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Abstract

Diverging economic inequality has become a common focus of economic debate in developed countries. In particular, the recent experience of Japan has started attracting international attention. We take advantage of a rich micro-level data set from the *Basic Survey on Wage Structure* (1989-2003) to perform an in-depth analysis of the change in the inequality and distribution of the hourly wage. We observe that lower returns to education and years of tenure contribute to diminishing income disparity between groups for both sexes. A larger variance within a group contributes to the wage disparity for males, while an increased heterogeneity of workers' attributes contributes to the wage disparity for females. The Dinardo, Fortin, and Lemieux decomposition also confirms the basic findings from a parametric variance decomposition.

Key Words: Wage Distribution, Wage Equation, Variance Decomposition, DiNardo-Fortin-Lemieux Decomposition, Japan.
JEL Classification Code: J31

1 Introduction

Economic inequality recently has become a major focus of political debate in many developed countries. In such debates, Japan's experience over the last 15 years has started attracting international attention (Economist, the [2006] and OECD [2006]). The long-lasting stagnation of the Japanese economy during the 1990s, rapid globalization and technological change, and the recent economic reform toward deregulation and a more market-oriented economy initiated by Prime Minister Koizumi from 2001 are claimed to be responsible for widening income inequality. While the debate on the reason for broadened inequality is heating up, the premise of the debates that Japan has experienced widening inequality has not yet been decisively confirmed.

The trend of the income inequality of Japan, which has the world's second-largest economy, also has attracted much attention from labor economists because it can offer a testing ground for determining whether the recent income dispersion in the US, UK, and Canada can be explained by such global factors as skill-biased technological change (SBTC) or globalization of the economy (Katz and Murphy [1992] and Juhn et al. [1993]) Similar to other developed countries, Japan has experienced the penetration of information technology (Kawaguchi [2006]) and an increased degree of competition with newly emerging economies, in particular, with neighboring Asian countries (Higuchi and Genda [1999], Head and Ries [2002], Fukao [2002] for the effect of FDI and Sakurai [2004] for the effect of trade) over the last 15 years. Thus, if these two factors explain the ongoing income disparity in the US, the UK, and Canada, we should observe a similar income dispersion in Japan, too. Considering the recent revisionist view that casts doubt on the traditional SBTC and globalization hypotheses for income or wage dispersion (Card and DiNardo [2002]), it is crucial to examine what happened to the income distribution in the world's second largest economy. In fact, Saez and Piketty [2005] reports that an increase in the concentration of income in the top 0.1 percent of the income distribution was not observed during 80s and 90s in Japan, contrary to findings from the US, the UK, and Canada.

In contrast to the high level of interest in the recent trend of income inequality of Japan among the general public and economists, there has not been a consensus regarding whether income inequality widened during the 1990s and onward. A few studies have arrived at different conclusions regarding the trend in income inequality. Tachibanaki [2005] claimed that income inequality widened during the 80s and 90s and that the Gini coefficient of pre-tax income increased to the point that it is as large as the number for the US and the UK. In contrast, Ohtake [2005] claims that the increase in income inequality is partly due to the aging population; the degree of income inequality is intrinsically high among elderly people and the aging population mechanically widens income inequality.[1]

[1] Although journalists have described the discrepancy between the two results as a controversy, the two authors' sets of results authors do not contradict. Tachibanaki [2005] reported unconditional income inequality, while Ohtake [2005] reported conditional inequality. Ohtake [2005] also pointed out that the income measure Tachibanaki [2005] used to calculate the Gini coefficient is not comparable to the income measure used for the US

Regarding wage inequality, Ohtake [2005] pointed out the decline of the between-group wage differential and the increase of the within-group wage differentials, but he did not decompose the movement of the inequality in a systematic way. Shinozaki [2002] reported an an exceptional study that analyzed the change in the wage distribution during the 1990s using the log wage variance decomposition based on aggregate data provided by the Ministry of Labor and Welfare. He found that wage inequality for both sexes remained the same during the 1990s. He could not, however, decompose the inequality by the education-experience-tenure cell due to limitations of the aggregate data.

Given the research results for Japan introduced above, this study focuses on the wage distribution, exploiting micro-level data of 1989-2003 from the *Basic Survey on Wage Structure (BSWS)* compiled by the Ministry of Health, Labor and Welfare (formerly, the Ministry of Labor) of the Japanese government. This study contributes to the existing literature in the following two ways. First, this is the first study to focus on the change in wage distribution using micro data. Focusing on labor income is important because it is the most important source of income for most people and hypotheses on income dispersions, such as the STBC hypothesis and the globalization hypothesis, predict a dispersion of labor income rather than total income. Al-

because the income measure that Tachibanaki [2005] used did not include a pre-tax pension payment, but the income measure used to calculate US number did include it. After adjusting for the discrepancies between the Japanese and US income measures, Ohtake [2005] concluded that the Gini coefficient for Japan is smaller than that of the US.

though this study does not aim to identify the specific reason for the change in wage inequality, it does offer descriptive evidence regarding whether the change in the wage distribution observed in Japan is consistent with the STBC or the globalization hypothesis. Second, exploiting the micro data feature, this study decomposes the log wage variance among finely defined groups of workers in a systematic way. Thus, we can precisely attribute the change in the log wage variance to between- and within- group changes. In addition, micro data enables us to visually examine the entire distribution of the log wage using the kernel density estimation without discarding information. Further, DiNardo et al. [1996] the decomposition technique enables us to calculate the counterfactual log wage distribution in 2003 if the distribution of worker and establishment attributes were the same as those in 1989. This enables us to infer whether the change in the log wage distribution is caused by a distributional change in attributes or a mapping from attributes to log wage.

We show that the modest decline in the variance of the log wage in the first half of the 1990s is attributable to the smaller variance between groups due to lower returns to education and years of tenure. The diminishing return to education is mainly caused by an increase of 2- and 4-year college graduates during the period due to the deregulation of college openings by the Ministry of Education. The diminishing return to job tenure is mainly caused by an increase in the average years of job tenure, partly due to the aging of the Japanese population (Chuma [1998] and Shimizutani and Yokoyama

[2006]). In contrast, the expansion in the variance among males after 1997 is explained by a larger variance within the group: a larger residual variance in the wage equation. The variance increase among female after the mid-1990s was mainly due to greater heterogeneity in terms of attributes (years of job tenure, in particular).

The kernel estimation of the log wage distribution shows that the shape of the wage distribution did not change much between 1989 and 2003. DiNardo et al. [1996]'s decomposition, however, reveals that this stability is the product of two opposing effects. The mapping from workers' and establishments' attributes to log wage has changed so that the wage distribution is compressed, mainly due to the diminished return to education and tenure, while the variance of attributes and residuals increased. In other words, between-group variance has decreased, while within-group variance has increased among males. The results for females are similar to those for males, but the effect of the change in the attribute distribution is much larger than the effect of the change in residual distribution for females. This finding is consistent with the findings from the log variance decomposition; female full-time workers became more heterogeneous from 1989 to 2003.

An additional finding from the DFL decomposition regarding the 1989-2003 change is that the mapping from the attributes to wage has changed such that the bottom half of the wage distribution increased. In contrast, the distributional change in the upper half of the distribution cannot be explained by the change in the relation between attributes and wage. The distributional change between 1989 and 2003 in the upper half of the distribution is mainly caused by the distributional change in the attributes and unexplained factors.

Our empirical examination proceeds as follows. Section 2 provides a brief data description, and Section 3 reports the estimation results of the wage equations for full-time workers by years and examines the change in the estimated parameters on workers' attributes, which is the basis for the remaining explorations. Section 4 performs a variance decomposition of wage rates for full-time workers into the change in the estimated coefficients in the wage equation, the variance of workers' attributes, and the residual variance. Contributions of each component uncover what is responsible for change in the wage rate variance. Section 5 turns to an application of the DiNardo et al. [1996] analysis. Section 6 expands our analysis by adding part-time workers to the sample and reexamines the change in the wage distribution for female workers, whose share of part- time workers is higher than that for male workers. The last section summarizes our empirical findings and discusses their policy implications.

2 Data

The data set used in this study is micro-level data from the *Basic Survey on Wage Structure* (*BSWS* hereafter), compiled annually by the Japanese government between 1989 and 2004. This survey holds some unusual advantages. First, it is a representative survey performed by the government with an unusually large number of observations randomly chosen from all regions and industries in Japan. The annual number of observations is approximately 1.5 million workers from 60-70 thousand establishments. The sample includes all establishments with 10 or more employees in both private and public sectors and all establishments that belong to private firms with five to nine permanent workers.

The establishments in the sample are randomly chosen in proportion to the size of prefectures, industries, and number of employees from the Survey of Firms and Establishments *SFE* that lists all the establishments in Japan. This list is revised every 2-3 years. In the relevant years for our analysis, the lists were revised in 1986, 1991, 1994, 1996, 1999, and 2001. The *BSWS* 1989-1992 sample is randomly picked from the 1986 *SFE* list, the 1993-1995 sample is from the 1991 list, the 1996-1997 sample is from the 1994 list, the 1998-2001 sample is from the 1996 list, and the 2002-2003 sample is from the 1999 list. While the sampling is based on the same list, about half of the establishments are picked in two consecutive years, but only about 1/10 of the establishments are picked in the sample at the time of the list revision. We should recognize the large discontinuity of the analysis sample at the times of the list revision: 1993, 1996, 1998, and 2002.

The randomly selected establishments were asked to extract their workers' information from their payroll records. A person in charge of personnel matters in each establishment was asked to randomly choose a number of workers from its pool of employees based on the given instructions for random sampling, including the sampling probability, which depended on the establishment size and industry. The establishment and individual files were merged using an establishment identification number.

Second, the survey contains a variety of variables. The unit of analysis is an individual worker with relevant information from the establishment to which he/she belongs. In addition to variables related to wages, the available information includes each worker's age, sex, educational attainment, full-time/part-time status, type of work or job, employment status (with or without permanent status), working days/hours, as well as the firm's attributes, including the number of permanent workers (*Joyo Rodo Sha*)[2], firm size, industry, and location.

Regarding wages, the individual data include the contracted hours of work and overtime hours between June 1 and June 30, and the total amount of payment for the corresponding period, including overtime pay and allowances, such as dependent allowance and transportation allowance. It also records the total bonus payment between January 1 and December 31 of the previous year. The wage rate in this study is defined as the hourly rate of pay, which is calculated by dividing the total payment in June plus one twelfth of the total bonus payment in the previous year by the sum of the contracted hours of work in June and the overtime work hours in June.

Table 1 reports the summary statistics of the main variables used in this

[2]Those workers who satisfy one of the following three criteria are classified as permanent workers: 1. On contracts that do not clearly specify a contractual time period, 2: On contracts that last more than a month, or 3: On contracts that last less than a month, but on which the workers worked 18 or more days in the last two months. This classification includes part-time workers if one of the criteria above is satisfied.

study. The sample presented in the table is confined to full-time workers in the private sector. We proceed with our analysis without placing any limitations on workers' age.[3]

First, the average nominal wage rate (*WageRate*) increased until 1993 and then leveled off after the period, which is common to both male and female workers. Although it decreased slightly after 2000, the average wage rate in real terms (W/p) deflated by Consumer Price Index at the 2000 constant price was almost constant due to deflation.

Second, potential years of experience (*Exper*), defined as age minus years of education minus 6, declined in the first half of the 1990s, but expanded again after the decade ended. Third, the average years of tenure (*Tenure*), defined as the years an employee had worked for the current firm, *extended* between 1989 and 2003 by 1.6 years for male and 2.2 years for female workers. As Shimizutani and Yokoyama [2006] discussed, the long-term employment practice survived for those workers within the scheme, and thus their years of tenure expanded, mainly due to the aging of the population and the extension of the mandatory retirement age in the 1990s.

Fourth, we observe a higher educational attainment between 1989 and 2003. The share of junior high school graduates ($Educ \leq 9$) decreased, while that of university graduates ($Educ \geq 16$) increased by 10 percentage points, which is common to both male and female workers. The share of senior high

[3]Our results are unchanged even after limiting the sample to workers whose ages are 15-65.

school graduates (*Educ=12*) decreased and that of two-year college graduates (*Educ=14*) gained substantially for female workers, though those shares were mostly unchanged for male workers.

Turning to firms' characteristics, firm size expanded in the first half of the 1990s for both male and female workers, reached their peaks during 1993-1995, and then returned to its level of the first half of the 1990s again.[4] The establishment size, defined as the number of permanent workers in an establishment, showed a smaller variation than firm size, though there was a slightly declining trend after the mid-1990s for male workers.

In sum, while the real wage rates leveled off after the mid-1990s, we observe remarkable increases in the workers' years of tenure and educational attainment. The average potential years of experience was not associated with the rapid speed of aging, partly because of the longer years of education.

Regarding wage inequality, Figure 1 draws four measures of log wage inequality: the difference between the 90th and 10th percentiles, the variance of the log wage, the Gini coefficient, and the Theil index. Regardless of the measure we used, the inequality in the log wage declined until the mid-1990s, kept the same level in the late-1990s, and started increasing from 2000 for males. The log wage inequality declined by 1995 and kept the level afterward for females. The sudden jumps in the log wage variance and the 90th and 10th

[4] The variable for firm size is classified into several intervals in the Basic Survey on Wage Structure. We assigned the mid-point for each interval: 5,000 for 5,000 and above persons, 3,000 for 1,000-4,999 persons, 750 for 500-999 persons, 400 for 300-499 persons, 200 for 100-299 persons, 65 for 30-99 persons, 20 for 10-29 persons, and 7 for 5-9 persons.

percentiles difference in 1993 were probably due to the revision of the list of establishments. We attempted to correct for this gap by using a re-weighting procedure without success. This point should be noted as a caveat. It is rather surprising that the log wage inequality declined throughout the 1990s, while Japanese academics and the media were debating about increased wage inequality. In the following decomposition analysis, we attempt to offer a solution for this puzzle.

3 Estimation of a wage equation for full-time workers

In this section, we employ the following wage equation to explore changes in the returns to each attribute of workers' human capital.

$$y_{it} = x_{it}\beta_t + u_{it},\ E(u|x) = 0 \tag{1}$$

The dependent variable (y_{it}) is the logarithm of hourly wage rates in real terms. Subscripts i and t refer to the ith individual and year t. The vector x_{it} is a vector of the explanatory variables that are reported in Table 1; dummies for educational attainment, squared potential years of experience, squared years of tenure, the interaction term between potential years of experience and years of tenure, as well as the logarithm of sizes of firms and establishments. The last term has a zero conditional expectation. We apply the ordinary least squared (OLS) method to male and female workers separately. All standard errors are calculated to be robust against the presence of heteroskedasticity.

First, all coefficients on educational attainment are positive and significant for male workers (the reference variable is the dummy for junior high school graduates). We should pay attention to the declining return to education during 1989-2003, evidenced by the smaller coefficients on the education dummies in the later sample year. In particular, we observe a large decline of 7 percentage points in the dummies for two-year college graduates and university graduates between 1989 and 2003, holding the other conditions constant.

We find a sharp contrast for female workers. Although the dummy for senior high school graduates (*Educ=12*) decreased as observed in male workers, the coefficient on the dummy for two-year college graduates (*Educ=14*) remained unchanged and that on the university graduate dummy (*Educ=16*) had a much smaller decline than that of male workers. Comparing the coefficients between male and female workers, the effect is larger for female workers, especially for those with higher educational attainment.

Second, the coefficient on potential years of experience implies a typical concave relation between the years of experience and the log wage. The slope decreased slightly for male workers, while that for female workers became larger. For male workers, the wage rate peaked at 28.44 years in 1990 and 27.82 years in 2003. In contrast, the peak-out year extended substantially for female workers: 7.13 years in 1990 and 15.82 years in 2003. Note that the magnitude of the coefficient is still larger for male workers than for female workers. Third, we observe smaller coefficients on years of tenure for both male and female workers.

In sum, we find three remarkable changes in the coefficients on workers' attributes in the wage equation estimates: 1: the effect of education on wages becomes smaller for both sexes, 2: the effect of potential years of experience becomes slightly larger for female workers, and 3: the effect of years of tenure becomes smaller, especially for female workers. These findings are consistent with what we reported in Table 1: A larger proportion of workers with higher educational levels and longer years of tenure made the returns to education and tenure smaller. The average years of education becomes longer partly due to supply factors, such as an increase in parents' income (Arai [1998]) and an increase in the number of college graduates because of the Ministry of Education's deregulations new college openings and expanding their capacity (1991 revision of University Establishment Standard (*Daigaku Setti Kijun*)). Workers' job tenure has extended, partly due to the aging of the population. The extended years of job tenure among females can be explained by the change in the social norm that now encourages women to stay in the labor force after marriage and child bearing (Kawaguchi and Miyazaki [2005]). These supply shocks decreased the equilibrium return to education and job tenure.

4 Decomposition of the variance in the wage rates for full time workers

As we observed in Table 1, the wage rate increased in real terms until 1993 and leveled off during the remaining period, while the variance in the wage rate declined until the mid-1990s and kept the same level after the period with a slight increase in 2002 for both sexes. In this section, we decompose the variance in the wage rates into that within a group and that between groups (i.e. the composition of groups).

The variance in the logarithm of wage rates is decomposed as follows without covariance between x and u due to the assumption $E(u|x) = 0$ in (1).

$$Var(y_t) = \beta_t' Var(x_t)\beta_t + Var(u_t). \tag{2}$$

The change in $Var(y)$ in period τ from the base period 1989 is decomposed as follows.

$$\begin{aligned} Var(y_\tau) - Var(y_{89}) &= \beta_\tau' Var(x_\tau)\beta_\tau - \beta_{89}' Var(x_{89})\beta_{89} + Var(u_\tau) - Var(u_{89}) \\ &= [\beta_\tau' Var(x_\tau)\beta_\tau - \beta_{89}' Var(x_\tau)\beta_{89}] \\ &+ [\beta_{89}' Var(x_\tau)\beta_{89} - \beta_{89}' Var(x_{89})\beta_{89}] \\ &+ [Var(u_\tau) - Var(u_{89})]. \end{aligned} \tag{3}$$

The first term corresponds to changes in the wage structure that are captured by the changes in the estimated coefficients in the wage equation β. The second term corresponds to the changes in the variance of workers' attributes, which are captured by the change in the variance of the explanatory variables in the wage equation $Var(x_t)$. The last term corresponds to the changes in the variance of the error term $Var(u_t)$.

Figure 2 reports the results of the decomposition in the change of the variance of log real wage rates. The temporal change of the variance is decomposed into the following three components: 1: the change due to the change in β, 2: the change due to the change in $Var(x_t)$, and 3: the change due to the change in $Var(u_t)$. We performed the decomposition for male and female workers separately.

First, we examine the decomposition for male workers. The actual coefficient of the variance in the wage rates declined, which is explained by the smaller wage variance among groups. This is evidenced by the fact that the graph that allows the changes in β for each year tracks the actual variance much better than the other cases. This is caused by the smaller disparities among workers with different degrees of educational attainment or years of tenure, as reported in Table 2. A larger portion of workers with higher educational levels and longer years of tenure made smaller returns to the wage rate, which resulted in a smaller variance between groups. At the same time, we notice that the variance in residuals, which stands for wage inequality within a group, expanded (2), though the effect of the larger residual variance is smaller.

In sum, we find that the components move in two opposite directions: a smaller variance between groups and a larger variance within a group, which results in the smaller variance in the total wage rates. One might argue that no expansion in wage inequality is observed by emphasizing the changes in β, but we should notice that this is only a part of the whole picture.

Similar to male workers, the variance of the log wage declined after the 1990s for female workers, and the structural change in β is the main cause for this change. Contrary to the male workers, the variance in residuals is on a slightly declining trend, but the variance in x contributes to a larger variance in the wage rates. This implies that while the disparity between groups was smaller due to the smaller returns of workers' attributes to wages, a larger variance in x in education or years of tenure expanded the wage disparity for female workers.

We further decompose the residual variance into the change in the distribution of x and the change in the mapping from x to the residual variance. To implement the decomposition, we assume the following functional form of heteroskedasticity:

$$Var(u_\tau|x) = \exp(x\gamma_\tau) \tag{4}$$

Under this assumption, $Var(u)$ is rewritten as

$$V^\tau = Var(u_\tau) = E_{x|t=\tau}[Var(u|x)] = E_{x|t=\tau}[\exp(x\gamma_\tau)] \tag{5}$$

The expectation is taken over x and the distribution of x and its parameters are time variant. This application of the law of iterated expectation articulates that the change in the residual variance is decomposed into the change in the distribution of x and the change in γ_τ, which stands for structural change. In other words, the residual variance can change due to a change in the population structure, due to such factors as aging, or due to the change in the variance within the group defined by x.

Exploiting this feature, we can calculate the artificial variance that has the variance structure of year τ, but the distribution of the attribute is that of year 1989 as follows, using the argument similar to DiNardo et al. [1996]:

$$\begin{aligned}
Var(u)^{\tau}_{x=89} &= E_{x|t=89}[\exp(x\gamma_{\tau})] \\
&= \int \exp(x\gamma_{\tau}) f(x|t=89)dx \\
&= \int \exp(x\gamma_{\tau}) \frac{P(t=89|x)f(x)}{P(t=89)} \frac{P(t=\tau)}{P(t=\tau|x)f(x)} f(x|t=\tau)dx \\
&= \int \exp(x\gamma_{\tau}) \frac{P(t=89|x)}{P(t=89)} \frac{P(t=\tau)}{P(t=\tau|x)} f(x|t=\tau)dx \\
&= E_{x|t=\tau}[\theta \exp(x\gamma_{\tau})] \qquad (6)
\end{aligned}$$

where $\theta = \frac{P(t=89|x)}{[1-P(t=89|x)]} \frac{[1-P(t=89)]}{P(t=89)}$. The numerator in the first term is the propensity score to be in the 1989 sample, given x. For example, consider a dummy variable for senior high school graduates as a part of x. The propensity score for 1989 is higher than that for 2003 among high school graduates because the share of senior high school graduates was larger in 1989 in the labor market. The proportion $P(t=89)$ is the share of the 1989 sample among all observations.

Using the counterfactual variance above, the change in the residual variance can be decomposed as

$$Var(u)^{\tau}_{x=\tau} - Var(u)^{89}_{x=89} = [Var(u)^{\tau}_{x=\tau} - Var(u)^{\tau}_{x=89}] + [Var(u)^{\tau}_{x=89} - Var(u)^{89}_{x=89}]. \tag{7}$$

The first term corresponds to the change in the residual variance due to the distributional change of x, and the second term corresponds to the change in the residual variance structure. In other words, the first term can be interpreted as the between-groups residual variance change because the change is induced by the change in x, while the second term is interpreted as the within-group change because the change occurs within a group indexed by x.

To implement the above decomposition of the variance of wage rate residuals, we pool the observations in 1989 and year τ and apply a probit estimation to regress the dummy variable that takes 1 if the observations are in 1989 sample on x_i. The propensity score from this probit regression is used to calculate the estimated value of $\theta_{\tau i}(=\hat{\theta}_{\tau i})$. The residual of the wage regression $\hat{u}_i$ is taken from the wage regression whose results are reported in Table 2 and discussed in the previous section. Then, the logarithm of $\hat{u}_i^2$ in year τ is regressed on x_i to obtain coefficients γ_τ. The results of this regression are reported in Table 4. Most of the coefficients are statistically significant. We calculate the exponential of the estimated value, which corresponds to $\exp(x_i\gamma_\tau)$ in (4) (we call this $\hat{v}_i^\tau$). Based on this predicted residual $\hat{v}_i^\tau$, we calculate $\hat{V}_{89}^\tau$ as the weighted average of $\hat{v}_i^\tau$ in year τ using $\hat{\theta}$ as the weight.

Figure 3 presents the results of the decomposition expressed in the equation (7) for male and female workers, respectively. The residual variance declined in the first half of the 1990s for male workers, and then began to increase after 1997. The "V-shaped" trend also is observed even after making the distribution of $x$constant at its 1989 level. This implies that the variance in residuals expanded, even removing the effect of longer years of education and tenure. The increase in the residual variance may suggest an increase in the return to unobserved skills after 1997, as pointed out by Juhn et al. [1993] in the US context.

The residual variance for females also has a "V-shaped" trend, but if the attributes distribution were that of 1989, the residual variance would have declined monotonically. This implies that the residual variance increased in the late 1990s mainly due to a shift in the population weight toward groups with intrinsically larger residual variance. This is natural because more-educated and long-experienced workers tend to have higher within-group variance, as evidenced by Table 4. After removing the effect of full-time workers' compositional change, we can conclude that the within-group residual variance was stable among female workers throughout the 1990s.

Overall, our findings demonstrate that there were two opposing trends for the log wage variance. One is declining wage inequality across groups, mainly due to the declining returns to education and tenure. The other, opposite trend is increased inequality within a group of workers indexed by the workers' attributes vector x among male and the increased heterogeneity of labor force (increased $Var(x)$) among females. The first trend dominates the second trend and, as a result, the overall log wage variance declined during the first half of the 1990s for both sexes. Behind the declining log wage variance, within-group variance increased for males, and this increase in within-group variance cannot be explained by a shift in the population weight due to such causes as aging. This phenomenon for male workers could well explain why Japanese people have a nagging sense of increased inequality, although we cannot confirm it from the trend of the aggregate statistics. As Clark and Oswald [1996] show, people tend to care more about their relative wage position within a reference group rather than their position in an aggregate distribution. As for females, behind the declining log wage variance, the variance has increased due to the increased heterogeneity of female workers. This can be understood as a transitional phenomenon. In 1989, females uniformly had relatively weaker attributes, but some females started to have stronger attributes, such as more years of education or job tenure. As a result, the female labor force became more heterogeneous in 2003.

So far, we explored the trend of the wage disparity after the 1990s by examining the variance as a representative indicator for income inequality. In the next section, we deal with the whole wage distribution directly.

5 Changes in the wage distribution: The DiNardo, Fortin, and Lemiuex decomposition

This section examines changes in the wage distribution using a kernel density estimation. The merit of the kernel density estimation is that we can confirm the change in the shape of the wage distribution without sacrificing any information. We further decompose the change in the distribution into the part due to the distributional change of the attributes x and the part due to the relation change between the attributes x and wage rates, employing the DFL decomposition (DiNardo et al. [1996] and Lemiuex [2002]).

We implement the kernel density estimation using the Epanechnikov kernel and an optimal bandwidth.[5] The estimation procedure is fairly well known, and we do not illustrate the procedure here. However, we will briefly describe the DFL procedure, using as an example a comparison between the 1989 and 2003 distributions. The wage distribution in 1989 can be understood as the product of the relation between wage and attributes and the distribution of x as follows:

$$f^{1989}(y) = \int f^{1989}(y|x)h(x|t = 1989)dx, \tag{8}$$

where $f^{1989}(y|x)$ is the wage determination mechanism in 1989 that maps workers' and firms' attributes x to the distribution of log wage, which is denoted as y. The density $h(x|t = 1989)$ is the p.d.f. of attributes in year

[5] The choice of kernel function and bandwidth does not essentially affect the results because of an extremely large sample size.

1989. Similarly, the distribution of wage in 2003 is

$$f^{2003}(y) = \int f^{2003}(y|x)h(x|t = 2003)dx. \tag{9}$$

The counterfactual wage distribution that is determined by the product of the wage determination mechanism in 2003 and the attributes distribution in 1989 is expressed as

$$f^{2003}_{1989}(y) = \int f^{2003}(y|x)h(x|t = 1989)dx. \tag{10}$$

The direct estimation of this counterfactual distribution is difficult to determine because many explanatory variables are included in vector x, and the integration takes place in a highly dimensional space. The DFL approach employs a re-weighting method to overcome this difficulty. Assuming that the 2003 distribution depends not on the distribution of 2003 attributes, but its distribution in 1989, the counterfactual distribution can be rewritten as:

$$f^{2003}_{1989}(y) = \int f^{2003}(y|x)h(x|t = 1989)dx = \int \omega f^{2003}(y|x)h(x|t = 2003)dx, \tag{11}$$

where $\omega \equiv \frac{h(x|t=1989)}{h(x|t=2003)}$. Based on the Beyse rule, we obtain $\omega = \frac{P(t=1989|x)}{P(t=2003|x)}\frac{P(t=2003)}{P(t=1989)}$. The conditional probabilities, $P(t = 1989|x)$ and $P(t = 2003|x)$ are propensity scores for the specific observations in 1989 and 2003, respectively, conditioned on x. These propensity scores are estimated by the probit model in this analysis. The terms $P(t = 1989)$ and $P(t = 2003)$ are calculated based on the proportions of the observations from 1990 and 2003 in the pooled data, respectively. Using a calculated weight ω, the counterfactual distribution is calculated by the kernel density estimation with analytical weights.

We note that the gap between the counterfactual distribution and the actual distribution in 1989 is captured by the change in the wage determination mechanism (change in β in equation (1)) and the residual distribution. In contrast, the gap between the counterfactual distribution and the actual distribution in 2003 is caused by the change in the distribution of workers' attributes (the change in the distribution of x in equation (1)), holding β and the residual distribution constant.

Figure 4 reports the actual wage distributions in 1994, 1999, and 2003, and the counterfactual wage distributions, assuming that workers' and firms' attributes had remained at their 1989 level, which are calculated separately for male and female workers. Several interesting findings emerge as follows.

First, if we examine the changes in the wage distribution between 1989 and 1994, the 1994 actual and the counterfactual distributions overlap. The same can be said for the case between 1989 and 1999. These observation imply that the changes in the distributions from 1989 to 1994 or 1999 are explained by the changes in the distribution of x, rather than the changes in the wage determination structure. This finding is common to both male and female workers. In contrast, if we examine changes in the distribution in 2003 compared with that in 1989, the counterfactual distributions in both years differ from the actual distributions, which implies that the distributional changes in attributes contributes to only a part of the changes in the distributions.

Second, the deviation between the actual distribution and the counterfactual distribution is particularly large at the top half of the wage distribution. This gap implies that the emergence of this chunk of high-wage people for both sexes cannot be explained by the change in the relation between attributes and wage. Thus the increase in high-wage people is likely to be caused by an increase in the number of people who have attributes that predict high wage or who have high residual. In addition, the gaps between the 1989 distribution and the counterfactual distributions in 1999 and 2003 are large for females. This is due to the increased heterogeneity of workers' attributes among female workers, as confirmed in the previous results. In contrast to the upper-tail distribution, the counterfactual distributions overlap the actual distributions for lower paid workers. This observation implies that the change in the wage rates for lower-paid workers are captured by the change in the mapping of workers' attributes to wage rate, or simply the shift in the coefficient for a constant in the wage equation.

Third, the degree of shift in the wage distribution to the right is larger among females than among males during the period. The faster wage growth of female workers than male workers is consistent with the gender wage convergence among full-time workers during the 1990s (Kawaguchi [2005], Kawaguchi and Naito [2006]). As the relative positions of actual wage distributions and counterfactual distributions show, the gender wage convergence occurred partly because of the convergence in attributes x and partly due to the change in the mapping from attributes to wage or the residual distribution. We do not necessarily find that the gender wage convergence occurred due to the rapid wage growth of highly paid workers; rather, the convergence happened because of an arguably uniform shift of the wage distribution among female workers.

6 The Effect of Increasing Part-Time Workers among Females

The decomposition analysis in the previous sections focused on only full-time workers. But some recent arguments insist that a larger income inequality may be due to a gap in wage rates between full time and part time workers. Shimizutani and Yokoyama [2006] observe that one of the remarkable trends in the recent Japanese labor market is bipolarization into full- and part-time permanent workers. Also, the proportion of workers who are not covered by the long-term employment system is increasing, which potentially contributes to the inequality of the income distribution.

As a robustness check, this section performs the same decomposition analysis by adding part-time workers, which are contained in the *Basic Survey on Wage Structure*, to the sample. Unfortunately, information on educational attainment is not available for those workers, and thus we assume that all part-time workers are senior high school graduates. The shares of part-time workers out of all the permanent workers are 1-3 percent for male workers and 15-30 percent for female workers, depending on the year. Since the proportion is so small for male workers that the findings are unchanged for all analyses in the previous section, we focus on female workers.

We rerun the wage regressions and perform the variance decomposition. The results are mostly unchanged from those reported in Table 2 and Figures 2-3. Moreover, the regression of the residuals obtained from the wage equation estimates are also similar to those shown in Table 4, and the decomposition of the variance in the residuals tracks the same trend reported in Figure 4. To save space, we do not report those results.

The only large changes in the findings from the previous section by adding part-time workers are observed in the DFL decomposition analysis. Figure 5 reports the results. If we compare the distributions in 1989 and 1994, we observe twin peaks: the peak for part-time workers on the left and that for full-time workers on the right. Turning to the distributions in 1999 and 2003, in contrast, the peak on the left gained height and that on the right lessened, and then disappeared in 2003. This is due to an increase in the proportion of part-time workers. The counterfactual distribution overlaps with the actual distribution, even in 2003 at the lower tail of the distribution, which implies that most of the change among low paid workers had occurred due to a change in the relation between attributes and the wage rate. This could be partly due to a steadily increasing real minimum wage during the 1990s (Kawaguchi and Yamada [2006]). Again, it is notable that the increase in highly paid female workers cannot be explained by the change in the relation between attributes and wage; instead, it should be explained by the distributional change in attributes, in particular, the increase in college-educated and long-tenured workers. Overall, the increase in part-time workers results in more dispersed wage distributions among female workers. The public may well perceive this phenomenon as evidence for expanding economic inequality.

7 Conclusion

This paper examined the change in the wage distribution among full-time workers during the 1990s in Japan. We take advantage of a rich micro-level data set from *Basic Survey on Wage Structure* (1989-2003) to perform an in-depth analysis of the changes in the variance and distribution of the wage rate.

Although simple aggregate statistics may give the impression that wage inequality had not changed during the period, the decomposition analysis reveals that the steady trend is a product of two opposing trends: 1. declining between-groups (defined by education, experience, tenure and firm/establishment size) wage inequality for both sexes, and 2. increased within-group inequality among male workers and increased observed heterogeneity among female workers.

The declining between-groups wage differentials are largely due to the decline of the return to education and job tenure because of the increase in college-educated and long-tenured workers. The deregulation of the Ministry of Education and the aging of the population exogenously increased the supply of college-educated and long-tenured workers and decreased the equilibrium return to these traits. After removing these exogenous supply effects, as evidenced by the increase in the within-group wage variance, inequality has increased from around 1997 for males. This trend is consistent with the increased wage inequality observed in the US, the UK, and Canada. Contrary to the main results by Ohtake [2005], as far as wage is concerned, our results show that the aging of the population in itself cannot explain the recent increase in wage inequality among males. As for females, the gradual increases in college-educated and long-tenured workers make the female full-time workers more heterogeneous. This contributes to the increase of wage inequality among them.

The increase of within-group inequality among male workers may well explain why the general public in Japan feels that inequality has increased in the last 15 to 20 years, while we can hardly confirm it in the aggregate statistics. An individual presumably perceives inequality by comparing the wage within a group to which one belongs rather than comparing his/her wage to the total distribution. The increase in the heterogeneity of female workers is consistent with the emergence of career-oriented women in the last 20 years, and this trend will continue mechanically as long as these career-oriented women stay on this track.

The major purpose of this study was to describe the change in the wage distribution between 1989 and 2003. We believe we have offered the first comprehensive picture of the wage distribution in the second- largest economy during a time of rapid technological change and globalization. However, several research topics are left for future research. First, the reason why within-group wage inequality has increased should be investigated, and the results should be reconciled with results from other developed countries. Second, how the increased within-group inequality among males and the increased heterogeneity among females translate into household-level income inequality through marriage should be investigated. Third, if an increase in temporal income inequality is associated with an increase in temporal income mobility, lifetime income may not become unequal. The change in temporal mobility should be further investigated. These additional considerations are indispensable for designing social welfare programs because current low-wage workers do not necessarily belong to low-income households in a dynamic sense.

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Table 1 Basic statistics

Sample: Full-time workers in establishments that hire 10 or more employees (full- and part-time workers combined) or in single establishments of firms that hire 5-9 employees.

Panel A: Male

Year	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Wage Rate	20.73	21.95	23.59	24.88	27.67	27.43	27.36	27.56	27.82	27.98	27.90	27.42	27.64	27.32	26.69
	(14.24)	(15.04)	(15.54)	(16.50)	(19.94)	(17.67)	(18.90)	(20.74)	(18.77)	(19.22)	(17.52)	(18.16)	(17.73)	(18.06)	(16.09)
Wage Rate	23.08	23.91	24.86	25.62	28.23	27.84	27.72	27.93	27.58	27.70	27.71	27.42	27.83	27.71	27.18
/ CPI	(15.85)	(16.39)	(16.37)	(17.00)	(20.34)	(17.94)	(19.15)	(21.01)	(18.60)	(19.03)	(17.40)	(18.16)	(17.86)	(18.32)	(16.39)
Experience	21.29	21.52	21.72	21.78	20.78	20.76	20.93	21.24	21.44	21.43	21.56	21.66	21.83	21.70	21.86
	(12.45)	(12.60)	(12.78)	(12.88)	(12.88)	(12.81)	(12.78)	(12.82)	(12.82)	(12.84)	(12.74)	(12.61)	(12.51)	(12.45)	(12.35)
Tenure	12.48	12.63	12.76	12.97	12.88	13.06	13.26	13.34	13.55	13.48	13.72	13.91	14.11	13.90	14.06
	(10.01)	(10.16)	(10.33)	(10.47)	(10.56)	(10.61)	(10.69)	(10.78)	(10.91)	(10.97)	(10.97)	(11.01)	(11.06)	(10.99)	(11.02)
Firm Size	1430.64	1437.37	1438.05	1488.27	1701.65	1710.73	1647.74	1463.83	1444.58	1444.14	1418.60	1430.75	1439.14	1411.77	1391.04
	(1919.82)	(1918.30)	(1918.65)	(1938.52)	(1986.10)	(1982.08)	(1959.02)	(1896.39)	(1881.05)	(1876.42)	(1857.81)	(1865.88)	(1862.54)	(1845.01)	(1835.54)
Estab Size	348.22	358.52	371.01	371.65	371.26	368.88	339.87	327.51	320.72	319.17	313.10	312.11	316.79	306.37	302.07
	(1012.44)	(1031.65)	(1104.61)	(1079.16)	(1015.03)	(949.44)	(889.14)	(867.06)	(863.60)	(827.64)	(835.69)	(810.11)	(833.76)	(786.00)	(853.64)
Educ≤9	0.24	0.23	0.22	0.20	0.16	0.15	0.14	0.14	0.13	0.12	0.12	0.11	0.10	0.09	0.08
Educ=12	0.52	0.52	0.53	0.53	0.52	0.52	0.52	0.53	0.53	0.53	0.52	0.52	0.52	0.52	0.51
Educ=14	0.04	0.04	0.04	0.05	0.05	0.06	0.06	0.06	0.07	0.07	0.07	0.08	0.08	0.09	0.09
Educ≥16	0.20	0.21	0.21	0.22	0.27	0.28	0.28	0.27	0.27	0.28	0.29	0.29	0.30	0.31	0.31
Observations	771824	767162	766722	768028	805650	769339	809180	823340	830670	810202	800890	764075	746800	729242	720047

Panel B: Female

Year	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Wage Rate	12.05	12.74	13.79	14.59	16.69	16.79	16.82	16.83	17.11	17.34	17.56	17.35	17.60	17.70	17.42
	(12.40)	(10.34)	(12.99)	(11.78)	(12.97)	(14.27)	(10.93)	(12.09)	(12.84)	(16.80)	(21.25)	(11.80)	(12.18)	(15.47)	(11.45)
Wage Rate	13.42	13.88	14.53	15.02	17.03	17.04	17.05	17.05	16.96	17.17	17.44	17.35	17.72	17.95	17.74
/ CPI	(13.81)	(11.27)	(13.69)	(12.13)	(13.24)	(14.48)	(11.08)	(12.25)	(12.72)	(16.63)	(21.10)	(11.80)	(12.27)	(15.69)	(11.66)
Experience	18.51	18.63	18.70	18.74	16.77	16.74	17.13	17.97	18.21	18.21	18.47	18.65	18.76	18.82	19.07
	(14.05)	(14.17)	(14.28)	(14.39)	(13.99)	(13.85)	(13.84)	(13.99)	(13.92)	(13.86)	(13.74)	(13.64)	(13.52)	(13.43)	(13.35)
Tenure	7.30	7.41	7.48	7.60	7.23	7.51	7.79	8.18	8.41	8.47	8.82	9.08	9.29	9.24	9.51
	(7.39)	(7.52)	(7.67)	(7.77)	(7.68)	(7.75)	(7.83)	(8.03)	(8.16)	(8.27)	(8.41)	(8.51)	(8.60)	(8.59)	(8.71)
Firm Size	1104.88	1121.60	1133.79	1166.68	1602.07	1620.51	1552.72	1187.42	1192.05	1190.69	1190.44	1182.36	1173.54	1159.72	1139.79
	(1758.39)	(1768.86)	(1773.59)	(1787.21)	(1986.19)	(1992.89)	(1964.36)	(1769.91)	(1767.91)	(1764.05)	(1757.74)	(1746.48)	(1733.38)	(1717.39)	(1703.57)
Estab Size	222.63	227.89	236.30	239.54	233.11	233.98	218.11	222.18	218.07	225.53	221.81	221.23	231.37	226.58	227.75
	(646.93)	(659.51)	(694.90)	(687.12)	(622.33)	(601.22)	(565.23)	(572.68)	(566.35)	(566.11)	(572.86)	(550.73)	(620.86)	(582.43)	(641.76)
Educ≤9	0.23	0.22	0.21	0.20	0.14	0.12	0.12	0.13	0.12	0.11	0.10	0.09	0.08	0.07	0.07
Educ=12	0.57	0.57	0.57	0.57	0.57	0.57	0.56	0.55	0.55	0.54	0.54	0.53	0.52	0.51	0.51
Educ=14	0.15	0.16	0.17	0.18	0.22	0.23	0.24	0.23	0.24	0.26	0.26	0.27	0.28	0.28	0.28
Educ≥16	0.04	0.04	0.05	0.05	0.07	0.07	0.07	0.08	0.09	0.10	0.10	0.11	0.12	0.13	0.14
Observations	345645	345524	350665	349714	393848	372342	384186	349742	347652	326698	317093	295286	280402	273781	267365

Table 2 Estimates of a wage equation for full-time workers

Panel A: Male

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Educ=12	0.157	0.159	0.155	0.150	0.157	0.153	0.149	0.155	0.140	0.134	0.132	0.127	0.125	0.125	0.121
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Educ=14	0.306	0.305	0.300	0.291	0.288	0.278	0.269	0.281	0.262	0.253	0.254	0.244	0.239	0.246	0.237
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Educ≥16	0.515	0.515	0.509	0.494	0.493	0.476	0.468	0.483	0.456	0.444	0.446	0.439	0.440	0.447	0.439
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Exper	0.040	0.040	0.040	0.039	0.041	0.041	0.040	0.040	0.040	0.039	0.038	0.037	0.038	0.038	0.038
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Exper^2/100$	-0.067	-0.067	-0.068	-0.067	-0.068	-0.069	-0.066	-0.065	-0.066	-0.065	-0.062	-0.062	-0.062	-0.062	-0.063
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.030	0.029	0.028	0.027	0.028	0.026	0.027	0.025	0.025	0.026	0.026	0.025	0.025	0.026	0.025
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Tenure^2/100$	-0.012	-0.009	-0.007	-0.006	-0.000	0.001	0.001	-0.000	-0.003	-0.004	-0.003	-0.002	-0.002	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exper·Tenure/100	-0.013	-0.015	-0.016	-0.017	-0.021	-0.019	-0.021	-0.018	-0.016	-0.016	-0.017	-0.018	-0.019	-0.025	-0.021
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(EstabSize)	0.006	0.007	0.008	0.016	0.001	0.002	-0.002	0.003	0.005	0.007	0.008	0.008	0.010	0.012	0.017
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(FirmSize)	0.068	0.066	0.062	0.058	0.063	0.062	0.062	0.065	0.060	0.060	0.061	0.063	0.065	0.068	0.065
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.647	1.683	1.760	1.788	1.855	1.861	1.882	1.858	1.882	1.889	1.882	1.868	1.846	1.819	1.806
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	771,824	767,162	766,722	768,028	805,650	769,339	809,180	823,340	830,670	810,202	800,890	764,075	746,800	729,242	720,047
R-squared	0.63	0.63	0.62	0.62	0.63	0.63	0.63	0.62	0.62	0.62	0.60	0.60	0.60	0.59	0.58

Note: Robust standard errors in parentheses. The reference variable for educational attainment is junior high school graduates.

Panel B: Female

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Educ=12	0.202	0.208	0.207	0.201	0.217	0.213	0.197	0.205	0.190	0.181	0.184	0.175	0.178	0.160	0.163
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Educ=14	0.409	0.411	0.412	0.395	0.407	0.403	0.396	0.418	0.403	0.397	0.407	0.405	0.412	0.416	0.415
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Educ≥16	0.600	0.612	0.609	0.587	0.592	0.579	0.560	0.601	0.574	0.562	0.571	0.561	0.571	0.565	0.568
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Exper	0.006	0.007	0.007	0.008	0.010	0.010	0.010	0.009	0.010	0.010	0.010	0.011	0.012	0.013	0.012
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Exper^2/100$	-0.005	-0.007	-0.010	-0.012	-0.018	-0.017	-0.018	-0.015	-0.016	-0.016	-0.018	-0.020	-0.022	-0.023	-0.022
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure	0.057	0.054	0.053	0.051	0.053	0.051	0.051	0.049	0.049	0.050	0.046	0.043	0.042	0.041	0.040
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Tenure^2/100$	-0.008	-0.001	-0.004	-0.005	-0.024	-0.019	-0.018	0.005	0.004	0.005	0.007	0.012	0.006	0.003	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exper·Tenure/100	-0.083	-0.081	-0.078	-0.073	-0.056	-0.056	-0.057	-0.074	-0.075	-0.077	-0.070	-0.068	-0.061	-0.057	-0.053
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(EstabSize)	-0.015	-0.015	-0.011	-0.000	-0.003	0.004	0.004	0.008	0.011	0.016	0.018	0.023	0.025	0.031	0.034
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(FirmSize)	0.101	0.099	0.090	0.084	0.076	0.067	0.063	0.064	0.057	0.052	0.050	0.047	0.048	0.049	0.048
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.452	1.495	1.572	1.605	1.679	1.702	1.741	1.736	1.751	1.764	1.766	1.760	1.740	1.721	1.707
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	345,645	345,524	350,665	349,714	393,848	372,342	384,186	349,742	347,652	326,698	317,093	295,286	280,402	273,781	267,365
R-squared	0.49	0.49	0.47	0.47	0.46	0.45	0.45	0.47	0.47	0.47	0.46	0.46	0.46	0.47	0.46

Note: Robust standard errors in parentheses. The reference variable for educational attainment is junior high school graduates.

Table 4: Regression of the residuals squared in the log wage equation on explanatory variables

Panel A: Male

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Educ=12	0.323	0.314	0.303	0.277	0.316	0.318	0.285	0.302	0.270	0.246	0.237	0.203	0.235	0.220	0.203
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.011)
Educ=14	0.404	0.402	0.386	0.345	0.366	0.382	0.339	0.345	0.363	0.300	0.305	0.285	0.338	0.326	0.309
	(0.015)	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Educ≥16	0.732	0.721	0.728	0.667	0.684	0.711	0.681	0.690	0.658	0.601	0.620	0.581	0.604	0.638	0.610
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)	(0.012)
Exper	0.056	0.056	0.058	0.058	0.066	0.068	0.071	0.063	0.066	0.068	0.066	0.070	0.067	0.070	0.070
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exper*Exper/100	-0.064	-0.065	-0.065	-0.065	-0.069	-0.074	-0.079	-0.063	-0.069	-0.070	-0.065	-0.070	-0.062	-0.069	-0.070
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Tenure	-0.054	-0.056	-0.057	-0.054	-0.058	-0.061	-0.062	-0.054	-0.060	-0.060	-0.054	-0.056	-0.052	-0.056	-0.053
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure*Tenure/100	0.037	0.040	0.060	0.044	0.060	0.046	0.047	0.049	0.045	0.052	0.041	0.037	0.033	0.030	0.023
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Exper*Tenure/100	0.090	0.091	0.075	0.078	0.067	0.088	0.086	0.065	0.081	0.070	0.064	0.068	0.058	0.071	0.073
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Ln(EstabSize)	-0.080	-0.081	-0.077	-0.057	-0.062	-0.028	-0.038	-0.047	-0.040	-0.026	-0.038	-0.038	-0.031	-0.039	-0.043
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln(FirmSize)	-0.025	-0.020	-0.030	-0.038	-0.024	-0.038	-0.035	-0.029	-0.031	-0.026	-0.013	-0.009	-0.005	-0.006	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-4.135	-4.138	-4.128	-4.195	-4.342	-4.465	-4.463	-4.406	-4.443	-4.525	-4.533	-4.550	-4.601	-4.535	-4.542
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.016)
Observations	771,824	767,162	766,722	768,028	805,650	769,339	809,180	823,340	830,670	810,202	800,890	764,075	746,800	729,242	720,047
R-squared	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.03

Note: Robust standard errors in parentheses. The reference variable for educational attainment is junior high school graduates.

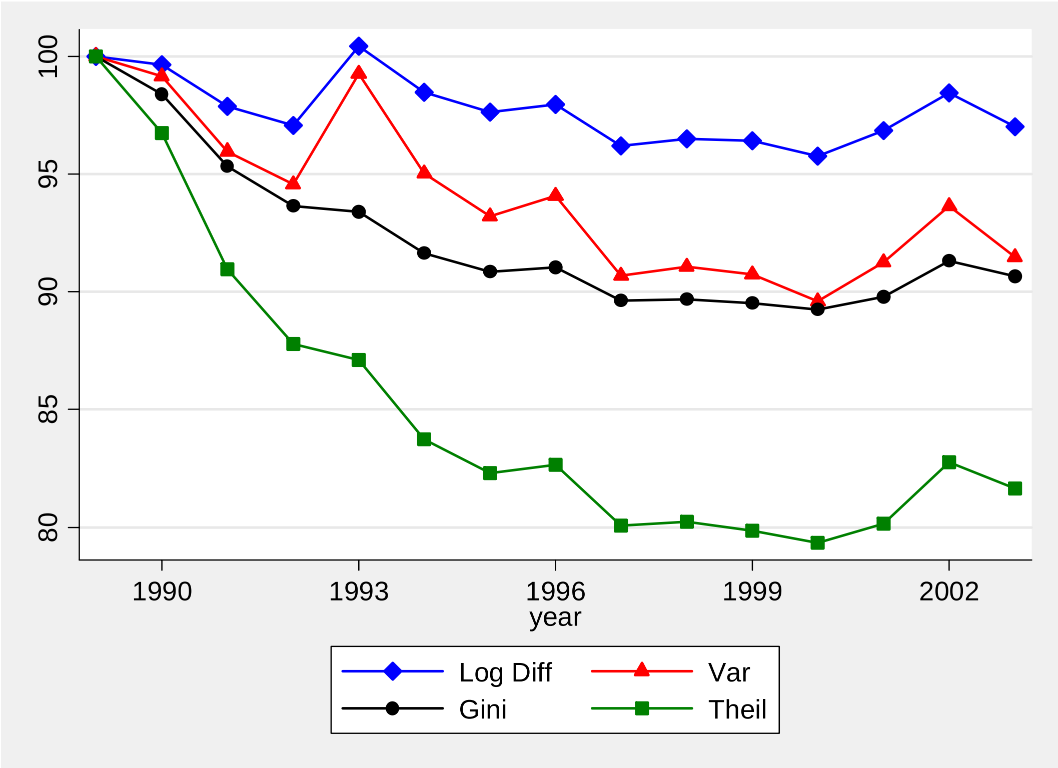
Panel B: Female

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Educ=12	0.464	0.466	0.408	0.385	0.341	0.334	0.311	0.360	0.302	0.308	0.311	0.338	0.352	0.305	0.304
	(0.011)	(0.011)	(0.011)	(0.012)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.015)	(0.016)	(0.017)	(0.018)	(0.019)	(0.020)
Educ=14	0.590	0.582	0.561	0.501	0.421	0.443	0.386	0.452	0.433	0.442	0.455	0.458	0.480	0.471	0.466
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.018)	(0.019)	(0.020)	(0.021)	(0.022)
Educ≥16	0.901	0.854	0.830	0.789	0.710	0.703	0.660	0.726	0.731	0.707	0.700	0.693	0.754	0.670	0.704
	(0.022)	(0.022)	(0.021)	(0.021)	(0.019)	(0.020)	(0.019)	(0.020)	(0.020)	(0.020)	(0.021)	(0.022)	(0.022)	(0.023)	(0.024)
Exper	0.090	0.087	0.092	0.092	0.111	0.118	0.118	0.093	0.098	0.095	0.095	0.101	0.100	0.091	0.095
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Exper*Exper/100	-0.176	-0.167	-0.179	-0.178	-0.220	-0.229	-0.234	-0.182	-0.188	-0.176	-0.179	-0.191	-0.195	-0.180	-0.186
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Tenure	-0.073	-0.068	-0.071	-0.074	-0.102	-0.107	-0.108	-0.075	-0.084	-0.078	-0.072	-0.079	-0.078	-0.072	-0.073
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Tenure*Tenure/100	-0.148	-0.131	-0.111	-0.112	-0.179	-0.128	-0.129	-0.072	-0.070	-0.068	-0.062	-0.065	-0.085	-0.089	-0.085
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Exper*Tenure/100	0.373	0.344	0.340	0.344	0.466	0.441	0.449	0.323	0.339	0.313	0.300	0.316	0.331	0.320	0.318
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Ln(EstabSize)	-0.081	-0.080	-0.083	-0.083	-0.043	-0.013	-0.015	-0.012	-0.010	-0.018	-0.033	0.000	0.009	0.021	0.025
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln(FirmSize)	0.055	0.050	0.044	0.042	0.013	-0.006	-0.011	-0.018	-0.015	-0.002	0.012	-0.000	-0.007	-0.023	-0.030
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	-4.653	-4.644	-4.596	-4.599	-4.601	-4.713	-4.674	-4.571	-4.635	-4.694	-4.697	-4.825	-4.794	-4.656	-4.699
	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)	(0.021)	(0.020)	(0.021)	(0.022)	(0.022)	(0.023)	(0.024)	(0.025)	(0.026)	(0.027)
Observations	345,645	345,524	350,665	349,714	393,848	372,342	384,186	349,742	347,652	326,698	317,093	295,286	280,402	273,781	267,365
R-squared	0.04	0.04	0.05	0.05	0.06	0.07	0.07	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04

Note: Robust standard errors in parentheses. The reference variable for educational attainment is junior high school graduates.

Figure 1: Change in the log wage inequality

Panel A: Male



Panel B: Female

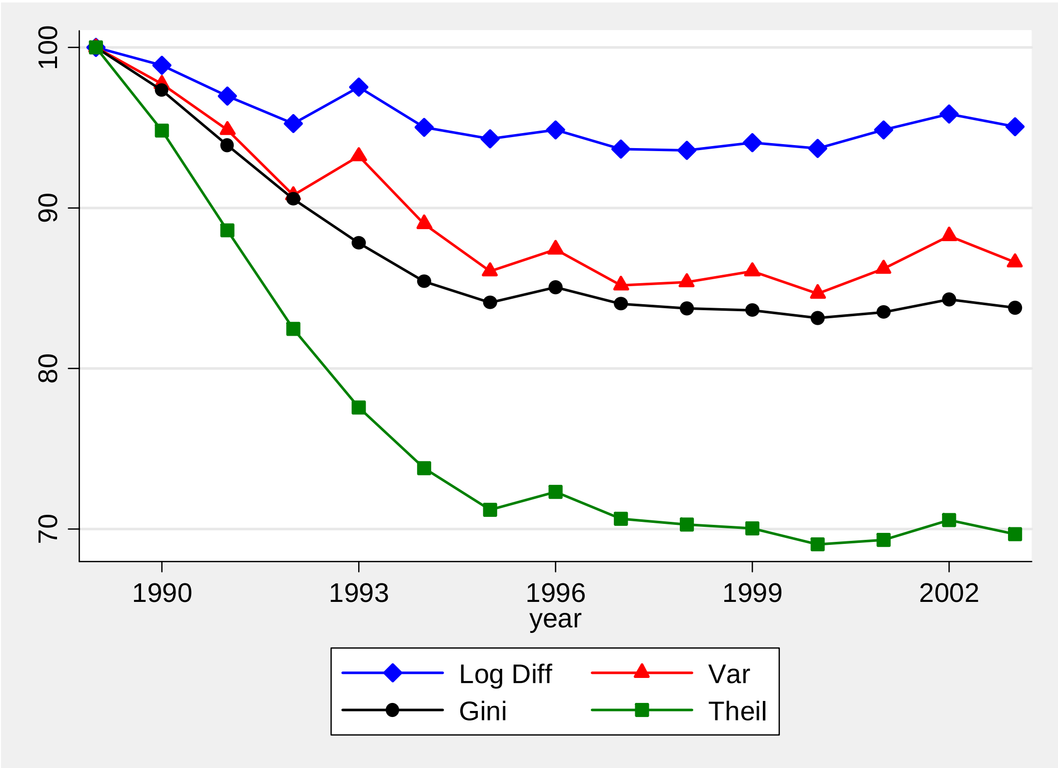
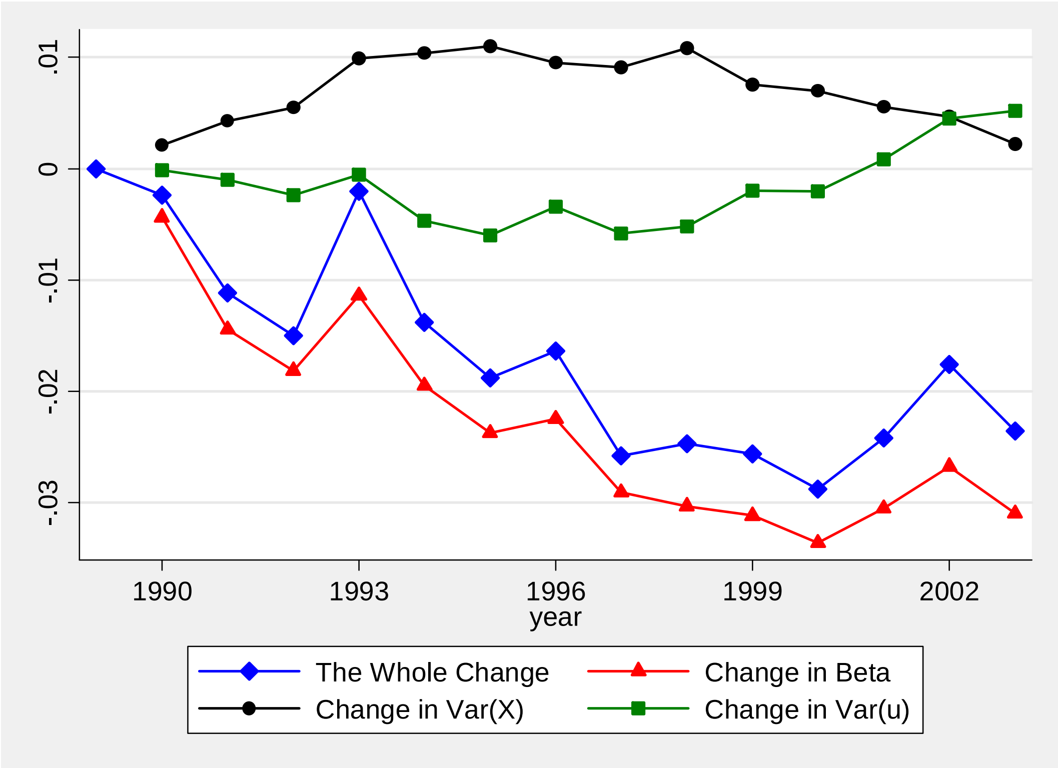


Figure 2: Decomposition of the variance of log wage

Panel A: Male



Panel B: Female

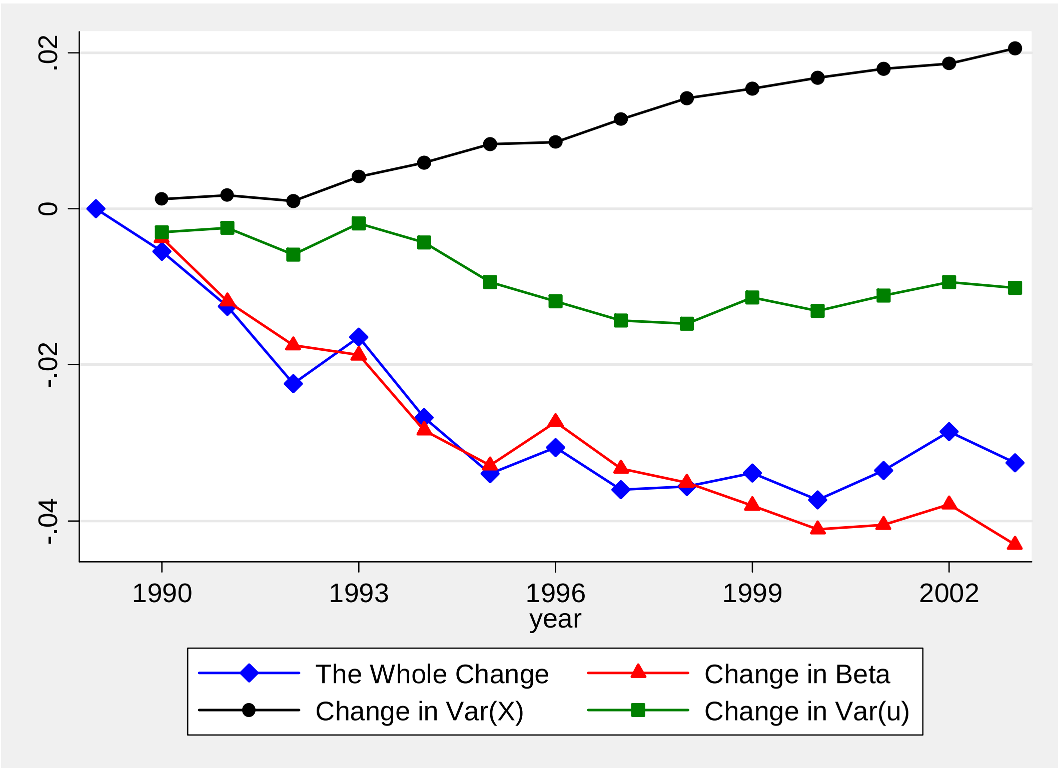
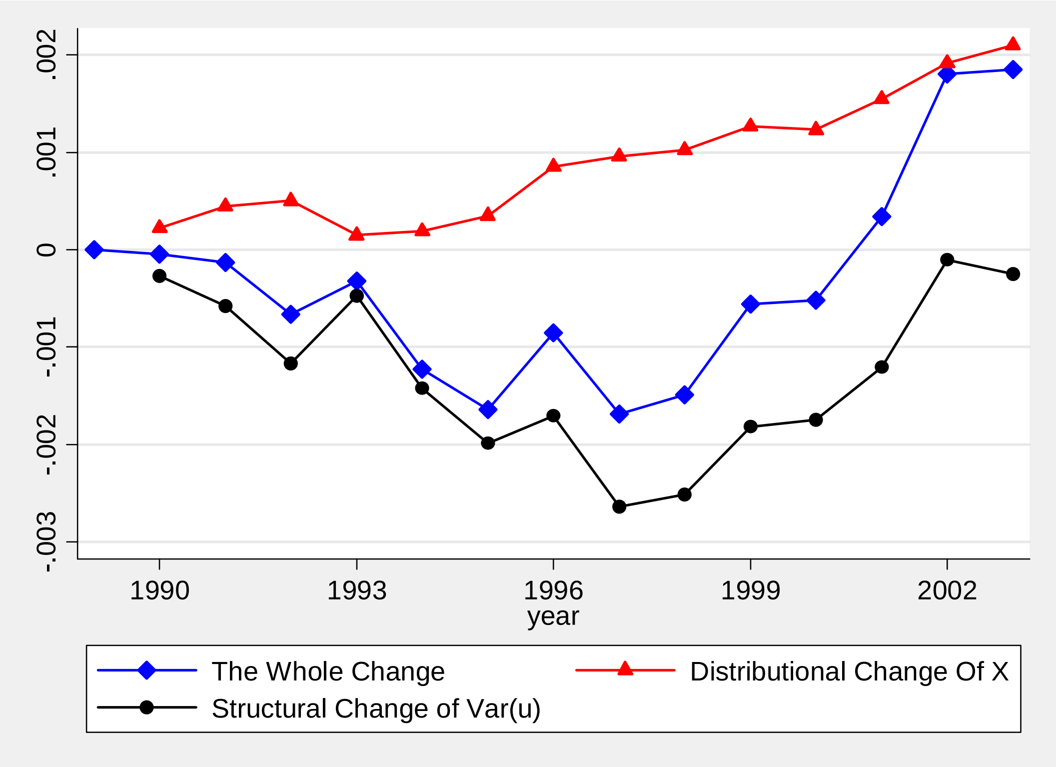


Figure 3 Decomposition of the residuals in the variance of the wage rate

Panel A: Male



Panel B: Female

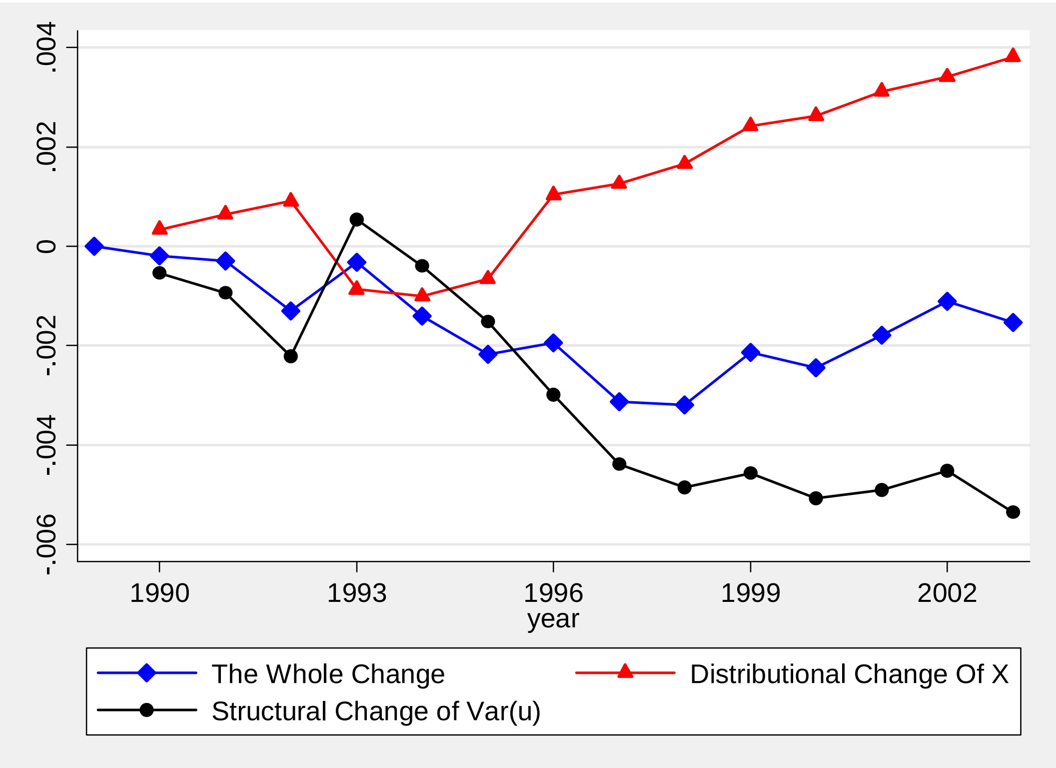
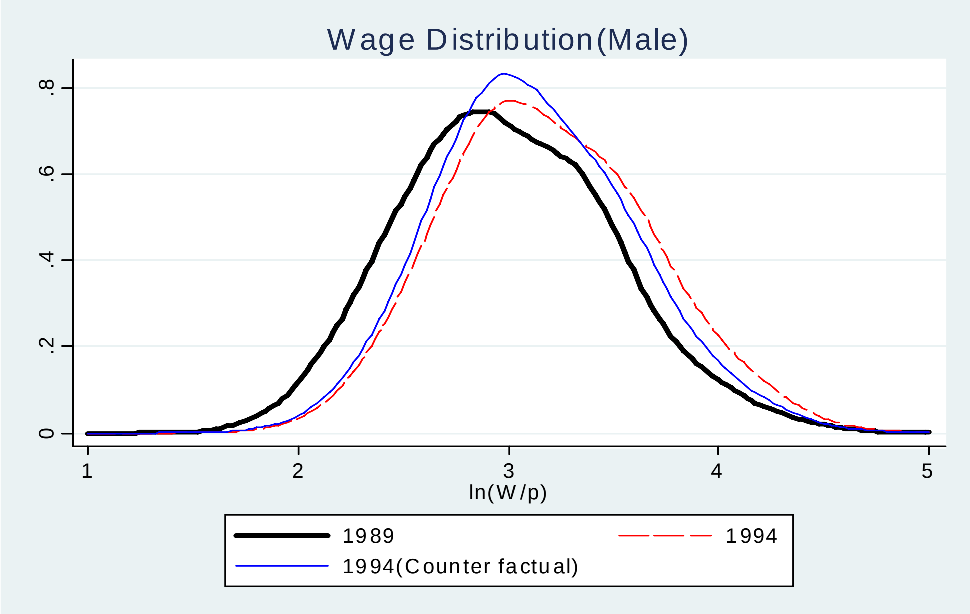
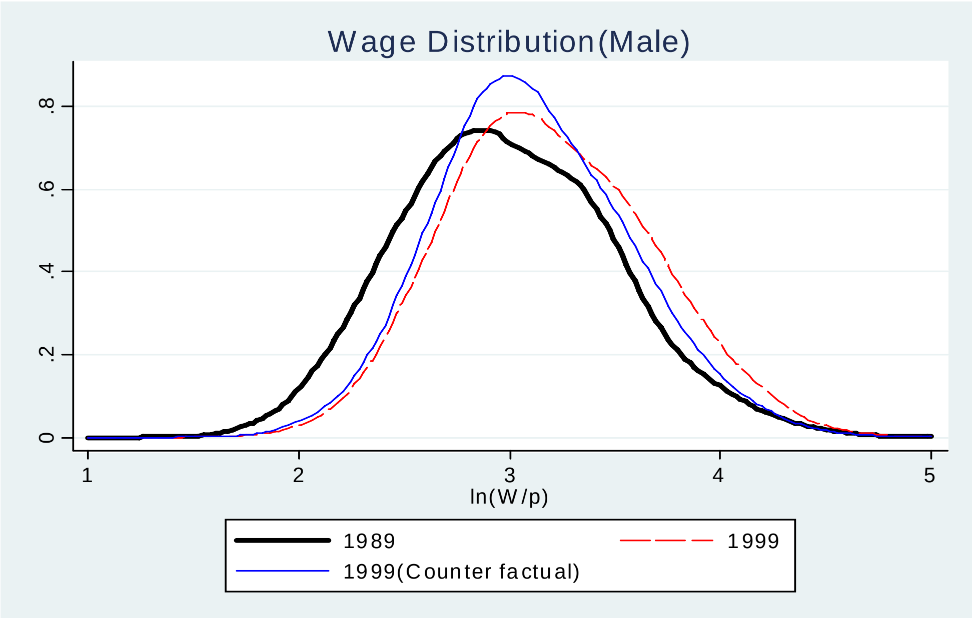
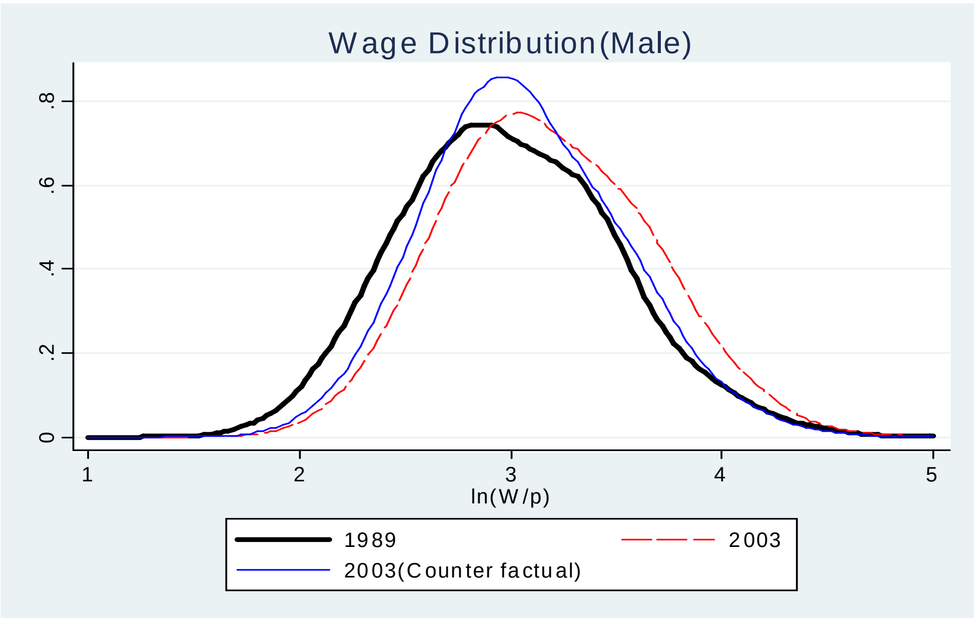


Figure 4 Real hourly wage distributions for full-time workers

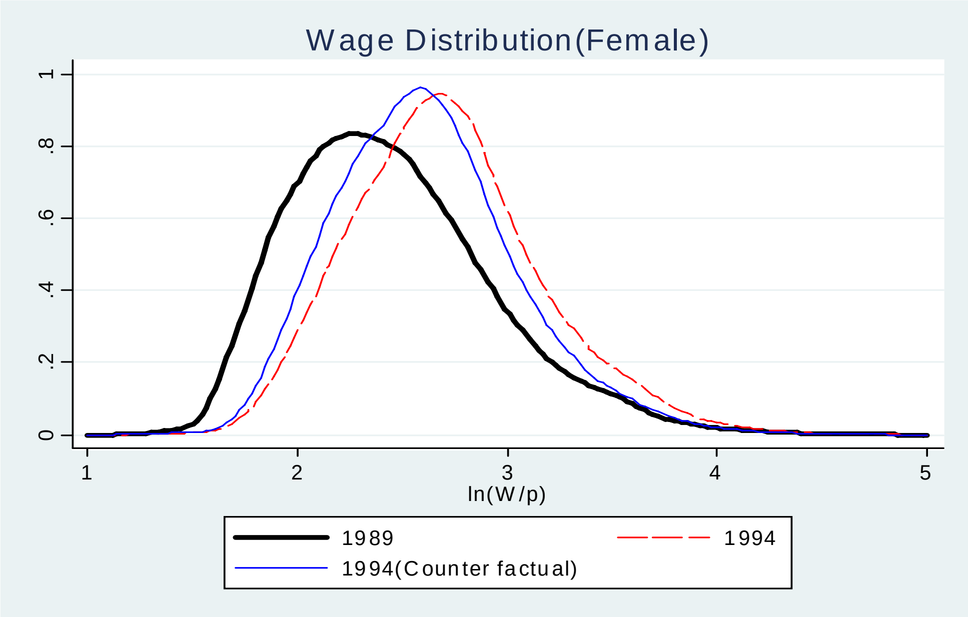
Panel A: Male workers

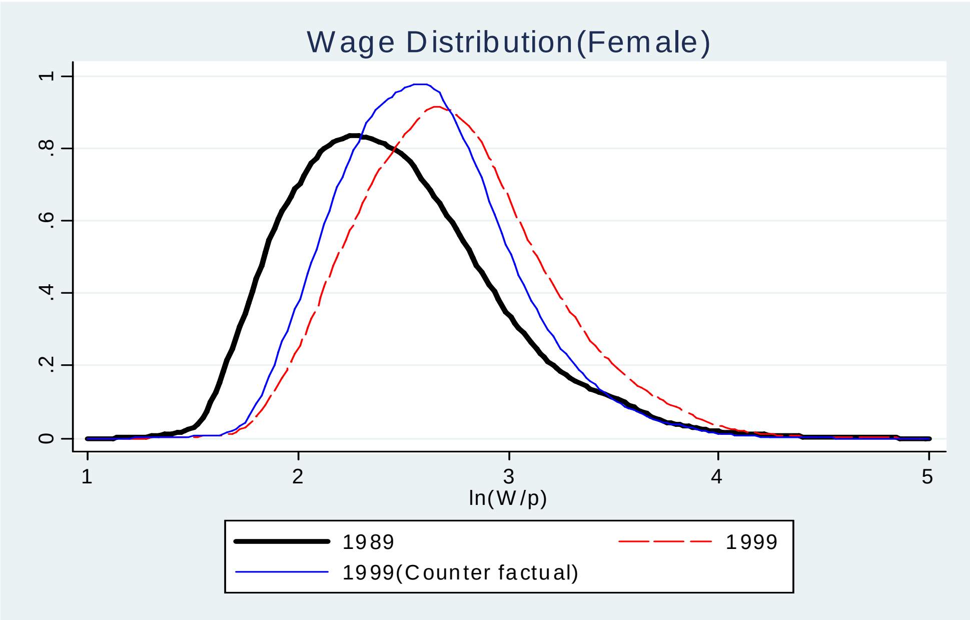






Panel B: Female workers





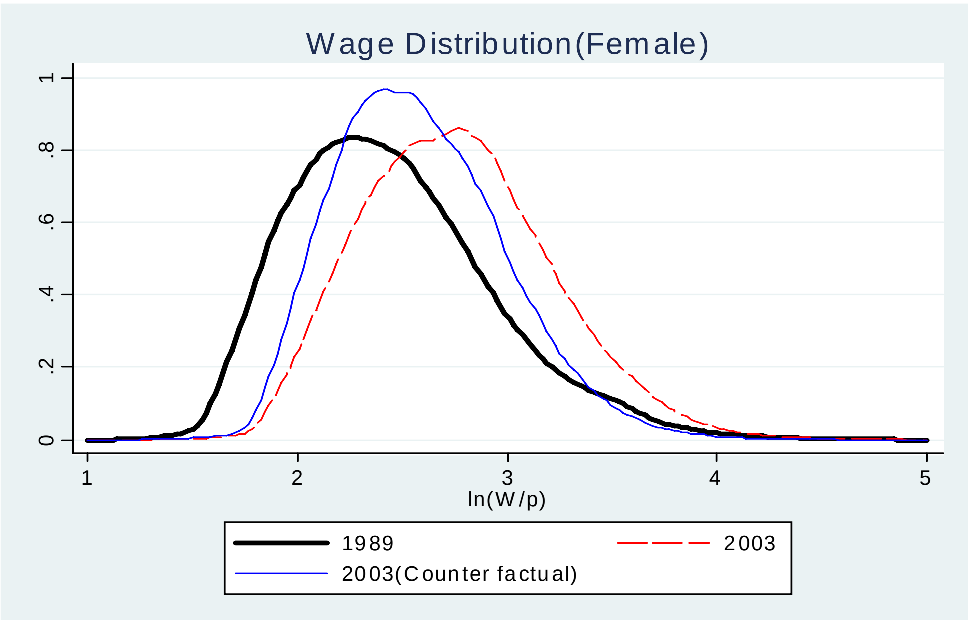


Figure 5 DFL decomposition of the real wage distribution for female workers, including part-time workers