July 26, 2004

Trends in U.S. Wage Inequality: Re-Assessing the Revisionists[*]

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Preliminary and incomplete: Please do not circulate

[*] We are particularly grateful to Josh Angrist, Paul Deveraux, Francis Kramarz, and Derek Neal for valuable comments and to Michael Anderson, Tal Gross and Ashwini Agrawal for excellent research assistance. Autor acknowledges generous support from the National Science Foundation (CAREER SES-0239538) and the Sloan Foundation. Katz acknowledges financial support from the Spencer Foundation.

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ABSTRACT

A large literature documents a substantial rise in U.S. wage inequality and educational wage differentials over the past several decades and finds that these trends can be primarily accounted for by shifts in the supply of and demand for skills reinforced by the erosion of labor market institutions affecting the wages of low- and middle-wage workers. Some recent ("revisionist") work concludes that (1) the rise in wage inequality was an "episodic" event of the first-half of the 1980s rather than a "secular" phenomenon, (2) it was largely caused by a falling minimum wage rather than by supply and demand factors, and (3) the rise in residual wage inequality since the mid-1980s is explained by confounding effects of labor force composition rather than true increases in inequality within detailed demographic groups. We re-examine these issues using wage data from the March Current Population Survey (CPS) covering 1963 to 2002 and from the May and Outgoing Rotation Group supplements of the CPS for 1973 to 2003. We find some limited support for these revisionist conclusions, but also significant puzzles. Although the growth of overall inequality in the U.S. slowed in the 1990s, upper tail inequality rose almost as rapidly during the 1990s as during the 1980s. While changes in the minimum wage can account for much of the movement in lower tail earnings inequality, strong time series correlations of the evolution of the real minimum wage and upper tail wage inequality raise questions concerning the causal interpretation of such relationships. We also find that changes in the college/high school wage premium appear to be well captured by standard models emphasizing rapid secular growth in the relative demand for skills and fluctuations in the rate of growth of the relative supply of college workers. Furthermore, a quantile decomposition applied to the CPS data reveals large and persistent rise in within-group earnings inequality over the past several decades, controlling for changes in labor force composition. These patterns are not adequately explained by either a 'unicausal' skill-biased technical change explanation or a revisionist hypothesis focused on minimum wages and mechanical labor force compositional effects. We speculate that these puzzles can be partially reconciled by a modified version of the skill-biased technical change hypothesis that generates a polarization of skill demands. The source of differences in the evolution of residual wage inequality in the March and May/ORG CPS samples in the 1970s and 1990s remains unclear.

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I. Introduction

Much research has documented a large increase in U.S. wage inequality in the 1980s that was associated with the widening of the wage structure along several dimensions (Bound and Johnson 1992; Katz and Murphy 1992; Levy and Murnane 1992; Murphy and Welch 1992; Juhn, Murphy and Pierce 1993). Wage differentials by education (particularly the college wage premium), occupation, and age/experience increased.[1] Residual wage inequality (wage dispersion within demographic and skill groups) also greatly expanded during the 1980s. This growth of wage inequality was reinforced by changes in non-wage compensation leading to a large increase in total compensation inequality (Pierce 2001). The labor market changes of the 1980s translated into a large rise in both household income inequality and consumption inequality implying a marked increase in the disparities of economic well-being for U.S. families (Cutler and Katz 1991, 1992; Attanasio and Davis 1996; Karoly and Burtless 1995).

The sharp U.S. wage structure changes of the 1980s were preceded by a narrowing of educational wage differentials and little overall change in wage inequality during the 1970s and have been followed by a period of slower growth of most measures of overall wage inequality and educational wage differentials (Mishel, Bernstein, and Boushey 2002). A large literature has attempted to place these changes in a broader historical and comparative perspective and to assess the roles of market forces affecting the supply and demand for skills and of labor market institutions in driving the recent evolution of the U.S. wage structure.[2]

This literature finds that strong secular growth in the demand for more-skilled workers (largely related to skill-biased technological change or SBTC) combined with fluctuations in the rate of growth of the supply of more-educated workers goes a substantial distance towards explaining movements in the educational wage differentials. The sharp rise in the college wage premium of the 1980s reflects a slowdown in the rate of growth of the relative supply of college equivalent workers (from a slowdown in

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[1] A substantial narrowing of gender wage differentials both overall and for all age and education groups is the primary exception to the broad pattern of a widening U.S. wage structure since 1980.

[2] See Katz and Autor (1999), Goldin and Katz (2001), and Acemoglu (2002) for overviews of this literature. See Berman, Bound and Machin (1998) and Machin and Van Reenan (1998) for international comparisons.

the growth of educational attainment for cohorts born starting around 1950) and some acceleration in demand shifts favoring more-skilled workers partially driven by skill-biased technological and organizational changes associated with the computer revolution (Autor, Katz, and Krueger 1998). Some have interpreted rising residual inequality as also reflecting rising price of (unobserved) skill and rapid demand growth favoring more skilled workers (Juhn, Murphy and Pierce 1993). This work also concludes that the 1980s erosion of the strength of labor market institutions protecting low-wage and middle-wage workers (the minimum wage and unions) exacerbated the effects of market forces in widening wage inequality (Bound and Johnson 1992; DiNardo, Fortin, and Lemieux 1996; Katz and Autor 1999).

Recent studies challenge this consensus view that the U.S. has experienced a persistent rise of wage inequality in recent decades that has contributed to a greater inequality of economic well-being and has been partially driven by market forces affecting skill supplies and demands. This new research takes advantage of actual experience of the last decade and re-examines analyses of the data on wage structure changes through the 1980s. These studies conclude that (1) rising wage inequality was an "episodic" event of the first half of the 1980s (Card and DiNardo 2002); it was largely caused by the erosion of the real value of the minimum wage with little role for SBTC and other market forces (Card and DiNardo 2002; Lee 1999; Lemieux 2004); and (3) the growth of residual wage inequality (at least since the mid-1980s) is substantially a "spurious" consequence of shifts in labor force composition (Lemieux 2004).

In this paper, we update the data on the U.S. wage structure and re-evaluate the traditional and revisionist explanations for the patterns, causes, and consequences of changes in the U.S. wage inequality. We use wage data from the March Current Population Surveys (CPS) covering 1963 to 2002 and from the May CPS samples for 1973-78 combined with the CPS Outgoing Rotation Group (ORG) files for 1979 to 2003 to examine changes in the U.S. wage structure over recent decades.

We find some support for both the revisionist and traditional stories and some puzzles for both schools of thought. Although the growth in overall wage inequality slowed in the 1990s, wage inequality in the upper half of the distribution (the 90-50 wage gap) rose almost as rapidly in the 1990s as in the 1980s. The rise in wage inequality in the lower half of the wage distribution in the first part of the 1980s was partially an episodic event, but the growth of upper tail inequality appears to be a secular phenomenon of at least the last two decades. Standard supply-demand models of the college wage premium do a reasonable job of explaining the evolution of the college wage premium over the past four decades but such models imply some slowdown in the rate of growth of demand shifts favoring more-educated workers over the last decade. The decline in the real minimum wage appears important for changes in skill differentials for younger workers and in the evolution of wage inequality in the lower part of the wage distribution. But the correlations of minimum wage changes with movements in upper-tail wage inequality are suggestive that some of this relationship may spuriously reflect other market or institutional factors. There appears to have been a substantial rise in within group wage inequality over the past two decades even after adjusting for changes in labor force composition.

In a companion paper (Autor, Katz and Kearney, 2004), we also evaluate the “revisionist” findings of a set of papers by Krueger and Perri (2002, 2003) that report that increases in U.S. *wage* inequality after the mid 1980s have not led to commensurate increase in *consumption* inequality, particularly within education groups. The authors propose that endogenous improvements in credit markets are responsible for this disjuncture. Our preliminary analysis suggests an alternative explanation. We find that consumption inequality has in fact closely tracked the evolution of *household income* inequality – that is, that there is no substantial divergence between income and consumption inequality. We do find, however, that inequality of household income has not kept pace with inequality of wage earnings during the 1990s.

The remainder of this paper is organized as follows. Section II documents the evolution of the U.S. wage structure from 1963 to 2003. Section III presents some basic time series models to assess the role of demand, supply, and institutional factors in the evolution of U.S. educational wage differentials. Section IV presents an analogous analysis of changes in overall wage inequality and explores the timing of correspondence of changes in different part of the wage distribution to changes in the federal real minimum wage. Section V uses a quantile regression methodology to decompose changes in overall and residual inequality and explores the importance of labor force composition changes. Section VI assesses alternative explanations for the observed changes in the U.S. wage structure. Section VII concludes.

II. U.S. Wage Structure Changes Over the Past Four Decades

We summarize the basic changes in the U.S. wage structure over the last four decades using data on the weekly earnings of full-time-full-year (FTFY), wage and salary workers (those working 35 or more hours per week and at least 40 weeks in the previous calendar year) from the March CPS of 1964 to 2003 (covering earnings from 1963 to 2002). Our core sample consists of those aged 16 to 64 years (in the earnings year).[3] The March CPS data have been widely used in studies of wage inequality. They have the advantage of providing reasonably comparable data on annual earnings, weeks worked in the previous year, and full-time/part-time status since the early 1960s allowing one to produce consistent weekly wage series for FTFY workers. We supplement this analysis with information on changes in the distribution of hourly wages (weighted by hours worked in the reference week) using point-in-time wage data from the May CPS for 1973-78 and CPS ORG samples for 1979-2003.

The March CPS data are less than ideal for analyzing the hourly wage distribution since they lack a point-in-time wage measure and thereby hourly wages must be computed by dividing annual earnings by the product of weeks worked last year and usual weekly hours last year. Estimates of hours worked last year from the March CPS appear to be quite noisy and data on usual weekly hours last year are not available prior to the 1976 March CPS. The May/ORG samples provide more accurate measures of the hourly wage distribution but cover a shorter time period than the March CPS. Both the March and May/ORG CPS samples have undergone various changes in processing procedures (especially involving the top-coding of high earnings and the flagging of earning imputations and algorithms used for allocating earnings to those individuals who do not answer earnings questions in the survey) that create challenges in producing consistent data series over time.[4] We have tried to account for these changes to the extent possible to make

[3] We also drop from the sample (full-time) workers with weekly earnings below ½ the value of the real minimum wage in 1982 ($67 a week in 1982 dollars or $112 a week in 2000 dollars).

[4] Card and DiNardo (2002) and Lemieux (2004) provide thoughtful discussions of the time-series data comparability issues involved in analyzing wage series from March and May/ORG CPS samples. As discussed below, we reach different conclusions from these authors about the relative validity of these series for consistent time-series, analysis.

the wage series as comparable as possible over time.

We have explored the robustness of our findings to choice of data set, sample, and wage concept. In particular, we have also examined hourly wage series for all workers using the March CPS and the weekly wages of full-time workers using the May/ORG CPS. Changes in the between-group component of wage structure changes (by education, age/experience, and gender groups) are not very sensitive to the choice of data set, wage concept, and sample restrictions. The patterns of changes in residual wage inequality are more sensitive to such choices. The data processing details for our various CPS wage samples are contained in the Data Appendix.

Figure 1 uses data on FTFY workers from the March CPS to illustrate the substantial overall widening of U.S. wage inequality for both men and women over the past 40 years. This figure plots the change in log real weekly wages by percentile for men and for women from 1963 to 2002.[5] The figure displays a substantial widening of both the male and female wage distributions with the 90th percentile earners rising by approximately 40 log points (almost 50 percent) relative to 10th percentile earners for both men and women. The figure also indicates a monotonic (and almost linear) spreading out of the entire wage distribution for women and for the wage distribution above around the 30th percentile for men. In contrast to the widening of wage inequality within gender, women have substantially gained on men throughout the wage distribution over last four decades.

We next explore the time pattern of changes in different dimensions of wage inequality. We focus on changes in overall wage inequality (summarized by the 90-10 log wage differential), inequality in the upper and lower halves of the wage distribution (summarized by 90-50 and 50-10 log wage gaps), between-group wage differentials (illustrated using the college-high school wage premium), and within-group (residual) wage inequality (summarized by the 90-10 residual wage gap conditioning on measures of education,

[5] The top-coding of CPS wage data makes it not very useful for measuring changes in the very top part of the wage distribution. Thus, we symmetrically trim the top and bottom parts of the distribution in Figure 1 and focus on wage changes from the 3rd to 97th percentile.

age/experience, and gender).[6] The differences in time patterns of movement in different measures of wage structure changes are highlighted in Figure 2, which displays the evolution of the 90-10 overall and residual wage gaps for males and the college-high school log wage premium (representing a fixed weighted average of the college plus/high school wage gaps separately estimated for males and for females in four different experience groups). Figure 2 indicates substantial growth in all three measures of wage inequality during the 1980s and some slowdown in the rate of growth in all these measures in the 1990s. But the series do not always move together suggesting it will be quite difficult for simple unicausal explanations for wage structure changes whether focused on SBTC or the minimum wage. The college wage premium declined substantially in the 1970s, while residual inequality for males in the March CPS (although not in the May/ORG CPS) started growing modestly in the 1970s. The college wage premium expanded in the 1960s in a period of little change in residual inequality.

Furthermore, changes in wage dispersion in the top and bottom halves of the wage distribution for both men and women have moved quite differently in recent decades. Figure 3 compares the evolution of the 90-10 log hourly and full-time weekly wage gaps for males and females from 1963-2002 using the March CPS samples and for the years 1973 to 2003 using the MORG samples. Figures 4 and 5 present more detailed measures of wage inequality by gender, providing separate panels for upper-tail (90/50) and lower-tail (50/10) wage inequality. Upper tail and lower tail wage inequality expanded rapidly in the first half of the 1980s for both men and women using FTFY weekly earnings data from the March surveys and hourly wages from the May/ORG surveys. But the 50-10 wage gap for the most part stopped growing and in the hourly wage series for both the March CPS and ORG CPS for males shows an actual decline since the late 1980s. In contrast, the 90-50 wage gap continues to grow with both wage measures in both the March CPS and ORG CPS for men and women from the mid-1980s to the present.

These differences in the growth of upper and lower half wage inequality in the 1980s and 1990s also are

[6] The robustness and sensitivity of conclusions concerning the timing of changes in overall and residual wage inequality changes to the choice of wage concept and sample are illustrated in Appendix Tables 1a and 1b which present changes over consistent sub-periods from 1975-2002 in different measures of inequality for males, females,

apparent in the microdata on wages and total compensation from the establishment-based Employment Cost Index (ECI) sample. Pierce (2001) in an analysis of the ECI microdata finds a large rise in 50-10 and 90-50 wage (and total compensation) differentials from 1982 to 1986 for a sample combining men and women. The rise in lower half inequality ceases and somewhat reverses itself in the ECI data from 1986 to 1996; the growth in upper half inequality continues steadily over the next decade after 1986. The rapid and steady growth of the relative wages of upper tier earnings is also clearly illustrated through the rising shares of wages of the top 1% and top decile earners in IRS tax data and the rising relative earnings of CEOs over the last three decades (including the 1970s) carefully documented by Piketty and Saez (2003).

Thus, the sharp growth in wage inequality of the lower-half of the wage distribution of the early 1980s seems to have been an episodic event that has not been reversed but has not re-occurred over the past fifteen years. The growth of the wage inequality in the upper half of the wage distribution appears to represent a rather steady secular increase over the past 25 years.[7]

Table 1 summarizes the major between-group wage structure changes by presenting mean log real wage changes by sub-period from 1963 to 2002 for various groups defined by sex, education, and potential experience. Mean (predicted) log real weekly wages were computed in each year for 40 detailed sex-education-experience groups and mean wage for broader groups are fixed-weighted averages of the relevant sub-group means (using the average share of total hours worked for each group over 1963 to 2002 as weights) to adjust for compositional changes within each group. The first row indicates that composition-adjusted real wages increased by 24 log points over the full period with rapid wage growth in the 1960s, stagnant and declining real wages from 1971 to 1995, and rapid real wage growth again in the late 1990s. The next two rows show that women gained substantially on males (by 15.5 log points over the full sample)

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and both combined using weekly earnings for full-time workers and hourly wages for all workers for the March CPS and May/ORG CPS.

[7] The differences in the growth of the 90-50 and 50-10 wage differentials have previously been emphasized by Mishel, Bernstein and Boushey (2002) and are also noted by Lemieux (2004). Using Census earnings data, Angrist, Chernozhukov and Fernández-Val (2004) document a sharp rise in residual inequality from 1980 to 1990, with a continuing increase from 1990 to 2000 concentrated in the upper half of the wage distribution.

with the growth in the relative earnings of women concentrated in the 1979 to 1995 period. The following six rows summarize real wage changes by educational groups and highlight expanding educational wage differentials with particularly large increases in the relative earnings of college graduates. The sharp differences across decades of rising educational wage differentials in the 1960s, narrowing educational wage differentials in the 1970s, sharp increases in educational gaps in the 1980s, and continued growth in the college wage premium in the 1990s are clearly indicated. The bottom part of the table contrasts changes in real wages for younger and older male high school and college graduates. Experience differentials expanded for college and high school graduates over the full sample period with the rise in experience differentials happening in the 1960s and 1970s for college graduates and being sharpest in the 1980s for high school graduates.

III. Understanding Changes in the College Wage Premium

Many studies, at least since Freeman (1975) and Tinbergen (1975), have used simple formal supply and demand frameworks to analyze changes in educational wage differentials. We follow this tradition and present simple time-series models of the U.S. college wage premium covering 1963 to 2002 and augment the specification to allow for an impact of changes in a key labor market institutional factor, the federal minimum wage.

Our illustrative conceptual framework starts with a CES production function for aggregate output Q with two factors, college equivalents (c) and high school equivalents (h):

(1) $$Q_t = [\alpha_t(a_tN_{ct})^{\rho} + (1-\alpha_t)(b_tN_{ht})^{\rho}]^{1/\rho}$$

where N_{ct} and N_{ht} are the quantities employed of college equivalents (skilled labor) and high-school equivalents (unskilled labor) in period t, a_t and b_t represent skilled and unskilled labor augmenting technological change, α_t is a time-varying technology parameter that can be interpreted as indexing the share of work activities allocated to skilled labor, and ρ is a time invariant production parameter. Skill-neutral technological improvements raise a_t and b_t by the same proportion. Skill-biased technological changes involve increases in a_t/b_t or α_t. The aggregate elasticity of substitution between college and high-school equivalents is given by $\sigma = 1/(1-\rho)$.

Under the assumption that college and high-school equivalents are paid their marginal products, we can use equation (1) to solve for the ratio of marginal products of the two labor types yielding a relationship between relative wages in year t, w_{ct}/w_{ht}, and relative supplies in year t, N_{ct}/N_{ht} given by

$$(2) \qquad \ln(w_{ct}/w_{ht}) = \ln(\alpha_t/[1-\alpha_t]) + \rho\ln(a_t/b_t) - (1/\sigma)\ln(N_{ct}/N_{ht}),$$

which can be rewritten as

$$(3) \qquad \ln(w_{ct}/w_{ht}) = (1/\sigma)[D_t - \ln(N_{ct}/N_{ht})],$$

where D_t indexes relative demand shifts favoring college equivalents and is measured in log quantity units. The impact of changes in relative skill supplies on relative wages depends inversely on the magnitude of aggregate elasticity of substitution between the two skill groups. The greater is σ, the smaller the impact of shifts in relative supplies on relative wages and the greater must be fluctuations in demand shifts (D_t) to explain any given time series of relative wages for a given time series of relative quantities. Changes in D_t can arise from (disembodied) skill-biased technological change, non-neutral changes in the relative prices or quantities of non-labor inputs, and shifts in product demand.

Following the approach of Katz and Murphy (1992), we directly estimate a version of equation (3) to explain the evolution from 1963 to 2002 of the overall log college/high school wage differential series for FTFY workers from the March CPS shown in Panel A of Figure 2. We substitute for the unobserved demand shifts D_t with simple time trends and a measure of labor market cyclical conditions (the unemployment rate of males aged 25-54 years). We also include an index of the log relative supply of college/high school equivalents.[8] Our full model includes the log real minimum wage as a control variable:

$$(4) \qquad \ln(w_{ct}/w_{ht}) = \gamma_0 + \gamma_1 t + \gamma_2\ln(N_{ct}/N_{ht}) + \gamma_3\ln(\text{Real Min Wage}_t) + \gamma_4\text{Unemp}_t + \varepsilon_t,$$

where γ_2 provides an estimate of $1/\sigma$.

The large increase in the college wage premium over the last 40 years coincided with a substantial

[8] We use a relatively standard measure of college/non-college relative supply calculated in "efficiency units" to adjust for changes in labor force composition among gender and experience groups. Full details are provided in the Data Appendix.

secular rise in the relative supply of college workers with the college graduate share of the full-time equivalent workforce increasing from about 10.6 percent in 1960 to over 31 percent in 2003. Figure 6 displays the growth of the log relative supply of college equivalents from 1963 to 2002 and illustrates sharp slowdown in the trend growth rate starting around 1982. Figure 6 also illustrates the growth of the relative supply of college workers accelerated a bit in the 1970s relative to the 1960s. Thus, rapid trend growth in the relative demand for college workers is going to be necessary in a market clearing model to reconcile growing relative supply with a rising college wage premium. The increased rate of growth of college relative supply in the 1970s and slowdown starting in the 1980s combined with constant trend growth in relative demand go some distance to explaining modest increases in the college premium in the 1960s, a decline in the college premium in the 1970s, and the sharp increase over the past two decades. The top panel of Figure 7 illustrates the explanatory power of such an approach by showing that the deviations in relative supply growth from a linear trend roughly fit the broad changes in the detrended college wage premium from 1963 to 2002.

Table 2 presents representative regression models for the overall college/high school log wage gap following this simple approach. The first column uses the basic specification of Katz and Murphy (1992) for the 1963 to 1987 period (the period analyzed by Katz-Murphy) with only a linear time trend and the relative supply measure included as explanatory variables. Although our data processing methods differ somewhat from those of Katz and Murphy, we uncover quite similar results with an estimate of $\gamma_2 = 0.64$ (implying σ=1.56) and with estimated trend growth in the college wage premium of 2.7 percent per annum. The lower panel of Figure 7 uses this replication of the basic Katz-Murphy model from col. (1) of Table 2 to predict the evolution of the college wage premium for the full sample period of 1963 to 2002 and compares the predicted and actual college wage gap measures. The Katz-Murphy model does a good job of forecasting the growth of the college wage premium through 1992 (with the exception of the late 1970s) but the continued slow growth of relative supply after 1992 leads it to over-predict the growth in the college wage premium over the last decade. The simple supply-demand model implication of this pattern is that there has been a slowdown in trend relative demand growth for college workers since 1992 as illustrated by a comparison of the models in columns (2) and (3) of Table 2 without and with allowing for a trend break in 1992. The model in column (3) covering the full 1963-2000 period indicates a significant slowdown of demand growth after 1992 but still indicates a large impact of relative supply growth with an estimated aggregate elasticity of substitution of 1.66 (1/0.601).[9]

The implied slowdown in trend demand growth in the 1990s is potentially inconsistent with a naïve SBTC story looking at the growth of computer investments since these continued most rapidly in the 1990s. But strong cyclical labor market conditions with low unemployment in expansion of the 1990s might account for some of this pattern and the differential impacts of labor market institutions such as the minimum wage might also play a role in the evolution of the college wage premium. As discussed by DiNardo, Fortin and Lemieux (1996) and Lee (1999), the real value of the U.S. minimum wage experienced a sharp decline in the 1980s and more modest movements in the 1960s, 1970s, and the past decade.

The roles of cyclical conditions and the minimum wage are examined in the augmented models illustrated in columns (4) and (5) of Table 2. The real minimum wage and prime age male unemployment rates have modest additional explanatory power in the expected directions and reduce the extent of unobserved slowdown in trend demand growth over the last decade. But the inclusion of these variables does not much alter the important roles for relative supply growth fluctuations and trend demand growth in explaining the evolution of the college wage premium over the past four decades. A model without the relative supply variable in column (6) leads to larger impacts of the real minimum wage but it also has much less explanatory power and generates a puzzling negative impact of prime age male unemployment on the college wage premium.

Changes in the college/high school wage gap have differed by age/experience groups over recent decades. We illustrate this pattern through a comparison of the evolution of the college wage premium for younger workers (those with 0-9 years of potential experience) and older workers (those with 20-29 years of potential experience) in the upper panel of Figure 8. The returns to college for younger workers have

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[9] Similar conclusions of a significant slowdown in trend relative demand growth for college workers arise in models allowing trends breaks in any year from 1989 to 1994.

increased much more substantially since 1980 than for older workers. To the extent that workers with similar education but different ages (or experience levels) are imperfect substitutes in production, one should expect age-group (or cohort-specific) relative skill supplies (as well as aggregate relative skill supplies) to affect the evolution of the college-high school by age (or experience) as emphasized in a careful analysis by Card and Lemieux (2001). The differences in the time series patterns of experience-group specific relative supplies of college equivalents are illustrated in the lower panel of Figure 8.

Table 3 presents estimates of regression models of the college wage by experience group that extend the basic specification in equation (4) to include own experience group relative skill supplies.[10] The first two columns of Table 3 present regressions pooled across 4 potential experience groups (those with 0-9, 10-19, 20-29, and 30-39 years of experience) allowing for group-specific intercepts but constraining the other coefficients to be the same for all experience groups. These models estimate:

(5) $$\ln(w_{cjt}/w_{hjt}) = \beta_0 + \beta_1[\ln(N_{cjt}/N_{hjt}) - \ln(N_{ct}/N_{ht})] + \beta_2\ln(N_{ct}/N_{ht}) + X_t\beta_3 + \delta_j + \eta_{jt},$$

where j indexes experience group, the δ_j are fixed effects for experience groups, and X_t includes measures of time trends and other demand shifters. This specification arises from an aggregate CES production function in college and high school equivalents of the form of equation (1) where these aggregate inputs are themselves CES sub-aggregates of college and high school labor by experience group (Card and Lemieux 2001). Under these assumptions, $-1/\beta_2$ provides an estimate of σ the aggregate elasticity of substitution and $-1/\beta_1$ provides an estimate of σ_E the partial elasticity of substitution between different experience groups within the same education group,

The estimates in the first two columns of Table 3 indicate substantial effects of own group and aggregate supplies on the evolution the college wage premium by experience group with implied estimates of the aggregate elasticity of substitution that are very similar to the aggregate models in Table 2. The implied value of the partial elasticity of substitution between experience groups is around 3.44 somewhat lower than the estimates in Card and Lemieux (2001). These estimates also imply that differences in own-

[10] An analogous set of regressions to explain the evolution of the college wage premium by age groups is presented in Appendix Table 2.

group relative college supply growth go a substantial distance towards explaining variation across experience groups in the evolution of the college wage premium in recent decades. For example, as seen in Figure 8, from 1980 to 2002 the college wage premium increased by .288 log points for the 0-9 year experience group and by .195 for the 20-29 year experience group. Over the same period the own group relative college supply for the 0-9 year experience group grew by .251 log points less rapidly than for the 20-29 year experience group. Thus, using the implied own-group relative supply elasticity of -.293 in column (1) of Table 3, we find that the slower relative supply growth for the younger (0-9 year) experience group explains most (79% or .074 of a .093 log point gap) of the larger increase in the college premium for the younger than for the older (20-29 year) experience group.

The final four columns of Table 3 present estimates of analogous regression models of the college wage premium separately estimated by experience group. Trend demand changes and relative skill supplies play an important role in changes in educational differentials for younger and prime age workers. The post-1992 slowdown in trend demand growth is apparent for the youngest experience group but not for prime age workers. The college wage premium for younger workers appears more sensitive to own group and aggregate relative skill supplies than the premium for older workers. We also do find that the real minimum wage is a significant determinant of changes in the college wage premium for younger workers (those with less than 20 years of potential experience).

IV. Overall Wage Inequality Changes and the Minimum Wage

As emphasized by Lee (1999), Card and DiNardo (2002) and Lemieux (2004), there is a striking time series relationship between the real value of the federal minimum wage and hourly wage inequality, as measured by the 90-10 log earnings ratio. This relationship is depicted in Figure 9. A simple regression of the 90-10 log hourly wage gap from the May/ORG CPS for the years 1973 to 2003 on the real minimum wage (deflated by the PCE deflator) and a constant yields a coefficient of -0.79 and an R-squared of 0.71. Based in part on this tight correspondence, Card and DiNardo and Lemieux argue that much of the rise in overall and residual inequality over the last two decades may be attributed to the minimum wage. Using a cross state analysis of minimum wage levels and earnings inequality, Lee (1999) also concludes that were it not for the falling U.S. minimum wage, there would have been no rise in inequality during the 1980s.

A potential problem for this line of argument is that the majority of the rise in earnings inequality over the last two decades occurred in the upper half of the earnings distribution (see Appendix Table 1a). Since it is not obvious why a declining minimum wage would cause upper-tail earnings inequality to rise, this observation suggests that the minimum wage is unlikely to provide a complete explanation for overall inequality growth. A further concern about the validity of this explanation is raised by comparing minimum wage levels with upper and lower-tail inequality. As shown in the upper panel of Figure 10, the level of the minimum wage is highly correlated with lower-tail earnings inequality between 1973 and 2003; a 1 log point rise in the minimum is associated with 0.28 log point compression on lower tail inequality. Somewhat surprisingly, however, the minimum wage is also highly correlated with upper tail inequality. Over this time interval, a 1 log point rise in the minimum is associated with a 0.51 log point compression in upper tail inequality (Figure 10, lower panel).

These bivariate relationships may potentially mask other confounds. To explore the relationships in slightly greater detail, we estimate in Table 4 a set of descriptive regressions for 90-10, 90-50 and 50-10 hourly earnings inequality over 1973 to 2003. In addition to the minimum wage measure used in Figures 9 and 10, these models add a linear time trend, a measure of college/high-school relative supply (calculated from the May/ORG CPS), and the male prime-age unemployment rate (as a measure of labor market tightness). The main finding from these models, visible in Table 4, is that the relationship between the minimum wage and *both* upper and lower-tail inequality is robust. In a specification that includes a linear time trend, the college/high school supply measure, and the prime-age unemployment rate variable, the minimum wage measure has a coefficient of -0.27 for lower tail inequality (t = 4.6) and a coefficient of -0.14 (t = 3.6) for upper tail inequality. Aside from the time trend and the minimum wage measure, the other explanatory variables in these regressions are insignificant.[11]

[11] When we use residual inequality as the dependent variable in comparable models, we also find significant effects of the minimum wage on upper and lower tail inequality.

These patterns suggest that the striking time series correlation between minimum wages and inequality likely provides a misleading metric of the causal effect of the minimum wage on earnings inequality. Indeed, we view the relationship between the minimum wage and upper tail inequality as evidence of spurious causation. While we have little doubt that the decline in the real minimum wage during the 1980s contributed to lower tail inequality – particularly for women – the robust correlation of the minimum wage with upper tail inequality suggests that other factors are at work.[12] One possible explanation for this link is that federal minimum wage shifts during these decades were in part a response to current economic conditions. The rapid fall in the minimum wage during 1980s took place during a deep recession. The legislated increases in the minimum wage in 1990 to 1991 and 1996 to 1997 occurred during relatively better economic conditions. If these macroeconomic shocks also directly affected earnings inequality, this would in part explain the coincidence of falling minimum wages and rising upper tail inequality.[13]

V. Rising inequality: The role of composition and prices

As emphasized by Juhn, Murphy and Pierce (1993; JMP hereafter), the observed dispersion of earnings at a point in time depends upon both the prices associated with worker given characteristics – that is, their 'returns' – and the distribution of those characteristics in the workforce. Consequently, a rise in earnings dispersion may be caused by a change in prices, a change in workforce composition, or the interaction of the two. JMP employ an extended Oaxaca-Blinder (1973) decomposition procedure to analyze the contribution of prices and composition to the growth of U.S. earnings inequality over 1964 to 1988. The JMP procedure uses OLS wage regressions to partition earnings dispersion into components due to prices, quantities, and residual dispersion (which they refer to as unmeasured prices and quantities). A key

[12] Indeed, Lee (1999) also noted a puzzling relationship between the 'effective' state minimum wage (that is, the log difference between the state median and the state minimum) and state level upper-tail inequality. Opposite to the simple time-series regressions above, Lee's cross-state analysis finds that increases in the effective state minimum wage appear to *reduce* upper-tail inequality, both for males and for the pooled-gender distribution (see Lee, 1999, Table II). Due to this puzzling result, Lee suggested caution in causally attributing trends in male and pooled-gender earnings inequality to the minimum wage.

[13] In a similar vein, Acemoglu, Aghion and Violante (2001) argue that the decline in union penetration in the United States and the United Kingdom is partly explained by changing skill demands that reduced the viability of rent sharing bargains between high and low skill workers.

conclusion of the JMP analysis is that the contribution of changing labor force composition to the growth of earnings inequality between 1964 and 1988 is negligible. Of 21 log points growth in the 90/10 earnings full-time weekly log earnings differential during this period, JMP's simulation exercise attributes only 0.6 log points to changes in workforce composition.

A limitation of the JMP methodology is that it implicitly models earnings residuals as being homoskedastic among all worker groups. Because of this homoskedasticity assumption, changes in workforce composition cannot contribute to residual inequality in the JMP model. An insightful recent paper by Lemieux (2004) calls this modeling assumption into question. Lemieux observes that, due to differential investments in on-the-job training, the canonical Mincer (1974) earnings model implies that earnings trajectories may tend to fan out (i.e., become more heteroskedastic) as workers gain labor market experience. Consequently, a change in the stock of education or experience of the labor force may cause residual earnings dispersion to rise or fall.

Since the average education and experience of the U.S. labor force rose substantially during the last three decades – particularly as the large 1970s college cohorts reached mid-career during the 1990s – Lemieux hypothesizes that changing workforce composition may have contributed to the widely documented increase in residual earnings dispersion over 1973 to 2003. Using a variant of the reweighting procedure developed by DiNardo, Fortin and Lemieux (1996), Lemieux (2004) simulates counterfactual trends in residual earnings inequality over 1973 to 2003, holding the education and experience of the labor force constant. This simulation suggests that the bulk of the growth in residual wage dispersion in the U.S. between 1973 and 2003 in the May/MORG CPS – and *all* of the growth after 1988 – is explained by changes in workforce composition rather than by true changes in residual inequality within defined worker groups – what we call "price effects." Hence, Lemieux concludes that the widely discussed rise the residual inequality of U.S. earnings is primarily a "spurious" effect of composition.

One puzzle for this conclusion, however, is that a comparable analysis of the March CPS does not yield a similar conclusion. As noted in an Appendix of Lemieux (2004), the contribution of labor force composition to the rise of residual inequality in the March CPS is only one-third as large as in the

May/ORG CPS.[14] To reconcile this inconsistency, Lemieux presents evidence to suggest that the March CPS overstates 'true' residual earnings inequality. The May/ORG CPS and March CPS use distinct methods to collect earnings information. The March CPS collects annual earnings, weeks worked, and average hours per week in the prior year for each respondent. These responses are typically used to impute an hourly wage. The May/ORG uses two sets of earnings questions (and many additional questions after 1994). All workers are asked to report usual weekly earnings, which are usually divided by hours worked in the previous week to calculate an hourly wage.[15] In addition, workers who are paid hourly (about 50 to 60 percent of the sample) directly report an hourly wage.[16] In Lemieux's analysis and in our own, precedence is given to the direct hourly wage report over the imputed wage measure based on weekly earnings. Lemieux's critique of the March CPS rests on the sensible observation that imputed hourly wage observations in the March CPS appear to be noisier (i.e., have more dispersion) than do direct hourly earnings reports in the May/ORG CPS. Interestingly, Lemieux also finds for non-hourly workers that imputed hourly wages in the March CPS (based on annual earnings) do not appear noisier than imputed hourly wages in the May/ORG CPS (based on weekly earnings). These facts imply that the March series will overstate residual earnings dispersion relative to the May/ORG CPS; because the May/ORG sample has lower measurement error for hourly earnings reporters, it will provide a lower (and likely more accurate) estimate of residual earnings dispersion at a point in time.

On its own, this observation has no implications for the relative precision of measured trends in residual inequality in the March versus May/ORG wage series. If, for example, measurement error in the March CPS were constant and additive, the March series would track changes in residual inequality without bias. However, Lemieux also observes, consistent with Hamermesh (2002), that the share of workers paid by the

[14] In addition, the rise in residual earnings inequality in the March CPS is smoother and more continuous than the rise in residual earnings inequality in the May/ORG. In the May/ORG, this rise is concentrated in the early to mid-1980s for men and is visible in both the 1980s and 1990s for women. In the March CPS, residual inequality rises in the 1970s, 80s and 90s for both genders, though most rapidly in the 1980s.

[15] We do not use the "usual weekly hours" variable since, starting in 1994, this is not reported for workers who report that their "hours vary." The Data Appendix provides further details.

[16] Starting in 1994, workers may report earnings in their preferred periodicity (hourly, weekly, etc.), regardless of their salaried or hourly-pay status.

hour within detailed education and experience cells rose substantially during the 1970s and 1980s (prior to commencing a modest decline in the mid 1990s). Since, as above, direct hourly earnings reports have relatively lower measurement error, the rise in hourly reporting will cause a divergence in trends in residual earnings inequality between the May/ORG and March CPS; observed earnings dispersion should rise less rapidly in the May/ORG than March CPS. This prediction is consistent with Lemiuex's findings and with our analysis in Section II. Due to this divergence, Lemieux concludes that the March CPS series is biased towards overstating the growth in residual inequality. He recommends that researchers refrain from drawing inferences about levels or trends in inequality from the March data and focus instead on the "better" May/ORG data.

In this section, we make an independent attempt to assess the contribution of composition to rising earnings inequality. Our approach is conceptually similar to Lemieux (2004), with two differences. First, and potentially less important, we apply and extend a quantile-regression-based modeling technique proposed by Machado and Mata (forthcoming 2004) to simulate counterfactual earnings distributions that account for the separate contributions of prices and composition. This quantile simulation is, in our view, a simple and conceptually appealing alternative to the DiNardo, Fortin and Lemieux (1996) reweighting approach, but its substantive differences with Lemieux (2004) are not consequential for our conclusions.

Of greater importance, we separately analyze the contribution of prices and composition to upper and lower tail earnings inequality. Consistent with our earlier results, we document distinct trends in upper and lower tail earnings inequality. Like Lemieux, we find that compositional changes in the education and experience of the labor force are potentially important for understanding trends in lower-tail residual inequality during the 1990s. Yet, compositional shifts are quantitatively unimportant for explaining the rise in upper tail earnings inequality highlighted above.

We also present a simple variance decomposition to analyze the claims that the March CPS data are biased towards overstating the growth of residual inequality and that the May/ORG CPS provides an unbiased estimate of trends in residual inequality. Our analysis suggests that these claims are not necessarily correct. Although we cannot be certain of the direction of the bias in residual inequality trends in the March CPS, we show that, due to the rise in hourly pay reporting, the May/ORG series appears to be unambiguously biased towards understating any "true" rise in residual inequality.

We begin by outlining our decomposition procedure.

A. A quantile decomposition

Let $Q_\theta(w \mid x)$ for $\theta \in (0,1)$ denote the θ^{th} quantile of the distribution of the log wage (w) given the vector x of covariates. We model these conditional quantiles as

(6) $$Q_\theta(w \mid x) = x'\beta(\theta),$$

where $\beta(\theta)$ is a vector of quantile regression (QR) coefficients. For given $\theta \in (0,1)$, $\beta(\theta)$ can be estimated by minimizing in β,

(7) $$n^{-1}\sum_{i=1}^{n}\rho_\theta(w_i - x_i'\beta) \text{ with}$$

$$\rho_\theta(u) = \begin{cases} \theta u & \text{for } u \geq 0 \\ (\theta - 1)u & \text{for } u < 0 \end{cases},$$

where the latter expression is referred to as the 'check function' (see Koenker and Bassett, 1978, Buchinsky, 1994, Koenker and Hallock, 2001, Angrist, Chernozhukov and Fernández-Val, 2004).

As discussed by Machado and Mata, if equation (5) is correctly specified, the conditional quantile process – that is, $Q_\theta(w \mid x)$ as a function of $\theta \in (0,1)$ – provides a full characterization of the conditional distribution of wages. In this case, realizations of w_i given x_i can be viewed as independent draws from the function $x_i'\beta(\theta)$ where the random variable θ is uniformly distributed on the open interval $(0,1)$. The conditional quantile model will hold exactly in a case where both location and scale depend linearly on the covariates (for example in the classical location shift model $w = x'\beta + \varepsilon$ where ε is a normal, *iid* error term). In more general cases, the conditional quantile model may provide a reasonable approximation to the true conditional quantile, and this approximation can generally be improved by specifying flexible functions of x when estimating $\beta(\theta)$.

Having estimated the conditional quantile function, we can use the estimated parameters to simulate the conditional distribution of w given x. As Machado and Mata note, this can be achieved via an application of the probability integral transformation: If U is a uniform random variable on $[0,1]$, then $F^{-1}(U)$ has the density F. Thus, if $\theta_1, \theta_2, ..., \theta_m$ are drawn from a uniform $(0,1)$ distribution, the corresponding m estimates of the conditional quantiles of wages at x_i, $w_i^* \equiv \{x_i'\hat{\beta}(\theta_m)\}_{i=1}^m$, constitute a random sample from the (estimated) conditional distribution of wages given x_i.

Our procedure so far characterizes the conditional quantiles of the data for any given x. It does not, however, provide the marginal density of w. This is because the marginal density depends upon both the conditional quantile function, $\beta(\theta)$, and the distribution of the covariates, $g(x)$. To generate a random sample from marginal density, we can draw rows of data (with replacement) from $g(x_i)$ and, for each row, draw a random θ_i from the uniform $(0,1)$ distribution. We then form $w_i^* \equiv x_i \hat{\beta}'(\theta_i)$, which is a draw from the wage density implied by the model. By applying this procedure repeatedly, we can draw an arbitrarily large random sample from the desired distribution.

This procedure has three useful properties. First, the conditional quantile model conveniently divides the observed wage distribution into 'price' and 'quantity' components. This is similar to a standard Oaxaca-Blinder procedure using OLS regression coefficients, with the key difference that the OLS model only characterizes the central tendency of the data (i.e., the conditional mean function). By contrast, the conditional quantile model can characterize both the central tendency of the data (in this case, the median) and the *dispersion* of the outcome variable conditional on the $x's$, i.e., the wage 'residuals.' This feature is critical for estimating the impact of composition on the shape of the residual wage distribution.

Second, under the unappealing but convenient partial equilibrium assumption that aggregate quantities of skills in the labor market do not affect skill prices, we can use the conditional quantile model to simulate the impact of changing composition or prices on distribution of wages. In particular, by applying the labor force composition data from a time period $g_t(x)$ to the price vector $\hat{\beta}_{t'}(\theta)$ from any other time period, we can simulate the counterfactual distribution of wages that would prevail if labor force composition were given as in time period t and labor market prices were given as in time period t'. Note that because the $\hat{\beta}_{t'}(\theta)$ vector describes the conditional *distribution* of wages for given values of x, this simulation captures the effects of composition on both 'between group' and 'residual' inequality.

Third, we can readily extend the Machado and Mata technique to model the evolution of residual inequality exclusively (which is the focus of Lemieux's analysis). To make this extension, we define the coefficient vector $\hat{\beta}_t(50)$ as our measure of 'between group' inequality. That is, $\hat{\beta}_t(50)$ estimates the expected conditional median difference in earnings between distinct workers groups x_i, x_j where $i \neq j$.[17] Following this logic, we define the measure of residual inequality as the difference between the estimated coefficient vector $\hat{\beta}_t(\theta)$ and the median coefficient vector $\hat{\beta}_t(50)$:

(8) $\hat{\beta}_t^w(\theta) \equiv [\hat{\beta}_t(\theta) - \hat{\beta}_t(50)]$ for $\theta \in (0,1)$.

Notice that, by construction, $\hat{\beta}_t^w(50) = 0$. Hence, the residual quantile coefficient vector is purged of 'between group' inequality, and measures the expected dispersion of w at any given value of x, holding the conditional median at zero. By applying $\hat{\beta}_t^w(\theta)$ to the distribution of covariates, $g(x)$, we can calculate the dispersion of w that is exclusively attributable to residual inequality. If, for example, $\hat{\beta}_t(\theta) = \hat{\beta}_t(50)\ \forall\ \theta$, then residual inequality would be zero in this model.

B. Quantile decomposition: Implementation

We implement the augmented Machado and Mata quantile decomposition procedure in three steps. First, we estimate quantile coefficient vectors for each time period and gender. Using the May/MORG samples above for 1973 through 2003 and the March hourly earnings series for 1975 to 2002, we estimate a series of quantile regressions for log hourly wages by year and gender. We specify a flexible wage model that includes a full set of interactions and main effects for 5 education categories (high school dropout, high

[17] In the classical location-shift model, the conditional median and mean will be identical. In many other cases, they will correspond closely. This is also true in our application, as we show below. Angrist, Chernozhukov and Fernández-Val (2004) show that if QR function is misspecified, it can be interpreted as minimizing a weighted mean-squared error loss for specification error, where the weighting function is an average density of the dependent variable near the true conditional quantile.

school graduate, some college, college graduate, and post-BA) and 13, 3-year potential experience categories ranging from 0 to 38 years. In the May/ORG models, we also include a dummy variable for hourly pay reporting. This allows us to directly model (and control for) the contribution of hourly pay reporting to residual inequality.[18] We denote the matrix of QR coefficients as $\hat{\beta}_t(\theta)$ where t indexes years and $\theta \in \{\theta_1, \theta_2, ..., \theta_{99}\}$. These QR coefficients (99 sets per year and gender) provide the 'prices' for our simulation exercise.

In the second step, we estimate the residual price vector $\hat{\beta}_t^w(\theta)$ using equation (7).

In the third step, we assemble 'quantity' series to be used for the simulation. From the May/ORG and March data for each year and gender, we draw 250 rows at random (with replacement) to be applied to each set of QR coefficients $\theta \in \{1,2,...,99\}$ in each year (24,750 draws per data set). We denote these data series as $x^*(t;\theta)$.

Using the price and quantity series, we can potentially simulate any counterfactual distribution of earnings or residual earnings by pairing the quantity series from one time period with the price series (overall or residual) from another. Before using this technique to simulate counterfactual distributions, however, we assess how well the model-based estimates of inequality replicate the observed level of overall and residual inequality.

To benchmark the quality of the approximation, we apply the QR coefficients $\hat{\beta}_t(\theta)$ to the quantity series from the contemporaneous time period to generate a simulated wage distribution $F(w^*, t_\beta = t, t_x = t)$. In Appendix Figure 1, we plot the observed 90/10 log wage ratio in the CPS data and the model-based simulation of that wage ratio. If the QR model were a perfect fit to the conditional wage distributions, these series would exactly overlap one another (in expectation). In practice, the observed correspondence between the actual statistic and the model-based simulation is extremely close. The log 90/10 wage ratio for the simulated wage distribution never deviates from the observed 90/10 wage ratio by more than 5 percent, and

[18] As above, all regressions are weighted by the product of CPS sampling weights and hours worked in the previous

generally by much less.[19]

To benchmark the performance of our simulation procedure for residual wage inequality, we plot in Appendix Figure 2 simulated and actual 90/10 residual wage dispersion by year and gender. The series labeled Observed LAD (Least Absolute Deviation) Residual is formed from median regressions of log hourly earnings on the covariates above. The series Simulated LAD Residual presents the corresponding statistics for the simulated series formed using $\hat{\beta}_t^w(\theta)$ and $x^*(t;\theta)$. Since all prior residual decompositions that we are aware of analyze OLS regression residuals, we also plot 90/10 residual inequality for an identically specified OLS model. Two conclusions are apparent from the Figure. First, OLS and LAD residuals have near identical dispersion in our application. Hence, the distinction between mean and median regression is not substantively import for interpreting our residual decomposition results. Second, as above, the simulated residual series corresponds closely to the data. While our model-based estimates do appear to slightly underestimate the extent of residual inequality in the data, the deviation is again always less than 5 percent. In addition, the simulated and actual series trend together extremely closely.

C. Descriptive statistics

Before presenting this decomposition, we summarize the basic evolution of residual inequality for the hourly wages of all workers and the weekly earnings of full-time workers in the March and the May/ORG CPSs.[20] Figure 11 displays the 90/10 residual wage inequality series by sex. Residual wage inequality increases sharply in the 1980s for men and women regardless of the wage measures or sample used. Residual wage inequality starts rising in the 1970s for males in the March CPS but shows little change in the 1970s for males in the May/ORG CPS. Upper and lower tail residual inequality series by sex are shown in Figures 12 and 13. Consistent with the trends for *overall* inequality in Figures 4 and 5, these figures show that trends in *residual* inequality did not move in parallel in the upper and lower tails of the earnings

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week.

[19] Other distributional statistics for the simulated data (not shown), such as the variance of wages, the 90/50 log wage ratio, and the 50/10 log wage ratio, are also extremely close to the corresponding statistics for the observed data.

[20] Covariates used in these OLS models for residual inequality are identical to those used for quantile regressions discussed immediately above.

distribution. Residual lower tail inequality rises sharply in the 1980s and slows down or even declines in the 1990s. Upper tail inequality steadily rises in the March CPS since the mid-1970s for males and females (but stops rising around 1994 for hourly wages from the ORG CPS).

Tables 5 and 6 provide descriptive statistics for the evolution of earnings inequality within narrow gender, education and experience groups over 1973 to 2003. The rows of Tables 5 and 6 display the estimated change in 90/10, 90/50 and 50/10 log hourly earnings inequality over the first and second half of the sample period: 1974 to 1988 and 1988 to 2002 (with slight variations due to the timeframes of the May/ORG and March data sets). We tabulate inequality metrics for those with exactly college and exactly high school degrees at potential experience levels of 4 to 6, 14 to 16, 24 to 26, and 24 to 26 years. Because these groups exactly correspond to the gender-education-experience categories directly controlled for (with dummy variables) in our regression specifications for residual inequality, earnings inequality within these cells corresponds precisely to the residual inequality construct used in our subsequent analysis.[21]

Panel A of Table 5 indicates that between 1974 and 1988, 90/10 residual inequality in the May/ORG data among college graduate males grew by 15 to 29 log points (depending on the experience group). Yet, 90/10 growth was considerably less pronounced over 1988 to 2002 period: between 4 and 17 log points (though highly significant in 2 of 4 cases). As is shown in the columns (4) – (6) of the table, this difference is entirely accounted for by trends in the lower half of the earnings distribution. Between 1974 and 1988, 50/10 growth was 7 to 26 log points, as compared to -3 to 8 log points between 1988 and 2002. By contrast, 90/50 growth was comparable in both periods: 3 to 11 log points during 1974 to 1988 and 7 to 11 points during 1988 to 2002. In all cases, the 1988 to 2002 changes are highly significant.

Subsequent panels of Table 5 present analogous statistics for college females and high school males and females. Among college females and high school males, we find similar patterns of rising upper-tail residual earnings inequality in both time periods and flattening or compressing lower-tail residual earnings inequality in the latter period. For high school females (most of whom are in the bottom of the aggregate

[21] To permit inference, standard errors are bootstrapped using 100 replications for each statistic.

wage distribution), we find compressing residual inequality at the top and bottom.

Table 6 repeats this exercise using the March CPS hourly sample. Trends in upper-tail residual inequality in the May and March hourly data are the most part comparable. Both show rapidly rising upper tail inequality for all groups (except for female high school graduates) during the first and second half of the sample. An important difference between these two series, however, is in their measurement of lower-tail residual inequality. Whereas the May/ORG data shows considerable compression of lower-tail residual inequality for most groups during the latter half of the sample, the March data suggest that lower-tail residual inequality was roughly stable during this period (in contrast to sharp growth in the first half of the sample). As we show below, the difference between the two series is important for estimating counterfactual trends in lower-tail inequality and overall inequality, though not for upper-tail inequality.

These comparisons underscore several substantive points for our analysis. First, because the rise in upper-tail residual inequality is detected within detailed gender-experience-education cells, it clearly cannot be termed an artifact of labor force composition. Second, since this rise is robustly visible across data sources, it is also not accounted for by discrepancies among wage reporting procedures in the March versus May/ORG surveys. However, the data do confirm a real compression (or 'plateauing') of lower-tail inequality within demographic groups. This suggest that any decomposition of overall (90/10) inequality into price and quantity components will be likely to aggregate over divergent trends at the upper and lower tails of the distribution. Moreover, the role attributed to prices versus composition is likely to be quite sensitive to the weight given to less educated and experienced groups (which had more compression) versus more educated and experienced groups (which had more expansion). We return to these points below.

D. *The contributions of between-group prices, residual prices, and composition: A quantile JMP decomposition*

As a compact method of summarizing the contributions of prices and quantities to rising earnings inequality, we implement a quantile analog of the well-known JMP decomposition. We write the observed distribution of wages at time t as a function of three components: the distribution of worker characteristics, $g_t(x)$, the 'between-group' prices for those characteristics, $\beta_t(50)$, and the within-group prices for those characteristics, $\beta_t^{\,w}(1,2...,99))$.[22]

(9) $\quad f_t(w) = f(g_t(x), \beta_t(50), \beta_t^{\,w}(1,2...,99))$,

The observed change in inequality between any two periods, t and τ can be decomposed into changes due to each of these components using the following sequential decomposition. Let $\Delta Q_\theta = Q_\theta(f_\tau(w)) - Q_\theta(f_t(w))$ equal the observed change in the θ^{th} wage quantile between periods t and τ. To reduce notation, we suppress the "hats" on the estimated β_t vectors.

(10) $\quad \Delta Q_\theta^x = Q_\theta(f(g_\tau(x), \beta_t(50), \beta_t^{\,w}(1,2...,99))) - Q_\theta(f(g_t(x), \beta_t(50), \beta_t^{\,w}(1,2...,99)))$

as the contribution of changing quantities (labor force composition) to ΔQ_θ. We define

(11) $\quad \Delta Q_\theta^b = Q_\theta(f(g_\tau(x), \beta_\tau(50), \beta_t^{\,w}(1,2...,99))) - Q_\theta(f(g_\tau(x), \beta_t(50), \beta_t^{\,w}(1,2...,99)))$

as the marginal contribution of changing between-group prices to ΔQ_θ. And, we finally define

(12) $\quad \Delta Q_\theta^w = Q_\theta(f(g_\tau(x), \beta_\tau(50), \beta_\tau^{\,w}(1,2...,99))) - Q_\theta(f(g_\tau(x), \beta_\tau(50), \beta_t^{\,w}(1,2...,99)))$

as the marginal contribution of changing within-group prices to ΔQ_θ. Notice that this decomposition sums to the total observed change: $\Delta Q_\theta^w + \Delta Q_\theta^b + \Delta Q_\theta^x = \Delta Q_\theta$.[23]

As is well known, the chosen order of a sequential decomposition implicitly corresponds to a set of weights reflecting which characteristics are held at their start or end period values as other components are varied. Consequently, the share of any observed change attributed to each component $(\Delta Q_\theta^w, \Delta Q_\theta^b, \Delta Q_\theta^x)$ will typically depend on which other components are varied first. Accordingly, we perform the decomposition above using two orderings. In the first, notated above, we first vary labor force characteristics, then between group prices, and finally within-group prices. In the second decomposition, we use an analogous procedure to first vary within-group prices, then between-group prices, and finally labor

[22] More precisely, this distribution corresponds to the simulated distribution of wages from our model-based procedure. As discussed above, there are small differences between the simulated and observed data (also see Appendix Figures 1 and 2). In the decomposition exercises, we not tabulate these differences and use the simulated distributions throughout.

[23] Hence, this decomposition does not suffer from the infirmity of the JMP procedure in which the 'residual price and quantity component' must be estimated as a remainder term after the other two components are calculated.

force composition.

Table 7 presents results of these decompositions for the May/ORG CPS. As shown in the upper left panel of the table, the rise of male earnings dispersion between 1973 and 1988 is almost entirely accounted for by prices rather than quantities. Echoing the findings of JMP, of 25.2 log points rise in male 90/10 inequality over this period, the decomposition attributes only 0.3 points to quantities, versus 18 points to between-group prices and 7 points to within group prices. When we reverse the order of the decomposition, we find that the estimated contribution of labor force composition to inequality remains small at 2 log points. Panel B for females also suggests a comparatively small role for composition, though this role is larger than for males and also more important in the lower tail of the earnings distribution. Similar patterns prevail when upper and lower tail inequality are decomposed separately: composition never explains more than a third of the growth of any 90/50 or 50/10 inequality metric; the remainder is explained by prices.

When we perform this decomposition for the growth of inequality between 1988 and 2003, an important difference with the earlier period emerges. Both prices *and* composition play a substantial role in explaining changes in lower-tail earnings inequality after 1988. Overall male 50/10 inequality contracted by 4.5 log points during 1988 to 2003. Holding prices constant, the change in composition alone would have been expected to *increase* lower tail inequality by 5.8 log points, reflecting, as noted by Lemieux, the increasing education and experience of the labor force. Offsetting this force, between and within-group prices reduced lower-tail inequality by -3.0 and -7.3 log points respectively during the same interval. On net, the 5.8 log points of observed lower-tail compression reflects the countervailing impacts of 'falling' prices and an increase in the prevalence of characteristics associated with higher earnings dispersion.

Yet, these discrepant forces are not responsible for trends in upper tail inequality. In fact, for both males and females, the contribution of labor force composition to rising upper tail inequality is negligible. Like the 1973 – 1988 period, the rise of upper-tail inequality after 1988 is almost entirely explained by rising between and within-group prices. Notably, these price increases are comparable in size for 1973 – 1988 and 1988 – 2002; for males, the estimated rise in within-group prices is larger in the latter period.

Table 8 presents the comparable decomposition for hourly wage inequality in the March CPS. In most cases, the qualitative conclusions are identical to those from Table 7. In particular, in the earlier period, the March data show a small role for composition and a uniform effect of between and within-group prices on upper and lower tail inequality. In the latter period, the March data show countervailing effects of prices and quantities in the lower half of the distribution and almost no role for composition in the upper half of the distribution. Consistent with our descriptive results in Table 6, we find considerably less evidence of price compression effects in the lower tail of the earnings distribution in the March data than in the May/ORG data.[24]

Before applying the quantile approach to a reanalysis of the Lemieux results, we offer three tentative conclusions. First, the rise in upper-tail inequality reflects secularly increasing within and between group price dispersion throughout the 1973 to 2003 period. That is, composition plays almost no role in the rise of upper tail inequality over the last three decades. Second, changing labor force composition has played an important role in raising (or, more precisely, dampening the decline of) lower tail inequality after 1988. Third, the plateau (or decline) of lower-tail earnings inequality after 1988 is largely due to a reduction in the dispersion of between and within-group prices. The magnitude of this decline is quite sensitive to the choice of CPS sample (May/ORG or March).

E. Quantile decomposition for overall inequality: Lemieux-type analysis

We now present quantile decomposition results in a format similar to that used by Lemieux. We begin with overall inequality and discuss results for residual inequality next. The results of our decomposition exercise for overall inequality in the May/ORG are shown in Figures 14 through 16 and Tables 9 and 10. Figure 14 compares the observed 90/10 log wage ratio by gender in each year for 1973 through 2003 with three counterfactual series, one each using the 1973, 1988 and 2003 the quantile regression price vectors, $\beta_t^w(50), \beta_t^b(1,2,...99)$. Under the maintained assumption that labor market prices and quantities can be treated as independent, these counterfactuals estimate the separate impacts of prices and composition on

[24] The March full-time data (not tabulated) show a rise in earnings inequality for males and females for the period of 1963 to 1973. This rise is much less pronounced than in the decades following and is primarily accounted for by changing prices rather than changing composition.

the evolution of earnings inequality.

To interpret these figures, note that the differences in the vertical height of each series for a given year shows the pure effect of prices (1973, 1988 and 2003) on earnings inequality, holding labor force composition at the appointed year's level. The changes in the level of each series over time (along the *x*-axis) show the pure effect of changing labor force composition, holding prices at their 1973, 1988 or 2003 level. Figures 15 and 16 also present analogous actual and counterfactual series for upper and lower tail earnings inequality. These actual and counterfactual series are summarized in Table 9.

Because these decompositions present similar information to the JMP-style analysis above using a different organization, we primarily highlight additional information that they make apparent. Three main results from this analysis stand out. First, there is a very large rise in overall earnings inequality during these three decades that is not attributable to compositional changes. The magnitude of the compositional effects – reflected in the shallow upward slope of the counterfactual series – is small relative to the substantial rise in inequality observed when applying prices from 1988 or 2003 relative to 1973 to any set of labor force characteristics. For example, the male 90/10 log hourly earnings ratio rose by 32 log points between 1973 and 2003. Holding composition at the 1973, 1988 or 2003 levels respectively, this earnings ratio would counterfactually have risen by 21, 25, or 28 log points. Hence, depending on the vintage of labor force characteristics used for the analysis (1973, 1988 or 2003), between one seventh and one third of the rise in male 90/10 earnings inequality may be accounted for by compositional shifts.

Second, as emphasized in earlier tables, the relative roles of composition and prices are not uniform over these periods. Of the 25 log point growth in 90/10 inequality during 1973 to 1988, only a small share is accounted for by changing demographic composition of the labor force. By contrast, a substantial share of the growth in male 90/10 inequality between 1988 and 2003 is potentially explained by composition. This may be seen in Figure 14 by comparing the height of the three counterfactual inequality series in each year. This comparison shows a very large gain in 90/10 inequality when applying the 1988 versus 1973 price series to the labor force data. However, comparing the 2003 to the 1988 series indicates only a minor further rise in inequality, suggesting that aggregate price movements were modest in this period. By contrast, all three counterfactual inequality series (i.e., those using 1973, 1988 and 2003 prices) show a parallel rise in 90/10 inequality commencing in the early to mid 1990s. This implies that compositional shifts become quantitatively important in the 1990s.

A third important result – relevant to comparisons with Lemieux (2004) – is that inferences about the contribution of prices and composition to the growth of inequality depends substantially on the base year at which labor force characteristics are held constant (that is, the choice of weights). For example, the first set of data points plotted in the top Panel of Figure 14 depicts the counterfactual level of 90/10 earnings inequality when applying 1973, 1988 and 2003 prices to 1973 labor force characteristics. This comparison indicates a very large price-induced rise in inequality between 1973 and 1988, but no further rise between 1988 and 2003. However, the identical price comparison using 1988 or 2003 labor force characteristics suggests a different conclusion – namely, that inequality rose by several additional log points between 1988 and 2003.

What explains this sensitivity to the choice of labor force weights? The answer is apparent from the comparisons of inequality by education and experience group in Table 5. As shown in the table, 90/10 inequality rose among better educated workers after 1988 but fell among less educated workers during the same interval. Since the labor force in 1973 was composed of considerably fewer highly educated workers and considerable more high school graduates and dropouts than in 1988 or 2003, the use of 1973 labor force characteristics puts substantial weight on the groups that experienced falling inequality and less weight on the groups that experienced rising inequality. Consequently, the use of 1973 characteristics suggests less of a rise in 'counterfactual' inequality than the same comparison made using 1988 or 2003 characteristics. Of course, under the maintained assumption that prices and quantities are independent, no one weighting scheme is 'correct'. However, the sensitivity of conclusions about trends in inequality to the choice of weights cautions researchers against focusing exclusively on one set of labor force characteristics.[25]

[25] In analyses of 90/10, 90/50 and 50/10 inequality, Lemieux (2004) uses exclusively 1973 weights. This appears to provide an incomplete picture of the evolution of prices in the latter half of the sample. For example, Lemieux concludes that there was no further price-induced rise in inequality after 1988. In our analysis, this conclusion is not maintained if 1988 or 2003 weights are applied.

An alternative way to observe this point is to compare counterfactual trends in upper and lower tail inequality, as is done in Figures 15 and 16. Since these upper and lower tail comparisons do not aggregate over divergent price-effects at the bottom and top of the distribution, the distinct roles of composition and prices are visible in each. These figures indicate that, for both genders, the rise in upper tail inequality is a robust consequence of changing prices throughout the three decades. For lower tail inequality, changing prices reduced lower tail inequality after 1988, while changing composition partly offset this effect. As above, the impact of composition for lower tail inequality depends on the choice of labor force weights. Using 1973 weights, lower tail inequality appears to return to its 1973 level between 1973 and 2003. Using 2003, weights, the implied reduction is only half as large for males and is basically undetectable for females.

F. Quantile decomposition: Results for residual inequality

The lower panel of Table 9 and Figures 17 through 19 present comparable exercises for residual earnings inequality in the May/ORG CPS. These residual results are qualitatively similar to those for overall earnings inequality. We find that counterfactual 90/10 inequality either did not rise or declined after 1988, depending on the selection of weights.

As with overall inequality, this aggregate result sums over opposite-signed trends in upper and lower tail inequality. Using any set of labor force weights, price changes caused lower tail residual inequality to fall for males and females after 1988. By contrast, upper-tail residual inequality appears to rise for both genders between 1988 and 2003. However, when labor force weights from 1973 are used in place of 1988 or 2003 weights, this rise is muted for males and reversed for females. Since the 1973 weights place considerable emphasis on the wage trends of groups of workers that are no longer particularly prevalent in the labor market, we believe that this inference is somewhat suspect. In any case, equally valid choices of weights (1988 or 2003) suggest a pronounced rise in upper tail residual inequality after 1988. This is consistent with the Table 5 results showing a continued rise in 90/50 residual inequality for most groups after 1988.

G. Comparison with the March CPS

Table 10 presents counterfactual simulations for March hourly earnings. The qualitative pattern of inferences is again quite similar for March versus May/ORG data. However, the estimated contribution of composition to the rise of overall or residual inequality is considerably smaller in these data, as would be expected from earlier tables. The principle reason for this discrepancy is that lower-tail inequality (both overall and residual) contracted by considerably less in the March than May/ORG data. Hence, placing greater weight on less educated workers in the March data (by holding composition constant at an early period level) has a comparatively minor offsetting effect on the observed rise of overall or residual inequality during this period.

Thus, consistent with Lemieux, we find that the March data reveal a considerably smaller role for composition and a correspondingly larger role for prices in the growth of overall and residual earnings inequality during the 1990s than do the ORG data. We now turn to an evaluation of Lemieux's conclusion that the May/ORG data provide a more accurate source for measuring trends in residual wage inequality.

H. Bias in the May/ORG versus March CPS data: Levels or Trends?

As summarized above, Lemieux (2004) forcefully argues that the May/ORG CPS sample provides a more accurate measure of the hourly wage distribution and, hence, a preferred measures of the recent evolution of U.S. wage inequality than does the March CPS.

The central issue in comparing trends in wage inequality is whether the differences in measurement error in the May/ORG and March CPS have remained stable over time. In fact, the share of workers who report being paid by the hour has increased substantially since 1973 (Hamermesh 2002) and this increase is found within education/experience groups (Lemieux 2004). This raises the question of whether the March or May/ORG CPS provides a more consistent measure of changes in residual wage inequality in an environment of a changing share of workers paid by the hour.

Lemieux (2004) correctly points out that a growth in the share of hourly workers will tend to lead to a growth in measured residual hourly wage inequality in the March CPS relative to the May/ORG as the share of workers with well-measured hourly wages increases in the May/ORG. Based on this fact, Lemieux concludes that the May/ORG will provide a less biased measure of *changes* in residual wage inequality. But this conclusion does not seem to follow. In fact, the growth in the share of hourly workers leads to a reduction in the wage variation from measurement error in the May/ORG and may have no effect on the extent of measurement error in the March CPS. Thus, even though the May/ORG CPS measure of the level of wage inequality becomes more accurate over time relative to the March CPS, changes in residual wage inequality in the May/ORG samples are likely to be systematically downward biased relative to true changes while those in the March CPS may not be affected by changes in the share of hourly workers.

This logic can be formalized as follows. Let m index the March CPS, o index the ORG/May CPS, j index sex-education-experience group, t index year, h index hourly workers (those paid by the hour), and n index non-hourly workers. We define V^m_{jt} and V^o_{jt} as the observed variances of hourly wages in the March and May/ORG CPS respectively for workers in group j in year t. We also define σ^2_{jt} as the true variance in hourly wages for group j in year t; σ^2_{hm} as the variance of measurement error in hourly wages for hourly workers in March CPS; and σ^2_{nm} as the variance of measurement error in hourly wages for non-hourly workers in March CPS. The measurement error variances for hourly and non-hourly workers in the May/ORG CPS are analogously given by σ^2_{ho} and σ^2_{no}. We also let H_{jt} equal the share of hourly workers in group j in year t.

Under the assumption of white noise measurement error in hourly wages, the observed variances of hourly wages for group j in year t in the March and May/ORG CPS can be written as

$$V^m_{jt} = \sigma^2_{jt} + H_{jt}\sigma^2_{hm} + (1-H_{jt})\,\sigma^2_{nm} \tag{13}$$

$$V^o_{jt} = \sigma^2_{jt} + H_{jt}\sigma^2_{ho} + (1-H_{jt})\,\sigma^2_{no}$$

Following Lemieux (2004), we assume that hourly wages are more accurately measured in the May/ORG CPS than in the March CPS: $\sigma^2_{hm} > \sigma^2_{ho}$. We also assume that measurement error in the hourly wages for non-hourly workers is equivalent in the March and May/ORG CPS: $\sigma^2_{nm} = \sigma^2_{no}$. These assumptions imply, as Lemieux notes, that the March CPS generates higher (and less accurate) measures of residual hourly wage inequality in levels than does the May/ORG CPS: $V^m_{jt} > V^o_{jt}$. It is also reasonable to assume that hourly wages are more accurately measured for hourly workers than non-hourly workers in the May/ORG samples: $\sigma^2_{no} > \sigma^2_{ho}$. And there is little reason to believe in differential measurement error for the hourly wages of non-hourly and hourly workers in the March CPS: $\sigma^2_{hm} \approx \sigma^2_{nm}$.

We next consider the accuracy of the different CPS samples for measuring changes in residual wage inequality from period t to period τ when the share of workers paid by the hour is rising (as has been the case since the 1970s). Let $\Delta x_t = x_t - x_\tau$. The changes in measured residual hourly wage variance for group j from t to τ in the different CPS samples are given by

(14) $$\Delta V^m_{jt} = \Delta\sigma^2_{jt} + \Delta H_{jt}(\sigma^2_{hm} - \sigma^2_{nm})$$

$$\Delta V^o_{jt} = \Delta\sigma^2_{jt} + \Delta H_{jt}(\sigma^2_{ho} - \sigma^2_{no}),$$

so that

(15) $$\Delta V^m_{jt} - \Delta V^o_{jt} = \Delta H_{jt}[(\sigma^2_{hm} - \sigma^2_{ho}) + (\sigma^2_{no} - \sigma^2_{nm})].$$

Under the assumptions given above, $\Delta V^m_{jt} - \Delta V^o_{jt} = \Delta H_{jt}(\sigma^2_{hm} - \sigma^2_{ho}) > 0$ if $\Delta H_{jt} > 0$. Thus, as emphasized by Lemieux (2004), a rise in the share of hourly workers should systematically lead to a rise in measured residual wage inequality in the March CPS relative to the May/ORG CPS. But this divergence does not mean that the May/ORG CPS provides a more accurate measure of changes in actual residual wage inequality. In fact, the May/ORG CPS provides a downward biased measure of changes in actual residual wage inequality ($\Delta V^o_{jt} < \Delta\sigma^2_j$) when the share of hourly workers increases since $\sigma^2_{ho} < \sigma^2_{no}$. And the March CPS provides an accurate measure of changes in actual residual wage inequality if $\sigma^2_{hm} = \sigma^2_{nm}$.

To provide a rough assessment of the bias that the rise of hourly pay reporting may induce in the May/ORG CPS, we plot in Figure 20 observed trends in residual wage inequality in the May/ORG CPS alongside counterfactual trends in residual inequality, holding the frequency of hourly wage reporting at its base (1973) level.[26] This counterfactual series is formed with our quantile simulation procedure, reweighting the data in each year to maintain the frequency of hourly pay reporting at its 1973 level within the gender by education by experience cells used for our analysis. No other adjustments are made for compositional changes in the counterfactual series; hence, the contrast between the observed and counterfactual series is exclusively due to hourly pay reporting.

These figures indicate that the rise in hourly pay reporting has probably led to a non-negligible *downward* bias in measured trends in residual inequality in the May/ORG CPS. For males, this bias cumulates over 1973 to approximately 1989, plateaus until 1994, and then appears to increase again between 1994 and 2003. For females, this bias cumulates gradually throughout the sample and then jumps upward starting in 1994. The continued rise in the hourly-pay bias in the MORG samples commencing in 1994 is unexpected since the frequency of hourly pay reporting stopped rising in the early 1990s. This may suggest that the difference in the precision of hourly versus non-hourly wage reports becomes more pronounced after the 1994 CPS redesign. This issue clearly deserves further investigation.

These comparisons suggest that the rise in hourly pay reporting in the May/ORG CPS is likely to cause it to understate the rise in residual earnings inequality. Moreover, this bias has become secularly larger as hourly pay reporting has risen. This bias can, however, be 'controlled' by using the same adjustments for composition that we apply for education and experience. In fact, our simulation procedure above makes this adjustment throughout by including hourly pay reporting among the explanatory variables used for the quantile analysis.[27] Accordingly, our analysis of residual inequality in the May/ORG may plausibly account for any bias in trends in residual inequality induced by changes in hourly pay reporting. Lemieux (2004) does not, to our knowledge, make a similar adjustment using his reweighting procedure. Consequently, the Lemieux analysis may tend to *understate* the composition-adjusted rise in residual inequality in the May/ORG CPS.

Thus, even though the May/ORG CPS provides more accurate *level* measures of residual hourly wage variance than the March CPS, there are good reasons to believe that the March CPS may provide more

[26] More precisely, we increase precision by using the mean frequency of hourly pay reporting within education by experience by gender cells for 1973, 1974 and 1975.

[27] Specifically, in our analysis of the May/ORG, hourly pay reporting is an element of $g_t(x)$ and the corresponding quantile coefficients are contained in $\beta_t^b(\cdot), \beta_t^w(\cdot)$.

accurate measures of *changes* (and trends) in residual hourly wage inequality when the share of workers paid by the hour is changing. Thus, we do not agree with Lemieux's (2004) suggestions to researchers to focus on the May/ORG CPS rather than the March CPS to study the evolution of U.S. wage inequality over recent decades. Of course, there are many other data processing changes (ranging from top coding, imputations of missing wage information, changes in the wage and hour questions) that may differentially affect the measurement error in wage measures in the different CPS samples. But both the March and May/ORG samples have strengths and weaknesses and should be viewed as complements in studying wage inequality.

I. Summary

We draw five conclusions from our reanalysis of the Lemieux findings. First, the majority of the rise of overall and residual inequality between 1973 and 2003 is real rather than artifactual; that is, it is explained by rising returns to observed skills and rising residual inequality within observed skill groups, not by composition. Second, as emphasized by Lemieux (2004), shifts in labor force composition have significantly contributed to the observed rise in earnings inequality during the 1990s. But these compositional shifts primarily operate on the lower tail of the earnings distribution. The bulk of the rise in upper tail overall and residual inequality appears to be explained by changing prices rather than changing composition. Third, the sensitivity of the counterfactual accounting exercise to choice of weights (i.e., labor force series) strongly suggests that using end point weights (1973, 2003) for this three decade period is likely to exaggerate (in the case of 1973 weights) or understate (in the case of 2003 weights) the contribution of compositional shifts to rising earnings inequality. Hence, we favor using either mid-period weights or performing a sensitivity analysis. Fourth, we do not agree with the Lemieux's contention that the May/ORG data should be preferred over the March series. While both series have notable flaws, the May/ORG data appear biased towards understating the rise of residual inequality. By contrast, the March data do not suffer from this bias. Moreover, the sharp observed decline in residual inequality among hourly workers in the MORG following the CPS redesign in 1994 suggests a further concern about the consistency of this series.

Finally, we stress that the informativeness of these counterfactual decomposition exercises depends critically on the maintained partial-equilibrium assumption that prices and quantities can be treated as independent. If this assumption is substantially violated, the counterfactual inequality series developed will not correspond to any potential state of the world (since altering labor force characteristics would necessarily alter the prices associated with those characteristics).[28] Lending weight to this concern, the careful analyses of earnings premiums by experience and education group performed by Card and Lemieux (2001) and Borjas (2003) – as well as the simple descriptive analysis in Table 3 and Appendix Table 2 – strongly affirm that the relative wages paid to education and experience (or age) groups are quite responsive to own supply as well as aggregate supply. Hence, shifts in composition and shifts prices will generally negatively covary, particularly over long time intervals (such as the three decades above!). This suggests that the impact of changing composition on prices could potentially be a first order source of bias in these counterfactual exercises. While it is difficult to judge the magnitude of the bias imparted, caution is clearly warranted. Assessing this bias remains an important item for future work.[29]

VI. Interpreting Changes in the Wage Structure

The incorporation of data covering the labor market developments of the full 1990s and the beginning of the 21st century provides a new opportunity to assess conclusions concerning explanations for the evolution of the U.S. wage structure. Our analysis provides two clear continuities and two clear discontinuities with earlier work covering wage structure changes through the early 1990s.

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[28] In addition, the counterfactual exercises assume that the changing selectivity into education and experience cells (as reflected, for example, by the contraction of low education cells and expansion of high education cells), has no effect on the dispersion of earnings in these cells. If, plausibly, expanding cells experiences increases in the dispersion of true productivity characteristics, this would in part explain why residual inequality has risen in high education-experience cells and contracted in low education-experience cells.

[29] Notably, in their analysis of the contributions of price and quantities to rising inequality in the 1980s, DiNardo, Fortin and Lemieux (1996) perform supply and demand adjustments for observed wages by education by experience cells (in addition to applying the re-weighting procedure used by Lemieux (2004)). These supply-demand adjustments are shown by DFL to be quantitatively important, explaining 21 to 33 percent of the growth in male 90/10 log hourly earnings inequality between 1979 and 1988 (Tables III and V).

The first reinforcing finding is that a simple framework emphasizing shifts in the relative demand for and relative supply of skills remains quite helpful for understanding changes in “between group wage inequality.” As emphasized by earlier work (including Katz and Murphy 1992; Murphy and Welch 1992; Autor, Katz, and Krueger 1998; and Card and Lemieux 2001), the evolution of the college-high school wage premium over the last four decades – a modest rise in the 1960s, a decline in the 1970s, and a steep rise in the 1980s continuing a more moderate rate in the 1990s – is well-explained by a strong and rather steady trend growth in the relative demand for college versus non-college labor overlaid with fluctuations in the rate of growth of the relative supply of college equivalents (particularly the surge in new college graduates of the 1970s and sharp slowdown of relative supply growth starting in the early 1980s). Furthermore, differences in group-specific relative supply changes help explain differences by experience (or age) groups in the evolution of the college wage premium over the past couple decades. Card and Lemieux (2001) reach similar conclusions concerning the role of secular relative demand growth combined with relative supply fluctuations for explaining aggregate and age-group specific movements in the college wage premium for Canada and the United Kingdom. And Fortin (2004) finds an important role for relative demand and supply shifts in explaining U.S. cross-state patterns of the evolution of the college wage premium over the last 25 years.

The second continuity with earlier findings is the almost linear rise in upper-tail wage inequality (including the 90-50 wage differential) from 1980 to the present for males and females. We also conclude that the persistent rise of upper-tail wage inequality since 1980 remain even after adjusting for composition to take into account the rising education and experience of the work force.

The first major discontinuity with findings based on data through the end of the 1980s is that there appears to be a significant deceleration in the trend growth of relative demand for college workers starting around 1992. This pattern represents a puzzle for naïve versions of explanations focusing exclusively on skill biased technical change (SBTC). An implied acceleration in the rate of growth of the relative demand for skills in the 1980s is often attributed to the computer revolution. This hypothesis would not predict an implied deceleration in relative demand in the 1990s given the continued rapid spread of information technology in that decade.[30]

The second discontinuity is the near plateau (and even decline) in lower-tail wage inequality in the 1990s. In the 1980s wage inequality (with the notable exception of gender wage differentials) expanded substantially along many dimensions (upper tail and lower tail inequality; between-group and within-group inequality). In contrast, wage structure changes were more asymmetric in the 1990s particularly with a divergence in upper-tail and lower-tail inequality trends.

The comparison of different data sets (March CPS vs. May/ORG CPS) and different wage samples and wage measures (hourly wages for all workers vs. weekly wages for full-time workers) leads to a fair amount of agreement concerning the basic evolution of the U.S. wage structure over the past several decades. These commonly used data sets and wage measures all imply declining educational wage differentials in the 1970s and rising educational wage differentials since 1980. They also imply no decline in overall wage inequality in the 1970s and rising overall wage inequality since 1980. Yet there remain some puzzling inconsistencies. The full-time weekly wage samples for men tend to show larger increases in wage inequality than do the broader hourly wage samples. Residual wage inequality increased in the 1970s in the March CPSs and did not expand over this same period in the May/ORG CPSs.[31] Residual wage inequality also has grown less rapidly since 1994 in the CPS ORG especially for hourly wages than for the other series.

The growth of the share of workers paid by the hour, emphasized by Lemieux (2004), may explain part of the divergence in residual inequality in the March and May/ORG samples. But the timing of this explanation does not fully fit the puzzle. Hourly pay frequencies stopped rising by the early 1990s, and yet the March and ORG series begin to further diverge in 1994.[32] An alternative possible explanation for this divergence meriting further study is the major redesign of the earnings questions in the ORG CPS in 1994.

[30] See also Machin (2003) for a discussion and interpretations of these trends.

[31] In Katz and Autor (1999), we report that residual inequality also rose in the May CPS between 1973 and 1979. As Lemieux (2004) correctly points out, this conclusion derives from a comparison of a 1973 CPS file excluding allocated earnings observations and a 1979 file including allocated observations. Once allocators are excluded from both samples, we find, consistent with DiNardo, Fortin and Lemieux (1996) and Lemieux(2004) that there is no rise in residual inequality in the May CPS between 1973 and 1979.

[32] Angrist, Chernozhukov, and Fernández-Val (2004) find increases in residual wage inequality from 1990 to 2000 in the decennial Census samples that are similar to those we find in the March CPSs.

We conclude, as emphasized by Katz and Autor (1999) and DiNardo and Card (2002), that it is unlikely that a single unicausal factor (whether it be SBTC, the minimum wage, declining unionization, immigration, or international trade) can explain the full pattern of the evolution of the U.S. wage structure over the past several decades. A key reason is that changes in different measures and components of wage inequality, as underscored by Figures 2, 4 and 5, have distinct timings that suggest the possibility of their being at least partially affected by distinctive sources.

We next turn to some brief comments on the competing explanations for changes in the U.S. wage structure. Secular demand growth for more educated workers driven by shifts in product demand and technology combined with fluctuations in relative skill supplies play an important role in the evolution of educational wage differentials. The evolution of the real federal minimum wage appears to be an important factor in explaining the sharp timing of movements in lower-tail wage inequality for women, and, to a lesser degree, for men. But the minimum wage explanation fails to account for the large and persistent rise in upper tail wage inequality that has been the largest component of rising overall wage inequality since 1980. The strong time series correlation of the evolution of the real minimum wage and upper-tail wage inequality leads one to be skeptical of simple time series correlations of the real minimum wage and alternative inequality measures and is suggestive of the political endogeneity of the minimum wage.

We believe the major new puzzle introduced by the last decades' experience is the asymmetric trends in upper and lower tail inequality. We speculate that two classes of explanations may be plausible. The first involves macro factors – tight labor markets in particular – that disproportionately 'raised the boats' of low-wage workers in the 1990s and offset secular labor market shifts against less-skilled workers. We doubt this can be a complete explanation.

A second class of explanation is the one offered by Autor, Levy and Murnane (2003; ALM hereafter) and amplified by Goos and Manning (2003) and Spitz (2004).[33] Skill Biased Technical Change is probably an insufficiently nuanced name for the shifts in skill demands that we believe were induced or abetted by

[33] A related earlier model along these lines is developed in Juhn (1994).

the rapid price declines in computer technology over the last three decades. As ALM argue, computerization is likely to have had non-monotonic impacts on the demand for skill throughout the earnings distribution: sharply raising demand for the cognitive and interpersonal skills used by educated professionals and managers; reducing demand for clerical and routine analytical skills that comprised many middle-educated white collar jobs; and reducing demand for routine manual skills of many previously high-paid manufacturing production jobs. Somewhat paradoxically, computerization has probably had little impact on the demand for the non-routine manual skills used in many 'low-skilled' service jobs such as health aides, orderlies, cleaners, servers, etc.[34] The ALM framework suggests that computerization (among other forces) may have raised demand for skill among higher-educated workers, depressed skill demands for 'middle-educated' workers, and left the lower echelons of the wage distribution comparatively unscathed.[35] Goos and Manning (2003) label this process a "polarization of work," and argues that it may have contributed to a hollowing out of the wage distribution in the United Kingdom during 1975 to 2000.[36]

To provide a rough assessment of the applicability of this polarization hypothesis to data for the United States, we use the Dictionary of Occupational Titles (DOT) task measures developed by ALM to examine predicted changes in employment by decile of the wage distribution over 1960 to 2000. To construct an employment demand index, we pair data from the 1960 Census of Population with the five broad ALM measures of job tasks: routine manual, routine cognitive, non-routine manual, non-routine analytic, and non-routine interactive tasks.[37] Using the paired Census-DOT sample, we calculate the mean level of task input in each decile of the wage distribution in 1960. We refer to these measures as the 'task intensity' in each wage decile, and we take them as fixed over the sample. Using Census samples for 1960, 1970 and 1980, and CPS MORG samples for 1980, 1990, and 2000, we calculate the proportionate economy-wide

[34] See also Levy and Murnane (2004) for numerous, paradigmatic examples.

[35] Welch (2000) and Weinberg (2000) argue that these technical changes are particularly likely to have been favorable to demand for female labor.

[36] Acemoglu (1999) offers an alternative theory of job polarization based on endogenous changes in production techniques as a response to a rise in the availability of skilled labor. See also Acemoglu (1998) and Beaudry and Green (1998).

[37] Task definitions are explained in detail in Autor, Levy, and Murnane (2003).

mean change in each measure of task input for all employed workers (weighting by the product of sampling weights and labor supply) over each decade. We multiply these aggregate proportionate changes by the 1960 task intensity in each wage decile and sum over the five task measures to estimate the aggregate predicted change in task demand by decile. Hence, if a wage decile is heavily 'tasked' in routine cognitive activities, an economy-wide decline in input of routine cognitive tasks is predicted to particularly depress task demand in that decile. Finally, to convert task changes by decile into a relative (cross-decile, within decade) measure, we express the change in each decile as a share of the total predicted changes observed in all deciles over the decade. If, for example, predicted employment shifts were equally distributed over all 10 deciles in a decade, each would have a value of 0.1 in our index.

The results of this exercise, depicted in Figure 21, show a pronounced twist in predicted employment demand by decile over four decades. During the 1960s, demand shifts are relatively uniformly distributed across deciles of the distribution, with the *lowest* relative growth in the highest three deciles. This pattern changes noticeably thereafter. In the 1970s, demand shifts are essentially monotonically increasing by decile. During the 1980s, positive demand shifts become even more concentrated in the top three deciles, while the most negative demand shifts are found in the bottom and middle of the distribution. In the 1990s, this twisting becomes most evident: essentially all relative demand growth in the most recent decade is concentrated in the upper three deciles, whereas relative shifts are relatively uniformly negative among the six deciles below. Notably, demand growth in the lowest decile appears *less negative* than in the four deciles above during this decade, consistent with modest polarization of demand.

In net, we view these results as suggestive of a growing twist in skill demand that is at least roughly consistent with the polarization hypothesis. We stress that this simple analysis does not provide a rigorous assessment of the hypothesis but merely provides a simple illustration of its potential relevance. In a more thorough analysis of changes in job quality for the 1970s and 1980s, Gittleman and Howell (1995) present evidence that employment shifts during the 1980s were strongly biased towards upper-tier jobs and against middle-tier jobs, but had essentially no impact on employment in the bottom third of the job-quality distribution.

VII. Conclusions

We conclude by re-considering the three key questions raised by the recent revisionist literature on U.S. wage inequality trends:

1. *Does the rise in U.S. wage inequality since 1980 reflect an 'episodic' event of the early 1980s or secularly evolving factors?* We conclude that the sharp rise of inequality in the 1980s was partially episodic but overall wage inequality has continued to grow since the mid-1980s and upper-tail wage inequality appears to have been secularly rising at a fairly steady rate since the mid-1970s.

2. *Does the rise in U.S. wage inequality since 1980 largely reflect the effects of a declining real minimum wage?* Our analysis suggests that the decline in the real minimum wage clearly contributed to the sharp increase in lower-tail wage inequality in the 1980s, particularly for females. But the secular rise in upper-tail wage inequality clearly is driven by other sources. Furthermore, secular growth in the demand for skills combined with fluctuations in the rate of growth in the supply of skills goes a substantial distance to explaining the evolution of the college wage premium.

3. *Does the growth of residual wage inequality primarily reflect spurious labor force composition effects?* We find that labor force composition changes are significant for recent changes in lower-tail residual inequality. But the majority of the rise in upper-tail residual inequality remains after adjusting for compositional changes.

The asymmetric pattern of changes of recent changes in upper- and lower-tail wage inequality raise puzzles for both the traditional and revisionist interpretations of changes in the wage structure. We speculate these trends can be partially reconciled by a reinterpretation of the skill biased technical change hypothesis along the lines developed by Autor, Levy and Murnane (2003) and Goos and Manning(2003) to emphasize the polarization of skill demands arising for the spread of computerization.

Finally, we find, even after attempts to make the data series as comparable and consistent as possible, that the March and May/ORG CPS samples continue to imply large differences in the evolution of residual wage inequality in the 1970s and 1990s. The magnitudes of wage inequality changes using weekly earnings for full-time (or full-time, full year) samples differ (sometimes substantially) from those for hourly wages for all workers in both the March and May/ORG CPSs. A better understanding of the sources of these differences across data sets, wage measures, and samples remains an important research priority.

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IX. Data appendix

A. Basic Processing of May/ORG CPS Data

We use the May CPS for 1973 to 1978 and the CPS Merged Outgoing Rotation Groups for years 1979 to 2003. All samples include wage/salary workers ages 16 to 64 with 0 to 39 years of potential experience in current employment. Earnings weights are used in all calculations. Full-time earnings are weighted by CPS sampling weights. Hourly earnings are weighted by the product of CPS sampling weights and hours worked in the prior week. Full-time earnings are the logarithm of reported usual weekly earnings. Hourly wages are the logarithm of reported hourly earnings for those paid by the hour and the logarithm of usual weekly earnings divided by hours worked last week (not usual weekly hours) for non-hourly workers. We use hours last week instead of usual weekly hours because usual weekly hours is not consistently available: starting with the CPS redesign in 1994, workers who report that their weekly hours vary are not asked to report usual weekly hours, yielding a non-report rate of 7.0 to 8.5 percent of workers in 1994 to 2003. To check sensitivity, we have tabulated and plotted overall and residual inequality measures using imputed usual weekly hours in place of hours last week in all years 1973 – 2003. This has little impact on our results.

Topcoded earnings observations are multiplied by 1.5. Full-time earnings of below $67/week in 1982$ ($112/week in 2000$) and hourly earners of below $1.675/hour in 1982 dollars ($2.80/hour in 2000$) are dropped, as are hourly wages exceeding 1/35th the topcoded value of weekly earnings. All earnings numbers are deflated by the chain-weighted (implicit) price deflator for personal consumption expenditures. Allocated earnings observations are excluded in all years, except where allocation flags are unavailable (January 1994 to August 1995). As discussed by Hirsch and Shumacher (2004 forthcoming), only about 25 percent of allocated observations in the MORG CPS are actually flagged as allocated between 1989 and 1993. Due to a processing oversight, these non-flagged allocated observations are currently retained in our MORG sample from 1989 to 1993. These will be discarded in the next version of the paper.

B. Basic Processing of March CPS Data

We use the March Current Population Survey for earnings years 1963 to 2002 for workers age 16 to 64 (during the earnings year) with 0 to 39 years of potential experience whose class of work in their longest job was private or government wage/salary employment. Hourly earnings are calculated as annual earnings divided by the product of weeks worked and usual hours in the prior year. Full-time, full-year workers are those who work 35 hours per week (using the Census Bureau's full-time worker flag) and worked 40+ weeks in the previous year. Full-time weekly earnings are calculated as the logarithm of annual earnings over weeks worked for the full-time, full-year sample. Allocated earnings observations are excluded after 1966 using family earnings allocation flags (1967 to 1974) or individual earnings allocation flags (1975 forward). Weights are used in all calculations. Full-time earnings are weighted by the product of the CPS sampling weight and weeks worked. Hourly earnings are weighted by the product of the CPS sampling weight, weeks worked, and hours worked in the prior year.

Prior to March 1989, all wage and salary income in the March CPS was reported in a single variable, which was topcoded at values between $50,000 and $99,999 in years 1964 to 1988. For these cases, we multiply the topcoded earnings value by 1.5, following Katz and Murphy (1992). Commencing in 1989, wage and salary incomes were collected in two separate earnings variables, corresponding to primary and secondary labor earnings. After adjusting for topcoding, we sum these values to calculate total wage and salary earnings. Topcodes after 1988 are handled as follows. For the primary earnings variable, topcoded values are reported at the topcode maximum up to 1996. We multiply these values by 1.5. Starting in 1996, topcoded primary earnings values are assigned the mean of all topcoded earners. In these cases, we simply reassign the topcoded value and, again, multiply by 1.5. For the secondary earnings value, the topcoded maximum is set at 99,999 from 1989 to 1995 and then falls to 25,000 in 1996 forward. For lack of a superior alternative, we again use the topcoded value multiplied by 1.5.

After making adjustments for topcoding, full-time earnings of below $67/week in 1982$ ($112/week in 2000$) and hourly earners of below $1.675/hour in 1982 dollars ($2.80/hour in 2000$) are dropped, as are hourly wages exceeding 1/35th the topcoded value of weekly earnings.

C. Coding of Education and Potential Experience in CPS Samples

To attain comparable educational categories across the redefinition of Census Bureau's education variable introduced in 1992 in the CPS, we use the method proposed by Jaeger (1997). In CPS samples coded with the pre-1992 education question, we defined high school dropouts as those with fewer than 12 years of completed schooling; high school graduates as those having 12 years of completed schooling; some college attendees as those with any schooling beyond 12 years (completed or not) and less than 16 completed years; and college plus graduates as those with 16 or more years of completed schooling. In CPS samples coded with the revised education question, we define high school dropouts as those with fewer than 12 years of completed schooling; high school graduates as those with either 12 completed years of schooling and/or a high school diploma or G.E.D.; some college as those attending some college or holding an Associate's Degree; and college plus as those with a B.A. or higher.

To calculate potential experience in data years coded with the revised education question, we use figures from Park (1994) to assign years of completed education to each worker based upon race, gender and highest degree held. Years of potential experience were calculated as age minus assigned years of education minus 6, rounded down to the nearest integer value.

D. Construction of Relative Wage Series

We calculate composition-adjusted college-high school relative wages overall and by age or experience using the March and May/ORG samples described above. These data were sorted into sex-education-experience groups based on a breakdown of the data into 2 sexes, 5 education categories (high school dropout, high school graduate, some college, college plus, and greater than college), and 4 potential experience categories (0-9, 10-19, 20-29, and 30+ years). Log weekly wages of full-time, full-year workers (March CPS) and all hourly workers (May/ORG) were regressed in each year separately by sex on the dummy variables for 4 education categories, a quartic in experience, 3 region dummies, black and other race dummies, and interactions of the experience quartic with 3 broad education categories (high school graduate, some college, and college plus). The (composition-adjusted) mean log wage for each of the 40 groups in a given year is the predicted log wage from these regressions evaluated for whites, living in the mean geographic region, at the relevant experience level (5, 15, 25 or 35 years depending on the experience group). Mean log wages for broader groups in each year represent weighted averages of the relevant (composition-adjusted) cell means using a fixed set of weights, equal to the mean share of total hours worked by each group over 1967 to 2002 from the March CPS.

E. Construction of Relative Supply Measures

We calculate college/high-school relative supply measures using the March and May/ORG samples described above. We first form a labor 'quantity sample' equal to total hours of worked by all employed workers (including those in self-employment) with 0 to 39 years of potential experience in 400 gender × education × potential experience cells: experience groups are single-year categories of 0 to 39 years; education groups are high school dropout, high school graduate, some college, college graduate, and post-college. The quantity data are merged to a corresponding 'price sample' containing real mean full-time weekly (March CPS) or real mean hourly (May/ORG CPS) earnings by year, gender, potential experience and education. (Wage data used for the price sample correspond to earnings samples described above.) We normalize wages in each of the 400 earnings cells in each year to an 'efficiency units' measure by dividing by the wage of high-school graduate males with 10 years of potential experience in the contemporaneous year. This normalization yields a relative wage measure for each earnings group in each year; the choice of the base earnings group is innocuous.

The quantity and price samples are combined to calculate relative log college/high-school supplies. Define the efficiency units of labor supply of a gender × education × potential experience group in year *t* as the efficiency unit wage measure for that group multiplied by the group's quantity of labor supply in year *t*. Following Autor, Katz and Krueger (1998) and Card and Lemieux (2001), we calculate aggregate college-equivalent labor supply as the total efficiency units of labor supplied by college or college-plus workers plus half of the efficiency units of labor supplied by workers with some college. Similarly, aggregate high-school equivalent labor supply is the sum of efficiency units supplied by high-school or lower workers, plus half of the efficiency units supplied by workers with some college. Our college/high-school log relative supply index is the natural logarithm of the ratio of college-equivalent to non-college equivalent labor supply in each year. This measure is calculated overall for each year and by 10 year potential experience groupings. For relative supply calculations using age instead of potential experience (Appendix Table 2), we repeat this procedure, replacing the 40 potential experience categories by 40 age groups: 25 to 64.

Table 1. Changes in Real, Composition-Adjusted Log Weekly wages for Full-Time, Full-Year Workers, 1963 - 2002.
(100 x Change in Mean Log Real Weekly Wages)

	1963-1971	1971-1979	1979-1987	1987-1995	1995-2002	1963-1987	1963-2002
All	19.4	0.7	-1.0	-4.9	10.0	14.2	24.2
Sex							
Men	21.1	0.1	-5.1	-7.8	9.4	8.3	17.7
Women	17.2	1.4	4.7	-0.9	10.8	22.5	33.2
Education (years of schooling)							
0-11	17.0	1.8	-8.4	-10.3	5.3	0.1	5.4
12	17.6	3.2	-3.3	-6.6	8.7	10.9	19.7
13-15	18.6	0.5	1.0	-5.4	11.7	14.7	26.4
16+	25.4	-4.3	6.8	2.7	14.2	30.6	44.8
16-17	22.8	-5.0	5.6	1.0	14.8	24.4	39.3
18+	31.4	-2.7	9.5	6.8	12.7	44.9	57.7
Experience (Males)							
5 years	20.0	-3.6	-8.5	-7.6	14.9	0.2	15.1
25-35 years	21.4	3.4	-1.7	-8.2	4.6	15.0	19.5
Education and Experience (Males)							
Education 12							
Experience 5	19.4	0.7	-16.1	-10.3	13.4	-6.4	7.0
Experience 25 - 35	17.0	6.3	-2.5	-7.6	1.9	13.2	15.1
Education 16+							
Experience 5	23.1	-11.0	9.3	-1.9	15.0	19.5	34.5
Experience 25 - 35	35.0	1.7	2.6	-2.3	10.7	37.1	47.8

Tabulated numbers are changes in the (composition-adjusted) mean log wage for each group, using data on full-time, full-year workers ages 16 to 64 from the March CPS covering earnings in calendar years 1963 to 2002. The data were sorted into sex-education-experience groups based on a breakdown of the data into 2 sexes, 5 education categories (high school dropout, high school graduate, some college, college graduate, and post-college), and 4 potential experience categories (0-9, 10-19, 20-29, and 30-39 years). Log weekly wages of full-time, full-year workers were regressed in each year separately by sex on the dummy variables for 4 education categories, a quartic in experience, 3 region dummies, black and other race dummies, and interactions of the experience quartic with 3 broad education categories (high school graduate, some college, and college plus). The (composition-adjusted) mean log wage for each of the 40 groups in a given year is the predicted log wage from these regressions evaluated for whites, living in the mean geographic region, at the relevant experience level (5, 15, 25 or 35 years depending on the experience group). Mean log wages for broader groups in each year represent weighted averages of the relevant (composition-adjusted) cell means using a fixed set of weights, equal to the mean share of total hours worked by each group over 1963 - 2002. All earnings numbers are deflated by the chain-weighted (implicit) price deflator for personal consumption expenditures. Earnings of less than $67/week in 1982$ ($112/week in 2000$). Allocated earnings observations are excluded in years 1967 forward using either family earnings allocation flags (1967 - 1974) or individual earnings allocation flags (1975 forward).

Table 2. Regression Models for the College/High School Log Wage Gap, 1963 - 2002

	(1)	(2)	(3)	(4)	(5)	(6)
	1963 - 1987	1963- 2002				
CLG/HS relative supply	-0.639 (0.129)	-0.489 (0.046)	-0.601 (0.065)	-0.637 (0.092)	-0.566 (0.070)	
Log real minimum wage				-0.067 (0.049)	-0.099 (0.041)	-0.147 (0.067)
Male prime-age unemp. rate				0.005 (0.003)	0.004 (0.003)	-0.018 (0.003)
Time	0.026 (0.005)	0.021 (0.001)	0.025 (0.002)	0.025 (0.003)	0.022 (0.002)	0.006 (0.001)
Time x Post-1992			-0.005 (0.002)	-0.003 (0.003)		
Constant	-0.168 (0.120)	-0.029 (0.038)	-0.133 (0.057)	-0.052 (0.149)	0.074 (0.108)	0.698 (0.125)
Observations	25	40	40	40	40	40
R-squared	0.572	0.940	0.948	0.955	0.953	0.864

Standard errors in parentheses. Each column presents an OLS regression of the fixed-weighted college high school wage differential on the indicated variables. Real minimum wage is deflated by the Personal Consumption Expenditure Deflator. Source data for supply and earnings measures: March CPS 1964 - 2003.

Table 3. Regression Models for the College/High School Log Wage Gap by Potential Experience Group, 1963-2002, Males and Females Pooled.

			Potential Experience Groups			
	All Experience Groups		0-9 yrs	10-19 yrs	20-29 yrs	30-39 yrs
Own Supply Minus Aggregate Supply	-0.290	-0.292	-0.111	-0.270	0.221	-0.031
	(0.029)	(0.028)	(0.095)	-(0.270)	(0.089)	(0.109)
Aggregate Supply	-0.600	-0.654	-0.833	-0.687	-0.150	-0.392
	(0.055)	(0.080)	(0.126)	(0.098)	(0.142)	(0.164)
Log Real Minimum Wage		-0.036	-0.250	-0.159	0.019	0.100
		(0.042)	(0.067)	(0.055)	(0.068)	(0.083)
Prime Age Male Unemployment		0.005	0.009	0.008	0.002	-0.001
		(0.003)	(0.005)	(0.004)	(0.004)	(0.006)
Time	0.024	0.025	0.032	0.025	0.006	0.017
	(0.002)	(0.003)	(0.004)	(0.003)	(0.005)	(0.006)
Time x Post-1992	-0.004	-0.003	-0.009	0.005	0.008	-0.007
	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.005)
Constant	-0.033	-0.024	0.121	0.003	0.349	-0.056
	(0.047)	(0.128)	(0.203)	(0.167)	(0.230)	(0.264)
N	160	160	40	40	40	40
R-squared	0.861	0.865	0.957	0.969	0.867	0.647

Standard errors in parentheses. Each column presents an OLS regression of the fixed-weighted college/high school wage differential on the indicated variables. The college/high school wage premium is calculated at the mid-point of each potential experience group. See Notes to Table 1 for information on fixed-weighting scheme. Real minimum wage is deflated by the Personal Consumption Expenditure Deflator. Columns 1 and 2 also include dummy variables for the 4 potential experience groups used in the table.

Table 4. Regression Models for Log Earnings Gaps: Males and Females combined, 1973 - 2003 (May/ORG CPS)

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	90/10 Earnings Gap				90/50 Earnings Gap				50/10 Earnings Gap			
CLG/HS relative supply	0.354		0.131	-0.074	0.033		-0.006	-0.047	0.321		0.137	-0.027
	(0.171)		(0.172)	(0.213)	(0.082)		(0.105)	(0.135)	(0.132)		(0.158)	(0.197)
Log real minimum wage		-0.405	-0.393	-0.318		-0.138	-0.138	-0.124		-0.267	-0.254	-0.194
		(0.063)	(0.065)	(0.079)		(0.038)	(0.040)	(0.051)		(0.058)	(0.060)	(0.074)
Male prime-age unemp. rate		0.003	0.000	0.002		-0.002	-0.002	-0.001		0.005	0.002	0.003
		(0.004)	(0.005)	(0.005)		(0.002)	(0.003)	(0.003)		(0.003)	(0.005)	(0.005)
Time	0.001	0.006	0.003	0.011	0.007	0.006	0.006	0.008	-0.006	0.000	-0.003	0.003
	(0.004)	(0.001)	(0.004)	(0.006)	(0.002)	(0.000)	(0.003)	(0.004)	(0.003)	(0.001)	(0.004)	(0.006)
Time x Post-1992				-0.006				-0.001				-0.005
				(0.004)				(0.003)				(0.004)
Constant	1.353	1.908	1.954	1.715	0.602	0.840	0.838	0.791	0.750	1.068	1.116	0.924
	(0.070)	(0.116)	(0.131)	(0.198)	(0.033)	(0.070)	(0.080)	(0.126)	(0.054)	(0.107)	(0.120)	(0.184)
Observations	31	31	31	31	31	31	31	31	31	31	31	31
R-squared	0.841	0.923	0.934	0.940	0.932	0.954	0.954	0.955	0.377	0.622	0.633	0.658

Standard errors in parentheses. Each column presents a separate OLS regression using May/ORG CPS data. The real minimum wage series is deflated by the Personal Consumption Expenditure Deflator.

Table 5. Comparison of Earnings Inequality Within Narrow Education and Experience Categories: 1974, 1988 and 2002 (May/ORG CPS)

	Δ 90/10		Δ 90/50		Δ 50/10	
Potential Experience	1974 - 1988	1988 - 2002	1974 - 1988	1988 - 2002	1974 - 1988	1988 - 2002
A.College Graduate Males						
4 - 6 yrs	0.146	0.042	0.075	0.069	0.071	-0.027
	(0.034)	(0.031)	(0.023)	(0.021)	(0.026)	(0.028)
14 - 16 yrs	0.169	0.140	0.103	0.110	0.067	0.030
	(0.062)	(0.033)	(0.034)	(0.025)	(0.047)	(0.029)
24 - 26 yrs	0.279	0.172	0.110	0.090	0.169	0.082
	(0.057)	(0.040)	(0.036)	(0.029)	(0.056)	(0.036)
24 - 36 yrs	0.289	0.058	0.032	0.087	0.257	-0.029
	(0.097)	(0.070)	(0.062)	(0.038)	(0.090)	(0.072)
B. High School Graduate Males						
4 - 6 yrs	0.127	-0.178	0.106	-0.065	0.021	-0.113
	(0.027)	(0.026)	(0.021)	(0.016)	(0.018)	(0.016)
14 - 16 yrs	0.195	-0.040	0.094	0.068	0.100	-0.108
	(0.026)	(0.017)	(0.019)	(0.014)	(0.016)	(0.011)
24 - 26 yrs	0.130	-0.015	0.042	0.035	0.087	-0.051
	(0.036)	(0.024)	(0.029)	(0.014)	(0.033)	(0.023)
24 - 36 yrs	0.211	-0.089	0.016	0.034	0.194	-0.123
	(0.038)	(0.029)	(0.025)	(0.020)	(0.034)	(0.023)
C. College Graduate Females						
4 - 6 yrs	0.170	-0.057	0.086	0.025	0.084	-0.082
	(0.041)	(0.029)	(0.032)	(0.019)	(0.034)	(0.020)
14 - 16 yrs	0.183	0.105	0.107	0.056	0.076	0.049
	(0.068)	(0.035)	(0.047)	(0.025)	(0.064)	(0.027)
24 - 26 yrs	0.165	0.075	0.133	0.059	0.032	0.017
	(0.066)	(0.037)	(0.045)	(0.027)	(0.056)	(0.032)
24 - 36 yrs	0.104	0.063	0.041	0.123	0.064	-0.060
	(0.098)	(0.053)	(0.059)	(0.040)	(0.077)	(0.047)
D. High School Graduate Females						
4 - 6 yrs	0.090	-0.165	0.039	-0.079	0.050	-0.086
	(0.024)	(0.018)	(0.023)	(0.015)	(0.020)	(0.014)
14 - 16 yrs	0.204	-0.161	0.101	-0.082	0.103	-0.080
	(0.027)	(0.020)	(0.025)	(0.016)	(0.019)	(0.016)
24 - 26 yrs	0.180	-0.076	0.092	-0.018	0.088	-0.058
	(0.029)	(0.022)	(0.026)	(0.017)	(0.017)	(0.018)
24 - 36 yrs	0.154	-0.079	0.061	-0.008	0.094	-0.072
	(0.027)	(0.022)	(0.023)	(0.018)	(0.021)	(0.017)

Source data: May/ORG CPS 1973 - 2003. Statistics pool three years of data centered on indicated year. Standard-errors in parentheses are bootstrapped using 100 replications.

Table 6. Comparison of Hourly Earnings Inequality Within Narrow Education and Experience Categories: 1976, 1988 and 2001 (March CPS)

Potential Experience	Δ 90/10 1976 - 1988	Δ 90/10 1988 - 2001	Δ 90/50 1976 - 1988	Δ 90/50 1988 - 2001	Δ 50/10 1976 - 1988	Δ 50/10 1988 - 2001
A.College Graduate Males						
4 - 6 yrs	0.152	0.052	0.021	0.124	0.131	-0.072
	(0.041)	(0.047)	(0.024)	(0.032)	(0.039)	(0.042)
14 - 16 yrs	-0.014	0.243	0.038	0.172	-0.053	0.071
	(0.068)	(0.057)	(0.036)	(0.033)	(0.063)	(0.048)
24 - 26 yrs	0.035	0.126	0.055	0.104	-0.020	0.022
	(0.082)	(0.071)	(0.066)	(0.058)	(0.063)	(0.054)
24 - 36 yrs	0.278	0.119	0.038	0.142	0.240	-0.023
	(0.122)	(0.118)	(0.068)	(0.070)	(0.111)	(0.105)
B. High School Graduate Males						
4 - 6 yrs	0.061	0.026	0.037	0.046	0.024	-0.020
	(0.030)	(0.028)	(0.019)	(0.020)	(0.022)	(0.023)
14 - 16 yrs	0.217	-0.021	0.106	0.054	0.111	-0.075
	(0.041)	(0.030)	(0.020)	(0.021)	(0.033)	(0.026)
24 - 26 yrs	0.245	-0.076	0.063	0.051	0.182	-0.127
	(0.043)	(0.040)	(0.031)	(0.028)	(0.034)	(0.031)
24 - 36 yrs	0.247	-0.006	0.066	0.051	0.182	-0.057
	(0.038)	(0.040)	(0.033)	(0.031)	(0.036)	(0.034)
C.College Graduate Females						
4 - 6 yrs	0.111	0.048	0.076	0.072	0.035	-0.024
	(0.044)	(0.047)	(0.028)	(0.030)	(0.033)	(0.037)
14 - 16 yrs	0.039	0.190	0.046	0.076	-0.007	0.114
	(0.077)	(0.052)	(0.054)	(0.035)	(0.057)	(0.039)
24 - 26 yrs	-0.017	0.107	-0.017	0.076	0.000	0.031
	(0.073)	(0.065)	(0.049)	(0.038)	(0.072)	(0.063)
24 - 36 yrs	0.411	0.036	0.254	0.010	0.157	0.026
	(0.151)	(0.138)	(0.103)	(0.100)	(0.102)	(0.081)
D. High School Graduate Females						
4 - 6 yrs	0.083	-0.010	0.023	0.013	0.060	-0.023
	(0.032)	(0.029)	(0.022)	(0.023)	(0.023)	(0.020)
14 - 16 yrs	0.152	-0.035	0.054	-0.020	0.097	-0.015
	(0.030)	(0.029)	(0.025)	(0.025)	(0.026)	(0.025)
24 - 26 yrs	0.140	-0.041	0.083	-0.033	0.057	-0.008
	(0.041)	(0.034)	(0.030)	(0.026)	(0.032)	(0.022)
24 - 36 yrs	0.047	0.033	-0.007	-0.016	0.054	0.049
	(0.044)	(0.040)	(0.040)	(0.033)	(0.029)	(0.028)

Source data: March CPS 1976 - 2003. Statistics pool three years of data centered on indicated year. Standard-errors in parentheses are bootstrapped using 100 replications.

Table 7. JMP-Like Decompositions of Earnings Inequality into Price and Quantity Components, May/ORG CPS 1973 - 2003 (100 x log point changes)

	1973 - 1988				1988 - 2003			
A. Males								
	Total	Quantities	Btwn Prices	Within Prices	Total	Quantities	Btwn Prices	Within Prices
90-10	25.2	0.3	17.8	7.0	7.1	4.4	5.2	-2.5
90-50	13.2	0.7	10.7	1.8	11.6	-1.4	8.2	4.8
50-10	12.0	-0.3	7.1	5.2	-4.5	5.8	-3.0	-7.3
	Total	Within Prices	Btwn Prices	Quantities	Total	Within Prices	Btwn Prices	Quantities
90-10	25.2	8.4	14.8	2.0	7.1	-0.8	4.8	3.1
90-50	13.2	5.3	9.1	-1.1	11.6	6.5	6.7	-1.6
50-10	12.0	3.2	5.6	3.2	-4.5	-7.3	-1.9	4.7
B. Females								
	Total	Quantities	Btwn Prices	Within Prices	Total	Quantities	Btwn Prices	Within Prices
90-10	25.2	0.1	10.0	15.1	9.5	2.9	5.3	1.3
90-50	11.0	-3.0	6.2	7.7	8.8	0.8	2.7	5.3
50-10	14.3	3.1	3.8	7.4	0.7	2.1	2.6	-4.0
	Total	Within Prices	Btwn Prices	Quantities	Total	Within Prices	Btwn Prices	Quantities
90-10	25.2	13.8	6.1	5.3	9.5	-5.0	2.8	11.8
90-50	11.0	7.0	3.1	0.9	8.8	2.7	3.3	2.8
50-10	14.3	6.8	3.0	4.5	0.7	-7.8	-0.5	9.0

Source data: May/ORG CPS 1973 - 2003. See text for details of quantile decomposition procedure.

Table 8. JMP-Like Decompositions of Earnings Inequality into Price and Quantity Components, March CPS 1975 - 2002 (100 x log point changes)

	1975- 1988				1988 - 2002			
A. Males								
	Total	Quantities	Btwn Prices	Within Prices	Total	Quantities	Btwn Prices	Within Prices
90-10	21.0	0.5	9.8	10.6	10.1	5.3	4.5	0.3
90-50	10.4	-1.0	6.2	5.2	11.2	-1.1	6.8	5.5
50-10	10.6	1.5	3.6	5.5	-1.1	6.4	-2.3	-5.2
	Total	Within Prices	Btwn Prices	Quantities	Total	Within Prices	Btwn Prices	Quantities
90-10	21.0	12.4	5.9	2.6	10.1	-0.1	6.2	4.0
90-50	10.4	6.2	5.2	-1.0	11.2	6.5	5.6	-0.9
50-10	10.6	6.2	0.7	3.6	-1.1	-6.5	0.6	4.9
B. Females								
	Total	Quantities	Btwn Prices	Within Prices	Total	Quantities	Btwn Prices	Within Prices
90-10	23.8	5.6	6.1	12.0	11.7	-0.5	5.2	7.0
90-50	9.4	0.5	5.3	3.6	9.1	-1.7	2.9	7.9
50-10	14.4	5.1	0.8	8.4	2.6	1.2	2.4	-1.0
	Total	Within Prices	Btwn Prices	Quantities	Total	Within Prices	Btwn Prices	Quantities
90-10	23.8	13.9	6.6	3.3	11.7	2.0	4.9	4.9
90-50	9.4	7.0	4.6	-2.2	9.1	4.7	4.1	0.3
50-10	14.4	6.9	2.0	5.5	2.6	-2.8	0.8	4.6

Source data: March CPS 1976 - 2003. See text for details of quantile decomposition procedure.

Table 9. Actual and counterfactual changes in upper and lower tail hourly earnings inequality: May/ORG Current Population Survey, 1973 - 2003

	Males			Females		
	1973-1988	1988-2003	1973-2003	1973-1988	1988-2003	1973-2003
	A. 100 x Observed and Composition-Constant Changes in Overall Inequality					
	Δ 90/10					
Observed	25.2	7.1	32.3	25.2	9.5	34.8
1973 X's	23.2	1.9	25.1	19.9	-1.7	18.2
1988 X's	24.9	4.0	28.9	25.1	-2.3	22.9
2003 X's	25.5	2.7	28.2	21.0	6.6	27.6
	Δ 90/50					
Observed	13.2	11.6	24.8	11.0	8.8	19.8
1973 X's	14.4	10.3	24.7	10.1	4.7	14.8
1988 X's	12.6	13.2	25.8	14.0	6.0	20.0
2003 X's	10.2	13.0	23.2	10.9	8.0	18.9
	Δ 50/10					
Observed	12.0	-4.5	7.5	14.3	0.7	15.0
1973 X's	8.8	-8.4	0.4	9.8	-6.4	3.4
1988 X's	12.3	-9.2	3.1	11.2	-8.3	2.9
2003 X's	15.3	-10.3	5.0	10.0	-1.3	8.7
	B. 100 x Observed and Composition-Constant Changes in Residual Inequality					
	Δ 90/10					
Observed	11.6	1.2	12.8	16.7	2.1	18.8
1973 X's	13.1	-6.0	7.0	12.8	-3.9	8.9
1988 X's	13.7	-3.4	10.3	16.0	-3.6	12.3
2003 X's	12.4	-0.8	11.6	15.1	-1.2	14.0
	Δ 90/50					
Observed	5.5	2.9	8.4	8.1	2.6	10.7
1973 X's	7.2	0.1	7.3	6.7	-1.4	5.3
1988 X's	6.1	1.9	8.0	7.7	-1.1	6.5
2003 X's	4.6	3.2	7.8	7.3	1.7	9.0
	Δ 50/10					
Observed	6.0	-1.7	4.4	8.6	-0.5	8.1
1973 X's	5.9	-6.2	-0.3	6.1	-2.5	3.7
1988 X's	7.6	-5.2	2.3	8.3	-2.5	5.8
2003 X's	7.8	-4.0	3.8	7.8	-2.9	4.9

Source data: May/ORG CPS 1973 - 2003. See text for details of quantile decomposition procedure.

Table 10. Actual and counterfactual changes in upper and lower tail hourly earnings inequality: March Current Population Survey, 1975 - 2002

	Males			Females		
	1975-1988	1988-2002	1975-2002	1975-1988	1988-2002	1975-2002
	A. 100 x Observed and Composition-Constant Changes in Overall Inequality					
	Δ 90/10					
Observed	21.0	10.1	31.0	23.8	11.7	35.5
1975 X's	18.3	4.5	22.8	20.5	4.0	24.5
1988 X's	20.5	6.1	26.6	18.2	6.9	25.1
2002 X's	21.1	4.8	25.9	16.4	12.2	28.6
	Δ 90/50					
Observed	10.4	11.2	21.6	9.4	9.1	18.5
1975 X's	11.3	10.0	21.3	11.6	3.8	15.4
1988 X's	11.4	12.1	23.4	8.9	8.9	17.8
2002 X's	8.1	12.3	20.4	5.3	10.8	16.2
	Δ 50/10					
Observed	10.6	-1.1	9.5	14.4	2.6	17.0
1975 X's	7.0	-5.5	1.5	8.9	0.2	9.1
1988 X's	9.1	-6.0	3.1	9.2	-2.0	7.3
2002 X's	13.0	-7.5	5.5	11.0	1.4	12.4
	B. 100 x Observed and Composition-Constant Changes in Residual Inequality					
	Δ 90/10					
Observed	13.1	4.5	17.6	15.4	3.2	18.6
1975 X's	13.7	1.2	14.9	13.8	-0.1	13.8
1988 X's	13.3	3.8	17.1	13.9	1.7	15.6
2002 X's	12.7	4.5	17.2	13.1	3.2	16.3
	Δ 90/50					
Observed	5.6	6.3	11.8	5.9	2.9	8.8
1975 X's	6.3	5.0	11.3	6.5	0.3	6.8
1988 X's	6.0	5.7	11.7	5.3	2.9	8.2
2002 X's	5.5	6.3	11.8	4.1	4.2	8.3
	Δ 50/10					
Observed	7.6	-1.7	5.8	9.5	0.3	9.8
1975 X's	7.4	-3.8	3.6	7.3	-0.4	7.0
1988 X's	7.4	-1.9	5.4	8.6	-1.2	7.4
2002 X's	7.2	-1.8	5.4	9.0	-1.0	8.0

Source data: March CPS 1976 - 2003. See text for details of quantile decomposition procedure.

Appendix Table 1a. Trends in Overall Inequality 1975 to 2002.
100 x Changes in Inequality Measures

A. 90th Percentile - 10th Percentile

	Males				Females				Overall			
	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly
1975 - 1981	10.5	5.7	5.6	1.5	1.5	3.4	3.9	5.1	1.9	2.8	4.3	3.1
1981 - 1988	17.4	24.3	13.0	16.6	23.1	20.1	19.9	23.3	14.8	16.7	9.4	16.0
1988 - 1994	13.8	3.5	6.3	5.8	8.0	10.4	7.9	6.1	5.0	2.2	4.3	3.1
1994 - 2002	1.6	3.7	4.1	0.6	1.0	2.7	5.1	0.3	5.5	9.9	2.9	0.6
1975 - 1988	28.0	30.0	18.6	18.1	24.6	23.5	23.9	28.4	16.8	19.5	13.7	19.0
1988 - 2002	15.4	7.2	10.4	6.4	9.0	13.1	12.9	6.4	10.5	12.0	7.2	3.7

B. 90th Percentile - 50th Percentile

	Males				Females				Overall			
	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly
1975 - 1981	2.2	-3.3	1.5	4.2	4.9	5.9	3.9	8.5	2.7	1.9	4.6	6.0
1981 - 1988	9.4	14.2	7.9	10.9	7.6	4.0	6.2	2.4	5.3	8.5	1.4	4.2
1988 - 1994	10.1	6.5	7.4	6.2	3.5	5.2	5.6	7.8	6.0	1.3	4.3	5.9
1994 - 2002	5.9	3.1	5.8	5.6	5.5	2.9	3.2	2.6	2.5	8.3	4.7	2.5
1975 - 1988	11.7	10.9	9.4	15.1	12.5	10.0	10.1	10.9	8.0	10.4	6.0	10.2
1988 - 2002	16.0	9.7	13.2	11.8	9.0	8.1	8.9	10.3	8.5	9.6	9.0	8.4

C. 50th Percentile - 10th Percentile

	Males				Females				Overall			
	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly
1975 - 1981	8.3	9.0	4.1	-2.6	-3.4	-2.6	0.0	-3.4	-0.8	0.9	-0.3	-2.9
1981 - 1988	8.0	10.1	5.1	5.7	15.4	16.1	13.7	20.9	9.5	8.2	8.0	11.7
1988 - 1994	3.8	-3.0	-1.1	-0.4	4.4	5.2	2.2	-1.7	-1.0	0.8	0.0	-2.8
1994 - 2002	-4.4	0.6	-1.7	-5.0	-4.4	-0.2	1.8	-2.3	3.0	1.6	-1.8	-1.9
1975 - 1988	16.3	19.1	9.2	3.0	12.0	13.5	13.7	17.5	8.8	9.1	7.7	8.8
1988 - 2002	-0.6	-2.4	-2.8	-5.4	0.0	5.1	4.1	-3.9	2.0	2.4	-1.8	-4.7

D. Variance

	Males				Females				Overall			
	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly
1975 - 1981	3.4	2.8	2.8	0.6	1.3	0.9	0.7	0.9	1.8	1.1	1.2	0.1
1981 - 1988	7.4	6.8	5.2	7.9	6.8	7.1	6.6	6.9	5.0	5.3	3.9	6.7
1988 - 1994	4.7	3.6	3.5	2.6	5.0	3.8	4.5	3.3	3.7	2.9	3.1	2.1
1994 - 2002	3.0	-0.5	2.1	-0.5	2.0	1.5	1.9	0.8	2.1	0.0	1.7	-0.1
1975 - 1988	10.8	9.5	8.0	8.5	8.0	8.0	7.3	7.8	6.8	6.5	5.2	6.8
1988 - 2002	7.7	3.1	5.5	2.1	7.0	5.3	6.4	4.1	5.9	2.9	4.7	2.0

Data sources for May/ORG statistics are May CPS for 1976 to 1978 and CPS Merged Outgoing Rotation Groups for years 1979 to 2002. Samples include wage/salary workers ages 16 - 64 with 0 - 38 years of potential experience in current employment. Full-time earnings is the logarithm of reported usual weekly earnings. Hourly wages are the logarithm of reported hourly earnings for those paid by the hour and the logarithm of usual weekly earnings divided by hours worked last week for non-hourly workers. Top-coded earnings observations are multiplied by 1.5. Full-time earnings of below $67/week in 1982$ ($112/week in 2000$) and hourly earners of below $1.675/hour in 1982 dollars ($2.80/hour in 2000$) are dropped, as are hourly wages exceeding 1/35th the top-coded value of weekly earnings. Allocated earnings observations are excluded in all years, except where allocation flags are unavailable (1994 and 1995). Full-time earnings are weighted by CPS sampling weights. Hourly earnings are weighted by the product of CPS sampling weights and hours worked in the prior week.

Data sources for March series is the March Current Population for earnings years 1975 to 2002 for workers age 16 - 64 (during earnings year) with 0 - 38 years of potential experience whose class of work in their longest job was private or government wage/salary employment. Hourly earnings are calculated as annual earnings divided by the product of weeks worked and usual hours in the prior year. Full-time, full-year workers are those who work 35 hours per week and worked 40+ weeks in the previous year. Full time weekly earnings are calculated as the logarithm of annual earnings over weeks worked for the full-time, full-year sample. Top-coded earnings observations are multiplied by 1.5. Full-time earnings of below $67/week in 1982$ ($112/week in 2000$) and hourly earners of below $1.675/hour in 1982 dollars ($2.80/hour in 2000$) are dropped, as are hourly wages exceeding 1/35th the top-coded value of weekly earnings. Allocated earnings observations are excluded after 1966 using family earnings allocation flags (1967 1974) or individual earnings allocation flags (1975 forward).

Appendix Table 1b. Trends in Residual Inequality 1975 to 2002
100 x Changes in Inequality Measures

A. 90th Percentile - 10th Percentile

	Males				Females				Overall			
	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly
1975 - 1981	11.3	9.0	8.0	2.3	5.2	5.9	2.4	2.3	8.0	6.4	5.4	1.3
1981 - 1988	9.3	9.2	4.9	8.1	13.2	13.3	12.8	13.4	11.3	10.4	7.7	9.8
1988 - 1994	6.5	5.9	4.9	1.8	5.1	4.8	4.3	2.5	4.4	5.5	4.0	1.8
1994 - 2002	1.5	1.2	0.5	-1.9	0.2	1.7	0.5	-0.5	0.5	0.9	-0.1	-2.0
1975 - 1988	20.7	18.2	12.9	10.3	18.3	19.2	15.2	15.7	19.3	16.8	13.0	11.1
1988 - 2002	8.0	7.1	5.4	-0.1	5.3	6.5	4.8	2.0	4.9	6.4	3.9	-0.2

B. 90th Percentile - 50th Percentile

	Males				Females				Overall			
	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly
1975 - 1981	5.6	5.1	3.8	2.4	2.6	6.8	1.8	3.9	4.1	3.8	3.5	3.6
1981 - 1988	3.6	2.9	1.9	2.7	5.4	1.5	3.6	2.2	4.5	3.4	2.9	2.7
1988 - 1994	4.7	5.0	5.3	3.6	2.9	3.5	3.8	2.8	3.6	3.8	4.2	2.5
1994 - 2002	4.1	1.6	1.7	0.2	1.8	2.8	0.2	-1.0	2.9	2.2	1.0	-0.2
1975 - 1988	9.2	8.0	5.7	5.0	8.0	8.3	5.4	6.0	8.6	7.3	6.4	6.2
1988 - 2002	8.8	6.6	7.0	3.8	4.7	6.3	4.1	1.7	6.5	6.0	5.2	2.3

C. 50th Percentile - 10th Percentile

	Males				Females				Overall			
	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly
1975 - 1981	5.7	3.9	4.2	-0.1	2.6	-0.9	0.6	-1.6	3.9	2.6	1.9	-2.2
1981 - 1988	5.8	6.3	3.0	5.4	7.7	11.7	9.2	11.2	6.8	6.9	4.8	7.1
1988 - 1994	1.8	0.9	-0.3	-1.9	2.2	1.3	0.5	-0.3	0.7	1.7	-0.1	-0.6
1994 - 2002	-2.6	-0.4	-1.2	-2.1	-1.6	-1.1	0.3	0.6	-2.4	-1.3	-1.1	-1.8
1975 - 1988	11.5	10.3	7.2	5.3	10.4	10.9	9.7	9.7	10.8	9.5	6.7	4.9
1988 - 2002	-0.8	0.5	-1.6	-3.9	0.5	0.1	0.7	0.2	-1.7	0.4	-1.3	-2.5

D. Variance

	Males				Females				Overall			
	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly	March FT	MORG FT	March Hourly	MORG Hourly
1975 - 1981	2.9	2.2	2.3	0.2	1.4	1.3	0.9	0.8	2.2	1.7	1.6	0.2
1981 - 1988	3.9	3.1	2.5	3.2	4.4	4.0	4.0	3.4	3.9	3.4	2.9	3.2
1988 - 1994	2.2	2.5	1.1	1.4	2.2	2.1	2.1	2.0	2.1	2.2	1.4	1.5
1994 - 2002	1.9	-0.9	1.5	-0.9	1.1	0.3	1.0	-0.6	1.3	-0.5	1.0	-0.9
1975 - 1988	6.7	5.4	4.8	3.5	5.8	5.3	4.8	4.2	6.1	5.0	4.5	3.4
1988 - 2002	4.1	1.7	2.6	0.5	3.3	2.4	3.1	1.4	3.4	1.7	2.5	0.6

Tabulated numbers are 100 times changes in indicated residual inequality statistics by gender and overall for full-time and all hourly workers. Data sources and samples are identical to Appendix Table 1a. Wage residuals are calculated from a regression of the indicated weekly or hourly wage measure on 5 education category dummies interacted with 13 dummies categorizing potential experience (64 dummies and 1 omitted). Education categories are high school dropout, high school graduate, some college, exactly college graduate, and post-college. Potential experience categories are 0-2 years, 3-5 years ... 36-38 years. Pooled-gender regressions also include a female dummy.

Appendix Table 2. Regression Models for the College/High School Log Wage Gap by Age Group, 1963-2002, Males and Females Pooled.

			Age Groups			
	All Age Groups		Age 25-34	Age 35-44	Age 45-54	Age 55-64
Own Supply Minus Aggregate Supply	-0.205 (0.017)	-0.206 (0.017)	-0.149 (0.048)	-0.077 (0.101)	-0.219 (0.113)	-0.045 (0.115)
Aggregate Supply	-0.498 (0.037)	-0.550 (0.053)	-0.676 (0.081)	-0.521 (0.096)	-0.605 (0.152)	-0.302 (0.177)
Log Real Minimum Wage		0.012 (0.034)	0.005 (0.045)	-0.014 (0.073)	0.192 (0.068)	0.018 (0.095)
Prime Age Male Unemployment		0.004 (0.002)	0.005 (0.003)	0.006 (0.004)	0.004 (0.005)	-0.004 (0.007)
Time	0.022 (0.001)	0.024 (0.002)	0.028 (0.003)	0.022 (0.004)	0.028 (0.006)	0.015 (0.006)
Time x Post-1992	-0.003 (0.002)	-0.003 (0.002)	-0.002 (0.003)	0.001 (0.004)	-0.008 (0.004)	-0.004 (0.005)
Constant	-0.146 (0.035)	-0.225 (0.098)	-0.195 (0.114)	-0.038 (0.190)	-0.497 (0.248)	0.149 (0.274)
N	160	160	40	40	40	40
R-squared	0.933	0.934	0.984	0.924	0.780	0.724

Standard errors in parentheses. Each column presents an OLS regression of the fixed-weighted college/high school wage differential on the indicated variables. The college/high school wage premium is calculated at the mid-point of each age range. See Notes to Table 1 for information on fixed-weighting scheme. Real minimum wage is deflated by the Personal Consumption Expenditure Deflator. Columns 1 and 2 also include dummy variables for the 4 age groups used in the table.

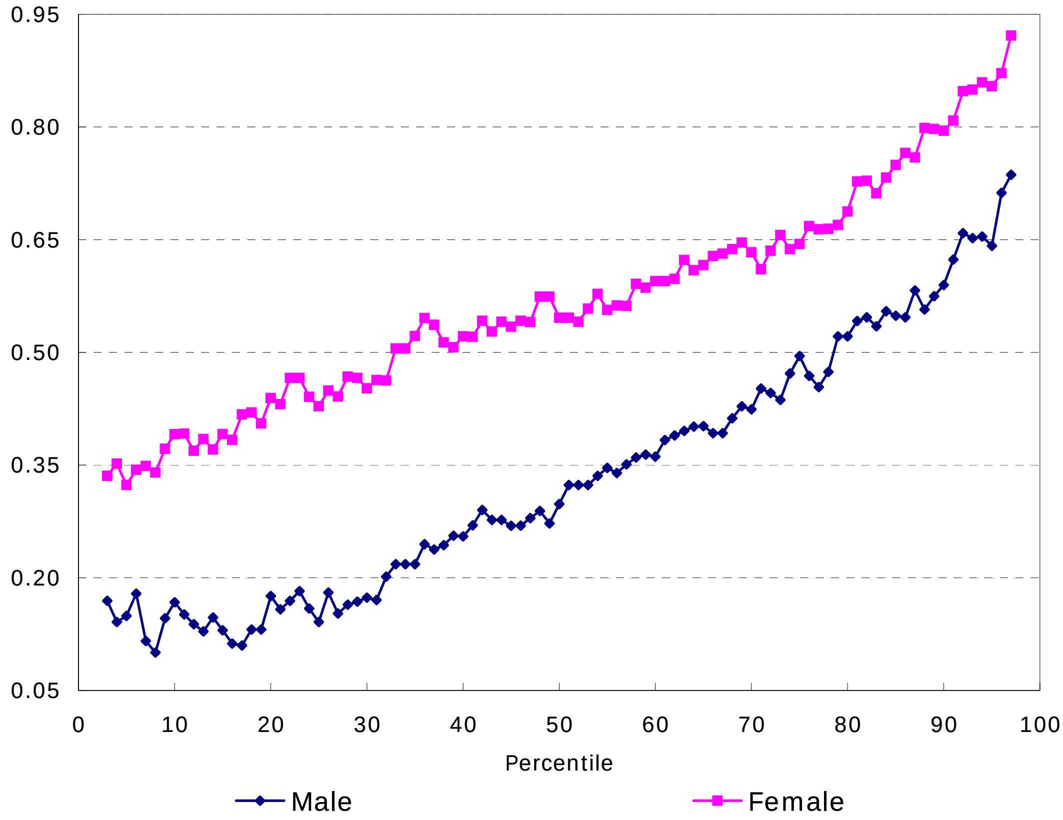
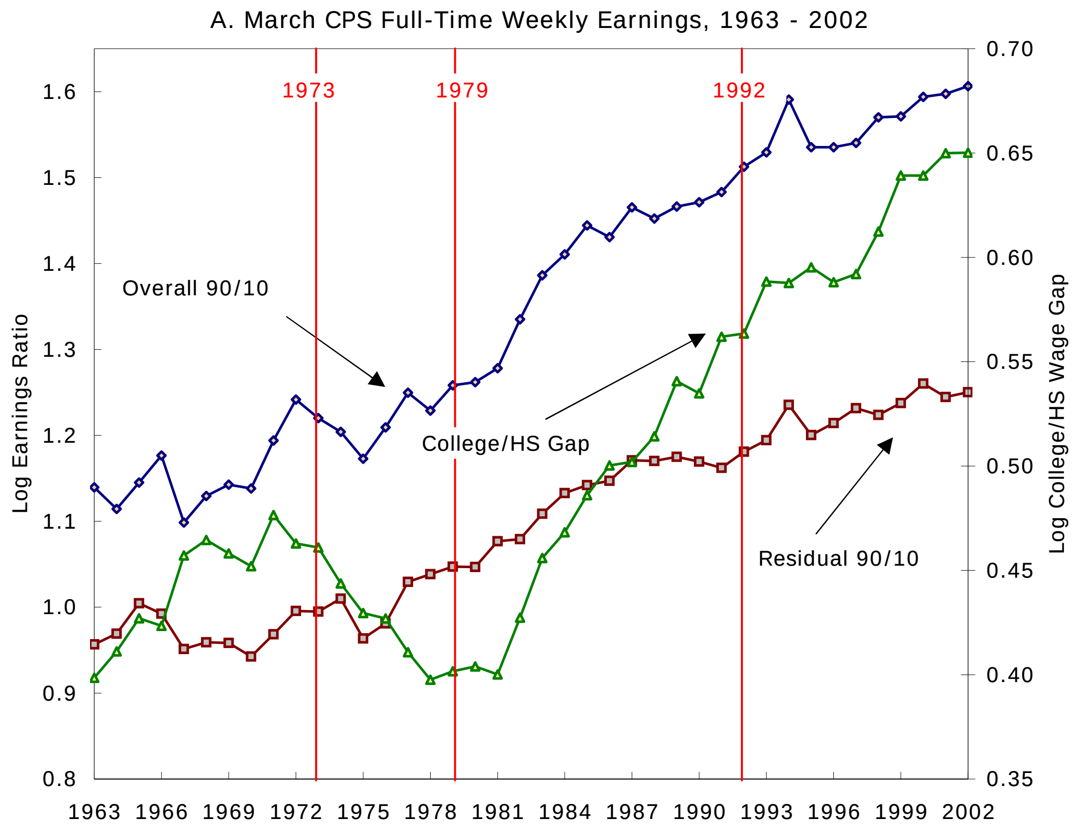


Figure 1. Change in Log Real Weekly Wage by Percentile, Full Time Workers, 1963 - 2002 (March CPS)



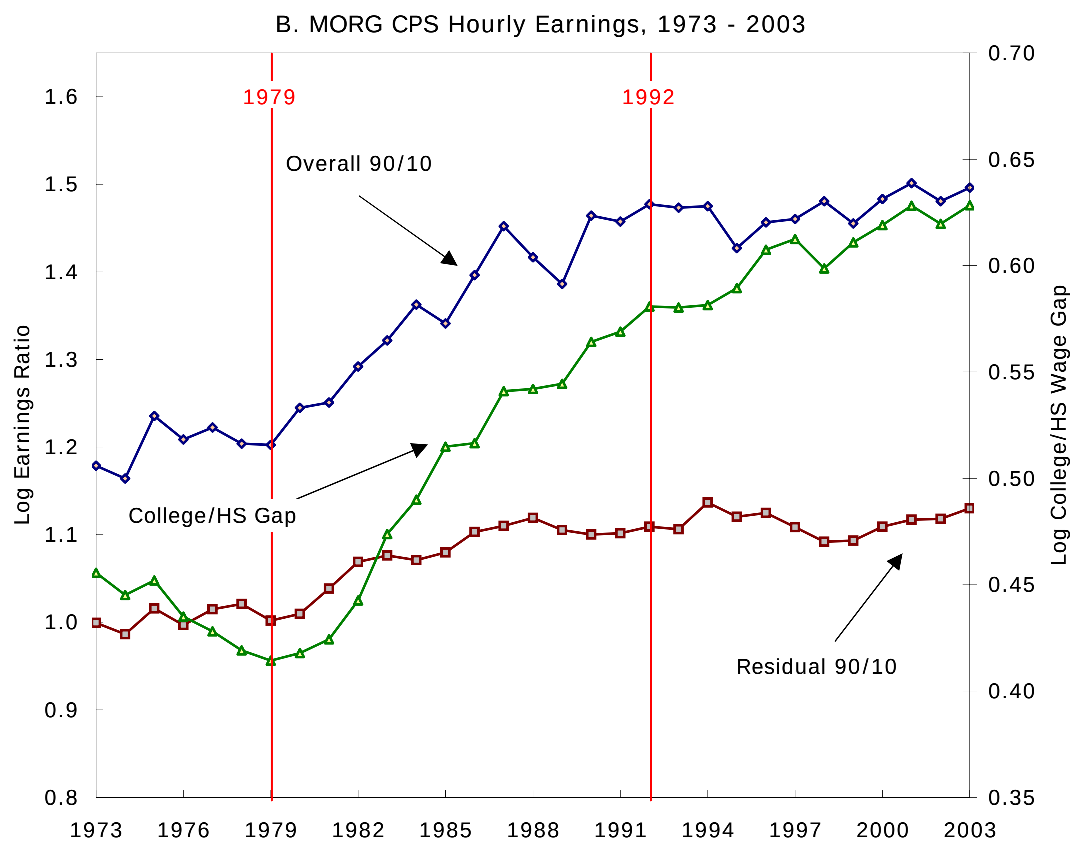
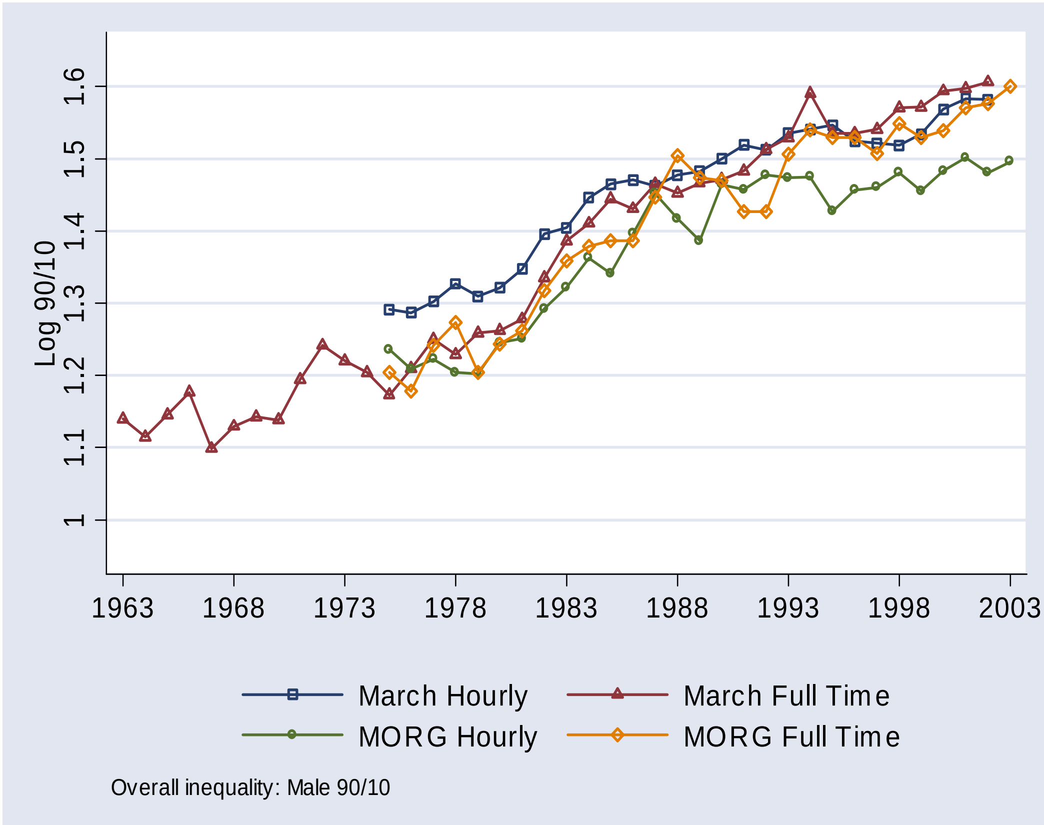


Figure 2. Three Measures of Wage Inequality: College/High School Premium, Male 90/10 Overall Inequality and Male 90/10 Residual Inequality



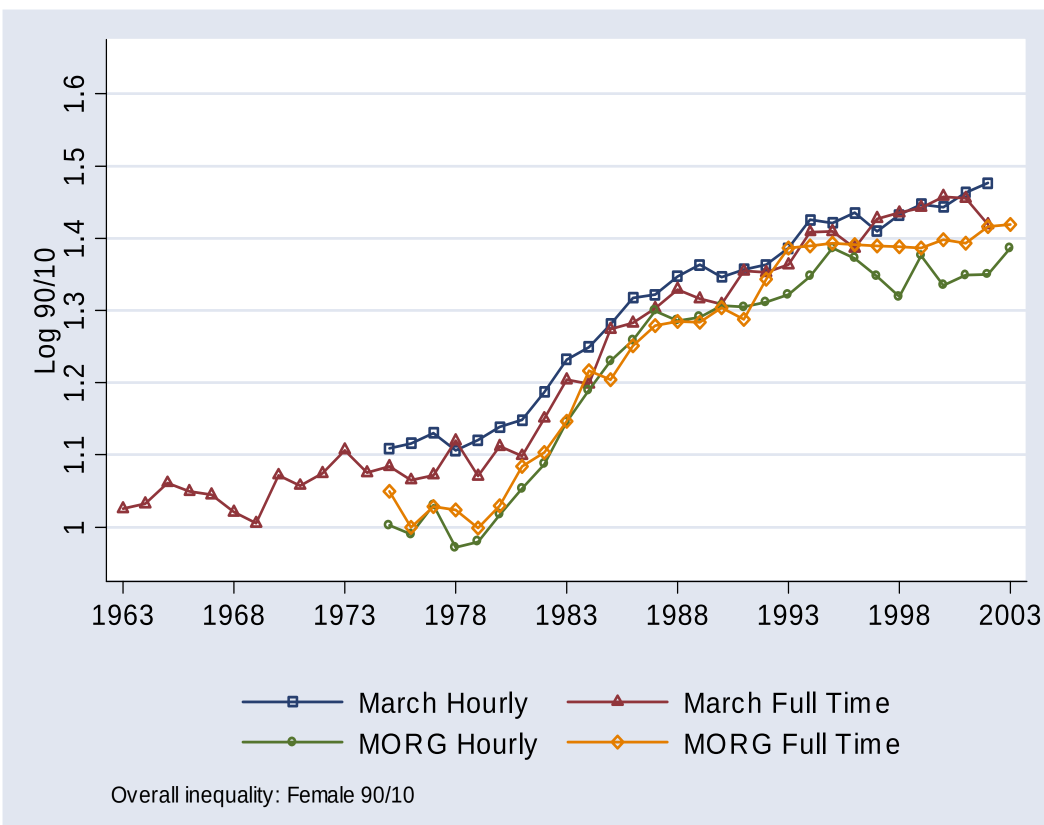
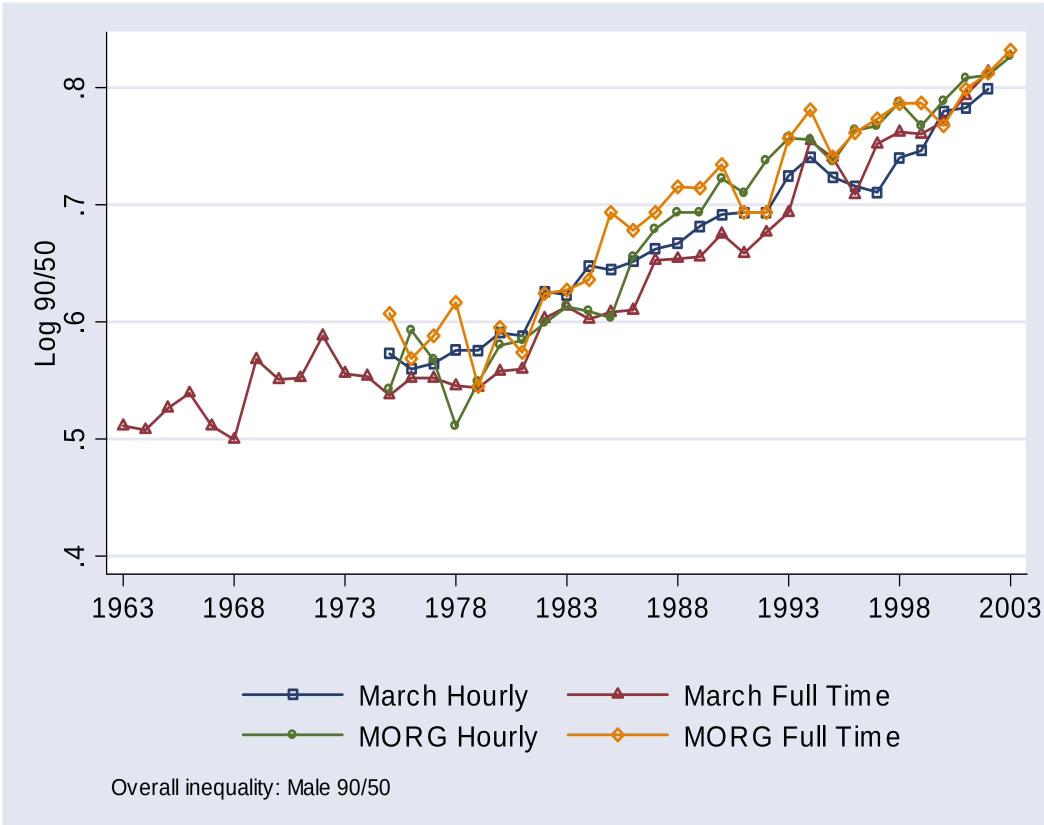


Figure 3. Overall 90/10 Hourly and Full-Time Weekly Wage Inequality:
1963 - 2003 (March and May/ORG CPS)



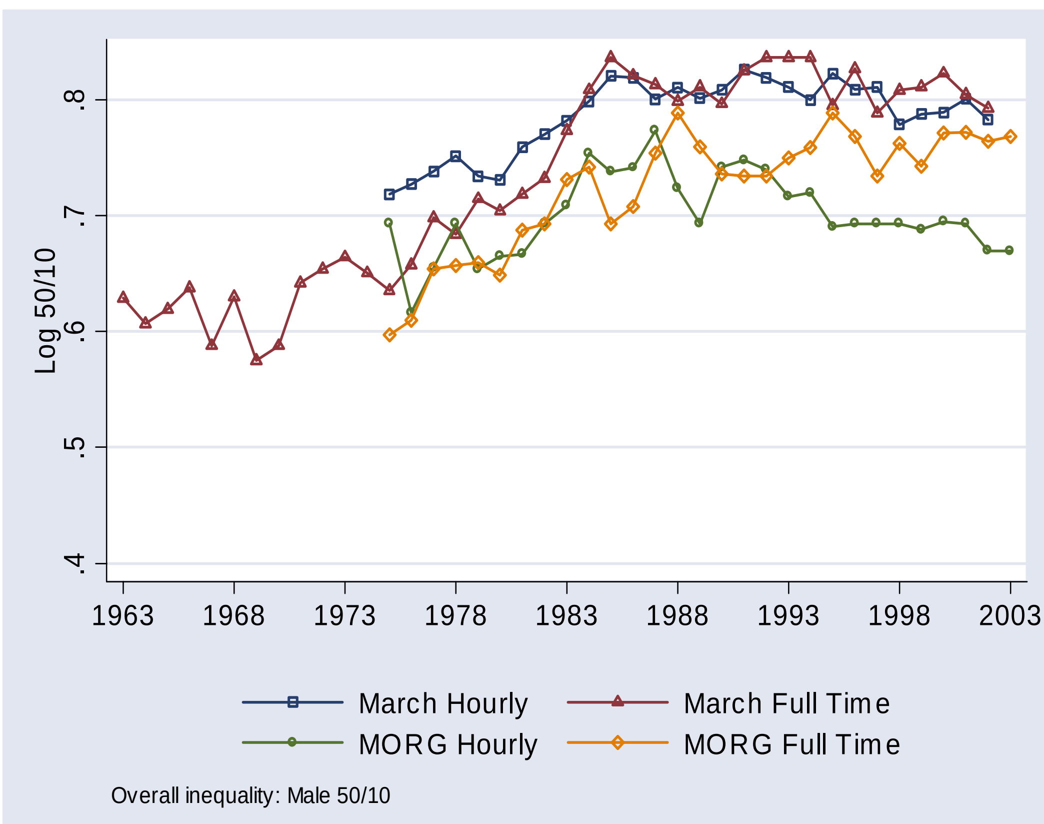
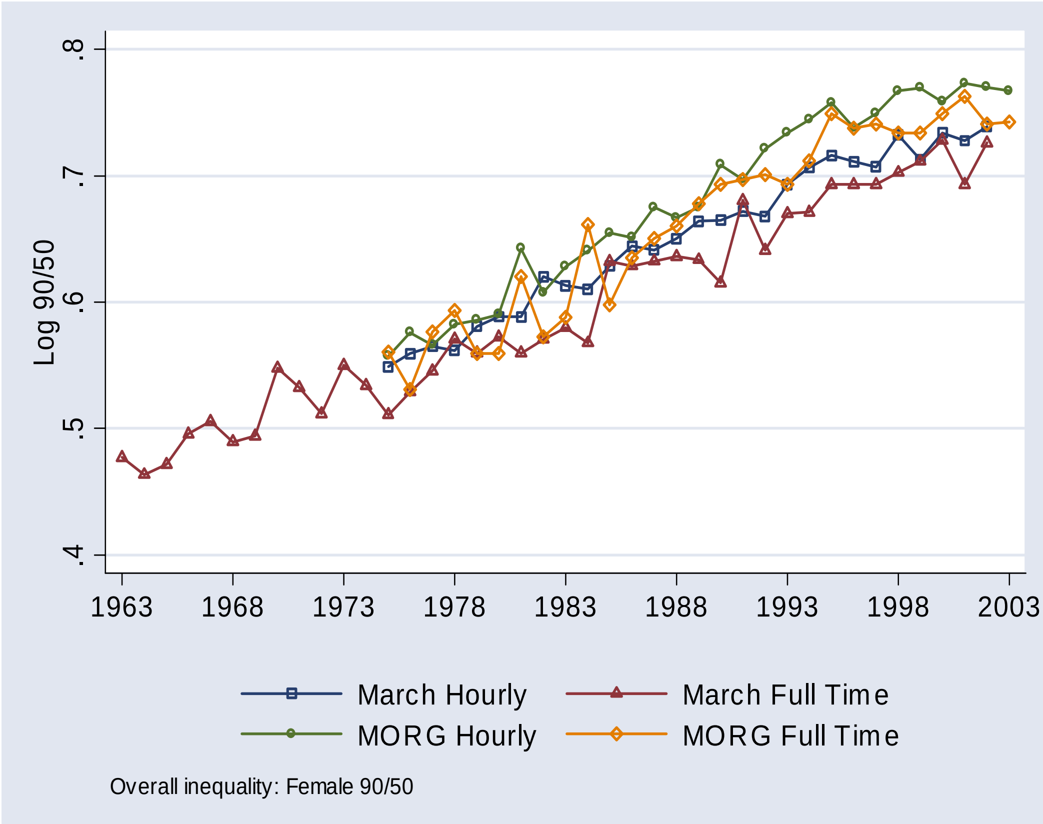


Figure 4. Male Upper and Lower Tail Hourly and Full-Time Weekly Wage Inequality: 1963 - 2003 (March and May/ORG CPS)



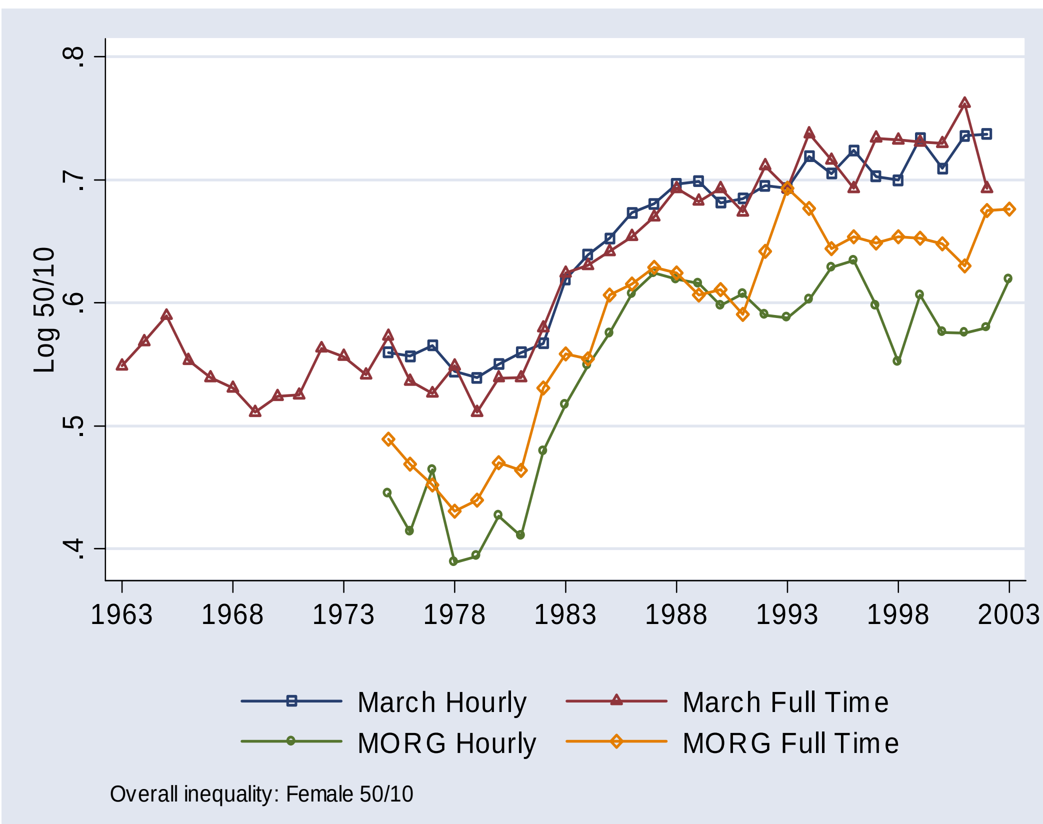


Figure 5. Female Upper and Lower Tail Hourly and Full-Time Weekly Wage Inequality: 1963 - 2003 (March and May/ORG CPS)

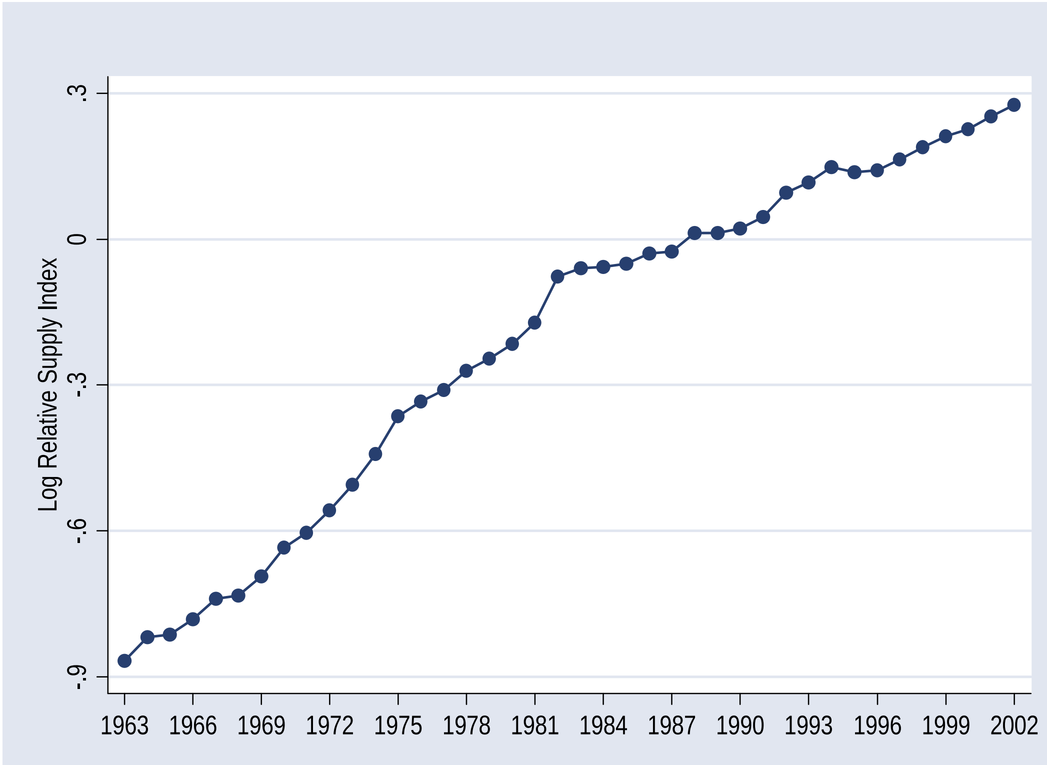


Figure 6. Relative Supply of College Equivalent Labor
1963 - 2002 (March CPS)

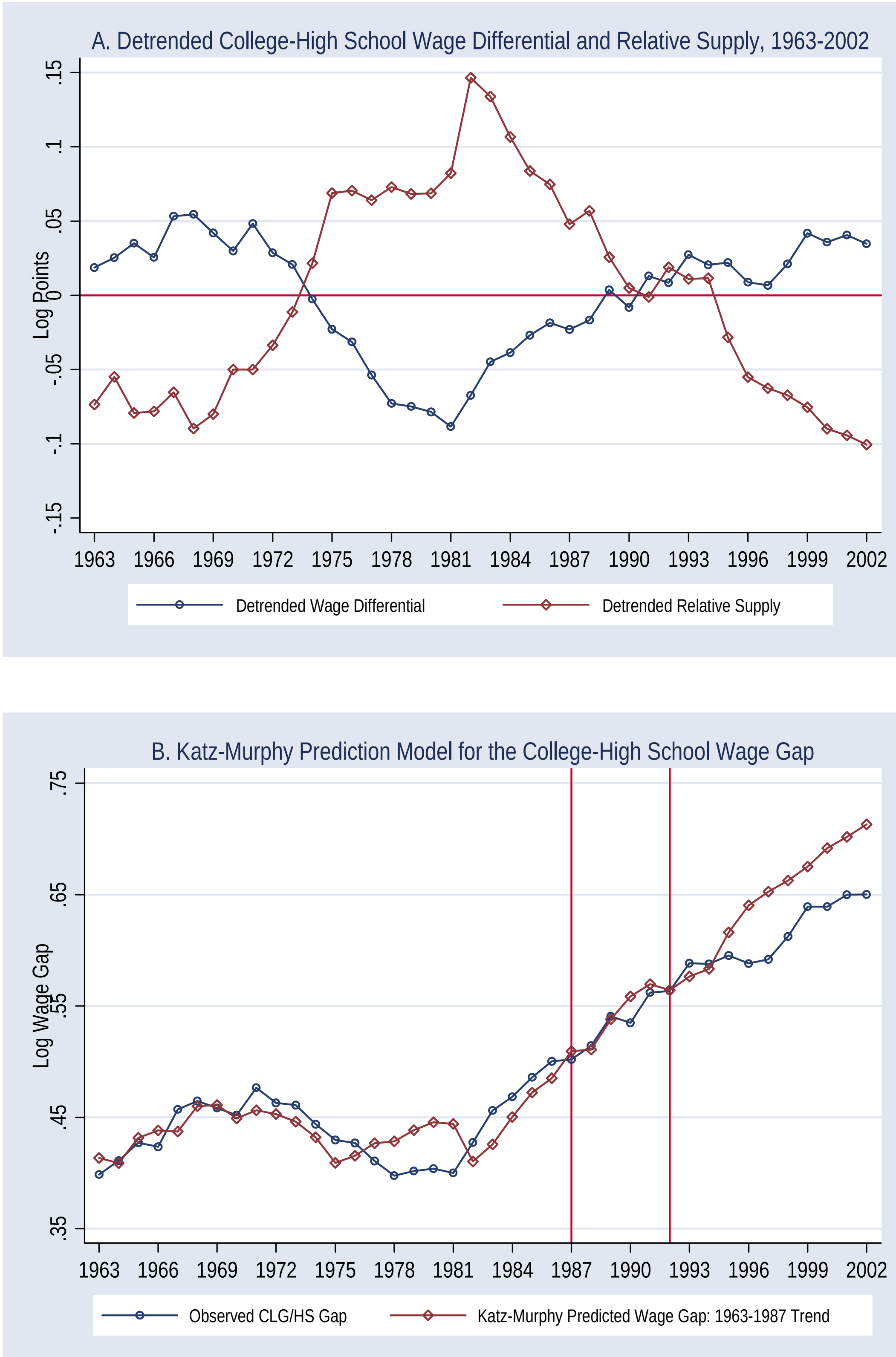


Figure 7. College/High School Relative Supply and Wage Differential, 1963 - 2002 (March CPS) — Panel A. Detrended Measures of Supply and Wage Differentials — Panel B. Katz-Murphy Model for College/HS Wage Differential: Observed and Predicted Values Using 1963 - 1987 Model Estimation

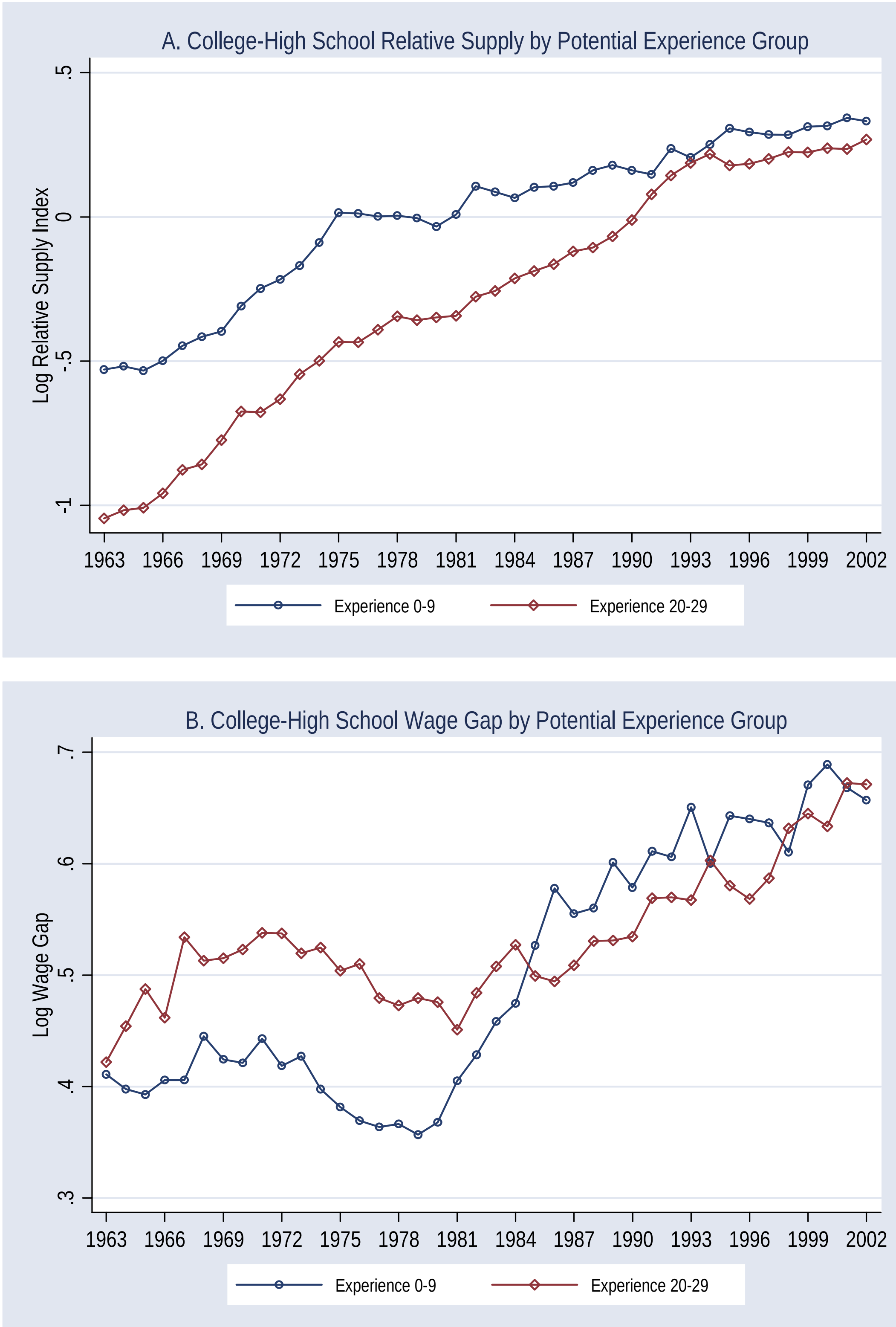


Figure 8. Composition Adjusted Log Relative College/High Relative Wage by Potential Experience and Age Groups, 1963 - 2003 (March CPS)

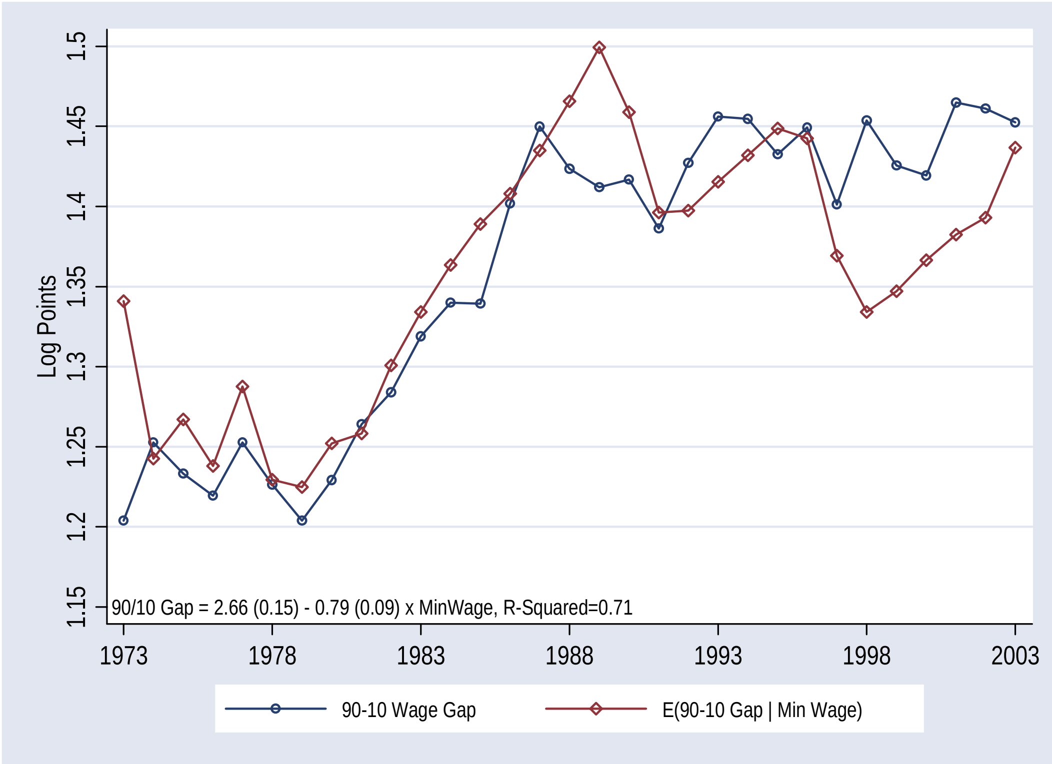
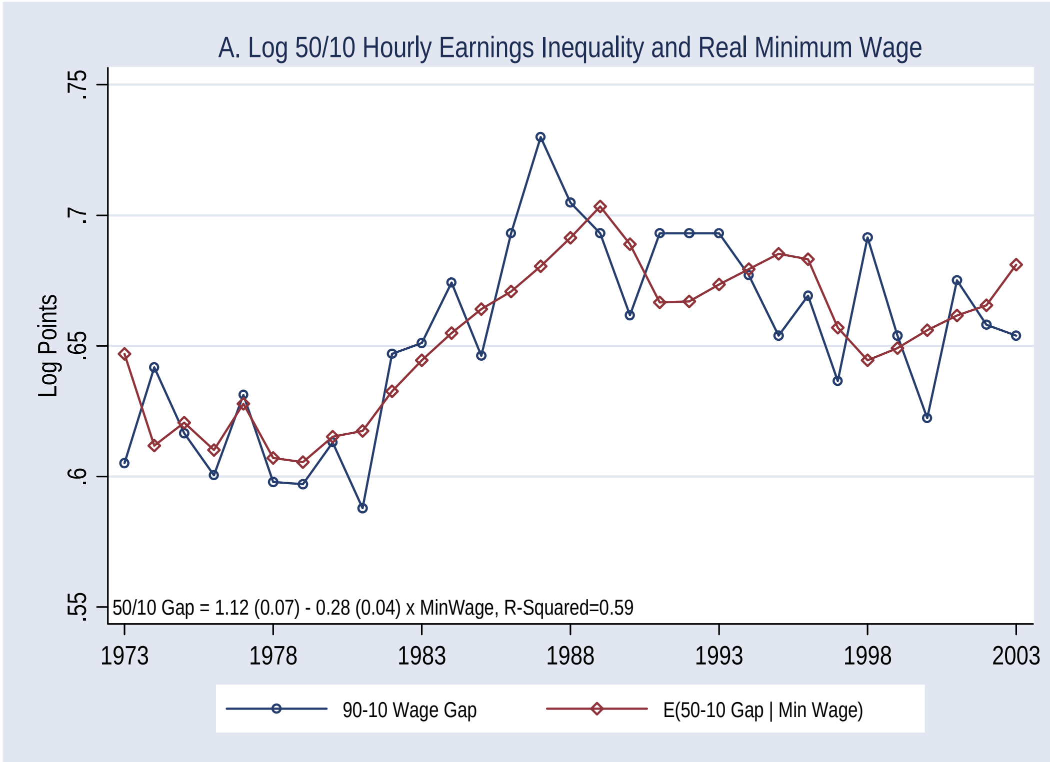


Figure 9. Log 90/10 Hourly Wage Differential and Log Real Federal Minimum Wage, 1973-2003 (May/ORG CPS)



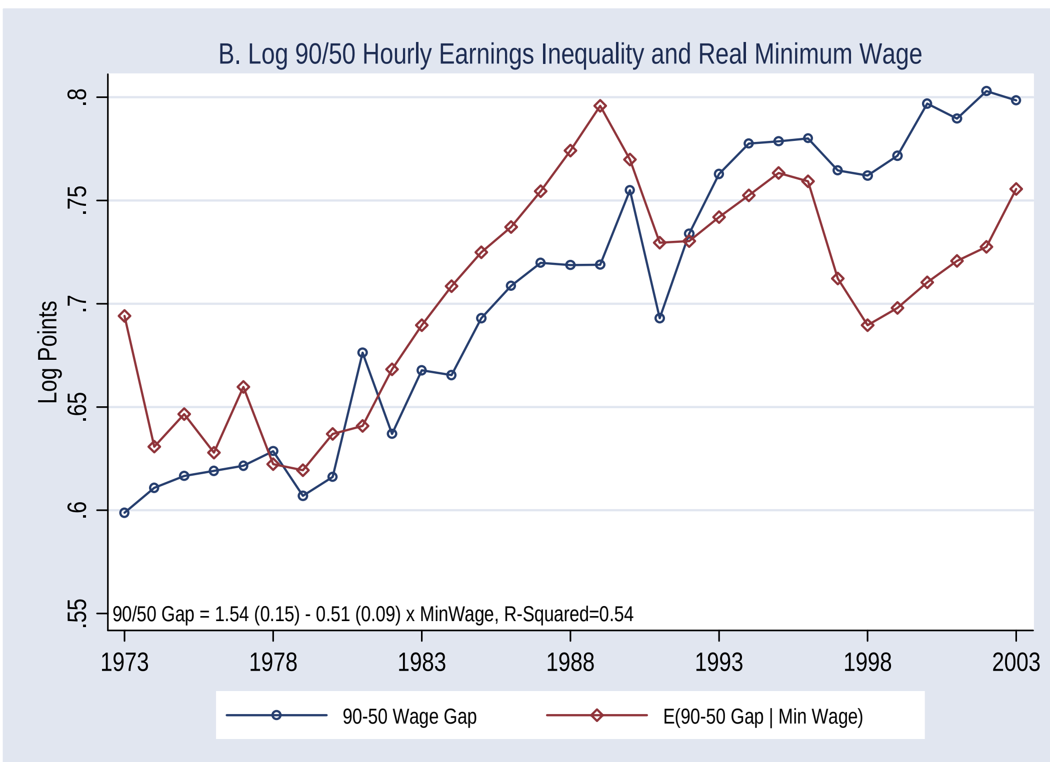
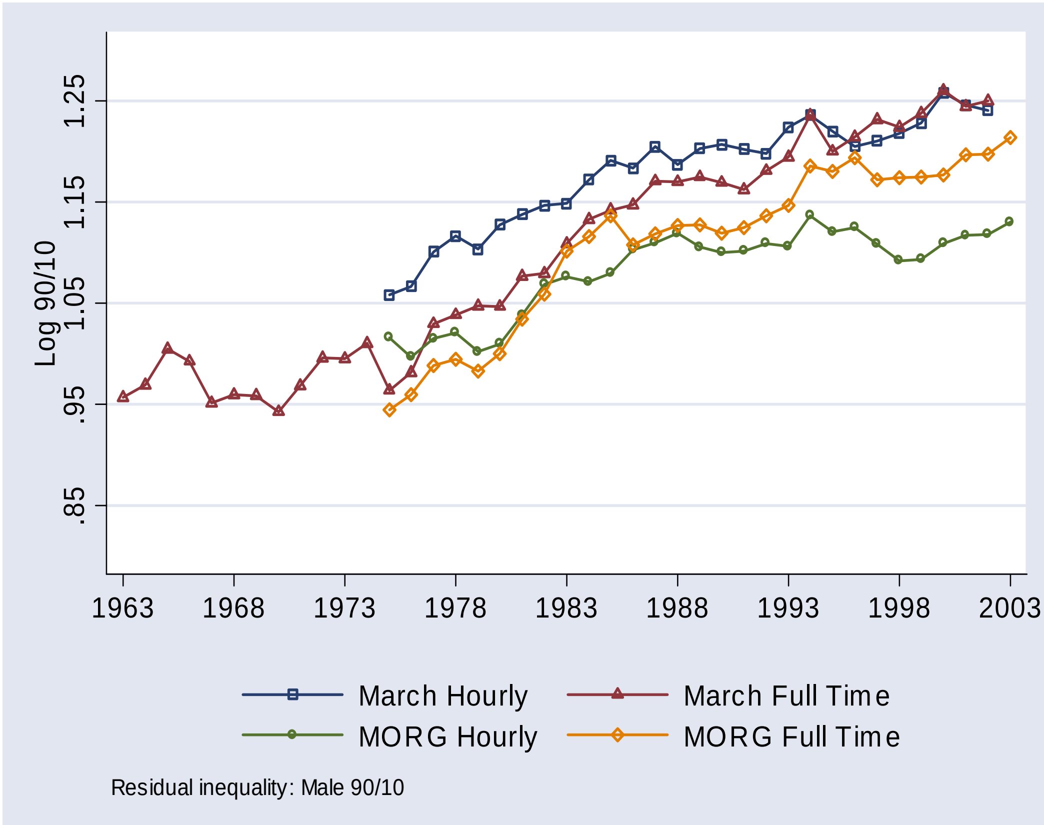


Figure 10. Log 50/10 and 90/50 Hourly Wage Differentials and Log Real Federal Minimum Wage, 1973-2003 (May/ORG CPS)



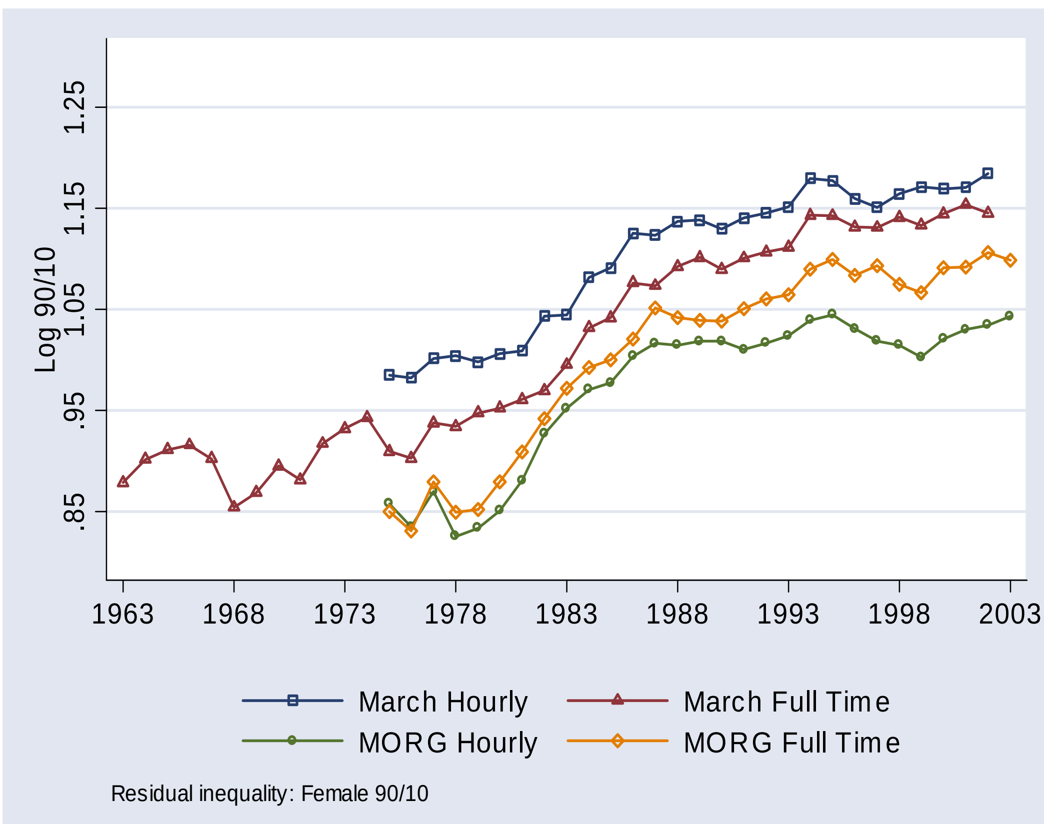
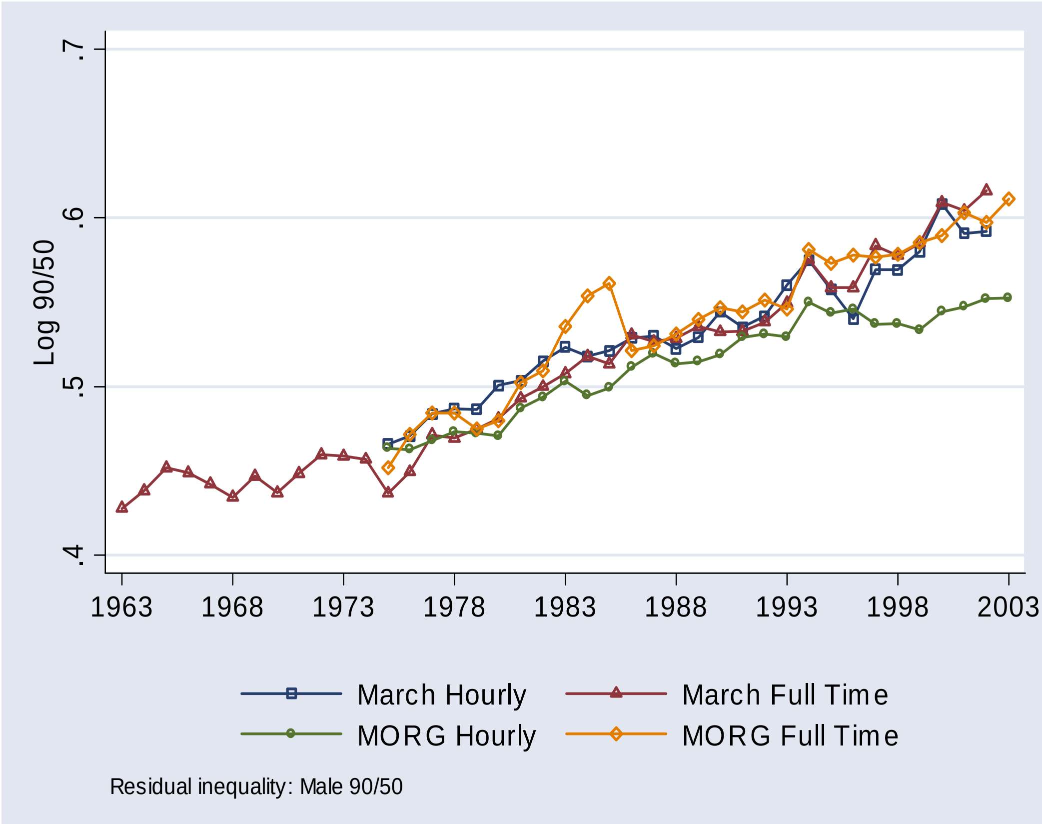


Figure 11. Residual 90/10 Hourly and Full-Time Weekly Wage Inequality:
1963 - 2003 (March and May/ORG CPS)



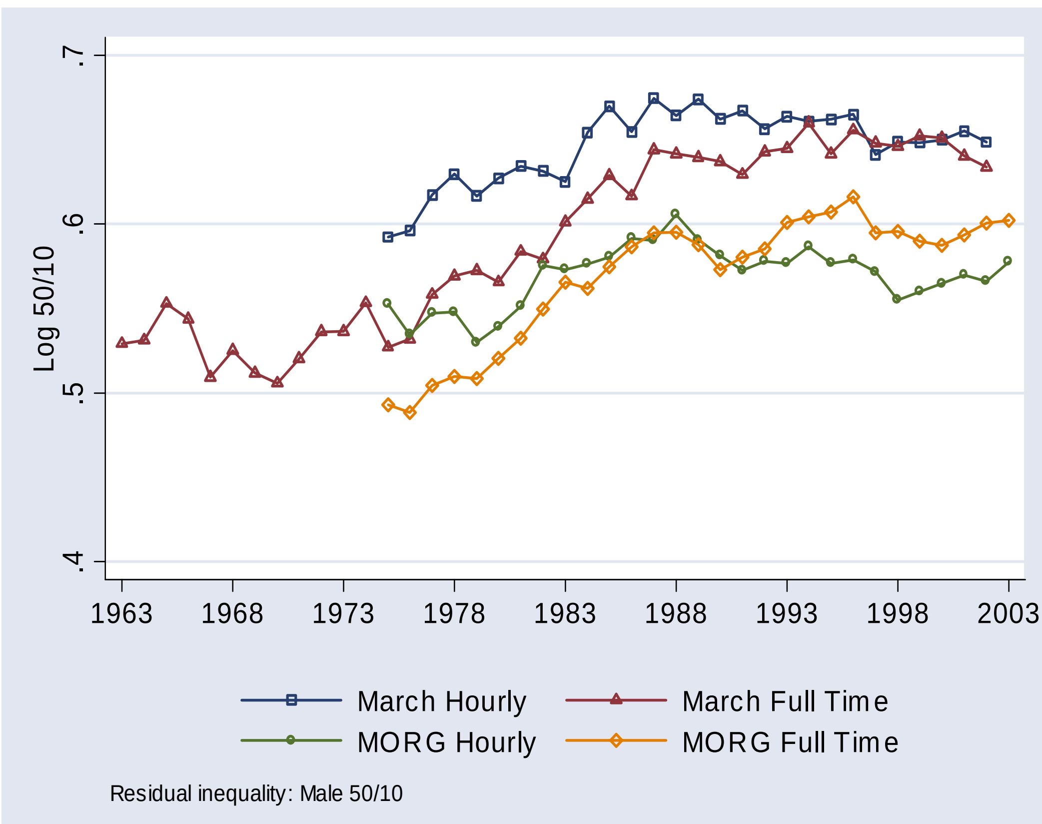
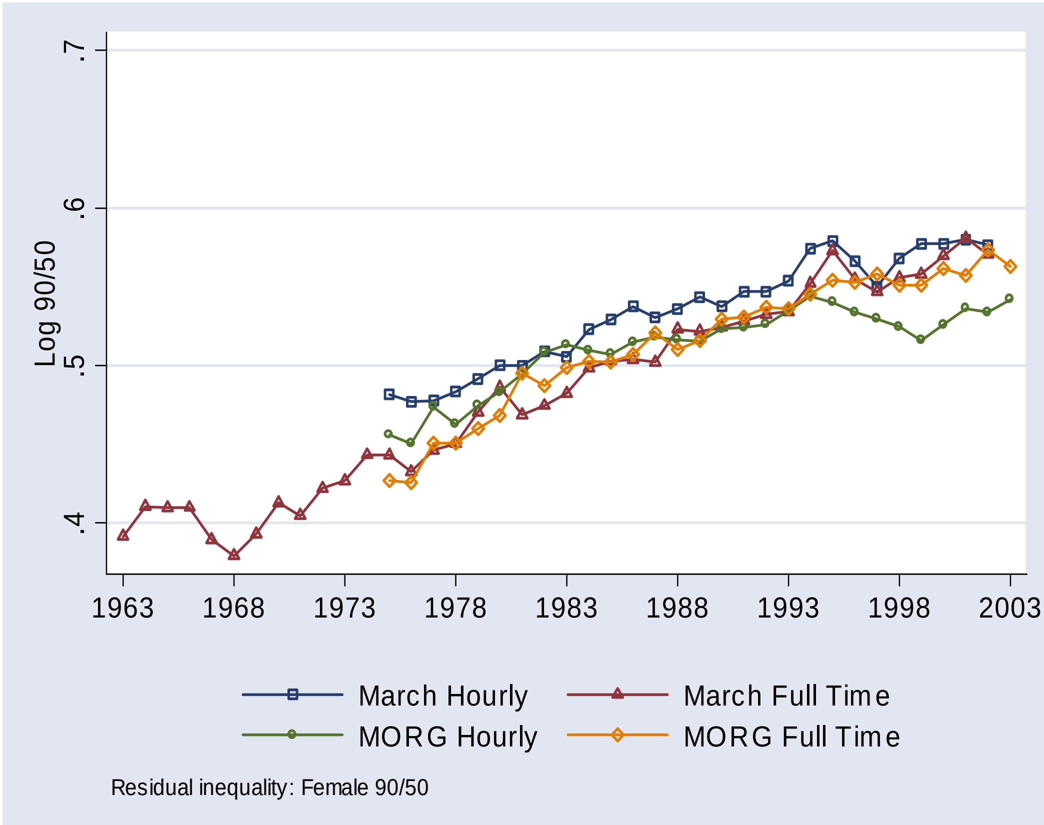


Figure 12. Male Upper and Lower Tail Hourly and Full-Time Weekly Residual Inequality: 1963 - 2003 (March and May/ORG CPS)



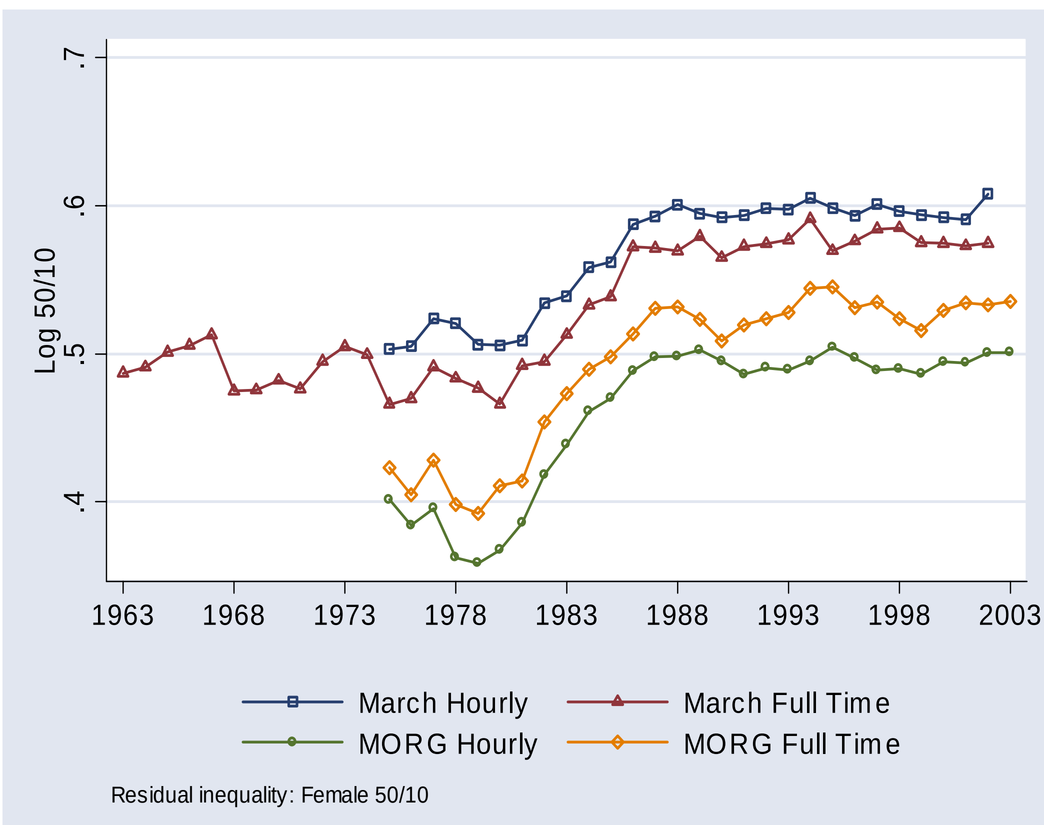
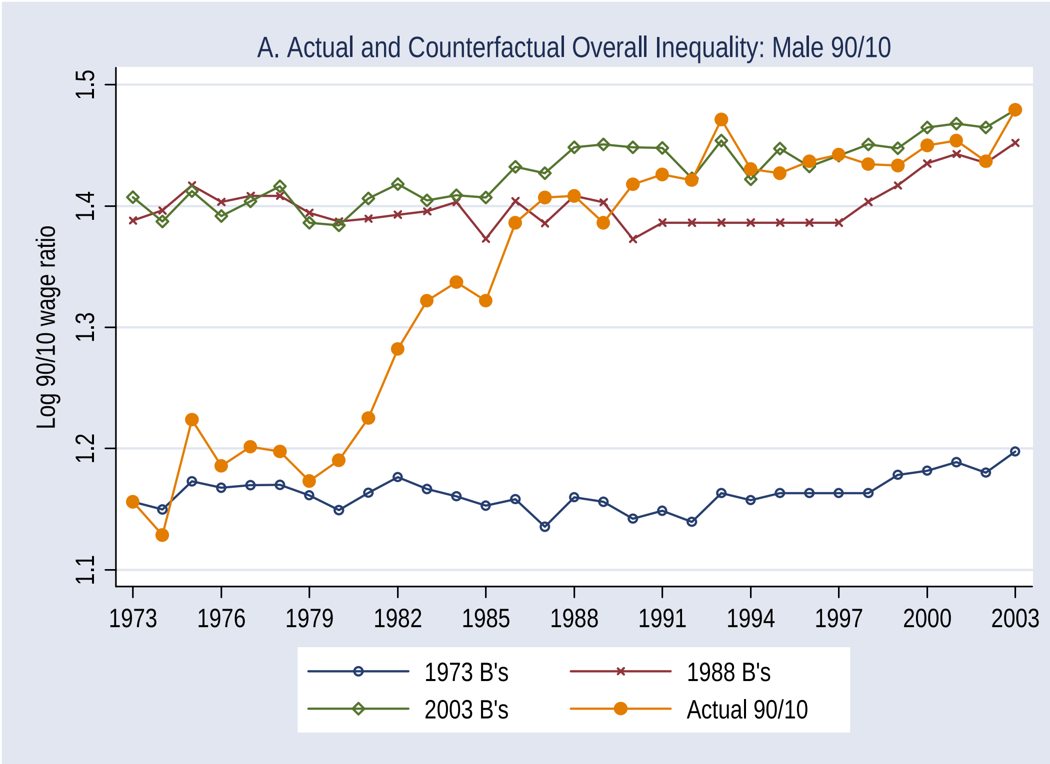


Figure 13. Female Upper and Lower Tail Hourly and Full-Time Weekly Residual Inequality: 1963 - 2003 (March and May/ORG CPS)



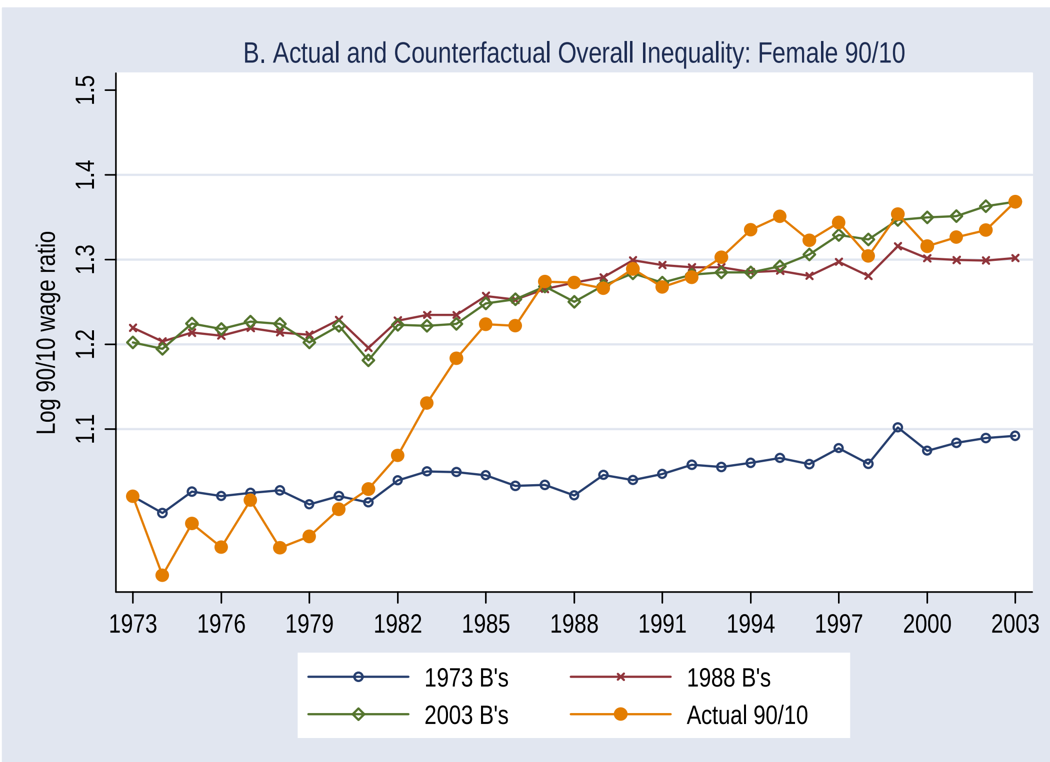
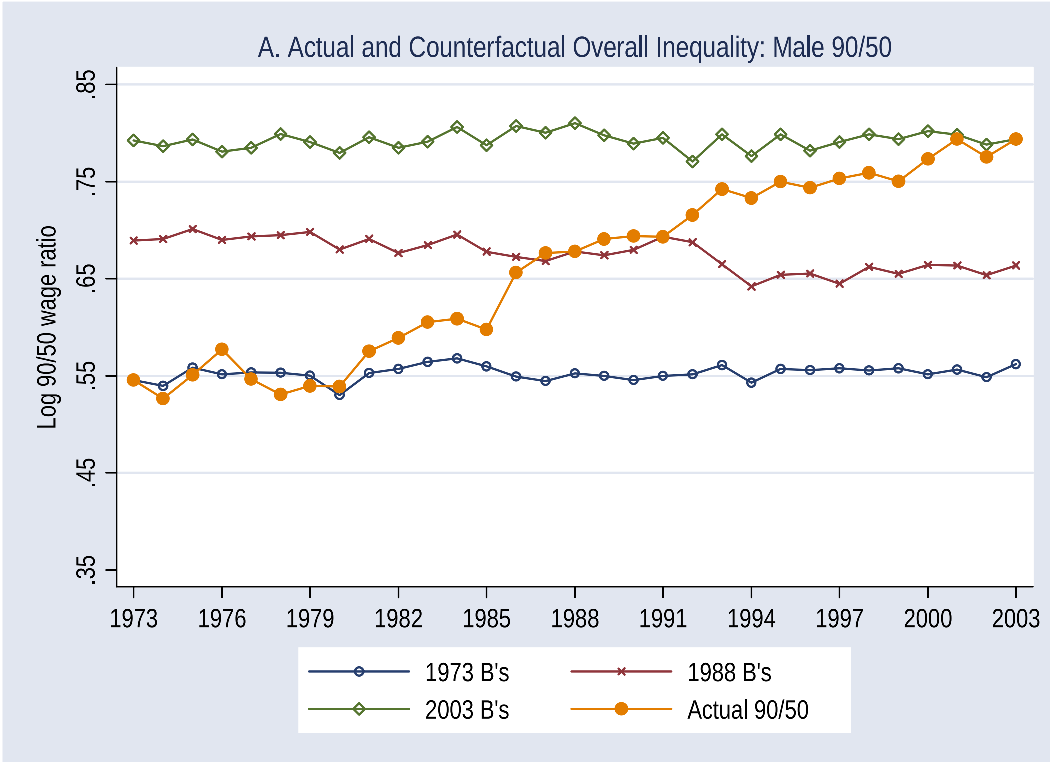


Figure 14. Composition adjusted actual and counterfactual log hourly 90/10 earnings ratios: May/ORG CPS data using wage coefficients from 1973, 1988 and 2003.



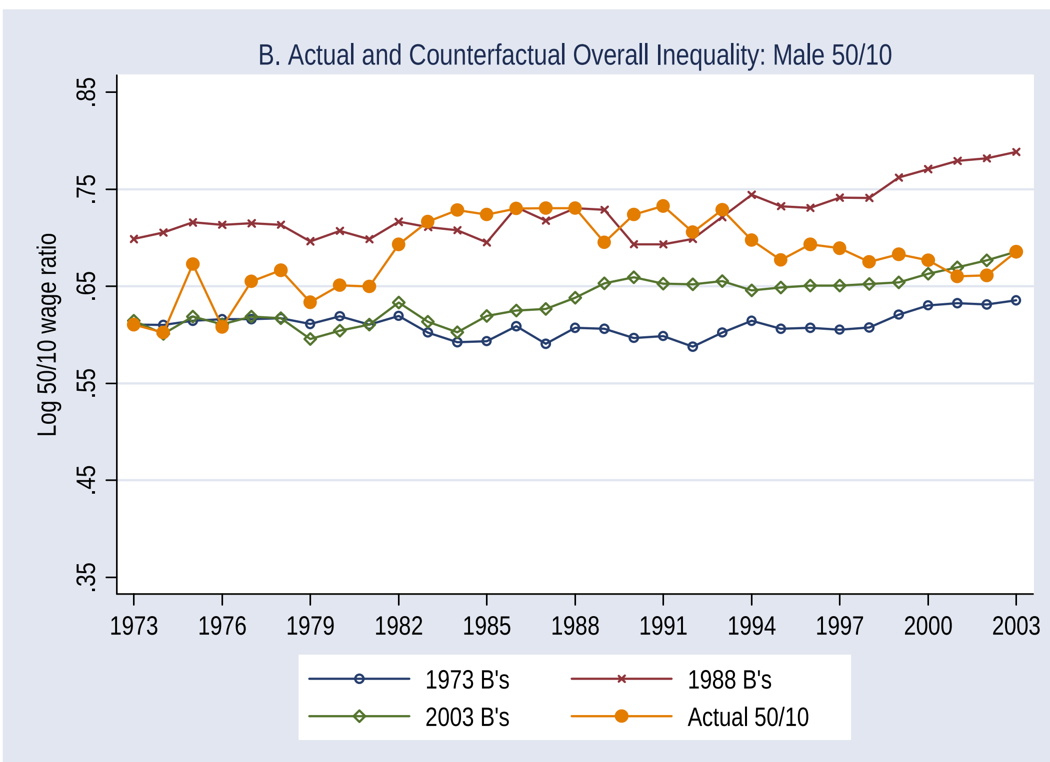
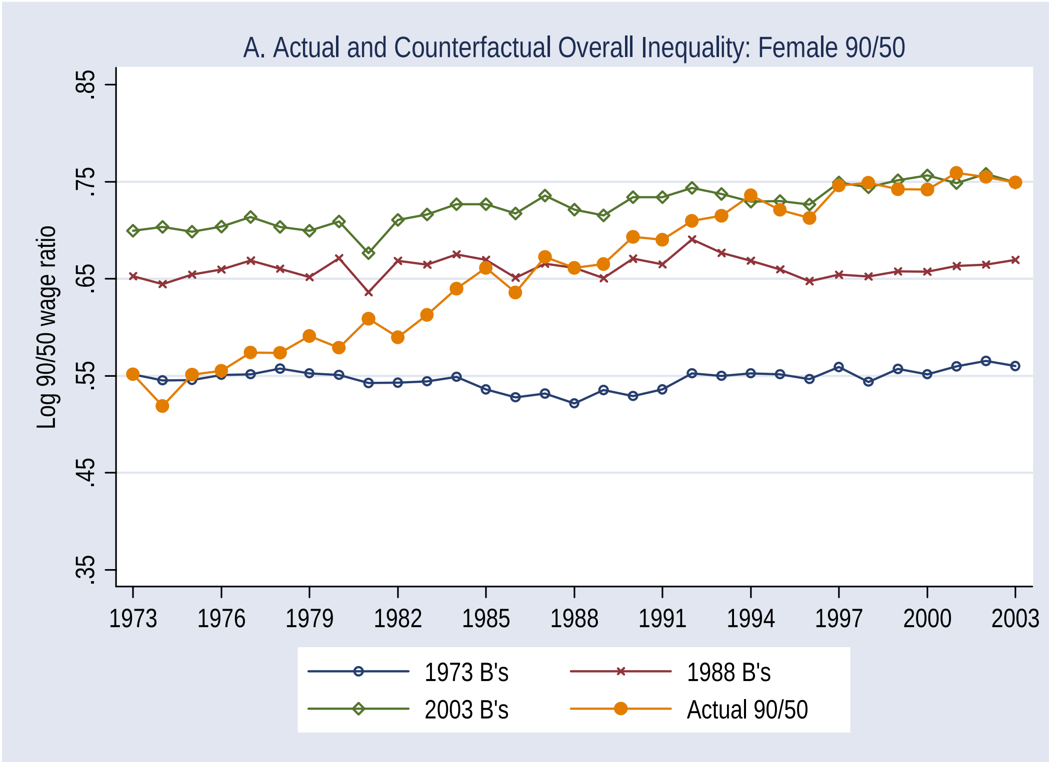


Figure 15. Composition adjusted upper and lower tail male log earnings ratios: May/ORG CPS data using wage coefficients from 1973, 1988 and 2003.



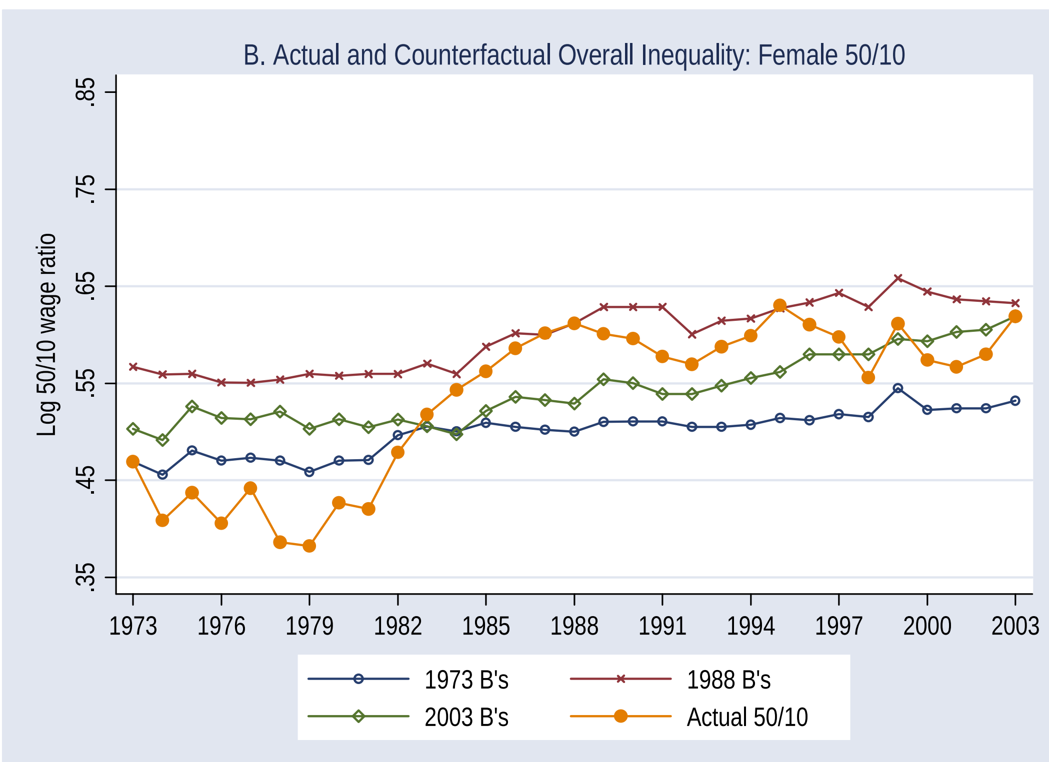


Figure 16. Composition adjusted upper and lower tail female log earnings ratios: May/ORG CPS data using wage coefficients from 1973, 1988 and 2003.

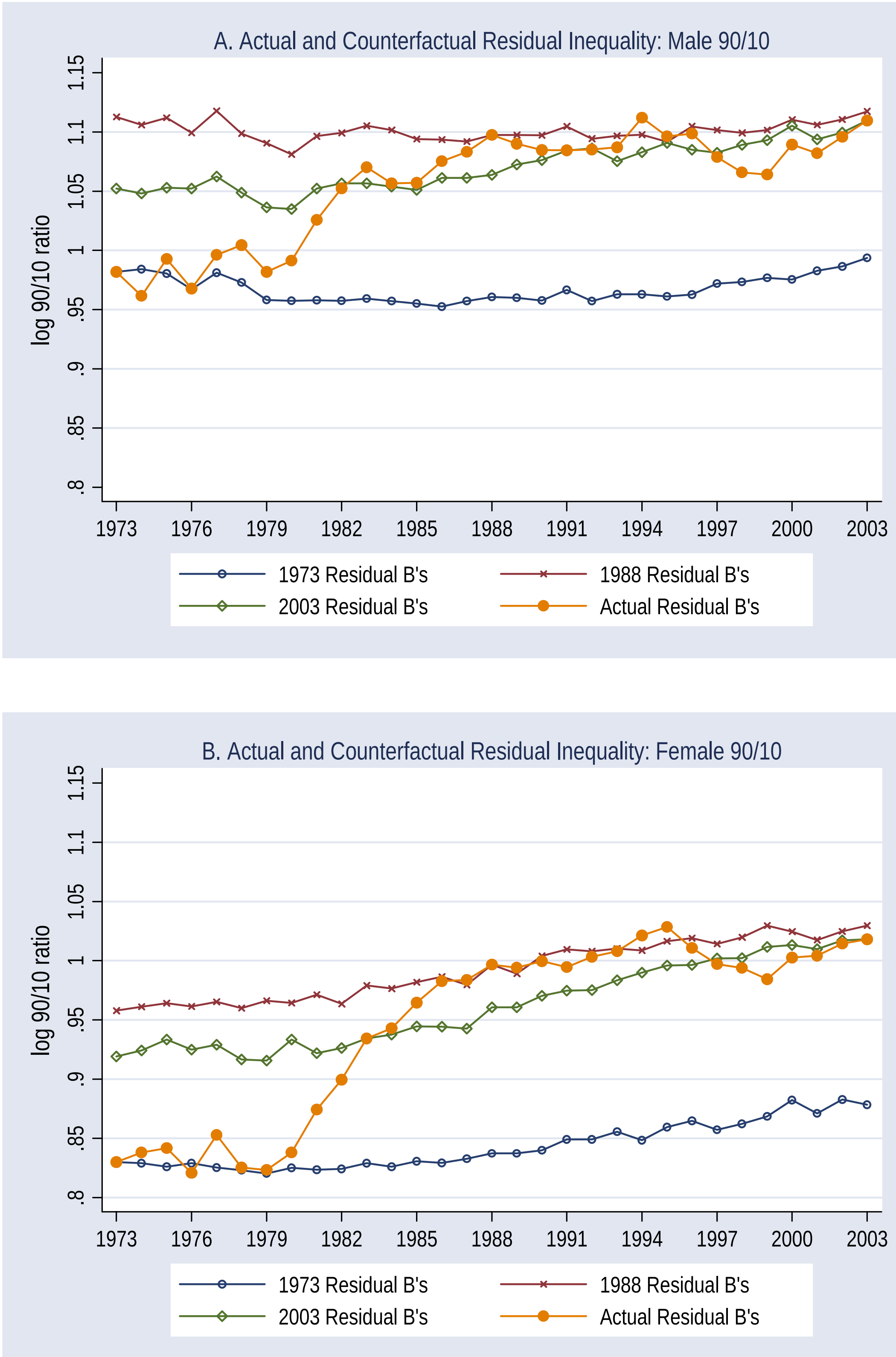
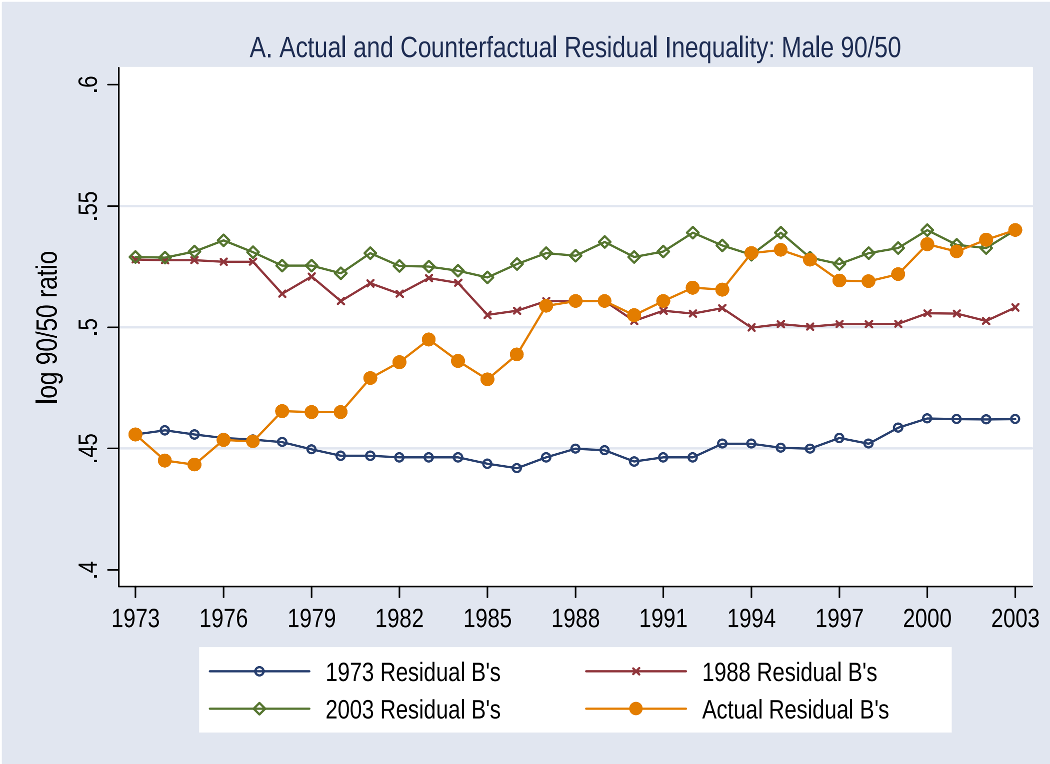


Figure 17. Composition adjusted actual and counterfactual log hourly 90/10 earnings residuals: May/ORG CPS data using wage coefficients from 1973, 1988, 2003.



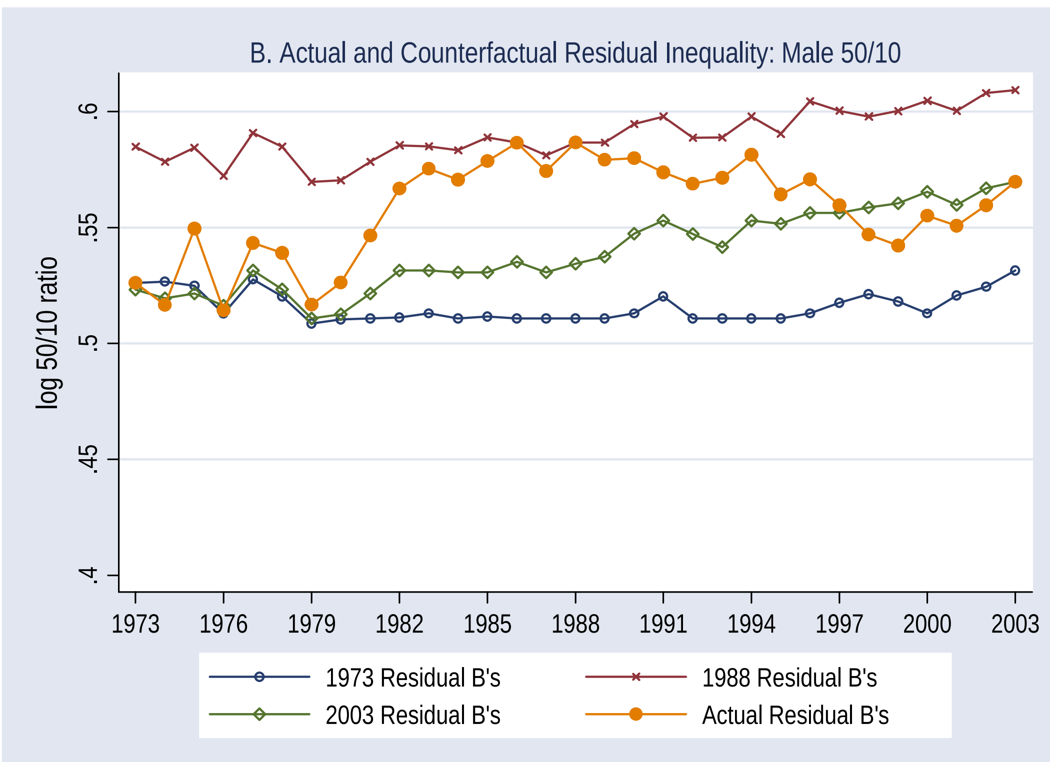


Figure 18. Composition adjusted upper and lower tail residual male log earnings residuals: May/ORG CPS data using wage coefficients from 1973, 1988 and 2003.

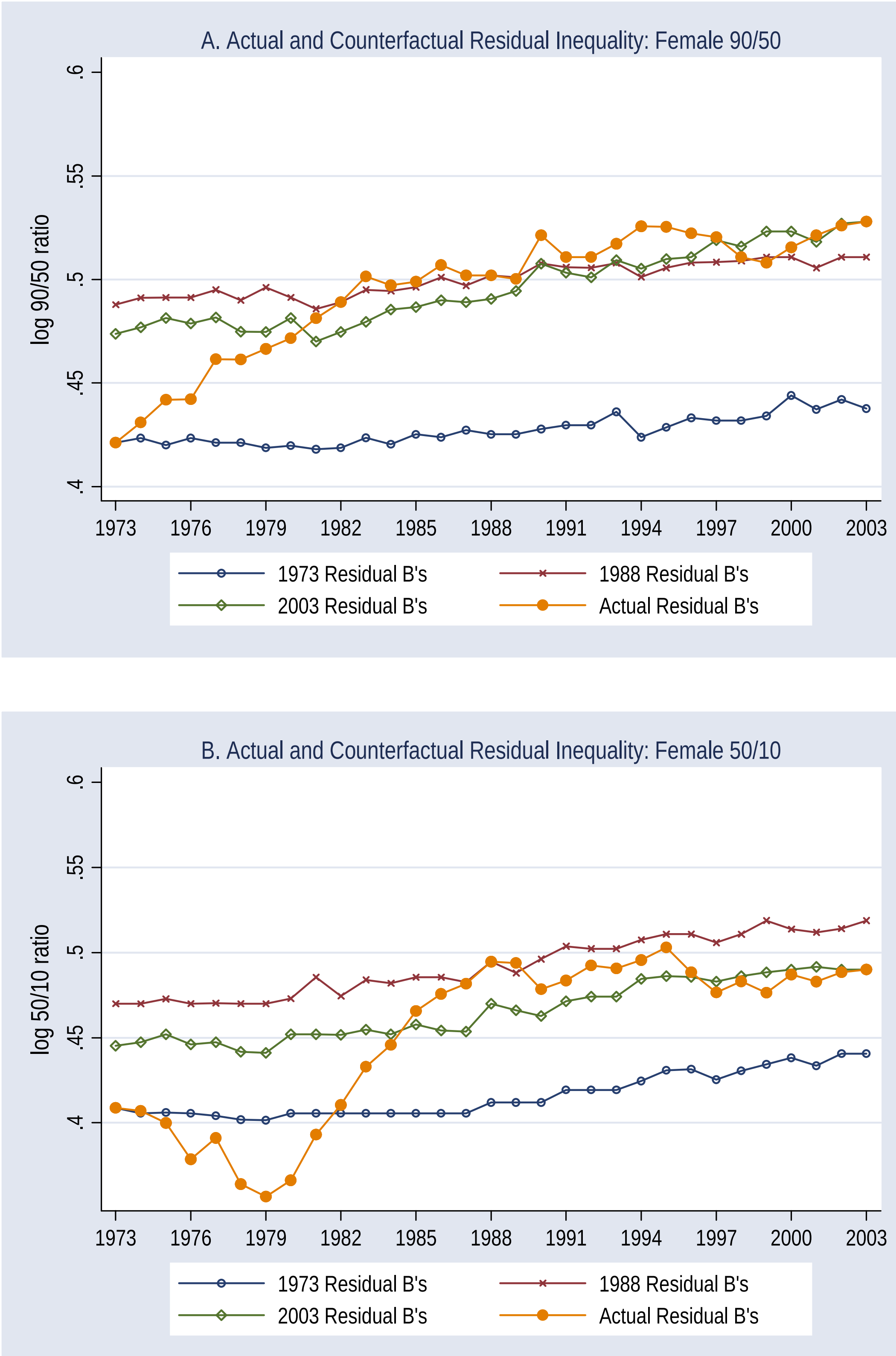
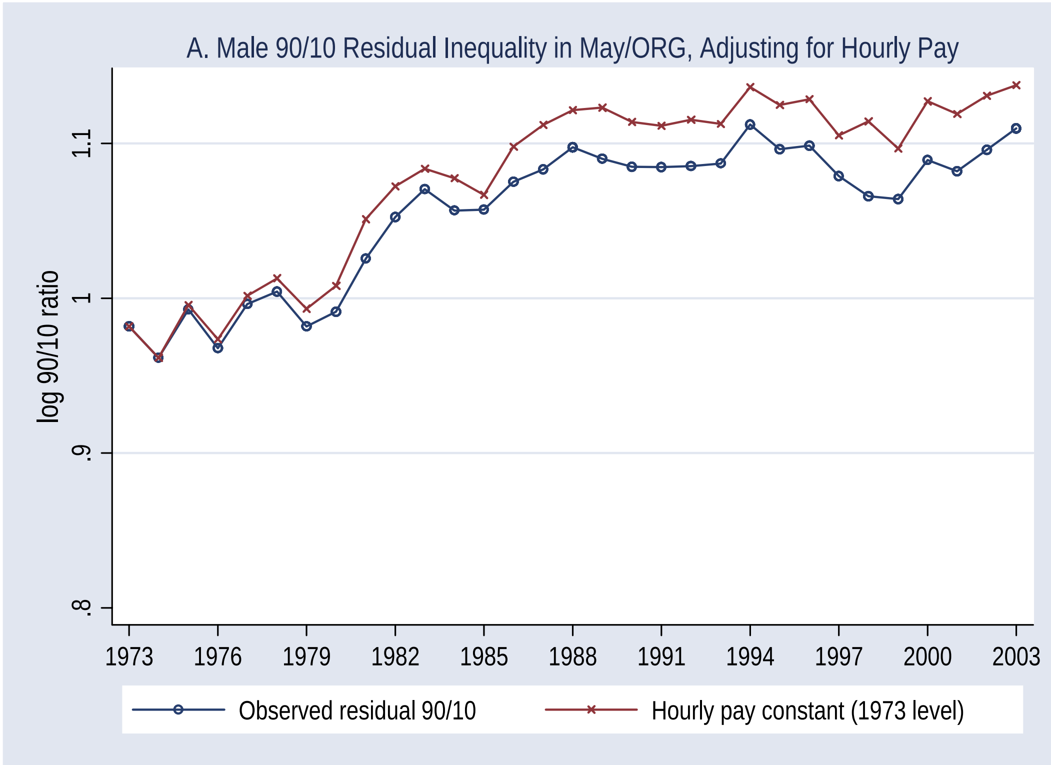


Figure 19. Composition adjusted upper and lower tail female log earnings residuals: May/ORG CPS data using wage coefficients from 1973, 1988 and 2003.



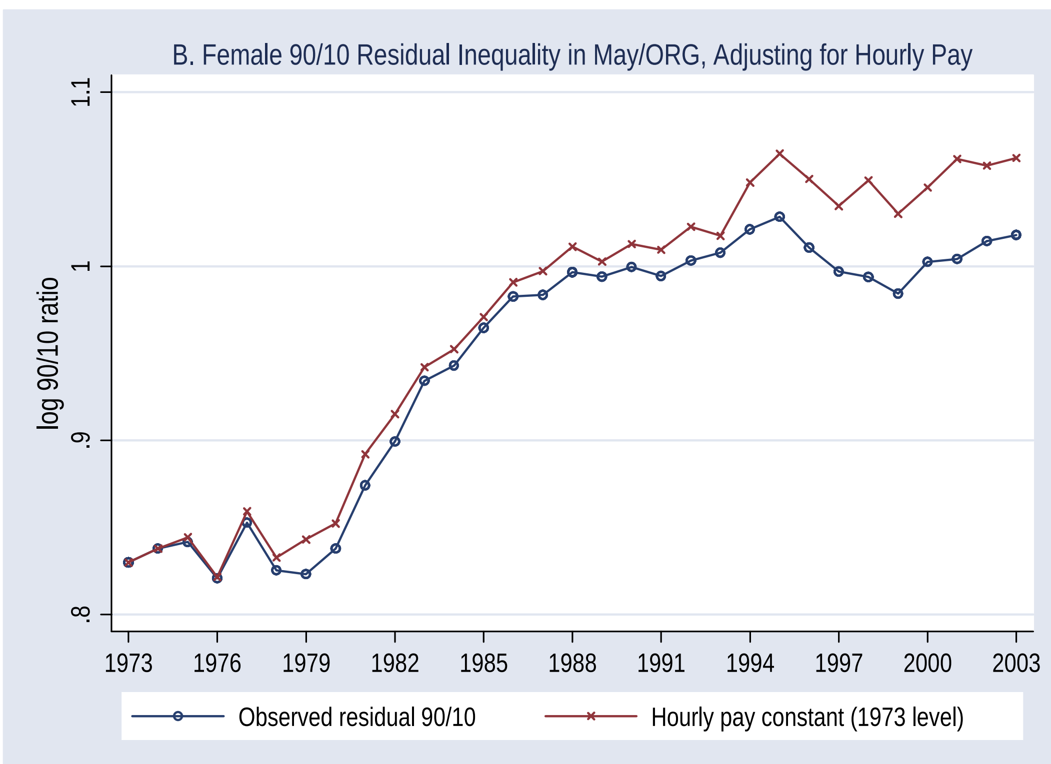


Figure 20. Residual 90/10 Earnings inequality in May/ORG CPS, 1973 - 2003: Observed Series and Series Adjusted for Rising Frequency of Hourly Pay.

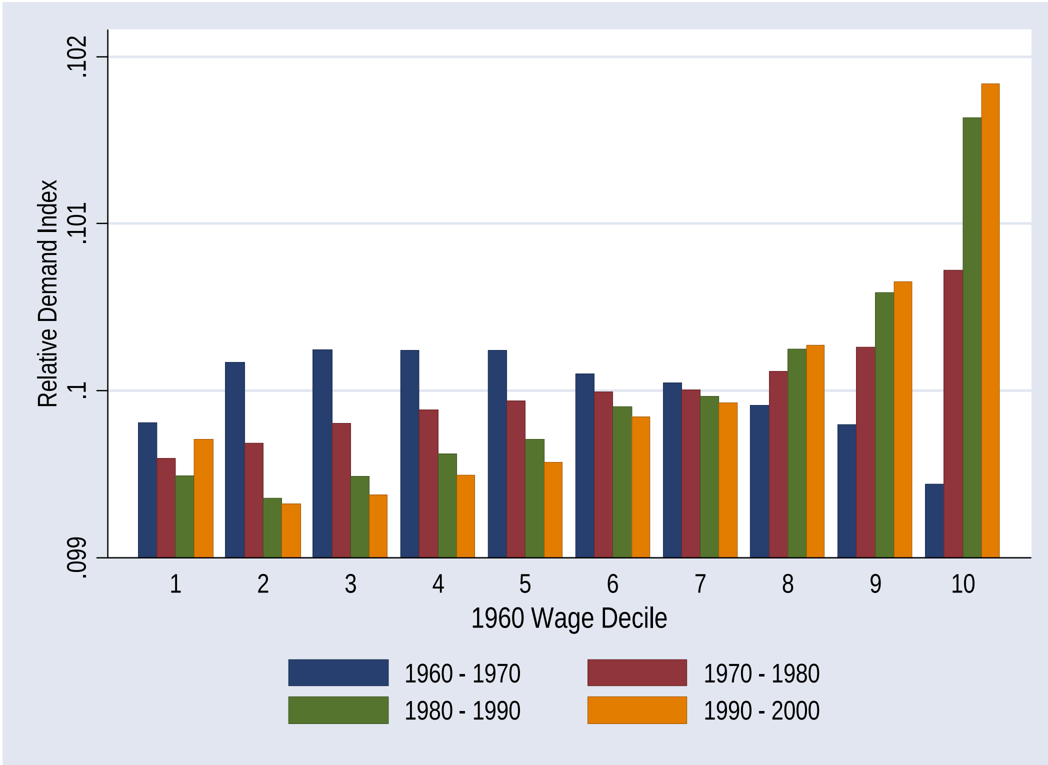
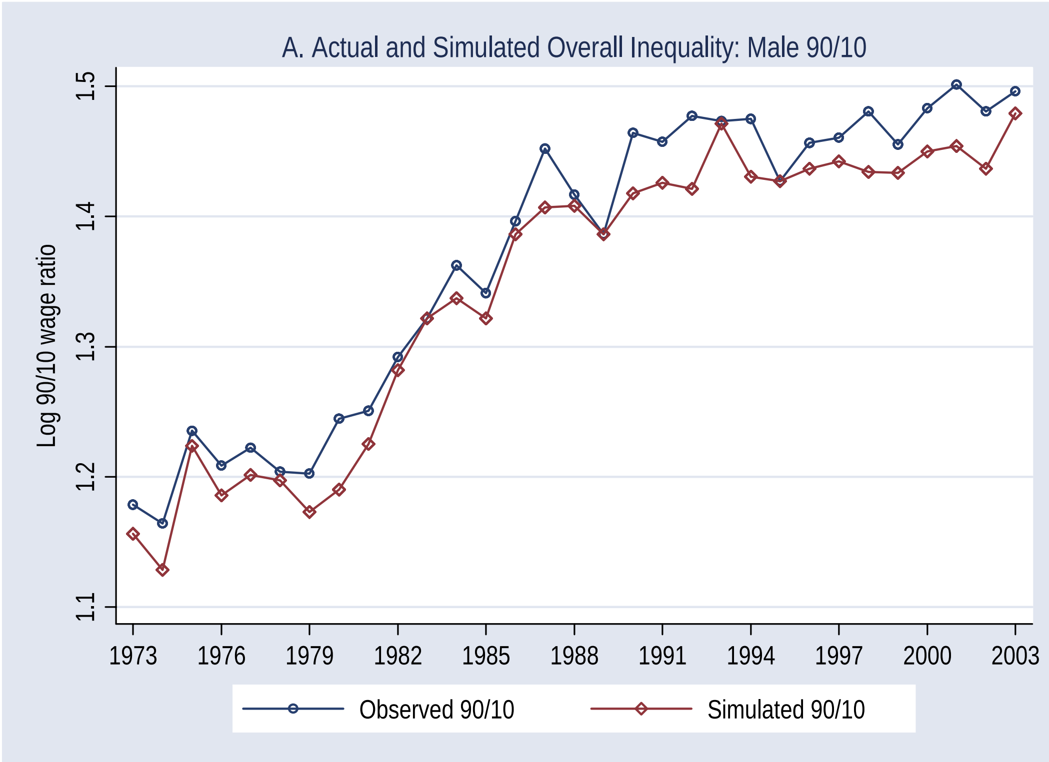
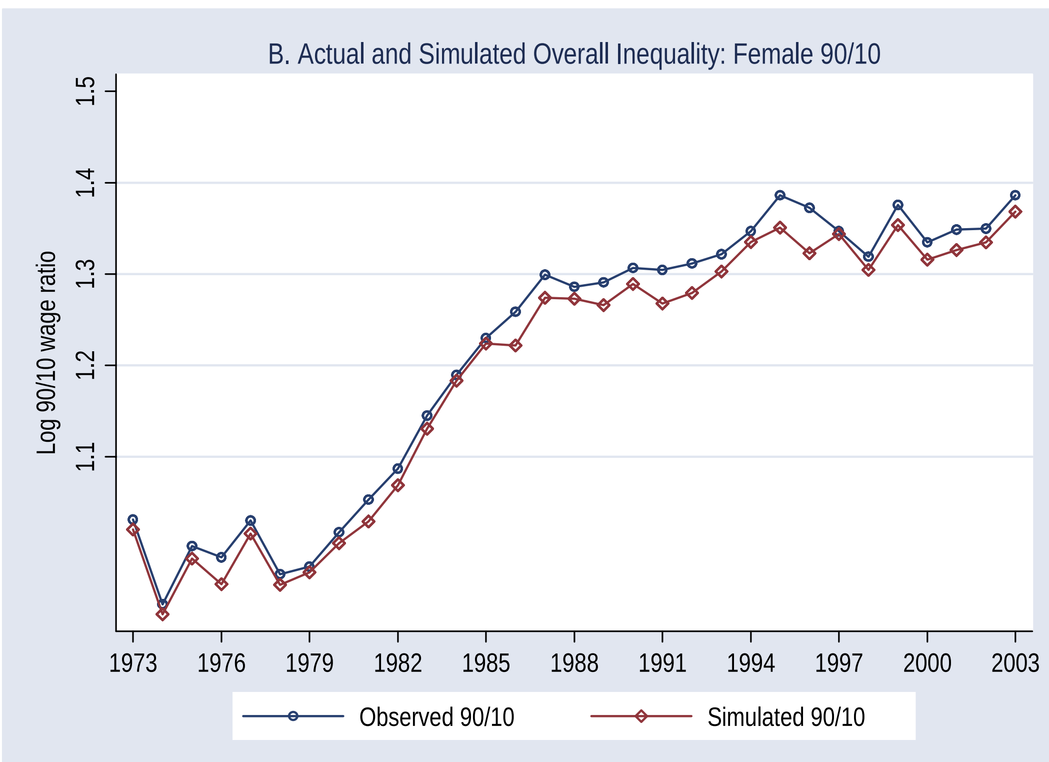
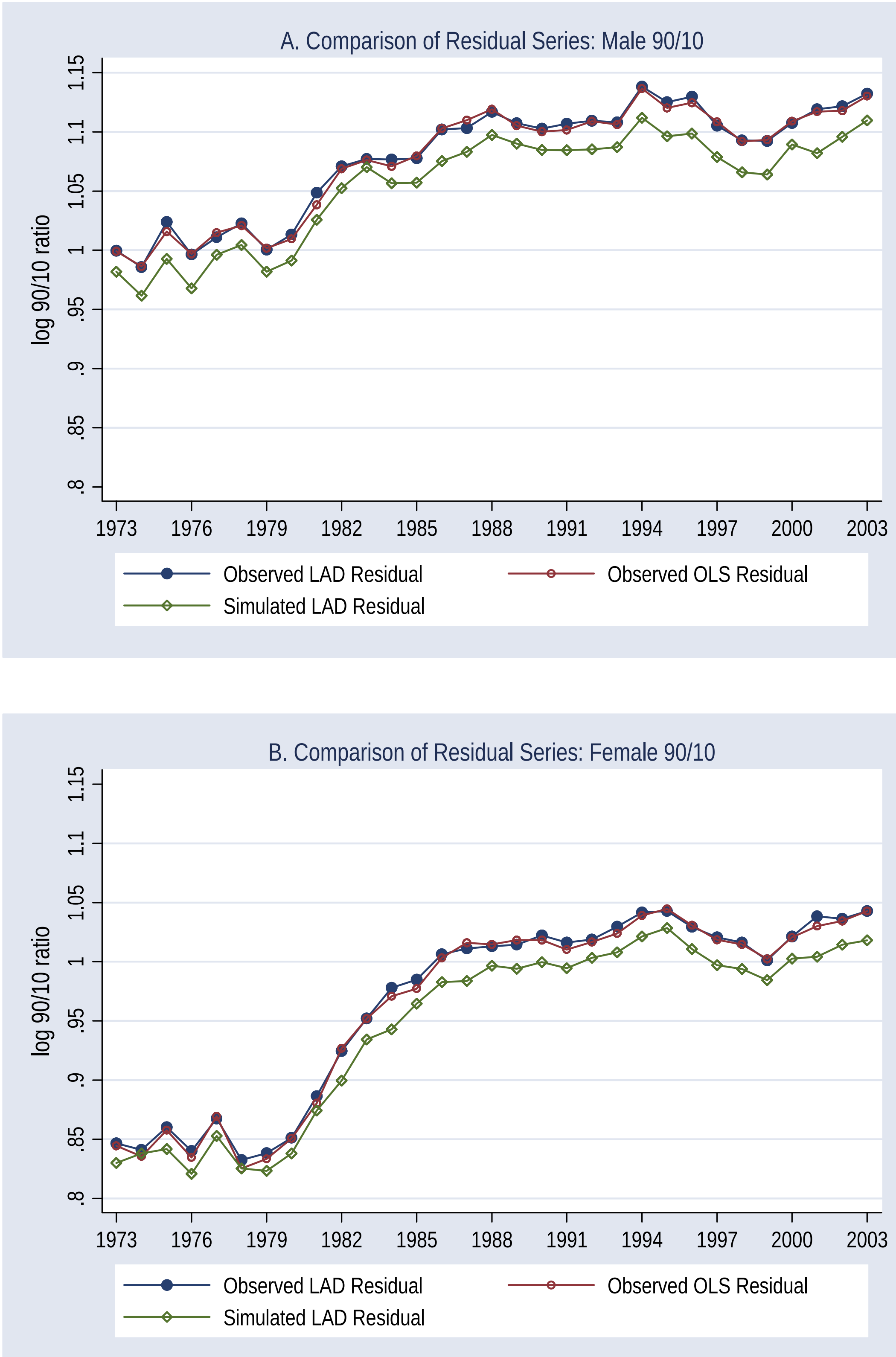


Figure 21. Estimated Relative Employment Demand Shifts by Wage Decile over Four Decades: 1960 - 2000





Appendix Figure1. Comparison of observed and simulated 90/10 log earnings ratios: May/ORG CPS.



Appendix Figure 2. Comparison of log 90/10 residual earnings ratios: OLS, median regression (LAD) and simulated median regression residuals.