What Do We Really Know About Changes in Wage Inequality?

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ABSTRACT

This paper provides a set of basic facts about changes in wage inequality and the wage structure using May-ORG and March CPS data. An important goal of the paper is show these facts as simply as possible while correcting for changes in the experience and education composition of the workforce. The paper also studies the robustness of the main findings to a number of measurement issues, including i) the nature of the adjustment for top-coding, ii) the treatment of allocated wage observations, and iii) the choice of the March vs. the May-ORG supplement of the CPS, and discusses some implications of the results.

1. INTRODUCTION

It is very well known that wage and earnings inequality has grown substantially over the last 30 years. The initial burst of inequality growth in the 1980s attracted a lot attention among labor economists. This resulted in a set of influential papers published 15 years ago, in particular Katz and Murphy (1992), Bound and Johnson (1992), Levy and Murnane (1992) and Juhn, Murphy and Pierce (1993). These papers laid down the main facts and possible explanations for the dramatic increase in wage inequality of the 1980s. At the time, the leading explanation that emerged was based on a pervasive increase in the demand for all dimensions of skills that was mitigated, in part, by swings in relative supply linked to the baby boom cohort. A number of papers later argued that the leading source of increase in the relative demand for skills was skill-biased technological change (SBTC) linked, in large part, to the computer and information technology revolution.[1]

Over the last 15 years, however, further research has casts some doubt on the basic view that inequality growth is driven by a combination of demand changes linked to SBTC and the computer revolution. This "revisionist" view, to borrow the term suggested by Autor, Katz and Kearney (2007), is mostly based on the observation that the bulk of broad-based inequality growth was concentrated in the 1980s. In particular, Card and DiNardo (2002) argue that this "episodic" aspect of inequality growth is inconsistent with a simple supply and demand explanation which should instead predict an unabated growth in inequality throughout the 1990s. The episodic view of inequality changes is corroborated in recent work by Lemieux (2006b), who argues that the growth in within-group inequality is also concentrated in the 1980s. This somehow contradicts the earlier work of Juhn, Murphy and Pierce (1993) who document a continuing growth in this dimension of inequality throughout the 1970s and 1980s.[2] Lemieux (2006b) argues that various measurement issues and composition effects account for these different views about the timing of the growth in within-group inequality.

In response to these recent findings, Autor, Katz and Kearney (2007) point out that inequality in the upper end of the distribution (top-end inequality) has kept growing

[1] See, in particular, Krueger (1993), Berman, Bound and Griliches (1994), Autor, Katz and Krueger (1998), Autor Levy and Murnane (2003).

[2] Katz and Autor (1999) and Acemoglu (2002) also find that within-group inequality kept increasing in the 1990s.

steadily throughout the 1990s and early 2000s, a trend that they attribute to relative demand shifts induced by technological change of the type proposed by Autor, Levy and Murnane (2003). The steady and continuing growth in top-end inequality has also been well documented by Piketty and Saez (2003) using tax data which, unlike data from the Current Population Survey (CPS) or the Census, are not top-coded.

In light of these seemingly diverging views, the main goal of this paper is to identify in the clearest possible way, using CPS data, what have been the main changes in inequality and the wage structure since the early 1970s. The purpose of this exercise is to establish the basic facts that are robust to the variety of measurement problems frequently encountered in the literature, i.e. identify what it is that we really know about changes in wage inequality. These leading measurement problems include top-coding, the growing non-response to earnings item in the CPS, and differences in wage measures in the March and outgoing rotation group (ORG) supplements of the CPS. A first substantive conclusion of the paper is that with the exception of the growth in within-group inequality for men in the 1970s, all the main trends appear to be highly robust to these measurement issues. More generally, the results confirm the view of both the "revisionists", who find that changes in "broad-based" measures of inequality are concentrated in the 1980s, and of Autor, Katz and Kearney (2006, 2007) who find smooth growth in top-end inequality.

The related goal of the paper is to assess what these trends tell us about the underlying sources of changes in inequality. I discuss what challenges these findings pose for existing explanations, and propose alternative explanations linked to broadly defined wage setting institutions (minimum wage, unions, performance pay) to help reconcile these often contradictory sets for facts.

One difference between this paper and most of the existing literature is that the majority of basic trends in inequality reported here have been adjusted for changes in the skill (experience and education) composition of the workforce. A more standard approach is to report basis trends without these adjustments for composition effects, and then perform decompositions where composition effects are one of the sources of overall change in inequality (see, for example, Juhn Murphy and Pierce, 1993). One drawback of these approaches is that what is often presented as the basic inequality trends end up mixing up composition effects and true underlying changes in the wage structure. Lemieux (2006b) shows this has important consequences in the case of within-group, or residual, inequality where composition effects are large. Since my goal here is to document the main trends in the wage structure, and in summary measures of inequality induced by changes in the wage structure, I focus on an approach where composition effects are systematically adjusted for.

For similar reasons, the wage measure used throughout the paper is the hourly wage that purely reflects the "price" of different types of labor, as opposed to earnings that mix up the hourly wage rate with hours decisions. The primary source of data used to do so is the 1979-2006 ORG supplements of the CPS, supplemented with similar wage data from the 1973-1978 May CPS. All inequality trends are also presented separately for men and women. Using hourly wage rates, as opposed to weekly earnings for full-time workers (or other earnings measures), is particularly important for women who are less likely to work full-time, and generally exhibit more variation in hours of work than men.

Section 2 briefly discusses the data and presents the measurement framework used to compute the various dimension of inequality adjusted for composition effects. The basic trends are presented in Section 3, and the robustness of these trends to a number of measurement issues is discussed in Section 4. The main findings are summarized in Section 5, while Section 6 concludes by discussing the implications of these findings for different explanations about the sources of change in wage inequality.

2. DATA AND MEASUREMENT FRAMEWORK

2a. Data Issues

Data issues are discussed in detail in the Data Appendix, which explains the construction of wage measures for the May/ORG and March CPS Supplements in detail. I only briefly discuss how the May and ORG supplements of the CPS are processed here. As mentioned above, the wage measure I use is the hourly wage rate. The main advantage of this measure is that theories of wage determination typically pertain to the hourly wage rate. For example, the interplay of demand and supply considerations has direct implications for the hourly price of labor. By contrast, the impact of these factors on weekly or annual earnings also depends on the responsiveness of labor supply to changes in the hourly wage rate.

The Dual Jobs Supplement of the May CPS for 1973 to 1978 asks questions about wages on the main job held during the survey week to all wage and salary workers. For workers paid by the hour, the May CPS asks workers directly about their hourly rate of pay. This is the hourly wage measure that I use for this group of workers (about sixty percent of the workforce). For the other workers, I compute an hourly wage rate by dividing usual weekly earnings by usual weekly hours of work. I use the same procedure for the 1979 to 1993 ORG supplements that ask the same wage questions as the May CPS. The wage questions in the 1994 to 2006 ORG supplements are similar except that workers not paid by the hour can choose the periodicity at which they report earnings. I compute their hourly wage rate by dividing earnings by hours over the corresponding time period. The merged outgoing rotation group (MORG) files combine this information for all 12 months of the year.

One important advantage of the MORG supplement is that it is roughly three times as large as the May or March supplements of the CPS.[3] Another advantage over the March CPS is that we know the union status of workers in the May-ORG CPS, but not in the March CPS. A potential disadvantage is that wage data in the May-ORG CPS only goes back to 1973, while it is possible to go back to the 1960s using the March CPS. This is of little consequence here, however, since most of the relevant movements in wage inequality and the wage structure only started in the 1970s.

Unlike in the ORG and March supplements of the CPS, in the 1973-78 May CPS wages were not allocated for workers who refused to answer the wage questions. To be consistent, I only keep workers with non-allocated wages in the 1979-2006 ORG supplements in most of the analysis. As a consequence, observations for 1994 and the first eight months of 1995 in which the CPS did not flag workers with missing wages are

[3] The May 1973-78 and March supplements are administered to all (eight) rotation groups of the CPS during these months. By contrast, only one quarter of respondents (in rotation groups 4 and 8) are asked the questions from the ORG supplement each month. Combining the 12 months of data into a single MORG file yields wage data for 24 rotation groups compared to 8 in the May or March supplements (plus the hispanic and Medicare (post-2000) over-samples in the March CPS).

dropped from the sample when only non-allocated observations are used. Following most of the literature, I trim extreme values of wages (less than \$1 and more than \$100 in 1979 \$), and keep workers age 16 to 64 with positive potential experience.

In the main results presented in the paper, I adjust for top-coding by multiplying top-coded earnings by a factor of 1.4. In the case of the March CPS, I also compare this rudimentary adjustment to a more sophisticated stochastic imputation procedure based on the assumption that top earnings follow a Pareto distribution with the a parameter estimated separately for each year in the tax data of Piketty and Saez (2003).

Finally, I weight all wage observations by hours of work (in addition to the usual CPS weights). In the case of the May-ORG CPS, weekly hours of work are used, while annual hours are used for the March CPS. Doing so has two main advantages. First, it effectively provides a distribution over all hours worked in the economy that do not put excessive focus on workers who only supply very few hours to the labor market. For instance, DiNardo, Fortin, and Lemieux (1996) argue that failing to do so would put excessive weight on the bottom end of the distribution where many workers around the minimum wage provide relatively less hours to the labor market than most other workers. Another advantage is that weighting by hours of work makes the March and May-ORG wage distributions more directly comparable (Lemieux, 2006b).[4]

2b. Measurement model

As discussed earlier, unadjusted trends in wage inequality may either reflect underlying changes in the wage structure or composition effects that confound the changes in the wage structure. A simple way of adjusting for composition effects is to reweight the data so that the distribution of education and potential experience remains constant over time (e.g. DiNardo, Fortin, and Lemieux, 1996). Doing so is straightforward in cases where the data can be divided up in a finite number of cells. In such cases, the weight attached to each cell can be held constant by multiplying the sample fraction in year *t* by the average fraction of observations in this cell for all years combined, or for an arbitrary

[4] Abraham, Speltzer, and Steward (1998) also weight by hours for the same reason (i.e. make different data srouces comparable) in their study comparing the evolution of average real wages rates from different data sources, including the March and May-ORG CPS.

base year. Since results can be sensitive to the choice of base year, I follow Juhn, Murphy, and Pierce (1993) and hold the sample composition constant at the average fraction for all years combined.

After various experimentations, I divided the data into 130 cells defined on the basis of six education groups (elementary, high school dropouts, high school graduates, college graduates, and college post graduates) and 22 two-year experience groups.[5] The R-square of a wage regression using this set of cell dummies is very close to the R-square for an unrestricted model, and using these broader cells limits the problem of very small cells that can generate excessive variability in the reweighting procedure.[6]

In the first set of results presented in the paper, the measure of wage dispersion used is the variance of log wages (between and within components) as well as standard wage differentials based on differences across education and experience groups. All these measures can be directly computed as functions of the mean and variance of wages in each cell. Let y_{jkt} denote the average wage of workers with education j and experience k in year t. The variance within this group is v_{jkt}, the share of workers in this group in year t is θ_{jkt}, while the average share over all years is θ_{jk}. The composition unadjusted within ($W_{t,u}$) and between ($B_{t,u}$) group variance in year t are:

$B_{t,u} = \Sigma_{jk}\ \theta_{jkt}(y_{jkt} - y_{t,u})^2$, and

$W_{t,u}= \Sigma_{jk}\ \theta_{jkt}v_{jkt}$,

where $y_{t,u} = \Sigma_{jk}\ \theta_{jkt}\ y_{jkt}$ is the unadjusted mean (grand mean) over all groups. The corresponding expressions adjusted for composition effects are obtained by simply replacing the year t weights, θ_{jkt}, with the average weights θ_{jk}:

[5] Note that the 22nd experience category includes workers with 42 years and more of potential experience because some of the two-year experience cells with very high level of experience (43-44 or 45-46) were too small. Note also that there are no observations in 1) the cell with the lowest level of education (eight years or less) and the lowest level of experience (0-1 years of experience), and 2) the cell with the highest level of education (18 year or more) and the highest level of experience (42 years or more of experience) since observation in these cell do not fall into the age range (16 to 64) used in this paper. This explains why 130, as opposed to 132 (22 experience times 6 education groups) cells are used in the empirical analysis.

[6] In the case of men the average R-square in 1973, 1979, 1989, 1999, and 2006 in the model with 120 cells is .3466, compared to .3511 in models with an unrestricted set of experience-education dummies based on single years of experience and education. The corresponding R-squares for women are .3110 and .3135, respectively.

$B_t = \Sigma_{jk}\ \theta_{jk}(y_{jkt} - y_t)^2$, and

$W_t = \Sigma_{jk}\ \theta_{jk}v_{jkt}$,

where $y_t = \Sigma_{jk}\ \theta_{jk}y_{jkt}$ is the composition adjusted mean over all groups.

A standard approach for estimating experience and education wage differentials is to run OLS regressions. I use a slightly different approach by computing separate measures of educations differentials for each experience category, and vice versa. The experience-group specific education wage differentials are then aggregated up into a single differential by averaging up the experience-group specific education differentials using the average sample fraction in each experience group over all years combined.

Let θ_j represent the fraction of workers (of all experience groups) with education j in all years combined, and θ_k represent the fraction of workers (of all education groups) with experience k in all years combined. The composition adjusted wage differential between education group j' and j in year t is defined as:

$D_{j',jt} = \Sigma_k\ \theta_k\ (y_{j'kt} - y_{jkt})$.

Similarly, the composition adjusted wage differential between experience group k' and k in year t is:

$D_{k',kt} = \Sigma_j\ \theta_j\ (y_{jk't} - y_{jkt})$.

One important advantage of the variance as a measure of wage inequality is that it can be exactly decomposed as the sum of the between and within group components W and B. The decomposition can be directly linked to various "price effects" once composition effects have been adjusted for using the above procedure. Using the terminology of Juhn, Murphy and Pierce (1993), the between-group component solely reflects "observable price effects", i.e. difference in mean wages among experience and education groups. By contrast, the within-group component solely captures "unobservable price effects" under the assumption that the distribution of unobservables (ability, school quality, etc.) within a fix experience-education group does not change over time.

One important disadvantage of the variance, however, is that it is only a summary measure of inequality that does not indicate what happens where in the distribution. This is a major problem in light of recent evidence that inequality is changing very differently at different points of the wage distribution. A simple and popular way of showing what happens at different points of the distribution is to look separately at each wage percentile, and compute summary measures such as the 90-50 gap (the difference between the 90th percentile and the median of log wages) and the 50-10 gap (the difference between the median and the 10th percentile of log wages). One important drawback of this approach is that these alternative inequality measures can no longer be decomposed as the sum of a within- and between-group component that add up to the overall inequality measure. For example, the 90-50 gap is not equal to the sum of the 90-50 gap in group means and the 90-50 gap in residuals. As a result, it is not completely clear how to compute the contribution of observable and unobservable prices to changes in the 90-50 or related gaps.

Following Juhn, Murphy, and Pierce (1993), Lemieux (2002), and Autor, Katz, and Kearney (2005), a number of approaches can nonetheless be used to get some indications on the contribution of the various price components to changes in inequality at different points of the distribution. One approach is to look at the distribution of residuals. Consider an individual wage observation y_{ijkt}. The residual u_{ijkt} can be readily computed as the difference between the individual wage observation and the cell mean y_{jkt}, so that $u_{ijkt} = y_{ijkt} - y_{jkt}$.[7] Looking at changes in the distribution of residuals provides some information on changes in unobservable prices.

Another possible approach is to perform a decomposition in spirit of Juhn, Murphy and Pierce (1993). First remember that the focus here is to first control for composition effects to then see what is explained by changes in the wage structure. Adjusting unconditional quantiles for composition effects is straightforward in the cell-by-cell case considered here. Observation i with education j and experience k in year t can simply be reweighted by the factor θ_{jk}/θ_{jkt} so that the distribution of education and experience remains constant over time (DiNardo, Fortin and Lemieux, 1996, Lemieux, 2002). Changes in observable prices can then be controlled for by replacing the actual conditional mean of wages y_{jkt} with the average conditional mean for the cell over all years combined, y_{jk}. This yields a counterfactual wage $y'_{ijkt} = y_{ijkt} + (y_{jk} - y_{jkt})$. Remaining

[7] It is not clear whether the residual should be defined relative to the conditional mean or median. Juhn, Murphy, and Pierce (1993) and Lemieux (2002) use the conditional mean, while Autor, Katz, and Kearney (2005) use the conditional median. A few experimentations suggested that this choice had little impact on the results.

changes in the counterfactual wage y'$_{ijkt}$ should then only depend on changes in unobservables prices.

3. BASIC RESULTS FROM THE MAY-ORG DATA

In this section, I present the basic descriptive facts as well as the decomposition results using the 1973-2006 May-ORG data. In this first set of results, I only keep observations with unallocated wages and fix for topcoding using the 1.4 correction factor. I later discuss in Section 4 what happens when i) the March CPS is used instead of the May ORG CPS, ii) allocated wage observations are included (for 1979 on), and iii) other assumptions are used to deal with top-coding.

3a. Variance over all experience and education groups

The evolution of the overall variance of wages (sum of the between and within component) is first reported in Figure 1a and 1b for men and women, respectively. A couple of clear facts emerge from these figures. First, the bulk of the growth in the variance is concentrated in the 1980s. Second, adjusting for composition effects noticeably reduces the long term growth in the variance. In the case of men, the variance is very stable in the 1970s and 1990s, but starts increasing again after 1999. The same pattern can roughly be observed for women, with the notable difference that the variance clearly declines in the 1970s.

Figure 2 presents a first decomposition by showing separately the evolution of the between-and within-group components of the variance. Three interesting patterns emerge from these figures. First, the pattern of change in the between- and within-group components are remarkably similar over time. For both men and women, both the within and between group components grow sharply in the 1980s, grow less in the 2000s, and remain stable or decline (for women in the 1970s) in the 1970s and 1990s. For men, both components decline slightly in the 1990s once composition effects are adjusted for. For women, the 1990s is the only period where the between- and within-components move in opposite directions. I argue below, however, that part of the growth in the between-group variance for women likely captures a more suddle type of composition effect linked to the growth in actual labor market experience given potential experience. So, on balance, the pattern of change in the within- and between-group components are very similar.

A second important finding is that, consistent with Lemieux (2006b), composition effects account for a very substantial part of the growth in the within-group variance. By contrast, composition effects play little role in long run changes in the between-group component. This results holds for both for men and women. The third finding is that the between-group component accounts for most of the growth in the overall variance, especially once composition effects are adjusted for. This particular result is sensitive to the data used (March vs. May-ORG CPS) and will be further discussed in Section 4.

3b. Relative wages and variances by education and experience groups

Since the groups (cells) used from the decomposition are solely based on education and experience, the source of the growth in the (composition adjusted) between-group component must either come from a growth in education and/or experience wages differentials. Figure 3 shows the evolution education wage differentials over time, while Figure 4 shows the evolution of the returns to experience. As is well known, education wage differentials increased for both men and women in the 1980s. Relative to high school graduates, Figure 3a shows that the wage advantage of men with some college or more increased, while the wage disadvantage of high school dropouts or those with eight years of education or less (elementary category in the figure) also expanded, albeit more modestly. By contrast, in the 1990s and 2000s most education wage differentials remained stable except for college graduates and post-graduates who kept gaining relative to high school graduates.

Looking at the whole 1973-2006 period, the striking fact is that most of the expansion in wage differentials has been happening at the top of the education distribution. In particular, the gap between college post-graduates and high school graduates more than doubled over time. College graduates and people with some college also experienced substantial gains, while relative wages among workers with a high school diploma or less remained very stable over time. This mirrors the finding by Lemieux (2006a) of a growing convexification in the relationship between wages and education. In other words, wage differentials at the top end of the education distribution have increased steadily over time, while wage differentials at the bottom end remained more or less stable. As I will show below, this fits with the general pattern that inequality has kept growing at the top end, but not at the low end of the distribution (Autor, Katz and Kearney, 2005). Note also that the results for women in Figure 3b are qualitatively similar to those for men.

The evolution of experience wage differentials is shown in Figure 4. Since it would not be very informative to present the differentials for each of the 21 experience groups, I have regrouped the 2-year experience groups into in four major experience groups (0-9, 10-19, 20-29, and 30-39 years of experience) by computing a weighted mean of the wages differentials for the smaller groups. The differentials reported in the figure show the gap relative to workers with 20-29 years of experience. Consistent with earlier studies such as Katz and Murphy (1992), there is a clear expansion in experience wage differentials in the 1980s. The differentials start contracting again, however, in the late 1980s, and by the end of the sample periods the differentials are more or less back to their initial 1973 levels. The situation is quite different for women (Figure 4b). Differentials keep expanding over time except in the late 1990s when inexperienced (0-9 years of experience) women gain ground again, probably because of the very strong labor market at that time. By 2006, the gap between experienced (20-29 years of experience) and inexperienced (0-9 years of experience) is three times as large as back in 1973, and has almost caught up with the level of the corresponding gap for men.

The most plausible explanation for growing experience gaps for women is that the large increases in female employment rates have lead to a large increase in the level of actual labor market experience conditional on potential experience.[8] For instance, women with 20 years of potential experience now have much more actual experience than they used to. As a result, their wage advantage over inexperienced women should have increased substantially even if the return to actual experience did not grow over time. If actual experience was measured in the CPS, changes in actual experience could be corrected for by holding the distribution of education and actual (as opposed to potential) experience constant over time. Since only potential experience is available in the CPS,

[8] Using PSID data, Blau and Kahn (1996) show that actual experience has indeed increased a lot over time for given levels of potential experience.

the change in experience wage differentials documented in Figure 4b should be interpreted with caution. Trends in experience differentials for men are more reliable and suggest that "real" returns to experience played little role in the growth in wage dispersion.

Taken together, the results in Figures 2 to 4 suggest that, at least for men, changes in the between-group variance induced by growing "top-end" education wage differentials account for most of the growth in the variance of wages, a results also found in more formal decompositions by Lemieux (2006a), Firpo, Fortin, and Lemieux (2007), and Goldin and Katz (2007).

Turning to the within-group component, Figures 5 and 6 show the evolution of the within-group component by education and experience groups. Like the wage differentials, the within-group variance by education groups are computed as fixed weighted averages across experience groups, and vice versa. So the within-group variance for education group j at time t is

$$V_{jt} = \Sigma_k \theta_k v_{jkt} ,$$

while the within-group variance for experience group k at time t is

$$V_{kt} = \Sigma_j \theta_j v_{jkt} .$$

As before, the different experience groups are combined into four broader groups for the ease of exposition.

Figure 5 shows that the within group-variance moves quite differently over time for different education groups. Dispersion increases among all education groups in the 1980s, keeps growing for the more educated groups (college graduates and post-graduates) after 1990, but remains stable or even declines for less educated groups. Interestingly, the evolution in within group dispersion closely mirrors the evolution of relative wages by education groups, which reinforces the earlier conclusion that inequality growth in concentrated at the top end of the distribution.

By contrast, changes in within-group wage dispersion by experience groups are more homogenous across groups. Roughly speaking, the within-group variance increases for all experience groups during the 1980s, but remains more or less constant after 1990. The only exception is inexperienced women for whom the within-group variance declines after reaching a peak in the late 1980s.

Taken together, the results in Figures 2 to 6 suggest that changes in the relative wages and variances of highly educated workers is a key element in the growth of wage inequality since the late 1970s. There is indeed a very intriguing parallel between what is happening to the between- and within-group components of the variances. For both components, changes are concentrated in the 1980s and long run growth is concentrated among college graduates and post-graduates. This suggests that both components may be reflecting the same underlying changes in the labor market, an issue to which I return in Section 6. This also suggests, consistent with Autor, Katz and Kearney (2005), that changes in the top end of the distribution are very different from changes at the low end. I now explore this issue in more detail by looking at what happened at different percentiles of the wage distribution.

3c. Changes at different percentiles

Figure 7 plots the changes in real wages at each percentile over the 1974-1989, 1989-2004, and the whole 1974-2004 period. I use 15 year changes for both periods for the sake of comparability, and also pool three years of data around 1974 (1973-75), 1989 (1988-1990), and 2004 (2003-2005) to increase the precision of estimates at each percentile. Similar results for wages residuals are presented in Figure 8. The results essentially reproduce the findings of Autor, Katz and Kearney. The main point is that, consistent with Juhn Murphy and Pierce (1993), wages changes are more or less a linear and positively sloped function of percentiles in the 1974-89 period, suggesting similar changes in wage dispersion at all points of the wage distribution. The situation is radically different in the 1989-2004 period, however. While wage dispersion keeps growing above the median, wages become more compressed below the median as real wage gains at the bottom end exceed those around the median, a phenomena Autor, Katz and Kearney refer to as the polarization of the labor market. Note that this phenomena can be observed both for wages and wage residuals (Figure 8).

Figure 9 then performs a Juhn, Murphy, and Pierce (1993) decomposition on the 90-50 and 50-10 gap using the procedure described in Section 3. The results are, once again, very similar to those of Autor, Katz, and Kearney (2005). Basically, the figures show that at the top end, composition effects explain little of the growth in the 90-50 gap, while prices of observables account for more than half of the growth in the gap. As shown above, the relevant observable prices that likely account for most of the growth in the 90-50 gap are the wage differentials between college graduates and post-graduates relative to high school graduates. The remaining change in the 90-50 gap is due to changes in unobservable prices that are also likely driven by changes (growing within-group variance) happening among highly educated workers.[9]

The situation is very different at the lower end of the distribution (50-10 gap). Unlike the case of the 90-50 gap, there are also more substantial differences for men and women. I thus discuss these two cases separately. For men, the unadjusted 50-10 gap reported in Figure 9b grows in the 1980s but more or less returns to its 1970s level by the late 1990s/early 2000s. After controlling for composition effects, however, the 50-10 declines substantially and is lower in the early 2000s then in the 1970s. While observable prices explain a substantial part of the growth in the 1980s and subsequent decline in the 1990s, they have little impact on long run changes between 1973 and 2006. The pattern of changes suggests that movements in the return to experience play an important role here. The fact that the relative wages of young workers fell in the 1980s and went back up in the 1990s likely accounts for the swings in the 50-10 gap, since young workers are overrepresented at the bottom of the wage distribution. Furthermore, the stability of education differentials at the low end of the education distribution is consistent with the lack of observable price effects in the change in the 50-10 gap. Finally, the "residual" explanation for the decline in the 50-10 after adjusting for composition and observable price effects likely has to do with the decline in the within-group variance among less educated workers.

In the case of women, there is a much steeper growth in the 50-10 gap in the 1980s, a phenomena likely linked to the large decline in the real value of the minimum wages over this period (DiNardo, Fortin, and Lemieux, 1996).[10] As a result, the 50-10

[9] Using a more sophisticated quantile decomposition, Firpo, Fortin, and Lemieux (2007) indeed find that education accounts for the bulk of the growth in the 90-50 gap. Their education "effects" include both the between- and within-group components.

[10] DiNardo, Fortin, and Lemieux (1996) find that over 60 percent of the increase in the 50-10 gap between 1979 and 1998 can be accounted for by the decline in the real value of the minimum wage.

gap in the early 2000s remains substantially higher than in the 1970s. As in the case of men, composition effects account for a substantial part of the growth in the 50-10 gap. Unlike men, however, changes in observable prices also account for a significant part of the growth in the 50-10 gap, which is consistent with the continuing growth in experience wage differentials documented in Figure 4b. Remember, however, that composition effects linked to the mismeasurement of actual experience likely accounts for much of these changes. By 2006, the 50-10 gap is a little smaller than back in 1973, suggesting that, as in the case of men, changes in unobservable prices lead to a small reduction in the 50-10 gap over time.

4. MEASUREMENT ISSUES: WHAT ARE THE ROBUST FACTS?

All the findings reported up to know are based on unallocated wage observations from the May-ORG CPS where top-coding is adjusted for using a 1.4 imputation factor. I now look at how robust the main results are to these data processing assumptions, focusing on trends in the (composition adjusted) within- and between-groups variance.

4a. Wage allocation

As mentioned in the Section 2, wages were not allocated (imputed) for individuals who failed to report their wages and earnings in the 1973-78 CPS. In 1979, the Census Bureau started allocating wages for these individuals using the well-known hot deck matching procedure. Back in 1979, 17.9 percent of male and 14.8 percent of female workers did not report their wages. By 2006, the non-response rate had grown to a staggering 35.6 percent for male workers, and 34.1 percent for female workers. Unless non-response is completely random, excluding workers with allocated wages could bias the trends in wage inequality measures. Of course, correcting for non-response is not perfect either, as assumptions have to be made about the determinants of non-response. The standard approach used by the Census Bureau to correct for non-response is to use a matching procedure where the missing wage is replaced with the wage of a donor with similar characteristics (location, education, age, race, etc). Note that this matching/hot decking procedure can be though of as a stochastic imputation procedure. Instead of imputing a wage based on a regression model (e.g. Lillard, Smith, and Welch, 1986), such a matching procedure preserves the wage dispersion conditional on characteristics, which is important when looking at wage dispersion, in general, and at within-group wage dispersion, in particular.

Figure 10 shows the difference in the between- and within-group variances computed with and without allocated wage observations. The series with allocated wage observations only starts in 1979 since, as mentioned earlier, the Census Bureau did not provide allocated wage observations in the 1973-78 May CPS (Hirsch and Schumacher, 2004). The main message from Figure 10 is that, fortunately, the trends in wage inequality are fairly robust to the treatment of allocated wage observations. For both men and women, adding back the allocated wage observations reduces the between-group variance and increases the within-group variances. In terms of trends, however, the only noticeable difference is that the between-group component grows a little slower over time when allocated wage observations are included. Another noticeable difference is the "blip" in the within-group variance in 1994, the year the redesigned and computer-based CPS was introduced. Since allocation flags were not included in the 1994 (and part of 1995, see Section 2) CPS, I computed the 1994 data points in the series without allocators as a simple interpolation based on the 1993 and 1995 numbers. As such, the two series are not comparable for 1994. Since 1994 seems to be just a one time blip, I did not perform any systematic adjustments to take account of the CPS redesign in 1994.[11]

4b. Top coding in the May-ORG CPS

Figure 11 compares the variances with and without the 1.4 top-coding adjustment. First notice that, in the case of women (Figure 11b), adjusting for top-coding has essentially no effect on either the between- or the within-group variance. This is hardly a surprise since only a small fraction of women have earnings at or above the top code.

The adjustment for top coding has a more noticeable impact in the case of men (Figure 11a). The impact of the increase in the top code in 1986 and 1998 is clearly

[11] If anything, the sharp increase in the within-group variance between 1993 and 1994 would suggest that the redesign lead to a spurious increase in the within-group variance, which reinforces the conclusion that the within-group variance did not increase after 1990.

visible in the case of the within-group variance, where the unadjusted series experience unusual jumps in those two years. The impact of the increases in the top code is also visible in the case of the between-group variance. Generally speaking, the impact of the correction for top coding is larger for the within- than for the between-group component. Overall, adjusting for top coding tends to modestly increase the growth in inequality over time. This pattern is consistent with the finding of Piketty and Saez (2003) that inequality at the very top end of the distribution has increased rapidly since the 1970s. Since an important part of these changes are missed because of the top-coding in the CPS, it is natural to expect the top-coding adjustment to result in more inequality growth. What is not clear, however, is whether a simple and time-invariant adjustment like the 1.4 imputation factor adequately captures all of the inequality growth at the very top end. I will return to this issue in more detail in the case of the March CPS where additional information from the tax data can be used to devise a better imputation procedure.

4c. March vs. May-ORG CPS

Differences in inequality trends in the May-ORG and March supplements of the CPS have been well documented by Lemieux (2006b) and Autor, Katz, and Kearney (2007). The most striking discrepancy between the series shown in Figure 12 is that the within-group variance is substantially higher in the March than in the May-ORG supplement of the CPS. Lemieux (2006b) shows that this gap mostly reflect the fact that wages of workers paid by the hour are less precisely measured in the March CPS relative to the May-ORG CPS. This particular finding is reproduced in Appendix Figure A1a (men) and A1b (women). The problem with the March CPS is that all workers are only asked about their annual earnings and hours. An hourly wage is then obtained by dividing annual earnings by hours. In the May-ORG CPS, however, workers paid by the hour are asked directly about their hourly wage rates, which yield a more precise measure of hourly wages than in the March CPS (Lemieux 2006b).

Since (classical) measurement error cancels out when wages are averaged out at the cell level, mismeasurement of hourly wages in the March CPS should not affect much the between-group variance. This yields the simple prediction, strongly supported by the data in Figure 12, that the between-group variance should be about the same in the March and May-ORG CPS, and that the within-group larger should be larger in the March than in the May-ORG CPS.

A more challenging pattern to explain on the basis of these measurement issues is that fact that the trend growth in the within-group variance is higher in the March than in the May-ORG CPS. One possible explanation suggested by Lemieux (2006b) is that the fraction of workers paid by the hour has increased over time (Hamermesh 2002), thereby magnifying the mismeasurement problems in the March CPS. As pointed out by Autor, Katz and Kearney, however, this could also bias down the trend in the within-group variance if there is less measurement error in wages of hourly than no-hourly paid workers in the May ORG CPS. In any case, Lemieux (2006b) also shows, using an error-components analysis, that changes in the fraction of hourly rated workers cannot account for most of the discrepancy between the two series. The evidence rather points out to measurement error (conditional on the hourly pay status) increasing over time in the March CPS, though no explicit story is provided for why this may be the case.

More importantly, however, both data sources show that the within-group variance grew much faster before than after the late 1980s, once composition effect are controlled for (as they are in Figure 12). The only difference is that the within-group variance completely stops growing in the May-ORG CPS, while it grows at a much slower rate in the March CPS. So while the two series yield slightly different patterns of growth, in both cases the secular trends in the within-group variance closely mirror those observed for the between-group variance, which also grows much more slowly after than before the late 1980s. The only exception is men in the 1970s. Consistent with Juhn, Murphy and Pierce (1993), the within-group variance for men in the March CPS increases in the 1970s, while the between-group component remains more or less stable during this period. This particular series stands out as the only exception where inequality grows in the 1970s. By contrast, the within-group variance for women, the within-group variance for men in the May-ORG CPS, and the between-group variance all remain stable in the 1970s. This suggests that, at a minimum, the growth in the within-group variance for men in the March CPS should be interpreted with caution as it is not a very robust finding.

Leaving the 1970s aside, an important point is that, for men, most of the growth in the variance of wages between 1980 and 2006 comes from the between-, as opposed to the within-group component. This is similar to what was documented earlier using the May-ORG CPS data. This highlights, once again, the importance of the growing education premia for college educated workers in the overall growth in wage inequality. For women, the growth in the overall variance during this period is, more or less, evenly split between the within- and between-group components. On balance, the earlier results that most of the growth in inequality is due to the between-group component are thus reasonably robust to the choice of data set.

4d. Top-coding in the March CPS

Figure 13 shows what happens to the within-and between-group variances when i) top coding is not corrected for (as was done for the May-ORG data), and ii) a more sophisticated imputation procedure is used to allocate earnings for top-coded observations. Unlike the May-ORG CPS, other data sources can be used to make reasonable assumptions about the distribution of annual earnings above the top-code. In particular, since tax data are not topcoded, they provide direct information on the distribution of earnings above the top-code. The usual assumption made is that the upper tail of the earnings distribution follows a Pareto distribution. Piketty and Saez (2003) use the Pareto distribution to smooth their data on top incomes from tax data, and I use their implied Pareto parameter for each year to impute earnings above the March CPS top code.[12]

Another limitation of the standard "fixed" imputation procedure base on a factor of 1.4 or 1.5 is that it does not preserve the distribution of earnings in the upper tail of the distribution. Intuitively, using a fixed as opposed to a stochastic imputation procedure likely has little impact for the between-group variance, but it could bias down the within-group variance by understating wage dispersion among top-coded workers.

Appendix Figure 2 shows the top-coding adjustment factors obtained from Piketty and Saez (2003)'s tax data. One very convenient feature of the Pareto distribution is that

[12] I use the updated series available on Emmanuel Saez's web site to compute the Pareto parameter up to 2005, and then use for 2006 the same parameter as in 2005.

the Pareto parameter, α, can be estimated using only the value of a topcode y_{TC}, and the mean value for observations above the topcode, μ_{TC}, using the formula:

$$\mu_{TC} / y_{TC} = \alpha/(\alpha\text{-}1).$$

Since we typically work with log wages, it is also convenient to compute the mean log value from a Pareto distribution. Another convenient property is that when y follows a Pareto distribution with a parameter α, then $\log(y/y_{TC})$ follows an exponential distribution with a parameter α. The mean of $\log(y/y_{TC})$ is thus $1/ \alpha$, which implies that

$$E[\log(y)] = \log(y_{TC}) + 1/\alpha.$$

With the standard 1.4 imputation factor, it follows that $y=1.4y_{TC}$. This corresponds to the case of a Pareto distribution with $1/\alpha = \log(1.4) = 0.336$, where the mean value of log(y) from this distribution is imputed to all observations. Appendix Figure 2 shows the actual value of $1/\alpha$ obtained from the tax data. This parameter has been growing over time as top-end inequality has expanded, though it decreased a bit following the end of the "high tech bubble" around 2000. The figure also shows another adjustment factor from the March CPS. Since 1995, top-coded observations in the March CPS have their earnings replaced by the average earnings for their relevant (broadly defined) demographic group. This is now doable since earnings are no longer top-coded in the CPS (computerized) questionnaire, though they are top-coded in public use files. The implied Pareto parameter is remarkably similar to the one from the tax data, which gives a lot of confidence in an imputation procedure based on the tax data.[13]

In practice, I implement the stochastic imputation procedure by randomly drawing value z from an exponential distribution (with mean 1), and transforming them into draws from a Pareto distribution by exploiting the link between the Pareto and the exponential distribution discussed above:[14]

$$\log(y) = \log(y_{TC}) + z/\alpha.$$

The results reported in Figure 13a for men show that using either the 1.4 fixed imputation factor or the stochastic imputation procedure yield very similar estimates of the between-group variance. As in the case of the May-ORG, failing to adjust for top-coding slightly

[13] I use the number of married white males, by far the largest group of top-coded workers to compute the Pareto parameter in the CPS.

[14] I use a three-year moving average for the adjustment factor from the tax data to smooth for some of the erratic behavior shown in Appendix Figure 2.

biases down the secular growth in the between-group variance, but the overall impact is very small.

Turning to the within-group variance, the fixed and stochastic imputation procedure yield, perhaps surprisingly, fairly similar results. In fact, the change in the within-group variance between 1973 and 2006 is essential identical under the two imputation procedures. One small difference is that the stochastic imputation procedure tends to produce a larger variance from the mid-1980s to the late 1990s, which slightly accentuates the slowdown in the growth in the within-group variance after the late 1980s. Another difference is that the within-group variance obtained using the stochastic imputation procedure does not change when the top code is raised in 1995 and 2002. By contrast, the within-group variance computed with the fixed 1.4 correction jumps almost as much as the uncorrected series in these two years. This suggests that the stochastic imputation procedure does generally a better job at correcting for topcoding, and that year to year changes are better measured using this procedure instead of the fixed imputation procedure. In terms of general inequality trends, however, Figure 13a suggests that the two top coding adjustments produce very similar results. Since the top code has been gradually increased over time, even the unadjusted series more or less capture the correct long run trends, though year to year variations are highly sensitive to changes in the value of the top code.

5. CHANGES IN WAGE INEQUALITY: A SUMMARY

The last two sections have shown that there are a number of clear patterns of changes in wage inequality and in the wage structure that are highly robust to measurement issues. The only notable exception has to do with changes in within-group wage inequality for men in the 1970s for which the March and May-ORG supplements of the CPS yield substantially different answers. I will underplay this particular aspect of inequality changes in this section, but discuss its implication for the interpretation of inequality changes in the next section.

The main results about “what we really know” about changes in wage inequality can be summarized as follows. Unless otherwise indicated, the results are based on inequality measures adjusted for composition effects:

1. Changes in broad based measures of inequality, such as the variance, are concentrated in the 1980s. This holds for both the between- and within-group components of wage dispersion
2. Trends in broad-based measures of inequality hide important differences at different points of the distribution. At the top-end of the distribution, inequality has grown steadily throughout the 1980s, 1990s, and 2000s. At the low-end of the distribution, inequality only grew in the 1980s and remained constant or declined during the 1970s, 1990s, and 2000s.
3. The pattern of change in inequality across education groups is highly consistent with the broader changes at the top end and low end of the distribution. Mean wages of college graduates and post-graduates increased steadily relative to high school graduates, though the growth in more marked in the 1980s. Similarly, the within-group variance of these two highly educated groups has grown steadily over time. By contrast, the wage disadvantage of workers without a high school degree relative to those with a high school degree only increased (by a small amount) in the 1980s. The within-group variance for workers with a high school degree or less increased a bit in the 1980s, but then remained stable or declined in the 1990s and 2000s.
4. Experience wage differentials go up and then down over time, but contribute little to long run changes in wage inequality. These differentials increase more for women, but this likely reflects spurious changes linked to the changing relationship between actual and potential experience for women.

6. POSSIBLE EXPLANATIONS? SOME CONCLUDING COMMENTS

Looking back at explanations suggested 15 years ago, the new developments documented above pose a major challenge to explanation for inequality growth based on a general increase in the demand for all dimensions of skill. A first puzzle is that if relative demand for skilled workers kept going up over the last 15 years, how can one explain the decline in the returns to experience over this period, or the stability of the skill premium between high school graduates and less educated workers?

In the case of the return to experience, a possible answer is that relative supply, as opposed to relative demand, is the key factor behind secular changes in this wage differential. Just like the entry of baby boomers first depressed the wages of young workers in the 1970s and early 1980s (Welch, 1979), as this cohort ages the negative pressure of supply on wages is increasingly moving to the upper end of the experience distribution, which reduces the experience premium. While this hypothesis should be probed in more detail, it is also reasonable to expect that relative demand pressures are less important in the case of experience than education. Indeed, while it is sensible to think that the computer and information technology revolution is “education-biased”, it is far from clear that it is also “experience-biased”. This suggests that the growth in both education and experience differentials in the early 1980s may simply be a coincidence linked to demand factors driving the growth in the education premium, and supply considerations driving the growth in the experience premium.

This view that the 1980s was a “perfect storm” where different factors resulted in an expansion in inequality at different points of the distribution, as opposed to a ubiquitous increase in the demand for skill, can also help shed light on some other puzzles. For instance, the large decline in the real value of the minimum wage during the 1980s helps explain why low-end inequality increased sharply during this period, but not in other periods. DiNardo, Fortin, and Lemieux (1996) and Lee (1999) find that most of the growth in the 50-10 gap in the 1980s was due to the minimum wage (all of the change in Lee, 1999). After adjusting for this factor, the remaining changes in 1980s were, thus, concentrated in the top end of the distribution.

Once several explanations are allowed to affect inequality at different points of the wage distribution, it becomes simpler to think of possible explanations for the secular growth in top-end inequality, without requiring these explanations to also account for swings in inequality growth at the bottom end. Since the growth in inequality at the top-end of the distribution has attracted a lot of attention in recent years, a number of candidate explanations are available in the literature. For instance, Autor, Katz and Kearney (2006) use Autor, Levy, and Murnane (2003)’s model of technological change to explain why the labor market became polarized in the 1990s and 2000s. The model is based on a distinction between skilled and routine tasks where computers are substitutes for the latter. In this model, the introduction of computer technologies depresses the middle of the distribution where workers perform skilled but routine tasks, which results in increasing inequality at the top end, but decreasing inequality at the low end. Firpo, Fortin and Lemieux (2007) show that continuing de-unionization yields similar predictions. Another possible explanation for the growing inequality at the top end includes the growth in pay for performance (Lemieux, MacLeod, and Parent, 2007). None of these three explanations can account very well, however, for why inequality at the low end increased in the 1980s and later decreased, which highlights the value of combining these explanations with changes in the minimum wage.

Another important finding presented here that does not sit well with explanations suggested 15 years ago is the fact that within-group inequality does not play as an important role in inequality changes as was thought back then. Note however, that the basic insight of Juhn, Murphy, and Pierce (1993) that changes in the between- and within-group components were driven by similar factors remains consistent with more recent developments. For example, the fact that both the relative wages and the within-group dispersion of highly educated workers grew over time suggests that these developments are closely linked. For example, Lemieux (2006a) shows that this follows naturally in a model with heterogenous returns to skill where the demand for college education increases. The fact that trends in the overall within- and between-group inequality are also similar over time also points out to similar factors explaining both phenomena.

The one finding of Juhn, Murphy, and Pierce (1993) that is much less clear now than 15 years ago is related to changes in within-group inequality in the 1970s. Using March CPS data, Juhn, Murphy, and Pierce (1993) argues that the growth in the within-group inequality in the 1970s provides evidence that relative demand was already increasing in the 1970s. As shown earlier, this last conclusion did not turn out to be very robust. This being said, whether or not within-group inequality increased in the 1970s does not play a crucial role in understanding why inequality has been changing over time. For both theoretical and empirical reasons, it is more appropriate to try to understand what drives changes in returns to education instead of within-group inequality over time. On the empirical side, the evidence presented in this paper shows that the basic facts about returns to education are very robust to measurement issues, which is not the case for within-group inequality. On the theoretical side, the basic idea of a race between relative supply and demand can be tested in the case of education, while the relative supply of unobserved skills underlying within-group dispersion is fairly nebulous concept.

In terms of potential for future research, arguably the most important fact documented in this paper and in related work (Lemieux, 2006a, Goldin and Katz, 2007) is the dramatic importance of education in changes in wage inequality. Fifteen years ago, most observers would probably not have thought that education could play such an important role in inequality growth. After all, R-squares of wage equations in the CPS are typically in the .3-.4 range, with only part of the explanation coming from education. Furthermore, Juhn, Murphy and Pierce (1993) had shown that most of the growth in wage inequality in the March CPS was coming from the within-group component, which was not surprising given the low R-square of wage regressions.

As I have shown in this paper, however, the dominant source of long-run growth in the between-group component is the growth in relative wages of college-educated workers, while the dominant source of growth in the within-group component is the increase in within-group inequality among the same workers. These two related facts also help explain why inequality has mostly increased in the top-end of the distribution where these workers are concentrated, as opposed to the low end of the distribution. In retrospect, this is a fairly unexpected development that deserves further investigation.

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DATA APPENDIX: May/ORG and March CPS Data

This appendix explains in more detail how the March and May/ORG CPS are processed to make the wage samples as comparable as possible. It closely follows the data appendix in Lemieux (2006b). Both the May/ORG and the March CPS can be used to compute hourly wage rates. The March Supplement of the CPS asks about total earnings during the previous year. An hourly wage rate can then be computed by dividing last year's earnings by total hours worked last year. The latter variable is computed by multiplying two other variables available in the March CPS, usual weekly hours of work last year and weeks worked last year.

For historical reasons, however, many studies based on March CPS data proxy for hourly wage rates by focusing only on the earnings of full-time (and sometimes full-year) workers. The reason is that prior to 1976, the March CPS only asked about full-time/part-time status last year (instead of usual hours of work last year). Furthermore, the information about weeks worked last year was limited to few intervals (0, 1-13, 14-26, 27-39, 40-47, 48-49, 50-52) in the pre-1976 March CPS. One important drawback of this alternative wage measure, however, is that it is limited to the subset of the workforce that works full-time (and sometimes full-year). This is particularly problematic for women. It also fails to control for the dispersion in hours of work among workers who work full-time (35 hours and more a week).

Since we now have over 30 years of data for which hourly wages rates can be directly computed for all workers, I limit the analysis of wages in the March CPS to the period starting with the earnings year 1975 (March 1976 survey). Another reason for starting with the wage data for 1975 is that the other wage measure available in the May/ORG CPS is only available from May 1973 on. Since one contribution of the paper is to compare the two data sources, the gain of using a more precise and comparable measure of hourly wages from the March CPS clearly outweighs the cost of losing two years of data for 1973 and 1974.[15]

[15] Another problem is that since missing wages were not allocated in the May 1973-78 CPS, allocated wages and earnings should be excluded from the March CPS for the sake of comparability. Unfortunately, individual earnings allocation flags are not available in the March CPS prior to the 1976 survey (Lillard, Smith, and Welch, 1986). Though family earnings allocation flags can be used instead (see Juhn, Murphy, and Pierce,

There are important differences between the way wages are measured in the March and May/ORG CPS. First, while the March CPS asks about retrospective measures of wages and earnings (last year), the May/ORG supplement asks about wages at the time of the survey. Second, the May/ORG wage questions are only asked to wage and salary workers. By contrast, the March CPS asks separate questions about wage and salary earnings and self-employment earnings. To get comparable wage samples, I limit my analysis of the March data to wage and salary earnings. One problem is that when workers have both wage and salary and self-employment earnings, we do not know how many hours of work pertain to wage and salary jobs vs. self-employment. To minimize the impact of these considerations, I limit my analysis to wage and salary workers with very limited self-employment earnings (less than ten percent of wage and salary earnings).

Another difference is that the ORG supplement only asks questions about the worker's main job (at a point in time) while the March CPS includes earnings from all jobs, including second jobs for dual job holders. Fortunately, only a small fraction of workers (around 5 percent typically) hold more than one job at the same time. Furthermore, these secondary jobs represent an even smaller fraction of hours worked.

Finally, since the May/ORG CPS is a "point-in-time" survey, the probability that an individual's wage is collected depends on the number of weeks worked during a year. By contrast, a wage rate can be constructed from the March wage information irrespective of how many weeks (provided that it is not zero) are worked during the year. This means that the May/ORG wage observations are implicitly weighted by the number of weeks worked, while the March wage observations are not.

One related issue is that several papers like DiNardo, Fortin, and Lemieux (1996) also weight the observations by weekly hours of work to get a wage distribution representative over the total number of hours worked in the economy. Weighting by weekly hours can also be viewed as a reasonable compromise between looking at full-time workers only (weight of 1 for full-time workers, zero for part-time workers) and looking at all workers as "equal" observations irrespective of the number of hours

1993), this is one more reason for focusing on the March CPS data starting with the earnings year 1975.

worked. Throughout the paper, I thus weight the March CPS observations by annual hours of work, and weight the May/ORG observations by weekly hours of work.

In both the March and ORG supplements of the CPS, a growing fraction of workers do not answer questions about wages and earnings. The Census Bureau allocates a wage or earnings item for these workers using the famous "hot deck" procedure. The CPS also provides flags and related sources of information that can be used to identify workers with allocated wages in all years except in the January 1994 to August 1995 ORG supplements.[16] By contrast, in the May 1973-78 CPS, wages were *not* allocated for workers who failed to answer wage and earnings questions. For the sake of consistency across data sources, all results presented in the paper only rely on observations with non-allocated wages, unless otherwise indicated.

Wages and earnings measures are topcoded in both the March and May/ORG CPS. Topcoding is not much of an issue for workers paid by the hour in the May/ORG CPS. Throughout the sample period, the topcode remains constant at $99.99 and only a handful of workers have their wage censored at this value. By contrast, a substantial number of workers in the March CPS, and non-hourly workers in the May/ORG CPS, have topcoded wages. When translated on a weekly basis for full-year workers, the value of the topcode for annual wages in the March CPS tends to be comparable to the value of the topcode for weekly wages in the May/ORG CPS. For instance, in the first sample years (1975 to 1980) the weekly topcode in the May/ORG CPS is $999 compared to $962 for full-year workers in the March CPS (annual topcode of $50,000). Towards the end of the sample period (1998 to 2002), the weekly topcode in the ORG CPS is $2884, which is identical to the implied weekly topcode for full-year workers in the March CPS (annual topcode of $150,000 divided by 52). Following most of the literature, I adjust for topcoding in both the May/ORG and the March CPS by multiplying topcoded wages by a factor 1.4.

For a variety of reasons, several data adjustments are performed before applying the 1.4 factor to topcoded wages. In the May/ORG CPS, the topcode on the edited

[16] Allocation flags are incorrect in the 1989-93 ORG CPS and fail to identify most workers with missing wages. Fortunately, the BLS files report both edited (allocated) and unedited (unallocated) measures of wages and earnings. I use this alternative source of information to identify workers with allocated wages in these samples.

weekly earnings variable for workers not paid by the hour goes from $999 in 1973-1988 to $1923 in 1989-1997, and $2884 in 1998-2006. Between 1986 and 1988, however, it is possible to use the unedited weekly earnings variable which is topcoded at $1999 instead of $999. Though the unedited variable is not computed for workers who fail to respond to the earnings question, this does not matter here since I only use data for workers with unallocated wages and earnings. I thus use the unedited earnings variable for the 1986-88 period.

Several adjustments also have to be performed before applying the 1.4 factor to the March CPS data. Until March 1989, wages and salaries were collected in a single variable pertaining to all jobs, with a topcode at $50,000 until 1981 (survey year), $75,000 from 1982 to 1984, and $99,999 from 1985 to 1988. Beginning in 1989, the March CPS started collecting wage and salary information separately for main jobs and other jobs, with topcodes at $99,999 for each of these two variables. The topcodes were later revised to $150,000 for the main job and $25,000 for other jobs in March 1996, and then to $200,000 for the main job and $35,000 for other jobs in March 2003.

Prior to March 1996, the earnings variable of workers who are topcoded simply takes the value of the actual topcode. Starting in March 1996, however, the value of earnings for topcoded workers is replaced by the mean earnings among all topcoded workers. Mean earnings are separately computed for different demographic groups. For example, in the March 2001 CPS, the mean for topcoded main job earnings ranges from $195,699 for white females not working full-time full-year, to $335,115 for full-time full-year white males. The corresponding means for these two groups are $39,320 and $56,879 for wage and salary earnings on other jobs.

To maintain consistency over time, I first construct a topcoded variable for total wage and salary earnings from March 1989 on. For 1989-1995, I simply keep the pre-1989 $99,999 topcode. Since both main job and other job earnings are separately topcoded at $99,999, I simply add these two earnings variables and topcode the sum at $99,999. After various experiments, I decided to use a topcode of $150,000 for total wage and salary earnings from 1996 on. Unfortunately, it is not possible to topcode total wage and salary earnings in a way that is completely consistent with the pre-1996 situation. The problem is with workers who earn less that $125,000 on their main job but have earnings from other jobs topcoded at $25,000. It is not possible to know whether total earnings of these workers are above or below $150,000. After some experiments, I decided to compute total earnings as the sum of main job earnings (censored at $150,000) and earnings on other jobs where I use the actual earnings provided in the CPS (where topcoded observations are imputed the actual mean earnings among topcoded workers).

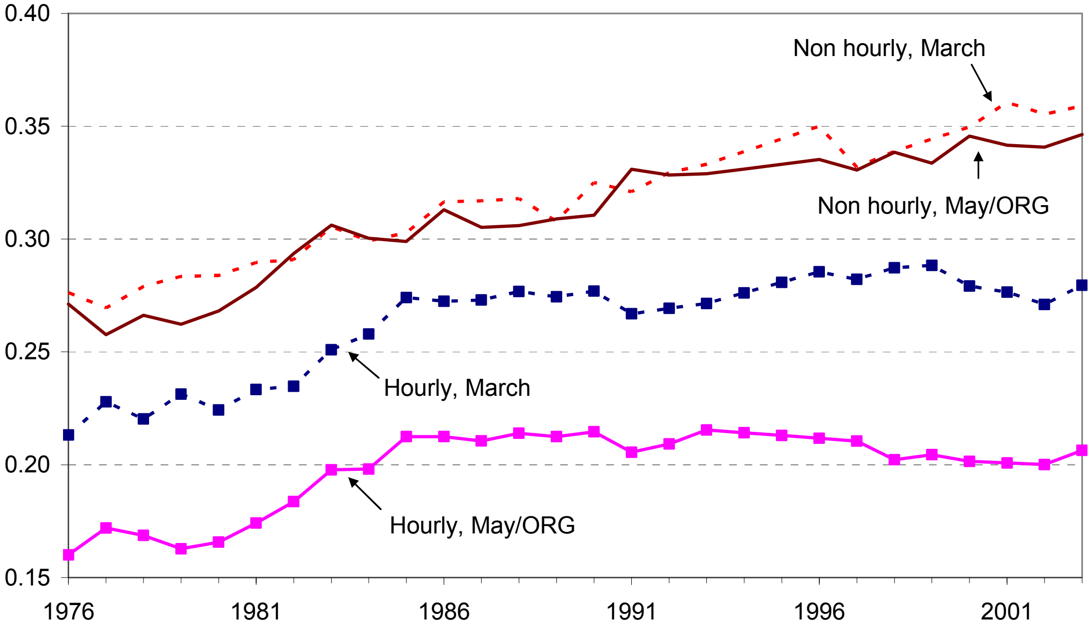
For example, consider a full-time full-year white male who earns $90,000 on his main job but has his earnings topcoded at $25,000 for other jobs in the March 2001 CPS. I compute total earnings as the sum of $90,000 and $56,879 (see above), which yields $146,876. Since this is below the $150,000 topcode, I do not compute further adjustments for this worker. By contrast, I would censor at $150,000 the total earnings of the same worker if he earned $100,000 instead of $90,000 on his main job (total of $156,876).

These adjustments likely have little impact since, in the March 1996-2007 CPS, since less than one percent of workers have main job earnings below $125,000 and are topcoded on their other jobs earnings. Finally, once total wage and salary earnings have been censored in a consistent fashion, I multiply the earnings of workers at this consistent topcode by the standard 1.4 factor.

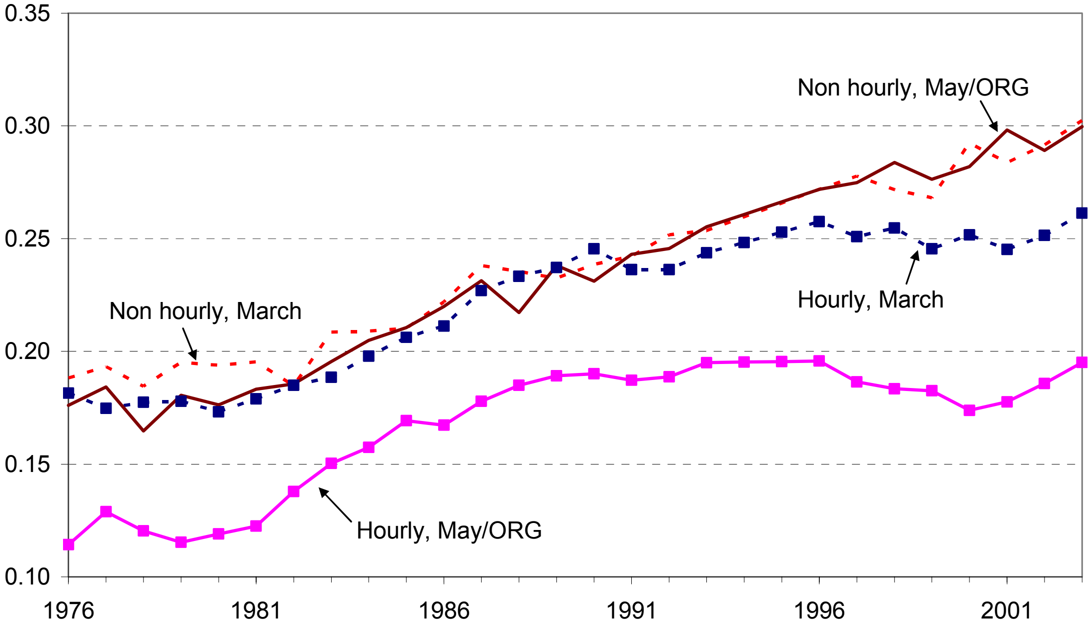
In both the May/ORG and March CPS, I also follow the existing literature by trimming very small and very large value of wages to remove potential outliers. Following Card and DiNardo (2002), I remove observations with an hourly wage of less than $1 or more than $100 in 1979 dollars. I also limit the analysis to workers age 16 to 64 with positive potential experience (age-education-6).

One last point about the ORG CPS is that, starting in 1994, workers are first asked what is the earnings periodicity (hourly, weekly, bi-weekly, annual, etc.) that they prefer to use in reporting their earnings on their current job. But as before, all workers paid by the hour are asked for their hourly wage rate. Hourly rated workers are asked this question even if "hourly" is not their preferred periodicity in the first question. Workers not paid by the hour are then asked to report their earnings for the periodicity of their choice. An hourly wage rate can again be computed by dividing earnings by usual hours of work over the relevant period. In 1994, The CPS also introduced "variables hours" as a possible answer for usual hours of work. I impute hours of work for these workers using a procedure suggested by Anne Polivka of the BLS.

Appendix Figure A1a: Variance of log hourly wages of men with both May/ORG and March wages (matched sample)



Appendix Figure A1b: Variance of log wages of women with both May/ORG and March wages (matched sample)



Note: Both graphs are from Lemieux(2006b).

Appendix Figure 2: Top-coding Adjustment Factor (1/α) Log Annual Earnings

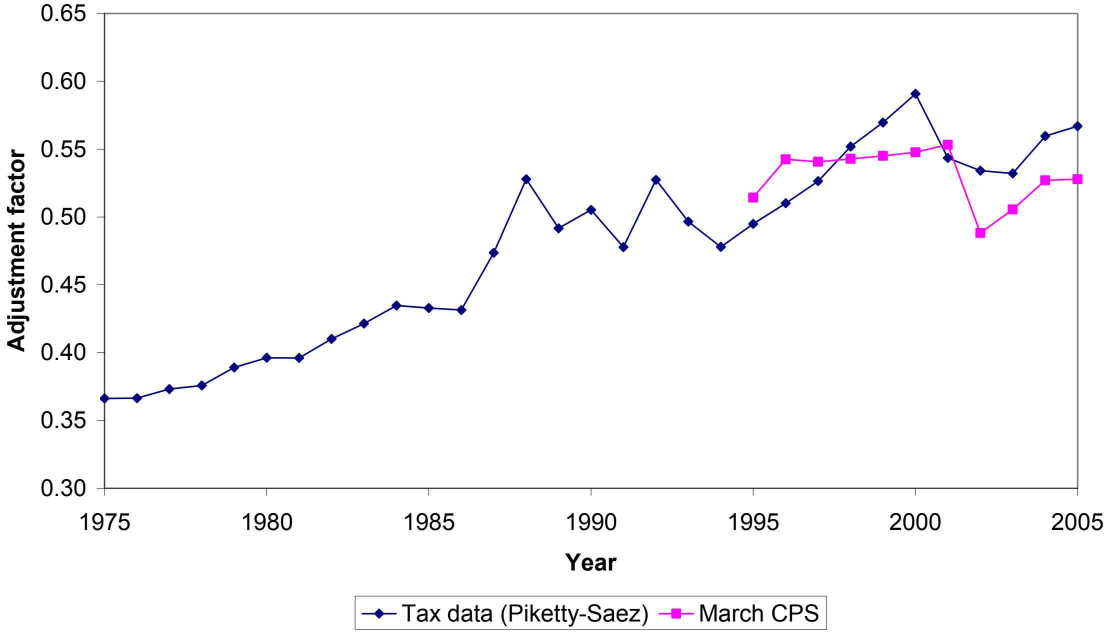


Figure 1a: Total Variance, Men

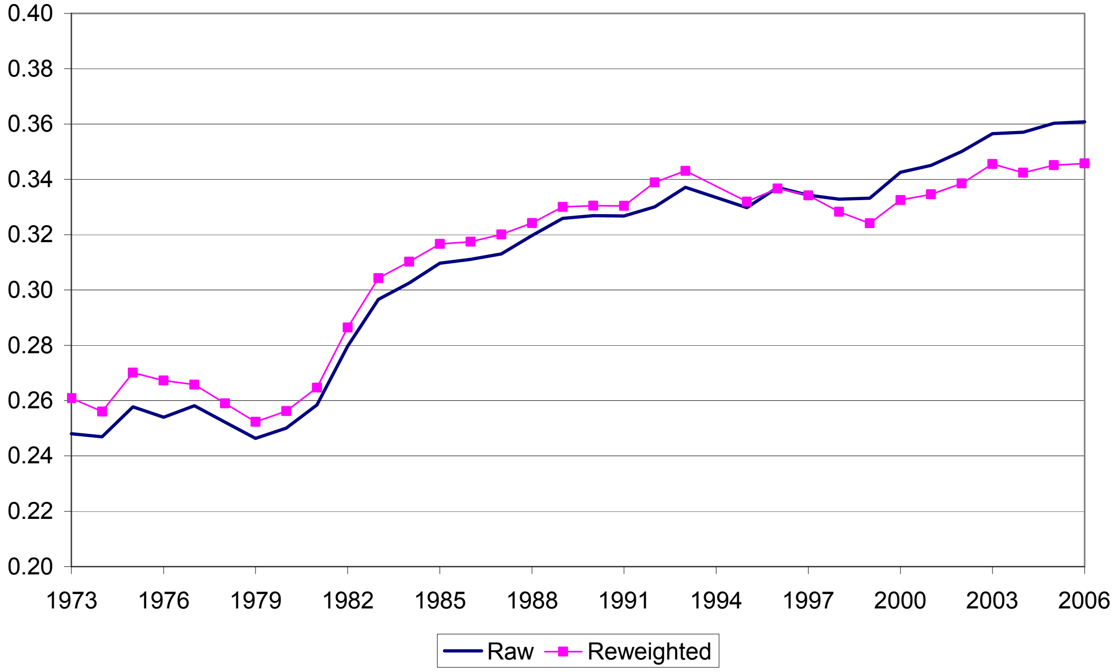


Figure 1b: Total Variance, Women

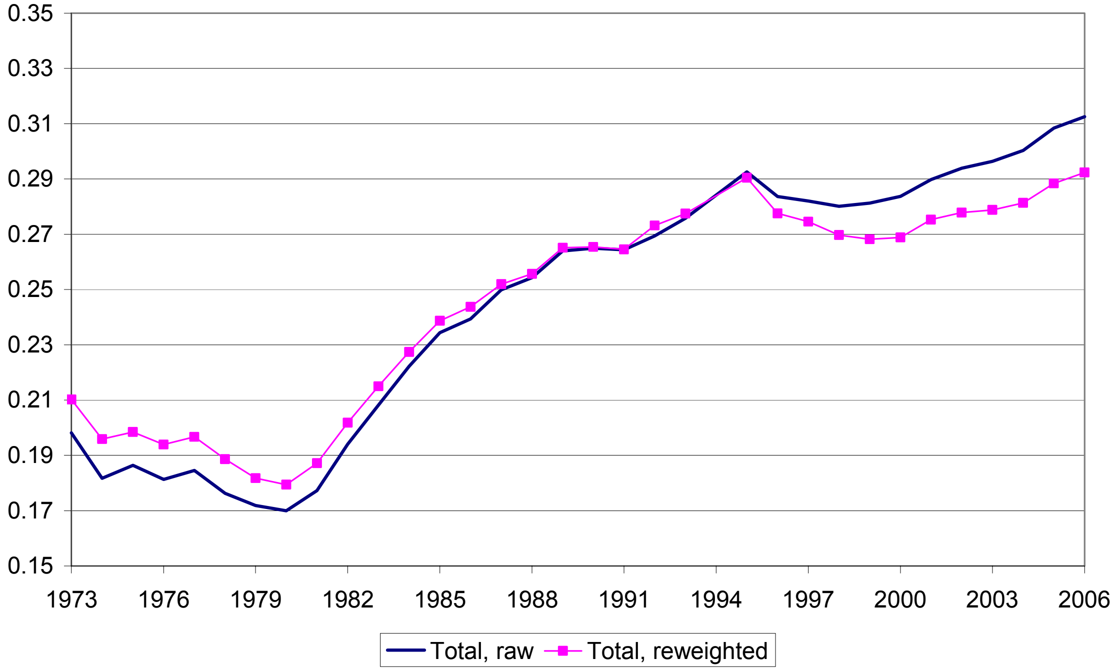


Figure 2a: Within- and Between-group Variances, Men

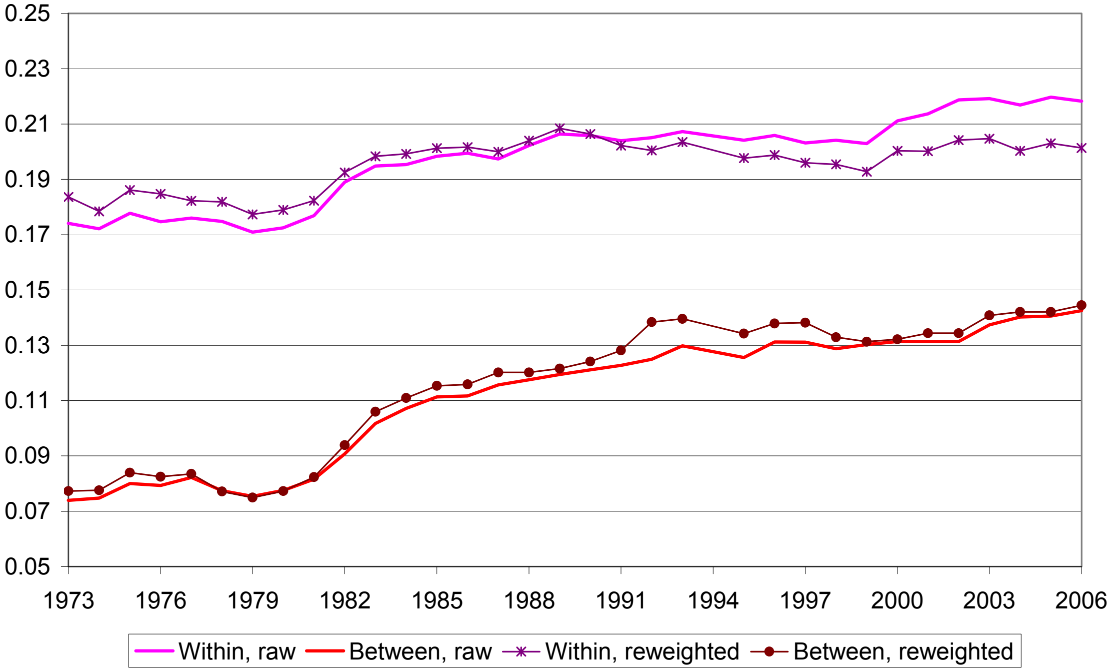


Figure 2b: Within- and Between-group Variances, Women

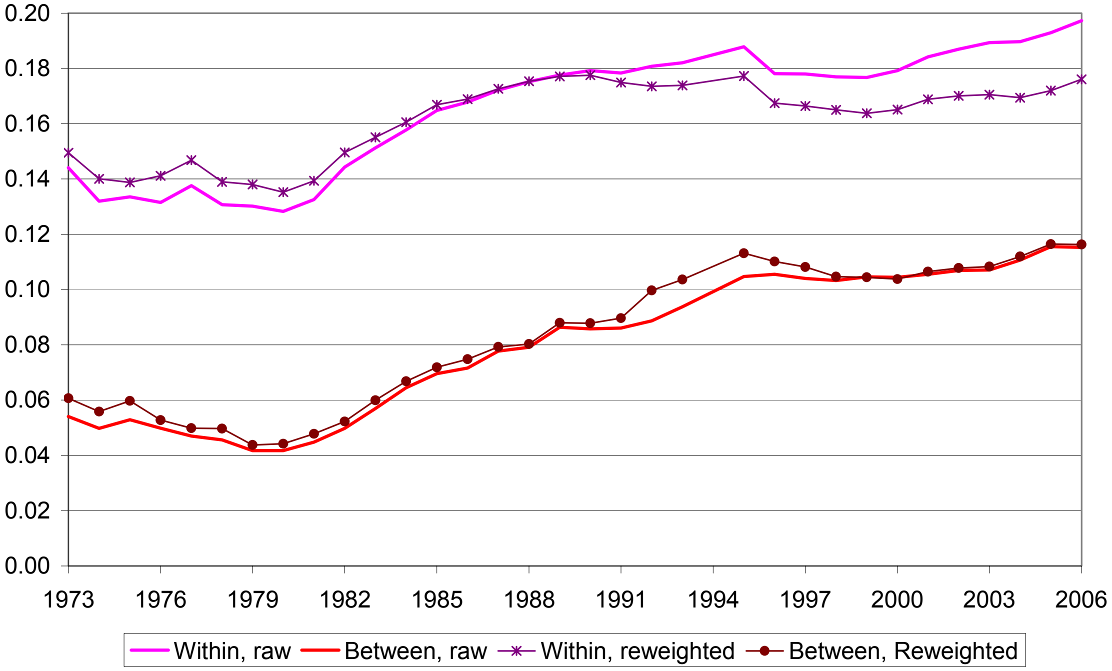


Figure 3a: Education Wage Differentials (Relative to High School Graduates), Men

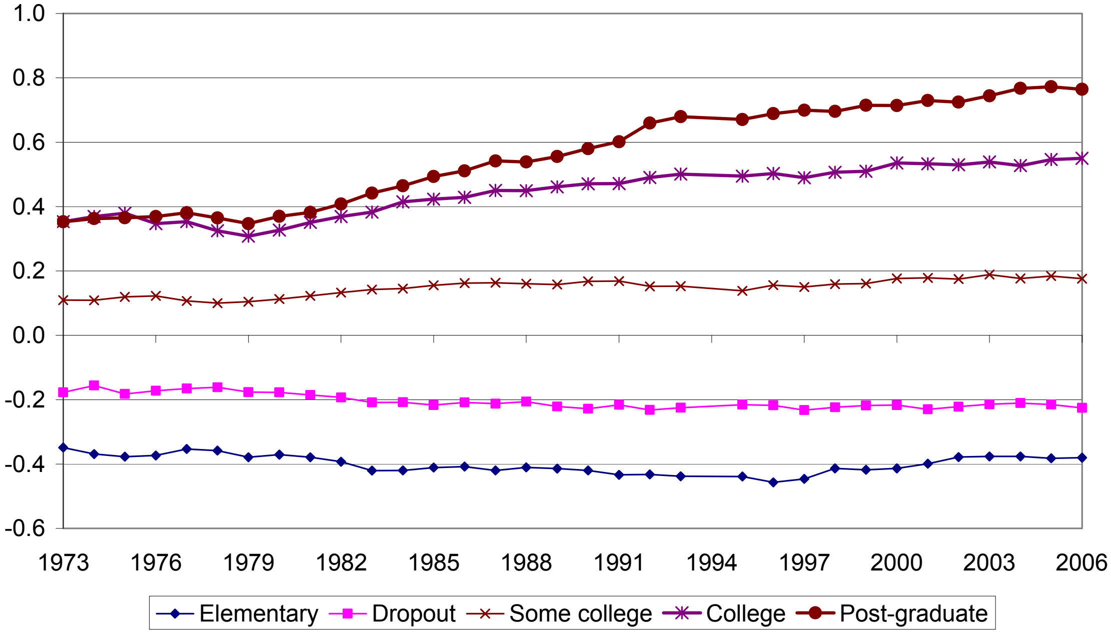


Figure 3b: Education Wage Differentials (Relative to High School Graduates), Women

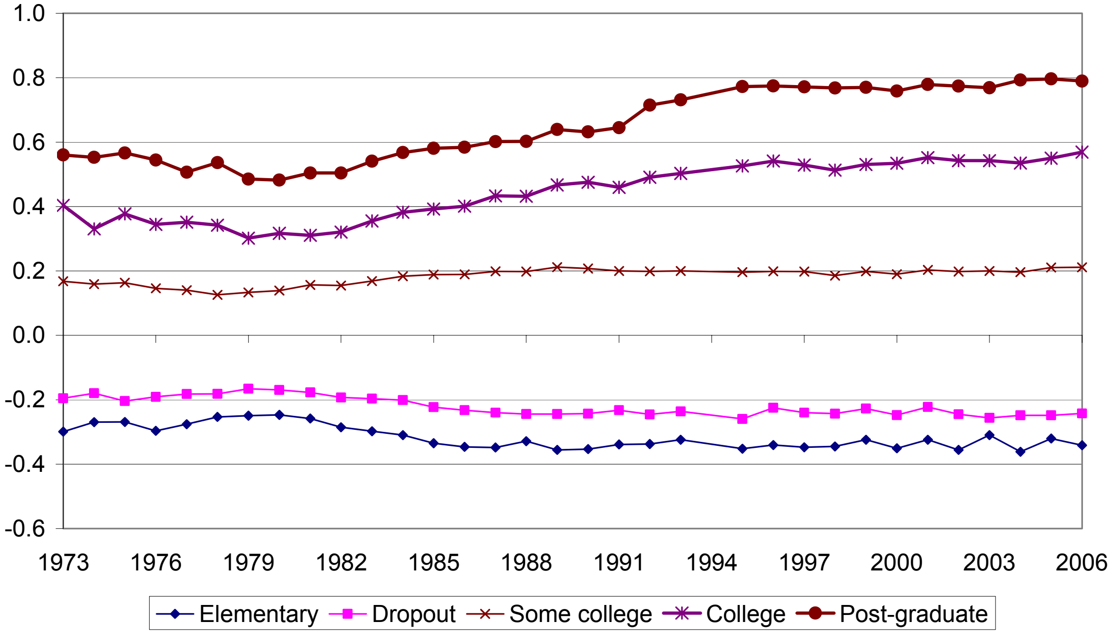


Figure 4a: Experience Wages Differentials (Relative to 20-29 Years of Experience), Men

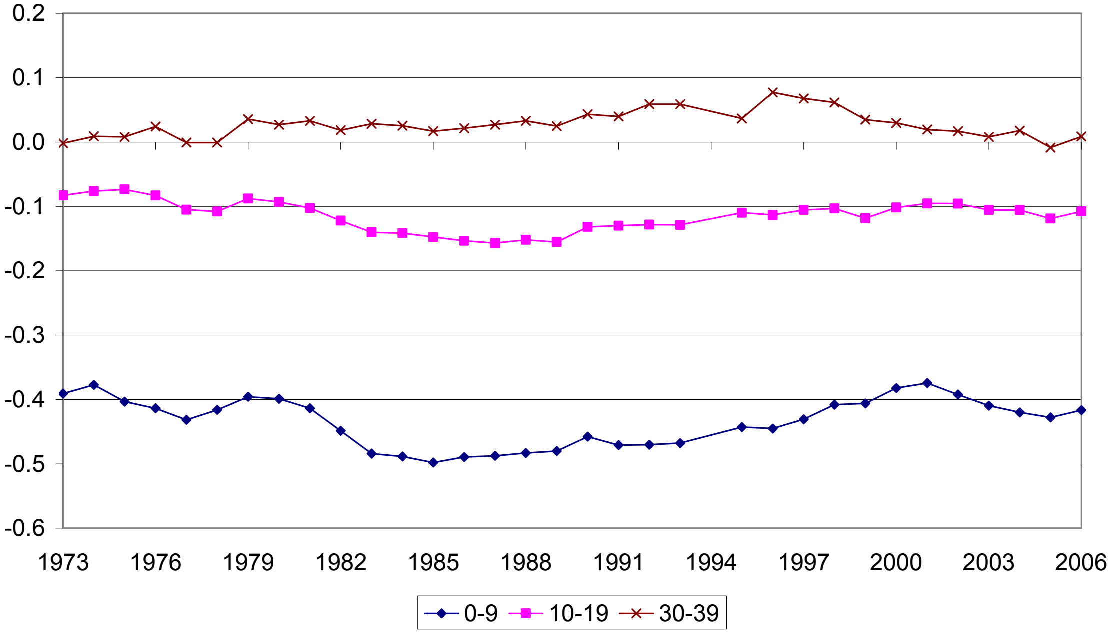


Figure 4b: Experience Wage Differentials (Relative to 20-29 Years of Experience), Women

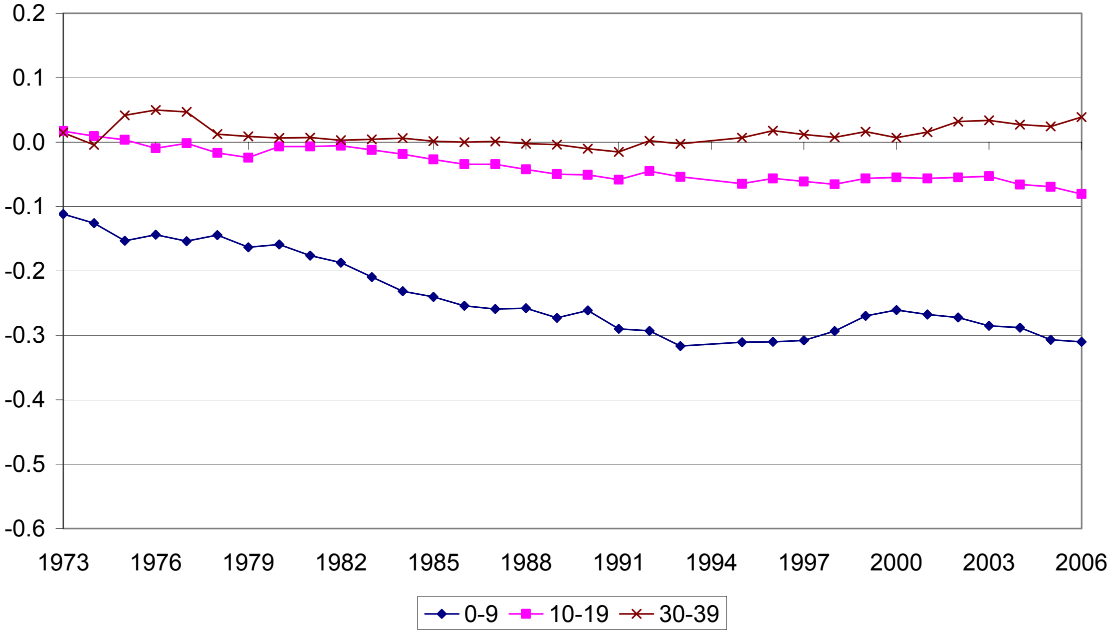


Figure 5a: Within-Group Variance by Education Groups, Men

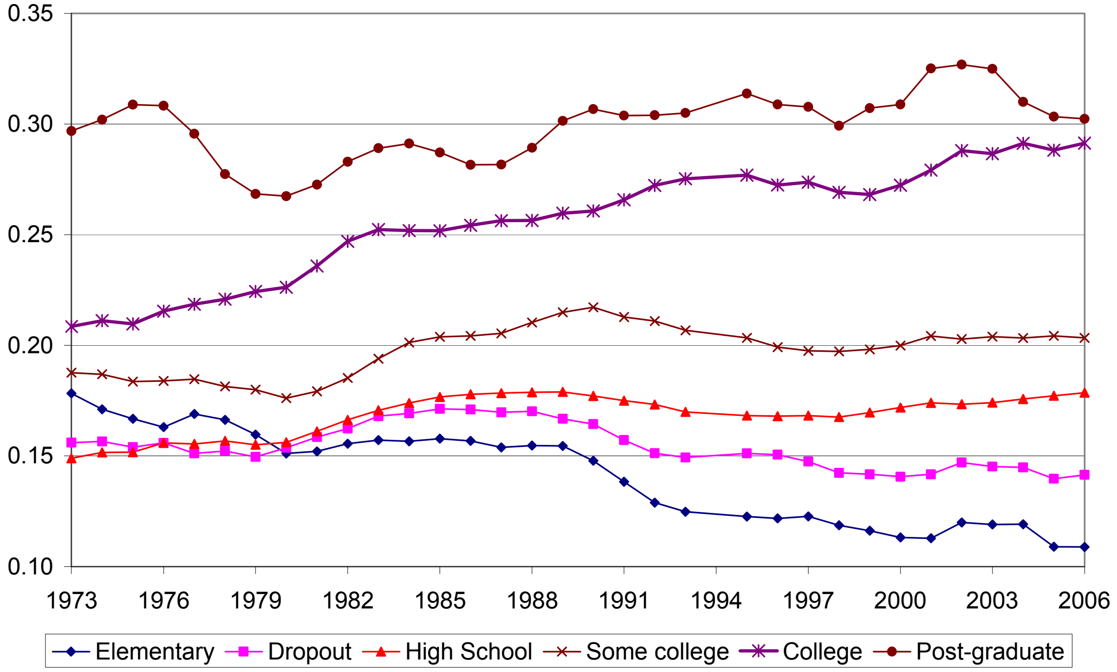


Figure 5b: Within-Group Variance by Education Groups, Women

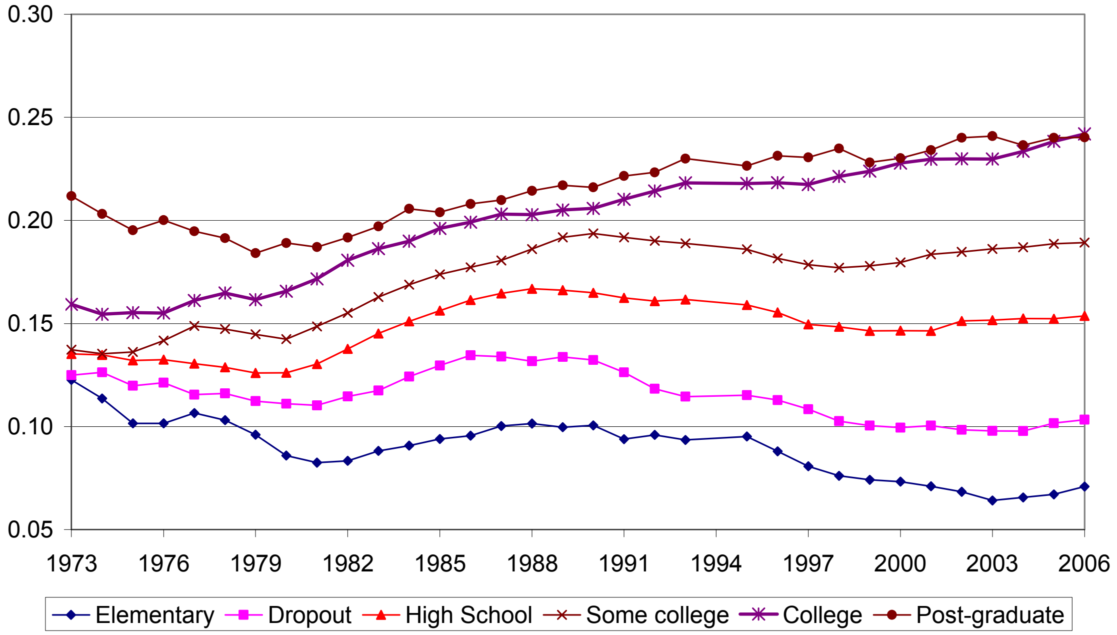


Figure 6a: Variance by Experience Groups, Men

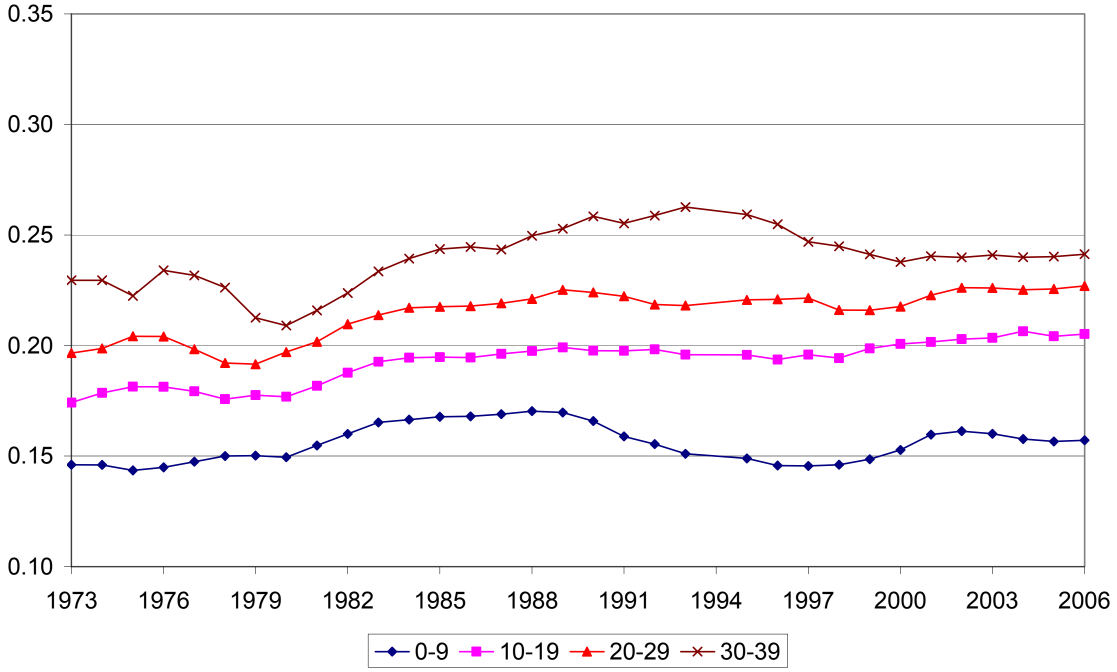


Figure 6b: Variance by Experience Groups, Women

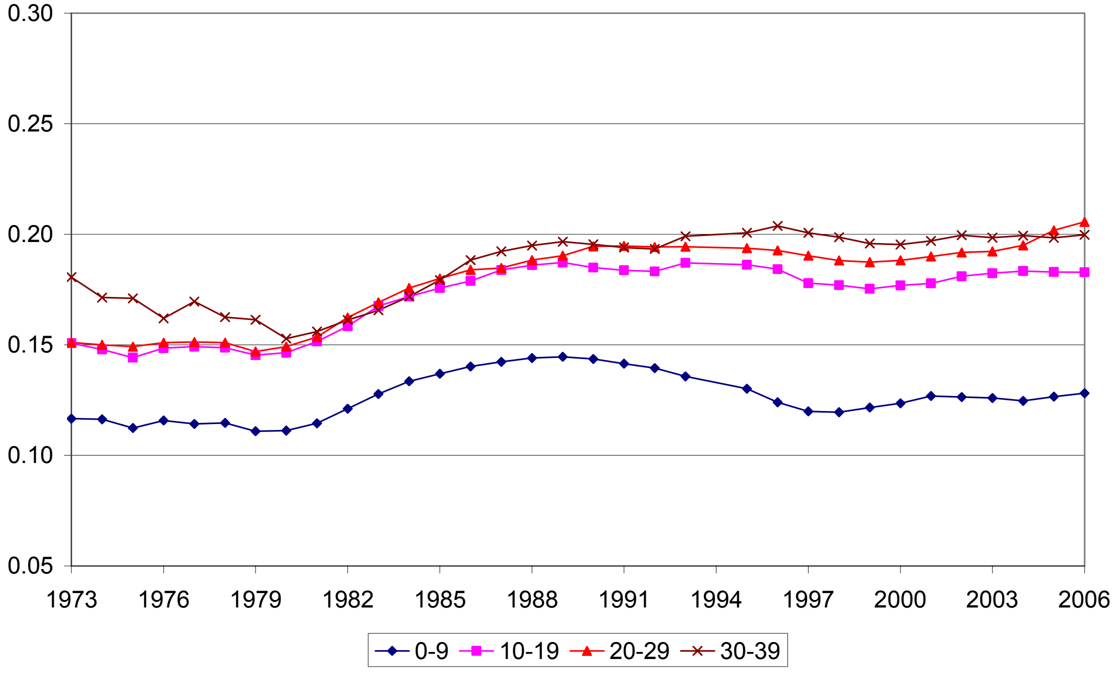


Figure 7a: Change in Real Wages by Percentile, Men

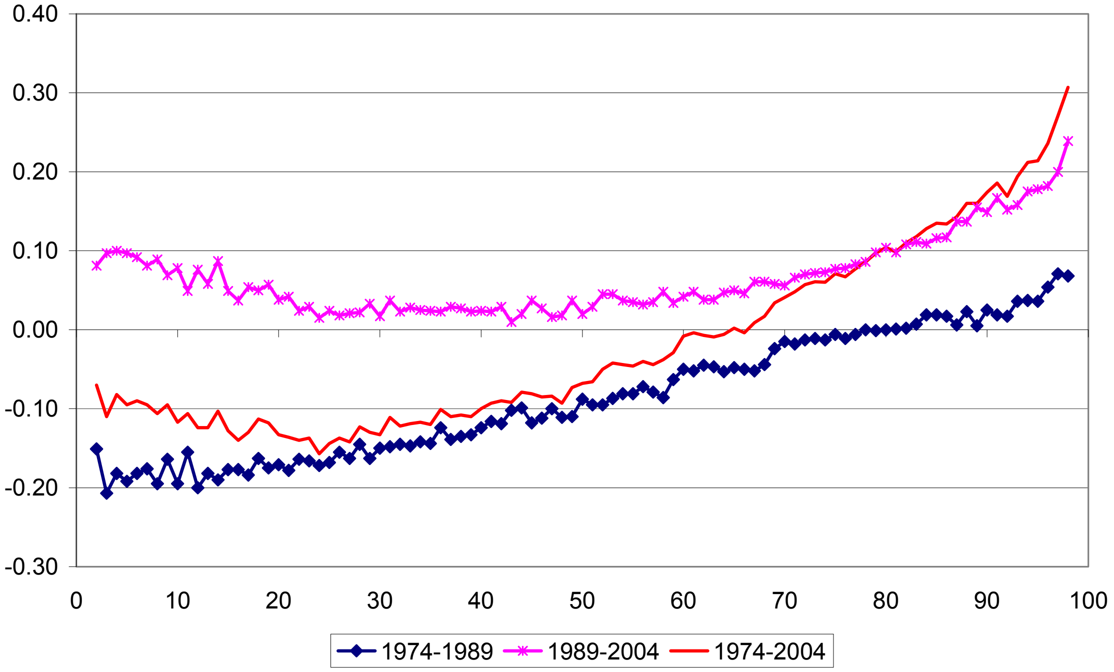


Figure 7b: Change in Real Wages by Percentile, Women

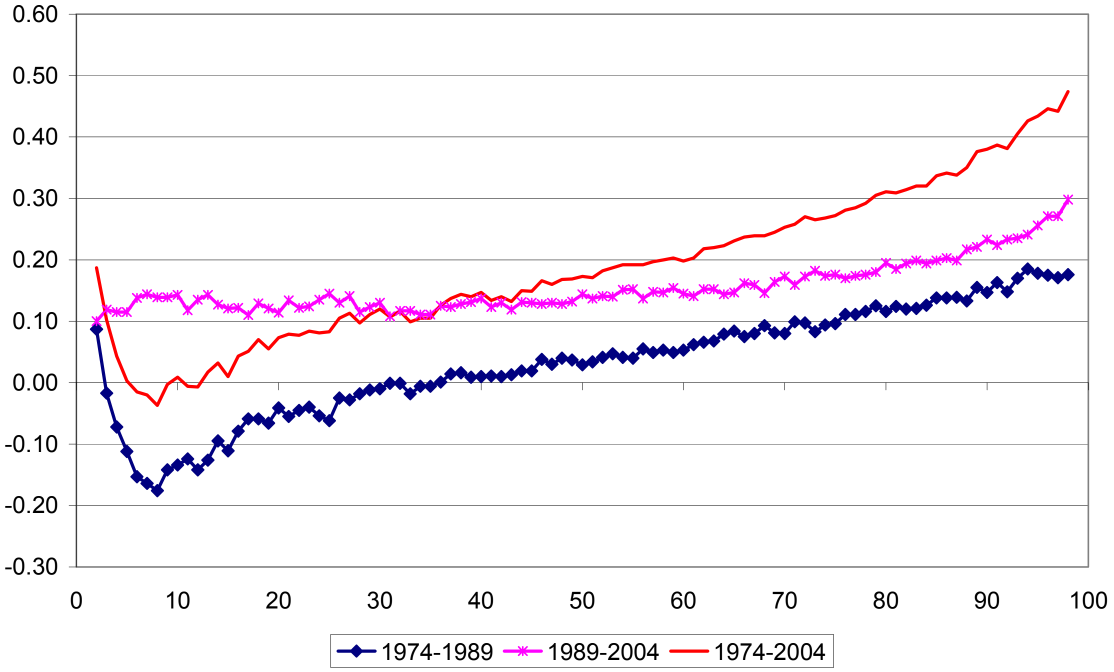


Figure 8a: Change in Wages Residuals by Percentile, Men

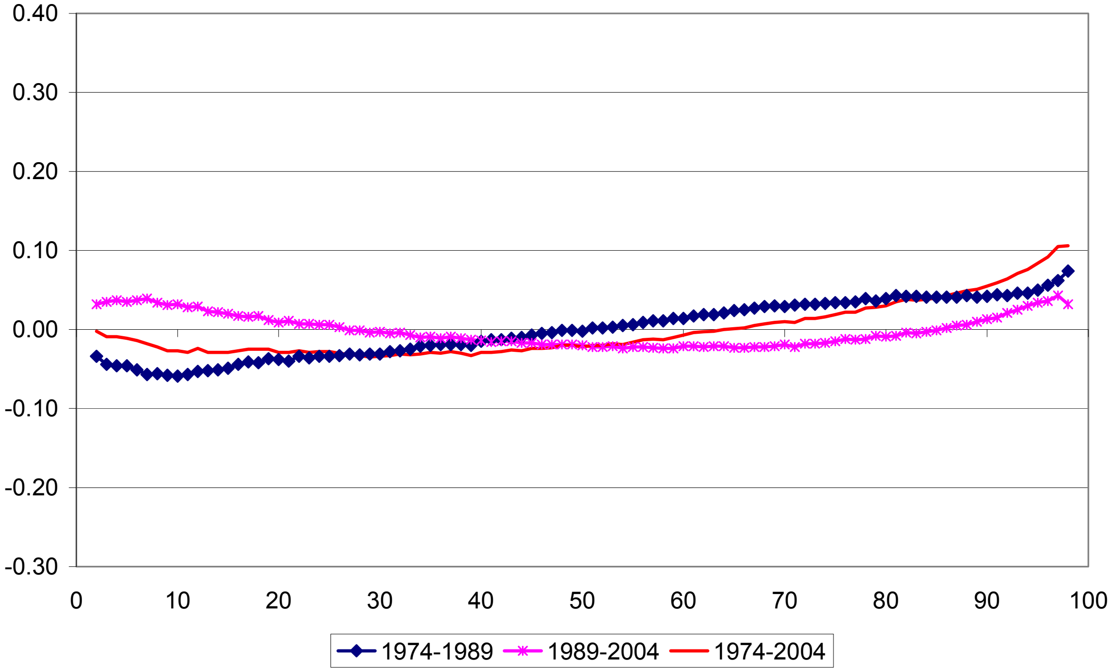


Figure 8b: Change in Wages Residuals by Percentile, Women

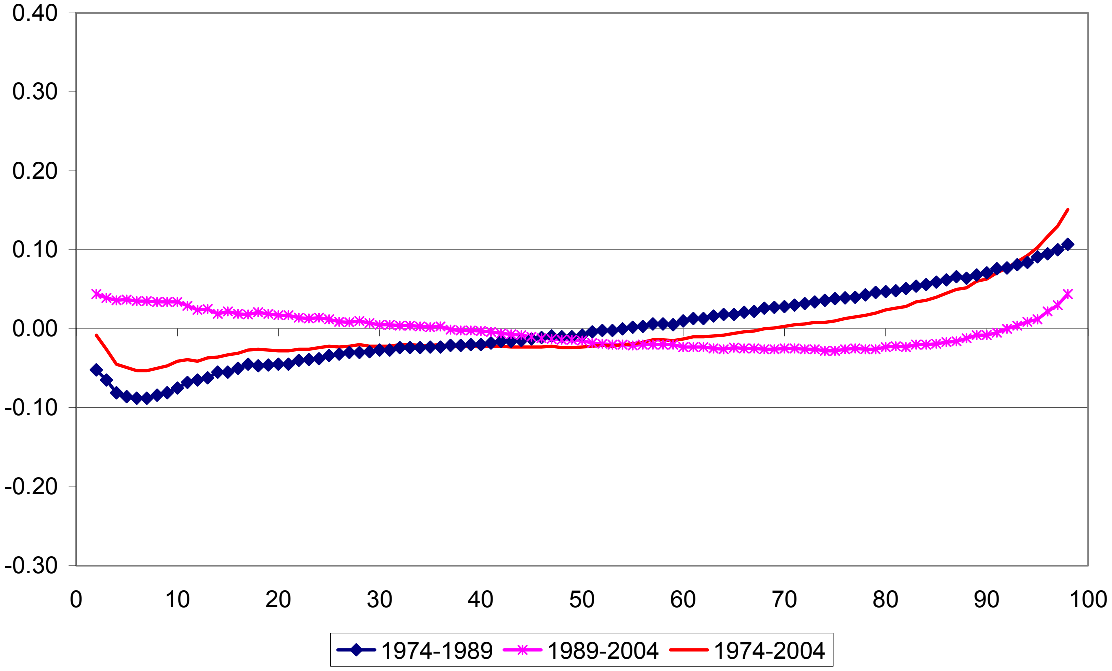


Figure 9a: Decomposition of Changes in 90-50 Gap, Men

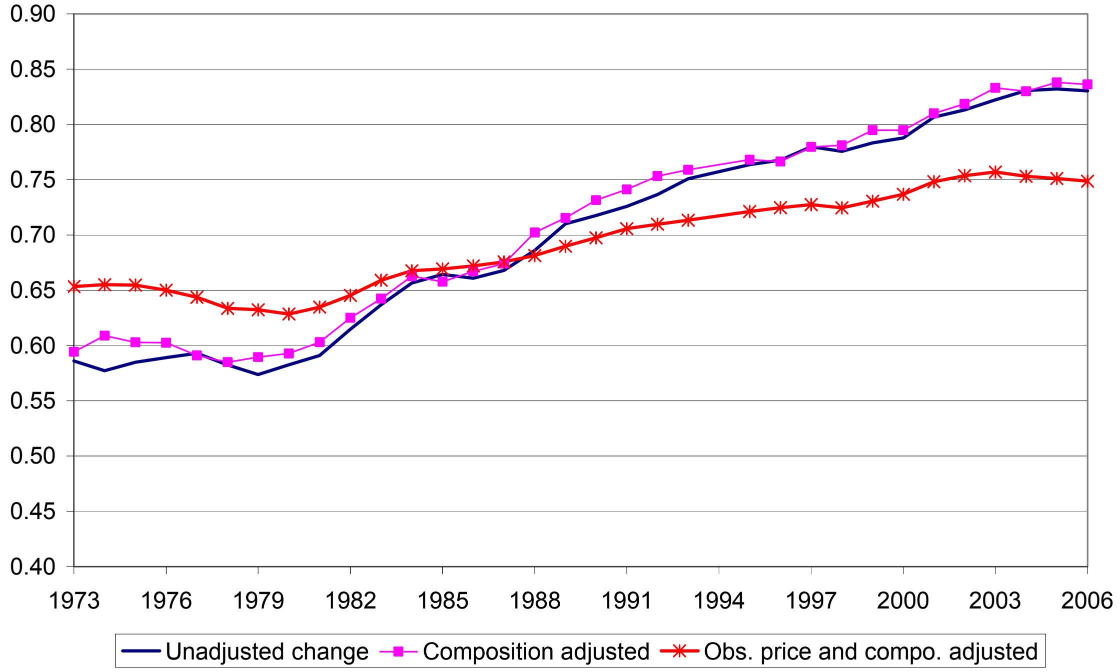


Figure 9b: Decomposition of Changes in the 50-10 Gap, Men

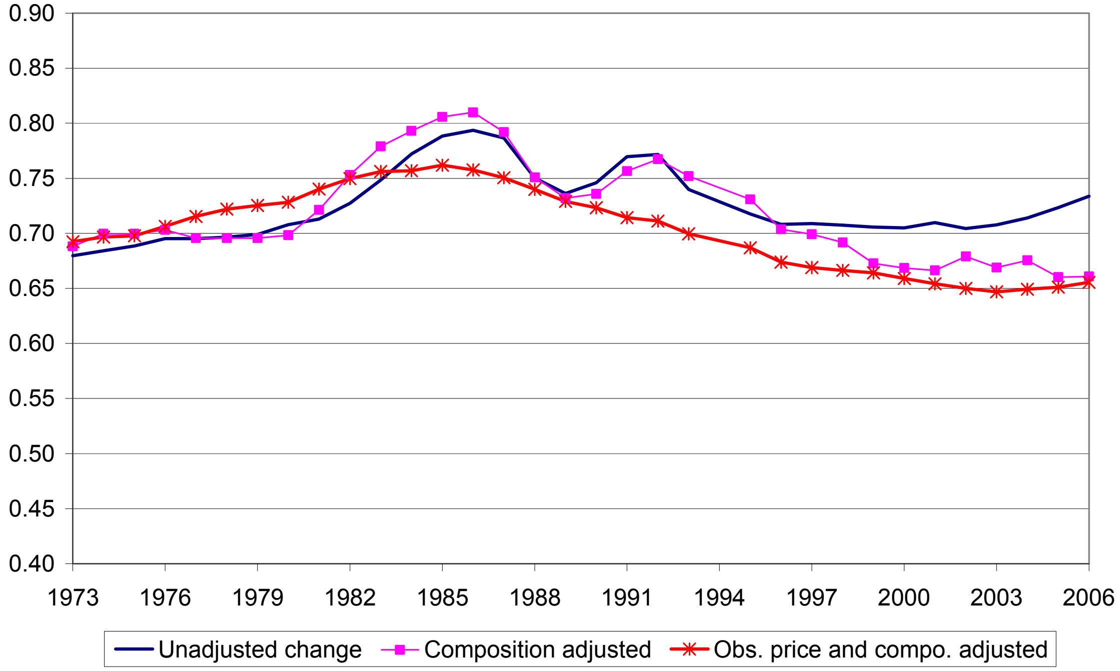


Figure 9c: Decomposition of Changes in 90-50 Gap, Women

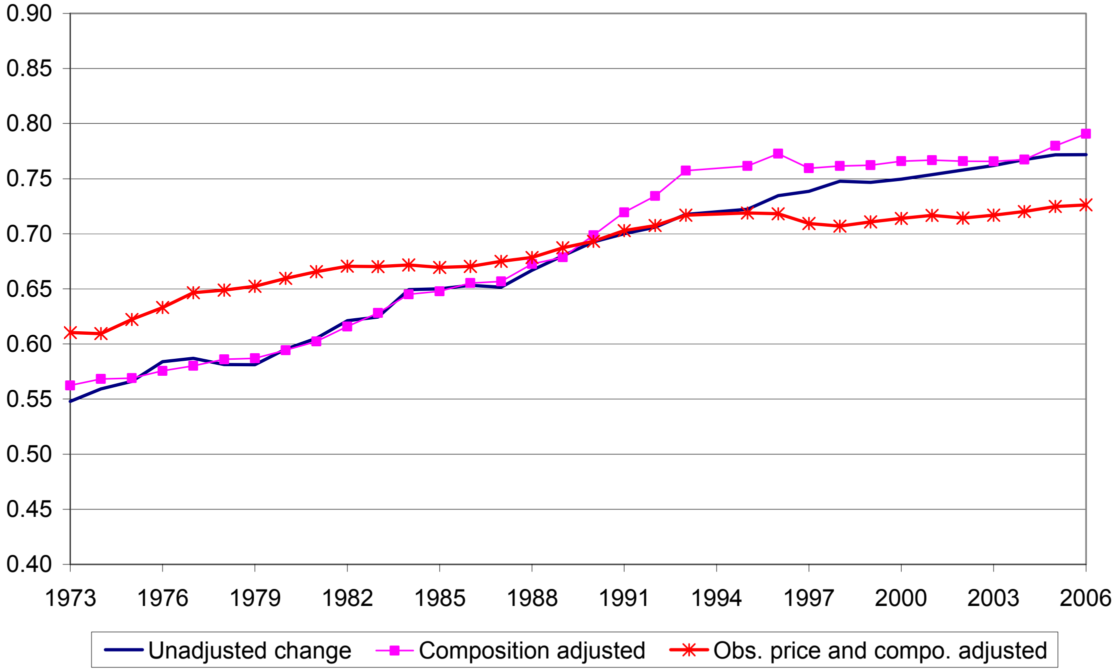


Figure 9d: Decomposition of Changes in 50-10 Gap, Women

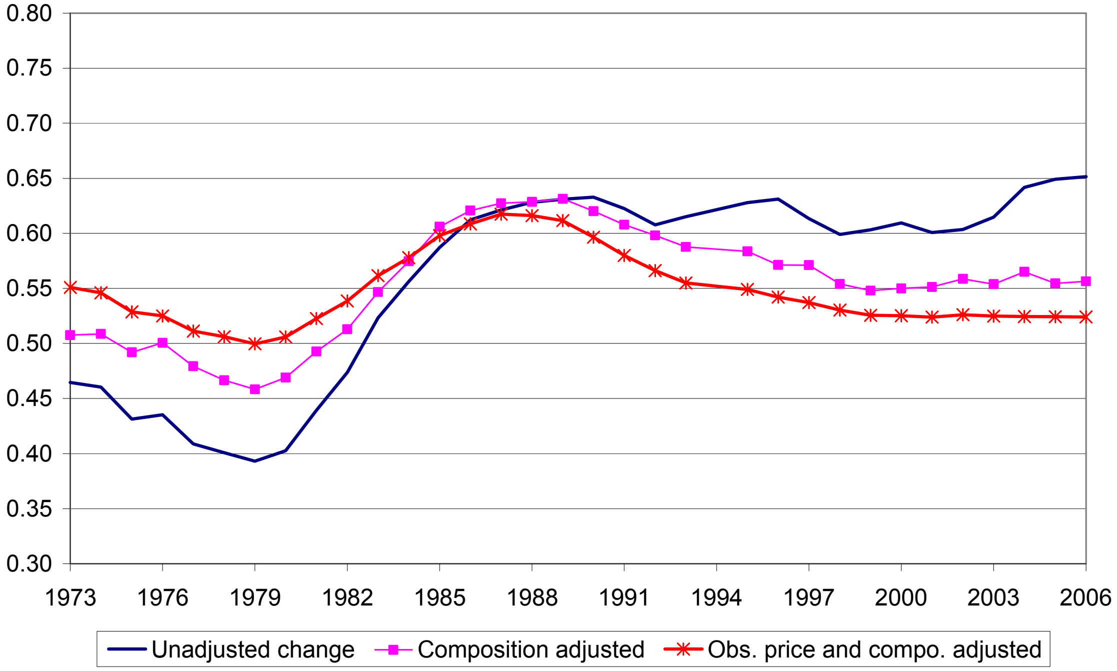


Figure 10a: Variance with and without Allocated Wages Controlling for Composition Effects, Men

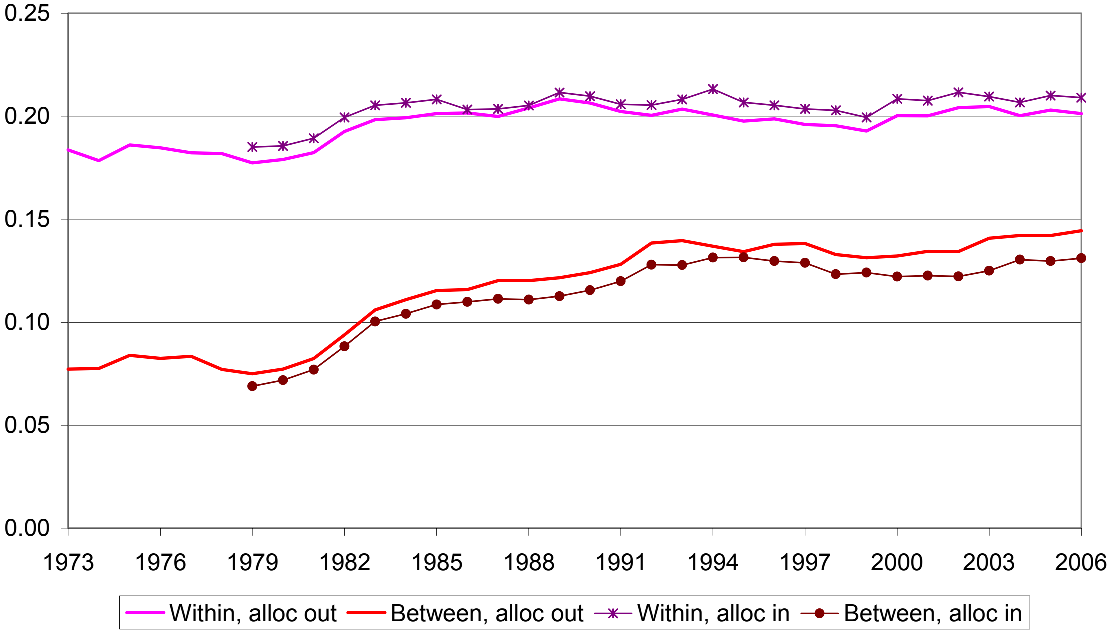


Figure 10b: Variance with and without Allocated Wages, Controlling for Composition Effects, Women

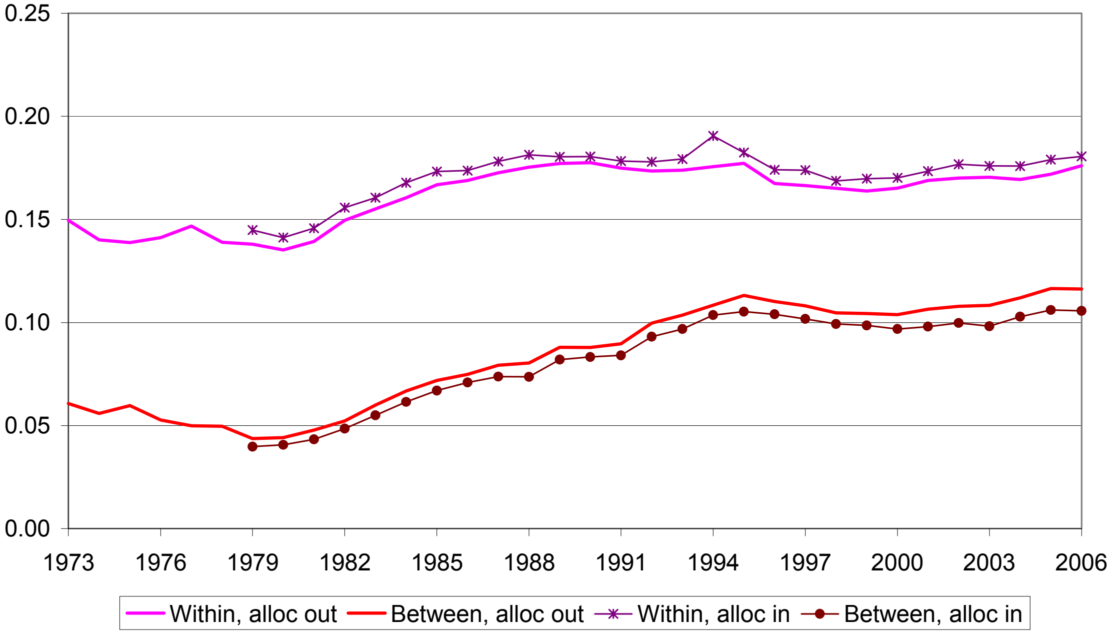


Figure 11a: Effect of Top-coding Adjustment, Controlling for Composition Effects, Men

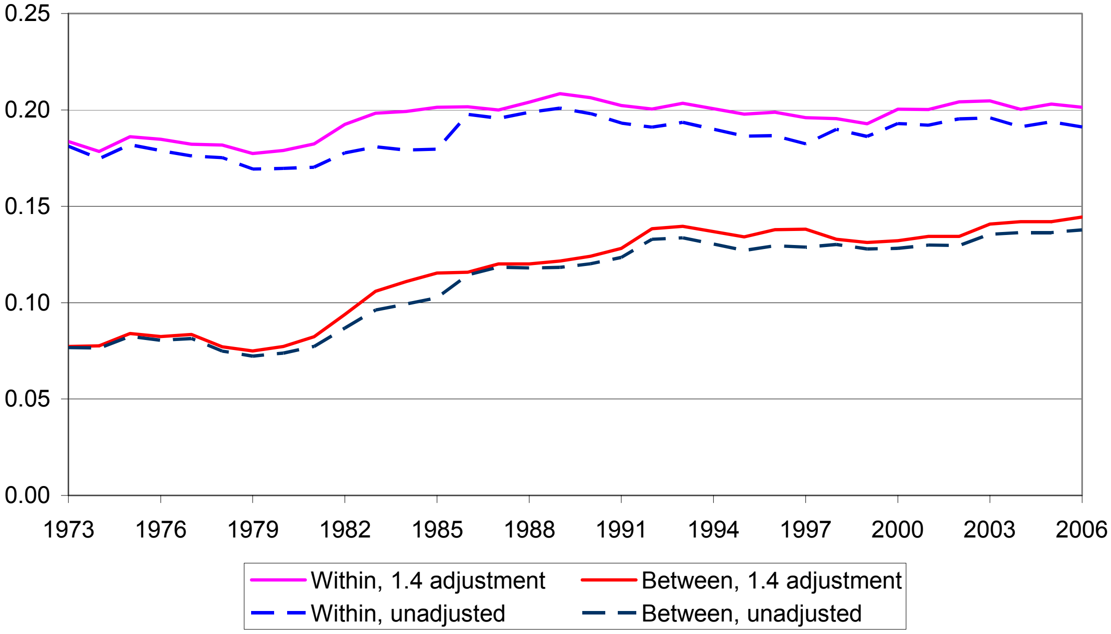


Figure 11b: Effect of Top-coding Adjustment, Controlling for Composition Effects, Women

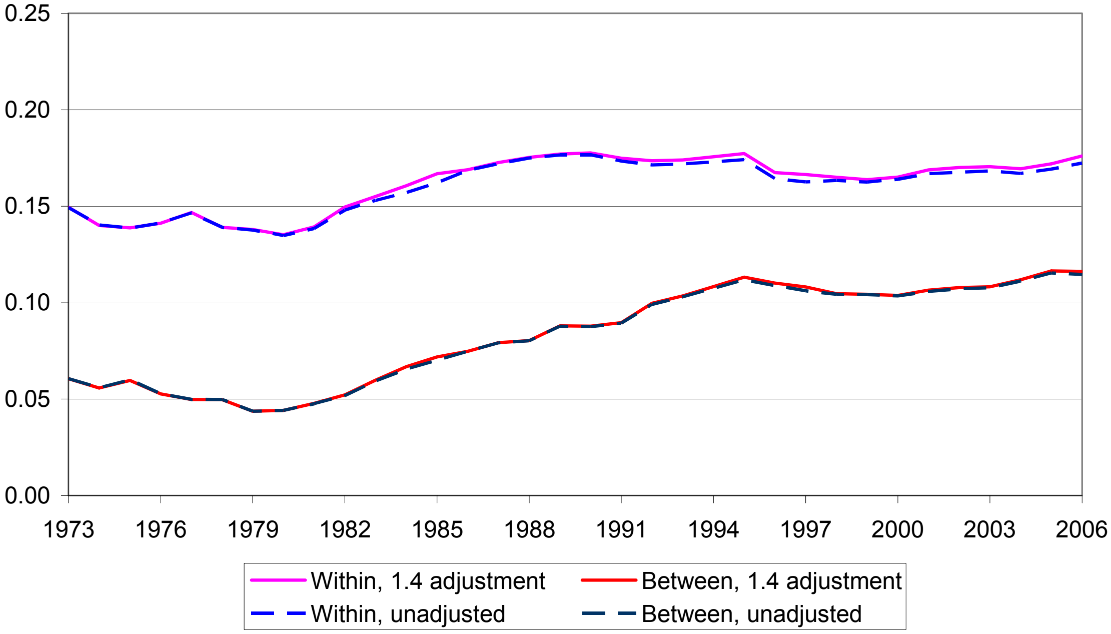


Figure 12a: Variance in May-ORG vs. March CPS Controlling for Composition Effects, Men

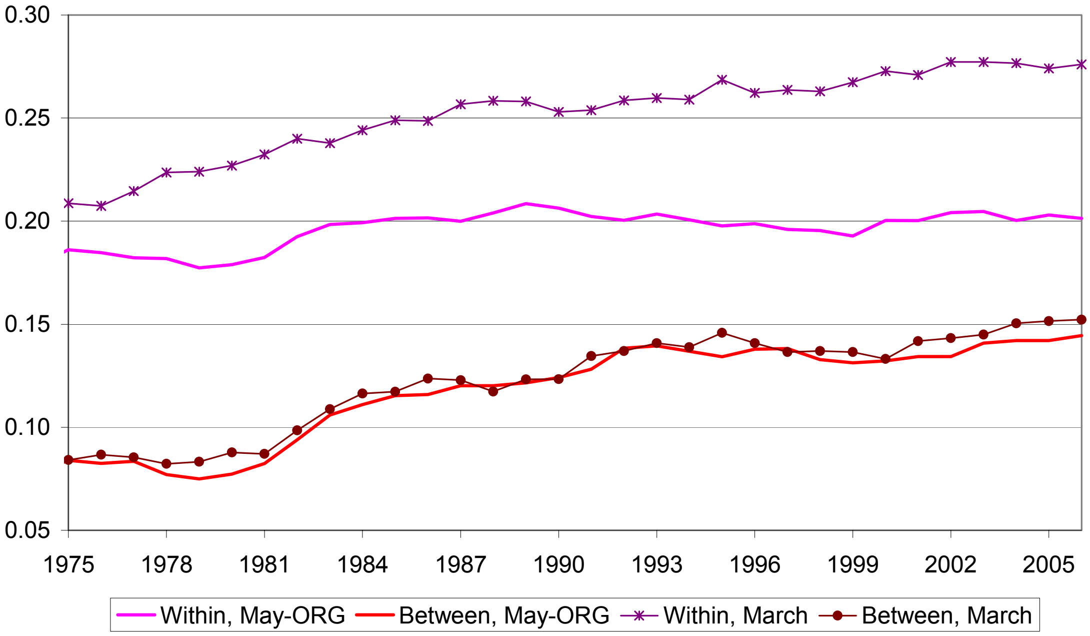


Figure 12b: Variance in May-ORG vs. March CPS Controlling for Composition Effects, Women

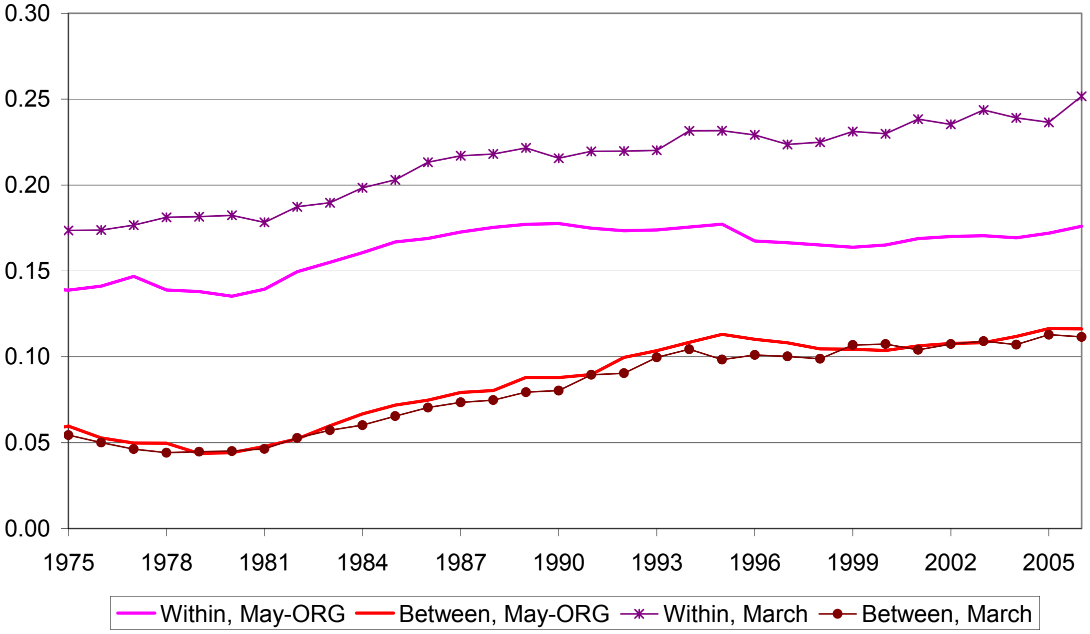


Figure 13a: Top-coding Adjustments in March CPS Controlling for Composition Effects, Men

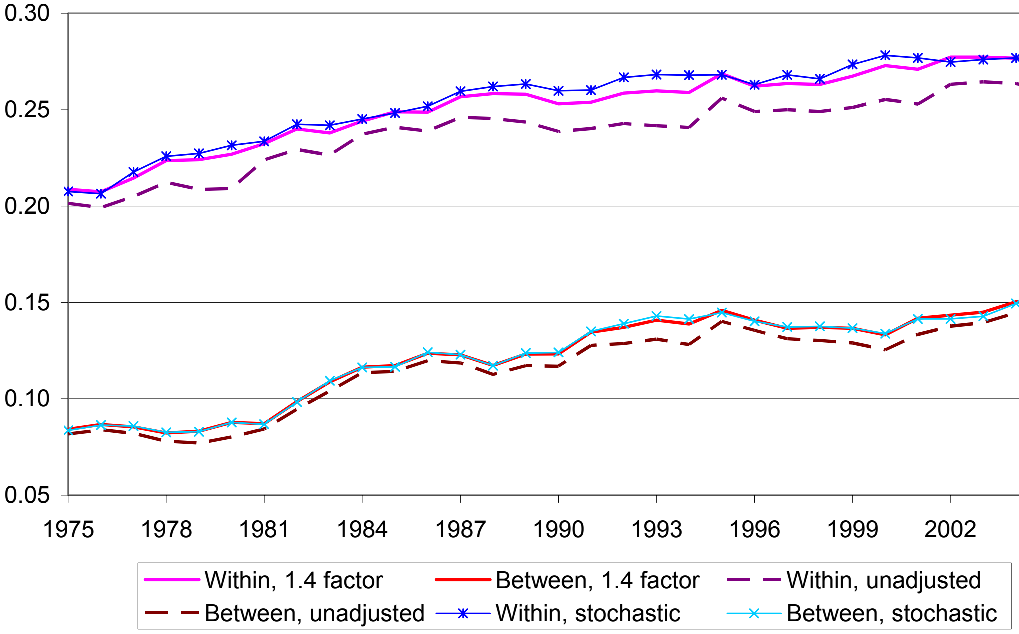
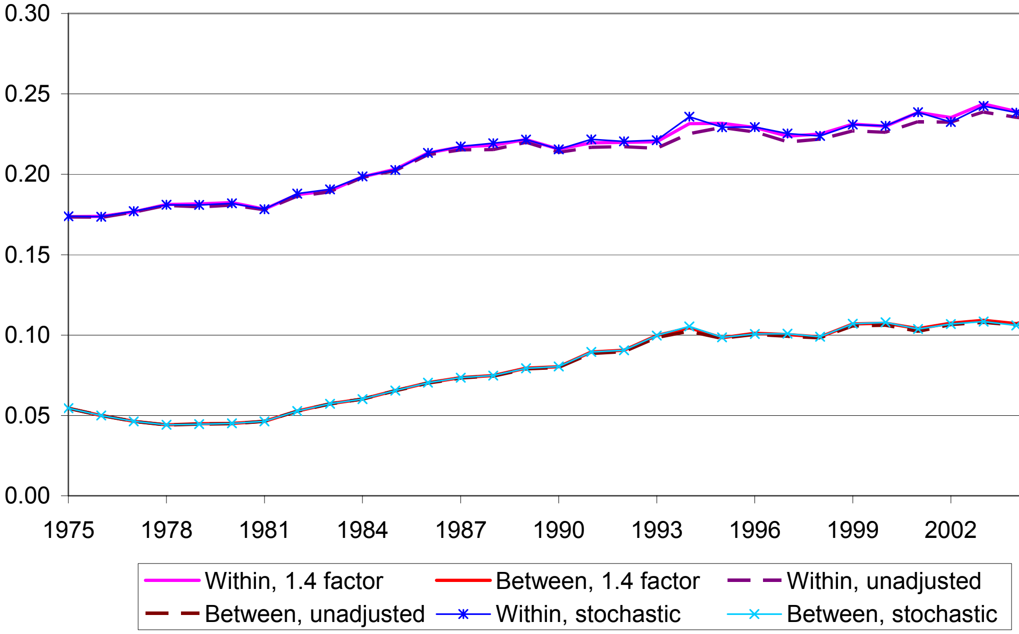


Figure 13b: Top-coding Adjustments in March CPS Controlling for Composition Effects, Women


Within, 1.4 factor
Between, 1.4 factor
Within, unadjusted
Between, unadjusted
Within, stochastic
Between, stochastic