Policy Research Working Paper 7392

A Decade of Declining Earnings Inequality in the Russian Federation

Paula Andrea Calvo
Luis Felipe López-Calva
Josefina Posadas

WORLD BANK GROUP
Poverty Global Practice Group
August 2015

Policy Research Working Paper 7392

Abstract

Wage inequality decreased significantly in the Russian Federation over the 2000s. The economic expansion experienced throughout the decade led to an improvement in social indicators, with a large reduction in poverty rates and an increase in higher education. In this context, wage inequality showed a sharp decline, with the Gini index on labor income decreasing by 18 percent between 2002 and 2012. Using data from the Russian Longitudinal Monitoring Survey, this paper documents the reduction in wage inequality and explores potential factors behind the trend. The analysis uses a decomposition technique proposed by Fortin, Lemieux, and Firpo (2011) to disentangle the main drivers behind changes in the wage distribution. The results suggest that wage structure effects are more important than composition effects for explaining changes in wage inequality. Institutional factors, such as minimum wage policies and changes in the returns to employment in different sectors and types of firms as well as the reduction of the skill premium, emerge as the most relevant factors for explaining changes in the wage structure.

This paper is a product of the Poverty Global Practice Group. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at lflopezcalva@worldbank.org and jposadas@worldbank.org

A Decade of Declining Earnings Inequality in the Russian Federation

Paula Andrea Calvo, Luis Felipe López-Calva and Josefina Posadas[1]

The World Bank

Keywords: earnings, inequality, quantile decomposition, Russian Federation, wages, RIF

JEL Classification: C21, D63, J21, J31

[1] The authors would like to thank comments from Maurizio Bussolo, Carolina Sanchez-Paramo, Birgit Hansl, Michal Rutkowski, Mikhail Matytsin, Andrea Atencio, Pedro Olinto, Vladimir Gimpelson and participants at the Higher School of Economics April Conference 2015 that took place in Moscow. This paper was prepared as a background paper for the project "Deconstructing the Recent Achievements in Shared Prosperity in Russia".

1. Introduction

The Russian Federation sustained significant economic growth over the past decade, accompanied by high rates of income mobility across the population. Between 2000 and 2013, increases in gross domestic product (GDP) averaged 5.15 percent a year, above the regional mean for Europe and Central Asia (ECA) (4.53 percent). Over the whole decade, the positive trend observed was only interrupted by the 2008-09 crisis (when GDP declined by around 7.8 percent), after which growth quickly resumed (Figure 1). Indeed, GDP per capita nearly doubled between 2000 and 2012 (from $8,613 to $15,177, in PPP 2005 dollars). The trend, however, has been decelerating and high growth is not expected to resume in the coming years.

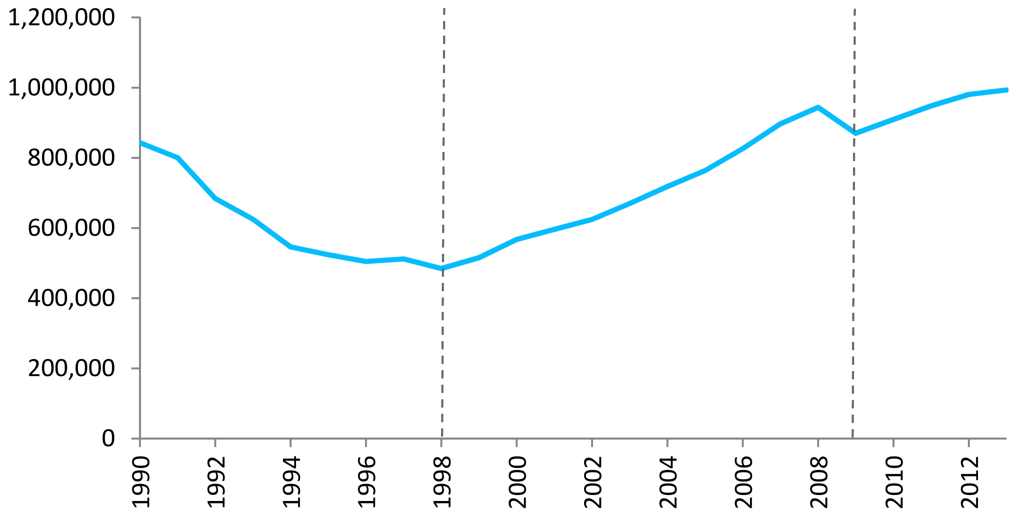
The positive outcomes in economic growth during the first decade of the 2000s have been accompanied by economic mobility for most households, reflected in substantial poverty reduction. The share of people living in poverty declined from around 30 percent in 2000, to about 11 percent in 2014, based on the national poverty line.[2] The overall positive trend, however, masks the fact that the declining trend stagnated in 2013-14 (after reaching a record low of 10.7 percent in 2012, the poverty rate remained at 10.8 percent in 2013 and increased to 11.2 percent in 2014). On the other hand, extreme poverty is nearly nonexistent in Russia. Considering the national extreme poverty line, roughly equivalent to US$2.50 a day, extreme poverty was well below 1 percent (0.77 percent) in 2012.

Income inequality has also decreased in the Russian Federation during the 2000s, though it still remains high for international standards (Figure 2). Along the transition to a market economy, income inequality escalated throughout the 1990s, with the Gini index increasing from 0.22 to 0.52 between 1989 and 1996 (Milanovic, 1999). In fact, according to Clarke (1997), the Gini index experienced a dramatic rise in the early 1990s, from 0.29 in 1992 to 0.50 in 1993. Then, after peaking during the 1998 crisis, income inequality per capita fell by 20 percent between 2002 and 2012 (see Figure 3).

[2] Poverty rates are even lower when considering international poverty lines. Based on the US$5 a day poverty line (in real 2005 PPP values), poverty was 7.3 percent in 2012. According to the international line of US$1.25 a day, the extreme poverty rate is virtually zero (0.03 percent in 2012).

Figure 1: Evolution of GDP in the Russia Federation, 1990-2013

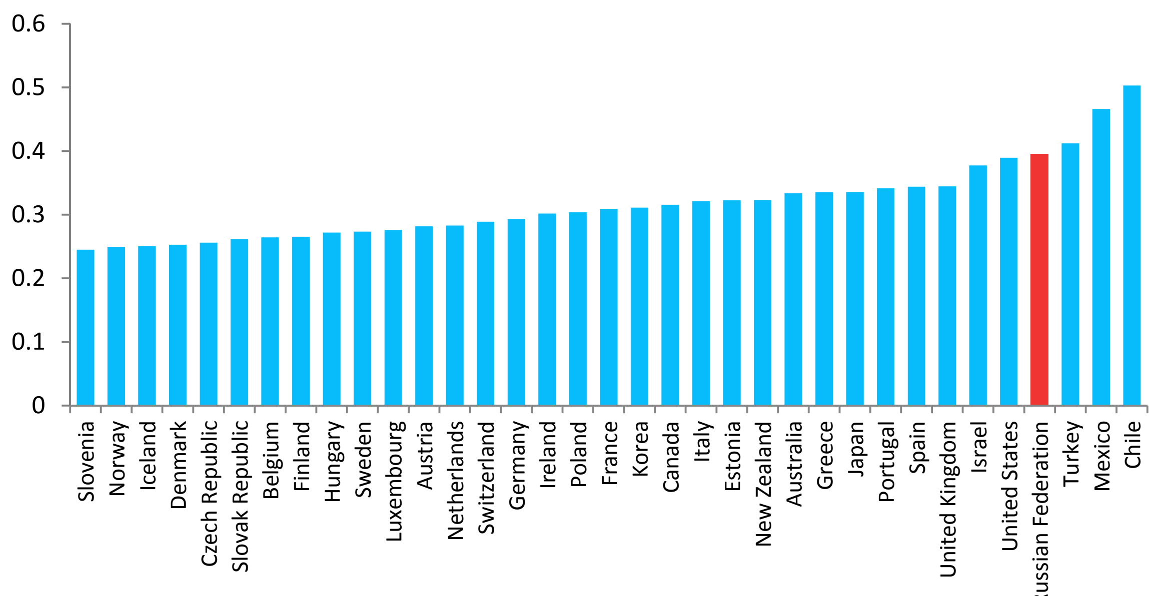
(2005 constant dollars, millions)



Source: WDI. *Notes:* The vertical dotted gray lines show the occurrence of the 1998 and the 2009 crises.

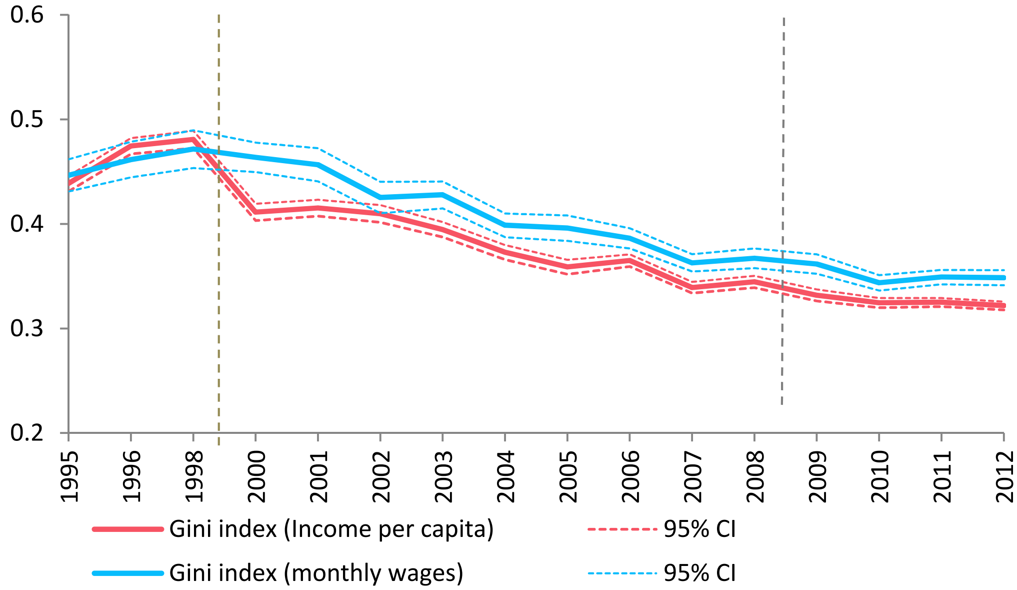
Figure 2: Income inequality in OECD countries, 2011

(Gini index, disposable income)



Source: OECD Stats. *Notes:* Data refers to 2011 for most countries; or next year available (2009 or 2010). In particular, the Gini index for the Russian Federation refers to 2010.

Figure 3: Evolution of inequality in the Russian Federation, 1995-2012
Gini index



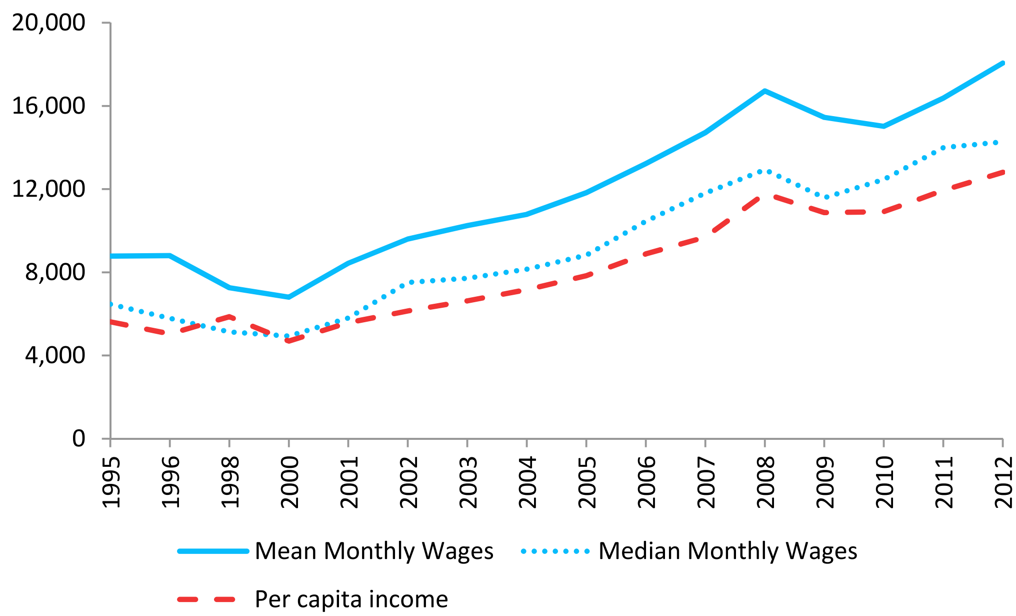
Source: RLMS (Rounds VI to XXI) *Notes:* The Gini index for wages is calculated on the basis of currently employed wage workers in the 18-60 age group, reporting at least 140 worked hours in the last 30 days. Per capita income is calculated for the entire population using the variable '*tincm_n*' of the RLMS. Wages and income for rounds VI and VII were divided by 1,000 to account for the nominal revaluation of the ruble in January 1998 (1,000 old rubles = 1 new ruble). The RLMS was not administered in 1997 and 1999.

Inequality in wages has followed the income trend in the 2000s. Average and median monthly wages nearly doubled between 2002 and 2012, with the growth trend only interrupted during the 2008-09 international crisis (Figure 4). But more importantly, increases in wages grew faster at the bottom of the distribution, contributing to the decrease in inequality. Indeed, the Gini index for monthly wages decreased by 18 percent between 2002 and 2012 (Figure 5).[3] While the upwards jump in wage inequality during the first years of the economic transition was driven by augmented dispersion both in the upper tail and the lower tail of the earnings distribution (Flemming and Micklewright 1999; Brainerd, 1998), the decline in wage inequality of the 2000s was driven by a greater compression *at the bottom*. Between 2000 and 2012, the 50-10th percentile ratio of hourly wages diminished by 32 percent while the 90-50th percentile ratio only declined by 24 percent (Figure 6). This, in turn, led to an increase in the share of wages out of total

[3] The reduction in inequality found is robust to the selection of the indicator. Measured by the 90-10th percentile ratio, inequality dropped by 35 percent between 2002 and 2012, while it decreased by 25 percent in terms of the coefficient of variation (Figure 5).

household income for the bottom 40 percent of the income distribution, from 34 percent in 2002 to 45 percent in 2012. For households at the top 60 percent of the income distribution, this share remained constant, close to 50 percent.

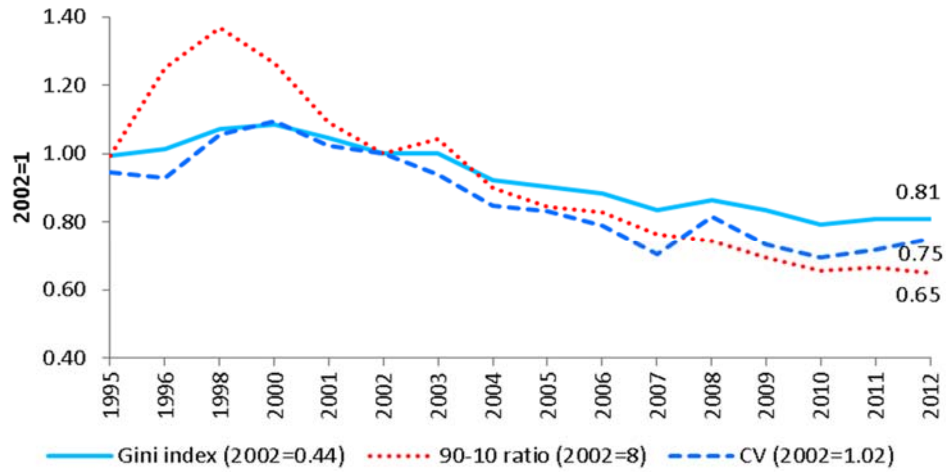
Figure 4: Per capita income and labor earnings in the Russian Federation, 1995-2012
(at 2011 constant rubles)



Source: RLMS (Rounds VI to XXI) *Notes:* Mean and median monthly wages are calculated for currently employed wage workers in the 18-60 age group, reporting over 140 worked hours in the last 30 days. Monthly wages were trimmed at the bottom and top 0.25 percent in each round, to remove outliers. Average per capita income is calculated for the entire population using the variable '*tincm_n*', divided by the number of household members and adjusted to 2011 constant rubles. Wages and income for rounds VI and VII were divided by 1,000 to account for the nominal revaluation of the ruble in January 1998 (1,000 old rubles = 1 new ruble). All values are expressed in 2011 rubles using WDI consumer price index. The RLMS was not administered in 1997 and 1999.

Figure 5: Evolution of earnings inequality in the Russian Federation, 1995-2012

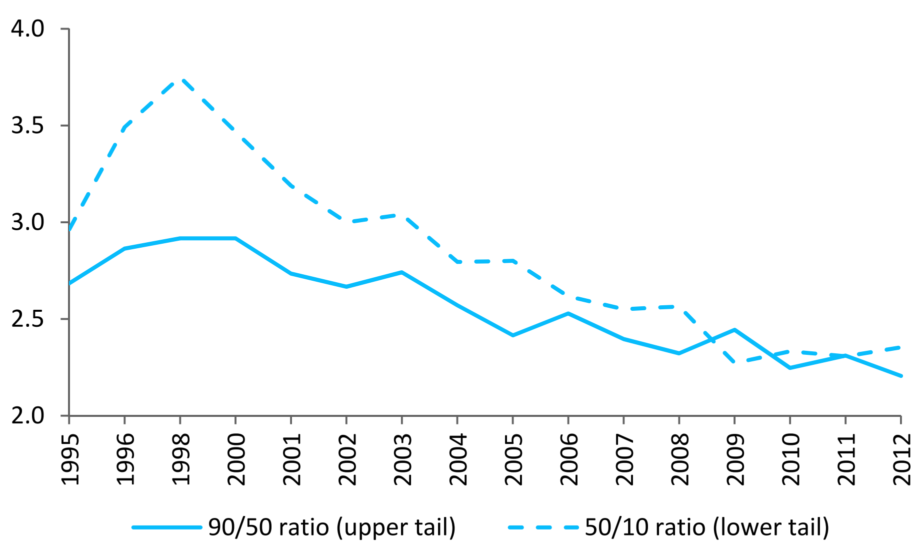
Different indicators, (2002 = 1)



Source: RLMS (Rounds VI to XXI) *Notes:* Inequality indicators are calculated using hourly wages, based on the sample of currently employed wage workers in the 18-60 age group, reporting at least 140 worked hours in the last 30 days. Hourly wages are trimmed at the bottom and top, by 0.25 percent in each round. Wages for rounds VI and VII were divided by 1,000 to account for the nominal revaluation of the ruble in January 1998 (1,000 old rubles = 1 new ruble). The RLMS was not administered in 1997 and 1999.

Figure 6: Evolution of inequality in the Russian Federation at the top and the bottom of the earnings distribution, 1995-2012

Different indicators, (2002 = 1)



Source: RLMS (Rounds VI to XXI) *Notes:* Inequality indicators are calculated using hourly wages., based on the sample of currently employed wage workers in the 18-60 age group, reporting at least 140 worked hours in the last 30 days. Hourly wages are trimmed at the bottom and top, by 0.25 percent in each round. Wages for rounds VI and VII were divided by 1,000 to account for the nominal revaluation of the ruble in January 1998 (1,000 old rubles = 1 new ruble). The RLMS was not administered in 1997 and 1999.

A large body of the literature has documented the increase in wage inequality that took place in the Russian Federation during the transition to a market economy and the financial crisis of 1998. Using data from the Russian Longitudinal Monitoring Survey (RLMS), Flemming and Micklewright (1999) find an increase in the 90-10th percentile ratio of monthly earnings from 6.2 in 1992 to 9.2 in 1995. Lukiyanova (2006) finds that inequality in earnings, measured by the Gini index, peaked in 2000 as a consequence of the financial crisis of 1998, and then started to decrease during the economic recovery. Yet, less evidence exists on the reduction in wage inequality experienced over the last decade (2002-2012) and its underlying causes.

This paper aims to fill in this gap, by investigating the determinants of the change in wage inequality during the 2002-2012 period. To do so, we make use of the decomposition technique recently proposed by Firpo, Fortin and Lemieux (2009, 2011) (FFL henceforth). Following Firpo, Fortin and Lemieux (2011), changes in the wage distribution may be decomposed into changes in the observable characteristics of the workers, the *composition effect*; and changes in the return to these characteristics, the *wage structure effect*. Moreover, the FFL methodology presents two main advantages with respect to those previously used: (i) it allows measuring the composition and wage structure effect at different percentiles of the wage distribution, and (ii) it allows further decomposing each of them into the contribution of individual covariates (such as education, firm characteristics, etc.), leading to a greater understanding of the factors behind changes in inequality. In this way, it can be speculated the importance of supply versus demand effects.[4]

The FFL methodology has recently been used to decompose changes in inequality only in a few settings. Firpo, Fortin and Lemieux (2011) first illustrate the application of the methodology looking at wage inequality in the United States between the 1980s and the early 2000s. More recently, Ferreira, Firpo, and Messina (2014) use the technique to explain changes in wage inequality in Brazil between 1995 and 2012. Atencio and Posadas (2013) use this methodology to assess the gender wage gap in pay in the Russian Federation.[5] Yet, to the best of our

[4] Other papers have used a different approach by measuring the elasticity of substitution between different types/groups workers: high skilled vs. low skilled, following Katz and Murphy (1992).
[5] Carrillo, Gandelman and Robano (2014) use FFL to measure sticky floors and glass ceilings for women in 12 Latin American countries. However, their results should be taken with caution as the FFL is based on two

knowledge, this is the first implementation of the FFL methodology to explain changes in wage inequality in the Russian Federation during the last decade (2002 – 2012).[6]

The rest of the paper is organized as follows. Section 2 describes some of the potential factors behind the reduction in wage inequality, exploring their evolution in the Russian Federation during the period of analysis. Section 3 describes the RLMS data. The decomposition methodology is explained in section 4, including the use of Recentered Influence Functions (RIF), which create a linear approximation for the moments of the distribution. Section 5 presents the main results of the RIF decompositions for the period 2002-2012. Section 6 concludes.

2. Factors behind the reduction of wage inequality

The potential factors behind wage inequality patterns can be grouped into: (i) changes in institutions (such as minimum wage policies and firm characteristics), (ii) changes in the education of the workforce and in returns to skills (which may be related to changes in the supply or the demand for skills), (iii) changes in the demographic composition of the labor force and the relative remunerations between groups (for example, changes in the gender wage gap), and (iv) changes in the relative demand for skills driven by structural transformations of the economy. These factors have been explored at different instances by Katz and Murphy (1992), DiNardo, Fortin and Lemieux (1996), Autor, Katz and Kearney (2008), and Ferreira, Firpo, and Messina (2014), among many others.

2.1. Institutions

The 2000s witnessed profound changes in labor market institutions in the Russian Federation. The Russian government committed to a minimum wage policy. The increase in nominal wages came alongside a steady reduction in inflation rates, which helped to protect real wages. Additionally, wage arrears—which had become a common feature of the Russian labor market in the 1990s and which largely affected low-pay workers (Earle and Sabirianova, 2002; Lehman,

---

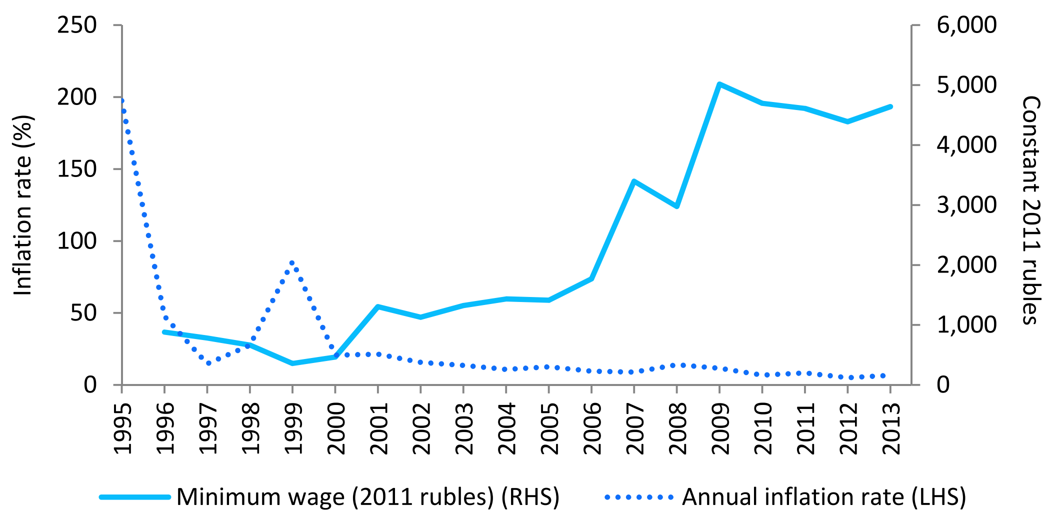
assumptions—ignorability and common support—that are unlikely to hold in this context as it has been shown there is selection bias in women's participation in Latin American labor markets.

[6] Recently, Gimpelson (2015) also investigates changes in wage inequality in the Russian Federation, using the FFL methodology for robustness. However, this is not the main technique used in such paper, while the author covers a different period than the present study, and includes a different set of variables in his estimations.

Wadsworth and Acquisti, 1999)—stopped being a generalized practice during the 2000s (Gimpelson and Kapeliushnikov, 2011).[7]

The minimum wage grew by 398 percent in real terms between 1996 and 2012. The two largest hikes were in 2001 and 2009, at increases of 180 and 69 percent, respectively (Figure 7). The real minimum wage markedly declined with the 2008 international crisis—as the average wage did, too. It is worth noting that this type of downward adjustment of the real minimum wage is a common feature of the Russian labor market used to cope with economic hardship (Gimpelson and Kapeliushnikov, 2011).

Figure 7: Annual inflation rate and minimum wages, 1995-2013



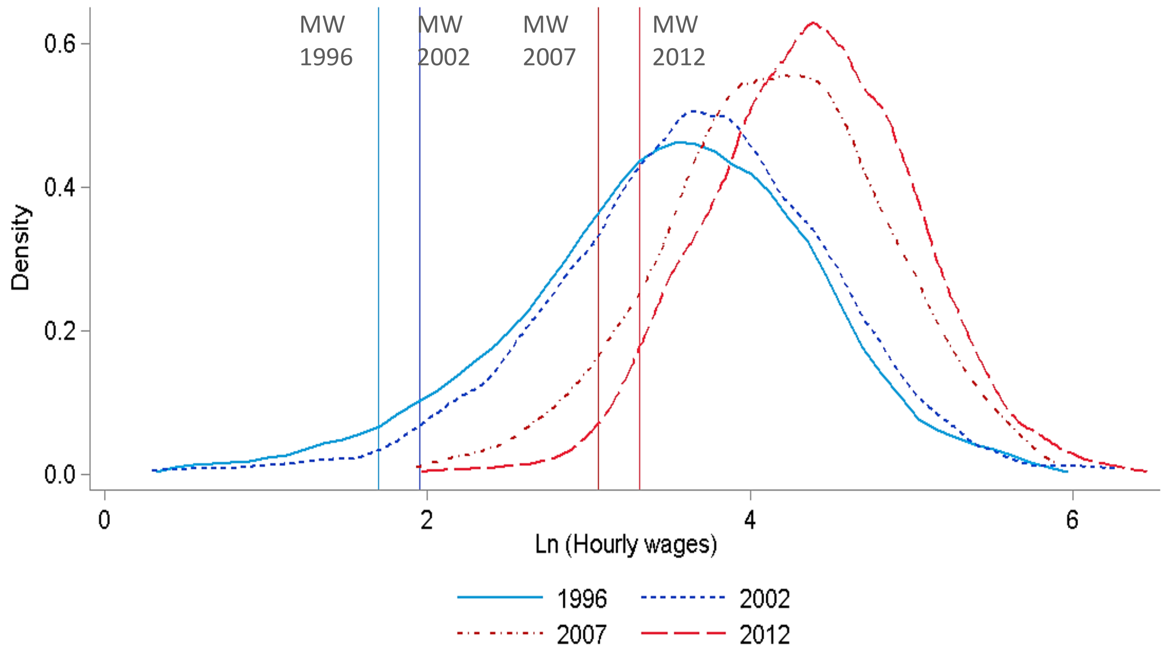
Source: WDI and ILOStats. *Notes:* Minimum wages were adjusted to 2011 rubles using the WDI consumer price index. Wages for 1996 and 1997 were divided by 1,000 to account for the nominal revaluation of the ruble in January 1998 (1,000 old rubles = 1 new ruble). Data on minimum wages for 1995 is not available.

The distribution of real wages also shifted to the right during the 2002 – 2012 period. At the same time, the ratio between the minimum to the average wage increased, from 12 percent in 2002 to 24 percent in 2012; and the share of workers earning less than the minimum wage remained at low levels, averaging 5 percent between 2002 and 2012, and peaking at 11 percent in 2009 (Figure 8). Thus, the increase in the minimum wage during the period of analysis

[7] See Annex A1 for a more detailed discussion on wage arrears and their implications for the distribution of wages.

appears as a potential factor behind the compression of wage inequality, contributing to lower inequality at the bottom of the wage distribution.

Figure 8: Minimum wage and distribution of the logarithm of hourly wages, selected years



Source: RLMS (Rounds VII, XI, XVI and XXI) *Notes:* Vertical lines represent the minimum real hourly wage in the corresponding year, estimated by dividing the minimum wage by 160 hours a month. The sample is restricted to currently employed wage workers in the 18-60 age group, reporting more than 140 worked hours in the last 30 days. The distribution of hourly wages was trimmed at the bottom and top 0.25 percent in each round, to remove outliers. Wages for rounds VI and VII were divided by 1,000 to account for the nominal revaluation of the ruble in January 1998 (1,000 old rubles = 1 new ruble).

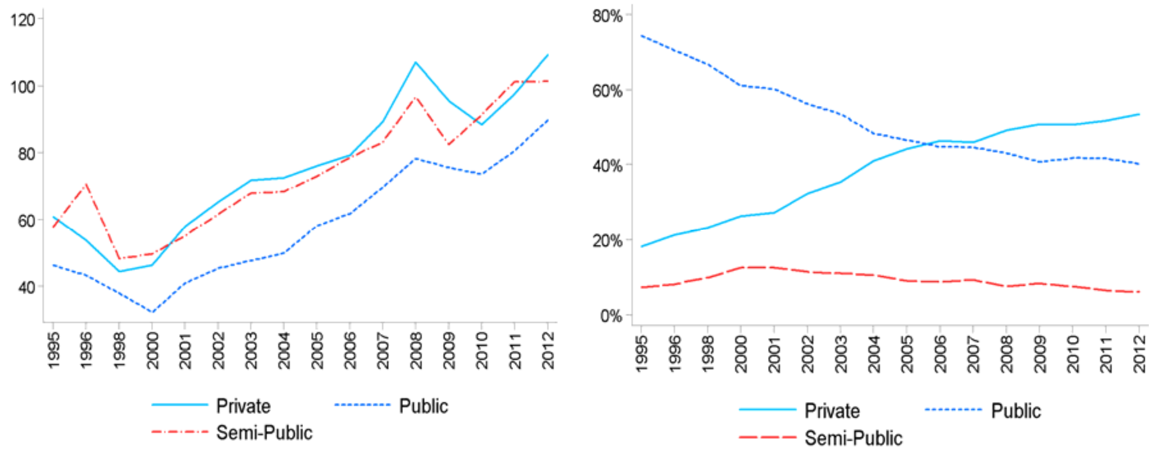
Another distinctive feature of the Russian labor market during this period is the change in the distribution of workers across different firms.[8] Firm characteristics changed importantly with the transition to a market economy. Notably, several public firms were privatized or closed. Between December 1992 and February 1994, over 9,500 large-scale state-owned enterprises (SOEs) were sold to managers and workers, through a mass privatization program (Lieberman and Rahula, 1995; Brown, Earle and Telegdy, 2006). Mechanically but also driven by market

[8] The available data only allows observing changes in the allocation of work across different types of firms (data on firm characteristics is self-reported by each individual in the survey), rather than in the distribution of firms in the economy.

forces, this lead to a substantial increase of employment in private firms, from 18 percent in 1995 to 53 percent in 2012 (Figure 9, panel b).[9]

Figure 9: Hourly wages and share of employment by firm ownership type, 1995-2012

(a) Average hourly wages (at 2011constant rubles) *(b) Share of employment (in %)*



Source: RLMS (Rounds VI to XXI). *Notes:* The type of firm ownership (public, private) is self-reported by the employee in the survey. The variable firm size was censored at 9,999 employees. Share of employment by property type was calculated based on the subsample of currently employed wage workers in the 18-60 age group, reporting more than 140 worked hours in the last 30 days. The distribution of hourly wages was trimmed at the bottom and top 0.25 percent in each round, to remove outliers. Wages for rounds VI and VII were divided by 1,000 to account for the nominal revaluation of the ruble in January 1998 (1,000 old rubles = 1 new ruble). The RLMS was not administered in 1997 and 1999.

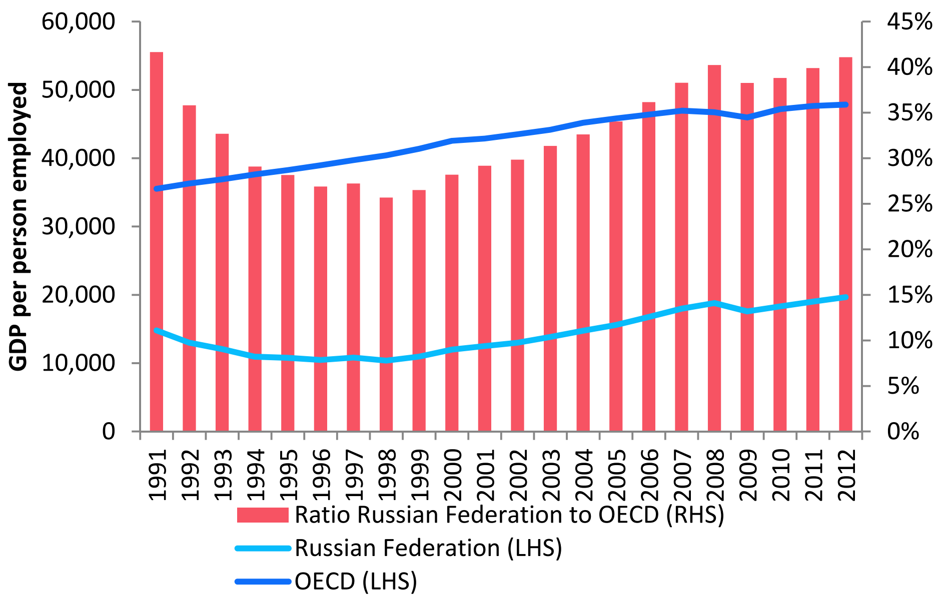
Private firms are generally expected to be more productive, and consequently, to pay higher wages than public enterprises. This was indeed the case in most transition countries, such as Hungary, Poland, Romania, and the Ukraine (see Brown, Earle and Telegdy, 2006; and Adamchik and Bedi, 2000). Yet, this did not appear to be the case in Russia. According to Brainerd (2002), privatized and state-owned firms had similar wages in the period between 1993 and 1998 (with privatized only exceeding public ones in the years 1993 and 1998). Furthermore, even though wages in private firms did exceed those in both public and privatized ones, this wage differential narrowed between 1993 and 1998 (Brainerd, 2002). This situation may reflect the fact that mass privatization in Russia did not immediately improve productivity (Black and Tarassova, 2003; Nellis, 1999), but in fact had negative dynamics during the first five years following the transition (Brown, Earle and Telegdy, 2006). Nevertheless, for the last decade, the

[9] The RLMS does not allow distinguishing between private and privatized firms. Then, when discussing firm ownership our analysis is restricted to private versus public/semi-public firms.

RLMS data show significantly higher wages in private firms than in public firms (Figure 9, panel a).

Lack of managerial skills among the CEOs who acquired firms, inefficiencies in the privatization mechanisms, and high corruption levels have been discussed among the main causes behind low productivity. Firms that were acquired by foreign investors were more productive,[10] as the aforementioned problems may have been less relevant. Indeed, productivity in Russia actually decreased every year between 1991 and 1998, increasing for the first time in 1999. Since then, productivity in the country has displayed positive growth rates every year, except for 2009, and the pace of growth has been faster than that of the OECD countries (Figure 10).

Figure 10: Productivity, 1991-2012



Source: WDI.

The trend observed in the 1990s, regarding increased employment in the private sector, continued into the 2000s, which witnessed a further increase in the share of workers in private firms. On the other hand, wages in the private sector did exceed public ones over the last decade

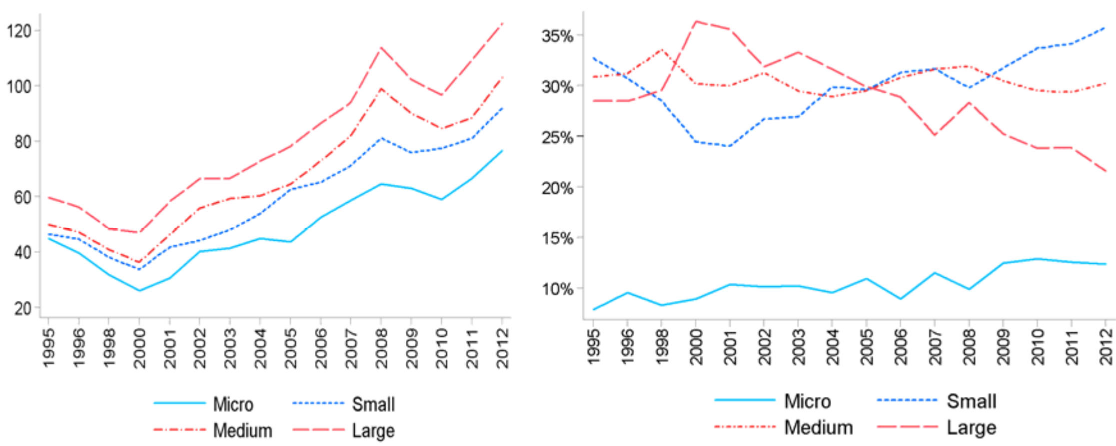
[10] Nevertheless, most privatizations took place between Russian nationals. According to Brown, Earle and Telegdy (2010), the share of firms sold to domestic owners by 1994 was 74.5 percent, compared to less than one percent towards foreign owners. As of 2004, these shares stood at 61.5 and 1.3 percent, respectively, indicating a very small increase in the share of firms that were privatized into foreign hands.

(unlike the situation in the 1990s). Indeed, Gimpelson and Lukiyanova (2009) find that average wages in public firms were lower than those in private firms by about 40 percent.

Another important transformation is the average firm size. During the 1990s, the share of workers in large firms increased—from 29 percent in 1995 to 36 percent in 2001. However, the trend reversed in the 2000s, and the share of employment in small firms surpassed the values of the beginning of the transition in 2012 (Figure 11, panel b). It has been argued that large firms are more productive and pay more (Abwowd and Kramaz, 1999), and the Russian Federation is not the exception (Figure 11, panel a). However, during the last decade the hourly rate of pay of small firms has been catching up to that of medium firms, except for 2008/9. Thus, the changes in the size of the firm and the productivity of firms of different size are good candidate factors behind the change in earnings inequality.

Figure 11: Hourly wages and share of employment by firm size, 1995-2011

(a) Average hourly wages (at 2011 constant rubles) *(b) Share of employment (in %)*



Source: RLMS (Rounds VI to XXI). *Notes:* The number of employees by firm is self-reported by each individual. Firm size categories are defined as follows, micro firms: less than 10 employees; small firms: 10-49 employees; medium firms: 50-249 employees; large firms: 250 or more employees. All figures are calculated based on the subsample of currently employed wage workers in the 18-60 age group. The distribution of hourly wages was trimmed at the bottom and top 0.25 percent in each round, to remove outliers. Wages for rounds VI and VII were divided by 1,000 to account for the nominal revaluation of the ruble in January 1998 (1,000 old rubles = 1 new ruble). The RLMS was not administered in 1997 and 1999.

2.2. Education and skills

Changes in the level of educational attainment and variations in the skill premium of workers are usually found to be an underlying factor behind changes in the wage distribution. For instance, the increase in the skill premium is considered the main factor explaining the increase in wage inequality observed in the United States during the 1960s, 1970s and 1980s (Juhn, Murphy and Pierce, 1993; Katz and Revenga, 1989; Katz and Murphy, 1992). On the other hand, the increase in educational attainment, coupled with a fall in the returns to schooling has been found to be a major cause behind wage compression in Latin America (Lustig, Lopez-Calva and Ortiz-Juarez, 2013; Gasparini, Galiani, Cruces and Acosta, 2011).

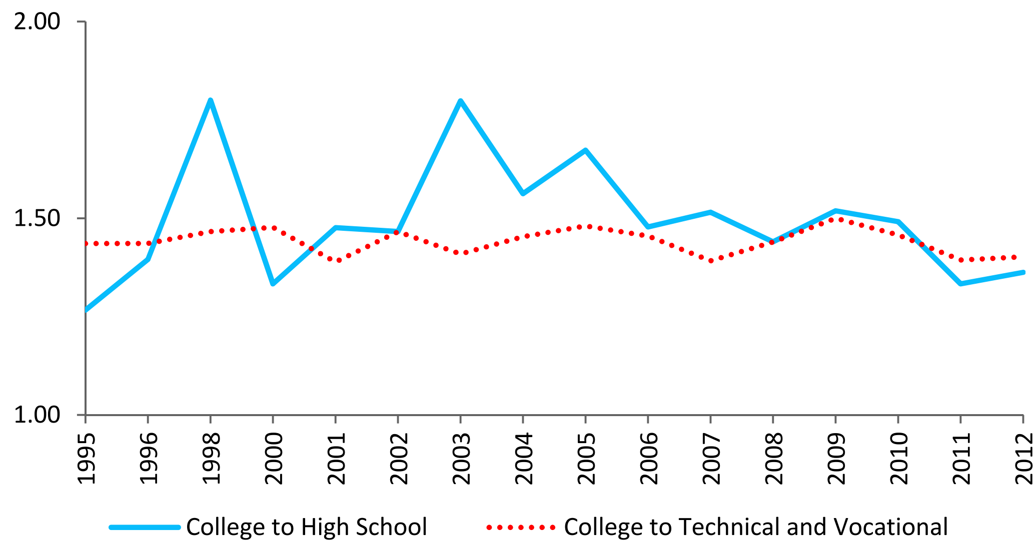
In the Russian Federation, educational attainment within the labor force has increased over the last years, with a rise of 34 percent in the share of college graduates between 2002 and 2012 (from 22.1 percent to 29.7 percent of the labor force, respectively).[11] This increase is mainly attributable to the rise in female college graduates.[12] College graduates are better paid than those with tertiary (vocational and technical) degrees or high school education, while there are no substantial differences in hourly wages between workers with high school diploma and tertiary education. High school dropouts, on the other hand, earn lower wages in every year of the period of study.

The university to high school wage ratio decreased between 2002 and 2012, reflecting the reduction in returns to schooling (Figure 12). The low quality of university education observed in the last years and the mismatch between the skills of the labor force and the requirements of the labor market (both for incoming workers and for senior workers, whose skills became obsolete after the transition to the market economy) may affect the demand for skills and contribute to the reduction in returns. The over-supply of new college graduates coming into the labor market may also play a role. The fact that returns to education appear higher for middle-age workers confirms these hypotheses.

[11] 'College' and 'university' graduates are used interchangeably in this paper.

[12] The share of female university graduates grew from 23.7 percent in 2002 to 35.6 percent in 2012; while the increase in the case of male workers was more modest (from 20.5 percent in 2002 to 23.4 percent in 2012—a return to its 1995 level).

Figure 12: Wage premium to college education, 1995-2012



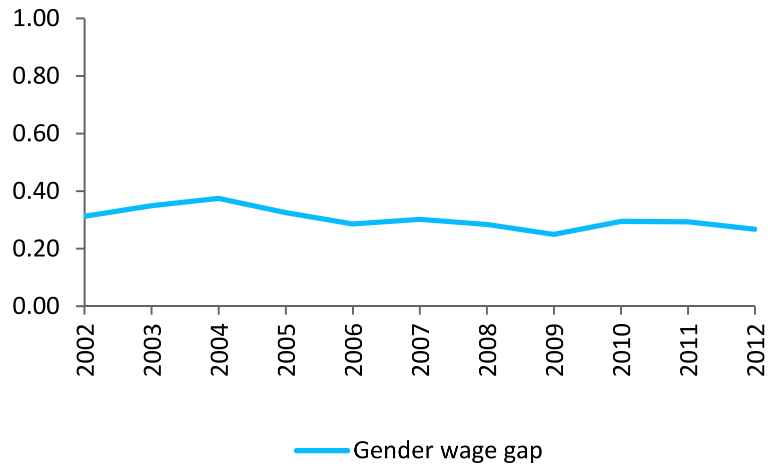
Source: own elaboration based on RLMS (Rounds VI to XXI) *Notes:* all indicators have been calculated based on the subsample of currently employed wage workers in the 18-60age group, reporting more than 140 worked hours in the last 30 days. The distribution of hourly wages was trimmed at the bottom and top 0.25 percent in each round, to remove outliers. Wages for rounds VI and VII were divided by 1,000 to account for the nominal revaluation of the ruble in January 1998 (1,000 old rubles = 1 new ruble). The RLMS was not administered in 1997 and 1999.

2.3. Gender and urbanization

Higher female labor force participation—particularly of more educated women— is one of the main factors explaining the decrease in wage inequality in the U.S. and in Latin America (Mulligan and Rubinstein, 2008; World Bank 2012). However, the case of the Russian Federation is different, as female labor force participation was already high during the soviet period, with female workers accounting for half of the labor force since 2002. Moreover, despite the increase in educational attainment, the gender wage gap remained almost constant between 2002 and 2012 (Figure 13), except for the widening of the gap in 2000-2001 and 2003-2004 (Atencio and Posadas, 2013).[13] Thus, women's role in the labor market seems to be a less relevant factor in the Russian Federation, except for the effect that could come from changes in occupational segregation and discrimination.

[13] According to Kosakova (2007), the temporary widening of the gender gap during the economic recovery of 2000-2001 responds to the fact that low-wage female workers became more likely to receive their full wages than low-wage male workers, during a period where wage arrears were a typical feature of the Russian labor market.

Figure 13. The gender wage gap



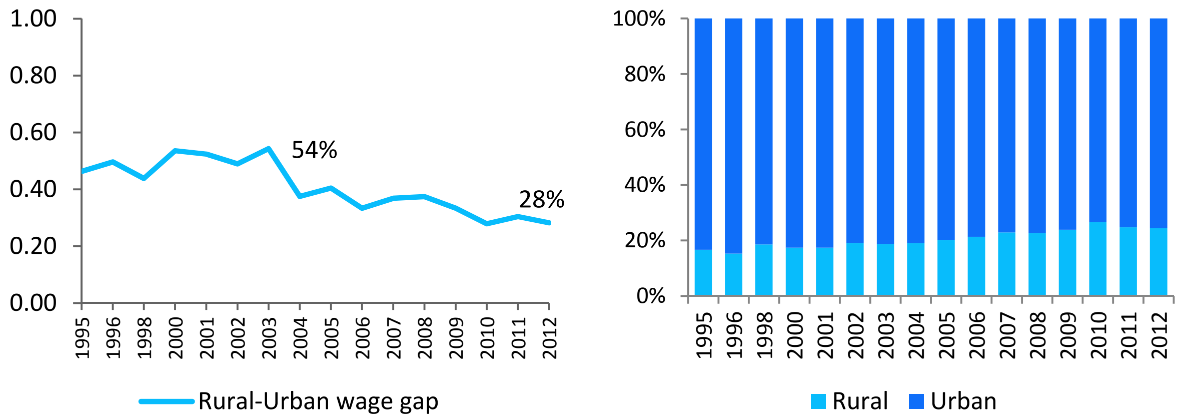
Source: RLMS (Rounds VI to XXI) *Notes:* all indicators have been calculated based on the subsample of currently employed wage workers in the 18-60 age group, reporting more than 140 worked hours in the last 30 days and with no missing data in wages. Hourly wages was trimmed at the bottom and top 0.25 percent in each round, to remove outliers. Wages for rounds VI and VII were divided by 1,000 to account for the nominal revaluation of the ruble in January 1998 (1,000 old rubles = 1 new ruble). The RLMS was not administered in 1997 and 1999.

Instead, regional differences, including rural/urban variation, may play a more important role in explaining changes in wage inequality. Lukiyanova (2006) finds that differences in the adjustment of wages across regions make up one of the main factors behind the spike in wage inequality following the financial crisis of 1998. In Brazil, the urbanization process and regional variables were responsible for about 15 percent of the reduction in wage inequality during the 1995-2012 period (Ferreira, Firpo and Messina, 2014).

Urban wages are typically higher than rural wages. However, in Russia the rural-urban wage gap has declined from 50 to 30 percent between 2002 and 2012 (Figure 14). Additionally, the share of rural workers out of total employment has increased during the same period, from 19 to 24 percent. The increase in the share of rural employment, coupled with an increase in the rural–urban wage ratio may contribute to explain the reduction in wage dispersion observed in Russia during the last decade.

Figure 14: Geographical structure of employment and wages, 1995-2012

(a) Rural-Urban wage gap (in %) *(b) Share in employment*



Source: RLMS (Rounds VI to XXI). *Notes:* all the indicators have been calculated based on the subsample of currently employed wage workers in the age group 18-60, reporting more than 140 worked hours in the last 30 days and with non-missing data in wages. The distribution of hourly wages was trimmed at the bottom and top 0.25 percent in each round, to remove outliers. Wages for rounds 6 and 7 were divided by 1,000 to account for the nominal revaluation of the ruble in January 1998 (1,000 old rubles = 1 new ruble). The RLMS was not administered in 1997 and 1999.

2.4. Demand-side factors: Industry affiliation of workers and occupation premium

Demand-side dynamics appear to have played a critical role in explaining the changes in the wage distribution during Russia's transition to a market economy and in the aftermath of the economic crisis of 1998. Lukiyanova (2006) finds that, together with regional variables, industry affiliation is one of the factors accounting for most of the variation in wage structure. In particular, the author finds negative wage premiums for agriculture, public health and education; coupled with higher wages in traditional industries than in the service sector.

Recent evidence suggests that, over the last decade, the reduction in wage inequality was driven by changes in the industrial composition of employment, with a significant reallocation of labor between industries towards higher-paying jobs, particularly, workers moved out of agriculture and manufacturing and into the service sector (Gimpelson, 2015). These changes were associated with a shift in production, from tradable to non-tradable sectors, as economic growth was fostered by high oil prices. Changes in the industrial affiliation of workers were accompanied by changes in the occupational composition of employment. The demand for professionals increased across sectors, at the same time that lower-skill occupations contracted as a share of total employment. As Gimpelson (2015) indicates, even within the lower-skill sector, workers moved from low-productivity to high-productivity activities, consistent with a process of labor upgrading.

High wages in the oil and gas industry and in the energy-services sector reflected the high commodity prices in international markets during the 2000s (before and after the 2009 recession). Wages in the financial sector make up the highest wages within the services industry, and the second highest of the overall economy. Within manufacturing, the average wages in heavy industry tend to be larger than those in light industry and machine construction, potentially reflecting higher average skills of workers. On the other side, both agriculture and public services (particularly health and education) make up the lowest remunerated sectors in the economy.

Despite the large earnings differentials, wages *between* and *within* industries tended to converge over the last years. The growth of real wages was faster in traditionally low-paying industries (agriculture, public health and public education), while the growth rate in the high-pay mining and finance sectors tended to decelerate. Results from a Shorrocks-Fields decomposition analysis confirm signs of intra-industry decreasing inequality (Gimpelson, 2015).

Industry information is not available prior to 2005, making it impossible to explore the role that the industry affiliation of workers may play in explaining changes in wage inequality over the last decade.[14] Additionally, a profound analysis on intra-industry dynamics is unfeasible, since the RLMS only contains industry data disaggregated into 17 different sectors. Thus, for the analysis performed (see details below), we only include occupational dummies for the 2002-2012 period. Industrial dummies are only considered when analyzing the sub-period 2007-2012.

3. Data

The data comprise Round VI (1995) to Round XXI (2012) of the Russian Longitudinal Monitoring Survey (RLMS), a longitudinal survey of nationally representative household and individual data. This survey, jointly conducted by the Carolina Population Center at the

[14] Industry information is also available for 2003 (Round XIII). However, data for this round has been excluded for the analysis for the sake of comparability in the industry classification over time.

University of North Carolina at Chapel Hill and the Demoscope team at the Higher School of Economics (HSE) in Russia, has been administered every year from 1992 to 2013, except for 1997 and 1999. The RLSM interviewed 3,783 households (8,417 adults) in 1995 and 8,440 households (18,687 adults) in 2012. The RLMS includes demographic information at the individual and household levels. Moreover, it includes questions on household income and expenditures, employment, education, health, and marital and fertility history information. The main limitation of the RLMS is that it is not representative at the regional level.

The main dependent variable for the decompositions is the log of hourly wages from worker primary occupation, expressed in 2011 constant rubles.[15,16] The sample has been restricted to individuals who: (a) are 18 to 60 years old, (b) currently have a job, (c) have received some money for their work in 30 days previous to the survey, (d) are not self-employed, and (e) are full- time workers, reporting to have worked at least 140 hours over the 30 days previous to the survey.

In the Russian Federation, the retirement age is 60 years for men and 55 years for women. However, women are more likely than men to continue working after retirement (Atencio and Posadas, 2013).[17] For this reason, we still use 60 as the sample eligibility threshold. However, in our estimations, we include a dummy variable that takes a value of 1 for women between 55 and 60 years old, to control for potential effects of legal retirement on wages.

Excluding unpaid workers might bias our results if wage arrears were a generalized practice—as employed workers would be excluded from the sample it they failed to report receiving any money for their job in the last 30 days. Wages arrears were indeed a typical feature of the Russian labor market in the very late 1990s and very early 2000s. However, this practice is not expected to affect our results. In fact, the share of unpaid workers as a percentage of total employment has declined from 19 percent in 2000 to only 5 percent in 2012. Wage arrears and their impact on wages and inequality are discussed in detail in Annex A1.

[15] In the Russian Federation, hourly wages are not substantially different when earnings from the secondary occupation are added. During 1995 and 2012, mean total wages are, on average, only 1.6 percent higher than mean wages from primary occupation.

[16] Nominal wages expressed in rubles have been deflated to 2011 rubles using the Consumer Price Index from the World Development Indicators (WDI). Wages for 1995 (Round VI) and 1996 (Round VII) have been divided by 1,000 to take into account the nominal revaluation of the ruble in January 1998 (1,000 old rubles = 1 new ruble).

[17] Women in the 60-64 age group work, on average, six years after retirement, which is two years more than men (Atencio and Posadas, 2013).

The definition of self-employment comprises owner/co-owner of a firm or organization and entrepreneurial work. Excluding self-employment is a common practice in this area of the literature since the earnings of the self-employed tend to be subject to higher measurement error and introduce too much noise on the results. As in the case of unpaid workers, excluding self-employment wages is not expected to affect the results since barely 7 percent of the employed population reports to be self-employed in 2012.[18]

We focus on full-time workers as this group is expected to obtain all their money from their primary occupation. Furthermore, in each round we exclude the top and bottom 0.25 percent of the hourly wage distribution.[19] These observations are considered as outliers.

Taking advantage of the richness of data in the RLMS, we include a wide set of variables that match the main factors outlined in the precious section: schooling variables, institutional characteristics (size and type of ownership of the firm), job characteristics to capture demand side factors (industrial affiliation and occupation), and demographic characteristics (gender, age, and geographic location). Further detail on the definition of the variables and their descriptive statistics can be found in Table A2.1and Table A2.2 in Annex A2.

4. Methodology: The RIF decompositions

The decomposition methodology developed by Firpo, Fortin and Lemieux (2007) seeks to decompose any moment in a distribution while still providing a detailed account of the contribution of each variable used in the regression. The decomposition builds on the use of Recentered Influenced Functions—widely called RIF—that create a linear approximation for the moments of the distribution. RIF regressions were also developed by the same authors (Firpo, Fortin, and Lemieux 2009). Following, we review the basic steps behind this approach, noting the interpretation changes compared to the traditional Oaxaca-Blinder decomposition.

[18] Including self-employed workers increases mean hourly wages by 2.2 percent, on average, between 2002 and 2012. Even if the wages of the self-employed are higher, on average, than the earnings of wage workers, they follow the same trend during the period of analysis.

[19] Lukiyanova (2006) also uses data from the RLMS and removes the top 0.25 percent of the monthly wage distribution in each round. However, for the bottom of the distribution, she adopts a different criteria, and removes all individuals reporting monthly earnings less than two thirds of 17,600 rubles (17,600 rubles was the mandatory minimum wage in November 1994).

Assuming wages Y_{it} depend on a set of characteristics X_i and some unobserved characteristics or components ε_i:

$$Y_{it} = g_t(X_i, \varepsilon_i) \quad \text{for} \quad t = 0{,}1 \tag{1}$$

where $g_t(X_i, \varepsilon_i)$ are unknown functions that can change over time, for which we are not imposing any functional form. The analyst does work under the assumption that there is some unknown joint distribution for (Y, T, X), where T is the time period. Thus from observed data (Y, T, X), $Y_1|T = 1 \sim F_1$ and $Y_0|T = 0 \sim F_0$.

The objective of the decomposition is to estimate a counterfactual distribution for wages where everything is left fixed except for the function governing wages. Thus, we are interested in estimating $Y_0|T = 1 \sim F_C$. This counterfactual distribution, F_C, is the one that would have prevailed under the wage structure of group 0, but with the distribution of the observed and unobserved characteristics of group 1.

The decomposition is performed in a certain distributional moment or statistic. Following the nomenclature of Firpo, Fortin and Lemieux (FFL), we call v the function that computes an statistic (functional) of the joint distribution of $(Y_0, Y_1)|T$. This function v can produce the mean, the variance, the Gini index or a quantile moment. Thus, the overall wage gap may be computed based on any statistic:

$$\Delta_O^v = v(F_1) - v(F_0) = v_1 - v_0 \tag{2}$$

where F_{vt} refer to real functions that produce the statistic v at time t. We then decompose, using the counterfactual distribution to compute *composition* and *wage structure* effects.

$$\Delta_O^v = (v_1 - v_C) + (v_C - v_0) \tag{3}$$

$$\Delta_O^v = \Delta_S^v + \Delta_X^v$$

where Δ_S^v is the "wage structure" component and Δ_X^v is the "composition" component of the overall wage gap. The wage structure component captures the change in the distribution function, from $g_1(.,.)$ to $g_0(.,.)$, keeping the distribution of $(X, \varepsilon)|T = 1$ fixed. The composition component, instead, leaves the distribution function fixed at $g_0(.,.)$ and captures the differences in the distribution of the characteristics $(X, \varepsilon)|T = 1$ to $(X, \varepsilon)|T = 0$. Notice that the composition effect identifies changes in both observable and unobservable characteristics. This is an important difference compared to other decomposition methodologies previously developed.

In order to be able to compute these counterfactual functions, two assumptions need to hold:

(i) *Ignorability. Let* (ε, T, X) *have a joint distribution. For all* x *in* χ*:* ε *is independent of* T *given* $X = x$.

The *Ignorablity* assumption simply states that there should not be a non-random selection of characteristics. For example, if we were analyzing gender wage gaps, this assumption will not hold for the majority of women, since more skilled women (both in terms of observable and unobservables) are more likely to work, and thus their wages will not represent the group.

(ii) *Overlapping Support. For all* x *in* χ, $p(x) = Pr[T = 1|X = x] < 1$. *Furthermore,* $Pr[T = 1] > 0$.

The *Overlapping Support* assumption requires that there is an overlap of all the observable characteristics of the two groups. In other words, all observed values of x should be observed in both groups.

Under these two assumptions, the counterfactual distribution can be estimated using a reweighting approach, similar to that employed in the program evaluation literature. The re-weighting scheme is

$$\begin{aligned} \omega_1(T) &\equiv \frac{T}{p} \\ \omega_0(T) &\equiv \frac{1-T}{1-p} \\ \omega_C(T, X) &\equiv \left(\frac{p(X)}{1-p(X)}\right)\left(\frac{1-T}{p}\right) \end{aligned} \tag{4}$$

where the first two re-weighting functions transform the features of the marginal distribution of Y into features of the conditional distribution of Y_1 given $T = 1$, and of of Y_0 given $T = 0$. The third re-weighting function transforms the marginal distribution of Y into features of the counterfactual distribution of Y_0 given $T = 1$.

If these two assumptions hold, then the function that computes the statistic of interest is identified

$$\begin{aligned} F_t(y) &= \mathbb{E}[\omega_t(T).\, \mathbb{I}\{Y \leq y\}] \quad \text{for} \quad t = 0{,}1 \\ F_C(y) &= \mathbb{E}[\omega_C(T, X).\, \mathbb{I}\{Y \leq y\}] \end{aligned} \tag{4}$$

which also allows the identification of Δ_S^v and Δ_X^v.

The authors continue by applying the RIFs to further divide the wage structure and the composition effects into the contribution of each covariate. At this point, Δ_S^v and Δ_X^v have been identified non-parametrically (via the re-weighting functions), so they are not linear. To further decompose into the effect of each covariate, FFL use RIFs to provide a linear approximation to each Δ_S^v and Δ_X^v. This linearization works as follows

$$RIF(y; v) = v(F) + IF(y; v) \tag{5}$$

where the influence function (IF) captures the portion of the variation (or mass of the distribution) that lies outside the 'point of linearization' (or point of mass concentration). Mathematically,

$$\begin{gathered} IF(y; v) = \lim_{\epsilon \to 0} \frac{(v(F_\epsilon) - v(F))}{\epsilon} \\ F_\epsilon(y) = (1 - \epsilon)F + \epsilon\delta_y \qquad \text{for } 0 \leq \epsilon \leq 1 \end{gathered} \tag{6}$$

where δ_y is the distribution that concentrates the mass around y.

The critical advancement is that the law of iterated expectations can be applied to RIF, and from there, the contributions of each covariate can be obtained. Then, the decomposition can be written as

$$\begin{gathered} \Delta_O^v = \Delta_S^v + \Delta_X^v \\ \Delta_O^v = (m_1 - m_C) + (m_C - m_0) \end{gathered} \tag{7}$$

where $m_t^v \equiv E[RIF(y; v)|X, T = t]$ for $t = 0{,}1$, and $m_C^v \equiv E[RIF(y_0; v)|X, T = 1]$.

We now move to the interpretation of each of the components, that is, the *composition* and *wage structure*. The first idea to be kept in mind is that, because we are working with RIF regressions, we only get first-order approximations. Thus, each of the components will include an approximation error term, which is expected to be small in size.

In terms of the composition effect, the contribution of each covariate should be interpreted as the "policy effect" of changing the distribution of the covariate between $T = 0$ and $T = 1$, while holding constant the distribution of the other covariates and the function that determines wages, i.e. the wage structure.

Interpreting the contributions of each covariate to the wage structure effect is more cumbersome, as it must be done with respect to the base category chosen. Unfortunately, the RIF decomposition does not address the problem of choice of base category, as in the seminal Oaxaca and Blinder approach. Moreover, the approximation residual term will vary with the choice of the base category. Albeit, independently of the choice of base category, the approximation residual terms should be small. Thus, both the residual difference and the wage structure associated to each covariate depend on the choice of base group. The contribution of each covariate can be interpreted as the "policy effect" of changing the distribution of X from its value in the base group at time $T = 1$. This is usually referred to as the change in the dispersion of the distribution over time, or simply, as the dispersion enhancing effect under $g_1(.,.)$ and $g_0(.,.)$.

5. Results

In this section, we discuss the results of applying the FFL decomposition methodology to the RLMS data. As the interest lies in studying the evolution of inequality over the last decade, we focus on the period 2002 – 2012.[20] By 2002, the Russian economy had almost fully recovered from the effects of the 1998 financial crisis, and real wages and inequality had returned to pre-crisis levels. The main reforms of the economic transition had been fully adopted. Thus, restricting the analysis to the 2002-2012 period allows us to explore the changes in the wage distribution that took place over the last decade, isolating them, to a good extent, from the main effects of the financial crisis and the economic transition. Since the 2008 crisis was of short duration in Russia, we also divide the analysis in two equally long sub-periods: 2002-2007 and 2007-2012. The main drawback of the RLMS data for our objective is that industry information is only available from 2005 onwards. Thus the analysis of demand side factors is only carried on for the second period 2007-2012.[21]

The variables included in the decomposition directly relate to the potential explanations for the reduction in wage inequality. These include minimum wage, type of firm, and firm size for *institutional factors*[22]; four different levels of education dummies (high school dropouts, complete

[20] While the RLMS survey was conducted in 2013 as well, this year is not included in the estimations as data is not yet available in English for this year at the time of the writing of this paper.
[21] Results for the sub-period 2007-2012 can be found in Annex A3.
[22] Ferreira, Firpo and Messina (2014) also include informality measures in their decomposition analysis. Although informality is such a concern in the Russian Federation as in Latin America, it has been on the rise and thus would have been interested to evaluate. However, the potential variables that could be used to measure it are not comparable between 2002 and 2012.

high school, tertiary schooling[23] and college education[24]) for *skills and education*; geographic location (urban versus rural); gender and age categories for *demographic characteristics*; and one-digit occupation dummies (ISCO -88) and 17 industry dummies to capture *demand side* factors.

Before discussing the results of the decomposition, we briefly analyze changes in the return of each covariate over time, across the wage distribution. Table 1 shows the estimates of the RIF regressions for the 10th, 50th and 90th percentiles, for the three selected years: 2002, 2007 and 2012, and Figures 15a, 15b and 15c display the estimates for each percentile and each covariate for the same years. The coefficients of the RIF regressions suggest three main factors explaining changes in the wage distribution over time.[25] These are: geographic location, university education, and firm characteristics.

There has been a decline in the skill premium during the last decade, especially for those at the top of the income distribution. On the one hand, the returns of tertiary education have decreased—or even disappeared—with respect to lower levels of education. This is indicated by the lack of significance of the coefficients for high school dropouts and complete high school. On the other hand, the returns to university education, which are consistently significant throughout the period, decreased especially for those in the middle and the top of the wage distribution (Figure 15a). Most part of this fall occurred between 2002 and 2007, while it continued during the next 5 years for those at the top of the distribution.

There might be several reasons behind the fall in returns to schooling. A first explanation for the decline of the skill premium is the fall in the quality of education. Belskaya and Sabirianova Peter (2013) suggest that the rapid expansion of private and tuition-based programs during the 2000s led to a sharp decline in the quality of university education. According to these authors, labor market forces worked well enough to offset the over-supply of university graduates, by reducing the wage premium of the graduates of lower-quality programs. A second explanation is the mismatch between the skills obtained at university and the requirements of firms.

[23] Tertiary schooling includes both vocational and technical education.
[24] College education includes individuals holding a university (Bachelors) degree as well as those with graduate degrees (Master, Ph.D. candidates, and Doctors).
[25] We use a linear approach to obtain the RIF regression, as suggested by Firpo, Fortin and Lemieux (2007). For the estimation, we utilize the STATA command *rifreg* proposed by Firpo, Fortin and Lemieux (2009), which is available at Nicole Fortin's website: http://faculty.arts.ubc.ca/nfortin/datahead.html. The results of our decompositions remain qualitatively the same compared to when we use a non-linear approach, as in Firpo, Fortin and Lemieux (2011).

According to the Enterprise Survey of 2012, around 25 percent of firms in Russia point to an inadequately educated workforce as a major constraint for business growth. Skills acquired before the transition might be obsolete in the new business environment, and firms might prefer to hire young workers than re-train older ones. This can also be confirmed by the flat wage-age profiles computed taking advantage of the longitudinal data (Atencio and Posadas, 2013). Thirdly, most of the increase in the share of college graduates is due to the higher educational attainment of female workers, who do not manage to obtain the full payoff of their education as the gender gap in pay has not shrunk during the last 25 years (Atencio and Posadas, 2013).

Geographical location (urban versus rural) became an important source of wage dispersion after the transition, with a large rural-urban wage gap. This gap narrowed throughout the period, such that, even though urban wages were still higher than rural ones in 2012, rural-urban location was a less important factor to explain wage differentials compared with 2002, particularly at the low end of the wage distribution.

Regional convergence of wages was also a relevant factor to explain wage compression. Guriev and Vakulenko (2015) suggest that the reduction of the barriers to mobility—which became possible due to the generalized economic growth of the 2000s—fostered convergence on incomes and earnings between regions. In line with this, Gimpelson (2015) suggest that regional convergence of earnings explains 2/3 of the decline in wage inequality between 2005 and 2013.

Convergence in productivity among different types of firms is a key factor behind the compression of the wage distribution, captured with type of ownership and size of firms. In 2002, large, foreign, private firms were paying higher wages, especially to workers at the top of the wage distribution. By 2012, these payoffs considerably decreased. On the one hand, there has been convergence in the wages paid by firms, with larger firms offering wages closer to that of smaller firms. On the other hand, the payoff of working for private and foreign firm has been fading away. All this process could be part of a one single phenomenon related to the continuation of the productivity change associated to the privatization of state owned enterprises (SOEs). Many SOEs were sold into smaller firms, which in turn gave birth to other smaller firms through backward and forward linkages. These firms could have needed more time to catch up in productivity. Consistent with this hypothesis is the shift of workers from large public firms to small private ones (Figures 9 and 11). It should be noticed that this process has not been monotonic over time.

The continuation of the transformation of the economic structure has also played a role in compressing the wage distribution. During this decade, the shift from manufacturing and agriculture towards services continued (Gimpelson 2015) enabling young workers to move to higher paying jobs. This is suggested by the changes over time in the coefficients of the occupational variables. Particularly, the coefficients for low-skill occupations (unskilled workers, operators and assemblers, clerks) increased at low levels of the wage distribution. Also supporting this hypothesis, Gimpelson's analysis of the labor force survey, which is richer in terms of occupation and industry information, suggests that there has been convergence of wages both between and within industries.

.

Table 1: RIF Regressions coefficients. Percentiles 10th, 50th and 90th, years 2002, 2007 and 2012

	2002			*2007*			*2012*		
	10	*50*	*90*	*10*	*50*	*90*	*10*	*50*	*90*
Rural	-0.180**	-0.386***	-0.164***	-0.061	-0.266***	-0.112*	-0.022	-0.204***	-0.157***
	(0.083)	(0.066)	(0.062)	(0.052)	(0.053)	(0.060)	(0.039)	(0.033)	(0.040)
HS dropout	0.016	-0.247**	-0.077	-0.019	-0.112	-0.043	0.112	-0.012	-0.081
	(0.161)	(0.125)	(0.160)	(0.098)	(0.108)	(0.112)	(0.099)	(0.085)	(0.061)
Complete HS	-0.112	0.064	0.122	-0.040	0.018	-0.144**	0.091*	0.085*	0.094
	(0.093)	(0.076)	(0.108)	(0.077)	(0.071)	(0.060)	(0.050)	(0.047)	(0.065)
University Education	0.074	0.343***	0.334***	0.133***	0.257***	0.192**	0.096***	0.232***	0.114**
	(0.054)	(0.071)	(0.103)	(0.034)	(0.057)	(0.083)	(0.032)	(0.034)	(0.053)
Micro Firm	0.068	0.040	-0.085	-0.189**	-0.189***	-0.052	-0.085	-0.149***	-0.116**
	(0.096)	(0.096)	(0.101)	(0.088)	(0.069)	(0.079)	(0.058)	(0.043)	(0.050)
Medium Firm	0.046	0.115*	0.068	0.030	0.126**	0.061	0.081**	0.021	0.006
	(0.064)	(0.067)	(0.083)	(0.042)	(0.054)	(0.070)	(0.035)	(0.033)	(0.046)
Large Firm	0.094	0.218***	0.299***	0.098**	0.365***	0.078	0.104***	0.144***	0.214***
	(0.063)	(0.068)	(0.099)	(0.040)	(0.058)	(0.079)	(0.037)	(0.038)	(0.061)
Private Ownership	0.092**	0.176***	0.414***	0.088**	0.142***	0.284***	0.170***	0.197***	0.192***
	(0.047)	(0.057)	(0.091)	(0.034)	(0.044)	(0.064)	(0.032)	(0.029)	(0.046)
Foreign Ownership	-0.057	0.392***	0.576**	-0.028	0.379***	0.596***	-0.013	0.207***	0.190
	(0.106)	(0.105)	(0.244)	(0.085)	(0.081)	(0.225)	(0.063)	(0.066)	(0.128)
Below Minimum Wage	-4.505***	-0.691***	-0.159***	-4.253***	-0.622***	-0.133***	-3.147***	-0.528***	-0.120***
	(0.062)	(0.061)	(0.054)	(0.050)	(0.046)	(0.042)	(0.038)	(0.032)	(0.031)
Constant	2.774***	3.249***	4.106***	3.348***	3.779***	4.597***	3.341***	3.999***	4.600***
	(0.133)	(0.135)	(0.182)	(0.103)	(0.110)	(0.144)	(0.094)	(0.073)	(0.085)
Age & Gender Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.688	0.227	0.118	0.715	0.230	0.095	0.463	0.207	0.097
Observations	1,342	1,342	1,342	1,784	1,784	1,784	3,105	3,105	3,105

Notes: RLMS (Rounds XI, XVI and XXI). *** p<0.01, ** p<0.05, * p< 0.1. Omitted categories are Urban, Tertiary Education, Small Firms, Public/Semi Public Ownership, Domestic Ownership and Above Minimum Wage.

Figure 15a. Unconditional quantile regressions coefficients: schooling & demographic

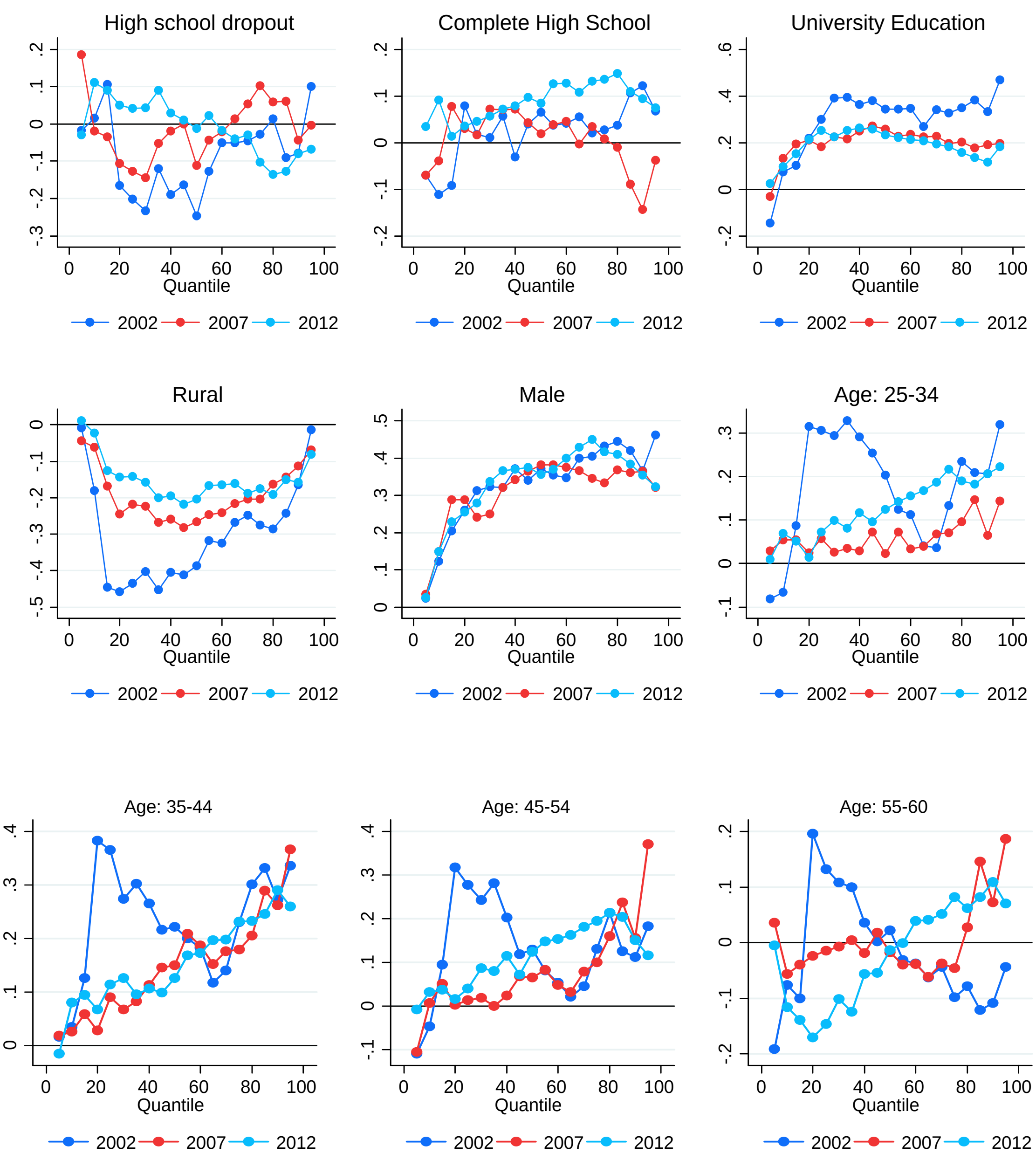


Figure 15b. Unconditional quantile regressions coefficients: institutional factors

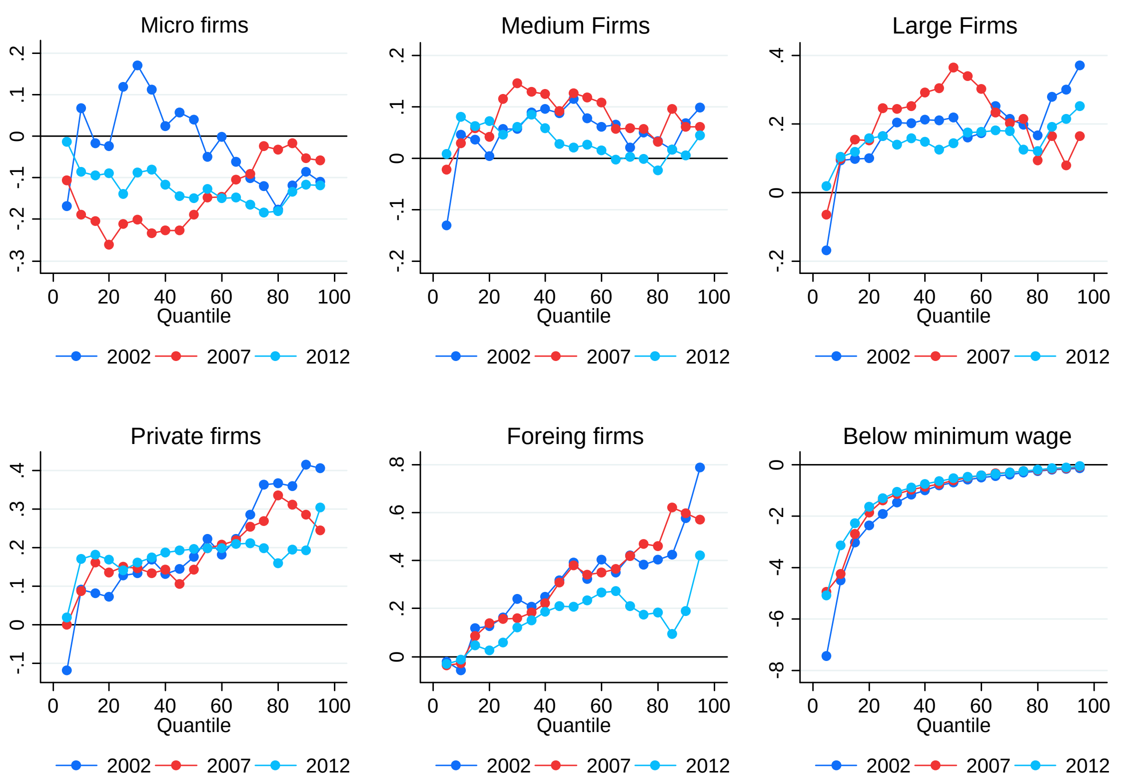
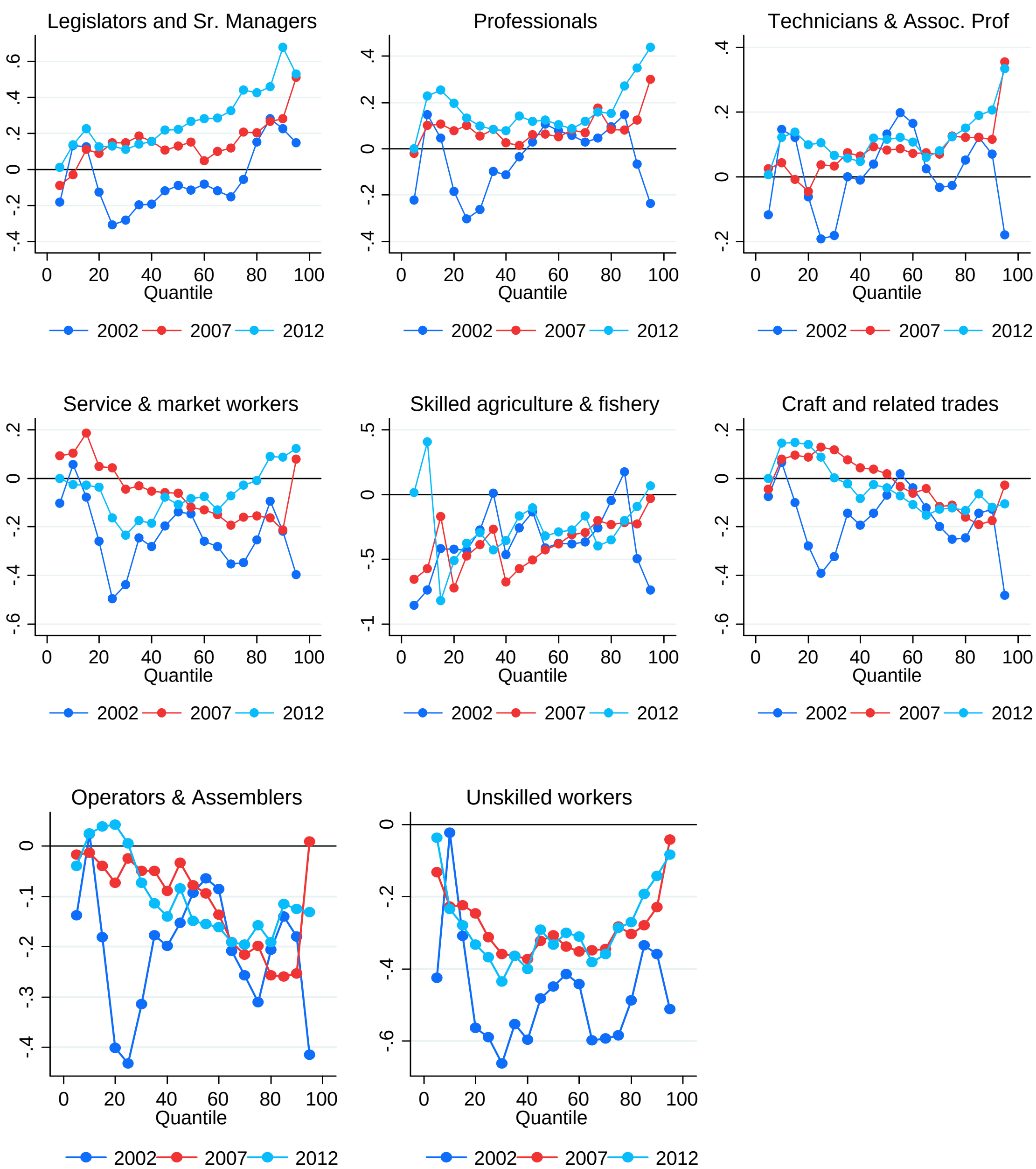


Figure 15c. Unconditional quantile regressions coefficients: occupations



Overall, the results from the RIF regressions indicate that the compression of the wage distribution is due to the fall in the returns to skills, the convergence between urban and rural wages, and changes in productivity of firms and the allocation of workers to different types of firms and jobs. Next, we use the FFL decomposition to measure the relative contribution of each of these factors in explaining the decline in wage inequality in the Russian Federation.

Decomposition results

The FFL decomposition technique allows us to decompose changes in wages and in inequality measures into two components: (i) changes in the composition or the characteristics of the labor force, the *composition effect*; and, (ii) changes in the returns or prices to these characteristics, the *wage structure effect*. Composition effects show the reshaping of the wage distribution. On the other hand, wage structure effects, such as changes in the skill premium show also forces that come from changes in the demand for workers of certain characteristics.

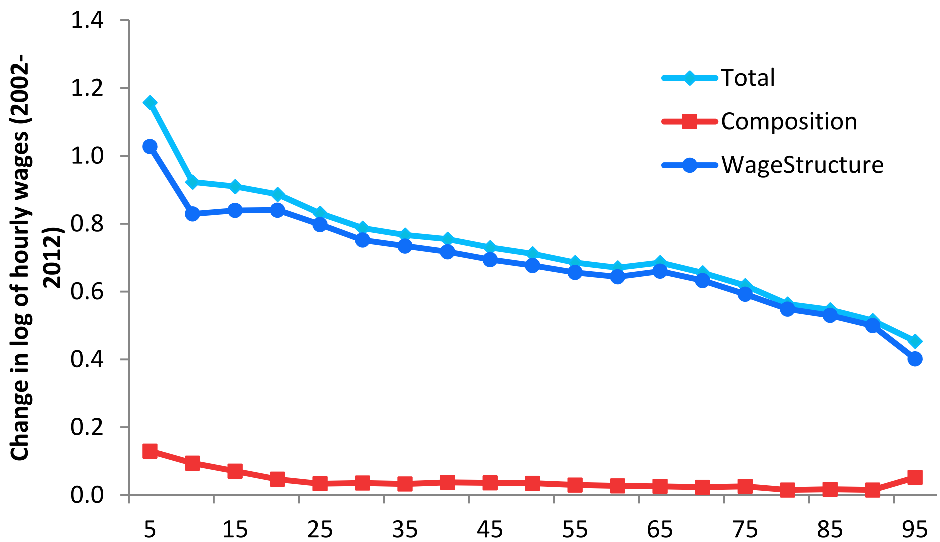
As largely discussed in the literature, the contribution of each factor to the wage structure effect is not invariant to the selection of the reference category within each group of variables. Yet, there is no clear agreement on the way of choosing the reference category (Firpo, Fortin and Lemieux, 2011). In the results discussed next, the reference group refers to rural, female workers, in the 18-24 age group, with tertiary education, working in small firms (between 10 and 49 employees), that are public/semipublic, and foreign firms. Nevertheless, we are cautious when discussing the role that each factor plays in explaining the wage structure effects—and thus the reduction in inequality—as changes in the base category may lead to changes in the wage structure effects (with no effects on the composition effects).[26] To allow for a greater flexibility of the functional form, we fully saturate the model. We fix the distribution of the labor force to reflect its 2002 composition. In this way, the composition effects show changes in wages when we adjust the composition of the labor force between 2002 and 2012, but fixing returns to those of 2012. On the other hand, the wage structure effects show how returns to labor market

[26] We also run the decompositions changing our base categories. Particularly, we change our reference group to use urban workers with complete high school, and foreign firms. The overall results with this specification are qualitatively similar. However, we observe some differences in the contribution from each group of variables to the reduction in inequality, but they are consistent with the interpretation of the results.

characteristics shifted over time, considering that the composition of the labor force remained unchanged, relative to 2002.[27]

Figure 16 presents results from the decompositions for 19 quantiles of the wage distribution. Two features are worth noticing. First, between 2002 and 2012, real hourly wages grew at all levels of the wage distribution. However, the increase was higher in the bottom of the wage distribution, which led to a reduction in wage inequality. Second, wage structure effects are more relevant than composition effects at all levels of the distribution. However, composition effects are important to explain the larger increase in wages at the bottom of the distribution than at the top, and, thus, contributing to the reduction in inequality (see Table 2).

Figure 16. Wage structure and composition effects (plus error, Oaxaca) (2002-2012)



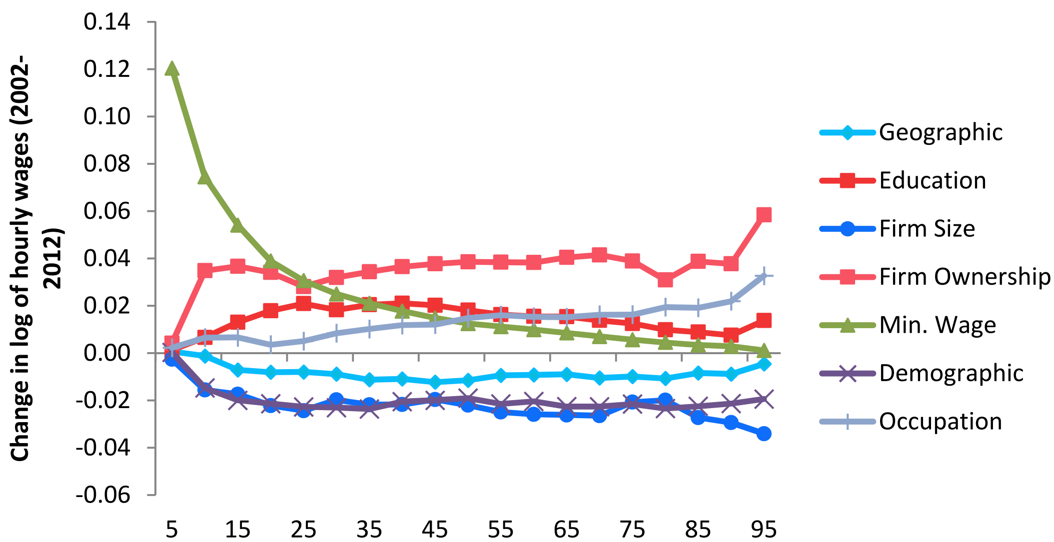
Source: Own elaboration based on RLMS (Rounds XI and XXI). *Notes:* decompositions results are based on the subsample of currently employed wage workers in the 18-60 age group, reporting more than 140 worked hours in the last 30 days and with non-missing data in wages. The distribution of hourly wages was trimmed at the bottom and top 0.25 percent in each round, to remove outliers.

An additional advantage of this methodology is that it allows us to disentangle the contribution of each individual variable (or group of variables) to the composition and wage structure effects.

[27] Firpo, Fortin and Lemieux (2011) use a different base year; fixing the characteristics of the last year to obtain the wage structure effects, and fixing the returns of the first year to obtain the composition effects. Along this line, we ran our model changing the reference year; fixing the 2002 returns to obtain the composition effect, and the 2012 characteristics to obtain the wage structure effect. Most results remained qualitatively the same under this specification, with a few differences. For example, firm ownership has a larger negative effect on the composition effects, while the geographic component plays a larger role in the overall wage structure effects, contributing to the reduction in inequality.

This is an improvement regarding previous techniques such as Machado Mata (2005) and Melly (2005), which only allowed the obtainment of grouped effects. Figure 17 shows the contribution of each of the main explanatory factors to the composition effect. In line with our previous discussion, the increase in the educational attainment of the labor force played an important role in decreasing inequality in the middle and bottom of the distribution. Moreover, the raise of the minimum wage is very important to for those at the very bottom of the distribution. In terms of changes in firm ownership type, the results suggest that an increase in the share of people employed in private organizations contributed to the reduce inequality in wages.

Figure 17. Composition effects by explanatory factor (2002-2012)



Source: Own elaboration based on RLMS (Rounds XI and XXI). *Notes:* decomposition results are based on the subsample of currently employed wage workers in the age group 18-60, reporting more than 140 worked hours in the last 30 days and with non-missing data in wages. The distribution of hourly wages was trimmed at the bottom and top 0.25 percent in each round, to remove outliers.

Table 2: Contribution to changes in inequality by factor, log of hourly wages (2002-2012)

	90-10	50-10	90-50	Variance	Gini Index
Total effects (in levels)	*-0.41*	*-0.21*	*-0.20*	*-0.31*	*-0.05*
Composition	**19%**	**28%**	**10%**	**7%**	**7%**
Geographic	2%	5%	-1%	0%	0%
Education	0%	-5%	5%	-1%	0%
Firm Size	3%	3%	4%	3%	1%
Firm Ownership	-1%	-2%	0%	-6%	-2%
Min. Wage	18%	29%	5%	12%	8%
Demographic	2%	2%	1%	2%	0%
Occupation	-4%	-4%	-4%	-3%	-2%
Specification Error	0%	0%	-1%	0%	0%
Wage structure	**81%**	**72%**	**90%**	**93%**	**93%**
Geographic	6%	-5%	18%	10%	9%
Education	23%	24%	21%	15%	6%
Firm Size	17%	28%	5%	24%	8%
Firm Ownership	32%	15%	50%	20%	9%
Min. Wage	8%	13%	3%	33%	23%
Demographic	9%	36%	-21%	6%	-14%
Occupation	-40%	-12%	-71%	-3%	10%
Constant	26%	-30%	87%	-12%	45%
Specification Error	0%	2%	-3%	-2%	-2%

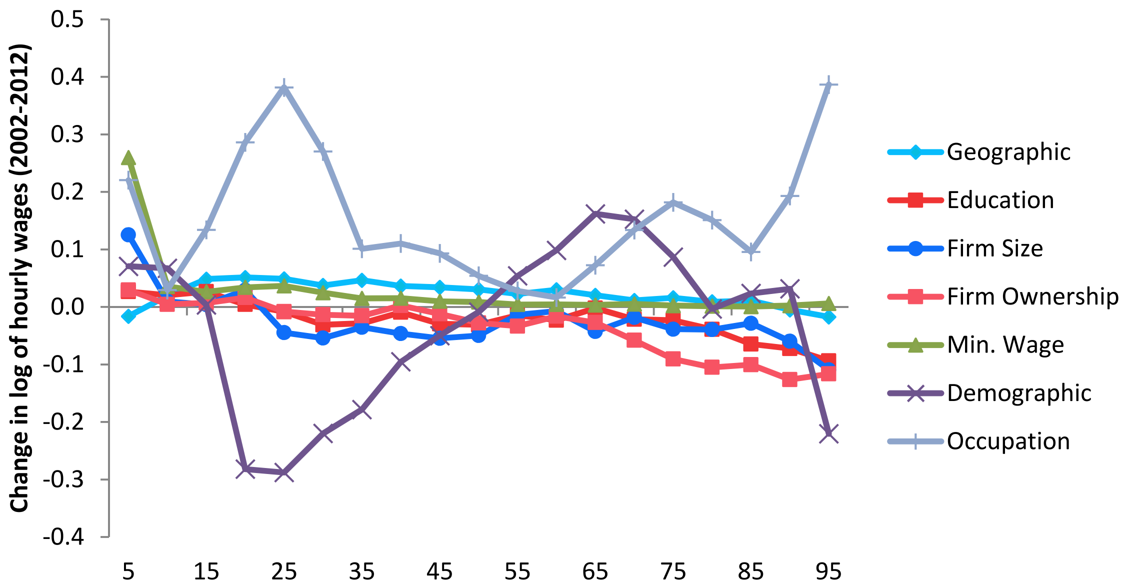
Source: Own elaboration. *Notes:* Total effects (in levels) are computed using the log of hourly wages. Each column shows the contribution (in percentage) of each individual factor to the reduction in each inequality index (then positive numbers reflect an inequality-reducing effect, while negative numbers reflect an inequality-enhancing effect). Composition and wage structure effects summarize the total contribution of individual factors to the reduction in inequality.

In terms of shifts in the geographic location of the labor force, an increase in rural work is found to have a decreasing effect on real wages.

The shift in terms of occupation has been characterized by an increase of employment in managerial and professional jobs and a decrease in low-skilled positions. This change contributes to the overall positive composition effect, increasing when moving to the right of the distribution.

Wage structure effects are more relevant than composition effects in explaining the reduction of wage inequality. Figure 18 shows the contribution of each individual factor to the wage structure effect.

Figure 18. Wage structure effects by explanatory factor (2002-2012)



Source: Own elaboration based on RLMS (Rounds XI and XXI). *Notes:* decomposition results are based on the subsample of currently employed wage workers in the age group 18-60, reporting more than 140 worked hours in the last 30 days and with non-missing data in wages. The distribution of hourly wages was trimmed at the bottom and top 0.25 percent in each round, to remove outliers.

The results suggest that returns to schooling decreased, potentially reflecting the expansion in the supply of university graduates and/or the decline in the quality of the university system. The reduction was higher for those at the top of the wage distribution, contributing to the overall decrease in wage inequality (see Table 2).

Regarding geographic location, returns to living in rural areas increased at the middle of the distribution. This contributed to the compression of the wage distribution, and its contribution was higher for those at the top of the distribution (90-50th percentile log wage differential) than those at the bottom (50-10th percentile log wage differential).

Changes in returns driven by firms' characteristics decrease when moving to the right of the wage distribution, especially in terms of firm ownership type. Both diminish returns to firm size and firm ownership contributed to the overall decrease in inequality, measured by the 90-10th percentile log wage differential, the variance, and the Gini index of the logarithm of hourly wages. Firm ownership type played a greater role in explaining the reduction in the 90-50th percentile log wage differential, while firm size had a larger impact on the decline of the 50-10th percentile log wage differential, consistent with the results of the RIF regressions. Once we disaggregate the ownership effect into its components, public/private ownership emerge as more important than foreign/domestic ownership to explain the reduction in inequality, as measured by the 90-10th percentile log wage differential.

Occupational variables play a positive role both at the bottom and the top of the distribution (if not at the middle), suggesting a higher return both to low skilled (unskilled workers, assemblers, machine operators) and high skilled workers (managerial and professional positions); consistent with the findings of Gimpelson (2015). However, when considered together, occupational variables had an inequality-enhancing effect, particularly at the top of the wage distribution (measured by the 90-50th percentile ratio).

As robustness, we have replicated our results including 7 regional dummies to control by geographic location.[28] As in our main specification, both composition and wage structure effects decrease when moving to the right of the wage distribution, but composition effects even become negative at the top of the distribution. Then, composition effects explain a large share of the total reduction in inequality, in comparison with our main specification. When we look at the composition effect, geographic factors are associated with a monotonic decrease in wages, with a greater decline as we move to the upper-tail of the distribution. The more relevant role played by geographic factors is in line with the findings of Gimpelson (2015) and Guriev and Vakulenko (2015), who suggest that regional mobility is behind the reduction in wage inequality. Then, even if rural vis-à-vis urban location is not very important to explain the drop in inequality, regional shifts of labor are key.[29] These findings suggest that the 2000s saw a reversal in the trends that operated during the 1998 financial crisis, when a large share of the rise in inequality was explained by differences in the speed of adjustment across regions (Lukiyanova, 2006). In the aftermath of the financial crisis, potential migrants faced higher financial constraints which hindered their movement, leading to geographic concentrated pockets of poverty and a rise in

[28] In this specification, we consider the Metropolitan areas of Moscow and Saint Petersburg as the reference category. The other regions are the Northern and North West, Central, Volga, North Caucasian, Ural, Western Siberia and Eastern Siberia and Far Eastern regions.

[29] The overall results remain consistent when we change the reference group for the regional variables, though the interpretation of each regional dummy varies considerably depending on the reference category.

inequality. Later, the economic growth experienced during the 2000s led to interregional convergences in wages and then to a reduction in inequality (Guriev and Vakulenko, 2015).

Overall, we find three main drivers behind the reduction in wage inequality. First, the positive context of sustained economic growth, followed by active minimum wage policies, which improved the well-being of the poorest workers, increasing their wages relatively more than those of workers at the top of the distribution. Second, changes in returns to firm characteristics played an important role in the re-shaping of the wage distribution. Returns to working in private firms decreased relative to those of working in public ones with inequality-reducing effects, especially at the top of the distribution. This differs from what happened following the 1998 financial crisis, when firm ownership played only a marginal role in explaining wage inequality (Lukiyanova, 2006). On the other hand, changes in returns to domestic versus foreign firms did not appear to have large effects on inequality.[30] Changes in returns to firm size also contributed to the wage compression, by reducing the wages in large firms relative to smaller ones. These firm-size effects were greater at the bottom of the distribution than at the top. Combining composition and wage structure effects, we find that firm-related variables largely contributed to the overall decline in inequality, as measured by different inequality indices (90-10th percentile log wage difference, variance of log wages, and Gini index for log wages). The fall in returns to education also contributed to the reduction in inequality. A declining quality of the educational system, a skills mismatch with the requirements of the labor market, and gender discrimination—particularly at the university level—may be factors behind this effect. Finally, as discussed, the interregional convergence in wages evidenced during the 2000s also seemed to play a key role in reducing inequality, reversing the trends operating during the 1990s.

6. Conclusion

Wage inequality declined in the Russian Federation during the 2002–2012 period, in a context of economic growth and overall reduction in poverty and income inequality. During this time, the Gini index for wages decreased by 18 percent. Reductions in inequality are robust to the selection of the measure of inequality, e.g. coefficient of variation and the 90-10 percentile ratio.

[30] The effects from domestic/foreign ownership are not robust to changes in the specification. In fact, when foreign is considered as the base category, firm ownership leads to inequality-enhancing effects explained by domestic/foreign ownership.

The causes underlying the reduction in wage inequality observed in Russia during the last decade are largely unexplored in the labor literature. In this paper, we fill this gap, analyzing the main drivers of the reduction in wage inequality in the Russian Federation during the 2000s. Using a recent decomposition technique proposed by FFL (2009, 2011), we assess the changes in the wage distribution between 2002 and 2012, and decompose them into a composition and a wage structure effect, and the contribution of each individual factor to the reduction in inequality.

The results of our decompositions firstly confirm that wage inequality indeed declined over the last decade in the Russian Federation. While wages increased all along the wage distribution, the overall wage compression was driven by higher increases in real wages at the bottom than at the top of the distribution. Second, both the increase in wages and the reduction in inequality are better explained by changes in the returns to the characteristics of the labor force than by compositional shifts in employment. Third, there is not a single factor leading to the re-shaping in the distribution, but rather the analysis suggests a multifactorial explanation.

On the one hand, institutional variables played a leading role. The minimum wage policy implemented during the last decade contributed to improve the earnings of low-pay workers, leading to a reduction in inequality at the bottom (measured by the 50-10th percentile log wage differential). Moreover, changes in the returns to firm characteristics also had inequality-reducing effects. The increase in employment in private firms was accompanied by a decline in the returns to these firms, particularly for better-paid workers. There was also an increase in the share of employment in small firms, at the same time that these companies improved their wages relative to larger ones. On the other hand, the increase in the educational attainment of the labor force was combined with a reduction in the skill premium, contributing to the overall decline in inequality. Interestingly, the increase in the educational attainment of the labor force was greatly explained by female workers. However, the gender wage gap was not reduced during this period, which is consistent with the decrease in returns to education. Gender-driven discrimination in the labor market, in addition to a reduction in the quality of university education may be factors behind the fall in the skill premium. Additionally, regional variables also emerge as an important explanation for the reduction in wage inequality. Even when rural-urban location on its own is not enough to explain the wage compression, adding regional indicators significantly increases the contribution of geographic factors to the overall decline in inequality.

A main drawback of the present study is that, due to data limitations, we are unable to include industry variables to explore the contribution of structural change to the reduction in wage inequality. However, as Gimpelson (2015) suggests, the industry affiliation of workers seems to have reduced inequality and thus should reinforce our findings. In particular, when we restrict the analysis to the sub-period 2007-2012, we find that while the industry component is not fundamental to explain the drop in the 90-10 log wage differential, it *is* relevant to explain the fall in the variance of the hourly wages logarithm (see Annex A3).

Finally, two interrelated issues deserve separate mention. First, inequality in Russia is still high in comparison to international standards. Second, economic growth has been decelerating in the last few years, as has the improvement in poverty rates that took place during the earlier 2000s. Trends in inequality are thus likely to decelerate, at the same time that the favorable external context reverts. We do not have data beyond 2012 to explore changes in inequality over the last few years (2012-2015), so we cannot explore whether the wage inequality reduction has already stopped or even reverted. Furthermore, it is not clear whether all the factors explaining the reduction in inequality over the last decade may help to further reduce gaps in pay. Specific policies intended to improve the situation of disadvantaged groups, such as female workers, may help to reinforce the reduction in wage inequality in the future. The fall in returns to education was important to explain the compression of the wage distribution. However, improving the overall quality of the educational system is not without challenges. It is not altogether unlikely that the reduction in wage inequality comes to an end at the same time that the productivity of the overall economy and real wages decrease, reflecting the lack of qualified resources.

References

Adamchik, V. and A. Bedi (2000). 'Wage differentials between the public and the private sectors: Evidence from an economy in transition'. *Labour economics*, *7*(2): 203-224.

Atencio, A. and J. Posadas (2013). 'Gender gap in pay in the Russian Federation: Twenty years later still a concern', mimeo.

Autor, D, L. Katz, and M. Kearney (2008). 'Trends in US wage inequality: Revising the revisionists.' *The Review of economics and statistics* 90.2: 300-323.

Belskaya, O. and K. Sabirianova Peter (2009). 'How does the expansion of higher education change the returns to college quality?. Insights from sixty years of Russian history', mimeo.

Brainerd, E. (1998). 'Winners and Losers in Russia's Economic Transition', The American Economic Review. Vol. 88, No. 5, pp. 1094-1116.

Brown, D., J. Earle and A. Telegdy. (2006). 'The Productivity Effects of Privatization: Longitudinal Estimates from Hungary, Romania, Russia, and Ukraine', *Journal of Political Economy,* 114(1):61-99.

Carrillo, Paul, Néstor Gandelman, and Virginia Robano. (2014) 'Sticky floors and glass ceilings in Latin America', Journal of Economic Inequality 12(3): 339-361

Clarke, S. (1997). 'Structural Adjustment Without Mass Unemployment. Lessons from Russia'. Edited by S. Clarke. Edward Elgar Publishing Inc, 1998.

Denisova, I. (2012). 'Income Distribution and Poverty in Russia', OECD Social, Employment and Migration Working Papers, No. 132, OECD Publishing.

DiNardo, J., N.M. Fortin, and T. Lemieux, (1996). 'Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach', *Econometrica*, 64, 1001-1044.

Earle, J. and K. Sabirianova (2002). 'How Late to Pay? Understanding Wage Arrears in Russia', Journal of Labor Economics, 20(3): 661-707.

Ferreira, F., S. Firpo and J. Messina (2014). 'A more level playing field? Explaining the decline in earnings inequality in Brazil, 1995-2012', IRIBA WP No. 12.

Firpo, S., N. Fortin, and T. Lemiuex. (2007). 'Decomposing Wage Distributions using Recentered Influenced Function Regressions' Working Paper British Columbia University

Firpo, S., N. Fortin, and T. Lemiuex. (2009). 'Unconditional quantile regressions', *Econometrica,* Vol. 77 (3): 953-973

Flemming, J. and J. Micklewright. (1999). 'Income Distribution, Economic Systems and Transition', Innocenti Occasional Papers, Economic and Social Policy Series no. 70.

Fortin, N., T. Lemieux and S. Firpo (2011). 'Decomposition Methods Economics', Chapter 1, Handbook of Labor Economics, Vol.4: Elsevier B.V.

Gimpelson, V. (2015). 'Industrial Foundations of the Russian Inequality: Looking from the Demand Side', mimeo

Gasparini, L., S. Galiani, G. Cruces, and P. Acosta (2011). 'Educational upgrading and returns to skills in Latin America: Evidence from a supply-demand framework, 1990-2010'. *World Bank Policy Research Working Paper*, N° 5921.

Gimpelson, V. and R. Kapeliushnikov (2011). 'Labor market adjustment: Is Russia different?', IZA Working Paper, 5588.

Gimpelson, V. and A. Lukiyanova (2009). 'Are Public Sector Workers Underpaid in Russia? Estimating the Public-Private Wage Gap', IZA Working Paper, 3941.

Guriev, S.and E. Vakulenko (2015). 'Breaking out of poverty traps: Internal migration and interregional convergence in Russia', *Journal of Comparative Economics* (forthcoming).

Juhn, C., K. Murphy, and B. Pierce (1993). 'Wage inequality and the rise in returns to skill' *Journal of political Economy*, 101(3): 410-442.

Katz, L. and K. Murphy (1992). 'Changes in Relative Wages, 1963-1987: Supply and Demand Factors', *Quarterly Journal of Economics*, 107(1): 35-78.

Katz, L. and A. Revenga (1989). 'Changes in the structure of wages: The United States vs Japan'. *Journal of the Japanese and International Economies*, 3(4), 522-553.

Kazakova, E. (2007). 'Wages in a growing Russia: When is a 10 percent rise in the gender wage gap good news?',*CERGE-EI Working Paper 257*

Lehmann, H., J. Wadsworth, and A. Acquisti (1999). 'Grime and Punishment: Job Insecurity and Wage Arrears in the Russian Federation', *Journal of Comparative Economics*, 27(4): 595-617.

Lukiyanova A. (2011). 'Effects of Minimum Wages on the Russian Wage Distribution', Working papers by NRU Higher School of Economics, Series EC Economics, No. 09.

Lukiyanova, A. (2006). 'Structure and Distribution of Earnings in Russia, 1994–2003', *The Journal of Comparative Economic Studies*, 4: 9–40.

Lustig, N., L.F. Lopez-Calva, and E. Ortiz-Juarez (2013). 'Declining inequality in Latin America in the 2000s: the cases of Argentina, Brazil, and Mexico'. *World Development*, 44: 129-141.

Machado, José AF, and José Mata. "Counterfactual decomposition of changes in wage distributions using quantile regression." Journal of applied Econometrics 20.4 (2005): 445-465.

Melly, Blaise. "Decomposition of differences in distribution using quantile regression." Labour Economics 12.4 (2005): 577-590.

Milanovic, B. (1999). 'Explaining the increase in inequality during the transition', *Economics of Transition,* 7(2): 299-341.

Nellis, J. (1999). 'Time to Rethink Privatization in Transition Economies?'*, Finance & Development,* 36 (132).

World Bank (2012). 'The Effect of Women's Economic Power in Latin America and the Caribbean'. Latin America and Caribbean Poverty and Labor Brief, August 2012. Washington, DC.

Annex A1. The effect of wage arrears in the wage distribution

Wage arrears became a common problem in the Russian labor market during the transition and until the earlier 2000s; being widespread across regions, sectors and different types of organizations (Earle and Sabirianova, 2002). If wage arrears remain significant during our period of analysis, they may impact the wage distribution and then bias our inequality measures.

We briefly explore the impact of wage arrears on average wages and earnings dispersion during the period 1995 -2012. To this end, we follow Lukiyanova (2006) and define contractual wages, as the monthly pay that we should expect a worker to receive, in the absence of wage debts. This variable is constructed adding to the reported monthly wage the monthly fraction of total wage arrears (calculated as the total sum of money owed by the firm divided by the number of months for which that money was not paid). Panel (a) of figure A2.1 shows the evolution of the average monthly reported wages and average monthly contractual wages. As can be seen, contractual wages were below reported wages from 1996 to 2002, reflecting that low-pay workers became the most affected by this practice. However, the difference between both wages decreased considerable after 2000s. After 2003, the contractual matched the reported wages, evidencing the end of wage arrears. Wage arrears resurged during 2008-2010 as a response to the international financial crisis, although the difference between reported and contractual wages remained small in comparison with the 1990s. It is worth noticing that, contrary to what happened during 1996-2002; during 2008-2010 the contractual wages were above the reported wages, suggesting that wage arrears had a larger impact on the earnings of high-paid workers. Failing to consider the effect of wage arrears leads to an underestimation of earnings inequality between 1996-2002 (Figure A2.1, panel (b)). However, due to the declining relevance of this practice after 2001, we feel confident that using reported wages in our estimation does not invalidate our results.

Figure A2.1: Contractual vs. reported wages: the impact of wage arrears, 1995-2012

(a) Monthly wages (at 2011 constant rubles) *(a) Gini index*

Source: own elaboration based on RLMS (Rounds VI to XXI). *Notes:* Averages wages are calculated based on the subsample of currently employed workers in the 18-60 age group. A round of the survey was administered each year, except for 1997 and 1999, when the survey was not conducted. Wages were adjusted to 2011 rubles using WDI consumer price index. Data on minimum wages is not available for 1995 (round VI). The distributions of reported and contractual wages were trimmed at the bottom and top 0.25 percent in each round, to remove outliers. Wages for rounds VI and VII were divided by 1,000 to account for the nominal revaluation of the ruble in January 1998 (1,000 old rubles = 1 new ruble).

Annex A2: Variable definitions and mean of key variables

Table A2.1: Variable Definitions

Variable	Variables in RLMS	Description
Wage	i#wagelm	*How much money did you receive in the last 30 days from your primary job after taxes? If you received all or part of the money in foreign currency, please convert that into rubles and report the total.*
hrp ln_hrp	i#wagelm i#hourlm	Hourly rate of pay (hrp) = wage/hours worked in the last 30 days. ln_hrp=log(hrp)
Demographic		
Age	h#bmth h#bday h#byr h#imonth h#iday h#iyear	Individual's age in years. It is the result of subtracting the date of birth to the date of the interview
Sex	h#sex	Categorical variable that indicates the gender of the individual
Geographical location	sett_typ	Categorical variable indicating the geographical location of the individual (urban, rural or pgt). Pgt urban-type settlements are included within urban areas.
Education	i#highsc i#profco i#ptufzu i#ptusec i#tecmed i#insuni i#gradre	Categorical variable that indicates the level of education of the individual: secondary incomplete, secondary, vocational, technical, university/postgraduate. For the regression analysis, each of the categories is represented by a dummy variable.
Occupation	i#ilopjb	Categorical variable that indicates the classification of the job performed by the individual (occupation). Occupations are originally coded according to the four-digit International Standard Classification of Occupations (ISCO-88) but were collapsed them into a one-digit code for the regression analysis.
Industry	i#priind	Categorical variable that indicates the industry to which the individual's job belongs. It has seventeen categories, each of which is represented by a dummy variable for the regression analysis.
Institutional variables		
Below minimum wage	i#wagelm i#hourlm	Dummy variables that takes the value 1 when the hourly wage is below a minimum hourly wage. Minimum hourly wage is calculated dividing the monthly legal minimum wage in each year by 160 hours, to take into account the hourly minimum wage of a full time worker. Minimum wages are adjusted to 2011 constant rubles.
Public or semi-public firm	i#entgov	Dummy variable that takes the value of 1 if the government is owner or co-owner of the enterprise or organization where the individual works.
Foreign firms owned or co-owned	i#entfor	Dummy variable that takes the value of 1 if foreign firms or foreign individuals own or co-own the enterprise or organization where the individual works.
Firm size	i#pjemps	Dichotomic variables for different size categories (micro firms < 10 employees, small between 10 and 50 employees, medium between 50 and 249 employees, and large firms with > 250 employees). Data on the size of the firm is self-reported by each individual in the survey and do not correspond to firm-level data.

Notes: # is the round indicator. The second column shows the name in the RLMS questionnaires of the variables used to construct the variables listed in the first column.

Table A2.2: Mean of key variables and differences of means

	2002	2007	2012	2012-2002	p-value
Age & Gender					
18-24	0.116	0.142	0.107	-0.009	0.286
25-34	0.240	0.260	0.281	0.041	0.001
35-44	0.321	0.275	0.253	-0.068	0.000
45-54	0.264	0.236	0.250	-0.014	0.234
55-60	0.058	0.088	0.108	0.050	0.000
Male	0.526	0.514	0.520	-0.006	0.646
Geographic Location					
Urban	0.822	0.798	0.773	-0.049	0.000
Education					
High school dropouts	0.029	0.046	0.028	-0.001	0.848
High school	0.120	0.106	0.096	-0.024	0.004
Tertiary	0.627	0.606	0.573	-0.054	0.000
University	0.223	0.242	0.295	0.072	0.000
Institutional Factors					
Below Minimum Wage	0.072	0.068	0.047	-0.025	0.000
Works in Private Firm	0.323	0.461	0.536	0.213	0.000
Works in Domestic Firm	0.952	0.965	0.966	0.014	0.010
Works in Micro Firm	0.099	0.113	0.123	0.024	0.021
Works in Small Firm	0.262	0.311	0.356	0.094	0.000
Works in Medium Firm	0.307	0.311	0.301	-0.006	0.671
Works in Large Firm	0.331	0.265	0.219	-0.111	0.000
Occupations					
Sr. Managers	0.055	0.047	0.039	-0.016	0.004
Professionals	0.140	0.162	0.169	0.028	0.005
Technicians	0.164	0.163	0.193	0.029	0.006
Clerks	0.062	0.059	0.064	0.002	0.770
Service Workers	0.105	0.117	0.113	0.007	0.385
Skilled Agricultural	0.004	0.003	0.003	-0.001	0.484
Craft Workers	0.162	0.162	0.149	-0.013	0.178
Plant Operators	0.201	0.178	0.162	-0.039	0.000
Unskilled Occupations	0.106	0.110	0.109	0.002	0.787
Industry affiliation					
Light Industry	-	0.071	0.074	-	-
Machine Construction	-	0.038	0.031	-	-
Military Industry	-	0.023	0.023	-	-
Oil & Gas	-	0.028	0.028	-	-
Heavy Industry	-	0.032	0.034	-	-
Construction	-	0.109	0.087	-	-
Transp & Comm	-	0.096	0.102	-	-

(cont.)

Table A2.2: Mean of key variables and differences of means

	2002	2007	2012	2012-2002	p-value
Agriculture	-	0.037	0.043	-	-
Public Adm.	-	0.022	0.029	-	-
Education	-	0.078	0.077	-	-
Sci. & Culture	-	0.024	0.029	-	-
Public Health	-	0.070	0.072	-	-
Army	-	0.058	0.051	-	-
Trade	-	0.171	0.201	-	-
Finances	-	0.018	0.025	-	-
Energy	-	0.016	0.024	-	-
Housing & CommServ	-	0.041	0.040	-	-
Wages					
Wage	9,912.1	14,774.9	18,173.3	8,261	0.000
Hourly Wage	53.866	79.362	98.519	44.65	0.000
Log of Hourly Wage	3.636	4.141	4.376	0.740	0.000

Annex A3: Decomposition analysis for the period 2007 - 2012

Table A3.1 replicates the RIF regressions presented in Table 2, for the sub-period 2007 – 2012. However, we have modified the specification to include industry variables, as discussed.

Briefly, returns to rural work decreased between 2007 and 2012, at the top of the distribution. The skill premium continued to decrease during this sub-period, with a further fall in the returns to university premium and an increase in the returns to high school in comparison with tertiary education.

For firm characteristics, returns to large firms continued to decrease at the bottom and at the middle of the wage distribution, but re-increased at the 90^{th} percentile. The opposite was evident for public versus private ownership, with a sharp decrease in returns to private ownership at the level of the 90^{th} percentile. Returns to foreign ownership showed a large fall during the sub-period 2007 – 2012 in comparison with domestic firms, particularly at the middle-top of the distribution, which explained most of the decrease in returns to foreign companies during the period of analysis, 2002-2012.

Changes in the returns to industry variables were not monotonic and were in different directions. Returns to the Heavy Industry, Oil & Gas complex and Transport and Communication increased at the 10^{th} and the 50^{th} percentiles, but decreased at the 90^{th} percentile. For Finances and Energy, the returns increased but some coefficients were not significant. Returns to public services, such as Public Administration, Public Health and Education also decreased compared with Agriculture, but once again, most coefficients arising from the RIF regressions are not significant.

	2007			2012		
	10	**50**	**90**	**10**	**50**	**90**
Rural	-0.039	-0.223***	-0.098	-0.001	-0.177***	-0.147***
	(0.054)	(0.053)	(0.061)	(0.039)	(0.033)	(0.040)
HS dropout	-0.014	-0.117	-0.053	0.128	0.014	-0.042
	(0.099)	(0.111)	(0.114)	(0.098)	(0.084)	(0.060)
Complete HS	-0.041	0.025	-0.126**	0.092*	0.099**	0.098
	(0.078)	(0.072)	(0.061)	(0.051)	(0.047)	(0.065)
University Education	0.111***	0.223***	0.178**	0.086***	0.219***	0.085
	(0.034)	(0.057)	(0.084)	(0.031)	(0.035)	(0.052)
Micro Firm	-0.230**	-0.246***	-0.078	-0.098*	-0.161***	-0.126**
	(0.091)	(0.072)	(0.085)	(0.058)	(0.044)	(0.052)
Medium Firm	0.036	0.122**	0.047	0.090**	0.024	0.007
	(0.043)	(0.054)	(0.070)	(0.035)	(0.033)	(0.046)
Large Firm	0.125***	0.363***	0.099	0.105***	0.116***	0.229***
	(0.046)	(0.061)	(0.084)	(0.040)	(0.040)	(0.067)
Private Ownership	0.066*	0.062	0.297***	0.135***	0.128***	0.148***
	(0.039)	(0.052)	(0.079)	(0.035)	(0.035)	(0.054)
Foreign Ownership	-0.023	0.369***	0.632***	-0.035	0.168**	0.184
	(0.075)	(0.083)	(0.227)	(0.064)	(0.068)	(0.127)
Below Minimum Wage	-4.216***	-0.546***	-0.070	-3.123***	-0.502***	-0.101***
	(0.055)	(0.049)	(0.043)	(0.041)	(0.033)	(0.033)
Male	0.112***	0.316***	0.311***	0.110***	0.291***	0.298***
	(0.038)	(0.049)	(0.073)	(0.035)	(0.032)	(0.053)
Age 25-34	0.072	0.041	0.062	0.074	0.134**	0.227***
	(0.061)	(0.073)	(0.086)	(0.055)	(0.053)	(0.065)
Age 35-44	0.046	0.172**	0.256***	0.090	0.133**	0.311***
	(0.065)	(0.072)	(0.091)	(0.057)	(0.053)	(0.067)
Age 45-54	0.031	0.101	0.167*	0.057	0.149***	0.187***
	(0.066)	(0.071)	(0.086)	(0.061)	(0.054)	(0.065)
Age 55-60	-0.027	0.035	0.098	-0.084	0.028	0.168**
	(0.086)	(0.089)	(0.106)	(0.078)	(0.061)	(0.073)
Sr. Manager	0.030	0.232**	0.332*	0.169*	0.275***	0.737***
	(0.113)	(0.115)	(0.185)	(0.087)	(0.083)	(0.144)
Professional	0.177*	0.184*	0.179	0.298***	0.215***	0.441***
	(0.092)	(0.101)	(0.135)	(0.075)	(0.065)	(0.088)
Technicians	0.090	0.154	0.147	0.171**	0.163***	0.247***
	(0.095)	(0.095)	(0.129)	(0.072)	(0.061)	(0.076)
Service Workers	0.115	-0.046	-0.152	-0.045	-0.123*	0.130*
	(0.108)	(0.108)	(0.126)	(0.089)	(0.068)	(0.075)
Skilled Agricultural	-0.507	-0.462**	-0.143	0.546***	0.044	-0.091
	(0.707)	(0.218)	(0.165)	(0.109)	(0.324)	(0.114)
Craft Workers	0.125	0.037	-0.181	0.197***	-0.032	-0.091
	(0.090)	(0.108)	(0.145)	(0.074)	(0.071)	(0.088)
Plant Operators	0.042	-0.035	-0.249*	0.067	-0.111	-0.117
	(0.108)	(0.106)	(0.136)	(0.080)	(0.070)	(0.084)
Unskilled Occupations	-0.182	-0.248**	-0.193	-0.208**	-0.295***	-0.099

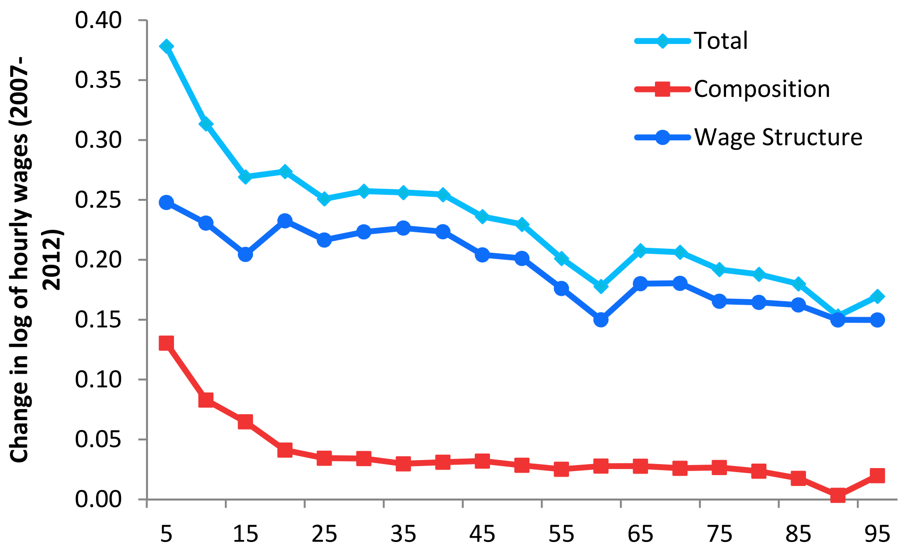
	2007			***2012***		
	10	***50***	***90***	***10***	***50***	***90***
	(0.133)	(0.108)	(0.131)	(0.099)	(0.069)	(0.072)
Light Industry	-0.024	0.113	-0.043	0.056	0.098	-0.072
	(0.111)	(0.107)	(0.140)	(0.086)	(0.071)	(0.097)
Machine construction	0.022	-0.051	-0.171	0.201***	-0.122	-0.247
	(0.128)	(0.142)	(0.161)	(0.069)	(0.116)	(0.154)
Military Complex	0.089	0.204	-0.238	0.072	0.111	-0.522***
	(0.075)	(0.166)	(0.149)	(0.106)	(0.117)	(0.114)
Oil & Gas	0.170**	0.274*	0.666**	0.215***	0.386***	0.414**
	(0.070)	(0.147)	(0.285)	(0.069)	(0.098)	(0.187)
Heavy Industry	0.016	0.171	-0.143	0.193***	0.407***	-0.218
	(0.104)	(0.140)	(0.190)	(0.069)	(0.091)	(0.138)
Construction	0.163**	0.357***	0.279*	0.104	0.357***	0.224*
	(0.067)	(0.092)	(0.146)	(0.079)	(0.071)	(0.123)
Transport & Comm.	0.172**	0.278***	0.291**	0.207***	0.275***	0.211**
	(0.080)	(0.095)	(0.137)	(0.074)	(0.067)	(0.105)
Public Adm.	0.216***	0.246*	0.144	0.076	0.003	-0.134
	(0.074)	(0.135)	(0.188)	(0.113)	(0.084)	(0.114)
Education	0.010	-0.118	-0.025	0.038	-0.043	-0.216**
	(0.099)	(0.089)	(0.103)	(0.087)	(0.066)	(0.085)
Science & Culture	0.112	0.070	0.151	0.070	0.024	0.023
	(0.119)	(0.127)	(0.198)	(0.097)	(0.082)	(0.129)
Public Health	-0.047	-0.113	0.019	-0.011	0.023	-0.165*
	(0.108)	(0.097)	(0.110)	(0.091)	(0.068)	(0.088)
Army	0.127	0.148	0.029	0.274***	0.289***	0.102
	(0.102)	(0.109)	(0.146)	(0.098)	(0.086)	(0.133)
Trade	0.205**	0.262***	0.022	0.205***	0.230***	-0.046
	(0.084)	(0.089)	(0.123)	(0.075)	(0.064)	(0.090)
Finances	0.137*	0.132	-0.038	0.163*	0.221**	0.278
	(0.070)	(0.176)	(0.228)	(0.091)	(0.094)	(0.170)
Energy	0.141**	0.433***	0.529	0.068	0.305***	-0.049
	(0.070)	(0.164)	(0.328)	(0.108)	(0.097)	(0.146)
Housing and Com. Services	0.109	-0.072	0.011	0.029	0.030	-0.210***
	(0.104)	(0.114)	(0.134)	(0.112)	(0.083)	(0.082)
Constant	3.209***	3.638***	4.505***	3.209***	3.864***	4.608***
	(0.124)	(0.130)	(0.172)	(0.116)	(0.092)	(0.113)
R-squared	0.719	0.253	0.115	0.468	0.231	0.121
Observations	1,784	1,784	1,784	3,105	3,105	3,105

Notes: RLMS (Rounds XVI and XXI). *** p<0.01, ** p<0.05, * p< 0.1. Omitted categories are Urban, Tertiary Education, Small Firms, Public/Semi Public Ownership, Domestic Ownership, Above Minimum Wage, Female workers, 18-24 age group, clerks and skilled agricultural workers.

During 2007-2012, the total effects on the log of hourly wages were lower than for the whole period at all levels of the wage distribution. Compositions effects explained a larger share of total changes in wages compared with the period 2002-2012 (see Figure A3.1). The detailed composition and wage structure effects for the sub-period 2007-2012 are presented in Figures A3.2 and A3.3.

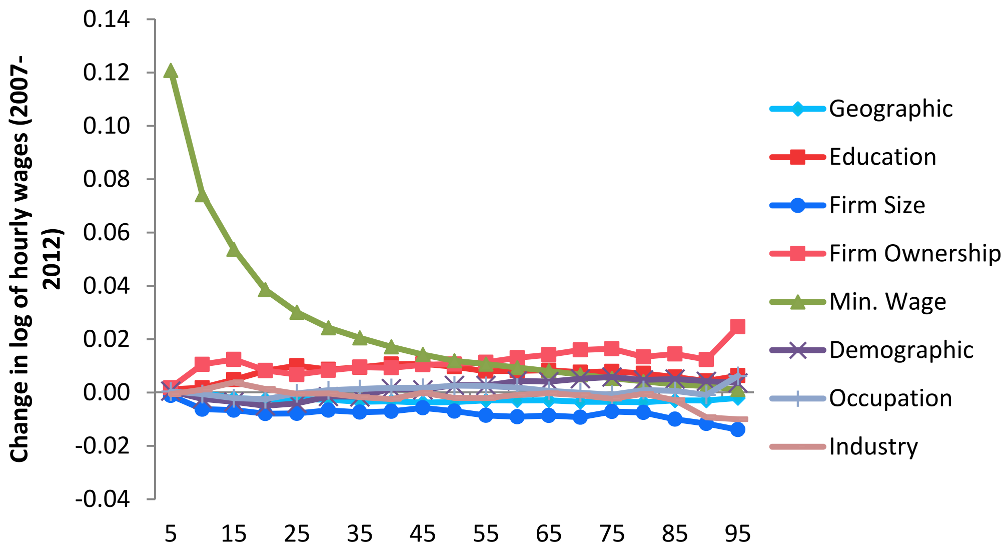
During 2007-2012, wage inequality continued to decrease. Composition effect explained half of the reduction in inequality measured by the 90-10 log wage differential and the variance, and two thirds of the decline in the Gini index (see Table A3.2). In particular, the industry component was not fundamental to explain the drop in this index, but it was relevant to explain the fall in variance of the logarithm of hourly wages.

Figure A3.1. Wage structure and composition effects (plus error, Oaxaca) (2007-2012)



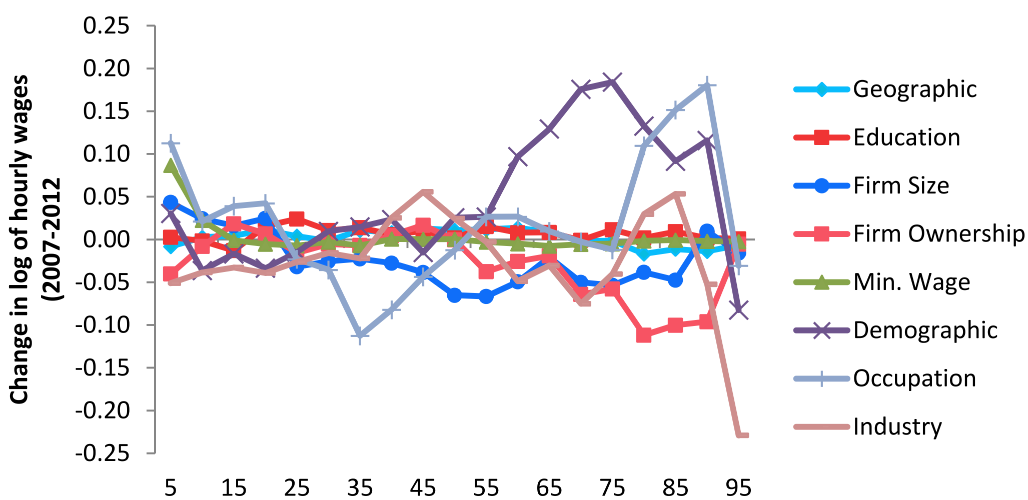
Source: Own elaboration based on RLMS (Rounds XVI and XXI). *Notes:* decomposition results are based on the subsample of currently employed wage workers in the 18-60 age group, reporting more than 140 worked hours in the last 30 days and with non-missing data in wages. The distribution of hourly wages was trimmed at the bottom and top 0.25 percent in each round, to remove outliers.

Figure A3.2. Detailed composition effects (2007-2012)



Source: Own elaboration based on RLMS (Rounds XVI and XXI). *Notes:* decompositions results are based on the subsample of currently employed wage workers in the age group 18-60, reporting more than 140 worked hours in the last 30 days and with non-missing data in wages. The distribution of hourly wages was trimmed at the bottom and top 0.25 percent in each round, to remove outliers.

Figure A3.3. Detailed composition effects (2007-2012)



Source: Own elaboration based on RLMS (Rounds XVI and XXI). *Notes:* decomposition results are based on the subsample of currently employed wage workers in the 18-60 age group, reporting more than 140 worked hours in the last 30 days and with non-missing data in wages. The distribution of hourly wages was trimmed at the bottom and top 0.25 percent in each round, to remove outliers.

Table A3.2: Contribution of each factor to changes in inequality, log of hourly wages (2007-2012)

	90-10	50-10	90-50	Variance	Gini Index
Total effects (in levels)	*-0.16*	*-0.08*	*-0.08*	*-0.06*	*-0.01*
Composition	**50%**	**65%**	**33%**	**56%**	**34%**
Geographic	2%	4%	-1%	1%	0%
Education	-2%	-9%	7%	-3%	0%
Firm Size	3%	1%	6%	7%	2%
Firm Ownership	-1%	0%	-2%	-12%	-4%
Min. Wage	45%	74%	12%	59%	35%
Demographic	-4%	-6%	-2%	-4%	-3%
Occupation	0%	-4%	5%	0%	0%
Industry	6%	4%	9%	7%	3%
Specification Error	0%	1%	-2%	1%	1%
Wage structure	**50%**	**35%**	**67%**	**44%**	**66%**
Geographic	10%	-10%	32%	5%	5%
Education	-2%	-4%	0%	5%	4%
Firm Size	9%	107%	-98%	-3%	-2%
Firm Ownership	55%	-9%	125%	12%	10%
Min. Wage	15%	26%	3%	32%	19%
Demographic	-95%	-73%	-118%	-67%	-35%
Occupation	-99%	40%	-252%	-35%	-22%
Industry	9%	-75%	101%	108%	33%
Constant	144%	25%	275%	1%	59%
Specification Error	5%	9%	0%	-15%	-7%

Notes: Total effects (in levels) are computed using the log of hourly wages. Each column shows the contribution (in percentage) of each individual factor to the reduction in each inequality index (positive numbers then reflect an inequality-reducing effect while negative numbers reflect an inequality-enhancing effect). Composition and wage structure effects summarize the total contribution of individual factors to the reduction in inequality.