Gender gap in pay in the Russian Federation: Twenty years later still a concern

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Abstract

This paper decomposes the gender gap in pay in the Russian Federation along the earnings distribution and over time (1996-2011). We use the reweighted recentered influence function decomposition proposed by Firpo et al. (2007) that allows estimating the contribution of each covariate on the wage structure and composition effects across the earnings distribution. Using data from the seventh, eleventh and twentieth round of the Russian Longitudinal Monitoring Survey we found that women are in flat career path compared to men, the importance of characteristics in the gender pay gap decreases along the earnings distribution, and if women were paid for their schooling degrees as much as men 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 earning distribution should be helped to increase their labor market skills and for women at the top of the distribution policies should be designed in order to help them access jobs that remunerate their skills as much as men.

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

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

1. Introduction

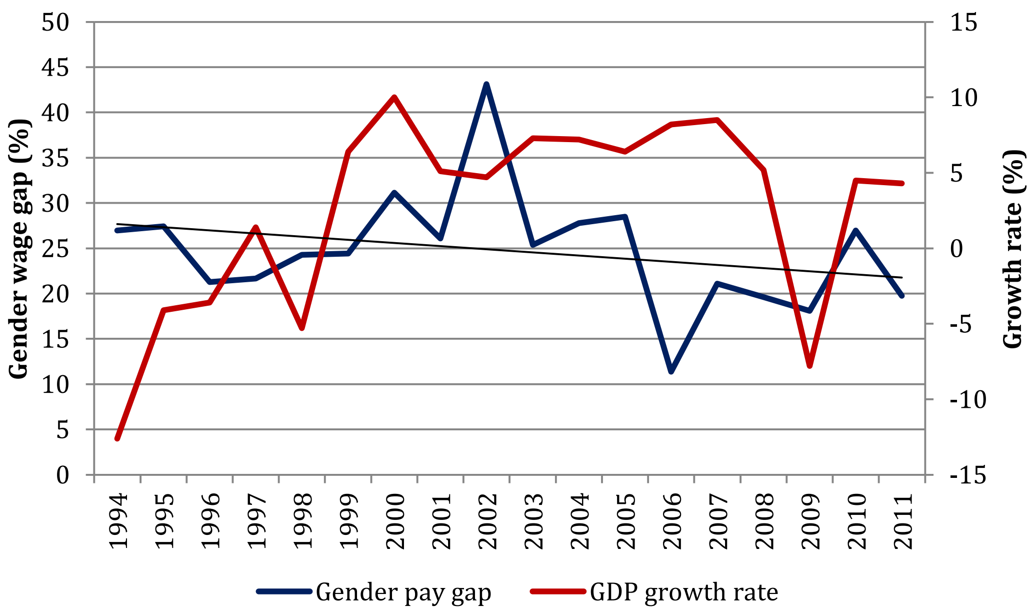
Women in Russia work. The gender gap in employment in Russia has been one of the smallest in the world, with less than 4 percentage points difference in labor force participation between men and women between the ages of 30 and 55. The low gender gap in employment is part of the legacy of the Soviet era where the equality motto was not only applying to class but to all groups of society including men and women. However, the gender gap in pay in Russia is one of largest among high-income countries. The gap is just above 30 percent and is the second to largest gender gap in pay in high-income countries, after South Korea (Figure A1). For some authors, the high gender gap is also part of the legacy of the Soviet era, 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 (Reza and Lau 1999). This legislation as well as the multiple restrictions to female employment in certain occupations are key factors determining the high occupational segregation observed in Russia.

The low gender gap in employment and the high gender gap in pay can be argued to go together. One of the facts is the negative correlation between the gender gap in pay and the gender gap in employment. The cross-country variation in the gender gap in pay has been attributed to the international differences in the wage dispersion (Blau and Kahn 1996, 2003) and to non-random 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 focus in understanding 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 their labor market and its evolution since the transition into a market economy. During the last 20 years, the gender wage gap in Russia has remained fairly constant in spite of the 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 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 (Figure 1). Second, during this period there has been a massive compression of the overall wage distribution in Russia, and for both men and women (Figure 2 and table A1). This compression of the wage structure was accompanied by changes in returns to labor market skills, typically of countries that open to trade and grow fast.

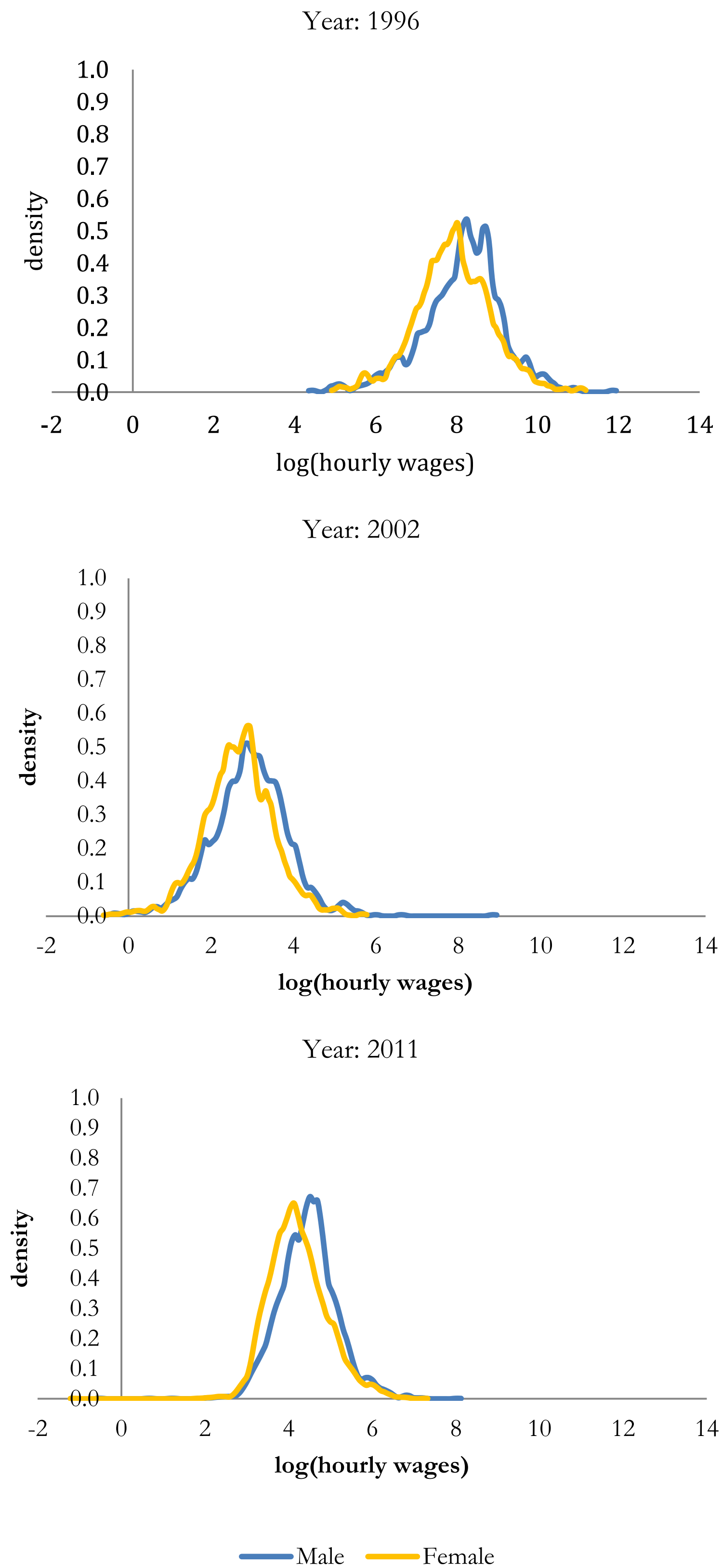
We apply a new decomposition methodology that allows us computing the wage structure and the composition effects at different percentiles of the earnings distribution. The methodology developed by Firpo, Fortin and Lemieux (2007) and applied to understand the increase in wage inequality in the U.S. during the last decade, has not yet been applied to analyzing gender wage gaps to our knowledge, with the exception of Chi and Li (2008) for urban China. Firpo, Fortin and Lemieux decomposition methodology is builds on econometrics 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 influeced 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 of identifying the contribution of each covariate to the wage structure and the composition effects. Previous methodologies designed to decomposed the gender wage gap at different percentiles such as Machado and Mata (2005) based on conditional quantile estimations could only disentangle the composition and the wage structure effect. Understanding the contribution of covariates is of particular importance, specially in the case of Russia, to analyze the links the between the gender gap in pay, the occupational segregation, the distribution of employment across economic sectors, and other factors.

Figure 1. Gender gap in pay 1994-2011



Source: RLMS and WDI. *Notes*:

Figure 2: Earnings distribution of wage workers, by gender



Source: authors using RLMS 1996, 2002 and 2011.

The RIF decomposition, however, is relies on two assumptions for identification: ignorability and common support. The first assumption simply states that unobservables are equality distributed in the two groups used for the decomposition, in this case men and women. Thus, with non-random 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 many countries and this is probably why there is only one other study applying this new methodology to gender wage gaps. However, given the high female labor 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.

Although we do not analyze selection issues, as the Russian Federation is not subject to this problem given the high levels of female labor force participation, this paper can also contribute to the understanding of gender wage gap across by describing the variation in of the gap across the earnings distribution and identifying the covariates associated to this gap. In this way, we can understand if there is either the presence of a 'sticky floor' or 'glass-ceiling' effect in Russia. We observe 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.

2. Methodology

Decomposition methodologies have been applied to gender wage differentials since the seminal work of Oaxaca (1973) and Blinder (1973). The Oaxaca-Blinder decomposition (OB hereafter) is one of the most used methods not only in labor economics but also in several microeconomics applications. Since then, however, much progress has been made with decomposition methods. Mainly, new methodologies allow decomposing the gaps for other statistics different than the mean, to handle nonlinear functions, and to tackle possible bias coming out from having individuals without a suitable treatment or comparable groups (i.e. the problem of no overlapping support). In this paper we use the recentered influence function (RIF hereafter) decomposition, recently introduced by Firpo, Fortin and Lemieux (2007). In adiditon, Fortin, Lemieux and Firpo (2011) provide a technical survey of the main decomposition methods available so far.

For easiness of the exposition, we first explain the OB decomposition and later we introduce the RIF, and its advantage relative to other methodologies. In a nutshell, 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 earnings equation (Mincer 1957, 1972, Becker 1964) assumes that—under no labor market imperfections—wages represent productivity, and thus they can be explained by labor market skills such as schooling and experience. Men's and women's wages can then be represented as:

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 equations for men and women and it 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 re-arranging terms we obtain

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

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, 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 markets skills between men and women as well as pure unexplained differences associated with discrimination.[1]

[1] For a more detailed but still simplified exposition of the Oaxaca and Blinder decomposition see ADePT Gender manual (World Bank forthcoming 2014), and for a more technical exposition Firpo, Fortin and Lemieux (2011).

In this paper we apply the recentered influenced function (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 non-parametric reweighting approach, as we do, doing this guarantees consistent estimates of the wage structure and composition effect when the conditional mean function is non-linear.

The reweighted RIF decomposition methodology offers several advantages allowing to go deeper than any previous work for the Russian Federation or even in the literature of gender pay in gap. It allows going beyond the mean and can be used to calculate other statistics, in particular, we are interested in the quantiles along the wage distribution, and still allowing inspecting the contribution of each covariate to the 'wage structure' and the 'composition' effects. Previous quantile decomposition methods could only disentangle the two main effects but without identifying the contribution of the covariates in both of them (Machado and Mata, 2005; DiNardo, Fortin and Lemieux 1996). Moreover, the RIF methodology is not path dependent as the aforementioned quantile decompositions and other methodologies that 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 observables (and unobservables) 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 the Recentered Influence Function (RIF regressions hereafter). RIF regressions consists of running a regression of a transformation of the outcome variable (its RIF) on the explanatory variables allowing 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 that is misleading in the conditional quantile regressions since the law of iterated expectations does not apply in these cases.

Firpo et al. (2009) 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 the a 'composition' and a 'wage structure' components, 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 recentered influence functions are estimated, the rest of the steps are similar to the OB since RIF coefficients can be consistently estimated using a simple OLS to regress $RIF(y_i, Q(Y_G))$ on X (Firpo et al. 2009),

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

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[2]. The contribution of combining a non-parametric reweighting approach with the RIF decomposition resides on using semi-parametric 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 base of the decomposition means moving from conditional to unconditional estimates of the moments of Y_G. Replacing $Q(Y_G)$, where $G = M, W, \widetilde{W}$, with their recentered influence functions we see with more clarity the results that can be obtained once we apply the decomposition methodology that we use,

[2] The reweighted factor is defined as $\psi = \left(\frac{p(X_i)}{1-p(X_i)}\right)\left(\frac{1-p}{p}\right)$. $p(X_i)$ is the probability of being a female given X, and p is the proportion of females in the population. Hence, $=YW$ which is the counterfactual distribrution of earnings.

$$\hat{q}_j(Y_M) - \hat{q}_j(Y_W)$$

$$= \left[\overline{X_W}\left(\hat{\beta}_{\widetilde{W}} - \hat{\beta}_W\right) + \left(\bar{X}_M - \bar{X}_{\widetilde{W}}\right)\hat{\beta}_{\widetilde{W}}\right] + \left[\left(\overline{X_M}\hat{\beta}_M - \overline{X_W}\hat{\beta}_{\widetilde{W}}\right) + \bar{X}_{\widetilde{W}}\left(\hat{\beta}_{\widetilde{W}} - \hat{\beta}_M\right)\right]$$

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

where $\hat{q}_j(Y_M) - \hat{q}_j(Y_W)$ is the raw gender earnings gap at the 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 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 (Firpo et al., 2011).

3. Data

The Russian Longitudinal Monitoring Survey (RLMS) is a unique source of rich information ideal to conduct this type of decomposition analysis. Jointly conducted by the Carolina Population Center at the University of North Carolina at 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 RLSM interviewed 3675 households (8,893 adults) in 1996 and 7923 households (17,810 adults) in 2010. The RLMS 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 the place of residence are available for the analysis but they are not valid for inference.

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. As a result, 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 sample who could have been observed since 1996. 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.

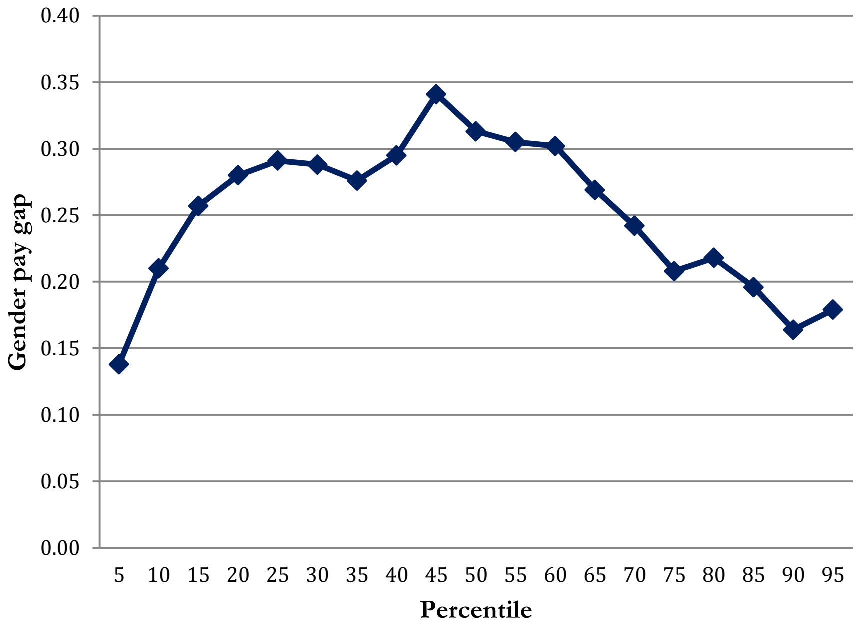
The sample for the analysis includes all wage workers. Self-employed workers are excluded since the information on their wages might not be comparable. In addition, self-employed workers constitute a small percentage of the labor force in Russia: 86 percent of men and 88 percent of employed women were 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 of 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 6 years after having retired while men worked only 4 (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 gap in pay, 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, 2007) 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 gaps is the use of additional variables that determine productivity and thus wages. The richness of the RLMS allow us to explore the effect 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 of occupational changes. However, this latter group of variables is only available for 2011. Table A.2 of the appendix shows the descriptive statistics for all the variables used in the decomposition analysis.

As it is usually the case in this literature, earnings are defined as log of hourly wages, to take into account differences in intensive margin. The difference in the intensive margin, though significant is smaller compared to other countries: women work on average 8 hours per day, what makes the full-time workers, while men work on average 9 hours per day. Though this additional hour might not be significant in terms of daily productivity, but associated to a career path of more responsibility. Gender differences in pay can be observed for most of the groups defined by the covariates, as indicated in table A3 of the appendix.

The raw gender wage gap varies considerable along the earnings distribution. As opposed to what it 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 percentile 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



Notes: Percentage gender gap in earnings by percentile

4. Results

The gender gap in pay 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

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 year 2011. First we computed the influenced function (IF) for each observation.[3] Figure 4 shows the estimates for each percentile and each covariate, giving a fuller visualization 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 non-monotonic and different for men and women. For both, men and women, the returns to labor

[3] [AA: add here details, is it using a bandwidth of 0.06 and the Epanechnikov kernel as FFL?]

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 the within-gender earnings inequality. More experienced workers earn more, and this effect is higher for workers at lower end of the wage distribution.

Schooling also shows non-monotonic 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 the university is associated with larger 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 a 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 the university has no effect on women's earnings but increases men's earnings in about 30 percent with respect to their counterparts with less than secondary or vocational university.

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 flat career path compared to men. This is usually referred in the literature of gender wage gaps 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 in figure A2.

To shed more light into the possible reasons contributing to 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 conclude that professional women at the top of the earnings distributions have lower returns than men. Conversely, women at the median of the earnings distribution have higher returns than men in service jobs.

Table 1: RIF regression coefficients, 2011

	Male			Female		
	10	50	90	10	50	90
Potential Experience	0.016**	0.010**	-0.000	0.010**	0.006*	0.006
	(0.007)	(0.004)	(0.007)	(0.005)	(0.004)	(0.007)
Potential Experience Squared	-0.000***	-0.000***	-0.000	-0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Secondary education	0.396***	0.146	0.035	0.067	-0.104	-0.190
	(0.144)	(0.093)	(0.156)	(0.117)	(0.104)	(0.176)
Vocational education	0.323**	0.087	0.170	0.066	-0.180*	-0.186
	(0.134)	(0.086)	(0.144)	(0.111)	(0.099)	(0.168)
Technical education	0.449***	0.174*	0.091	0.221**	-0.147	-0.269
	(0.139)	(0.090)	(0.150)	(0.110)	(0.098)	(0.167)
Universitary education	0.527***	0.280***	0.302*	0.286**	0.220**	0.166
	(0.144)	(0.093)	(0.156)	(0.113)	(0.101)	(0.171)
Legislators, Senior managers, officials	0.084	-0.095	0.613***	0.233*	0.074	0.195
	(0.197)	(0.128)	(0.213)	(0.121)	(0.107)	(0.183)
Professionals	0.184	0.021	0.777***	0.336***	0.181***	0.417***
	(0.173)	(0.112)	(0.187)	(0.072)	(0.064)	(0.109)
Technicians and Associate Professionals	0.054	-0.084	0.282	0.129**	0.075	0.289***
	(0.167)	(0.108)	(0.180)	(0.065)	(0.058)	(0.098)
Service and market workers	0.107	-0.414***	0.096	-0.087	-0.276***	-0.007
	(0.187)	(0.121)	(0.202)	(0.074)	(0.066)	(0.111)
Skilled agricultural and fishery workers	-0.051	-0.250	0.162	0.425	-0.093	0.075
	(0.418)	(0.270)	(0.451)	(0.433)	(0.385)	(0.655)
Craft and related trades	0.171	-0.104	0.229	0.230**	0.041	0.269
	(0.163)	(0.106)	(0.176)	(0.111)	(0.099)	(0.168)
Plant and machine operators	0.082	-0.168	0.222	0.124	0.027	0.083
	(0.161)	(0.104)	(0.174)	(0.101)	(0.090)	(0.153)
Unskilled occupations	-0.535***	-0.552***	0.018	-0.300***	-0.229***	0.157
	(0.167)	(0.108)	(0.181)	(0.080)	(0.071)	(0.121)
Public or semi-public firm	-0.053	-0.116***	-0.020	-0.154***	-0.185***	-0.343***
	(0.059)	(0.038)	(0.064)	(0.049)	(0.044)	(0.074)
Foreign firms owned or co-owned	0.079	0.198**	0.582***	0.036	0.334***	0.957***
	(0.126)	(0.082)	(0.136)	(0.103)	(0.091)	(0.155)
Firm size	0.145**	0.151***	0.136*	0.051	0.110***	0.252***
	(0.072)	(0.047)	(0.078)	(0.046)	(0.041)	(0.069)
Subordinates	0.208***	0.094*	0.213***	0.113*	0.159***	0.228**
	(0.075)	(0.049)	(0.081)	(0.060)	(0.054)	(0.091)
Changed place of work	-0.013	0.063	0.154	0.050	0.128*	-0.044
	(0.095)	(0.061)	(0.102)	(0.082)	(0.073)	(0.124)
Changed occupation but not place of work	0.086	0.194*	0.037	0.075	-0.022	-0.508**
	(0.168)	(0.109)	(0.181)	(0.138)	(0.123)	(0.209)
Changed occupation and place	-0.061	-0.125**	-0.085	-0.097	0.024	0.118
	(0.084)	(0.054)	(0.091)	(0.073)	(0.065)	(0.111)
Observations	2,071	2,071	2,071	2,466	2,466	2,466
R-squared	0.133	0.195	0.131	0.104	0.176	0.119

Notes: RLMS 2011. RIF regression with robust standard errors in parentheses. *** denotes p-value smaller than 0.01, ** denotes p-value smaller than0.05, * denotes p-value smaller than 0.1. The RIF regressions also include industry dummies and the coefficients estimates are reported in table A2 of the appendix. The ommited categories are [COMPLETE]. Controls include place of residence defined as

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 so wages) can also depend on firm characteristics such as type of ownership or firm size. Ideally, firm effects are quantified using employer-employee data (Cardoso, Cabral and Portela 2005). Fortunately, the richness of the RLMS allows exploring these effects by adding covariates to describe firm characteristics. There is evidence that public owned firms are less productive than private firms since they face less market competition. For women, and to a lesser extent for men, working for a public or semi-public 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 90^{th} percentile women working for a public firm earn 34% less than women working for a private firm. Larger firms many times are also thought to have higher productivity since they make higher investments in capital. The effect of firm size is highly non-monotonic 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 exploring 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 there were found gender differences. 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 a better match are larger than the cost of on-the-job search. Empirical evidence supports this theory and found that for the US two thirds of the long-run wage (or the wage at the end of the work career) occurred during the first 10 years employed and that a third of the wage increase it is explained by job-to-job transitions (Topel and Ward 1992). Similarly, it has been found for the US that women are less likely to switch jobs, i.e. experience job-to-job transitions, and that this explains about 8 percent of gender wage gap in the US (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).

To test these hypotheses we add a few covariates that might be capturing these effects, at least partially. The RLMS asks the adult respondents whether they have changed occupation, place of work, or both within the last 12 months. It can be thought that changes in place of work are associated to the on-the-job search theory, and they 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 occupations!) increases earnings in almost 13 percent. Interestingly, the effect for men is smaller and not significant. Unfortunately there is 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 be indicating either a promotion within the same firm or horizontal (even a

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

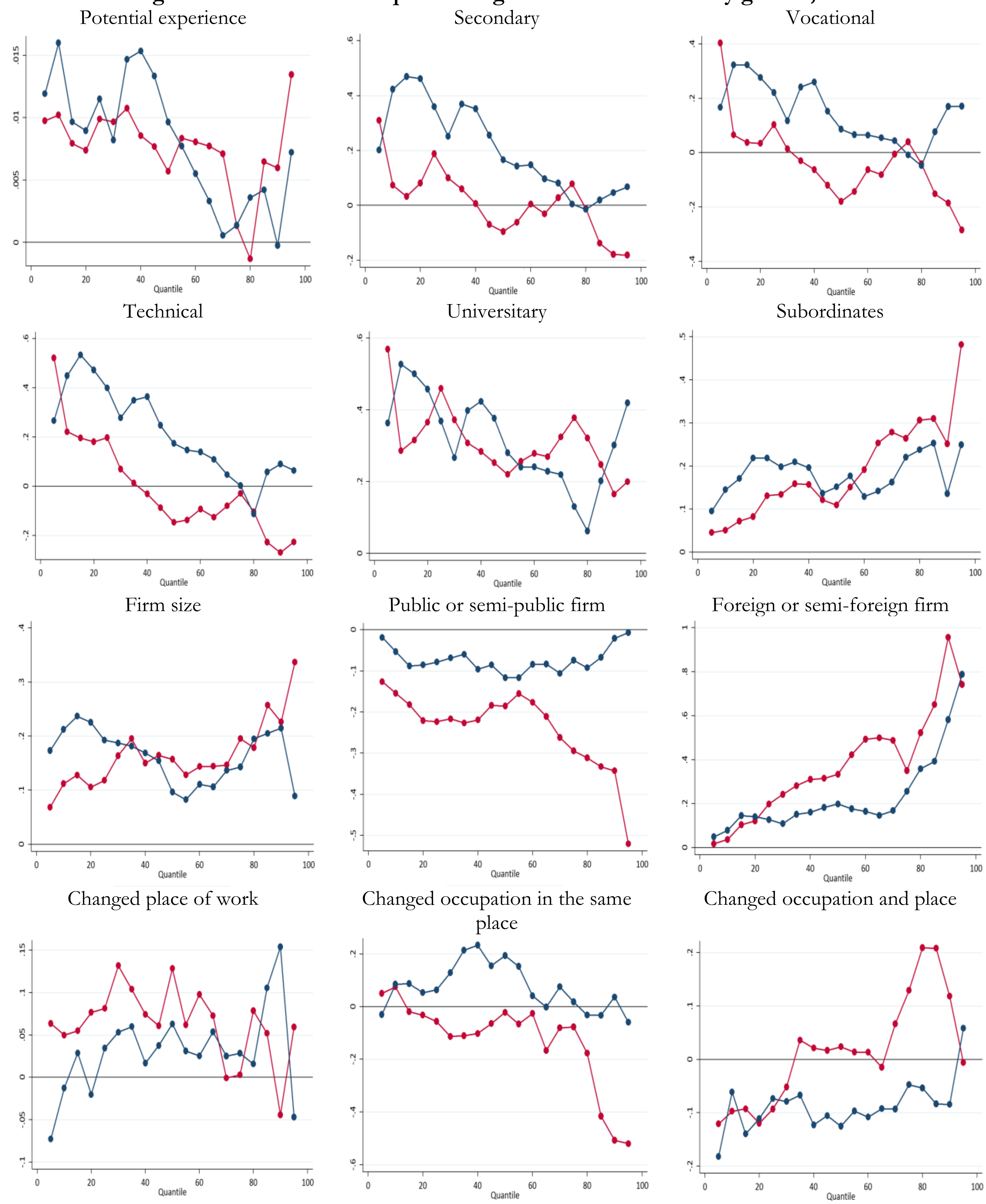


Figure 4b: Unconditional quantile regressions coefficients by gender, 2011

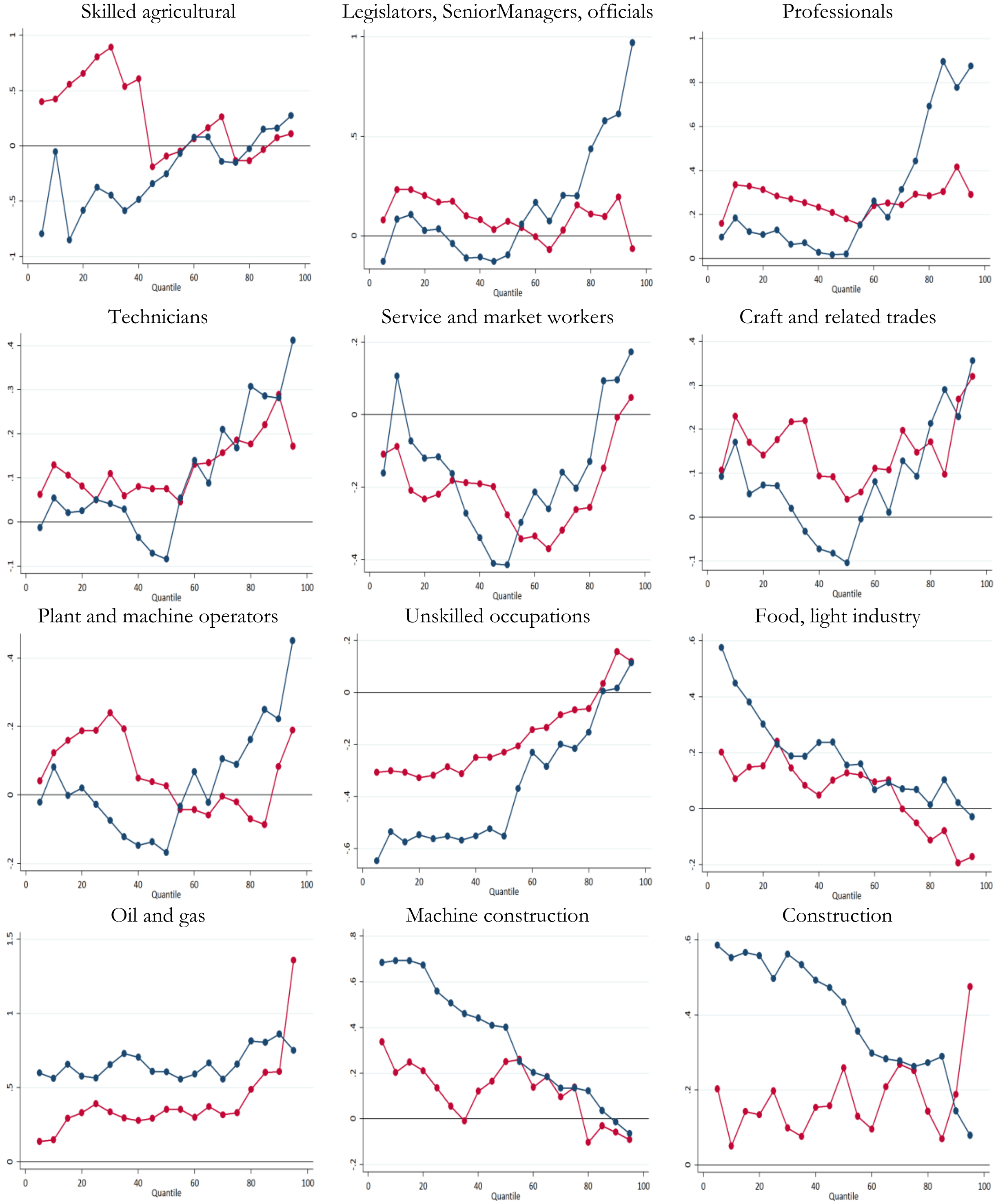
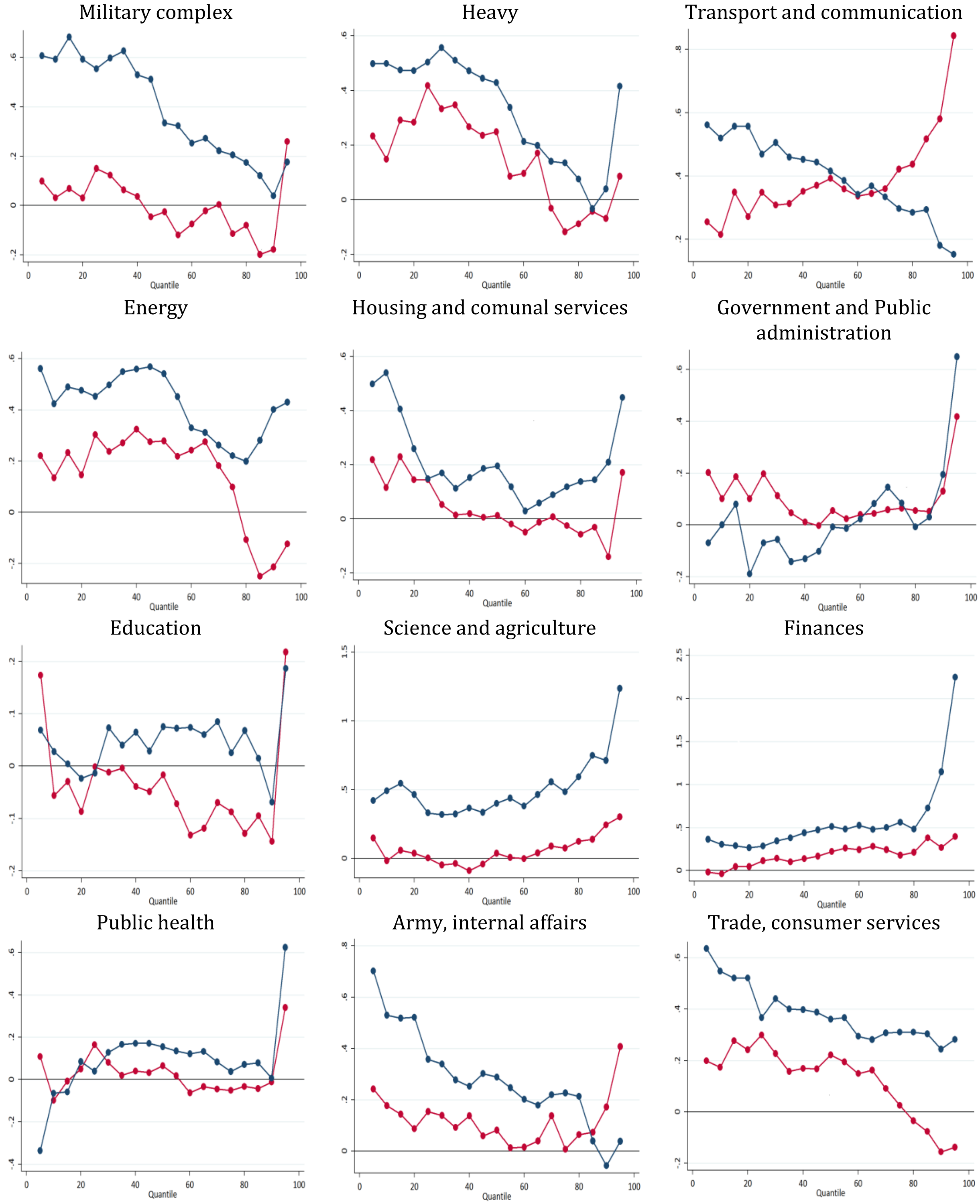


Figure 4c: Unconditional quantile regressions coefficients by gender, 2011



Overall, the results coming out from the estimates from the RIF regression seem to indicate that the impacts of the covariates are highly non-monotonic for both men and women and that impacts are different for men and women, and these gender differences are statistically significant in some cases.

demotion). As with most of the previous covariates the estimates are highly non-monotonic along the wage distribution, and very different for men and women. The RIF coefficient shows up to be positive and significant at the 50th percentile; while it is decreasing along the wage distribution for women and negative and significant at the top 90th percentile.

The results are consistent with the situation where women are in jobs with fewer options of career development, either by choice or by lack of opportunities. Women tend to be found in less productive occupations.

4.2. Decomposition results

The results of the decomposition are presented in figures 5 to 7 and table 2. The top part of table/figure shows the gender gap in earnings at each percentile (Table A4 in the appendix shows the detailed decomposition results). As expected, the FFL shows a very different story than the one coming out from previous studies.

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 evaluated at the median of the earnings distribution corroborate those findings. However, 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 while at the top of the 90th percentile the composition effect is negative. Having a negative composition effect and a wage structure effect (and thus a wage structure effect that is larger than the gender gap in pay) indicates that women are overqualified compared to men at the same percentile. In other words, if women were paid as men, and men would have the same characteristics as women, the gender gap in pay would be 35 percent smaller.

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

Second, the results inside the composition effect also show a very non-monotonic pattern along the wage distribution. The most striking result is that the importance of occupation and industry decreases along the wage distribution. For women at the bottom of the distribution (10th percentile) the problem is that they are employed in low wages industries, though doing the same occupations as men. If women were employed in the same economic sectors as men their gender wage gap would decrease in half. Instead, for women at the top of the distribution (90th percentile) the problem is the type of occupation they do and not the economic sector. Lastly, all women, and in particular for those at the bottom, are more educated than men in similar jobs and position in the earnings distribution.

Table 2: Decomposition Results (RIF) 2011

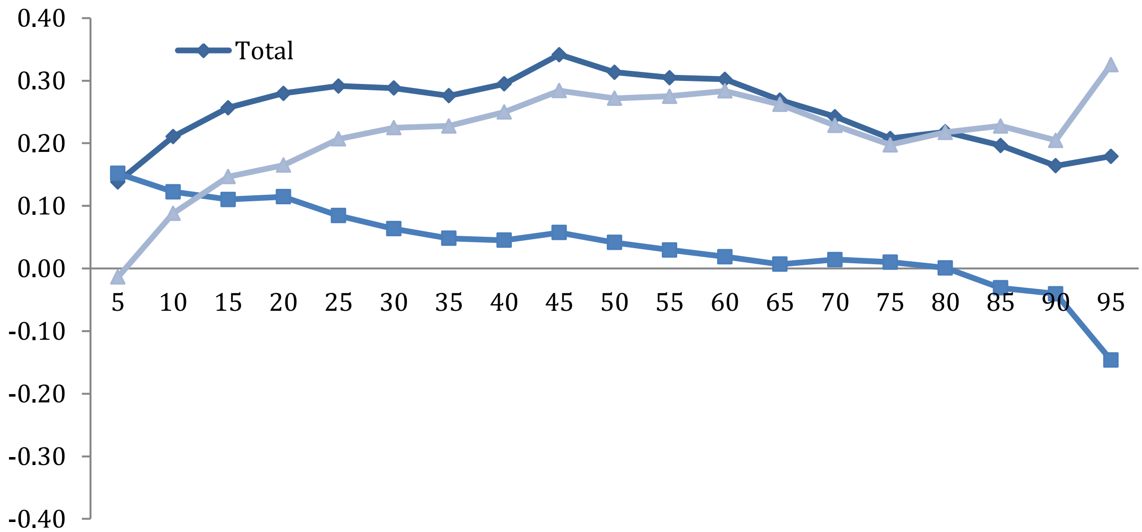
	10	50	90
Gap	0.21	0.313	0.164
	-0.031	-0.024	-0.039
Composition effect			
Experience	10	4	7
Education	-21	-12	-12
Occupation	-2	-17	-41
Industry	56	22	4
Firm	3	5	4
Subordinates	1	1	2
Job Mobility	-1	0	1
Total	**46**	**4**	**-35**
Residual	12	9	11
Wage structure			
Experience	-116	-15	-158
Education	154	102	268
Occupation	-118	26	57
Industry	43	18	265
Firm	-19	-8	-12
Subordinates	13	1	-25
Job Mobility	-1	-2	-10
Total	**17**	**76**	**124**
Residual	25	11	1

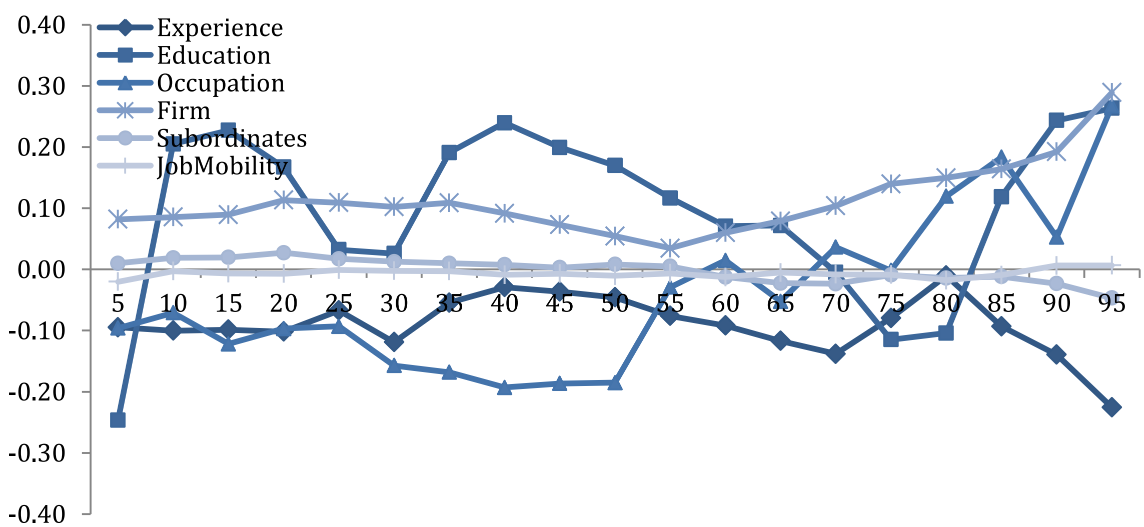
Notes:

Third, inside the wage structure effect, the effects are also highly non-monotonic along the earnings distribution. Returns to education are smaller for women relatively to men, contributing to increase the gender gap in pay at any point of the earnings distribution. If were paid for their schooling decrees as much as men—other things constant—the gender gap would disappear (or even reversed! for women at the top of the earnings distribution). As with the composition effect, occupation and industry have 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, we see that the returns for being employed in certain industries would increase the gender gap in pay.

Finally, the two terms that capture the error coming from the local linearization are small: 9 percent for the composition effect and 11 percent for the wage structure effect.

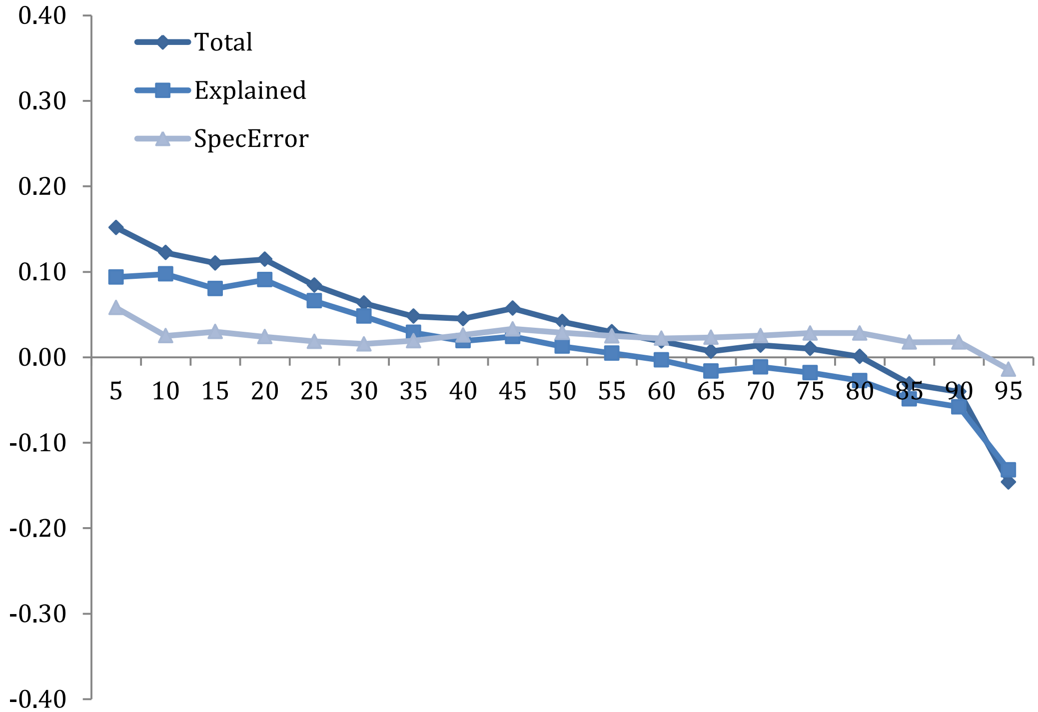
Figure 5: Decomposition of total gender pay gap into composition and wage structure effects (plus error)

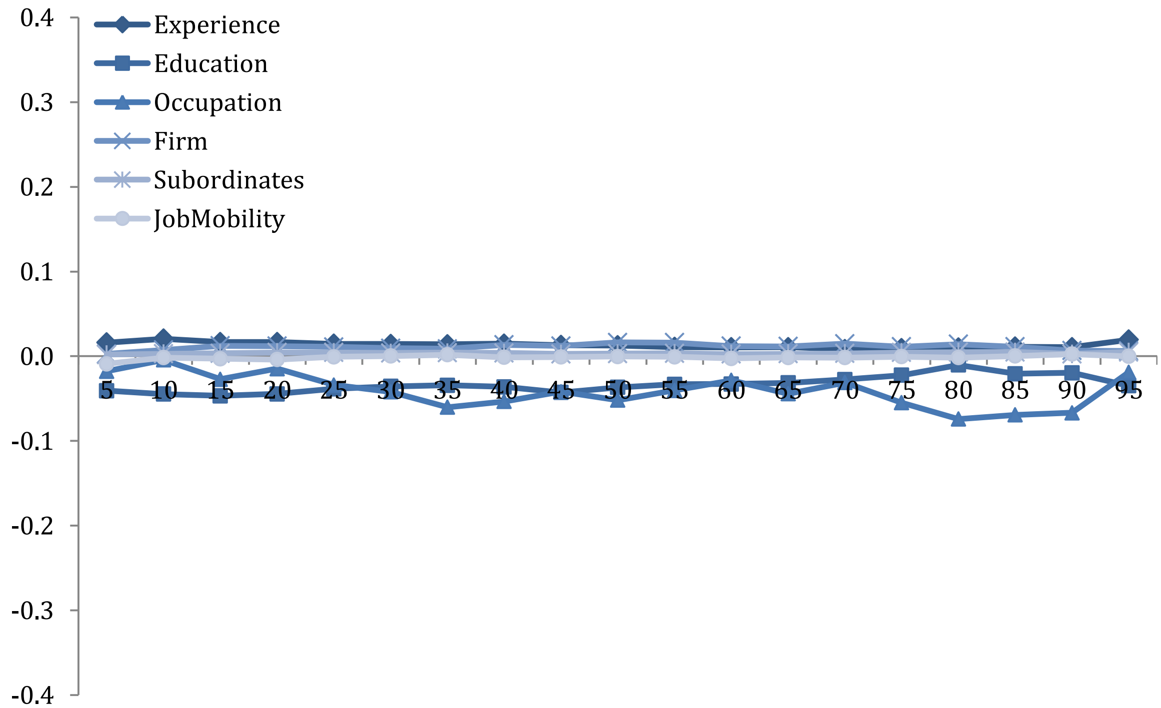




Note: Each category includes: Experience: Potential experience, potencial experience 2. Education: Secondary, Technical, Vocational, Universitary. Firm: Public or semi-public firm, foreign firm owned or co-owned. Job Mobility: Changed occupation but not place of work, changed occupation and place, changed place of work.

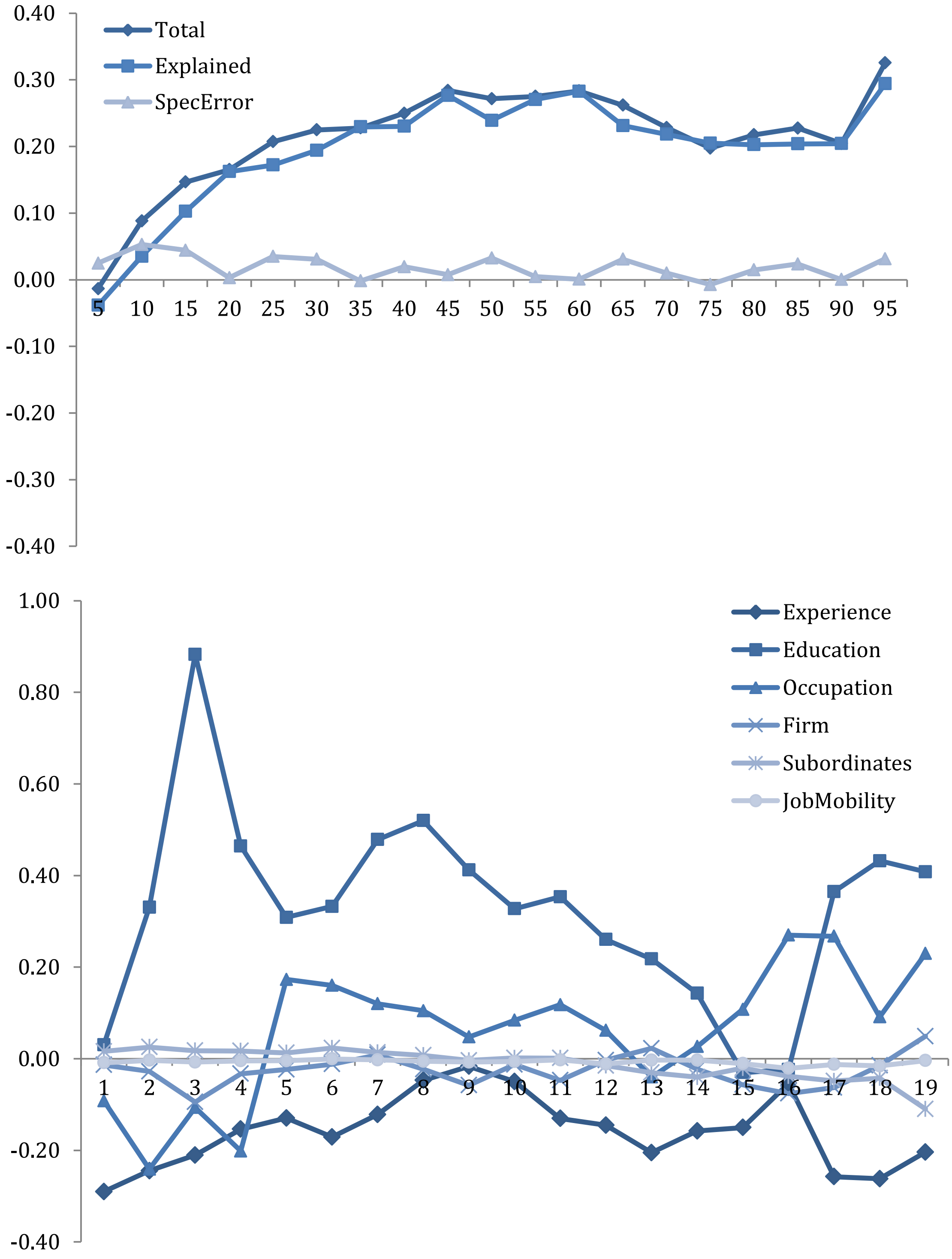
Figure 6: Decomposition of composition effects





Notes: Each category includes: Experience: Potential experience, potencial experience 2. Education: Secondary, Technical, Vocational, Universitary. Firm: Public or semi-public firm, foreign firm owned or co-owned. Job Mobility: Changed occupation but not place of work, changed occupation and place, changed place of work.

Figure 7: Decomposition of Wage structure effects



Note: Each category includes: Experience: Potential experience, potencial experience 2.
Education: Secondary, Technical, Vocational, Universitary. Firm: Public or semi-public firm, foreign firm owned or co-owned. Job Mobility: Changed occupation but not place of work, changed occupation and place, changed place of work.

4.3. Decompositions results over time

The comparison of the RIF decomposition for 1996, 2002 and 2011 shows the important variations in the wage structure occurred in the Russian Federation since the transition into a market economy in 1992. 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 been always negative but much larger in absolute magnitude in 2002 than in the two other years. Or the importance of the experience covariate has been always decreasing along the earnings distribution, but the slope of the changes has increased between 1996 and 2011.

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

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	6.9245	6.9245	8.2451	8.2451	9.252	9.252	1.8007	1.8007	2.9591	2.9591	4.0407	4.0407
	0.082	0.082	0.0387	0.0387	0.0603	0.0603	0.052	0.052	0.0321	0.0321	0.0467	0.0467
Female	6.8202	6.8202	7.942	7.942	9.0909	9.0909	1.6757	1.6757	2.7102	2.7102	3.692	3.692
	0.0524	0.0524	0.0349	0.0349	0.0566	0.0566	0.0423	0.0423	0.0275	0.0275	0.0404	0.0404
Gap	0.1044	0.1044	0.3031	0.3031	0.1611	0.1611	0.125	0.125	0.2489	0.2489	0.3487	0.3487
	0.0974	0.0974	0.0521	0.0521	0.0827	0.0827	0.0671	0.0671	0.0423	0.0423	0.0617	0.0617
Composition effect												
Experience	0.0078	0.0082	0.0016	-0.0038	0.0241	0.028	0.0027	0.0016	0.0005	0.0011	0.0012	0.001
	0.014	0.0197	0.0082	0.0105	0.0133	0.0169	0.005	0.0051	0.0057	0.0059	0.0039	0.0039
Education	-0.0111	-0.0268	-0.046	-0.0534	-0.013	-0.0159	-0.076	-0.0867	-0.0417	-0.0453	-0.0389	-0.041
	0.0384	0.038	0.02	0.02	0.0269	0.0265	0.0247	0.0278	0.0152	0.0171	0.0231	0.026
Occupation	-0.0158	-0.0209	0.0025	0.0151	0.0036	0.0283	-0.0991	-0.0996	-0.0751	-0.0797	0.045	0.038
	0.132	0.1556	0.0607	0.0716	0.0975	0.115	0.0705	0.0718	0.0437	0.0446	0.0642	0.0655
Total	-0.0192	-0.0394	-0.042	-0.0421	0.0147	0.0403	-0.1724	-0.1847	-0.1164	-0.1239	0.0073	-0.002
	0.1304	0.1534	0.0612	0.0717	0.0964	0.1134	0.069	0.0704	0.0432	0.0442	0.0625	0.0638
Wage structure effect												
Experience	-0.1067	-0.2062	-0.0689	-0.1501	-0.1681	-0.537	-0.047	-0.0868	0.1671	0.0606	0.2028	0.2675
	0.2846	0.3633	0.1499	0.1619	0.2439	0.2275	0.1849	0.1928	0.1138	0.1133	0.1733	0.1557
Education	-0.4046	-0.9658	0.0043	0.075	0.2086	0.1012	-0.3805	-0.0975	-0.2549	-0.4063	0.3377	0.1596
	0.4625	0.5358	0.2501	0.2536	0.4078	0.3704	0.3768	0.3887	0.2325	0.2303	0.3546	0.3216
Occupation	-0.2664	-0.5658	0.0277	0.0934	0.268	0.0254	-0.2786	-0.4975	-0.6667	-0.4344	-1.0234	-0.9027
	0.7066	0.2714	0.3326	0.1275	0.5345	0.1853	0.3751	0.1908	0.2288	0.1128	0.3464	0.1567
Constant	0.9012	1.8562	0.3819	0.2956	-0.162	0.4911	1.0034	0.9504	1.1198	1.1388	0.8245	0.8045
	0.9673	0.7014	0.4735	0.3234	0.7644	0.4648	0.5743	0.4612	0.352	0.2725	0.5348	0.3791
Total	0.1235	0.1184	0.3451	0.3138	0.1464	0.0807	0.2973	0.2685	0.3653	0.3587	0.3414	0.329
	0.1605	0.1087	0.078	0.0499	0.1256	0.0715	0.0933	0.0673	0.0577	0.0401	0.0868	0.0554

Notes: NR= No reweighting; R=Reweighting

Table 3 (continued): RIF decompositions

	2011					
	10		50		90	
	NR	R	NR	R	NR	R
Male	3.6328	3.6328	4.4722	4.4722	5.3031	5.3031
	0.0225	0.0225	0.0153	0.0153	0.0251	0.0251
Female	3.4159	3.4159	4.1806	4.1806	5.1533	5.1533
	0.0165	0.0165	0.0148	0.0148	0.0252	0.0252
Gap	0.2169	0.2169	0.2916	0.2916	0.1497	0.1497
	0.0279	0.0279	0.0213	0.0213	0.0355	0.0355
Composition Effect						
Experience	0.0156	0.0136	0.0108	0.0093	0.0082	0.0067
	0.005	0.0049	0.0034	0.0033	0.0038	0.0032
Education	-0.0472	-0.0497	-0.0405	-0.0431	-0.0271	-0.032
	0.0122	0.0125	0.0084	0.0086	0.0136	0.014
Occupation	-0.007	-0.0062	-0.0076	-0.0131	-0.0626	-0.0675
	0.0288	0.0286	0.0196	0.0195	0.0326	0.0324
Total	-0.0385	-0.0424	-0.0374	-0.0469	-0.0815	-0.0929
	0.0281	0.0272	0.0194	0.0188	0.0317	0.0308
Wage Structure Effect						
Experience	-0.0409	-0.1692	0.0251	0.0617	-0.0169	-0.0271
	0.0923	0.0999	0.0691	0.0707	0.118	0.1226
Education	0.0551	0.0848	0.1755	0.0256	0.1864	0.3362
	0.1459	0.1657	0.1114	0.1185	0.1909	0.2057
Occupation	-0.1027	-0.0202	-0.0647	-0.0132	0.2089	0.1313
	0.136	0.0865	0.0952	0.0615	0.1605	0.1067
Constant	0.344	0.3385	0.1931	0.2673	-0.1472	-0.1962
	0.224	0.2153	0.1646	0.153	0.2802	0.2655
Total	0.2554	0.2338	0.329	0.3413	0.2313	0.2442
	0.0381	0.0288	0.0271	0.0203	0.0458	0.0351

Notes: NR= No reweighting; R=Reweighting

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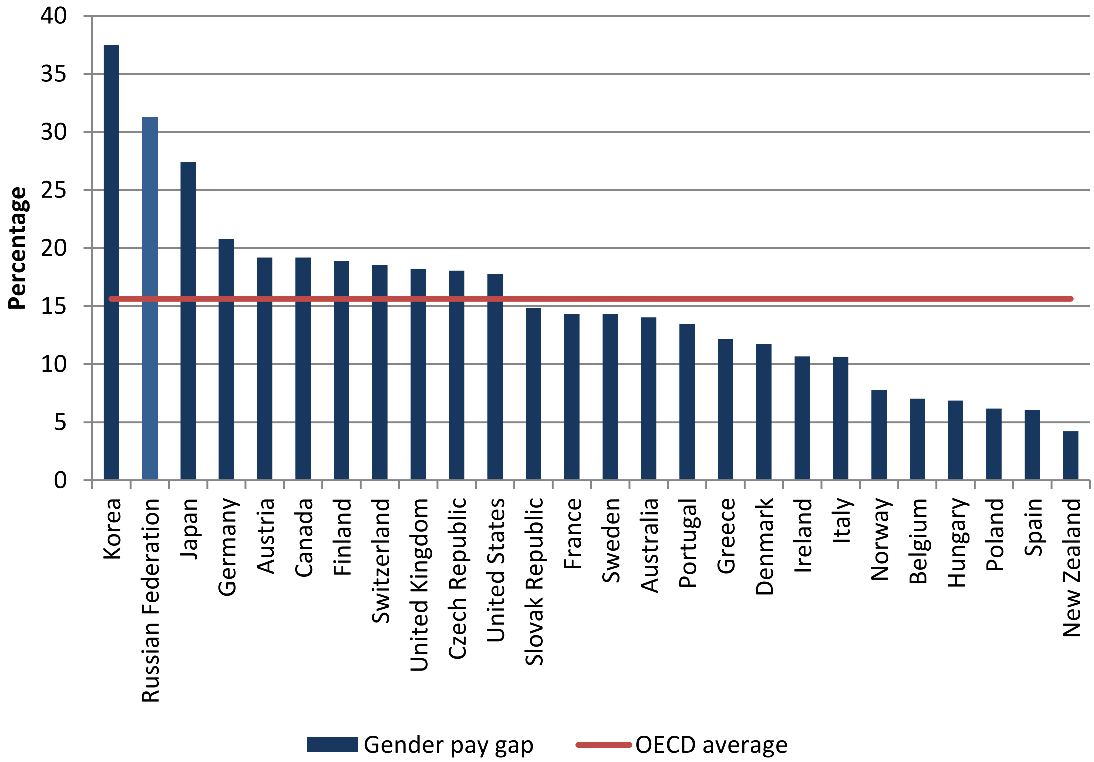
Appendix

Figure A1. Gender pay gap in monthly earning 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			
90 Percentile / 10 Percentile	10.124	9.802	10.398
Coefficient of Variation	1.377	1.342	1.377
Gini Coefficient	0.500	0.501	0.490
2002			
90 Percentile / 10 Percentile	8.432	7.504	9.338
Coefficient of Variation	5.699	1.113	6.320
Gini Coefficient	0.542	0.448	0.590
2011			
90 Percentile / 10 Percentile	5.689	5.650	5.375
Coefficient of Variation	1.023	0.976	1.035
Gini Coefficient	0.402	0.405	0.389

Source: Authors calculations using RLMS.

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
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

	2011		
Covariate	Women	Men	M-W
Age			
18-24	0.103	0.122	0.019
25-34	0.215	0.300	0.085
35-44	0.269	0.226	-0.043
45-54	0.292	0.234	-0.058
55-60	0.121	0.118	-0.003
Experience			
0-4	0.069	0.080	0.011
5-9	0.035	0.052	0.018
10-14	0.038	0.055	0.017
15-19	0.090	0.108	0.018
20-24	0.100	0.116	0.016
25-29	0.106	0.114	0.008
30-34	0.133	0.103	-0.031
35-39	0.110	0.100	-0.010
40-44	0.127	0.106	-0.021
45+	0.192	0.167	-0.025
Education			
Secondary Incomplete	0.024	0.033	0.009
Secondary	0.102	0.131	0.029
Vocational	0.196	0.378	0.182
Technical	0.313	0.202	-0.110
University	0.363	0.252	-0.111
Occupation			
Senior Managers	0.027	0.043	0.016
Professionals	0.267	0.120	-0.147
Technicians	0.273	0.116	-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	0.221	0.187
Plant Operators	0.044	0.288	0.244
Unskilled Occupations	0.098	0.126	0.028
Industry			
Food, Light indu	0.063	0.058	-0.005
Machine Construction	0.021	0.039	0.018
Military Complex	0.014	0.026	0.012
Oil and gas	0.012	0.038	0.027

Heavy	0.019	0.050	0.032
Construction	0.025	0.128	0.103
Transport and Communication	0.058	0.130	0.072
Agriculture	0.029	0.060	0.031
Gov and Public Adm	0.041	0.018	-0.023
Education	0.179	0.043	-0.136
Science and culture	0.046	0.020	-0.026
Public Health	0.149	0.029	-0.119
Army, internal affairs	0.026	0.090	0.064
Trade, consumer services	0.212	0.147	-0.065
Finances	0.034	0.013	-0.021
Energy	0.017	0.033	0.016
Housing and communal services	0.028	0.051	0.023
Firm characteristics			
Public or semi-public firm	0.581	0.415	-0.166
Foreign firms owned or co-owned	0.029	0.040	0.012
Firm size	0.097	0.129	0.032
Job			
Subordinates	0.200	0.199	-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	0.058	0.096	0.038

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

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

	1996			2002		
	Women	Men	W/M %	Women	Men	W/M %
Age						
18-24	7.89	8.09	81.83	2.54	2.89	70.80
25-34	8.01	8.24	79.37	2.71	3.05	70.82
35-44	7.98	8.16	83.79	2.76	3.01	78.00
45-54	7.88	8.22	71.20	2.64	2.85	81.27
55-60	7.67	7.91	79.04	2.73	2.77	96.19
Experience						
0-4	7.99	8.25	77.06	2.71	2.94	79.23
5-9	7.98	8.14	84.84	2.65	3.07	65.62
10-14	7.99	8.15	85.26	2.70	3.07	68.84
15-19	8.00	8.16	85.32	2.86	2.96	90.27
20-24	7.98	8.29	73.68	2.71	3.07	69.71
25-29	7.91	8.23	72.59	2.65	2.94	74.67
30-34	7.81	8.00	82.06	2.61	2.77	85.25
35-39	7.71	7.99	75.92	2.46	2.51	95.34
40-44	7.44	7.64	82.55	2.41	2.89	62.30
45+	7.16	8.22	34.71	3.26	2.86	149.73
Education						
Secondary Incomplete	7.58	7.96	68.45	2.26	2.57	73.57
Secondary	7.82	8.27	63.97	2.54	2.93	67.65
Vocational	7.77	7.98	80.90	2.48	2.80	72.91
Technical	7.94	8.16	80.51	2.62	3.01	67.73
University	8.15	8.43	75.76	3.09	3.28	82.38
Occupation						
Senior Managers	7.95	8.25	74.38	2.91	3.20	74.70
Professionals	8.06	8.40	71.56	2.95	3.20	77.70
Technicians	7.88	8.47	55.58	2.76	3.23	62.54
Clerks	7.92	8.30	68.54	2.69	3.53	43.27
Service Workers	7.72	8.15	65.09	2.43	3.01	55.81
Skilled Agricultural	7.94	7.26	197.39	1.45	2.00	57.51
Craft	7.99	8.15	85.02	2.65	3.05	67.43
Plant Operators	8.23	8.16	107.00	2.65	2.87	79.91
Unskilled Occupations	7.72	7.78	93.74	2.34	2.33	100.57

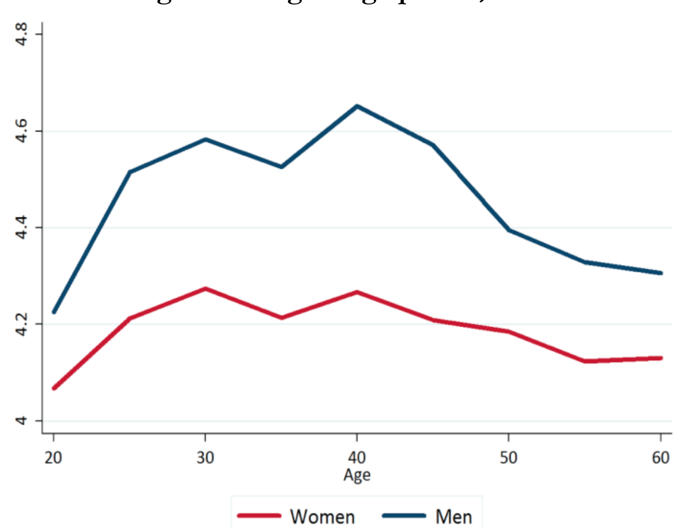
Table A3b: Gender gap in pay by covariates groups, 2011

	2011		
	Women	Men	W/M%
Age			
18-24	4.148	4.398	77.866
25-34	4.320	4.601	75.500
35-44	4.296	4.577	75.480
45-54	4.206	4.398	82.544
55-60	4.138	4.218	92.287
Experience			
0-4	4.234	4.545	73.261
5-9	4.357	4.698	71.115
10-14	4.229	4.621	67.564
15-19	4.268	4.459	82.598
20-24	4.324	4.608	75.237
25-29	4.302	4.532	79.467
30-34	4.350	4.569	80.363
35-39	4.165	4.445	75.579
40-44	4.188	4.407	80.324
45+	4.135	4.224	91.494
Education			
Secondary Incomplete	3.865	4.155	74.824
Secondary	4.036	4.409	68.874
Vocational	4.024	4.326	73.988
Technical	4.112	4.493	68.331
University	4.548	4.771	79.996
Occupation			
Senior Managers	4.402	4.799	67.287
Professionals	4.482	4.857	68.718
Technicians	4.302	4.653	70.400
Clerks	4.215	4.557	71.089
Service Workers	3.965	4.341	68.652
Skilled Agricultural	4.133	3.964	118.358
Craft	4.315	4.526	81.010
Plant Operators	4.215	4.413	82.045
Unskilled Occupations	3.804	3.971	84.547
Industry			
Food, Light indu	4.262	4.397	87.316
Machine Construction	4.354	4.579	79.808
Military Complex	4.178	4.667	61.340
Oil and gas	4.708	4.878	84.374

Heavy	4.449	4.583	87.420
Construction	4.588	4.571	101.795
Transport and Communication	4.501	4.543	95.952
Agriculture	3.859	3.900	95.930
Gov and Public Adm	4.304	4.246	106.005
Education	4.168	4.157	101.102
Science and culture	4.239	4.850	54.266
Public Health	4.086	4.347	77.033
Army, internal affairs	4.275	4.394	88.852
Trade, consumer services	4.208	4.548	71.192
Finances	4.531	5.089	57.228
Energy	4.363	4.597	79.155
Housing and communal services	4.137	4.294	85.472
Firm characteristics			
Public or semi-public firm	4.172	4.407	79.073
Foreign firms owned or co-owned	4.759	4.981	80.089
Firm size	4.479	4.740	77.068
Job			
Subordinates	4.522	4.764	78.535
Changed place of work	4.303	4.533	79.404
Changed occupation but not place of work	4.163	4.601	64.483
Changed occupation and place	4.246	4.349	90.137

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

Figure A2: Age-wage profile, 2011



Source: Authors' calculations based on RLMS 2011

Table A4: Decomposition Results (RIF) 2011

	10	50	90
Male	3.633***	4.501***	5.315***
	(0.026)	(0.017)	(0.028)
Female	3.423***	4.187***	5.151***
	(0.018)	(0.016)	(0.027)
Gap	0.210***	0.313***	0.164***
	(0.031)	(0.024)	(0.039)
Composition effect			
Experience	0.021***	0.013***	0.011**
	(0.006)	(0.004)	(0.005)
Education	-0.045***	-0.037***	-0.020
	(0.015)	(0.010)	(0.016)
Occupation	-0.004	-0.052**	-0.067*
	(0.035)	(0.023)	(0.038)
Industry	0.117***	0.070***	0.006
	(0.029)	(0.019)	(0.031)
Firm	0.007	0.016***	0.007
	(0.008)	(0.006)	(0.009)
Subordinates	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)
JobMobility	-0.002	-0.000	0.002
	(0.005)	(0.003)	(0.005)
Total	0.097**	0.013	-0.058
	(0.040)	(0.027)	(0.043)
Residual	0.025	0.029	0.018
Wage structure			
Experience	-0.244**	-0.047	-0.259*
	(0.104)	(0.081)	(0.137)
Education	0.323*	0.320**	0.439*
	(0.193)	(0.148)	(0.252)
Occupation	-0.247***	0.081	0.093
	(0.084)	(0.066)	(0.112)
Industry	0.091	0.056	0.434*
	(0.167)	(0.130)	(0.221)
Firm	-0.040	-0.025	-0.019
	(0.050)	(0.039)	(0.066)
Subordinates	0.027	0.004	-0.041*
	(0.017)	(0.013)	(0.022)
JobMobility	-0.003	-0.006	-0.016
	(0.011)	(0.009)	(0.015)
Total	0.035	0.239***	0.204***
	(0.032)	(0.024)	(0.041)
Residual	0.053	0.033	0.001

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A5: RIF regressions coefficients

	1996						2002					
	Male			Female			Male			Female		
	10	50	90	10	50	90	10	50	90	10	50	90
Potential Experience	-0.003	0.017	-0.019	-0.000	0.024**	-0.001	0.013	0.039***	0.019	0.007	0.014	-0.007
	(0.026)	(0.012)	(0.021)	(0.018)	(0.011)	(0.020)	(0.017)	(0.010)	(0.014)	(0.014)	(0.009)	(0.015)
Potential Experience2	-0.000	-0.001**	0.000	0.000	-0.001***	-0.000	-0.001	-0.001***	-0.001*	-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)
Secondary education	0.419	0.220	-0.095	0.199	0.020	-0.388	0.011	0.184	0.360*	0.421	0.266*	0.022
	(0.470)	(0.199)	(0.315)	(0.406)	(0.196)	(0.339)	(0.353)	(0.190)	(0.214)	(0.393)	(0.159)	(0.258)
Vocational education	-0.149	-0.108	-0.209	0.276	-0.008	-0.497	-0.099	-0.020	0.136	0.491	0.220	-0.188
	(0.469)	(0.184)	(0.274)	(0.378)	(0.185)	(0.335)	(0.329)	(0.173)	(0.171)	(0.381)	(0.151)	(0.245)
Technical education	-0.150	0.105	-0.145	0.514	0.197	-0.262	0.312	0.168	0.237	0.520	0.311**	-0.111
	(0.486)	(0.199)	(0.311)	(0.375)	(0.191)	(0.341)	(0.328)	(0.182)	(0.196)	(0.381)	(0.155)	(0.250)
Universitary education	0.410	0.474**	-0.011	0.858**	0.356*	-0.239	0.344	0.329*	0.667***	0.755**	0.849***	0.292
	(0.493)	(0.204)	(0.341)	(0.388)	(0.205)	(0.367)	(0.329)	(0.190)	(0.229)	(0.384)	(0.161)	(0.267)
Legislators, Senior managers, officials	-0.653	0.049	0.183	-0.612	-0.007	0.222	-0.389**	-0.648***	-0.875	0.232	-0.163	0.468*
	(0.418)	(0.413)	(0.298)	(0.642)	(0.388)	(0.606)	(0.176)	(0.206)	(0.572)	(0.151)	(0.154)	(0.273)
Professionals	-0.777***	0.192	0.595***	-0.468***	0.158	0.188	-0.463***	-0.742***	-1.026*	0.029	0.080	0.108
	(0.270)	(0.377)	(0.204)	(0.164)	(0.135)	(0.205)	(0.151)	(0.189)	(0.550)	(0.147)	(0.107)	(0.152)
Technicians and Associate Professionals	-0.570**	0.302	0.921***	-0.478***	0.045	0.378**	-0.255**	-0.462**	-1.019*	-0.002	0.048	0.187
	(0.282)	(0.385)	(0.300)	(0.162)	(0.121)	(0.187)	(0.115)	(0.187)	(0.547)	(0.149)	(0.104)	(0.146)
Service and market workers	-0.376	0.066	0.051	-0.323*	0.004	0.107	-0.111	-0.818***	-1.082**	-0.265	-0.168	0.095
	(0.312)	(0.400)	(0.229)	(0.192)	(0.136)	(0.188)	(0.121)	(0.221)	(0.551)	(0.174)	(0.108)	(0.137)
Skilled agricultural and fishery workers	-2.837**	-0.544	0.796	-0.177	0.895***	-0.557***	-2.949***	-1.218***	-1.204**	-1.823	-1.250***	-0.455**
	(1.337)	(0.451)	(0.666)	(0.150)	(0.134)	(0.205)	(0.896)	(0.310)	(0.524)	(1.665)	(0.209)	(0.193)
Craft and related trades	-0.323*	0.201	0.395***	-0.251	0.385**	0.494	-0.287**	-0.630***	-0.711	0.174	-0.132	0.271
	(0.181)	(0.370)	(0.135)	(0.265)	(0.178)	(0.300)	(0.112)	(0.175)	(0.530)	(0.200)	(0.150)	(0.226)
Plant and machine operators and	-0.467**	0.227	0.655***	0.132	0.518***	0.539*	-0.520***	-0.765***	-0.737	-0.010	0.255*	0.147

assemblers												
	(0.210)	(0.372)	(0.174)	(0.178)	(0.169)	(0.295)	(0.124)	(0.174)	(0.526)	(0.197)	(0.131)	(0.170)
Unskilled occupations	-1.391***	-0.152	0.437**	-0.408*	0.033	0.140	-1.158***	-1.352***	-1.104**	-0.743***	-0.149	0.092
	(0.315)	(0.376)	(0.183)	(0.219)	(0.142)	(0.182)	(0.226)	(0.180)	(0.527)	(0.222)	(0.115)	(0.151)
Observations	746	746	746	928	928	928	1,043	1,043	1,043	1,284	1,284	1,284
R-squared	0.044	0.083	0.030	0.030	0.057	0.019	0.074	0.105	0.030	0.054	0.115	0.025

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5a (continued): RIF regressions coefficients

	2011					
	Male			Female		
	10	50	90	10	50	90
Potential Experience	0.019***	0.013***	0.005	0.009*	0.004	0.003
	(0.006)	(0.004)	(0.007)	(0.005)	(0.004)	(0.007)
Potential Experience2	-0.000***	-0.000***	-0.000	-0.000**	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Secondary education	0.284*	0.213***	0.062	0.167	-0.027	-0.093
	(0.145)	(0.081)	(0.100)	(0.146)	(0.095)	(0.130)
Vocational education	0.188	0.137*	0.160*	0.182	-0.079	-0.109
	(0.138)	(0.075)	(0.093)	(0.140)	(0.090)	(0.124)
Technical education	0.343**	0.263***	0.128	0.279**	-0.031	-0.171
	(0.139)	(0.079)	(0.101)	(0.137)	(0.090)	(0.126)
Universitary education	0.457***	0.376***	0.389***	0.395***	0.335***	0.327**
	(0.137)	(0.081)	(0.111)	(0.136)	(0.092)	(0.138)
Legislators, Senior managers, officials	-0.000	0.028	0.674***	0.188**	0.017	0.227
	(0.136)	(0.118)	(0.209)	(0.084)	(0.096)	(0.195)
Professionals	-0.008	0.039	0.803***	0.162***	0.013	0.230**
	(0.121)	(0.105)	(0.165)	(0.060)	(0.058)	(0.096)
Technicians and Associate Professionals	-0.064	-0.027	0.324**	0.054	0.015	0.249***
	(0.122)	(0.103)	(0.143)	(0.064)	(0.055)	(0.088)
Service and market workers	0.054	-0.367***	-0.037	-0.090	-0.248***	-0.184**
	(0.125)	(0.113)	(0.135)	(0.074)	(0.058)	(0.076)
Skilled agricultural and fishery workers	-0.270	-0.226	-0.094	0.297***	-0.275	0.558
	(0.412)	(0.227)	(0.120)	(0.065)	(0.353)	(0.763)
Craft and related trades	0.090	-0.029	0.196	0.253***	0.130	0.102
	(0.115)	(0.099)	(0.124)	(0.082)	(0.091)	(0.139)
Plant and machine operators and assemblers	-0.033	-0.127	0.193	0.181**	0.091	0.012
	(0.116)	(0.098)	(0.123)	(0.087)	(0.084)	(0.115)
Unskilled occupations	-0.659***	-0.534***	-0.070	-0.322***	-0.305***	-0.058

	(0.140)	(0.100)	(0.119)	(0.093)	(0.064)	(0.091)
Observations	2,512	2,512	2,512	2,972	2,972	2,972
R-squared	0.079	0.109	0.070	0.060	0.108	0.058

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1