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Roger Wahlberg

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SCHOOL OF BUSINESS, ECONOMICS AND LAW, UNIVERSITY OF GOTHENBURG

Department of Economics
Visiting adress Vasagatan 1,
Postal adress P.O.Box 640, SE 405 30 Göteborg, Sweden
Phone + 46 (0)31 786 0000

Differences in Wage Distributions between Natives, Non-Refugees, and Refugees

Roger Wahlberg[1]

University of Gothenburg and IZA

Abstract:

This study examines differences in wage distributions between natives, non-refugees, and refugees in Sweden. We find that the wage differentials between natives and non-refugee immigrants decrease across the distribution, while those between natives and refugee immigrants increase. There is evidence of a glass ceiling effect for refugee males in Sweden, and we also find evidence of a glass ceiling effect for native-born women and non-refugee women in the Swedish labor market in comparison with native-born and non-refugee men, respectively. In addition, there is evidence of a double disadvantage effect for refugee women in the Swedish labor market.

Keywords: Wage distribution, quantile regression, counterfactual distribution, natives, non-refugees, refugees.

JEL Classification: J15, J31

[1] Corresponding author: Roger Wahlberg, University of Gothenburg, Department of Economics, Box 640, SE-405 30 Gothenburg, Sweden. E-mail: roger.wahlberg@economics.gu.se. Financial support from the Jan Wallander and Tom Hedelius Foundation for Research in Economics is gratefully acknowledged.

1. Introduction

Between World War II and the 1970s, labor immigrants dominated the Swedish immigration activity. This changed in the 1980s when the focus shifted to refugee immigration. From 1986 to 2003 about 400,000 immigrants, generally refugees from the Balkan countries and Asia, arrived in Sweden. In 2006, 12.9 percent of the Swedish populations were foreign born.

Most labor market research on immigrants in Sweden has looked at how immigrants assimilate into the Swedish labor force and the problems they face when entering the labor market. Edin *et al.* (2000) found that while immigrants' well-being improves over time in Sweden relative to the native population, their yearly earnings never catch up. Rooth (2002) found that adoptees who look "non-Swedish" have a lower probability of being employed than those who look "Swedish." Hammarstedt (2003) showed that immigrants have lower yearly earnings than natives, and that recently arrived immigrants have considerably lower yearly earnings than immigrant cohorts with a longer history in Sweden. Åslund and Rooth (2006) investigated the long-term effects on immigrant annual income and found that having a longer history in the Swedish labor market affects future achievement. Rooth and Åslund (2007) found that education and good command of the Swedish language have a significant effect on the likelihood of being employed.

Few previous studies focus on wage differentials across the wage distributions of natives and immigrants. Albrecht *et al.* (2003) found the immigrant wage gap in Sweden to be more or less constant at about 10 percent over the entire wage distribution. Chiswick *et al.* (2008) found for the U.S. labor market that male immigrants from English-speaking countries have higher log hourly earnings than native-born males over most of the wage distribution. Male immigrants from non-English-speaking countries have lower wages than native-born males over almost the whole earnings distribution (by up to 18 percent at the 50th percentile of the wage distribution). They found no indications of sticky floor or glass ceiling effects for immigrant males in the U.S. labor market. Le and Miller (2008) examined the variation in the gender pay gap across the earnings distribution in the United States. They found that females are disadvantaged across the entire wage distribution. However, they did not find any evidence of glass ceiling effects. Immigrant females from non-English-speaking countries experience a double disadvantage in the U.S. labor market; i.e., they receive lower wages both because they are women and because they are immigrants.

Against this background, our aim is to examine differences in wage distributions between natives, non-refugee, and refugee immigrants in Sweden. We will first analyze these differences separately for women and men, investigating the ethnicity effect. We will then investigate the gender effect; i.e., we will study the differences in wage distributions between men and women, by ethnicity. Finally, we are going to investigate the possibility of a double disadvantage effect in Sweden; i.e., whether refugee immigrant women are disadvantaged in the Swedish labor market and receive lower wages both because they are women and because they are refugee immigrants.

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 working hour's choice provided by employers.

We estimate separate quantile regressions by ethnicity and gender, and find considerable differences between ethnicity and gender in the coefficients at various percentiles of the distributions. Consequently, we carry out a decomposition analysis to decompose the differences in the native-immigrant wage gap and the gender-ethnicity wage gap across the whole wage distribution.

Our results show that there is evidence of a glass ceiling effect for refugee men in Sweden compared to native-born men. We also find evidence of a glass ceiling effect for native-born and non-refugee women in comparison to native-born and non-refugee men, respectively. This is contrary to the results found for the U.S. labor market in Chiswick *et al.* (2008) and Le and Miller (2008), where there is no evidence of glass ceiling effects. Furthermore, we find that refugee women in the Swedish labor market experience a double disadvantage, i.e., refugee women receive lower wages both because they are women and because they are refugee immigrants. This was also found by Le and Miller (2008) for immigrant females from non-English-speaking countries in the U.S. labor market.

The paper is organized as follows. Section 2 presents the data used in this paper. The empirical specification is presented in Section 3, while the results are presented in Section 4. The final section contains a summary of the paper.

2. Data

The data used in this paper is taken from a Swedish register-based data set, Longitudinal Individual Data (LINDA). LINDA contains a three-percent representative random sample of the Swedish population, corresponding to approximately 300,000 individuals each year. The sampled population consists of all individuals, including children and elderly persons, who lived in Sweden in a particular year. The sampling procedure used in constructing the panel data set ensures that each cross section is representative of the population in each year. The sample used in this study consists of information from the 2006 wave of LINDA. For a more detailed description of LINDA, see Edin and Fredriksson (2000).

An interesting feature of this data set 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 and do not suffer from the potential measurement errors that are common in self-reported wages.

We limit the analysis to sampled persons aged 18 to 64, excluding self-employed workers, students, and individuals with missing values on observed characteristics. After these selections we end up with 41,682 native males, 2,710 non-refugee males, 2,540 refugee males, 39,759 native females, 2,611 non-refugee females, and 2,394 refugee females.

A person is defined as an immigrant if he/she was born abroad, and as a refugee immigrant if he/she was born in a refugee country, as defined by the Swedish Migration Board. LINDA does not provide any information about refugee status. However, by using the countries defined by the Swedish Migration Board as refugee countries (which vary over time) along with information on country of birth as well as time of arrival in Sweden, we can obtain an approximate measure of refugee status.

Explanatory variables used in the empirical analysis include information on: potential experience (i.e., age – education – 6), highest educational degree (high school, university), region of residence (urban areas, medium-sized cities), working full time, marital status (i.e.

married), and local unemployment rate. Full-time work is defined as working 75 % or more of the workers' contracted full time, and the local unemployment rates are tabulated for each municipality (there are 290 municipalities in Sweden), gender, and age group.

Table 1 presents descriptive statistics for the sample used in this paper, revealing that natives have higher hourly wages, immigrants are more concentrated in urban areas, and refugee immigrants have less education.

Figures 1 and 2 show the observed native-refugee and native-non-refugee wage gaps at each percentile of the wage distribution, for men and women respectively. Thus, for example, we have a male native-refugee wage gap of about 17 percent at the 50th percentile. That is, the log wage of a male refugee immigrant at the 50th percentile of the male refugee immigrant wage distribution is about 17 points below that of a native-born man at the 50th percentile of the native-born male wage distribution.

The important feature of these figures is that the native-refugee wage gap, for both men and women, is more or less constant at the bottom of the wage distribution. Then there is a steady increase as we move up in the distribution (more so for men than for women).

The situation where the native-immigrant wage gap is typically wider at the top of the wage distribution is known as a glass ceiling effect. It is seen as a barrier to further advancement once the immigrant worker has attained a certain level. In contrast, a sticky floor effect is the opposite situation; then the native-immigrant wage gap is the widest at the bottom of the wage distribution.

Native and refugee wages are very unequal for men up to a maximum log wage differential of about 0.34 at the 90th percentile. The increase in the native-refugee wage gap speeds up for men at about the 60th percentile. Hence, it seems that there could be a glass ceiling effect for refugee men compared to native men in the Swedish labor market. We do not see the same pattern for women in Figure 2, even if the observed native-refugee wage gap increases slightly as we move up in their wage distribution.

The pattern is the reverse for the size of the native-non-refugee wage gap. There is a steady decrease as we move up in the wage distribution, especially for women. The decreasing trend in the native-non-refugee wage gap accelerates for women around the 75th percentile. At the 10th percentile the female native-non-refugee wage gap is about 6 percent in favor of natives, while at the 90th percentile it is 3 percent in favor of the immigrants. Hence, it seems that there could be a sticky floor effect for non-refugee women in the Swedish labor market.

Figures 3 and 4 show kernel density estimates of the wage distributions of natives, non-refugees, and refugees, for men and women respectively. It can be seen that the refugee wage distribution is characterized by a lower mean, a higher density function around the mean, and a lower dispersion, for both men and women.

Figure 5 presents the observed gender wage gaps by ethnicity. The wage differential between native-born men and native-born women is similar to the one between non-refugee men and non-refugee women; it is rather stable up to the 60th percentile and then begins to accelerate. Thus, it seems that there could be a glass ceiling effect for native-born and non-refugee women compared to native-born men and non-refugee men, respectively.

We do not see the same pattern for the refugee gender wage gap, even if it does increase slightly as we move up in the wage distribution. As seen in Figure 1, refugee men have much lower wages than native-born men, and Figure 5 shows that refugee women have lower wages across the whole wage distribution than refugee men. This could indicate that refugee women encounter a double disadvantage effect in the Swedish labor market.

Figure 6 shows kernel density estimates of the wage distributions of natives, non-refugees, and refugees by gender. Overall, women are characterized by a lower mean, a higher density function around the mean, and a lower dispersion.

3. Empirical specification

We are interested in analyzing wage differentials across the wage distributions of natives, non-refugees, and refugees. 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 θ^{th} quantile of a variable conditional on some covariates. It allows us to estimate the effect of some control variables on a variable at the bottom of the distribution, at the median, and at the top of the distribution.

Let us assume that (y_i, x_i), $i = 1,\ldots, n$ is a sample of the population, y_i is the dependent variable, and x_i is the k by 1 vector of explanatory variables, for the θ^{th} quantile of y_i conditional on the explanatory variable vector x_i. The relation is given by

$$y_i = x_i\beta(\theta) + \varepsilon(\theta)_i \quad \text{with} \quad q_\theta(y_i / x_i) = x_i\beta(\theta) \qquad (1)$$

where $q_\theta\left(y_i/x_i\right)$ refers to the conditional quantile of *y*, conditional on the vector of the explanatory variables *x*, for $\theta \in (0,1)$. It is assumed that $q_\theta\left(y_i/x_i\right)$ = 0. The θ^{th} conditional quantile regression estimator for β(θ) is obtained by

$$\min_{\beta(\theta)}\left\{\sum_{(i:y_i \geq x_i\beta(\theta))} \theta\left|y_i - x_i\beta(\theta)\right| + \sum_{(i:y_i \leq x_i\beta(\theta))} (1-\theta)\left|y_i - x_i\beta(\theta)\right|\right\} \qquad (2)$$

In other words, β(θ) is chosen to minimize the weighted sum of the absolute value of the residuals.

Once we have estimated the coefficients of the quantile regression model, we are interested in decomposing the native-immigrant differences in log wage distributions into one component that is based on differences in characteristics and one component that is based on differences in coefficients (a measure of discrimination) across the wage distribution. We use an approach developed by Melly (2006). In the first step, the distribution of log wages conditional on the covariates is estimated using linear quantile regression. The conditional distribution of log wages is then integrated over the control variables to obtain the unconditional distribution. Let $\hat{\beta} = \left(\hat{\beta}(\theta_1), \hat{\beta}(\theta_2), \ldots\ldots, \hat{\beta}(\theta_J)\right)$ be the quantile regression parameters estimated at *J* different quantiles 0 < θ_j < 1, *j* = 1, 2, …, *J*. Integrating over all quantiles and over all observations, an estimator of the θ^{th} unconditional quantile of the independent variable is given by

$$q(\theta, X, \beta) = \inf\left\{q : \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{J}\left(\theta_j - \theta_{j-1}\right)1\left(x_i\hat{\beta}\left(\theta_j\right) \leq q\right) \geq \theta\right\} \qquad (3)$$

where $1(\cdot)$ is the indicator function.

Now we can estimate the counterfactual distribution by replacing either the estimated parameters or the distribution of characteristics for natives with the estimated parameters or the distribution of characteristics for foreign-born. It is thus possible to split the difference at each quantile of the unconditional distribution into one component that is based on differences in the rewards that the two groups receive for their labor market characteristics and one component that is based on differences in labor market characteristics between the two groups:

$$\begin{aligned} & q(\theta, X^f, \beta^f) - q(\theta, X^n, \beta^n) = \\ & \left[q(\theta, X^f, \beta^f) - q(\theta, X^f, \beta^n) \right] + \left[q(\theta, X^f, \beta^n) - q(\theta, X^n, \beta^n) \right] \end{aligned} \tag{4}$$

where f = foreign born, n = native born, the first bracket represents the differences in the rewards that the two groups receive for their labor market characteristics (the counterfactual distribution), and the second bracket represents the effect of differences in labor market characteristics between the two groups. This can be considered a generalization of the Oaxaca-Blinder decomposition of the mean. A more complete description of this method and its statistical properties can be found in Melly (2006), who show that the method is numerically identical to the Machado and Mata (2005) method of estimating counterfactual unconditional 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 of differences in distributions is done using the Stata command rqdeco.ado; 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

Tables 2, 3, and 4 present quantile wage regressions by ethnicity for men, and Tables 5, 6, and 7 present them by ethnicity for women. The tables show the extent to which returns to observable characteristics differ between natives, non-refugees, and refugees for men and women separately. The returns to a university education differ among the percentiles, and men have a higher payoff than women. Non-refugee men in the 10th percentile on average earn 59 percent more per hour than non-refugee men with compulsory school as their highest educational attainment, while non-refugee men with a university education in the 90th percentile on average earn 113 percent more per hour than non-refugee men with compulsory school as their highest educational attainment (see Halvorsen and Palmquist, 1980, for an interpretation of dummy variables in semi logarithmic equations). The corresponding figures for non-refugee women are 40 percent and 72 percent, respectively. The full-time premium is similar for native and refugee men, while non-refugee men have a higher payoff. A full-time working non-refugee man in the 50th percentile earns on average 17.4 percent more per hour than a part-time non-refugee man. Native women and non-refugee women have more or less the same full-time premium, while refugee women have a low or no full-time premium. A native woman in the 90th percentile working full time earns on average 10.4 percent more per hour than a part-time counterpart. The corresponding figure for refugee women is 2.2 percent (not significantly different from zero).

Tables 2, 3, 4, 5, 6, and 7 clearly indicate that the returns to observable characteristics are different for natives, non-refugees, and refugees for both men and women. Now we will look at the native-immigrant wage gap across the whole wage distribution and the wage gap that is due to differences in the rewards that the two groups receive for their labor market characteristics.

Figures 7 to 10 show the counterfactual wage gaps and a 95% confidence interval. The raw and the OLS wage gaps (the unexplained difference) are also shown.

Figure 7 shows the differences in wage distribution between native and non-refugee men. The wage gap is more or less constant until it begins to decrease at the 80th percentile. This indicates that a possible sticky floor effect is due to differences in rewards at the bottom of the wage distribution. The estimated wage gap across the distribution is rather close to that using OLS. However, using OLS leads to an underestimation of the gap at the 80th and higher percentiles of the wage distribution. The native-non-refugee wage gap in Sweden shows the same pattern as that between native and English-speaking foreign-born men in the U.S. labor market; see Chiswick *et al.* (2008). However, English-speaking foreign-born men are relatively better off in the U.S. labor market than non-refugee men in the Swedish labor market.

Figure 8 illustrates the differences in wage distributions between native and refugee men. The estimated wage gap rises across the distribution, which could be evidence of a glass ceiling effect for refugee men in the Swedish labor market. More exactly, the estimated wage gap is stable up to around the 30th percentile, where it begins to increase. Thus, even after correcting for the effect of characteristics, there is a speeding up effect in the native-refugee wage gap starting around the 30th percentile in the wage distribution. This indicates that the glass ceiling effect is due to differences in rewards for the characteristics across the native-refugees distribution at the top of the wage distribution rather than to differences in characteristics. By using OLS we overestimate the wage gap up to the 50th percentile and underestimate it thereafter. Chiswick *et al.* (2008) found that non-English-speaking foreign-born men have up to 18 percent lower wages than native-born men in the U.S. labor market at the 50th percentile. Thus, when comparing the two groups, it seems that refugee men in the Swedish labor market are relatively better off toward the bottom of the wage distribution, while non-English-speaking foreign-born men in the U.S. labor market are relatively better off toward the top of the wage distribution.

In Figure 9 we investigate the native-non-refugee wage gap for women. It decreases throughout the distribution and is close to the OLS curve. The wider gap toward the bottom of the wage distribution could indicate that there is a sticky floor for non-refugee women in the Swedish labor market. Starting at the 80th percentile there is a sharp acceleration in the decrease of the wage gap, indicating that the possible sticky floor effect is due to differences in rewards at the bottom of the wage distribution.

Figure 10 shows the differences in wage distribution between native and refugee women. The counterfactual ethnicity wage gap demonstrates that the native-refugee wage gap rises across the distribution. Up to the 50th percentile the gap is smaller than the OLS estimate, and after the 50th percentile the OLS ends up underestimating the difference. The widening gap toward the top of the wage distribution could indicate that there is a glass ceiling effect for refugee women in the Swedish labor market. There is also a speeding up effect in the gap starting around the 40th percentile, indicating that the possible glass ceiling effect is due to differences in rewards for the characteristics at the top part of the wage distribution.

Figure 11 illustrates the gender wage gap across the whole wage distribution, by ethnicity. As can be seen, native and non-refugee women experience similar wage gaps throughout the distribution. The speeding up effect that starts around the 60th percentile for these two groups indicates that a potential glass ceiling effect is due to differences in rewards for the gender-related characteristics at the top of the wage distribution rather than to differences in characteristics between natives and non-refugees. The gender wage gap for natives is similar to what Albrecht *et al.* (2003) found for Sweden using data from 1998. Le and Miller (2008) found the native-born gender wage gap in the U.S. labor market to be stable around 28 percent throughout the wage distribution up to the 90th percentile. Hence, it seems that native women in the Swedish labor market are relatively better off than native-born women in the U.S. labor market. The gender wage gap for non-refugee immigrants in Sweden is rather stable throughout the whole wage distribution, although there is speeding up effect at the 80th percentile. A similar pattern was found by Le and Miller (2008) for the U.S. labor market, a rather stable wage gap between men and women from non-English-speaking countries up to the 90th percentile and then a rapid increase. Even if the patterns for refugees in Sweden and persons from non-English-speaking countries in the U.S. are similar, the U.S. gender wage gap is about 20 percent up to the 90th percentile, while the Swedish refugee gender wage gap is more or less stable at about 8 percent up to the 80th percentile. Thus, refugee women in Sweden are relatively better off than women from non-English-speaking countries in the U.S. labor market.

Figures 7 and 8, together with Figure 11, indicate that refugee women in Sweden experience a double disadvantage effect; i.e., they are disadvantaged in the Swedish labor market and receive lower wages both because they are women and because they are refugee immigrants. Similarly, Le and Miller (2008) found that immigrant women from non-English-speaking countries encounter a double disadvantage effect in the U.S. labor market. Figure 12 shows the wage differential across the whole wage distribution between native-born men and native-born women, non-refugee women, and refugee women respectively. Together with Figures 7 and 11, it clearly shows evidence of a double disadvantage effect for refugee women in the Swedish labor market.

We find indications of a glass ceiling effect for refugee immigrants and a possible sticky floor effect for non-refugee immigrants, for both males and females. There are also indications of a gender-related glass ceiling effect regardless of ethnicity. To be more confident of our result, we would like to perform a more formal test. Arulampalam *et al.* (2007) suggested that a glass ceiling exists if the 90th percentile wage gap is higher than the 75th percentile gap by at least 2 points, and that there is a sticky floor if the 10th percentile wage gap is higher than the 25th percentile wage gap by at least 2 points. When evaluating our material using these criteria, we find evidence of a glass ceiling effect for refugee men in Sweden compared to native men, but not of a sticky floor for refugee and non-refugee immigrants. We also find evidence of a glass ceiling effect for native women, non-refugee women, and refugee women in the Swedish labor market compared to native men, non-refugee men, and refugee men respectively. This is contrary to the results found for the U.S. labor market in Chiswick *et al.* (2008) and Le and Miller (2008), where no evidence of any glass ceiling effects were found.

5. Conclusions

In this paper, we have examined differences in wage distributions between natives, non-refugees, and refugees in Sweden. Our study is based on the 2006 wave of the Swedish register-based data set LINDA. An interesting feature of LINDA is the possibility of matching individual records with wage information and working hour’s choice provided by employers. The hourly wage rates obtained in this fashion correspond to the workers' contracted wages and do not suffer from the potential measurement errors that are common in self-reported wages.

We estimated separate quantile regressions by ethnicity and gender, and found considerable gender and ethnicity-related differences in the coefficients at various percentiles of the native, refugee, and non-refugee wage distributions. Consequently, we carried out a decomposition analysis to decompose the differences in the various native-immigrant wage gaps across the wage distribution.

We found that the wage differentials between natives and non-refugee immigrants decrease throughout the distribution, while those between natives and refugee immigrants increase. There is evidence of a glass ceiling effect for refugee men in Sweden. These results are in contrast to Albrecht *et al.* (2003) who found a constant immigrant-non-immigrant wage gap of about 10 points across the whole wage distribution. However, they did not distinguish between refugee and non-refugee immigrants. We also found evidence of a glass ceiling effect for native-born women and non-refugee women in the Swedish labor market compared to native-born men and non-refugee men respectively. This is in contrast with the result found for the U.S. labor market in Chiswick *et al.* (2008) and Le and Miller (2008), where no evidence of any glass ceiling effects in the U.S. labor market was found. Finally, we also found evidence of a double disadvantage effect for refugee women in the Swedish labor market.

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Table 1

Descriptive statistics, means

	Men			Women		
Variable	*Native*	*Non-refugee*	*Refugee*	*Native*	*Non-refugee*	*Refugee*
ln(wage)	5.07	5.02	4.88	4.92	4.89	4.81
	(0.33)	(0.35)	(0.27)	(0.25)	(0.28)	(0.23)
Experience	21.60	21.98	19.84	21.64	21.16	19.67
	(11.99)	(11.46)	(10.34)	(12.19)	(10.92)	(10.12)
Compulsory school	0.15	0.23	0.23	0.10	0.18	0.21
High school	0.69	0.54	0.61	0.66	0.54	0.59
University	0.16	0.23	0.16	0.24	0.28	0.20
Living in urban areas	0.32	0.51	0.55	0.34	0.53	0.55
Living in medium-sized cities	0.41	0.29	0.30	0.39	0.29	0.29
Living on the countryside	0.27	0.20	0.15	0.26	0.18	0.16
Working full time	0.96	0.93	0.88	0.72	0.78	0.77
Married	0.58	0.57	0.67	0.62	0.57	0.65
Local unemployment rate	3.93	3.89	4.02	3.44	3.38	3.53
	(1.16)	(1.09)	(1.06)	(0.92)	(0.87)	(0.83)
Number of observations	41,682	2,170	2,540	39,759	2,611	2,394

Table 2

OLS and quantile regression estimates, native men

Variable	**OLS**	**0.1**	**0.25**	**0.50**	**0.75**	**0.9**
Constant	4.561***	4.473***	4.535***	4.585***	4.622***	4.710***
	(0.010)	(0.012)	(0.008)	(0.010)	(0.014)	(0.021)
Experience	0.017***	0.010***	0.011***	0.014***	0.018***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience Squared/100	-0.028***	-0.017***	-0.019***	-0.024***	-0.029***	-0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
High school	0.113***	0.048***	0.063***	0.091***	0.142***	0.197***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.007)
University	0.429***	0.258***	0.305***	0.405***	0.513***	0.595***
	(0.005)	(0.006)	(0.005)	(0.007)	(0.008)	(0.011)
Urban areas	0.152***	0.059***	0.086***	0.139***	0.193***	(0.242***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.009)
Medium-sized cities	0.031***	0.016***	0.016***	0.024***	0.032***	0.038***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.007)
Full time	0.125***	0.117***	0.110***	0.117***	0.122***	0.088***
	(0.007)	(0.009)	(0.006)	(0.007)	(0.009)	(0.017)
Married	0.091***	0.061***	0.062***	0.070***	0.097***	0.131***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)
Local Unemployment	-0.016***	-0.014***	-0.012***	-0.013***	-0.011***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)

Note: Standard errors are given in parentheses; robust standard errors presented for OLS coefficients and the quantile regression standard errors are obtained by bootstrapping (1,000 repetitions). *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively. Results based on sample of 41,682.

Table 3

OLS and quantile regression estimates, non-refugee men

Variable	OLS	0.1	0.25	0.50	0.75	0.9
Constant	4.529***	4.386***	4.494***	4.560***	4.655***	4.721***
	(0.045)	(0.050)	(0.045)	(0.049)	(0.054)	(0.095)
Experience	0.015***	0.008***	0.012***	0.016***	0.017***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Experience Squared/100	-0.023***	-0.010**	-0.018***	-0.025***	-0.025***	-0.033***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.006)	(0.009)
High school	0.102***	0.034*	0.035**	0.058***	0.130***	0.247***
	(0.013)	(0.018)	(0.015)	(0.012)	(0.019)	(0.030)
University	0.464***	0.218***	0.268***	0.449***	0.619***	0.758***
	(0.022)	(0.026)	(0.026)	(0.029)	(0.032)	(0.042)
Urban areas	0.054***	0.016	0.006	0.038***	0.081***	0.111***
	(0.017)	(0.022)	(0.018)	(0.015)	(0.023)	(0.037)
Medium-sized cities	0.021	0.010	0.001	0.000	0.027	0.030
	(0.019)	(0.024)	(0.019)	(0.018)	(0.026)	(0.042)
Full time	0.198***	0.171***	0.158***	0.160***	0.156***	0.162***
	(0.023)	(0.036)	(0.026)	(0.029)	(0.036)	(0.055)
Married	0.052***	0.046***	0.034**	0.050***	0.045**	0.047*
	(0.013)	(0.017)	(0.014)	(0.013)	(0.018)	(0.028)
Local Unemployment	-0.026***	-0.016***	-0.018***	-0.023***	-0.032***	-0.036***
	(0.007)	(0.006)	(0.006)	(0.007)	(0.008)	(0.012)

Note: Standard errors are given in parentheses; robust standard errors presented for OLS coefficients and the quantile regression standard errors are obtained by bootstrapping (1,000 repetitions). *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively. Results based on sample of 2,170.

Table 4

OLS and quantile regression estimates, refugee men

Variable	**OLS**	**0.1**	**0.25**	**0.50**	**0.75**	**0.9**
Constant	4.589***	4.421***	4.515***	4.632***	4.691***	4.709***
	(0.028)	(0.014)	(0.034)	(0.030)	(0.035)	(0.045)
Experience	0.006***	0.006**	0.004**	0.005**	0.005**	0.008***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Experience Squared/100	-0.011***	-0.012**	-0.008**	-0.010**	-0.011**	-0.014**
	(0.004)	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)
High school	0.104***	0.096***	0.087***	0.094***	0.093***	0.124***
	(0.009)	(0.014)	(0.012)	(0.011)	(0.013)	(0.014)
University	0.364***	0.182***	0.196***	0.292***	0.488***	0.694***
	(0.020)	(0.024)	(0.023)	(0.022)	(0.035)	(0.039)
Urban areas	0.058***	-0.002	0.020	0.047***	0.049***	0.124***
	(0.013)	(0.017)	(0.015)	(0.005)	(0.016)	(0.021)
Medium-sized cities	0.013	-0.007	0.003	0.021	0.001	0.037
	(0.013)	(0.019)	(0.015)	(0.014)	(0.016)	(0.024)
Full time	0.117***	0.080***	0.103***	0.094***	0.094***	0.104***
	(0.013)	(0.015)	(0.017)	(0.016)	(0.015)	(0.023)
Married	0.036***	0.031**	0.019*	0.027**	0.053***	0.047**
	(0.010)	(0.013)	(0.011)	(0.011)	(0.014)	(0.019)
Local Unemployment	-0.014***	-0.012*	-0.009*	-0.015***	-0.004	-0.008
	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)	(0.008)

Note: Standard errors are given in parentheses; robust standard errors presented for OLS coefficients and the quantile regression standard errors are obtained by bootstrapping (1,000 repetitions). *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively. Results based on sample of 2,540.

Table 5

OLS and quantile regression estimates, native women

Variable	OLS	0.1	0.25	0.50	0.75	0.9
Constant	4.590***	4.454***	4.505***	4.591***	4.695***	4.727***
	(0.007)	(0.008)	(0.006)	(0.007)	(0.010)	(0.017)
Experience	0.011***	0.009***	0.010***	0.010***	0.010***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience Squared/100	-0.019***	-0.013***	-0.016***	-0.016***	-0.018***	-0.026***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
High school	0.083***	0.065***	0.068***	0.078***	0.085***	0.106***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.008)
University	0.302***	0.253***	0.267***	0.275***	0.300***	0.386***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)	(0.011)
Urban areas	0.126***	0.048***	0.066***	0.106***	0.168***	0.230***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.005)	(0.008)
Medium-sized cities	0.018***	0.010***	0.008***	0.013***	0.024***	0.027***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.006)
Full time	0.068***	0.045***	0.048***	0.050***	0.069***	0.099***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.006)
Married	0.023***	0.015***	0.013***	0.017***	0.026***	0.029***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.006)
Local Unemployment	-0.011***	-0.006***	-0.006***	-0.008***	-0.014***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)

Note: Standard errors are given in parentheses; robust standard errors presented for OLS coefficients and the quantile regression standard errors are obtained by bootstrapping (1,000 repetitions). *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively. Results based on sample of 39,759.

Table 6

OLS and quantile regression estimates, non-refugee women

Variable	OLS	0.1	0.25	0.50	0.75	0.9
Constant	4.635***	4.477***	4.416***	4.653***	4.733***	4.796***
	(0.030)	(0.036)	(0.022)	(0.029)	(0.043)	(0.068)
Experience	0.008***	0.002	0.005***	0.005***	0.009***	0.012***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.004)
Experience Squared/100	-0.011***	-0.003	-0.004	-0.006**	-0.015***	-0.021***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.005)	(0.008)
High school	0.102***	0.059***	0.091***	0.086***	0.102***	0.150***
	(0.010)	(0.011)	(0.008)	(0.011)	(0.016)	(0.025)
University	0.340***	0.182***	0.275***	0.306***	0.372***	0.544***
	(0.015)	(0.017)	(0.013)	(0.013)	(0.028)	(0.045)
Urban areas	0.064***	0.016	0.029***	0.044***	0.095***	0.080**
	(0.012)	(0.012)	(0.009)	(0.011)	(0.017)	(0.033)
Medium-sized cities	0.030**	0.000	0.010	0.006	0.038**	0.021
	(0.013)	(0.013)	(0.010)	(0.013)	(0.017)	(0.039)
Full time	0.079***	0.067***	0.064***	0.052***	0.076***	0.109***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.014)	(0.028)
Married	0.024**	0.012	0.017**	0.030***	0.023*	0.043*
	(0.010)	(0.010)	(0.007)	(0.009)	(0.013)	(0.025)
Local Unemployment	-0.033***	-0.017**	-0.018***	-0.026***	-0.038***	-0.040**
	(0.006)	(0.007)	(0.004)	(0.005)	(0.007)	(0.017)

Note: Standard errors are given in parentheses; robust standard errors presented for OLS coefficients and the quantile regression standard errors are obtained by bootstrapping (1,000 repetitions). *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively. Results based on sample of 2,611.

Table 7

OLS and quantile regression estimates, refugee women

Variable	OLS	0.1	0.25	0.50	0.75	0.9
Constant	4.676***	4.541***	4.637***	4.695***	4.773***	4.840***
	(0.027)	(0.025)	(0.024)	(0.026)	(0.039)	(0.062)
Experience	0.002*	0.002	0.001	0.002	0.001	0.002
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.004)
Experience Squared/100	-0.000	-0.001	0.001	-0.001	0.002	-0.002
	(0.003)	(0.005)	(0.003)	(0.004)	(0.004)	(0.009)
High school	0.101***	0.054***	0.063***	0.092***	0.106***	0.135***
	(0.008)	(0.001)	(0.008)	(0.008)	(0.013)	(0.019)
University	0.343***	0.206***	0.240***	0.288***	0.388***	0.554***
	(0.015)	(0.015)	(0.011)	(0.013)	(0.029)	(0.042)
Urban areas	0.047***	0.005	-0.002	0.022**	0.057***	0.106***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.016)	(0.025)
Medium-sized cities	0.014	-0.003	-0.007	0.010	0.006	0.031
	(0.011)	(0.013)	(0.012)	(0.011)	(0.016)	(0.021)
Full time	0.028***	0.028***	0.034***	0.027***	0.018	0.022
	(0.009)	(0.009)	(0.009)	(0.009)	(0.014)	(0.021)
Married	-0.006	-0.010	-0.008	-0.005	-0.012	-0.007
	(0.009)	(0.009)	(0.008)	(0.009)	(0.012)	(0.019)
Local Unemployment	-0.025***	-0.020***	-0.027***	-0.031***	-0.021***	-0.023***
	(0.005)	(0.004)	(0.004)	(0.006)	(0.007)	(0.011)

Note: Standard errors are given in parentheses; robust standard errors presented for OLS coefficients and the quantile regression standard errors are obtained by bootstrapping (1,000 repetitions). *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively. Results based on sample of 2,394.

Figure 1

Raw Wage Gaps between Natives-Non-refugees and Natives-Refugees, Men

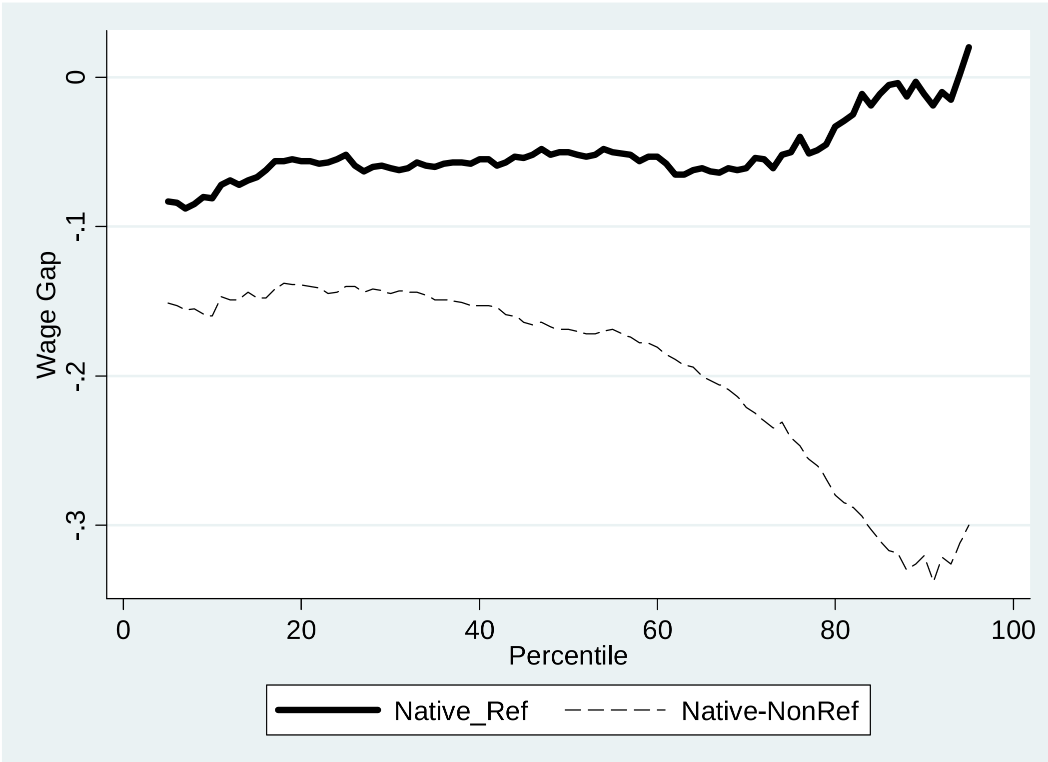


Figure 2

Raw Wage Gaps between Natives-Non-refugees and Natives-Refugees, Women

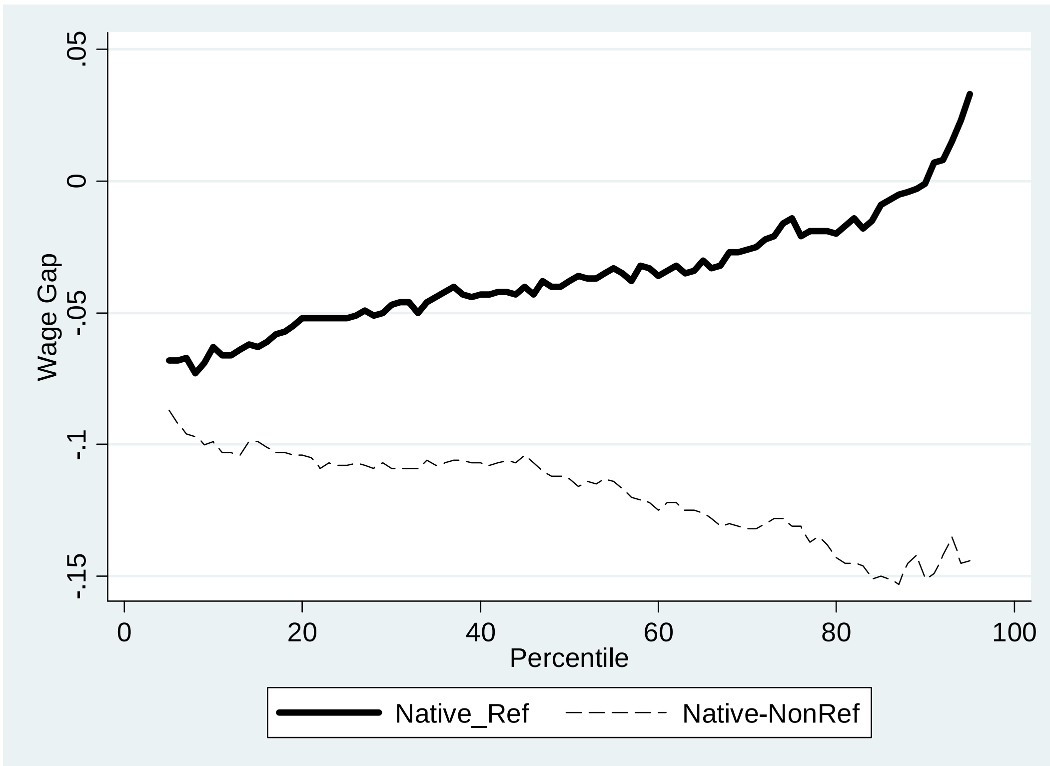


Figure 3

Kernel Density Estimates of the Wage Distributions of Natives, Non-refugees, and Refugees, Men

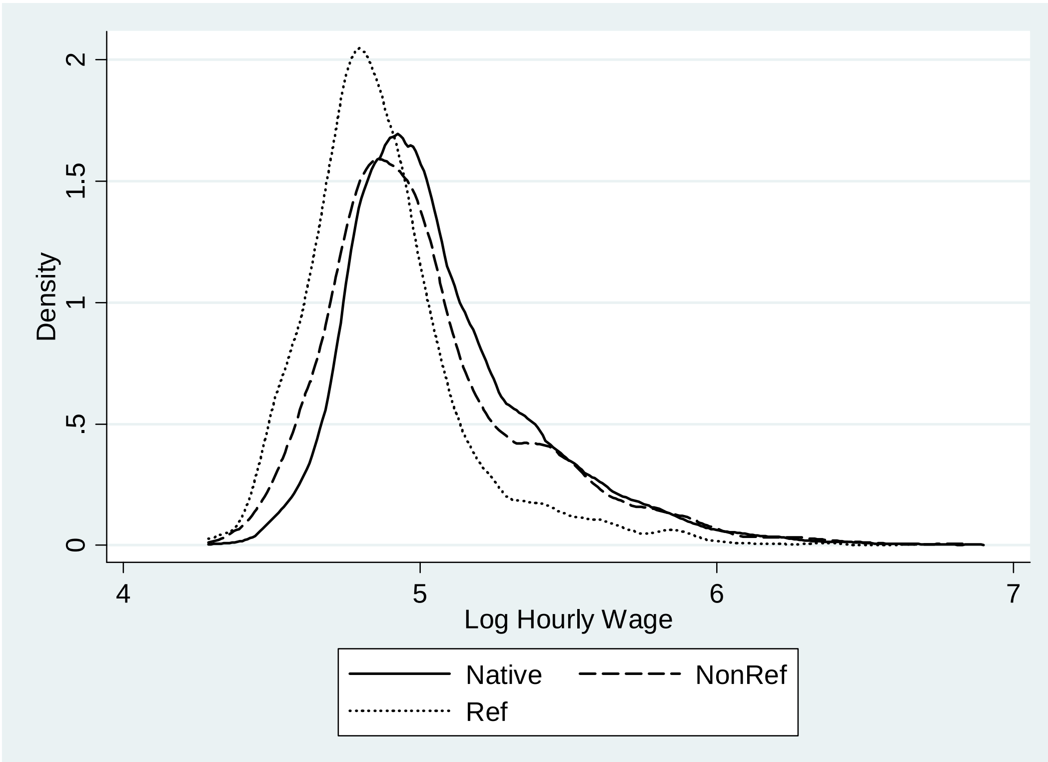


Figure 4

Kernel Density Estimates of the Wage Distributions of Natives, Non-refugees, and Refugees Women

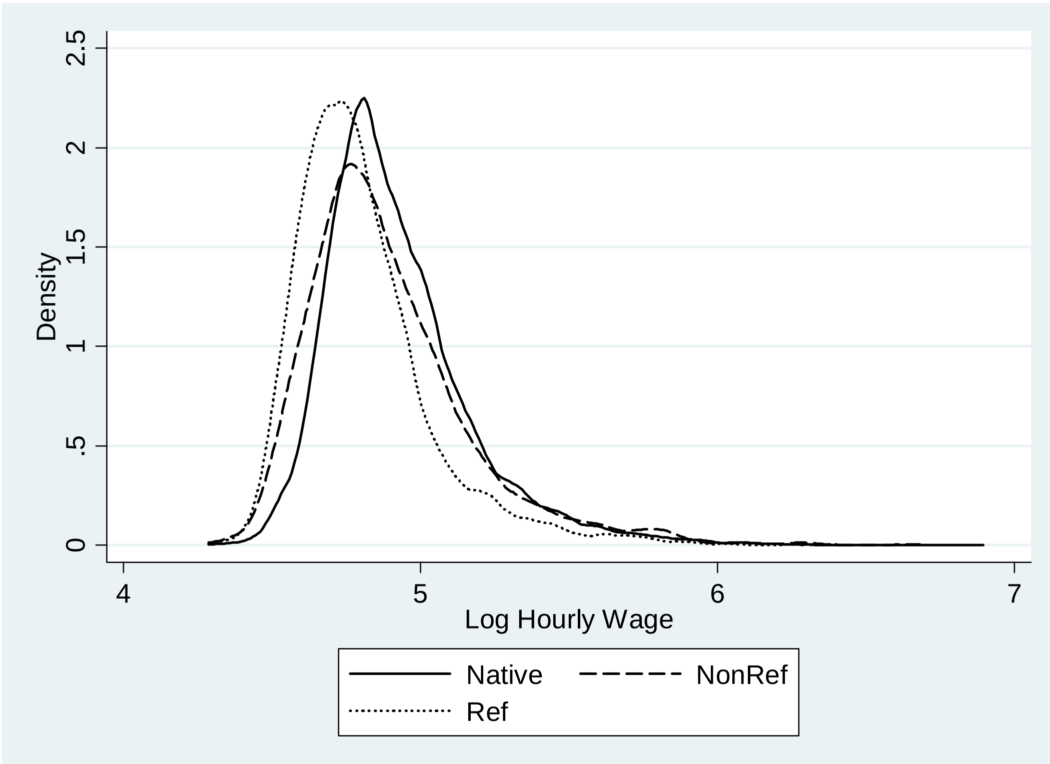


Figure 5

Raw Gender Wage Gap, by Ethnicity

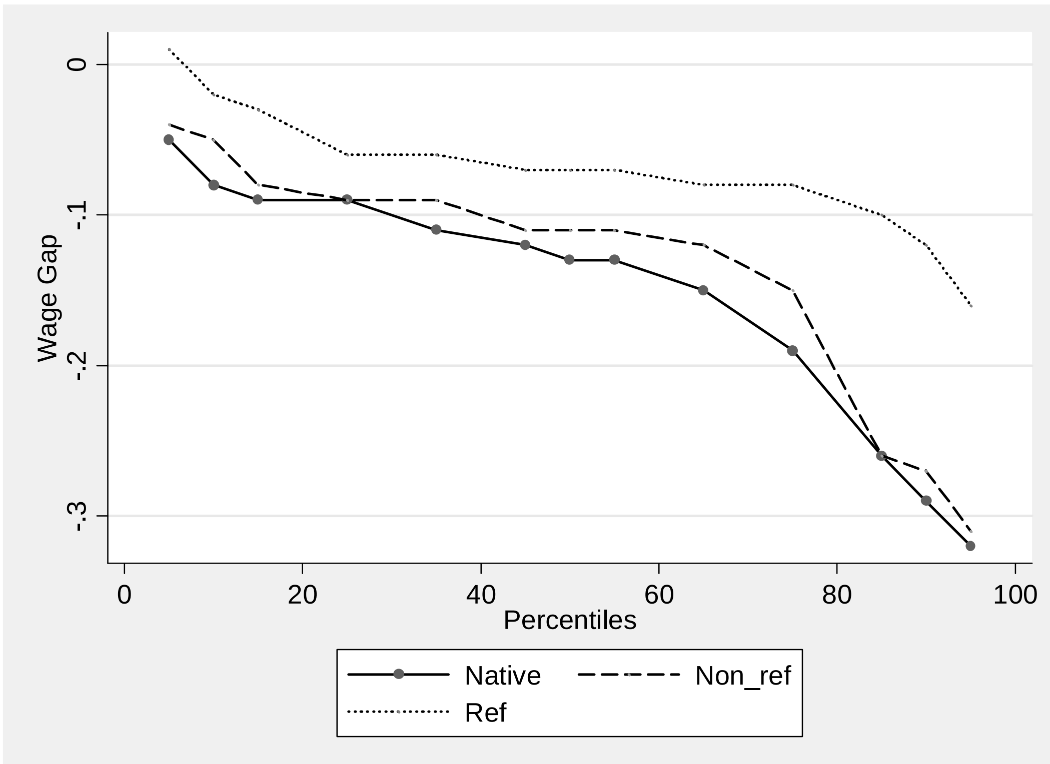


Figure 6

Kernel Density Estimates of the Wage Distributions, by Gender and Ethnicity

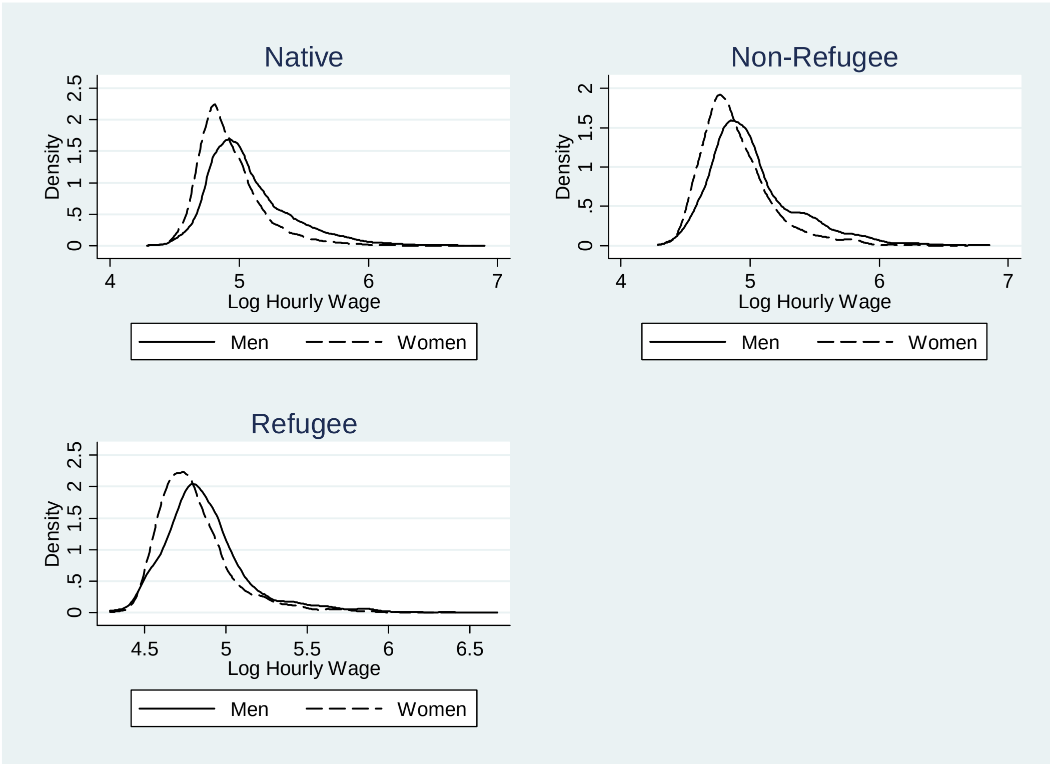
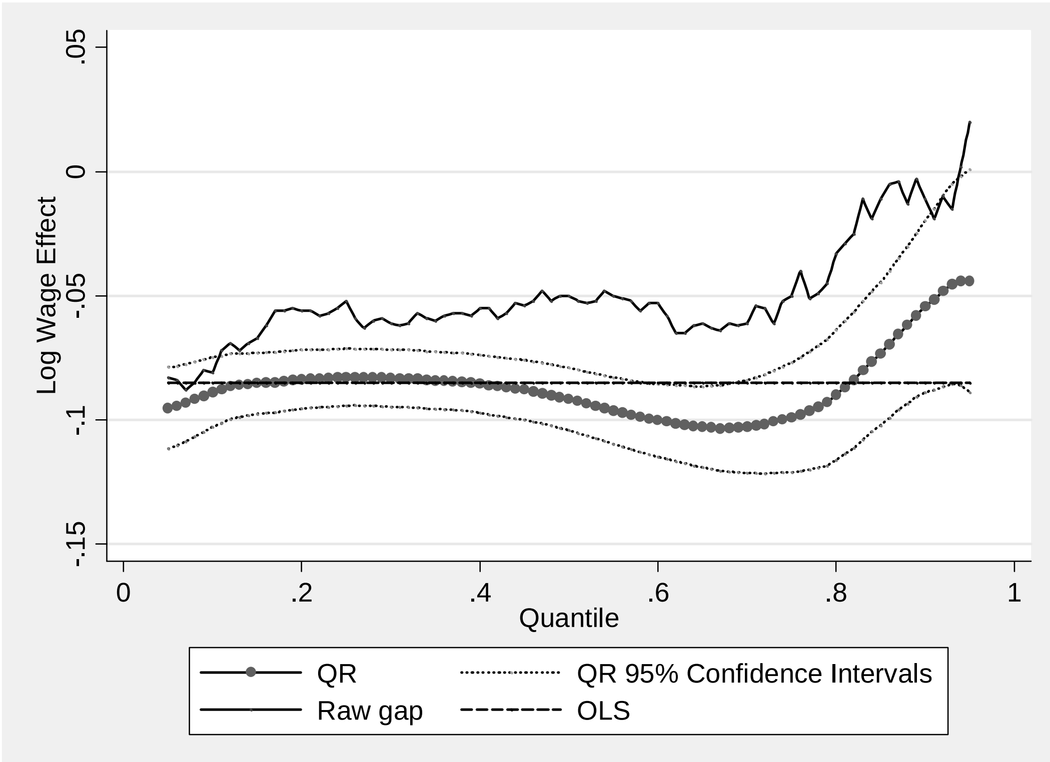


Figure 7

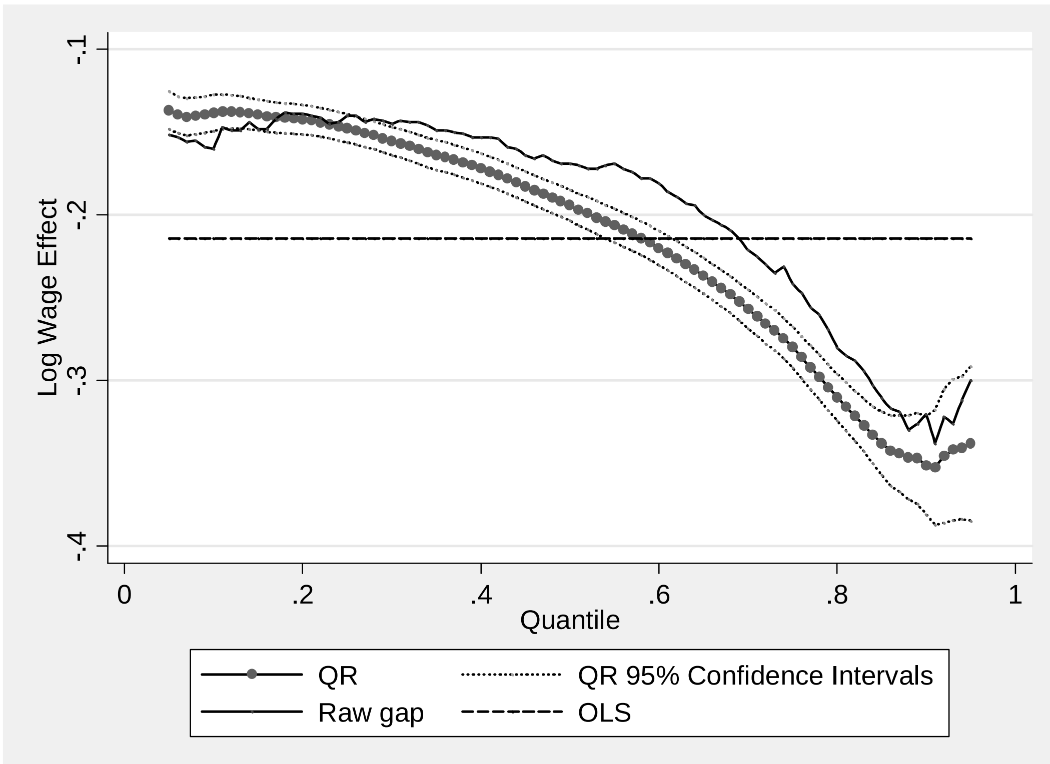
Decomposition of Differences in Wage Distribution between Natives and Non-refugees, Men



Note: We estimate 100 quantile regressions in the first step and estimate the standard errors by bootstrapping the results 100 times.

Figure 8

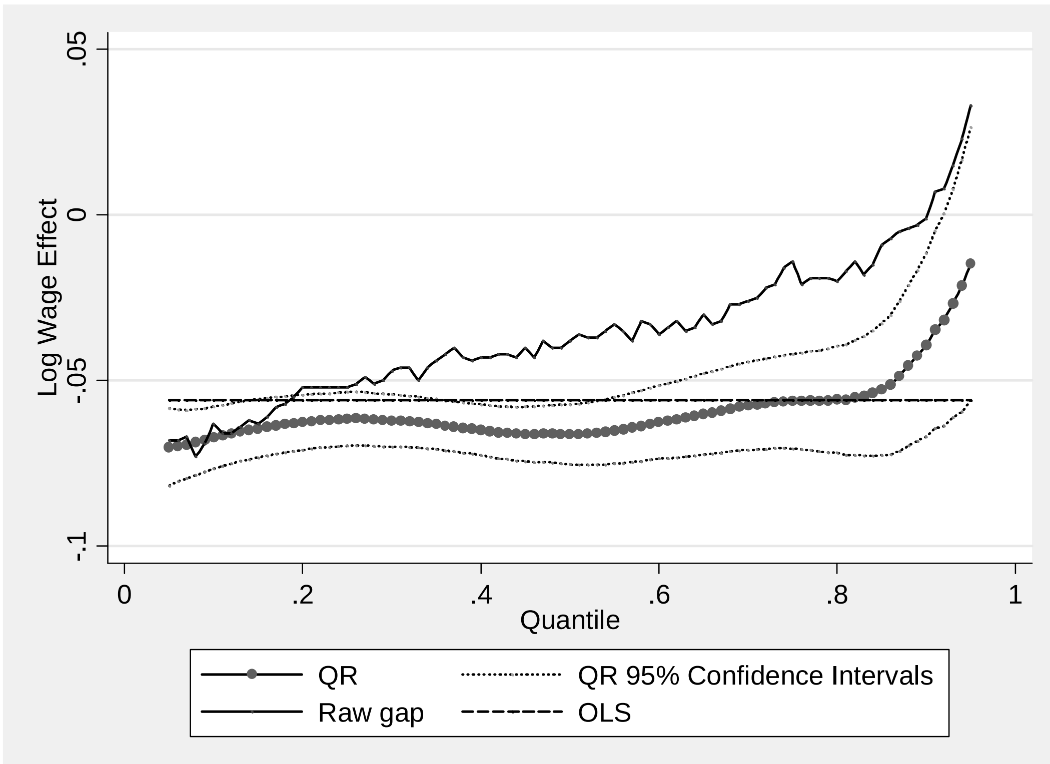
Decomposition of Differences in Wage Distribution between Natives and Refugees, Men



Note: We estimate 100 quantile regressions in the first step and estimate the standard errors by bootstrapping the results 100 times.

Figure 9

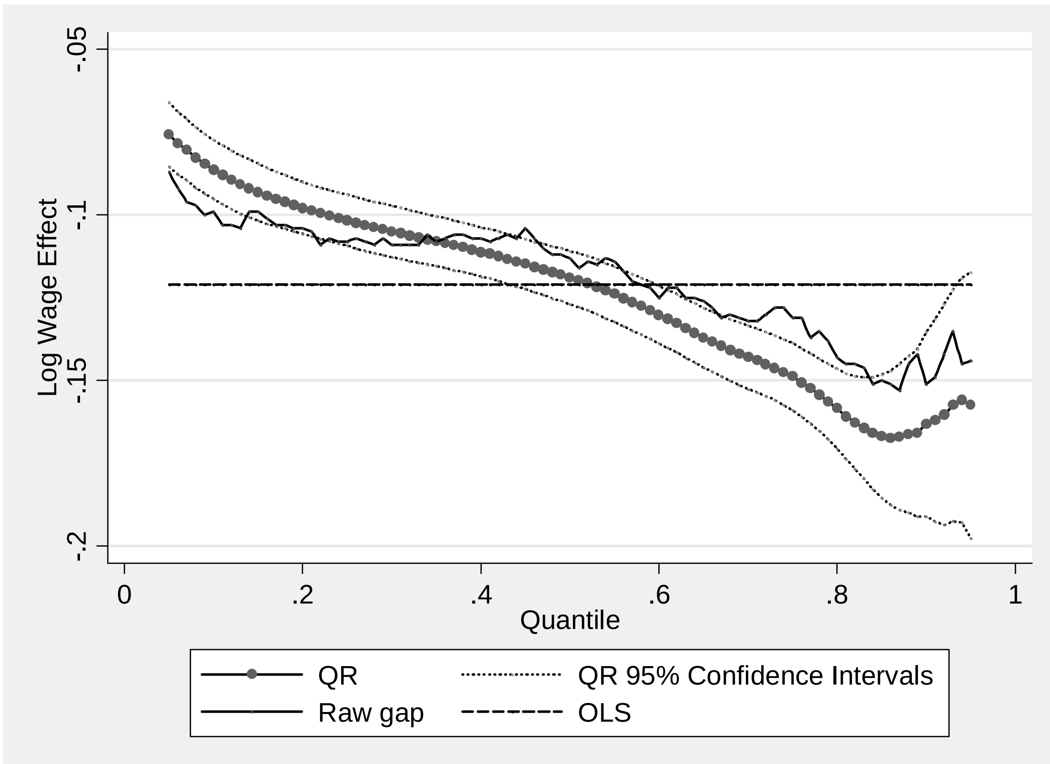
Decomposition of Differences in Wage Distribution between Natives and Non-refugees, Women



Note: We estimate 100 quantile regressions in the first step and estimate the standard errors by bootstrapping the results 100 times.

Figure 10

Decomposition of Differences in Wage Distribution between Natives and Refugees, Women



Note: We estimate 100 quantile regressions in the first step and estimate the standard errors by bootstrapping the results 100 times.

Figure 11

The gender wage effect, by ethnicity

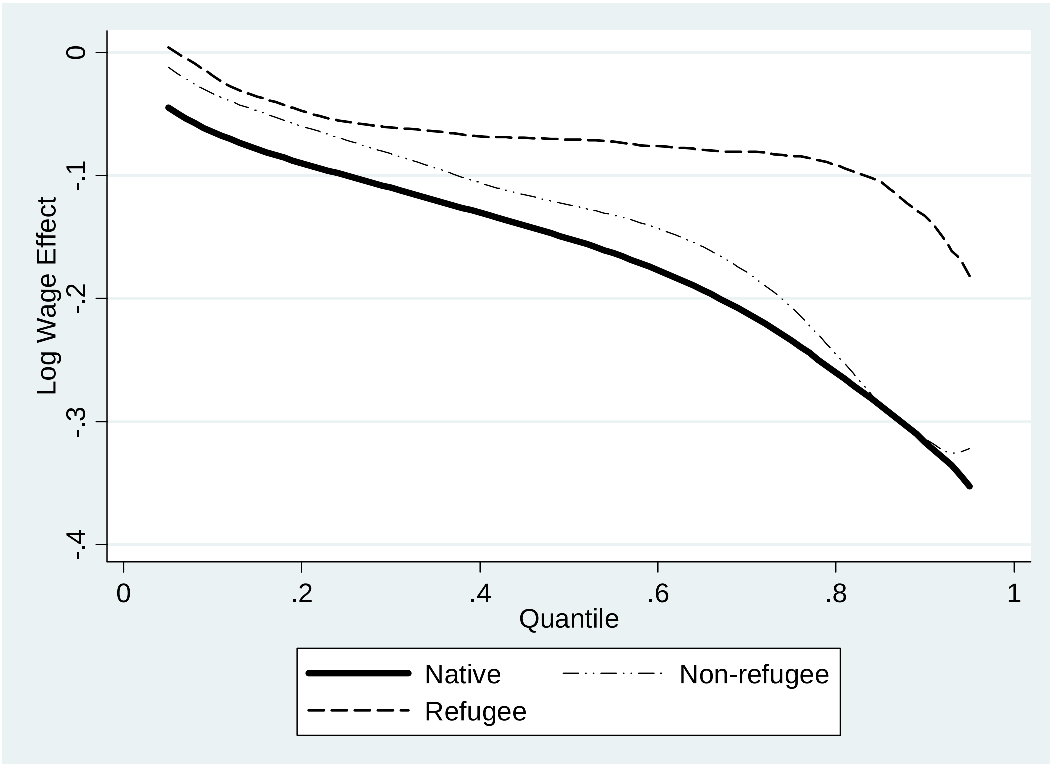


Figure 12

The double disadvantage effect, by ethnicity