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The Gender Wage Gap across the Wage Distribution in the Private and Public Sectors

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Abstract:

This study examines gender wage differentials across the wage distribution in the Swedish private and public sectors using quantile regression. Women have lower wages than men across the entire wage distribution. The gender gap increases throughout the distribution and there is a speeding-up effect in the gender gap starting around the 75th percentile, especially in the public sector. Hence, there is evidence of a glass ceiling effect in both the private and public sectors in the Swedish labor market. Using OLS leads to an overestimation of the wage gap at the bottom of the wage distribution, and an underestimation at the top. By focusing only on the mean gender wage gaps, considerable variations in the gender wage gap pass unnoticed.

Keywords: Quantile regression, counterfactual distribution, gender wage gap, sector

JEL Classification: J16, J31

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1. Introduction

This paper estimates private and public gender wage differentials across the whole wage distribution in the Swedish labor market. Investigating the gender wage gap across the entire wage distributions for both sectors may inform us more about the differences in the wages that men and women receive.

In 2006, the number of employed persons in the Swedish public sector had remained constant since 1997 at 1.5 million, and the number for the private sector was approximately 2.8 million. Consequently, the public sector comprised roughly one-third of the labor force in the Swedish labor market. In the same year, the public sector's contribution to GDP regarding consumption indicated that the Swedish public sector constituted 26 percent of GDP, a high figure compared to many other European countries.

Few previous studies have examined the gender wage gap across the whole wage distribution in the private and public sectors. Kee (2006) studied the gender wage gaps across the entire wage distributions in the public and private sectors in Australia, and found them both to be positive throughout. He also found that there is a strong glass ceiling effect in the private sector. Arulampalam *et al.* (2007) investigated the gender wage gap by sector across the wage distribution for eleven European countries, and found that it is generally higher at the top than at the bottom of the distributions, suggesting that a glass ceiling effect is more common than a sticky floor effect. The gender wage gap differs considerably across the public and the private sector wage distributions in each of the eleven countries. Miller (2008) studied the sector gender gap in the U.S. labor market, and found that women have lower hourly wages than men across the whole wage distribution and that there is a sticky floor effect in the government sector.

This study is based on the 2006 wave of the Swedish register-based data set LINDA. An interesting feature of this data set is the possibility of matching individual records with wage information and choice of working hours choice provided by employers. The hourly wage rates obtained in this fashion correspond to the workers' contracted wage and do not suffer from the potential measurement errors that are common in self-reported wages.

We estimate separate quantile regressions by sector and gender, and find considerable differences between the sectors and the genders in the coefficients of the explanatory variables at various percentiles of the respective wage distributions. Consequently, we carry out a decomposition analysis to decompose the differences between the male and female log wage distributions in the private and public sector into one component that is based on the difference in labor market characteristics between the genders, and one component that is based on the difference in rewards that the two genders receive for their labor market characteristics (the counterfactual distribution).

We find that women are disadvantaged across the entire wage distributions. Using OLS leads to an overestimation of the wage gap at the bottom of the wage distribution and an underestimation at the top, for both the private and public sectors. By focusing only on the mean gender wage gap, considerable variations of the gender wage gap are overlooked. The gender wage gap increases throughout the distribution and there is a speeding-up effect starting around the 75th percentile, suggesting a glass ceiling effect, for both sectors; women with high wages in the private and public sectors are more likely to be disadvantaged. This is especially pronounced for high-paid women in the public sector.

The paper is organized in the following way. Section 2 describes the data used in this paper. The empirical specification is presented in Section 3, and the results are presented in Section 4. A final section contains a summary of the paper.

2. Data

The data used in this paper is from the Swedish Longitudinal Individual Data (LINDA), administrated by Statistics Sweden. LINDA consists of a large panel of individuals and their household members, representative of the population from 1968 to 2006. The first wave took place in 1994 when 300,000 individuals were drawn, which corresponded to about three percent of the Swedish population. These individuals were followed back to 1968, but also forward, in order to create a panel that is updated annually. Each wave is a representative cross section of the population, since new individuals replace individuals who leave (divorce, die, or emigrate). The sample used in this study consists of information from the 2006 wave of LINDA. For more information about LINDA, see Edin and Fredriksson (2000).

An interesting feature of LINDA is the possibility of matching individual records with wage information provided by employers. Employers report monthly earnings to Statistics Sweden, expressed in full-time equivalents. To obtain hourly wage rates, the monthly earnings are divided by 165. The hourly wage rates obtained in this fashion correspond to the workers' contracted wage.

We limit the analysis to persons aged 18 to 64, excluding self-employed workers, students, and individuals with missing values on the observed characteristics, and end up with

46,392 males and 44,764 females. In total 7,822 men and 23,209 women work in the public sector, while 38,570 men and 21,555 women work in the private sector.

Explanatory variables used in the empirical analysis include information on: potential experience (i.e., age – education – 6), highest educational degree (high school, university), area of living (urban areas, medium-sized cities), two dummy variables for full-time work and ethnicity (i.e., native born), and local unemployment rate. Full-time work is defined as working 75 % or more of the workers' contracted full-time.

Table 1 presents descriptive statistics for the sample used in this paper, revealing that 52 percent of the women work in the public sector, while 17 percent of the men do. Private sector workers have higher wages, are more likely to work full-time, and are more concentrated in urban areas, while public sector workers are higher educated.

3. Empirical specification

We are interested in examining wage differentials across the wage distributions in the public and private sectors. This means that using ordinary least squares is not appropriate since it characterizes the wage distribution only at the mean of the distribution. Instead we choose the quantile regression method (see Koenker and Bassett, 1978; Buchinsky, 1998; Albrecht *et al.*, 2003; and Machado and Mata, 2005), which is a method for estimating the τ^{th} quantile of log wage conditional on some explanatory variables. It allows us to estimate the effect of some explanatory variables on a variable at the bottom, median, and top of the distribution.

The quantile regression model specifies the conditional quantile as a linear function of some control variables. Let y_i be the dependent variable and x_i a vector of explanatory variables. The relation is given by

$$y_i = x_i\beta(\tau) + \varepsilon_i \qquad \text{with} \qquad F_{\varepsilon}^{-1}(\tau \mid X) = 0 \tag{1}$$

where $F_{\varepsilon}^{-1}(\tau \mid x)$ denotes the τ^{th} quantile of ε conditional on x. Koenker and Basset (1978) estimated the τ^{th} regression quantile by solving

$$\hat{\beta}(\tau) = \arg\min_{\beta \in \mathbb{R}^K} \sum_{i=1}^{N} \rho_\tau\left(y_i - x_i'\beta\right)$$

where ρ_τ is the check function, $\rho_\tau = z\left(\tau - 1(z \leq 0)\right)$, and $1(\cdot)$ is the indicator function. Estimation by quantile regression gives us an indication of whether returns to observable characteristics differ by sector and gender, and of how these differences change as we move across the wage distribution.

Once we have estimated the parameters of the quantile regression model, we will be interested in decomposing the difference between the male and female log wage distributions into one component that is based on the difference in labor market characteristics between the genders, and one component that is based on the difference in rewards that the two genders receive for their labor market characteristics (the counterfactual distribution). Melly (2006) proposed a procedure to decompose differences at different quantiles of the unconditional distribution. First the conditional distribution is estimated by quantile regression. Then the conditional distribution of log wages is integrated over the range of the explanatory variables. Let $\hat{\beta} = \left(\hat{\beta}(\tau_1), \ldots.., \hat{\beta}(\tau_j), \ldots..., \hat{\beta}(\tau_J)\right)$ be the quantile regression parameters estimated at J

different quantiles $0 < \tau_j < 1$, j = 1, ……., J. Integrating over all quantiles and over all observations, an estimator of the θ^{th} unconditional quantile of log wage is given by

$$q\left(\theta, x, \beta\right) = \inf\left\{q : \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{J}\left(\tau_j - \tau_{j-1}\right)1\left(x_i\hat{\beta}\left(\tau_j\right) \leq q\right) \geq \theta\right\} \tag{2}$$

where $1(\cdot)$ is the indicator function. Now we can estimate the counterfactual distribution by replacing either the estimated parameters of the distribution of characteristics for men with the estimated parameters or the distribution of characteristics for women. Thus, we can separate the difference at each quantile of the unconditional distribution into one component that is based on differences in the rewards that the two genders receive for their labor market characteristics and one that is based on differences in labor market characteristics between the genders.

$$\begin{aligned} &q\left(\theta, x^f, \beta^f\right) - q\left(\theta, x^m, \beta^m\right) \\ &= \left[q\left(\theta, x^f, \beta^f\right) - q\left(\theta, x^f, \beta^m\right)\right] + \left[q\left(\theta, x^f, \beta^m\right) - q\left(\theta, x^m, \beta^m\right)\right] \end{aligned} \tag{3}$$

where f = female, m = male, the first brackets represent the differences in the rewards that the two genders receive for their labor market characteristics (the counterfactual distribution), and the second brackets represent the effect of differences in labor market characteristics between genders. This can be seen as undertaking an Oaxaca-Blinder type of decomposition across the distribution. Complete details of this approach and its statistical properties can be found in Melly (2006), who also showed that the method is numerically identical to the Machado and Mata (2005) method of estimating counterfactual wage distributions when the number of simulations in the Machado and Mata (2005) method goes to infinity.

We use Stata 10 to estimate the coefficients of the quantile regression model, and the decomposition is done using the Stata command rqdeco.do, see Melly (2007). We estimate 100 quantile regressions in the first step, and estimate the standard errors by bootstrapping the results 100 times (due to the computational burden).

4. Results

Figure 1 shows the raw gender gaps at each percentile of the wage distribution by sector. Thus, for example, at the 40^{th} percentile, there is a gender wage gap in the private and public sector of about 10 percent. That is, the log wage of a woman in the public (private) sector at the 40^{th} percentile of the female public (private) wage distribution is about 10 log points below that of a man in the public (private) sector at the 40^{th} percentile of the public (private) male wage distribution.

The important feature of this figure is that the gender wage gaps in the public and private sectors are close to each other at the bottom of the wage distribution. Then there is a steady increase as we move up in the distribution (more so for the public sector than for the private sector). Public and private wages are unequal for men and women, up to a maximum log wage differential of about 0.22 at the top of the distribution in the private sector and about 0.42 in the public sector. The increase in the public sector gender wage gap speeds up around the 75^{th} percentile. The situation where the wage gap is wider at the top of the wage distribution is known as a glass ceiling. It implies a barrier to further advancement once a woman has attained a certain level. Hence, it seems that there could be a glass ceiling for women in the public sector. We do not see the same pattern for men and women in the private sector, even if the observed private sector gender wage gap increases slightly as we move up in the distribution.

To examine the effects of differences in characteristics on the gender wage gap across the distribution, quantile regressions on the pooled dataset with a dummy variable for gender were computed. These pooled quantile regressions impose the restriction that the returns to included labor market characteristics are the same for males and females. The estimated gender dummy parameter in these regressions shows how much of the gender wage gap that remains unexplained at the various quantiles when we control for observable characteristics.

Table 2 presents the estimated gender dummy coefficients by sector at the 10th, 25th, 50th, 75th, and 90th percentile of the pooled quantile regression. As a comparison, the least squares gender dummy parameter is also presented. Rows 1 and 4 show the observed gender gap without any covariates. These estimated gender dummy parameters are identical to the raw gender gaps in Figure 1. As we saw in Figure 1, the gender wage gap increases steadily as we move up the wage distribution, and then increases rapidly after the 75th percentile, especially in the public sector.

Rows 2 and 5 in Table 2 show that controlling for basic control variables does not account for much of the wage gaps. However, by controlling for basic covariates we decrease the effect of gender at the 90th percentile in the public sector. This suggests that gender differences in characteristics explain a considerable part of the possible glass ceiling effect for those workers. To study the effect of gender differences in occupation, we use occupational dummies at the one digit level. The results are given in Rows 3 and 6 of Table 2. The unexplained gender gap falls to 14.4 percent and 16.1 percent at the 90th percentile and to 6.8 percent and 1.8 percent at the 10th

percentile, for the private and public sector, respectively (compared to 18.9 percent, 23.0 percent, 8.5 percent, and 2.9 percent in Rows 2 and 4 of Table 2). Hence, incorporating occupation decreases the gender gap considerably throughout the wage distribution in both sectors.

Tables 3 and 4 present quantile log wage regressions by sector for men, and Tables 5 and 6 present them by sector for women. The tables show the extent to which returns to observable characteristics differ among individuals in the sectors and between the genders. It relaxes the assumption of equal coefficients for males and females presented in Table 2.

The returns to a university education differ among the percentiles, and men have a higher pay-off than women. Men in the public sector with a university degree in the 10^{th} percentile on average earn 35 percent more per hour than a man with only compulsory schooling, while a man with a university education in the 90^{th} percentile on average earns 108 percent more per hour than a man with compulsory school as his highest educational attainment (see Halvorsen and Palmquist, 1980, for an interpretation of dummy variables in semi logarithmic equations). The corresponding figures for women are 29 percent and 52 percent, respectively. The returns to full-time work are lower for men and women in the public sector. A woman working full-time in the public sector at the 50^{th} percentile on average earns 2 percent more per hour than a woman who works part-time in the same sector at the same percentile, and a woman at the 50^{th} percentile working full time in the private sector earns an average of 7.5 percent more per hour than a woman working part-time in the same sector at the same percentile. These figures are 6.6 percent and 13.9 percent, respectively, for men. The immigrant effect is stronger in the private sector than in the public sector. A native-born man in the 90^{th} percentile on average earns 20 percent more per hour than a foreign-born man, while the wage differential in the public sector is only 3.7 percent at that percentile.

The results in Tables 3, 4, 5, and 6 clearly show that the returns to observable characteristics are different for men and women, which means that the results in Table 2 could be misleading. Therefore, the remaining analysis will examine the gender wage gap across the whole wage distribution and decompose the difference between the male and female log wage distributions into one component that is based on the difference in labor market characteristics between the genders, and one that is based on the difference in rewards that the two genders receive for their labor market characteristics (the counterfactual distribution).

The results from the counterfactual decomposition are presented in Table 7. The estimated least squares and observed gender gaps are also shown for comparison. The estimated gender wage gaps, with 95 percent confidence intervals, are presented for each quantile of the distribution in Figures 2-5. Rows 1 and 4 in Table 7 present the observed gender gaps, Rows 2 and 5 show the decomposition with basic control variables, and Rows 3 and 5 show the decomposition with basic control variables and occupation dummies included. The reason we present results with and without occupation dummies is that occupational attainment may be endogenous.

Women are disadvantaged across both wage distributions. All estimates are significantly different from zero at the 1 percent significance level. A negative gender wage gap means that the market returns for women are lower than for men. Using OLS leads to an overestimation of the wage gap at the bottom of the wage distribution, and an underestimation at the top, for both the private and the public sectors. By focusing only on the mean gender wage gap, substantial variations of the gender wage gap pass unnoticed. The gender gap increases throughout the distribution, and there is a speeding-up effect starting around the 75th percentile, in both sectors.

Arulampalam *et al.* (2007) suggested that a glass ceiling exists if the 90th percentile gender wage gap is higher than the 75th percentile part-time wage gap by at least 2 log points. Thus, the results in Table 7 is evidence of a glass ceiling, meaning that women with high wages are more likely to be disadvantaged. While this is true for both sectors, it is especially pronounced in the public sector.

It is interesting to compare the results from Table 2 and Table 7. Table 2 shows the gender gaps adjusting for differences in labor market characteristics assuming that men and women obtain equal rewards for these characteristics. The remarkable difference between Table 2 and Table 7 is at the top of the distribution, for both the private and public sectors. While Table 2 implies that differences in characteristics explain a considerable part of the gender gap at the top of the distribution, Table 7 reveals the exact opposite. In Table 7, when we control for basic covariates, the gender gap increases throughout the entire distribution. This suggests that it is not obviously gender differences in the basic control variables that explain the gender wage gap at the top of the distribution. Rather, it is differences in rewards that women obtain for these characteristics. Hence, the glass ceiling effect is due to differences in returns between the genders at the top of the distribution.

Rows 3 and 6 of Table 7 show that even after controlling for occupation there is a considerable increase in the gender gap across the distribution, suggesting that we have a glass ceiling effect, both in the private and public sectors. This is even clearer in Figures 3 and 5 where the speeding-up effect after the 75th percentile is still clear even after controlling for occupation.

Kee (2006) analyzed the gender wage gap in the private and public sectors in Australia, and found it to be positive across the whole distribution in both sectors. However, a glass ceiling effect was only found in the private sector. The gender wage gap across the wage distribution in the private sector is similar in Sweden and Australia. On the other hand, the estimated wage gap in the Swedish public sector is lower at the bottom of the distribution and much higher at the top compared to the public sector gender wage gap in Australia. Thus, it seems that Swedish women in the public sector are relatively better off at the bottom of the distribution, while women in the Australian public sector are relatively better off at the top. Miller (2008) found that in the U.S. labor market, women have lower wages than men across the entire earnings distribution, both in the private and government sectors. However, he did not find evidence of a glass ceiling effect in the U.S. labor market. The private sector gender wage differential is higher across the entire U.S. distribution compared to in Sweden. Thus, women working in the Swedish private sector are relatively better off than women working in the U.S. private sector. However, women at the top of the wage distribution in the Swedish public sector are relatively worse off than women at the top of the distribution in the U.S. government sector; the Swedish gender wage gap is about 27 percent at the 90th percentile, while it is only about 15 percent in the U.S. government sector. Arulampalam *et al.* (2007) showed that Finland was the only country among the eleven analyzed European countries that had a gender wage gap across the entire wage distribution in the public sector that was similar to in Sweden (they investigated Austria, Belgium, Britain, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, and Spain). All other countries in their study had a lower gender wage gap across the whole distribution in the public sector. However, in the private sector the gender wage gap across the wage distribution in Sweden is similar or a little lower than that in all eleven investigated European countries. Thus, the gender wage differentials across the whole distribution are lower in the private sector in Sweden in comparison to the U.S. labor market and most of the eleven European countries in Arulampalam *et al.* (2007), while the gender wage gap in the public sector is higher in Sweden across the entire distribution than in the public sector in Australia, in most of the eleven European countries in Arulampalam *et al.* (2007), and in the U.S. government sector.

5. Conclusions

In this paper, we have examined the gender wage differentials across the wage distribution in the Swedish private and public sectors. The study is based on the 2006 wave of the Swedish register-based data set LINDA. An interesting feature of this data set is the possibility of matching individual records with wage information and choice of working hours provided by employers. The hourly wage rates obtained in this fashion correspond to the workers' contracted wage and do not suffer from the potential measurement errors that are common in self-reported wages.

We estimate separate quantile regressions by sector and gender, and find considerable differences between the parameters in the public and private sectors and for men and women at various percentiles in the public and private distributions. Consequently, we carry out a decomposition analysis to decompose the differences in the public-private wage gap across the whole wage distribution into one component that is based on the difference in labor market characteristics between the genders, and one component that is based on the difference in rewards that the two genders receive for their labor market characteristics.

The gender wage differentials across the whole distribution in the private sector are lower in Sweden than in the U.S. and in eleven European countries, while the opposite can be said about the public sector; here the gap is higher across the entire distribution in Sweden compared to the U.S. government sector and the public sector in eleven European countries and in Australia.

We found that there is a glass ceiling effect for women both in the private and public sectors in Sweden. Albrecht *et al.* (2003) also found a glass ceiling for women in Sweden. They did not, however, distinguish between the public and private sectors, as we have done. As we have shown, it is the women in the public sector that could be the main contributor to the glass ceiling effect that was found by Albrecht *et al.* (2003).

Given the existence of the considerable glass ceiling effect for public sector women in Sweden, it is tempting to reflect on probable causes. If we look in Tables 3-6, we can see that returns to work experience are more or less constant across the wage distribution for women in the public sector, while returns to potential work experience begin to increase dramatically at the 75^{th} percentile for men in the private and public sector, and women in the private sector. Thus, the experience-wage profiles for women in the private sector, and men in the private and public sectors, are steeper than the experience-wage profile for women in the public sector. Sweden has generous maternity/parental leave policies and heavily subsidized public day-care, which together give strong incentives for women to enter the labor force but not to make a career. This result is consistent with the hypothesis that some women choose to work in the public sector where the penalty for work interruptions is low; see for instance Polachek (1981), Polachek (1985), Polachek (2006), and Hansen and Wahlberg (2008).

Another reason may be that Swedish women ask for low wages. Säve-Söderbergh (2007) analyzed individual wage bargaining of university graduates who had at least three years of university education, and found that gender differences exist in both wage bargaining and bargaining outcomes; i.e., women ask for lower wages and receive lower counter offers from employers. Today, Sweden has individual wage negotiations also in the public sector. Perhaps unions should offer their members courses in wage negotiation, or perhaps there should even be wage negotiation courses offered at the university level targeted at women.

References

Albrecht, J., Björklund, A., and Vroman S. (2003). “Is There a Glass Ceiling in Sweden?”, *Journal of Labor Economics* 21: 145–77.

Arulampalam W., Booth, A., and Bryan M. (2007). “Is There a Glass Ceiling over Europe? Exploring the Gender Pay Gap across the Wages Distribution”, *Industrial and Labor Relations Review* 60: 163–186.

Buchinsky, M. (1998). “Recent Advances in Quantile Regression Models: A Practical Guideline for Empirical Research”, *Journal of Human Resources* 33: 88-126.

Edin, P-A. and Fredriksson, P. (2000). “LINDA – Longitudinal Individual Data for Sweden”, Working Paper 2000:19, Uppsala University.

Halvorsen, R., and Palmquist, R. (1980). “The Interpretation of Dummy Variables in Semilogarithmic Equations”, *American Economic Review* 70: 474-475.

Hansen, J. and Wahlberg, R. (2008). “Occupational Gender Composition and Wages in Sweden”, *Research in Labor Economics* 28: 355-371.

Kee, H.J. (2006). “Glass Ceiling or Sticky Floor? Exploring the Australian Gender Pay Gap”, *The Economic Record* 82: 408–427.

Koenker, R. and Bassett, G. (1978). “Regression Quantiles”, *Econometrica* 46: 33-50.

Machado, J. and Mata, J. (2005). “Counterfactual Decomposition of Changes in Wage Distributions using Quantile Regression”, *Journal of Applied Econometrics* 20: 445–465.

Melly, B. (2006). “Estimation of Counterfactual Distributions using Quantile Regression”, m*imeo*, University of St. Gallen, http://www.alexandria.unisg.ch/Publikationen/22644

Melly, B. (2007). “Rqdeco: A Stata Module to Decompose Differences in Distribution”, m*imeo*, University of St. Gallen, http://www.alexandria.unisg.ch/Publikationen/40161

Miller, P. (2008). “The Gender Pay Gap in the US: Does Sector Make a Difference?”, *Journal of Labor Research*, forthcoming.

Polachek, S. (1981). “Occupational Self-Selection: A Human Capital Approach to Sex Differences in the Occupational Structure”, *Review of Economics and Statistics* 63: 60-69.

Polachek, S. (1985). “Occupational Segregation: A Defense of Human Capital Predictions”, *Journal of Human Resources* 20: 437-40.

Polachek, S. (2006). “How the Human Capital Model Explains Why the Gender Gap Narrowed”, F. Blau, M. Brinton, and D. Grusky, (eds.) The Declining Significance of Gender?, New York: Russell Sage Foundation.

Säve-Söderbergh, J. (2007). “Are Women Asking for Low Wages? An Empirical Analysis of Individual Wage Bargaining and Ability Signaling”, mimeo, Swedish Institute for Social Research, Stockholm.

Table 1

Sample Means

	Men			Women		
Variable	*All*	*Public Sector*	*Private Sector*	*All*	*Public Sector*	*Private Sector*
Public sector	0.17	---	---	0.52	---	---
ln(wage)	5.06	5.03	5.07	4.92	4.89	4.94
	(0.33)	(0.31)	(0.33)	(0.25)	(0.21)	(0.28)
Experience	21.53	22.32	21.36	21.51	22.88	20.02
	(11.89)	(12.21)	(11.82)	(12.02)	(11.92)	(11.96)
Compulsory school	0.16	0.07	0.17	0.11	0.08	0.14
High school	0.68	0.55	0.70	0.65	0.61	0.69
University	0.17	0.38	0.13	0.24	0.31	0.17
Living in urban areas	0.34	0.32	0.35	0.36	0.29	0.44
Living in medium-sized cities	0.40	0.45	0.39	0.39	0.43	0.34
Living on the countryside	0.26	0.23	0.26	0.25	0.28	0.22
Working full time	0.95	0.90	0.96	0.78	0.75	0.82
Native	0.90	0.89	0.90	0.89	0.89	0.88
Local unemployment rate	3.93	4.05	3.91	3.44	3.47	3.42
	(1.16)	(1.10)	(1.16)	(0.92)	(0.87)	(0.96)
Number of observations	46,392	7,822	38,570	44,764	23,209	21,555

Note: Standard deviations in parentheses.

Table 2

Estimated Gender Dummy Coefficients by Sector

	Private sector					
	OLS	10th	25th	50th	75th	90th
(1) Observed gender gap	-0.123*** (0.003)	-0.093*** (0.003)	-0.093*** (0.002)	-0.106*** (0.003)	-0.137*** (0.005)	-0.194*** (0.007)
(2) Gender gap with basic control variables	-0.136*** (0.002)	-0.085*** (0.003)	-0.099*** (0.002)	-0.122*** (0.002)	-0.153*** (0.003)	-0.189*** (0.006)
(3) Gender gap with basic control variables and occupation	-0.116*** (0.002)	-0.068*** (0.002)	-0.089*** (0.002)	-0.105*** (0.002)	-0.127*** (0.003)	-0.144*** (0.004)
	Public sector					
	OLS	10th	25th	50th	75th	90^{th}
(4) Observed gender gap	-0.142*** (0.004)	-0.030*** (0.004)	-0.068*** (0.004)	-0.125*** (0.004)	-0.177*** (0.006)	-0.313*** (0.011)
(5) Gender gap with basic control variables	-0.128*** (0.003)	-0.029*** (0.004)	-0.063** (0.003)	-0.114*** (0.003)	-0.178*** (0.005)	-0.230*** (0.008)
(6) Gender gap with basic control variables and occupation	-0.100*** (0.003)	-0.018*** (0.004)	-0.042*** (0.003)	-0.078*** (0.003)	-0.136*** (0.004)	-0.161*** (0.006)

Note: OLS = Ordinary Least Squares. Standard errors are given in parentheses; robust standard errors presented for OLS coefficients and quantile regression standard errors are obtained by bootstrapping (1000 repetitions). *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 3

Quantile Regression of Private Sector Men (Percentiles)

Variable	**OLS**	**10th**	**25th**	**50th**	**75th**	**90th**
Constant	4.435***	4.336***	4.409***	4.470***	4.511***	4.602***
	(0.011)	(0.015)	(0.010)	(0.010)	(0.015)	(0.026)
Experience	0.019***	0.012***	0.013***	0.016***	0.020***	0.026***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience Squared/100	-0.030***	-0.020***	-0.022***	-0.025***	-0.031***	-0.040***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
High school	0.122***	0.049***	0.067***	0.095***	0.153***	0.216***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.008)
University	0.504***	0.302***	0.392***	0.494***	0.582***	0.675***
	(0.006)	(0.009)	(0.007)	(0.008)	(0.010)	(0.015)
Urban areas	0.139***	0.049***	0.071***	0.121***	0.188***	0.236***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.006)	(0.009)
Medium-sized cities	0.028***	0.017***	0.014**	0.024***	0.030***	0.044***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.008)
Full time	0.137***	0.134***	0.124***	0.130***	0.127***	0.095***
	(0.008)	(0.011)	(0.007)	(0.007)	(0.009)	(0.021)
Native	0.160***	0.146***	0.130***	0.134***	0.156***	0.182***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.010)
Unemployment	-0.019***	-0.015***	-0.013***	-0.014***	-0.016***	-0.023***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)

Note: OLS = ordinary least squares. Standard errors are given in parentheses; robust standard errors presented for OLS coefficients and the quantile regression standard errors are obtained by bootstrapping (1000 repetitions). *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively. Results based on a sample of 38,570.

Table 4

Quantile Regression of Public Sector Men (Percentiles)

Variable	**OLS**	**10th**	**25th**	**50th**	**75th**	**90th**
Constant	4.418***	4.334***	4.403***	4.451***	4.505***	4.550***
	(0.020)	(0.025)	(0.021)	(0.023)	(0.025)	(0.038)
Experience	0.018***	0.011***	0.012***	0.016***	0.019***	0.026***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Experience Squared/100	-0.028***	-0.019***	-0.018***	-0.024***	-0.029***	-0.037***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
High school	0.157***	0.099***	0.109***	0.154***	0.194***	0.223***
	(0.008)	(0.012)	(0.009)	(0.012)	(0.012)	(0.020)
University	0.473***	0.328***	0.332***	0.391***	0.555***	0.731***
	(0.010)	(0.013)	(0.010)	(0.013)	(0.016)	(0.021)
Urban areas	0.077***	0.044***	0.059***	0.082***	0.092***	(0.094***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)	(0.015)
Medium-sized cities	0.039***	0.020**	0.020***	0.034***	0.031***	0.065***
	(0.007)	(0.008)	(0.007)	(0.009)	(0.010)	(0.016)
Full time	0.068***	0.080***	0.065***	0.064***	0.065***	0.048***
	(0.010)	(0.012)	(0.011)	(0.011)	(0.013)	(0.019)
Native	0.076***	0.101***	0.099***	0.087***	0.072***	0.036*
	(0.011)	(0.011)	(0.012)	(0.012)	(0.017)	(0.020)
Unemployment	-0.013***	-0.016***	-0.014***	-0.016***	-0.015***	-0.007
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.005)

Note: OLS = ordinary least squares. Standard errors are given in parentheses; robust standard errors presented for OLS coefficients and the quantile regression standard errors are obtained by bootstrapping (1000 repetitions). *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively. Results based on a sample of 7,822.

Table 5

Quantile Regression of Private Sector Women (Percentiles)

Variable	**OLS**	**10th**	**25th**	**50th**	**75th**	**90th**
Constant	4.487***	4.373***	4.416***	4.497***	4.575***	4.647***
	(0.012)	(0.013)	(0.011)	(0.011)	(0.017)	(0.025)
Experience	0.013***	0.009***	0.010***	0.011***	0.014***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience Squared/100	-0.022***	-0.013***	-0.015***	-0.018***	-0.023***	-0.030***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
High school	0.096***	0.057***	0.069***	0.087***	0.110***	0.145***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.010)
University	0.382***	0.237***	0.301***	0.366***	0.443***	0.513***
	(0.007)	(0.008)	(0.006)	(0.007)	(0.009)	(0.017)
Urban areas	0.128***	0.056***	0.078***	0.114***	0.163***	0.209***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)	(0.012)
Medium-sized cities	0.013***	0.005	0.008**	0.008*	0.021***	0.017*
	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.009)
Full time	0.080***	0.065***	0.071***	0.072***	0.080***	0.093***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.010)
Native	0.116***	0.102***	0.106***	0.111***	0.112***	0.107***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.010)	(0.014)
Unemployment	-0.015***	-0.011***	-0.011***	-0.013***	-0.014***	-0.012**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)

Note: OLS = ordinary least squares. Standard errors are given in parentheses; robust standard errors presented for OLS coefficients and the quantile regression standard errors are obtained by bootstrapping (1000 repetitions). *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively. Results based on a sample of 21,555.

Table 6

Quantile Regression of Public Sector Women (Percentiles)

Variable	**OLS**	**10th**	**25th**	**50th**	**75th**	**90th**
Constant	4.513***	4.395***	4.428***	4.518***	4.606***	4.679***
	(0.008)	(0.009)	(0.009)	(0.008)	(0.012)	(0.020)
Experience	0.011***	0.008***	0.010***	0.010***	0.010***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience Squared/100	-0.017***	-0.011***	-0.016***	-0.015***	-0.015***	-0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
High school	0.105***	0.068***	0.081***	0.099***	0.117***	0.139***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.009)
University	0.333***	0.258***	0.290***	0.305***	0.327***	0.417***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.012)
Urban areas	0.062***	0.031***	0.036***	0.052***	0.074***	0.104***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.009)
Medium-sized cities	0.020***	0.011***	0.009***	0.013***	0.024***	0.031***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)
Full-time	0.033***	0.035***	0.027***	0.020***	0.025***	0.037***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)
Native	0.048***	0.079***	0.060***	0.053***	0.041***	0.030***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.007)	(0.009)
Unemployment	-0.009***	-0.008***	-0.005***	-0.007***	-0.010***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)

Note: OLS = ordinary least squares. Standard errors are given in parentheses; robust standard errors presented for OLS coefficients and the quantile regression standard errors are obtained by bootstrapping (1000 repetitions). *, **, *** denote significance at the 10, 5 and 1 percent levels, respectively. Results based on sample of 23,209.

Table 7

Estimated Wage Gaps by Sector

	OLS	10th	25th	50th	75th	90th
Private Sector						
(1) Raw	-0.123***	-0.093***	-0.093***	-0.106***	-0.137***	-0.194***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.005)	(0.007)
(2) Decomposition with basic control variables	-0.133***	-0.061***	-0.086***	-0.117***	-0.174***	-0.225***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.006)
(3) Decomposition with basic control variables and occupational dummies	-0.133***	-0.037***	-0.057***	-0.089***	-0.148***	-0.187***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)
Public Sector						
(4) Raw	-0.142***	-0.030***	-0.068***	-0.125***	-0.177***	-0.313***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.011)
(5) Decomposition with basic control variables	-0.085***	-0.017***	-0.061***	-0.110***	-0.165***	-0.270***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.005)	(0.008)
(6) Decomposition with basic control variables and occupational dummies	-0.109***	0.013***	-0.030***	-0.076***	-0.124***	-0.227***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)	(0.007)

Note: Standard errors are given in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Figure 1

Raw Gender Gaps

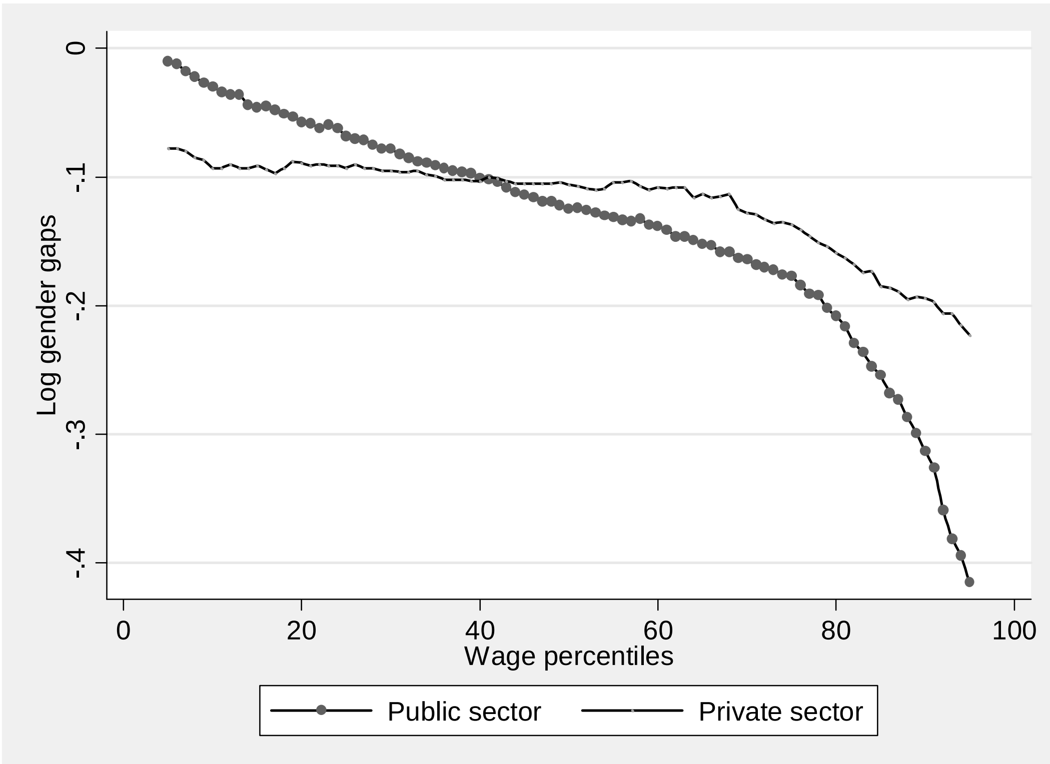

Figure 2

Gender Wage Gap in the Private Sector

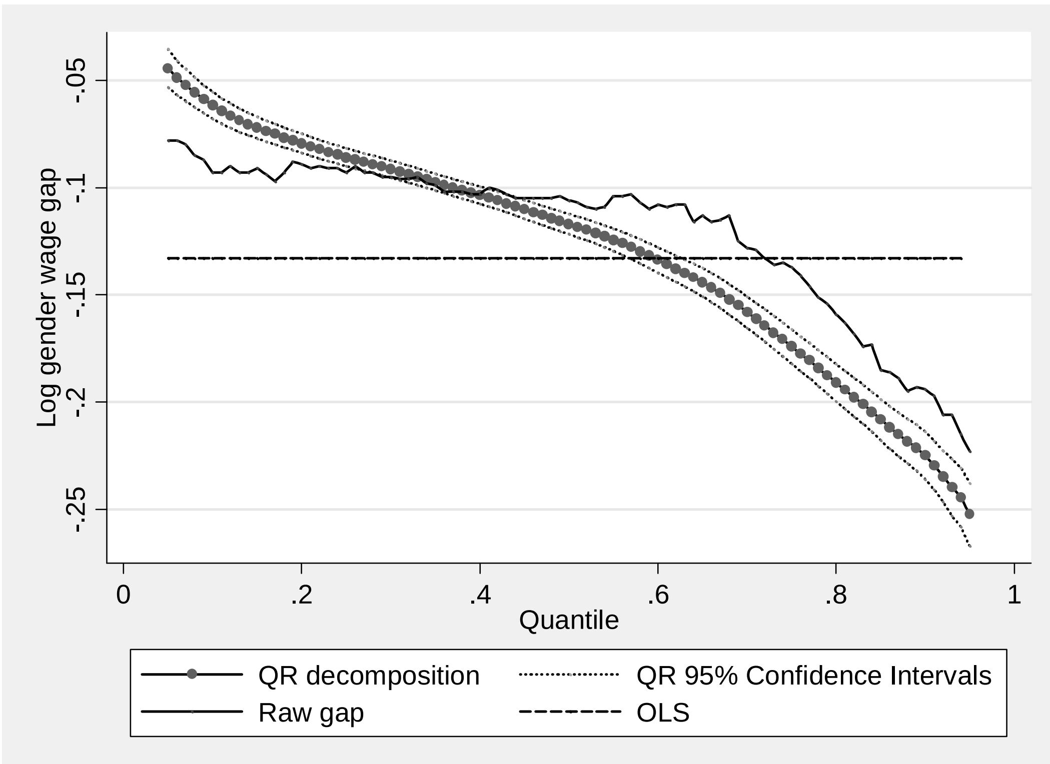

Figure 3

Gender Wage Gap in the Private Sector, occupational dummies included

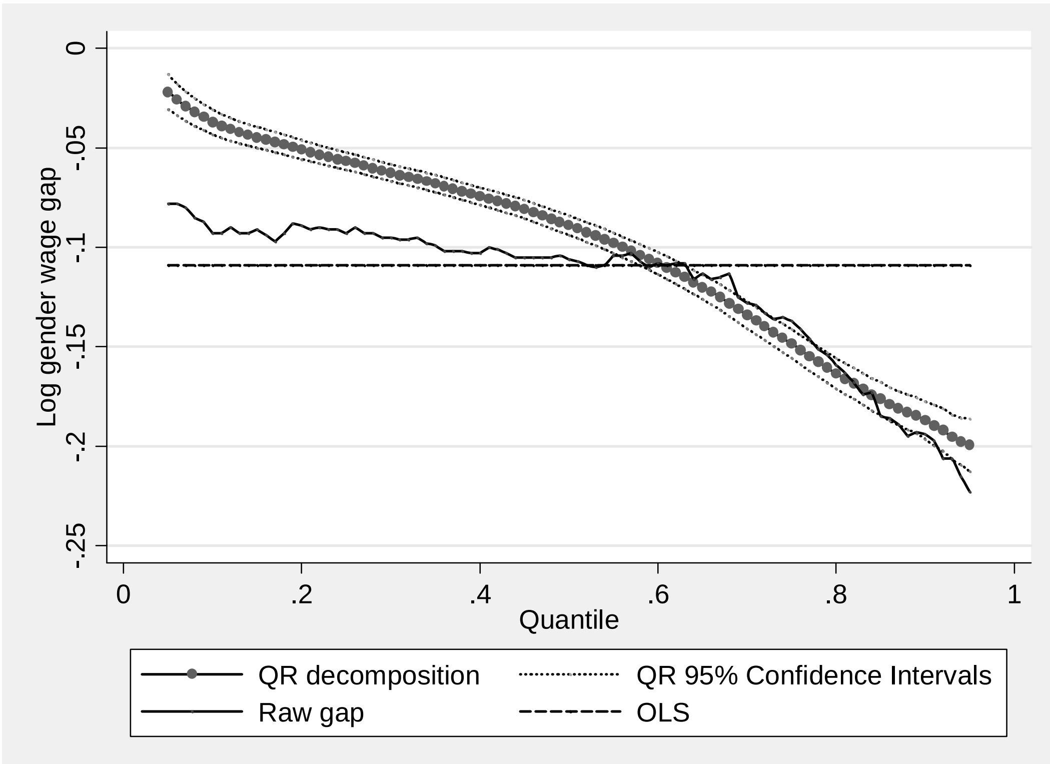

Figure 4

Gender Wage Gap in the Public Sector

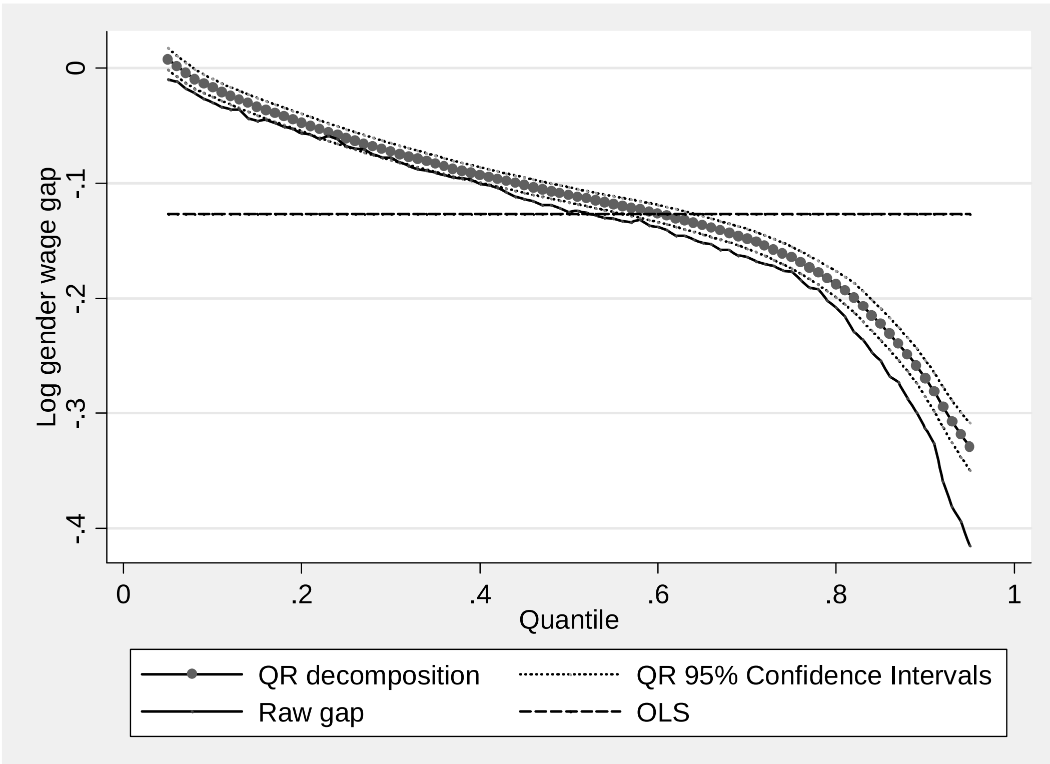

Figure 5

Gender Wage Gap in the Public Sector, occupational dummies included