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Gender Gap in Pay in the Russian Federation

Twenty Years Later, Still a Concern

Andrea Atencio
Josefina Posadas

World Bank Group
Poverty Global Practice Group
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Abstract

This paper decomposes the gender gap in pay in the Russian Federation along the earnings distribution for the period 1996–2011. The analysis uses a reweighted, recentered influence function decomposition that allows estimating the contribution of each covariate on the wage structure and composition effects along the earnings distribution. The paper finds that women are in flat career paths compared with men; the importance of observable characteristics that proxy human capital in the gender pay gap decrease along the earnings distribution; and if women's pay took into account their educational degrees as much as men's, the gender pay gap would disappear or even reverse at the top of the earnings distribution. The results suggest that women at the bottom of the earnings distribution should be helped to increase their labor market skills, and women at the top of the distribution should be helped to break the glass ceiling and be remunerated for their skills to the same extent as men.

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Gender Gap in Pay in the Russian Federation:

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Andrea Atencio
World Bank

Josefina Posadas
World Bank

Key words: Gender pay gap, Russian Federation, Recentered Influence Function, RIF regression, RIF decomposition, RLMS.

JEL codes: J24, J31, J40, J71, J78

1. Introduction

Women in Russia work. Russia's gender gap in employment has been one of the smallest in the world, with less than 4 percentage points' difference in labor force participation between men and women between the ages of 30 and 55. The low gender gap in employment is part of the legacy of the Soviet era, where the equality motto was not only applied to class but to all groups of society, including men and women. However, the gender gap in pay in Russia is one of the largest among high-income countries. This gap is just above 30 percent and is the second-to-largest gender gap in pay in high-income countries, after the Republic of Korea (see Figure A1). For some scholars, the high gender gap in pay is also part of the Soviet era's legacy, where the "Equal Pay for Equal Work" legislation was interpreted in terms of productivity disfavoring women in occupations where men have a physical comparative advantage (Arabsheibani and Lau, 1999). Moreover, this legislation, as well as the multiple restrictions to female employment in certain occupations (for example, even today, women cannot work as trained machinists, although with current technologies this job does not require any special physical aptitude) are key factors determining the high occupational segregation observed in Russia.

It can be argued that the low gender gap in employment and the high gender gap in pay go together. One piece of evidence is the negative correlation between the gender gap in pay and the gender gap in employment. The negative cross-country variation in the gender gap in pay has been attributed to international differences in wage dispersion (Blau and Kahn, 1996, 2003) and to a nonrandom selection of women into the labor force (Olivetti and Petrongolo, 2008). Selection correction explains nearly half of the observed negative correlation between wage and employment gaps. In this paper, we explore how the gender gap in pay varies along the earnings distribution (and over time). The case of the Russian Federation is of particular interest because of the peculiarities of its labor market and its evolution since the transition to a market economy. During the last 20 years, the gender wage gap in Russia has remained fairly constant despite huge changes in the economic structure—now an open economy—and the changes in the wage structure. With the exception of a spike in 2002 that was mainly due to the use of wage arrears that disproportionately affected women (Gerry, Kim, and Li, 2004; Oglobin, 2005) and a drop in 2006, the hourly adjusted gender gap in pay has fluctuated around 28 percent, with an average decline of less than 5 percentage points since 1994 (see Figure 1). Second, there has been a massive compression of the overall wage distribution in Russia, and for both men and women (see Figure 2 and Table A1).[1] This compression of the wage structure was accompanied by changes in returns to labor market skills, which is typical of countries that are open to trade and grow

[1] For more details on the measurement of the compression of the wage distribution over the same period, see Calvo, López-Calva, and Posadas (2015).

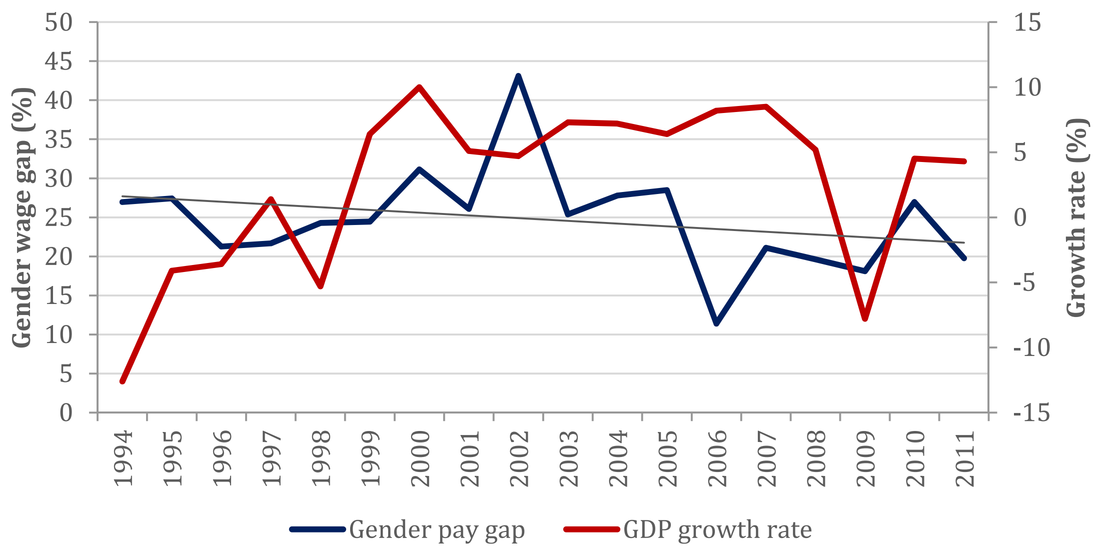
quickly. The change in the wage structure is documented in Calvo, López-Calva, and Posadas (2015). We apply a new decomposition methodology that allows us to compute the wage structure and the composition effects at different percentiles of the earnings distribution. The methodology, which was developed by Fortin, Lemieux, and Firpo (2011), was used to analyze the increase in wage inequality in the United States during the last decade. This methodology was applied to analyze gender wage gaps only in two studies, but with countries that do not comply with the assumptions that make it valid, namely nonrandom selections of women into the labor force. These two studies are Chi and Li (2008) and Carrillo, Gandelman, and Robano (2014), for urban China and for 12 Latin American countries, respectively, where there is evidence of selection effects in women's employment (World Bank, 2011).

Firpo, Fortin, and Lemieux's decomposition methodology (FFL hereafter) builds on econometric methods used in the program evaluation literature, and presents several advantages with respect to other decomposition methodologies as discussed in Fortin, Lemieux, and Firpo (2011). The methodology is based on the estimation of recentered influence functions (RIF) as opposed to other estimates of the earnings equations. The most important advantage is that it can be used to compute several statistics (not only the mean) without losing the ability to identify the contribution of each covariate to the wage structure and the composition effects. Previous methodologies designed to decompose the gender wage gap at different percentiles—such as Machado and Mata (2005), which was based on conditional quantile estimations—could only disentangle the composition and the wage structure effect. Understanding the contribution of covariates is of particular importance, especially in the case of Russia, to analyze the links between the gender gap in pay, occupational segregation, the distribution of employment across economic sectors, and other factors.

However, the RIF decomposition relies on two assumptions for identification: ignorability and common support. The first assumption simply states that unobservables are equally distributed in the two groups used for the decomposition; in this case, men and women. Thus, with nonrandom selection of women into the labor force, this decomposition cannot be applied since it will violate the ignorability assumption. This assumption limits the applicability of the RIF decomposition to analyze the gender gap in pay in many countries. However, given the high female labor force participation in Russia, and as we test below, this is not a concern for our study. The second assumption requires that there is at least one observation for men and women for each combination of observable characteristics. In this way, a counterfactual can be computed for each observation in the sample.

This paper contributes to the understanding of the gender wage gap along the earnings distribution by describing the changes in the covariates associated with this gap. In this way, we can understand if there is either a "sticky-floor" or "glass-ceiling" effect in Russia. We observe that the largest gender wage gap appears at the median of the distribution, but at the same time—and consistent with other high-income countries—the largest unexplained gap is found at the top of the distribution, indicating there is a glass-ceiling effect in Russia.

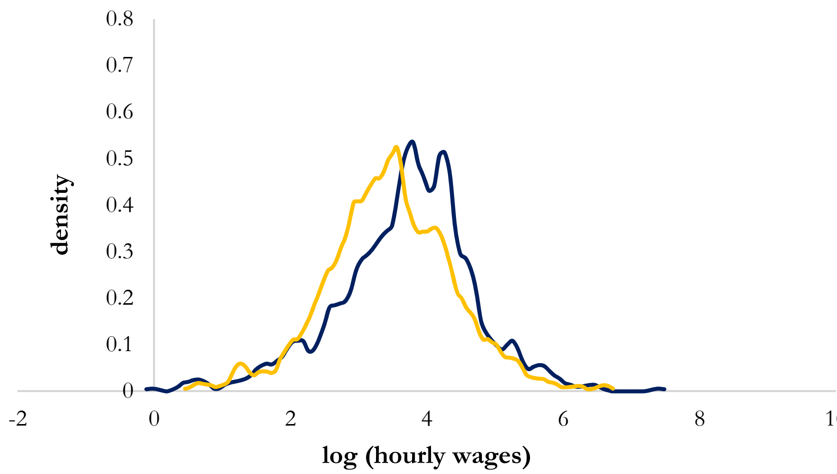
Figure 1. Gender gap in pay, 1994–2011



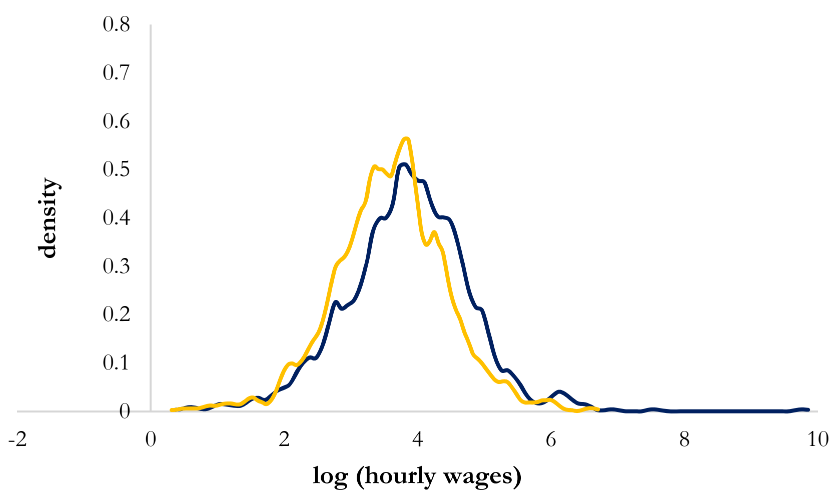
Source: World Bank (2014). *Notes:* The gender wage gap for the working-age population (18–60) is defined as the difference between male and female hourly rate pay (2011 prices) as a percentage of the male rate. The GDP growth rate is measured as the annual percentage growth rate of GDP per capita based on constant local currency. Aggregates are based on constant 2005 U.S. dollars.

Figure 2. Earnings distribution of wage workers, by gender

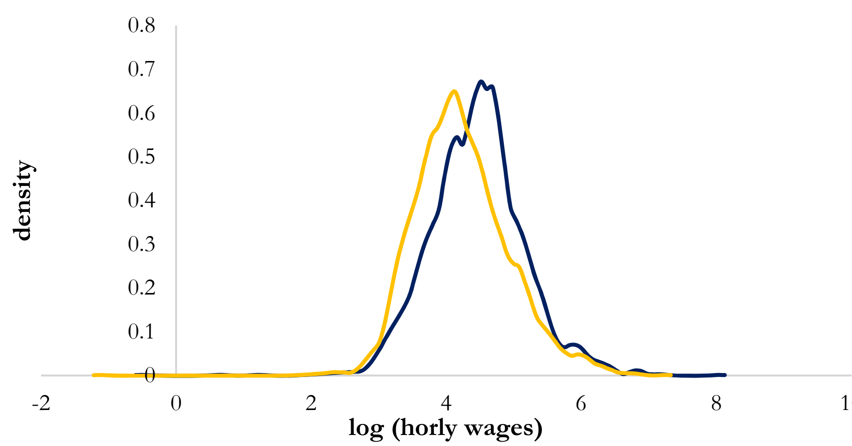
Year: 1996



Year: 2002



Year: 2011



Source: Authors' calculations using RLMS 1996, 2002, and 2011. *Notes:* Hourly wages in 2011 prices.

2. Methodology

Decomposition methodologies have been applied to gender wage differentials since the seminal work of Oaxaca (1973) and Blinder (1973). The Oaxaca–Blinder (OB) decomposition is one of the most widely used methods, not only in labor economics but also in several microeconomics applications. Since its inception, however, much progress has been made with decomposition methods. New methodologies allow analysts to decompose the gaps for other statistics beside the mean; to handle nonlinear functions; and to tackle possible bias stemming from observing individuals without a suitable treatment or comparable group (i.e., the problem of lacking overlapping support). In this paper we use the RIF decomposition recently introduced by Fortin, Lemieux, and Firpo (2011). In addition, Fortin, Lemieux, and Firpo (2011) provide a technical survey of the main decomposition methods available thus far.

For ease of exposition, we first explain the OB decomposition and later introduce the RIF and its advantage relative to other methodologies. What follows draws on Fortin, Lemieux, and Firpo (2011). In short, decomposition methods aim at disentangling how much of the gender gap in pay is explained by differences in observable (and unobservable) characteristics of men and women and how much remains unexplained. The unexplained component captures differences in the returns to labor market skills and other factors usually pooled as gender discrimination.

The seminal work of OB is based on the Mincer earnings equation (Mincer, 1958, 1974; Becker, 1964; Mincer and Polacheck, 1974), which assumes that—under no labor market imperfections—wages represent productivity, and thus can be explained by labor market skills such as schooling and experience. Men's and women's wages can then be represented as:

$$Y_G = X_G\beta_G + \varepsilon \qquad G = M, W \qquad (1)$$

The OB decomposition uses the linear earnings equation for men and women and compares the differences at the mean of earnings for men and women,

$$\overline{Y_G} = \overline{X_G}\hat{\beta}_G \qquad G = M, W \qquad (2)$$

by adding and subtracting the term $\overline{X_M}\hat{\beta}_W$, and rearranging the terms we obtain

$$\overline{Y_M} - \overline{Y_W} = \left[(\overline{X_M} - \overline{X_W})\hat{\beta}_W\right] + \left[\overline{X_W}(\hat{\beta}_M - \hat{\beta}_W)\right] \qquad (3)$$

where $\overline{Y_G}$ is the mean earnings of gender G (men, women); X_G is a vector of characteristics that influence labor market productivity (and thus earnings) such as education and experience, as well as additional controls such as area of residence; and β_G are the estimates of a linear regression. The first term is called the "composition" effect or explained component, and it captures the part of the gender gap in pay that is explained by differences in labor market skills between men and women. The second term is the so-called "wage structure" effect or unexplained effect. This term captures both differences in returns to labor market skills between men and women, as well as pure unexplained differences associated with discrimination.[2]

In this paper we apply the RIF methodology to decompose the gender pay gap in the Russian Federation. This methodology can be combined with estimation techniques of the program evaluation literature to construct a counterfactual distribution using a nonparametric reweighting approach, as we do. Doing this guarantees consistent estimates of the wage structure and composition effect when the conditional mean function is nonlinear.

The reweighted RIF decomposition methodology offers several advantages that allow us to go deeper than any previous work on the Russian Federation, or even in the literature pertaining to the gender pay gap. It allows us to go beyond the mean and can be used to calculate other statistics. In particular, we are interested in the quantiles along the wage distribution, while still allowing the inspection of the contribution of each covariate to the wage structure and composition effects. Previous quantile decomposition methods could only disentangle the two main effects without identifying the contribution of the covariates (Machado and Mata, 2005; Melly, 2005; DiNardo, Fortin, and Lemieux, 1996). Moreover, the RIF methodology is not path dependent as are some of the aforementioned quantile decompositions and other methodologies, which also build on instruments coming from the program evaluation literature (Ñopo, 2008). Against these advantages, the RIF methodology imposes two additional assumptions in order to have identification. Firstly, the RIF decomposition assumes *ignorability*, implying that the unobservables are equally distributed in the two groups used for the decomposition. In the case of the gender gap in pay, ignorability means there is no random selection of women into the labor force. Secondly, the RIF decomposition assumes common support over the observable variables, implying that there are no combinations of individual characteristics for which it is possible to find males but not females, and vice versa.

The RIF decomposition uses unconditional quantile regressions based on RIF regressions. RIF regressions consist of running a regression of a transformation of the outcome variable (its RIF) on

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[2] For a more detailed but still simplified exposition of the Oaxaca–Blinder decomposition, see ADePT Gender manual (World Bank, 2015), and for a more technical exposition see Fortin, Lemieux, and Firpo (2011).

the explanatory variables, allowing one to evaluate the marginal impact of changes in the distribution of the explanatory variables on the quantiles of the marginal distribution of the dependent variable. This means that the estimated RIF coefficients can be interpreted as the effect of increasing the mean value of X on the unconditional quintile Q_j. Interpretation is misleading in the conditional quantile regressions since the law of iterated expectations does not apply in these cases.

Firpo, Fortin, and Lemieux (2007) define the RIF as

$$RIF(yi, v) = IF(yi, v) + v$$

Where $IF(y_i, v)$ is the influence function that represents the influence of an individual observation on a distributional statistic, v, of the distribution of the variable of interest, y. For quantiles, the RIF can be expressed as

$$RIF(Y_i, q_j) = q_j + \left(t - \frac{I(Y \leq q_j)}{f_Y(q_j)}\right)$$

Where I is an indicator function, $f_Y(.)$ is the density of the marginal distribution of Y, and $q_j = Q_j(Y)$is the population j-quantile of the unconditional distribution of Y.

Let $Q(Y_G)$ be a quantile of the unconditional earnings distribution of men or women, Y_G. To decompose the difference in earnings between men and women for a certain quantile, $Q(Y_M) - Q(Y_W)$, into a composition and a wage structure component, we need to produce a counterfactual distribution of earnings that represents what women could have earned had they received the same return to their labor market skills as men, $Y_{\widetilde{W}}$. Once the counterfactual distribution and the RIFs are estimated, the rest of the steps are similar to the OB, since RIF coefficients can be consistently estimated using a simple ordinary least squares (OLS) to regress $RIF(y_i, Q(Y_G))$ on X (Fortin, Lemieux, and Firpo, 2011).

$$Q(Y_M) - Q(Y_W) = [Q(Y_M) - Q(Y_{\widetilde{W}})] + [Q(Y_{\widetilde{W}}) - Q(Y_W)]$$

where $Q(Y_M) - Q(Y_{\widetilde{W}})$ is the composition effect and $Q(Y_{\widetilde{W}}) - Q(Y_W)$ is the wage structure effect. The counterfactual distribution $Y_{\widetilde{W}}$ can be obtained by reweighting to take into account the different distribution of characteristics of male and female workers in the population.[3] The contribution of

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[3] The reweighted factor is defined as $\psi = \left(\frac{p(X_i)}{1-p(X_i)}\right)\left(\frac{1-T}{p}\right)$. Where $p(X_i)$ is the probability of being a female given X, and p is the proportion of females in the population. Hence, $FC\ (y) = \mathrm{E}[\psi \mathrm{C}(T, X) \cdot \mathrm{I}\{Y \leq y\}] = YW$ which is the counterfactual distribution of earnings.

combining a nonparametric reweighting approach with the RIF decomposition resides in using semiparametric methods to estimate the counterfactual distribution $Y_{\widetilde{W}}$, which guarantees consistent estimates of the wage structure and composition effect when the conditional mean of earnings is not linear, as mentioned. Using RIF regressions as the base of the decomposition means moving from conditional to unconditional estimates of the moments of the distribution of Y_G. Replacing $Q(Y_G)$, where $G = M, W, \widetilde{W}$, with their RIFs, we see with more clarity the results that can be obtained once we apply the decomposition methodology,

$$\hat{q}_j(Y_M) - \hat{q}_j(Y_W)$$
$$= \left[\overline{X_W}\left(\hat{\beta}_{\widetilde{W}} - \hat{\beta}_W\right) + \left(\bar{X}_M - \bar{X}_{\widetilde{W}}\right)\hat{\beta}_{\widetilde{W}}\right] + \left[\left(\overline{X_M}\hat{\beta}_M - \overline{X_W}\hat{\beta}_{\widetilde{W}}\right) + \bar{X}_{\widetilde{W}}\left(\hat{\beta}_{\widetilde{W}} - \hat{\beta}_M\right)\right]$$
$$\hat{q}_j(Y_M) - \hat{q}_j(Y_W) = \left[\overline{X_W}\left(\hat{\beta}_{\widetilde{W}} - \hat{\beta}_W\right) + \widehat{R_J^{WS}}\right] + \left[\left(\overline{X_M}\hat{\beta}_M - \overline{X_W}\hat{\beta}_{\widetilde{W}}\right) + \widehat{R_J^C}\right]$$

where $\hat{q}_j(Y_M) - \hat{q}_j(Y_W)$ is the raw gender earnings gap at quantile *j*, $\overline{X_G}$ is the vector of mean covariates, $\hat{\beta}_{\widetilde{W}}$ is the vector of estimates coming from the counterfactual distribution that gives the male returns to labor market skills for women in the labor market, $\overline{X_W}\left(\hat{\beta}_{\widetilde{W}} - \hat{\beta}_W\right) + \widehat{R_J^{WS}}$ is the wage structure effect, and $\left(\overline{X_M}\hat{\beta}_M - \overline{X_W}\hat{\beta}_{\widetilde{W}}\right) + \widehat{R_J^C}$ is the estimate of the composition effect. $\widehat{R_J^C}$ and $\widehat{R_J^{WS}}$ are the reweighting and specification error that would not exist if the reweighting factor were consistently estimated and if the model was truly linear, respectively (Fortin, Lemieux, and Firpo, 2011).

3. Data

The Russian Longitudinal Monitoring Survey (RLMS) is a unique source of rich information ideal for undertaking this type of decomposition analysis. Jointly conducted by the Carolina Population Center at the University of North Carolina, Chapel Hill, and the Demoscope team at the Higher School of Economics (HSE) in Russia, it provides a longitudinal series of nationally representative household and individual data since 1996. The RLMS interviewed 3,675 households (8,893 adults) in 1996 and 8,440 households (18,687 adults) in 2012.[4] It includes questions on household income and expenditures, housing and land property rights, employment and education variables, and health and other marital and fertility history information. The main limitation of the RLMS is that it is not representative at the regional level. Control variables about place of residence are available for analysis but are not valid for inference.

[4] 2012 was the latest year available when conducting this analysis.

In this paper, we do not exploit the longitudinal nature of the data. In order to maintain the representativeness of the national population and because of the high attrition, the sampling frame of the RLMS was revised in several years. For example, of the 18,302 adults interviewed in 2011, only 1,788 were also interviewed in 1996. In addition, the attrition bias was tested by comparing the estimates coming from a Mincer earnings equation for 2011 using those in the sample that survived the attrition (i.e., were observed since 1996) with those in the full 2011 sample (i.e., whether observed since 1996 or not). Both Wald and likelihood ratio tests indicated the two samples were not comparable. Thus, we analyze three years—1996, 2002, and 2011—as if they were three cross-sections.[5]

The sample for the analysis includes all wage workers. Self-employed workers are excluded since the information on their wages might not be comparable. In addition, self-employed workers constitute a small percentage of the labor force in Russia: 86 percent of employed men and 88 percent of employed women were wage workers in 2010 (Gamberoni and Posadas, 2013). The analysis is restricted to men and women between 18 and 60 years of age. We chose to use 60 as the upper cutoff for the working age population, as it is the mandatory retirement age for men. Although women can retire at 55, many of them continue working after retirement. On average, women between 60 and 64 years of age worked six years after having retired, while men worked only four (Gamberoni and Posadas, 2013). We repeated the analysis for the age range 18–55 and the main conclusions of the study were not altered.

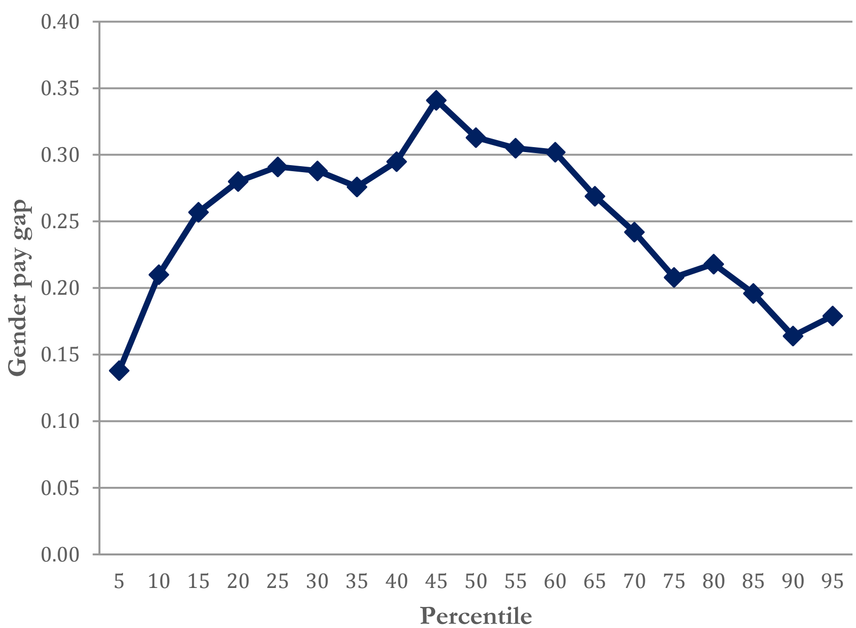
In this section we describe the variables used for the decomposition of the gender pay gap, and we restrict the summary statistics to the sample used for the regression estimates. We follow previous studies performing decomposition analysis (Blau and Kahn, 1997, 2003) and estimate an augmented Mincer earnings model. The most conservative specification includes measures of experience and schooling, with controls for place of residence. Augmented models also include a set of dummies for occupation and industry, and in some cases union affiliation. An additional contribution of this study to the literature of the gender wage gap is the use of additional variables that determine productivity and thus wages. The richness of the RLMS data allows us to explore the effect of additional firm characteristics such as type of ownership (public, foreign) or size of the firm, degree of responsibility approximated by the number of subordinates, quality of employer–employee match, and changes in occupation. However, this latter group of variables is only available for 2011. Tables A2a and A2b in the appendix show the descriptive statistics for all the variables used in the decomposition analysis.

[5] Regression results were also estimated for 2012 when they became available, showing similar conclusions.

As is usually the case in this literature, earnings are defined as log of hourly wages, to take into account differences in intensive margin. Though significant, the difference in the intensive margin is smaller compared to other countries—women work on average eight hours per day, which makes them full-time workers, while men work on average nine hours per day. Though this additional hour might not be significant in terms of daily productivity, it might be associated with a career path that involves more responsibility. Gender differences in pay can be observed for most of the groups defined by the covariates, as indicated in Tables A3a and A3b in the appendix.

The raw gender wage gap varies considerably along the earnings distribution. As opposed to what is observed for other high-income countries (Christofides, Polycarpou, and Vrachimis, 2013), the raw gap is larger in the center of the earnings distribution. The raw wage gap for men and women in the median is almost 35 percent, while the raw wage gap at the 10th and 90th percentiles is about 15 percent. In the next section, we analyze the possible factors determining the gender wage gap at each percentile applying the FFL decomposition methodology.

Figure 3. Gender pay gap by percentile, 2011



Source: Authors' calculations using RLMS 1996, 2002, and 2011. *Notes:* Percentage gender gap in earnings by percentile. Earnings measured as log-hourly wage.

4. Results

The gender pay gap in the Russian Federation is one of the highest among high-income countries. Previous studies have found that most of the gender gap in pay remains unexplained when applying

OB decompositions. These studies, however, cannot explain whether this applies to all working women, or some of them, and if this is the case, who the women are that are most affected. The decomposition along the earnings distribution can shed some light on this issue.

4.1 RIF regressions

Before showing the decomposition results, Table 1 shows the estimates of the RIF regression for three quantiles: the 10th, the 50th, and the 90th for 2011. First, we computed the influenced function for each observation.[6] Figure 4 shows the estimates for each percentile and each covariate, painting a fuller picture of the impacts of each covariate along the earnings distribution for men and women.

Table 1 shows that the returns to labor market skills across the different quantiles are highly nonmonotonic and different for men and women. For both men and women, the returns to labor market experience are positive but decrease along the earnings distribution. In addition, the effect of experience on earnings is larger for men than for women, but not statistically different along the earnings distribution. Experience also reduces earnings inequality within gender. More experienced workers earn more, and this effect is higher for workers at the lower end of the wage distribution.

Schooling also shows nonmonotonic effects across the earnings distribution, with very different impacts on men and women. As expected, the impact of schooling on wages is larger the higher the education level. Thus, for both men and women, completing university is associated with higher wages than completing technical certificates. Moreover, the effect of education is larger at the bottom of the earnings distribution than at the top for both men and women, but the impact of education at each quantile is larger for men than for women. For example, having completed secondary education increases male earnings in the 10th quintile, but not female earnings. The impact of having a technical certificate is two times larger for men than for women in the bottom of the distribution. At the top of the distribution, having completed university has no effect on women's earnings but increases men's earnings by about 30 percent, with respect to their counterparts with less than secondary or vocational university.

[6] RIF was calculated using a 0.0 width, which calculates the optimal value, and the Gaussian kernel as FFL.

Table 1. RIF regression coefficients, 2011

	Male			Female		
	10	50	90	10	50	90
Potential experience	0.023 (0.008)***	0.013 (0.005)**	0.005 (0.009)	0.015 (0.005)***	0.012 (0.005)**	0.016 (0.008)*
Potential experience squared	-0.001 (0.000)***	-0.000 (0.000)***	-0.000 (0.000)	-0.000 (0.000)***	-0.000 (0.000)**	-0.000 (0.000)*
Secondary education	0.397 (0.145)***	0.125 (0.093)	0.024 (0.157)	0.032 (0.117)	-0.155 (0.104)	-0.225 (0.177)
Vocational education	0.349 (0.135)***	0.080 (0.087)	0.166 (0.145)	0.040 (0.112)	-0.227 (0.099)**	-0.241 (0.169)
Technical education	0.437 (0.140)***	0.154 (0.090)*	0.076 (0.151)	0.188 (0.111)*	-0.195 (0.098)**	-0.316 (0.168)*
University education	0.478 (0.146)***	0.231 (0.094)**	0.248 (0.158)	0.243 (0.115)**	0.149 (0.102)	0.108 (0.174)
Legislators, senior managers, officials	0.070 (0.198)	-0.110 (0.128)	0.620 (0.214)***	0.255 (0.122)**	0.129 (0.108)	0.234 (0.184)
Professionals	0.193 (0.174)	0.016 (0.112)	0.800 (0.188)***	0.349 (0.073)***	0.200 (0.064)***	0.437 (0.110)***
Technicians and associate professionals	0.063 (0.167)	-0.091 (0.108)	0.272 (0.180)	0.144 (0.065)**	0.098 (0.058)*	0.304 (0.098)***
Service and market workers	0.138 (0.188)	-0.391 (0.121)***	0.111 (0.203)	-0.074 (0.074)	-0.255 (0.066)***	0.019 (0.112)
Skilled agricultural and fishery workers	0.011 (0.419)	-0.227 (0.270)	0.150 (0.453)	0.406 (0.430)	-0.130 (0.382)	-0.002 (0.650)
Craft and related trades	0.163 (0.164)	-0.119 (0.105)	0.202 (0.177)	0.226 (0.111)**	0.043 (0.098)	0.242 (0.167)
Plant and machine operators	0.089 (0.161)	-0.177 (0.104)*	0.204 (0.174)	0.122 (0.101)	0.039 (0.090)	0.073 (0.153)
Unskilled occupations	-0.506 (0.168)***	-0.541 (0.108)***	0.013 (0.181)	-0.301 (0.080)***	-0.234 (0.071)***	0.121 (0.121)
Public or semipublic firms	-0.012 (0.060)	-0.096 (0.039)**	-0.013 (0.065)	-0.133 (0.050)***	-0.161 (0.044)***	-0.310 (0.075)***
Foreign firms, owned or co-owned	0.077 (0.128)	0.202 (0.082)**	0.555 (0.138)***	0.032 (0.103)	0.328 (0.091)***	0.955 (0.155)***
Subordinates	0.113 (0.072)	0.126 (0.047)***	0.112 (0.078)	0.049 (0.046)	0.097 (0.041)**	0.220 (0.070)***
Firm size	0.168 (0.076)**	0.069 (0.049)	0.194 (0.082)**	0.093 (0.061)	0.127 (0.054)**	0.189 (0.092)**
Changed place of work	-0.016 (0.096)	0.069 (0.062)	0.166 (0.103)	0.054 (0.083)	0.118 (0.073)	-0.021 (0.125)
Changed occupation but not place of work	0.065 (0.168)	0.172 (0.108)	0.020 (0.181)	0.089 (0.138)	-0.009 (0.123)	-0.472 (0.209)**
Changed occupation and place of work	-0.038 (0.085)	-0.119 (0.055)**	-0.072 (0.092)	-0.094 (0.074)	0.043 (0.066)	0.157 (0.112)
Observations	2,050	2,050	2,050	2,438	2,438	2,438
R-squared	0.141	0.204	0.131	0.110	0.184	0.121

Source: RLMS, 2011. *Notes:* RIF regression with robust standard errors in parentheses. *** denotes p-value smaller than 0.01, ** denotes p-value smaller than 0.05, * denotes p-value smaller than 0.1. The RIF regressions also include industry dummies. The omitted categories are incomplete secondary (education), clerks (occupation) and agriculture (industry). Controls include if the place of residence is urban or rural.

These results indicate that although men and women are equally engaged in the labor market in Russia, the jobs they do are very different—and they are rewarded very differently, too. Women are in a flat career path compared to men. This is usually referred to in the literature as women having jobs, not careers (Goldin, 2006; Bertrand, 2011). The two main labor market skills—education and experience—show larger payoffs for men than for women, especially at the bottom of the earnings distribution. This can be corroborated when we look at the age–wage profiles for men and women (see Figure A2).

To shed more light on the possible reasons for women's flat earnings, we have estimated an augmented human capital model that includes occupation, industry, and other covariates related to job productivity. By looking at the RIF estimates of the dummy variables for the occupations, it can be concluded that professional women at the top of the earnings distribution have lower returns than men. Conversely, women at the median of the earnings distribution have higher returns than men in service jobs.

All the results so far suggest that women—either by their own choice or by lack of access—occupy jobs that have lower returns to labor skills. Moreover, productivity (and thus wages) can also depend on firm characteristics such as type of ownership or size. Ideally, firm effects are quantified using employer–employee data (Vieira, Cardoso, and Portela, 2005). Fortunately, the richness of the RLMS data allows us to explore these effects by adding covariates to describe firm characteristics. There is evidence that publically owned firms are less productive than private firms since they face less market competition. With the transition to a market economy, private firms as well as privatized firms, had gone through important increases in productivity, and the wedge between the public and the private sector increased (Calvo et al., 2015). For women, and to a lesser extent men, working for a public or semipublic firm has a negative impact on earnings, and the size of the impact is larger at the top of the earnings distribution. In particular, at the 90th percentile, women who work for a public firm earn 34 percent less than women who work for a private firm. Larger firms are also often thought to have higher productivity since they make higher investments in capital. The effect of firm size is highly nonmonotonic along the earnings distribution for women, while it shows very little variation for men. For women the impact of working in a large firm is always positive and it increases along the earnings distribution.

Finally, the RLMS allows us to explore the importance of promotion and job-to-job transitions in earnings with a reduced-form approach. There are two strings of the labor economics field that further explain wage determination, and in each of them gender differences were found. First, job-matching theory predicts that job changes result in wage increases. Employed workers spend time searching for a better match if the chances of finding one are larger than the cost of the on-the-job search. Empirical evidence supports this theory and finds that for the United States, two-thirds of the long-run wage (or the wage at the end of a career) occurred during the first 10 years employed, and that one-third of the wage increase is explained by job-to-job transitions (Topel and Ward, 1992). Similarly, it has been found that in the United States, women are less likely to switch jobs (that is, experience job-to-job transitions), and this explains about 8 percent of the gender wage gap in the United States (Royalty, 1998; Posadas, 2009). The other main theory comes from personnel economics. Employers might provide less training and fewer promotions to women, in particular during the early years of their careers, if they are expected to quit the firm because of maternity interruptions (Lazear and Rosen, 1990). Empirical evidence also supports this stream of research (Bertrand, 2011). Also supporting these theories, Kunze (2015) finds there is a family gap, as women with children are less likely to be promoted within an organization or suffer a wage penalty when changing jobs or working part-time. These results are consistent with those obtained by Francesconi (2002).

To test these hypotheses, we add a few covariates that might capture these effects, at least partially. The RLMS asks adult respondents whether they have changed occupation, place of work, or both within the last 12 months. It can be assumed that changes in place of work are associated with the on-the-job search theory, and should result in wage increases. This effect is only present for women in the median percentile. For this group, having changed place of work (but not occupation) increases earnings by almost 13 percent. Interestingly, the effect for men is smaller and not significant. Unfortunately, the RLMS asks no direct question on promotion opportunities; the survey only asks whether there has been a change in occupation within the same place of work. This latter variable, however, could indicate either a promotion within the same firm or horizontal move not associated with a promotion.

Figure 4a. Unconditional quantile regressions coefficients by gender, 2011

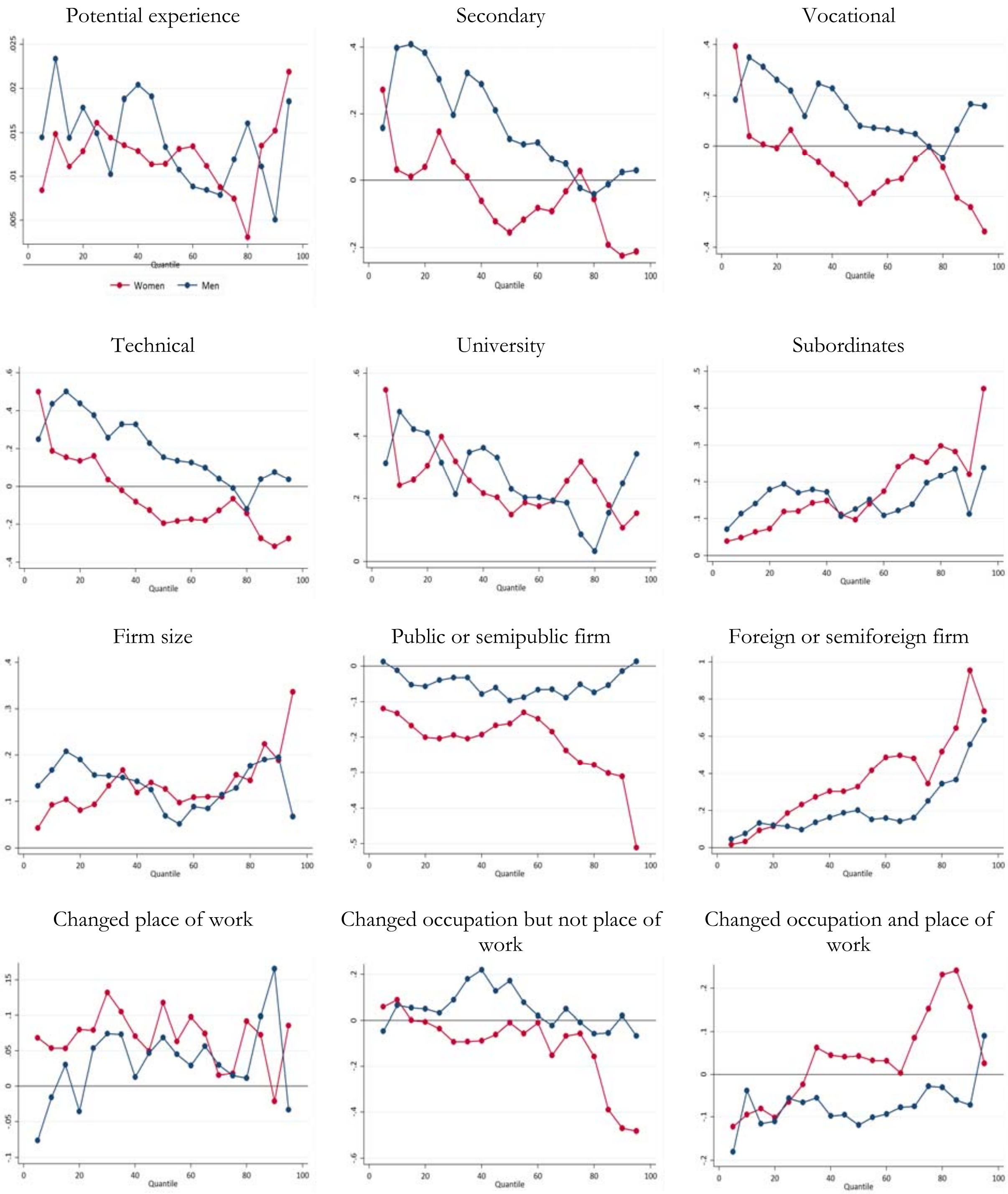


Figure 4b. Unconditional quantile regressions coefficients by gender, 2011

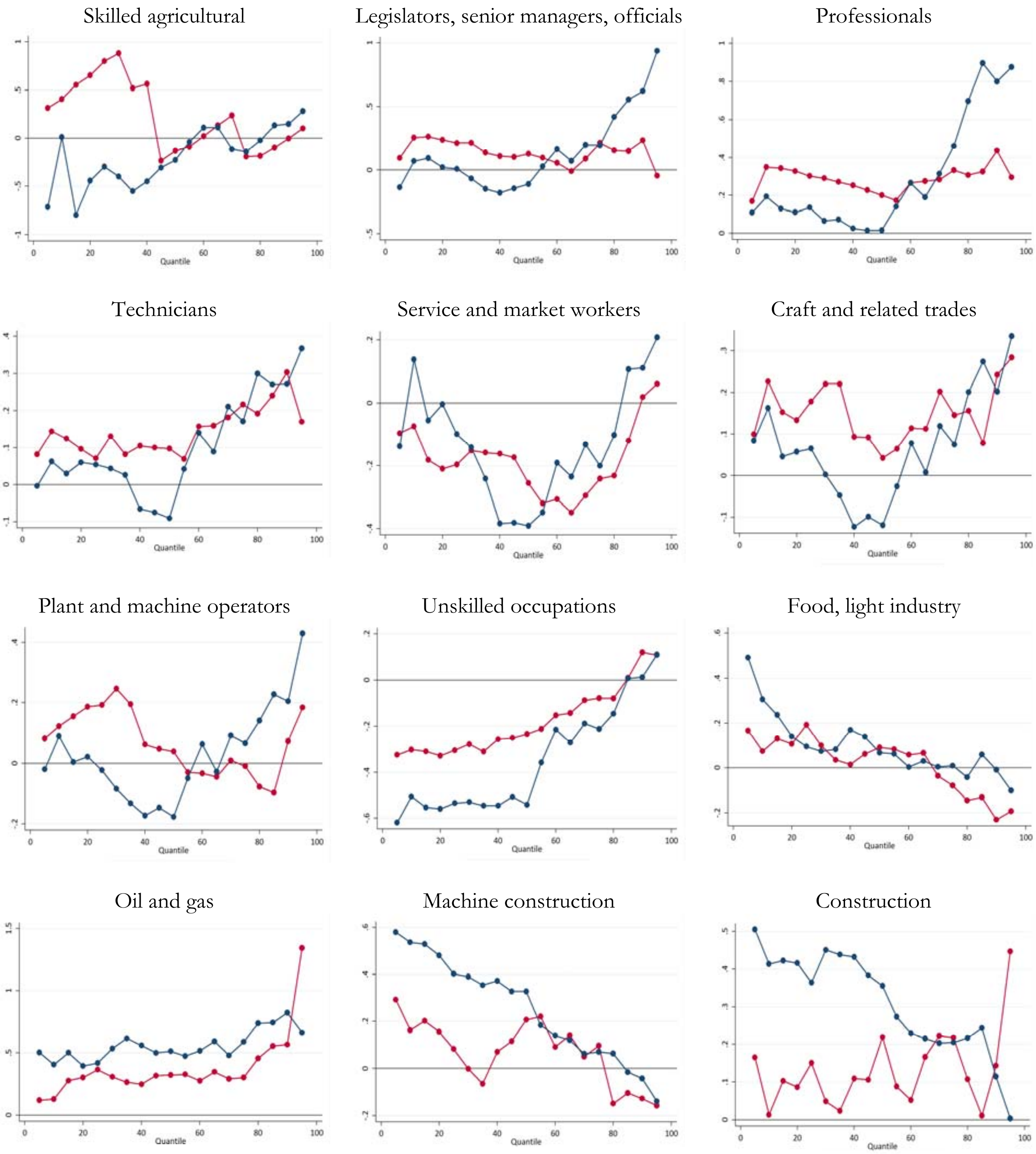
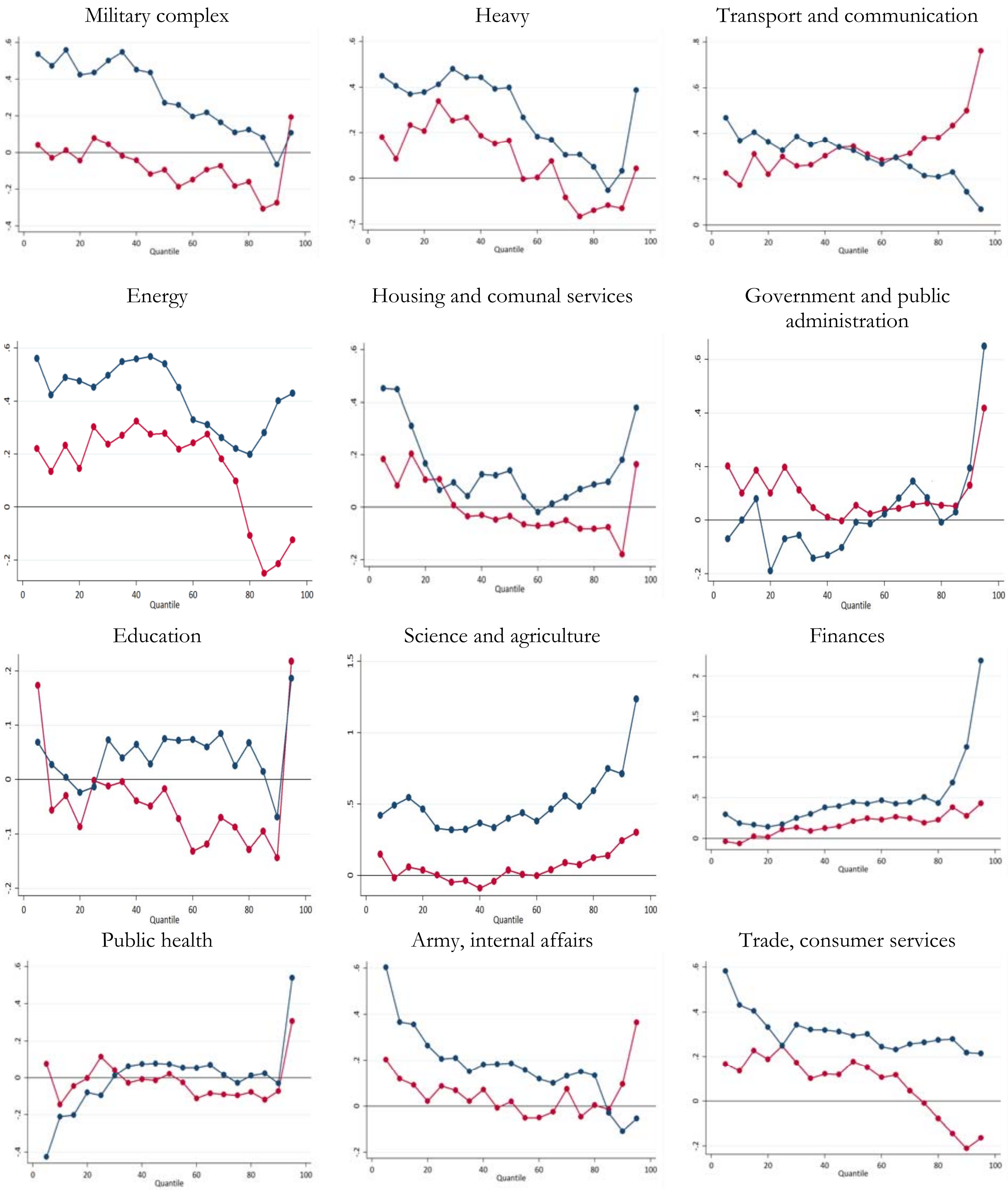


Figure 4c. Unconditional quantile regressions coefficients by gender, 2011



Overall, the results coming out of the estimates from the RIF regression seem to indicate that the impacts of the covariates are highly nonmonotonic for both men and women. They also indicate that impacts are different for men and women, and these gender differences are statistically significant in some cases. As with most of the previous covariates, the estimates are highly nonmonotonic along the wage distribution, and very different for men and women. The RIF coefficient Changed occupation but not work of place shows up to be positive and significant at the 50th percentile, while it decreases along the wage distribution for women and is negative and significant at the 90th percentile.

The results are consistent with the fact that women are in jobs with fewer options for career development, either by choice or by lack of opportunity. Women tend to hold less productive occupations (that is, occupations that pay relatively less).

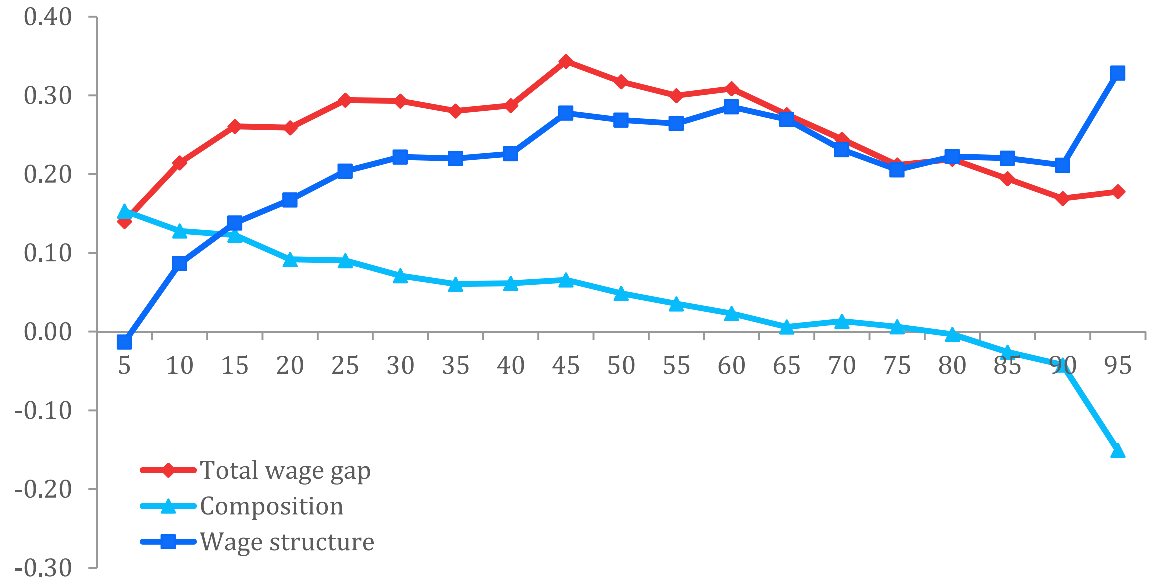
4.2. Decomposition results

The results of the decomposition are presented in Figures 5–7 and Table 2.[7] The top part of table/figure shows the gender gap in earnings at each percentile (see Table A4 in the appendix, which shows the detailed decomposition results). As expected, the FFL tells a very different story than the one that has emerged from previous studies. The results that follow use as a base group (reflected in the coefficient of the constant) rural nonmarried workers with secondary education or less, in private domestic small firms that do not have any subordinates nor have switched jobs or occupations during the last year. When including occupation and industry, the base group is clerks and agriculture.

First, the decomposition results of the gender gap in pay into the composition and wage structure effect vary along the earnings distribution. Most of the existent studies for the Russian Federation find that differences in labor market characteristics of men and women explain about 30 percent of the gender gap in pay. Our results tell a very different story. The importance of characteristics (composition effect) decreases along the earnings distribution. At the 10th percentile, the composition effect explains almost half of the gender gap in pay (46 percent), while at the 90th percentile, the composition effect is negative. Having a negative composition effect indicates that women are overqualified compared to men at the same percentile. In other words, if women had the same characteristics as men, other factors held constant, the gender pay gap would be 37 percent larger. The composition effect is small at the median (5 percent of total gender pay gap) and crosses the zero value at the 80th percentile (see Figure 5).

[7] Tables A2–A4 in the appendix show more details about the regressions.

Figure 5. Decomposition of total gender pay gap into composition and wage structure effects, by percentile in 2011



Note: Based on Oaxaca–Blinder decompositions similar to those presented in Table A3b for each percentile indicated in the Y-axis.

Thus, the fact that the composition effect decreases along the wage distribution indicates that women are more subject to discrimination or lack access to jobs that pay as well as men's jobs, given their qualifications. The policy recommendation of this finding would be to help women at the bottom of the earnings distribution increase their labor market skills, since equalizing their characteristics to those of men at the bottom of the earnings distribution would reduce the gender pay gap by half. Meanwhile, for women at the top of the distribution, policies should be designed to help them access jobs that remunerate their skills as much as men.

Second, some of the covariates inside the composition effect also show a very nonmonotonic pattern along the wage distribution. The most striking result is that the importance of industry decreases along the wage distribution. The problem for women at the bottom of the distribution (10th percentile) is that they are employed in low-wage industries, though performing similar occupations as men (or occupations slightly better paid than men as the occupation line falls below zero). If women in the 10th percentile were employed in the same economic sectors as men, their gender wage gap would decrease by half. Meanwhile, women at the top of the distribution (90th percentile) are working in high-wage occupations: If women were employed in the same occupations as men, the gap in pay would be 37 percent larger. Lastly, all women, and in particular those at the bottom of the distribution, are more educated than men who hold similar jobs and are in a similar position in the earnings distribution.

Table 2: RIF decomposition results for 10th, 50th, and 90th percentile in 2011, as percentage of the wage gap

	10		50		90	
Gap	0.21	***	0.32	***	0.17	***
Composition effect						
Experience	2.86		1.13		1.10	
Married	4.60		4.14	***	5.09	
Education	-14.18	**	-9.24	***	-6.84	
Occupation	-3.71		-17.58	**	-46.00	**
Industry	57.06	***	22.08	***	3.26	
Firm	1.88		4.64	***	4.52	
Subordinates	1.41		1.06	*	1.77	
Job mobility	-0.49		0.00		1.71	
Urban	-3.50	*	-1.49	*	-1.35	
Total	45.92	**	4.74		-36.75	
Residual	13.78		10.61		11.76	
Wage structure						
Experience	-30.92		-10.28		-91.68	
Married	-19.61		26.43	***	-1.35	
Education	281.21	***	119.55	**	255.15	*
Occupation	-105.84	***	21.12		32.33	
Industry	101.63	*	12.88		204.96	**
Firm	-18.15		-19.64		-17.76	
Subordinates	10.39		0.78		-18.77	
Job mobility	-0.03		-2.39		-9.80	
Urban	0.76		52.49	***	33.98	
Total	28.58	***	81.42	***	132.82	***
Residual	11.72		3.23		-7.83	

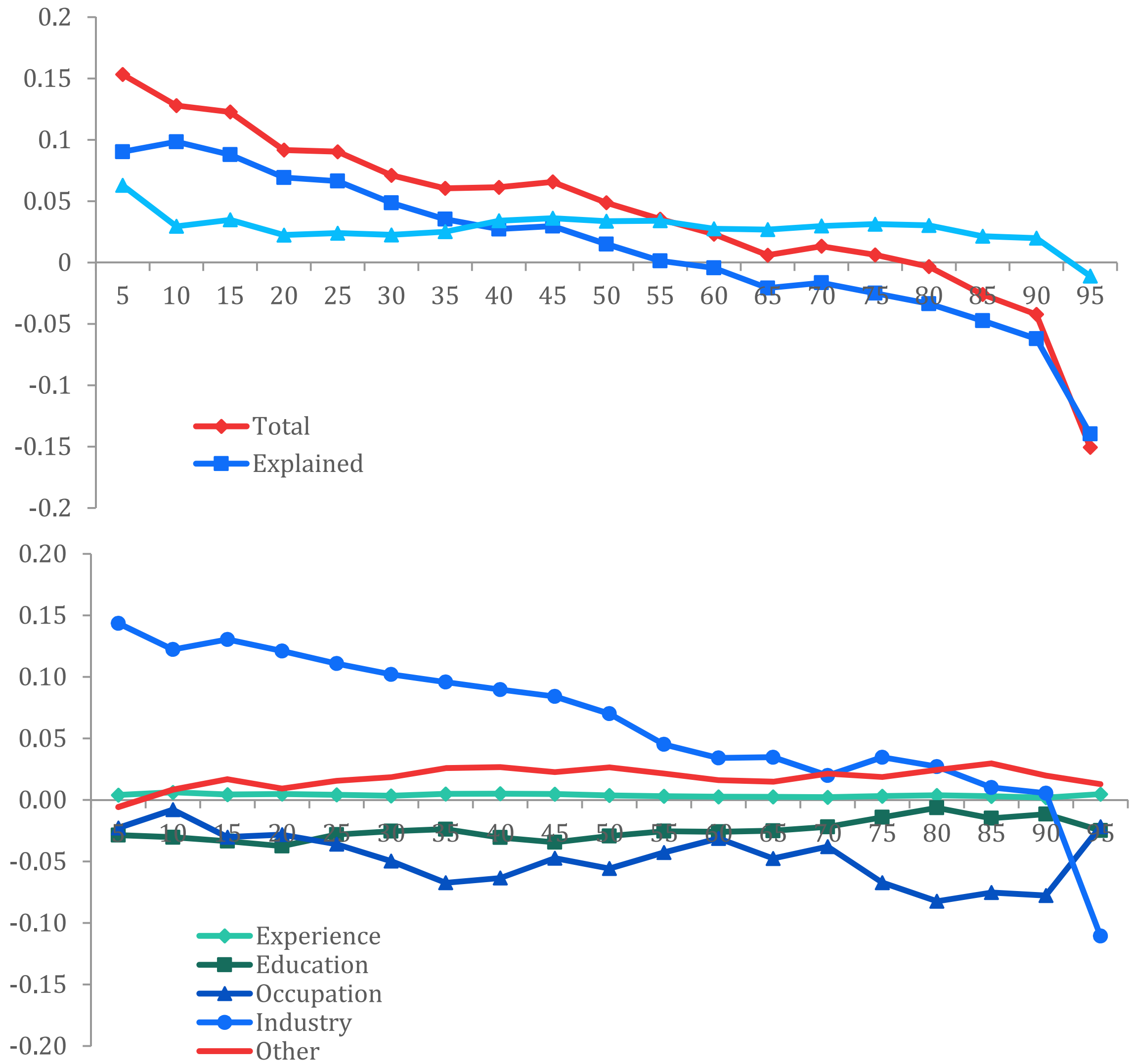
Note: (a) The underlying coefficient has a: *** p-value<0.01, ** p-value<0.05, * p-value<0.1. (b) Each category includes: Experience: potential experience, potencial experience squared. Education: secondary, technical, vocational, university. Firm: Public or semipublic firm, foreign owned or co-owned, firm size. Job mobility: Changed occupation but not place of work, changed occupation and place of work, changed place of work.

Third, inside the wage structure effect, the effects are also highly nonmonotonic along the earnings distribution. Returns to education are smaller for women relative to men, which helps increase the gender gap in pay at any point of the earnings distribution. If women's pay reflected their educational degrees as much as men—other things constant—the gender gap would disappear (or even be reversed for women). As with the composition effect, occupation and industry play a different role depending on the position in the earnings distribution. At the bottom of the earnings distribution, women are employed in occupations that pay relatively more and industries that pay less, but at the top of the distribution, the returns for being employed in certain industries would increase the gender gap in pay.

However, some of these results should be taken with caution as they are more volatile than the composition effects.

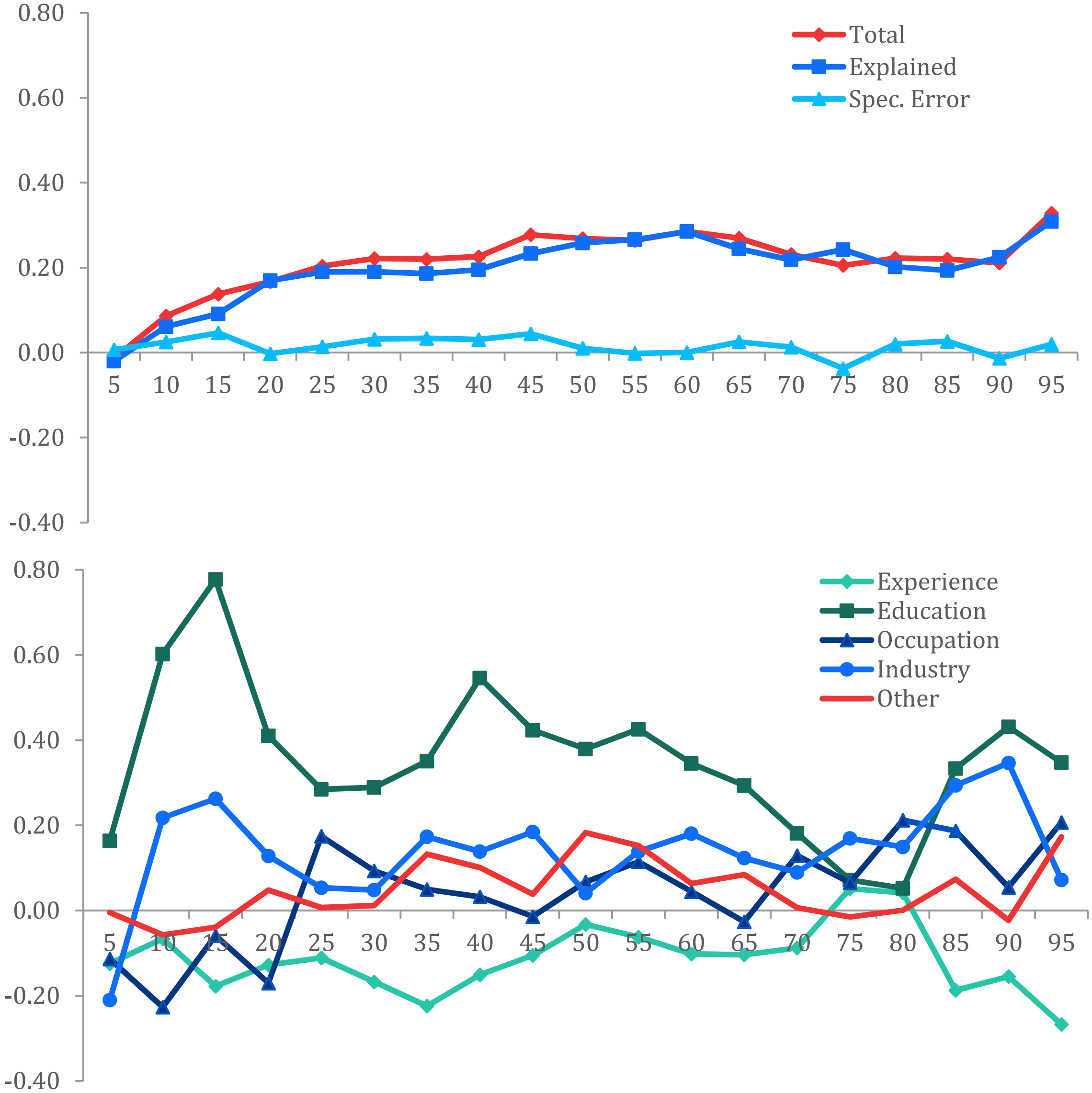
Finally, the two terms that capture the error coming from the local linearization are still relatively small (between 3 and 14 percent of the total gender wage gap depending on the percentile and the effect) and comparable in magnitude to those obtained by Firpo, Fortin, and Lemieux (2007) when analyzing inequality in the United States.

Figure 6. Decomposition of composition effects, by percentile in 2011



Notes: Each category includes: Experience: potential experience, potential experience squared; Education: secondary, technical, vocational, university; Firm: public or semipublic, foreign owned or co-owned; Other: changed occupation but not place of work, changed occupation and place of work, changed place of work.

Figure 7. Decomposition of wage structure effects, by percentile in 2011



Note: Each category includes: Experience: potential experience, potential experience squared; Education: secondary, technical, vocational, university; Firm: public or semipublic, foreign owned or co-owned, firm size; Other: changed occupation but not place of work, changed occupation and place of work, changed place of work.

4.3. Decomposition results over time

The comparison of the RIF decomposition for 1996, 2002, and 2011 shows that important variations in the wage structure occurred in the Russian Federation since the transition to a market economy in 1992 (for a more detailed discussion see Calvo et al., 2015). The general conclusions are maintained, since the largest gap is always observed in the middle of the wage distribution. However, over time, there have been changes in the importance of the wage structure and the composition effect, as well as of the covariates along the wage distribution. For example, the importance of the composition effect in the median percentile has always been negative, but much larger in absolute magnitude in 2002 than in the other two years. Conversely, the importance of the experience covariate has always been decreasing along the earnings distribution, but the slope of the changes increased between 1996 and 2011.

In a future version of this paper, we plan to conduct a double decomposition to show changes in the components of the gender wage gap over time.

5. Conclusions

This paper decomposes the gender gap in pay in the Russian Federation along the earnings distribution for the period 1996–2011. We use the reweighted recentered influence function decomposition proposed by Fortin, Lemieux, and Firpo (2011) that allows estimating the contribution of each covariate on the wage structure and composition effects along the earnings distribution. We find that women are in flat career paths compared to men; the importance of observable characteristics that proxy human capital in the gender pay gap decrease along the earnings distribution; and if women's pay took into account their educational degrees as much as men's, the gender pay gap would disappear or even reverse at the top of the earnings distribution.

The results suggest that women at the bottom of the earnings distribution should be helped to increase their labor market skills, and women at the top of the distribution should be helped to break the glass ceiling and be remunerated for their skills to the same extent as men.

The Government of the Russian Federation has a few policy options to consider if interested in reducing the gender pay gap. To tackle the difference type of human capital investment between men and women at the bottom of the wag distribution—both in levels but also in fields of study—cheap but effective information campaigns could be delivered, starting with young students but including adults. Moreover, women from disadvantaged backgrounds would benefit from support in order to increase their level of skills. After conducting additional studies to narrow the constraints of this specific group of the population, a system of scholarships and training could be adopted. But more importantly, and in sync with demography problems and policy recommendations, it is fundamental to maintain policies that facilitate family-work balance—mostly through quality affordable childcare—for women to have an incentive to fully engage in the labor market during their childrearing stage of life. Another simple policy action would be to review or even eliminate the legal constraints for women to participate in certain occupations. In spite of having the law revisited not long ago, the origins and principles of it are now obsolete.

The problem of the glass-ceiling is more difficult to tackle and mostly requires a change of mindset. In order to change it, some countries have imposed quotas in boards and tax incentives for firms that show female participation at the top. Firms interested in breaking the glass-ceiling—mostly managed by women—provide training for women and men to break stereotypes. However, there is still little evidence about the impact of these types of policies (Bertrand 2011). More evidence on quotas is available from the political and public sector arena, suggesting that the quotas may contribute to change the mindset of the society but also to gain transparency and thus reduce corruption.

Table 3. RIF decompositions

	1996						2002					
	10		50		90		10		50		90	
	NR	R	NR	R	NR	R	NR	R	NR	R	NR	R
Male	2.467	2.467	3.787	3.787	4.794	4.794	2.718	2.718	3.879	3.879	4.961	4.961
	0.082	0.082	0.039	0.039	0.060	0.060	0.052	0.052	0.032	0.032	0.047	0.047
Female	2.362	2.362	3.484	3.484	4.633	4.633	2.594	2.594	3.630	3.630	4.611	4.611
	0.052	0.052	0.035	0.035	0.057	0.057	0.042	0.042	0.027	0.027	0.040	0.040
Gap	0.104	0.104	0.303	0.303	0.161	0.161	0.124	0.124	0.249	0.249	0.350	0.350
	0.097	0.097	0.052	0.052	0.083	0.083	0.067	0.067	0.042	0.042	0.062	0.062
Composition effect												
Experience	0.017	0.019	0.004	-0.002	0.024	0.023	0.002	0.002	0.001	0.006	0.003	0.002
	0.015	0.020	0.008	0.010	0.014	0.017	0.003	0.004	0.005	0.005	0.004	0.004
Married	0.037	0.027	0.008	0.006	-0.002	-0.001	-0.011	-0.011	0.002	0.002	0.029	0.028
	0.027	0.020	0.012	0.009	0.020	0.014	0.018	0.017	0.011	0.011	0.017	0.017
Education	0.016	0.012	-0.036	-0.031	-0.008	-0.007	-0.044	-0.052	-0.025	-0.027	-0.027	-0.026
	0.037	0.033	0.019	0.017	0.027	0.024	0.023	0.027	0.014	0.017	0.023	0.026
Urban	-0.034	-0.060	-0.013	-0.023	-0.007	-0.012	-0.008	-0.038	-0.004	-0.019	-0.003	-0.012
	0.026	0.027	0.010	0.011	0.006	0.009	0.019	0.019	0.009	0.010	0.006	0.007
Occupation	0.014	0.004	0.014	0.033	0.010	0.045	-0.102	-0.104	-0.072	-0.080	0.044	0.031
	0.128	0.161	0.060	0.075	0.098	0.123	0.068	0.070	0.043	0.044	0.064	0.066
Total	0.049	0.002	-0.023	-0.017	0.017	0.048	-0.164	-0.202	-0.098	-0.119	0.045	0.022
	0.133	0.165	0.063	0.077	0.100	0.124	0.072	0.074	0.045	0.046	0.065	0.067
Wage structure effect												
Experience	-0.317	-0.638	-0.139	0.082	-0.182	-0.552	-0.037	-0.103	0.148	0.187	0.082	-0.042
	0.298	0.352	0.157	0.172	0.259	0.225	0.195	0.198	0.121	0.118	0.187	0.159
Married	0.248	0.421	0.079	-0.214	0.001	-0.057	-0.068	-0.014	-0.033	-0.203	0.092	0.173
	0.163	0.159	0.084	0.079	0.138	0.105	0.102	0.096	0.063	0.057	0.097	0.077
Education	-0.410	-1.140	0.017	0.030	0.232	0.193	-0.452	-0.039	-0.314	-0.350	0.293	0.234
	0.453	0.490	0.248	0.254	0.408	0.354	0.376	0.382	0.234	0.229	0.362	0.315
Urban	0.619	1.338	0.167	0.135	-0.019	-0.159	0.322	0.484	0.130	0.066	-0.092	-0.330
	0.236	0.273	0.126	0.136	0.208	0.182	0.141	0.151	0.087	0.090	0.135	0.122
Occupation	-0.156	-0.324	0.068	-0.047	0.287	-0.026	-0.268	-0.472	-0.668	-0.558	-1.025	-0.764
	0.688	0.253	0.327	0.130	0.535	0.178	0.362	0.185	0.224	0.111	0.345	0.152
Constant	0.070	0.343	0.134	0.365	-0.175	0.688	0.791	0.385	1.084	1.226	0.956	1.041
	0.975	0.717	0.485	0.359	0.794	0.483	0.577	0.477	0.358	0.286	0.553	0.391
Total	0.056	0.000	0.326	0.350	0.144	0.087	0.287	0.241	0.347	0.368	0.304	0.311
	0.160	0.103	0.078	0.051	0.128	0.068	0.092	0.066	0.058	0.040	0.089	0.054

Notes: NR= no reweighting; R=reweighting. Each category includes: Experience: potential experience, potencial experience squared. Education: secondary, technical, vocational, university.

Table 3 (cont'd)

	2011					
	10		50		90	
	NR	R	NR	R	NR	R
Male	3.631	3.631	4.473	4.473	5.311	5.311
	0.023	0.023	0.016	0.016	0.026	0.026
Female	3.407	3.407	4.162	4.162	5.141	5.141
	0.017	0.017	0.015	0.015	0.026	0.026
Gap	0.224	0.224	0.311	0.311	0.170	0.170
	0.029	0.029	0.022	0.022	0.037	0.037
Composition effect						
Experience	0.008	0.000	0.005	0.000	0.005	0.000
	0.005	0.005	0.003	0.003	0.004	0.003
Married	0.010	0.007	0.019	0.013	0.016	0.011
	0.007	0.005	0.005	0.004	0.008	0.006
Education	-0.028	-0.030	-0.029	-0.031	-0.021	-0.026
	0.012	0.012	0.008	0.008	0.014	0.014
Urban	-0.006	-0.009	-0.004	-0.007	-0.002	-0.004
	0.004	0.005	0.003	0.003	0.002	0.002
Occupation	0.005	0.008	-0.005	-0.013	-0.053	-0.060
	0.029	0.029	0.020	0.020	0.034	0.033
Total	-0.013	-0.025	-0.014	-0.037	-0.056	-0.078
	0.031	0.029	0.021	0.020	0.035	0.032
Wage structure effect						
Experience	-0.071	-0.108	-0.019	0.026	-0.066	0.045
	0.080	0.079	0.059	0.059	0.102	0.103
Married	0.016	0.001	0.069	0.057	0.045	0.002
	0.030	0.030	0.022	0.023	0.038	0.039
Education	0.078	0.084	0.249	0.195	0.239	0.325
	0.148	0.162	0.113	0.123	0.197	0.214
Urban	0.124	0.129	-0.008	0.043	-0.119	-0.012
	0.052	0.053	0.039	0.040	0.067	0.070
Occupation	-0.066	-0.057	-0.096	-0.025	0.163	0.150
	0.138	0.082	0.096	0.062	0.165	0.108
Constant	0.155	0.176	0.130	0.031	-0.036	-0.261
	0.227	0.206	0.166	0.156	0.287	0.271
Total	0.237	0.226	0.325	0.327	0.226	0.249
	0.040	0.028	0.028	0.021	0.049	0.037

Notes: NR= no reweighting; R= reweighting. Each category includes: Experience: potential experience, potencial experience squared. Education: secondary, technical, vocational, university.

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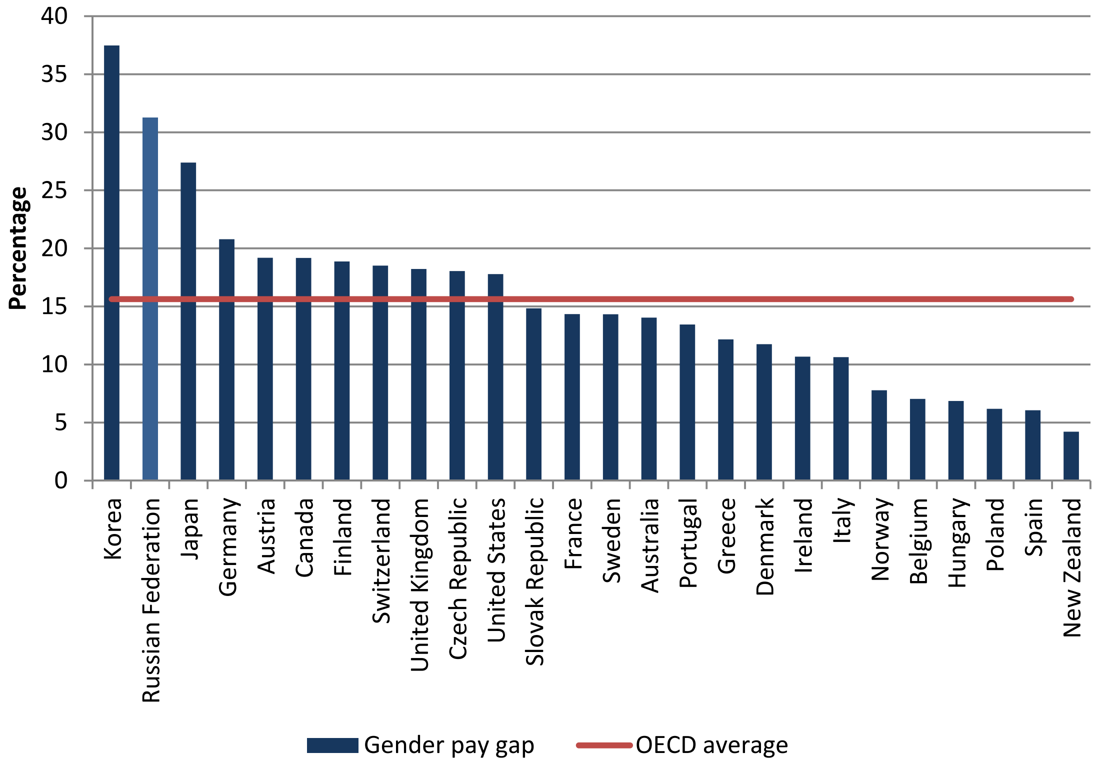
Appendix

Figure A1. Gender pay gap in monthly earnings in OECD countries



Source: OECD Employment Database, 2012. For Russia, RLMS, 2011. *Notes:* Full-time employees. The gender wage gap is unadjusted and defined as the difference between male and female median wages divided by the male median wages. Latest year available reported.

Table A1. Earnings inequality measures for wage earners

Measure *Year*	All workers	Women only	Men only
1996			
90th percentile/10th percentile	10.124	9.805	10.398
Coefficient of variation	1.377	1.342	1.377
Gini coefficient	0.500	0.501	0.490
2002			
90th percentile/10th percentile	8.464	7.527	9.353
Coefficient of variation	5.701	1.113	6.322
Gini coefficient	0.542	0.448	0.590
2011			
90th percentile/10th percentile	5.691	5.650	5.378
Coefficient of variation	1.023	0.976	1.035
Gini coefficient	0.402	0.405	0.389

Source: Authors' calculations using RLMS data.

Table A2a. Distribution of men and women across main covariates, 1996–2002

	1996			2002		
	Women	Men	M–W	Women	Men	M–W
Age						
18–24	0.111	0.166	0.055	0.124	0.125	0.001
25–34	0.228	0.285	0.057	0.221	0.255	0.034
35–44	0.362	0.277	-0.085	0.317	0.321	0.004
45–54	0.210	0.181	-0.029	0.281	0.240	-0.041
55–60	0.089	0.091	0.002	0.057	0.058	0.002
Marital status						
Married	0,671	0,790	0,120	0,641	0,774	0,134
Place of residence						
Urban	0,868	0,845	-0,024	0,825	0,818	-0,007
Experience						
0–4	0.106	0.145	0.039	0.135	0.135	0.000
5–9	0.123	0.139	0.016	0.096	0.119	0.023
10–14	0.120	0.148	0.027	0.113	0.122	0.008
15–19	0.172	0.167	-0.004	0.141	0.131	-0.009
20–24	0.155	0.127	-0.028	0.168	0.174	0.006
25–29	0.152	0.113	-0.039	0.154	0.144	-0.011
30–34	0.081	0.070	-0.011	0.136	0.096	-0.040
35–39	0.055	0.051	-0.004	0.047	0.064	0.016
40–44	0.030	0.035	0.005	0.008	0.013	0.005
45+	0.006	0.005	-0.000	0.001	0.001	0.001
Education						
Secondary incomplete	0.043	0.051	0.008	0.028	0.029	0.001
Secondary	0.124	0.147	0.023	0.127	0.124	-0.002
Vocational	0.258	0.403	0.145	0.262	0.442	0.180
Technical	0.298	0.167	-0.131	0.323	0.187	-0.137
University	0.277	0.232	-0.046	0.260	0.215	-0.045
Occupation						
Senior managers	0.009	0.037	0.028	0.041	0.055	0.013
Professionals	0.276	0.135	-0.141	0.236	0.099	-0.138
Technicians	0.234	0.072	-0.161	0.213	0.099	-0.114
Clerks	0.128	0.011	-0.117	0.107	0.016	-0.091
Service workers	0.125	0.064	-0.062	0.166	0.048	-0.118
Skilled agricultural	0.001	0.008	0.007	0.002	0.008	0.006
Craft	0.056	0.277	0.221	0.046	0.263	0.217
Plant operators	0.060	0.257	0.197	0.078	0.297	0.219
Unskilled occupations	0.112	0.140	0.028	0.111	0.115	0.004

Table A2b. Distribution of men and women across main covariates, 2011

Covariate	2011		
	Women	Men	M–W
Age			
18–24	0,104	0,122	0,018
25–34	0,216	0,301	0,085
35–44	0,268	0,226	-0,042
45–54	0,292	0,235	-0,058
55–60	0,120	0,117	-0,003
Marital status			
Married	0,501	0,660	0,159
Place of residence			
Urban	0,783	0,782	-0,001
Experience			
0–4	0,141	0,149	0,009
5–9	0,110	0,158	0,048
10–14	0,100	0,111	0,011
15–19	0,111	0,111	0,000
20–24	0,127	0,105	-0,022
25–29	0,129	0,107	-0,021
30–34	0,158	0,124	-0,034
35–39	0,094	0,100	0,006
40–44	0,030	0,034	0,003
45+	0,000	0,001	0,000
Education			
Secondary incomplete	0,024	0,033	0,009
Secondary	0,102	0,132	0,030
Vocational	0,196	0,377	0,181
Technical	0,313	0,203	-0,110
University	0,363	0,252	-0,111
Occupation			
Senior managers	0,027	0,042	0,016
Professionals	0,266	0,120	-0,146
Technicians	0,274	0,117	-0,157
Clerks	0,104	0,026	-0,078
Service workers	0,152	0,056	-0,096
Skilled agricultural	0,002	0,004	0,002
Craft	0,034	0,220	0,186
Plant operators	0,044	0,289	0,245
Unskilled occupations	0,097	0,125	0,027
Industry			

Food, light industry	0,063	0,058	-0,006
Machine construction	0,021	0,038	0,017
Military complex	0,014	0,026	0,012
Oil and gas	0,012	0,039	0,027
Heavy	0,018	0,050	0,031
Construction	0,026	0,128	0,102
Transport and communication	0,058	0,131	0,073
Agriculture	0,029	0,059	0,030
Govt. and public administration	0,041	0,018	-0,023
Education	0,179	0,043	-0,136
Science and culture	0,046	0,020	-0,026
Public health	0,148	0,030	-0,119
Army, internal affairs	0,026	0,090	0,064
Trade, consumer services	0,212	0,145	-0,067
Finances	0,033	0,013	-0,021
Energy	0,017	0,033	0,016
Housing and communal services	0,028	0,051	0,024
Firm characteristics			
Public or semipublic	0.581	0.415	-0.166
Foreign, owned or co-owned	0.029	0.040	0.012
Firm size	0.097	0.129	0.032
Job			
Subordinates	0,199	0,200	0,001
Changed place of work	0.046	0.071	0.025
Changed occupation but not place of work	0.015	0.021	0.006
Changed occupation and place of work	0.058	0.096	0.038

Source: RLMS data. *Notes:* Sample of wage workers between 18 and 60 years of age, with positive response to all covariates.

Table A3a. Gender gap in pay by covariates groups, 1996–2002

	1996			2002		
	Women	Men	W/M, %	Women	Men	W/M%
Age						
18–24	3,430	3,630	81,831	3,459	3,804	70,802
25–34	3,548	3,779	79,366	3,627	3,972	70,818
35–44	3,521	3,698	83,794	3,681	3,926	78,250
45–54	3,419	3,758	71,200	3,560	3,770	81,078
55–60	3,213	3,448	79,038	3,650	3,689	96,192
Marital status						
Not married	3,474	3,628	85,678	3,592	3,842	77,911
Married	3,465	3,716	77,783	3,613	3,880	76,594
Place of residence						
Rural	3,022	2,964	106,038	3,150	3,187	96,372
Urban	3,536	3,833	74,270	3,702	4,024	72,514
Experience						
0–4	3,533	3,794	77,058	3,624	3,857	79,228
5–9	3,519	3,683	84,845	3,565	3,986	65,625
10–14	3,535	3,694	85,262	3,616	3,990	68,844
15–19	3,543	3,702	85,321	3,774	3,876	90,268
20–24	3,522	3,828	73,683	3,632	3,993	69,707
25–29	3,450	3,771	72,590	3,569	3,861	74,670
30–34	3,349	3,547	82,060	3,534	3,680	86,408
35–39	3,256	3,532	75,916	3,379	3,422	95,752
40–44	2,986	3,178	82,551	3,332	3,805	62,298
45+	2,700	3,758	34,711	4,182	4,736	57,500
Education						
Secondary incomplete	3,121	3,500	68,450	3,178	3,484	73,571
Secondary	3,366	3,812	63,966	3,460	3,848	67,835
Vocational	3,309	3,521	80,905	3,401	3,717	72,910
Technical	3,485	3,702	80,507	3,541	3,930	67,729
University	3,696	3,974	75,765	4,008	4,202	82,379
Occupation						
Senior managers	3,496	3,792	74,379	3,830	4,122	74,698
Professionals	3,604	3,939	71,556	3,873	4,122	77,938
Technicians	3,427	4,014	55,575	3,677	4,147	62,541
Clerks	3,462	3,840	68,542	3,610	4,447	43,266
Service workers	3,265	3,695	65,092	3,349	3,917	56,687
Skilled agricultural	3,484	2,804	197,391	2,370	2,923	57,507
Craft	3,530	3,692	85,023	3,572	3,970	67,156
Plant operators	3,771	3,703	107,000	3,566	3,790	79,915
Unskilled occupations	3,257	3,322	93,739	3,255	3,249	100,574

Source: RLMS data. *Notes:* Sample of wage workers between 18 and 60 years of age, with positive response to all covariates. Earnings variable is log of hourly wage (2011 prices).

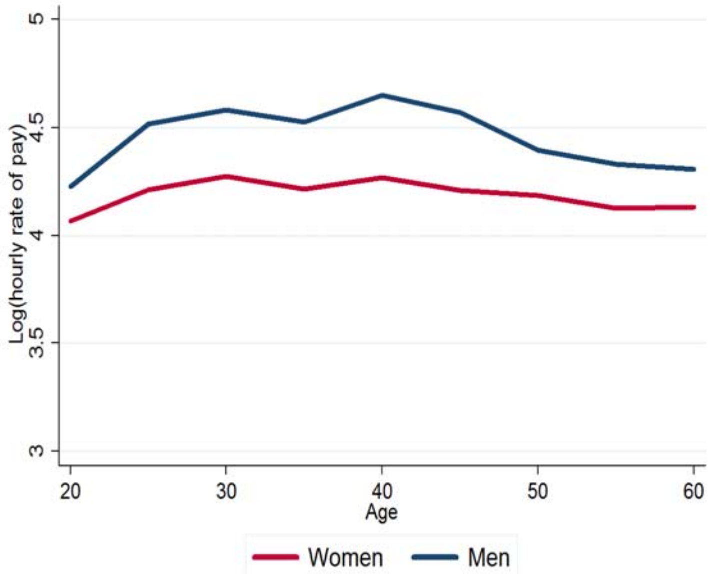
Table A3b. Gender gap in pay by covariates groups, 2011

	2011		
	Women	Men	W/M %
Age			
18–24	4,148	4,399	77,744
25–34	4,318	4,600	75,466
35–44	4,294	4,580	75,173
45–54	4,205	4,400	82,266
55–60	4,139	4,225	91,772
Marital status			
Not married	4,223	4,428	81,442
Married	4,256	4,507	77,833
Place of residence			
Rural	3,988	4,175	82,980
Urban	4,309	4,565	77,425
Experience			
0–4	4,283	4,537	77,612
5–9	4,328	4,606	75,734
10–14	4,350	4,612	76,976
15–19	4,261	4,521	77,114
20–24	4,249	4,589	71,175
25–29	4,245	4,460	80,658
30–34	4,233	4,347	89,196
35–39	4,012	4,257	78,272
40–44	3,964	3,954	101,031
45+	3,298	4,135	43,294
Education			
Secondary incomplete	3,865	4,162	74,325
Secondary	4,035	4,413	68,561
Vocational	4,022	4,327	73,699
Technical	4,113	4,495	68,217
University	4,547	4,771	79,874
Occupation			
Senior managers	4,407	4,804	67,247
Professionals	4,486	4,861	68,674
Technicians	4,301	4,644	70,942
Clerks	4,213	4,557	70,936
Service workers	3,964	4,345	68,291
Skilled agricultural	4,133	3,964	118,358
Craft	4,315	4,529	80,792
Plant operators	4,217	4,414	82,073
Unskilled occupations	3,791	3,975	83,233
Industry			

Food, light industry	4,263	4,395	87,610
Machine construction	4,354	4,588	79,154
Military complex	4,178	4,667	61,340
Oil and gas	4,708	4,878	84,374
Heavy	4,447	4,587	86,935
Construction	4,588	4,571	101,731
Transport and communication	4,493	4,541	95,353
Agriculture	3,859	3,908	95,191
Govt. and public administration	4,300	4,256	104,430
Education	4,169	4,161	100,838
Science and culture	4,236	4,850	54,135
Public health	4,086	4,347	77,050
Army, internal affairs	4,275	4,395	88,712
Trade, consumer services	4,207	4,548	71,049
Finances	4,543	5,089	57,893
Energy	4,360	4,601	78,592
Housing and communal services	4,128	4,294	84,684
Firm characteristics			
Public or semipublic	4,172	4,409	78,860
Foreign, owned or co-owned	4,759	4,965	81,346
Firm size	4,474	4,745	76,318
Job			
Subordinates	4,522	4,767	78,278
Changed place of work	4,303	4,535	79,270
Changed occupation but not place of work	4,163	4,601	64,483
Changed occupation and place of work	4,255	4,353	90,627

Source: RLMS data. *Notes:* Sample of wage workers between 18 and 60 years of age, with positive response to all covariates. Earnings variable is log of hourly wage (2011 prices).

Figure A2. Age–wage profile, 2011



Source: Authors' calculations based on RLMS, 2011.

Table A4. Decomposition results (RIF), 2011

	10	50	90
Male	3.635	4.504	5.320
	(0.026)***	(0.017)***	(0.028)***
Female	3.421	4.187	5.151
	(0.018)***	(0.016)***	(0.027)***
Gap	0.214	0.317	0.169
	(0.031)***	(0.024)***	(0.039)***
Composition effect			
Experience	0.006	0.004	0.002
	(0.005)	(0.003)	(0.003)
Married	0.010	0.013	0.009
	(0.008)	(0.005)***	(0.008)
Education	-0.030	-0.029	-0.012
	(0.015)**	(0.010)***	(0.016)
Occupation	-0.008	-0.056	-0.078
	(0.035)	(0.023)**	(0.038)**
Industry	0.122	0.070	0.006
	(0.030)***	(0.019)***	(0.032)
Firm	0.004	0.015	0.008
	(0.008)	(0.006)***	(0.010)
Subordinates	0.003	0.003	0.003
	(0.002)	(0.002)*	(0.002)
Job mobility	-0.001	0.000	0.003
	(0.005)	(0.003)	(0.005)
Urban	-0.008	-0.005	-0.002
	(0.004)*	(0.003)*	(0.002)
Total	0.098	0.015	-0.062
	(0.041)**	(0.027)	(0.044)
Residual	0,030	0,034	0,020
Wage structure			
Experience	-0,066	-0,033	-0,155
	(0.084)	(0.069)	(0.114)
Married	-0,042	0,084	-0,002
	(0.032)	(0.026)***	(0.043)
Education	0,603	0,379	0,431
	(0.184)***	(0.152)**	(0.251)*
Occupation	-0,227	0,067	0,055
	(0.081)***	(0.068)	(0.113)
Industry	0,218	0,041	0,346
	(0.117)*	(0.098)	(0.162)**
Firm	-0,039	-0,062	-0,030
	(0.049)	(0.041)	(0.067)
Subordinates	0,022	0,002	-0,032
	(0.016)	(0.014)	(0.022)
Job mobility	0,000	-0,008	-0,017
	(0.011)	(0.009)	(0.015)

Table A4. Decomposition results (RIF), 2011

	10	50	90
Urban	0,002	0,167	0,057
	(0.060)	(0.050)***	(0.082)
Total	0,061	0,258	0,225
	(0.031)**	(0.026)***	(0.041)***
Residual	0,025	0,010	-0,013

Notes: (a) Standard errors in parentheses (b) *** p<0.01, ** p<0.05, * p<0.1 (c). Each category includes: Experience: potential experience, potential experience squared. Education: secondary, technical, vocational, university. Firm: Public or semipublic firm, foreign owned or co-owned, firm size. Job mobility: Changed occupation but not place of work, changed occupation and place of work, changed place of work. Omitted categories: incomplete secondary (education), clerks (occupation), and agriculture (industry).

Table A5a. RIF regression coefficients

	1996						2002					
	Male			Female			Male			Female		
	10	50	90	10	50	90	10	50	90	10	50	90
Potential experience	-0.021	0.013	-0.019	0.004	0.027	0.001	0.013	0.035	0.007	0.013	0.015	-0.006
	(0.027)	(0.012)	(0.020)	(0.018)	(0.011)**	(0.020)	(0.017)	(0.011)***	(0.016)	(0.014)	(0.009)	(0.016)
Potential experience sq.	0.000	-0.000	0.000	-0.000	-0.001	-0.000	-0.000	-0.001	-0.000	-0.000	-0.000	0.000
	(0.001)	(0.000)*	(0.000)	(0.000)	(0.000)***	(0.000)	(0.000)	(0.000)***	(0.000)	(0.000)	(0.000)*	(0.000)
Married	0.310	0.069	-0.014	-0.061	-0.049	-0.015	-0.081	0.016	0.214	0.025	0.067	0.070
	(0.230)	(0.101)	(0.153)	(0.111)	(0.075)	(0.124)	(0.123)	(0.083)	(0.131)	(0.087)	(0.055)	(0.092)
Secondary education	0.345	0.192	-0.108	0.132	-0.013	-0.416	-0.141	0.080	0.281	0.434	0.278	0.032
	(0.470)	(0.196)	(0.314)	(0.396)	(0.187)	(0.336)	(0.370)	(0.195)	(0.224)	(0.378)	(0.154)*	(0.254)
Vocational education	-0.105	-0.086	-0.193	0.246	-0.023	-0.509	-0.103	-0.052	0.094	0.471	0.207	-0.203
	(0.469)	(0.180)	(0.273)	(0.370)	(0.176)	(0.330)	(0.349)	(0.180)	(0.184)	(0.367)	(0.146)	(0.242)
Technical education	-0.252	0.072	-0.157	0.424	0.151	-0.299	0.144	0.053	0.141	0.437	0.260	-0.166
	(0.489)	(0.195)	(0.311)	(0.365)	(0.183)	(0.338)	(0.349)	(0.189)	(0.210)	(0.369)	(0.150)*	(0.247)
University education	0.211	0.404	-0.041	0.731	0.292	-0.291	0.132	0.191	0.546	0.649	0.784	0.223
	(0.499)	(0.203)**	(0.339)	(0.378)*	(0.199)	(0.368)	(0.350)	(0.196)	(0.238)**	(0.373)*	(0.158)***	(0.265)
Urban	1.453	0.561	0.288	0.740	0.369	0.310	1.155	0.583	0.357	0.765	0.425	0.469
	(0.313)***	(0.094)***	(0.133)**	(0.205)***	(0.093)***	(0.122)**	(0.180)***	(0.072)***	(0.085)***	(0.140)***	(0.064)***	(0.064)***
Legislators, etc.	-0.551	0.096	0.215	-0.460	0.076	0.281	-0.351	-0.633	-0.886	0.262	-0.141	0.490
	(0.432)	(0.413)	(0.297)	(0.677)	(0.389)	(0.634)	(0.201)*	(0.218)***	(0.575)	(0.157)*	(0.149)	(0.272)*
Professionals	-0.648	0.245	0.626	-0.426	0.181	0.205	-0.443	-0.732	-1.016	0.047	0.097	0.123
	(0.265)**	(0.380)	(0.205)***	(0.163)***	(0.135)	(0.208)	(0.169)***	(0.203)***	(0.554)*	(0.148)	(0.106)	(0.152)
Technicians and professionals	-0.461	0.346	0.946	-0.451	0.061	0.388	-0.261	-0.467	-1.025	-0.000	0.051	0.189
	(0.279)*	(0.387)	(0.299)***	(0.155)***	(0.121)	(0.188)**	(0.146)*	(0.202)**	(0.552)*	(0.147)	(0.101)	(0.145)
Service and market workers	-0.132	0.161	0.100	-0.335	-0.002	0.102	-0.106	-0.846	-1.099	-0.256	-0.163	0.101
	(0.279)	(0.401)	(0.231)	(0.188)*	(0.135)	(0.188)	(0.155)	(0.233)***	(0.556)**	(0.169)	(0.105)	(0.136)
Skilled ag. workers	-1.904	-0.190	0.972	-0.173	0.905	-0.559	-2.174	-0.838	-0.979	-1.619	-1.146	-0.342
	(1.172)	(0.489)	(0.686)	(0.154)	(0.136)***	(0.221)**	(0.879)**	(0.301)***	(0.536)*	(1.410)	(0.342)***	(0.325)
Craft and related trades	-0.226	0.239	0.414	-0.238	0.392	0.500	-0.326	-0.640	-0.717	0.112	-0.170	0.230
	(0.180)	(0.373)	(0.134)***	(0.267)	(0.175)**	(0.298)*	(0.148)**	(0.191)***	(0.533)	(0.198)	(0.153)	(0.229)
Machine operators	-0.246	0.316	0.706	0.112	0.509	0.531	-0.505	-0.761	-0.750	-0.084	0.213	0.101
	(0.215)	(0.376)	(0.175)***	(0.178)	(0.170)***	(0.296)*	(0.155)***	(0.191)***	(0.530)	(0.193)	(0.129)	(0.171)
Unskilled occupations	-1.184	-0.073	0.477	-0.345	0.066	0.166	-1.073	-1.303	-1.053	-0.685	-0.118	0.127
	(0.288)***	(0.379)	(0.186)**	(0.215)	(0.139)	(0.184)	(0.236)***	(0.197)***	(0.531)**	(0.214)***	(0.112)	(0.150)
Observations	746	746	746	928	928	928	1,040	1,040	1,040	1,283	1,283	1,283
R-squared	0.099	0.118	0.033	0.054	0.071	0.022	0.140	0.148	0.040	0.090	0.141	0.040

Table A5a (cont'd)

	2011					
	Male			Female		
	10	50	90	10	50	90
Potential experience	0.023	0.015	0.010	0.012	0.007	0.012
	(0.008)***	(0.005)***	(0.008)	(0.006)**	(0.005)	(0.008)
Potential experience squared	-0.001	-0.001	-0.000	-0.000	-0.000	-0.000
	(0.000)***	(0.000)***	(0.000)**	(0.000)**	(0.000)**	(0.000)*
Married	0.067	0.133	0.113	0.035	-0.006	0.023
	(0.050)	(0.034)***	(0.056)**	(0.032)	(0.029)	(0.052)
Secondary education	0.263	0.183	0.013	0.094	-0.134	-0.188
	(0.150)*	(0.079)**	(0.103)	(0.148)	(0.095)	(0.144)
Vocational education	0.202	0.123	0.129	0.121	-0.201	-0.197
	(0.143)	(0.072)*	(0.097)	(0.141)	(0.089)**	(0.139)
Technical education	0.290	0.210	0.077	0.214	-0.136	-0.267
	(0.144)**	(0.077)***	(0.105)	(0.138)	(0.089)	(0.140)*
University education	0.367	0.297	0.326	0.310	0.180	0.202
	(0.144)**	(0.079)***	(0.115)***	(0.137)**	(0.093)*	(0.153)
Urban	0.365	0.256	0.135	0.207	0.266	0.287
	(0.061)***	(0.034)***	(0.051)***	(0.044)***	(0.034)***	(0.049)***
Legislators, senior managers, officials	0.002	-0.026	0.560	0.205	0.061	0.195
	(0.138)	(0.119)	(0.222)**	(0.090)**	(0.095)	(0.199)
Professionals	0.043	0.021	0.749	0.182	0.048	0.231
	(0.123)	(0.105)	(0.183)***	(0.059)***	(0.059)	(0.103)**
Technicians and associate professionals	-0.035	-0.036	0.210	0.056	0.027	0.156
	(0.124)	(0.104)	(0.160)	(0.064)	(0.055)	(0.093)*
Service and market workers	0.101	-0.388	-0.144	-0.072	-0.207	-0.205
	(0.130)	(0.114)***	(0.151)	(0.073)	(0.058)***	(0.084)**
Skilled agricultural and fishery workers	-0.048	-0.141	-0.137	0.311	-0.238	0.511
	(0.408)	(0.216)	(0.143)	(0.080)***	(0.358)	(0.732)
Craft and related trades	0.145	-0.041	0.141	0.224	0.112	0.030
	(0.116)	(0.099)	(0.144)	(0.084)***	(0.092)	(0.146)
Plant and machine operators and assemblers	0.032	-0.130	0.133	0.157	0.067	-0.074
	(0.117)	(0.098)	(0.143)	(0.089)*	(0.087)	(0.122)
Unskilled occupations	-0.589	-0.531	-0.147	-0.332	-0.295	-0.028
	(0.143)***	(0.100)***	(0.138)	(0.096)***	(0.065)***	(0.103)
Observations	2,410	2,410	2,410	2,766	2,766	2,766
R-squared	0.105	0.141	0.078	0.074	0.124	0.063

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Omitted categories: incomplete secondary (education), clerks (occupation).