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ABSTRACT

Hours Worked and the U.S. Distribution of Real Annual Earnings 1976–2016

We examine the impact of annual hours worked on annual earnings by decomposing changes in the real annual earnings distribution into composition, structural and hours effects. We do so via a nonseparable simultaneous model of hours, wages and earnings. We provide identification results and estimators of the objects required for the decompositions. Using the Current Population Survey for the survey years 1976–2016, we find that changes in the level of annual hours of work are important in explaining movements in inequality in female annual earnings. This captures the substantial changes in their employment behavior over this period. The impact of hours on males' earnings inequality operates only through the lower part of the earnings distribution and reflects the sensitivity of these workers' annual hours of work to cyclical factors.

JEL Classification: C14, I24, J00

Keywords: earnings inequality, sample selection, decompositions, nonseparable model

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1 Introduction

Empirical studies of the hourly wage distribution in the U.S. assign the divergent patterns for males and females at different points of the distribution to a variety of factors (see, for example, Katz and Murphy 1992, Murphy and Welch 1992, Juhn, Murphy, and Pierce 1993, Welch 2000, Autor, Katz, and Kearney 2008, Acemoglu and Autor 2011, Autor, Manning, and Smith 2016, Murphy and Topel 2016, and Fernández-Val et al. 2019). These include skill-biased technical change, international trade and globalization, the decline of the U.S. manufacturing sector, cohort size effects, the slowdown of the trend towards higher educational attainment, the reductions in unionization rates and the associated union premium, and the falling real value of the minimum wage. Gottschalk and Danziger (2005) argue that hourly wages are most frequently examined in studies of inequality because they most accurately measure changes in the relative demand and supply of skills. However, an analysis of hourly wages does not fully describe income inequality, which is perhaps more important for policy purposes. For example, understanding changes in poverty requires an examination of family earnings, while evaluating growth at the top of the income distribution (as in, for example, Piketty and Saez 2003) requires accounting for capital income. We extend the analysis of inequality beyond hourly wages by examining changes in annual labor earnings in the U.S. over the period 1976 to 2016. While earnings are only part of total income, they are nevertheless an important component. The Bureau of Labor Statistics reports the labor share in total income to be 61.5 percent at the beginning of 1976 and 58.4 percent at the end of 2016.

The differences between the changes over time in the respective distributions of hourly wages and annual earnings reflect movements in the distribution of annual hours of work.

These can be potentially important when there are changes in the employment behavior on either the extensive or the intensive margins. During the 1976–2016 period we examine here, the U.S. experienced a strong upward trend in female employment, large short-term swings in employment reflecting business cycle fluctuations, and the effects from the Baby Boomers entering the labor force, progressively aging and then exiting into retirement. Each of these factors has had an important influence on the distribution of annual hours of work. We examine how they, combined with movements in the wage distribution, changed the distribution of annual earnings.

A challenge in evaluating the impact of annual hours worked on annual earnings is accounting for the selection bias resulting from only observing wages for those reporting positive hours of work. Fernández-Val, Peracchi, Van Vuuren, and Vella (2019), hereafter FPVV, address this in an investigation of changes in the real hourly wage distribution. Their paper employs the methodology of Fernández-Val, Van Vuuren, and Vella (2019), hereafter FVV, to estimate the determinants of changes in the real wage distribution while accounting for the selection associated with annual hours worked. It decomposes changes at different quantiles of the gender specific hourly wage distributions into three components: i) a “selection effect” that captures changes from the selection rule given the distribution of observed and unobserved individual characteristics, ii) a “composition effect” that reflects changes due to the movements in the distribution of the observed and unobserved characteristics, and iii) a “structural effect” that measures changes in the conditional distribution of hourly wages given changes in observed and unobserved individual characteristics. FPVV find that composition effects have increased real hourly wages at all quantiles but that the patterns of wage movements are primarily determined by the structural effects. Moreover, selection effects only appear at the lower quantiles of the female wage distribution. These various

components combine to produce a substantial increase in wage inequality.

The present paper focuses on the role of annual hours in determining annual earnings. We follow FPVV and first model an individual's annual hours of work. This provides estimates of a control function which accounts for the selection bias when estimating the determinants of hourly wages. The estimated model of annual hours can also be used to construct counterfactual annual hours. Using these estimated hours and wage equations, and exploiting that annual earnings are the product of annual hours and hourly wages, we model annual earnings. We employ a nonseparable sample selection model with a censored selection variable based on the approach of Imbens and Newey (2009) and FVV. We decompose the changes in real annual earnings into four components via the use of counterfactual earnings distributions. The first two, namely the structural and composition effects noted above, are those typically identified in decomposition exercises, although their interpretation is more complicated in a multiple equation setting. We also provide two hours effects. The first is the extensive effect and captures the role of the work decision on annual earnings and measures how the movement from non employment to positive annual hours worked affects the earnings distribution. This is called the selection effect in FPVV as it captures the impact of entering or exiting employment. The second is the intensive effect and this captures how changes in the annual hours of those working affects annual earnings.

We model annual earnings using data from the Annual Social and Economic Supplement of the Current Population Survey, or March CPS, for the survey years 1976–2016. The data are a sequence of annual cross-sections containing information on earnings and hours of work in the previous year.¹ FPVV find important structural and composition effects when evaluating changes in the distribution of real hourly wages for these data. Our measure of

¹ In what follows we refer to the survey year rather than the year for which the data are collected.

annual hours is constructed as the product of weeks worked last year and usual hours of work per week last year. These are separately reported in the March CPS. This construction is important for interpreting the estimated hours effects, as weeks of nonemployment reduce annual hours worked but may be captured as movements along the intensive rather than the extensive margin. While this does not invalidate our approach, care is required in interpreting the results. To assist in this regard we examine the relative contribution of the variation in average hours per week and weeks worked last year in explaining the variation in annual hours.

While this is the first paper to treat the role of the distribution of annual hours worked as endogenous in decomposing changes in the distribution of annual earnings, we acknowledge that Checchi et al. (2016) investigate the contribution of both hours and wages to changes in earnings dispersion. Their employed measure of dispersion is the mean log deviation of earnings, or Theil's L -index. They decompose this measure into three components reflecting the variance of wages, the variance of hours, and the covariance between hours and wages. Employing micro-level data for France, Germany, the U.K., and the U.S. for the period 1989–2012, they find differences in the dispersion of hours and wages across the four countries, different role and trends for the covariance between hours and wages, but similar patterns for the effects of gender and education. Compared to the other three countries the level of hours dispersion in the U.S. is moderate and it plays a smaller role in explaining earnings dispersion among those with positive earnings. The relative contributions of wages and hours, and the covariance between hours and wages, are relatively stable over time. Gottschalk and Danziger (2005) found similar results for the U.S. over the period 1975–2002. They focus on individuals with positive annual hours and earnings, ignoring the role of selection into employment. We consider these previous studies more descriptive as they ignore the endogeneity of working

hours. Also, in contrast to these studies we provide decompositions at different points of the earnings distribution.

The next section discusses the CPS data and its features related to the annual earnings distribution. Section 3 discusses issues related to the patterns of variation in annual hours worked. Section 4 presents the model and discusses identification of the local objects of interest and the decomposition methodology. Section 5 presents the estimation approach. Section 6 reports and discusses the results. Section 7 concludes.

2 Data

We employ data from the Annual Social and Economic Supplement of the Current Population Survey (or March CPS) for the 41 survey years from 1976 to 2016, which report annual earnings, weeks worked, and usual hours of work per week in the previous calendar year. We restrict our analysis to those aged 24–65 years in the survey year. This produces a sample of 1,794,466 males and 1,946,957 females, with an average annual sample size of 43,767 males and 47,487 females. Annual sample sizes range from a minimum of 30,767 males and 33,924 females in 1976 to a maximum of 55,039 males and 59,622 females in 2001.

Annual hours worked last year (hereafter referred to as annual hours) are the product of weeks worked and usual hours of work per week. This definition allows the same number of annual hours to be produced by different combinations of hours and weeks. For example, we do not distinguish between an individual working 40 hours a week for 25 weeks from one working 20 hours a week for 50 weeks. While FPVV provide evidence that this is unimportant for evaluating hourly wage rates in the U.S., in that hours do not appear to have a direct influence on wage rates, it is important in evaluating the role of movements in

hours due to changes along the extensive and intensive margins.² It is useful to highlight the distinction between the conventional definition of unemployment in the monthly CPS and our employment measure based on annual hours of work last year. According to the former, people are classified as unemployed if: (i) they are not employed during the survey reference week, (ii) they are available for work during the survey reference week (except for temporary illness), and (iii) either they made at least one specific, active effort to find a people job during the 4-week period ending with the survey reference week or were temporarily laid off and expecting to be recalled to their job. This definition of unemployment does not depend on the number of hours or weeks worked in the year before the survey, as recorded in the March CPS.³ Our employment measure means that an individual who works even one hour for one week of the year while unemployed for the remaining weeks of the year is considered as employed. Thus, if the same individual worked 40 hours per week for 50 weeks in the next year, the resulting change in earnings would be assigned to the intensive hour margin (assuming no further changes due to structural and composition effects). There is no extensive hour effect from increasing annual hours from one hour to 2000 hours a year. This is an important issue and we discuss it below.

Individuals reporting zero hours worked last year generally respond that they were not in the labor force in the week of the March survey. As hourly wages are defined as the ratio of reported annual earnings and annual hours worked in the year before the survey they are only available for those in the labor force. This has implications for those in the Armed Forces, the self-employed, and unpaid family workers as their annual earnings and annual

² FPVV investigate the robustness of their results to the construction of the annual hours variable by replicating the analysis after restricting their sample to full-time full-year workers. This excludes observations that work many hours for one week or few hours for many weeks. They find that their results are robust to the exclusion of these observations.

³ A small fraction of individuals reporting zero annual hours of work last year also report being unemployed in the March survey. Most report that they were out of the labor force.

hours tend to be poorly measured. Accordingly, we confine attention to civilian dependent employees with positive hourly wages and people out of the labor force last year. This sample contains 1,551,796 males and 1,831,220 females (respectively 86.5 and 94.1 percent of the original sample of people aged 24–65), with an average annual sample size of 37,849 males and 44,664 females. The subsample of civilian dependent employees with positive hourly wages contains 1,346,918 males and 1,276,125 females, with an average annual sample size of 32,852 males and 31,125 females. We refer to these two samples as the full sample and the earners sample respectively.

Figure 1 presents the time series behavior of various quantiles of the annual earnings distribution separately for the full sample (top panels) and the earners sample (bottom panels). We report both, as some of the change in earnings inequality reflects individuals exiting and/or entering employment. The quantiles considered are the lower decile (D1), the lower quartile (Q1), the median (Q2), the upper quartile (Q3), and the upper decile (D9). Consider the full sample. First, as the female employment rate is lower than 60 percent in some years, the lowest quartile of female earnings is zero. Second, there are substantial differences between male and female earnings at each of the quantiles reported. Third, male earnings have remained relatively stable at each of the quantiles reported below the top decile although there are notable declines for the lowest quartile coinciding with periods of economic slowdown. Female annual earnings are instead increasing at all quantiles considered. Fourth, male earnings growth is only noticeable at the top decile. Finally, the contrasting experiences of females and males is reflected in earnings dispersion. Male earnings dispersion has increased while that of females decreased.

Now consider the earners sample. Female earnings have steadily increased at all quantiles considered. At the top of the distribution the increases are dramatic, with gains of about 50

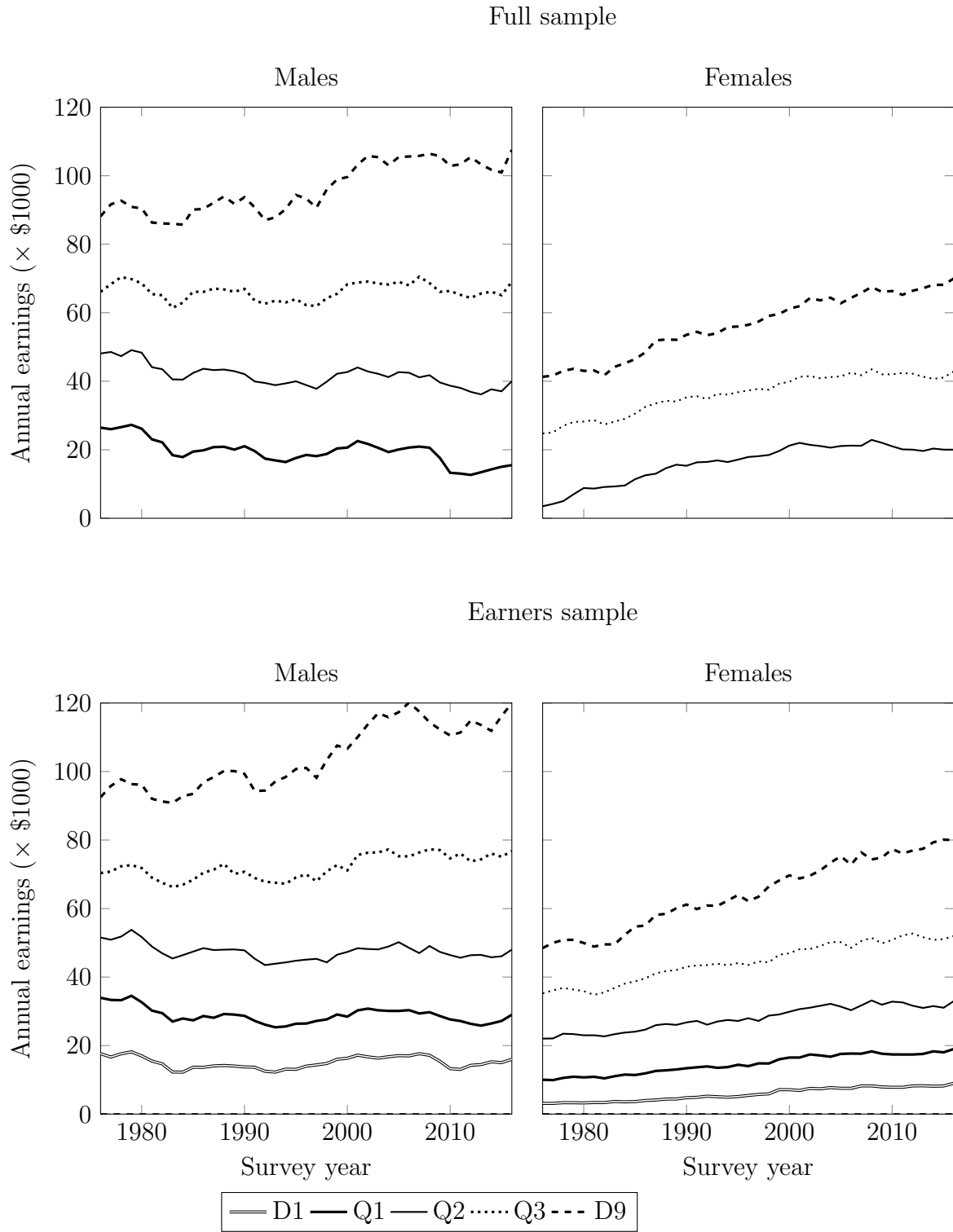


Figure 1: Time profile of selected quantiles of annual earnings.

percent at the top quartile and 40 percent at the top decile. The figures for males are similar to those in FPVV, suggesting the patterns are primarily driven by changes in hourly wages and/or the changes in annual hours are working in the same direction as those generating the changes in hourly wages. While the increases at the higher quantiles are remarkable, the changes at the lower quantiles are concerning. Over the period we consider, annual earnings decrease by 10 percent at the lower decile, 17 percent at the lower quartile, and 7 percent at the median.

The most notable difference between these patterns in annual earnings and those reported for hourly wages by FPVV is that at lower quantiles for females there is an earnings increase not reflected in wages. This suggests that changes in annual hours are more important in determining earnings changes at lower quantiles. Figure 2 presents the distribution of annual hours for our sample period. The level of males' hours are stable at all points of the hours distribution although this may partially reflect the shortcomings of using quantile methods to describe data in the presence of bunching. However, they display a cyclical behavior which is particularly important at lower quantiles. To relate this cyclical behavior to the business cycle the recessions are marked with a shaded vertical bar.⁴ There has been a consistent increase in female annual hours at all quantiles, except the median, with the largest increases at the bottom of the distribution. Cyclical effects for females are weaker and are manifested as occasional dips in otherwise upward trends. The median for males and the upper quartile for females show no variation over our sample and this also partially reflects the bunching of hours. Approximately 40 percent of males and 30 percent of females were working exactly 2080 hours per year in 1976. This corresponds to 52 weeks of a 40-hour work week. Almost

⁴ During the period we consider, the NBER's Business Cycle Dating Committee distinguishes five recessions: January to July 1980 (6 months), July 1981 to November 1982 (16 months), July 1990 to March 1991 (8 months), March to November 2001 (8 months), and December 2007 to June 2009 (18 months), known as the Great Recession.

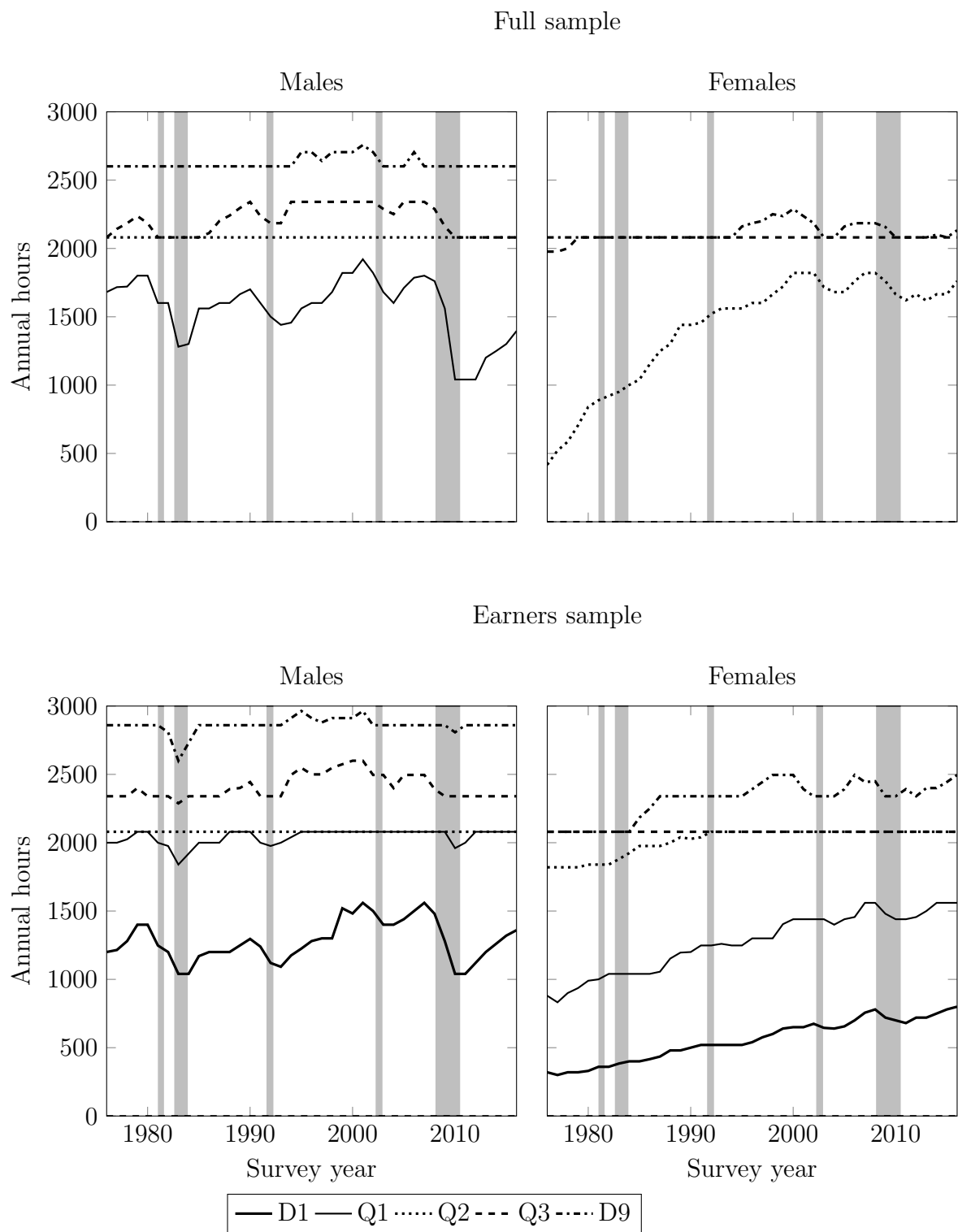


Figure 2: Time profile of selected quantiles of annual hours of work.

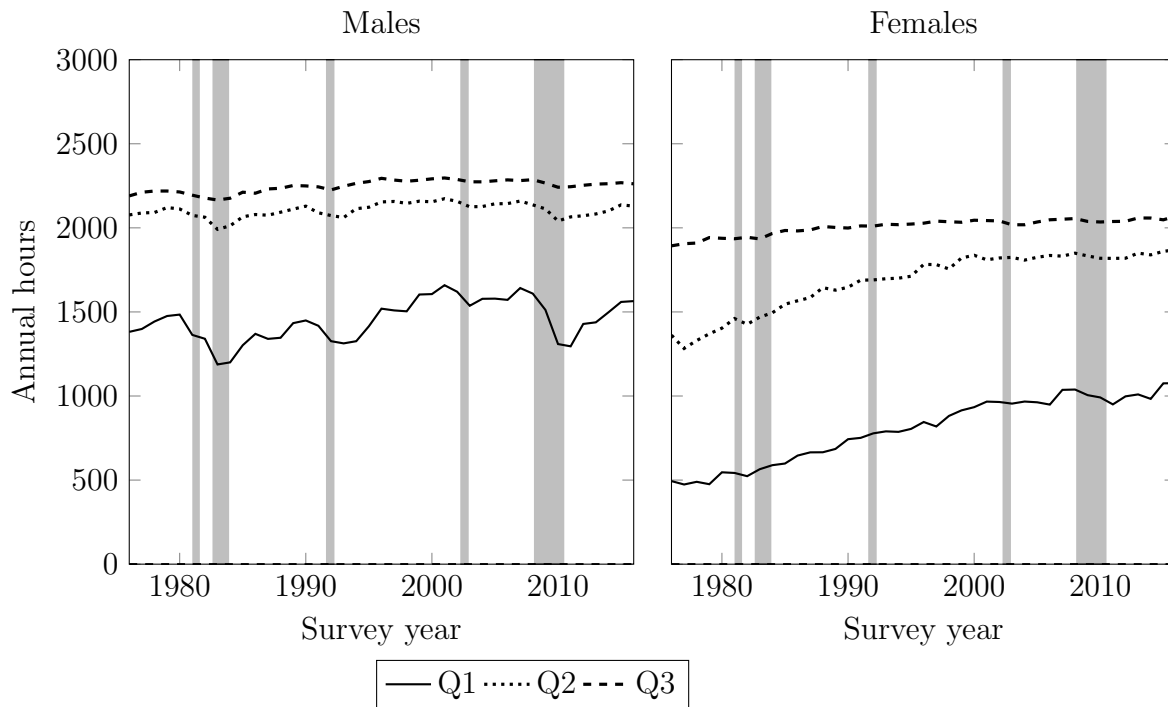


Figure 3: Time profile of mean annual hours of work by location in the annual earnings distribution (e.g., Q1 is the mean of annual hours for individuals with annual earnings up to the lower quartile, etc.).

50 percent of males and 40 percent of females have annual working hours of exactly 2080 by the year 2016. This increasing bunching of annual hours is an important feature of the data that has recently received some attention in the macroeconomic literature (see Bick, Blandin and Rogerson 2019).

Figure 3 presents mean hours for those in different quartiles of the earnings distribution. Thus, Q1 denotes mean hours for workers with labor income less than the lower quartile of earnings, Q2 denotes mean hours for those with labor earnings between the first quartile and the median, and Q3 denotes mean hours for those with labor earnings between the median and the upper quartile. Male hours have not substantially increased at any point in the earnings distribution and the cyclicity of male hours is more evident for those with lower

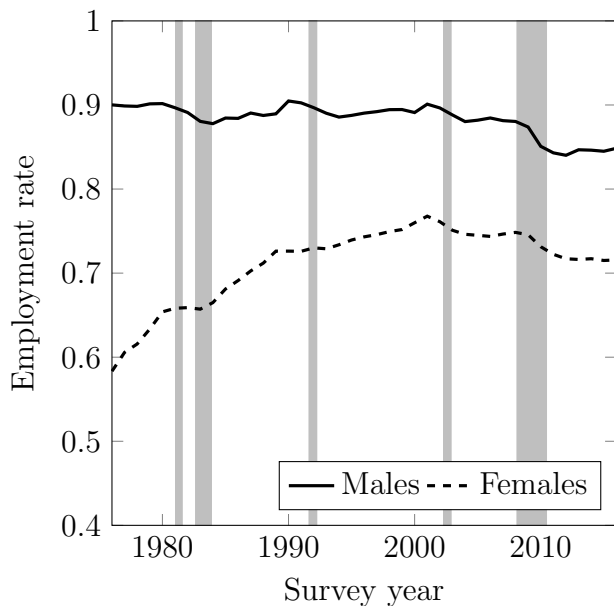


Figure 4: Time profile of the fraction of people with positive annual hours of work.

earnings. There are small increases at higher female earnings and larger increases at the median and below.

The previous figures reflect movements on the intensive margin of hours worked. Figure 4 focusses on the extensive margin and plots the time profile of employment rates, defined as the fraction of people working positive annual hours last year. For both males and females, the trends change around year the 2000. For males it goes from being relatively flat to negative, while for females the change is from positive to negative.

3 Patterns of variation in annual hours

To investigate the patterns of variation in annual hours, Figure 5 presents the standard deviations of usual weekly hours of work and weeks worked, σ_{H_w} and σ_W , along with their correlation, $\rho_{H_w, W}$. The left-hand scale is for the standard deviations and the right-hand

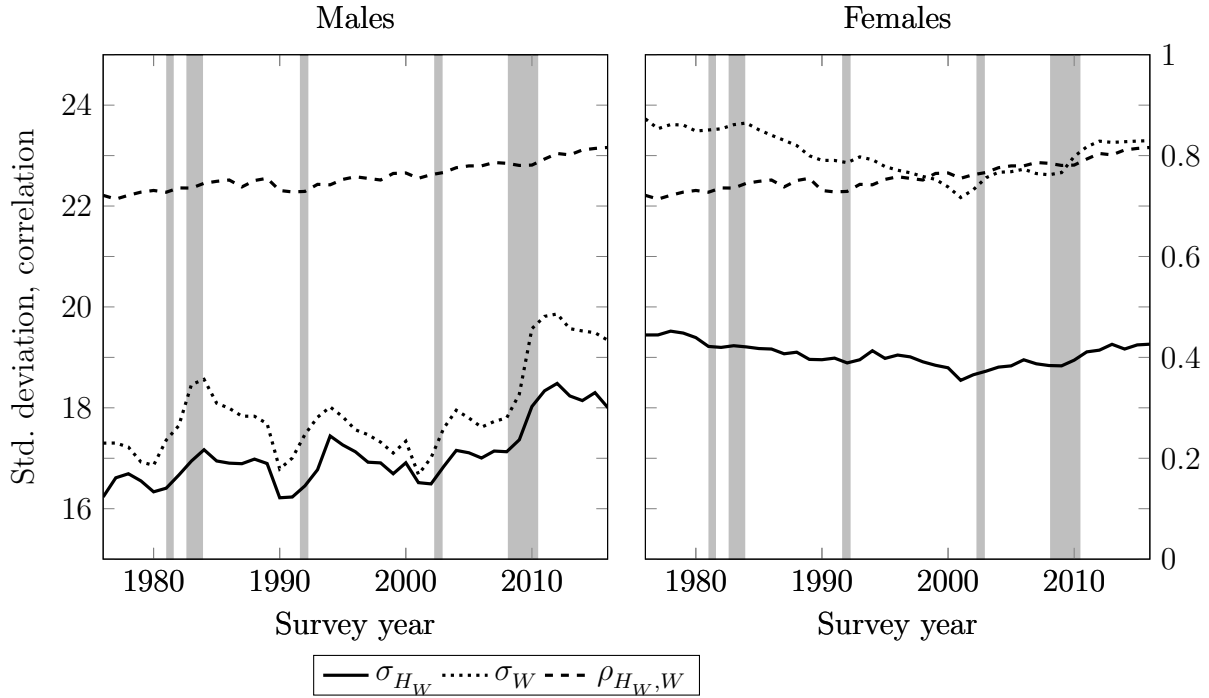


Figure 5: Standard deviation of weekly hours of work, σ_{H_W} , standard deviation of weeks worked, σ_W , and correlation between weekly hours of work and weeks worked, $\rho_{H_W, W}$.

scale is for the correlation.

For males there is slightly greater variability in weeks than in weekly hours, but both show clear evidence of strong cyclical movements around an upward trend. There is also a steady increase in the correlation between weekly hours and weeks, indicating that these two components of annual hours are more closely tied at the end of the period than the beginning. For females the standard deviations of both weekly hours and weeks are higher than for males. In contrast to males, they show little cyclical movement and their behavior is dominated by trends. Interestingly, these trends are negative until about year 2000 at which point they become positive. Despite the large differences by gender in the variability of weekly hours and weeks, the behavior of their correlation is similar, namely steadily increasing over the period.

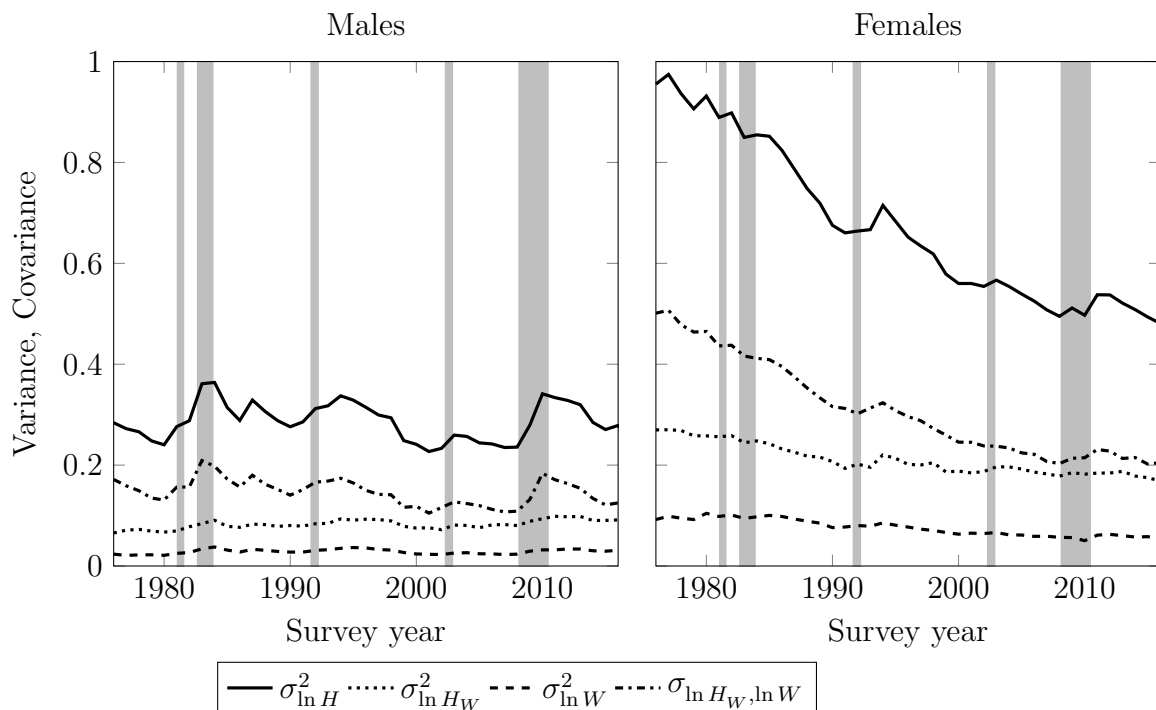


Figure 6: Variance of log annual hours of work, $\sigma_{\ln H}^2$, variance of log weekly hours of work, $\sigma_{\ln H_W}^2$, variance of log weeks worked, $\sigma_{\ln W}^2$, and covariance of log weekly hours and weeks worked, $\sigma_{\ln H_W, \ln W}$.

Figure 6 decomposes the variance of log annual hours into three components reflecting, respectively, the variance of log weekly hours, $\sigma_{\ln H_W}^2$, the variance of log weeks, $\sigma_{\ln W}^2$, and the covariance between log weekly hours and log weeks, $\sigma_{\ln H_W, \ln W}$. This evidence supports that from Figure 5. That is, there is greater variability for females than for males. For males all three components display strong cyclical fluctuations but no trend, while for females they all display a downward trend but no cyclicity. This suggests that male behavior is more influenced by cyclical factors, while female behavior is more influenced by long-run trends.

For both genders the primary source of the variation in log annual hours is $\sigma_{\ln H_W, \ln W}$, followed by $\sigma_{\ln H_W}^2$ and $\sigma_{\ln W}^2$. The time trends in the two variance components differ by gender. They are flat or slightly positive for males while being strongly negative for females.

As a result of these trends the relative contributions of the three component show little difference by gender by the end of the sample period.

4 The model and the objects of interest

Our goal is to decompose changes in the real annual earnings distribution into contributions reflecting the changing impact of labor force composition in terms of observable and unobservable characteristics, structural effects reflecting these characteristics' prices, and hours effects capturing the level of annual hours worked. We first estimate a model of annual hours for each cross section. This provides the control function required to account for selection in estimating the determinants of hourly wages over the sample of workers. We now outline our model, introduce the control function and the other objects of interest, and describe the decomposition of changes in the distribution of annual earnings.

4.1 The model

Our model consists of the following three equations:

$$Y = \mathbf{1}\{H > 0\} WH, \tag{1}$$

$$W = g(X, E), \text{ if } H > 0, \tag{2}$$

$$H = \max\{k(X, Z, U), 0\}, \tag{3}$$

where Y , W , and H denote annual earnings, hourly wages, and annual hours of work respectively, X and Z are vectors of observable explanatory variables, and $\mathbf{1}\{A\}$ denotes the indicator function of the event A . The functions g and k are smooth but unknown, while E and U are potentially mutually dependent unobservable random vectors with stochastic

properties described below. Equations (1)-(3) may be regarded as the reduced form of a model of individual labor supply where the annual hours worked and the hourly wage rate are jointly determined as functions of the observable variables in X and Z , and the unobservable variables E and U . We estimate functionals related to g and k noting that W is only observed when H is positive.

We make the following assumptions:

Assumption 1

- (a) (X, Z) are independent of (E, U) .
- (b) The function $u \mapsto k(\cdot, \cdot, u)$ is strictly increasing on the support of U .
- (c) U has a uniform distribution on $[0, 1]$.

These assumptions are standard in this literature (see, for example, Imbens and Newey 2009 and FVV). Assumption 1(a) restricts the endogeneity in equation (2) to operate via the selection $H > 0$. The model could be extended to include additional endogenous explanatory variables in equation (2). Assumption 1(b) requires that H is continuous and, together with Assumption 1(a), restricts the dimension of the unobservables responsible for the endogeneity in equation (3). Given Assumption 1(b), Assumption 1(c) is an innocuous normalization (Matzkin, 2003).

The control function for those who work positive hours, $H > 0$, is the random variable $F_{H|X,Z}(H | X, Z)$ where $F_{H|X,Z}(h | x, z)$ is the distribution of H conditional on $X = x$ and $Z = z$ evaluated at $H = h$. Formally:

Lemma 1 (Control function) *The random variable $V := F_{H|X,Z}(H | X, Z)$ is a control function for E conditional on $H > 0$. That is, E is independent of X and Z conditional on V and $H > 0$.*

The proof of this result is presented in FVV and shows that U and V are identical when $H > 0$. Then, conditioning on X , Z and V , or equivalently on U , makes the statement that $k(X, Z, U) > 0$, and hence $H > 0$, deterministic. It implies that the distribution of E conditional on X , Z , V , and $H > 0$ is identical to the distribution of E conditional on X , Z and U . The assumption that E and U are independent from X and Z concludes the proof.

4.2 Objects of interest

The decomposition of the changes in the earnings distribution requires some structural functions from the model in (1)-(3). We first establish the region where these functions are identified. We then relate the structural functions and distributions of the explanatory variables and control function to the distribution of earnings exploiting that $Y = WH$.

We denote the support of a random variable in the entire population by calligraphic letters. Hence, \mathcal{X} is the support of X . Also, \mathcal{XZ} and \mathcal{XV} denote the respective joint support of the random vectors (X, Z) and (X, V) . The support of the random vector Z conditional on $X = x$ and $V = v$ is denoted by $\mathcal{Z}_{(x,v)}$.

We start with the following definitions:

Definition 2 (Identification set) *Let*

$$\mathcal{XV}^* := \{(x, v) \in \mathcal{XV} \mid \exists z \in \mathcal{Z}_{(x,v)} : k(x, z, v) > 0\}.$$

The set \mathcal{XV}^* represents the support of the random vector (X, V) for those individuals with a positive value of H . The size of this set depends on the availability of variables in Z that satisfy the exclusion restriction in equation (2) and their relevance in equation (3).

Definition 3 (Local objects) *The local average structural function (LASF) of hourly wages*

is defined as:

$$\mu(x, v) = \mathbb{E}[g(x, E) \mid V = v]$$

provided that the expectation exists. The local distribution structural function (LDSF) of hourly wages is defined as:

$$G(w, x, v) = \mathbb{E}[\mathbf{1}\{g(x, E) \leq w\} \mid V = v].$$

Let $W(x) = g(x, E)$, be the potential hourly wage when $X = x$. The LASF is the mean of $W(x)$ conditional on $V = v$. It represents the mean wage that would be observed when everyone in the sample who has a value of V equal to v is assigned a value of X equal to x . The LDSF is the corresponding distribution function at w . Identification of the LASF and the LDSF is established in FVV and is summarized by the following lemma.

Lemma 4 (Identification of the local objects) *The LASF and the LDSF are identified for all $(x, v) \in \mathcal{XV}^*$.*

The proof of Lemma 4 relies on the result that the expectation defining the LDSF can be made conditional on $(X, Z, V) = (x, z, v)$ by Lemma 1. Then, for any $(x, v) \in \mathcal{XV}^*$, there is a $z(x, v) \in \mathcal{Z}_{x,v}$ such that $k(x, z(x, v), v) > 0$, so that the distribution of $g(x, E)$ conditional on $V = v$, *i.e.* the LDSF, is the same as the distribution of Y conditional on $X = x$, $Z = z(x, v)$ and $H > 0$.

4.3 Counterfactual distributions and means of annual earnings

To quantify the role of hours in determining annual earnings we use the local objects to characterize counterfactual distributions and means of annual earnings that we would observe

if we change the distributions of the explanatory variables, control function, wages and hours worked. We focus on distributions as means can be obtained by replacing the LDSF with the LASF in the analysis that follows.

We first rewrite the observed marginal distribution of earnings as a mapping of the distributions of the explanatory variables, control function, wages and hours worked. By the law of iterated expectations:

$$F_Y(y) = \mathbb{P}[Y \leq y] = \int \mathbb{P}[Y \leq y \mid X = x, Z = z, V = v] dF_{X,Z,V}(x, z, v).$$

Using $Y = WH$ and $H = k(X, Z, V)$ when $k(X, Z, V) > 0$, the definition of W from (2) gives:

$$F_Y(y) = \int_{k(x,z,v)>0} \mathbb{P} \left[g(X, E) \leq \frac{y}{k(X, Z, V)} \mid X = x, Z = z, V = v \right] dF_{X,Z,V}(x, z, v) + \int_{k(x,z,v)\leq 0} dF_{X,Z,V}(x, z, v).$$

Then, by the definition of the LDSF $G(w, x, v)$:

$$F_Y(y) = \int_{k(x,z,v)>0} G \left(\frac{y}{k(x, z, v)}, x, v \right) dF_{X,Z,V}(x, z, v) + \int_{k(x,z,v)\leq 0} dF_{X,Z,V}(x, z, v).$$

We define the counterfactual distributions of earnings as:

$$G_{(q,r,s,p)}(y) = \int_{k^q(x,z,v)>0} G^p \left(\frac{y}{k^r(x, z, v)}, x, v \right) dF_{X,Z,V}^s(x, z, v) + \int_{k^q(x,z,v)\leq 0} dF_{X,Z,V}^s(x, z, v), \quad (4)$$

which correspond to the distribution that we would observe if the labor force participation

were as in year q , distribution of working hours as in year r , distribution of explanatory variables and control function as in year s , and distribution of wages as in year p . For example, the observed distribution of earnings in year t corresponds to $G_{\langle t,t,t,t \rangle} = F_Y^t$. In the previous expressions we use superscripts in the functions to denote the year from which the function is taken. For example, $F_{X,Z,V}^s$ denotes the distribution of (X, Z, V) in year s .

The identification conditions for these counterfactual distributions are based on three separate requirements. First, it must be possible to evaluate $G^p(\cdot, x, v)$ for all $(x, v) \in \mathcal{XV}^{*,s}$. This requires that $\mathcal{XV}^{*,s} \subseteq \mathcal{XV}^{*,p}$. However, we only need to consider the elements of $\mathcal{XV}^{*,s}$ that satisfy $k^q(x, z, v) > 0$. Thus, the first restriction is $(\mathcal{XV}^{*,q} \cap \mathcal{XV}^{*,s}) \subseteq \mathcal{XV}^{*,p}$. Second, it must be possible to evaluate the function $k^r(x, z, v)$ for all the values of (x, z, v) in the first integral. By Assumption 1(b), $k^r(x, z, v)$ is identified for all $(x, z) \in \mathcal{XZ}^r$ because we can set $k^r(x, z, v) = 0$ for all v such that $k^r(x, z, v) < 0$. Then, a similar reasoning as for the first restriction gives the second restriction $(\mathcal{XZ}^q \cap \mathcal{XZ}^s) \subseteq \mathcal{XZ}^r$. Third, it must be possible to evaluate $k^q(x, z, v) > 0$ for all $(x, z, v) \in \mathcal{XZV}^s$. By Assumption 1(b), this gives the third restriction $\mathcal{XZ}^s \subseteq \mathcal{XZ}^q$. Finally, combining the three restrictions yields the identification conditions $(\mathcal{XV}^{*,q} \cap \mathcal{XV}^{*,s}) \subseteq \mathcal{XV}^{*,p}$ and $\mathcal{XZ}^s \subseteq (\mathcal{XZ}^q \cup \mathcal{XZ}^r)$.

4.4 Decompositions

Let $Q_{\langle q,r,s,p \rangle}(\tau)$ denote the counterfactual τ -quantile of earnings corresponding to the left-inverse of the counterfactual distribution $y \mapsto G_{\langle q,r,s,p \rangle}(y)$.⁵ The definitions above allow the following decomposition of the observed change in the τ -quantile of earnings between the

⁵ That is, $Q_{\langle q,r,s,p \rangle}(\tau) = \inf\{y \in \mathbb{R}: G_{\langle q,r,s,p \rangle}(y) \geq \tau\}$, for $\tau \in (0, 1)$.

baseline year (labeled as year 0) and any other year t :

$$\begin{aligned}
 Q_{\langle t,t,t,t \rangle}(\tau) - Q_{\langle 0,0,0,0 \rangle}(\tau) &= \underbrace{[Q_{\langle t,t,t,t \rangle}(\tau) - Q_{\langle t,t,t,0 \rangle}(\tau)]}_{[1]} + \underbrace{[Q_{\langle t,t,t,0 \rangle}(\tau) - Q_{\langle t,t,0,0 \rangle}(\tau)]}_{[2]} \\
 &+ \underbrace{[Q_{\langle t,t,0,0 \rangle}(\tau) - Q_{\langle t,0,0,0 \rangle}(\tau)]}_{[3]} + \underbrace{[Q_{\langle t,0,0,0 \rangle}(\tau) - Q_{\langle 0,0,0,0 \rangle}(\tau)]}_{[4]}. \quad (5)
 \end{aligned}$$

Term [1] in (5) is a “structural effect” reflecting earnings changes from movements in the distribution of hourly wages for those who work conditional on the explanatory variables and control function; term [2] is a “composition effect” reflecting changes in the distribution of earnings resulting from changes in the distribution of the explanatory variables and control function for those who work; term [3] is an “intensive hours effect” reflecting changes in earnings resulting from changes in the distribution of hours worked for those who work conditional on the explanatory variables and control function; while term [4] is an “extensive hours effect” capturing how individuals who change their employment status, from non working to working, increase their earnings from zero to a positive amount. FPVV discuss the role of composition, structural, and selection effects for the changes in the distribution of hourly wages and highlight the complications which arise in a nonseparable model. These are even greater here, as changes operating through hours directly enter the earnings equations. Accordingly, we further discuss their respective interpretations.

The extensive hours effect corresponds to the selection effect in FPVV.⁶ It captures the difference between the quantiles of earnings in year t and the quantiles of earnings that would have prevailed if individuals from year t participated as in year 0 (based on their observed

⁶ The extensive margin effect is positive as, given the choice of base years, it reflects the impact from going from zero hours to positive hours worked on annual earnings. In FPVV the selection effect is the impact on the observed wage distribution as we expand the number of people working. Thus in that context the effect can be negative.

and unobserved characteristics). Due to the identification assumptions for $G_{(1,0,0,0)}$, this effect is always positive. That is, someone with a positive probability to be working in the base year 0 should also have a positive probability in year t . By Assumption 1(c), those who do not work in year 0, and therefore have a low level of the control function V , will have a low number of working hours in year t . A violation of this assumption would result in an underestimation of the extensive hours effect.

The intensive hours effect is the difference between the quantiles of earnings that would result from changing the distribution of hours from year t to year 0, when individuals participate as in year t . More specifically, it changes the function k from year t to year 0, while keeping the functions G and $F_{X,Z,V}$ as in year 0 and the condition $k(x, z, v) > 0$ as in year t . As we move from the base year to year t this will capture differences in the hours distribution of those working. We highlight again that since we are employing annual hours, these differences may reflect either changes in weekly hours or unemployment spells.

The composition effect contains the impact on earnings of changes in the distribution of both observable and unobservable characteristics that affect wages and/or working hours. For example, increases in the level of female higher education could shift the distribution of earnings to the right due to both increases in the hourly wages and the number of working hours. Due to the nonseparable and nonparametric nature of the model, it does not seem possible to disentangle these two effects. However, note that the higher educational levels which increased hours, and thus higher annual earnings, are interpreted here as composition effects and not hours effects.

Finally, consider the structural effect. This captures the manner in which the individual's characteristics, both the explanatory variables and control function, map into the distribution of hourly wages and thus annual earnings. In separable models the manner in which the

control function affects the distribution of wages is sometimes referred to as a component of the selection effect. FPPV show that in nonseparable selection models it is not generally possible to isolate the effect of the control function.

It is important to clearly state what is, and what is not, included in the structural effects. When we consider changes in the hours distribution below, we are able to isolate the structural and composition effects of the explanatory variables. When considering earnings, however, the structural effects only operate through their impact on wages. The impact of the structural effects operating on earnings through hours are assigned either the interpretation of extensive or intensive hours effects. Studies that estimate parametric models which account for selection sometimes attribute changes resulting from movements in the control function and changes in its coefficient as selection effects. FPPV show that in a nonseparable model this attribution is generally not possible and argue that these selection effects should be interpreted as structural effects. We follow FPPV and assign the changes in annual earnings operating through the impact of the control function on wages to the structural effect. We interpret the impact of changes in the value of the control function as a composition effect.

Consider the role of Assumption 1(c) in interpreting these various components in these cross year comparisons. This assumption implies that individuals entering employment when going from a workforce with a low employment level to a workforce with a high employment level, will always have lower hours than those who work in the “low employment” scenario level. If this assumption is violated, then we would underestimate the extensive hours effect since we would underestimate the hours of those entering the labor market under the less restrictive selection rule. In contrast, the intensive hours effect will be overestimated since we will mistakenly consider an increase in the working hours of those that entered the labor market as an increase of the working hours of those already in the labor market.

5 Estimation

Our objective is to estimate the decomposition shown in (5). This requires estimation of the counterfactual distributions in equation (4) which are comprised of components from different samples. We start by rewriting this equation as:

$$G_{(q,r,s,p)}(y) = \int \mathbf{1} \left(F_{H|X,Z}^q(0 | x, z) < v \right) \left[G^p \left(\frac{y}{Q_{H|X,Z}^r(v | x, z)}, x, v \right) - 1 \right] dF_{X,Z,V}^s(x, z, v) + 1, \quad (6)$$

where $v \mapsto Q_{H|X,Z}^r(v | x, z)$ is the inverse function of $h \mapsto F_{H|X,Z}^r(h | x, z)$. Next, we estimate the components of this equation in the following manner:

Step 1: Estimation of the control function. We estimate the control function using logistic distribution regression (Foresi and Peracchi 1995, and Chernozhukov et al. 2013). That is, for every year s and every observation in the selected sample with $H_i^s > 0$, we set:

$$\widehat{V}_i^s = \Lambda(P_i^{s\top} \widehat{\pi}^s(H_i^s)), \quad i = 1, \dots, n^s,$$

where $\Lambda(u) = (1 + e^{-u})^{-1}$ is the standard logistic distribution function, $P_i^s = p(X_i^s, Z_i^s)$ is a d_p -dimensional vector of transformations of X_i^s and Z_i^s with good approximating properties and, for any h in the empirical support of H at time s , $\widehat{\pi}^s(h)$ is the logistic distribution regression estimator:

$$\widehat{\pi}^s(h) = \arg \max_{\pi \in \mathbb{R}^{d_p}} \sum_{i=1}^{n^s} [\mathbf{1}\{H_i^s \leq h\} P_i^{s\top} \pi + \log \Lambda(-P_i^{s\top} \pi)].$$

Step 2a: Estimation of the LDSF of hourly wages. Our estimation method is based on a trimmed sample with respect to annual hours and we employ the following trimming function:

$$T_i^s = \mathbf{1}\{0 < H_i^s \leq \bar{h}\},$$

for some $0 < \bar{h} < \infty$ such that $\mathbb{P}[T_i^s = 1] > 0$. The estimator of the LDSF of hourly wages is:

$$\widehat{G}^s(w, x, v) = \Lambda(m(x, v)^\top \widehat{\theta}^s(w)),$$

where $m(x, v)$ is a d_m -dimensional vector of transformations of (x, v) with good approximating properties. The vector $\widehat{\theta}^s(w)$ is the logistic distribution regression estimator:

$$\widehat{\theta}^s(w) = \arg \max_{\theta \in \mathbb{R}^{d_m}} \sum_{i=1}^{n^s} [\mathbf{1}\{W_i^s \leq w\} M_i^{s\top} \theta + \log \Lambda(-M_i^{s\top} \theta)] T_i^s,$$

and $M_i^s = m(X_i^s, \widehat{V}_i^s)$.

Step 2b: Estimation of the LASF of hourly wages. The estimator of the LASF of hourly wages is $\widehat{\mu}^s(x, v) = m(x, v)^\top \widehat{\beta}^s$, where $m(x, v)$ is a d_m -dimensional vector of transformations of (x, v) with good approximating properties, $\widehat{\beta}^s$ is the ordinary least squares estimator:

$$\widehat{\beta}^s = \left(\sum_{i=1}^{n^s} T_i^s M_i^s M_i^{s\top} \right)^{-1} \sum_{i=1}^{n^s} T_i^s M_i^s W_i^s,$$

and $M_i^s = m(X_i^s, \widehat{V}_i^s)$.

Step 3: Estimation of the counterfactual distribution function of annual earnings.

Using the analogy principle, $G_{(q,r,s,t)}(y)$ is estimated by the empirical counterpart of (6),

namely:

$$G_{\langle q,r,s,p \rangle}(y) = \frac{1}{n^s} \sum_{i=1}^{n^s} \mathbf{1} \left(\Lambda(P_i^{s\top} \widehat{\pi}^q(0)) < \widehat{V}_i^s \right) \left[\widehat{G}^p \left(\frac{y}{\widehat{Q}_{H|X,Z}^r(\widehat{V}_i^s | X_i^s, Z_i^s)}, X_i^s, Z_i^s \right) - 1 \right] + 1,$$

where $\widehat{Q}_{H|X,Z}^r(v | X_i^s, Z_i^s) = \int_0^\infty \mathbf{1}\{\Lambda(P_i^{s\top} \widehat{\pi}^r(h)) \leq v\} dh$ is the generalized inverse of $h \mapsto \Lambda(P_i^{s\top} \widehat{\pi}^r(h))$.⁷

The standard errors and confidence intervals for these objects and the components of the decomposition can be calculated using the weighted bootstrap. This method obtains the bootstrap version of the estimator of interest by repeating all the estimation steps using sampling weights drawn from a nonnegative distribution. More details regarding this procedure are provided in FVV. We do not provide standard errors for all of the decompositions that follow although we produce them for the decompositions of median earnings. We do so to obtain some indication of their magnitude.

6 Empirical results

We now report and discuss our empirical results. Section 6.1 decomposes changes over time in the quantiles of annual hours, Section 6.2 decomposes changes over time in the quantiles of annual earnings and Section 6.3 decomposes changes over time in a measure of earnings inequality. Section 6.4 discusses the main findings.

⁷The integral in the expression of $\widehat{Q}_{H|X,Z}^r(v | X_i^s, Z_i^s)$ is approximated by a Riemann sum at the sample values of H^r .

6.1 Annual hours

We estimate equation (3) separately by gender and survey year. The vector X includes three dummy variables indicating the highest level of education (less than high school, some college, and college), a quadratic polynomial in age fully interacted with the education dummies, a dummy variable indicating that the individual is not married or cohabiting, a dummy variable indicating that the individual is nonwhite, and three dummy variables for the region of residence (North-East, South, and Central). The vector Z includes the size of the household (in deviations from two), a dummy variable for the presence of own children in the household, a dummy variable for the presence of children under 5 years of age, and a dummy variable for the presence of other household members besides spouse or dependent children. The reference case is a white high-school graduate, married or cohabiting, resident in a Western state, in a two-member household without children or other household members.

The decomposition exercises require a base year for each gender.⁸ We follow FPVV and employ 1976 for females and 2010 for males. Irrespective of the base year, we present the changes relative to 1976. The female employment rate is at its lowest in 1976 and we assume that females with a certain combination (x, z, v) of observed and unobserved characteristics working in this period will have a positive probability of working in subsequent years. We use the same logic in choosing 2010, the bottom of the financial crisis, for males. As we employ different base years, we can compare trends but not hours and earnings across gender.

We start with an examination of changes in mean annual hours of work. Figure 7 presents the relative changes in mean annual hours relative to 1976. For males they vary little over

⁸ This decomposition only distinguishes between composition and structure effects as in DiNardo, Fortin and Lemieux (1996). The composition effect reflects changes in the distribution of annual hours resulting from changes in the distribution of the explanatory variables, while the structure effect reflects changes resulting from changes in the conditional distribution of annual hours given the explanatory variables.

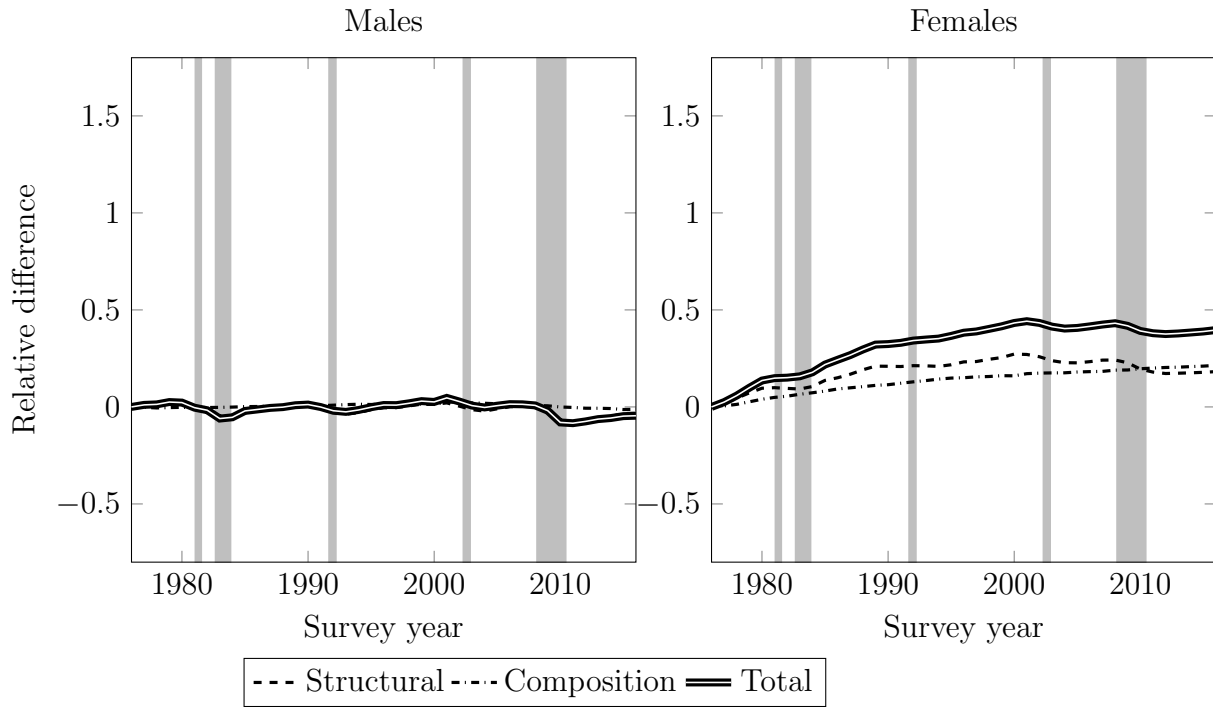


Figure 7: Decomposition of the relative changes in mean annual hours of work with respect to 1976.

the period and the changes are cyclical. The largest change, an approximately 8 percent decrease, occurs during the Great Recession. Movements in mean male hours mostly reflect the structural effect, with a negligible role for the composition effect. Females mean annual hours increase by approximately 40 percent and this occurs from 1976 to 2000. Female mean annual hours are stable or declining after the 2001 recession. There is evidence of cyclicity in the female mean, but before year 2000 this is dominated by the strong upward trend. The structural effect is the primary component before year 2000 but it declines post 2000. The composition effect rises steadily and, by the end of our period, is the slightly larger of the two.

Figure 8 presents the time profile of the changes relative to 1976 in the lower quartile of annual hours for males. The corresponding profile for females is zero throughout the

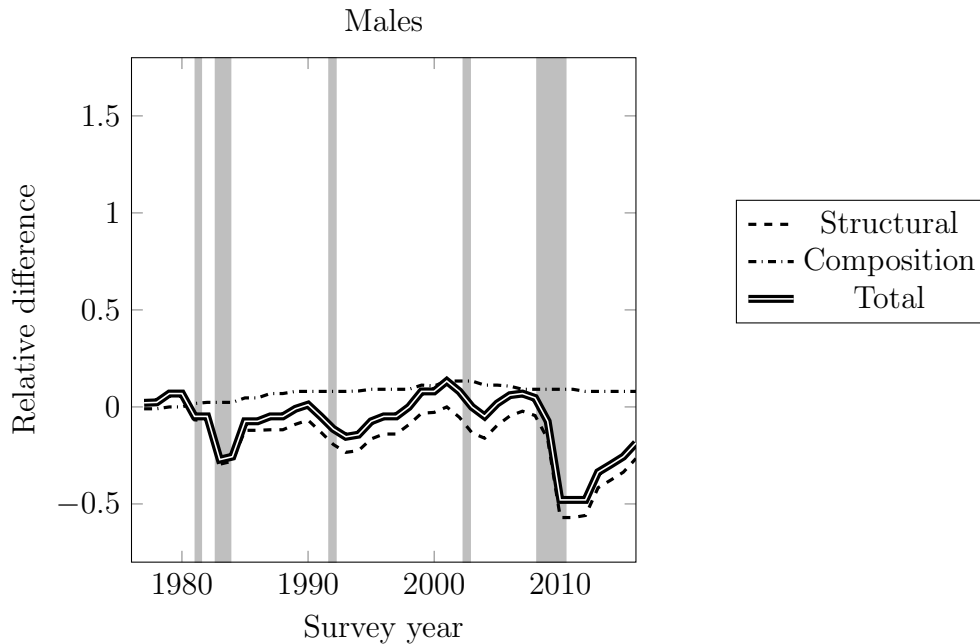


Figure 8: Decomposition of the relative changes in the lower quartile of annual hours of work with respect to 1976.

period, as more than 25 percent of females work zero annual hours. Male hours are highly cyclical with a decrease of over 20 percent during the early 1980s and 40 percent during the Great Recession. The composition effect is positive, and most likely reflects increasing education attainments. However, the dominant component is the negative structural effect which follows the business cycle and somewhat resembles the surge in unemployment rates during recessions.

Figure 9 shows the time profile of the relative changes in median annual hours for females with respect to 1976. For males, which we do not present, the median remains constant at 2080 annual hours. Although quantiles are less informative in characterizing distributions which are discrete or feature substantial bunching, changes over time in the quantiles can still be indicative of the movements in the underlying distribution and this is why we employ them here. The female profile resembles that of the mean but the increase is much larger

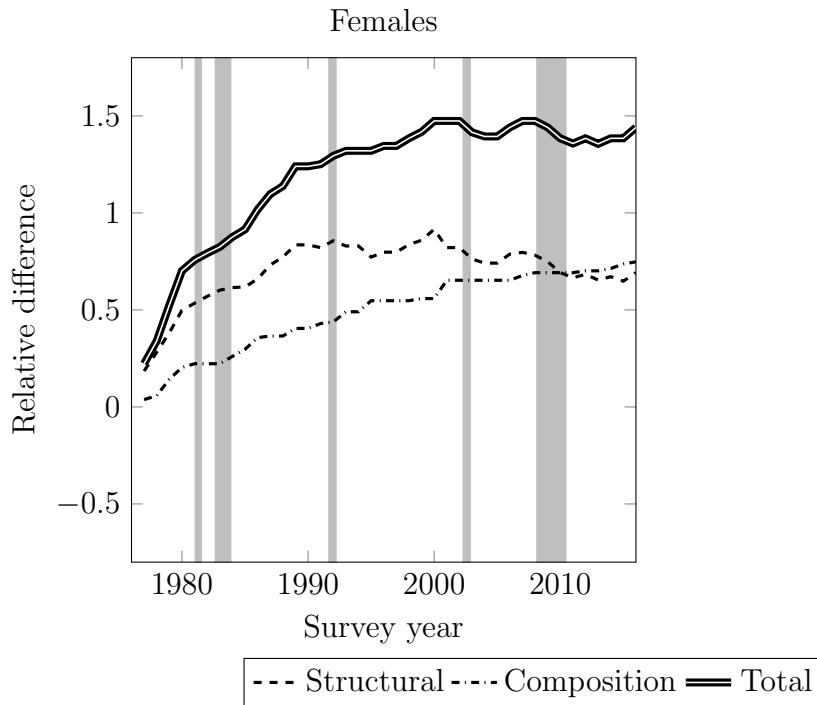


Figure 9: Decomposition of the relative changes in median annual hours of work with respect to 1976.

(over 140 percent) and reflects the large increase in both female employment rates and hours worked by those working. The large contribution of the composition effect has implications for earnings decompositions and we return to this below.

Figures 10 and 11 provide the time profiles of the relative changes with respect to 1976 in, respectively, the upper quartile and the upper decile of annual hours of work. These figures reveal two striking features common across gender. First, there is little variation at these quantiles and there are long periods in which they remain unchanged. This reflects that the upper tail of the hours distribution has changed little over time. Given the magnitude of the changes, both the structural and the composition effects play a negligible role. The absence of these effects is important in understanding their impact on earnings.

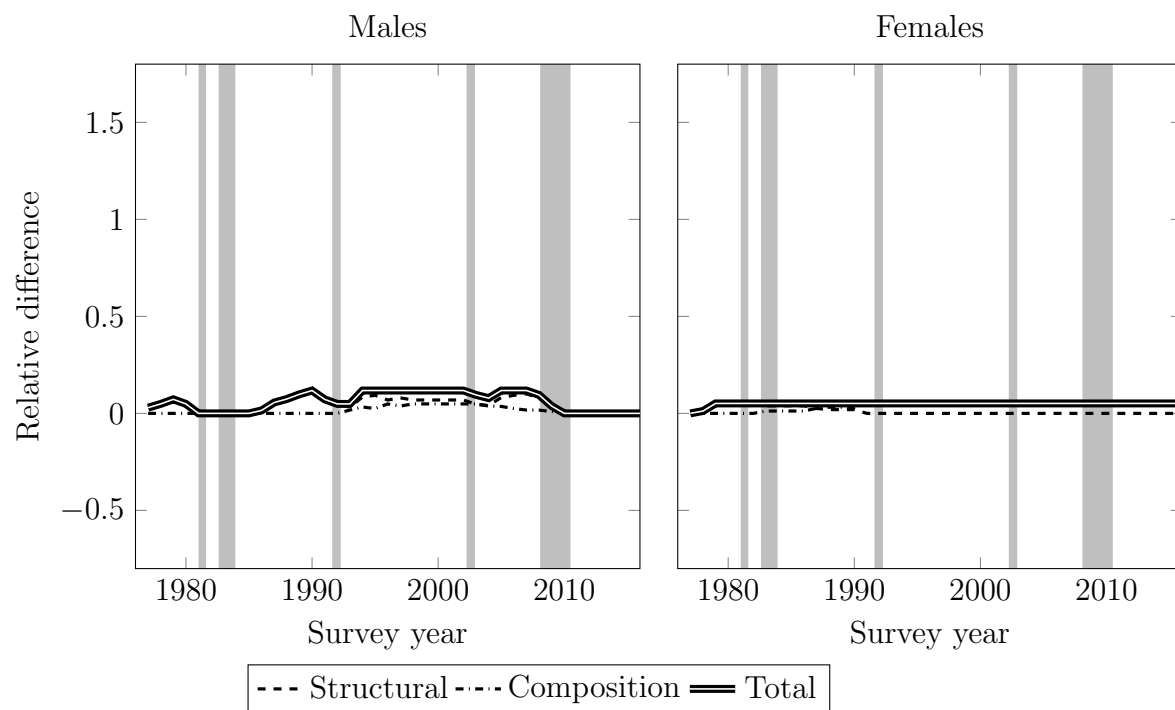


Figure 10: Decomposition of the relative changes in the upper quartile of annual hours of work with respect to 1976.

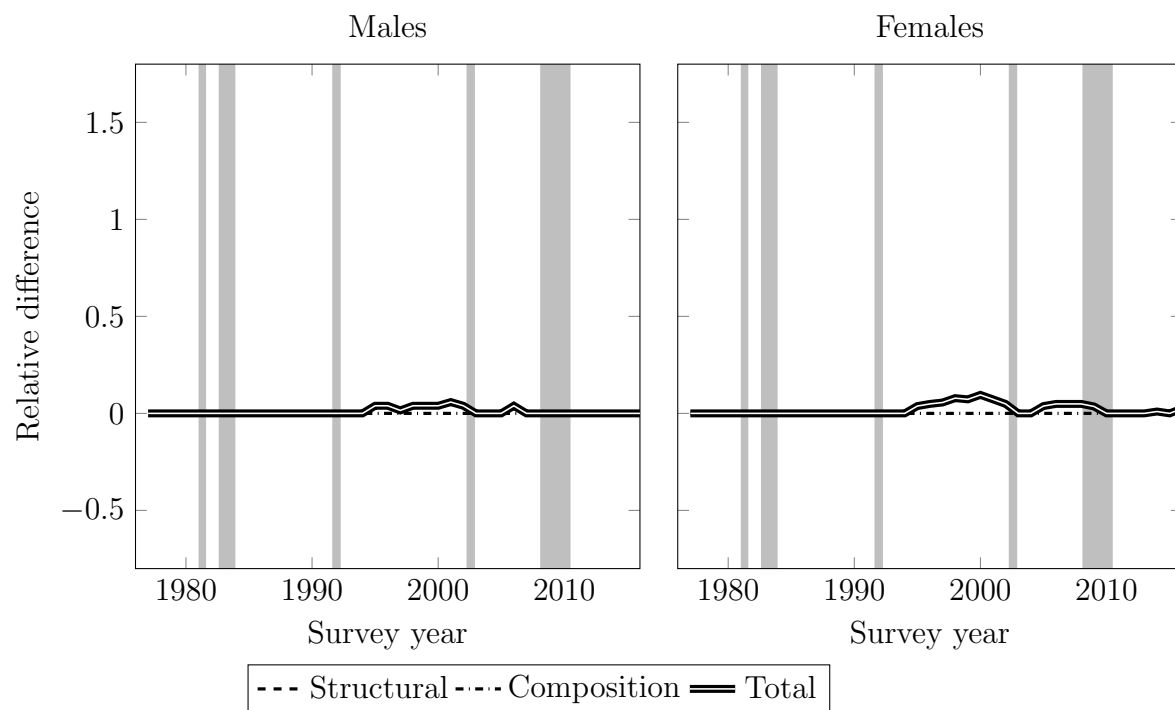


Figure 11: Decomposition of the relative changes in the upper decile of annual hours of work with respect to 1976.

6.2 Annual earnings

We now decompose the changes in the annual earnings distribution. We estimate the hourly wage equation (2) for the selected sample using the same conditioning variables in X as above, with the variables in Z excluded for identification purposes. The estimated control function \widehat{V} and its square are included, in addition to their product with the other included variables. We employ the same base years as above. The earnings decompositions require estimates from the annual hours equation and the selection-corrected hourly wage equation. The results for annual hours are above and those for hourly wages are provided in FPVV.⁹

The bunching at 2080 working hours per year probably reflects the convenience for an individual to respond that he/she works 40 hours per week for 52 weeks per year. However, it creates a difficulty in predicting an individual's working hours given his or her observed characteristics and control function. Accordingly, we modify our method as follows.

Suppose H^* is the actual number of working hours of an individual, while H is the observed number of working hours. Hence, H^* is the left-hand side variable as in (3). Furthermore, assume the relationship between actual and observed working hours is:

$$H = j \text{ if } h_j < H^* \leq h_{j+1}.$$

From the monotonicity assumption it follows that $h_j < H^* \leq h_{j+1}$ implies that the control function V is between the values $v_j(x, z)$ and $v_{j+1}(x, z)$. From the definition above, this holds when $H = j$. We also know that V is uniformly distributed between these values although we are not able to estimate the control function of the individual observations. However, it

⁹ FPVV illustrate the lack of sensitivity of the wage equation decompositions to various specification issues. These included the choice of exclusion restrictions, changes to the sample, and the exclusion of annual hours from the wage equation.

is possible to estimate the values $v_j(x, z)$ and $v_{j+1}(x, z)$ for every j based on the observed levels of working hours. This suggests that we can randomly sample the values of V between the two estimated values to obtain draws of the control function. We use these sampled values rather than the estimated values based on H to calculate the counterfactual earnings distributions.

Figure 12 presents the decomposition of the changes in mean annual earnings relative to 1976. We retain the same vertical scale to allow easier comparisons. Mean male earnings are cyclical and highly variable, with increases and decreases of up to 10 percent. Over the sample period they increase by 5 percent. The trend in mean male earnings is strongly correlated with the structural effect operating through wages. The composition effect is positive with an inverse U-shaped profile. The absence of composition effects in the changes in mean male hours indicates that the positive composition effect in mean male earnings is also operating through wages. There is no evidence of an extensive hours effect for mean male earnings while the intensive hours effect is cyclical but small.

In contrast to the modest growth for males, female mean earnings increase by over 70 percent. This reflects a steadily increasing composition effect which accounts for over half of this increase. Important contributions also come from the structural effect and the intensive hours effect. Surprisingly, the contribution from changes in the extensive margin are small, reflecting our earlier discussion of what the hours effects capture. The large composition effects are interesting and, as we saw above, they also reflect their impact on mean hours. Moreover, FPVV suggest that they are important for females at all points of the wage distribution. Perhaps the most interesting feature of this figure is the large intensive hours effect at the mean. It indicates that the shift in the hours distribution for those working has increased females earnings by 20 percent.

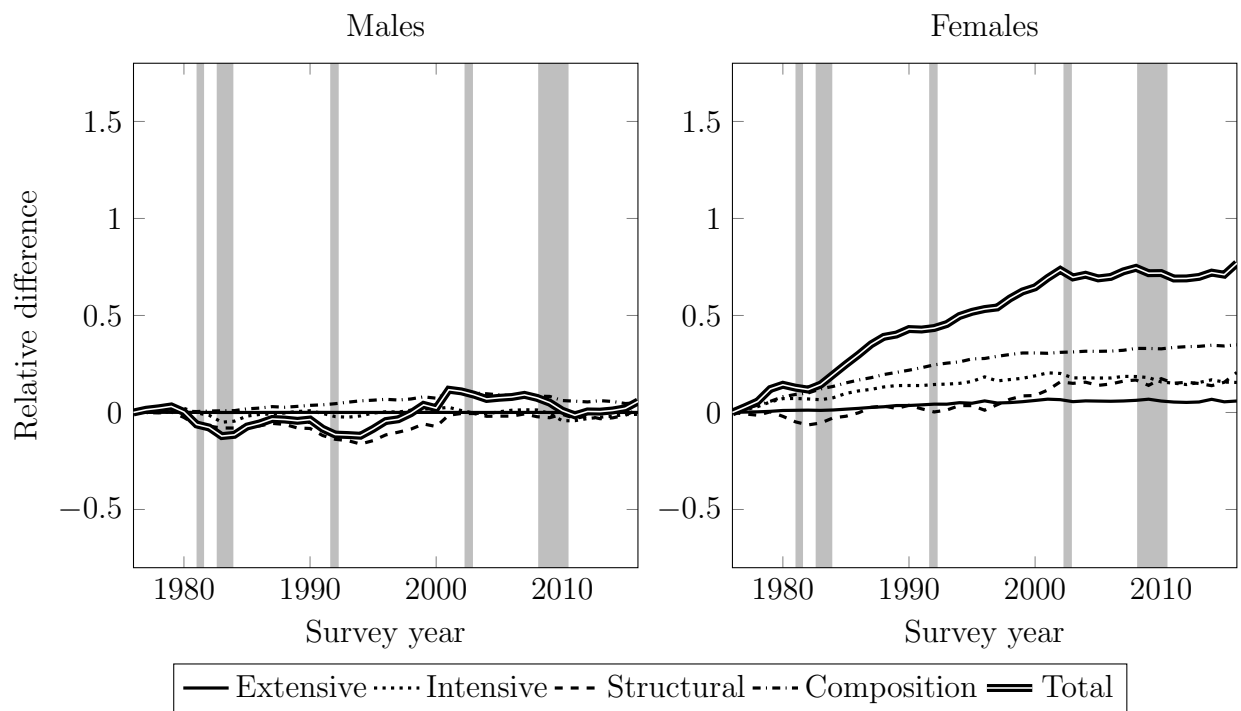


Figure 12: Decomposition of the relative changes in mean annual earnings with respect to 1976.

FPVV provide compelling evidence that the magnitude of the structural and composition effects vary notably across the distribution of real hourly wages for both genders. We explore the presence of similar relationships for earnings. Figure 13 provides the decomposition of the changes in the lower quartile of annual earnings relative to 1976. The first quartile of male earnings for the full sample corresponds to the first decile for the earners sample.¹⁰ As the female employment rate is as low as 60 percent in some periods, we are unable to conduct our decomposition for females at the lower quartile.

The figure provides a bleak portrait of the labor market experience for males at the lower quartile of annual earnings. There are several instances of large decreases in earnings resulting in a substantial reduction of around 70 percent from 1976 to 2010 before a small rebound at the end of the period. The two most striking decreases occur at the beginning of the 1980s and during the Great Recession. The structural effect, operating through real wage rates decreases, is large. The composition effect is small and generally positive until the year 2009.

Consider now the impact of hours. Since there are relatively small changes in male participation rates, there is little impact along the extensive margin. Perhaps the most interesting feature is the impact of movements on the intensive margin, recalling that this not only captures variations in weekly hours but potentially also periods of zero hours per week for some fraction of the year. This intensive hours effect is negative and frequently large. More strikingly, the intensive margin accounts for the largest decrease in annual earnings at Q1, which occurs in 2010. The intensive hours effect is responsible for almost half of this notable decline. We stress again that this decline reflects both increased weeks

¹⁰ Let $Q_{0.25}$ be the lower quartile of earnings for the full sample. This value corresponds to the p th quantile for the earners sample, where $p = F_Y(Q_{0.25}|Y > 0)$. Since $F_Y(y|Y > 0) = (F_Y(y) - F_Y(0))/(1 - F_Y(0))$ and $F_Y(Q_{0.25}) = 0.25$, it follows that $p = (0.25 - F_Y(0))/(1 - F_Y(0)) < .25$. From Figure 4, $F_Y(0)$ ranges between 0.1 and 0.15, so we obtain values for p between 0.11 and 0.17.

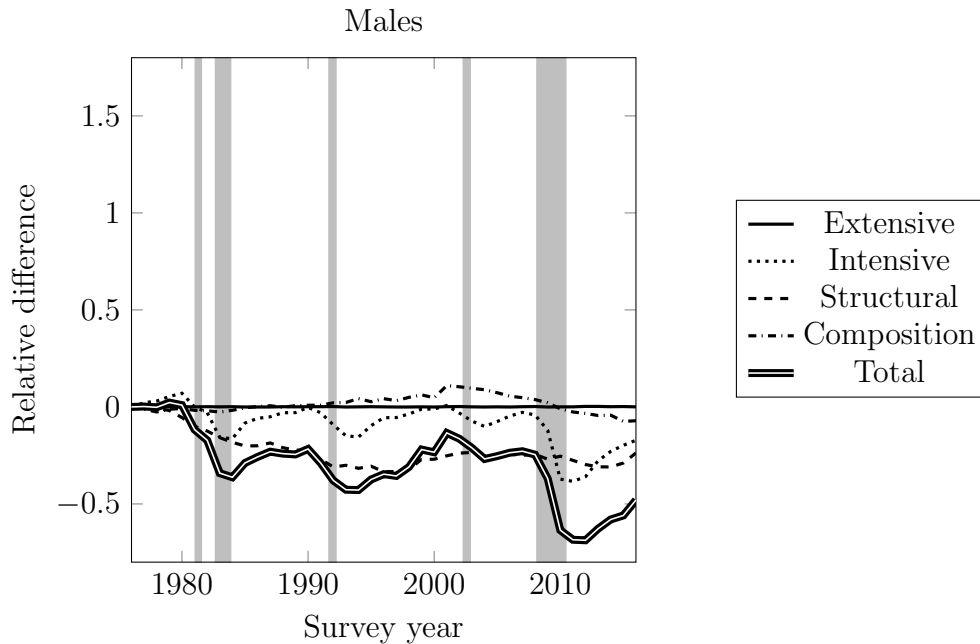


Figure 13: Decomposition of the relative changes in the lower quartile of annual earnings with respect to 1976.

of zero work and reduced hours in working weeks.

Figure 14 shows the decomposition of the changes in median annual earnings with respect to 1976. For males, they fall by approximately 20 percent over our period. Moreover the patterns of change follow closely the business cycle. Interestingly, although unsurprisingly, the changes in male median earnings largely reflect the structural component. The structural component is more negative than the total effect as the composition effect is positive and generally increasing over this period. The composition effect is approximately 10 percent by 2016 and most likely captures the impact of increasing education levels on wages. The profile of the intensive hours effect is largely negative and mirrors the business cycle. Moreover, there is no evidence of any effect on the extensive margin recalling that some fraction of the reported intensive hours effect reflects an increase in the number of zero weeks of positive hours.

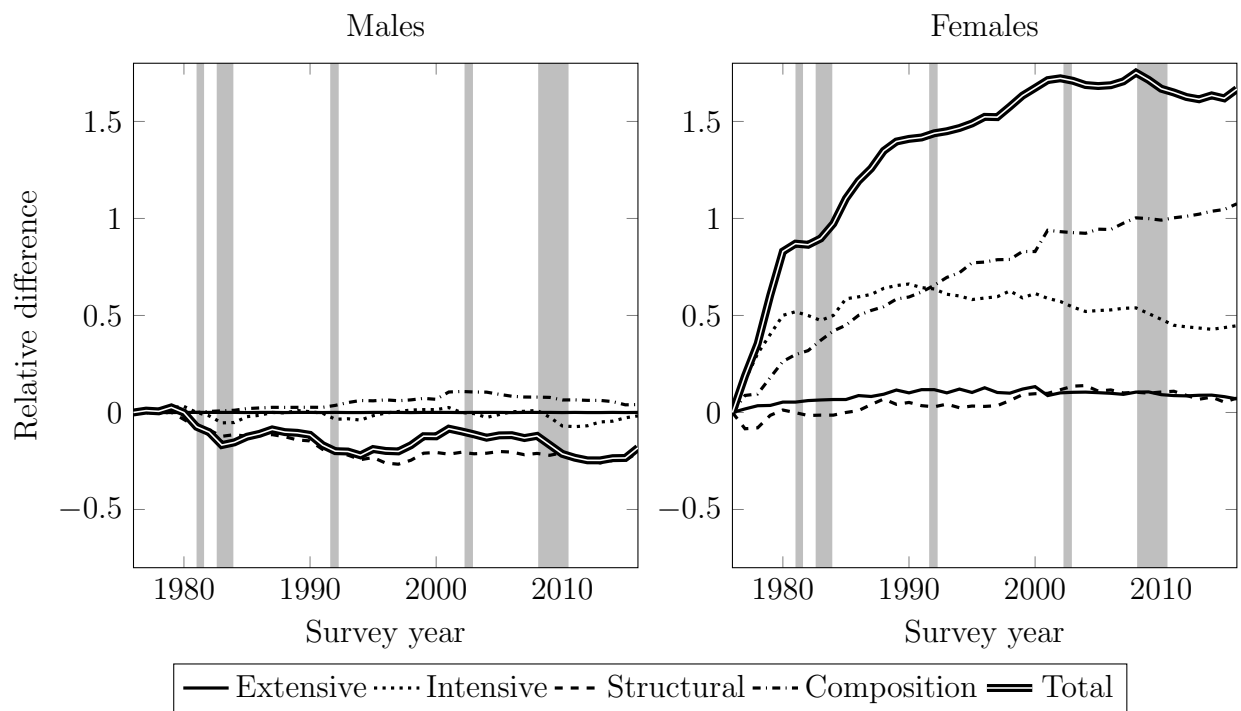


Figure 14: Decomposition of the relative changes in median annual earnings with respect to 1976.

There is a 150 percent increase in female median earnings, most of which occurs before the year 2000. All elements of the decomposition contribute positively to this large change but their relative importance differ. The largest is the composition effect, which captures the impact on earnings both through wages and hours, followed by the intensive hours effect, which captures the drastic shift to the right in the hours distribution of females. The structural effect is relatively small and so is the extensive hours effect, which captures the increased female participation rate. The higher education levels have clearly contributed to increasing earnings through their impact on both wages and annual hours.

As noted above, we computed the 95% confidence intervals for the decompositions of the changes in the median annual earnings. These are based on 500 bootstrap replications. We present these results in Appendix A and they are generally small indicating that the point estimates are precise. This precision reflects the large sample sizes and we conclude that this evidence for the medians suggests the effects at other quantiles are likely to also be accurately estimated.

Figure 15 shows the decomposition of the relative changes in the upper quartile of annual earnings with respect to 1976. While male earnings display strong cyclical fluctuations but no trend, female earnings show a strong positive trend with some cyclical fluctuations. The flat profile for males reflects the opposing forces of the structural and composition effects in terms of sign and magnitude. The structural effect reflects the decreasing value of labor occurring at most parts of the wage distribution, which is documented in FPVV. The positive composition effect, also documented in FPVV, reflects the increased skill levels of the male workforce in the upper tail of the wage distribution. Hours effects do not appear to matter. The extensive hours effect is zero over the whole sample, while the intensive margin contributes pro-cyclically but in a minor fashion. This is unsurprising as one would

not expect large changes in annual work at this location of the male distribution.

The upper quartile of female annual earnings displays a large increase of about 55 percent. Two thirds of this increase can be attributed to the composition effect which probably reflects the increasing educational attainments of the female workforce. The remaining third is due to the intensive hours effect. While part of this large increase reflects the increasing female participation, the level of hours worked is also important. The extensive hours effect is positive but small, while the structural effect is cyclical but relatively flat.

Figure 16 reports the decomposition of the relative changes in the upper decile. Here we finally see positive male earnings growth, at least for the period after 2000. This increase largely reflects the composition effect although it is the absence of a negative structural effect which ensures that earnings growth is positive at the end of our period. Both effects are operating through wages, as the extensive and intensive hours effects are negligible. This is not surprising as it is not expected that the labor supply of individuals in this location of the earnings distribution is greatly influenced by cyclical factors.

There is a steady increase in female earnings which exceeds 50 percent by the end of the period. This reflects not only a large positive composition effect but also a positive structural effect which is growing from the mid-1980s onwards. These patterns are similar to those found for wage rates in the upper tail of the female wage distribution by FPVV. There is also a substantial intensive hours effect which reflects that even at this location in the hours distribution females appear to be increasing their annual hours of work. The extensive hours effect is small and reflects the relative stability of female participation in this location of the earnings distribution.

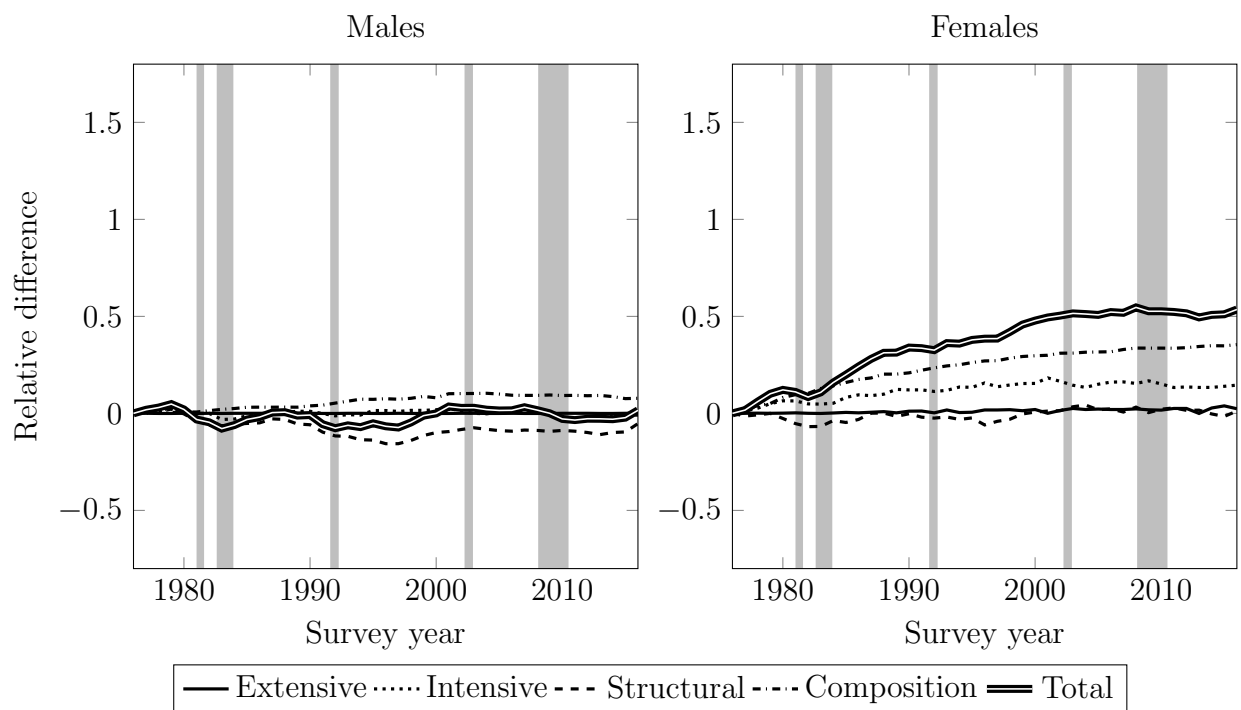


Figure 15: Decomposition of the relative changes in the upper quartile of annual earnings with respect to 1976.

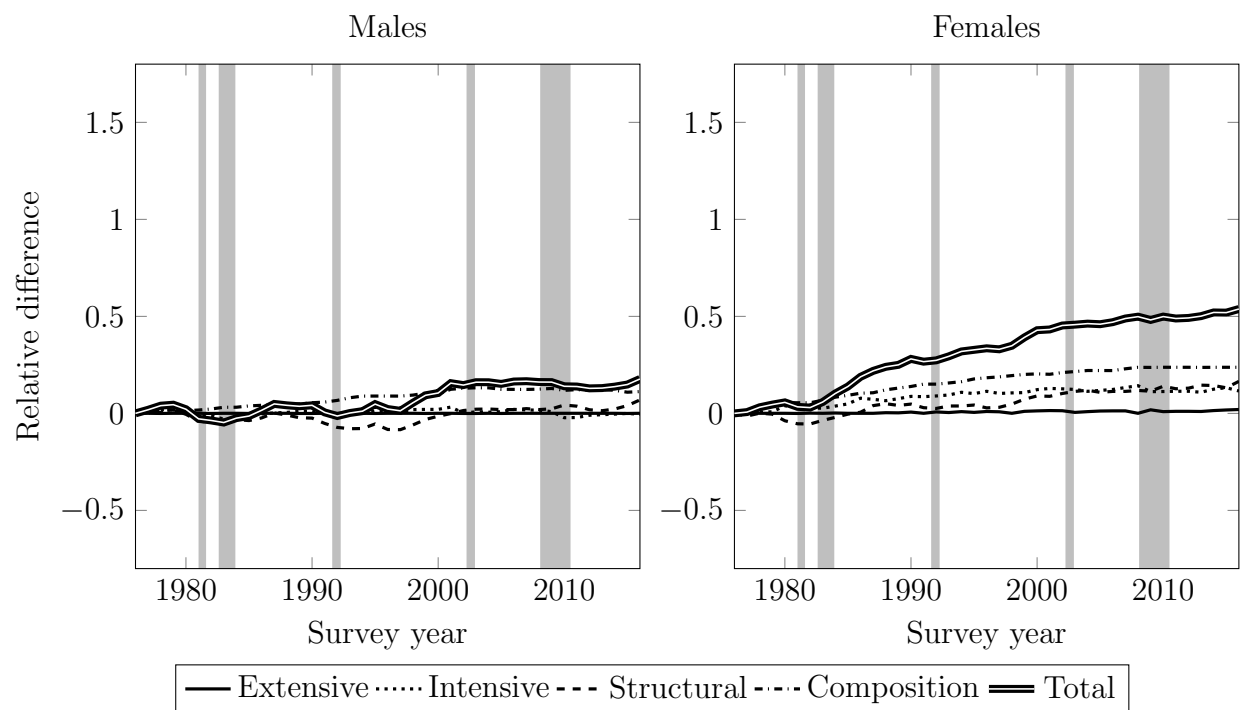


Figure 16: Decomposition of the relative changes in the upper decile of annual earnings with respect to 1976.

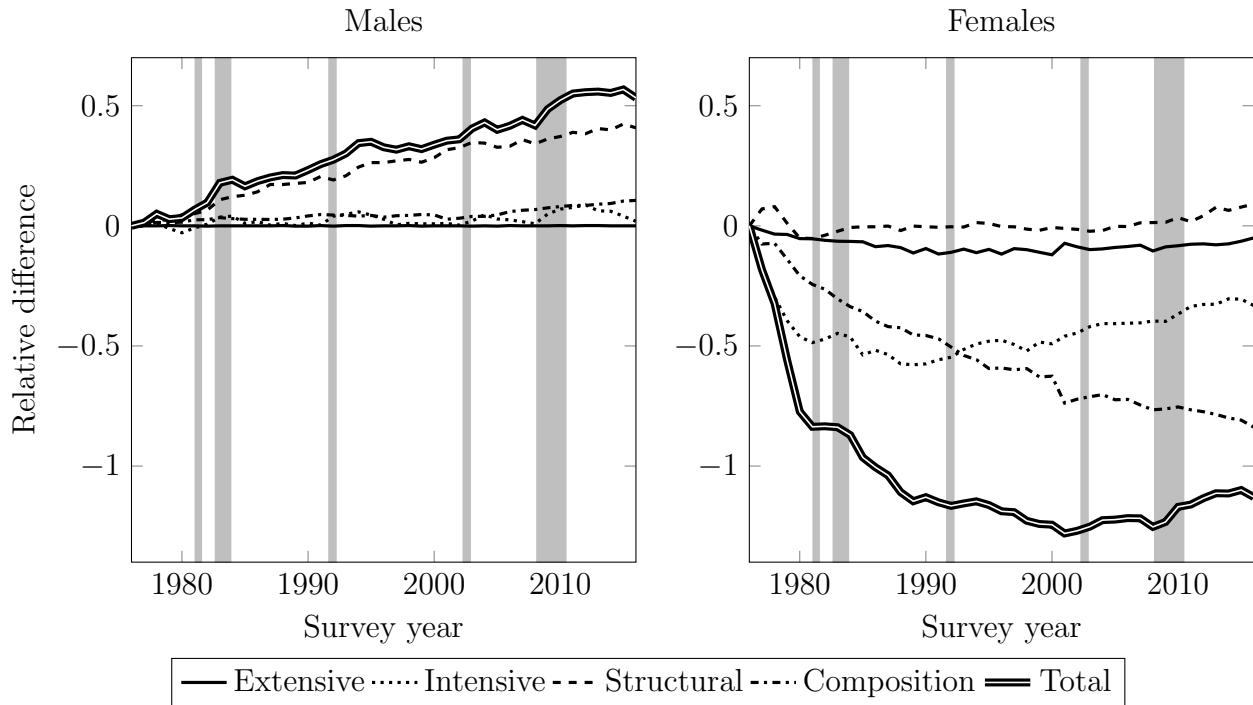


Figure 17: Decomposition of the relative changes with respect to 1976 in the ratio of the upper decile to the median of annual earnings.

6.3 Decomposing changes in earnings inequality

The evidence above documents the drastic changes in the distribution of annual hours of work and annual earnings. We now examine the implications of these changes for the level of earnings inequality. Studies of inequality typically examine the ratio of quantiles above and below the median, and how they vary over time. Popular choices are the quartile ratio ($Q75/Q25$) or the decile ratio ($D9/D1$), although their selection is somewhat arbitrary. Given the inclusion of those working zero hours in our sample, the female participation rate of 56.5 in 1976 does not allow for comparisons for females involving earnings below the fourth decile. Accordingly, we focus on relative changes with respect to 1976 in the ratio of the upper decile to the median for both males and females. These are provided in Figure 17.

The increase in male inequality of around 60 percent is substantial. Although all components are positive, this increase largely reflects the role of the structural component. The evidence above, combined with that of FPVV, suggests this captures the role of the structural component in wage growth. That is, male wage rates at the upper quantiles have drastically increased relative to those at lower quantiles. Unsurprisingly, there is little evidence of hours and composition effects. The hours effects at the median and the 9th decile do not appear to be important and the composition effects appear to offset each other.

The corresponding figure for females is strikingly different in several ways. First, there is a drastic decrease of over one hundred percent in this measure of inequality. The fall occurs primarily during the 1976 to 1990 period, although it is maintained for the remainder of the time examined. This large effect is the result of increased participation rates and hours worked. Interestingly, this is captured either by the composition effects operating through hours or the intensive hours effect directly. For different parts of the sample period these two effects take on the dominant role. Note again that the intensive margin appears to be capturing those who were working relatively few hours early in the sample period but greatly increased their hours of work in subsequent years. Second, the structural effect is relatively unimportant for this measure of female earnings inequality. The evidence in FPVV suggests the structural effects should be increasing inequality as those at the upper quantiles of the wage distribution have experienced much larger wage increases from this source than those lower in the wage distribution. This, however, does not appear to be the case when we consider the median and ninth deciles. Finally, the extensive hours effect has the expected effect but is small. This highlights the subtle distinction between the intensive and extensive margins given our construction of the annual hours variable.

6.4 Discussion

The patterns of change in the distribution of annual earnings are very different for males and females. This is especially so for the period 1976 to 2000. While the male distribution is dominated by cyclical fluctuations, the female distribution is driven by long-run trends. Another notable difference is the contribution of composition, structural, and hours effects. Structural effects closely reflect the business cycle and are more important for males, while composition effects closely reflect long-run demographic and social trends and are more important for females. Further, while for males structural and composition effects have different signs, for females they are both positive and reinforce each other. For females, the intensive hours effect is important, especially until the early 2000s, but is smaller than the composition effect. However, recall that the increased education which affects the number of hours worked is reflected here in the composition effect. For both genders, the extensive hours effect is negligible at all quantiles considered. While the pre-2000 trends differ greatly by gender, the post-2000 trends appear more similar.

The patterns of change in the distribution of annual earnings are also different across quantiles of the earnings distribution. Male annual earnings have been falling steadily at the median and below, remained stable around the upper quartile, and increased at the upper decile and above. For females, they have been rising over the whole distribution. Female annual earnings have increased more at the bottom of the distribution than at the top with the larger increases occurring in the first half of our period. Identifying the various components of this drastic increase in female earnings is arguably our most striking empirical contribution.

7 Conclusions

This paper examines the relationship between the changes in the distribution of annual hours of work and those in the distribution of annual earnings. This is done through a decomposition of movements in the distribution of annual earnings into composition, structural and hours effects. This requires the estimation of a nonseparable model of hours and wages in the presence of a censored selection rule. Our empirical work has a number of interesting results. Changes in the hours of annual work are important for the lower quartile of male annual earnings but their importance diminishes as we examine higher quantiles. At the lower quartile the effects operate through the intensive margin although the nature of the annual hours of work variable allows movements at the intensive margin to incorporate spells of unemployment. While the upper decile to median ratio for male annual earnings increases by over 50 percent for our sample period a very small fraction of this can be attributed to changes in the male hours distribution. This increase in annual earnings inequality appears to be almost entirely to structural effects operating through the hourly wage equation. Changes in the female distribution of annual hours have increased earnings at all quantiles of the female annual earnings. These effects are generally operating through the intensive margin. The female upper decile to median ratio decreases dramatically indicating a drastic reduction in earnings inequality. This reduction is due to large effects at the intensive margin of annual hours of work but also to composition effects, such as increased levels of education, which increase wages at all quantiles but also increase the level of annual hours of work.

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Appendix A : Bootstrapped confidence intervals for decompositions at median annual earnings

Figure 18: 95 percent bootstrap confidence intervals at the median for females.

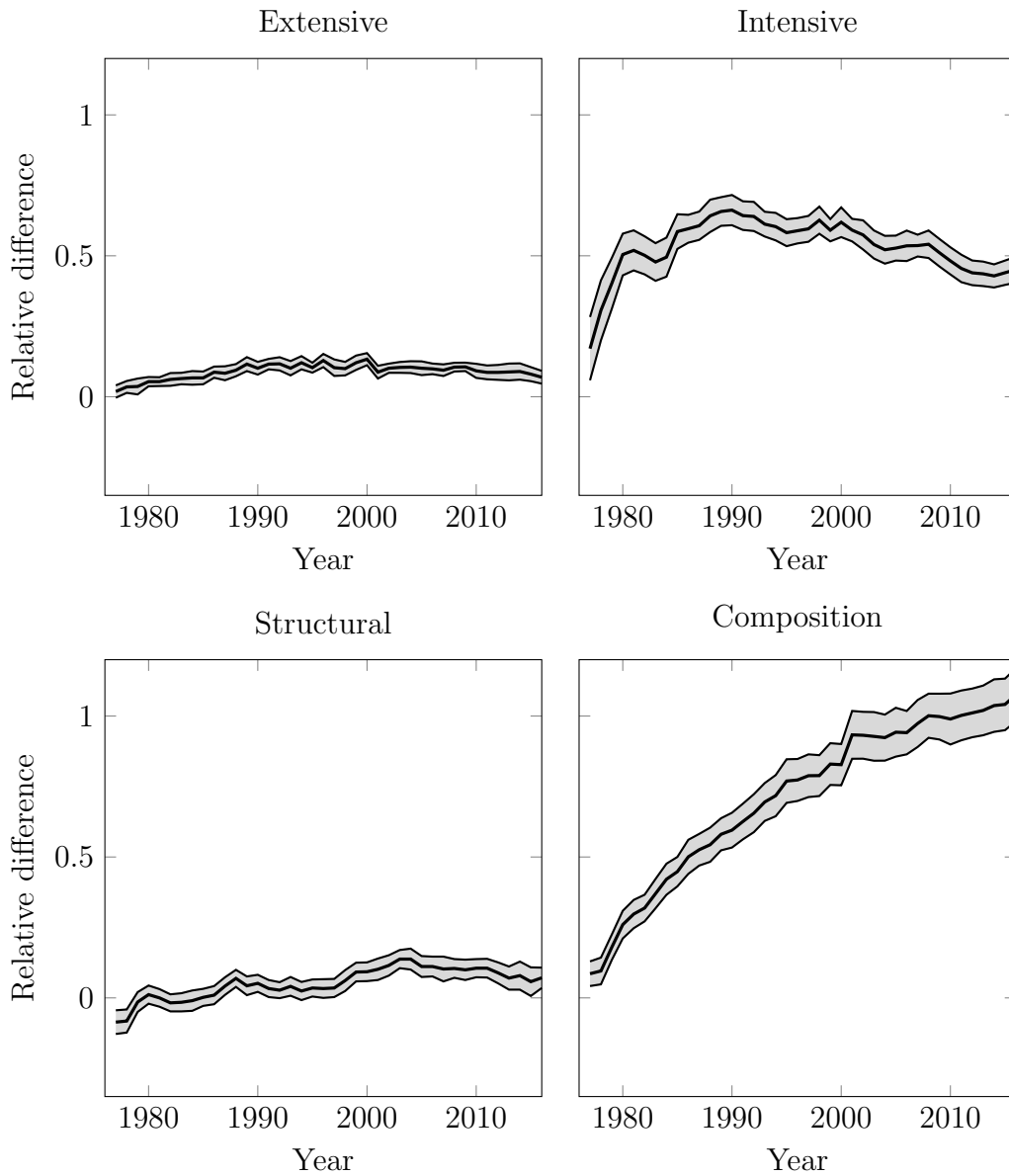


Figure 19: 95 percent bootstrap confidence intervals at the median for males.

