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Richard Blundell
Hugo Lopez
James P. Ziliak

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LABOR MARKET INEQUALITY AND THE CHANGING LIFE CYCLE PROFILE OF MALE AND FEMALE WAGES*

Richard Blundell, University College London and Institute for Fiscal Studies

Hugo Lopez, University of Chicago and Institute for Fiscal Studies

James P. Ziliak, University of Kentucky and Institute for Fiscal Studies

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Abstract: We estimate the distribution of life cycle wages for cohorts of prime-age men and women in the US. A quantile selection model is used to consistently recover the full distribution of wages accounting for systematic differences in employment, permitting us to construct gender- and education-specific age-wage profiles, as well as measures of life cycle inequality within- and between-education groups and gender. Although common within-group time effects are shown to be a key driver of labor market inequalities, important additional differences by birth cohort emerge with older cohorts of higher educated men partly protected from the lower skill prices of the 1970s. The gender wage gap is found to increase sharply across the distribution in the first half of working life, coinciding with fertility cycles of women. After age 40, there has been substantial gender wage convergence in recent cohorts relative to those born prior to the 1950s.

JEL Codes: J3, J1
Keywords: Wage Inequality, Life Cycle Earnings, Employment, Quantile Selection, Gender Gaps

*Address correspondence to Richard Blundell at Department of Economics, University College London, Gower Street, London WC1E 6BT, UK. Tel: +44 (0)20 7679 5863, email: r.blundell@ucl.ac.uk. We thank Johannes Schmieder, and participants at the 2022 American Economic Association Meetings, Rutgers University, University of Oregon, and Washington State University for helpful comments on an earlier draft. We thank the University of Kentucky Center for Computational Sciences and Information Technology Services Research Computing for their support and use of the Lipscomb Supercomputer Cluster. All errors are our own. Blundell would like to thank the ESRC Centre for the Microeconomic Analysis of Public Policy (CPP) at IFS for funding under grant number ES/M010147/1.

Inequality in labor market outcomes of men and women has been at the fore of research and policy debates for several decades, focusing on changes in the skill composition of the labor force, in the returns to observed and unobserved skills, and in institutions such as unions, the minimum wage, and trade agreements (Bound and Johnson 1992; Katz and Murphy 1992; Juhn, Murphy, and Pierce 1993; DiNardo, Fortin, and Lemieux 1996; Gosling, Machin, and Meghir 2000; Card and DiNardo 2002; Lemieux 2006; Blundell et al. 2007; Autor, Katz, and Kearney 2008; Autor, Dorn, and Hanson 2013). Most of this research examines cross-sectional inequality over time rather than over the life cycle, even though the sources and patterns of lifetime inequality may differ considerably from the cross section (Deaton and Paxson 1994; Heathcote, Storesletten, and Violante 2005; Blundell, Pistaferri, and Preston 2008; Huggett, Ventura, and Yaron 2011; Guvenen et al. 2021; Magnac and Roux 2021). Moreover, with some exceptions, the inequality literature has not formally modeled the potential nonrandom selection of who is observed in work. Historically this was not likely a major source of bias among prime-age men since most worked at some point in the year. However, there has been a long-term retreat from work among men (Blundell et al. 2018; Abraham and Kearney 2020; Aguiar et al. 2021), and the employment patterns of women have changed in recent cohorts (Goldin and Mitchell 2016), suggesting that the assumption of exogenous selection into work may no longer be tenable for men, and probably never has been for women (Blau and Kahn 2017).

In this paper we provide new estimates of wage inequality across the working life within and between gender and education in the presence of nonrandom sample selection. We develop a quantile model for wages that combines the long literature on estimating age, cohort, and time effects (Weiss and Lillard 1978; Welch 1979; Berger 1985; Heckman and Robb 1985; Deaton and Paxson 1994; MaCurdy and Mroz 1995; Beaudry and Green 2000; Gosling et al. 2000; Card and Lemieux 2001; Fitzenberger and Wunderlich 2002; Kambourov and Manovskii 2009; Lagakos et al. 2018) with the equally long literature of estimating wages in the presence of nonrandom sample selection (Heckman 1979; Lee 1982; Buchinsky 1998; Neal 2004; Olivetti and Petrongolo 2008; Mulligan and Rubinstein 2008; Bollinger, Ziliak, and Troske 2011; Arellano and Bonhomme 2017; Bayer and Charles 2018; Maasoumi and Wang 2019; Ashworth et al. 2020; Fernández-Val et al. 2020; Blau et al. 2021). Some in the age-cohort-time literature have estimated quantiles, and some in the quantile literature have estimated models with nonrandom selection. We bring these literatures together in a unified framework.

A well-known identification problem emerges in models with age, birth cohort, and period effects because any period can be written as the sum of age and cohort (Heckman and Robb 1985). Heathcote et al. (2005) tested whether time effects or cohort effects matter more for the age profile of inequality by assuming age, cohort, and time additively affect wages and then estimated the models with the time or cohort channels shut down. They found that aggregate time effects are the more important channel and are needed to account for observed trends in inequality. Assuming additive separability in age and time effects in the absence of cohort effects guarantees identification of a life cycle age-wage profile from cohort data, but is potentially restrictive. MaCurdy and Mroz (1995) proposed a flexible parameterization of age, cohort, and time that relaxed separability in age and time effects, and thus embedded a direct test of whether life cycle wage profiles can be constructed independently of time (Fitzenberger and Wunderlich 2002). This is the approach we take.

Because of the potential importance of common trends, we compare two sets of profiles. First, we estimate the selection-corrected wage profiles in the presence of nonseparable age and time effects by gender and skill group. Second, we filter the predicted offer wages on unrestricted time effects to net out common trends that vary by gender and skill. As we reject separability of time effects for both men and women, we characterize the resulting profiles that are absent of these common within group time effects as *pseudo* life cycle wage profiles.

A similarly challenging identification issue is found in models with nonrandom selection that require separating the extensive margin of employment from the intensive margin of wages. The issues include whether to model selection based on observables or unobservables, whether to identify the selection rule with exclusion restrictions, or whether to impose monotonicity in the selection rule such as positive selection (Vella 1998). Much of the inequality literature eschewed these issues altogether by focusing on groups with a strong attachment to the labor force such as prime age full-time working men, and thus implicitly imposed a so-called identification at infinity assumption whereby selection is exogenous by construction (Chamberlain 1986; Heckman 1990). The concern is that this group is not representative of the evolving labor market, and indeed, the gender wage gap literature has long taken seriously concerns of selection bias because of the lower labor force attachment of women (Blau and Kahn 2017). In studying the median gender wage gap, Neal (2004), Olivetti and Petrongolo (2008), and Blau et al. (2021) filled in missing wages by using actual wages from adjacent periods, and predicted wages when actual wages were not available. This is attractive in that it only requires assumptions on the position of imputed wages vis-à-vis the median and not the level. However, it relies on selection on the observed wages in the panel and is not consistent in the presence of nonrandom selection.

The standard mean selection on unobservables model from Heckman (1979), as well as the more recent quantile extensions in Arellano and Bonhomme (2017), is generally identified through nonlinearity of the underlying structural selection rule, though in practice most applications also impose exclusion restrictions that determine the employment decision but not wages. For example, recent gender wage gap papers have used the presence and age composition of children to identify the selection rule (Mulligan and Rubinstein 2008; Maasoumi and Wang 2019; Fernández-Val et al. 2020). Blundell et al. (2007) adopt a nonparametric approach and calculate bounds on the distribution of wages that relax the reliance on exclusion restrictions but strengthen the restrictions underlying worse case bounds. The advantage is greater flexibility in the selection rule, though at the cost of losing point identification. Neal and Johnson (1996) and Bayer and Charles (2018) impose monotonicity and a median selection rule in examining black-white wage gaps. The assumption is that nonworkers, were they to work, would be drawn from the bottom half of the distribution, and thus it is still possible to recover the median and upper quantiles of the wage distribution. The cost is that this model is silent on changes in wages in the bottom half of the distribution, and it is likely not a credible assumption for high-skilled women who have periods of nonwork during child-rearing years. Our approach is to point identify wage profiles and gaps of men and women across the whole distribution. Instead of using potentially correlated family structure variables like the age composition of children to identify the selection rule, we propose a set of plausibly exogenous exclusion restrictions based on policy parameters set at the state and federal levels; namely, the real maximum benefit guarantees in two means-tested transfer programs—Temporary Assistance for Needy Families (TANF) and Supplemental Nutrition Assistance Program (SNAP, aka food stamps).

Using data from the Annual Social and Economic Supplement of the Current Population Survey for calendar years 1976-2018, we focus on prime-age men and women (aged 25-55) and make several contributions to the extant wage inequality and gender gap literatures. First, we document that employment rates of less-educated men have fallen at all ages starting with the 1950s cohort and peak a decade earlier in the life cycle compared to older cohorts (age 30 instead of age 40), while employment rates of less educated women from Millennial cohorts have fallen back to levels last seen in the 1930s and 40s birth cohorts. Employment rates of high-educated men have fallen at all ages across cohorts, whereas for comparably educated women the cross-cohort changes have been more in the profile of employment, evolving from U-shaped to L-shaped to flat across the life course. Reflecting these employment changes, we find that controlling for nonrandom selection into work matters for the wages of men and women, affecting both the level and shape of lifecycle profiles.

Second, we find that common within group time effects by gender and education are a key driver of the distribution of life cycle wages across cohorts. In the data, younger cohorts of more educated men have higher wages and steeper profiles at all quantiles and ages compared to older cohorts, but this is just the reverse among less-educated men. For women, wages increase strongly with age and with each successive cohort. However, once we filter the pseudo life cycle age-wage profiles through common within group time effects the patterns in the data generally reverse, especially among the higher educated. The lower time effects for the educated in the 1970s were less pronounced among older cohorts at that time as it appears that these older cohorts of higher educated were partly protected from the lower skill prices that prevailed in the 1970s. The implication is that although time effects have increased real wages for the high educated, had recent cohorts of high-educated men and women faced the same favorable conditions of earlier cohorts then cross-sectional wage inequality would have been even more pronounced.

Third, within-education group inequality of men is monotonically increasing over the working life in both the lower and upper tails of wages. On the other hand, between-group inequality of men initially doubles in the first part of the working life across the distribution, before plateauing and even declining in the second part of the life cycle. However, cohorts of less-educated men born after 1960 experienced a reversal of fortunes in later working life, consistent with the cross-sectional literature highlighting a rising return to skill (Autor et al. 2008). Among women, within-group inequality increases in early working years, and then plateaus, though the level fell in recent cohorts. Between-group inequality of women mirrors that of men.

Fourth, given the divergent life cycle wage profiles of men and women, we find that the gender wage gap increases sharply across the distribution in the first half of the working life, coinciding with fertility cycles of women. After age 40, there has been substantial gender wage convergence in recent cohorts relative to those born prior to the 1950s. This helps resolve a debate in the cross-sectional gender wage gap literature. Mulligan and Rubinstein (2008) found no evidence of convergence, whereas Maasoumi and Wang (2019), Blau et al. (2021), and Sloane, Hurst and Black (2021) found the opposite. The discrepancy is in the cohorts of data in each respective sample; Mulligan and Rubinstein's sample contained more workers from older cohorts for whom little convergence occurred.

Our paper proceeds as follows. In the next section we present stylized facts on the evolution of employment and wages across life cycle cohorts, highlighting the potential concerns of nonrandom selection in work. Section III then develops our life cycle model of wage determination, including a discussion of identification and estimation of distributional wage profiles. Section IV presents the results of wage profiles of men and women in the presence of nonrandom selection. The fifth section then discusses the implications of the distributional profiles for within- and between-group inequality and gender wage gaps across the life course. The final section concludes.

II. Trends in Employment and Wages of Cohorts

We begin by presenting stylized facts on life cycle employment and hourly wages across cohorts. The aim is to highlight the changing selection into the labor force among men and women across cohorts. As described in the Appendix, the data come from repeated cross sections of the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) spanning the 1976 to 2018 calendar years. The sample consists of men and women born between the years 1921 and 1993 who are ages 25 to 55, capturing the prime working years for most after formal schooling is completed and prior to retirement decisions. Cohorts are defined as single year-of-birth, but to ease presentation the descriptive figures take averages within decades at each age. We include men and women of all education levels, but we group them into those with at least four years of college ("college or more") and those with three or fewer years of college ("some college or less").

[Figure I here]

Figure I depicts employment rates for men and women by decadal birth cohort and education level. The figure shows that among men with less than a college degree employment has fallen over time at any given age starting with the 1950s cohort, and that employment rates progressively peak earlier in the working life. For example, employment among less skilled men in the 1930s cohort peaked just before age 40, but that peak occurred a decade earlier among those born in the 1970s.[1] For men with at least a college degree, employment remains high over much of the working life, though it has fallen at each age and there is some evidence that it peaks at younger ages starting with the 1960s cohort.

[1] The sharp decline in employment of the 1990s cohort of less-skilled men reflects poor labor-market opportunities for those entering work during the Great Recession.

The employment patterns across cohorts of women are striking. For example, employment rates among less-skilled women born in the 1940s were stable at around 65 percent from ages 25-35, before accelerating and taking on the familiar hump-shaped life cycle profile. Women born in the 1950s began the upward climb five years younger and thus sustained higher employment rates across more of their working life. Less-skilled women born in the 1960s and 1970s had even higher employment rates at young ages, but in an important departure from earlier cohorts, employment rates trended downward over the entire working life. Perhaps most striking, employment rates among less skilled women under age 35 born in the 1980s and 1990s have fully reverted to levels last observed with the 1940s cohort.

Employment rates of highly educated women born in the 1940s were U-shaped between the ages of 25 and 50, declining for the first decade, then increasing for the next 15 years, before turning down after age 50 (the 1930s cohort has a similar pattern over ages 35-55). This U-shape was replaced with more of an L-shaped profile for cohorts born in the 1950s and 60s, but starting with the 1970s most of this life cycle curvature was eliminated and with employment rates lower after age 30. Figure A.1 shows that among those employed, the aggregate share working full time has increased over time; that is, aggregate employment declines for men and women are coming from marginally attached workers. Figure A.2 decomposes these trends into decadal cohorts, revealing striking changes across cohorts in the share of workers employed full time. This is especially notable for women where the share of workers at full time is increasing across the working life, and is higher at each age among younger cohorts. This is also true for less-skilled men starting with the 1960s cohort.

[Figures II and III here]

Figures II and III present the corresponding age profiles of log real wages for men and women, respectively, at the 10th, 50th, and 90th quantiles by education and cohort. We express wages in constant 2010 dollars, using the Personal Consumption Expenditure Deflator (PCE). Less-skilled men born in the 1940s had notably higher median log wages than more recent cohorts until at least age 40, suggesting cumulative lifetime wages have declined for less-skilled men among younger cohorts. The exact opposite occurs among highly educated men, where younger cohorts have substantially higher hourly wages at all quantiles and most ages across the life cycle. This is consistent with the rising return to skill underlying the secular rise in wage inequality in the cross section. This secular rise for men with college or more education seems particularly strong for the higher quantiles. Importantly, the profile of skilled men is steeper at younger ages among more recent cohorts, suggesting greater lifetime inequality across education groups, and while flattening out around age 45, wages of higher-educated men do not turn down at older ages. The wage profile of women is more similar across skill groups than among men, but cross-cohort differences are greater across the distribution. Wages increase strongly with age, with higher real wages at each age among younger cohorts, pointing to heightened within-group inequality across cohorts of skilled women.

These stylized facts point to the potential importance of three key features that guide our choice of specification for modeling wage profiles. First, the employment patterns suggest that differential selection into work could affect the labor-market fortunes of birth cohorts. Second, the descriptive wage profiles uncover important differences in the pattern of cohort age profiles across quantiles. Third, changes in profiles across cohorts point to large secular changes in wages that differ by gender and education group. In the next section, we develop an empirical framework of wages across the distribution that accounts for these three key features. Because of potential differences between those who choose part-time and full-time work, we estimate our empirical models separately for selection into any work and into full-time work.

III. Quantile Model of Cohort Wages in the Presence of Selection

Our econometric specification for wages extends the cohort models of MaCurdy and Mroz (1995), Gosling et al. (2000), and Fitzenberger and Wunderlich (2002) by incorporating nonrandom selection into work across the wage distribution (Arellano and Bonhomme 2017). Consider an individual *i* of gender *j* with schooling level *s* who is age *a* in cohort *c* at time *t* with latent log wages, lnw_{ij}^{s*}, given by

(1) $$lnw_{ij}^{s*} = X_{ij}(a, c, t; l)'\beta_j^s(U)$$

where

(2) $$X_{ij}(a, c, t; l)'\beta_j^s(U) \equiv A(a_{it})'\beta_{aj}^s(U) + C(c_i)'\beta_{cj}^s(U) + T(t)'\beta_{tj}^s(U) + L(l_{it})'\beta_{lj}^s(U) + R(a_{it}, t_i)'\beta_{a,cj}^s(U),$$

represents a flexible function of age (*A*), cohort (*C*), time (*T*), and other determinants (*L*) such as demographics and local business-cycle conditions found in a standard Mincer earnings equation, and $\beta_j^s(U)$ is a vector of unknown parameters that vary by gender and education level and depend on unobserved heterogeneity U. The *R* term includes interactions between age and time that relaxes additive separability in wage profiles, which has been found to be important for the Mincer model (Heckman, Lochner, and Todd 2006). If we assume *U* to be distributed independently of *X* and normalize it to be uniformly distributed, then we obtain the linear quantile model of Koenker and Bassett (1978).

A complication of directly applying the quantile estimator to (1) arises from the fact that wages in education group *s* are observed only for those individuals who are employed. Denote the employment indicator as E^s, such that

(3) $E_{ij}^s = \mathbf{1}\left\{V \leq p_j^s\left(D_{ij}(a,c,t;z)\right)\right\}$,

where $p_j^s(D)$ is a gender and education-group specific propensity score whose index is a function of at least all the same variables found in *X*. In general, the vector of socioeconomic characteristics *l* in equation (1) will be a proper subset of *z* in equation (3), implying that identification of the parameters of the wage distribution are obtained not just from functional form assumptions, but also exclusion restrictions. Observed log wages are then found as the product of latent wages and the employment indicator (3), i.e. $lnw_{ij}^s = E_{ij}^s * lnw_{ij}^{s*}$.

Imposing the standard assumptions underlying the Heckman Gaussian selection model, we get the propensity score $p_j^s(D_{ij}(a,c,t;z)) = \Phi(D_{ij}{}'\gamma_j^s)$, where $\Phi(.)$ is the cdf of the standard normal distribution evaluated at the index $D_{ij}{}'\gamma_j^s$ (Arellano and Bonhomme 2017). Furthermore, assuming that *V* is uniformly distributed on the unit interval and independent of *D*, and that (U,V) follows a bivariate Gaussian copula with dependence parameter ρ_j^s that is independent of *D*, then we obtain the conditional copula of *U* given *V*, $G\left(\tau, p_j^s; \rho_j^s\right) = K(\tau, p_j^s; \rho_j^s)/p_j^s$, where $K(.)$ is the unconditional copula of (*U*, *V*).[2] This implies that the τ^{th} conditional quantile of log wages given $E_{ij}^s = 1$ and *D* is written as

(4) $Q_j^s\left(\tau, D_{ij}\right) = X_{ij}(a,c,t;l)'\beta_j^s(\tau^*(D_{ij}))$,

with $\tau^*\left(D_{ij}\right) = G^{-1}(\tau, \Phi\left(D_{ij}'\gamma_j^s\right); \rho_j^s)$ and G^{-1} is the inverse conditional quantile function. This model is therefore non-additive in the propensity score and covariates *D*.

III.A Parameterization of Wages

To parameterize the wage model, each individual is allocated to a birth cohort *c* based on the calendar year *t*, normalized with respect to the first year of the sample (1976), and on their

[2] A positive value of the dependence parameter implies negative selection, and vice-versa for a negative value of ρ_j^s.

age normalized to the age at labor market entry (age 25); namely, $c = t - e$, where $t = (year - 1976)/10$ and e is the entry age defined as $e = (age - 25)/10$. This means that cohort 0 consists of those individuals whose age is 25 in 1976, persons older than age 25 in 1976 are assigned negative cohort values, and those that reach age 25 after 1976 are assigned positive cohort values.[3]

The baseline empirical specification for log wages is given as

(5) $$lnw_{ij}^{s*} = \beta_{0j}^{s}(U) + \sum_{f=1}^{3} \beta_{a,fj}^{s}(U) e_{ij}^{f} + \sum_{g=1}^{5} \beta_{t,gj}^{s}(U) t^{g} + \sum_{h=1}^{3} \beta_{c,hj}^{s}(U)((1-\theta) c_{ij}^{h} + \theta c_{ij}^{h-1}) + \sum_{m=1}^{4} \beta_{R,mj}^{s}(U) R_{ij}^{m} + \delta_{j}^{s}(U),$$

which includes a cubic in labor-market entry age, a quintic in time, a cubic in cohort, a quartic in interactions between entry age and time, and a normalized set of time fixed effects ($\delta_j^s(U)$). The cubic in entry age provides curvature for capturing pure life cycle age effects, assuming strong separability with time, i.e. that $\beta_{R,mj}^{s} = 0$. The quintic in time is a flexible parameterization for capturing macroeconomic trends in wages, while the normalized time dummies control for common shocks affecting all cohorts the same, but differently across gender and education.[4]

In equation (5) we set the parameter θ=1 for cohorts entering in 1976 and later, and zero otherwise, and thus a cubic in cohort is admitted for the pre-1976 labor-market entrants and a quadratic in cohort for the 1976 and later cohorts. The identifying assumption for pinning down the cohort effects is to normalize around the linear cohort term and set $\beta_{c,0j}^{s} = 0$.

[3] The literature on labor-market scarring (e.g. Kahn 2010; Altonji, Kahn, and Speer 2016; Rothstein 2020) tends to focus on college-educated workers and to drop those older cohorts with negative cohort values. This implies that they follow entry cohorts (see also Kambourov and Manovskii 2009). Admitting older cohorts and the less educated has the advantage of larger samples and a longer look at cohort changes over the life cycle, and is more akin to the earlier research on cohort earnings (Welch 1979; Berger 1985; Gosling, Machin, and Meghir 2000).

[4] With a fifth-order polynomial in time and a constant term, the minimum number of time dummies that must be omitted is 6. However, with the linear age effect, and age and time interactions, we had to omit 8 time effects, four at the beginning of the sample period, and four at the end.

We admit nonseparability between entry age and time by including four entry age-time interaction terms in R_{ij}^{m} that are found by integrating over entry age—$e_{ij}t, e_{ij}t^2, e_{ij}^2t, e_{ij}^2t^2$ (see Fitzenberger and Wunderlich (2002) for details). Again, using the relation that $t = c + e$, plugging this into the interactions prior to integrating, and solving yields the four regressors of $(\frac{c_i e_{it}^2}{2} + \frac{e_{it}^3}{3})$, $(\frac{c_i^2 e_{it}^2}{2} + \frac{2c_i e_{it}^3}{3} + \frac{e_{it}^4}{4})$, $(\frac{c_i e_{it}^3}{3} + \frac{e_{it}^4}{4})$, and $(\frac{c_i^2 e_{it}^3}{3} + \frac{2c_i e_{it}^4}{4} + \frac{e_{it}^5}{5})$.[5] If these interaction terms are found to be jointly zero, then it is possible to interpret the coefficients on the cubic in entry age as a pure life cycle aging effect, and that wage-age profiles across cohorts are parallel. However, rejecting the null hypothesis implies that cohort age profiles are not parallel and thus the entry age coefficients are a convolution of age and trend effects, yielding what we refer to as *pseudo* life cycle age-wage profiles. This is a key test in our empirical results.

III.B Estimation and Inference

We implement the three-step estimation procedure proposed by Arellano and Bonhomme (2017) for the conditional quantile selection model, separately for each gender and education group. The first step involves estimating the probability of employment (or probability of full-time work when examining wages of full-time workers), yielding estimates of $\hat{\gamma}_j^s$ in the propensity score. We estimate the first stage via probit maximum likelihood. Given estimates of the selection model parameters, the next step involves estimating the copula dependence parameter ρ_j^s. This parameter is estimated with generalized method of moments using functions of *D* as "instruments", which in this case are functions of the cdf of the normal distribution parameterized by the first-stage probit estimates, $\Phi\left(D_{ij}\hat{\gamma}_j^s\right)$. We use the Frank copula because it is comprehensive in its dependence structure allowing for both negative and positive selection, as

[5] The constants of integration are set equal to 0.

well as independence. Estimation of ρ_j^s involves a grid search over different values of ρ_j^s and τ, and we follow Arellano and Bonhomme and search over 100 values of ρ_j^s from -0.98 to +0.98 in steps of 0.02, along with four points of τ from 0.2 to 0.8 in steps of 0.2. The third stage involves estimating the quantile parameters at selected quantiles, using rotated quantile regression, where the rotation is a function of the degree of selection and is person-specific as determined by $D_{ij}(\hat{\gamma}_j^s)$ conditional on the estimated dependence parameter $\hat{\rho}_j^s$.

Beyond the age, time, and cohort controls discussed in the previous section, the employment and wage models within each education group include indicators for race (white is omitted), Hispanic ethnicity, whether married, and whether reside in a metropolitan area, as well as household size and numbers of children ages 0-5 and 6-18. To control for state business cycles we include the state unemployment rate in both the employment and wage models, the latter of which is justified on the long literature on the cyclicality of real wages (Bils 1985; Keane, Moffitt, and Runkle 1988; Solon, Barsky, and Parker 1994; Ziliak, Wilson, and Stone 1999; Schwandt and von Wachter 2019). All models contain state fixed effects to control for permanent differences in state labor markets, and normalized common time fixed effects.

Inference in the three-step model is quite complicated, especially given that stages two and three of estimation are functions of estimated parameters. In their application, Arellano and Bonhomme conducted inference on the dependence parameter using the *m*-out-of-*n* bootstrap (Shao and Tu 1995; Politis, Romano, and Wolf 1999), whereby they randomly sampled a subset of observations with replacement, selecting the subsample as a fixed constant plus the square root of the sample size. This is computationally attractive compared to the standard bootstrap when using large samples with a large number of covariates as in our application. However, we are interested in conducting inference on not just $\hat{\rho}_j^s$, but also the first- and third-stage parameters. In order to retain the dependence structure of the model, we conduct the bootstrap across all three stages of estimation using the full sample of observations. Our sample sizes for the four groups of men and women range from over 300,000 to just under 900,000, and because we have 110 parameters to estimate, we set the number of bootstraps at 100.[6]

III.C Identification

The wage selection model is formally identified through nonlinear functional form restrictions provided there is sufficient variation in the covariates (Vella 1998). However, we use additional exclusion restrictions to increase the power of the model to detect deviations from random sorting into work. Instead of using the presence and ages of young children as in recent gender wage gap papers, our exclusion restrictions are the real maximum benefit guarantees in two means-tested transfer programs—Temporary Assistance for Needy Families (TANF) and Supplemental Nutrition Assistance Program (SNAP, aka food stamps).

The TANF program replaced Aid to Families with Dependent Children (AFDC) as part of the 1996 welfare reform, but the target population of both AFDC and TANF is low-income and low-asset families with dependent children under age 18 (Ziliak 2016). AFDC, and its successor TANF, provide cash and in-kind assistance on a monthly basis, with benefits set at the state level and that vary by household size. AFDC had no formal work requirement for eligibility, and thus is often construed as “welfare” in the traditional sense, and while TANF does have a work requirement, there are numerous exemptions available across states and over time.

SNAP, which replaced its predecessor the Food Stamp Program as part of the 2008 Farm Bill, provides in-kind monthly benefits to low-income and low-asset individuals and households

[6] Estimation and bootstrap inference is conducted in Matlab, modifying the programs made available with the published version of Arellano and Bonhomme (2017). The bootstraps were conducted on the University of Kentucky supercomputing cluster.

for the purchase of food for home production. There are no age restrictions or requirements for the presence of children, and there are no formal work requirements except for a limited population of non-disabled adults without dependents (Hoynes and Schanzenbach 2016). Benefits are set nationally, with upward adjustments in Hawaii and Alaska, but they do vary by household size. Although research suggests that household fertility and structure are not endogenous responses to the size of the welfare benefit, at least once one controls for state fixed effects as we do here (Hoynes 1997; Kearney 2004; Ziliak 2016; Moffitt, Phelan, and Winkler 2020), we abstract from household-size effects and use the *maximum* TANF and SNAP benefits for a three-person family, deflated by the PCE with 2010 base year.[7]

Figure A.3 depicts the time series of the level and variation in the real maximum benefit in TANF and SNAP. Panel A of the figure shows that the average real value of TANF has plunged by half over the sample period. Although some states elect to periodically increase the nominal benefit, many do not, and when they do the benefit does not keep up with inflation, eroding the real value of TANF assistance over time. The SNAP benefit is adjusted annually for the cost of the food basket used in constructing the maximum guarantee, and thus is gently trending upward after adjusting for the broader PCE. There was a permanent adjustment made in the late 1980s to the value of the food benefit, and then a temporary increase in response to the Great Recession that took about a decade to return to his pre-recession trend. After 2007, the real SNAP benefit exceeded the average benefit in TANF.

The bottom panel of Figure A.3 shows that although the purchasing power of TANF has declined, there is still considerable cross-state variation over time in the program, as

[7] We use the AFDC maximum benefit for years 1976-1996 and TANF thereafter, and the food stamp benefit for 1976-2008, and SNAP thereafter. We refer to the programs as TANF and SNAP, respectively, for ease of presentation. The information on state unemployment rates and welfare benefits is obtained from the University of Kentucky Center for Poverty Research http://ukcpr.org/resources/national-welfare-data.

demonstrated by the normalized coefficient of variation.[8] Because SNAP is fixed nationally, there is no comparable cross-state variation over time and it not depicted in the bottom panel. Thus, the TANF policy variable offers two-way variation across states and time, and provided the variation is above and beyond that absorbed in the state fixed effects and parameterized time effects, and has no effect on wages conditional on work, then it is a valid exclusion restriction. However, the variation of SNAP is limited solely to changes over time, but again provided that variation is above and beyond the included time effects in the model, and likewise has no effect on wages conditional on employment, then it too will be a valid exclusion restriction. We show below that our results are robust to using an experimental state-price index for welfare benefits.

Because both programs are means-tested, and incomes and education are positively correlated, we expect the SNAP and TANF benefits to be more salient for labor-market decisions among the lower-educated sample. As Figure I shows it is among the lower-educated samples where non-employment is greatest. Figure A.4 shows the fraction of men and women by education group in our sample of 25-55 year-olds residing in households receiving either SNAP or TANF. It is clear that participation in SNAP is much more widespread than TANF, and trending upward, and that participation is much higher among those men and women with less than college. However, both programs provide a consumption floor in the event of a negative economic shock and thus on the margin have the potential to influence employment decisions even among the educated.

IV. Quantile Estimates of Life Cycle Wage Profiles across Cohorts

We begin the empirical results with estimates of wage profiles from the conditional quantile models with selection at the 10th, 50th, and 90th quantiles. We focus on all workers, but

[8] The normalized coefficient of variation (CV) is defined as CV/(1+CV) and is bounded between 0 and 1.

also present a parallel set of estimates in the Appendix for those working full time. Tables A.1-A.3 contain summary statistics of the model covariates for all workers and nonworkers, full-time workers only, and nonworkers, respectively. Table A.3 shows that nonworking men compared to men overall in Table A.1 are less likely to be married, less likely to be white, and reside in smaller households with fewer children. Nonworking women, on the contrary, are more likely to be married and to reside in larger households with children.

[Tables I-IV here]

Tables I-IV present the point estimates and associated bootstrap standard errors from the first-stage employment selection model as well as the quantile with selection log wage models. The first two tables are for men with some college or less and those with college or more, respectively, while the subsequent tables are for women. All models control for fixed state effects and normalized common time fixed effects. For brevity, we focus our discussion on the employment and median wage estimates.

The first stage probit estimates for male and female employment suggest that employment declines in response to higher SNAP benefits for all four samples, while TANF also reduces the employment rates of women. This is consistent with the demographic composition of the programs where SNAP is open to all ages, family structures, and employment status, while TANF has historically been dominated by single mother families. The p-values on the Wald test of the joint significance of SNAP and TANF as exclusion restrictions are zero for all samples, suggesting that they have statistical power to help identify the selection equation in the model. The demographic and business-cycle factors operate in expected ways in the employment equations, with non-White men less likely to work, married men more likely to work, men with more children more likely to work, and men with higher state unemployment rates less likely to work. Among women, some of these patterns reverse. For example, high-skilled Black women are more likely to work than White women, married women and women with more children of both education groups are less likely to work.

The first column of each table also reports estimates of the copula dependence parameter, $\hat{\rho}_j^s$. There we see that there is both positive and negative selection into work—negative selection among less educated men and higher-educated women, and positive selection among high-educated men and less-educated women. The negative selection into work among less-skilled men is consistent with recent work of Aguiar et al. (2021), who highlight the shift toward leisure particularly among younger men. At the same time, negative selection among skilled women is ostensibly consistent with earlier work by Mulligan and Rubinstein (2008); however, their sample was of full-time working women, and as demonstrated in Table A.7, we find positive selection into full-time work among high-skill women, though statistically we cannot reject the null of random selection on unobservables into full-time work. This suggests that there might be a cohort shift among women on who selects into part-time and full-time work. Below we discuss some of these implications on the gender wage gap across cohorts.

At the bottom of Tables I-IV we present Wald tests of the joint significance of the cohort terms, the interaction terms between time and entry age (R1-R4 in the tables), and both cohort and the R1-R4 terms. Failing to reject the null that time and entry age interactions are zero implies that we can construct pure lifecycle age-wage profiles, i.e. cohorts have common wage growth with age. Additionally, failing to reject both cohort and the interaction terms means we not only have uniform wage growth across cohorts, but also that the cross-section age-wage profile is shifted over time by a common amount given by macroeconomic wage growth. For both men and women, tests that the cohort terms and the entry age and time interactions are jointly equal to zero are strongly rejected. We interpret the results as suggesting that age-wage profiles are not parallel across cohorts, and thus refer to the profiles as *pseudo* lifecycle age-wage profiles.

The estimated coefficients and all the interactions are difficult to interpret in the log wage equations, and thus in Figures IV-V we produce the pseudo profiles across age and cohort of prime-age men and women based on the regression estimates in Tables I-IV. Specifically, for each individual in the various subsamples we randomly generate an integer, *q*, that takes on a value of 1, 5 or 9 for the 10th, 50th, and 90th quantiles. Then, following the conditional quantile decomposition method of Machado-Mata (2005), we use the quantile coefficients associated with the draw of *q* for each individual—including both workers and nonworkers—to produce a prediction of the *qth* quantile offer wage distribution. To reduce sampling variation associated with any given draw, we repeat this process 30 times and then take the mean across the simulated samples. Finally, because Heathcote et al (2005) found that common within group time effects were the primary channel for the age profile of inequality, we net out additive within group time effects on offer wages by regressing the predicted gender-education specific wage at each quantile on a full set of time dummies, saving the residual, and adding back the group- and quantile-specific mean prediction. This provides a distributional framework which can then be used to estimate a variety of statistics, including measures of wage inequality and gender gaps in the next section. Similar to Figures II and III, we compute the gender-age-quantile-specific ten-year birth cohort mean and plot the mean at each age and cohort.

[Figures IV-V here]

The upper panel of Figures IV(V) are for men(women) with some college or less, and the respective lower panel is for those with college or more education. Among men, Figure IV shows that in the left tail of the wage distribution wages peak around age 35 for both education groups, roughly a full decade before those at the median and 90th quantiles. Moreover, there is some evidence that wages actually turn down at later ages at the 10th quantile, which is not the case higher up the wage distribution. Figure A.5 depicts the selection-corrected offer wage profiles prior to netting out the time effects. There you see that more recent cohorts of lower-educated men started off their working life at lower wages but eventually caught up to older cohorts. Figure IV, on the other hand, suggests that net of within group time effects those men with some college or less born in the 1940s experienced the highest life-cycle profile across the distribution at all ages, especially at the median and above. At the same time, those workers from the 1920s cohort of less-educated men had notably lower wages in the last decade of their life cycle, suggesting these workers bore the brunt of the stagflationary slowdown of the late 1970s.

Among men with at least a college education, Figure A.5 indicates that more recent cohorts start out their life cycles with *higher* wages and *steeper* slope compared to older cohorts. That is particularly the case for the higher quantiles where we see male wages at the 90th quantiles for younger cohorts strongly pulling away. As we will show below, this divergence in the path of life cycle male wages strongly influences the pattern of male wage inequality and gender inequality. As the comparison of profiles with and without common within group time effects shows, recent cohorts of college-educated men would have faired even better had they experienced conditions similar to men born in the 1920s and 1930s. The implication is that had recent cohorts of high-educated men faced the same favorable conditions as older cohorts then cross-sectional wage inequality would have been more pronounced.

As seen in the selection-corrected profiles inclusive of common time effects in Figure A.6, more recent cohorts of women start out their working life with offer wages higher than older cohorts across both education groups. However, Figure V suggests that net of time effects, pseudo life cycle age-wage profiles of women are quite flat across the distribution. That is, had recent cohorts of women experienced the time trends of the older cohorts, they would do even better than seen in Figure V at those early ages. Indeed, net of these common time effects, wages of college-educated women peak by age 35 at the 10th, 50th, and 90th quantiles. This is a similar age as men at the 10th quantile, but is a full decade earlier compared to men at the median and 90th quantiles. This implies depressed wage mobility at what should be peak earning years among older working women.[9] Moreover, this effect is nonlinear with respect to age across education groups of women. Among the lower educated, the more recent cohorts do even better later in the life cycle and have less wage curvature, but among the college educated, there is little cross-cohort difference in the pseudo age-offer wage profile after age 35.

In Figures A.7 and A.8 we repeat the exercise in Figures IV-V, but now restricted to those working full time. The first stage estimates a probit model of the probability of full-time employment, and then the second and third stages estimate the dependence parameter and rotated quantile log wage function among full-time workers. Tables A.4-A.7 contain the corresponding parameter estimates for the four samples of men and women. There we find evidence of positive selection into full-time work across the gender and education groups, which is statistically different from zero at least at the 10 percent level except for women with college or more. The welfare variables in most cases continue to serve as strong predictors of work in the full-time

[9] In results not tabulated, we estimated the model using an experimental state-price index developed by Berry, Fording, and Hanson (2000) and Carillo, Early, and Olsen (2014) in lieu of the aggregate PCE. This index is anchored to housing prices in 2000 and then adjusted forward and backward using the CPI (or PCE). Our results were little changed using this alternative price index. Additionally we also estimated pseudo life cycle age-wage profiles at the 50th and 90th quantiles under a median selection rule. Similar to Bayer and Charles (2018), under the median selection rule we retained nonworkers and set their log wage to zero, and then estimated the median and 90th quantiles. The results of that exercise suggest that the age-wage profiles reported in Figures IV and V are robust to the less parametric selection rule.

models. As in the main sample with part- and full-time workers, we still reject the null hypothesis of common age-wage profiles across cohorts and constant growth among entry ages. Figures A.7-A.8 demonstrate that the overall shape of pseudo lifecycle age-offer wage profiles among the full-time differ little from those that include part-time workers as well.

V. Implications for Life Cycle Wage Inequality and Gender Gaps

We now use the implied wage distributions of men and women to estimate wage inequality and gender wage gaps across the working life. Here we aim to distinguish inequality that occurs within groups from that which occurs between groups. For our within-group measures we adhere to the recent wage inequality literature that decomposes inequality into upper-tail (90-50) and lower-tail (50-10) inequality (Autor et al. 2008). These measures are constructed within gender and education group. Our between-group measures of inequality are once again within gender, but between education groups at a fixed quantile, i.e. comparing the 10^{th}, 50^{th}, and 90^{th} quantiles of those with college or more to the corresponding quantiles among those with less than a college degree. For the gender wage gaps, we present those within education groups at a fixed quantile, e.g. 50^{th} quantile of college-educated men to 50^{th} quantile of college-educated women. We construct the inequality and gender gaps by subtracting the relevant log offer wage of one group from the other, and thus the differences roughly approximate percent changes. The main figures in the text are each based on predictions after taking out the aggregate time effects, though we present the full set of corresponding figures inclusive of the time effects in the Appendix.

[Figures VI and VII here]

In Figures VI and VII we present within- and between-education group estimates of wage inequality of men across the working life. Figure VI suggests that net of common time effects within-group wage inequality is increasing sharply across the working life in both the upper and lower halves of the offer wage distribution, suggesting that disadvantage accumulates over the life course. However, with a couple of exceptions, the within-group inequality age profiles are similar across cohorts. This is in marked contrast to Figure A.9, which shows the parallel figure but with the education and gender specific time effects still in the predicted wages. There you see that upper-tail inequality not only increases over the working life, but is higher with each successive cohort. Among men with less than college education we also find evidence that lower-tail inequality is declining among recent cohorts, and when combined with rising upper-tail inequality, is consistent with the cross-sectional literature suggesting a hollowing out of the middle class (Autor et al. 2008). These results are also consistent with Heathcote et al. (2005) in underscoring the importance of time effects on the profile of male inequality.

The between-group inequality estimates in Figure VII show the difference in male wages across education groups at a fixed quantile. Across all cohorts between-group inequality accelerates early in the life cycle, more than doubling between ages 25 and 40, but then leveling off thereafter. The between-group profiles are quite similar across cohorts except among those born before 1940, as we saw previously in within-group inequality. These patterns are driven by the strong time effects that affected cohorts at different times of their working life. Figure A.10 shows that with time effects included there are pronounced increases in between-group male inequality with each successive cohort, though the age profile is similar as in Figure VII.

[Figures VIII and IX]

Figures VIII and IX contain the equivalent set of within- and between-group wage inequality estimates over the working life of women, with the corresponding figures inclusive of time effects in Figures A.11 and A.12. Similar to men, there are sharp differences across cohorts when time effects are included (Figure A.11), but unlike men, in Figure VIII we see many of these cohort differences remain in the within-group inequality estimates of women at both the lower and upper tails of the distribution. Whereas lower-tail inequality of men was increasing over the life cycle within each skill group, among women this increase only occurs in the first decade of work. In addition, net of time effects, the level of within-group inequality fell considerably at younger ages in more recent cohorts relative to older cohorts. However, like we saw for men, upper tail inequality of women fell across cohorts early in the life cycle, but then widened after age 40 in the cohorts born after 1960 relative to earlier cohorts. The life cycle pattern of between-group inequality of women depicted in Figure IX is similar to that of men—there was sharp increase in the first decade of work, followed by a plateauing or even narrowing of between-group wage inequality whether including or netting out aggregate time effects.

[Figure Xa here]

[Figure Xb here]

In Figure Xa we examine the lifecycle within-education gender offer wage gap across cohorts at the 10th, 50th, and 90th quantiles, and Figure Xb is the same but with the time effects included. The gender wage gap in Figure Xa increases sharply early in the working life—more than doubling—followed by a leveling off. This pattern is consistent with female fertility cycles where there is reduced work effort when children are young, followed by a return to work and catching up of wages when children are older. Figure Xb indicates that while the level of the gender wage gap was substantially higher at each age for those born before 1960, these older cohorts also experienced convergence in gender gaps after age 40. However, once we filter the offer wage profiles through the common time effects as seen in Figure Xa, the cross-cohort gender gaps are substantially muted after the 1940s cohort, and there is no longer convergence in the later working life. Moreover, the figure shows some evidence of gender-gap retrenchment at young ages among Millennials born after 1980. Figure A.13 shows that this same pattern of gender wage gaps over the life cycle holds when we estimate the model for full-time working men and women. Mulligan and Rubinstein (2008) and Maasoumi and Wang (2019) focused on full-time workers in their analysis, but reached different conclusions regarding gender-wage convergence. Mulligan and Rubinstein found no evidence of gender wage convergence, where Maasoumi and Wang did find wage convergence. Our estimates suggest that the difference likely stems from the fact that the sample used in Mulligan and Rubinstein pulled more from the 1920s to 1940s cohorts compared to Maasoumi and Wang. As shown here, the level of the gender gap was much higher in older cohorts, and once we net out common time effects, there was little improvement in the lifecycle gender wage gap in older cohorts.

[Figure XI here]

To further illuminate the role of education and gender specific time effects on the gender wage gap, Figure XI presents the coefficients on the aggregate time dummies from the 50th quantile regressions of the predicted offer wages on the time effects, averaged across the 30 replications. Within each education group there is clear evidence that common within group time effects favored female wages over male wages from the mid 1970s to the mid 1990s, with the time effects of women converging towards those of men. In the subsequent two and a half decades the aggregate effects followed parallel trends. The gender wage gap with time effects included shows substantially elevated gaps at each age among cohorts born before 1960, but because common time effects disproportionately favored female workers in the labor force before the mid 1990s, once we net these time effects out, the cross-cohort gender wage gap is substantially attenuated. The parallel trends in time effects in the last 25 years implies a stalling out of progress favoring women in labor markets and thus little improvement in gender gaps in the second half of the working life.

VI. Conclusion

We estimated the distribution of life cycle wage profiles and gaps for cohorts of prime-age men and women in the presence of nonrandom sample selection using data from the Current Population Survey for calendar years 1976-2018. We found that controlling for both nonrandom selection into work and for within group common time effects were important for our understanding of life cycle wage profiles and inequality. In the data, younger cohorts of more educated men have higher wages and steeper profiles at all quantiles and ages compared to older cohorts, but this is just the reverse among less-educated men. For women, wages increase strongly with age and with each successive cohort. However, once we filter the pseudo life cycle age-wage profiles through common within group time effects, the patterns in the data generally reverse, especially among the higher educated. These results imply that the lower overall time effects in the 1970s were less pronounced among older cohorts at the time and it appears these older cohorts of higher educated were partly protected from the lower skill prices. This suggests that the forces of rising return to skill feeding increasing within- and between-skill group wage inequality over the life cycle in recent cohorts were partially mitigated. The implication is that although the common time effects have increased real wages for the high educated, had recent cohorts of high-educated men and women faced the same favorable conditions of earlier cohorts then cross-sectional wage inequality would have been even more pronounced.

We also found that the gender wage gap increased sharply across the distribution in the first half of the life cycle, coinciding with fertility cycles of women. After age 40, there was substantial gender wage convergence in recent cohorts relative to those born prior to the 1960s.

However, there are hints that economic progress of women relative to men may have stalled, or even reversed, among Millennials, and if it persists then this could have long-term implications for gender equality. The recent shock of the Covid-19 pandemic has unraveled child-care markets, disproportionately affecting women's employment decisions with potential negative consequences for life cycle wage progression. This development underscores the importance of continued research on wage differences within- and between-genders both over time and the life course.

References

Abraham, Katherine G., and Melissa S. Kearney. 2020. "Explaining the Decline in the US Employment-to-Population Ratio: A Review of the Evidence," *Journal of Economic Literature* 58(3): 585-643.

Aguiar, Mark, Mark Bils, Kerwin Kofi Charles, and Erik Hurst. 2021. "Leisure Luxuries and the Labor Supply of Young Men," *Journal of Political Economy* 129(2): 337-382.

Altonji, Joseph G., Lisa B. Kahn, and Jamin D. Speer. 2016. "Cashier or Consultant? Entry Labor Market Conditions, Field of Study, and Career Success," *Journal of Labor Economics* 34(S1): S361-S401.

Arellano, Manuel, and Stephane Bonhomme. 2017. "Quantile Selection Models with an Application to Understanding Changes in Wage Inequality," *Econometrica* 85(1): 1-28.

Ashworth, Jared, V. Joseph Hotz, Arnaud Maurel, and Tyler Ransom. 2020. "Changes Across Cohorts in Wage Returns to Schooling and Early Work Experience," *Journal of Labor Economics*, forthcoming.

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review* 103(6): 2121-2168.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. "Trends in U.S. Wage Inequality: Revising the Revisionists," *Review of Economics and Statistics* 90(2): 300-323.

Bayer, Patrick, and Kerwin Kofi Charles. 2018. "Divergent Paths: A New Perspective on Earnings Differences Between Black and White Men since 1940." *Quarterly Journal of Economics* 133(3): 1459-1501.

Beaudry, Paul, and David A. Green. 2000. "Cohort Patterns in Canadian Earnings: Assessing the Role of Skill Premia in Inequality Trends," *Canadian Journal of Economics* 33(4): 907-936.

Berger, Mark C. 1985. "The Effect of Cohort Size on Earnings Growth: A Reexamination of the Evidence," *Journal of Political Economy* 93(3): 561-573.

Berry, William, Richard Fording, and Russell Hanson. 2000. "An annual cost of living index for the American states, 1960–95," *Journal of Politics*, 62(2): 550–567.

Bils, Mark J. 1985. "Real Wages over the Business Cycle: Evidence from Panel Data," *Journal of Political Economy* 93(4): 666-689.

Blau, Francine D., and Lawrence M. Kahn. 2017. "The Gender Wage Gap: Extent, Trends, Explanations," *Journal of Economic Literature* 55(3): 789-865.

Blau, Francine D., Lawrence M. Kahn, Nikolai Boboshko, and Matthew L. Comey. 2021. “The Impact of Selection into the Labor Force on the Gender Wage Gap,” NBER Working Paper 28855.

Blundell, Richard, Amanda Gosling, Hidehiko Ichimura, and Costas Meghir. 2007. “Changes in the Distribution of Male and Female Wages Accounting for Employment Composition Using Bounds,” *Econometrica* 75(2): 323-364.

Blundell, Richard, Luigi Pistaferri, and Ian Preston. 2008. “Consumption Inequality and Partial Insurance,” *American Economic Review* 98(5): 1887-1921.

Blundell, Richard, Robert Joyce, Agnes Norris Keiller, and James P. Ziliak. 2018. “Income Inequality and the Labour Market in Britain and the US,” *Journal of Public Economics*, 162: 48-62

Bollinger, Christopher R., James P. Ziliak, and Kenneth R. Troske. 2011. “Down from the Mountain: Skill Ugrading and Wages in Appalachia,” *Journal of Labor Economics* 29(4): 819-857.

Borella, Margherita, Mariacristina De Nardi, and Fang Yang. 2020. “The Lost Ones: The Opportunities and Outcomes of White, Non-College-Educated Americans Born in the 1960s,” In *NBER Macroeconomics Annual 2019,* Volume 34, M. Eichenbaum, E. Hurst, and J. Parker (eds.), 67-115.

Bound, John, and George Johnson. 1992. “Changes in the Structure of Wages in the 1980s: An Evaluation of Alternative Explanations,” *American Economic Review*, 82(3): 371-392.

Buchinsky, Moshe. 1998. “The Dynamics of Changes in the Female wage Distribution in the USA: A Quantile Regression Approach,” *Journal of Applied Econometrics* 13(1): 1-30.

Card, David, and John E. DiNardo. 2002. “Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles,” *Journal of Labor Economics* 20(4): 733-783.

Card, David, and Thomas Lemieux. 2001. “Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis,” *Quarterly Journal of Economics* 116(2): 705-746.

Carrillo, Paul, Dirk Early, and Edgar O. Olsen. 2014. “A panel of interarea price indices for all areas in the United States 1982–2012,” *Journal of Housing Economics*, 26(C): 81–93.

Chamberlain, Gary. 1986. “Asymptotic Efficiency in Semi-Parametric Models with Censoring,” *Journal of Econometrics*, 32(2): 189-218.

Chernozhukov, Victor, and Ivan Fernández-Val. 2005. “Subsampling Inference on Quantile Regression Processes,” Sankhya: The Indiana Journal of Statistics 67(2): 253-276.

Deaton, Angus. 1997. *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*. Baltimore, MD: Johns Hopkins University Press.

Deaton, Angus, and Christina Paxson. 1994. “Intertemporal Choice and Inequality,” *Journal of Political Economy* 102(3): 437-467.

DiNardo, John, Nicole Fortin, and Thomas Lemieux. 1996. “Labor Market Institutions, and the Distribution of Wages, 1973-1992: A Semi-parametric Approach,” *Econometrica,* 64(5): 1001-1044.

Fernández-Val, Iván, Franco Peracchi, Aico van Vuuren, and Francis Vella. 2020. “Decomposing Changes in the Distribution of Real Hourly Wages in the U.S.,” Mimeo, Boston University.

Goldin, Claudia, and Joshua Mitchell. 2016. “The New Lifecycle of Women’s Employment: Disappearing Humps, Sagging Middles, Expanding Tops,” NBER Working Paper 22913.

Gosling, Amanda, Stephen Machin, and Costas Meghir. 2000. “The Changing Distribution of Male Wages in the U.K.,” *Review of Economic Studies* 67(4): 635-666.

Guvenen, Fatih, Greg Kaplan, Jae Song, and Justin Weidner. 2021. “Lifetime Earnings in the United States over Six Decades,” Mimeo, University of Minnesota.

Heathcote, Jonathan, Kjetil Storesletten, and Giovanni Violante. 2005. “Two Views of Inequality over the Life Cycle,” *Journal of the European Economic Association* 3(2/3): 765-775.

Heckman, James J. 1979. “Sample Selection Bias as a Specification Error,” *Econometrica* 47(1): 153-161.

Heckman, James J. 1990. “Varieties of Selection Bias,” *American Economic Review Papers and Proceedings* 80(2): 313-318.

Heckman, James J., Lance Lochner, and Petra Todd. 2006. “Earnings Functions, Rates of Return, and Treatment effects: The Mincer Equation and Beyond,” In *Handbook of Economics of Education*, Vol 1, E. Hanushek and F. Welch (eds), Amsterdam: Elsevier, 307-458.

Heckman, James, and Richard Robb. 1985. “Using Longitudinal Data to Estimate Age, Period, and Cohort Effects in Earnings Equations,” in *Cohort Analysis in Social Research: Beyond the Identification Problem*, William M. Mason and Stephen E. Fienberg (eds.), New York, NY: Springer-Verlag, 137-150.

Hoynes, Hilary W. 1997. “Does Welfare Play Any Role in Female Headship Decisions?” *Journal of Public Economics* 65(2): 89-117.

Hoynes, Hilary W., and Diane W. Schanzenbach. 2016. "U.S. Food and Nutrition Programs," In *Economics of Means-Tested Transfer Programs in the United States, Volume 1*, Robert A. Moffitt (ed.), National Bureau of Economic Research and University of Chicago Press, 219-301.

Huggett, Mark, Gustavo Ventura, and Amir Yaron. 2011. "Sources of Lifetime Inequality," *American Economic Review* 101(7) 2923-2954.

Juhn, Chinhui, Kevin M. Murphy, and Brooks Pierce. 1993. "Wage Inequality and the Rise in the Returns to Skill," *Journal of Political Economy*, 101(3): 410-433.

Kahn, Lisa B. 2010. "The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy," *Labour Economics* 17(2): 3-3-316.

Kambourov, Gueorgui, and Iourii Manovskii. 2009. "Accounting for the Changing Life-Cycle Profile of Earnings," Mimeo, University of Toronto.

Katz, Lawrence F. and Kevin M. Murphy. 1992. "Changes in Relative Wages, 1963-87: Supply and Demand Factors." *Quarterly Journal of Economics* 107(1): 35–78.

Keane, Michael, Robert Moffitt, and David Runkle. 1988. "Real Wages over the Business Cycle: Estimating the Impact of Heterogeneity with Micro Data," *Journal of Political Economy* 96(6): 1232-1266.

Kearney, Melissa S. 2004. "Is There an Effect of Incremental Welfare Benefits on Fertility Behavior?," *Journal of Human Resources* 39(2): 295-325.

Koenker, Roger, and Gilbert Bassett 1978. "Regression Quantiles," *Econometrica* 46(1): 33-50.

Kong, Yu-Chien, Ravikumar, B., and Guillaume Vandenbroucke. 2018. "Explaining Cross-Cohort Differences in Life Cycle Earnings," *European Economic Review*, 107: 157-184.

Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman. 2018. "Life Cycle Wage Growth across Countries," *Journal of Political Economy* 126(2): 797-849.

Lee, Lung-Fei. 1982. "Some Approaches to the Correction of Selectivity Bias," *Review of Economic Studies* 49(3): 355-372.

Lemieux, Thomas. 2006. "Increasing Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill?" *American Economic Review* 96(3): 461-498.

Maasoumi, Esfandiar, and Le Wang. 2019. "The Gender Gap between Earnings Distributions," *Journal of Political Economy* 127(5): 2438-2504.

Machado, Jose A.F., and Jose Mata. 2005. "Counterfactual Decomposition of Changes in Wage Distributions Using Quantile Regression," *Journal of Applied Econometrics* 20(4):445-465.

MaCurdy, Thomas E., and Thomas Mroz. 1995. "Measuring Macroeconomic Shifts in Wages from Cohort Specifications," Mimeo, Stanford University.

Magnac, Thierry, Sébastian Roux. 2021. "Heterogeneity and Wage Inequalities over the Life Cycle," *European Economic Review* 134 (103715): 1-23.

Moffitt, Robert A., Brian J. Phelan, Anne E. Winkler. 2020. "Welfare Rules, Incentives, and Family Structure," *Journal of Human Resources* 55(1): 1-42.

Mulligan, Casey B., and Yona Rubinstein. 2008. "Selection, Investment, and Women's Relative Wages over Time," *Quarterly Journal of Economics* 123(3): 1061-1110.

Neal, Derek. 2004. "The Measured Black-White Wage Gap among Women is too Small," *Journal of Political Economy* 112(S1): S1-S28.

Neal, Derek, and William R. Johnson. 1996. "The Role of Pre-Market Factors in Black-White Wage Differences," *Journal of Political Economy* 104(5): 869-895.

Olivetti, Claudia, and Barbara Petrongolo. 2008. "Unequal Pay or Unequal Employment? A Cross-Country Analysis of Gender Gaps," *Journal of Labor Economics* 26(4): 621-654.

Olsen, Randall J. 1980. "A Least Squares Correction for Selectivity Bias," *Econometrica* 48(7): 1815-1820.

Politis, Dimitris, Joseph Romano, and Michael Wolf. 1999. *Subsampling*. Springer.

Rothstein, Jesse. 2020. "The Lost Generation? Labor Market Outcomes for Post Great Recession Entrants," NBER Working Paper 27516.

Schwandt, Hannes, and Till von Wachter. 2019. "Unlucky Cohorts: Estimating the Long-Term Effects of Entering the Labor Market in a Recession in Large Cross-Section Data Sets," *Journal of Labor Economics* 37(S1): S161-S198.

Shao, Jun, and Dongsheng Tu. 1995. *The Jackknife and Bootstrap*. Springer.

Sloane, Carolyn M., Erik G. Hurst, and Dan A. Black. 2021. "College Majors, Occupations, and the Gender Wage Gap," *Journal of Economic Perspectives* 35(4): 223-248.

Solon, Gary, Robert Barsky, and Jonathan A. Parker. 1994. "Measuring the Cyclicality of Real Wages: How Important is Composition Bias?," *Quarterly Journal of Economics* 109(1) 1-25.

Vella, Francis. 1998. "Estimating Models with Sample Selection Bias: A Survey," *Journal of Human Resources* 33(1): 127-169.

Weiss, Yoram, and Lee A. Lillard. 1978. "Experience, Vintage, and Time Effects in the Growth of Earnings: American Scientists," *Journal of Political Economy* 86(3): 427-447.

Welch, Finis. 1979. "Effects of Cohort Size on Earnings: The Baby Boom Babies' Financial Bust," *Journal of Political Economy* 87(5): S65-S97.

Ziliak, James P. 2016. "Temporary Assistance for Needy Families," In *Economics of Means-Tested Transfer Programs in the United States, Volume 1*, Robert A. Moffitt (ed.), National Bureau of Economic Research and University of Chicago Press, 303-393.

Ziliak, James P., Beth Wilson, and Joe Stone. 1999. "Spatial Dynamics and Heterogeneity in the Cyclicality of Real Wages," *Review of Economics and Statistics* 81(2): 227–236.

Figure I. Life Cycle Employment Rates across Cohorts

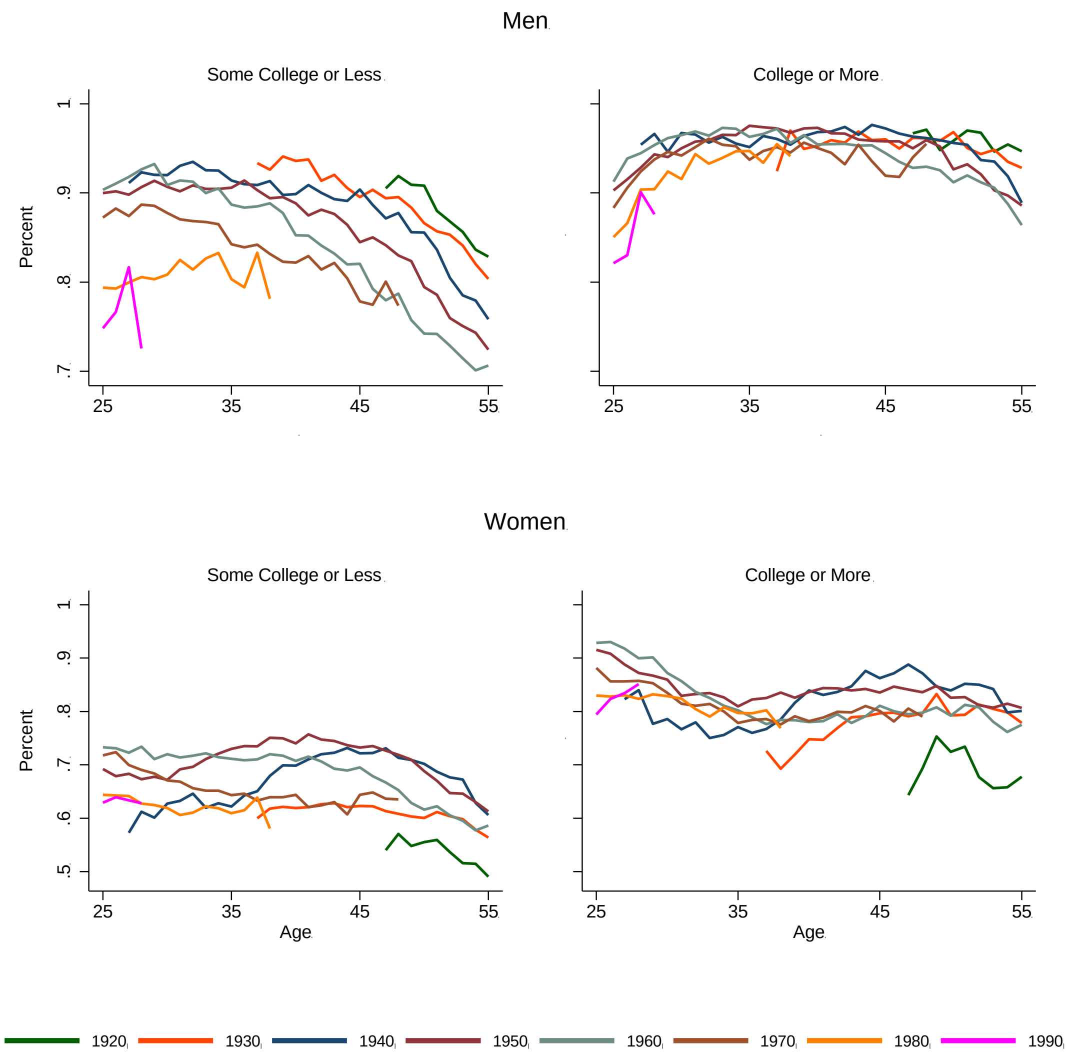

Figure II. Distribution of Life Cycle Real Hourly Wages of Men across Cohorts

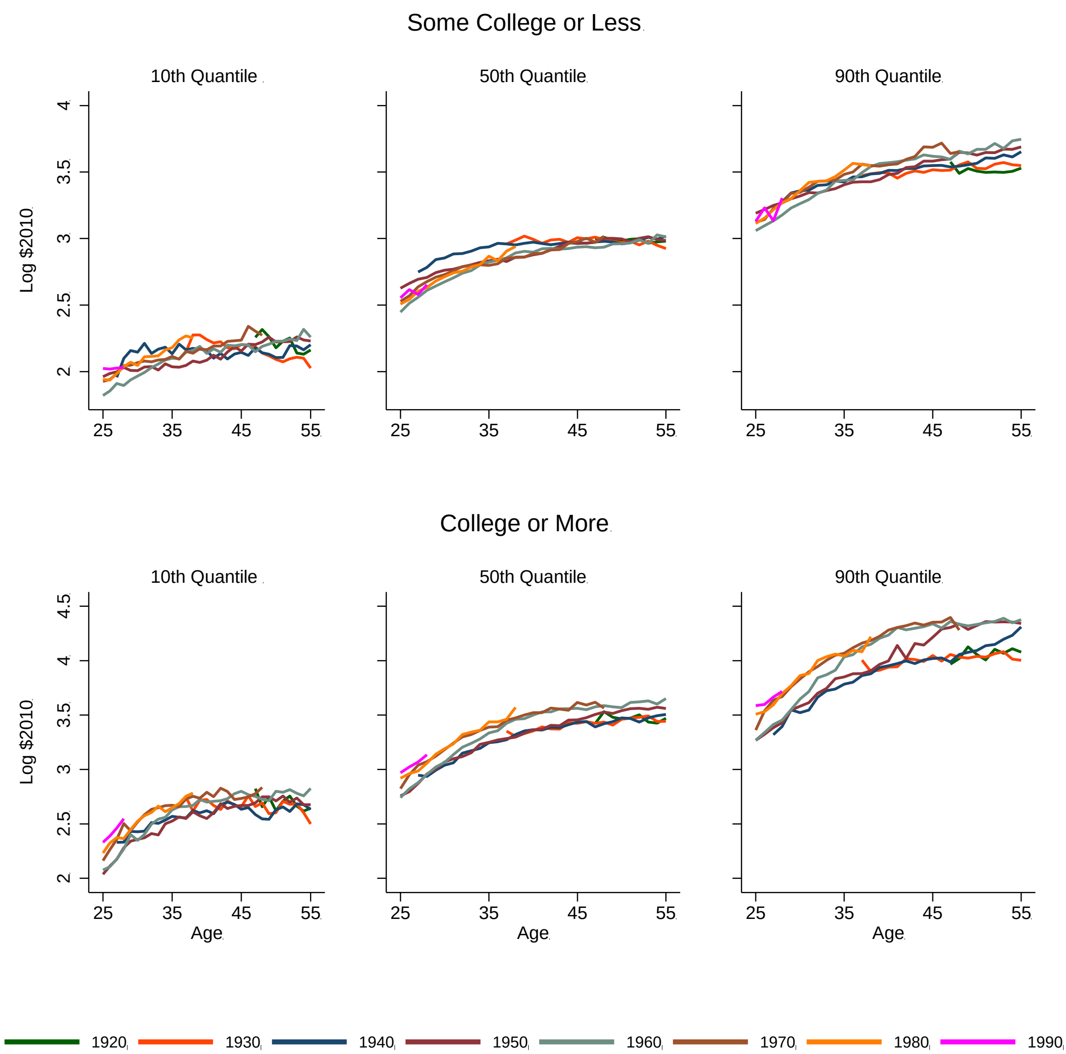

Figure III. Distribution of Life Cycle Real Hourly Wages of Women across Cohorts

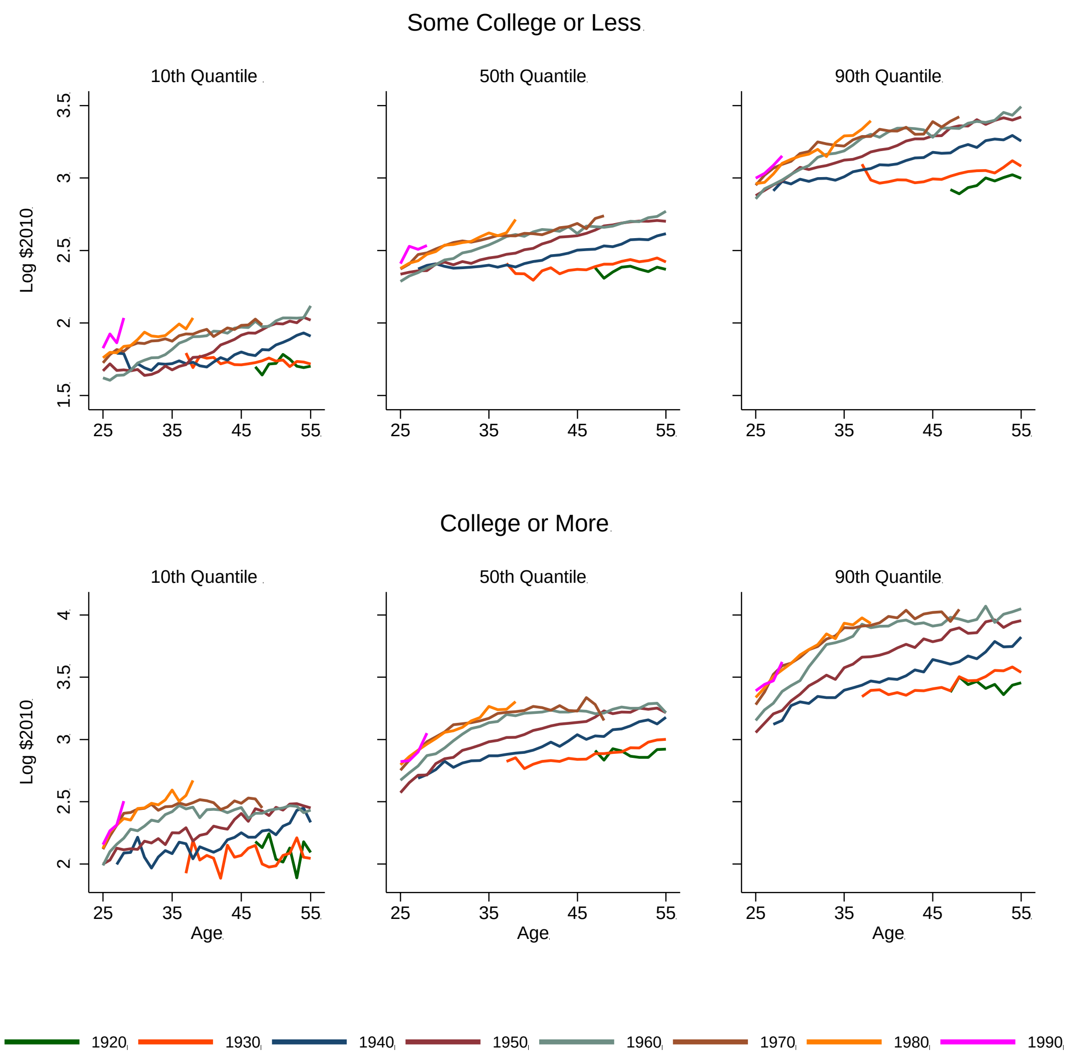

Figure IV. Quantile Selection Pseudo Life Cycle Age-Offer Wage Profiles of Men

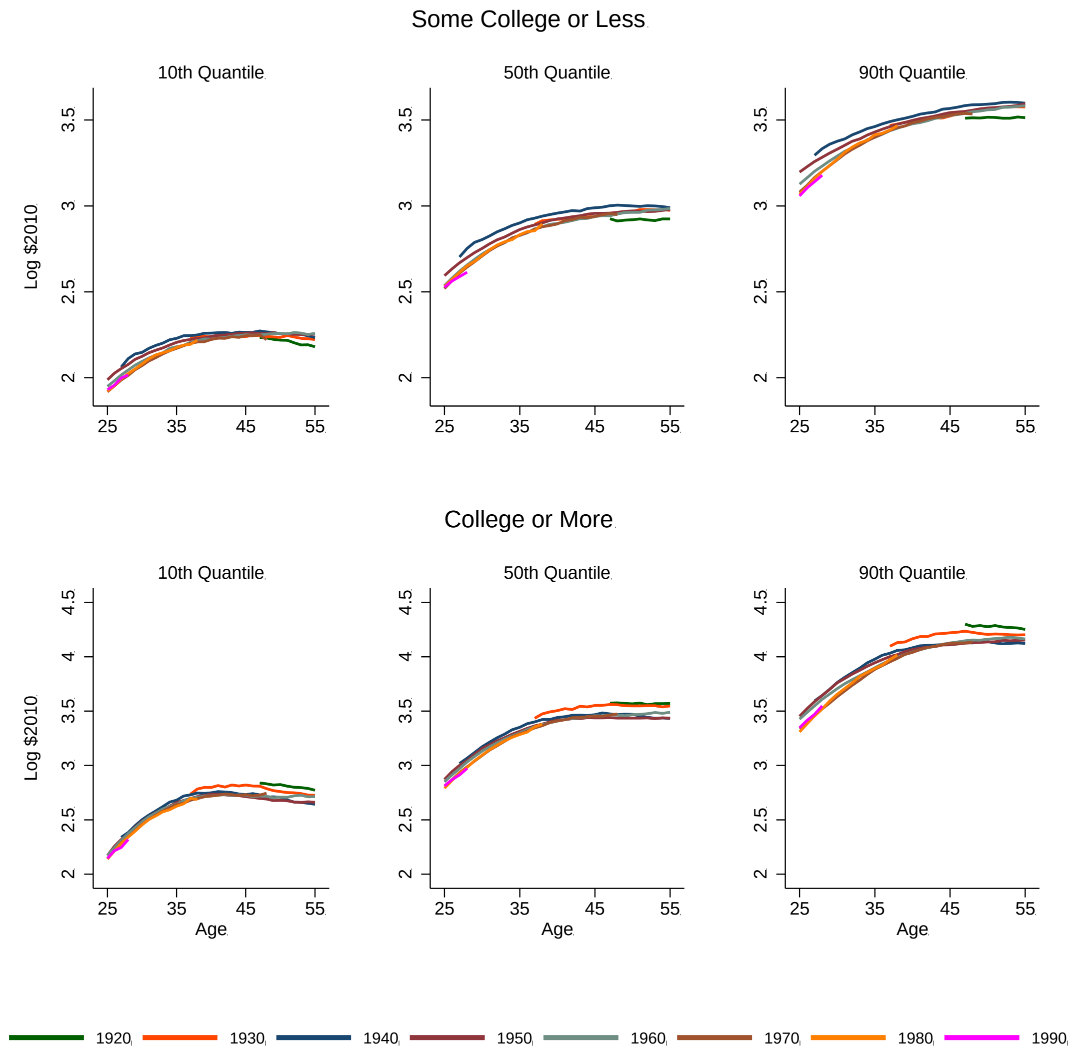

Figure V. Quantile Selection Pseudo Life Cycle Age-Offer Wage Profiles of Women

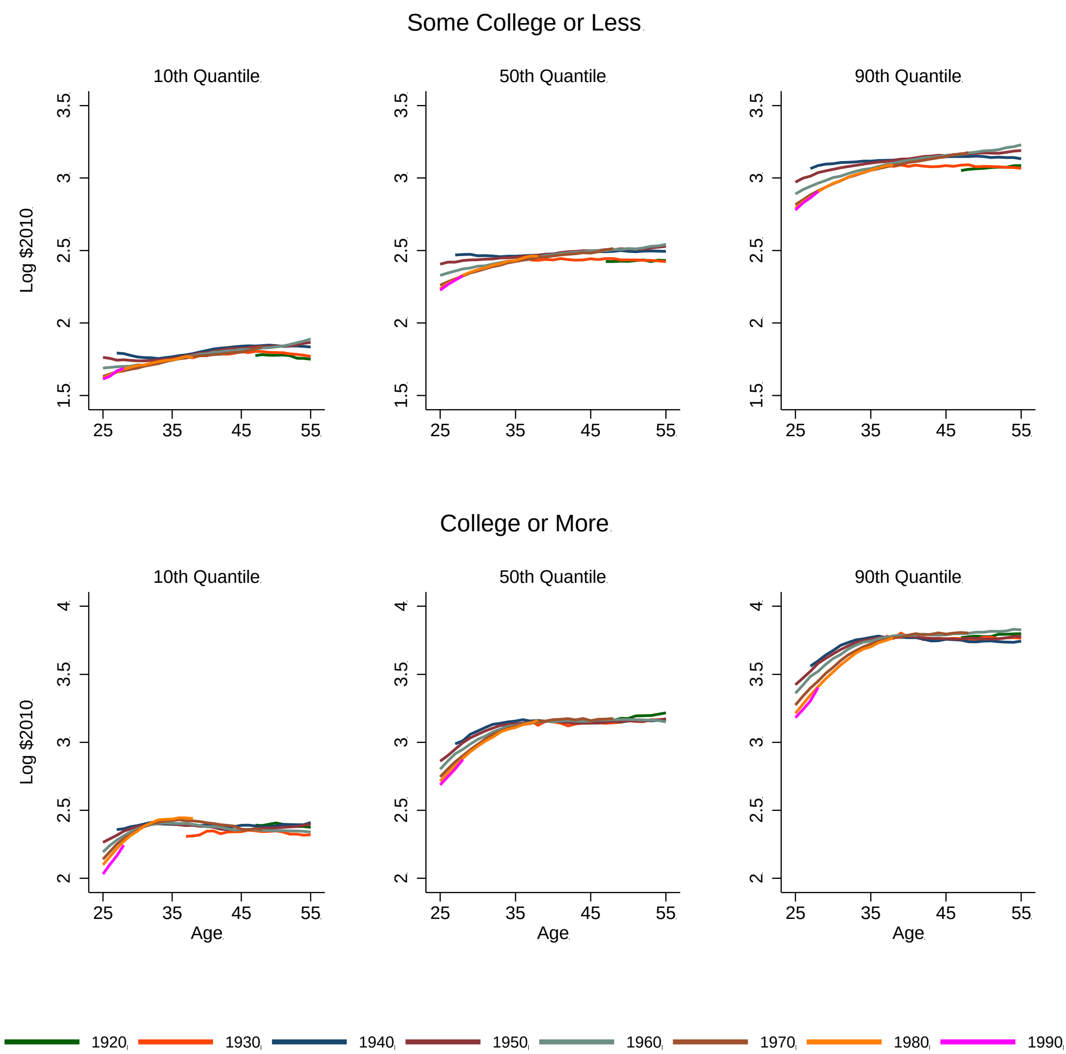

Figure VI. Within-Education Group Inequality of Male Offer Wages over the Life Cycle

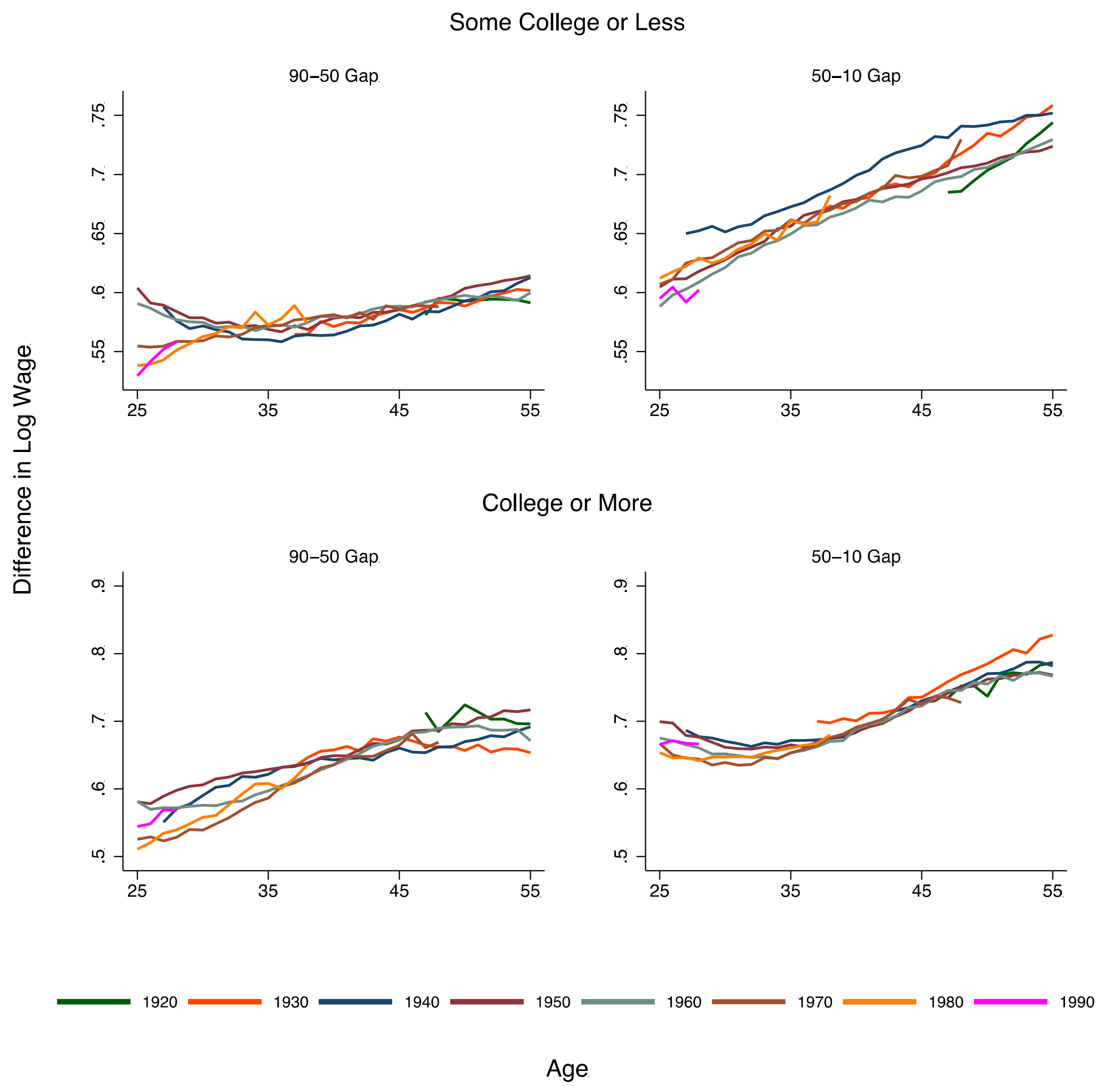

Figure VII. Between-Education Group Inequality of Male Offer Wages over the Life Cycle

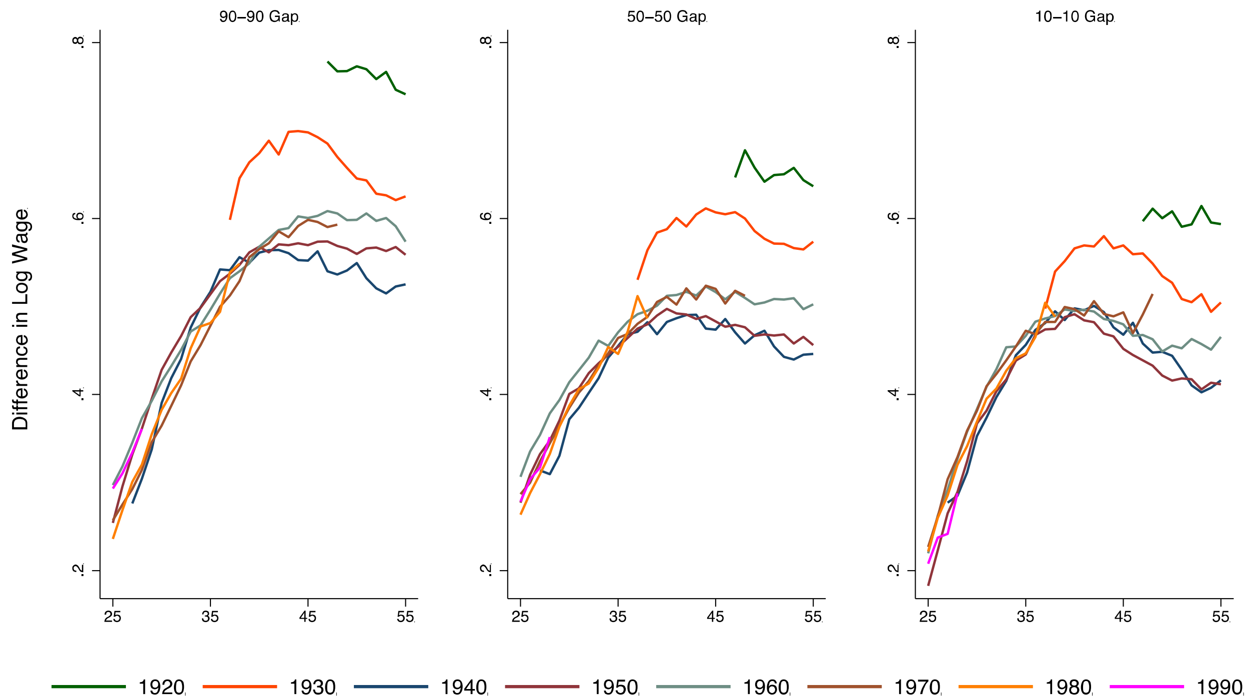

Figure VIII. Within-Education Group Inequality of Female Offer Wages over the Life Cycle

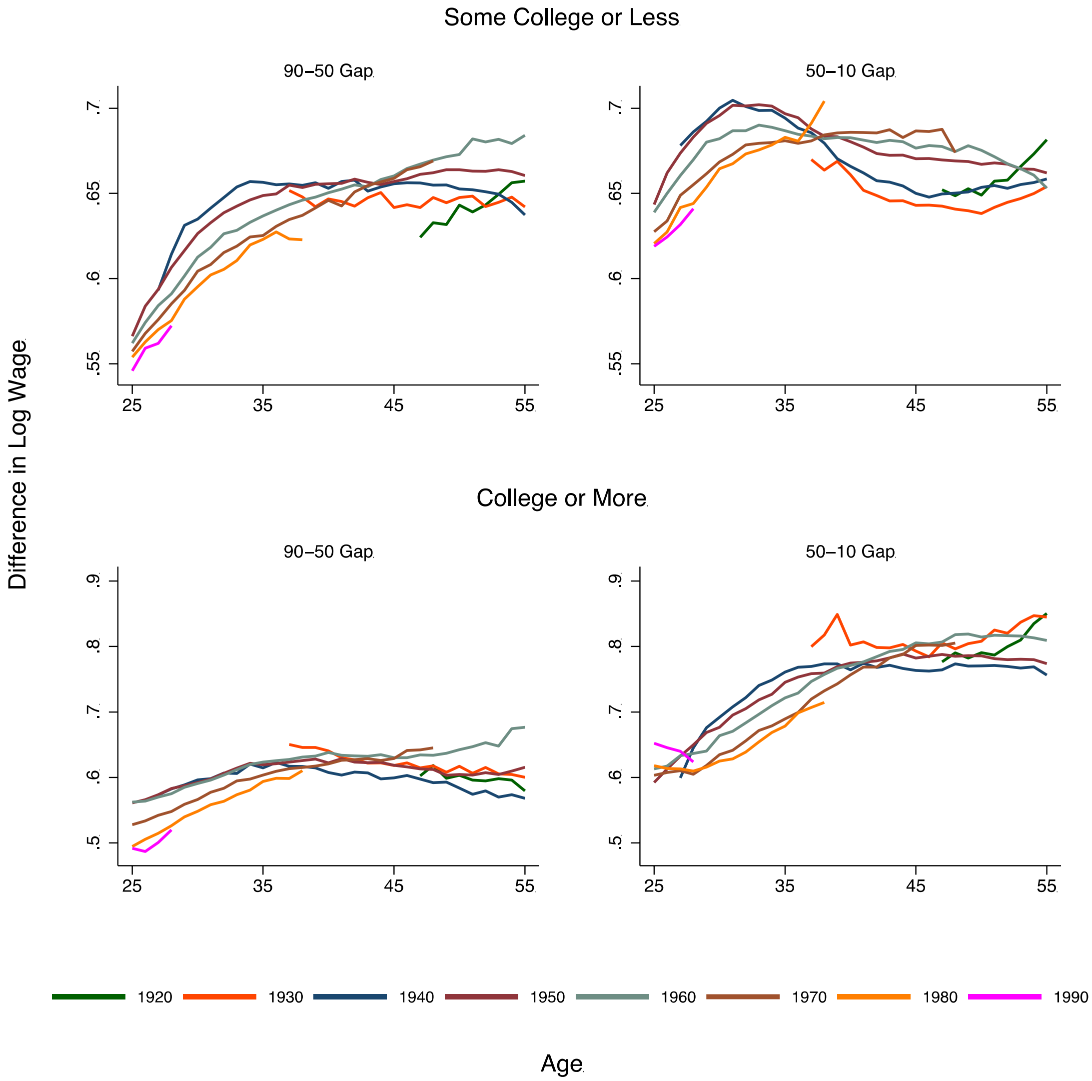

Figure IX. Between-Education Group Inequality of Female Offer Wages over the Life Cycle

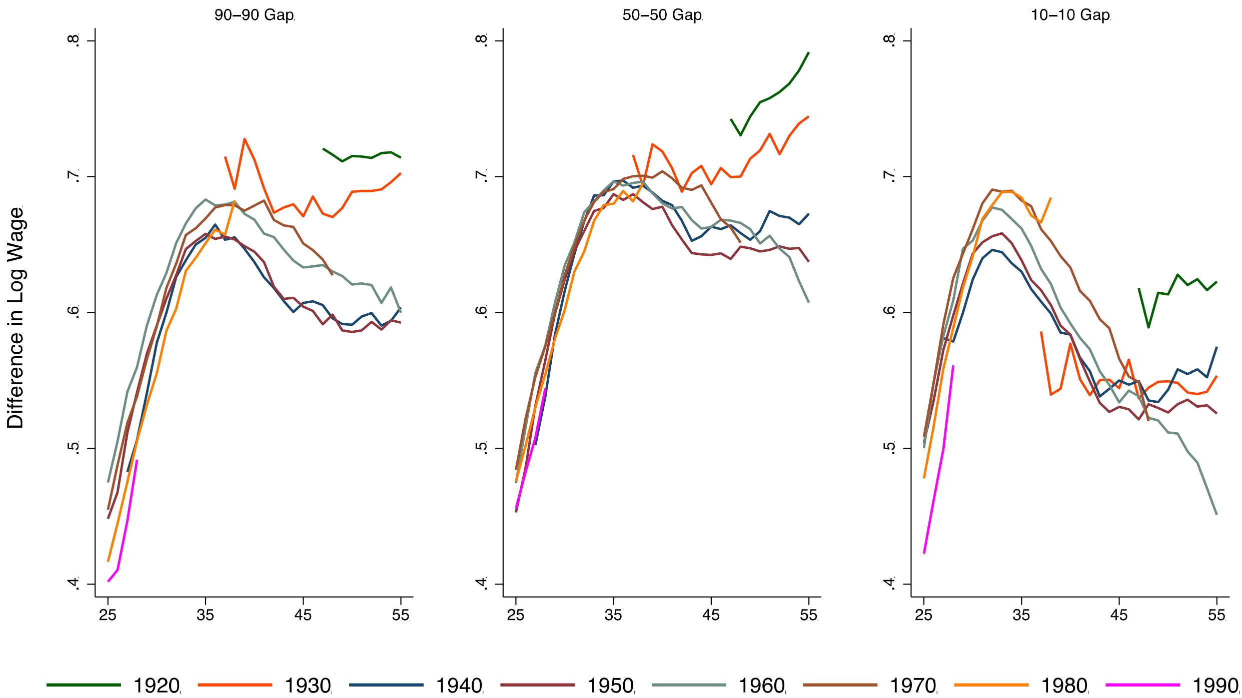

Figure Xa. Within-Education Group Gender Offer Wage Gaps over the Life Cycle

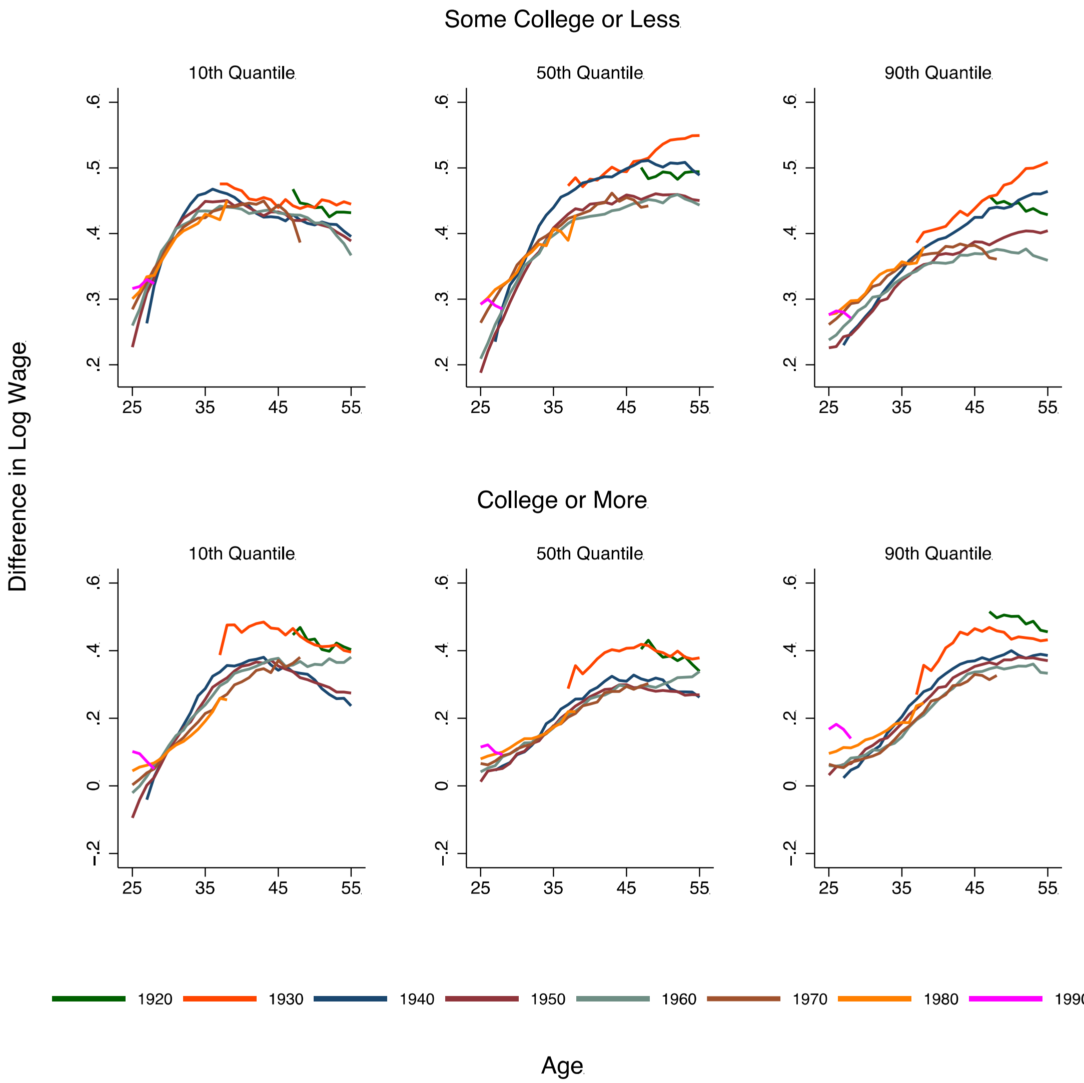

Figure Xb. Within-Education Group Gender Offer Wage Gaps over the Life Cycle with Time Effects

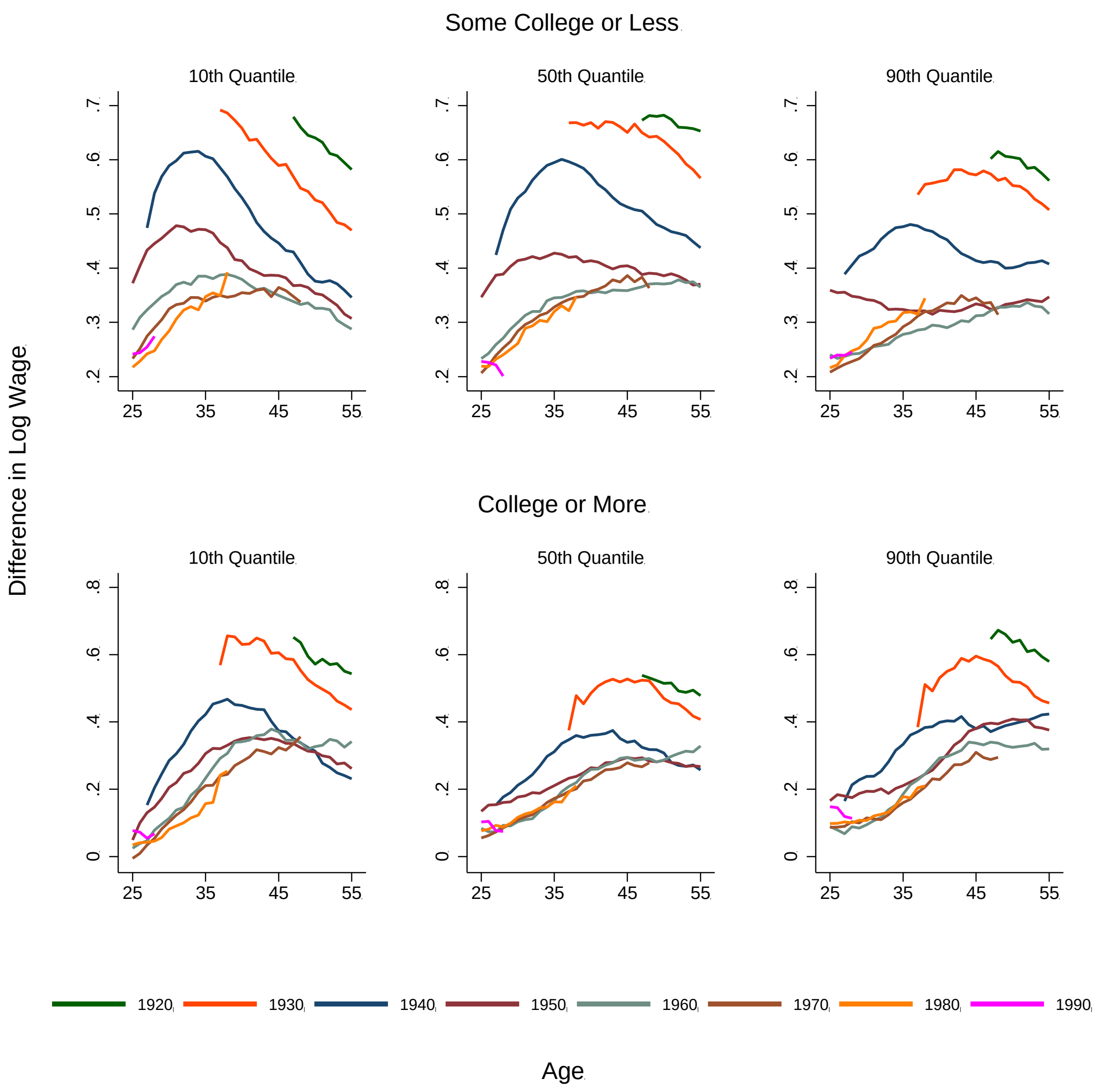

Figure XI. Aggregate Time Effects from Median Selection Offer Wages of Men and Women

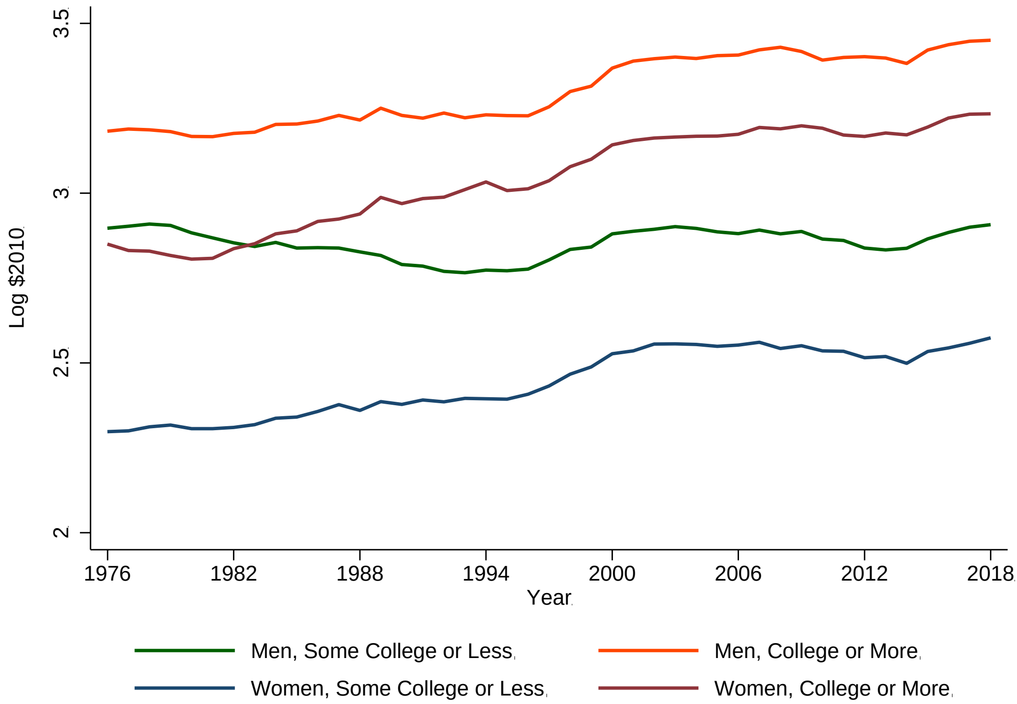

Table I. Quantile Selection Estimates of Log Wages for Men with Some College or Less

	Employment	10th Quantile	50th Quantile	90th Quantile
Constant	1.900	1.942	2.518	3.055
	(0.100)	(0.018)	(0.013)	(0.016)
Entryage	-0.255	0.271	0.359	0.276
	(0.040)	(0.021)	(0.013)	(0.015)
$Entryage^2$	0.163	-0.088	-0.057	-0.005
	(0.038)	(0.022)	(0.013)	(0.017)
$Entryage^3$	-0.070	0.007	0.005	-0.006
	(0.008)	(0.006)	(0.003)	(0.004)
Time	0.143	0.082	-0.002	0.083
	(0.264)	(0.145)	(0.080)	(0.090)
$Time^2$	0.192	-0.528	-0.111	-0.093
	(1.030)	(0.586)	(0.308)	(0.372)
$Time^3$	-0.556	0.413	-0.027	-0.028
	(0.690)	(0.406)	(0.214)	(0.290)
$Time^4$	0.236	-0.116	0.031	0.029
	(0.176)	(0.108)	(0.060)	(0.087)
$Time^5$	-0.027	0.011	-0.004	-0.004
	(0.016)	(0.010)	(0.006)	(0.009)
$Cohort^2$	-0.040	0.009	0.011	-0.015
	(0.008)	(0.005)	(0.003)	(0.004)
$Cohort^2$*delta	0.165	-0.008	-0.092	-0.085
	(0.027)	(0.016)	(0.009)	(0.013)
$Cohort^3$	0.041	0.000	0.004	-0.000
	(0.005)	(0.004)	(0.002)	(0.003)
R1	-133.680	17.067	-85.062	-94.761
	(41.500)	(26.202)	(16.009)	(25.305)
R2	10.892	-2.409	20.347	10.017
	(8.572)	(5.884)	(3.598)	(5.194)
R3	66.236	-5.719	8.515	19.728
	(16.047)	(11.680)	(6.761)	(10.388)
R4	-4.749	1.638	-1.571	-1.312
	(3.543)	(2.733)	(1.608)	(2.316)
Black	-0.455	-0.203	-0.197	-0.170
	(0.006)	(0.005)	(0.003)	(0.004)
Other Race	-0.332	-0.257	-0.205	-0.129
	(0.009)	(0.007)	(0.005)	(0.006)
Hispanic	-0.014	-0.326	-0.349	-0.262
	(0.006)	(0.003)	(0.002)	(0.003)
Married	0.646	0.218	0.173	0.134
	(0.005)	(0.003)	(0.002)	(0.003)
Live in Metro Area	0.111	0.164	0.139	0.111
	(0.006)	(0.004)	(0.002)	(0.003)
State Unemployment Rate	-0.027	-0.010	-0.002	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Household Size	-0.097	-0.028	-0.030	-0.027
	(0.002)	(0.001)	(0.001)	(0.001)
Number of Children Ages 0-5	0.100	0.013	0.020	0.029
	(0.004)	(0.002)	(0.001)	(0.002)
Number of Children Ages 6-18	0.107	0.029	0.029	0.026
	(0.003)	(0.002)	(0.001)	(0.002)
3-Person SNAP Benefit	-0.142			

	(0.022)			
3-Person TANF Benefit	0.009			
	(0.003)			
Rho	0.96			
	(0.07)			
P-value on SNAP and TANF	0.00			
P-value on Cohort terms		0.10	0.00	0.00
P-value on R terms		0.01	0.00	0.00
P-value on R and Cohort terms		0.00	0.00	0.00

Note: The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

Table II. Quantile Selection Estimates of Log Wages for Men with College or More

	Employment	10th Quantile	50th Quantile	90th Quantile
Constant	2.266	1.883	2.546	3.024
	(0.169)	(0.039)	(0.019)	(0.025)
Entryage	0.055	0.532	0.482	0.541
	(0.078)	(0.047)	(0.020)	(0.030)
Entryage^2	0.186	-0.197	-0.160	-0.190
	(0.079)	(0.047)	(0.020)	(0.031)
Entryage^3	-0.063	0.018	0.019	0.015
	(0.018)	(0.012)	(0.005)	(0.008)
Time	-0.467	-0.008	0.012	0.436
	(0.564)	(0.282)	(0.113)	(0.203)
Time^2	2.610	-0.719	0.046	-0.980
	(2.187)	(1.138)	(0.463)	(0.808)
Time^3	-2.054	0.476	-0.063	0.466
	(1.427)	(0.785)	(0.345)	(0.551)
Time^4	0.590	-0.104	0.025	-0.071
	(0.358)	(0.202)	(0.098)	(0.152)
Time^5	-0.056	0.008	-0.003	0.003
	(0.032)	(0.018)	(0.010)	(0.015)
Cohort^2	-0.114	0.009	-0.004	-0.007
	(0.016)	(0.009)	(0.005)	(0.007)
Cohort^2*delta	-0.119	0.070	0.105	0.137
	(0.066)	(0.031)	(0.015)	(0.024)
Cohort^3	-0.009	0.016	0.030	0.005
	(0.016)	(0.008)	(0.004)	(0.006)
R1	-260.660	6.441	62.377	140.390
	(88.193)	(51.821)	(25.429)	(43.167)
R2	-31.470	-2.380	-17.935	-33.781
	(18.512)	(11.083)	(5.742)	(9.750)
R3	21.132	-2.920	-32.827	-22.609
	(37.124)	(23.584)	(10.892)	(20.140)
R4	25.842	3.458	9.161	5.763
	(8.530)	(5.210)	(2.481)	(4.638)
Black	-0.337	-0.239	-0.233	-0.246
	(0.015)	(0.013)	(0.006)	(0.009)
Other Race	-0.348	-0.220	-0.036	-0.031
	(0.013)	(0.010)	(0.006)	(0.008)
Hispanic	-0.148	-0.332	-0.195	-0.170
	(0.015)	(0.010)	(0.006)	(0.008)
Married	0.413	0.241	0.160	0.105
	(0.011)	(0.007)	(0.005)	(0.005)
Live in Metro Area	0.081	0.224	0.209	0.189
	(0.013)	(0.006)	(0.004)	(0.005)
State Unemployment Rate	-0.016	-0.006	-0.005	-0.007
	(0.004)	(0.002)	(0.001)	(0.002)
Household Size	-0.092	-0.032	-0.024	-0.014
	(0.005)	(0.003)	(0.001)	(0.003)
Number of Children Ages 0-5	0.117	0.061	0.052	0.060
	(0.009)	(0.004)	(0.002)	(0.004)
Number of Children Ages 6-18	0.137	0.065	0.053	0.057
	(0.007)	(0.004)	(0.002)	(0.004)
3-Person SNAP Benefit	-0.214			

	(0.034)			
3-Person TANF Benefit	0.015			
	(0.007)			
Rho	-0.84			
	(0.45)			
P-value on SNAP and TANF	0.00			
P-value on Cohort terms		0.13	0.00	0.00
P-value on R terms		0.00	0.00	0.00
P-value on R and Cohort terms		0.00	0.00	0.00

Note: The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

Table III. Quantile Selection Estimates of Log Wages for Women with Some College or Less

	Employment	10th Quantile	50th Quantile	90th Quantile
Constant	0.986	1.677	2.195	2.642
	(0.074)	(0.026)	(0.013)	(0.017)
Entryage	-0.166	0.061	0.215	0.337
	(0.026)	(0.026)	(0.013)	(0.018)
Entryage^2	0.085	0.036	-0.077	-0.129
	(0.026)	(0.027)	(0.014)	(0.020)
Entryage^3	-0.037	-0.011	0.010	0.020
	(0.006)	(0.006)	(0.004)	(0.005)
Time	-0.228	-0.193	-0.089	0.121
	(0.173)	(0.225)	(0.098)	(0.125)
Time^2	2.672	0.742	0.303	-0.289
	(0.656)	(0.864)	(0.375)	(0.489)
Time^3	-2.188	-0.580	-0.165	0.197
	(0.444)	(0.579)	(0.273)	(0.358)
Time^4	0.609	0.170	0.037	-0.046
	(0.119)	(0.146)	(0.076)	(0.104)
Time^5	-0.056	-0.016	-0.003	0.004
	(0.011)	(0.013)	(0.007)	(0.010)
Cohort^2	-0.041	-0.037	-0.025	-0.013
	(0.006)	(0.006)	(0.003)	(0.005)
Cohort^2*delta	-0.069	-0.108	-0.095	-0.085
	(0.019)	(0.020)	(0.011)	(0.016)
Cohort^3	-0.029	-0.008	-0.016	-0.017
	(0.004)	(0.005)	(0.003)	(0.004)
R1	24.705	-130.460	-60.127	20.119
	(32.581)	(33.790)	(19.743)	(28.178)
R2	-33.569	1.496	-0.618	-12.073
	(6.329)	(6.838)	(4.450)	(5.896)
R3	-10.969	29.948	12.024	-23.305
	(12.564)	(14.376)	(8.305)	(11.857)
R4	12.139	2.268	1.277	7.608
	(2.814)	(3.165)	(1.974)	(2.639)
Black	-0.085	-0.059	-0.083	-0.110
	(0.004)	(0.006)	(0.003)	(0.004)
Other Race	-0.223	-0.121	-0.114	-0.100
	(0.007)	(0.007)	(0.006)	(0.007)
Hispanic	-0.251	-0.177	-0.246	-0.216
	(0.005)	(0.006)	(0.005)	(0.005)
Married	-0.109	0.034	0.048	0.062
	(0.003)	(0.003)	(0.003)	(0.003)
Live in Metro Area	0.038	0.166	0.165	0.174
	(0.004)	(0.004)	(0.002)	(0.002)
State Unemployment Rate	-0.018	-0.009	-0.003	0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Household Size	-0.033	-0.025	-0.044	-0.047
	(0.001)	(0.002)	(0.001)	(0.001)
Number of Children Ages 0-5	-0.281	-0.066	0.001	0.046
	(0.003)	(0.008)	(0.006)	(0.005)
Number of Children Ages 6-18	-0.094	-0.057	-0.028	0.001
	(0.002)	(0.004)	(0.002)	(0.003)
3-Person SNAP Benefit	-0.007			

	(0.017)			
3-Person TANF Benefit	-0.022			
	(0.002)			
Rho	-0.82			
	(0.31)			
P-value on SNAP and TANF	0.00			
P-value on Cohort terms		0.00	0.00	0.00
P-value on R terms		0.00	0.00	0.01
P-value on R and Cohort terms		0.00	0.00	0.00

Note: The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

Table IV. Quantile Selection Estimates of Log Wages for Women with College or More

	Employment	10th Quantile	50th Quantile	90th Quantile
Constant	2.333	2.101	2.505	2.861
	(0.140)	(0.047)	(0.015)	(0.030)
Entryage	-0.864	0.283	0.414	0.409
	(0.057)	(0.046)	(0.023)	(0.029)
Entryage^2	0.808	-0.003	-0.156	-0.179
	(0.055)	(0.047)	(0.025)	(0.030)
Entryage^3	-0.198	-0.022	0.019	0.026
	(0.013)	(0.011)	(0.006)	(0.008)
Time	-0.090	-0.444	-0.232	-0.543
	(0.445)	(0.437)	(0.152)	(0.226)
Time^2	2.376	0.946	0.572	2.731
	(1.760)	(1.627)	(0.555)	(0.919)
Time^3	-1.711	-0.693	-0.498	-1.916
	(1.168)	(1.078)	(0.380)	(0.635)
Time^4	0.452	0.209	0.160	0.488
	(0.287)	(0.265)	(0.101)	(0.168)
Time^5	-0.040	-0.021	-0.017	-0.042
	(0.025)	(0.023)	(0.009)	(0.016)
Cohort^2	-0.243	-0.059	-0.012	-0.022
	(0.012)	(0.010)	(0.005)	(0.007)
Cohort^2*delta	-0.429	-0.204	-0.026	0.061
	(0.039)	(0.033)	(0.015)	(0.025)
Cohort^3	-0.056	-0.037	-0.011	0.009
	(0.010)	(0.009)	(0.004)	(0.007)
R1	-852.680	-333.660	-8.022	83.699
	(58.101)	(51.953)	(28.318)	(42.599)
R2	54.235	45.275	4.661	-19.190
	(11.157)	(9.938)	(5.046)	(9.278)
R3	315.580	126.830	6.020	-35.732
	(25.806)	(22.619)	(11.657)	(19.222)
R4	-31.162	-19.880	-3.298	7.669
	(5.491)	(4.784)	(2.371)	(4.252)
Black	0.136	-0.001	-0.062	-0.101
	(0.012)	(0.008)	(0.004)	(0.006)
Other Race	-0.389	-0.104	0.018	0.037
	(0.010)	(0.009)	(0.008)	(0.008)
Hispanic	-0.125	-0.212	-0.111	-0.112
	(0.010)	(0.010)	(0.005)	(0.007)
Married	-0.291	0.056	0.069	0.071
	(0.007)	(0.005)	(0.003)	(0.004)
Live in Metro Area	-0.133	0.118	0.133	0.176
	(0.009)	(0.007)	(0.003)	(0.005)
State Unemployment Rate	-0.007	-0.008	-0.001	-0.001
	(0.003)	(0.002)	(0.001)	(0.002)
Household Size	-0.069	-0.070	-0.061	-0.053
	(0.004)	(0.003)	(0.002)	(0.002)
Number of Children Ages 0-5	-0.332	0.048	0.112	0.156
	(0.006)	(0.006)	(0.004)	(0.006)
Number of Children Ages 6-18	-0.129	-0.033	0.029	0.054
	(0.005)	(0.004)	(0.003)	(0.004)
3-Person SNAP Benefit	-0.089			

	(0.032)			
3-Person TANF Benefit	-0.017			
	(0.005)			
Rho	0.84			
	(0.24)			
P-value on SNAP and TANF	0.00			
P-value on Cohort terms		0.00	0.00	0.00
P-value on R terms		0.00	0.00	0.32
P-value on R and Cohort terms		0.00	0.00	0.00

Note: The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

NOT FOR PUBLICATION—

Online Data Appendix

The data come from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) spanning survey years 1977 to 2019 (1976-2018 calendar years). The ASEC, which is collected by the United States Census Bureau as a supplement to the monthly CPS labor-force survey, serves as the official source of U.S. income and poverty statistics and has been the leading dataset for research on wage determinants and inequality. The ASEC is primarily collected in March of each year, consisting of about 60,000 households prior to the 2001 survey, and roughly 90,000 households and 200,000 individuals thereafter. Information on basic demographics and family structure refers to the interview week, while data on earnings, income and work effort refers to the prior calendar year. The sample we use consists of men and women ages 25 to 55, the age range when most have completed formal schooling and prior to labor-force exit for retirement reasons.

A.1 Measurement of Employment and Hourly Wages

The focal outcomes for our analysis are employment and real average hourly wages. We classify an individual as employed if they reported both positive weeks worked and usual hours per week in the previous year. In some specifications we restrict attention to full-time, full-year workers defined as those working at least 35 hours per week for 50 weeks. Annual earnings are defined as the sum of before-tax earnings generated from all jobs, inclusive of self-employment farm and non-farm business income. Self-employment income is reported after expenses and thus may be negative. Annual hours of work are defined as the product of weeks worked in the prior year and usual hours worked per week. Average hourly wages are then the ratio of annual earnings to annual hours. Nominal wages are converted to real terms using the Personal Consumption Expenditure Deflator with 2010 base year.[10]

The Census Bureau top codes the earnings and incomes of high-income earners to ensure respondent confidentiality. The method of top coding has varied over the years, complicating analyses of income inequality and potentially this paper as well. The top-code value was a fixed dollar threshold until 1996 when Census started using the mean value of top-coded individuals within cells (determined by up to 12 demographic variables). For example, if in 1995 a person reported $500,000 in earnings, then the Census recorded the earnings of that person as $150,000. In 1996, that same person earning $500,000 would be assigned the mean earnings of all persons within their demographic cell. This creates the possibility of a jump discontinuity that could affect research with the CPS, especially upper-tail inequality (Larrimore et al. 2008). Beginning with the 2011 survey year, Census replaced the cell-mean top code with so-called rank proximity swapping whereby top-coded earners are ordered from lowest to highest and earnings are randomly swapped out between individuals within a bounded range. Unlike the cell-mean series, rank-proximity swapping preserves the distribution of earnings above the top code. Census has released these updated top codes back to 1975 and thus we replace original top codes with their rank-proximity values.[11]

In addition to top-coding earnings, the Census Bureau imputes missing earnings data in the ASEC, whereby individuals with missing earnings get assigned the values from a randomly matched donor based on a set of observed demographic characteristics (known as "hot deck" imputation). Moreover, some households refuse to answer any, or enough, questions on the

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[10] The PCE is obtained from the FRED database, https://fred.stlouisfed.org .
[11] These top codes are available at https://www2.census.gov/programs-surveys/demo/datasets/income-poverty/time-series/data-extracts/asec-incometopcodes-swappingmethod-corrected-110514.zip

ASEC to be usable, and these households receive a complete imputed record from a donor using a similar hot-deck imputation procedure. As shown in Bollinger et al. (2019), earnings nonresponse in the ASEC is pervasive and has increased over time, with combined earnings nonresponse and supplement nonresponse over 40 percent among workers in recent years. For our analysis we drop those individuals with imputed earnings or hours worked, as well as those with a completely imputed ASEC record. We then reweight the sample by using an inverse probability weight. Specifically, we estimate a probit model of the probability of not being imputed as a function of a cubic in age, indicators for education attainment, race, ethnicity, marital status, and region, along with interactions of these variables. The ASEC person weight is then divided by the fitted probability of nonimputation from the probit model. Weights are used in the descriptive figures in the text, and for sample summary statistics, but are not used for estimation of the quantile selection model.

A final adjustment to the data involves trimming the first and 99.9th percentiles of the positive gender- and year-specific wage distributions in order to minimize the undue influence of very low or high wages. Thus, to be employed a worker must have positive weeks worked and hours per week, as well as real wages above the first percentile and below the 99.9th percentile of the gender- and year-specific weekly earnings distribution.[12] Likewise, full-time workers must not only have worked at least 50 weeks for 35 or more hours per week, but also must have real wages in the range from (1, 99.9).

[12] In trimming out low earnings, we compute the 1st percentile for those with positive earnings. This means negative self-employment earnings may pull down positive earnings from an employer, but combined self-employed and employer earnings must be positive. Those whose total earnings are negative are trimmed from the sample.

A.2 Construction of Cohorts

Each individual is allocated to a cohort *c* based on the calendar year *t* normalized with respect to the first year of the sample (1976) and on their age *e* normalized to the age at labor market entry (age 25); specifically, $c = t - e$, where $t = (year - 1976)/10$ and $e = (age - 25)/10$. This means cohort 0 is those individuals age 25 in 1976, and persons older than age 25 in 1976 are assigned negative cohort values and those younger than age 25 in 1976 are assigned positive cohort values (Fitzenberger and Wunderlich 2002).

We admit cohort-specific heterogeneity by splitting the cohort into two groups by education attainment—those with some college or less and those with college or more. In the 1977-1991 survey years, the measure of education provides information on whether an individual completed the n^{th} year of education, but it does not provide details on whether the individual obtained a degree. Starting in 1992, it is possible to differentiate between those who completed the n^{th} year of education and obtained a credential. For example, before 1992 we know if someone attended 16 years of schooling, but we do not know if they received a college degree. After 1991, we know both years of college completed and whether they graduated. In order to have a consistent measure over time, we consider completion of at least 16 years of schooling to be equivalent to obtaining a college degree, and thus anyone with 15 or fewer years of schooling are placed into the some college or less group.

Figure A.1. Trends in Employment among Men and Women, 1976-2018

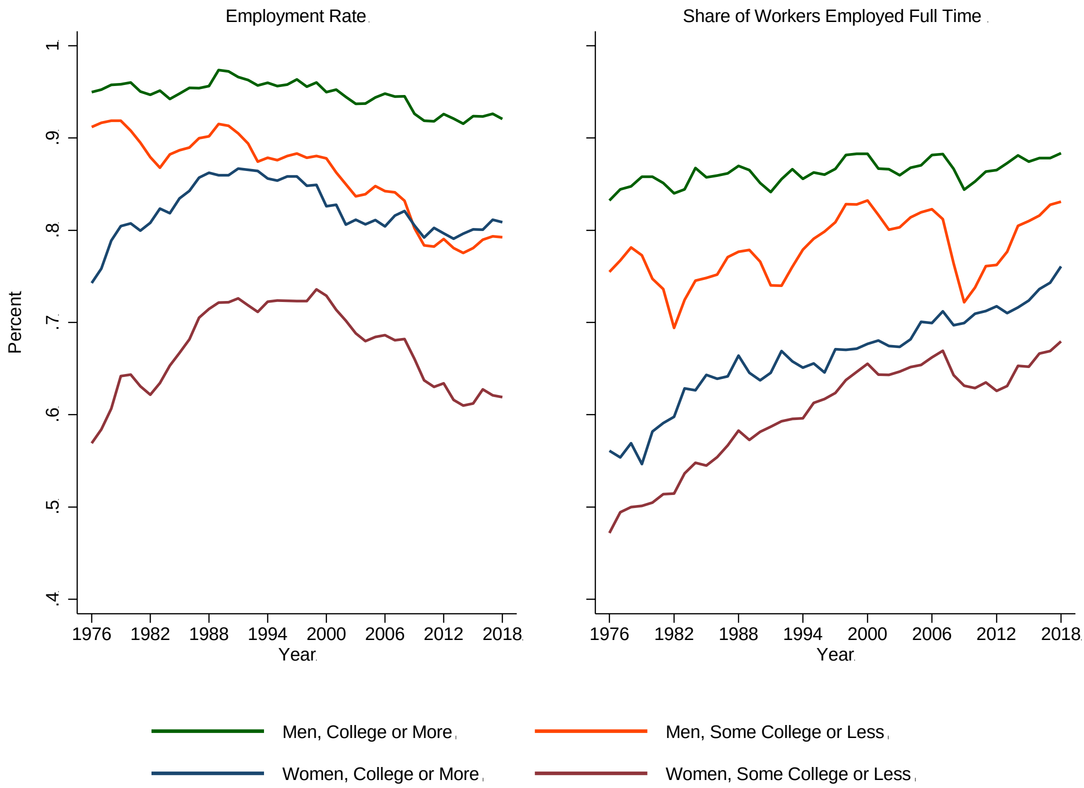

Figure A.2. Share of Workers Employed Full Time Across the Life Cycle

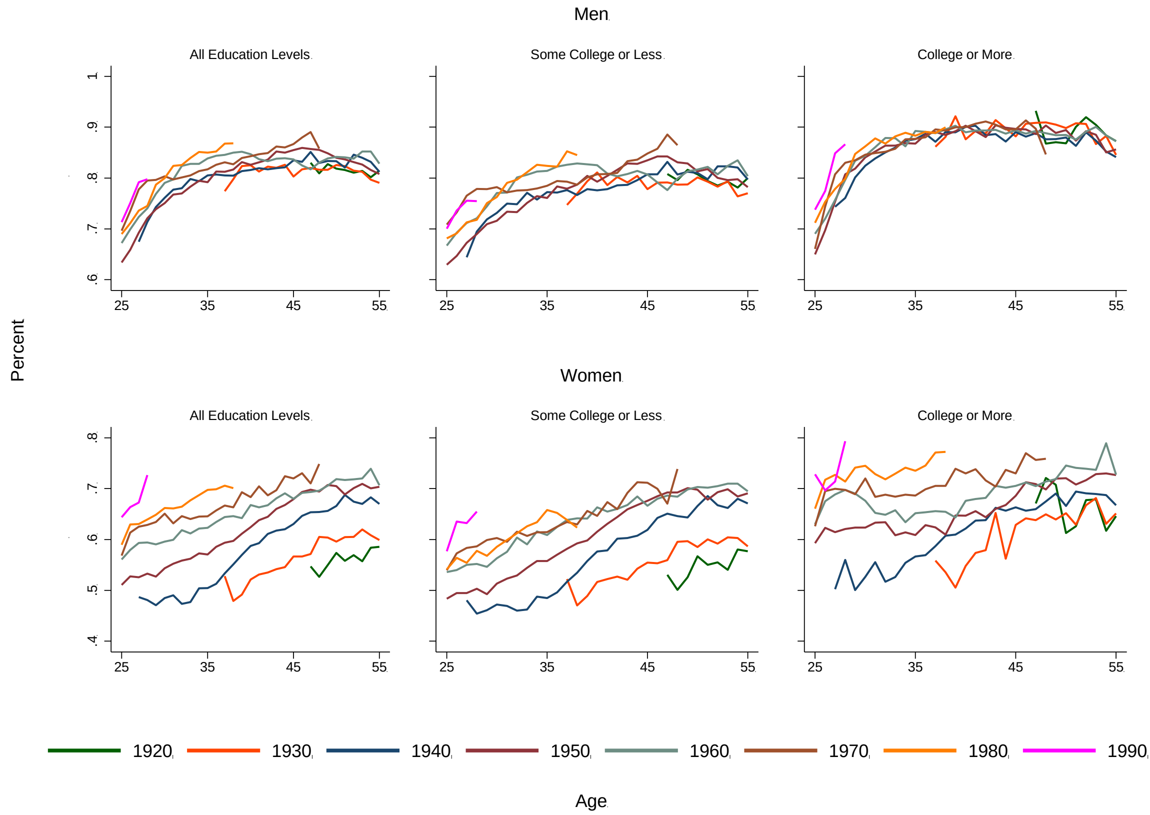

Figure A.3. Trends in the Level and Variation in Maximum Monthly Welfare Benefits

Figure A.4. Trends in Participation in SNAP and TANF

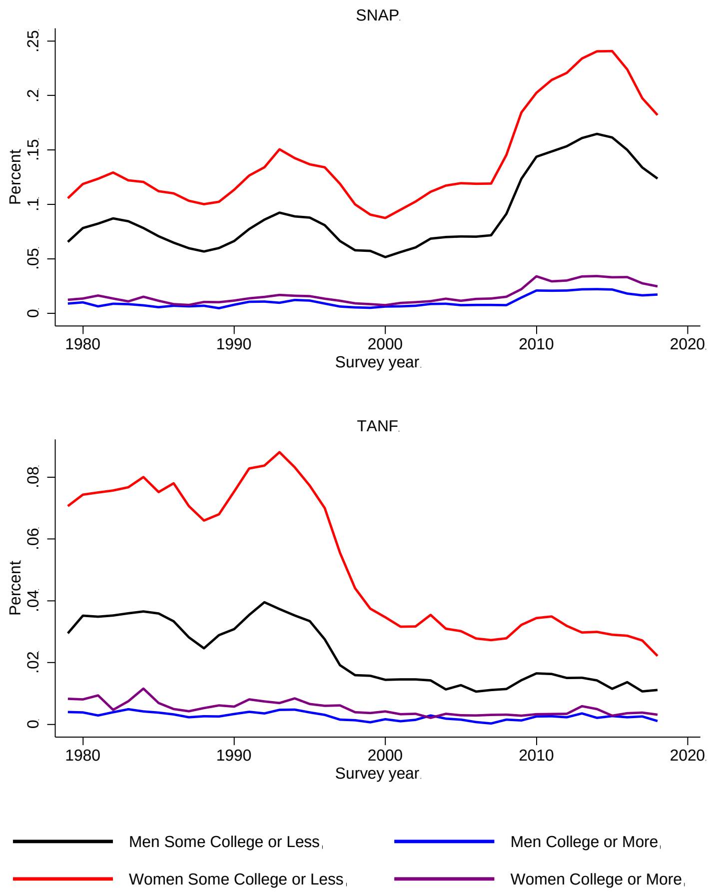

Figure A.5. Quantile Selection Pseudo Life Cycle Age-Wage Profiles of Men with Time Effects

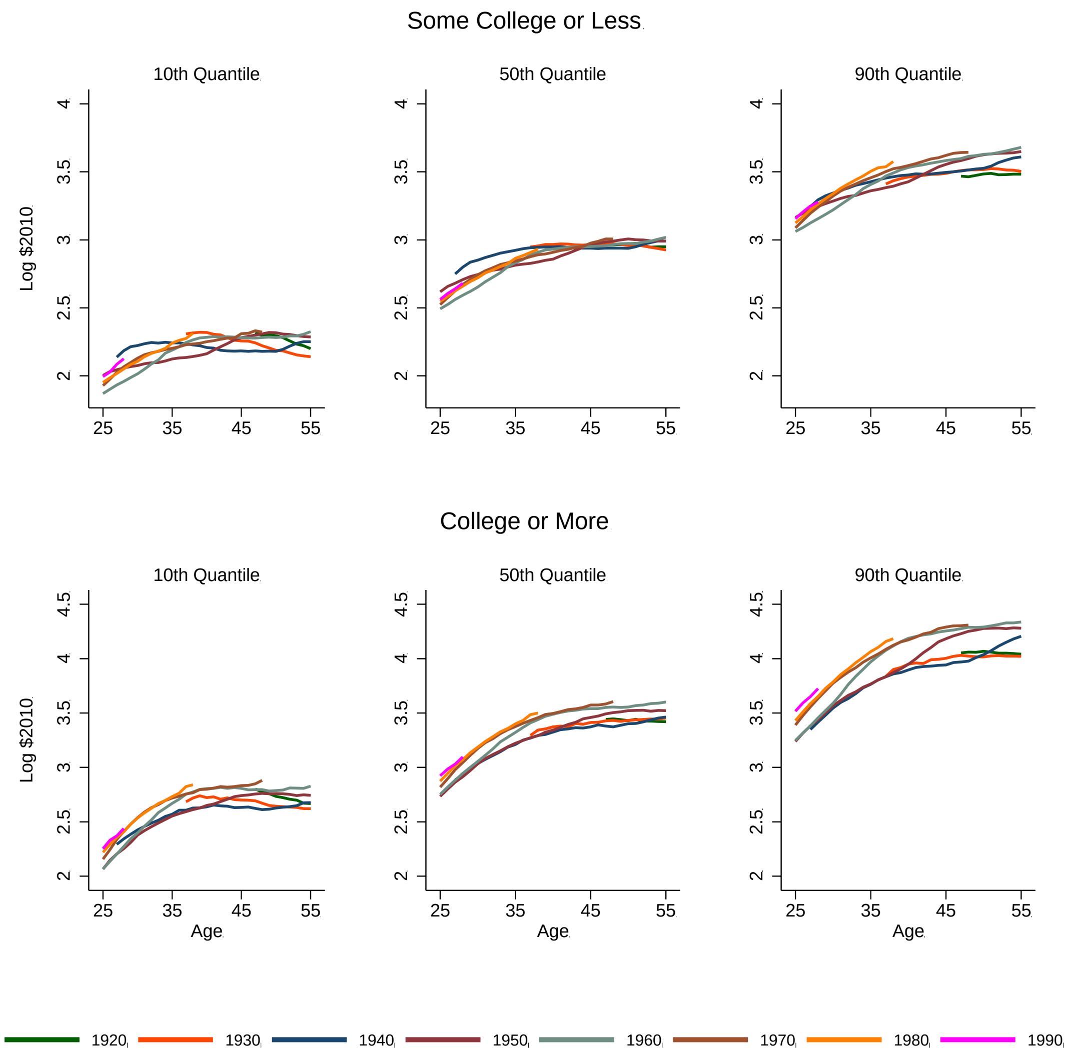

Figure A.6. Quantile Selection Pseudo Life Cycle Age-Wage Profiles of Women with Time Effects

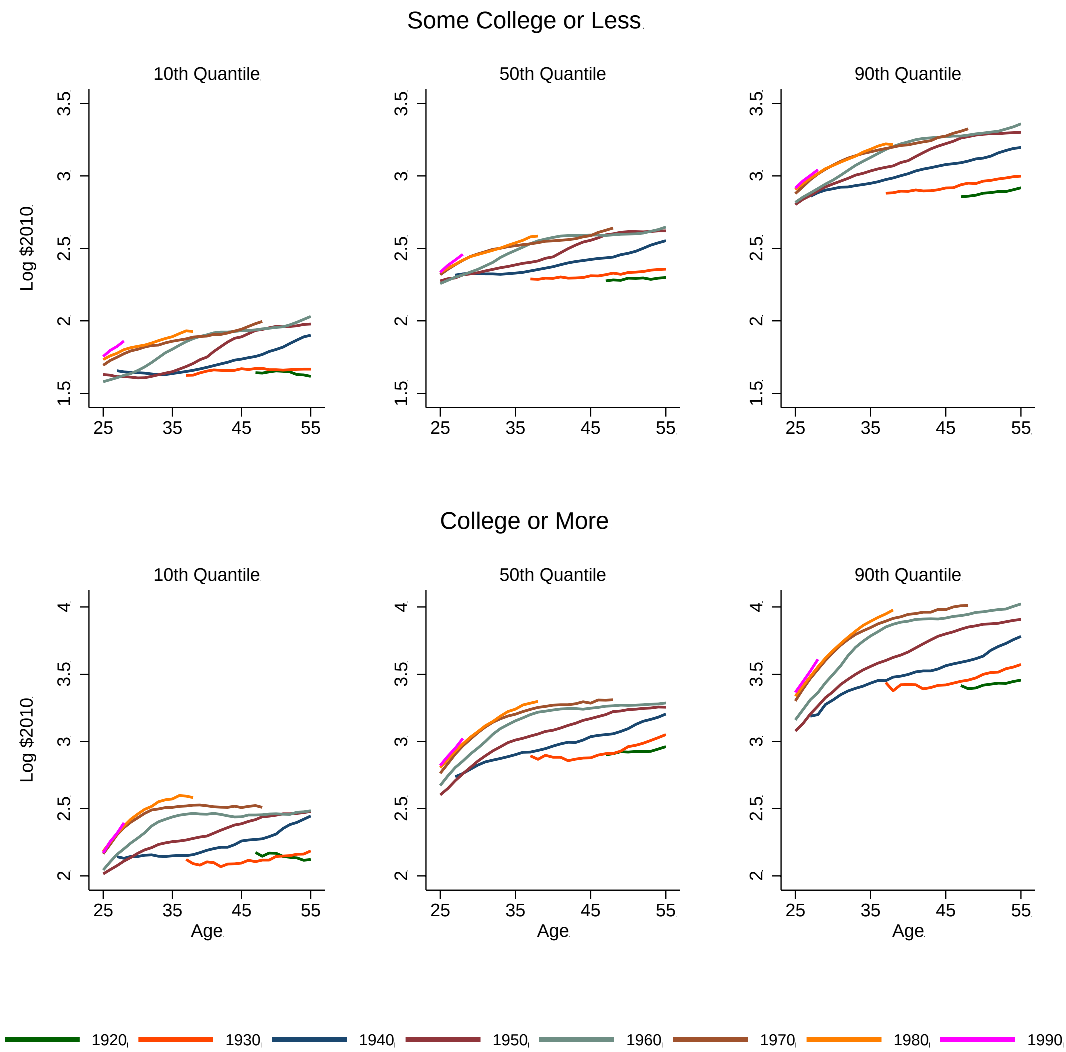

Figure A.7. Quantile Selection Pseudo Life Cycle Age-Wage Profiles of Full-Time Men

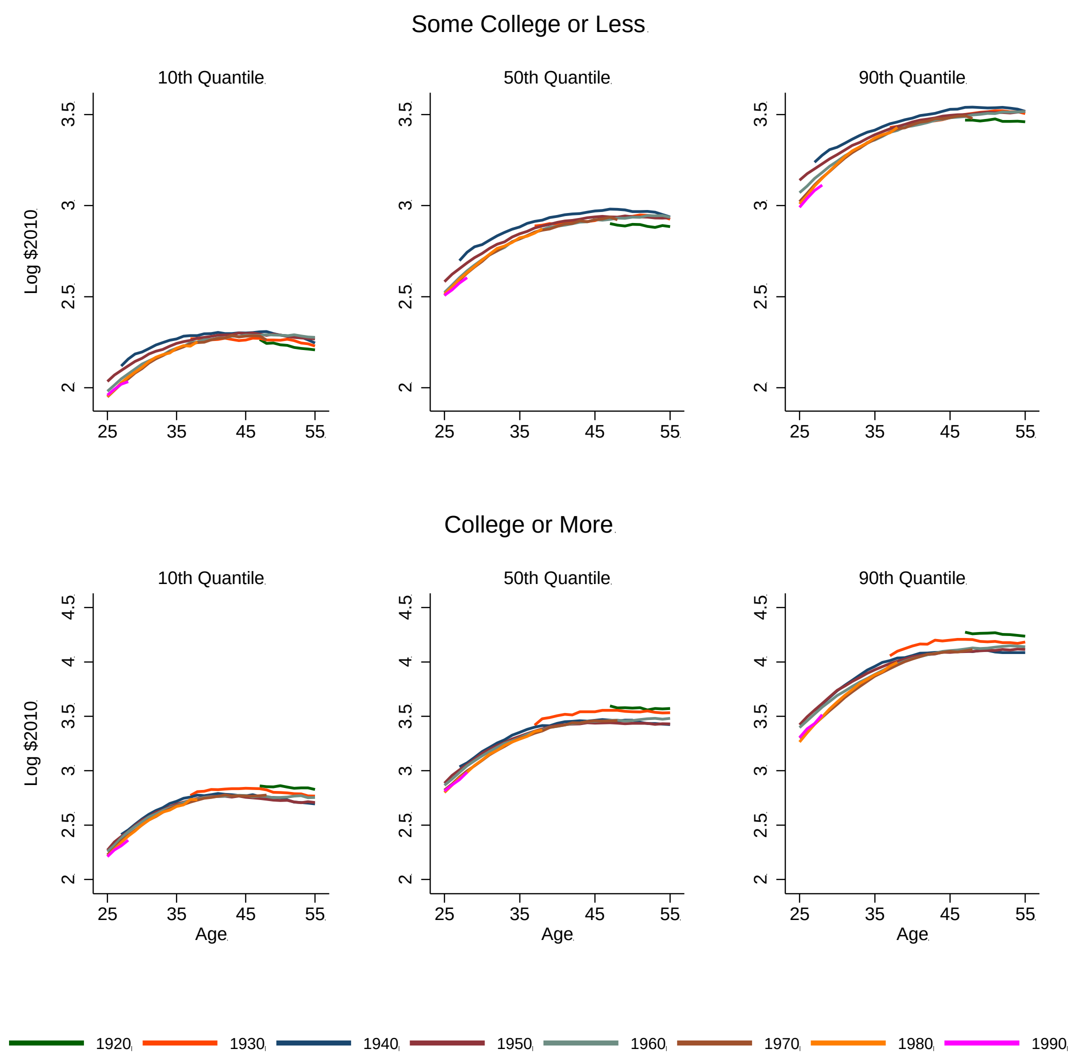

Figure A.8. Quantile Selection Pseudo Life Cycle Age-Wage Profiles of Full-Time Women

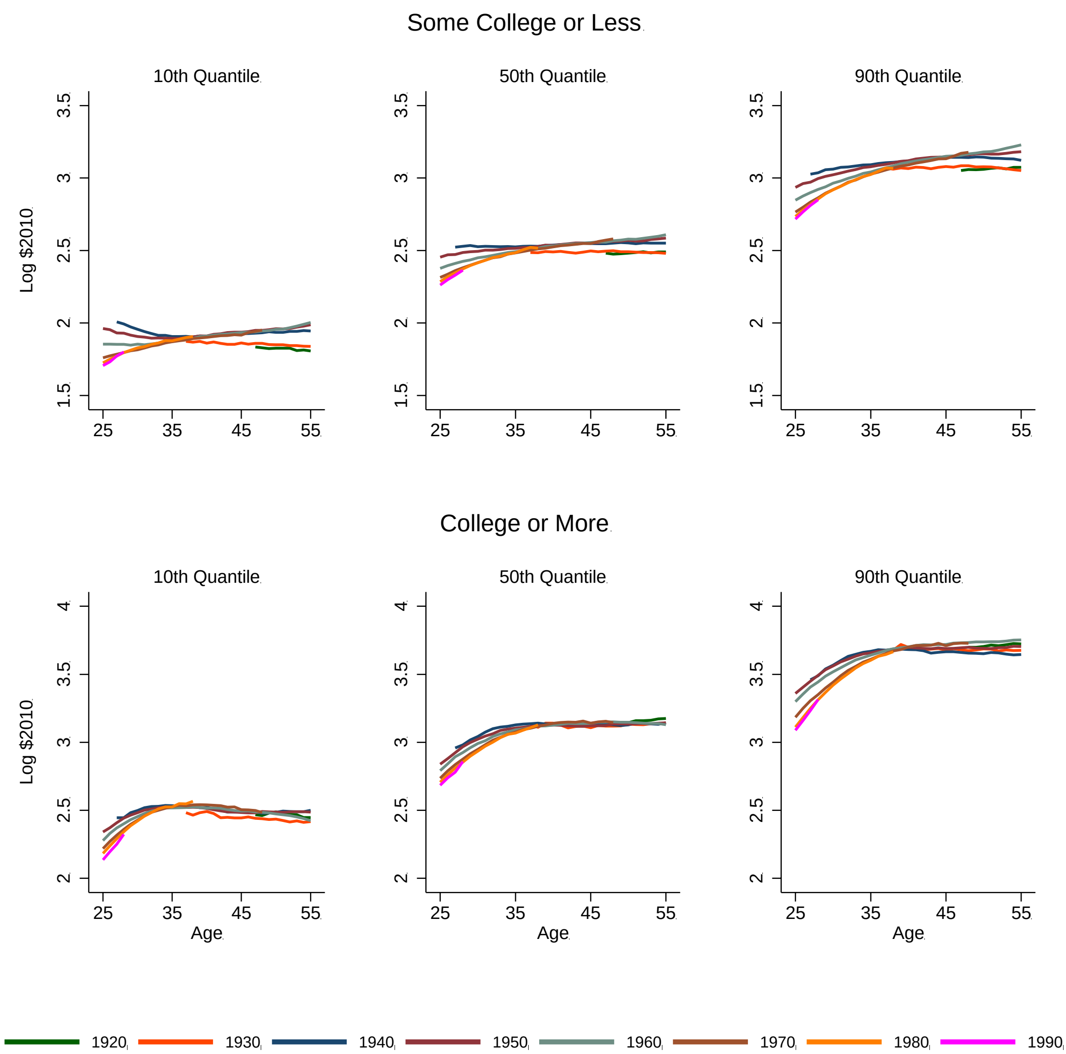

Figure A.9. Within-Education Group Inequality of Male Wages over the Life Cycle with Time Effects

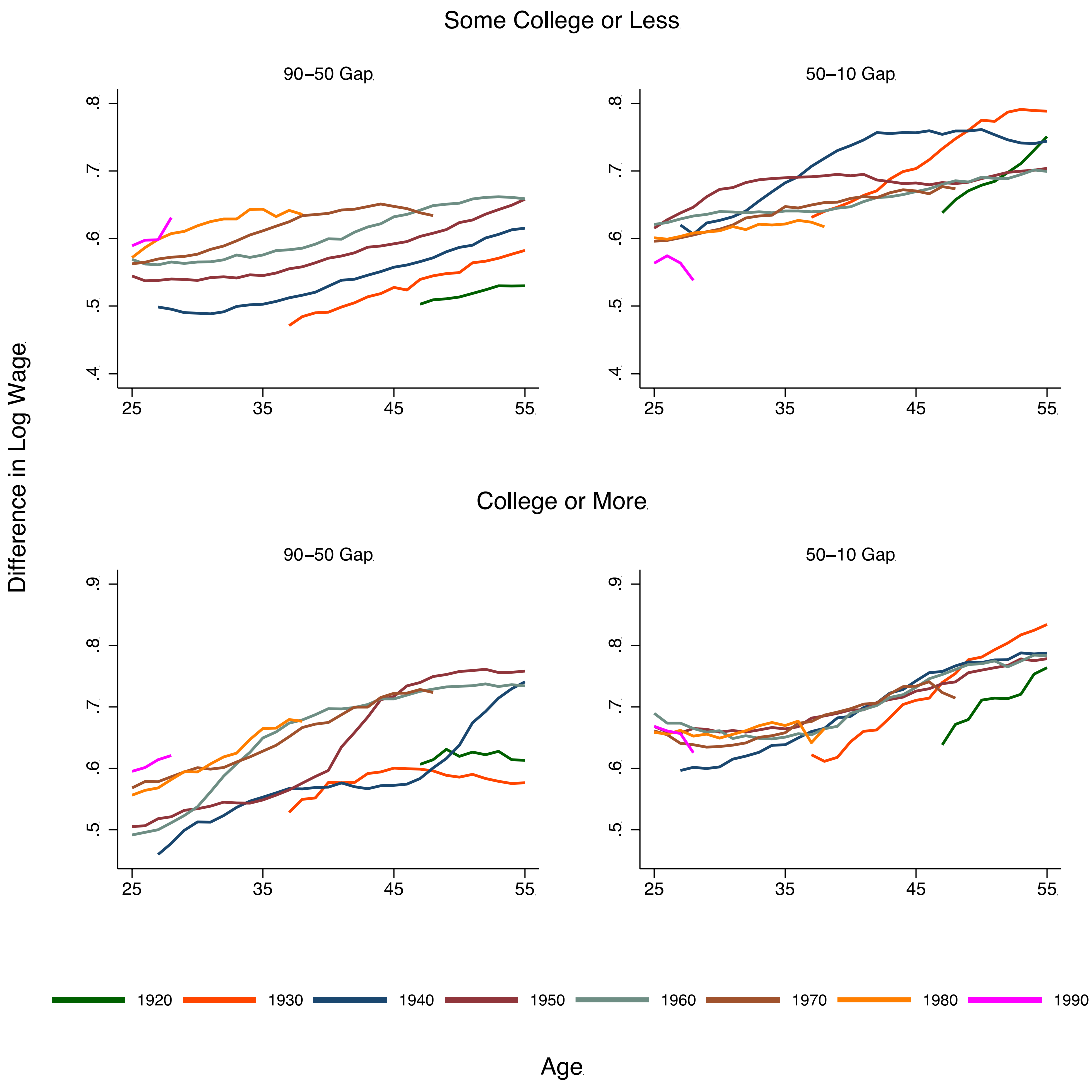

Figure A.10. Between-Education Group Inequality of Male Offer Wages over the Life Cycle with Time Effects

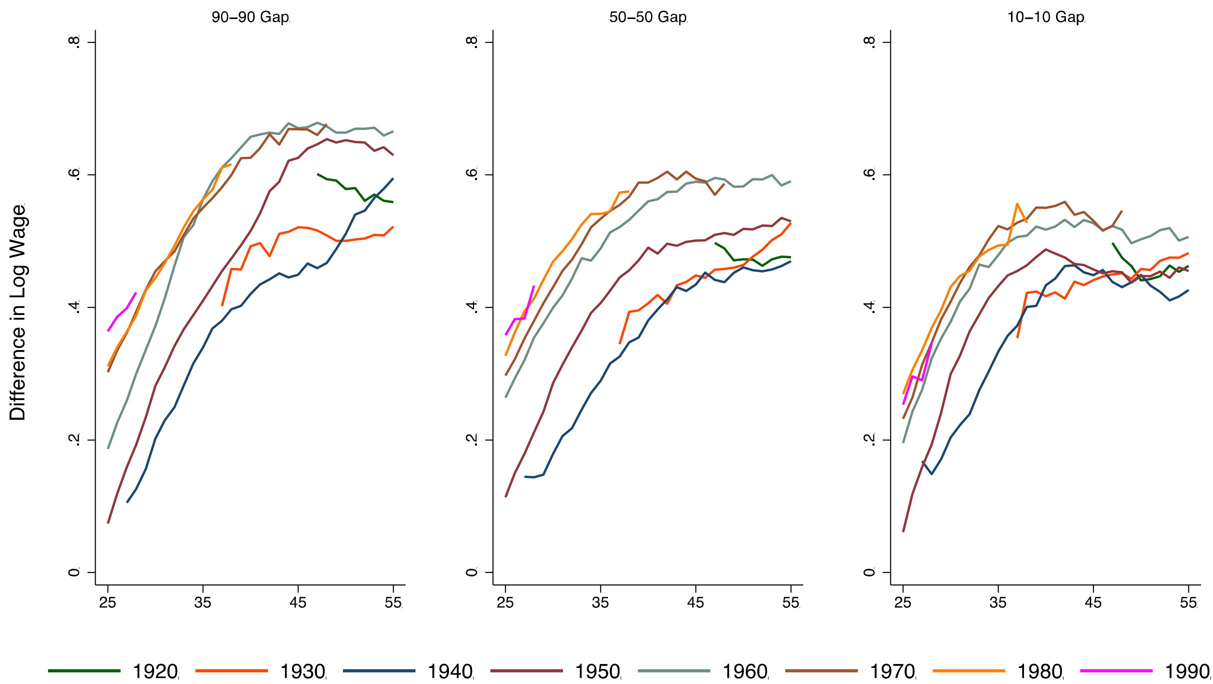

Figure A.11. Within-Education Group Inequality of Female Wages over the Life Cycle with Time Effects

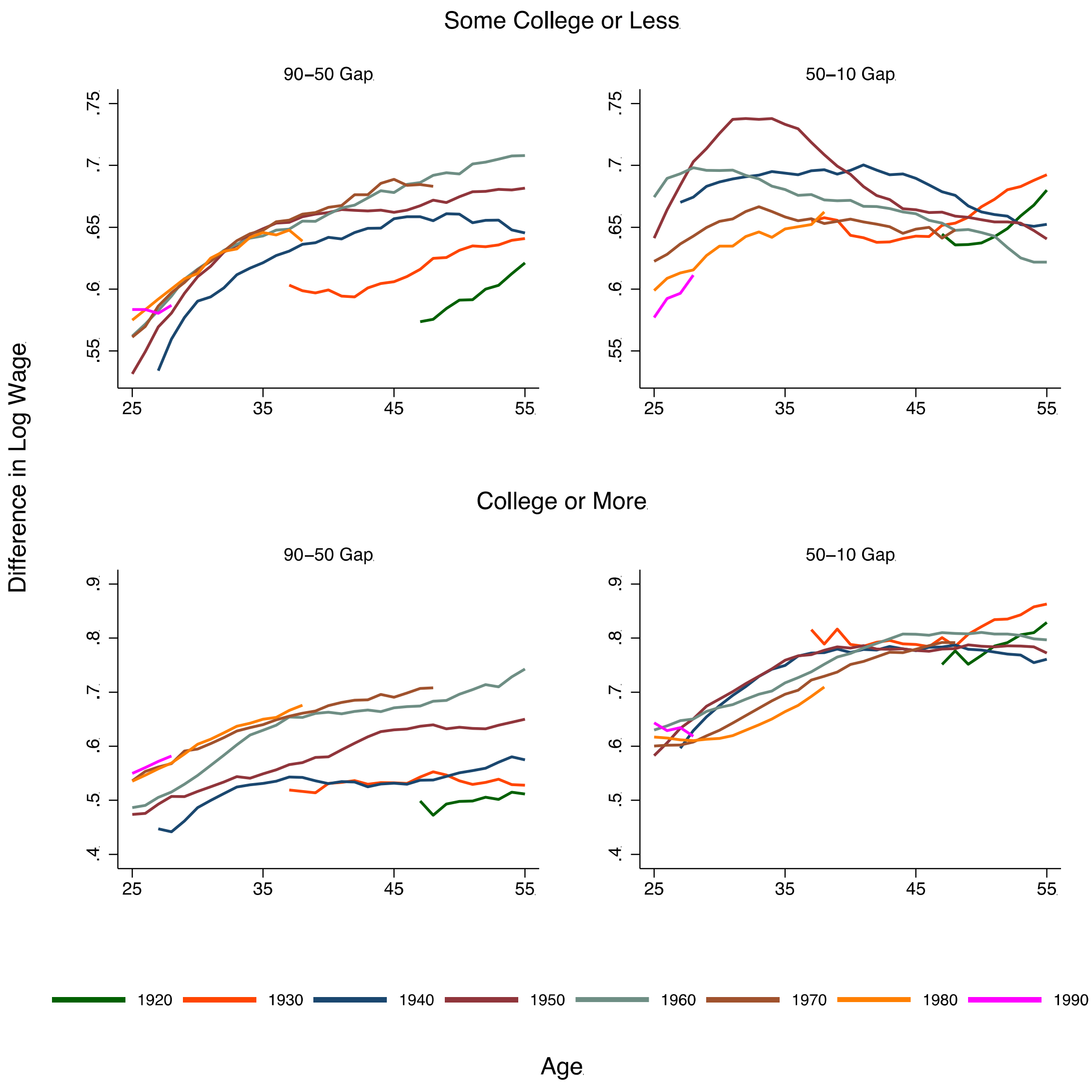

Figure A.12. Between-Education Group Inequality of Female Offer Wages over the Life Cycle with Time Effects

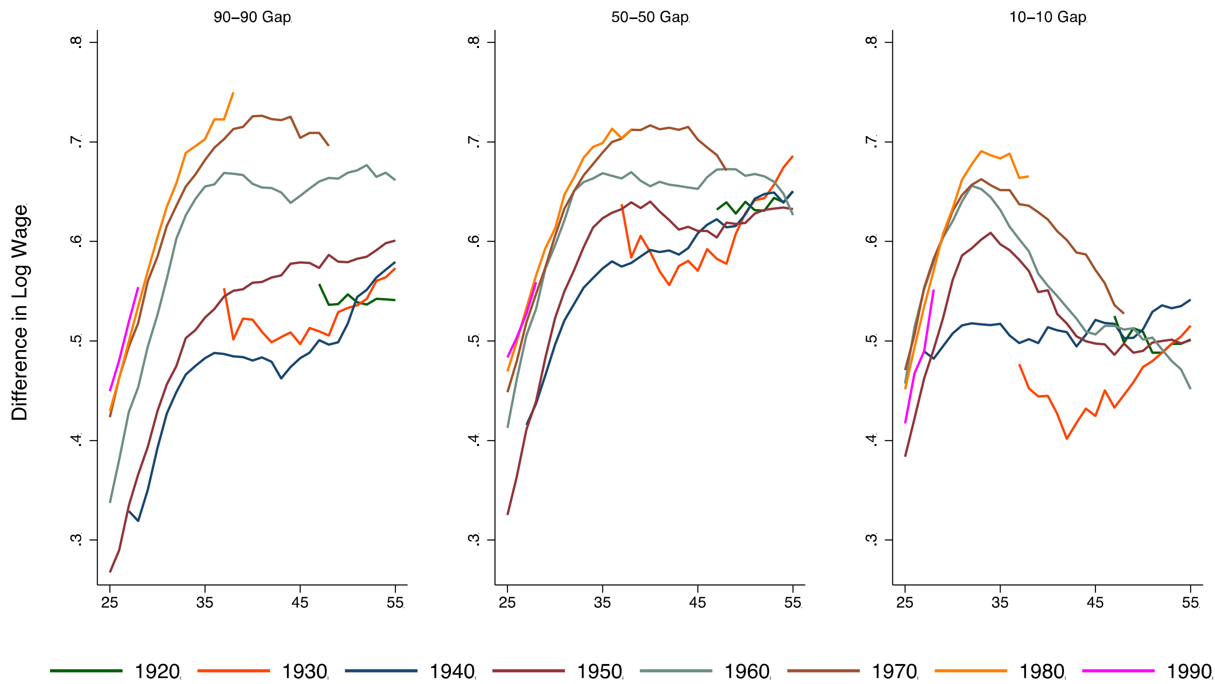

Figure A.13. Within-Skill Group Gender Wage Gaps over the Life Cycle among Full-Time Workers

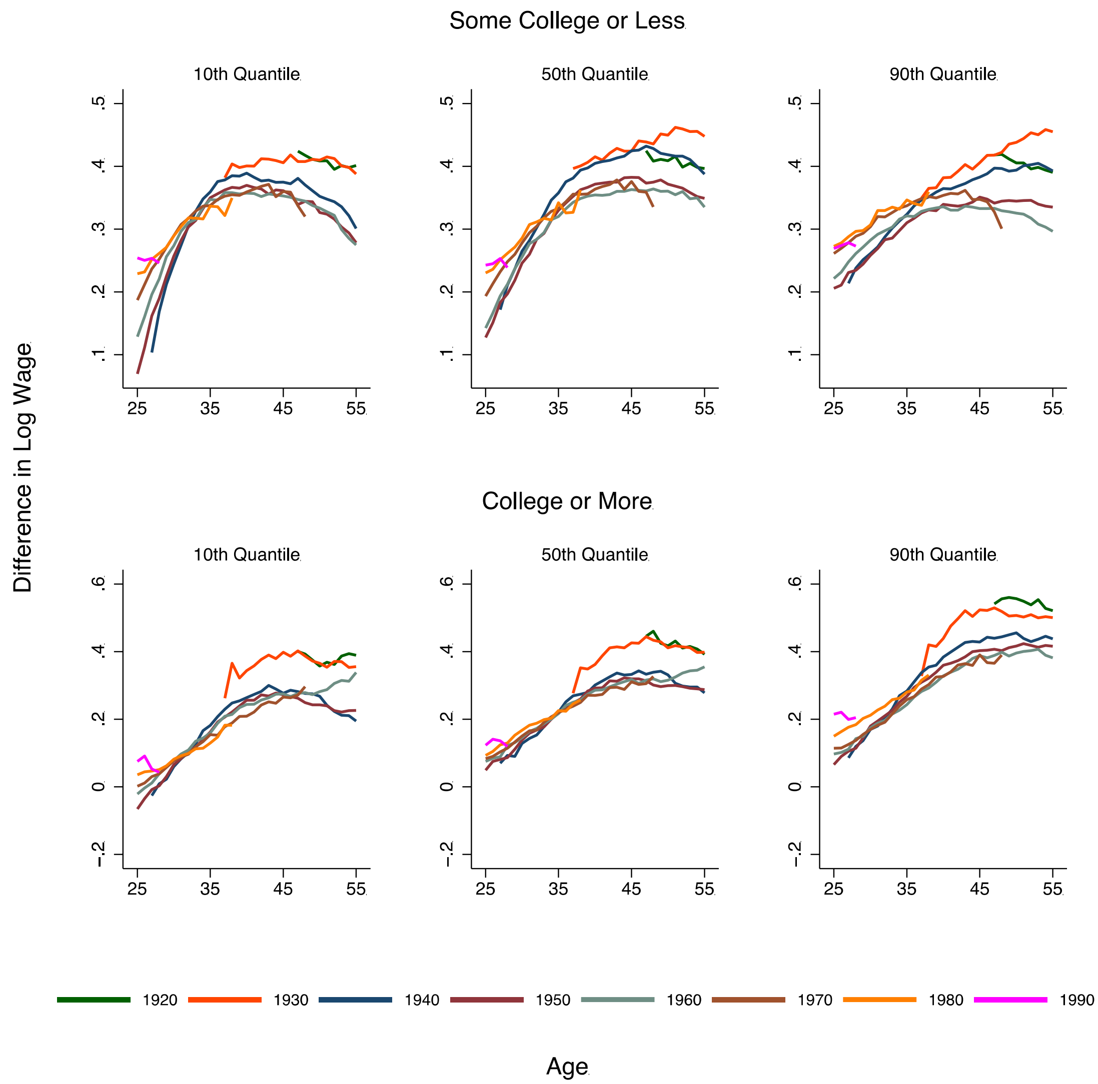

Table A.1. Weighted Sample Summary Statistics of Men and Women by Education Attainment

	Men				Women			
	Some college or less		College or more		Some college or less		College or more	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev
Employed	0.85	0.35	0.94	0.23	0.67	0.47	0.82	0.38
Full-Time Worker	0.67	0.47	0.82	0.39	0.41	0.49	0.56	0.50
Log Wage ($2010)	2.82	0.57	3.32	0.63	2.50	0.58	3.05	0.61
Age	39.14	8.85	39.18	8.60	39.47	8.88	38.66	8.58
Married	0.62	0.49	0.69	0.46	0.63	0.48	0.68	0.47
White	0.82	0.38	0.84	0.36	0.80	0.40	0.81	0.39
Black	0.13	0.34	0.06	0.24	0.15	0.36	0.09	0.28
Other Race	0.04	0.20	0.09	0.29	0.04	0.21	0.09	0.29
Hispanic	0.16	0.36	0.06	0.23	0.14	0.35	0.06	0.24
Household Size	3.30	1.61	3.06	1.44	3.44	1.58	3.04	1.39
Number of Kids Ages 0-5	0.33	0.66	0.35	0.67	0.36	0.68	0.35	0.66
Number of Kids Ages 6-18	0.52	0.86	0.47	0.82	0.66	0.93	0.48	0.81
Live in Metro Area	0.78	0.41	0.89	0.31	0.79	0.41	0.89	0.32
State Unemployment Rate (%)	6.31	2.03	6.18	2.01	6.35	2.03	6.13	1.99
Maximum SNAP Benefit ('00s)	4.26	0.45	4.31	0.45	4.24	0.44	4.36	0.46
Maximum TANF Benefit ('00s)	5.23	2.33	5.36	2.26	5.28	2.36	5.18	2.18

Note: There are 758,831 men with some college or less; 311,006 men with college or more; 891,622 women with some college or less; and 332,723 women with college or more.

Table A.2. Weighted Sample Summary Statistics of Full-Time Working Men and Women by Education Attainment

	Men				Women			
	Some college or less		College or more		Some college or less		College or more	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev
Log Wage ($2010)	2.86	0.53	3.36	0.60	2.60	0.51	3.10	0.54
Age	39.18	8.64	39.48	8.38	39.89	8.72	38.67	8.68
Married	0.70	0.46	0.73	0.44	0.58	0.49	0.60	0.49
White	0.85	0.35	0.85	0.35	0.80	0.40	0.80	0.40
Black	0.10	0.31	0.06	0.24	0.16	0.36	0.11	0.31
Other Race	0.04	0.19	0.08	0.28	0.04	0.20	0.08	0.28
Hispanic	0.15	0.36	0.05	0.22	0.12	0.33	0.06	0.24
Household Size	3.34	1.56	3.12	1.44	3.10	1.44	2.75	1.31
Number of Kids Ages 0-5	0.35	0.67	0.37	0.69	0.23	0.53	0.23	0.54
Number of Kids Ages 6-18	0.56	0.87	0.51	0.84	0.53	0.82	0.38	0.71
Live in Metro Area	0.78	0.41	0.89	0.31	0.80	0.40	0.88	0.32
State Unemployment Rate (%)	6.18	1.98	6.14	1.99	6.15	1.96	6.07	1.98
Maximum SNAP Benefit ('00s)	4.24	0.44	4.30	0.45	4.25	0.44	4.37	0.46
Maximum TANF Benefit ('00s)	5.24	2.32	5.32	2.25	5.13	2.27	5.05	2.14

Note: There are 521,636 men with some college or less; 256,820 men with college or more; 355,760 women with some college or less; and 181,776 women with college or more.

Table A.3. Sample Summary Statistics of Non-Working Men and Women by Education Attainment

	Men				Women			
	Some college or less		College or more		Some college or less		College or more	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev
Age	40.86	9.33	39.01	9.90	39.91	9.12	39.29	8.34
Married	0.36	0.48	0.47	0.50	0.67	0.47	0.83	0.38
White	0.69	0.46	0.72	0.45	0.79	0.41	0.78	0.42
Black	0.25	0.43	0.12	0.32	0.15	0.36	0.06	0.24
Other Race	0.06	0.23	0.16	0.36	0.05	0.22	0.15	0.36
Hispanic	0.15	0.36	0.08	0.27	0.18	0.39	0.07	0.26
Household Size	3.16	1.73	2.90	1.52	3.76	1.71	3.65	1.42
Number of Kids Ages 0-5	0.21	0.56	0.19	0.52	0.49	0.79	0.60	0.84
Number of Kids Ages 6-18	0.36	0.78	0.27	0.66	0.76	1.01	0.68	0.94
Live in Metro Area	0.79	0.41	0.90	0.30	0.79	0.41	0.91	0.28
State Unemployment Rate (%)	6.50	2.10	6.40	2.08	6.55	2.09	6.26	2.03
Maximum SNAP Benefit ('00s)	4.38	0.48	4.41	0.49	4.26	0.46	4.40	0.46
Maximum TANF Benefit ('00s)	4.95	2.24	5.26	2.23	5.32	2.44	5.19	2.22

Note: There are 93,622 men with some college or less; 15,183 men with college or more; 292,428 women with some college or less; and 59,521 women with college or more.

Table A.4. Quantile Selection Estimates of Log Wages for Full-Time Men with Some College or Less

	Employment	10th Quantile	50th Quantile	90th Quantile
Constant	0.570	1.972	2.510	3.005
	(0.083)	(0.027)	(0.022)	(0.019)
Entryage	0.235	0.272	0.341	0.275
	(0.026)	(0.026)	(0.016)	(0.015)
Entryage^2	-0.087	-0.074	-0.040	0.009
	(0.026)	(0.027)	(0.015)	(0.016)
Entryage^3	-0.013	0.006	0.000	-0.010
	(0.006)	(0.007)	(0.003)	(0.004)
Time	0.606	0.154	0.052	0.147
	(0.202)	(0.159)	(0.085)	(0.086)
Time^2	-1.857	-0.870	-0.258	-0.210
	(0.772)	(0.593)	(0.326)	(0.355)
Time^3	0.906	0.633	0.101	0.070
	(0.528)	(0.417)	(0.228)	(0.282)
Time^4	-0.141	-0.167	-0.009	-0.001
	(0.140)	(0.113)	(0.064)	(0.087)
Time^5	0.005	0.015	-0.000	-0.001
	(0.013)	(0.011)	(0.006)	(0.009)
Cohort^2	0.005	0.008	0.007	-0.019
	(0.006)	(0.006)	(0.003)	(0.004)
Cohort^2*delta	0.170	-0.040	-0.094	-0.089
	(0.020)	(0.019)	(0.010)	(0.013)
Cohort^3	0.036	-0.001	0.004	0.002
	(0.005)	(0.005)	(0.002)	(0.003)
R1	28.777	0.109	-88.805	-110.970
	(33.452)	(30.117)	(16.128)	(25.589)
R2	-5.108	1.410	18.339	10.698
	(7.653)	(6.101)	(3.384)	(5.642)
R3	-3.821	-9.583	6.715	19.122
	(14.521)	(12.923)	(6.814)	(10.782)
R4	2.752	2.283	-0.273	-0.070
	(3.500)	(2.783)	(1.623)	(2.488)
Black	-0.357	-0.204	-0.216	-0.193
	(0.005)	(0.006)	(0.007)	(0.004)
Other Race	-0.298	-0.287	-0.222	-0.157
	(0.008)	(0.010)	(0.007)	(0.008)
Hispanic	-0.125	-0.366	-0.360	-0.265
	(0.005)	(0.004)	(0.005)	(0.004)
Married	0.569	0.212	0.187	0.167
	(0.003)	(0.009)	(0.009)	(0.007)
Live in Metro Area	0.132	0.185	0.147	0.121
	(0.004)	(0.005)	(0.003)	(0.003)
State Unemployment Rate	-0.045	-0.007	-0.003	-0.003
	(0.002)	(0.002)	(0.001)	(0.001)
Household Size	-0.064	-0.031	-0.032	-0.029
	(0.001)	(0.002)	(0.001)	(0.001)
Number of Children Ages 0-5	0.045	0.015	0.021	0.027
	(0.003)	(0.003)	(0.001)	(0.002)
Number of Children Ages 6-18	0.061	0.029	0.031	0.028
	(0.002)	(0.002)	(0.001)	(0.002)
3-Person SNAP Benefit	-0.074			
	(0.018)			

3-Person TANF Benefit	0.010			
	(0.002)			
Rho	-0.68			
	(0.30)			
P-value on SNAP and TANF	0.00			
P-value on Cohort terms		0.00	0.00	0.00
P-value on R terms		0.04	0.00	0.00
P-value on R and Cohort terms		0.00	0.00	0.00

Note: The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

Table A.5. Quantile Selection Estimates of Log Wages for Full-Time Men with College or More

	Employment	10th Quantile	50th Quantile	90th Quantile
Constant	0.531	1.991	2.562	2.999
	(0.141)	(0.049)	(0.029)	(0.028)
Entryage	0.770	0.454	0.466	0.558
	(0.053)	(0.055)	(0.026)	(0.033)
$Entryage^2$	-0.355	-0.161	-0.162	-0.205
	(0.053)	(0.050)	(0.023)	(0.033)
$Entryage^3$	0.031	0.015	0.019	0.018
	(0.012)	(0.011)	(0.005)	(0.008)
Time	0.152	-0.086	-0.007	0.439
	(0.447)	(0.260)	(0.121)	(0.207)
$Time^2$	1.051	-0.368	0.238	-0.823
	(1.712)	(1.079)	(0.491)	(0.823)
$Time^3$	-0.817	0.226	-0.155	0.382
	(1.145)	(0.736)	(0.358)	(0.577)
$Time^4$	0.209	-0.039	0.037	-0.057
	(0.291)	(0.188)	(0.100)	(0.159)
$Time^5$	-0.018	0.002	-0.003	0.002
	(0.026)	(0.017)	(0.010)	(0.015)
$Cohort^2$	-0.011	0.001	-0.007	-0.014
	(0.011)	(0.010)	(0.005)	(0.007)
$Cohort^2$*delta	0.129	0.057	0.114	0.148
	(0.033)	(0.029)	(0.016)	(0.025)
$Cohort^3$	0.005	0.013	0.028	0.007
	(0.008)	(0.008)	(0.004)	(0.006)
R1	46.449	11.216	74.947	138.770
	(57.149)	(51.337)	(25.965)	(46.871)
R2	-30.678	-5.357	-21.395	-37.714
	(12.069)	(10.988)	(6.045)	(10.584)
R3	-5.698	-8.141	-34.627	-23.902
	(25.251)	(22.961)	(11.180)	(22.098)
R4	10.395	4.330	9.547	7.317
	(5.833)	(5.190)	(2.674)	(5.023)
Black	-0.229	-0.224	-0.239	-0.262
	(0.012)	(0.013)	(0.007)	(0.009)
Other Race	-0.234	-0.216	-0.029	-0.035
	(0.010)	(0.013)	(0.009)	(0.008)
Hispanic	-0.152	-0.336	-0.196	-0.164
	(0.010)	(0.014)	(0.007)	(0.008)
Married	0.394	0.215	0.154	0.107
	(0.008)	(0.011)	(0.009)	(0.009)
Live in Metro Area	0.114	0.245	0.220	0.194
	(0.009)	(0.008)	(0.004)	(0.005)
State Unemployment Rate	-0.020	-0.004	-0.004	-0.007
	(0.003)	(0.002)	(0.001)	(0.002)
Household Size	-0.042	-0.029	-0.020	-0.011
	(0.003)	(0.003)	(0.002)	(0.003)
Number of Children Ages 0-5	0.093	0.051	0.048	0.058
	(0.006)	(0.004)	(0.003)	(0.003)
Number of Children Ages 6-18	0.100	0.055	0.048	0.056
	(0.005)	(0.004)	(0.002)	(0.003)
3-Person SNAP Benefit	-0.064			
	(0.030)			

3-Person TANF Benefit	0.007			
	(0.004)			
Rho	-0.88			
	(0.47)			
P-value on SNAP and TANF	0.02			
P-value on Cohort terms		0.21	0.00	0.00
P-value on R terms		0.01	0.00	0.00
P-value on R and Cohort terms		0.00	0.00	0.00

Note: The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

Table A.6. Quantile Selection Estimates of Log Wages for Full-Time Women with Some College or Less

	Employment	10th Quantile	50th Quantile	90th Quantile
Constant	0.135	1.820	2.237	2.636
	(0.073)	(0.036)	(0.023)	(0.027)
Entryage	0.016	-0.001	0.218	0.310
	(0.024)	(0.040)	(0.016)	(0.022)
Entryage^2	0.050	0.049	-0.067	-0.090
	(0.024)	(0.037)	(0.016)	(0.022)
Entryage^3	-0.030	-0.010	0.008	0.011
	(0.006)	(0.009)	(0.004)	(0.005)
Time	0.076	-0.030	-0.028	0.237
	(0.174)	(0.316)	(0.124)	(0.131)
Time^2	0.778	0.499	-0.052	-0.871
	(0.668)	(1.145)	(0.465)	(0.524)
Time^3	-0.795	-0.381	-0.001	0.589
	(0.475)	(0.774)	(0.334)	(0.382)
Time^4	0.256	0.107	0.016	-0.139
	(0.132)	(0.198)	(0.092)	(0.110)
Time^5	-0.026	-0.010	-0.003	0.011
	(0.013)	(0.018)	(0.009)	(0.011)
Cohort^2	-0.059	-0.050	-0.021	-0.022
	(0.006)	(0.009)	(0.004)	(0.006)
Cohort^2*delta	-0.107	-0.142	-0.108	-0.099
	(0.019)	(0.023)	(0.013)	(0.018)
Cohort^3	-0.028	-0.018	-0.015	-0.017
	(0.005)	(0.006)	(0.003)	(0.004)
R1	-98.603	-122.350	-72.679	-7.945
	(31.708)	(37.305)	(21.154)	(30.056)
R2	-14.319	-1.605	6.234	-11.677
	(7.082)	(8.210)	(4.301)	(6.692)
R3	30.664	28.914	13.607	-15.962
	(14.022)	(17.748)	(9.598)	(12.400)
R4	4.485	1.624	-0.119	7.897
	(3.316)	(4.081)	(2.058)	(2.998)
Black	0.009	-0.075	-0.093	-0.108
	(0.004)	(0.006)	(0.003)	(0.004)
Other Race	-0.072	-0.181	-0.127	-0.103
	(0.007)	(0.010)	(0.007)	(0.009)
Hispanic	-0.116	-0.255	-0.262	-0.197
	(0.004)	(0.007)	(0.009)	(0.005)
Married	-0.178	0.024	0.049	0.049
	(0.003)	(0.008)	(0.004)	(0.004)
Live in Metro Area	0.089	0.196	0.170	0.175
	(0.003)	(0.009)	(0.003)	(0.003)
State Unemployment Rate	-0.023	-0.003	-0.000	0.003
	(0.001)	(0.002)	(0.001)	(0.001)
Household Size	-0.032	-0.038	-0.046	-0.045
	(0.001)	(0.002)	(0.001)	(0.002)
Number of Children Ages 0-5	-0.302	-0.028	0.014	0.023
	(0.003)	(0.013)	(0.006)	(0.005)
Number of Children Ages 6-18	-0.146	-0.031	-0.010	0.005
	(0.002)	(0.006)	(0.004)	(0.004)
3-Person SNAP Benefit	-0.014			
	(0.017)			

3-Person TANF Benefit	-0.010			
	(0.002)			
Rho	-0.82			
	(0.45)			
P-value on SNAP and TANF	0.00			
P-value on Cohort terms		0.00	0.00	0.00
P-value on R terms		0.00	0.00	0.01
P-value on R and Cohort terms		0.00	0.00	0.00

Note: The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

Table A.7. Quantile Selection Estimates of Log Wages for Full-Time Women with College or More

	Employment	10th Quantile	50th Quantile	90th Quantile
Constant	0.872	2.188	2.496	2.786
	(0.119)	(0.056)	(0.016)	(0.026)
Entryage	-0.150	0.311	0.423	0.411
	(0.045)	(0.052)	(0.022)	(0.034)
Entryage^2	0.352	-0.068	-0.170	-0.207
	(0.050)	(0.056)	(0.026)	(0.033)
Entryage^3	-0.120	-0.009	0.021	0.029
	(0.013)	(0.014)	(0.007)	(0.008)
Time	0.092	-0.517	-0.208	-0.149
	(0.360)	(0.566)	(0.170)	(0.205)
Time^2	0.191	1.824	0.501	1.353
	(1.360)	(2.015)	(0.672)	(0.789)
Time^3	-0.008	-1.278	-0.466	-1.052
	(0.922)	(1.327)	(0.451)	(0.559)
Time^4	-0.008	0.336	0.154	0.292
	(0.234)	(0.324)	(0.114)	(0.153)
Time^5	0.002	-0.030	-0.016	-0.027
	(0.021)	(0.027)	(0.010)	(0.014)
Cohort^2	-0.167	-0.031	-0.005	-0.033
	(0.010)	(0.013)	(0.005)	(0.008)
Cohort^2*delta	-0.295	-0.127	-0.011	0.093
	(0.036)	(0.042)	(0.020)	(0.024)
Cohort^3	-0.057	-0.036	-0.008	0.007
	(0.008)	(0.012)	(0.005)	(0.006)
R1	-738.300	-184.680	4.501	125.420
	(57.376)	(58.489)	(33.140)	(41.181)
R2	75.373	33.178	7.294	-33.793
	(10.218)	(9.721)	(6.515)	(9.451)
R3	314.070	91.353	5.491	-42.410
	(25.018)	(25.575)	(13.677)	(18.182)
R4	-43.493	-18.883	-4.727	10.323
	(4.982)	(4.767)	(2.938)	(4.266)
Black	0.271	-0.035	-0.068	-0.103
	(0.011)	(0.010)	(0.006)	(0.009)
Other Race	-0.097	-0.151	0.000	0.031
	(0.008)	(0.011)	(0.009)	(0.008)
Hispanic	0.013	-0.249	-0.110	-0.117
	(0.009)	(0.013)	(0.005)	(0.008)
Married	-0.260	0.082	0.061	0.064
	(0.006)	(0.008)	(0.005)	(0.006)
Live in Metro Area	-0.057	0.143	0.140	0.196
	(0.006)	(0.007)	(0.004)	(0.005)
State Unemployment Rate	-0.013	-0.006	0.001	-0.001
	(0.002)	(0.003)	(0.001)	(0.002)
Household Size	-0.063	-0.076	-0.061	-0.057
	(0.003)	(0.004)	(0.003)	(0.003)
Number of Children Ages 0-5	-0.353	0.087	0.083	0.093
	(0.005)	(0.010)	(0.006)	(0.009)
Number of Children Ages 6-18	-0.171	0.021	0.035	0.048
	(0.004)	(0.007)	(0.004)	(0.005)
3-Person SNAP Benefit	-0.043			
	(0.025)			

3-Person TANF Benefit	-0.013			
	(0.003)			
Rho	-0.60			
	(0.44)			
P-value on SNAP and TANF	0.00			
P-value on Cohort terms		0.00	0.08	0.00
P-value on R terms		0.00	0.04	0.00
P-value on R and Cohort terms		0.00	0.00	0.00

Note: The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.