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Abstract

The gender wage gap among full-time workers has narrowed in the last 15 years in Japan. The demographic characteristics of full-time employees also has changed during the same period. The changed composition of workers could result in an observed gender wage convergence without any change in the underlying structure of the equilibrium offered wages. This paper develops a new method for estimating the convergence of the gender wage gap when the composition of workers of both genders changes. The newly developed estimators trim the wage distribution of certain groups characterized by observed characteristics so that the composition of workers in terms of these characteristics is stable over time. Applying two extreme trimming rules, based on two extreme distributional assumptions of unobserved characteristics, the trimming estimators identify the upper- and lower-bounds of the true gender wage convergence. The regression-adjusted gender wage gap for full-time workers has narrowed by 6 percentage points, changing from 33 percent in 1987 to 27 percent in 2002. However, the lower-bound estimate indicates an 18-percentage-point divergence and the upper- bound estimate indicates a 33-percentage-point convergence. However, once we assume that spousal income determines reservation wage, but not offered wage, we can significantly tighten the bounds. The results highlight that the prediction from economic theory, combined with a reasonable excluded variable assumption, is crucial to making inferences about gender wage convergence in Japan. The method developed in this paper is applicable to other cases for examining the temporal variation of the average wage when the employment composition changes.

JEL Classification: C25

Key Words: Gender Wage Gap, Roy Model, Self-Selection, Trimming Estimator, Japan.

Contents

1 Introduction

In Japan, the average, hourly wage of full-time, employed women ages 23-65 was about 62% of men's in 1987, and this wage gap was one of the largest gender wage gaps found in developed countries. Fifteen years later, the same figure became about 70% (Table 1). The government enacted the Equal Employment Opportunity Law (EEOL) in 1986 to fight the possible discrimination against women suggested by the gender wage differential. The law was revised in 1997 to give slightly more power to the government for its enforcement. Also, the results of several national opinion surveys pointed to people's changing attitudes toward gender roles; people became more supportive of women's employment (Kawaguchi and Miyazaki [2005]). An immediate question is whether these laws and the change in people's attitudes narrowed the gender wage gap over last 15 years.

The convergence of male and female wages is not surprising because an average female worker in 2002 was more educated and had longer job tenure than an average female worker in 1987. However, Kawaguchi [2005] and Rebick [2005] report that the gender wage gap among full-time workers narrowed during the 1990s, even after controlling for such observable characteristics as educational attainment, job experience, and job tenure.

However, whether the gender wage gap has narrowed is still uncertain because the labor force composition of men and women has changed over the last 15 years. First, the full-time employment rate of women ages 15-65 who are out of school was stable, around 27% between 1987 and 2002, while the corresponding figure for men dropped slightly from 64% to 61% (Table 1). Second, the effect of education on full-time participation became stronger and women were less likely to drop off from full-time employment as they aged, as we will see later. Thus, those women who presumably had higher human capital became more likely to be employed full-time over the last 15 years.

From the strengthened, positive self-selection mechanism based on observed characteristics, we could speculate whether the same selection rule would work based on unobserved characteristics. If so, the convergence of the gender wage gap among the employed population, conditioned on changes in observed characteristics, might have occurred merely because of changes in the composition of the full-time employed population's unobserved characteristics.

This paper aims to identify the change in the mean, offered wage gap of males and females for the whole population, including those who do not work. A similar attempt was made using US data by Mulligan and Rubinstein [2004] and Mulligan and Rubinstein [2005]. Their straightforward strategy for dealing with the sample-selection issue was to look at the gender wage gap of those with advanced degrees because this group's labor force participation rate was almost 100 percent for the entire sample period. Thus, the sample-selection issue can be essentially ignored. In addition, they also employed the Heckman sample-selection correction method, using spouse's characteristics as an excluded variable from the wage equation. They concluded that the observed male-female wage convergence in the US was largely due to the labor force's compositional change for both sexes. Blundell et al. [2004] also attempted to identify the change in the offered wage gap using British data. Their analysis was based on Manski [1994]'s bound estimator, which imposes a moderately weak assumption on the distribution of the non-participant's offered wage. Exploiting predictions from economic theory, they attempted to tighten the bounds by imposing several plausible assumptions on the distribution of non-participants' offered wage in relation with the distribution of the participants' actual wage. They rejected the hypothesis that the observed gender wage convergence was due to only composition effects.

Closely related research has been conducted on the convergence of the wage gap between African-Americans and whites in the US. Butler and Heckman [1977] first pointed out that dropping out of the labor force could be a source of the wage convergence between these two groups. Brown [1984] suggested a method for calculating the median wage convergence under an assumption that the median offered wages for non-working people are lower than the median offered wages for working people. Johnson et al. [2000] pursued this idea using micro data with a wage imputation for non-working people. Chandra [2000] conducted a variation of this study. Most of these studies focused on the median wage convergence rather than the mean wage convergence because the median value is not directly affected by the imputed value to the extent that the employment rate exceeds 50% and labor market drop out occurs from the bottom of the wage distribution. This method is not applicable to our analysis because, in many groups, women's full-time employment rate is below 50%.

The empirical strategy in this paper is straightforward. To eliminate the change in the observed wage gap due to sample selection, we trim some observations from either the 1987 or the 2002 wage distribution so that the full-time employment rates are identical for these two years. For example, if the employment rate of female college graduates with 5 potential years of experience is increased by 5 percentage points in 2002 from 1987, we trim the top or bottom 5 percent of the wage distribution of the same group in 2002. Whether we trim from the top or from the bottom determines whether we estimate the upper bound or the lower bound of the gender wage convergence. We apply the same trimming for all groups, and this trimming artificially creates a sample whose employment rates are identical for 1987 and 2002 for all groups. A regression applied to this trimmed data estimates the upper and lower bounds for the true gender wage convergence. This approach enables us to estimate sharp bounds without imposing any assumption on the non-participants' wage distribution. Instead, we essentially impose an assumption on the distribution of unobserved characteristics among the employed population.

The contribution of this paper to the literature is two-fold. First, we suggest a sharp bound estimator to estimate the change in the mean wage across genders when the composition of workers for each group is changing, without relying on a strong assumption. Second, we credibly identify the change in the gender wage gap for Japan where the gender wage gaps narrowed when the composition of male and female workers changed simultaneously.

It is worth noting that the purpose of this paper is not to identify a causal mechanism of wage determination, such as the return to education. This is principally due to the lack of a good instrument for potentially endogenous variables and thus is a limit of this study. Assuming the exogeneity of explanatory variables in the whole population, we focus our discussion on the issues of biases due to sample selection.

The results of the analysis are summarized as follows. First, we find gender wage convergence among full-time workers, even after adjusting for their observed characteristics. The regression-adjusted gender wage gap narrowed from 31 percent to 26 percent between 1987 and 2002. Second, the bound estimation based on very agnostic assumptions render a wide range of bounds, and thus we cannot rule out the possibility that the observed gender wage convergence is due to a change in the workers' composition. Third, the bound estimation under an excluded variable assumption that spousal income affects reservation wage, but not offered wage renders very narrow bounds. Thus, if we believe in the excluded variable assumption, we could conclude that the observed gender wage convergence during the period was not an illusion.

The paper is organized as follows. Section 2 lays out a simple Roy model to illustrate changes in the selection pattern into employment and discusses the empirical strategy. Section 3 describes the Japanese micro data used in this study and describes the change in the gender wage gap and the workforce composition in terms of males and females. Section 4 reports the results of the trimming regressions. Section 5 discusses the trimming estimation under an excluded variable assumption and reports the results. The last section concludes.

2 Methodology

2.1 Bound Estimators

This section discusses the identification of bounds on the change in the underlying gender wage gap, allowing for a change in the unobserved distribution of human capital. Instead of identifying the exact parameter value of the wage convergence, the discussion here attempts to identify the bounds of the parameter value. The identification of the sharp upper- and lower-bounds of the wage gap convergence is based on the discussion by Lee [2005] in the context of program evaluation under non-ignorable sample attrition.

To discuss the convergence of the gender wage gap, we assume that the equilibrium offered wage is determined by the following equation.

$$w^o = x\beta_0 + f\beta_1 + tx\beta_2 + tf\beta_3 + u, \tag{1}$$

where w^o is the log of hourly offered wage and x is the vector of education, potential experience, and job tenure. The dummy variable f takes 1 if the individual is female, and t is the time dummy that takes 1 if the year is 2002. We do not allow for different coefficients for education experience and tenure between sexes. The same potential experience most likely corresponds to the different actual experiences of males and females. Thus, the estimated coefficient for potential experience should be interpreted as the coefficient for the age conditioning variable, rather than the return to general human capital. By specifying the wage equation in this way, the coefficient β_3 corresponds to the gender wage convergence.

We assume the exogeneity of the error term $E[u|x, f, t] = 0$. This is a strict assumption that is likely to be violated. Thus, we cannot interpret the estimated coefficient as causal. The focus of this study is limited to examining the bias due to sample selection. To save space, we denote $[w|x, f = 0, t = 0] = w_x^{m87}$, $[w|x, f = 1, t = 0] = w_x^{f87}$, $[w|x, f = 0, t = 1] = w_x^{m02}$ and $[w|x, f = 1, t = 1] = w_x^{f02}$. We also denote the conditional distribution of u following the same convention.

The reservation wage for each individual is given as

$$w^r = x_1\alpha_0 + fx_1\alpha_1 + tx_1\alpha_2 + tfx_1\alpha_3 + e, \tag{2}$$

where x_1 is a part of x that includes education and potential experience variables. The reservation wage could be higher among women with high human capital because of assortative mating and the income effect due to husband's income. This implies a positive α_1. If the degree of positive assortative mating has changed between 1987 and 2002, we expect $\alpha_3 \neq 0$.

Each individual is a full-time worker when the offered wage exceeds the reservation wage. Thus, the reduced-form equation for full-time employment is defined as follows:

$$s = 1[x\theta_0 + fx\theta_1 + tx\theta_2 + tfx\theta_3 + v \geq 0], \tag{3}$$

The log hourly wage w is observed when $s = 1$. We denote $P[s = 1|x, f = 0, t = 0] = p_x^{m87}$, $P[s = 1|x, f = 0, t = 1] = p_x^{m02}$, $P[s = 1|x, f = 1, t = 0] = p_x^{f87}$, and $P[s = 1|x, f = 1, t = 1] = p_x^{f02}$.

The convergence of the wage gap that we want to estimate is

$$(Ew_x^{m87} - Ew_x^{f87}) - (Ew_x^{m02} - Ew_x^{f02}) = \beta_3. \tag{4}$$

We, however, cannot estimate this because we observe w only for $s = 1$. Instead, we can estimate

$$\begin{aligned} &(E[w_x^{m87}|s = 1] - E[w_x^{f87}|s = 1]) - (E[w_x^{m02}|s = 1] - E[w_x^{f02}|s = 1]) \\ &= \beta_3 + (E[u_x^{m87}|s = 1] - E[u_x^{f87}|s = 1]) - (E[u_x^{m02}|s = 1] - E[u_x^{f02}|s = 1]). \end{aligned} \tag{5}$$

The last bias terms are likely to be non-zero due to the change in the sample-selection structure. The sample-selection structure could have changed because of changes in the offered wage structure or the reservation wage structure. Instead of specifying the sample-selection terms, we estimate the bound for these bias terms and for β_3.

We attempt to identify the sharp upper and lower bounds of β_3, which critically depends on the following assumption.

Assumption 1 *The joint distribution of (u, v), conditional on x, f and t, is invariant over time.*

It is important to note that this assumption still allows for changes in the offered-wage structure and the reservation-wage structure because the coefficients can change over time. This assumption implies that under the same selection rules for 1987 and 2002, the conditional means of the unobserved wage determinants among employed populations are identical. This is to say

$$E[u_x^{g87}|v \geq -(x\theta_0+fx\theta_1+tx\theta_2+txf\theta_3)] = E[u_x^{g02}|v \geq -(x\theta_0+fx\theta_1+tx\theta_2+txf\theta_3)]$$

for all $g = (m, f)$, $t = (0, 1)$, and $f = (0, 1)$. Note that $u_x^{m87} = [u|x, f = 0, t = 0]$ for example.

Claim 1 *Under assumption 1, the sharp upper- and lower- bounds of the gender wage convergence parameter, β_3, is given as*

$$\begin{aligned}
\beta_3^u &= 1(p_x^{f02} > p_x^{f87})\{E[w_x^{f02}|s=1, u > u_{(p_x^{f02}-p_x^{f87})/p_x^{f02}}] - E[w_x^{f87}|s=1]\} \\
&+ 1(p_x^{f02} \leq p_x^{f87})\{E[w_x^{f02}|s=1] - E[w_x^{f87}|s=1, u \leq u_{1-(p_x^{f87}-p_x^{f02})/p_x^{f87}}]\} \\
&- 1(p_x^{m02} > p_x^{m87})\{E[w_x^{m02}|s=1, u < u_{1-(p_x^{m02}-p_x^{m87})/p_x^{m02}}] - E[w_x^{m87}|s=1]\} \\
&- 1(p_x^{m02} \leq p_x^{m87})\{E[w_x^{m02}|s=1] - E[w_x^{m87}|s=1, u \geq u_{(p_x^{m87}-p_x^{m02})/p_x^{m87}}]\},
\end{aligned}$$

$$\begin{aligned}
\beta_3^l &= 1(p_x^{f02} > p_x^{f87})\{E[w_x^{f02}|s=1, u < u_{1-(p_x^{f02}-p_x^{f87})/p_x^{f02}}] - E[w_x^{f87}|s=1]\} \\
&+ 1(p_x^{f02} \leq p_x^{f87})\{E[w_x^{f02}|s=1] - E[w_x^{f87}|s=1, u \geq u_{(p_x^{f87}-p_x^{f02})/p_x^{f87}}]\} \\
&- 1(p_x^{m02} > p_x^{m87})\{E[w_x^{m02}|s=1, u > u_{(p_x^{m02}-p_x^{m87})/p_x^{m02}}] - E[w_x^{m87}|s=1]\} \\
&- 1(p_x^{m02} \leq p_x^{m87})\{E[w_x^{m02}|s=1] - E[w_x^{m87}|s=1, u \leq u_{1-(p_x^{m87}-p_x^{m02})/p_x^{m87}}]\},
\end{aligned}$$

where, $1(\cdot)$ *is the indicator function. The notation* u_p *stands for the pth percentile of the distribution of* u*. The condition* $u > u_p$ *implies that the very bottom p percent is trimmed from the wage distribution, and* $u \leq u_{1-p}$ *implies that the very top p percent is trimmed from the wage distribution.*

The reasoning behind β_3^u is the following. When the employment rate of women with characteristics x increases by $p_x^{f02} - p_x^{f87}$, we obtain the upper bound of women's average wage growth by trimming the bottom $(p_x^{f02} - p_x^{f87})/p_x^{f02}$ proportion of the 2002 women's wage distribution. After this trimming, the artificial labor force participation rate of group x becomes p_x^{f87}, because $(p_x^{f02} - p_x^{f02}\frac{(p_x^{f02}-p_x^{f87})}{p_x^{f02}}) = p_x^{f87}$. In contrast, when the labor force participation rate declines by $p_x^{f87} - p_x^{f02}$, we obtain the upper bound of women's average wage growth by trimming the top $(p_x^{f87} - p_x^{f02})/p_x^{f87}$ proportion of the women's 1987 wage distribution.

Similarly, if the employment rate of men with characteristics x increases by $p_x^{m02} - p_x^{m87}$, we obtain the lower bound of men's average wage growth by trimming the bottom $(p_x^{m02} - p_x^{m87})/p_x^{m87}$ proportion from the 1987 men's wage distribution. In contrast, when the employment rate decreases by $p_x^{m87} - p_x^{m02}$ we obtain the lower bound of men's wage growth by trimming the top $(p_x^{m87} - p_x^{m02})/p_x^{m02}$ proportion of the men's 2002 wage distribution.

The upper bound of women's wage growth minus the lower bound of men's wage growth defines the upper bound of the gender wage convergence, β_3^u. In addition, the lower bound of women's wage growth minus the upper bound of men's wage growth defines the the lower bound of the gender wage convergence, β_3^l.

Now we give the proof for Claim 1.

Proof

The β_3^u is decomposed into the true convergence part and the bias terms as follows:

$$\begin{aligned}
\beta_3^u &= \beta_3 \\
&+ 1(p_x^{f02} > p_x^{f87})\{E[u_x^{f02}|s=1, u > u_{(p_x^{f02}-p_x^{f87})/p_x^{f02}}] - E[u_x^{f87}|s=1]\} \\
&+ 1(p_x^{f02} \leq p_x^{f87})\{E[u_x^{f02}|s=1] - E[u_x^{f87}|s=1, u \leq u_{1-(p_x^{f87}-p_x^{f02})/p_x^{f87}}]\} \\
&- 1(p_x^{m02} > p_x^{m87})\{E[u_x^{m02}|s=1, u < u_{1-(p_x^{m02}-p_x^{m87})/p_x^{m02}}] - E[u_x^{m87}|s=1]\} \\
&- 1(p_x^{m02} \leq p_x^{m87})\{E[u_x^{m02}|s=1] - E[u_x^{m87}|s=1, u \geq u_{(p_x^{m87}-p_x^{m02})/p_x^{m87}}]\}.
\end{aligned}$$

When $p_x^{f02} > p_x^{f87}$, from the selection equation $s = 1[x\alpha_0 + fx\alpha_1 + tx\alpha_2 + tfx\alpha_3 + v \geq 0]$, we know that $x\alpha_2 + fx\alpha_3 > 0$. Then, $\{E[u_x^{f02}|s=1, u > u_{(p_x^{f02}-p_x^{f87})/p_x^{f02}}] - E[u_x^{f87}|s=1]\}$ is positive. To see this, $E[u_x^{f02}|s=1, u > u_{(p_x^{f02}-p_x^{f87})/p_x^{f02}}] = E[u_x^{f02}|v \geq -x\alpha_0 - x\alpha_1 - x\alpha_2 - x\alpha_3, u > u_{(p_x^{f02}-p_x^{f87})/p_x^{f02}}$ is obtained by removing the very bottom $(p_x^{f02} - p_x^{f87})/p_x^{f02}$ proportion of u_x^{f02} from the conditional distribution of u_x^{f02} on $v \geq -x\alpha_0 - x\alpha_1 - x\alpha_2 - x\alpha_3$. However, $E[u_x^{f87}|s=1] = E[u_x^{f87}|v \geq -x\alpha_0 - x\alpha_1] = E[u_x^{f87}|v \geq -x\alpha_0 - x\alpha_1, v \geq -x\alpha_0 - x\alpha_1 - x\alpha_2 - x\alpha_3] = E[u_x^{f02}|v \geq -x\alpha_0 - x\alpha_1, v \geq -x\alpha_0 - x\alpha_1 - x\alpha_2 - x\alpha_3]$ is obtained by removing

$(p_x^{f02} - p_x^{f87})/p_x^{f02}$ proportion of u_x^{f02} from the conditional distribution of u_x^{f02} on $v \geq -x\alpha_0 - x\alpha_1 - x\alpha_2 - x\alpha_3$. The former expectation is obtained by removing $(p_x^{f02} - p_x^{f87})/p_x^{f02}$ proportion from the bottom, and the latter expectation is obtained by removing $(p_x^{f02} - p_x^{f87})/p_x^{f02}$ proportion that does not satisfy $v \geq -x\alpha_0 - x\alpha_1$. Thus, the former expectation should be larger than or equal to the latter expectation.

We can repeat exactly the same argument for the other three terms and show that all four selection-bias terms are non-negative. Thus $\beta_3^u \geq \beta_3$. The same argument is used to show $\beta_3^l \leq \beta_3$. The bound is sharp because the bias term can be zero. Under Assumption 1, if the employment rate does not change for all groups, the exact value of the parameter is identified (i.e., $\beta_3^l = \beta_3 = \beta_3^u$).

2.2 Estimation Procedure

The estimation of the upper- and lower-bounds of the gender wage convergence discussed above is implemented by the following procedure.

1. Calculate the employment rate by gender and x_1 (education and potential experience) for 1987 and 2002. The conditioning is implemented based on x_1 instead of x (education, potential experience, tenure) because tenure is not observed among non-employed individuals. Call the predicted value $\hat{p}_{x_1}^{jt}$ for $t = 87, 02$ and $j = (male, female)$.

2. Define the upper-bound variable, $\overline{w}$, by trimming the bottom $(\hat{p}_{x_1}^{f02} - \hat{p}_{x_1}^{f87})/\hat{p}_{x_1}^{f02}$ fraction of the distribution of $w_{x_1}^{f02}$ if $\hat{p}_{x_1}^{f02} > \hat{p}_{x_1}^{f87}$, and by trimming the top $(\hat{p}_{x_1}^{f87} - \hat{p}_{x_1}^{f02})/\hat{p}_{x_1}^{f87}$ fraction of $w_{x_1}^{f87}$ if $\hat{p}_{x_1}^{f02} \leq \hat{p}_{x_1}^{f87}$. Note that the trimming based on w is identical to the trimming based on u because x_1 is conditioned.

3. Define the upper-bound variable, $\overline{w}$, by trimming the top $(\hat{p}_{x_1}^{m02} - \hat{p}_{x_1}^{m87})/\hat{p}_{x_1}^{m02}$ fraction of the distribution of $w_{x_1}^{m02}$, if $\hat{p}_{x_1}^{m02} > \hat{p}_{x_1}^{m87}$. If $\hat{p}_{x_1}^{m02} \leq \hat{p}_{x_1}^{m87}$, trim the bottom $(\hat{p}_{x_1}^{m87} - \hat{p}_{x_1}^{m02})/\hat{p}_{x_1}^{m87}$ fraction from the distribution of $w_{x_1}^{m87}$.

4. Define the lower-bound variable, $\underline{w}$, by trimming the top $(\hat{p}_{x_1}^{f02} - \hat{p}_{x_1}^{f87})/\hat{p}_{x_1}^{f02}$ of the distribution of $w_{x_1}^{f02}$ if $\hat{p}_{x_1}^{f02} > \hat{p}_{x_1}^{f87}$, and by trimming the bottom $(\hat{p}_{x_1}^{f87} - \hat{p}_{x_1}^{f02})/\hat{p}_{x_1}^{f87}$ from $w_{x_1}^{f87}$ if $\hat{p}_{x_1}^{f02} \leq \hat{p}_{x_1}^{f87}$.

5. Define the lower-bound variable, $\underline{w}$, by trimming the bottom $(\hat{p}_{x_1}^{m02} - \hat{p}_{x_1}^{m87})/p_{x_1}^{m02}$ fraction of the distribution of $w_{x_1}^{m02}$, if $\hat{p}_{x_1}^{m02} > \hat{p}_{x_1}^{m87}$. If $\hat{p}_{x_1}^{m02} \leq \hat{p}_{x_1}^{m87}$, trim the top $(\hat{p}_{x_1}^{m87} - \hat{p}_{x_1}^{m02})/\hat{p}_{x_1}^{m87}$ fraction from the distribution of $w_{x_1}^{m87}$.

6. Run the OLS regression of $\overline{w}$ on x, f, tx, and tf where x is education, potential experience, its squared, its cubic, its quartic, tenure and its squared, its cubic, and its quartic. The dummy variable f is the female dummy, and t is 2002 dummy. The coefficient for tx is the estimate for β_3^u.

7. Similarly, run the OLS regression of $\underline{w}$ on explanatory variables to obtain β_3^l.

3 Data and Descriptive Statistics

The Employment Status Survey (ESS, *Shugyo Kozo Kihon Chosa*) for the years 1987, 1992, 1997, and 2002 is used in this study. The ESS is conducted every 5 years on household members 15 years old or more in approximately 440,000 households dwelling in sampled units that cover the complete population.[1] The survey collects information on household members and each member's labor force status on October 1 of each survey year. This study utilizes micro data and extracts information on age, educational attainment, employment status, annual work days, weekly work hours, and annual income from the main job during the previous year. The file contains about 1 million individuals with a half-million males and a half-million females for each year that the survey was conducted. The analysis sample is restricted to those ages 15-64 and out of school. The sample is further restricted to observations with a valid age, educational background, and employment status. Those without job tenure conditioned on being employed are dropped from the wage regression sample. The sizes of the analysis sample are about 600,000 males 600,000 females for the following year combinations: 1987 and 1992, 1987 and 1997, and 1987 and 2002. Although the previous discussion

[1]Foreign diplomats, foreign military personnel and their dependents, persons dwelling in camps or ships of the Self Defense Force, and persons serving sentences in correctional institutions are excluded.

on identification and estimation was based on the 1987-2002 case, the same method is applied to the 1987-1992 and 1987-1997 cases.

Regarding the construction of variables, we transformed the highest educational attainment into a continuous variable. For junior high- school graduates and high-school graduates, 9 and 12 years of education are assigned, respectively. Twelve years of education is assigned for junior-college and technical-college graduates, and 16 years of education is assigned for 4-year college graduates and graduate school graduates. The survey records the annual earnings in ranges.[2] This range is transformed into a continuous variable by using the center value for each range. For the highest open bracket range, the lowest value for the range is assigned for each year. Weekly work hours and annual work days are also recorded by ranges, and we transformed them into continuous variables using the same rule[3].

Constructing the hourly wage from these brackets could result in a biased estimate for the true hourly wage, but what we care about is the change in the

[2]The annual income ranges denominated by thousand yen are: 500 or less, 500-990, 1,000-1490, 1,500-1990, 2,000-2,490, 2,500-2,990, 3,000-3,990, 4,000-4,990, 5,000-5,990, 6,000-6,990, 7,000-7,990, 8,000-8,990, 9,000-9,900, 10,000-14,900 and 15,000 or above for year 2002. The ranges for 1992 and 1997 are: 500 or less, 500-990, 1,000-1,490, 1,500-1,990, 2,000-2,490, 2,500-2,990, 3,000-3,990, 4,000-4,990, 5,000-6,990, 7,000-9,900, 10,000-14,900, and 15,000 or above. The ranges for 1987 are: 500 or less, 500-990, 1,000-1,490, 1,500-1,990, 2,000-2,490, 2,500-2,990, 3,000-3,990, 4,000-4,990, 5,000-6,990, 7,000-9,900, 10,000 or above.

[3]The ranges of annual work day are: less than 50, 50-99, 100-149, 150-199, 200-249, and 250 and more for all survey years. The ranges of work hours are: less than 15, 15-21, 22-34, 35-42, 43-48, 49-59, and 60 and more for 1987; less than 15, 15-21, 22-34, 35-42, 43-45, 46-48, 49-59, and 60 and more for 1992; less than 15, 15-21, 22-34, 35-42, 43-48, 49-59, and 60 and more for 1997; less than 15, 15-19, 20-21, 22-34, 35-42, 43-48, 49-59, and 60 and more for 2002.

hourly wage over time rather than the wage level. The ranges of the brackets for work days are consistent over the years, as are the ranges for weekly work hours. Regarding the annual income range, the change in the range of the brackets in the middle of annual income distribution does not change the hourly wage if the annual income is uniformly distributed within the range. Although the uniform distribution assumption is likely to be violated, the bias due to this would be minimal.

The critical change of the brackets for our purpose is the increase in the largest range from 10 million or above to 15 million or above between 1987 and 1992. If a disproportionately large number of males earns more than 15 million, conditional on earning more than 10 million,[4] the change of this brackets increased the annual earnings of males in 1992 and after, even if the underlying annual earnings had not changed.

To avoid this issue, we imputed those who might have earned more than 15 million in 1987 by the following procedure. First, we calculated the proportion of people who earned more than 15 million conditional on earning more than 10 million, using the 1992 sample by sexes. Let us call this proportion $p_{>15}$. Second, we ran separate probit regressions for both sexes, whose dependent variable is the dummy variable indicating earning more than 15 million, and the independent variables, which are education, experience, its squared, tenure and its squared, using the individuals who earned more than

[4]In fact, we do not find this in our 1992 sample, as the proportion was 0.27 for males and 0.30 for females.

10 million in 1992 as the analysis sample. Third, we assigned 15 million earnings for $p_{>15}$ proportion of people who earned more than 10 million in 1987 based on the predicted probability to earn more than 15 million, using the probit coefficient of 1992 for both sexes. Hourly wage is calculated based on these imputed annual earnings.

Full-time workers in this study are defined as those who work without a term contract (*Joyo Rodosha*) and work regular hours for an employer (*Ippan Rodosha*).

Table 2 tabulates the full-time employment rate by sex, age, and education groups. The overall, full-time employment rate did not change much between 1987 and 2002 for either sex. However, the age- specific, full-time employment rate has changed substantially. In particular, among males, youths' full-time employment rate declined drastically in the last 15 years, as articulated by Genda [2001]. In contrast, the full-time employment rate has increased among the elderly, as articulated by Chuma [1997]. Thus, those who presumably have more human capital are more likely to be employed full-time in terms of the age structure among males.

With respect to years of education, the employment rate has fallen for almost all educational and age categories. However, the rate of drop is smaller among those with more years of education. This tendency is stronger among women.

Table 3 reports the estimation results of the linear regression of the full-time employment dummy on education and age, using the male out-of-school sample. We again can confirm that males over 50 years old were less likely to retire from full-time employment in 2002. The estimation results for females reported in Table 4 indicate that females with junior- or 4-year-college education were more likely to be full-time workers. Also those females aged 25-29, 30-34, and 35-39 were less likely to drop off from full-time employment in 2002.

These figures suggest that the average human capital level among full-time workers increased for both males and females from 1987 to 2002, but the degree of change seems larger for females. Thus the convergence of the observed wage distribution can be attributed to the convergence in the unobserved wage determinants, if the observed wage determinants and the unobserved wage determinants are positively correlated.

4 Results

To address the possibility that the gender wage convergence occurred due to a compositional change in full-time employment, this section implements the bound estimation of the gender wage convergence, allowing for a change in the distribution of unobserved characteristics. Table 5 reports the descriptive statistics of the analysis sample used in the wage regression analysis.

Table 6 reports the estimation results of the log wage equations for 1987, 1992, 1997, and 2002. The adjusted gender wage differential narrowed from 33 to 27 percent during this period; and the gender wage convergence is estimated to be about 6 percentage points. The estimated coefficients for education, potential job experience, and tenure are similar across years. This stable wage structure already has been pointed out by Ohtake [2005].

As discussed previously, about 7 percentage points of the convergence in the gender wage differential could be a product of the convergence in the distribution of unobserved wage determinants. To allow for the change in the distribution of unobserved wage determinants, we now estimate the bound of the true gender wage convergence following the empirical strategy discussed in the previous sections. This strategy trims some observations so that the full-time employment ratios are identical between 1987 and 2002, conditional on the subset of workers' education and potential years of experience.

We obtain $\overline{w}$ and $\underline{w}$ by trimming the bottom or top tail of the wage distribution for each sex and year.

The results of the trimming estimations using the 1987-1992 sample are reported in Table 7. Column (1) reports the OLS regression result applied to the untrimmed log (wage) that replicates the results reported in Table 6. We do not observe a convergence of the gender wage differentials during this period among working people. The second column reports the OLS regression coefficients applied to $\overline{w}$. The number of observations is dropped from the number used for column (1) due to the trimming. This estimate is based on the assumption that the observed, stable gender wage differential is observed regardless of the *divergence* of the unobserved wage determinant between the sexes. Thus, the underlying gender wage gap could have converged up to 21 percentage points. The second column reports the OLS regression result applied to $\underline{w}$. This estimate attributes the observed wage convergence to the *convergence* of the unobserved wage determinant between the sexes at the maximum possible strength. This estimate implies that the offered wage gap for the sexes could have been *diverged* by 22 percentage points, while a stable gender wage gap is observed.

Table 8 reports the results of the trimmed estimation applied to the 1987 and 1997 data. We do not observe a convergence of wages for this period among working people (the gender wage convergence was only 2 percentage points). However, the underlying offered wage might have converged by 26 percentage points during this period as the upper bound. In contrast, the lower-bound estimate implies a possible 20-percentage-point widening gender wage gap during the period. Again, we cannot rule out a wide range of stories underlying the observed 2-percentage-point gender wage convergence between 1987 and 1997.

Finally, Table 9 reports the results of the trimming estimations applied to the 1987 and 2002 sample. We observe a 6-percentage-point convergence in the gender wage gap in these 15 years among full-time employees. However, the upper-bound estimate implies a possible 33-percentage- point convergence of the mean offered wage between genders. However, the lower-bound estimate indicates a possible gender wage divergence of 18 percentage points.

Overall, the bound estimates based on the worst-case scenario tend to indicate a wide bound, and we cannot informatively infer the sexes' mean wage convergence. However, at least the results reported in this section warn us to infer the gender wage convergence at the mean only for full-time, employed workers. We must carefully consider the effects of sample selection.

5 Tightening the Bounds Using the Excluded Variable Assumption

We now consider how to exploit more economic information from the data to tighten the bound. We assume that there is an excluded variable that determines full-time employment status, but not offered wage. We use spousal income as the excluded variable. The analysis sample for this section includes only married couples to use spousal income as an excluded variable.

The structural equations for the offered wage are the following, as before.

$$w^o = x\beta_0 + f\beta_1 + tx\beta_2 + tf\beta_3 + u \tag{6}$$

The wage w is observed only among full-time workers $s = 1$. We assume a binary response model for full-time participation, and the conditional probability of being a full-time worker is given as:

$$s = 1(x\theta_0 + fx\theta_1 + xt\theta_2 + fxt\theta_3 + z\theta_4 + fz\theta_5 + v \geq 0), \tag{7}$$

where z is spousal income. We assume that leisure is a normal good, i.e. $\partial P(s = 1|x, f, z, t)/\partial z > 0$ for all (x, f, t). We also assume that the coefficients for spousal income are constant over time, and this is a crucial assumption for identifying the upper and lower bounds.

The error terms of two equations are assumed to have a positive correlation. This is natural because both the wage equation error term u and the participation equation error term v should include the unobserved wage determinants. Among full-time workers, those who have high, non-own labor, household income should have a high, unobserved earning ability v and thus a higher u, conditional on x, f, and t.

We now assume that (u, v) are stationary, conditional on x, f, z, and t in the wage and selection equations. We exploit the information given by the positive correlation between u and v. Because u and v are positively correlated, trimming observations from the higher value of v (the higher value of non-labor income among full-time workers) is equivalent to trimming the observations from the higher value of u.

The following upper- and lower-bound estimators implement this idea:

$$\begin{aligned}
\beta^u_{3\{x,z\}} &= 1(p_x^{f02} > p_x^{f87})\{E[w_x^{f02}|s=1, z \geq z_{\frac{p_x^{f02}-p_x^{f87}}{p_x^{f02}}}] - E[w_x^{f87}|s=1]\} \\
&+ 1(p_x^{f02} \leq p_x^{f87})\{E[w_x^{f02}|s=1] - E[w_x^{f87}|s=1, z < z_{1-\frac{p_x^{f87}-p_x^{f02}}{p_x^{f87}}}]\} \\
&- 1(p_m^{f02} > p_x^{m87})\{E[w_x^{m02}|s=1, z \leq z_{1-\frac{p_x^{f02}-p_x^{f87}}{p_x^{f02}}}] - E[w_x^{m87}|s=1]\} \\
&- 1(p_m^{f02} \leq p_x^{m87})\{E[w_x^{m02}|s=1] - E[w_x^{m87}|s=1, z > z_{\frac{p_x^{f87}-p_x^{f02}}{p_x^{f87}}}]\}
\end{aligned} \tag{8}$$

$$
\begin{aligned}
\beta^l_{3\{x,z\}} &= 1(p^{f02}_x > p^{f87}_x)\{E[w^{f02}_x|s=1, z < z_{1-\frac{p^{f02}_x - p^{f87}_x}{p^{f02}_x}}] - E[w^{f87}_x|s=1]\} \\
&+ 1(p^{f02}_x > p^{f87}_x)\{E[w^{f02}_x|s=1] - E[w^{f87}_x|s=1, z \geq z_{\frac{p^{f87}_x - p^{f02}_x}{p^{f87}_x}}]\} \\
&- 1(p^{m02}_x > p^{m87}_x)\{E[w^{m02}_x|s=1, z > z_{\frac{p^{m02}_x - p^{m87}_x}{p^{m02}_x}}] - E[w^{m87}_x|s=1]\} \\
&- 1(p^{m02}_x \leq p^{m87}_x)\{E[w^{m02}_x|s=1] - E[w^{m87}_x|s=1, z \leq z_{1-\frac{p^{m87}_x - p^{m02}_x}{p^{m87}_x}}]\}
\end{aligned} \tag{9}
$$

We can show that $\beta^u_{3\{x,z\}} \geq \beta_3$ and $\beta^l_{3\{x,z\}} \leq \beta_3$. To see this, $\beta^u_{3\{x,z\}}$ is decomposed into the true parameter and the bias term:

$$
\begin{aligned}
\beta^u_{3\{x,z\}} &= \beta_3 \\
&+ 1(p^{f02}_x > p^{f87}_x)\{E[u^{f02}_x|s=1, z \geq z_{\frac{p^{f02}_x - p^{f87}_x}{p^{f02}_x}}] - E[u^{f87}_x|s=1]\} \\
&+ 1(p^{f02}_x \leq p^{f87}_x)\{E[u^{f02}_x|s=1] - E[u^{f87}_x|s=1, z < z_{1-\frac{p^{f87}_x - p^{f02}_x}{p^{f87}_x}}]\} \\
&- 1(p^{f02}_m > p^{m87}_x)\{E[u^{m02}_x|s=1, z \leq z_{1-\frac{p^{f02}_x - p^{f87}_x}{p^{f02}_x}}] - E[u^{m87}_x|s=1]\} \\
&- 1(p^{f02}_m \leq p^{m87}_x)\{E[u^{m02}_x|s=1] - E[u^{m87}_x|s=1, z > z_{\frac{p^{f87}_x - p^{f02}_x}{p^{f87}_x}}].\}
\end{aligned} \tag{10}
$$

This bias term is positive if the error terms of the wage equation and the selection equation are positively correlated in the way that $u = \rho v + e$, where $E[e|x, z] = 0$.

The following discussion heuristically shows that the bias terms are positive. Given an increase in the full-time employment rate among females for group x, (i.e. $p_x^{f02} > p_x^{f87} > 0$), the first two terms become

$$\rho\{E[v_x^{f02}|s=1, z \geq z_{\frac{p_x^{f02}-p_x^{f87}}{p_x^{f02}}}] - E[v_x^{f87}|s=1]\}. \tag{11}$$

The term $E[v_x^{f02}|s = 1, z \geq z_{\frac{p_x^{f02}-p_x^{f87}}{p_x^{f02}}}] - E[v_x^{f87}|s = 1]$ is positive because $E[v_x^{f02}|v \geq -x(\theta_0 + \theta_1 + \theta_2 + \theta_3) - z(\theta_4 + \theta_5), z \geq z_{\frac{p_x^{f02}-p_x^{f87}}{p_x^{f02}}}] - E[v_x^{f87}|v \geq -x(\theta_0 + \theta_1 + \theta_2 + \theta_3) - z(\theta_4 + \theta_5), v \geq -x(\theta_0 + \theta_1) - z(\theta_4 + \theta_5)]$ is positive. Given $v \geq -x(\theta_0 + \theta_1 + \theta_2 + \theta_3) - z(\theta_4 + \theta_5)$ is satisfied, the proportion $(p_x^{f02} - p_x^{f87})/p_x^{f02}$ should be trimmed from the 2002 distribution to balance the full-time employment for 1987 and 2002. Once the value of x is fixed, the largest value of $-x(\theta_0+\theta_1+\theta_2+\theta_3)-z(\theta_4+\theta_5)$ is attained by trimming the bottom $(p_x^{f02}-p_x^{f87})/p_x^{f02}$ proportion of z because $(\theta_4+\theta_5) < 0$ under the assumption that leisure is a normal good. Because $-x(\theta_0 + \theta_1 + \theta_2 + \theta_3) - z(\theta_4 + \theta_5)$ attains highest value under $z_{\frac{p_x^{f02}-p_x^{f87}}{p_x^{f02}}}$ after fixing the value of x, $E[v_x^{f02}|v \geq -x(\theta_0 + \theta_1 + \theta_2 + \theta_3) - z(\theta_4 + \theta_5), z \geq z_{\frac{p_x^{f02}-p_x^{f87}}{p_x^{f02}}}] - E[v_x^{f87}|v \geq -x(\theta_0 + \theta_1 + \theta_2 + \theta_3) - z(\theta_4 + \theta_5), v \geq -x(\theta_0 + \theta_1) - z(\theta_4 + \theta_5)]$ is positive.

Repeating a similar argument for all the terms, we can confirm that all the bias terms are non-negative. We can show $\beta_3^{l,\{x,z\}} \leq \beta_3$ by the same argument.

The actual implementation of the estimation is identical to the trimming estimator based on wage trimming. Instead of trimming certain observations, we trimmed the observation based on the non-labor income within 185 cells based on education × experience. We balanced the full-time employment rate for two years for all 185 cells.

The analysis sample is restricted to those who are married and who are the household head or his/her spouse. This sample restriction is applied because spousal income is identified for these individuals. We dropped the individuals whose spouse is employed, but for whom annual income is not reported. Because the analysis sample is restricted to married individuals different from the previous analysis, we repeated the trimming estimation without the excluded variable assumption for this analysis sample.

The results of the analysis appear in Table 7. The first column reports the gender wage convergence between 1987 and 1992, 1997, or 2002. Among married people, we do not observe a mean wage convergence between 1987 and 1992, but a 3-percentage-point convergence is observed between 1987 and 1997. Between 1987 and 2002, the gender wage gap converged by 11 percentage points. This number is even larger than the gender wage convergence observed among the entire working population reported in the previous table.

The upper- and lower-bound estimates for the wage convergence under the agnostic assumption are reported in Columns (2) and (3), respectively. For all sample years, the upper bound is about 20 percentage points higher than the point estimate and the lower bound is about 20 percentage points lower than the point estimate. The bound is so wide that we cannot rule out the possibility that the observed gender wage convergence occurred due to a compositional change of full-time workers.

Columns (4) and (5) report the upper- and lower-bound estimates based on the trimming by spousal annual income. The excluded variable assumption turns out to add much information, and the bounds for the gender wage convergence become very narrow. For the period between 1987 and 1992, the convergence was bounded between -1 and 1 percentage points where the untrimmed estimate indicates a -1 percentage point convergence (in fact, a 1 percentage point divergence). The estimation results for the 1987 - 1997 period are a bit problematic because the untrimmed estimate does not reside in the range of lower- and upper-bound estimates. The point estimate is 0.03 and the bounds are 0.04 and 0.05. However, this could occur due to sampling error.

The highlight of the bound estimation based on the excluded variable assumption is the results between 1987 and 2002. We observe an 11- percentage-point convergence of the gender wage gap for this 15- year period among all full-time workers. The bound estimates based on spousal income trimming renders a 10-percentage-point convergence as the lower bound and a 15-percentage-point convergence as the upper bound. This rather narrow bound clearly excludes the possibility that the observed gender wage convergence among full-time workers is an illusion due to a change in employment composition.

6 Conclusion

This paper discusses the identification and estimation of the gender wage convergence among full-time, regular workers. The identification of the gender wage convergence is generally difficult because the composition of full-time workers tend to change contemporaneously. The identification strategy is essentially based on trimming the wage distribution, and this strategy contrasts with the identification strategy proposed by previous studies that have been based on imputing the non-employed population's offered wage.

The adjusted gender wage differentials narrowed from 33 percent to 27 percent during the corresponding period. Thus, among the working population, a 6- percentage-point gender wage convergence was observed. The upper and lower bounds of the gender wage convergence based on agnostic assumption was 33 percentage points and -18 percentage points, based on an agnostic assumption.

However, the knowledge that leisure is a normal good and spousal income affects the reservation wage, but not offered wage, helps to tighten the bounds dramatically. Among married men and women, the gender wage differential converged by 11 percentage points between 1987 and 2002. The lower- and upper-bound estimates under the assumption that spousal income is excludable were 10 and 13 percentage points, respectively. Based on this tight bound, we exclude the possibility that the observed wage convergence among full-time workers is spurious due to a change in workers' composition.

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Table 1: Trend in Full-time Population Ratio and Gender Wage Differential

Sample: Age 15-64, Out of School

	Full-time/Population Ratio		Full-time Hourly Wage (Yen, Year 2000 Value)		Female/Male Wage Ratio
	Male	Female	Male	Female	
1987	0.64	0.27	2788	1690	0.61
1992	0.66	0.31	3290	1995	0.60
1997	0.67	0.31	3562	2291	0.64
2002	0.61	0.27	3467	2413	0.70

Table 2: Full-Time Employment Population Ratio by Gender, Education and Age.

	Male				Female			
	1987	1992	1997	2002	1987	1992	1997	2002
Total	0.64	0.66	0.67	0.61	0.27	0.28	0.31	0.27
Educ=9								
15-19	0.47	0.51	0.37	0.21	0.33	0.29	0.17	0.05
20-24	0.62	0.65	0.61	0.41	0.29	0.30	0.23	0.11
25-29	0.65	0.66	0.62	0.50	0.21	0.22	0.18	0.13
30-34	0.64	0.65	0.61	0.53	0.20	0.21	0.16	0.13
35-39	0.62	0.63	0.60	0.52	0.22	0.27	0.21	0.14
40-44	0.62	0.61	0.61	0.51	0.24	0.27	0.26	0.16
45-49	0.56	0.60	0.60	0.52	0.25	0.29	0.26	0.21
50-54	0.50	0.57	0.60	0.52	0.22	0.26	0.25	0.20
55-59	0.39	0.48	0.53	0.48	0.13	0.18	0.20	0.17
60-64	0.15	0.21	0.22	0.17	0.05	0.07	0.07	0.06
Educ=12								
15-19	0.59	0.64	0.57	0.46	0.72	0.74	0.54	0.38
20-24	0.80	0.82	0.77	0.61	0.65	0.68	0.59	0.41
25-29	0.82	0.84	0.81	0.73	0.33	0.40	0.40	0.35
30-34	0.79	0.81	0.81	0.75	0.23	0.26	0.27	0.25
35-39	0.74	0.76	0.78	0.75	0.23	0.27	0.26	0.23
40-44	0.72	0.72	0.75	0.72	0.25	0.29	0.28	0.25
45-49	0.68	0.70	0.70	0.68	0.25	0.29	0.29	0.26
50-54	0.62	0.66	0.68	0.63	0.23	0.25	0.26	0.23
55-59	0.46	0.56	0.61	0.56	0.15	0.18	0.21	0.19
60-64	0.59	0.21	0.21	0.16	0.72	0.08	0.07	0.07
Educ=14								

20-24	0.82	0.86	0.81	0.66	0.73	0.81	0.72	0.60
25-29	0.82	0.84	0.84	0.77	0.43	0.51	0.53	0.49
30-34	0.79	0.80	0.82	0.78	0.31	0.32	0.33	0.34
35-39	0.74	0.75	0.77	0.73	0.29	0.32	0.30	0.29
40-44	0.73	0.70	0.70	0.69	0.29	0.31	0.32	0.30
45-49	0.67	0.67	0.68	0.68	0.31	0.29	0.33	0.32
50-54	0.73	0.66	0.67	0.60	0.31	0.29	0.30	0.30
55-59	0.58	0.62	0.61	0.55	0.19	0.21	0.26	0.22
60-64	0.18	0.17	0.18	0.19	0.06	0.07	0.09	0.09
Educ=16								
20-24	0.86	0.91	0.82	0.66	0.70	0.81	0.69	0.60
25-29	0.89	0.91	0.89	0.81	0.51	0.63	0.61	0.55
30-34	0.86	0.88	0.89	0.85	0.36	0.41	0.45	0.43
35-39	0.81	0.82	0.86	0.84	0.36	0.38	0.38	0.39
40-44	0.77	0.77	0.80	0.81	0.34	0.35	0.37	0.37
45-49	0.75	0.72	0.75	0.75	0.41	0.33	0.35	0.36
50-54	0.68	0.71	0.70	0.67	0.37	0.35	0.36	0.34
55-59	0.57	0.59	0.61	0.57	0.27	0.28	0.28	0.28
60-64	0.24	0.25	0.23	0.19	0.13	0.09	0.11	0.10
N	305994	361858	334095	315915	325956	357262	345187	328547

Table 3: The OLS regression of full-time employment

Dependent variable: Full-time=1; Sample: Male

	(1)	(2)	(3)	(4)
	1987	1992	1997	2002
Educ=12	0.11	0.09	0.10	0.12
	(0.00)	(0.00)	(0.00)	(0.00)
Educ=14	0.12	0.09	0.10	0.13
	(0.00)	(0.00)	(0.00)	(0.00)
Educ=16	0.18	0.15	0.15	0.18
	(0.00)	(0.00)	(0.00)	(0.00)
20-24	0.21	0.19	0.23	0.19
	(0.01)	(0.01)	(0.01)	(0.01)
25-29	0.23	0.21	0.27	0.31
	(0.01)	(0.01)	(0.01)	(0.01)
30-34	0.20	0.18	0.27	0.33
	(0.01)	(0.01)	(0.01)	(0.01)
35-39	0.15	0.13	0.24	0.33
	(0.01)	(0.01)	(0.01)	(0.01)
40-44	0.13	0.08	0.20	0.30
	(0.01)	(0.01)	(0.01)	(0.01)
45-49	0.09	0.06	0.16	0.26
	(0.01)	(0.01)	(0.01)	(0.01)
50-54	0.03	0.03	0.14	0.21
	(0.01)	(0.01)	(0.01)	(0.01)
55-59	-0.10	-0.07	0.07	0.15
	(0.01)	(0.01)	(0.01)	(0.01)
60-64	-0.37	-0.38	-0.29	-0.21
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.48	0.54	0.44	0.30
	(0.01)	(0.00)	(0.01)	(0.01)

Observations	305994	361858	334095	315915
R^2	0.16	0.15	0.15	0.15

Note: Heteroskedasticity robust standard errors are reported in the parenthesis.

Table 4: The OLS regression of full-time employment

Dependent variable: Full-time=1; Sample: Female

	(1)	(2)	(3)	(4)
	1987	1992	1997	2002
Educ=12	0.03	0.02	0.04	0.05
	(0.00)	(0.00)	(0.00)	(0.00)
Educ=14	0.10	0.09	0.11	0.13
	(0.00)	(0.00)	(0.00)	(0.00)
Educ=16	0.16	0.14	0.16	0.19
	(0.00)	(0.00)	(0.00)	(0.00)
20-24	-0.02	0.03	0.12	0.13
	(0.01)	(0.01)	(0.01)	(0.01)
25-29	-0.31	-0.23	-0.05	0.06
	(0.01)	(0.01)	(0.01)	(0.01)
30-34	-0.41	-0.39	-0.20	-0.06
	(0.01)	(0.01)	(0.01)	(0.01)
35-39	-0.41	-0.38	-0.22	-0.08
	(0.01)	(0.01)	(0.01)	(0.01)
40-44	-0.39	-0.37	-0.20	-0.07
	(0.01)	(0.01)	(0.01)	(0.01)
45-49	-0.38	-0.37	-0.19	-0.06
	(0.01)	(0.01)	(0.01)	(0.01)
50-54	-0.41	-0.39	-0.21	-0.07
	(0.01)	(0.01)	(0.01)	(0.01)
55-59	-0.50	-0.46	-0.25	-0.11
	(0.01)	(0.01)	(0.01)	(0.01)
60-64	-0.58	-0.57	-0.38	-0.23
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.62	0.63	0.44	0.26
	(0.01)	(0.01)	(0.01)	(0.01)

Observations	325956	383213	345187	328547
R^2	0.12	0.13	0.10	0.07

Note: Heteroskedasticity robust standard errors are reported in the parenthesis.

Table 5: Descriptive Statistics

Male				
	1987	1992	1997	2002
Hourly Wage	2788	3290	3562	3469
	(2365)	(2828)	(2576)	(2768)
Education	12.32	12.51	12.80	12.99
	(2.36)	(2.34)	(2.31)	(2.27)
Potential Experience	20.40	21.06	21.12	22.00
	(11.70)	(12.30)	(12.29)	(11.90)
Tenure	13.27	13.78	14.06	14.84
	(10.01)	(10.73)	(11.02)	(11.28)
N	192382	235707	221867	190354
Female				
	1987	1992	1997	2002
Hourly Wage	1690	1995	2291	2413
	(1528)	(1780)	(1892)	(2508)
Education	12.03	12.27	12.61	12.92
	(1.91)	(1.89)	(1.87)	(1.85)
Potential Experience	17.66	18.16	18.71	19.91
	(12.89)	(13.24)	(13.11)	(12.80)
Tenure	8.66	9.00	9.87	11.39
	(8.01)	(8.56)	(8.98)	(9.78)
N	87937	117633	104266	85570

Note: Standard deviations are in parenthesis.

Table 6: Wage equations for 1987, 1992, 1997 and 2002

Dependent Variable: log (hourly wage)

	(1)	(2)	(3)	(4)
=1 if female	-0.34	-0.35	-0.31	-0.26
	(0.00)	(0.00)	(0.00)	(0.00)
High Shool	0.28	0.28	0.26	0.26
	(0.00)	(0.00)	(0.00)	(0.00)
Junior College	0.48	0.48	0.45	0.43
	(0.00)	(0.00)	(0.00)	(0.00)
4 Yr College +	0.60	0.63	0.60	0.62
	(0.00)	(0.00)	(0.00)	(0.00)
Potential Experience	0.02	0.03	0.05	0.05
	(0.00)	(0.00)	(0.00)	(0.00)
Experience^2	0.01	-0.15	-0.26	-0.20
/100	(0.01)	(0.01)	(0.01)	(0.01)
Experience^3	-0.13	0.43	0.70	0.45
/10000	(0.04)	(0.03)	(0.03)	(0.04)
Experience^4	0.07	-0.55	-0.78	-0.45
/1000000	(0.04)	(0.03)	(0.04)	(0.04)
Job Tenure	0.03	0.02	0.04	0.04
	(0.00)	(0.00)	(0.00)	(0.00)
Tenure^2	-0.05	-0.07	-0.27	-0.27
/100	(0.01)	(0.01)	(0.01)	(0.01)
Tenure^3	0.15	0.54	1.17	1.14
/10000	(0.05)	(0.04)	(0.04)	(0.05)
Tenure^4	-0.26	-0.97	-1.59	-1.51
/1000000	(0.07)	(0.05)	(0.05)	(0.06)
Constant	6.84	7.04	6.98	6.88
	(0.00)	(0.00)	(0.00)	(0.01)
Observations	280319	353340	326133	275924

R-squared	0.45	0.44	0.45	0.40

Table 7: The estimation of the upper and lower bounds of the gender wage convergence

Sample: 1987 and 1992 pooled, 1987 and 1997 pooled; 1987 and 2002 pooled.

	(1)	(2)	(3)
Trimming Rule	Untrimmed	Upper Bound	Lower Bound
1987 and 1992	-0.01	0.15	-0.18
	(0.00)	(0.00)	(0.00)
Observations	633659	601909	594794
R^2	0.45	0.47	0.50
1987 and 1997	0.03	0.21	-0.15
	(0.00)	(0.00)	(0.00)
Observations	606452	564752	564858
R^2	0.48	0.49	0.51
1987 and 2002	0.08	0.30	-0.11
	(0.00)	(0.00)	(0.00)
Observations	556243	509995	511886
R^2	0.45	0.48	0.46

Note: Upper bound and lower bound estimates are calculated based on trimming. Trimming is based on actual wage within 185 cells created by Education * Job Experience. The numbers of observations should match up for columns (2) and (3), but differ due to rounding in the cut point quintiles and observation bunching at a certain quintile. Each specification includes education category dummy variables, potential experience, its squared, its cubic, its quartic, tenure, its squared, its cubic, its quartic and a constant. The estimated coefficients for these variables are suppressed.

Table 7: The estimation of the upper and lower bounds of the gender wage convergence

Sample: 1987 and 1992 pooled, 1987 and 1997 pooled; 1987 and 2002 pooled. The sample includes married individuals who are household head or his/her spouse only.

	(1)	(2)	(3)	(4)	(5)
Trimming Rule	Untrimmed	Upper Bound	Lower Bound	Upper Bound	Lower Bound
Trimming by		Wage	Wage	Spousal Income	Spousal Income
1987 and 1992	-0.01	0.17	-0.21	0.01	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	360961	339309	335485	329897	313026
R^2	0.45	0.46	0.50	0.45	0.44
1987 and 1997	0.03	0.23	-0.17	0.05	0.04
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	340365	315104	318715	308777	294606
R^2	0.46	0.47	0.51	0.46	0.45
1987 and 2002	0.11	0.31	-0.10	0.13	0.10
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	318242	297786	295113	279596	264719
R^2	0.43	0.46	0.46	0.44	0.41

Note: Upper bound and lower bound estimates are calculated based on trimming. Trimming is based on actual wage within 185 cells created by Education * Job Experience. The numbers of observations should match up for columns between (2) and (5), but differ due to rounding in the cut point quintiles and observation bunching at a certain quintile. Each specification includes education category dummy variables, potential experience, its squared, its cubic, its quartic, tenure, its squared, its cubic, its quartic and a constant. The estimated coefficients for these variables are suppressed.