Wage Inequality and the Gender Wage Gap: are American Women Swimming Against the Tide?

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Abstract

For over three decades wage inequality has been growing in the US while the gender wage gap declined. Current literature argues that the gender wage gap would have decreased even more, had overall wage inequality not grown so women have had to swim against the tide to reduce the gender wage gap. The statistical method currently used assumes that there is only one wage structure, miscalculating the relationship between wage structure and gender pay gap. This paper uses a new method that takes into account gender differences in wage structure and shows that increase in wage inequality went in tandem with the narrowing of the gender wage gap.

Introduction

Since the late 1970s a growing number of Americans have been earning smaller wages than the average wage, while the relative advantage of those with the highest wages has been growing. In this regard, American society has become more unequal. At the same time however, the average wages of men and women have grown closer together (although women generally still earn considerably less than men). Many researchers have wondered what explains these contradictory trends and how might they be linked.

It has been shown that the main gender wage gap decreased because women's labor market skills, such as their overall level of education, choices of occupation and especially their growing work experience, improved. Though it wasn't as influential, growing inequality also had an effect on the gender wage gap. This paper focuses on the interaction between these two measures - wage structure and the gender difference in pay.

Current literature shows or assumes that women's progress would have been greater, had growing wage inequality not exerted its hindering influence. The most influential argument put forward by Blau and Kahn (1994a, 1996b, 1997a, 1999) states that women had to swim against the tide, and calculates that the gender pay gap in fact widened by 3 to 5 percent because inequality has grown. This effect is not observed, because the net outcome has been a narrowing of the gender wage gap, owing to women's improved labor market skills, as mentioned before. The theory behind the Blau and Kahn studies builds upon the observation that changes in the overall wage structure were increasingly unfavorable to low-wage workers. Since women's wages are concentrated in the lower end of the wage distribution, and men's more in the upper end, more women than men experienced a decline in their wages relative to the median wage, so the gender wage gap became larger.

These empirical results are based on a method introduced by Juhn, Murphy and Pierce (1991) to study the wage gap between white and black men. When applied to studying the gender wage gap, this method assumes that inequality grows the same way among men and women. Yet, while inequality has grown among people of all races, and among both men and women, there are great differences in the extent to which it has increased in these different groups, as well as in the resulting shapes of their wage distributions. Growing earnings inequality has been driven by an increase in the relative wages of the college-educated, but also by the falling wages of the non-college educated, who make up most of the workforce. The result has been a decline in the real value of men's median wages. However, wages have not been falling to the same extent among women. Men from the lower and middle part of the male wage distribution have been experiencing greater relative decline in wages than anyone else. This translated into greater male inequality and it affects overall inequality as well, of course. As men's wages declined the difference between women's and men's mean wages decreased.

The existing literature measures changes in wage inequality in terms of whether the distribution became more or less dispersed. While this is an important aspect of inequality, the shape of a wage distribution also merits attention. For example, although men's wage distribution is more dispersed than women's, which corresponds to greater inequality among men, the mode of women's distribution is more to the left, which points to greater inequality among women. Therefore, it behooves researchers to compare the shape of distributions as well, and to do so for both men and women. It is also useful to study changes in the shape of each wage distribution, and to compare those changes.

Measuring wage inequality is complicated by the fact that it has two dimensions. One the one hand, wage inequality is higher when wages are more dispersed, but it is also higher when wages are concentrated closer to the bottom of the wage distribution (as opposed to being concentrated in the middle). These two dimensions make comparing wage distributions difficult, because if we have one distribution that is less dispersed but more skewed to the right, it is hard to tell whether it is more or less equal than another distribution that is slightly more dispersed, but is at the same time less skewed to the left. There are several measures of inequality, and they differ in their ability to capture one or the other dimension of inequality. For example, the Gini coefficient standardizes dispersion and compares shapes, and is more sensitive to changes in the lower part of the wage distribution. Other measures, such as the variance of the natural log of earnings and the coefficient of variation, capture differences in dispersion.

Fortin and Lemieux (1998, 2000) found that women's wages have shifted toward the middle of the total wage distribution, and thus less skewed to the right, so inequality among women declined in this regard. In men's distribution the kurtosis declined, i.e. there is less of a sharp peak and a there has been a shift to the left of the mode. This shift towards the left means growing inequality. Both men's and women's wages have become more dispersed, which means increasing inequality for both genders. In spite of their differences, measures of inequality have shown that inequality has been increasing and that it has been increasing more among men than among women.

Measuring the gender wage gap. The gender wage gap is by definition the difference between the mean wages of men and women. American women earned approximately 60 cents to a man's dollar during a major part of the 20th century. The gap started to narrow in the early 1980s, and continued to narrow until the mid 1990s. However, there has been a slow down in improvement in recent years, even though women have been continuously upgrading their human capital.

Our human capital models are able to explain only about 30 percent of the variation in wages. Thus it is not surprising that we are not able to account for most of the difference in men's and women's wages either. But the gender wage gap cannot be explained simply by our inability to measure important factors, because the returns for the skills that we do measure, also differ by gender. There are in-depth studies that prove the existence of discrimination, but we cannot measure discrimination directly, and we certainly cannot differentiate between different forms of it with our regressions.

Swimming upstream

Blau & Kahn (1994a, 1996b, 1997a, 1999, and 2003) argue that when women managed to narrow the wage gap in the U.S. in recent decades, they had to swim upstream. In their analysis they make a distinction between 'gender specific' factors and the wage structure, as two separate sets of factors affecting the gender wage gap. They define gender specific factors as gender differences in qualifications and labor market treatment of similarly qualified individuals. In other words, gender specific factors are the gender difference in skills, plus our inability to explain the gender wage gap only with the difference in measured skills. When comparing the wage gap at two different points in time, the two gender specific factors are changes in the male-female difference in skills, and the change in our inability to explain the wage gap simply with the difference in skills (change in discrimination). The wage structure in their definition encompasses the array of prices set for various labor market skills, both measured and unmeasured. For example, because women have less experience than men, increasing return to experience causes the gender wage gap to rise. This increasing return to experience is a wage structure effect.

When explaining changes over time in the gender wage gap, the effects of the wage structure are measured with the change in men's return to skills and the change in our ability to explain male wages with men's returns to skill.

However, taking the male return to skill as the reference point to calculate the effect of the rise in return, biases the estimate. Indeed, using the overall wage structure as a reference wage structure instead of using men's, produces different results (Datta Gupta, Oaxaca and Smith 2006; Fortin and Lemieux 1997).

In terms of the effect of the changing wage structure, Blau and Kahn find that as the wage distribution became more dispersed, returns to measured skills increased. This widened the gender pay gap because male returns increased for characteristics where men already had an advantage. Blau and Kahn argue that all else being equal, returns to unmeasured skills would have also increased the wage gap. But apart from improving their relative measured skills, women seem to have improved their unmeasured skills too, or discrimination against them decreased, as there was a substantial decline in the unexplained portion of the wage gap. Assuming that price changes affects men and women equally, rising inequality widens the wage gap. However, the overall effect of these countervailing trends has been a decline in the gender pay gap, as improvements in women's skills counterbalanced the effect of changing returns to skills.

Blau and Kahn argue that it is important to make a distinction between gender specific factors and labor market effects. I agree with their point, that it is important to consider the context as well, and not only individual characteristics, and that it can be useful the analyze the wage structure. However, I find the statistical model that they use inadequate for their aim.

<u>The method: the Juhn, Murphy and Pierce decomposition</u>. This method was originally designed to decompose the wage gap between black and white male

workers (Juhn et.al. 1991). The method's main aim is to distinguish the effect of factors that are black specific from the effect of skill prices – the prices both measured and unmeasured skills. In order to be able to do so, the authors set out to measure the effect of changes in prices of unmeasured skills. We know that the difference in measured skills doesn't fully explain the gender wage gap. But differences in skills do not fully explain wages in general either. Thus, assuming that our ability to estimate wages with skills is the same for men and women, we can isolate the effect of our limited ability to estimate's men's wages, and capture gender differences in unmeasured skills and returns to these unmeasured skills.

When comparing the mean wages for two groups the model first divides the wage gap into a 'predicted gap', which is the difference between the mean wages of women and men assuming that women are paid as men, and the 'residual gap' which is the difference between the predicted and the actual wage of women.

The regression equation predicting wages at time t for the i-th individual is:

$$Y_{it} = X_{it}\beta_t + \sigma_t\theta_{it}$$

Where:

- X_{it} is a vector of the observable characteristics of an individual;

- β_t gives the coefficients on these characteristics in year t;

- θ_{it} is a standardized residual[1] with mean 0 and variance 1, and

- σ_t is the standard deviation of wages in year t.

Applying this formula to calculate the gender difference in pay, the equation that gives mean wages for men is really:

$$Y_{it} = X_{it}\beta_t$$

because the residual is by definition 0 for the mean wage. Note, that we estimate both women's and men's wages using the male vector of coefficients, noted simply as β_t.

Similarly to the Oaxaca decomposition, the difference between men's and women's mean wages in year t can be written as:

$$D_t = Y_{mt} - Y_{ft} = \Delta X_t \beta_t + \sigma_t \Delta\theta_t$$

where $\Delta X = X_{mt} - X_{ft}$, the gender difference in measured skills in year t. The second term is the residual or unexplained gap, expressed in the Oaxaca model as $X_m \Delta\beta$, and interpreted as the effect of gender difference in return to skills. Given that the male standardized residual is actually $\theta_{mt} = 0$, the gender difference of the standardized residuals is in fact the female residual $\Delta\theta_t = \theta_{ft}$. Thus, the gender wage gap can be rewritten as:

$$D_t = \Delta X_t \beta_t + \sigma_t \theta_{ft}$$

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[1] For definitions of the standardized residual and standard deviation see Appendix 1.

Which makes it easier to see why is the residual interpreted as the relative position of women in the distribution of (male) residuals.

The change in the wage gap over time can then be calculated with the following formula:

$$\Delta D = D_t - D_{to} = (\Delta X_t - \Delta X_{to})B_t + \Delta X_{to}(B_t - B_{to}) + \sigma_{to}(\Delta\theta_t - \Delta\theta_{to}) + (\sigma_t - \sigma_{to})\Delta\theta_t$$

Where:

- ΔD is the difference between gender wage gaps measured at two time points Dt – Dto (t and to are our two points in time);
- θit is a standardized residual (with mean 0 and variance 1), from the equation predicting individual wages Yit = Xitβt + σt θit;
- Δθ is the difference between the average standardized residual for men and women, which is really θ_f or in other words it is women's standardized residual calculated with men's β and men's σ;
- σt is the standard deviation of male wages in year t.

The interpretation of the different components of the decomposition given by the authors is as follows:

1) The first term is called the observed skills effect and it measures the contribution of changing gender differences in skills. An increase in women's relative level of skill reduces the gender wage gap.

2) The second term is the observed prices effect. This term reflects the impact of changing returns to men's observed skills.
3) The third term is the gap effect, which captures the changing differences in the relative wage positions of men and women after controlling for their measured characteristics. In other words, it measures the change in our inability to explain the wage gap based on the gender difference in skills only.
4) The fourth term is the unobserved prices effect. It reflects changes in the relative position of men and women in the residual wage distributions of men. It shows whether women are moving up or down in the residual wage distribution of men. In other words, it reflects changes in our ability to explain change in male wages with our skill measures.

The sum of the first and the third terms represents the impact of the gender specific factors, and the second and fourth terms reflect the effect of the wage structure.

Assumptions used. My main concern is that the assumption that the wage structure is the same for men and women (and it is also assumed that it changes the same way over time) is incorrect. Existing research has clearly shown that both the dispersion and the shape of women's and men's wage distributions are markedly different, and the unexplained part of wages does not have the same variance for men and women, or whites and blacks either. Assuming that the wage structure is identical for men and women overlooks important gender differences. Also, even though the model uses the same set of variables to measure the skills of men and women, there are gender differences in what these skills mean. For example, a college degree versus a high-school degree might translate into a different wage differential for men than for women, because there are gender differences in the field of study and thus in the returns to education as well. The model does measure gender differences in the return to measured and unmeasured skills, but using as the reference category the changes that occurred over time in the return to skills experienced by men, probably biases these estimate for women's returns upward (given that women's returns for education have been smaller and women's returns have been growing slower than men's).

The authors' argument for choosing the male wage structure as the distribution of reference is that the male wage structure is not affected by improvements in the relative position of women. Even if this is true, it does not solve the problem of the male wage structure not being an adequate substitute or reference for the female wage structure.

Another assumption explicitly stated both by Juhn et. al. (1991) and by Blau and Kahn (1992, etc.) is that workers earning the same wage will be affected by market forces in the same way. In other words, people with equal wages have equal skills and are interchangeable regardless of other attributes, such as gender. This assumption forms the base of their argument, that when workers earning wages lower than the average fall further behind in the wage distribution, their wages will decrease the same way, irrespective of race or gender. Juhn et.al. (1991) claim that blacks and whites earning the same wages are interchangeable:

> "Market forces that cause the lower quartile of whites to lose relative to the average white might well be expected to increase black-white wage inequality,

> because the same forces will cause the average black (with wages and perhaps marketable skills similar to someone at the 24th percentile of the white wage distribution) to lose relative to the average white." (Juhn et. al 1991, p119)

Decomposing the gender wage gap with the same method implies that men and women are interchangeable. Yet, we know that because that there is a persisting and high level of occupational segregation, most men and women are not interchangeable, and there are important differences in the industries that they work in. So this assumption is not valid.

An important assumption which is closely related to the former one is that wages reflect skills. This in fact is a claim that workers who earn the same wages have the same skill level. So even though women on average have higher measured skills than men earning the same wages, their total marketable 'skills' are the same. While the Oaxaca decomposition assumes that workers with equal sets of measured skills have the same unmeasured characteristics as well, this method claims that workers with the same wages have the same total skills. Accordingly, even when a woman has higher measured skills than a man earning the same wage, she must in fact have lower unmeasured skills than her male counterpart. Even though I understand that their argument is simply that workers with the same wages are equal in the eyes of employers and not equal in some objective sense, I wonder what justifies this assumption. The authors' conclusion is that if relative skills don't change, then growing wage inequality will affect women and men in (or blacks and whites) the same way. Unless of course discrimination changes, but the fact is that we cannot distinguish the effects of changing unmeasured skills from changes in discrimination. Juhn et. al. recognize that this assumption might interfere with their aim of separating the effects of wage structure from the effects of discrimination. Here is what they say about this:

> "When we compare the wage change for a black with the wage change for a white at the same initial wage level we are comparing a typical black to a less-skilled white. This then causes us to overstate the extent by which any increase in the returns to skill should have lowered the wages of these blacks, thus leading to an overcorrection for the effect of skill prices. Hence, when discrimination is a significant component of the wage gap between whites and blacks, "correcting" for the residual inequality effect as we have shown will overstate the price change effect." (Juhn et. al. 1991, p128)

In the case of the gender wage gap, given that there is evidence for discrimination, using this decomposition means correcting for the increase in men's inequality, and thus overstating the effect of price change (also referred to as the wage structure).

Variations of the Blau and Kahn method

Datta Gupta, Oaxaca and Smith (2003) also used the Juhn et. al. decomposition method to compare changes in the gender wage gap over time in the U.S. and in Denmark. However, instead of using the male wage distribution as the distribution of reference, they chose to use the overall wage distribution because they wanted to allow women's relative wage gains -or losses- to affect the overall wage distribution. They recognized that the wage distribution is significantly different for men and women and that choosing on model wage structure over another affects the results. Yet, their decomposition rests on the assumption that the overall wage structure applies to both men and women.

Fortin and Lemieux (1997) introduced a new rank-based procedure to decompose changes in the gender wage gap into three components: changes in the skill distribution, changes in the wage structure and improvements in the position of women in a distribution of reference (male or overall wage distribution). Their procedure relies on one of the same assumption that the Juhn et.al. decomposition also relies on: that wages reflect skills and thus changes in the wage structure have the same effect on workers earning the same wages. They considered the possibility that the impact of changes in the wage structure varies at different points of the wage distribution, but did not consider the possibility that the impact differs by gender as well. They too found that the results of the decomposition are sensitive to the choice of distribution of reference, i.e. male versus overall distribution. Using the overall wage distribution as the distribution of reference and assuming that the relative position of women does not affect the wage structure, they found that the residual improvement in women's position decreased inequality among women and increased wage inequality among men. They explain this by the fact that women increased their skills and moved from lower wage jobs to better wages that are closer to the median, and thus 'pushed' men out from the middle of the wage distribution into jobs with lower or higher wages, thus increasing inequality among men.

An alternative decomposition that accounts for gender differences in wage distributions

This paper introduces an alternative decomposition that not only takes into account that women and men have different wage distributions, but it links both the shape and the dispersion of their wage distributions to their mean wages, thus allowing us to capture both dimensions of inequality. It still doesn't answer the question of how to evaluate the relative importance of these measures, but it does allow us to separate their effects on the gender wage gap. Thus, for example it allows us to capture how much of the gender wage gap can be associated with the fact that men's wage distribution is more skewed to the left and women's to the right, and how much of the gap is due to their wages being more dispersed. The method can be applied to compare the effects of changes in the two wage distributions over time as well. Our ability to assess changes over time makes it possible to link the convergence in shape of the male and female wage distributions is related to the change in the gender wage gap.

Because this alternative decomposition relies on the use of kernel density estimates, in what follows I give a brief review of this estimation method.

Kernel density estimation

Kernel density estimations are a modified version of histograms (which are bar charts of frequency distributions). To construct a histogram, we divide the interval covered by the data into equal sub-intervals and then build blocks on these subintervals (bins) with the height of the blocks corresponding to the number of data points that fall into each subinterval. Thus, histograms depend on the width of the subintervals, and they are not smooth. They also depend on the endpoints of the subintervals, especially if the bins are too wide, as we might unknowingly miss dips or peaks of the curve and find ourselves misrepresenting the actual shape.

Kernel density estimates are smooth and are calculated as the average of kernels centered on observations. The width of subintervals (bandwidth) of the kernels are a measure of the variance of the kernels. Kernel density estimates do not depend on the endpoints of subintervals.

However, kernel density estimates do still depend on our choice of bandwidth. Luckily, statistical programs can compute the optimal bandwidth with a choice of methods and in fact, in the case of large datasets, a range of bandwidths can be. In order to be able to compare different wage distributions, I use the same number of bands for both women's and men's wage distribution. In what follows I will use 10 bands to illustrate the method.

<u>The kernel density decomposition</u>

Using kernel density estimators, the mean wage equals the area under the graph, and the wages of women and men respectively can be expressed with the following formulas:

$$W_m = \sum_{i=0}^{9} w_{mi} p_{mi}$$
$$W_f = \sum_{i=0}^{9} w_{fi} p_{fi}$$

Where:

- W is the estimated mean wage,

- the m and f subscripts stand for male and female,

- w stands for the kernel density wage estimate in a given band, and

- p stands for the probability of being in a given band. (It is calculated by dividing the number of people in each band by the total number of people. Σpi=1.)

We know that the mode of women's wage distribution is left of men's mode, or in other words men cluster around a higher wage value. As a result, the *p* values for men are higher at higher values of wages (higher w values) so men's sum of the *pw* product (i.e. mean wage) will be higher than the sum of women's *pw* product.

Given that hourly wages start at the same minimum wage for both men and women, more dispersed wages mean reaching up to a larger *w* or wage estimate. If one group has higher *w* values on average, and a higher sum of *w*-s, inequality within that group is higher.

The difference in men's and women's average wages at time t can be decomposed in the following way:[2]

$$\Delta W^{t} = W^{t}{}_{m} - W^{t}{}_{f} = \sum w_{m}^{t} p_{m}^{t} - \sum w_{f}^{t} p_{f}^{t} = \sum \left[\left(w_{m}^{t} - w_{f}^{t} \right) p_{m}^{t} + w_{f}^{t} \left(p_{m}^{t} - p_{f}^{t} \right) \right]$$

Where:

1) the first term shows the gender difference in dispersion and
2) the second term captures the difference in shape, or distribution.

The change in the gender wage gap between time t and t_0 can be further decomposed and turned into the following formula:

$$\Delta W^{t} - \Delta W^{to} =$$

$$\sum \left(\Delta w^{t} - \Delta w^{to} \right) p_{m}^{t} +$$

$$\sum \Delta w^{to} \left(p_{m}^{t} - p_{m}^{to} \right) +$$

$$\sum \left(w_{f}^{t} - w_{f}^{to} \right) \Delta p^{t} +$$

$$\sum w_{f}^{to} \left(\Delta p^{t} - \Delta p^{to} \right)$$

1) The first term measures the change in the gender difference in wage dispersion,
2) the second term measures changes in the shape of men's distribution,

[2] The gender difference in wages expressed in terms of what percentage of men's wages do women make, can be calculated with the formula: D = (Wm – Wf)/Wm

3) the third term reflects changes in the dispersion of women's wages and

4) the fourth term reflects changes in the gender difference in distribution (or convergence between the shape of men's and women's wage distribution).

We can assess the effect of each component in terms of what percentage of the change in the gender wage gap is associated with them.

Limitations. If the optimal number of bands is quite different either for the two groups compared or over time, the results of this method might become imprecise, although we could always use more bands. If our dataset is large enough, we can still obtain a smooth graph and not pick up too much noise.[3]

Data

Of the two datasets that have been used to decompose the gender wage gap with the Juhn et.al. method the Panel Study of Income Dynamics and the Current Population Survey (CPS) I chose the March CPS because it is the source of official income statistics. For the descriptive part I use data on 31 years, from 1976 to 2007, for the decompositions I use data from 1976, 1986, 1996 and 2006.

[3] A test of whether the number of bands gives adequate kernel density estimates is calculating the sum of *pw* and comparing it to the actual mean wage. This way we can check whether we have a precision of as many decimals as we wish or whether we want to up the number of bands.

Comparability over time

To enable cross-time comparisons using the March CPS data, variables of the dataset I use have been coded identically or "harmonized", and detailed documentation covering comparability issues for each variable are provided in the codebook. Given that I am comparing earnings over time I make adjustments for inflation with the help of the Consumer Price Index (CPI), [4] the reference period being 1982-1984.

The CPS top-codes earnings that exceed a certain threshold biasing inequality measurements downwards, especially the Gini coefficient, which is very sensitive to changes in the upper tail of the distribution. As thresholds vary by earnings components and years, top-coding further biases overtime comparisons. Even though there are official lists of top-codes, most top-code values are left to be determined by users. For example, where there were very few observations over a value, even if that value was under the originally set threshold, the CPS determined that respondents could possibly be individually identified, and in effect created a new top-code. Also, after 1995 the CPS contains values that are above the official top-code. In these cases, to protect respondent anonymity the CPS grouped numerous high value cases together and assigned to all of them one high value (hopefully the mean of each such group?). Where I found such groups of values above the top-code I kept them instead of estimating a mean value above the top-code.[5] Given that total earnings are the sum

[4] CPI reflects changes in the prices paid by urban consumers for a representative, fixed basket of goods and services.

[5] While these groups of values are generally close to the true value of earnings, one must note that the CPS does not record the true value of earnings not

of different types of earnings, all of which have top-codes, I estimated average wages for each of these categories assuming that the upper-tail is Pareto distributed and then recalculated the total annual wage.

Variables

One problem of analyzing the CPS data on earnings is that almost all measures of earnings refer to the prior year, while all the variables characterizing respondents, such as occupation, place of residence, etc. reflect their status in March when the data was collected.

Wages. Earnings from wages are the most important variables in this study. The wage variable that is available for all the years is each employee's total pre-tax wage and/or salary income received for the previous calendar year.[6] Using annual earnings limits the sample to employees who worked year-round, or else their wages wouldn't be comparable. For the sake of a wider sample that better represents America's working population I chose weekly earnings calculated from annual earnings by dividing it with the number of weeks respondents worked.

Control variables used: age, education, usual hours worked, weeks employed, race, occupation and industry.

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even for internal use if the value is above a certain truncation value. Truncation values are not known for all years and earnings categories.

[6] Note that even though I use data from 1976 to 2007, data for wages refer to 1975-2006.

Sample

The CPS provides information about the U.S. non-institutionalized population. The sample used in this paper is further restricted to civilian employees between ages 25 to 54, who were employed and earned non-zero wages or salaries.[7] Members of the armed forces are excluded because they are not part of the same labor market as the rest of the employees. Another restriction used to create my sample is excluding those who didn't work for at least six weeks (six weeks typically corresponding to summer jobs for students). I further exclude the self-employed and those working part time (i.e. less than 35 hours per week). The original CPS sample has a few observations with 0 weights which I also exclude. I decided to exclude observations with imputed wages and wages that correspond to less than 1 dollar per hour (in 1982-1984 dollars) as I consider these unrealistic and therefore faulty. From 1988 on, less than 2 percent of the wages are allocated but prior to 1988 15 to 18 percent of the wages were allocated. Table 1 shows how my final sample compares to the original CPS sample. Another table on sample sizes for each year together with the proportion of allocated wages can be found in Appendix 3.[8]

[7] Blau and Kahn use the 18 to 65 age group, but people who work full-time between ages 18 and 24 are a select group, which biases our wage estimates downward. People who work between 55-64 are also a select group earning higher than average wages, biasing our estimates upward. I choose to restrict my sample to employees in the 25-54 age group.

[8] There are imputed values among the control variables too, i.e. age, education, race, and the work related variables such as industry, occupation, number of weeks worked and usual weekly hours. However, information on which observations have imputed values is available only from 1988 on, so there is no way to exclude observations before 1988. For the sake of consistency I don't exclude observations in any of the years.

Descriptive statistics

By presenting measures of the wage distribution separately for men and for women, plus the changes that their wage distributions underwent over time, I intend to test the following hypotheses:

- The wage distributions of men and women are different.
- The wage distributions of men and women evolved differently over time.
- Earnings inequality among men has been higher than among women.

Graphs 1 to 7 allow us to compare women's and men's wage distributions in 1975, 1985, 1995, and 2005. The distributions of annual wages, annual wages adjusted for inflation and logged weekly wages all tell the same story but comparing logged weekly wages offers the best visual comparison. Looking at men's wage distribution over time, we find that their distribution has grown more dispersed both in terms of clustering around a value and in terms of having a longer tail (this remains true after adjusting for inflation too). Women's distribution has also become more dispersed which is most apparent from the lower density at the mode and the wider shape of the mode. It is also apparent that while women's peak has moved towards higher wages, the peak in men's wage distribution moved in the opposite direction, toward lower wages. It appears therefore, that the gender wage gap narrowed not only because on average women's wages improved but also because the wages of a considerable number of men declined. Of the periods studied in this paper the biggest shift in the shape and place of the mode in men's wage distribution occurred between 1976 and 1986. It is probably not a coincidence that the gender wage gap narrowed most during that period. It is clear that while men's and women's wage distributions have been gradually becoming more similar, they are still significantly different.

Graphs 8 and 9 illustrate how the median and selected other wage percentiles of weekly wages changed over the years, comparing men and women. Graph 9 illustrates that while the real wages of men belonging to the 90^{th} percentiles have been increasing, real wages between the 50^{th} and 75^{th} percentiles stagnated and the percentiles below that experienced a downward trend. Women, on the other hand, did not loose ground. Their real wages at the 10^{th} and 25^{th} percentiles stagnated, while all the other percentiles experienced upward trends, the higher percentiles experiencing a more pronounced increase in their wages.

We can conclude that the wage distributions of men and women have been different and changed differently over time. Also, as Graph 10 illustrates, earnings inequality as measured by the ratio of 50/10 and 90/50 percentiles has been higher among men than among women. Graph 11 shows the Gini coefficient of men and women over time. Once again, we find that while inequality has been increasing both among men and women, it has been consistently higher among men than among women.

It is true, that the wage distributions of men and women experienced similar trends. Therefore one could argue that women would've experienced the exact same trends as men did, had they not have improved their skills. But even though the trends have been similar, the wage structures have not been the same. Thus using men's wage structure and the way it changed to calculate the effect that wage structure as such played on women's wages is surely imprecise and inaccurate.

We also know that even controlling for human capitals variables and other characteristics, women's wages on average are still lower than men's wages on average. We also know from an extensive literature that the returns for skills are not the same for men and women. Assuming that they are and calculating an estimate for women's mean wage using men's returns to skills (as by applying the Juhn et. al. decomposition method we do) does not bring us closer to understanding the unexplained part of the wage gap because we cannot capture a universal 'wage structure effect'. There might be a pure wage structure that affects everyone in the same way irrespective of gender and race, in addition to which there are separate gender and race effects, but using men's or women's or the total wage structure is not an adequate substitute for it.

Comparing the results of the two decompositions

Tables 2 and 3 summarize mean wages by sex, their differences in selected years and the change that occurred between these years. The greatest change in the gender wage gap occurred between 1975 and 1985 when the gap narrowed by 13 percent. Thus, in this sample, while women earned 58 cents to man's dollar in 1975 they earned 65 percent to man's dollar in 1985. The change between 1985 and 1995 was 8 percent and between 1995 and 2005 it was a further 6 percent, leading to women earning 72 percent to man's dollar in 2005. Expressed in 1982-1984 dollars (which are almost exactly half the value of today's dollars) in 2005 women on average earned \$395 per week while men earned \$551. Note that these results or based on mean wages, without controlling for individual characteristics.

The Juhn et. al. decomposition

Table 3 shows the results of the Juhn et. al. decomposition method. Based on this decomposition, women's relative gain is more than explained by the fact that their market skills improved. But part of the gains that they made was reclaimed by effects of the wage structure: 37 percent of the gain between 1975 and 1985, 44 percent between 1985 and 1995 and the more modest 7 percent between 1995 and 2005. According to these calculations, the wage gap would have narrowed a further 4.7 percent between 1975 and 1985, 3.5 percent between 1985 and 1995 and finally 0.5 percent between 1995 and 2005.

Decomposition of kernel density estimates

Kernel density estimates are a descriptive statistic so decomposing change in the gender wage gap with heir help will also be descriptive.[9] Table 5 shows the results of decompositions in several periods.

[9] A further step could be decomposing the gender wage gap after controlling for labor market skills.

Between 1975 and 1985 the shapes of men's and women's distribution shifted closer to each other (as Graph 7 illustrates), which corresponds to a narrowing of the gender wage gap by 20.3 percent. The actual change in the gender wage gap was 12.6 percent because the growing gender difference in the dispersion of wages amounted to a 7.7 percent increase in the wage gap. Of the periods studied in this paper, men's wage distribution underwent the most spectacular change during this period, especially in terms of a portion of men loosing ground – the left tail of their distribution shifted left. Graph 8 also illustrates a such a change as it shows that the real wages of men at the 10th, 25th and 50th percentiles have all slightly decreased. Thus, while women had increasing wages (as illustrated by Graphs 6 and 9) and men at the highest wage percentiles had their wages increasing too, the wage gap narrowed not only because women's wages improved but also because the relative wages of many men decreased. The narrowing of the gender wage gap would've been greater had the wages of a part of the working men not increased relative to the rest of the men and relative to most women.

Between 1985 and 1995 further shifts of men's and women's wage distribution meant a 23.5 percent decrease of the wage gap which was in great part counterbalanced by a changing gender difference in wage dispersions of 15.2 percent. Thus, the actual narrowing of the gender wage gap was the more modest 8.4 percent. During this period the left tail of the male wage distribution shifted further to the left (though not as greatly as in the former period) while the right tail of their distribution also moved somewhat to the right. Women's wage distribution continued to shift right and both distributions became more dispersed.

Between 1995 and 2005 the gender wage gap narrowed only 6.4 percent. Based on Graphs 3, 6 and 7, while the female wage distributions continued to move further to the right, the male wage distribution stopped moving left and moved somewhat to the right. Both wage distributions have become more dispersed this is illustrated by lower peaks and wider tails. The kernel density decomposition tells us that the gender wage gap during this period narrowed not because the to distributions moved closer to each other, in fact the way they moved meant a lowering of the wage gap, but because the difference in their dispersions has decreased. The Juhn et. al.

decomposition calculated that the wage gap would have further narrowed by 0.5 percent were it not for changes in the gender difference in wage dispersion (true, the method uses residual wage dispersion). The decomposition based on kernel density estimates calculates that the wage gap narrowed by 19.6 percent along with changes in wage dispersion that was offset in part by a 13.2 percent change due to shifts in shape. It appears that increasing returns to skills have not hurt women, at least not within the last decade.

Conclusion and discussion

This paper demonstrated that using men's wage structure - and the way in which it changed over time - as reference points for women's wage structure leads to inaccurate results. Men’s and women’s wage distributions are different and there are several reasons to expect the residual male wage structure to be different from the residual female wage structure. As stated earlier, men and women operate in fairly different labor markets mostly because many occupations are either male or female dominated and also because different industries have different gender compositions. Thus, changes in the economy don’t always affect women and men in the same way. For example, the loss of jobs in the manufacturing of durable goods and de-unionization affected men much more than it affected women. On the other hand, the increased need for clerical personnel and generally the expansion of the service sector provided work opportunities for women more than for men.

Further problems in using this decomposition stem not so much from the model itself, but from the uses that it has been put to, and the interpretations given. For example, even though the method uses the dispersion of the <u>unexplained</u> part of the wages, researchers interpret it as the wage structure or wage dispersion and often even as wage inequality in general, which is misleading.

Another problem appears when we apply this method to comparing wage gaps across countries. In this case, the proportion of the wage that remains unexplained might be different across countries, in part because the independent variables that we control for are different in these countries. And even if the variables are the same, their ability to estimate wages may differ within countries for reasons unrelated to their level of wage inequality but due to the fit of these variables. Also, using the male residual wage dispersion might be a better proxy for the female dispersion in one country than in another. Thus, differences in the variation of the residual male wage cannot be attributed only to differences in return to skills.

I also wish to argue against applications of the results of the Blau and Kahn studies that state (or imply by the models used) that a measure of wage inequality is an independent variable for predicting differences in gender wage gaps. Both the gender wage gap and measures of inequality are calculated from the wages of a sample of all the employees and cannot be considered independent of each other. Moreover, they should not be used in causal arguments.

One conclusion of this study is that decomposing the gender wage gap over time with a method that takes into account existing differences in wage distributions, leads to a different conclusion on the relationship between wage inequality and the gender wage gap, than the conclusion based on the Juhn et.al. decomposition method. The alternative decomposition method used in this paper is not a variation on the Juhn et. al. decomposition and it does not correct for the problem identified. I do not know whether there is a way to interpret the unmeasured part of wages or the unexplained part of the wage gap. Maybe there is a way to decompose and interpret part of the unexplained wage gap but this paper does not offer such a decomposition. The decomposition method used does not analyze the wage structure defined as returns to skills. It is applied to wage distributions instead and helps us understand how different dimensions of wage distributions are related to changes in the gender wage gap. The method could perhaps be applied to racial and to international gender wage gaps as well.

Appendix 1

Standard deviation is the square root of the squared distance between the data points and the mean. It is a statistic that tells us how tightly all the various values are clustered around the mean. When the values are crowded together and the bell-shaped curve is steep, the standard deviation is small. When the values are spread out and the bell curve is flat, the standard deviation is large. The formula with which we calculate it is:

$$\sigma = \sqrt{\frac{\Sigma(y_i - \hat{y})^2}{n}}$$

Note that this measure is a characteristic of the data and is not dependent on an estimation method.

A residual (or error) in a regression is the difference between the actual value of the dependent variable and its predicted value. $e_i = y_i - x_i'\hat{\beta}$

It is assumed that the residual is a random variable and the coefficients are determined so that the residual has a mean zero, and the sum of the square residuals is as small as possible. This measure depends on the estimation method used.

The standard error of a regression is the estimated standard deviation of the residual in that regression.

$$s_e \equiv \sqrt{\hat{\sigma}^2}$$

The standard error of the mean is the standard deviation of the sampling distribution of the mean

$$S_E = \frac{\hat{\sigma}}{\sqrt{n}}$$

Standardized residuals are the residuals divided by the estimates of their standard errors and thus they have mean 0 and standard deviation 1.[10]

Standardized residuals are mostly used to identify influential observations. The formula for calculating them is:

$$\theta_i = \frac{y_i - x_i^{'}\hat{\beta}}{\hat{\sigma}}$$

In our case

- y_i is the observed wage of an individual,

- $x_i^{'}$ is the vector of the individual's measured skills and

- $\hat{\beta}$ is the vector of coefficients calculated for the whole sample.

- $x_i^{'}\hat{\beta}$ is the expected wage.

Note that the above formula can be rewritten as $y_i = x_i^{'}\hat{\beta} + \hat{\sigma}\theta_i$

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[10] There are two ways to calculate the standardized residual for the i^{th} observation. One uses the residual mean square error from the model fitted to the full dataset (internally studentized residuals). The other uses the residual mean square error from the model fitted to all of the data except the i^{th} observation (externally studentized residuals).

Appendix 2

Annual wage and salary, percent imputed by year, in the original CPS sample

Year	Percent imputed
1975	11.40
1976	13.08
1977	10.87
1978	11.60
1979	10.38
1980	10.89
1981	7.86
1982	7.76
1983	7.60
1984	8.50
1985	8.02
1986	8.37
1987	0.64
1988	0.63
1989	0.64
1990	0.61
1991	0.53
1992	0.51
1993	0.77
1994	0.83
1995	0.60
1996	0.89
1997	1.01
1998	1.07
1999	0.80
2000	1.09
2001	1.04
2002	0.20
2003	0.84
2004	0.86
2005	0.78
2006	0.76

Appendix 3

Appendix Table 3. Sample sizes by year and sex

Year	CPS sample Men	CPS sample Women	CPS sample Total	My sample Men	My sample Women	My sample Total
1975	65,278	70,073	135,351	15,431	8,250	23,681
1976	77,799	83,000	160,799	19,118	10,340	29,458
1977	75,207	80,499	155,706	18,492	10,431	28,923
1978	74,436	80,016	154,452	18,143	10,710	28,853
1979	87,852	93,636	181,488	22,185	13,692	35,877
1980	87,676	93,682	181,358	21,999	13,780	35,779
1981	78,606	84,097	162,703	19,838	12,583	32,421
1982	78,570	84,065	162,635	19,506	12,596	32,102
1983	77,622	83,545	161,167	19,398	13,019	32,417
1984	77,535	83,827	161,362	19,698	13,670	33,368
1985	76,024	81,637	157,661	20,365	13,964	34,329
1986	74,757	80,711	155,468	19,999	14,208	34,207
1987	75,158	80,822	155,980	23,979	17,235	41,214
1988	69,838	74,849	144,687	22,624	16,385	39,009
1989	76,131	81,948	158,079	24,988	18,351	43,339
1990	76,354	82,123	158,477	24,915	18,537	43,452
1991	75,138	80,658	155,796	24,477	18,564	43,041
1992	74,655	80,542	155,197	24,095	18,336	42,431
1993	72,364	78,579	150,943	23,235	17,606	40,841
1994	71,769	77,873	149,642	23,551	17,899	41,450
1995	62,424	68,052	130,476	20,875	15,911	36,786
1996	63,404	68,450	131,854	21,487	16,372	37,859
1997	63,515	68,102	131,617	21,248	16,354	37,602
1998	63,870	68,454	132,324	21,534	16,759	38,293
1999	64,791	68,919	133,710	22,128	17,162	39,290
2000	62,625	66,196	128,821	21,336	16,693	38,029
2001	105,340	111,879	217,219	35,570	27,880	63,450
2002	105,322	111,102	216,424	34,601	27,054	61,655
2003	103,349	109,892	213,241	33,376	26,133	59,509
2004	102,202	108,446	210,648	32,922	25,740	58,662
2005	101,216	107,346	208,562	32,884	25,456	58,340
2006	100,549	106,090	206,639	32,627	25,545	58,172
Total	2,521,376	2,699,110	5,220,486	756,624	547,215	1,303,839

Appendix 4

Official top-codes, highest values and percent top-coded of various income measures, by year.

This appendix contains three tables.

Appendix table 4.1.Total income from salary and wage

Survey year	official topcode = highest value	Percent topcoded
1976	50,000	0.34%
1977	50,000	0.41%
1978	50,000	0.53%
1979	50,000	0.69%
1980	50,000	1.04%
1981	50,000	1.35%
1982	75,000	0.41%
1983	75,000	0.61%
1984	75,000	0.70%
1985	99,999	0.34%
1986	99,999	0.44%
1987	99,999	0.60%

Appendix table 4.2. Salary and wage from longest job

Survey year	Official topcode	Highest value	Percent topcoded
1988	99,999	99,999	0.72%
1989	99,999	99,999	0.88%
1990	99,999	99,999	1.07%
1991	99,999	99,999	1.10%
1992	99,999	99,999	1.10%
1993	99,999	99,999	1.33%
1994	99,999	99,999	1.72%
1995	99,999	99,999	1.94%
1996	150,000	576,372	na
1997	150,000	454,816	na
1998	150,000	442,040	na
1999	150,000	492,657	na
2000	150,000	362,302	na
2001	150,000	337,173	na
2002	150,000	477,562	na
2003	150,000	595,494	na
2004	150,000	556,932	na
2005	150,000	713,263	na
2006	150,000	543,488	na
2007	150,000	619,221	na

Appendix table 4.3. Salary and wage from other jobs

Survey year	Official top-code	Highest value	Number of observations with highest value
1988	99,999	95,000	1
1989	99,999	99,999	2
1990	99,999	90,000	2
1991	99,999	99,999	3
1992	99,999	99,999	1
1993	99,999	99,999	9
1994	99,999	99,999	24
1995	99,999	99,999	7
1996	25,000	183,748	8
1997	25,000	257,102	40
1998	25,000	88,513	148
1999	25,000	59,925	3
2000	25,000	236,224	7
2001	25,000	76,729	5
2002	25,000	65,493	133
2003	25,000	91,360	8
2004	25,000	156,017	140
2005	25,000	77,282	2
2006	25,000	106,075	5
2007	25,000	240,674	

Bibliography

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney, 2005. 'Rising Wage Inequality: The Role of Composition and Prices' *NBER Working Papers* 11628, National Bureau of Economic Research, Inc. Issued in August 2005.

Bernhardt, Annette, Martina Morris, Mark S. Handcock.1995. 'Women's Gains or Men's Losses? A Closer Look at the Shrinking Gender Gap in Earnings' *American Journal of Sociology*, Vol. 101, No. 2. (Sep., 1995), pp. 302-328.

Bertola, Giuseppe & Francine D. Blau & Lawrence M. Kahn, 2001. 'Comparative Analysis of Labor Market Outcomes: Lessons for the U.S. from International Long-Run Evidence,' *NBER Working Papers* 8526, National Bureau of Economic Research, Inc.

Bianchi, Suzanne M. 1999. 'Feminization and Juvenilization of Poverty: Trends, Relative Risks, Causes, and Consequences' *Annual Review of Sociology* 25: 307-333.

Bianchi, Suzanne M., Daphne Spain. 1986. *American Women in Transition* New York: Russel Sage.

Bianchi, Suzanne M., Nancy Rytina. 1986. 'The Decline of Occupational Sex Segregation During the 1970s: Census and CPS Comparisons' *Demography* 23 (February): 79-86.

Bernstein, Jared, Lawrence Mishel. 1997. 'Has wage inequality stopped growing?' *Monthly Labor Review*, dec. 1997, p.3-16.

Blau, Francine D., Lawrence M. Kahn. 1992. 'The Gender Earnings Gap: Learning from International Comparisons' *The American Economic Review*, Vol. 82, No. 2, Papers and Proceedings of the Hundred and Fourth Annual Meeting of the American Economic Association (May, 1992), pp. 533-538.

Blau, Francine D., Lawrence M. Kahn. 1994. 'Rising Wage Inequality and the U.S. Gender Gap' *The American Economic Review*, Vol. 84, No. 2, Papers and Proceedings of the Hundred and Sixth Annual Meeting of the American Economic Association (May, 1994), pp. 23-28.

Blau, Francine D., Lawrence M. Kahn. 1995. 'The Gender Earnings Gap: Some International Evidence. ' In *Differences and Changes in Wage Structures,* edited by Richard Freeman and Lawrence Katz, pp. 105–43. Chicago: University of Chicago Press, 1995.

Blau, Francine D., Lawrence M. Kahn. 1996a. 'International Differences in Male Wage Inequality: Institutions versus Market Forces' *The Journal of Political Economy*, Vol. 104, No. 4 (Aug., 1996), pp. 791-837.

Blau, Francine D., Lawrence M. Kahn. 1996b. 'Wage Structure and Gender Earnings Differentials: An International Comparison' *Economica*, New Series, Vol. 63, No. 250, Supplement: Economic Policy and Income Distribution (1996), pp. S29-S62.

Blau, Francine D., Lawrence M. Kahn. 1997. 'Swimming Upstream: Trends in the Gender Wage Differential in the 1980s' *Journal of Labor Economics*, Vol. 15, No. 1, Part 1. (Jan., 1997), pp. 1-42.

Blau, Francine D., Lawrence M. Kahn. 1997b. 'The Impact of Wage Structure on Trends in U.S. Gender Wage Differentials1975-1987,' *NBER Working Papers* 4748, National Bureau of Economic Research, Inc.

Blau, Francine D., Lawrence M. Kahn. 1999. 'Analyzing the gender pay gap' *The Quarterly Review of Review of Economics and Finance* 39 (1999) 625-646.

Blau, Francine D., Lawrence M. Kahn. 2000. 'Gender Differences in Pay' *The Journal of Economic Perspectives*, Vol. 14, No. 4. (Autumn, 2000), pp. 75-99.

Blau, Francine D., Lawrence M. Kahn. 2003. 'Understanding International Differences in the Gender Pay Gap,' *Journal of Labor Economics*, University of Chicago Press, vol. 21(1), pages 106-144, January.

Blau, Francine D., Lawrence M. Kahn. 2004. 'The U.S. Gender Pay Gap in the 1990s: Slowing Convergence,' *NBER Working Papers* 10853, National Bureau of Economic Research, Inc.

Card, David, Thomas Lemieux. 'Changing Wage Structure and Black-White Wage Differentials' (in Rising Wage Inequality in the United States: Causes and Consequences) *The American Economic Review*, Vol. 84, No. 2, Papers and Proceedings of the Hundred and Sixth Annual Meeting of the American Economic Association. (May, 1994), pp. 29-33.

Cotter, David A., Joan M. Hermsen, and Reeve Vanneman. 1999. 'Systems of Gender, Race, and Class Inequality: Multilevel Analyses' 1999. *Social Forces* 78 (December): 433-460.

Cotter, David A., Joan M. Hermsen, and Reeve Vanneman. 2004 '*Gender Inequality at Work'* A volume in the series, The American People: Census 2000. New York,NY: Russell Sage Foundation and Population Reference Bureau.

Cotter, David A., Joan M. Hermsen, Reeve Vanneman. 2001. 'Women's Work and Working Women: The Demand for Female Labor' *Gender and Society*, Vol. 15, No. 3. (Jun., 2001), pp. 429-452.

Cotter, David A., JoAnn DeFiore, Joan M. Hermsen, Brenda Marsteller Kowalewski, Reeve Vanneman 1998. 'The Demand for Female Labor' *The American Journal of Sociology*, Vol. 103, No. 6. (May, 1998), pp. 1673-1712.

Cotter, David A., JoAnn M. DeFiore, Joan M. Hermsen, Brenda Marsteller Kowalewski, and Reeve Vanneman. 1997. 'All Women Benefit: The Macro-Level Effect of Occupational Segregation on Gender Earnings Equality' *American Sociological Review.* 62(October):714-734.

Datta Gupta, Nabanita, Ronald L. Oaxaca, Nina Smith. 2006. 'Swimming Upstream, Floating Downstream: Comparing Women's Relative Wage Positions in the U.S. and Denmark' *Industrial and Labor Relations Review*, 2006, 59 (2), 243-266.

DiNardo, John, Nicole M. Fortin, Thomas Lemieux 1995. 'Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach' *NBER Working Paper* No. w5093* Issued in April 1995.

Fields, Judith and Edward N. Wolff.1991. 'The Decline of Sex Segregation and the Wage Gap, 1970-80' *The Journal of Human Resources*, Vol. 26, No. 4. (Autumn, 1991), pp. 608-622.

Fortin, Nicole M., Thomas Lemieux. 1997. 'Institutional Changes and Rising Wage Inequality: Is there a Linkage?' *The Journal of Economic Perspectives*, Vol. 11, No. 2. (Spring, 1997), pp. 75-96.

Fortin, Nicole M., Thomas Lemieux. 1998. 'Rank Regressions, Wage Distributions, and the Gender Gap' *The Journal of Human Resources*, Vol. 33, No. 3. (Summer, 1998), pp. 610-643.

Fortin, Nicole M., Thomas Lemieux. 2000. 'Are Women's Wage Gains Men's Losses? A Distributional Test' *The American Economic Review*, Vol. 90, No. 2, Papers and Proceedings of the One Hundred Twelfth Annual Meeting of the American Economic Association. (May, 2000), pp. 456-460.

Freeman, Richard B. 1982. 'Union Wage Practices and Wage Dispersion within Establishments' *Industrial and Labor Relations Review*, Vol. 36, No. 1. (Oct., 1982), pp. 3-21.

Freeman, Richard B., 2002. 'The Labour Market in the New Information Economy' (October 2002). *NBER Working Paper* No. W9254.

Hirsch, Barry T, David A. Macpherson, Union Membership and Earnings Data Book: Compilations from the Current Population Survey. Washington: Bureau of National Affairs, 2006, p. 6.

Juhn, Chinhui, Dae Il Kim. 1999. 'The Effects of Rising Female Labor Supply on Male Wages' *Journal of Labor Economics*, Vol. 17, No. 1. (Jan., 1999), pp. 23-48.

Juhn, Chinhui, Kevin M. Murphy and Brooks Pierce. 'Accounting for the Slowdown in Black-White Wage Convergence', in M. H. Kosters: *Workers and Their Wages: Changing Patterns in the United States.* AEI Studies, no. 520 Washington, D.C.: AEI Press, 1991, pp. 107-43.

Juhn, Chinhui, Kevin M. Murphy and Brooks Pierce. 1993 'Wage Inequality and the Rise in Returns to Skill. ' *Journal of Political Economy*, 1993, *101*(3), pp. 410-42.

Kawachi, Ikiro and Bruce P. Kennedy. 2002. *The Health of Nations: Why Inequality is Harmful to Your Health.* New York: The New York Press.

Kidd, Michael P. & Michael Shannon. 1996. 'The Gender Wage Gap: A Comparison of Australia and Canada,' *Canadian Journal of Economics*, Canadian Economics Association, vol. 29(s1), pages 121-25, April.

King, Miriam, Steven Ruggles, Trent Alexander, Donna Leicach, and Matthew Sobek. *Integrated Public Use Microdata Series, Current Population Survey: Version 2.0*. [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor], 2004. www.ipums.org/cps.

Kuznets, Simon.1953. 'International Differences in Income Levels: Reflections on Their Causes' *Economic Development and Cultural Change* > Vol. 2, No. 1 (1953), pp. 3-26.

Levy, Frank, Richard J. Murnane.1992. 'U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations' *Journal of Economic Literature*, Vol. 30, No. 3. (Sep., 1992), pp. 1333-1381.

Lorence, Jon. 1991. 'Growth in Service Sector Employment and MSA Gender Earnings Inequality: 1970-1980' *Social Forces*, Vol. 69, No. 3. (Mar., 1991), pp. 763-783.

Loury, Linda Datcher 1997. 'The gender earnings gap among college-educated workers' *Industrial and Labor Relations Review* v. 50 p. 580-93.

Mandel, Hadas and Moshe Semyonov. 2005. 'Family Policies, Wage Structures, and Gender Gaps: Sources of Earnings Inequality in 20 Countries' *American Sociological Review.* 70(December):949-967.

McCall Leslie. 2000. 'Gender and the New Inequality: Explaining the College/Non-College Wage Gap' *American Sociological Review*, Vol. 65, No. 2 (Apr., 2000), pp. 234-255.

Morris, Martina, Annette D. Bernhardt, Mark S. Handcock. 1994. 'Economic Inequality: New Methods for New Trends' *American Sociological Review*, Vol. 59, No. 2. (Apr., 1994), pp. 205-219.

Morris, Martina, Bruce Western. 1999. 'Inequality in Earnings at the Close of the Twentieth Century' *Annual Review of Sociology*, Vol. 25. (1999), pp. 623-657.

Nelson, Joel I., Jon Lorence 1988. 'Metropolitan Earnings Inequality and Service Sector Employment' *Social Forces*, Vol. 67, No. 2. (Dec., 1988), pp. 492-511.

Nielsen, Francois, Arthur S. Alderson. 1997. 'The Kuznets Curve and the Great U-Turn: Income Inequality in U.S. Counties, 1970 to 1990 (in Macro-Level Studies of Inequality)' *American Sociological Review*, Vol. 62, No. 1. (Feb., 1997), 12-33.

Oaxaca, Ronald. 1973. 'Male-Female Wage Differentials in Urban Labor Markets,' *International Economic Review*, vol. 14(3), pages 693-709, October.

O'Neill, June & Solomon Polachek 1993. 'Why the Gender Gap in Wages Narrowed in the 1980s' *Journal of Labor Economics* vol. 11, no.1, part 1. p. 205-228.

O'Neill, June. 2003. 'Catching Up: The Gender Gap in Wages, circa 2000' *The American Economic Review*, Vol. 93, No. 2, Papers and Proceedings of the One Hundred Fifteenth Annual Meeting of the American Economic Association, Washington, DC, January 3-5, 2003. (May, 2003), pp. 309-314.

Oppenheimer, Valerie K. 1973. 'Demographic Influence on Female Employment and the Status of Women. ' *American Journal of Sociology* 78(January): 946-961.

Semyonov, Moshe. 1980. 'The Social Context of Women's Labor Force Participation: A Comparative Analysis' *The American Journal of Sociology*, Vol. 86, No. 3 (Nov., 1980), pp. 534-550.

Sicilian, Paul, Adam J. Grossberg. 2001. 'Investment in human capital and gender wage differences: evidence from NLSY' *Applied Economics,* 2001. 33, 463-471.

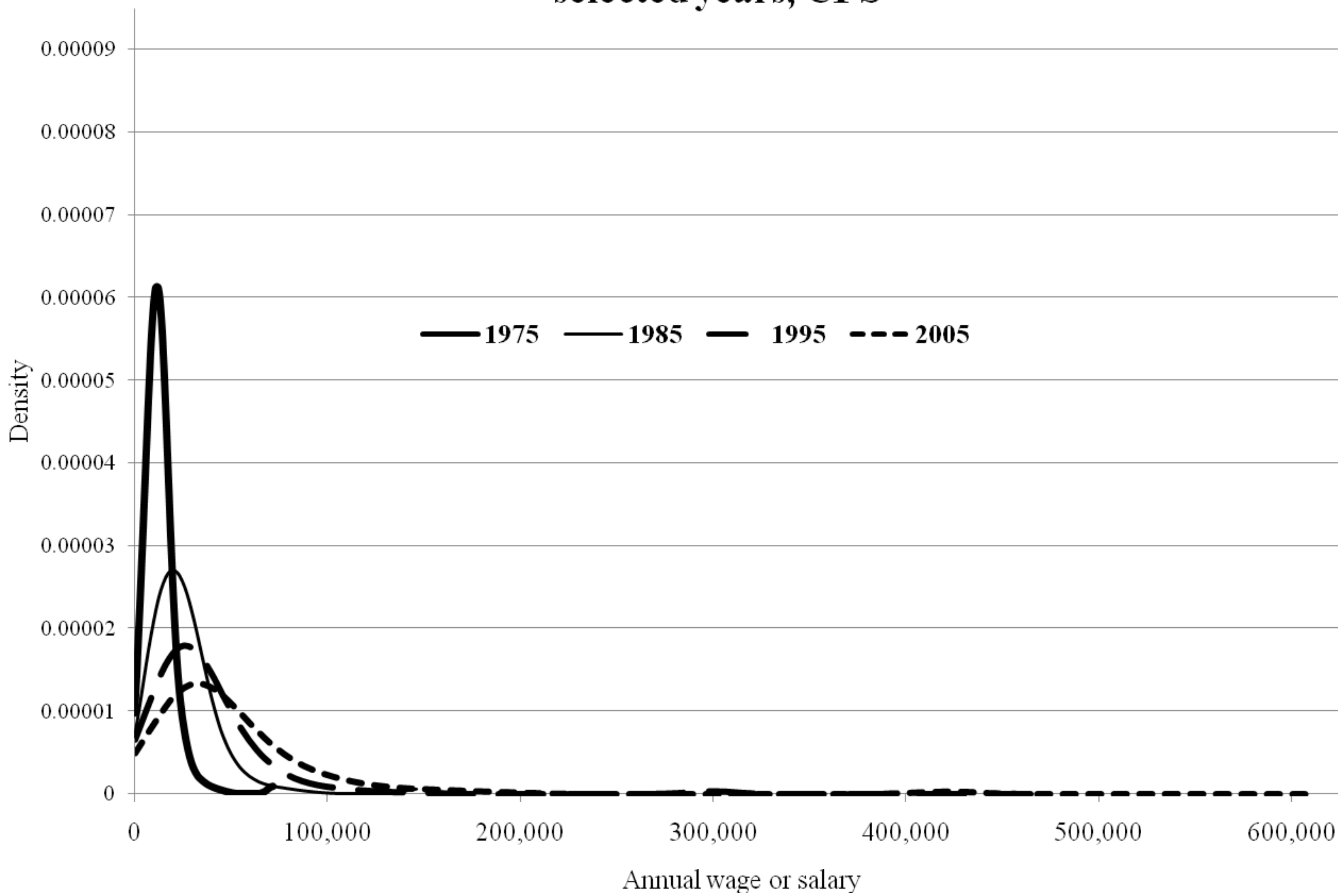
Tyree, Andrea, Moshe Semyonov, Robert W. Hodge. 1979. 'Gaps and Glissandos: Inequality, Economic Development, and Social Mobility in 24 Countries' *American Sociological Review*, Vol. 44, No. 3 (Jun., 1979), pp. 410-424.

Table 1. The CPS sample used in this study

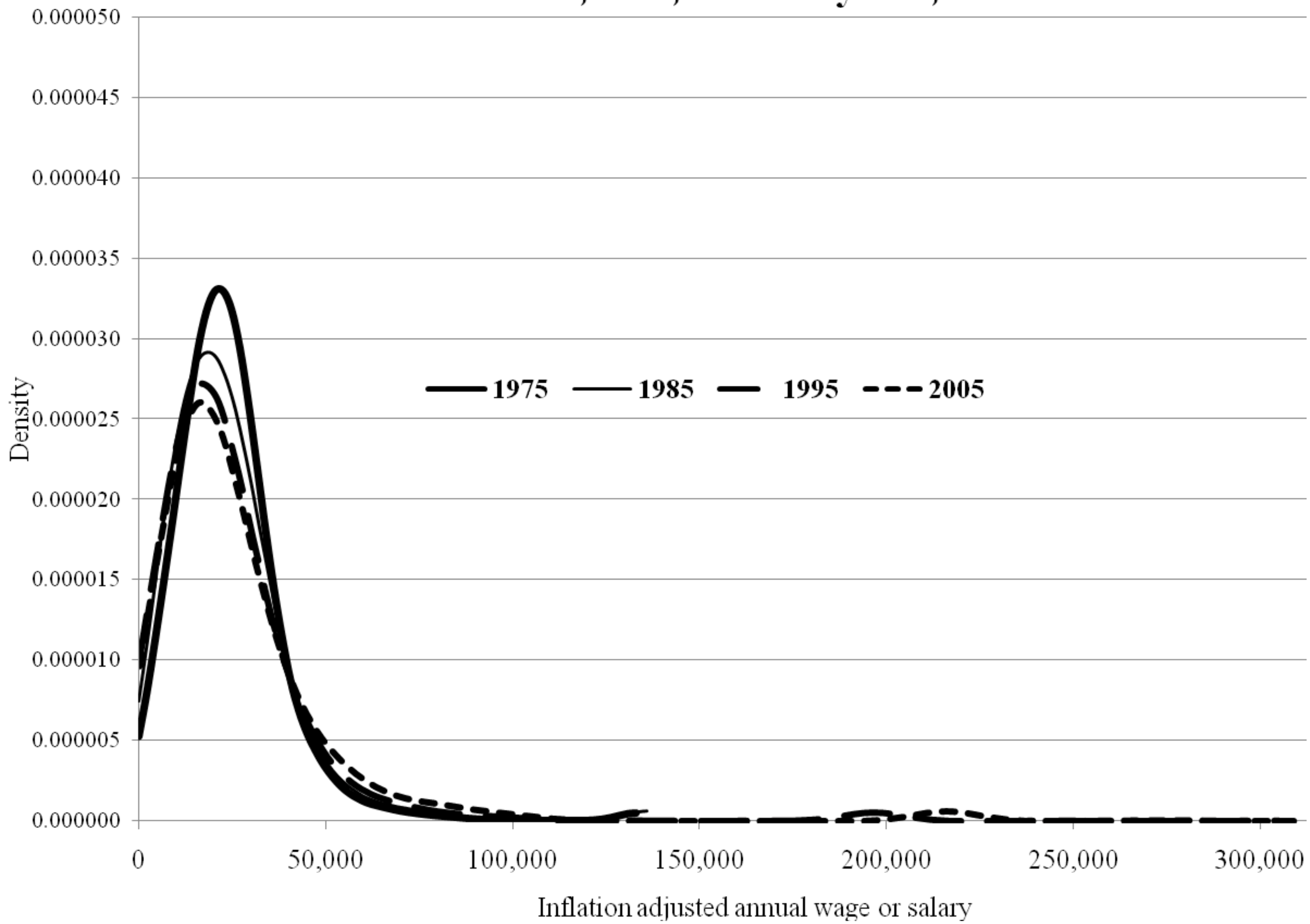
Universe/variables	Number of observations
Original IPUMS CPS, 1976-2007	**5,220,486**
My Universe after restricting the sample to meet the following criteria:	
Adult civilian	3,957,250
Age 25-54	2,131,350
Worked at least 6 weeks in former year	1,761,707
Earned wage or salary (excludes self-employed)	1,399, 758
Excluding observations with 0 weight	1,399, 693
Subsample	1,399, 693
Further excluding imputed wages	1,312,134
Excluding those who earn less than $1/hour in '82-'84 dollars	1,303,958
Final subsample (93,13% of the subsample)	**1,303,958**

Source: IPUMS CPS, survey years 1976-2007.

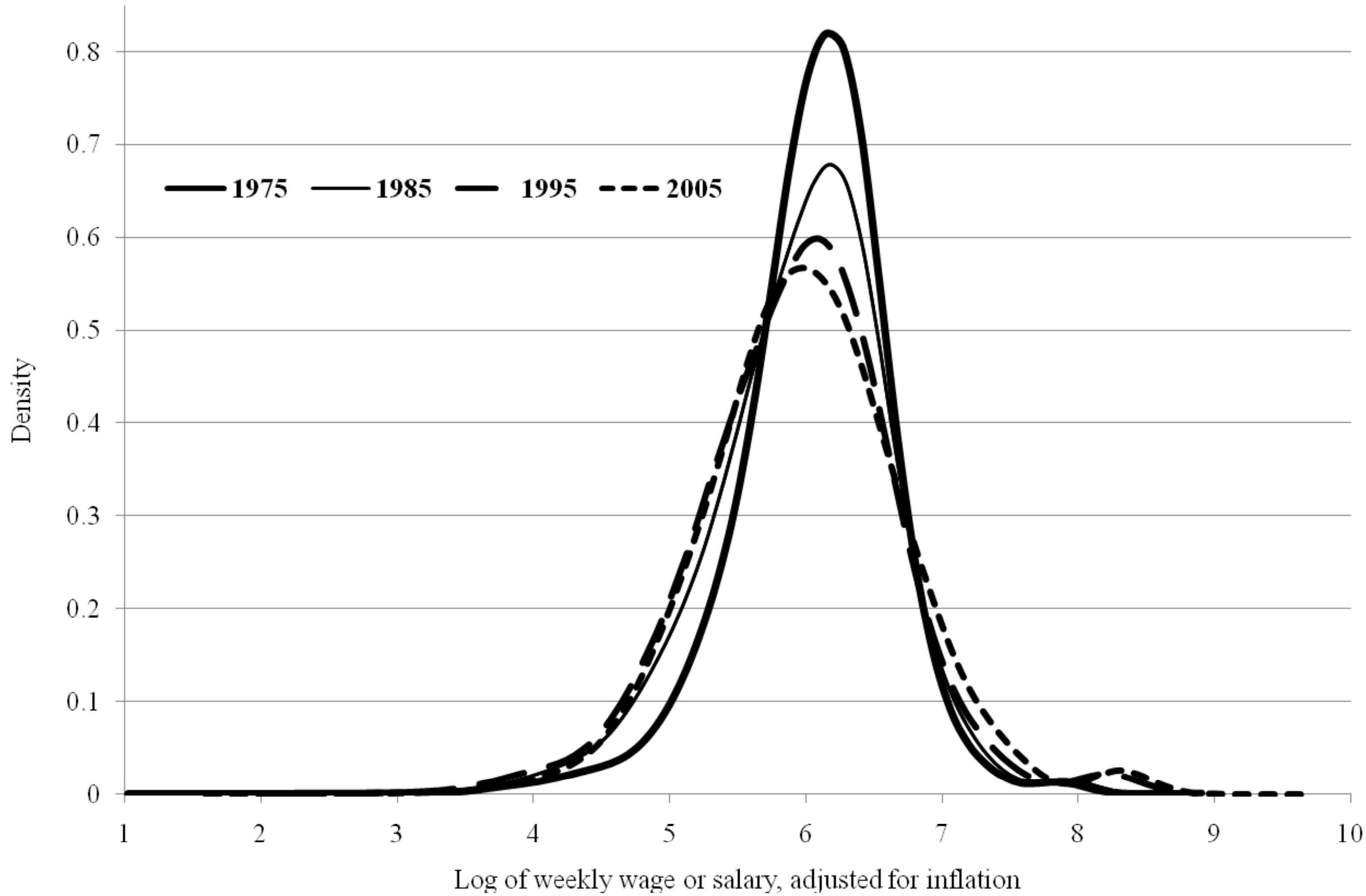
Graph 1. Wage distribution of annual wages, men, selected years, CPS



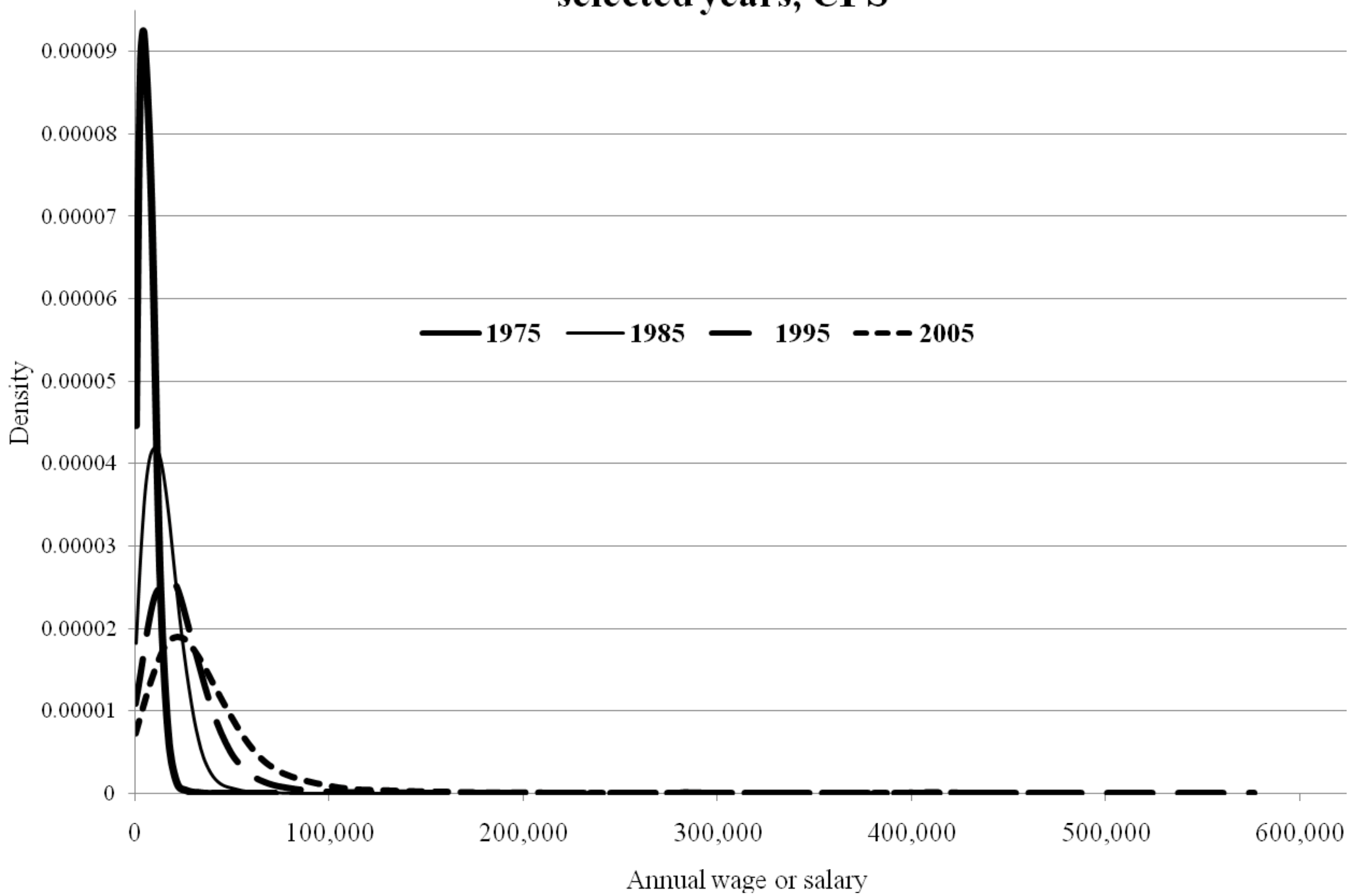
Graph 2. Wage distribution of annual wages adjusted for inflation, men, selected years, CPS



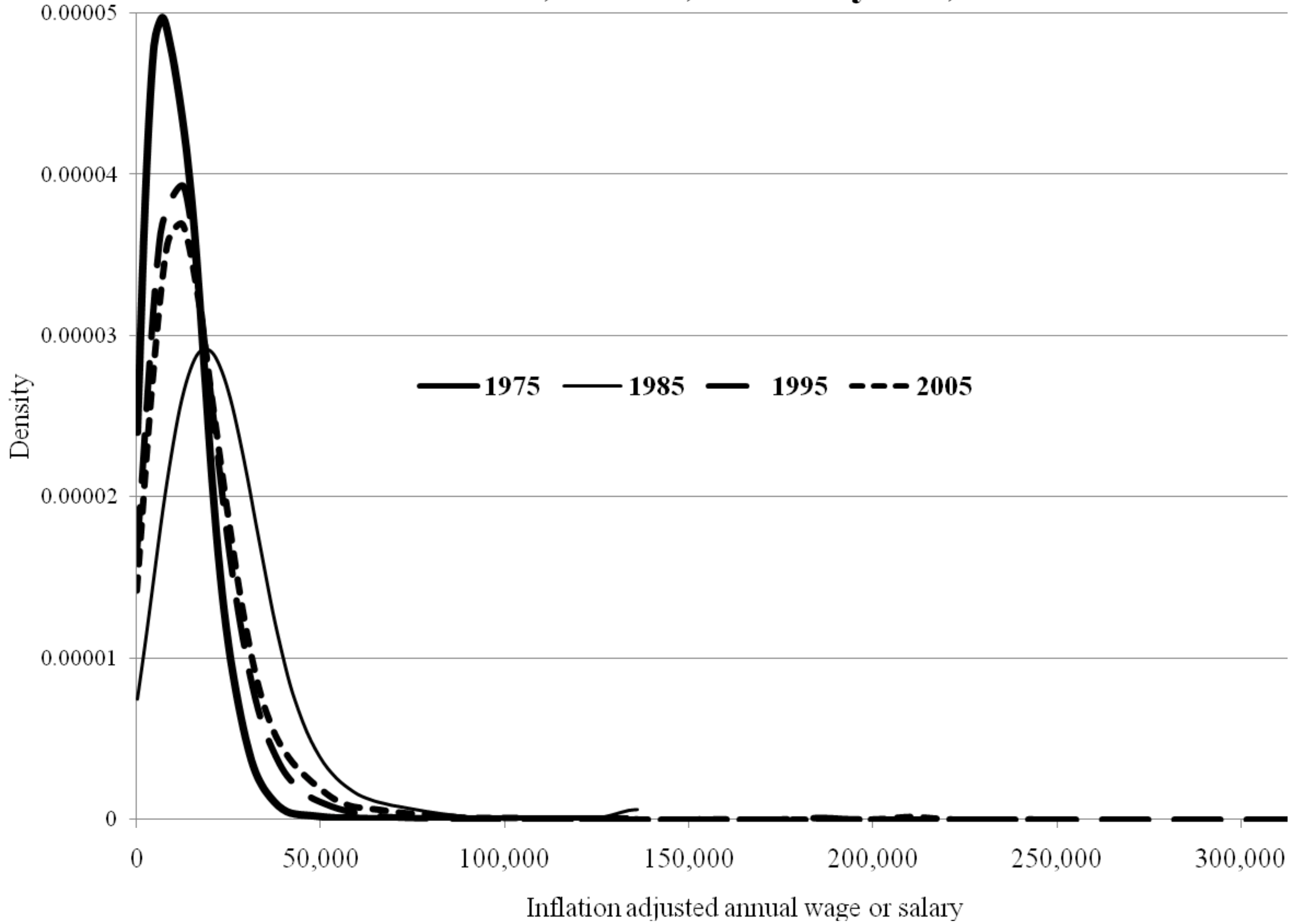
Graph 3. Wage distribution of logged, inflation adjusted weekly wages, men, selected years, CPS



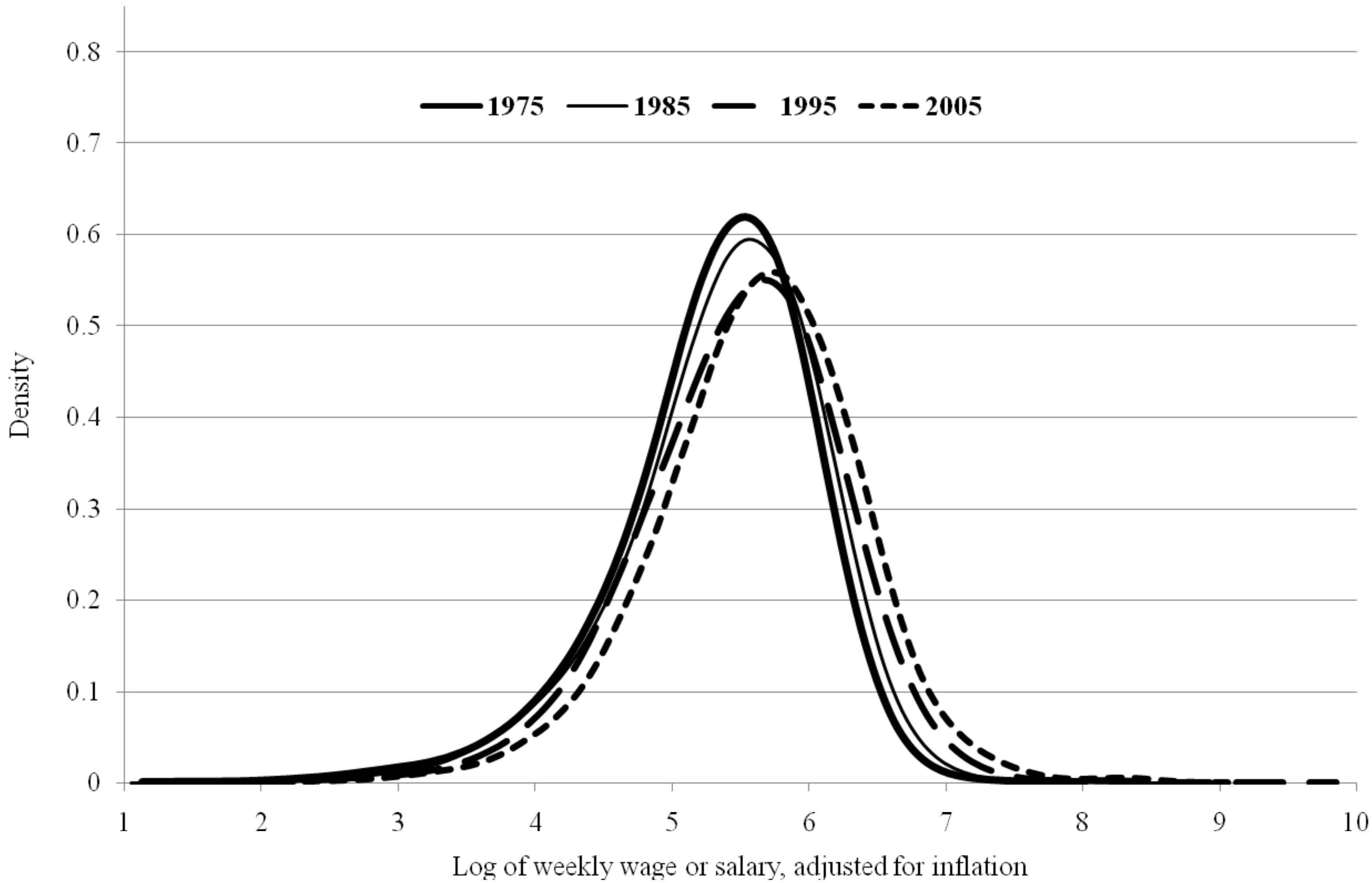
Graph 4. Wage distribution of annual wages, women, selected years, CPS



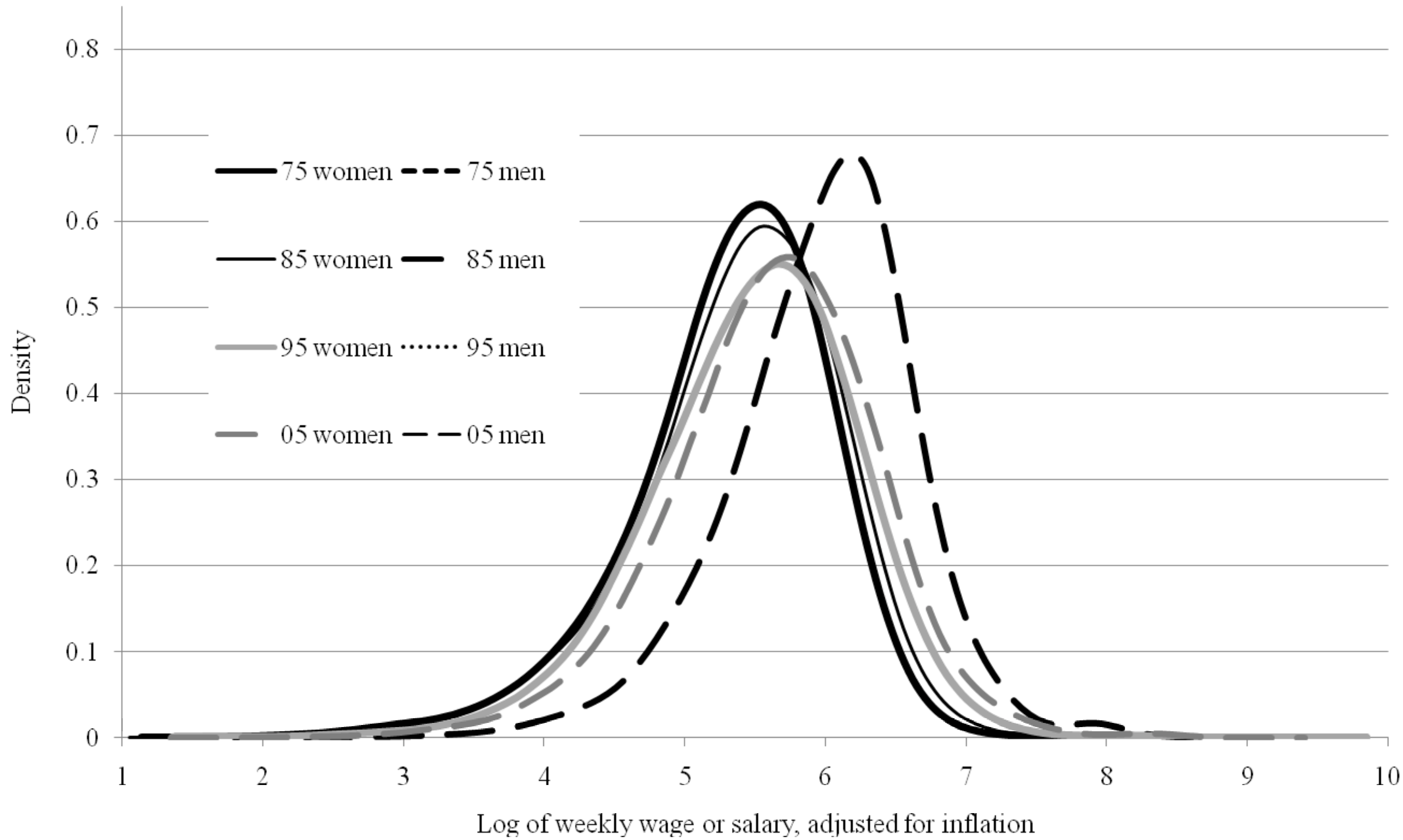
Graph 5. Wage distribution of annual wages adjusted for inflation, women, selected years, CPS



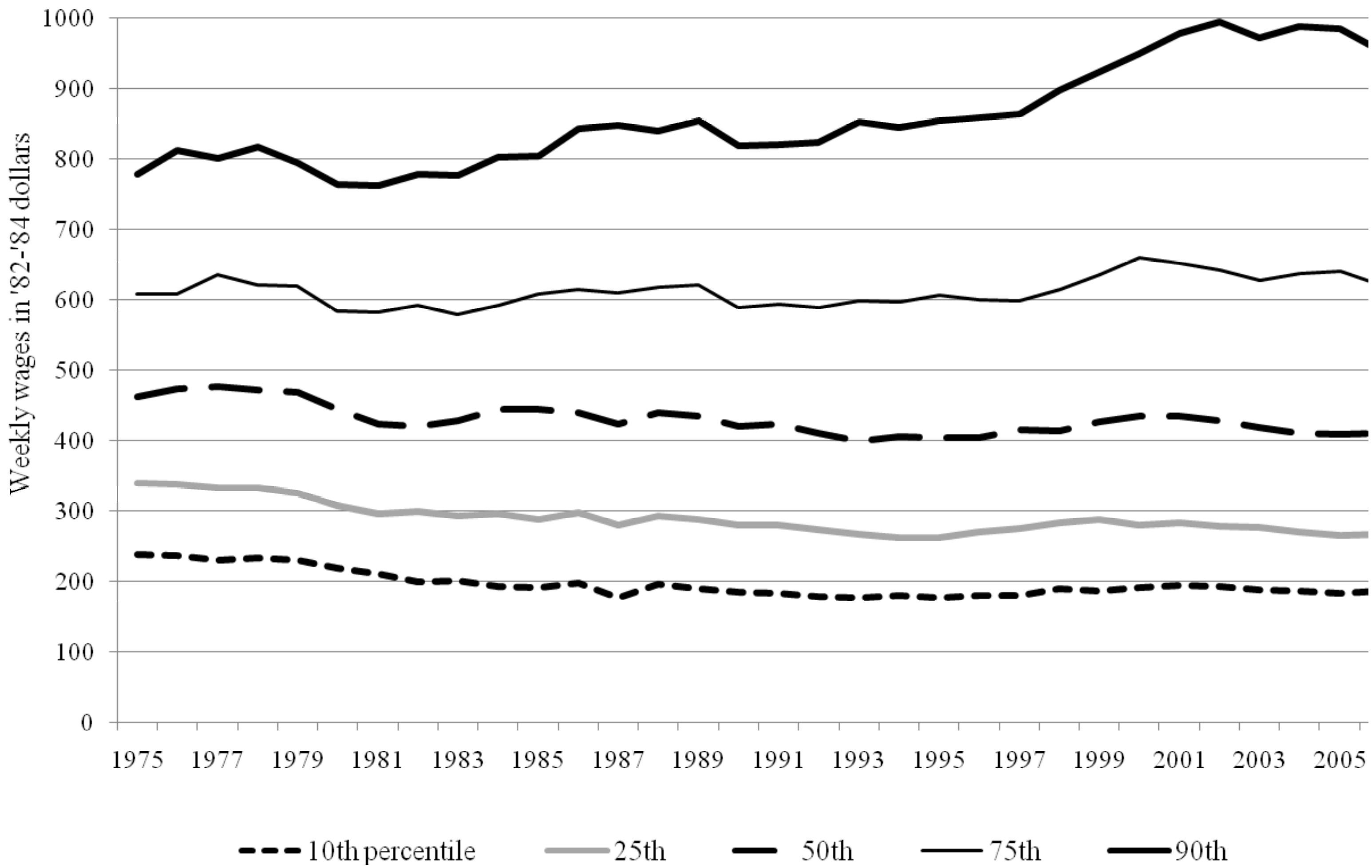
Graph 6. Wage distribution of logged, inflation adjusted weekly wages, women, selected years, CPS



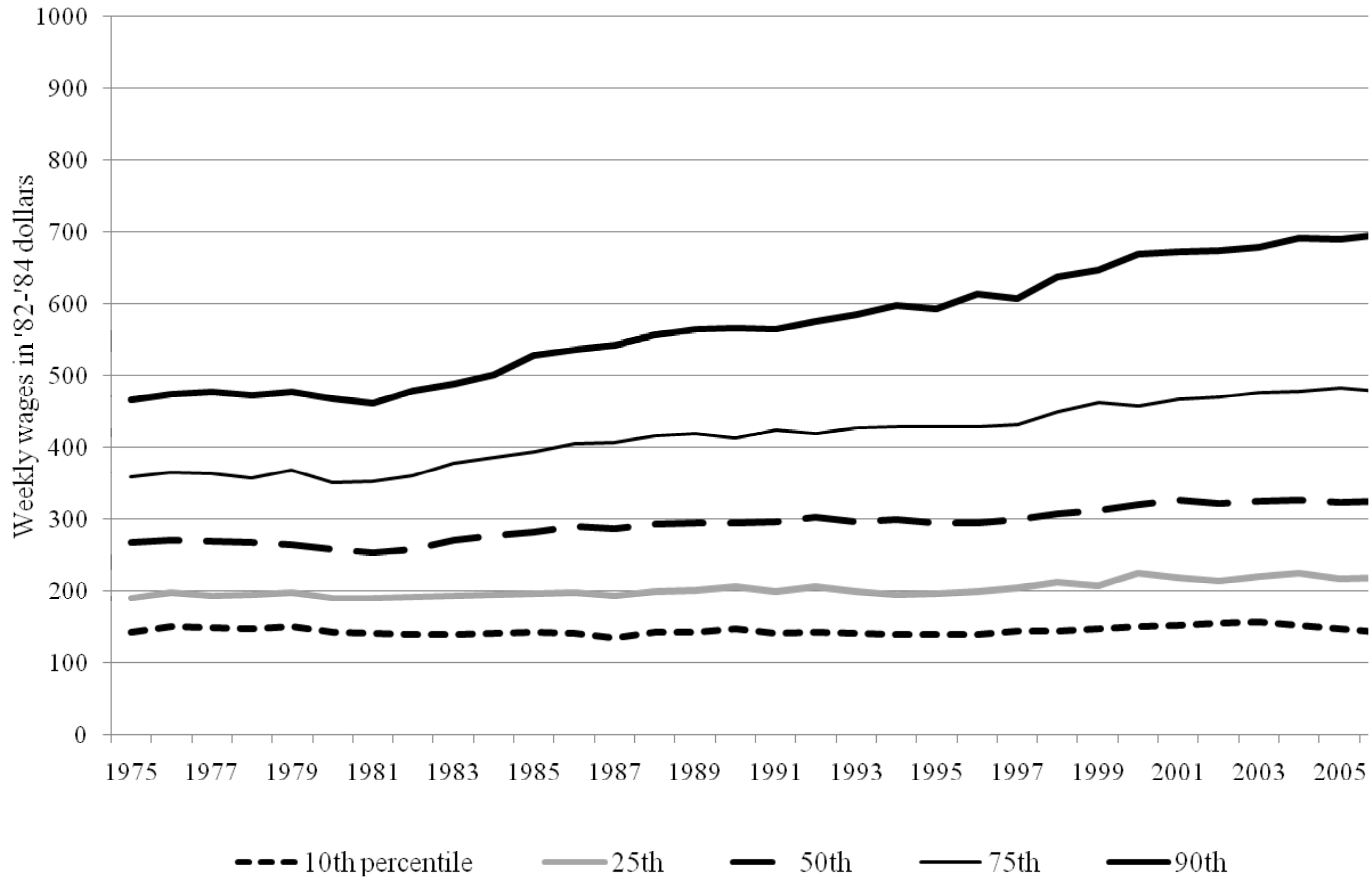
Graph 7. Wage distribution of logged, inflation adjusted weekly wages, men and women compared, selected years, CPS



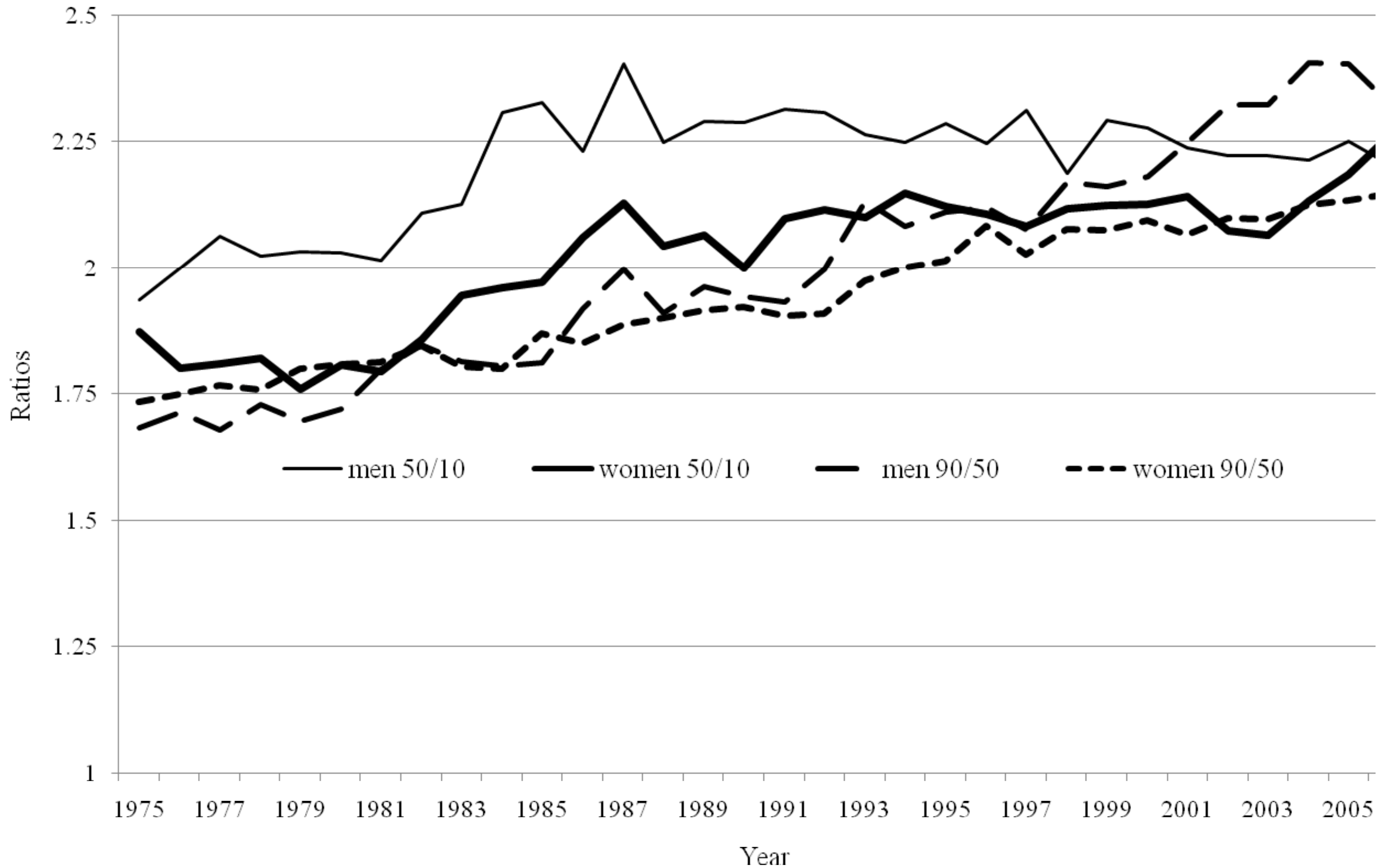
Graph 8. Selected wagepercentiles, over time, men (weekly wages adjusted for inflation, 1975-2006, CPS)



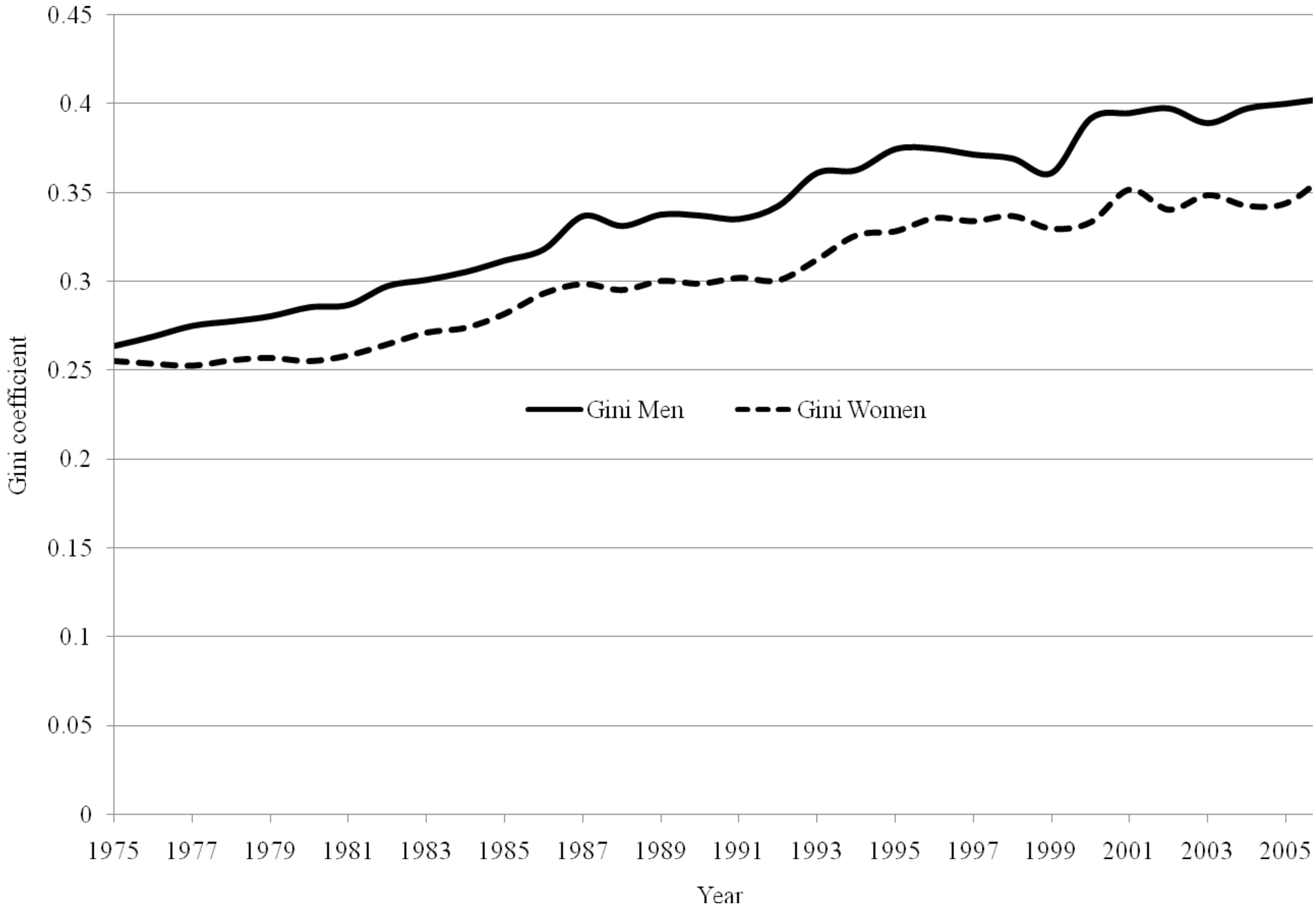
Graph 9. Selected wagepercentiles, over time, women (weekly wages adjusted for inflation, 1975-2006, CPS)



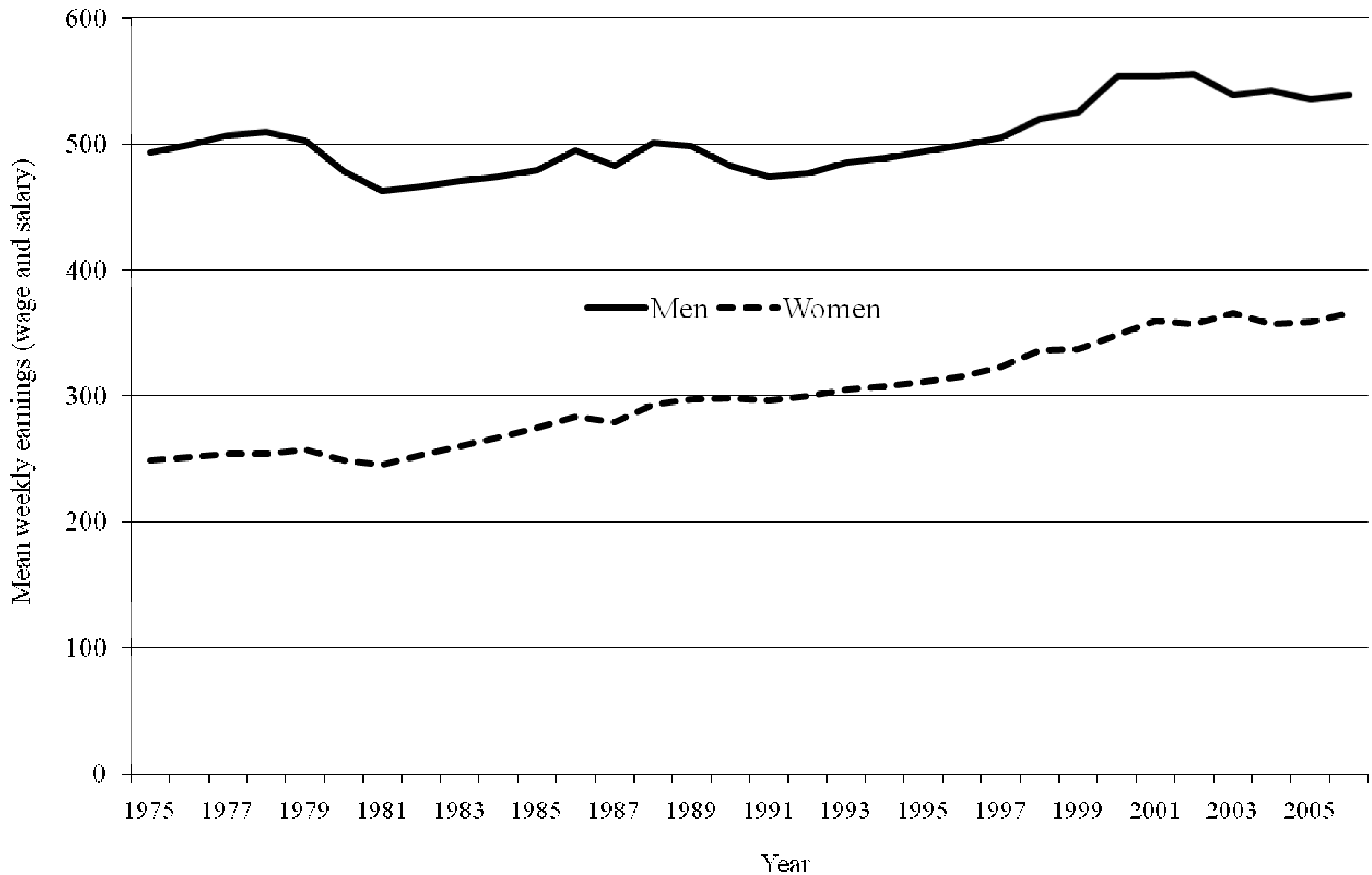
Graph 10. Ratios of selected wagepercentiles, men and women compared (weekly wages adjusted for inflation, 1975-2006, CPS)



Graph 11. The Gini coefficient of men and women, 1975-2006, CPS



Graph 12. Mean weekly earnings of men and women (1975-2006, CPS)



Graph 13. Median weekly earnings of men and women (1975-2006, CPS)

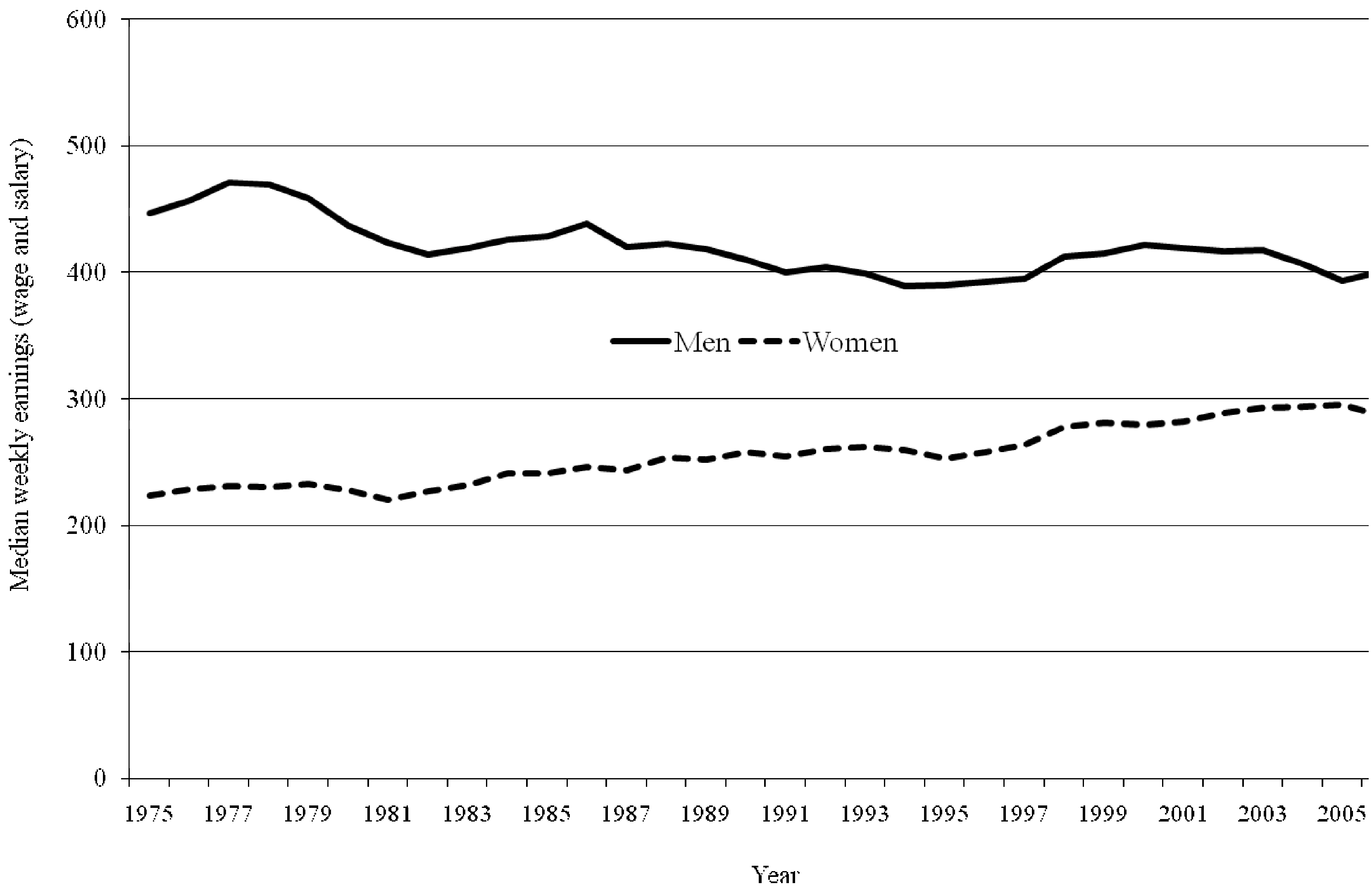


Table 2. Mean wages and the gender wage gap in selected years

	1975	1985	1995	2005
Weekly wage				
Mean wage men	501.6	492.2	510.7	550.7
Mean wage women	291.2	317.4	349.9	395.5
Gender difference in means	210.4	174.9	160.8	155.2
Women's mean wage as percentage of men's	58.1%	64.5%	68.5%	71.8%
Log of weekly wage				
Mean wage men	6.09	6.03	6.00	6.04
Mean wage women	5.56	5.63	5.67	5.78
Gender difference in means	0.53	0.40	0.32	0.26
N men	15,431	20,365	20,875	32,884
N women	8,250	13,964	15,911	25,456

Source: IPUMS CPS, survey years 1976, 1986, 1996 and 2006

Table 3. Difference in the gender wage gap between selected years

	1975-1985	1985-1995	1995-2005
Difference in the gap of real weekly wages	35.5	14	5.6
Difference in gap of logged weekly wages	0.13	0.08	0.07
The wage gap narrowed by	12.7%	8.0%	6.6%

Source: IPUMS CPS, survey years 1976, 1986, 1996 and, 2006

Table 4. Juhn et. al type decomposition of changes in the wage gap (log of weekly wages)

	1975-1985		1985-1995		1995-2005	
	change	percent of total change	change	percent of total change	change	percent of total change
Change in the gender wage gap	0.127		0.080		0.066	
Predicted gap	0.061	48%	0.036	44%	0.041	62%
quantity effect (gender specific)	0.057	45%	0.042	52%	0.042	63%
price effect (wage structure specific)	-0.011	-8%	-0.022	-27%	0.004	6%
qauntity and price interaction	0.014	11%	0.016	20%	-0.005	-7%
Unexplained or residual gap	0.066	52%	0.045	56%	0.025	38%
quantity effect (gender specific)	0.102	80%	0.062	77%	0.033	49%
price effect (wage structure specific)	-0.049	-38%	-0.024	-30%	-0.009	-13%
qauntity and price interaction	0.013	10%	0.007	8%	0.001	2%
Sum of the effects of gender specific changes	0.159	125%	0.104	129%	0.074	113%
Sum of the wage structure effects	-0.059	-46%	-0.046	-57%	-0.005	-8%
Sum of interaction effects	0.027	21%	0.023	28%	-0.004	-5%
Percent of women's gains claimed by rising inequality	37.0%		44.0%		7.0%	
Percent by which the wage gap would've further narrowed if not for the effect of the wage structure	4.7%		3.5%		0.5%	

Source: IPUMS CPS, survey years 1976, 1986, 1996 and 2006.