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Part-Time Penalty in Sweden:
Evidence from Quantile Regression

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Abstract:

This study analyzes the part-time penalty in Sweden using quantile regression. We find that the estimated part-time wage differential is negative across the whole wage distribution. OLS overestimates the part-time penalty at the bottom of the distribution, and underestimates it at the top. The estimated part-time wage gap rises across the distribution, and there is a sharp acceleration in the increase starting around the 75th percentile, especially for men. Consequently, we find evidence of a glass ceiling in part-time employment for both men and women in the Swedish labor market.

Keywords: Part-time penalty, quantile regression, counterfactual distribution, glass ceiling

JEL Codes: J16, J31

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1. Introduction

Is there a glass ceiling in part-time employment in the Swedish labor market? Using data from 2006, we find that the part-time penalty increases throughout the wage distribution and that there is a speeding up effect starting around the 75th percentile. We interpret this as evidence of a glass ceiling in part-time employment for both genders in the Swedish labor market.

Few previous studies have focused primarily on the effect of part-time work on wages and they only examined the average log wage gap between part-time and full-time employment. Rodgers (2004) investigated part-time and full-time employment in Australia, and found the wage differentials to be statistically insignificant for both men and women. Hardoy and Schone (2006) did not find a significant part-time wage gap for women in Norway. O´Dorchai *et al.* (2007) analyzed the wage gap between male part- and full-timers in the private sector of six European countries, and found that part-time working males in Belgium, Denmark, Ireland, Italy, Spain, and the UK incur a wage penalty of 14 percent, 7 percent, 9 percent, 12 percent, 41 percent, and 38 percent, respectively. Bardasi and Gornick (2008) investigated female part- and full-time workers in six OECD countries, and found a part-time wage penalty of 11.5 percent in Canada, 20.8 percent in the US and Italy, 10 percent in UK, and 9 percent in Germany, along with a 2.7 percent advantage in Sweden. Manning and Petrongolo (2008) analyzed part-time penalty for UK women and found a wage disadvantage of about 10 percent.

Against this background, our aim is to examine whether part-time workers receive lower hourly wages than full-time workers in Sweden using quantile regression. Quantile regression allows us to estimate the effect of some control variables on log wages at the bottom, median, and top of the distribution. Once we have estimated the coefficients of the quantile regression model, we are interested in decomposing the part-time wage disadvantage into one component that is based on the difference in labor market characteristics between part-time and full-time workers, and one component that is based on the difference in the rewards that the two groups receive for their labor market characteristics across the wage distribution, i.e., the counterfactual distribution; see Albrecht *et al.* (2003) and Machado and Mata (2005). This can be considered a generalization of the Oaxaca-Blinder decomposition of the mean. We are not aware of any previous studies that have analyzed the part-time penalty using quantile regression and counterfactual distribution.

The paper is organized in the following way. Section 2 describes the empirical specification used in the paper. The data is presented in Section 3, and the results are presented in Section 4. Finally, Section 5 summarizes the paper.

2. Empirical specification

We are interested in analyzing the part-time pay penalty across the wage distribution of part-time and full-time workers, for both men and women. Using least squares would be inappropriate for this purpose, since it characterizes the distribution only at its mean. Instead we choose the quantile regression approach (see Koenker and Basset, 1978, and Buchinsky, 1998), which is a method for estimating the τ^{th} quantile of a log wage conditional on some control variables. Contrary to using least squares, it allows us to estimate the effect of some covariates on log wage 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 covariates. 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

$$\hat{\beta}(\tau) = \arg\min_{\beta \in \mathbb{R}^K} \sum_{i=1}^{N} \rho_\tau \left(y_i - x_i^{'}\beta \right) \tag{2}$$

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

Once we have estimated the parameters of the quantile regression model, we want to decompose the difference between the two choices of working hours' log wage distributions into one component that is based on the difference in labor market characteristics between part-time and full-time workers, and one component that is based on the difference in rewards that the two groups receive for their labor market characteristics (the counterfactual distribution). Melly (2006) suggests 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 $\hat{\beta} = \left(\hat{\beta}(\tau_1), \ldots\ldots, \hat{\beta}(\tau_j), \ldots\ldots, \hat{\beta}(\tau_J)\right)$ 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

$$q\left(\theta, x, \beta\right) = \inf\left\{q : \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{J}\left(\tau_j - \tau_{j-1}\right)1\left(x_i\hat{\beta}\left(\tau_j\right) \leq q\right) \geq \theta\right\} \tag{3}$$

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 of full-time workers with those of part-time workers. Thus, we can separate the difference at each quantile of the unconditional distribution into one component that is based on the difference 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 part-time and full-time workers:

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

where p = part time, f = full time, the first brackets represent the difference in the rewards that the two groups receive for their labor market characteristics (the counterfactual distribution), and the second brackets represent the effect of differences in labor market characteristics between the two groups. This can be seen as undertaking an Oaxaca-Blinder type of decomposition across the distribution. A comprehensive description of this approach and its statistical properties can be found in Melly (2006).

We use Stata 10 to estimate the parameters 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).

3. Data

The data used in this paper is taken from the Swedish register-based data set Longitudinal Individual Data (LINDA), which 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 our 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 persons aged 18 to 64, excluding self-employed workers, students, and individuals with missing values on observed characteristics, and end up with 46,392 men and 44,764 women.

The 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 (Stockholm, Gothenburg, or Malmo), ethnicity (i.e., native born), sector (i.e., public sector), and local unemployment rate. Full-time work is defined as working more than 75 % of the workers' contracted full-time hours.

Table 1 presents descriptive statistics for the sample used in this paper, revealing that part-time work was performed by 22 percent of the women and 5 percent of the men. Part-time workers have lower wages and are to a greater extent than full-time workers found in the public sector. Men who work part time are generally younger and single, while women who work part time are married to a greater extent than women with full-time jobs. Individuals with part-time jobs have lower work experience than those with full-time jobs.

4. Results

Figure 1 shows the observed part-time wage penalty at each percentile of the wage distribution, for men and women respectively. Thus, for example, we have a part-time wage penalty of about 15 percent for men at the 50th percentile. That is, the log wage of male part-time workers at the 50th percentile of the male part-time wage distribution is about 15 log points below the log wage of male full-time workers at the 50th percentile of their wage distribution.

The important feature of this figure is that the part-time wage penalty, for both men and women, starts out more or less constant at the bottom of the wage distribution and then increases steadily as we move up in the distribution, especially for men. The increase in the part-time penalty speeds up considerably around the 75th percentile, for both men and women. The situation where the wage gap is typically wider at the top of the wage distribution is known as a glass ceiling. It is seen as a barrier to further advancement once the part-time worker has attained a certain level. Hence, it seems that there could be a glass ceiling effect for part-time workers in the Swedish labor market.

Table 2 presents estimated part-time dummy coefficients at the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles using pooled data. It also shows the corresponding part-time dummy parameter from OLS regressions for comparison. The first and third sections show the observed part-time penalty without any covariates. The estimated part-time dummy coefficients are identical to the part-time penalty in Figure 1, which increases as we move up the wage distribution, especially for men, and shows a speeding up effect at the 75^{th} percentile, for both men and women.

The second and fourth sections of Table 2 present the estimated part-time dummy coefficients with control variables. When controlling for covariates we find a reduction in the part-time penalty across the whole wage distribution. Individual characteristics account for a large part of the part-time penalty. However, the widest distance is still found at the top of the distribution, which could be a sign of a glass ceiling in part-time jobs for both genders.

Tables 3, 4, 5, and 6 present results of quantile log wage regressions for part-time and full-time workers, by gender. The tables show the extent to which returns to observable characteristics differ between part-time and full-time workers, for men and women separately. The returns to a university education differ among the percentiles, and men have a higher relative return than women. University-educated part-time male workers at the 10^{th} percentile on average earn 18.3 percent more per hour than part-time workers with compulsory school as their highest educational attainment (see Halvorsen and Palmquist, 1980, for an interpretation of dummy variables in semi logarithmic equations). University-educated full-time male workers at the 90th percentile on average earn 104.4 percent more than male full-time workers with only compulsory education. The corresponding figures for women are 24.0 percent and 61.9 percent respectively. Foreign-born generally have lower wages than native-born individuals. Native-born part-time female workers at the 90th percentile on average earn 4.9 percent more per hour than their foreign-born counterparts. The corresponding figure for full-time male workers is 15.8 percent. Men and women in the private sector have a wage premium compared to men and women working in the public sector, and more so for full-time workers than part-time workers.

Tables 3, 4, 5, and 6 clearly reveal that, for both men and women, the returns to observable characteristics were different for part-time and full-time workers. We will now examine the part-time penalty across the whole wage distribution and investigate the part-time wage differential that is due to difference in the rewards that part-timers and full-timers receive for their labor market characteristics.

The results from the counterfactual decomposition are presented in Table 7. The estimated least squares and unconditional raw part-time wage gap are also listed for comparison. The first noticeable result is that the estimated part-time pay gap is negative across the whole wage distribution. A negative part-time pay gap implies that the market return for full-time workers is higher than for part-time workers, for both men and women. Using OLS leads to an overestimation of the part-time penalty at the bottom of the wage distribution, and an underestimation at the top, for both males and females. The estimated part-time wage gap rises across the distribution, and there is a sharp acceleration in the increase starting around the 75th percentile, especially for men. These findings indicate that there is a glass ceiling for part-time workers in the Swedish labor market.

Arulampalam *et al.* (2007) suggest that a glass ceiling exists if the part-time penalty at the 90th percentile is at least 2 log points higher than at the 75th percentile. When evaluating our material using this criterion, we do find evidence of a glass ceiling effect for part-time workers in Sweden compared to full-time workers, for both men and women.

5. Conclusions

In this paper we have analyzed part-time employment in the Swedish labor market. The main objective has been to analyze whether part-time workers receive lower hourly wages than full-time workers with similar levels of human capital.

The study was 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. Full time was defined as more than 75 percent of the contracted number of full time working hours.

We examined the part-time pay gap by quantile regression, which enabled us to estimate the effect of some control variables on log wages at the bottom, median, and top of the wage distribution. Once we had estimated the coefficients of the quantile regression model, we were interested in decomposing the part-time wage disadvantage into one component based on the difference in labor market characteristics between part-time and full-time workers, and one component based on the difference in rewards that the two groups receive for their labor market characteristics across the distribution (the counterfactual distribution). This can be considered a generalization of the Oaxaca-Blinder decomposition of the mean.

We found that the estimated part-time wage differential was negative across the whole wage distribution. Using OLS leads to an underestimation of the part-time penalty at the top of the distribution, and an overestimation at the bottom, for both males and females. The estimated part-time wage gap rises across the distribution, and there is a sharp acceleration in the increase starting around the 75th percentile, especially for men. This finding is evidence of a glass ceiling in part-time jobs in the Swedish labor market.

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Table 1

Descriptive Statistics for Part-Time and Full-Time Workers (Standard Deviation in Parentheses)

	Men		Women	
Variable	*Part-Time*	*Full-Time*	*Part-Time*	*Full-Time*
Choice of working hours	0.05	0.95	0.22	0.78
Log of hourly wage rate	4.89 (0.29)	5.07 (0.33)	4.84 (0.21)	4.94 (0.26)
Age	40.55 (12.30)	42.68 (11.14)	42.36 (11.48)	43.25 (10.94)
Experience	19.19 (12.90)	21.64 (11.83)	21.28 (12.11)	21.57 (12.00)
Local unemployment rate	4.12 (1.19)	3.92 (1.15)	3.49 (1.02)	3.43 (0.89)
Native born	0.79	0.90	0.88	0.89
Public Sector	0.35	0.16	0.60	0.50
Compulsory school	0.19	0.15	0.14	0.10
High school	0.64	0.68	0.69	0.64
University	0.17	0.17	0.17	0.26
Urban areas	0.39	0.34	0.29	0.38
Medium-sized cities	0.39	0.40	0.41	0.38
Countryside	0.22	0.26	0.30	0.26
Number of observations	2,127	44,265	9,727	35,037

Table 2

Estimated Part-Time Dummy Coefficients by Gender

	OLS	10th	25th	50th	75th	90th
Men						
Observed part-time gap	-0.180***	-0.153***	-0.137***	-0.159***	-0.219***	-0.287***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.009)	(0.021)
Part-time gap with control variables	-0.114***	-0.113***	-0.101***	-0.108***	-0.109***	-0.066***
	(0.006)	(0.007)	(0.007)	(0.006)	(0.008)	(0.014)
Women						
	OLS	10th	25th	50th	75th	90th
Observed part-time gap	-0.102***	-0.062***	-0.071***	-0.081***	-0.114***	-0.189***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)
Part-time gap with control variables	-0.054***	-0.046***	-0.043**	-0.040***	-0.046***	-0.051***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(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). *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 3

Quantile Regression of Male Part-Time Workers (Percentiles)

Variable	**OLS**	**10th**	**25th**	**50th**	**75th**	**90th**
Constant	4.595***	4.471***	4.551***	4.618***	4.718***	4.910***
	(0.034)	(0.037)	(0.030)	(0.035)	(0.045)	(0.070)
Experience	0.008***	0.001	0.005***	0.007***	0.007	0.007**
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
Experience	-0.009**	-0.002	-0.005	-0.010**	-0.008*	-0.002
Squared/100	(0.004)	(0.017)	(0.004)	(0.004)	(0.004)	(0.010)
High school	0.059***	0.022	0.030*	0.058***	0.070***	0.088***
	(0.013)	(0.004)	(0.016)	(0.015)	(0.016)	(0.031)
University	0.322***	0.168***	0.194***	0.240***	0.372***	0.600***
	(0.023)	(0.026)	(0.021)	(0.023)	(0.038)	(0.092)
Urban areas	0.063***	0.013	0.035**	0.053***	0.069***	0.048*
	(0.015)	(0.020)	(0.015)	(0.017)	(0.021)	(0.028
Medium-sized	0.007	-0.003	0.013	0.006	-0.013	-0.014
cities	(0.014)	(0.018)	(0.014)	(0.016)	(0.020)	(0.036)
Native born	0.153***	0.088***	0.126***	0.118***	0.129***	0.136***
	(0.014)	(0.018)	(0.016)	(0.016)	(0.017)	(0.028)
Public sector	-0.030**	0.021	-0.004***	0.006	-0.038**	-0.146***
	(0.012)	(0.015)	(0.013)	(0.013)	(0.015)	(0.025)
Local	-0.009*	-0.002	-0.014***	-0.012**	-0.006	-0.013
Unemployment	(0.005)	(0.006)	(0.004)	(0.006)	(0.006)	(0.011)

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 (500 repetitions). *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Results based on a sample of 2,127.

Table 4

Quantile Regression of Male Full-Time Workers (Percentiles)

Variable	**OLS**	**10th**	**25th**	**50th**	**75th**	**90th**
Constant	4.572***	4.472***	4.534***	4.602***	4.641***	4.701***
	(0.008)	(0.010)	(0.008)	(0.008)	(0.013)	(0.016)
Experience	0.019***	0.012***	0.014***	0.016***	0.021***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience	-0.031***	-0.020***	-0.022***	-0.026***	-0.032***	-0.042***
Squared/100	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
High school	0.131***	0.054***	0.074***	0.104***	0.164***	0.232***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.007)
University	0.500***	0.307***	0.367***	0.459***	0.578***	0.715***
	(0.005)	(0.007)	(0.005)	(0.006)	(0.008)	(0.012)
Urban areas	0.133***	0.050***	0.072***	0.027***	0.175***	0.210***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.006)	(0.009)
Medium-sized	0.032***	0.017***	0.016***	0.027***	0.034***	0.051***
cities	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.007)
Native born	0.144***	0.139***	0.124***	0.125***	0.142***	0.147***
	(0.005)	(0.006)	(0.004)	(0.005)	(0.007)	(0.010)
Public sector	-0.138***	-0.081***	-0.104***	-0.114***	-0.140***	-0.187***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.008)
Local	-0.019***	-0.016***	-0.013***	-0.015***	-0.018***	-0.022***
Unemployment	(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 (500 repetitions). *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Results based on a sample of 44,265.

Table 5

Quantile Regression of Female Part-Time Workers (Percentiles)

Variable	**OLS**	**10th**	**25th**	**50th**	**75th**	**90th**
Constant	4.602***	4.423***	4.465***	4.555***	4.700***	4.852***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.016)	(0.028)
Experience	0.007***	0.006***	0.007***	0.008***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience Squared/100	-0.011***	-0.009***	-0.011***	-0.013***	-0.011***	-0.010***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
High school	0.082***	0.048***	0.070***	0.091***	0.096***	0.107***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.011)
University	0.293***	0.215***	0.263***	0.283***	0.303***	0.353***
	(0.008)	(0.009)	(0.008)	(0.007)	(0.009)	(0.017)
Urban areas	0.070***	0.026***	0.033***	0.061***	0.082***	0.098***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.013)
Medium-sized cities	0.011***	0.004	0.005	0.004	0.011*	0.016**
	(0.004)	(0.005)	(0.004)	(0.005)	(0.006)	(0.008)
Native born	0.067***	0.081***	0.070***	0.062***	0.048***	0.048***
	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.017)
Public sector	-0.040***	0.018***	0.005	-0.019***	-0.063***	-0.106***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)	(0.010)
Local Unemployment	-0.006***	-0.006***	-0.003	-0.003	-0.003	-0.009**
	(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 (500 repetitions). *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Results based on a sample of 9,727.

Table 6

Quantile Regression of Female Full-Time Workers (Percentiles)

Variable	**OLS**	**10th**	**25th**	**50th**	**75th**	**90th**
Constant	4.593***	4.437***	4.489***	4.588***	4.719***	4.824***
	(0.008)	(0.009)	(0.006)	(0.007)	(0.011)	(0.018)
Experience	0.014***	0.009***	0.011***	0.012***	0.013***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience	-0.022***	-0.012***	-0.016***	-0.018***	-0.021***	-0.028***
Squared/100	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
High school	0.113***	0.069***	0.080***	0.100***	0.127***	0.162***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.007)
University	0.371***	0.260***	0.306***	0.329***	0.385***	0.482***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.006)	(0.011)
Urban areas	0.107***	0.045***	0.063***	0.089***	0.130***	0.173***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.007)
Medium-sized	0.022***	0.011***	0.011***	0.016***	0.030***	0.037***
cities	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.007)
Native born	0.088***	0.091***	0.084***	0.084***	0.080***	0.071***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.006)	(0.008)
Public sector	-0.109***	-0.015***	-0.052***	-0.091***	-0.145***	-0.189***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.006)
Local	-0.017***	-0.012***	-0.011***	-0.013***	-0.020***	-0.025***
Unemployment	(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 (500 repetitions). *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Results based on a sample of 35,037.

Table 7

Estimated Part-Time Penalty by Gender

	OLS	10th	25th	50th	75th	90th
Men						
Raw	-0.180***	-0.153***	-0.137***	-0.159***	-0.219***	-0.287***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.009)	(0.021)
Decomposition	-0.113***	-0.072***	-0.078***	-0.104***	-0.162***	-0.201***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.016)
Women						
Raw	-0.102***	-0.062***	-0.071***	-0.081***	-0.114***	-0.189***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)
Decomposition	-0.053***	-0.028***	-0.032***	-0.038***	-0.062***	-0.104***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.008)

Note: Standard errors are given in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. In the last four panels we control for occupation.

Figure 1

Observed Part-Time Wage Penalty