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Labor Market Inequality and the Changing Life Cycle Profile of Male and Female Wages†

By Richard Blundell, Hugo Lopez, and James P. Ziliak*

We estimate the full distribution of life cycle wages for cohorts of men and women in the United States using a quantile selection model to account for systematic differences in employment by gender and education group. Although common within-group time effects are shown to be a key driver of labor market inequalities across gender, important additional differences by birth cohort emerge with more recent cohorts of women delaying child rearing and, by implication, the onset of child penalties in wages. These cross-cohort differences help account for the stalling of progress in gender wage gaps over the past quarter century. (*JEL* D15, J13, J16, J24, J31)

Women's relative economic progress in the second half of the twentieth-century United States was nothing less than "revolutionary" (Goldin 2006). This is exemplified in Figure 1, which shows gender wage gaps were cut in half across the distribution from the mid-1970s to the mid-1990s.[1] However, in a sharp reversal, progress stalled in the subsequent quarter century, especially in the top half of the wage distribution. These time-series patterns hold among full-time workers and by education group (see Supplemental Appendix Figure A1). Most of the extant literature on gender wage gaps has focused on levels and determinants in the cross-section over time (Blau and Beller 1988; Blau and Kahn 1997; Olivetti and Petrongolo 2008, 2016; Mulligan and Rubinstein 2008; Kleven et al. 2019; Maasoumi and Wang 2019; Fernández-Val et al. 2023; Blau et al. 2024), even though the sources and patterns of lifetime gender inequality may differ considerably both within and between birth cohorts. The latter includes life cycle and cohort changes in selection into employment, in education attainment, in fertility and family formation, in promotion opportunities, and in exposure to macroeconomic shocks, among others (Deaton and Paxson 1994; Blundell et al. 2007; Bertrand

* Blundell: University College London and Institute for Fiscal Studies (email: r.blundell@ucl.ac.uk); Lopez: University of Chicago (email: hugolopez@uchicago.edu); Ziliak: University of Kentucky (email: jziliak@uky.edu). Camille Landais was coeditor for this article. We thank Johannes Schmieder, participants at the 2022 American Economic Association Meeting, Rutgers University, University of Iowa, University of Oregon, and Washington State University for helpful comments on earlier drafts. 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.

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[1] The sample is workers aged 25–55 in the Current Population Survey Annual Social and Economic Supplement. See Supplemental Appendix A for details.

2011; Huggett, Ventura, and Yaron 2011; Goldin 2014; Goldin and Mitchell 2016; Juhn and McCue 2017; Kleven et al. 2019; Borella, Nardi, and Yang 2020; Sloane, Hurst, and Black 2021).

In this paper, we provide new estimates of the life cycle gender wage gap across birth cohorts, education groups, and wage distributions in the presence of nonrandom selection into work. 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, Machin, and Meghir 2000; Card and Lemieux 2001; Fitzenberger and Wunderlich 2002; Kambourov and Manovskii 2009; Kong, Ravikumar, and Vandenbroucke 2018; 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; Blundell et al. 2007; 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. 2021; Fernández-Val et al. 2023; Blau et al. 2024). Some in the cohort 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 to study wage gaps over the working life of cohorts of men and women.

A well-known identification problem in models with age, birth cohort, and period effects is that any period can be written as the sum of age and cohort, and thus, restrictions on functional form are necessary (Heckman and Robb 1985). We expand upon the cohort wage specification of MaCurdy and Mroz (1995) and Fitzenberger and Wunderlich (2002) that includes a highly nonlinear parameterization of age, cohort, and time to flexibly capture changes in wages over the life cycle as well as macroeconomic trends, while controlling for gender and education-group time shocks. We also relax separability in age and time effects—meaning we do not assume age-wage profiles are parallel across cohorts (Mincer 1974)—but the specification embeds a direct test of whether life cycle age-wage profiles are parallel.

A similarly challenging identification issue is found in models with nonrandom selection that requires 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). While the gender gap literature has long been concerned about selection of women on unobservables into work (Blau and Kahn 2017), with some recent exceptions (e.g., Maasoumi and Wang 2019; Fernández-Val et al. 2023; Blau et al. 2024), these issues were often eschewed for men on the assumption that their high labor force attachment rendered selection exogenous (and thus implicitly imposed a so-called identification at infinity assumption; c.f. Chamberlain 1986; Heckman 1990). However, there has been a retreat from work among men, especially among those at lower education levels (Blundell et al. 2018; Abraham and Kearney 2020; Aguiar et al. 2021), suggesting that the assumption of exogenous selection of men on unobservables may no longer be tenable.

We estimate the cohort wage model using the recently developed quantile with selection estimator proposed by Arellano and Bonhomme (2017). This estimator extends the canonical conditional mean selection on unobservables model from Heckman (1979) to the full distribution of wages, generalizing earlier efforts (Buchinsky 1998). Like the Heckman model, the power of the Arellano and Bonhomme estimator is strengthened by exclusion restrictions to identify the extensive margin of employment from the intensive margin of wages. 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. 2023). Instead of using potentially correlated family structure variables like the age composition of children to identify the selection rule, our approach to identification of the selection process is to exploit the dramatic changes in the tax and transfer system since the 1970s to create simulated disposable income instruments—one capturing disposable income if one or both partners (in married couples) are out of work and a second a weighted sum of disposable income across eight categories of no work, part-time work, and full-time work for the partners—as well as changes in the tightness of local labor markets as proxied by state unemployment rates. The use of tax and transfer policy reforms to construct simulated instruments is well established, and has been used to study such diverse topics as the effect of health insurance on birth outcomes (Currie and Gruber 1996), the effect of tax credits on labor supply (Meyer and Rosenbaum 2001; Blundell et al. 2016; Hoynes and Patel 2018), the effect of marginal tax rates on taxable income (Gruber and Saez 2002; Weber 2014; Burns and Ziliak 2017), and the effect of the safety net on food insecurity (Schmidt, Shore-Sheppard, and Watson 2016), among many others. To our knowledge, we are the first to use this approach in the gender wage gap literature.

Using a sample of prime-aged men and women from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey for calendar years 1976–2018, the model estimates show striking convergence in gender wage gaps across cohorts at a given age, especially for those born before the 1960s, which helps account for the time-series decline before the mid 1990s depicted in Figure 1. At the same time, we find sharply increasing life cycle gender wage gaps until around age 45 across both the wage distribution and education level. Whether these life cycle gaps fall at older ages varies by cohort, education level, and location in the wage distribution. The gender wage gaps tend to be more quadratic in age among workers without a college degree, but there is little life cycle convergence among college-educated women born after 1960 in the upper half of the wage distribution and indeed some divergence among high-educated, high-wage millennials. This helps account for the observed stagnation of gender wage gaps in the time series over the last quarter century. These cohort and life cycle patterns are robust to alternative approaches to specification of both the selection and wage equations.

We explore three possible mechanisms for the estimated cohort patterns of life cycle gender age gaps, including the role of gender and education group-specific shocks common to cohorts, changes in the life cycle timing of child rearing across cohorts, and the rise of full-time work among women. These time shocks could include technological change affecting the returns to skill (Bound and Johnson 1992; Katz and

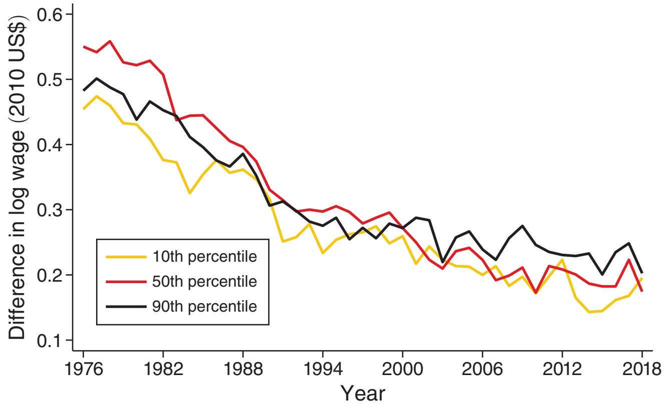

Figure 1. Time Series of Gender Gap in Log Hourly Wages of Workers

Notes: The figure depicts the difference in log wages of men and women at the tenth, fiftieth, and ninetieth percentiles of the gender-specific wage distributions. Wages are defined as the ratio of annual earnings to annual hours of work and are in real 2010 US$ using the Personal Consumption Expenditure Deflator. Sample consists of employed men and women aged 25–55. Workers with imputed earnings or hours are dropped, as are those with wages below the first percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

Sources: Authors' calculations; Current Population Survey Annual Social and Economic Supplement, Survey Years 1977–2019

Murphy 1992; Juhn, Murphy, and Pierce 1993; Card and DiNardo 2002), legislative and judicial changes affecting access to employment (Goldin and Katz 2002; Berger and Waldfogel 2004; Bailey 2006), and shifting cultural norms and expectations (Bertrand 2011). Many of these developments, including the rise of full-time work among women, would be expected to lead to reductions in gender gaps. At the same time, delays in fertility could result in postponement in the onset of large child penalties in wages (Kleven et al. 2019; Cortés and Pan 2023), and thus exacerbate gender gaps at older ages.

Our estimates indicate that common group-specific time effects eliminate much of the cross-cohort differences in gender wage gaps, both in levels and life cycle profiles, suggesting that common shocks differentially favored women over men. These time effects were more neutral across gender starting with the 1960s birth cohort. However, just as the cohorts of women less likely to differentially benefit from common shocks were entering the labor force, they also started to delay fertility, with peak age of raising a child increasing by at least five years between the 1940s and 1960s birth cohorts. This suggests that delayed child rearing likely has resulted in the child wage penalties kicking in later in the life cycle, which helps account for the stalling of the gender gap in recent cohorts. Importantly, our approach allows children to have a direct impact on wages, as well as an impact through selection into work. Both avenues are important. Indeed, excluding the number and age distribution of children from the wage equation has a systematic impact on our estimates of selection, suggesting that positive selection for college-educated women appears to be largely driven by children, most likely through the impact on past human capital investments.

The 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 gender wage gaps across the life course. The final section concludes.

I. 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 Supplemental Appendix A, the data come from repeated cross sections of the Annual Social and Economic Supplement of the Current Population Survey spanning the 1976–2018 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 birth years, but to ease presentation, we take averages within decades at each age for the figures. 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").[2] Employment is defined as any paid work in the calendar year, and hourly wages are defined as the ratio of annual earnings to annual hours, deflated to 2010 base year with the Personal Consumption Expenditure Deflator. Additional details are in Supplemental Appendix A.

Figure 2 depicts employment rates for men and women by decadal birth cohort and education level. The figure shows that employment among men with less than a college degree falls over time at any given age starting with the 1950s cohort and that employment rates progressively peak earlier in their working life. For example, employment among noncollege men in the 1930s cohort peak just before age 40, but that peak occurs a decade earlier among those born in the 1970s.[3] For men with at least a college degree, employment remains high over much of their working life, although it falls at each age, and there is some evidence that it peaks at younger ages starting with the 1960s cohort.

The employment patterns across cohorts of women are striking. For example, employment rates among noncollege women born in the 1940s are stable at around 65 percent from ages 25–35, before accelerating and taking on the familiar

[2] Because of secular trends in education attainment, Bailey, Guldi, and Hershbein (2014) split by quartiles of the education-attainment distribution. In Supplemental Appendix E and discussed in the robustness section below, we split the sample into the top quartile for the high-education group and pool the bottom three quartiles for the lower-education group. Because the top quartile coincides with the college-and-more group for over half the sample period, this has no substantive effects on the estimated parameters and gaps.

[3] 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.

Figure 2. Life Cycle Employment Rates across Cohorts

Notes: Employment refers to any paid work in the calendar year. Sample consists of men and women aged 25–55 who do not have imputed earnings or hours of work.

Sources: Authors' calculations; Current Population Survey Annual Social and Economic Supplement, Survey Years 1977–2019

hump-shaped life cycle profile. Women born in the 1950s begin the upward climb five years younger and thus sustain higher employment rates across more of their working life. Women born in the 1960s and 1970s have even higher employment rates at young ages, but in an important departure from earlier cohorts, employment rates trend downward over their entire working life. Perhaps most striking, employment rates among noncollege women under age 35 born in the 1980s and 1990s fully revert to levels last observed in the 1940s cohort.

Employment rates of college-educated women born in the 1940s are 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 is 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 is eliminated—and with employment rates lower after age 30. Supplemental Appendix Figure A2 shows that among those employed, the aggregate share working full time (defined as working at least 35 hours per week for 50 weeks) increases over time; that is, aggregate employment declines for men and women come from marginally attached workers. Supplemental Appendix Figure A3

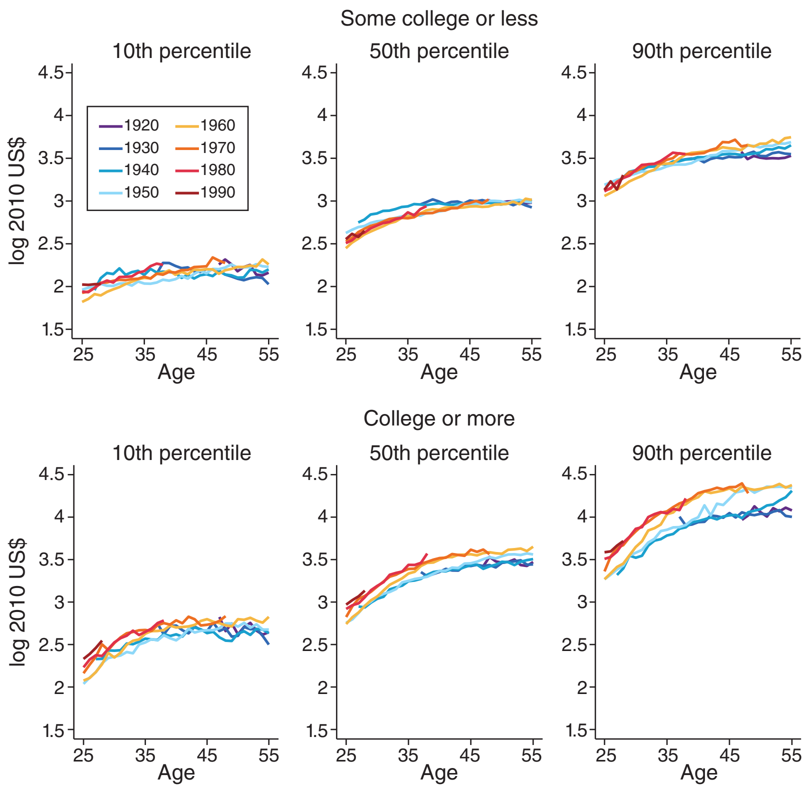

Figure 3. Distribution of Life Cycle Real Hourly Wages of Working Men across Cohorts

Notes: Wages are defined as the ratio of annual earnings to annual hours of work and are in real 2010 US$ using the Personal Consumption Expenditure Deflator. Sample consists of employed men aged 25–55. Workers with imputed earnings or hours are dropped, as are those with wages below the first percentile or above the 0.1 percentile of the real male- and year-specific wage distributions.

Sources: Authors' calculations; Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019

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 working full time increases across their working life, and it is higher at each age among younger cohorts. This is also true for noncollege men starting with the 1960s cohort.

Figures 3 and 4 present the corresponding age profiles of log real wages for men and women, respectively, at the tenth, fiftieth, and ninetieth percentiles by education and cohort. Noncollege men born in the 1940s have notably higher median log wages than more recent cohorts until at least age 40, suggesting cumulative lifetime wages decline for less skilled men among younger cohorts. The exact opposite occurs among college-educated men, where younger cohorts have substantially higher hourly wages at all percentiles and most ages across the life cycle. This is consistent with the rising return to skill underlying the secular rise in wage

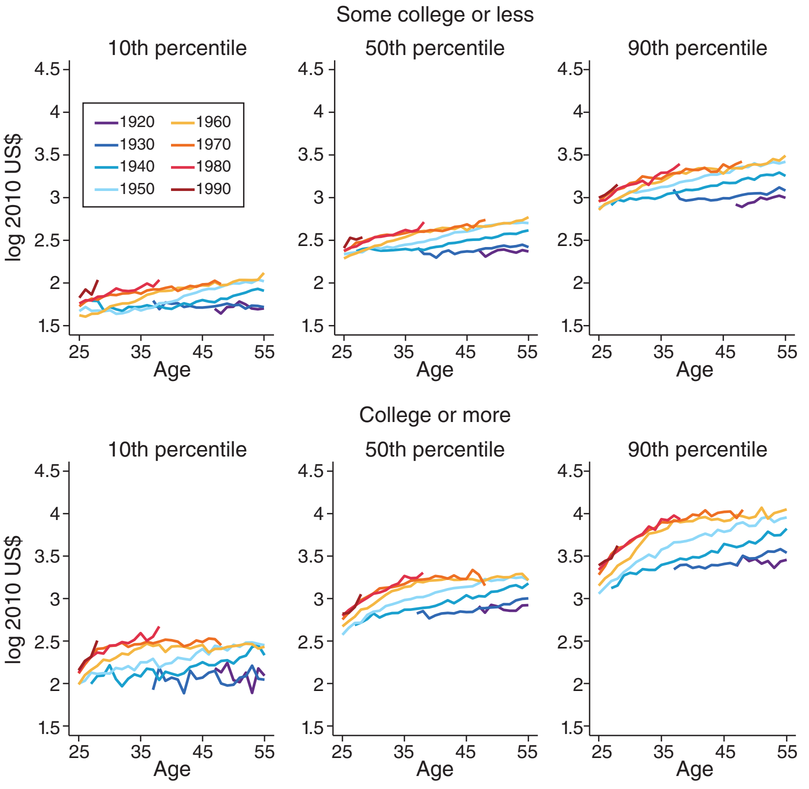

FIGURE 4. DISTRIBUTION OF LIFE CYCLE REAL HOURLY WAGES OF WORKING WOMEN ACROSS COHORTS

Notes: Wages are defined as the ratio of annual earnings to annual hours of work and are in real 2010 US$ using the Personal Consumption Expenditure Deflator. Sample consists of employed men aged 25–55. Workers with imputed earnings or hours are dropped, as are those with wages below the first percentile or above the 0.1 percentile of the real male- and year-specific wage distributions.

Sources: Authors' calculations; Current Population Survey Annual Social and Economic Supplement, Survey Years 1977–2019

inequality in the cross section (Lemieux 2006; Autor, Katz, and Kearney 2008). This secular rise for men with college or more education is particularly strong for the higher quantiles. Importantly, the profile of college 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. Supplemental Appendix Figure A4 shows a similar pattern obtains when restricting the sample to full-time workers.

The wage profile of women in Figure 4 reveals substantial fanning out across cohorts from the 1920s to the 1960s over the distribution, but then little cohort differences thereafter. Wages increase linearly with age, especially with the 1940s and 1950s cohorts, but then after rapid growth up to age 35 in the 1960s cohort and beyond, there is a noticeable slowdown (curvature) in life cycle wage growth in more recent cohorts of women, especially those with at least college and in the upper half of the wage distribution. As with men, these patterns persist when restricting the sample to full-time working women in Supplemental Appendix Figure A5.

These stylized facts point to the potential importance of three key features that guide our choice of specification for modeling wage profiles underlying life cycle gender wage gaps. First, the employment patterns suggest that differential selection into work of both women and men 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. This is exemplified in Supplemental Appendix Figure A6, which depicts the gender gap in log wages for all workers across their working life and cohorts (Supplemental Appendix Figure A7 restricted to full-time workers). There, we see very large gender wage gaps in the older cohorts of workers that decline with each successive birth cohort from the 1920s to the 1950s, which helps account for the trend decline from the mid-1970s to mid-1990s depicted in Figure 1. Starting in the 1960s, there are not only no additional gains in younger cohorts at any given age, but unlike older cohorts of women who narrow the wage gap after age 40, the gender wage gap continues to increase across their working life.

In the next section, we develop an empirical framework of wages across the distribution that accounts for these 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.

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

We are interested in how the natural log of hourly wages $\ln w$ vary over time t and working ages a across different birth cohorts c. Holding cohort constant, growth in wages can be a result of both time and aging. On the other hand, holding age constant, wages differ both because of cohort effects and time effects. This results in a well-known identification problem because any given time period is comprised of individuals from different cohorts at different ages, that is, $t = c + a$, and thus it is necessary to impose restrictions in order to separately identify age from cohort from time (Heckman and Robb 1985). Notably, in the event that growth in wages over the life cycle is independent of time, then it is possible to identify the pure age-wage profile, implying that wages are parallel across cohorts (Mincer 1974). This suggests that we want to adopt a wage specification that has lots of flexibility but also nests the pure life cycle model. This is exactly the approach of MaCurdy and Mroz (1995) and Fitzenberger and Wunderlich (2002), who used different parametric functional forms in age, cohort, and time to identify the separate factors. At the same time, we are interested not just in mean wages but wages across the distribution and how that distribution changes when workers select nonrandomly into the labor force. This leads us to a framework that extends the standard cohort models by incorporating nonrandom selection into work across the wage distribution as proposed in Arellano and Bonhomme (2017). A more complete description of the model, estimation, and identification is found in Supplemental Appendix B. Here we sketch out the key details.

Specifically, let the natural log of the latent log wage $(\ln w^*)$ of an individual of gender j with schooling level s be given as

$$\ln w_j^{s*} = \mathbf{X}_j^s(a,c,t;l)'\boldsymbol{\beta}_j^s(U_j^s), \tag{1}$$

where $\mathbf{X}$ is a flexible function in age, cohort, time, and demographics l, all terms found in the prototypical Mincer wage equation. $\boldsymbol{\beta}$ is a vector of unknown parameters that depend on unobserved heterogeneity U that varies across gender j and education group s. The unobserved heterogeneity is assumed to be independent of $\mathbf{X}$ and distributed uniformly on the $(0,1)$ interval reflecting the rank of the individual in the distribution of latent wages conditional on covariates $\mathbf{X}$ for gender j of schooling level s.

Wages are observed, $\ln w_j^s$, if the individual of gender j and education level s participates in the labor market according to the participation decision

$$E_j^s = \mathbf{1}_{\{V_j^s \leq p_j^s(D_j^s(a,c,t,l;z))\}}, \tag{2}$$

where the indicator variable takes a value of 1 if the rank of the uniformly distributed unobserved heterogeneity V is less than the propensity score $p(D)$, with index D that is a flexible function of age, cohort, time, and demographics, as well as additional identifying excluded covariates of the decision to work z beyond the variables in l from the wage equation (1). As discussed in detail below, the unobservables in the log wage equation are assumed to be independent of these excluded "instruments" conditional on the flexible function of the age, cohort, time, and demographic variables included in the regression. That is, observed log wages are the product of latent wages and the employment indicator, that is, $\ln w_j^s = E_j^s \times \ln w_j^{s*}$. The propensity score is assumed to be independent of V.

A. *Specification of Wages*

To parameterize the model of observed wages, we expand upon the specification of Fitzenberger and Wunderlich (2002) where different polynomial orders are selected in order to permit separate identification of age, cohort, and time effects. Each individual is allocated to a birth cohort c based on the calendar year t, normalized both with respect to the first year of the sample (1976), and on their age normalized at the labor market entry age of 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.[4]

[4] The literature on labor market scarring (e.g., Kahn 2010; Altonji, Kahn, and Speer 2016; Schwandt and von Wachter 2019; 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).

The corresponding wage equation for gender j and schooling level s is given as

$$(3) \qquad \ln w_j^s = \beta_{0j}^s(U_j^s) + \sum_{f=1}^{3} \beta_{a,fj}^s(U_j^s) e_j^f + \sum_{g=1}^{5} \beta_{t,gj}^s(U_j^s) t^g + \sum_{h=1}^{3} \beta_{c,hj}^s(U_j^s)\left[(1-\theta)c_j^h + \theta c_j^{h-1}\right] + \sum_{m=1}^{4} \beta_{R,mj}^s(U_j^s) R_j^m + l_j^s \beta_{l,j}^s(U_j^s) + \delta_j^s(U_j^s) + \eta_j^s(U_j^s),$$

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, a vector of sociodemographic controls, a normalized set of time fixed effects $(\delta_j^s(U))$, and a set of state fixed effects $(\eta_j^s(U))$. The cubic in entry age provides curvature for capturing pure life cycle age effects, assuming strong separability with time, that is, 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.[5] The state fixed effects control for permanent differences in state labor markets that may have differential effects across gender and education. We set the parameter $\theta = 1$ 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 $\beta_{c,0j}^s = 0$.

Nonseparability between entry age and time is admitted into the model by including four entry age-time interaction terms in R_j^m that are found by integrating over entry age—et, et^2, e^2t, e^2t^2 (see Supplemental Appendix B 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 $(ce^2/2 + e^3/3)$, $(c^2e^2/2 + 2ce^3/3 + e^4/4)$, $(ce^3/3 + e^4/4)$, and $(c^2e^3/3 + 2ce^4/4 + e^5/5)$.[6] 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 wage-age profiles across cohorts as 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.

Beyond the age, cohort, time (trends and common shocks), and state controls, the employment and wage equations within each gender-education group include indicators for race (White is omitted), Hispanic ethnicity, whether married, and whether residing in a metropolitan area, as well as the numbers of children ages

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

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

0–5 and 6–18. We discuss identification of the employment equation from the selection equation in the next section. In Supplemental Appendix E, we include a comprehensive set of robustness tests on the specification of the wage and selection equations.

B. *Estimation and Identification*

A number of approaches have been adopted in the literature to address selection into employment. In studying the median gender wage gap, Neal (2004); Olivetti and Petrongolo (2008); and Blau et al. (2024) filled in missing wages of nonworkers 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 on unobservables. 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 worst-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 remains possible to recover the median and upper quantiles of the wage distribution. The cost is that wages in the bottom half of the distribution are not identified and not likely a credible assumption for high-skilled women who have periods of nonwork during child-rearing years.

As detailed in Supplemental Appendix B, our approach to consistently estimate the quantile model in the presence of nonrandom selection is to point identify the parameters of the wage and selection process using the three-step method of Arelleno and Bonhomme (2017). Assuming that the joint distribution of (U_j^s, V_j^s) in equations (1) and (2) follows a bivariate Gaussian copula with dependence parameter ρ_j^s that is independent of the propensity score index D_j^s, the first step involves estimating the probability of employment (or probability of full-time work when examining wages of full-time workers) in equation (2) via probit maximum likelihood, much like in a standard Heckman-selection model. Given estimates of the selection model parameters, the second step involves estimating the copula dependence parameter ρ_j^s via a generalized method of moments using functions of the fitted propensity score index $\hat{D}_j^s$ from the first-stage probit estimates as "instruments." The copula parameter captures the correlation between the unobserved heterogeneity in the wage (U) and participation (V) equations. If this correlation is negative, then selection on unobservables into work is positive, that is, those with higher wages are more likely to work, and likewise, if the correlation is positive, then selection into work is negative. We use the Frank copula because it is comprehensive in its dependence structure, allowing for both negative and positive selection, as well as independence. The third step involves estimating the parameters from the wage equation (3) at selected quantiles, using a rotated quantile regression, where the rotation is a function of the degree of selection and is person specific as determined by the estimated propensity score index in each gender-education group, $\hat{D}_j^s$, conditional on the estimated dependence parameter, $\hat{\rho}_j^s$. Note that the flexible parametric specifications for the quantile wage equation and the propensity score reduce the restrictiveness of the probit assumption in the first stage. In order to retain the dependence structure of the model, we conduct inference via 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 to 100.[7]

A common approach in the literature is to use the ages of children as exclusion restrictions to identify the system in equations (1)–(3) under the assumption that children affect the decision to work—but not the wage conditional on working (Mulligan and Rubinstein 2008; Maasoumi and Wang 2019; Fernández-Val et al. 2023; Blau et al. 2024). This is consistent with a simple formulation of the wage-determination process for spot-market hourly wages. However, children may affect accumulated labor market experience and the timing of promotion opportunities, which could have a direct effect on the wage rate. Thus, we include the age composition of children in both the selection and wage equation, though in Supplemental Appendix E, we present estimates of the gender wage gap under this typical identification strategy.

Instead, our approach to identification of the selection process is to exploit changes in the tax and transfer system to create simulated disposable income instruments—one capturing disposable income if one or both partners (in married couples) are out of work and a second a weighted sum of disposable income across eight categories of no work, part-time work, and full-time work for the partners—as well as changes in the tightness of local labor markets as proxied by state unemployment rates. Over the span of our sample period, there were numerous changes to the US tax and transfer system. On the tax side, major federal legislation was passed in 1981, 1986, 1990, 1993, 1997, 2001, and 2017. The 1980s reforms included reductions in the number of marginal tax brackets from 16 to 4, along with reductions in the top marginal tax rate from 70 percent to 28 percent. Subsequent changes in the 1990s increased the number of brackets to 7 and top marginal rates to 39 percent, with incremental changes in rates (both up and down) in the 2000s. These reforms also included substantial expansions of the refundable Earned Income Tax Credit (EITC) program for low-wage workers in 1986 and 1993, and the introduction of a partially refundable Child Tax Credit (CTC) program in 1997 followed with substantial expansions in 2001 and 2017. On the welfare side, federal provision of cash assistance was fundamentally altered with the 1996 Welfare Reform Act that created the Temporary Assistance for Needy Families (TANF) program. Among other changes, this reform also had significant implications for the eligibility of food assistance from the near-cash Food Stamp Program, later renamed the Supplemental

[7] 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.

Nutrition Assistance Program (SNAP) in 2008. See Auerbach and Slemrod (1997) and Piketty and Saez (2007) for references on the tax changes and Grogger and Karoly (2005) and Moffitt and Ziliak (2019) for summaries of changes to the transfer system.

Supplemental Appendix B contains extensive details on the construction of the simulated disposable income instruments, as well as evidence on the variation and support to identify the employment equation. Some of these tax and transfer changes were adopted at the federal level and some at the state level, and our simulated instruments aim to capture variation at both levels. The key features are that the instrument for no work captures gender-education specific variation across states and year in rent, interest, and dividend income as well as the generosity of welfare payments from SNAP and TANF, while the simulated instrument for in-work income captures changes in federal and state taxation of labor and nonlabor income, including the refundable EITC and partially refundable CTC. We then identify the selection equation from the wage equation by including in the selection model the two simulated disposable income instruments and the state unemployment rate described above. The unobservables in the log wage equation are assumed to be independent of these excluded "instruments" conditional on the flexible function of the age, cohort, time, and demographic variables included in the regression, along with the year and state fixed effects. That is, identification of wages is based on the independence of U_j^s and z_j^s conditional on a, c, t, l, δ, η. This means that the selection model is identified via the residual variation in potential disposable income derived from the interaction of federal-state-time policy changes in taxes and transfers and the wage and nonwage incomes across states and demographic groups. In Section V, we consider a number of robustness checks of this specification including a specification of the baseline model to include state-specific linear time trends.

Supplemental Appendix Figures B1 and B2 show box and whisker plots of the two simulated income instruments for select years. Supplemental Appendix Figure B1 shows a real decline in the out-of-work instrument from 1976 to 1990, reflecting real declines in maximum benefit guarantees in TANF noted by others (see Ziliak 2016) and then relative stability thereafter. Real median incomes hover around \$10,000 in a typical year with an interquartile range of about \$5,000. Supplemental Appendix Figure B2 depicts much more variation in the weighted simulated income instrument across education groups, reflecting the differences in both average wages and private nonlabor incomes, as well as tax liabilities. Again, we see a decline in real simulated median incomes among the some-college-or-less group, where in this case it reflects the decline in real wages in the 1980s. At the same time, we see substantial increases in median incomes among those with at least college after 1990, owing to rising real wages. In Supplemental Appendix Figure B3, we present kernel density estimates by employment status of the predicted probability from the first-stage probit equation for each gender and education group used in estimation. There we see substantial overlap in the underlying support in the first stage, which is fundamental to identification of the selection model. The key takeaway is that the simulated instruments offer substantial variation to aid in identification of the selection equation.

Table 1—Quantile Selection Estimates of Log Wages for Men with Some College or Less

	Employment	10th quantile	50th quantile	90th quantile
Constant	1.115	1.799	2.438	3.005
	(0.036)	(0.015)	(0.011)	(0.011)
Entryage	−0.113	0.313	0.391	0.311
	(0.035)	(0.020)	(0.012)	(0.016)
Entryage^2	0.022	−0.125	−0.091	−0.042
	(0.034)	(0.021)	(0.012)	(0.016)
Entryage^3	−0.033	0.016	0.014	0.004
	(0.008)	(0.005)	(0.003)	(0.004)
Time	0.564	0.134	−0.020	0.043
	(0.256)	(0.121)	(0.082)	(0.103)
Time^2	−1.198	−0.490	0.037	0.066
	(0.945)	(0.481)	(0.328)	(0.411)
Time^3	0.329	0.375	−0.130	−0.111
	(0.627)	(0.348)	(0.235)	(0.326)
Time^4	0.022	−0.107	0.056	0.043
	(0.161)	(0.098)	(0.066)	(0.102)
Time^5	−0.009	0.010	−0.007	−0.005
	(0.015)	(0.010)	(0.006)	(0.011)
Cohort^2	−0.030	0.011	0.009	−0.015
	(0.008)	(0.005)	(0.003)	(0.004)
Cohort^2 × delta	0.142	−0.013	−0.100	−0.092
	(0.024)	(0.016)	(0.009)	(0.012)
Cohort^3	0.039	0.001	0.003	0.000
	(0.006)	(0.004)	(0.002)	(0.003)
R1	−98.206	16.120	−81.678	−94.268
	(37.238)	(26.824)	(14.904)	(21.313)
R2	9.049	0.065	18.901	11.294
	(7.845)	(5.556)	(3.562)	(4.861)
R3	43.776	−7.401	3.968	15.811
	(16.231)	(11.705)	(6.352)	(9.315)
R4	−1.986	1.190	−0.633	−1.191
	(3.725)	(2.514)	(1.607)	(2.330)

(*continued*)

III. Estimates of Cohort Wage Profiles

We begin the empirical results with estimates of wage profiles from the conditional quantile models with selection at the tenth, fiftieth, and ninetieth percentiles. We focus on all workers but also present a parallel set of estimates in Supplemental Appendix D for those working full time. Supplemental Appendix Tables A1–A3 contain summary statistics of the model covariates for all workers and nonworkers, full-time workers only, and nonworkers, respectively. Supplemental Appendix Table A3 shows that nonworking men compared to men overall in Supplemental Appendix Table A1 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 1–4 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. Table 1 and Table 2 are for men with some college or less

Table 1—Quantile Selection Estimates of Log Wages for Men with Some College or Less (*continued*)

	Employment	10th quantile	50th quantile	90th quantile
Black	−0.455	−0.203	−0.198	−0.172
	(0.005)	(0.005)	(0.003)	(0.004)
Other race	−0.363	−0.267	−0.218	−0.141
	(0.008)	(0.007)	(0.004)	(0.007)
Hispanic	−0.037	−0.339	−0.361	−0.268
	(0.006)	(0.004)	(0.002)	(0.003)
Married	0.492	0.209	0.158	0.115
	(0.006)	(0.003)	(0.002)	(0.003)
Live in metro area	0.111	0.164	0.139	0.111
	(0.005)	(0.003)	(0.002)	(0.002)
Number of children ages 0–5	−0.020	−0.016	−0.008	0.004
	(0.004)	(0.002)	(0.001)	(0.002)
Number of children ages 6–18	−0.038	−0.000	−0.001	−0.001
	(0.004)	(0.001)	(0.001)	(0.001)
State unemployment rate	−0.027			
	(0.002)			
Simulated disposable income at no work	−0.018			
	(0.001)			
Simulated disposable income at work	0.006			
	(0.000)			
ρ	0.98			
	(0.05)			
p-value on excluded variables	0.00			
p-value on cohort terms		0.00	0.00	0.00
p-value on R terms		0.02	0.00	0.00
p-value on R and cohort terms		0.00	0.00	0.00

Notes: The table contains estimates from the quantile with selection model as described in the text for men with some college or less education. The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

Sources: Authors' calculations; Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019

and those with college or more, respectively, while Table 3 and Table 4 contain the corresponding estimates for women. All models control for fixed state effects and normalized common time fixed effects.

The first stage probit estimates for male and female employment suggest that the demographic factors generally operate in expected ways, with married men and men residing in metro areas more likely to work and non-White men and men with more children less likely to work. Among women, some of these patterns reverse. For example, college-educated Black women are more likely to work, as are college-educated women residing in nonmetro areas compared to metro areas. The p-value on the joint significance of the three extra regressors in the employment equation is < 0.00 in all four models, and with one exception (simulated disposable income from work among non-college-educated women), they are all individually statistically significant, suggesting that they are predictive of the first stage. Employment is procyclical with respect to state business cycles. Moreover, employment declines with increases in simulated disposable income from no work, which is akin to a nonlabor income effect on the extensive margin from a canonical

Table 2—Quantile Selection Estimates of Log Wages for Men with College or More

	Employment	10th quantile	50th quantile	90th quantile
Constant	1.122	1.806	2.487	2.958
	(0.071)	(0.032)	(0.017)	(0.021)
Entryage	0.389	0.569	0.532	0.555
	(0.080)	(0.048)	(0.019)	(0.031)
Entryage^2	−0.089	−0.232	−0.210	−0.208
	(0.080)	(0.044)	(0.020)	(0.033)
Entryage^3	−0.003	0.028	0.032	0.019
	(0.020)	(0.011)	(0.005)	(0.008)
Time	0.405	−0.056	0.047	0.481
	(0.548)	(0.282)	(0.120)	(0.228)
Time^2	−0.215	−0.503	−0.019	−1.054
	(2.147)	(1.128)	(0.476)	(0.876)
Time^3	−0.523	0.371	−0.028	0.561
	(1.440)	(0.785)	(0.330)	(0.615)
Time^4	0.284	−0.089	0.017	−0.108
	(0.364)	(0.206)	(0.093)	(0.165)
Time^5	−0.036	0.007	−0.002	0.007
	(0.032)	(0.019)	(0.009)	(0.015)
Cohort^2	−0.074	0.011	0.002	−0.003
	(0.017)	(0.010)	(0.005)	(0.008)
Cohort^2 × delta	−0.112	0.061	0.103	0.135
	(0.054)	(0.026)	(0.016)	(0.027)
Cohort^3	−0.004	0.015	0.029	0.003
	(0.015)	(0.007)	(0.004)	(0.006)
R1	−179.660	10.979	82.872	148.340
	(82.396)	(43.881)	(25.431)	(48.727)
R2	−26.792	−1.028	−17.892	−31.780
	(17.512)	(9.125)	(5.324)	(10.278)
R3	−12.658	−5.695	−40.890	−22.255
	(36.417)	(20.006)	(11.210)	(21.183)
R4	26.577	3.096	9.267	4.291
	(8.366)	(4.327)	(2.446)	(4.731)

(*continued*)

labor supply model. On the other hand, increases in the amount of simulated income earned from work serve as an inducement to employment for men of both education groups and a deterrent to work among college-educated women, suggesting some household substitution in work among partners.

The first column of each table also reports estimates of the copula dependence parameter, $\hat{\rho}_j^s$. There we see evidence of negative selection on unobservables into work for all four groups. 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. Negative selection among college-educated women is consistent with earlier work by Mulligan and Rubinstein (2008), although they found it became less negative over time. Maasoumi and Wang (2019) estimate the copula dependence parameter year by year in the cross section, finding a trend from negative selection to positive selection over time among women, though their sample is a full-time working sample. In Supplemental Appendix Table D4, we find no evidence of nonrandom selection among full-time college-educated women. The

TABLE 2—QUANTILE SELECTION ESTIMATES OF LOG WAGES FOR MEN WITH COLLEGE OR MORE (*continued*)

	Employment	10th quantile	50th quantile	90th quantile
Black	−0.321	−0.226	−0.222	−0.238
	(0.016)	(0.011)	(0.006)	(0.010)
Other race	−0.353	−0.209	−0.027	−0.021
	(0.014)	(0.009)	(0.006)	(0.008)
Hispanic	−0.141	−0.334	−0.194	−0.168
	(0.015)	(0.010)	(0.006)	(0.007)
Married	0.209	0.212	0.132	0.084
	(0.013)	(0.007)	(0.005)	(0.006)
Live in metro area	0.082	0.221	0.207	0.188
	(0.014)	(0.006)	(0.003)	(0.006)
Number of children ages 0–5	−0.026	0.030	0.031	0.049
	(0.011)	(0.003)	(0.001)	(0.003)
Number of children ages 6–18	−0.037	0.031	0.029	0.045
	(0.010)	(0.002)	(0.001)	(0.003)
State unemployment rate	−0.016			
	(0.004)			
Simulated disposable income at no work	−0.031			
	(0.002)			
Simulated disposable income at work	0.009			
	(0.000)			
ρ	0.92			
	(0.48)			
p-value on excluded variables	0.00			
p-value on cohort terms		0.10	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

Notes: The table contains estimates from the quantile with selection model as described in the text for men with college or more education. The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

Sources: Authors' calculations; Current Population Survey Annual Social and Economic Supplement, Survey Years 1977–2019

finding of negative selection among college-educated men is perhaps surprising, though there are few estimates to compare to in the literature on this demographic as selection is almost always assumed random for men. As shown in Figure 2, employment rates are consistently higher for college-educated men, reducing the importance of selection bias for this group. Maasoumi and Wang (2019) estimate selection among full-time men, where in some years they find negative selection, though the modal estimate is positive selection. Ashworth et al. (2021) find that men are negatively selected on unobservables into part-time work. Blau et al. (2024) find positive selection on *observables* for both women and men but little evidence on selection on unobservables. Fernadez-Val et al. (2023), like Maasoumi and Wang (2019), provide annual cross-sectional estimates of gender gaps and find that selection matters for women only in lower quantiles, where it is U-shaped, becoming less positive from the mid-1970s to 2000 and then more positive.

As described in Supplemental Appendix E and discussed in the next section, we estimate a number of alternative models of selection, including using the age composition of children as the identifying instruments. Excluding the number and age

Table 3—Quantile Selection Estimates of Log Wages for Women with Some College or Less

	Employment	10th quantile	50th quantile	90th quantile
Constant	0.857	1.629	2.152	2.624
	(0.023)	(0.019)	(0.012)	(0.018)
Entryage	−0.151	0.099	0.253	0.378
	(0.025)	(0.026)	(0.015)	(0.022)
Entryage^2	0.053	−0.003	−0.118	−0.177
	(0.025)	(0.023)	(0.015)	(0.023)
Entryage^3	−0.028	0.001	0.025	0.034
	(0.006)	(0.005)	(0.003)	(0.006)
Time	−0.251	−0.284	−0.135	0.150
	(0.182)	(0.187)	(0.082)	(0.139)
Time^2	2.909	1.222	0.300	−0.434
	(0.700)	(0.713)	(0.342)	(0.536)
Time^3	−2.357	−0.980	−0.134	0.286
	(0.504)	(0.486)	(0.252)	(0.384)
Time^4	0.652	0.284	0.025	−0.066
	(0.140)	(0.127)	(0.071)	(0.109)
Time^5	−0.060	−0.027	−0.001	0.005
	(0.014)	(0.012)	(0.007)	(0.011)
Cohort^2	−0.041	−0.031	−0.025	−0.012
	(0.006)	(0.006)	(0.003)	(0.006)
Cohort^2 × delta	−0.075	−0.109	−0.110	−0.087
	(0.019)	(0.015)	(0.010)	(0.017)
Cohort^3	−0.029	−0.007	−0.013	−0.016
	(0.004)	(0.004)	(0.002)	(0.004)
R1	39.124	−127.680	−76.342	14.125
	(35.603)	(24.758)	(17.700)	(27.253)
R2	−35.282	6.793	5.117	−7.924
	(7.682)	(6.229)	(3.992)	(6.102)
R3	−18.957	27.736	10.008	−21.734
	(14.320)	(10.708)	(7.417)	(12.075)
R4	13.142	0.420	0.706	6.018
	(3.243)	(2.871)	(1.853)	(2.946)

(*continued*)

distribution of children from the wage equation has a systematic impact on our estimates of selection. Our results suggest that positive selection for college-educated women appears to be largely driven by children—most likely through the impact on past human capital investments. For college-educated men, employment rates are sufficiently high to make selection less of an issue anyway. For some-college-or-less women and men, it looks like there is a different story where negative selection is common. While the selection parameter is sensitive for some groups based on exclusion restrictions, the implied pattern of life cycle gender wage gaps presented in Supplemental Appendix E is quite robust.

Turning to the parameter estimates in the wage equation, we see that wage gaps of race-ethnicity minority groups tend to be most pronounced in the bottom half of the distribution for both men and women, while the premium to marriage tends to be higher in the bottom half for men and (slightly) higher in the top half of wages for women. The effects of children on wages are near zero for men without a college education, while they are a small positive for college-educated men, a result

Table 3—Quantile Selection Estimates of Log Wages for Women with Some College or Less (*continued*)

	Employment	10th quantile	50th quantile	90th quantile
Black	−0.088	−0.051	−0.083	−0.111
	(0.005)	(0.005)	(0.003)	(0.004)
Other race	−0.231	−0.105	−0.105	−0.094
	(0.007)	(0.007)	(0.006)	(0.008)
Hispanic	−0.257	−0.168	−0.234	−0.206
	(0.004)	(0.005)	(0.005)	(0.005)
Married	−0.121	0.030	0.032	0.042
	(0.004)	(0.003)	(0.002)	(0.003)
Live in metro area	0.038	0.155	0.164	0.171
	(0.004)	(0.004)	(0.002)	(0.004)
Number of children ages 0–5	−0.299	−0.052	−0.010	0.034
	(0.003)	(0.006)	(0.006)	(0.007)
Number of children ages 6–18	−0.112	−0.065	−0.058	−0.029
	(0.002)	(0.003)	(0.002)	(0.003)
State unemployment rate	−0.018			
	(0.001)			
Simulated disposable income at no work	−0.011			
	(0.001)			
Simulated disposable income at work	0.000			
	(0.000)			
ρ	0.92			
	(0.29)			
p-value on excluded variables	0.00			
p-value on cohort terms		0.00	0.00	0.00
p-value on R terms		0.00	0.00	0.04
p-value on R and cohort terms		0.00	0.00	0.00

Notes: The table contains estimates from the quantile with selection model as described in the text for women with some college or less education. The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

Sources: Authors' calculations; Current Population Survey Annual Social and Economic Supplement, Survey Years 1977–2019

consistent with Lundberg and Rose (2002). These child effects on wages tend to be negative only in the bottom half of the female wage distribution, though as discussed previously, the negative impact is quite sizable on the extensive margin of employment.

At the bottom of Tables 1–4, 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. The rejection of the null that time and entry age interactions are zero implies that we cannot construct pure life cycle age-wage profiles—that is, cohorts do not have common wage growth with age. Additionally, rejecting that both cohort and the interaction terms are zero means we do not have uniform wage growth across cohorts and that the cross-section age-wage profile is not shifted over time by a common amount given by macroeconomic wage growth. We interpret the results as suggesting that cohort age-wage profiles are not parallel and thus refer to them as *pseudo*–life cycle age-wage profiles.

TABLE 4—QUANTILE SELECTION ESTIMATES OF LOG WAGES FOR WOMEN WITH COLLEGE OR MORE

	Employment	10th quantile	50th quantile	90th quantile
Constant	1.858	1.889	2.395	2.746
	(0.051)	(0.040)	(0.015)	(0.023)
Entryage	−0.785	0.393	0.505	0.466
	(0.055)	(0.052)	(0.021)	(0.033)
Entryage^2	0.757	−0.117	−0.250	−0.249
	(0.049)	(0.055)	(0.023)	(0.035)
Entryage^3	−0.187	0.005	0.044	0.045
	(0.012)	(0.014)	(0.006)	(0.009)
Time	−0.190	−0.353	−0.165	−0.382
	(0.397)	(0.419)	(0.149)	(0.275)
Time^2	2.726	0.941	0.275	2.099
	(1.609)	(1.622)	(0.574)	(1.067)
Time^3	−1.882	−0.705	−0.276	−1.439
	(1.107)	(1.062)	(0.393)	(0.736)
Time^4	0.475	0.210	0.101	0.358
	(0.282)	(0.258)	(0.103)	(0.191)
Time^5	−0.040	−0.021	−0.011	−0.030
	(0.025)	(0.022)	(0.009)	(0.017)
Cohort^2	−0.238	−0.056	−0.011	−0.022
	(0.011)	(0.011)	(0.005)	(0.008)
Cohort^2 × delta	−0.447	−0.208	−0.044	0.064
	(0.033)	(0.038)	(0.017)	(0.028)
Cohort^3	−0.055	−0.037	−0.013	0.012
	(0.009)	(0.009)	(0.005)	(0.007)
R1	−845.320	−309.910	14.074	110.820
	(52.203)	(63.591)	(26.531)	(43.438)
R2	59.455	44.570	2.750	−24.042
	(11.791)	(11.196)	(5.323)	(10.292)
R3	310.090	117.440	−9.722	−52.472
	(25.388)	(27.040)	(12.244)	(19.501)
R4	−32.637	−19.897	−1.515	10.363
	(5.880)	(5.108)	(2.656)	(4.618)

(*continued*)

IV. The Evolution of Gender Gaps in the Pseudo–Life Cycle Distribution of Offer Wages

With the estimated coefficients from Tables 1–4, in this section, we examine the implications for the evolution of gender wage gaps across the life cycle. As detailed in Supplemental Appendix C, with the quantile coefficients, we construct counterfactual offer wage distributions for both working and nonworking men and women in each education group using the conditional quantile decomposition method of Machado and Mata (2005). The idea is that for each gender-education group, we randomly assign a set of quantile coefficients from the *qth* quantile, $q = 0.1, 0.5, 0.9$, to produce a prediction of the *qth* quantile offer wage distribution; that is, the offer wage is the wage that the individual in a particular gender-education group is predicted to earn at a particular quantile based on their demographics and other determinants of wages in equation (3) along with parameters estimated in Tables 1–4, regardless of whether

Table 4—Quantile Selection Estimates of Log Wages for Women with College or More (*continued*)

	Employment	10th quantile	50th quantile	90th quantile
Black	0.124	0.001	−0.066	−0.103
	(0.012)	(0.008)	(0.004)	(0.006)
Other race	−0.397	−0.115	0.005	0.025
	(0.009)	(0.010)	(0.008)	(0.009)
Hispanic	−0.143	−0.231	−0.125	−0.124
	(0.010)	(0.010)	(0.006)	(0.007)
Married	−0.195	0.017	0.028	0.032
	(0.008)	(0.006)	(0.004)	(0.004)
Live in metro area	−0.126	0.118	0.133	0.179
	(0.009)	(0.007)	(0.003)	(0.005)
Number of children ages 0–5	−0.315	−0.017	0.054	0.107
	(0.004)	(0.008)	(0.005)	(0.007)
Number of children ages 6–18	−0.116	−0.100	−0.031	0.002
	(0.005)	(0.003)	(0.003)	(0.004)
State unemployment rate	−0.007			
	(0.002)			
Simulated disposable income at no work	−0.020			
	(0.001)			
Simulated disposable income at work	−0.003			
	(0.000)			
ρ	0.78			
	(0.28)			
p-value on excluded variables	0.00			
p-value on cohort terms		0.00	0.01	0.00
p-value on *R* terms		0.00	0.00	0.04
p-value on *R* and cohort terms		0.00	0.00	0.00

Notes: The table contains estimates from the quantile with selection model as described in the text for women with college or more education. The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

Sources: Authors' calculations; Current Population Survey Annual Social and Economic Supplement, Survey Years 1977–2019

they are in actual work or not. Because Heathcote, Storesletten, and Violante (2005) found that common within-group time effects were a primary channel affecting 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. 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, the life cycle gender gap in offer wages is found by taking the difference in predicted log wages of men and women at each age in a given education group at the tenth, fiftieth, and ninetieth percentiles, and we plot the gender-age-quantile-specific ten-year birth cohort mean at each age and cohort.

Figure 5 presents the within-education group gender offer wage gaps over the life cycle and wage distribution.[8] The patterns across cohorts, and across the life

[8] Note that all graphs in Figure 5 are net of within-education-and-gender time effects. We return to examine the role of time effects in subsection B below.

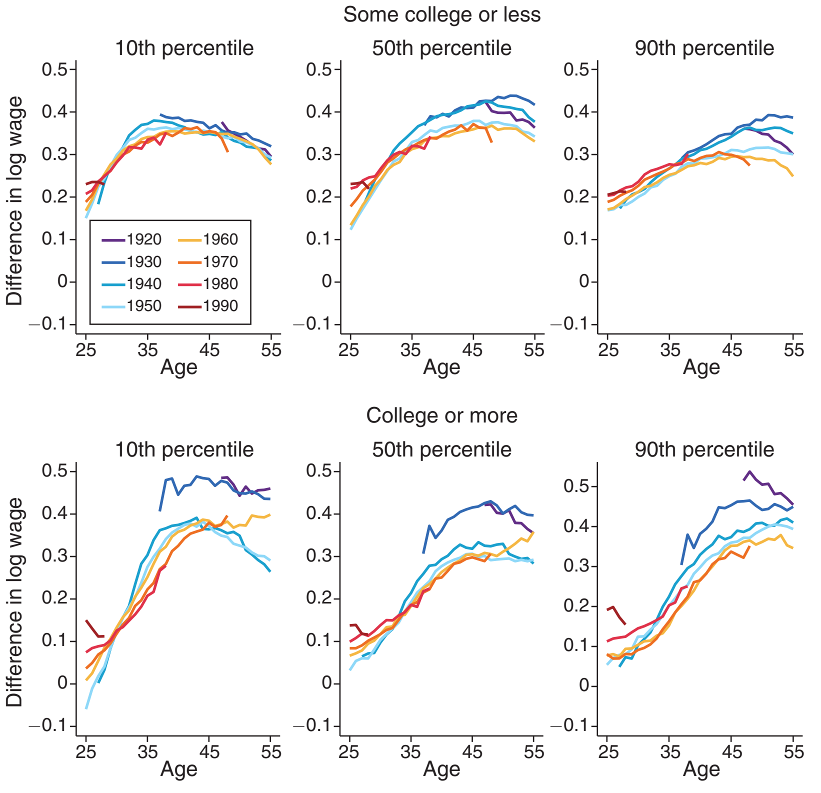

Figure 5. Within–Education Group Gender Offer Wage Gaps over the Life Cycle

Notes: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile selection model net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men and women aged 25–55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the first percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

Sources: Authors' calculations; Current Population Survey Annual Social and Economic Supplement, Survey Years 1977–2019

cycle within cohorts, are striking. Among men and women with some college or less, the life cycle gender offer wage gap is quadratic at the tenth percentile, nearly doubling from 20 percent at age 25 to 40 percent a decade later and then tapering back to about 30 percent in the latter half of working life. There is little difference across cohorts. At the median, however, there are substantial differences across the cohorts born before the 1960s and those born after, particularly from age 35 onward. In the pre-1960s cohorts, the level gap in the offer wages at older ages was quite substantial, but it declined with successive cohorts and with age within a cohort. Starting with the 1960s, however, there are few differences across cohorts in median life cycle profiles, with gaps increasing sharply early in the working life and also not tapering back as much later in the working life as in older cohorts (or in the tenth percentile). At the ninetieth percentile of the some-college-or-less group, the gender gaps tend to increase until age 45 before tapering off. There is substantial convergence across cohorts at the top of the wage distribution at older working ages that continue to the 1960s birth cohort, as well as some narrowing of the gender gap with age, but never a return to levels seen early in the working life.

In the bottom panel of Figure 5, we depict the corresponding pseudo–life cycle gender wage gaps for those women and men with at least four years of college education. At low wages, there is evidence of very sharply increasing wage penalties against women over the first two decades of the working life. These wage gaps reached levels of about 50 percent for cohorts of women born in the 1920s and 1930s, but there was substantial narrowing for the 1940s and 1950s cohorts that started around age 40 and continued through age 55. For the 1960s cohort, however, there is no narrowing of the gender wage gap after age 45, and it appears that the 1970s cohort is on that same trajectory. A similar pattern is observed at the median of the college-educated group where, for the 1960s cohort, the gender offer wage gap increases linearly through age 55 and reaches levels found in the 1920s cohort. At the ninetieth percentile, where we might expect substantial improvements in life cycle gender gaps among more recent cohorts given these are high-wage workers with similar levels of human capital, we do in fact observe some modest improvements in the 1960s cohort relative to earlier ones, but the 1970s cohort is no better, and, in fact, there appears to be retrenchment in both the 1980s and 1990s cohorts of women at young ages.

The pseudo–life cycle profiles of gender gaps across cohorts in Figure 5 help shed light on the time series of the raw gender wage gap at the bottom, middle, and top of the wage distribution in Figure 1. There we saw a decline in the gender gap from the mid-1970s to mid-1990s across the distribution, followed by a stalling that was more pronounced at the top of the distribution. The time series decline is largely driven by the relative wage gains in the cohorts of women in the 1940s and 1950s that reduced the level gap at middle working ages and with further progress in later working ages, while the plateauing of the time series gap after the mid-1990s stems from a stalling of progress across the life cycle in cohorts after the 1950s. Gender progress at the top of the wage distribution among the highly educated in recent cohorts has actually retreated more than at the middle and bottom.

A. *Robustness*

In Supplemental Appendix E, we provide a detailed examination of the robustness of the life cycle gender wage gaps presented in Figure 5 to assumptions on the identification and specification of the selection model, on the functional form of the wage-determination process in equation (3), on how we split the sample based on education attainment, and on the potential influence of very old and very young cohorts.

More specifically, instead of the three excluded instruments used in the baseline model of Figure 5 (i.e., state unemployment rates, simulated disposable income from no work, and weighted simulated disposable income from work), we drop the simulated in-work instrument so the model is more akin to a standard labor supply model identification based on nonlabor income (Supplemental Appendix Figure E1). We then drop both simulated disposable income instruments and replace them with the maximum benefit guarantee from the SNAP and TANF welfare programs as they are based solely on policy decisions and not a mix of policy decisions and household demographics as with the simulated instruments (Supplemental Appendix Figure E2). This is then followed by a model where we drop all three extra regressors and thus rely on the nonlinear restrictions in our flexible parametric framework to identify the selection from the wage model (Supplemental Appendix Figure E3). The fourth check is to implement the so-called median selection rule frequently used in the racial wage gap literature whereby anyone out of work is assumed to pull from the bottom half of the wage distribution, and after adding non-workers back to the sample with a log wage of 0, we reestimate wages at the median and above (Supplemental Appendix Figure E4). The next test uses the age composition of children to identify the selection model as in Mulligan and Rubinstein (2008); Maasoumi and Wang (2019); Blau et al. (2024); and Fernández-Val et al. (2023) instead of the simulated disposable income instruments (Supplemental Appendix Figures E5 and E6). The next test drops the selection model altogether and assumes that men and women in work are randomly selected from the population (Supplemental Appendix Figure E7). We then return to the baseline specification of the selection model with the three exclusion restrictions and instead split the sample based on quartiles of the education-attainment distribution rather than a sheepskin effect of a college degree (Supplemental Appendix Figure E8). We next take a much more parsimonious specification of wage determination in equation (3) by assuming a quadratic in cohort, entry age, and time (Supplemental Appendix Figure E9). This is then followed by an expanded specification of the baseline model to include state-specific linear time trends (Supplemental Appendix Figure E10). The final two specification checks examine whether there was undue influence on the parameter estimates from the oldest (1920s) and youngest (1990s) birth cohorts given their relatively smaller sample sizes (Supplemental Appendix Figures E11 and E12).

The takeaway from these various specification tests is that the key patterns depicted in Figure 5—reduced levels of gender wage gaps at older ages across cohorts born before the 1960s along with a stalled progress among more recent cohorts across the working life—remain robust. However, there are a few differences worth highlighting in these specifications. First, when we use the median selection rule to identify the employment from the wage equation, we find substantive differences among older cohorts, especially those with some college or less. The reason is that many older women were not in the labor force, and thus, inclusion of zeros pulls the median substantially lower, and inflates the gender gap. This is particularly pronounced among the 1920s and 1930s cohorts. However, by the 1950s cohort, the life cycle profiles of the gender gap, particularly among the college educated, are much more similar to our baseline estimates, suggesting our results are robust to less parametric alternatives, at least starting with the 1950s cohorts. Second, when identification is based on the standard approach of the age composition of children in the employment equation but not the wage equation, we find more of a narrowing of the gender wage gap than in our baseline estimates. This is more pronounced among the college educated. That is, omitting children from the wage equation results in too low of a gender wage gap. Indeed, our results suggest that positive selection for college-educated women is largely driven by children, most likely through the impact of accumulated work experience.[9] For college-educated women, experience capital is likely to be a particularly important determinant of wages (see Blundell et al. 2016). For college-educated men, employment rates are sufficiently high to make selection less of an issue anyway. For both women and men with some college or less, it appears there is a different story in which negative selection is common. Third, when we assume selection into work on unobservables is random, we find that for most cohorts, the gender wage gap is attenuated at most ages and that the life cycle gender wage gaps among the college educated have much less curvature later in the working life than we find when selection is modeled in Figure 5, meaning less catch-up of women relative to men.

B. *Potential Mechanisms*

To further understand the evolution of the life cycle gender gaps across cohorts in Figure 5, in this section, we explore three potential mechanisms—the role of common (group-specific) shocks, the life cycle timing of child rearing, and the rise of full-time work.

Heathcote, Storesletten, and Violante (2005) emphasize the importance of time effects in accounting for the life cycle inequality of wages, and thus, in our baseline counterfactuals, we first filtered the predicted offer wage for each working and nonworking individual through a set of gender and education group-specific unrestricted time dummies prior to constructing the gender gaps at each age in a cohort. In Figure 6, we present the corresponding life cycle gender gaps without netting out the common group-specific time effect. There we see much more fanning out of gender gaps across cohorts at each age akin to that observed in the actual data in Supplemental Appendix Figure A6; that is, there are sharp reductions in gender gaps from the 1920s to the 1950s birth cohorts. Moreover, in Figure 6, we see a gender wage gap peak earlier in the life cycle through the 1950s cohort and then a sharp reversal to later in the life cycle starting with the 1960s cohort (except among the college educated at the ninetieth percentile where the reversal started with the 1950s cohort).

This reduction in peak life cycle gender gap is less in evidence in Figure 5 with time effects netted out. To explore this further, in Supplemental Appendix C, we present the pseudo–life cycle offer wage profiles for men with and without time effects netted out (Supplemental Appendix Figures C1 and C2) separately from the profiles of women (Supplemental Appendix Figures C3 and C4). Those figures show that the common group-specific time effects eliminate most cohort differences in life cycle offer wages for both men and women and, in fact, for the case of college-educated men, reorder which cohorts had the highest wages (1920s and 1930s cohorts) compared to actual data and the model predictions with time effects. Moreover, for women, taking out the time effects results in a more uniform life cycle peak age of wages, which helps explain why in Figure 5 we do not observe a reduction in peak age of the gender gap as we do in Figure 6.

[9] If we retain our instruments but just remove age composition of kids in the wage equation, we still get positive selection for college women.

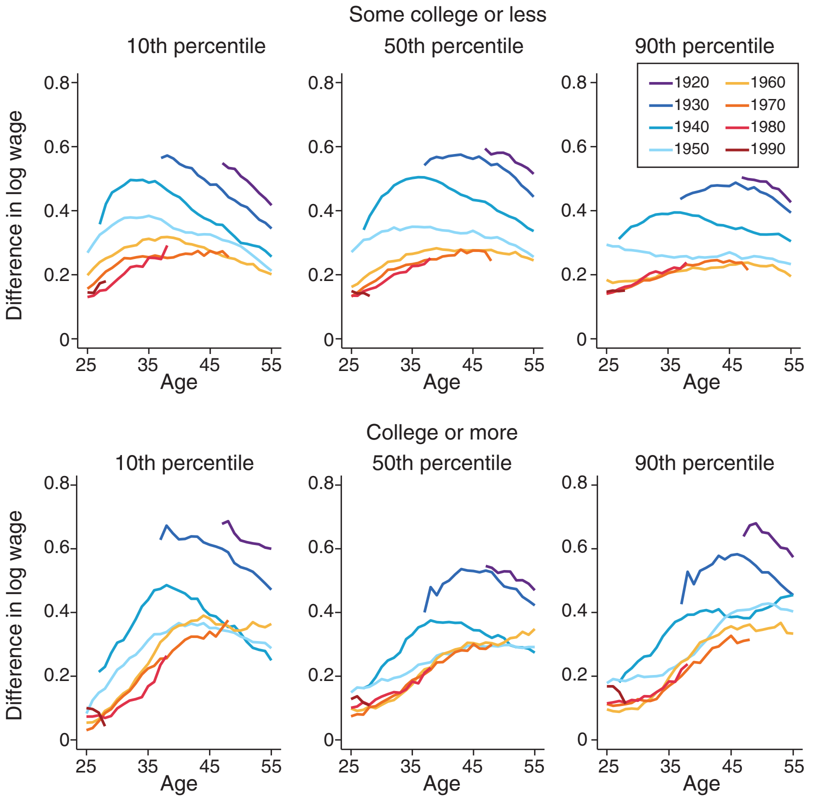

Figure 6. Within–Education Group Gender Offer Wage Gaps over the Life Cycle with Time Effects

Notes: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile selection model inclusive of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men and women aged 25–55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the first percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

Sources: Authors' calculations. Current Population Survey Annual Social and Economic Supplement, Survey Years 1977–2019.

This becomes more readily apparent in Figure 7, where we plot the coefficients on the time effects for men and women of each education group from the fiftieth 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 favor the wages of women over men from the mid-1970s to the mid-1990s, with the time effects of women converging toward those of men. In the subsequent two-and-a-half decades, the time 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 favor 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

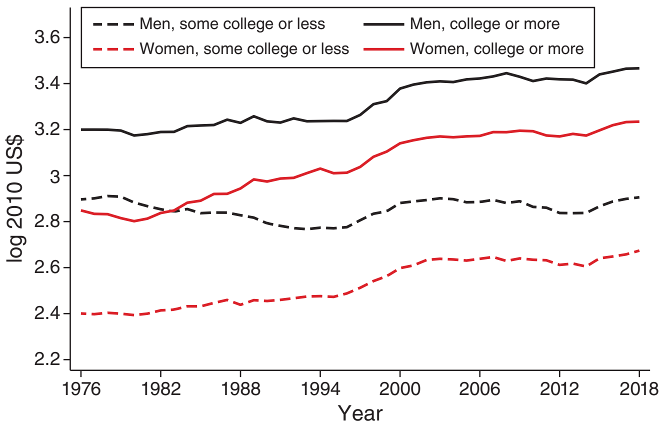

Figure 7. Aggregate Time Effects from Median Selection Offer Wages of Men and Women

Notes: Aggregate time effects are the coefficients on year dummies in a regression of log offer wages at the median. Median wages are counterfactual offer wage distributions based on median coefficients from the quantile selection model. See text for additional details. Sample consists of working and nonworking men and women aged 25–55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the first percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

Sources: Authors' calculations; Current Population Survey Annual Social and Economic Supplement, Survey Years 1977–2019

of progress favoring women in labor markets and thus little improvement in gender gaps in the second half of the working life.

Part of the stall in the gender gap is likely attributable to changes in life cycle fertility and child rearing, which is the second mechanism we explore. Evidence from Juhn and McCue (2017); Kleven et al. (2019); and Cortés and Pan (2023) suggest that these "child penalties" to women's wages from childbirth are on the order of 30 percent in the United States.[10] In Figure 8, we present life cycle profiles of the share of women by education and cohort with children aged 0–5 in the top panel and aged 6–18 in the bottom panel. Across both education groups, there has been a rightward shift in the distribution of child rearing to older ages among more recent cohorts, and this is especially pronounced among those women with at least a college education. In other words, delayed child rearing likely has resulted in these child penalties kicking in later in the life cycle, which helps account for the stalling of the life cycle gender gap in recent cohorts. Importantly, our approach allows children to have a direct impact on wages, most likely through their impact on past work experience, as well as an impact through selection into work. Based on the coefficients in Tables 1–4, both avenues are important, and much of the penalty appears to operate through the extensive margin of employment.

The third mechanism we explore is whether much of the patterns observed in life cycle gender wage gaps fall upon those women in recent cohorts with weaker attachment to the labor force, for example, through part-time work. Supplemental

[10] Note that in our model, we have numbers of children aged 0–5 and aged 6–18, not indicators for the presence of children or arrival of "first birth" as used in some of the child penalty literature.

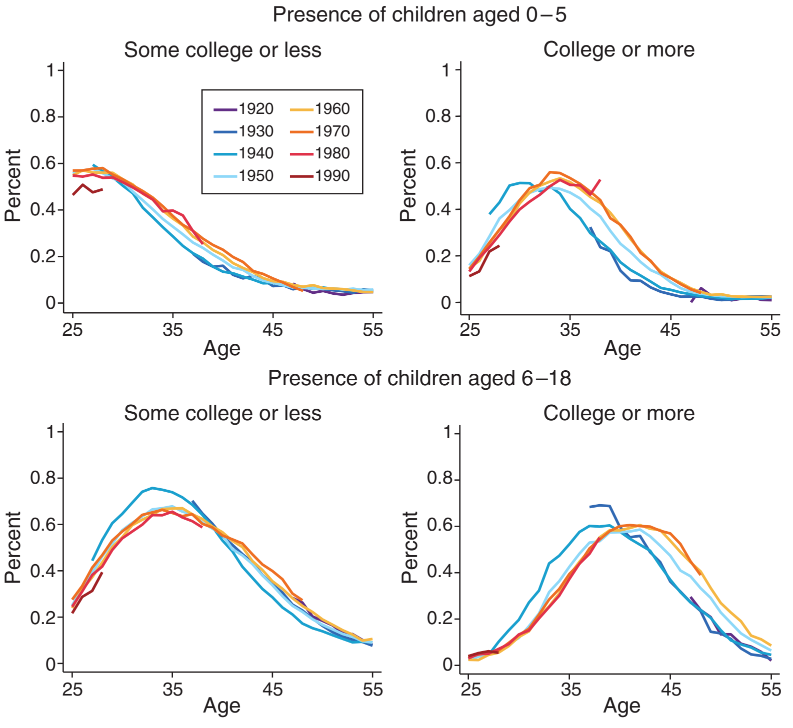

Figure 8. Share of Women with Children over the Life Cycle by Age of Child

Notes: The figure shows the fraction of women at a given age by education who have any children in the household aged 0–5 (top panel) and 6–18 (bottom panel). Sample consists of working and nonworking women aged 25–55.

Sources: Authors' calculations; Current Population Survey Annual Social and Economic Supplement, Survey Years 1977–2019

Appendix Figure A2 depicts a secular rise in the share of working women who are employed full time over our sample period, increasing about 25 percentage points for both education groups. Figure 9 presents the life cycle gender offer wage gaps for workers who select into full-time work. That is, the model is specified the same as our baseline model in equations (1)–(3), but instead of selecting into any work, we redefine it into selection into full-time work, defined as working at least 35 hours per week for 50 weeks per year. The parameter estimates along with the associated gender- and education-specific pseudo–life cycle wage profiles are presented in Supplemental Appendix D. Figure 9 shows that the life cycle gender offer wage gaps are substantively unchanged from Figure 5 for all workers. This was perhaps foreshadowed in the Supplemental Appendix Figure A1 time series of full-time workers, where, similar to the sample overall, there is a sharp decline in the gender wage gap from the 1970s to the mid-1990s, followed by a stalling in the gap, which is more pronounced in the top half of the wage distribution. However, current full-time work is unlikely to be enough to draw definitive conclusions about the impact of part-time work and labor market attachment. The history of labor market attachment

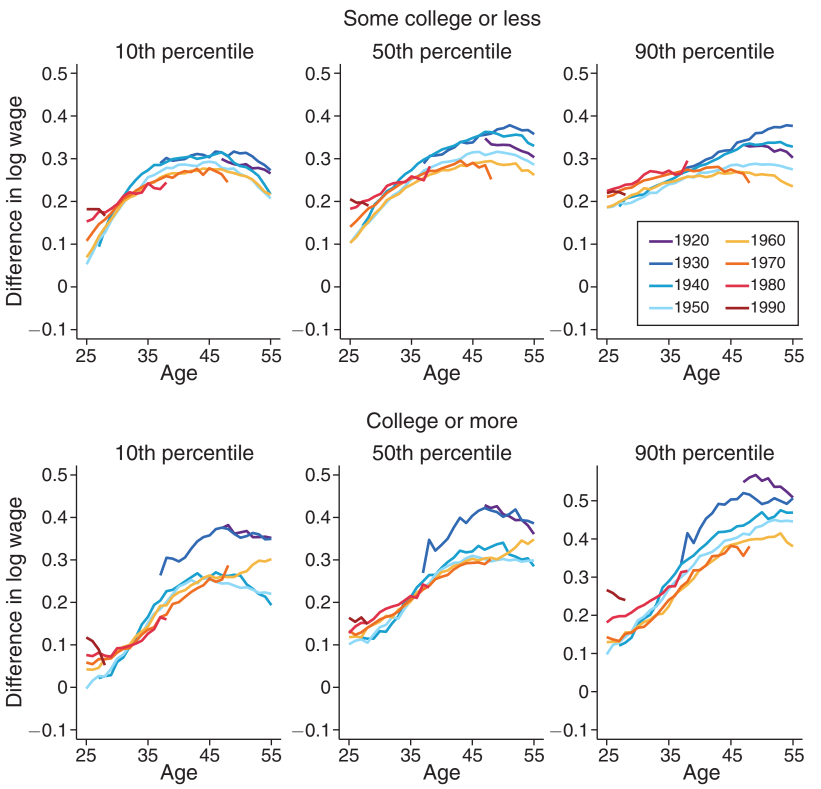

FIGURE 9. WITHIN–EDUCATION GROUP GENDER OFFER WAGE GAPS OVER THE LIFE CYCLE: FULL-TIME EMPLOYMENT

Notes: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile selection model for full-time employment net of gender- and education-specific time effects. See text for additional details. Sample consists of full-time working and nonworking (and less than full-time working) men and women aged 25–55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the first percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

Sources: Authors' calculations; Current Population Survey Annual Social and Economic Supplement, Survey Years 1977–2019

will impact the current wage of women through investment in experience capital.[11] This history will be driven largely by the numbers and ages of children, which we account for directly in our approach to modeling wages and selection into work.

V. Conclusion

We estimated the distribution of life cycle gender wage 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 the evolution of gender wage gaps varied dramatically across cohorts, the

[11] See Blundell et al. (2016).

working life, education groups, and the wage distribution. Moreover, controlling for both nonrandom selection into work and for within-group common time effects was important for our understanding of those life cycle gender wage gaps. Most of the gains in women's relative wages across the life cycle and distribution occurred among the cohorts born in the 1940s and 1950s relative to those born before 1940 and those born after 1960. This led to a substantial convergence in the time series of women's wages relative to men's until the mid-1990s when progress stalled. This lack of progress for women born after the 1950s occurred across the working life and distribution. Indeed, this stalling of convergence coincided with an increase in the age of the peak gender gap, likely a result of delayed fertility and child-rearing among recent cohorts of women.

There are hints that the economic progress of women relative to men 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 childcare 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 over both time and life course.

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Supplemental Appendix

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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Appendix A. Data and Descriptive Statistics

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).[1] 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

[1] The CPS ASEC data were downloaded from the IPUMS website at https://cps.ipums.org/cps/ Flood et al. (2023). In the accompanying online data replication package the Stata data file is denoted as IPUMS7519.dta, where you will also find original source code and data.

earnings to annual hours. Nominal wages are converted to real terms using the Personal Consumption Expenditure Deflator with 2010 base year.[2]

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.[3]

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"

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[2] The PCE is obtained from the FRED database, https://fred.stlouisfed.org/series/PCEPI. In the accompanying online data replication package the Stata data file is denoted as PCE.dta, where you will also find original source code and data.

[3] 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. In the accompanying online data replication package the Stata data file is denoted as RPSprocessed.dta, where you will also find original source code and data.

imputation). Moreover, some households refuse to answer any, or enough, questions on the 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.[4] 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.[5] 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).

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[4] When beginning this project IPUMS did not make available the flag for whole supplement imputation. We instead obtained the flags from James Ziliak (email: jziliak@uky.edu), who used them in a separate project (Hardy et al. 2022). In the accompanying online data replication package the Stata data file for imputation flags is denoted as AllFlags.dta.

[5] 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.

Appendix Tables A.1 – A.3 contain weighted summary statistics of employment, wages, and demographic variables used in estimation of the main sample of workers and non-workers (A.1), the subsample of full-time workers (A.2), and the sample of nonworkers (A.3). The latter sample of nonworkers tends to be older, with higher shares of minority racial and ethnic groups, and with more children.

Appendix Table A1. 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
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

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.

Appendix Table A2. 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
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

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.

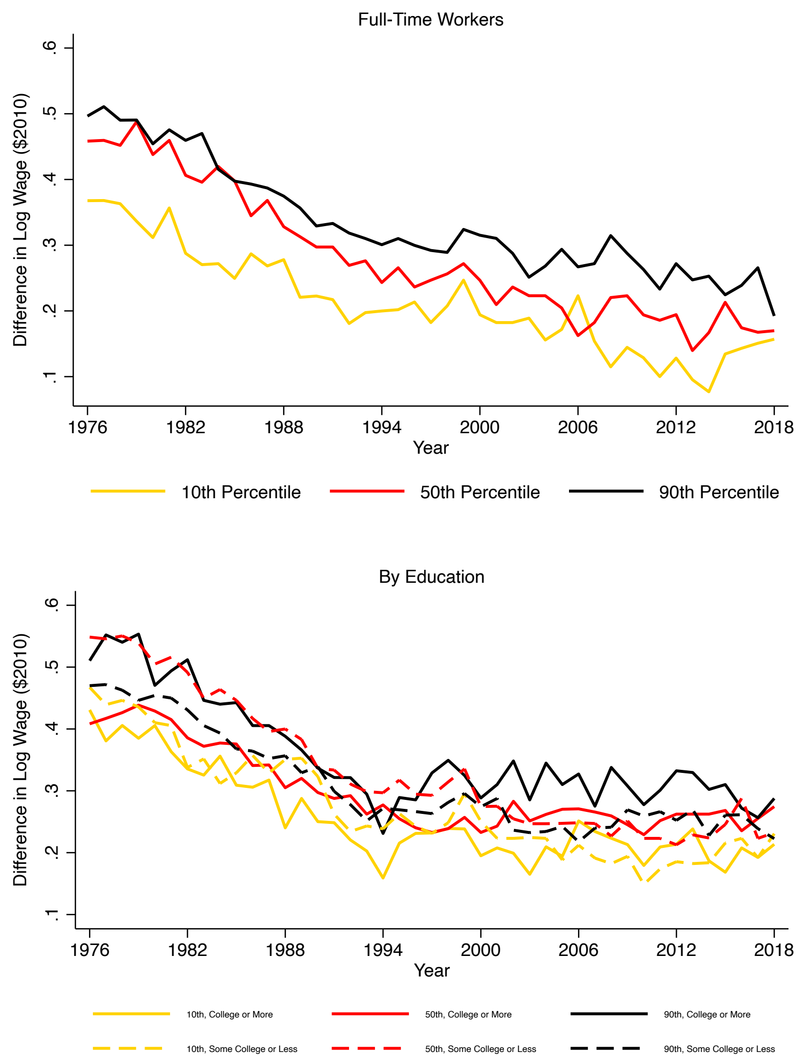
Appendix Table A3. Sample Summary Statistics of Non-Working Men and Women by Education Attainment

	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
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

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.

Figure A1 depicts the time series of gender wage gaps, but unlike Figure I of the text, we condition on full-time workers only in the top panel, and in the bottom panel we include all workers but split the sample based on whether they have at least a college education. In both cases the time series pattern is the same as Figure I of strong secular decline until the mid 1990s and then a plateauing out of progress, especially at the 90th percentile.

Appendix Figure A1. Time Series of Gender Gap in Log Hourly Wages of Full-Time Workers and All Workers by Education Attainment



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: The figure depicts the difference in log wages of men and women at the 10th, 50th, and 90th percentiles of the gender-specific wage distributions. Wages are defined as the ratio of annual earnings to annual hours of work, and are in real 2010 dollars using the Personal Consumption Expenditure Deflator. Sample in the top panel consists of

full-time employed men and women aged 25-55, and the bottom panel consists of all female and male workers. Workers with imputed earnings or hours are dropped, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

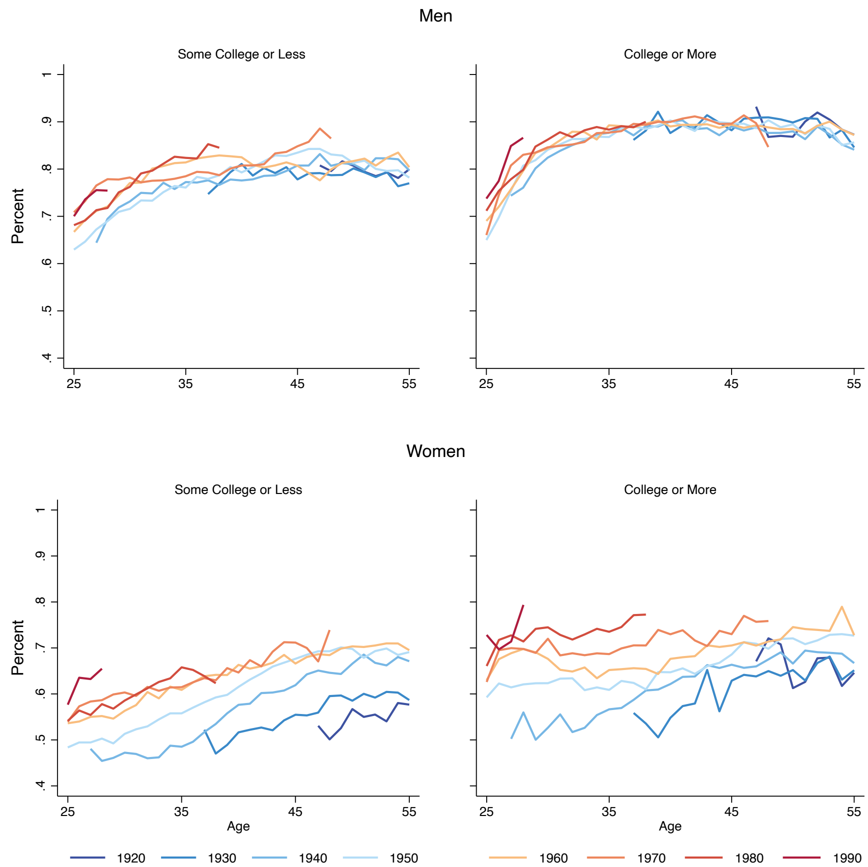
Figure A2 presents the time series of employment of men and women ages 25-55 in our sample from 1976-2018. The left panel is of the share in any work, and the right panel is the share of workers who are employed full time, defined as working at least 35 hours per week for 50 weeks out of the year. The figure shows strong secular decline in employment of lower educated men and women--for men over the whole period and for women starting in the mid 1990s. College educated men also show a decrease in employment, while employment of prime-age college-educated women peaked around 1990. The right panel shows that the shares of working women employed full time increased over the period, while it was fairly stable for men, though highly cyclical especially for those men without college.

Appendix Figure A2. Trends in Employment among Men and Women

Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Employment refers to any paid work in the calendar year, and full-time work implies working at least 35 hours per week for 50 weeks. Sample consists of men and women aged 25-55. Workers with imputed earnings or hours are dropped, as are those with wages below the 1st percentile or above the 0.1 percentile of work. the real gender-year specific wage distributions.

Figure A3 presents the lifecycle pattern of the share of prime-age working men and women employed full-time across cohorts by education attainment. The figure shows that younger cohorts of men are more likely to work full time at young ages, but for most of the working life there has been little change across cohorts, explaining the stability in the right panel of Figure A2. Among women there has been an increase at every age across cohorts, pushing up the aggregate share over time.

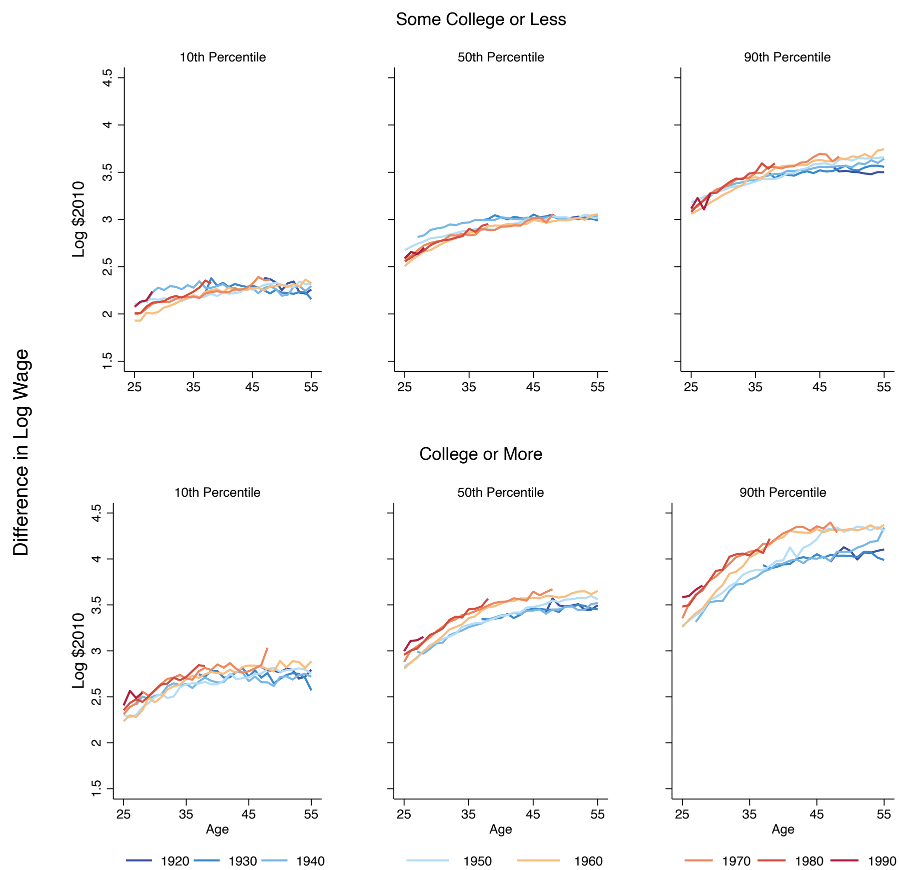
Appendix Figure A3. Share of Workers Employed Full Time Across the Life Cycle



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Employment refers to any paid work in the calendar year, and full-time work implies working at least 35 hours per week for 50 weeks. Sample consists of men and women aged 25-55. Workers with imputed earnings or hours are dropped, as are those with wages below the 1st percentile or above the 0.1 percentile of work. the real gender-year specific wage distributions.

Figure A4 presents the lifecycle profile of log hourly wages of men across cohorts for full-time workers at the bottom, middle, and top of the wage distribution. As in the figure in the main text, wages of younger cohorts of full-time workers in the middle of the distribution for lower educated men have declined in the first decade of work, while they have increased among college-educated men, highlighting a between-group increase in cohort wage inequality. A similar pattern holds at the 90th percentile, but there has been little change at the bottom.

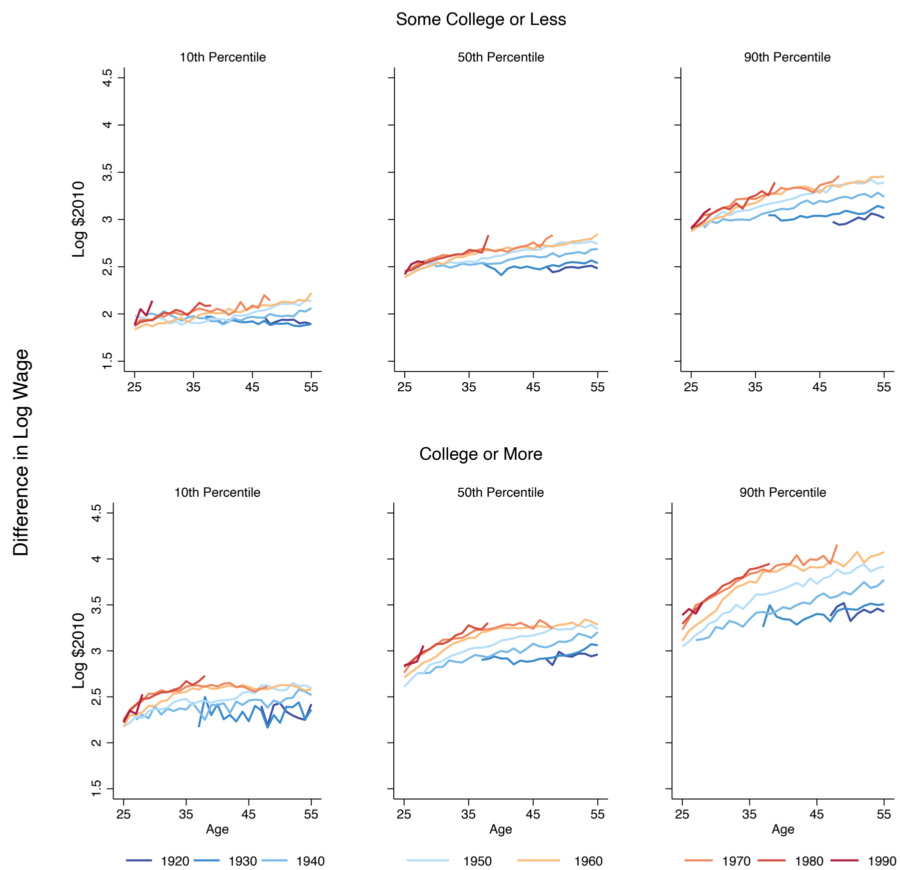
Appendix Figure A4. Distribution of Life Cycle Real Hourly Wages of Full-Time Working Men across Cohorts



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are defined as the ratio of annual earnings to annual hours of work, and are in real 2010 dollars using the Personal Consumption Expenditure Deflator. Sample consists of full-time working men aged 25-55. Workers with imputed earnings or hours are dropped, as are those with wages below the 1st percentile or above the 0.1 percentile of the real male-year-specific wage distributions.

Figure A5 presents the lifecycle profile of log hourly wages of women across cohorts for full-time workers at the bottom, middle, and top of the wage distribution. As in the figure in the main text, there is pronounced fanning out of wages in recent cohorts, especially at the 50th and 90th percentiles, but even at the 10th for college-educated women. However, the lifecycle profile of these high-educated high-wage women has noticeably slowed down in younger cohorts at younger ages.

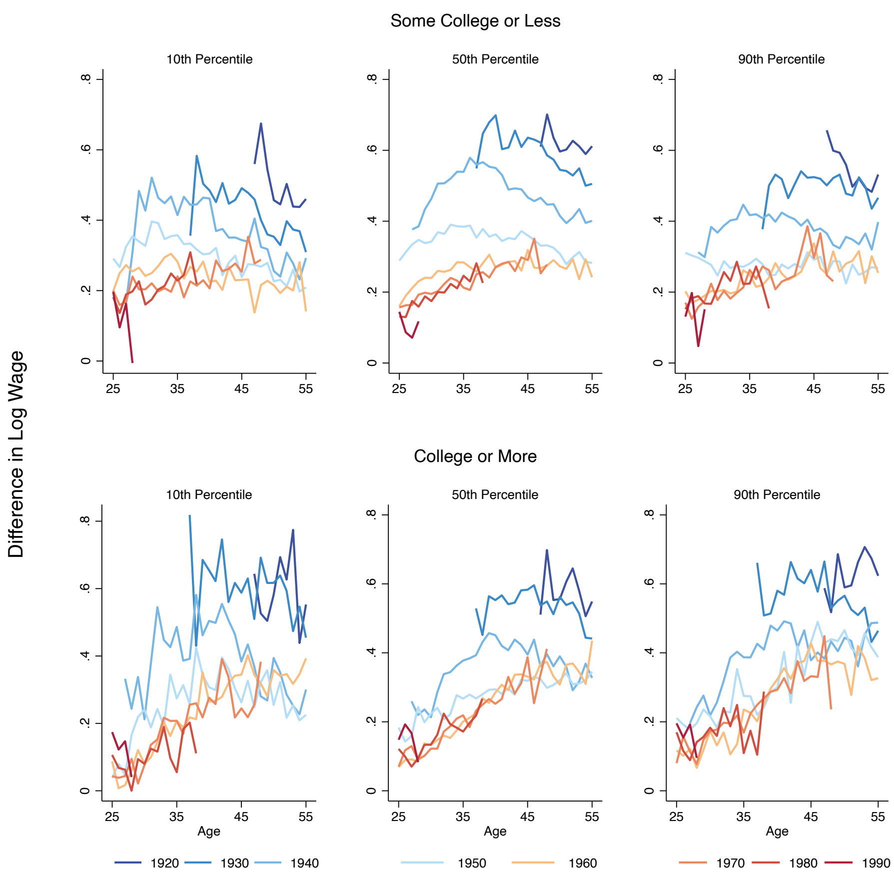
Appendix Figure A5. Distribution of Life Cycle Real Hourly Wages of Full-Time Working Women across Cohorts



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are defined as the ratio of annual earnings to annual hours of work, and are in real 2010 dollars using the Personal Consumption Expenditure Deflator. Sample consists of full-time working women aged 25-55. Workers with imputed earnings or hours are dropped, as are those with wages below the 1st percentile or above the 0.1 percentile of the real female-year-specific wage distributions.

Figure A6 presents the difference in the log wages of working men and women at each age within each cohort. All workers are included here, and this is the raw data version of the quantile-selection offer wage profiles in Figure 5 of the main text. Here we see substantial convergence across the 1920s to 1940s cohorts , and also substantial life-cycle catch-up after age 40, but there is little difference across cohorts starting in 1950 (except for the 10th and 50th percentiles of some college or less group), and not only is there no longer any catch-up after age 40 there is either no progress or even widening of gaps at older working ages.

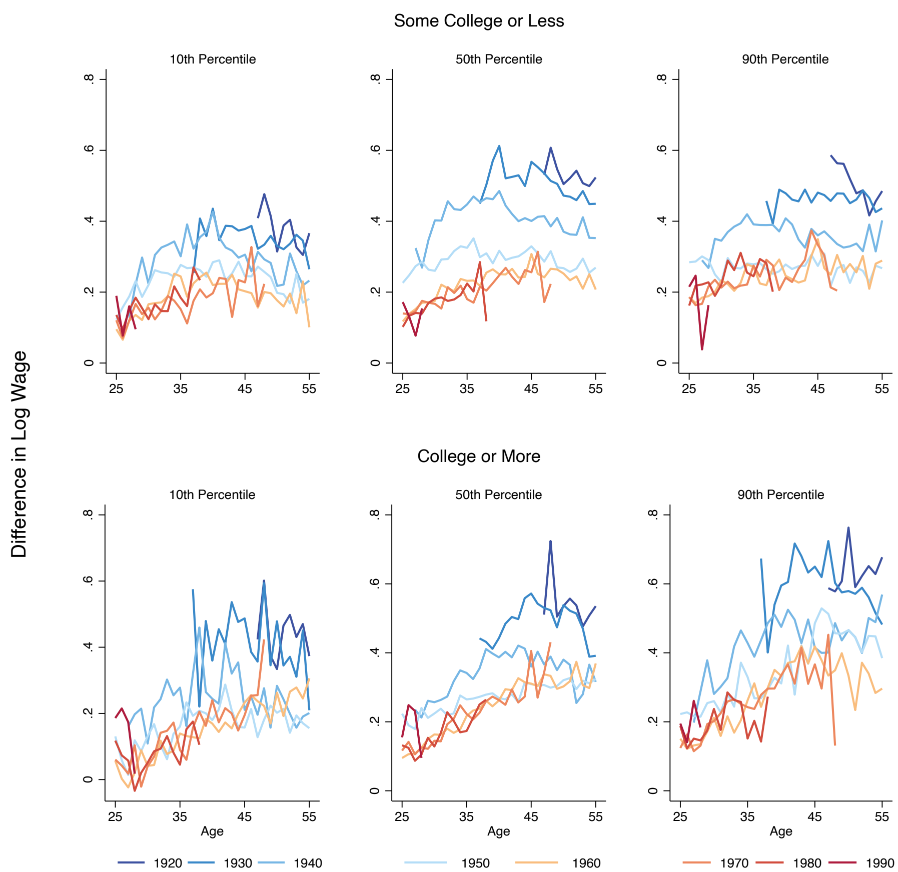
Appendix Figure A6. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are defined as the ratio of annual earnings to annual hours of work, and are in real 2010 dollars using the Personal Consumption Expenditure Deflator. Sample consists of working men and women aged 25-55. Workers with imputed earnings or hours are dropped, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender-year-specific wage distributions.

Figure A7 presents the difference in the log wages of full-time working men and women at each age within each cohort. Only full-time workers are included here, and this is the raw data version of the quantile-selection offer wage profiles in Figure 9 of the main text. While the level of the gaps at any given age tend to be lower among full-time workers compared to all workers in Figure A6, this is less in evidence among more recent cohorts where gaps are similar sized and follow similar lifecycle profiles.

Appendix Figure A7. Within-Education Group Gender Wage Gaps over the Life Cycle Among Full-Time Workers



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are defined as the ratio of annual earnings to annual hours of work, and are in real 2010 dollars using the Personal Consumption Expenditure Deflator. Sample consists of full-time working men and women aged 25-55. Workers with imputed earnings or hours are dropped, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender-year-specific wage distributions.

Appendix B. Quantile Wage Model and Identification

In this appendix we provide additional details on the derivation of our cohort wage specification as well as the identification of the quantile selection model.

B.1 Specification of Wages

We are interested in how the natural log of wages *lnw* vary over time *t* and working ages *a* across different birth cohorts *c*. Holding cohort constant, growth in wages can be a result of both time and aging. On the other hand, holding age constant, wages differ both because of cohort effects and time effects. This results in a well-known identification problem because any time period is comprised of individuals from different cohorts at different ages, i.e., $t = c + a$, and thus it is necessary to impose restrictions in order to separately identify age from cohort from time (Heckman and Robb 1985). Notably, in the event that growth in wages over the lifecycle is independent of time, then it is possible to identify the pure age-wage profile and wages are parallel across cohorts. This suggests that we want to adopt a wage specification that has lots of flexibility, but also nests the pure lifecycle model. This is exactly the approach of MaCurdy and Mroz (1995) and Fitzenberger and Wunderlich (2002) who used different parametric functional forms in age, cohort, and time to make it transparent how the separate factors were identified. At the same time, we are interested not just in mean wages, but wages across the distribution and how that distribution changes when workers select nonrandomly into the labor force. This leads us to a framework that extends the standard cohort models by incorporating nonrandom selection into work across the wage distribution as proposed in Arellano and Bonhomme (2017).

Specifically, equation (1) of the text relates the natural log of the latent wage (lnw^*) of an individual of gender *j* with schooling level *s* as

(B1) $lnw_j^{s*} = X_j^s(a, c, t; l)'\beta_j^s(U_j^s),$

where X is a function of age, cohort, time, and demographics l found in the prototypical Mincer wage equation; β is a vector of unknown parameters that depend on unobserved heterogeneity U distributed uniformly on the (0,1) interval reflecting the rank of the individual in the distribution of latent wages conditional on covariates X for gender j of schooling level s. Wages are observed, lnw_j^s, if the individual participates in the labor market according to the participation decision

(B2) $$E_j^s = \mathbf{1}\{V_j^s \leq p_j^s(D(a,c,t,l;z))\},$$

where the indicator variable takes a value of 1 if the rank of the uniformly distributed unobserved heterogeneity V is less than the propensity score $p(D)$ (Arellano and Bonhomme 2017). The index D is a flexible function of age, cohort, time, and demographics, as well as additional identifying excluded covariates of the decision to work z beyond the variables in l from the wage equation. As discussed below, the unobservables in the log wage equation are assumed to be independent of these excluded 'instruments' conditional on the flexible function of the age, cohort, time, and demographic variables included in the regression.

To parameterize the wage function in (B1) we implement an expanded version of the specification of Fitzenberger and Wunderlich (2002) as

(B3) $$lnw_j^s = \beta_{0j}^s(U_j^s) + \sum_{f=1}^{3} \beta_{a,fj}^s(U_j^s)e_j^f + \sum_{g=1}^{5} \beta_{t,gj}^s(U_j^s)t^g + \sum_{h=1}^{3} \beta_{c,hj}^s(U_j^s)((1-\theta)c_j^h + \theta c_j^{h-1}) + \sum_{m=1}^{4} \beta_{R,mj}^s(U_j^s)R_j^m + l_j^s\beta_{l,j}^s(U_j^s) + \delta_j^s(U_j^s) + \eta_j^s(U_j^s),$$

which adopts different polynomial orders in age, time, and cohort to permit identification. They replace age with a normalization around age of labor-market entry e, defined as $e = (a-25)/10$, which takes a value of 0 for the youngest worker in the sample and a value of 3 for the oldest workers and where the division by 10 is only used to inflate the coefficients on the cubic entry age polynomial. The cubic provides greater curvature in lifecycle age profiles than a standard quadratic. The quintic in time is a very flexible parameterization for capturing macroeconomic trends in wages. The effects of cohorts are permitted to be nonlinear based on year of labor-market entry by setting $\theta = 0$ for t < 1976 entry cohorts and $\theta = 1$ for t >= 1976, which means a cubic for cohorts entering before 1976 (the first year of our sample) and a quadratic for cohorts entering in 1976 and after.

Fitzenberger and Wunderlich (2002) assume that the model in Equation (B3) admits nonseparability between age and time in the term R_j^m. They assumed that the *growth* of wages over the lifecycle are captured by a quadratic in the age-time interactions of et, et^2,e^2t, and e^2t^2. Noting that the model in (B3) is of wage levels and not growth, and recalling that $t = c + e$, then it is necessary to integrate each of those four terms over entry age as

(E4) $$R^1 = \int e(c+e)de = \frac{ce_t^2}{2} + \frac{e_t^3}{3}$$

$$R^2 = \int e(c+e)^2 de = \frac{c^2e_t^2}{2} + \frac{2ce_t^3}{3} + \frac{e_t^4}{4}$$

$$R^3 = \int e^2(c+e)\, de = \frac{ce_t^3}{3} + \frac{e_t^4}{4}$$

$$R^4 = \int e^2(c+e)^2 de = \frac{c^2e_t^3}{3} + \frac{2ce_t^4}{4} + \frac{e_t^5}{5},$$

where we have assumed that the constant of integration is negligible in each term. This means that a test of separability in age and time amounts to a joint test across the four terms that $\beta_{R,mj}^s = 0$. Failure to reject the null of separability yields the pure lifecycle age-wage profile, while rejecting separability means that wage profiles are not parallel across cohorts, and thus in the text we refer to the model in equations (B1 – B4) as *pseudo* lifecycle age-wage profiles.

The model in equation (B3) admits common shocks that deviate from trends with a set of normalized time dummies, δ. We assume the shocks affect all cohorts within a given gender and education group the same in a given year, but they vary over time. As explained in the text, 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. Beyond the age, time, and cohort controls, for the sociodemographic controls the employment and wage models within each gender-education group include indicators for race (white is omitted), Hispanic ethnicity, whether married, and whether reside in a metropolitan area, as well as the numbers of children ages 0-5 and 6-18. All employment and wage models contain state fixed effects to control for permanent differences in state labor markets.

B.2 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. Assume that V_j^s is uniformly distributed on the unit interval and independent of *D*, and that $(U_j^s V_j^s)$ follows a bivariate Gaussian copula with dependence parameter ρ_j^s that is independent of *D*. The copula dependence parameter ρ_j^s captures the correlation between the unobserved heterogeneity in the wage (*U*) and participation (*V*) equations. If this correlation is negative, then selection on unobservables into work is positive, i.e. those with higher wages have lower "resistance" to work. Under these assumptions 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 $(U_j^s V_j^s)$. This implies that the τ^{th} conditional quantile of log wages given $E_j^s = 1$ and *D* is written as

(B5) $$Q_j^s\left(\tau, D_j\right) = X_j^s(a, c, t; l)'\beta_j^s(\tau^*(D_j^s)),$$

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

The first step of the three-step procedure 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. Imposing the standard assumptions underlying the Heckman Gaussian selection model, we get the propensity score in equation (B2) of $p_j^s(D(a,c,t;z)) = \Phi(D_j{}'\gamma_j^s)$, where $\Phi(.)$ is the cdf of the standard normal distribution evaluated at the index $D_{ij}{}'\gamma_j^s$. Under these assumptions consistent estimates of $\hat{\gamma}_j^s$ are obtained from probit maximum likelihood.

The second step of estimation then involves estimating the copula dependence parameter 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, $\Phi\left(D_j^s\hat{\gamma}_j^s\right)$. We use the Frank copula because its dependence structure admits both negative and positive selection, as 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. Finally, 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 within gender-education group as determined by the index $D_j\left(\hat{\gamma}_j^s\right)$ conditional on the estimated dependence parameter $\hat{\rho}_j^s$. All estimates are performed on a desktop workstation using modified Matlab programs provided online by Arellano and Bonhomme (2017).

Inference in the three-step model is quite complicated, especially given that stages two and three of estimation are functions of estimated parameters, and thus we rely on the bootstrap. 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. Specifically, we estimate the model of equations (B1) – (B3) using the Arellano and Bonhomme (2017) three-step procedure

100 times, and compute the standard deviation across the estimated parameters for inference. In their application, Arellano and Bonhomme conducted inference on the copula dependence parameter $\hat{\rho}_j^s$ using what is known as the *m*-out-of-*n* bootstrap (Shao and Tu 1995; Politis, Romano, and Wolf 1999), whereby one randomly samples a subset (*m*) of observations (*n*) with replacement, selecting the size of the subsample *m* as a fixed constant plus the square root of the sample size *n*. Our sample sizes for the four groups of men and women range from over 300,000 to just under 900,000, and we have 109 x 2 x τ parameters to estimate in each gender-education group (plus the dependence parameter and coefficients on the exclusion restrictions in the first stage). While the *m*-out-of-*n* bootstrap is computationally attractive when using large sample sizes with a large number of covariates as in our application, we opted to conduct the bootstrap on the full sample, running the models in parallel on the University of Kentucky supercomputer.

B.3 Identification

It is well known that the standard Heckman-type wage selection model under normality is formally identified through nonlinear functional form restrictions provided there is sufficient variation in the covariates (Vella 1998), and this result carries over to our flexible, parametric specification of the Arellano and Bonhomme (2017) quantile selection estimator. However, we use additional exclusion restrictions to increase the power of the model to detect deviations from random sorting into work. A common approach in the literature is to use the ages of children as exclusion restrictions under the assumption that children affect the decision to work, but not the wage conditional on working (Mulligan and Rubinstein 2008; Maasoumi and Wang 2019; Fernandez-Val et al. 2022; Blau et al. 2023). This is consistent with a standard Mincer (1974) formulation of the wage determination process for spot-market hourly wages. However, in this application (and in most of the literature) wages are measured as average hourly earnings defined as the ratio of annual earnings to annual hours, and the presence and age composition of children likely affects the intensive margin of hours of work. Moreover, children may affect accumulated labor-market experience and the timing of promotion opportunities, which could have a direct effect on the wage rate. Thus, we include the age composition of children in both the selection and wage equation, though in Appendix E below we present estimates of the gender wage gap under this alternative identification strategy.

Our approach to identification of the selection process is instead to exploit changes in the tax and transfer system to create simulated disposable income instruments. The use of tax and transfer policy reforms to construct simulated instruments is well established, and has been used to study such diverse topics as the effect of health insurance on birth outcomes (Currie and Gruber 2006), the effect tax credits on labor supply (Meyer and Rosenbaum 2001; Blundell et al. 2016; Hoynes and Patel 2018), the effect of marginal tax rates on taxable income (Gruber and Saez 2002; Weber 2014; Burns and Ziliak 2017), and the effect of the safety net on food insecurity (Schmidt, Shore-Sheppard 2016), among many others.

Over the span of our sample period 1976-2018 there were numerous changes to the U.S. tax and transfer system. On the tax side, there was major federal legislation passed in 1981, 1986, 1990, 1993, 1997, 2001, and 2017. These included reductions in the number of marginal tax brackets from 16 to 4 in the 1980s reforms along with reductions in the top marginal tax rate from 70 percent to 50 percent in 1981 to 28 percent in 1986, followed by increases in the number of brackets to 7 and top marginal rates to 39 percent in 1993 with incremental changes in rates (both up and down) in later years. These reforms also included substantial expansions of the refundable Earned Income Tax Credit (EITC) for low-wage workers in 1986 and 1993, and the introduction of a partially refundable Child Tax Credit (CTC) in 1997 followed with substantial expansions in 2001 and 2017. On the welfare side, federal provision of cash assistance was fundamentally altered with the 1996 Welfare Reform Act that created the Temporary Assistance for Needy Families (TANF) program. This reform also had significant implications for the eligibility of food assistance from the Food Stamp Program, later renamed the Supplemental Nutrition Assistance Program (SNAP) in 2008. There were also major changes to the eligibility for and generosity of health insurance for children in the 1997 legislation, and then for childless adults in the Affordable Care Act of 2010. See Auerbach and Slemrod (1997) and Piketty and Saez (2007) for references on the tax changes, and Grogger and Karoly (2005) and Moffitt and Ziliak (2019) for summaries of changes to the transfer system.

Some of the changes to taxes and transfers occurred at the federal level, some at the state level, and in many cases concurrently at both levels. We attempt to leverage many of these changes in the rewards to work and welfare across states and over time with our simulated instruments, under the maintained assumption that the policy changes are exogenous to the individual. In addition, we assume that family structure (i.e. marriage, fertility) is exogenous, but individual incomes (both labor and nonlabor) and labor supply choices are endogenous and thus we use aggregates at the state level for incomes and restrict the labor supply choice set. The procedure is as follows.

For each gender, education group (Some College or Less; College or More), state, and year we construct the average hourly wage, and average annual private nonlabor income from rental, interest, and dividend income. We then simulate annual earnings as the product of the gender-education-state-year average wage times hours of work under the assumption of 0 hours of work, 20 hours of work, and 40 hours of work. For couples there are 9 combinations where both partners are out of work, both part-time, both full-time, and the reminder where the partners are assumed to differ in their labor supply choice across no work, part-time, and full-time.

Next, we use household relationship pointers available in the CPS ASEC to construct tax units within the household (noting that some households have multiple filers) in order to calculate their tax liability with NBER's TAXSIM program.[6] Taxable income is the sum of simulated annual earnings and simulated rent/interest/dividend income in the tax unit at the gender-education-state-year cell. Simulated tax liability from TAXSIM includes federal, state, and payroll tax payments, inclusive of refundable EITC and Child Tax Credits at federal and state level. This will capture the many changes to tax rates and credits over the 43-year sample.

We then add to this after-tax income a streamlined version of the welfare state approximated by the value of transfers from Aid to Families with Dependent Children (AFDC) and the Food Stamp Program for the period before the 1990s welfare reforms, and their corresponding counterparts of TANF and SNAP after welfare reform. For ease of exposition, we refer to the programs by their current monikers of TANF and SNAP. These programs are historically the main source of income assistance for non-disabled low-income families, and are not taxable at the federal or state levels and thus are not included in the TAXSIM calculations. TANF requires dependent children under age 18 to qualify for assistance, while SNAP is available to those with or without children.

The income eligibility for TANF varied over states and time, but as the vast majority of recipients had incomes below the federal poverty line (FPL), we approximate gross income (*GI*)

[6] Tax filing units must be estimated because the CPS does not record who in the household files taxes and which members are part of the tax unit. We obtained these variables from James Ziliak (email: jziliak@uky.edu), as applied in Blundell et al. 2018; Hardy et al. 2022; and Jones and Ziliak 2022. Interested users may contact him directly for the data, and a sample version of code is available at https://taxsim.nber.org/to-taxsim/cps/. In the accompanying online data replication package the Stata data file for imputation flags is denoted as Addvars_CPS_Taxsim.dta.

eligibility based for households with simulated labor (L) and private nonlabor incomes (N) below the family-size specific FPL in each year, i.e. $GI \equiv L + V < FPL$. The federal guideline for gross income eligibility for SNAP 1.3 times the family-size specific FPL, $GI < 1.3 * FPL$. TANF maximum benefits vary across states, time and family size, while SNAP benefits vary across time and family size. Both programs reduce maximum benefits as gross income increases, after accounting for some deductions from gross income. The so-called benefit reduction rate in TANF is 100% for most states over time, while the rate in SNAP has been fixed at 30%. We limit deductions from gross income to those associated with work, using the old AFDC rule of deducting \$120 per month from labor earnings and using the SNAP rule of deducting 20% of monthly labor earnings from gross income.

The basic formula for TANF benefits is given as

(B.6) $$B_t^T = 12 * Max_{st}^T - ((L_t - 12 * 120) + V_t)\ if\ L_t > 0\ \&\ GI_t < FPL_t$$

$$B_t^T = 12 * Max_{st}^T - V_t\ if\ L_t = 0\ \&\ V_t < FPL_t,$$

where Max_{st}^T is the state (s) by year (t) maximum monthly benefit in TANF, which we allow to vary for 2-person, 3-person, and 4 or more person households and is assumed to be received for all 12 months in the year. The formula varies whether the family has one or both partners simulated as working, or none. The corresponding formula for SNAP is

(B.7) $$B_t^S = 12 * Max_t^S - 0.3 * ((L_t - 0.2 * L_t) + V_t + B_t^T)\ \ if\ L_t > 0\ \&\ (GI_t + B_t^T) < 1.3 * FPL_t$$

$$B_t^S = 12 * Max_t^S - 0.3 * (V_t + B_t^T)\ \ if\ L_t = 0\ \&\ (V_t + B_t^T) < 1.3 * FPL_t,$$

where Max_t^S is the maximum monthly benefit in SNAP in year t, which we allow to vary for 1-person, 2-person, 3-person, and 4 or more person households. As with TANF, for SNAP we assume benefits are received for 12 months, and the work-related deductions vary whether the household has simulated labor earnings. Besides how work expenses are modeled, another key difference in SNAP is that the program treats income from TANF as another form of nonlabor income and is thus subject to the benefit reduction rate and gross income eligibility test. We capture that programmatic detail in our simulations. While each program has multiple nuances determining eligibility and benefit amounts, the formulas in (B.6) and (B.7) capture key salient features of program design.

To summarize, simulated disposable income for the household is the sum of earnings, nonlabor income from rent/interest/dividend income as well as TANF and SNAP, less federal, state, and payroll taxes inclusive of refundable tax credits. Simulated disposable income is converted to real terms using a state-specific version of the PCE using 2010 as the base year.[7] From this we construct 2 instruments, one we call Simulated Disposable Income at No Work, which is the simulated income when no one in the tax unit works and is akin to the traditional nonlabor income used in scores of labor supply studies. The other instrument we call Simulated Disposable Income at Work, which is the weighted sum of the simulated values from the other 8 possible outcomes of individuals and their partners across no-work, part-time work, and full-time work. The weights are the share of each simulated value relative to total income from the 8 combinations. For example, for simulated labor supply choice where the head of household is assumed to be out of work and the partner is assume to work part time, the weight is the weight is simulated disposable income for that combination as a ratio of the sum of simulated disposable income from all 8 combination. Meyer and Rosenbaum (2001) use a similar weighting scheme as

[7] The state-price index was developed by Berry, Fording, and Hanson (2000) and Carillo, Early, and Olsen (2014), and updated in Hartley, Lamarche, and Ziliak (2022). This index is anchored to housing prices in 2000 and then adjusted forward and backward using the CPI (or PCE). We obtained the series from Robert Paul Hartley at Columbia University (Email: rh2845@columbia.edu), and interested users may contact him directly. In the accompanying online data replication package the Stata data file for state prices is denoted as state_prices_revised.dta.

it obviates potential redundancies if each of the 8 no work-work combinations were used independently. For the full-time models the choice set is reduced to the four options of both partners out of work, both full time, and one out of work and one full time.

Beyond these two simulated income instruments, we also include the state- and year-specific unemployment rate in the selection equation to capture tightness in local labor market opportunities.[8] That is, we assume that the unemployment rate affects the extensive participation margin but not the average hourly wage conditional on working.

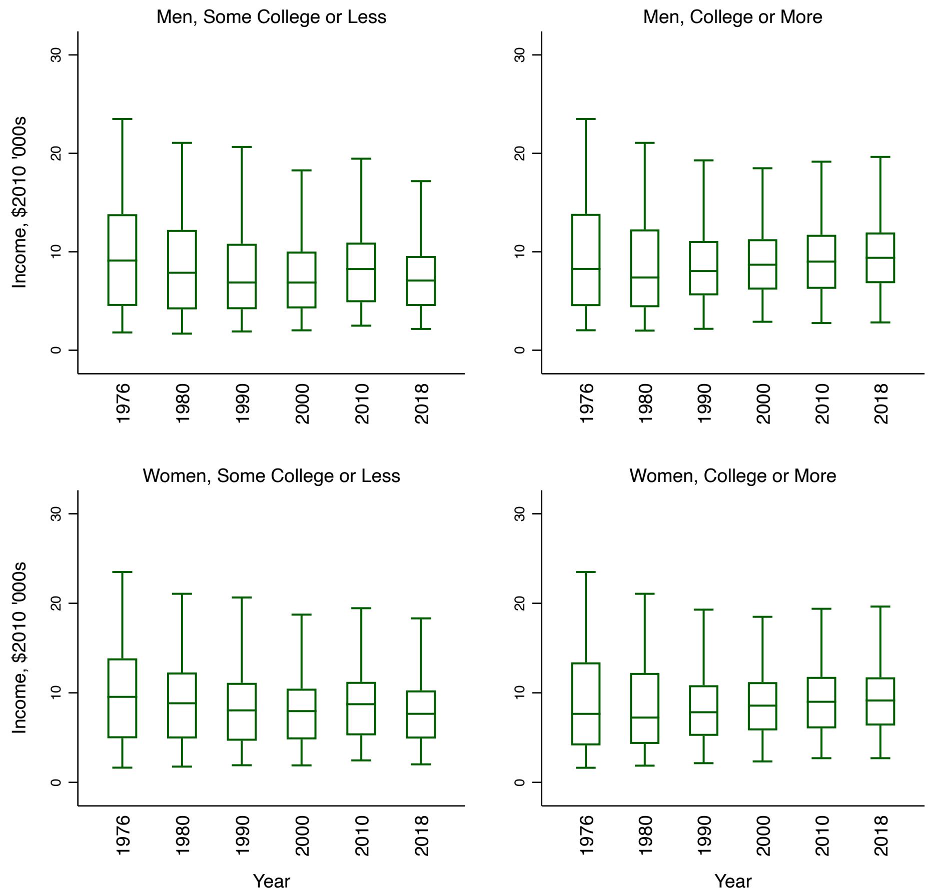
We then identify the selection equation from the wage equation by including in the selection model the two simulated disposable income instruments and the state unemployment rate described above. The unobservables in the log wage equation are assumed to be independent of these excluded 'instruments' conditional on the flexible function of the age, cohort, time, and demographic variables included in the regression, along with the year and state fixed effects. That is, identification of wages is based on the independence of U_j^s and z_j^s conditional on a,c,t,l,δ,η. This means that the selection model is identified via the residual variation in potential disposable income derived from the interaction of federal-state-time policy changes in taxes and transfers and the wage and nonwage incomes across states and demographic groups.

Appendix Figures B1 and B2 show box and whisker plots of the two simulated income instruments for select years for the no-work and work cases, respectively. Figure B1 shows a real decline in the out-of-work instrument from 1976 to 1990, reflecting real declines in maximum

[8] State unemployment rates for 1980-2018 are downloaded from the University of Kentucky National Welfare Database at https://www.ukcpr.org/resources/national-welfare-data and those for 1975-1979 come from James Ziliak (Email: jziliak@uky.edu), who used them in Figlio and Ziliak (1999). The maximum benefits for the EITC, SNAP, and TANF come from the same UKCPR database as unemployment rates for 1980-2018, and for 1975-1979 these data are obtained from Robert Paul Hartley at Columbia University (Email: rh2845@columbia.edu). In the accompanying online data replication package the Stata data file for unemployment rates and welfare benefits is denoted as state_data_for_stata.dta.

benefit guarantees in TANF noted by others (see Ziliak 2016), and then relative stability thereafter. Real median incomes hover around $10,000 in a typical year with an interquartile range of about $5,000.

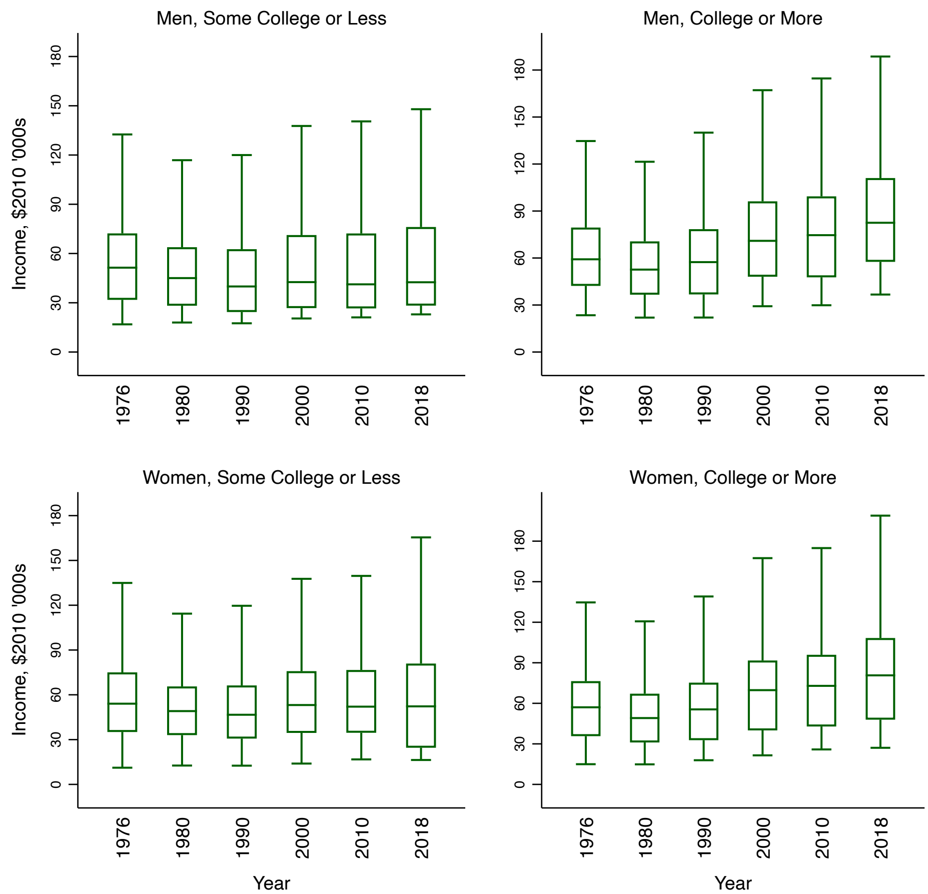
Appendix Figure B1. Simulated Disposable Income Instrument-No Work, Over Time



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: The figure is a box and whisker plot depicting the 25th, 50th, and 75th percentiles of simulated income instruments across individuals aged 25-55.

Appendix Figure B2 depicts much more variation in the weighted income instrument across education group, reflecting the differences in both average wages and private nonlabor incomes, as well as tax liabilities. Again we see a decline in real simulated median incomes among the Some College or Less group, where in this case it reflects the decline in real wages in the 1980s. At the same time we see substantial increases in median incomes among those with at least College after 1990, owing to rising real wages. The key takeaway is that the simulated instruments offer lots of variation to offer robust identification of the selection equation.

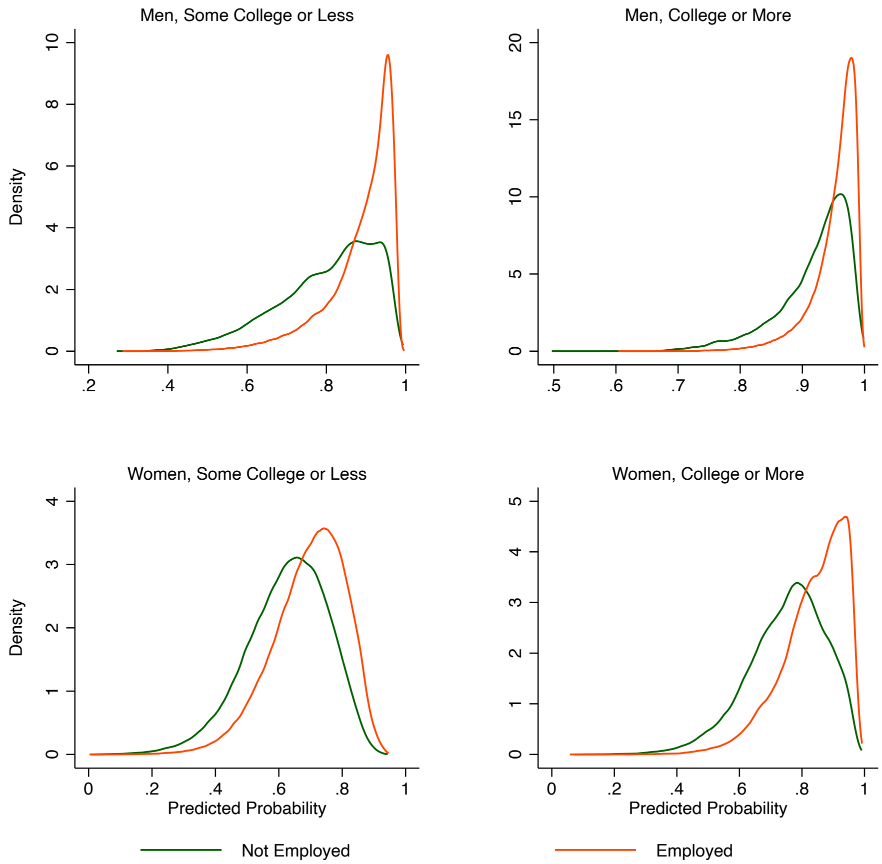
Appendix Figure B2. Simulated Weighted Disposable Income Instrument-Work, Over Time



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: The figure is a box and whisker plot depicting the 25^{th}, 50^{th}, and 75^{th} percentiles of simulated income instruments across individuals aged 25-55.

To explore identification further, in Appendix Figure B3 we present kernel density estimates of the predicted probability from the first-stage employment probit equation for each gender and education group used in estimation by employment status. There we see substantial overlap in the underlying support in the first stage, which is fundamental to identification of the selection model.

Appendix Figure B3. Kernel Density Estimates of Overlap of Support for Selection Equation



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: The figure is a box and whisker plot depicting the 25th, 50th, and 75th percentiles of simulated income instruments across states and year.

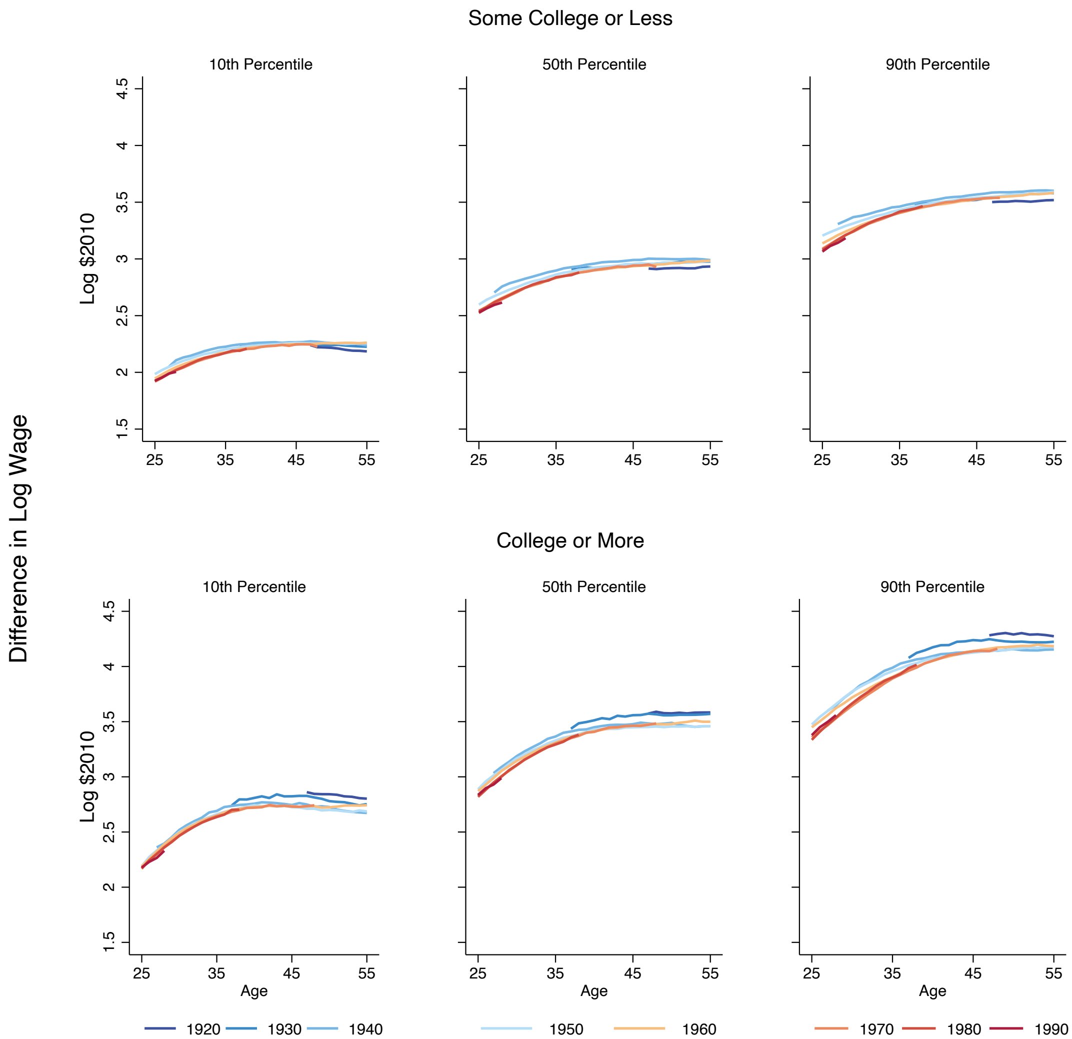
Tables 1-4 with all workers in the main text and Appendix Tables D1-D4 for full-time workers demonstrate that the three exclusion restrictions individually and jointly affect the decision to work. Across men and women in each education group higher levels of Simulated Disposable Income at No Work reduce the probability of employment, which is consistent with a canonical static model nonlabor income effect Higher levels of state unemployment rates are associated. Among men, weighted Simulated Income from Work increases the probability of employment, while the opposite is found for women, suggesting possible household substitution in work between men and their partner. The state unemployment rate is consistently negative, indicating that employment is countercyclical across state labor markets.

Appendix C. Model-Based Wage Profiles

In this appendix we present the quantile with selection pseudo life-cycle wage profiles for men and women that underlie the model-based gender wage gaps in Figures V and VI in the main text. In Appendix Figures C1-C4 we produce the pseudo profiles across age and cohort of prime-age men and women based on the regression estimates in Tables 1-4. 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 10^{th}, 50^{th}, and 90^{th} percentiles. 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. To highlight the importance of common time effects (to each gender-education group), we present the wage profiles with (Figures C1 and C3) and without (Figures C2 and C4) time effects netted out.

The upper panel of Figure C1 (C3) is for men (women) with some college or less, and the respective lower panel is for those with college or more education. Among men, Figure C1 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 90^{th} percentiles. Moreover, there is

Appendix Figure C1. Quantile Selection Pseudo Life Cycle Age-Offer Wage Profiles of Men Net of Time Effects

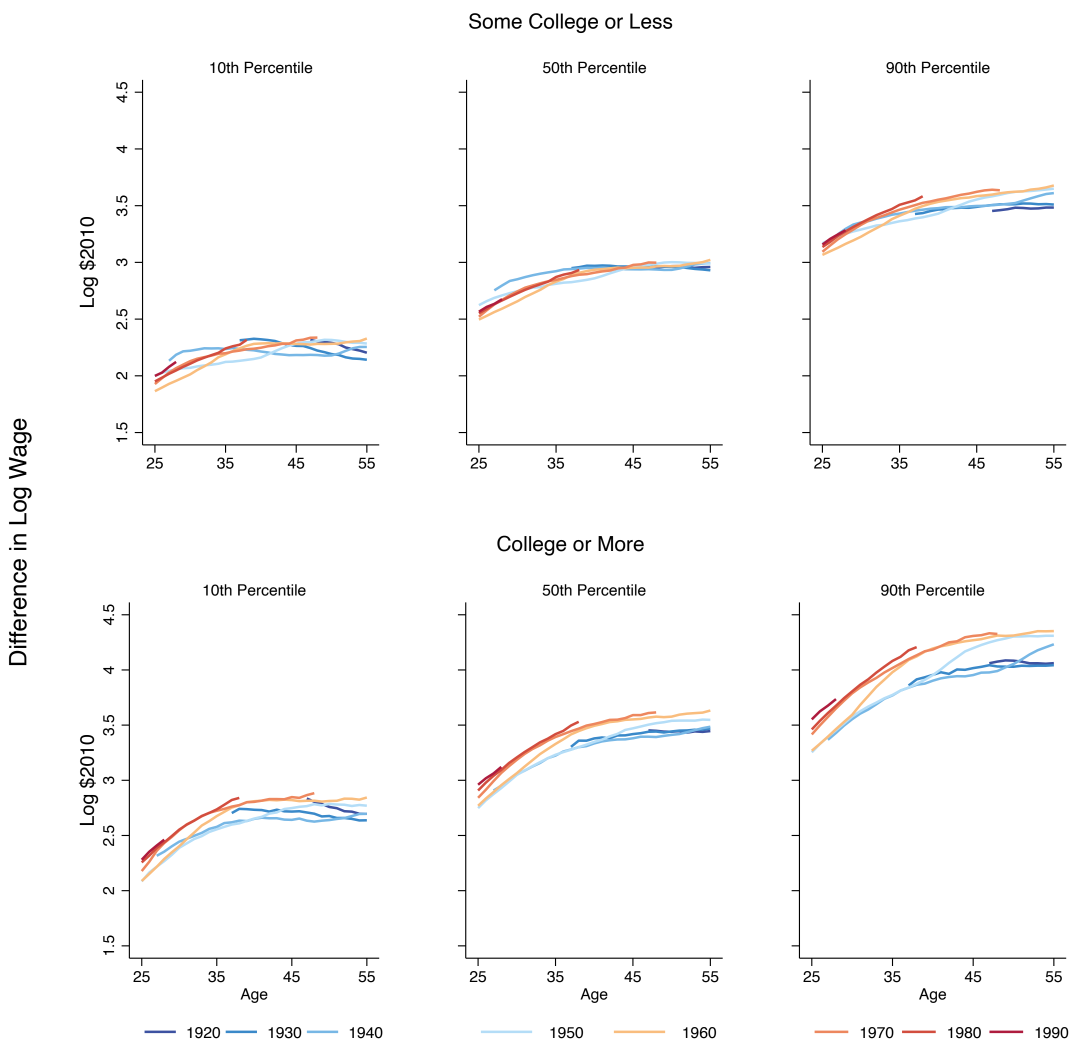


Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are based on counterfactual offer wage distributions based on coefficients from the quantile selection model net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender-year-specific wage distributions.

some evidence that wages actually turn down at later ages at the 10th percentile, which is not the case higher up the wage distribution. The figure 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 C2 with time effects still included indicates that more recent cohorts start out their life cycles with *higher* wages and *steeper* slope

Appendix Figure C2. Quantile Selection Pseudo Life Cycle Age-Offer Wage Profiles of Men Inclusive of Time Effects



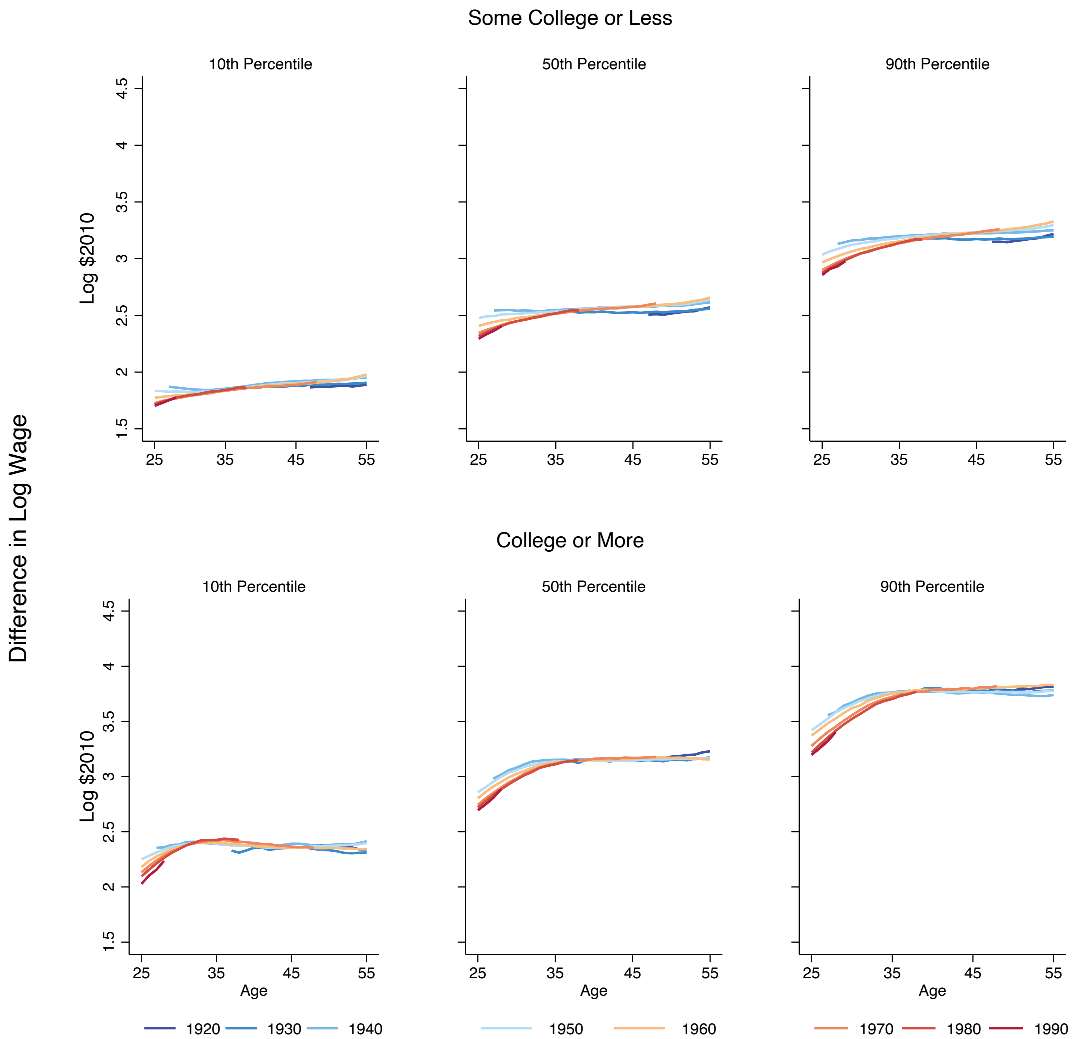
Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are based on counterfactual offer wage distributions based on coefficients from the quantile selection model inclusive of gender- and education-specific time effects. See text for additional details. Sample consists of

working and nonworking men aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender-year-specific wage distributions.

compared to older cohorts. That is particularly the case for the higher quantiles where we see male wages at the 90th percentile for younger cohorts strongly pulling away. As the comparison of profiles in Figure C1 with time effects netted out 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.

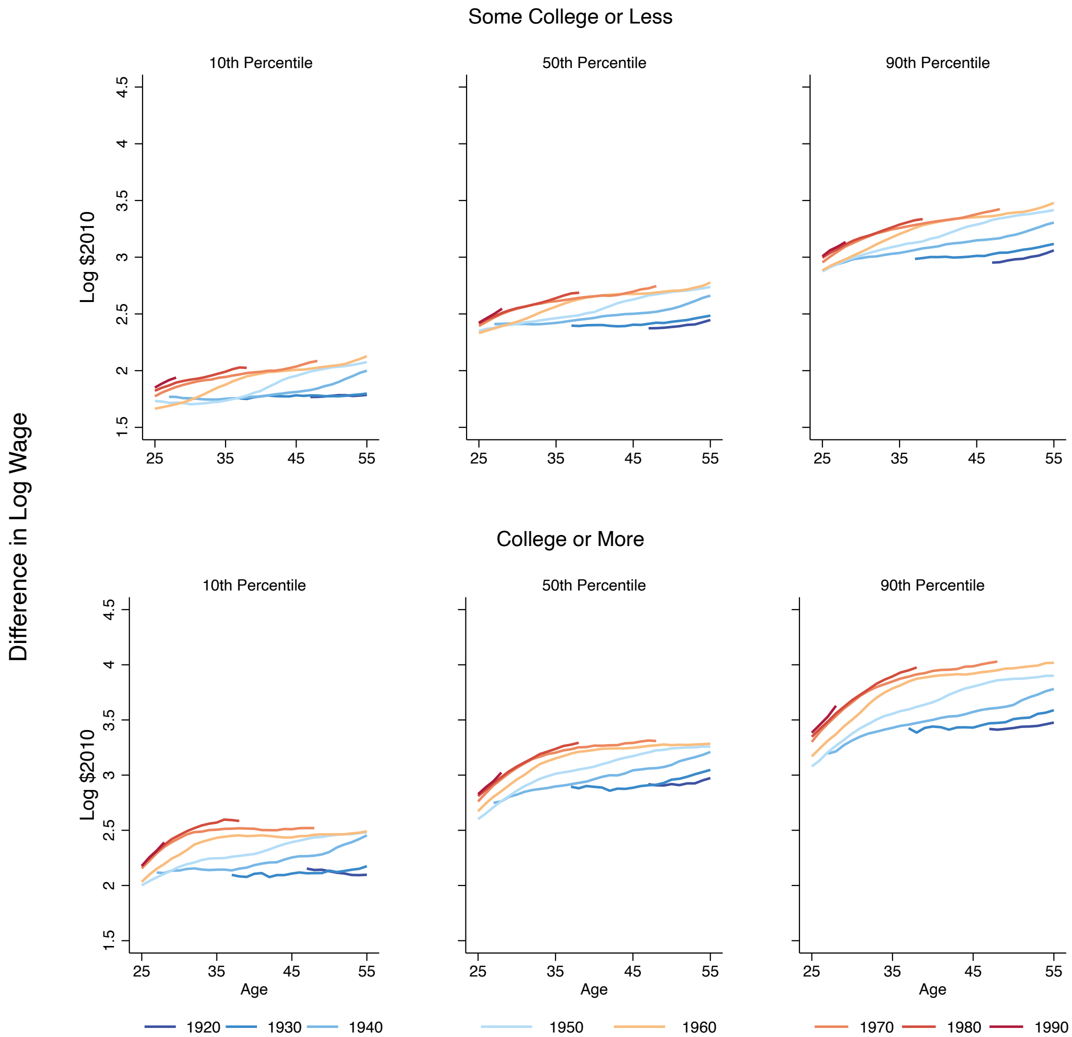
Figure C3 suggests that net of time effects, pseudo life cycle age-wage profiles of women are quite flat across the distribution, whereas inclusive of common time effects in Figure C4 more recent cohorts of women start out their working life with offer wages higher than older cohorts across both education groups. The implication is that had recent cohorts of women experienced the time trends of the older cohorts, they would do even better than seen in Figure C3 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. 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.

Appendix Figure C3. Quantile Selection Pseudo Life Cycle Age-Offer Wage Profiles of Women Net of Time Effects



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are based on counterfactual offer wage distributions based on coefficients from the quantile selection model net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender-year-specific wage distributions.

Appendix Figure C4. Quantile Selection Pseudo Life Cycle Age-Offer Wage Profiles of Women Inclusive of Time Effects



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are based on counterfactual offer wage distributions based on coefficients from the quantile selection model inclusive of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender-year-specific wage distributions.

Appendix D. Quantile Selection for Full Employment Model

This appendix presents the parameter estimates for the quantile selection model for the sample of full-time workers. Full time is defined as working at least 35 hours per week for 50 weeks of the year. These parameter estimates are used in constructing the gender offer wage gaps in Figure IX of the main text, and the offer wage profiles below in Appendix Figures D1-D4.

Appendix Table D1. Quantile Selection Estimates of Log Wages for Men with Some College or Less, Full-Employment Model

	Employment	10th Quantile	50th Quantile	90th Quantile
Constant	0.132	1.979	2.552	3.021
	(0.026)	(0.016)	(0.011)	(0.011)
Entryage	0.329	0.278	0.349	0.286
	(0.026)	(0.023)	(0.013)	(0.018)
Entryage2	-0.193	-0.080	-0.057	-0.020
	(0.025)	(0.023)	(0.013)	(0.019)
Entryage3	0.016	0.011	0.008	-0.001
	(0.006)	(0.005)	(0.003)	(0.005)
Time	0.886	-0.026	-0.007	0.057
	(0.193)	(0.141)	(0.081)	(0.107)
Time2	-2.764	-0.245	-0.068	0.167
	(0.719)	(0.551)	(0.317)	(0.423)
Time3	1.457	0.120	-0.056	-0.181
	(0.502)	(0.397)	(0.230)	(0.332)
Time4	-0.267	-0.017	0.039	0.059
	(0.137)	(0.110)	(0.066)	(0.103)
Time5	0.015	0.001	-0.005	-0.006
	(0.013)	(0.010)	(0.007)	(0.011)
Cohort2	0.011	0.006	0.003	-0.021
	(0.006)	(0.005)	(0.003)	(0.005)
Cohort2*delta	0.151	-0.071	-0.122	-0.096
	(0.017)	(0.015)	(0.010)	(0.015)
Cohort3	0.033	-0.005	-0.000	-0.001
	(0.005)	(0.003)	(0.003)	(0.003)
R1	52.190	-15.306	-100.790	-102.820
	(29.352)	(25.962)	(16.490)	(26.887)
R2	-6.204	2.380	19.088	9.356
	(6.954)	(5.242)	(3.994)	(5.352)
R3	-19.044	-9.531	7.401	17.596
	(14.074)	(10.674)	(7.237)	(10.932)
R4	4.532	2.795	-0.351	-0.420
	(3.443)	(2.389)	(1.829)	(2.409)
Black	-0.357	-0.184	-0.183	-0.178
	(0.005)	(0.005)	(0.003)	(0.004)
Other Race	-0.319	-0.272	-0.197	-0.140
	(0.007)	(0.007)	(0.005)	(0.008)
Hispanic	-0.140	-0.375	-0.349	-0.261
	(0.005)	(0.004)	(0.003)	(0.003)
Married	0.445	0.159	0.123	0.109
	(0.005)	(0.003)	(0.003)	(0.003)

Live in Metro Area	0.132	0.168	0.134	0.112
	(0.004)	(0.003)	(0.002)	(0.003)
Number of Children Ages 0-5	-0.058	-0.015	-0.006	0.003
	(0.004)	(0.002)	(0.001)	(0.002)
Number of Children Ages 6-18	-0.059	-0.004	-0.001	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
State Unemployment Rate	-0.045			
	(0.002)			
Simulated Disposable Income at No Work	-0.005			
	(0.001)			
Simulated Weighted Disposable Income at Full-Time Work	0.004			
	(0.000)			
Rho	0.94			
	(0.06)			
P-value on Excluded Variables	0.00			
P-value on Cohort terms		0.00	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

Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: The table contains estimates from the quantile with selection into full-time employment model as described in the text. The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

Appendix Table D2. Quantile Selection Estimates of Log Wages for Men with College or More, Full-Employment Model

	Employment	10th Quantile	50th Quantile	90th Quantile
Constant	0.097	2.037	2.586	2.983
	(0.047)	(0.043)	(0.029)	(0.025)
Entryage	0.943	0.412	0.447	0.540
	(0.058)	(0.045)	(0.026)	(0.037)
Entryage2	-0.506	-0.144	-0.162	-0.200
	(0.058)	(0.039)	(0.023)	(0.036)
Entryage3	0.066	0.017	0.022	0.016
	(0.014)	(0.009)	(0.005)	(0.009)
Time	0.544	-0.077	0.043	0.467
	(0.330)	(0.276)	(0.140)	(0.208)
Time2	-0.197	-0.375	0.008	-0.809
	(1.239)	(1.086)	(0.538)	(0.824)
Time3	-0.152	0.145	-0.018	0.466
	(0.850)	(0.742)	(0.378)	(0.588)
Time4	0.080	0.001	0.008	-0.104
	(0.226)	(0.192)	(0.104)	(0.161)
Time5	-0.010	-0.003	-0.001	0.008
	(0.021)	(0.017)	(0.010)	(0.015)
Cohort2	0.007	-0.001	-0.007	-0.008
	(0.013)	(0.009)	(0.005)	(0.009)
Cohort2*delta	0.129	0.036	0.097	0.139
	(0.040)	(0.026)	(0.016)	(0.028)
Cohort3	0.007	0.016	0.026	0.000
	(0.009)	(0.007)	(0.004)	(0.007)
R1	89.724	-8.513	68.743	150.290
	(62.866)	(41.145)	(26.565)	(54.214)

R2	-29.437	-0.230	-18.628	-35.189
	(11.992)	(8.786)	(5.479)	(11.414)
R3	-26.402	-7.953	-33.601	-18.432
	(25.278)	(18.826)	(11.383)	(24.231)
R4	11.556	3.486	8.561	4.117
	(5.403)	(4.249)	(2.511)	(5.382)
Black	-0.219	-0.204	-0.223	-0.255
	(0.012)	(0.010)	(0.007)	(0.010)
Other Race	-0.235	-0.194	-0.008	-0.029
	(0.010)	(0.013)	(0.009)	(0.008)
Hispanic	-0.148	-0.313	-0.184	-0.164
	(0.012)	(0.013)	(0.006)	(0.008)
Married	0.263	0.162	0.110	0.074
	(0.010)	(0.011)	(0.008)	(0.007)
Live in Metro Area	0.113	0.231	0.213	0.190
	(0.009)	(0.007)	(0.004)	(0.006)
Number of Children Ages 0-5	-0.006	0.021	0.028	0.049
	(0.007)	(0.003)	(0.002)	(0.003)
Number of Children Ages 6-18	-0.012	0.023	0.026	0.045
	(0.006)	(0.002)	(0.002)	(0.003)
State Unemployment Rate	-0.019			
	(0.003)			
Simulated Disposable Income at No Work	-0.008			
	(0.001)			
Simulated Weighted Disposable Income at Full-Time Work	0.005			
	(0.000)			
Rho	0.92			
	(0.44)			
P-value on Excluded Variables	0.00			
P-value on Cohort terms		0.17	0.00	0.00
P-value on R terms		0.05	0.02	0.00
P-value on R and Cohort terms		0.00	0.00	0.00

Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: The table contains estimates from the quantile with selection into full-time employment model as described in the text. The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

Appendix Table D3. Quantile Selection Estimates of Log Wages for Women with Some College or Less, Full-Employment Model

	Employment	10th Quantile	50th Quantile	90th Quantile
Constant	0.083	1.842	2.257	2.682
	(0.025)	(0.021)	(0.010)	(0.018)
Entryage	0.069	0.074	0.264	0.356
	(0.026)	(0.025)	(0.017)	(0.026)
Entryage2	0.006	-0.016	-0.118	-0.141
	(0.025)	(0.026)	(0.017)	(0.028)
Entryage3	-0.021	0.003	0.024	0.023
	(0.006)	(0.006)	(0.004)	(0.007)
Time	-0.065	-0.171	-0.027	0.214
	(0.175)	(0.208)	(0.100)	(0.169)
Time2	1.252	0.825	-0.189	-0.688
	(0.632)	(0.794)	(0.396)	(0.624)

Time3	-1.088	-0.619	0.098	0.392
	(0.451)	(0.555)	(0.280)	(0.456)
Time4	0.322	0.171	-0.008	-0.074
	(0.126)	(0.147)	(0.077)	(0.129)
Time5	-0.031	-0.016	-0.001	0.004
	(0.012)	(0.014)	(0.007)	(0.013)
Cohort2	-0.054	-0.039	-0.019	-0.016
	(0.007)	(0.006)	(0.004)	(0.007)
Cohort2*delta	-0.105	-0.125	-0.105	-0.091
	(0.018)	(0.019)	(0.012)	(0.020)
Cohort3	-0.026	-0.019	-0.012	-0.018
	(0.004)	(0.004)	(0.003)	(0.004)
R1	-70.540	-134.210	-62.309	-2.686
	(31.037)	(32.816)	(19.754)	(36.400)
R2	-15.154	10.387	6.983	-6.764
	(6.758)	(6.583)	(4.204)	(7.253)
R3	17.627	43.570	3.656	-11.380
	(12.506)	(14.193)	(8.536)	(14.798)
R4	5.351	-4.463	0.930	4.701
	(2.968)	(3.100)	(1.956)	(3.153)
Black	0.007	-0.078	-0.102	-0.119
	(0.005)	(0.005)	(0.003)	(0.005)
Other Race	-0.079	-0.176	-0.123	-0.101
	(0.008)	(0.007)	(0.006)	(0.009)
Hispanic	-0.122	-0.269	-0.246	-0.196
	(0.004)	(0.004)	(0.003)	(0.004)
Married	-0.126	0.029	0.037	0.031
	(0.004)	(0.003)	(0.002)	(0.003)
Live in Metro Area	0.091	0.170	0.163	0.166
	(0.003)	(0.004)	(0.002)	(0.004)
Number of Children Ages 0-5	-0.270	-0.027	-0.007	0.001
	(0.003)	(0.004)	(0.003)	(0.003)
Number of Children Ages 6-18	-0.109	-0.047	-0.037	-0.020
	(0.002)	(0.002)	(0.002)	(0.002)
State Unemployment Rate	-0.024			
	(0.001)			
Simulated Disposable Income at No Work	-0.020 (0.001)			
Simulated Weighted Disposable Income at Full-Time Work	-0.002 (0.000)			
Rho	0.96			
	(0.10)			
P-value on Excluded Variables	0.00			
P-value on Cohort terms		0.00	0.00	0.00
P-value on R terms		0.00	0.00	0.22
P-value on R and Cohort terms		0.00	0.00	0.00

Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019

Note: The table contains estimates from the quantile with selection into full-time employment model as described in the text. The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

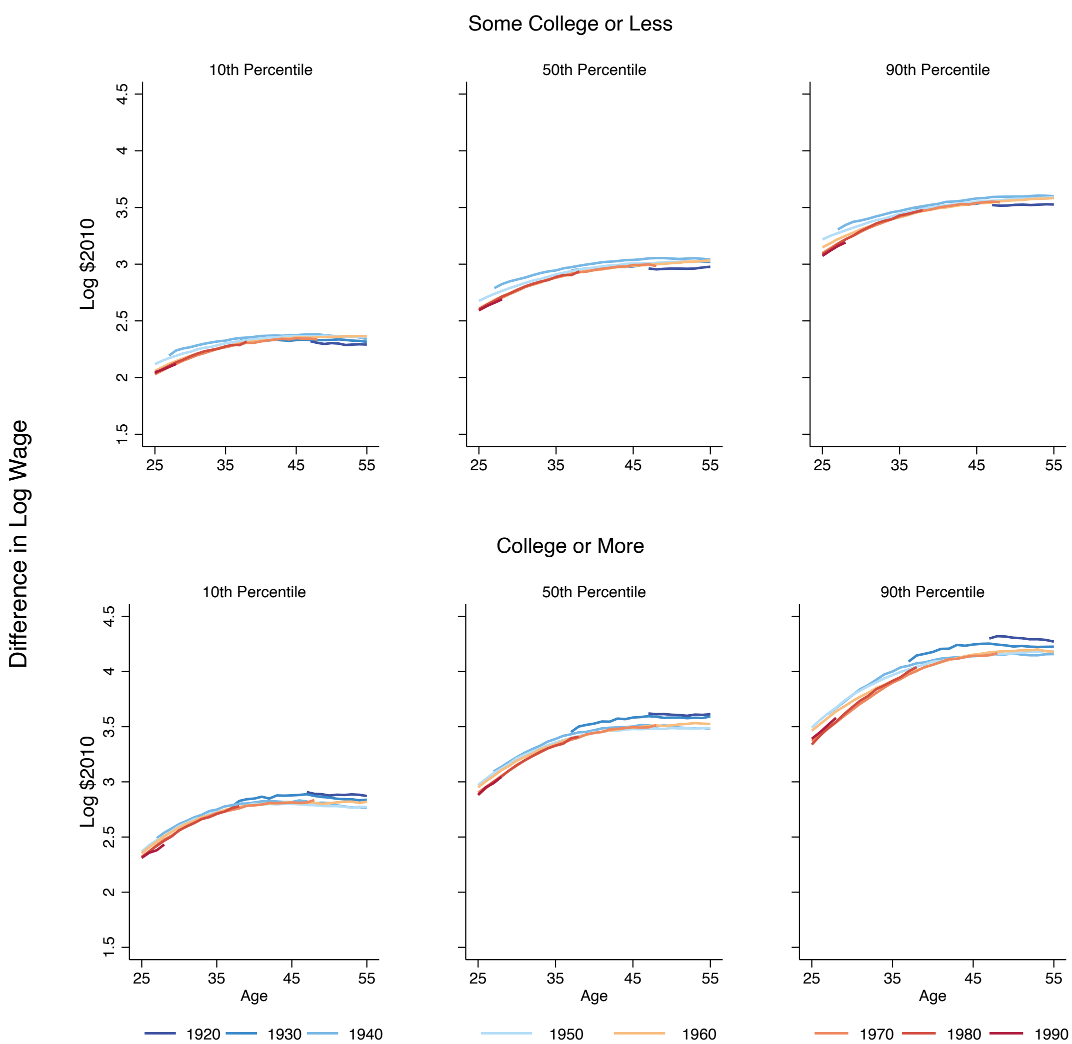
Appendix Table D4. Quantile Selection Estimates of Log Wages for Women with College or More, Full-Employment Model

	Employment	10th Quantile	50th Quantile	90th Quantile
Constant	0.642	2.053	2.398	2.715
	(0.047)	(0.049)	(0.018)	(0.026)
Entryage	-0.108	0.413	0.506	0.467
	(0.045)	(0.048)	(0.023)	(0.033)
Entryage2	0.351	-0.169	-0.266	-0.272
	(0.048)	(0.049)	(0.025)	(0.034)
Entryage3	-0.124	0.021	0.047	0.049
	(0.012)	(0.013)	(0.007)	(0.008)
Time	-0.198	-0.465	-0.008	-0.292
	(0.432)	(0.545)	(0.176)	(0.280)
Time2	1.196	1.630	-0.315	1.766
	(1.678)	(1.915)	(0.646)	(1.073)
Time3	-0.627	-1.104	0.092	-1.260
	(1.115)	(1.262)	(0.429)	(0.736)
Time4	0.131	0.282	0.015	0.326
	(0.275)	(0.310)	(0.109)	(0.190)
Time5	-0.009	-0.025	-0.004	-0.028
	(0.024)	(0.026)	(0.010)	(0.017)
Cohort2	-0.163	-0.023	-0.001	-0.031
	(0.009)	(0.010)	(0.005)	(0.008)
Cohort2*delta	-0.310	-0.147	-0.011	0.090
	(0.031)	(0.040)	(0.020)	(0.027)
Cohort3	-0.057	-0.032	-0.008	0.012
	(0.008)	(0.012)	(0.006)	(0.007)
R1	-749.020	-157.350	52.825	147.630
	(51.518)	(54.186)	(32.836)	(47.589)
R2	84.254	32.446	0.780	-36.233
	(9.855)	(10.822)	(6.107)	(10.457)
R3	321.100	64.664	-19.637	-62.969
	(22.577)	(26.035)	(15.001)	(21.058)
R4	-47.204	-15.032	-1.076	13.644
	(4.774)	(5.494)	(2.972)	(4.724)
Black	0.259	-0.051	-0.080	-0.120
	(0.009)	(0.008)	(0.006)	(0.008)
Other Race	-0.103	-0.160	0.002	0.024
	(0.008)	(0.009)	(0.007)	(0.007)
Hispanic	-0.004	-0.266	-0.120	-0.130
	(0.009)	(0.013)	(0.006)	(0.007)
Married	-0.118	0.046	0.031	0.031
	(0.007)	(0.007)	(0.005)	(0.006)
Live in Metro Area	-0.050	0.144	0.144	0.204
	(0.007)	(0.007)	(0.004)	(0.006)
Number of Children Ages 0-5	-0.295	0.034	0.041	0.055
	(0.005)	(0.009)	(0.006)	(0.009)
Number of Children Ages 6-18	-0.117	-0.040	-0.012	0.005
	(0.005)	(0.006)	(0.005)	(0.005)
State Unemployment Rate	-0.015			
	(0.002)			
Simulated Disposable Income at No Work	-0.025			
	(0.001)			
Simulated Weighted Disposable Income at Full-Time Work	-0.004			
	(0.000)			

Rho	0.18			
	(0.32)			
P-value on Excluded Variables	0.00			
P-value on Cohort terms		0.00	0.33	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

Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: The table contains estimates from the quantile with selection into full-time employment model as described in the text. The models include indicators for state fixed effects and normalized aggregate time effects. Bootstrap standard errors are in parentheses.

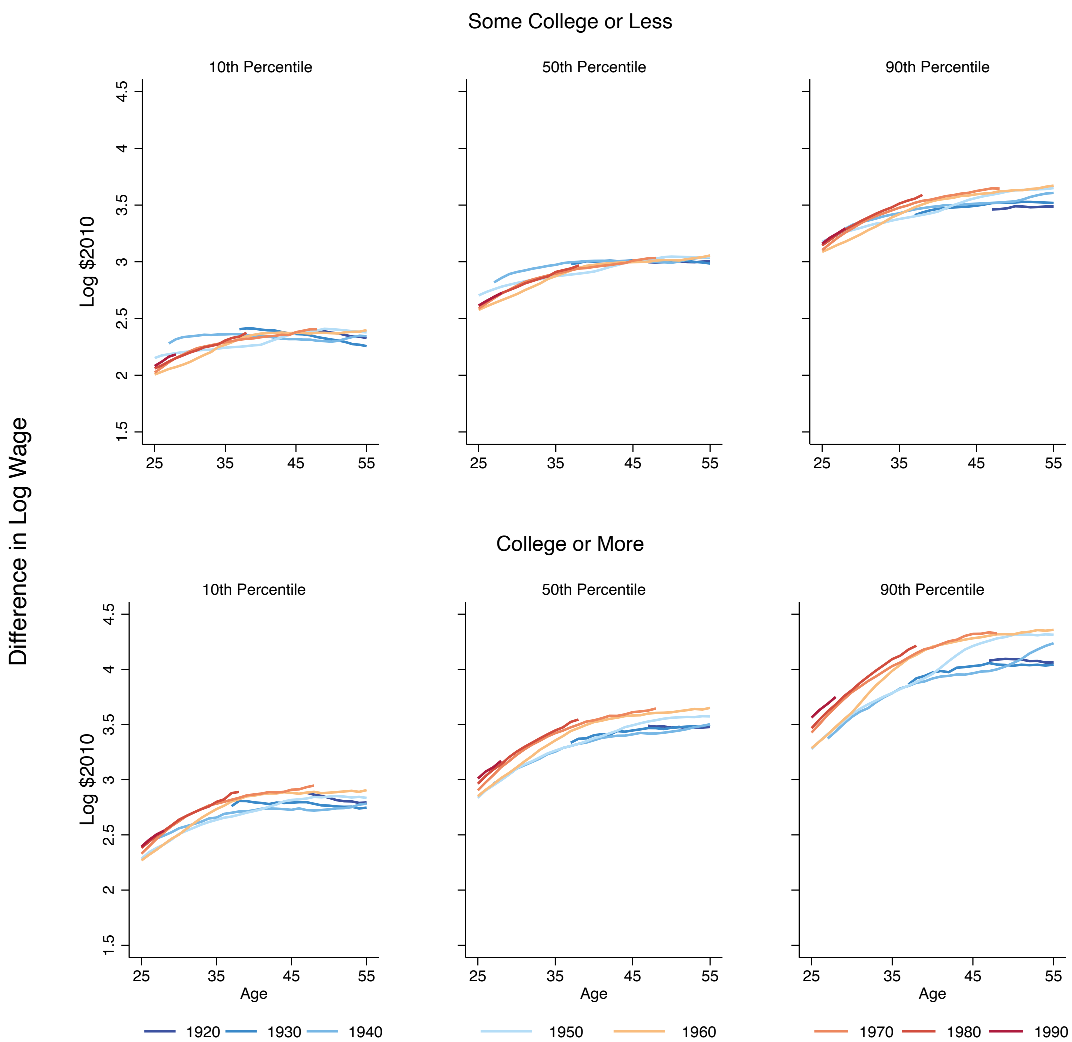
Appendix Figure D1. Quantile Selection Pseudo Life Cycle Age-Offer Wage Profiles of Full-Time Working Men Net of Time Effects



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019

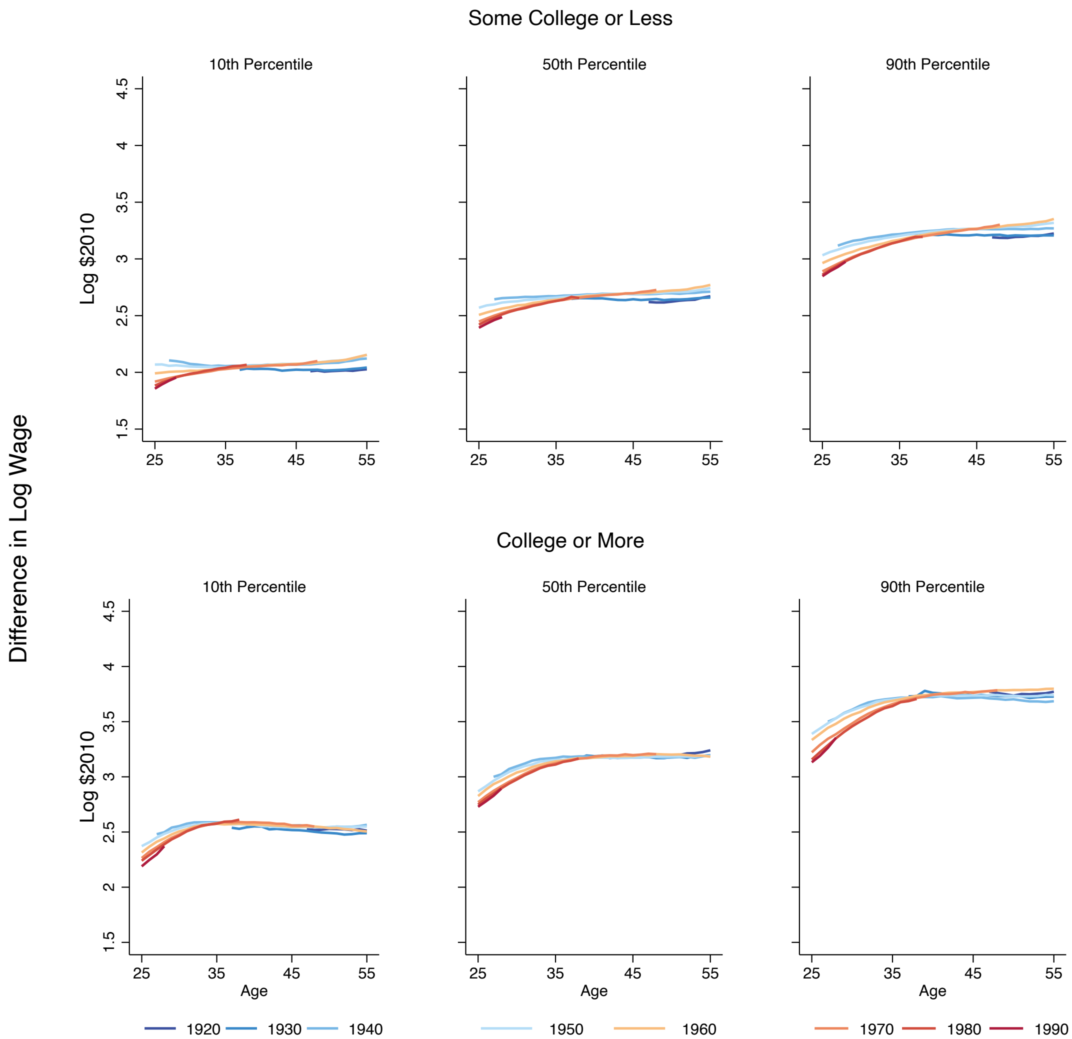
Note: Wages are based on counterfactual offer wage distributions based on coefficients from the quantile selection model of full-time workers net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender-year-specific wage distributions.

Appendix Figure D2. Quantile Selection Pseudo Life Cycle Age-Offer Wage Profiles of Full-Time Men Inclusive of Time Effects



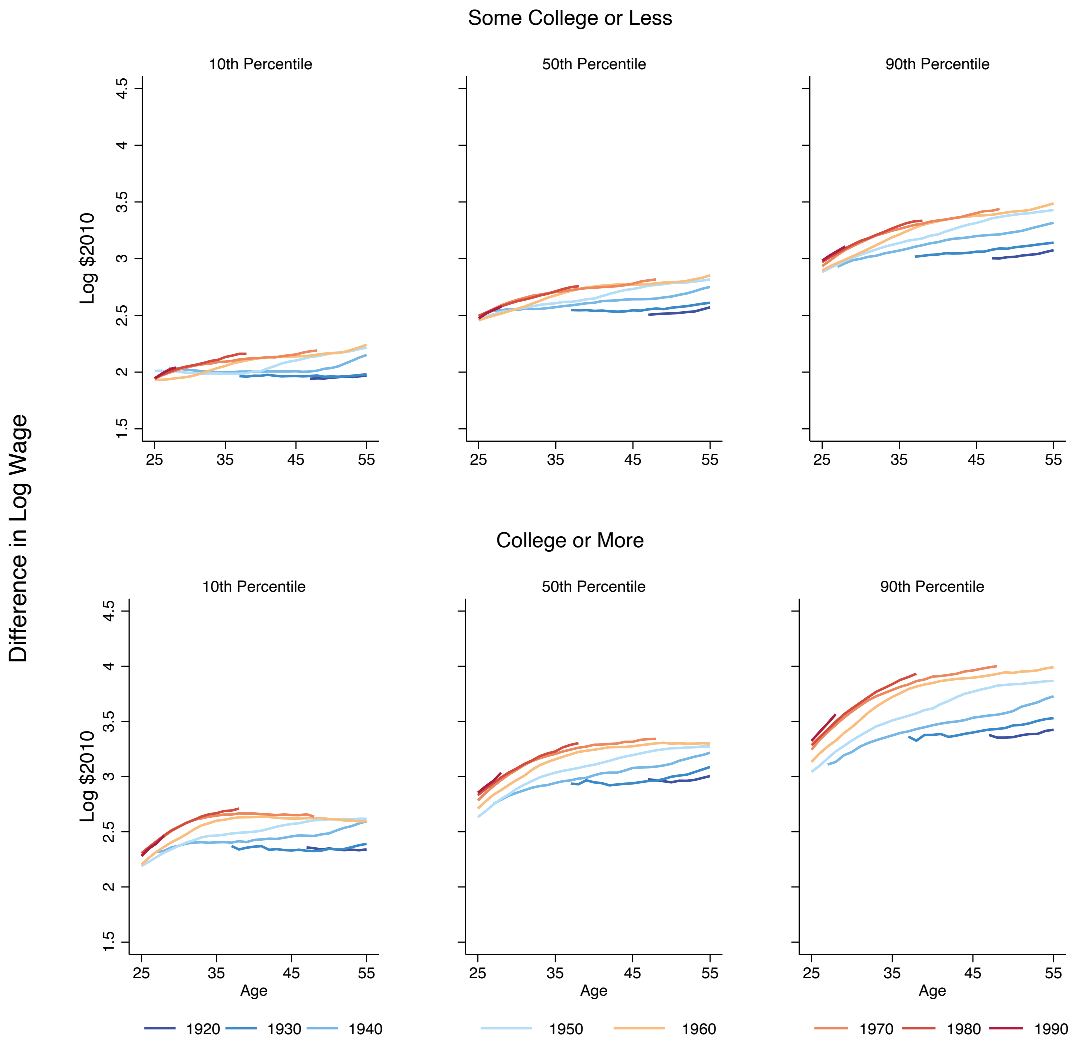
Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are based on counterfactual offer wage distributions based on coefficients from the quantile selection model of full-time workers inclusive of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender-year-specific wage distributions.

Appendix Figure D3. Quantile Selection Pseudo Life Cycle Age-Offer Wage Profiles of Full-Time Women Net of Time Effects



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are based on counterfactual offer wage distributions based on coefficients from the quantile selection model of full-time workers net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender-year-specific wage distributions.

Appendix Figure D4. Quantile Selection Pseudo Life Cycle Age-Offer Wage Profiles of Full-Time Women Inclusive of Time Effects



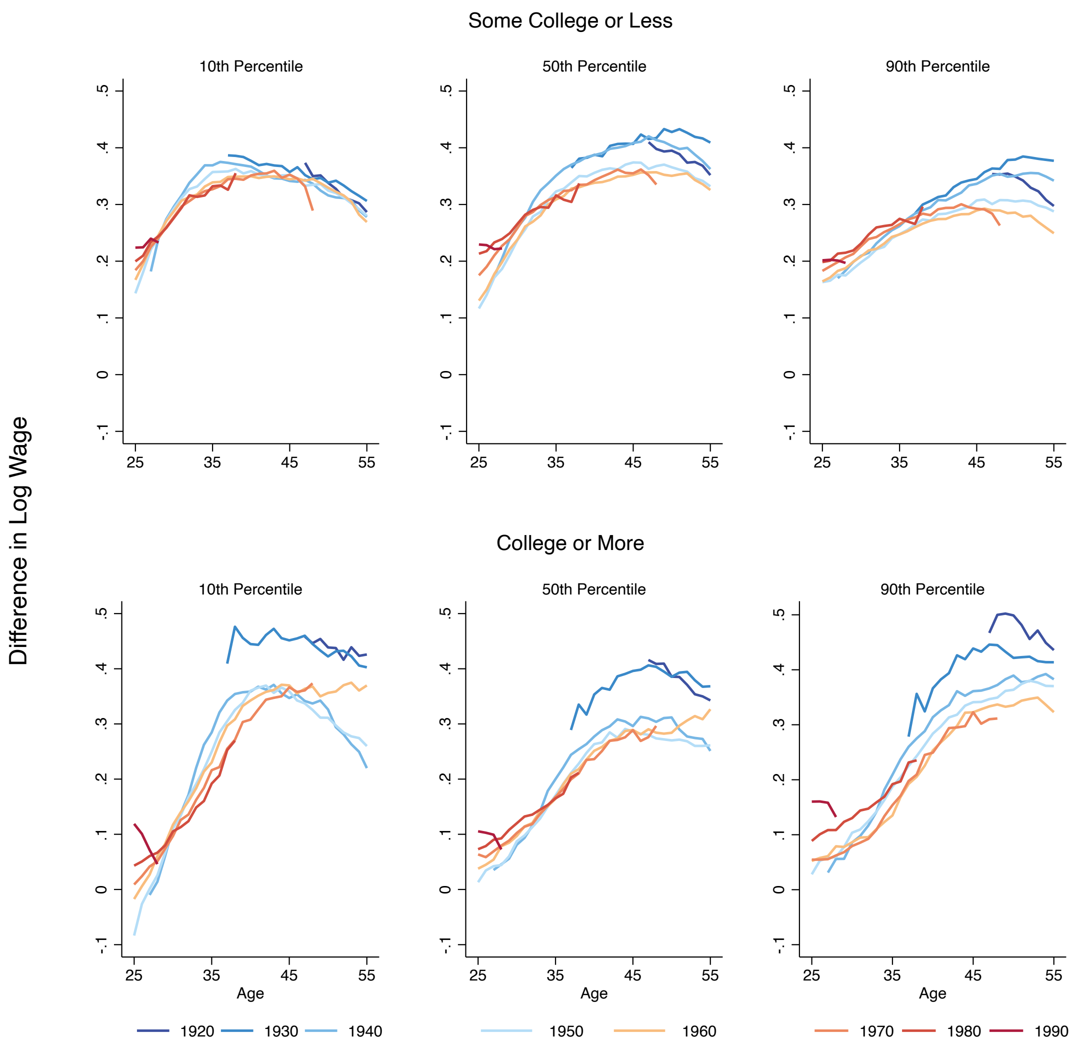
Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are based on counterfactual offer wage distributions based on coefficients from the quantile selection model of full-time workers inclusive of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender-year-specific wage distributions.

Appendix E. Sensitivity of Gender Gap Estimates

This appendix presents a host of sensitivity checks on the key outcome of the paper—the gender offer wage gap presented in Figure V of the main text. Our robustness focuses primarily on the specification of the selection equation. This includes using only a subset of instruments, using a different set of instruments, using no instruments, using a median selection rule, and assuming no endogenous selection. Furthermore, we consider a model that characterizes an identification strategy found in Mulligan and Rubinstein (2008), Maasoumi and Wang (2019), Blau et al. (2023), and Fernandez-Val et al. (2023) that involves using the age composition of children in the selection equation and omitting children from the wage equation. Beyond the selection equation, we also consider models that change the functional form of age, cohort, and time; that change the sample split from some college or less and college or more to those in the top quartile of the education distribution and those below the top quartile; that add controls for state-specific linear trends to both the selection and wage equations; and models that drop the youngest and oldest birth cohorts.

The baseline estimates in the paper rely on three exclusion restrictions to assist in identifying the selection equation from the wage equation—the state unemployment rate that varies across states and year; simulated nonlabor income if the individual (or couple) are out of work; and the weighted average of simulated incomes from part-time and full-time work of the individual or couple. The first robustness check drops the simulated income from work instrument; that is, the only exclusion restrictions in the first stage are the state unemployment rate and simulated disposable nonlabor income. This type of identification is more typical of canonical Heckman wage models with selection whereby nonlabor income is assumed to affect the decision to work, but not the wage conditional on working. Comparing Appendix Figure E1 to Figure V in the text reveals some slight differences in the age profile of older cohorts of college education workers, but overall there is very little discernable difference in the gender wage gaps.

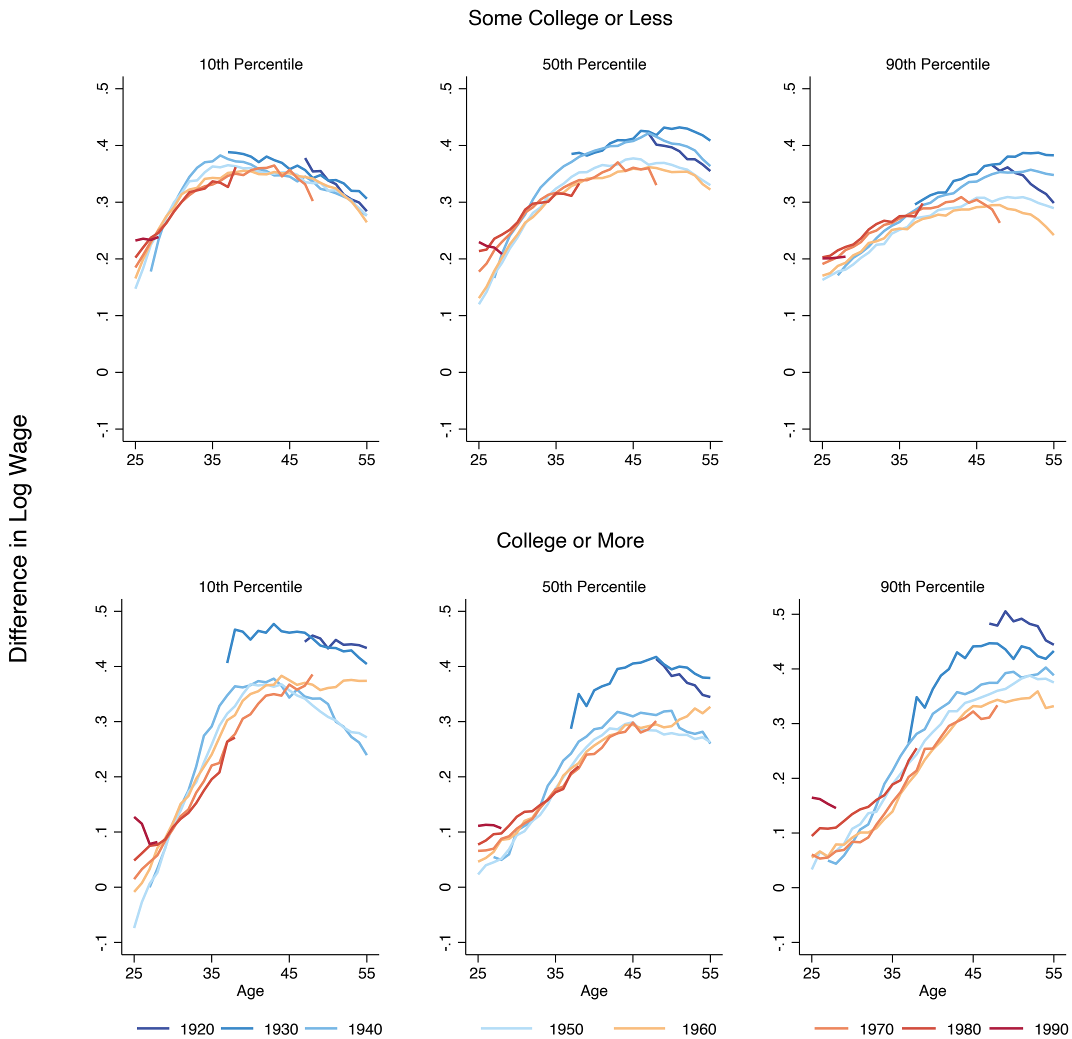
Appendix Figure E1. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Excluding Simulated Instrument from Work in Selection Equation



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile selection model net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men and women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

The second robustness check drops both simulated instruments and replaces them with the maximum 3-person benefit guarantee in the SNAP and TANF transfer programs. The SNAP maximum benefit is set at the federal level, while the TANF maximum benefit is set at the state level, and both are deflated by a state-price index that adjusts the PCE for cross-state differences in cost-of-living. The advantage of these instruments is that they only involve policy decisions and are not a function of household demographics, and thus are plausibly more exogenous than the simulated income instruments. This exogeneity comes at a cost of reduced variation across states and over time. Comparing Appendix Figure E2 to Figure V in the text reveals no substantive difference in the gender wage gaps.

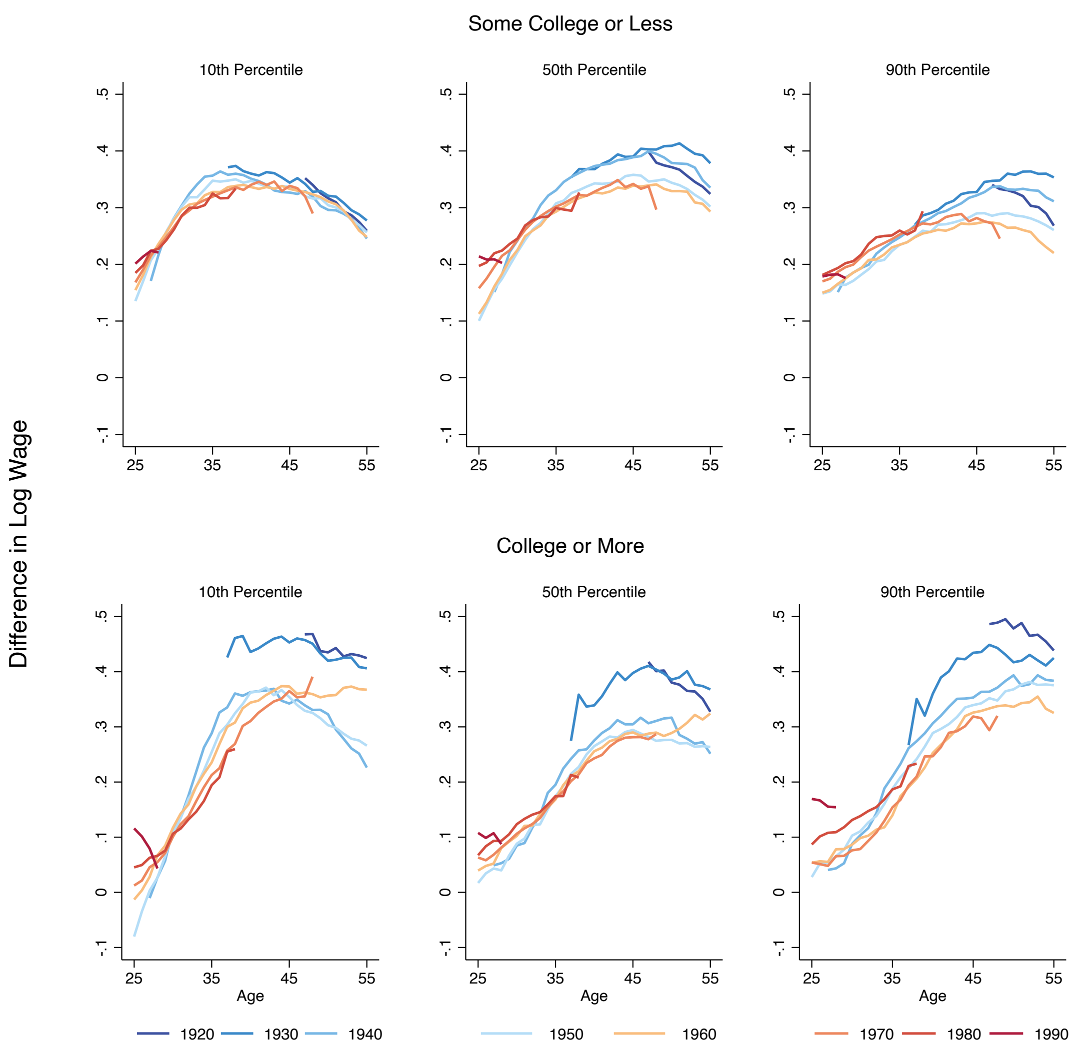
Appendix Figure E2. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: SNAP and TANF Maximum Benefits as Exclusion Restrictions in Selection Equation



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile selection model net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men and women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

The third robustness check drops all three instruments from the base case model. This means the selection equation is identified solely from the nonlinear functional form. This approach to identification hinges on there being adequate overlap of support in the control variables to identify both the first stage employment equation and the second state wage equation. Comparing Appendix Figure E3 to Figure V in the text suggests that like the first robustness check there are some subtle differences at older ages among the older cohorts, especially those with college education, but overall the lifecycle patterns and levels of gaps are quite comparable, suggesting much of the power from identification stems from the overlap of support as presented previously in Appendix B.

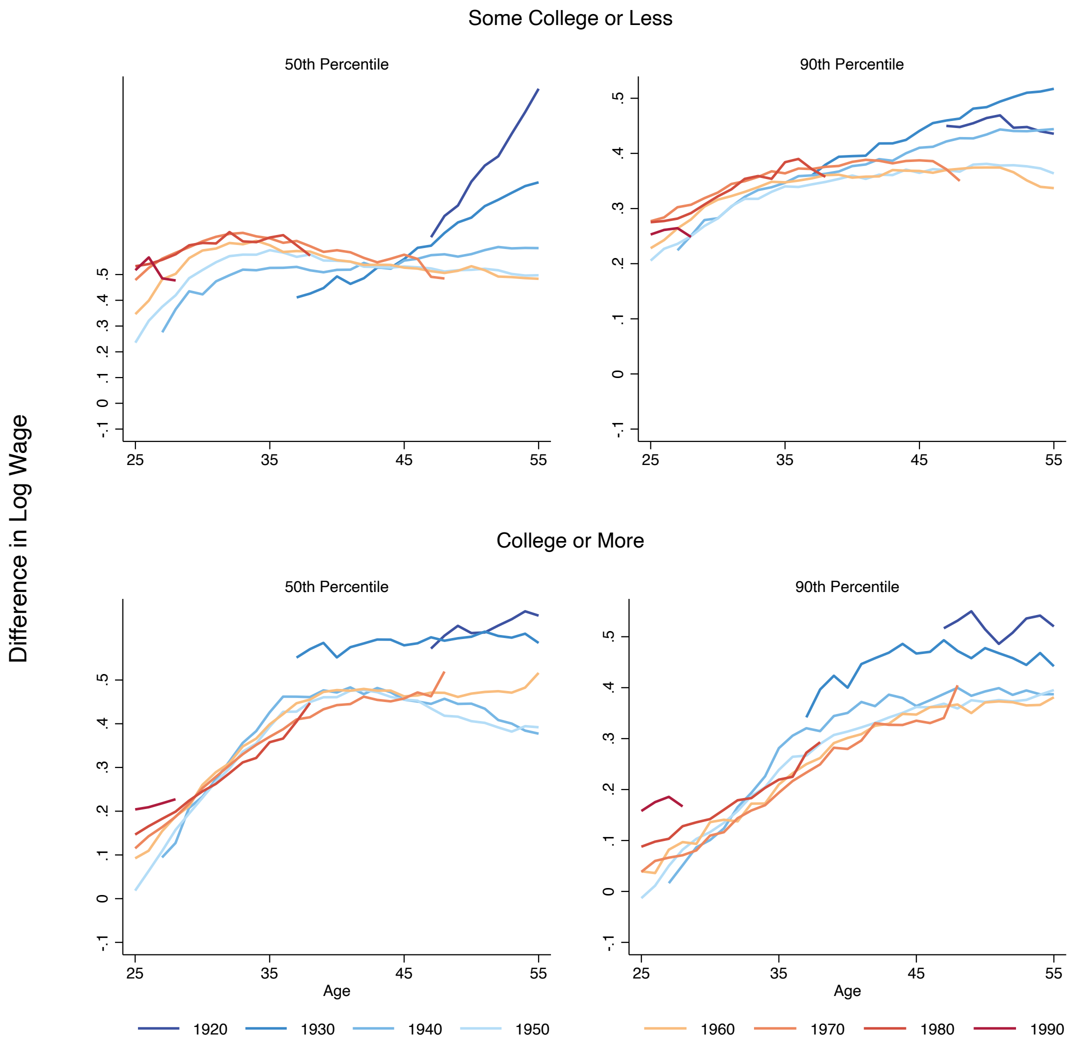
Appendix Figure E3. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: No Exclusion Restrictions in Selection Equation



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile selection model net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men and women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

The fourth robustness check implements an alternative approach to modeling selection known as the median selection rule, which is often used in research on racial wage gaps (Neal and Johnson 1996; Chandra 2000; Bayer and Charles 2018). The idea is that nonworkers are drawn from the bottom half of the wage distribution, meaning that if they were to work they would receive an offer wage below the median wage. To implement this approach nonworkers are retained in estimation by replacing the missing log wage with a log wage of $0, and then estimating a standard quantile regression model. The cost of this approach is that it is no longer possible to identify the wage function at wage levels below the median. Thus, Appendix Figure E4 drops the 10th quantile and presents only the median and 90th quantiles, but using the same y-axis scale as in Figure V to ease comparisons. There we see substantive differences among older cohorts, especially those with some college or less. The reason is that many older women were not in the labor force and thus inclusion of zeros pulls the median substantially lower, and inflates the gender gap. This is particularly pronounced among the 1920s and 1930s cohorts. However, by the 1950s cohort, the lifecycle profiles of the gender gap, particularly among the college educated, are much more similar to our baseline estimates, albeit still slightly elevated because of the inclusion of zero wages. This suggests that our approach to identification is robust to a much less parametric alternative, at least starting with the 1950s birth cohort.

Appendix Figure E4. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Median Selection Rule

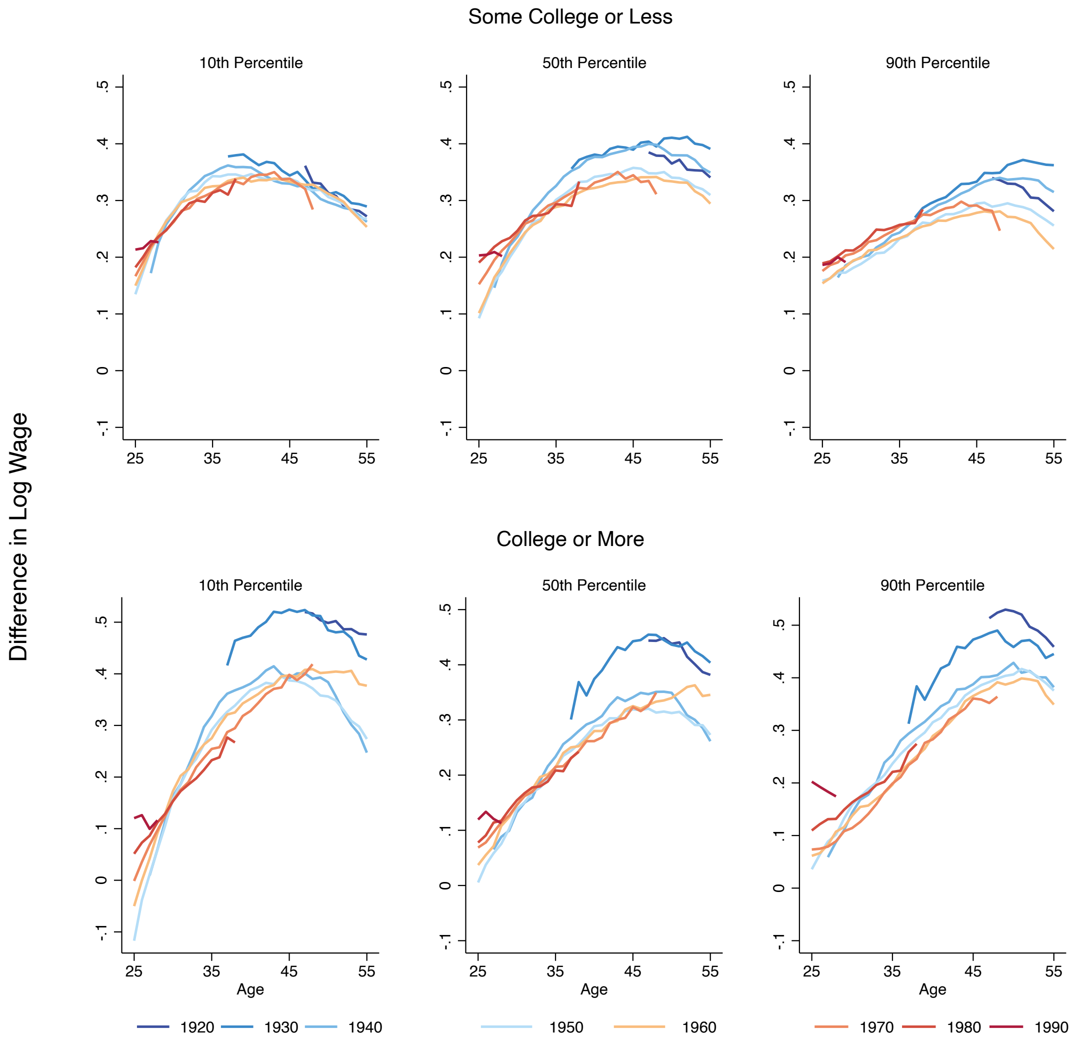


Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile median selection model net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men and women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions. Because of the assumption that nonworkers are drawn from the bottom half of the wage distribution, we only present gaps at the median and above.

In the next robustness check we adopt an approach on the structure of identification common to the gender gap literature; namely, using the age structure of children in the household to identify selection from the wage equation (Mulligan and Rubinstein 2008; Maasoumi and Wang 2019; Blau et al. 2023; Fernandez-Val et al. 2023). The assumption is that the age composition of children will affect the decision to work or not, but not the hourly wage conditional on work. The latter hinges on the assumption that children do not affect the intensity of work or promotion profiles or other on-the-job human capital accumulation activities that can affect average hourly earnings. In our analysis we relax that assumption, and find that the age composition of children substantively affects average hourly wages. However, in this exercise we respecify the model by dropping the state unemployment rate and simulated income instruments from the selection equation, and then drop the two age composition of children variables from the wage equation. The results are presented in Appendix Figure E5 where we see that both the level of the gaps and lifecycle patterns are quite comparable to those found in Figure V of the text with some exceptions. Specifically, there are some differences in the curvature of the pseudo wage profiles after age 45 where we find more of a narrowing of the gender wage gap in the standard selection model than we find in our baseline estimates. This is more pronounced among the college educated.

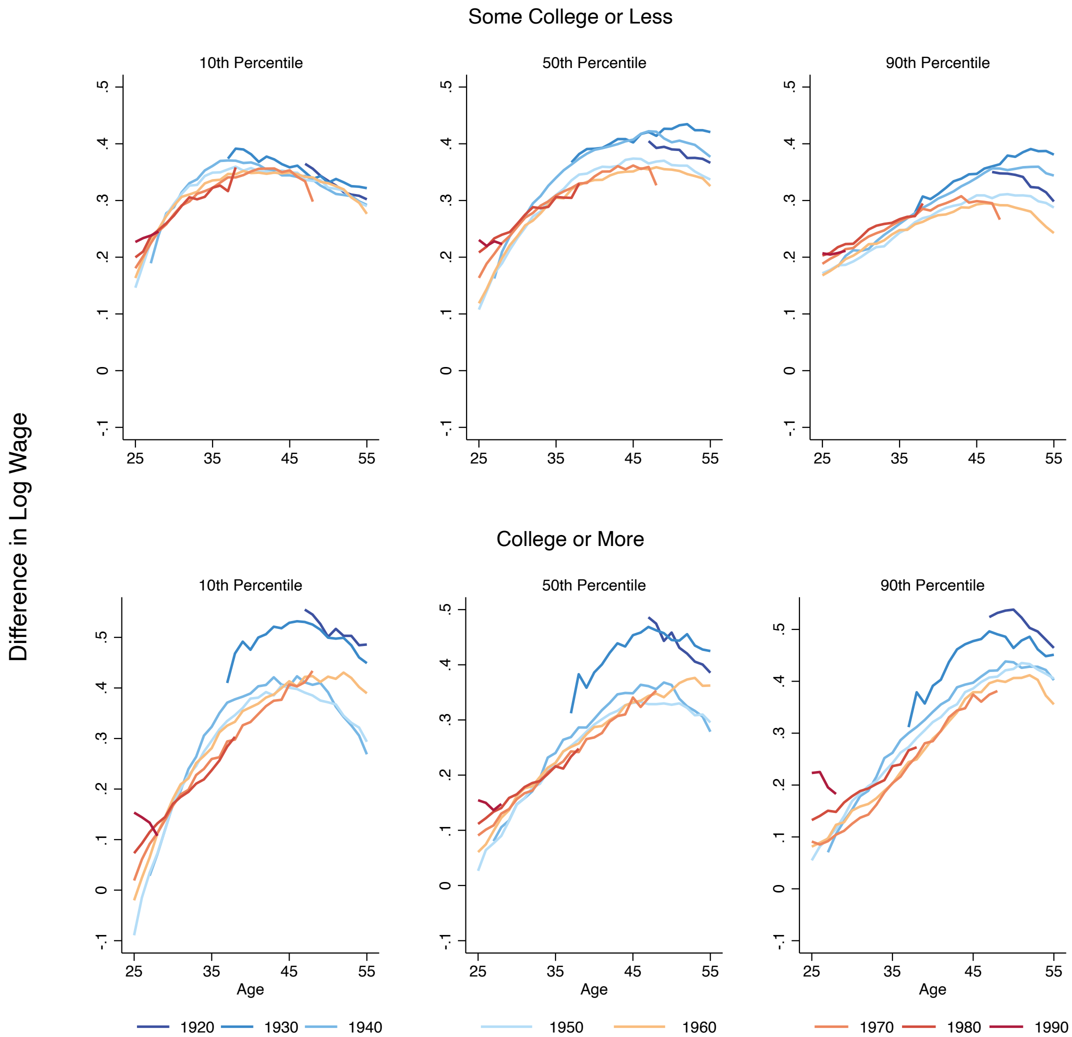
To assess how much this is due to omitting the three instruments from the selection equation, as opposed to omitting the age composition of children from the wage equation, in Appendix Figure E6 we repeat our baseline estimates from Figure V of the paper, but in this case we drop the age composition of children from the wage equation, meaning that the selection equation is identified by five exclusion restrictions—both age of children variables, state unemployment rates, and the two simulated income instruments. The post age 45 downturn in the gender gap among the college educated in Appendix Figure E5 persists in Appendix Figure E6, suggesting that omitting children from the wage equation results in too low of a gender gap.

Appendix Figure E5. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Selection Rule Identified by Age Composition of Children



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile selection model net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men and women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

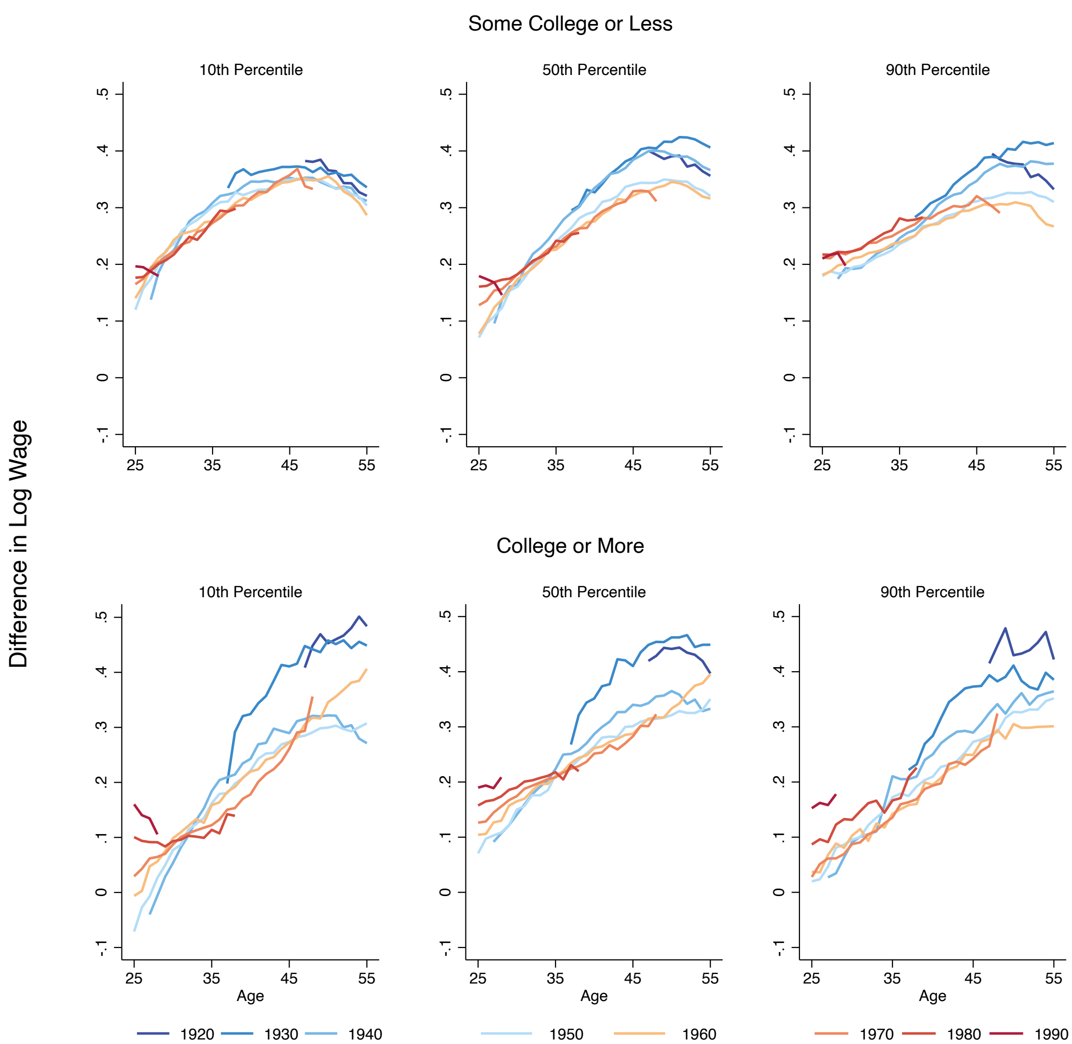
Appendix Figure E6. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Exclude Children Variables from Baseline Wage Equation



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile selection model net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men and women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

We next take the extreme position and assume that there is no selection on unobservables into work, and thus estimate the quantile gender wage gaps based on the standard quantile regression estimator. The results of this exercise are presented in Appendix Figure E7. There we see two important differences compared to the base case in Figure V of the paper. First, for most cohorts the gender wage gap is attenuated at most ages when assuming no selection. Second, the lifecycle profiles of the gender wage gaps among the college educated are notably different under the assumption of no selection. There tends to be much less curvature later in the working life than we found when selection is modeled in Figure V, meaning less catch-up of women relative to men.

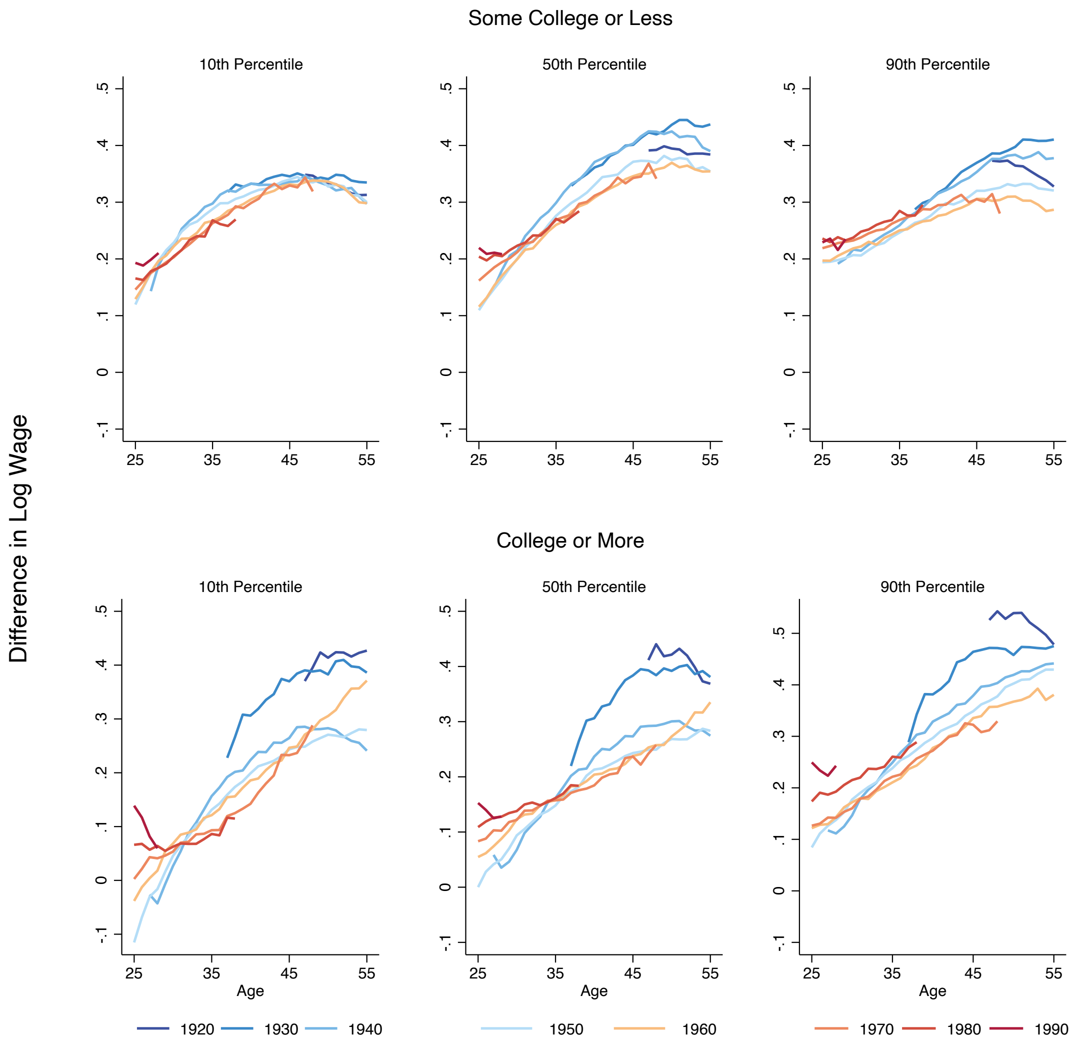
Appendix Figure E7. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: No Nonrandom Selection into Employment



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile model without selection, but net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men and women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

Throughout the paper we split the sample based on whether the individual attained four years of college or more. However, there has been substantial secular upgrading in education attainment across cohorts, and thus the composition of the college or more group may have changed sufficiently (beyond the demographics we control for in the model) across cohorts to skew the gender gaps. Bailey, Guildi, and Hershbein (2014) make this argument in their study of fertility decline over the 20th Century, and instead they propose defining human capital as a relative measure based on quartiles of the education attainment distribution. We adopt this approach in Appendix Figure E8 where in keeping with the prior analyses of two education groups we split the sample into the top quartile of education and the bottom three quartiles. As depicted in the figure the general levels and trends in the gender gaps align whether we define education attainment in absolute terms as in Figure V of the paper or in relative terms. For the 1960s cohort there are some differences after age 45 among the college educated, where the relative approach doesn't identify as much narrowing of the gender gap as the absolute approach, likely because this is the cohort just before the transition from where the top quartile overlaps strongly with the absolute level of education attainment.

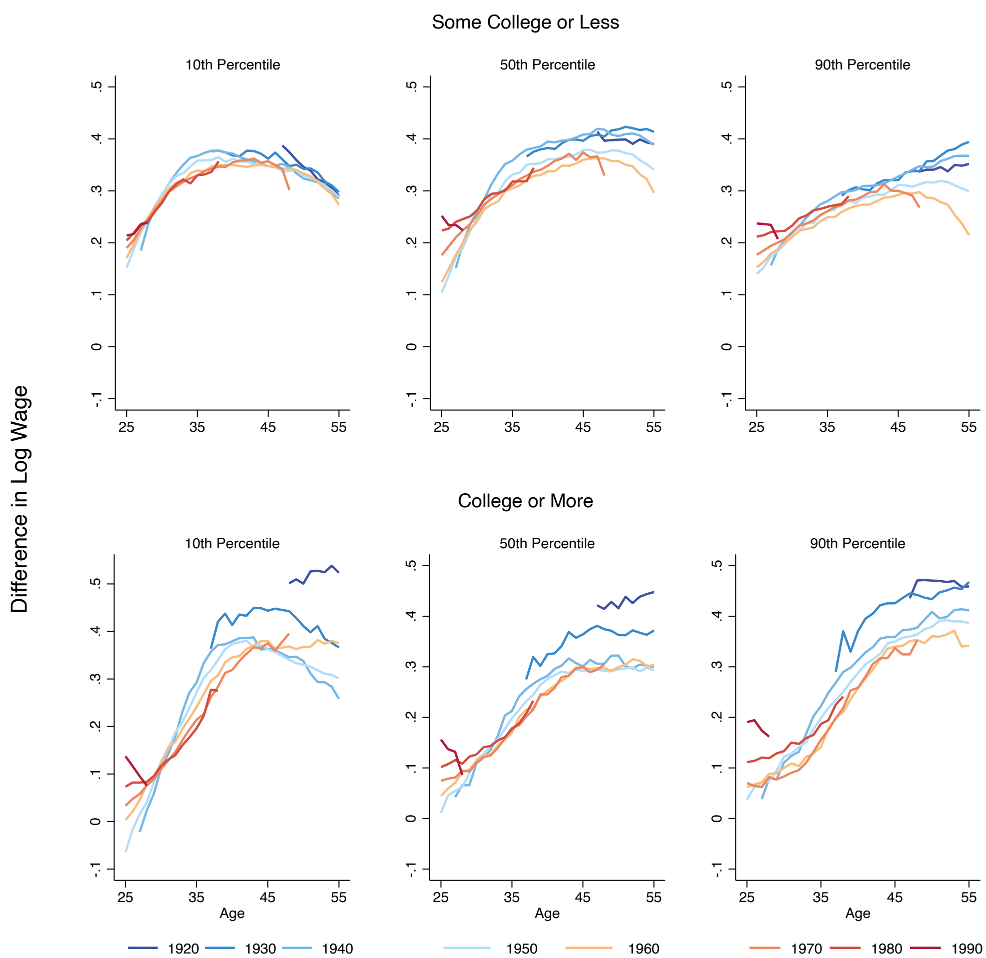
Appendix Figure E8. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Samples Split by Quartiles of Education Attainment



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile selection model net of gender- and education-specific time effects. Education is measured in relative terms based on whether the individual is in the top quartile of the education distribution. See text for additional details. Sample consists of working and nonworking men and women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

The empirical model described in the paper and in Appendix B relies of a fairly flexible functional form with a quartic in age and cohorts, and a quintic in time. We reduce this flexibility by assuming age, cohort, and time are well approximated by a quadratic. Appendix Figure E9 presents the gender wage gaps under this alternative wage and selection model specification. There we see substantial differences at the 90th quantile of the Some College or Less group, especially among the 1920s-1940s cohorts, where there is little evidence of women catching up to men compared to our baseline model in Figure V. Likewise, under the quadratic we see much more fanning out (higher) of older cohorts among the College or More group, and less retreat of the gender gap (i.e. women narrowing the gap) at older ages among those in the top half of the wage distribution.

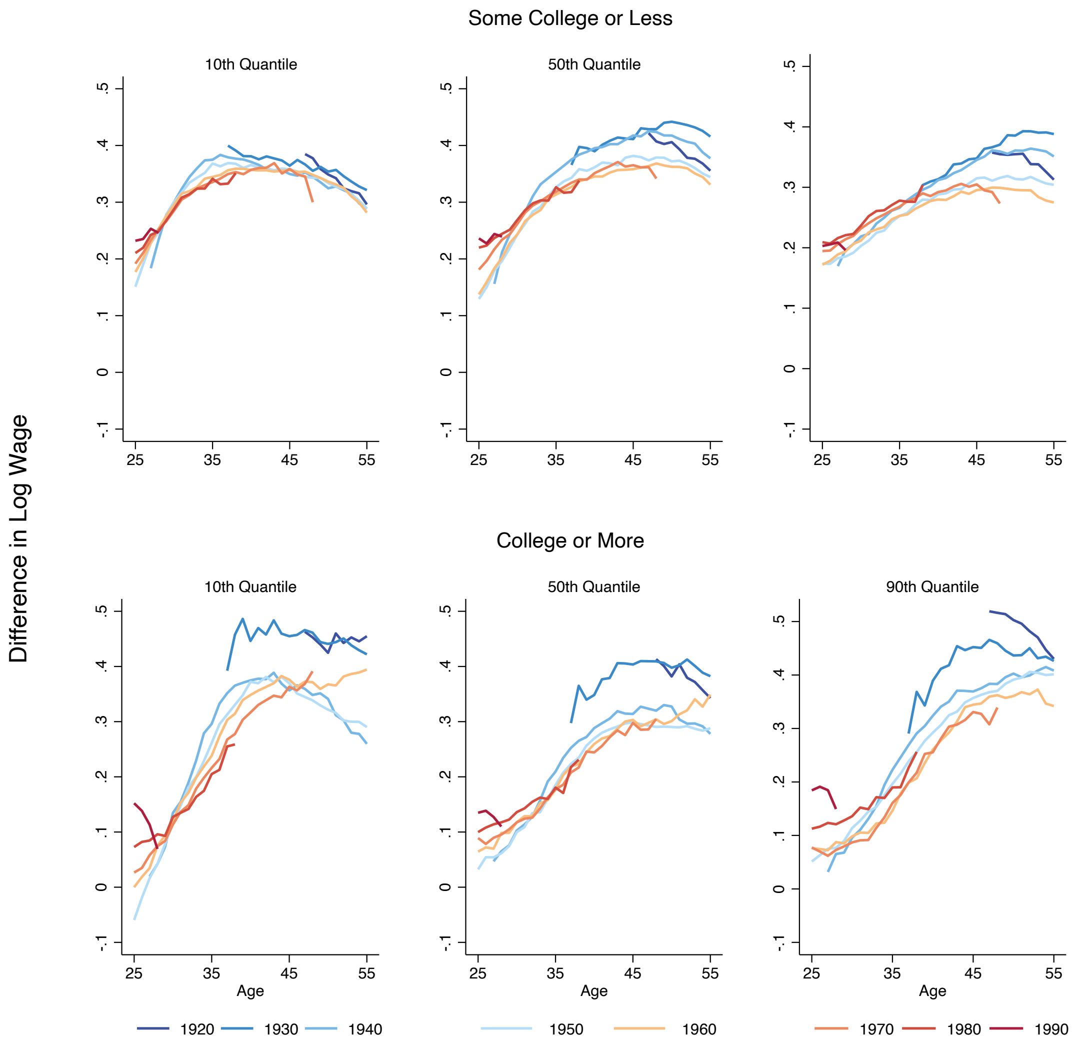
Appendix Figure E9. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Wage Model Based on Quadratic in Age, Time, and Cohort



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile selection model net of gender- and education-specific time effects. Age, time, and cohort in the wage and selection model are quadratic. See text for additional details. Sample consists of working and nonworking men and women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

We next take the alternative perspective that the baseline model is too parsimonious by appending state-specific linear trends to both the selection and wage equations. The baseline model controls for high-order age, time, and cohort trends, macroeconomic shocks, sociodemographics such as gender, education, race, ethnicity, marital status, age composition of children, and metropolitan residential status, and state fixed effects. However, if there are slow-moving demographic trends that vary idiosyncratically across states not captured by the set of controls, then the gender gap estimates could suffer from omitted variable bias. We test this by including a full set of state-specific linear trends in the model. Appendix Figure E10 presents the gender wage gaps under this alternative wage and selection model specification. As depicted in the figure the general levels and trends in the gender gaps are largely unchanged compared to Figure V of the paper with the inclusion of state trends.

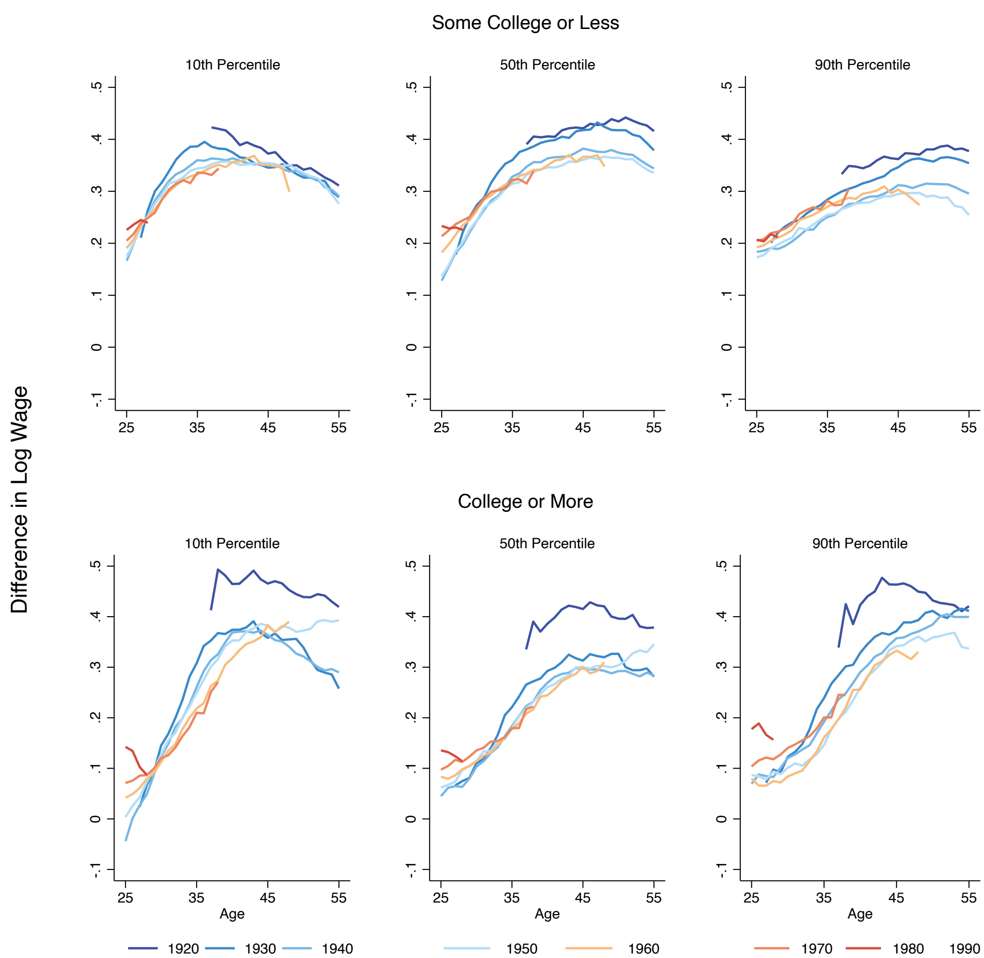
Appendix Figure E10. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Model With State-Specific Linear Time Trends



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile selection model net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men and women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

The last robustness check examines whether the finding of negative selection on unobservables into work is based on the relatively small numbers in the oldest (1920s) and youngest (1990s) birth cohorts. We alternatively drop the 1920s cohort in Appendix Figure E11 and the 1990s cohort in Appendix Figure E12. The two figures show that there is no substantive change in the gender gaps with the omission of those cohorts, and in results not tabulated, selection on unobservables remains negative.

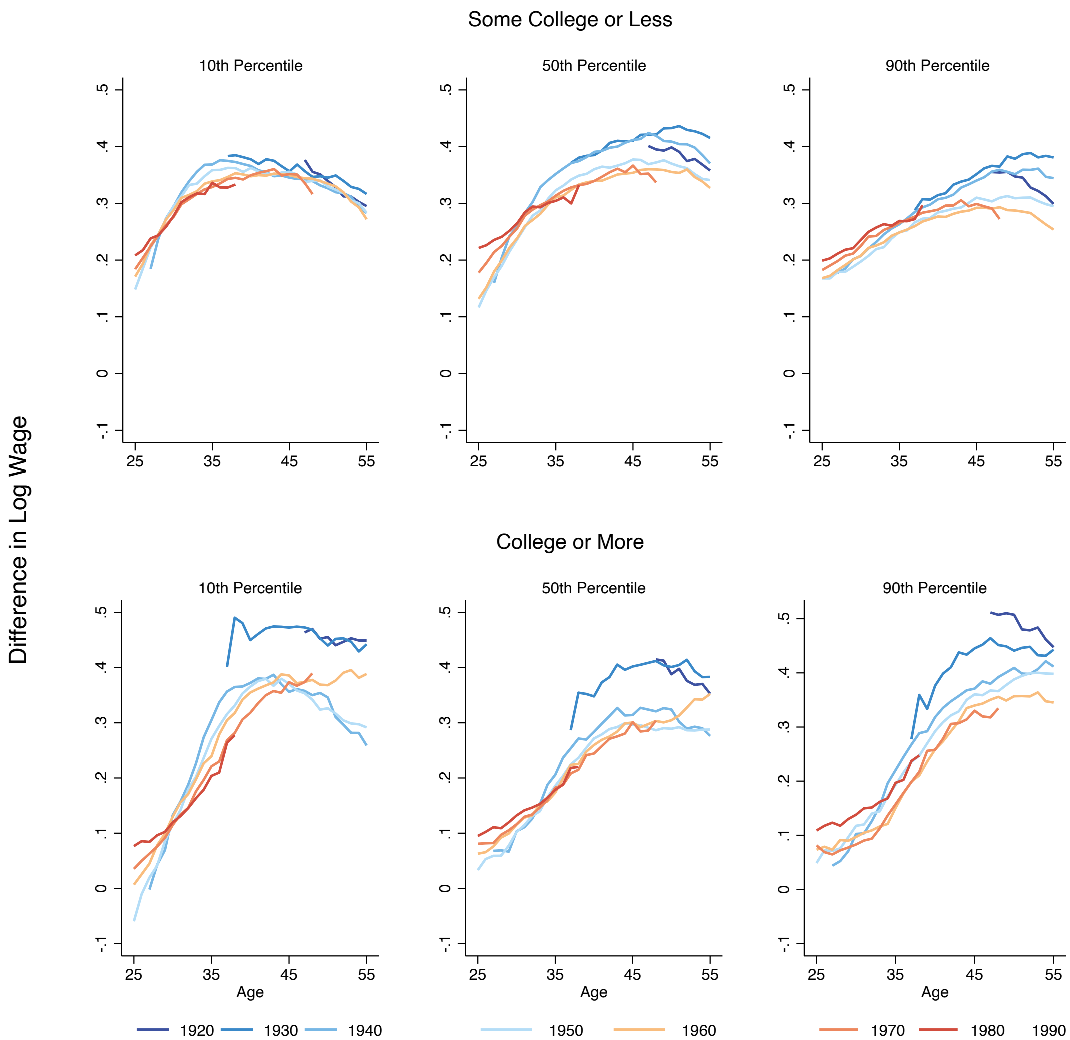
Appendix Figure E11. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Model Without 1920s Birth Cohort



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019

Note: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile selection model net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men and women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

Appendix Figure E12. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Model Without 1990s Birth Cohort



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile selection model net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men and women aged 25-55. Workers with imputed earnings or hours are dropped from estimation of quantile coefficients, as are those with wages below the 1st percentile or above the 0.1 percentile of the real gender- and year-specific wage distributions.

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