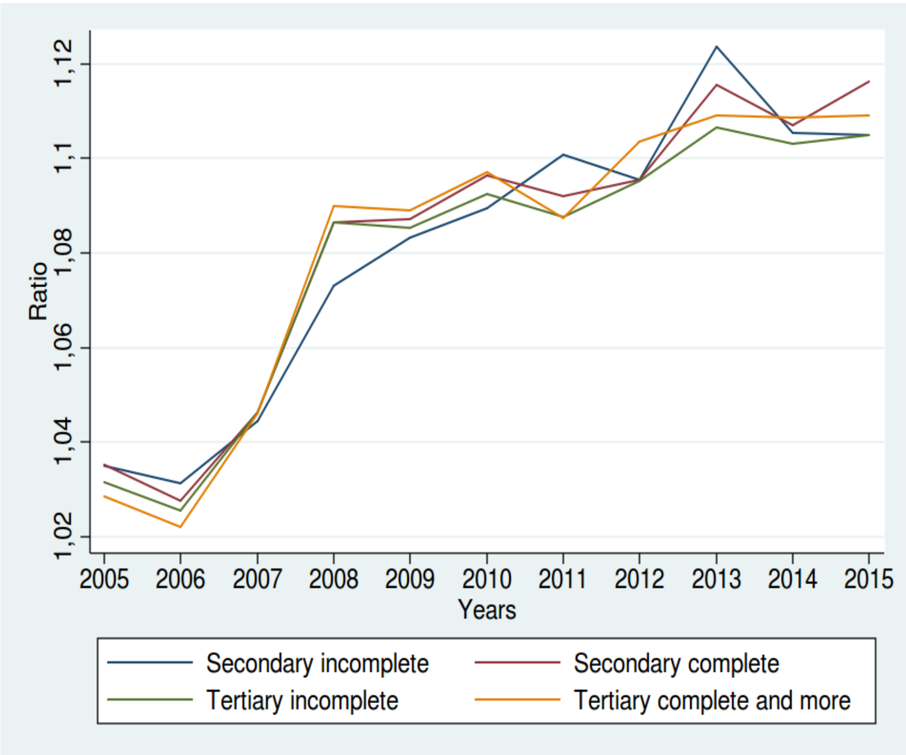


Figure 9: Variation 2005-2015 of Returns to Education

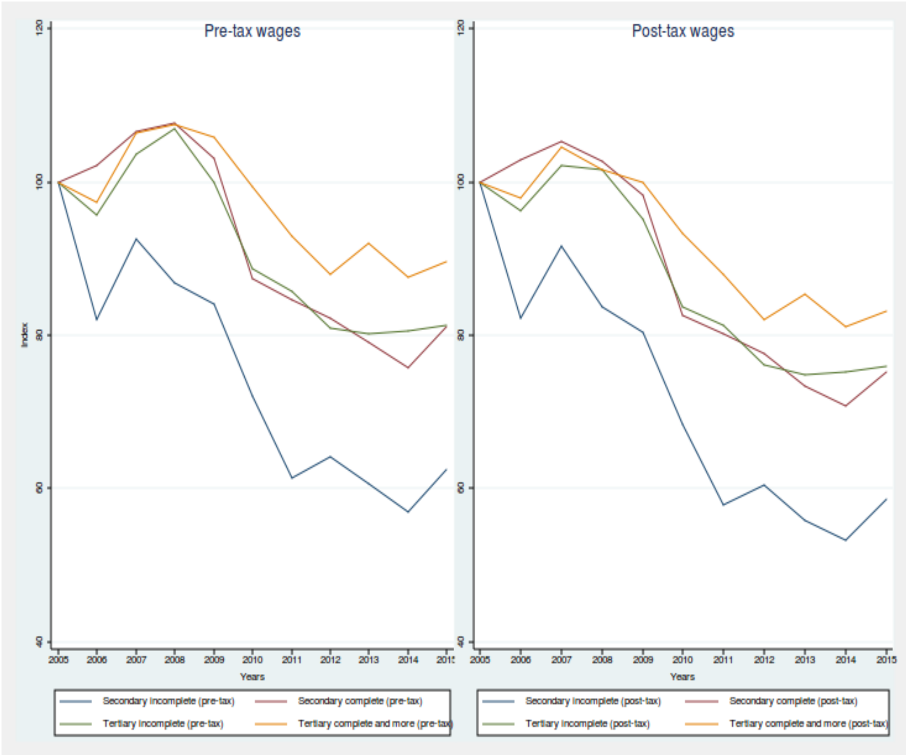


Figure 10: RIF-regression Coefficients

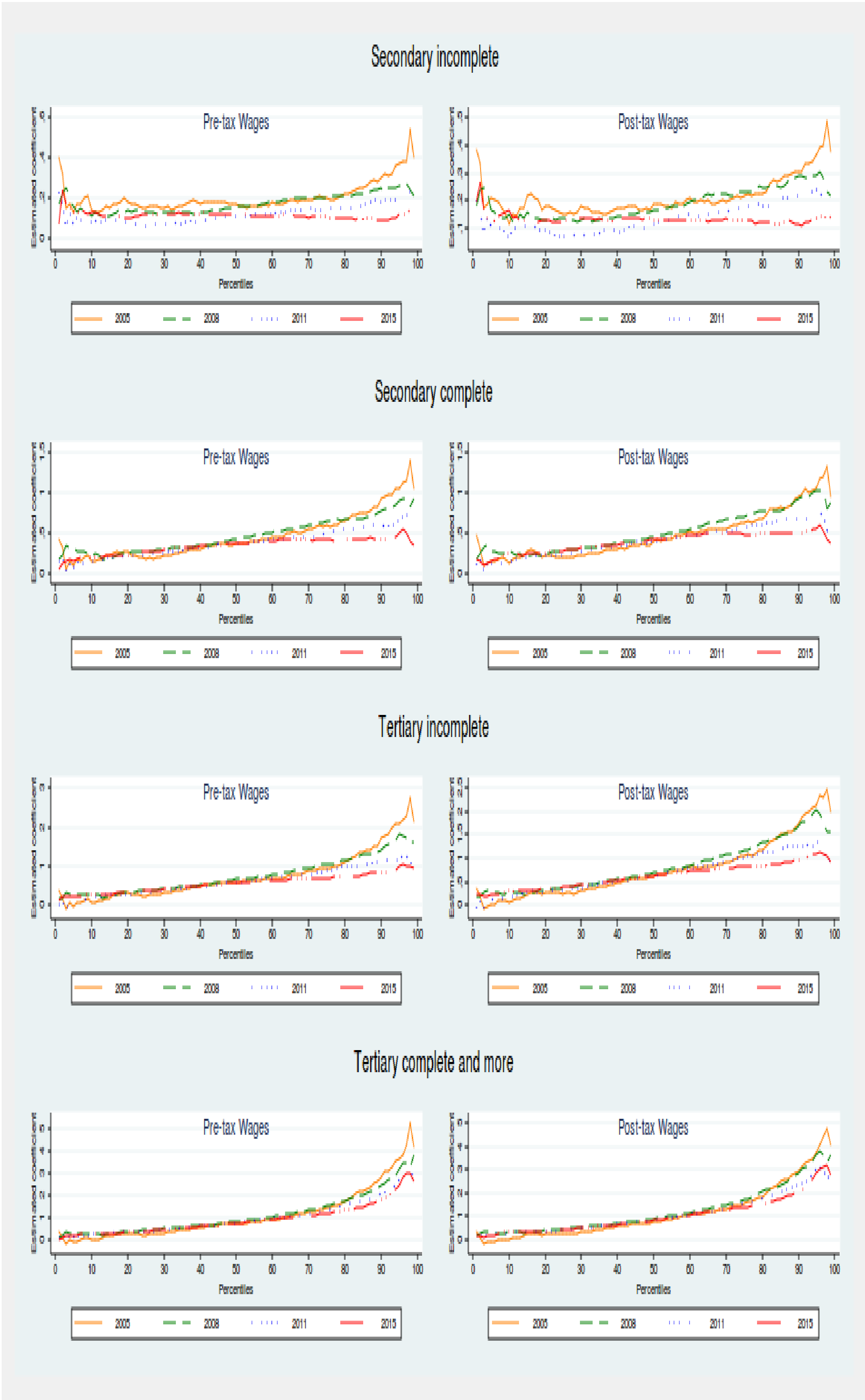


Figure 11: Empirical distribution of Schooling coefficients - Year 2005

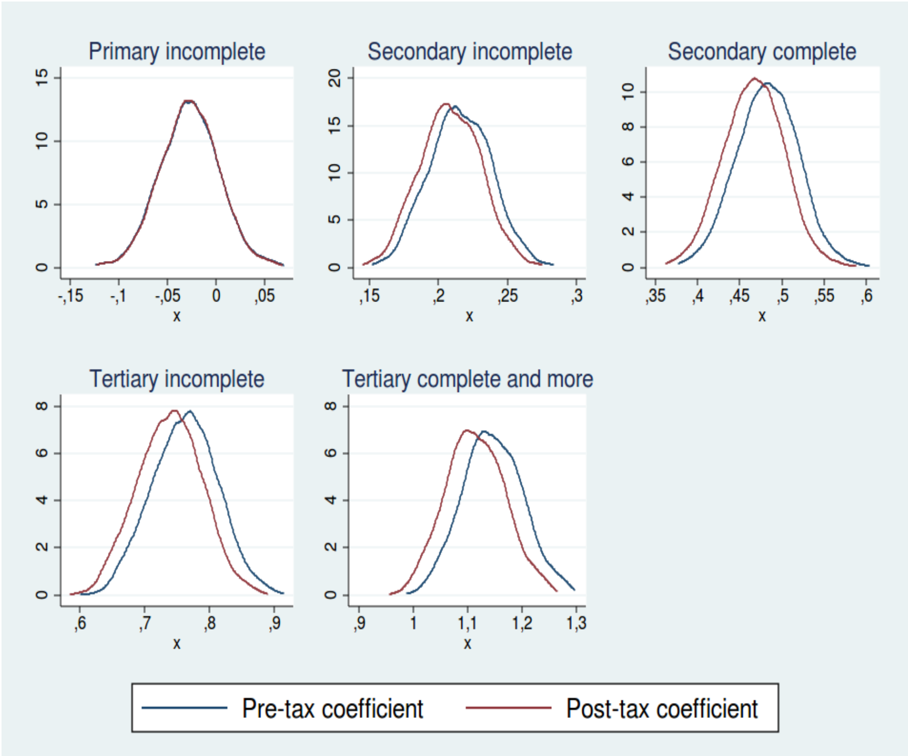


Figure 12: Empirical distribution of Schooling coefficients - Year 2015

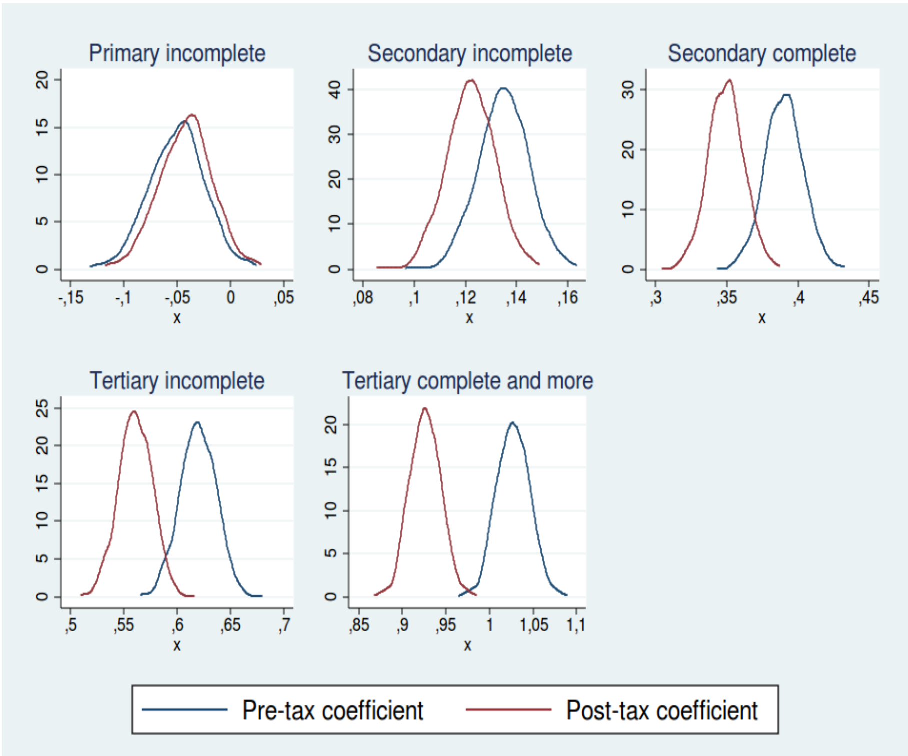


Figure 13: Decomposition of Total Change into Composition and Wage Structure Effects 2005/06 to 2014/15

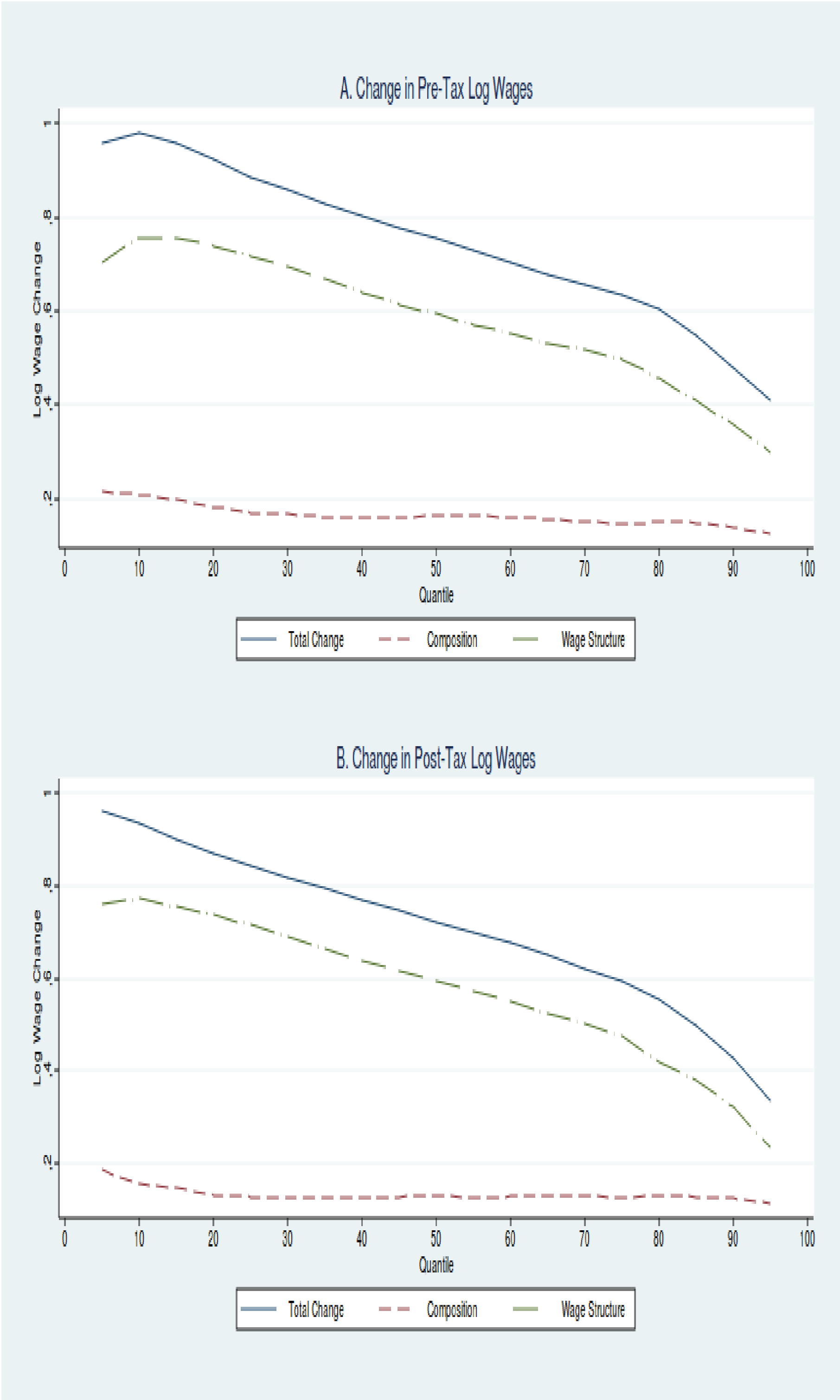


Figure 14: Detailed Decomposition of Composition Effects 2005/06 to 2014/15

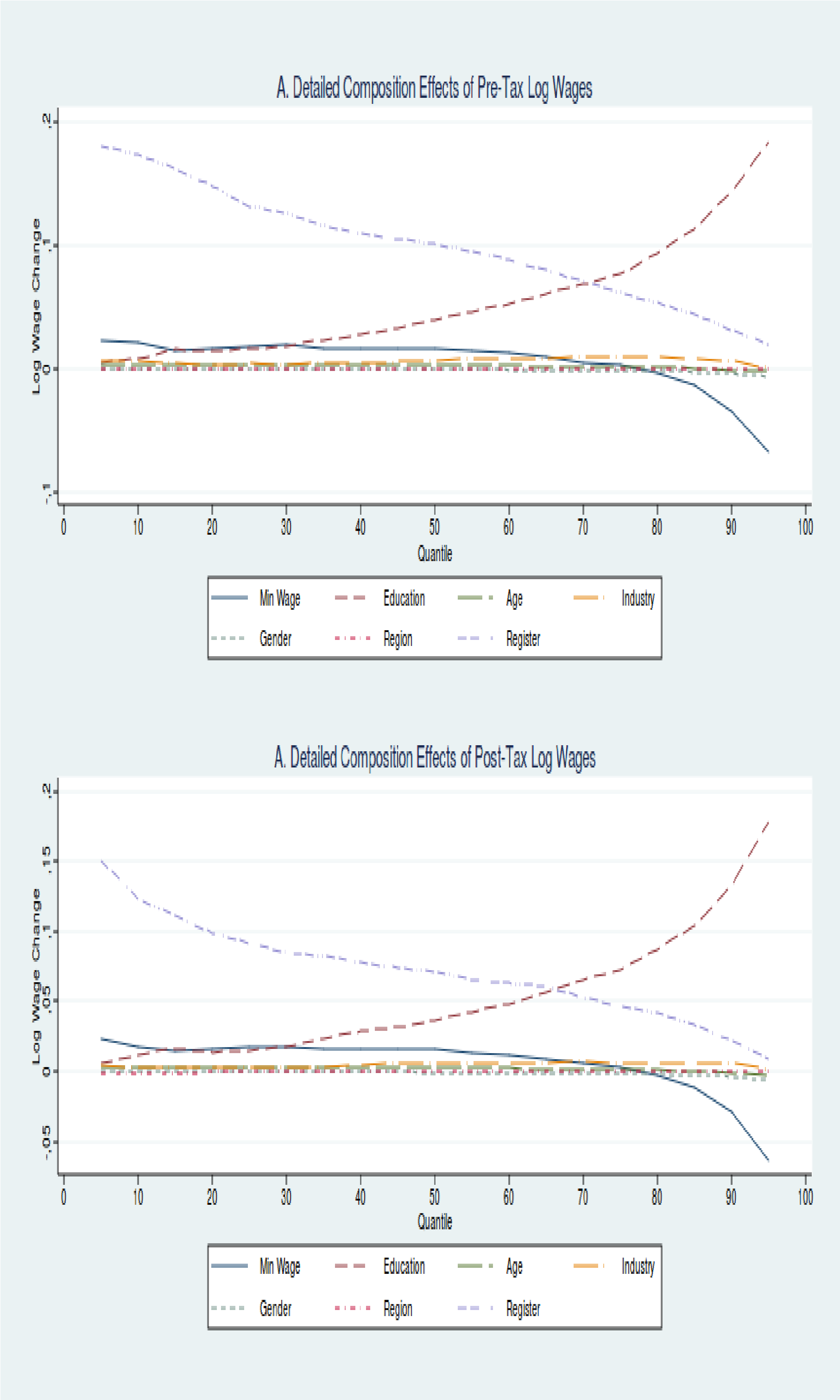
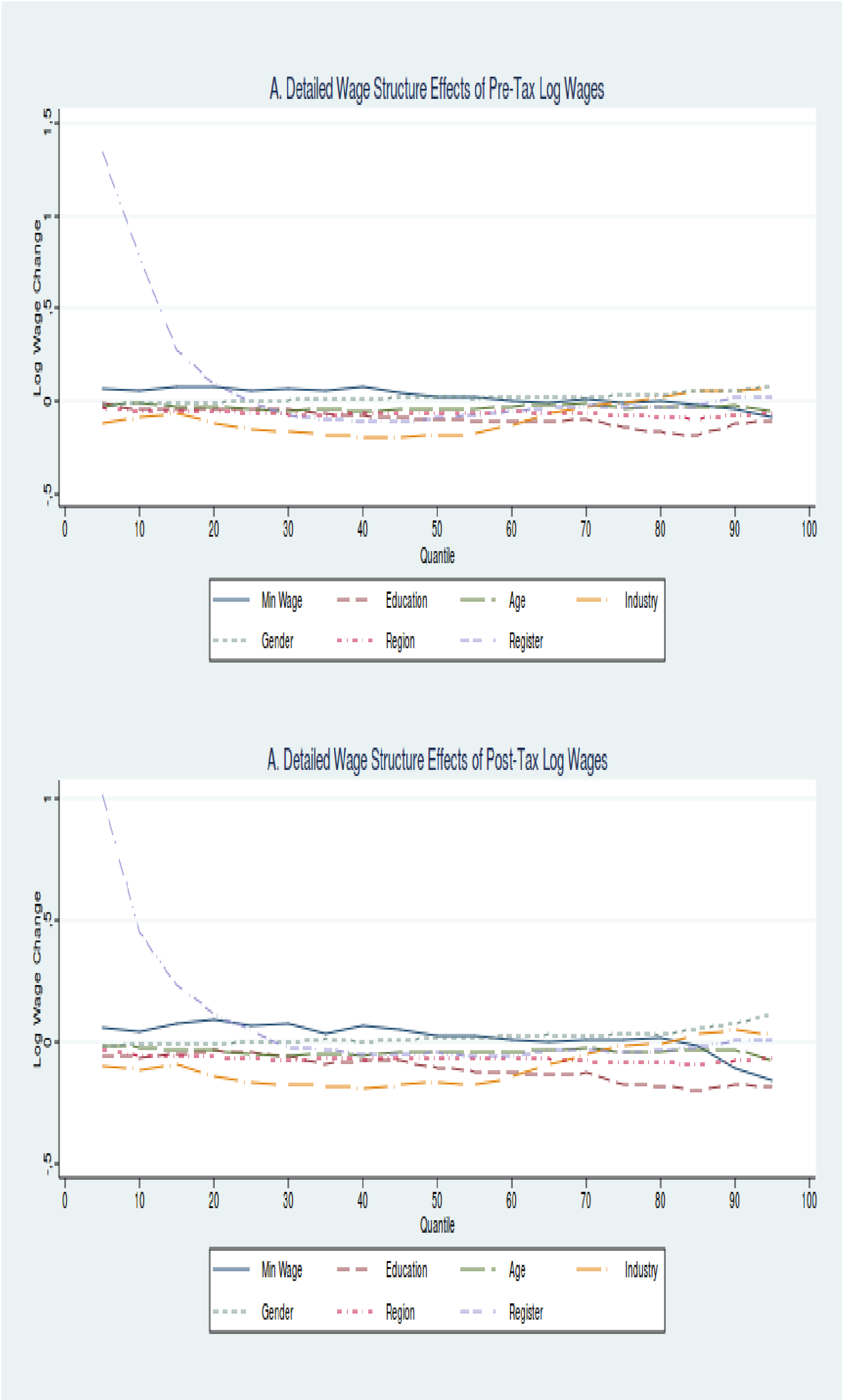


Figure 15: Detailed Decomposition of Wage Structure Effects 2005/06 to 2014/15



APPENDICES

Appendix 1

Pre-tax Income Recovery Process

1.1 Detailed procedure

Recovery nominal wages is a necessary step in order to obtain the amount paid of taxes, given that the ECH does not collect this information. The gross-up procedure (i.e. go from liquid or post-taxes to nominal or pre-taxes wages) can be divided into four steps. The first one imply to define the universe of potential tax informants, i.e. the workers who are potential recipients of a nominal income. Both for the years prior to the tax reform (from 2005 to June 2007, taxpayers of Impuesto a las Retribucones Personales, IRP) and for the subsequent (IRPF taxpayers, from July 2007 to 2015), the universe of workers include: public employees, private salaried employees, cooperative members and self-employed workers, who declare to contribute to a retirement fund[1].

The second step is to compute the net labor income declared in the ECH, taxed by social security[2]. Given that liquid income, in third place correspond to obtain a first estimate of the contribute to social security and health insurance. To do so, it was necessary to collect information on the retirement deduction rates for the categories of workers mentioned in step 1. Applied this rates at the liquid wage and then applied at this amount the rates of contribution to health insurance, in order to obtain the first 'nominal income'. This

[1]Workers who do not contribute to social security have the same nominal and liquid income.

[2]To do this, it is necessary to define what is taxable matter and what is not, which can be found in Table A1

value is used like tax base to estimate the first direct taxes to work (IRP and IRPF as appropriate[3]). The final stage of step three is to repeat steps 1 and 2 but considering as new 'liquid labor income' the sum of the original liquid income, contributions to social security and direct taxes. The result of these three steps is a 'second nominal labor income'.

But this income does not coincide with the real nominal income, to the extent that the rates of contribution and taxes are applied to the latter and not to the intermediate nominal. One way to approximate the true nominal labor income is to iterate the procedure from steps 1 to 3, considering each iteration as 'liquid' income at the last estimated nominal income. This is the procedure used in this work and representing the fourth step of the procedure. In our case, we apply 15 iterations. As can be seen in Table A4, the difference between iteration 14 and 15 is almost zero for all years.

Applying this gross-up procedure we arrive a very accurate results compared with administrative data provided by the General Tax Directorate (Dirección General Impositiva, DGI), like can be seen in Table A3 and Figures A1 and A2. In addition, in order to go deep in the comparison with the administrative data, we reproduce the analysis of income tax collection and effective tax rate by income intervals that perform the DGI. The results for selected years are shown in Tables A5, A7.

[3]see Table A2 for a detailed presentation of the tax rate applicable each year.

1.2 Tables

Table A1: Tax Matter

General Definition: Any income that, in a regular and permanent manner, is in cash or in kind, susceptible of pecuniary appreciation, the dependent or non-dependent worker receives, as compensation and as a result of his personal activity, within the respective area of affiliation. (Art. 153 of Law 16,713 and Art.2 of Decree 113/96).
Include: • Salaries, wages, piecework, overtime, commissions, seniority, productivity, nocturnality, breaks, etc. • Gratifications that have the characters of regularity and permanence • Cash losses and similar that the worker actually perceives • Subsidies for sickness, maternity, unemployment and temporary disability insurance, • 50% of the total per diem without accountability • Personal taxes • Tips for a fictional 3 BFC • Legal bonus • Benefits in kind • The days of license effectively enjoyed
Exclude: • Gratifications in a discretionary manner, for reasons not directly related to the job • Complement to subsidies payed by the company • The vacation salary or sum for the best enjoyment of the license • The food that the worker receives, whether in kind or that his cash payment is assumed by the employer • The amount assumed by the employer corresponding to the total or partial payment of medical coverage

Table A2: Tax Rates of IRP and IRPF, 1986-2015

Year / NMW	Privates ≤3	Privates 3<x≤6	Privates >6	Publics ≤3	Publics 3<x≤6	Publics >6	Source
1986 1987 1988 1989	1	2	2	1	2	2	Law N° 15294, art.25-28
1990	3,5	5,5	7,5	3,5	5,5	5,5	Law N° 16107, art.14-16
1991	2,5	5	7,5	2,5	5	5,5	Law N° 16170, art.618, Num.I-II
1992	1,5	4	7	1,5	4	4	Law N° 16170, art.618, Num.III-IV
1993 1994	1	2	2	1	2	2	Law N° 16170, art.618, Num.V
1995 1996 1997	1	3	6	1	3	6	Law N° 16697, art.22-24
1998 1999 2000	1	2	6	1	2	6	Law N° 16904, art.1
2001	0	2	6	0	2	6	Law N° 17296, art.583
2002 2003	See tables on article 5 of Law N° 17502						Law N° 17502, art.5-8
2004	0	2	(1)	0	2	(1)	Law N° 17706, art.1
2005	0	2	6	0	2	6	
2006	0	2	6	0	2	6	Dec.270/004, art.1
06/2007	0	2	6	0	2	6	
07/2007 - 08/2008	IRPF - First version						Law N° 18083, art.8, Dec.148/007
08/2008-2009 2010 2011 07/2012	IRPF - Second version						Law 18341, Dec.778/008
08/2012 - 2013 2014 2015	IRPF - Third version						Dec.254/012

(1) See Law N° 17502, article 5 for detailed tax rates.

Note: all values are expressed in percentage.

Table A3: Income tax collection, Taxpayers and Informants - Period: 2008-2015

Years	Tax collection			Taxpayers			Informants		
	ECH	DGI	%	ECH	DGI	%	ECH	DGI	%
2008	1,1e+10	1,2e+10	0,891	406.204	511.646	0,794	936.040	1.779.575	0,526
2009	1,2e+10	1,1e+10	1,025	328.883	302.095	1,089	958.969	1.210.506	0,792
2010	1,2e+10	1,3e+10	0,906	331.508	327.932	1,011	980.246	1.193.114	0,822
2011	1,3e+10	1,6e+10	0,780	438.069	374.487	1,170	1.016.017	1.246.245	0,815
2012	1,5e+10	1,9e+10	0,823	441.066	391.082	1,128	1.052.453	1.226.613	0,858
2013	1,8e+10	2,2e+10	0,820	464.671	445.388	1,043	1.062.157	1.277.210	0,832
2014	2,2e+10	2,7e+10	0,812	505.807	484.998	1,043	1.083.632	1.303.434	0,831
2015	2,5e+10	3,1e+10	0,825	524.850	432.462	1,214	1.067.942	1.321.461	0,808

Source: Author's own calculation based on ECH and DGI Administrative data.
Note: ECH = author's estimations; DGI = administrative data.

Table A4: Differences between iteration 14 and 15
IRP or IRPF according to the year

Years	Mean	Min	Max	Sd
2007	1,93e-09	-0,000244	0,000244	0,00000141
2008	8,79e-09	-0,000244	0,00195	0,00000801
2009	-3,17e-08	-0,000977	0,000244	0,00000484
2010	-2,80e-08	-0,000977	0,000244	0,00000552
2011	-2,31e-08	-0,000977	0,000244	0,00000522
2012	-6,46e-08	-0,000977	0,000244	0,00000706
2013	0,000000138	-0,000977	0,00781	0,0000326
2014	0,000000826	-0,00195	0,0312	0,000137
2015	-3,42e-08	-0,000977	0,00391	0,0000219

Source: Author's own calculation based on ECH data.

Table A5: Income tax collection and Effective rate by income intervals - Year 2008

	Income interval		Informants						Average effective rate	
	Min.	Max.	N	%	Taxpayers	Scope of the tax	Average income (informants)	sd	Informants	Taxpayers
Income intervals according to BPC										
Less than or equal to 7	$0	$12425	480.488	0,50	30.809	0,06	7.762	2.749	0,000	0,005
Between 7 and 10,5	$12426	$18638	198.080	0,20	122.675	0,62	15.031	1.774	0,010	0,017
Between 10.5 and 14	$18638	$24850	95.286	0,10	90.683	0,95	21.373	1.813	0,036	0,037
Between 14 and 21	$24851	$37275	83.935	0,09	83.786	1,00	29.683	3.515	0,066	0,066
Between 21 and 28	$37276	$49700	35.309	0,04	35.309	1,00	42.409	3.677	0,100	0,100
Between 28 and 42	$49701	$74550	27.572	0,03	27.572	1,00	59.055	6.985	0,122	0,122
Between 42 and 56	$74551	$99400	8.761	0,01	8.761	1,00	84.920	7.325	0,143	0,143
Between 56 and 112	$99401	$198800	5.768	0,01	5.768	1,00	127.715	23.708	0,165	0,165
More than 112	$198801		841	0,00	841	1,00	311.101	123.029	0,208	0,208
Total	$11114	$22440	936.040	0,32	406.204	0,43	17.203	18.946	0,022	0,050

Source: Author's own calculation based on ECH data.

Table A7: Income tax collection and Effective rate by income intervals - Year 2015

	Income interval		Informants						Average effective rate	
	Min.	Max.	N	%	Taxpayers	Scope of the tax	Average income (informants)	sd	Informants	Taxpayers
Income intervals according to BPC										
Less than or equal to 7	$0	$21364	317.517	0,28	0	0,00	15.055	4.725	0,000	
Between 7 and 10,5	$21365	$32046	301.513	0,27	94.384	0,31	26.051	3.077	0,002	0,007
Between 10.5 and 14	$32047	$42728	162.548	0,15	144.765	0,89	36.697	3.027	0,023	0,026
Between 14 and 21	$42729	$64092	163.992	0,15	163.329	1,00	51.134	6.318	0,055	0,055
Between 21 and 28	$64093	$85456	61.304	0,05	61.304	1,00	72.503	6.431	0,089	0,089
Between 28 and 42	$85457	$128184	40.090	0,04	40.090	1,00	102.052	12.150	0,112	0,112
Between 42 and 56	$128185	$170912	11.322	0,01	11.322	1,00	146.112	13.029	0,131	0,131
Between 56 and 112	$170913	$341824	9.068	0,01	9.068	1,00	217.727	41.149	0,156	0,156
More than 112	$341825		588	0,00	588	1,00	595.405	1.515.054	0,204	0,204
Total	$27357	$46202	1.067.942	0,21	524.850	0,49	36.987	47.743	0,025	0,050

Source: Author's own calculation based on ECH data.

1.3 Figures

Figure A1: Kernel Density of IRPF-CatII collection - ECH and DGI - 2010

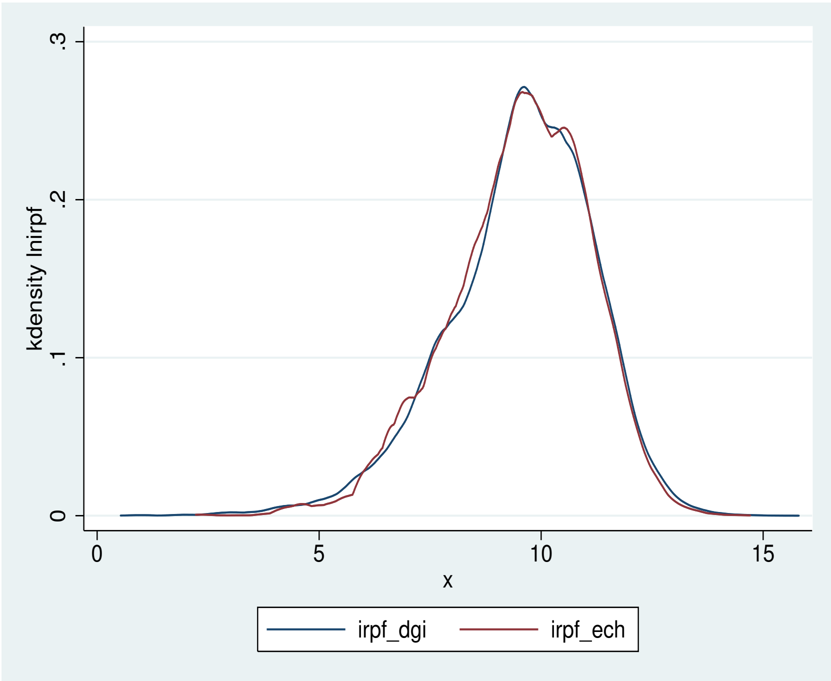


Figure A2: Kernel Density of IRPF-CatII collection - ECH and DGI - 2012