Supplemental Appendix

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

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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.

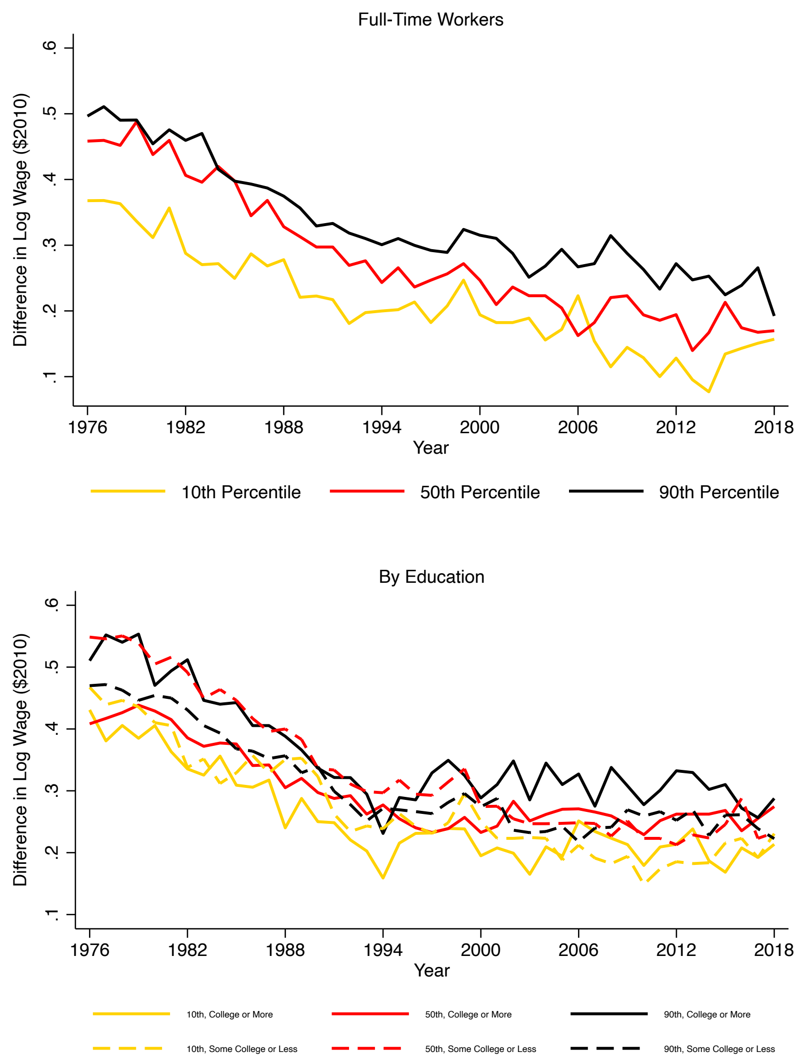
Appendix Table A3. Sample Summary Statistics of Non-Working Men and Women by Education Attainment

	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.

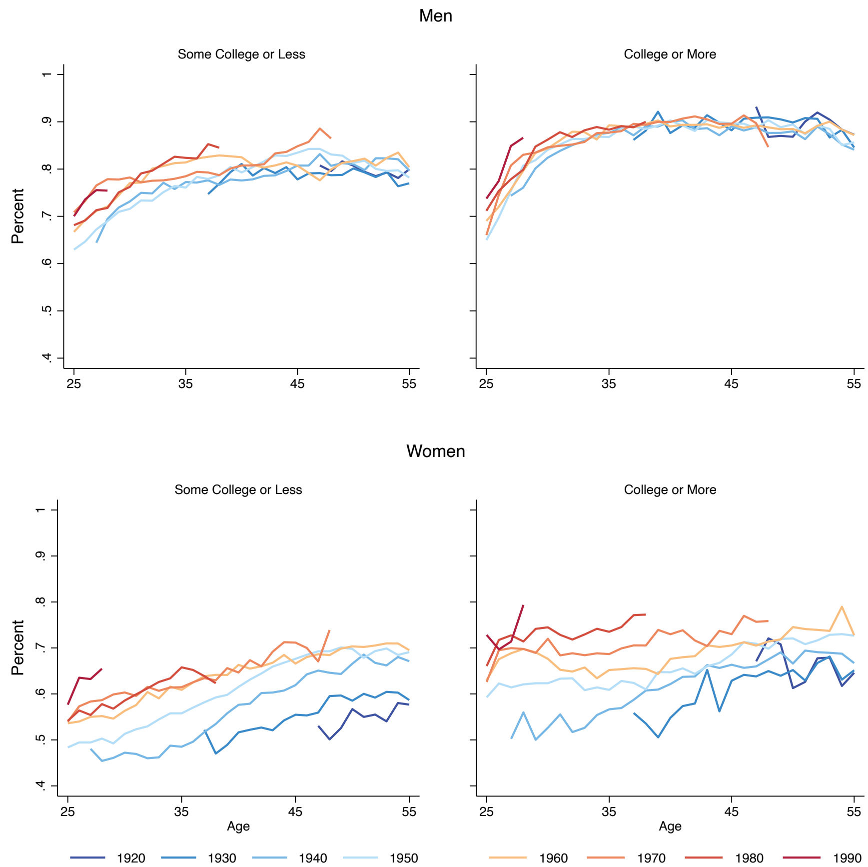
Figure A2 presents the time series of employment of men and women ages 25-55 in our sample from 1976-2018. The left panel is of the share in any work, and the right panel is the share of workers who are employed full time, defined as working at least 35 hours per week for 50 weeks out of the year. The 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.

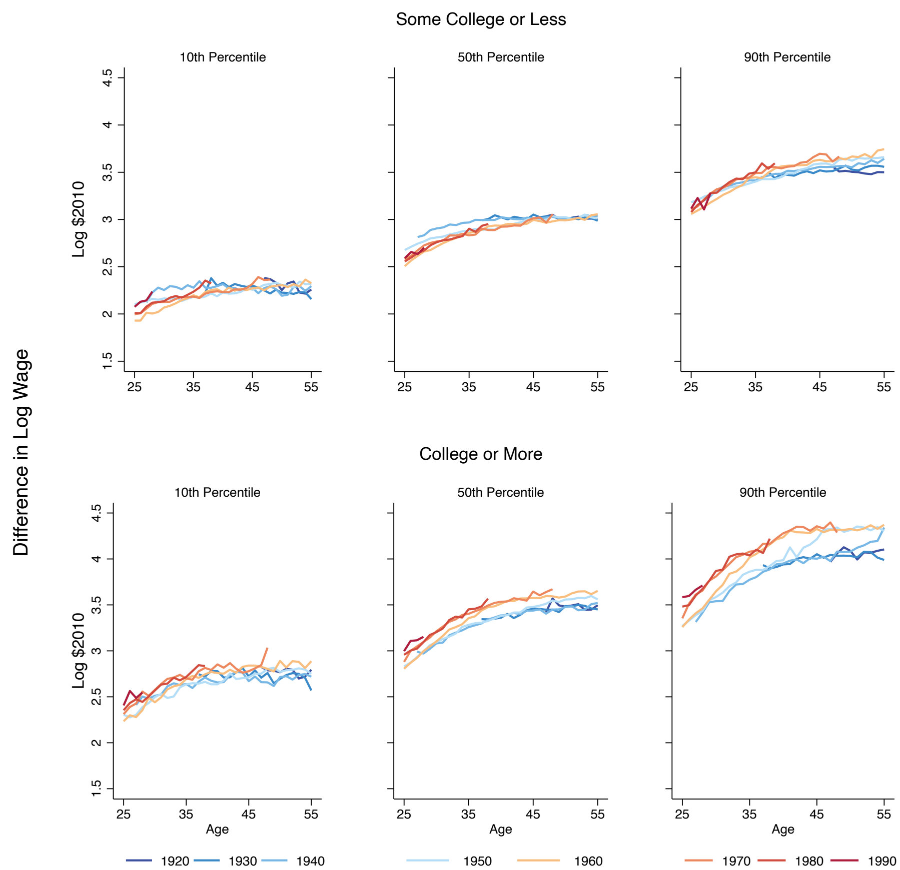
Appendix Figure A3. Share of Workers Employed Full Time Across the Life Cycle



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.

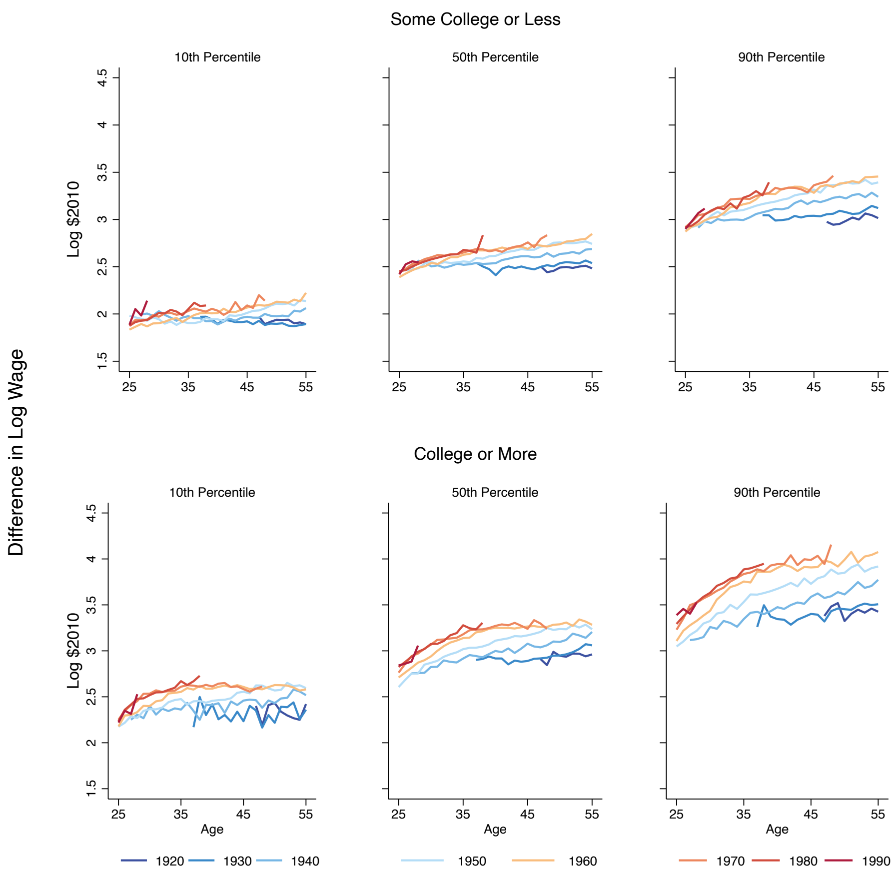
Appendix Figure A4. Distribution of Life Cycle Real Hourly Wages of Full-Time Working Men across Cohorts



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.

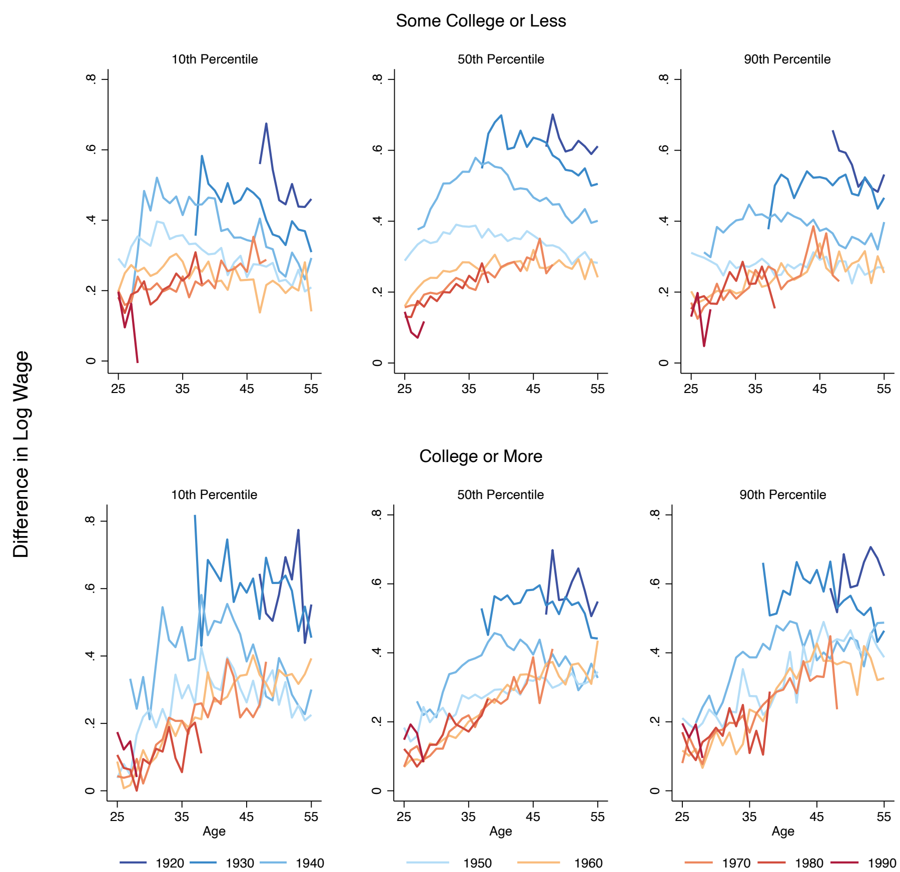
Appendix Figure A5. Distribution of Life Cycle Real Hourly Wages of Full-Time Working Women across Cohorts



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.

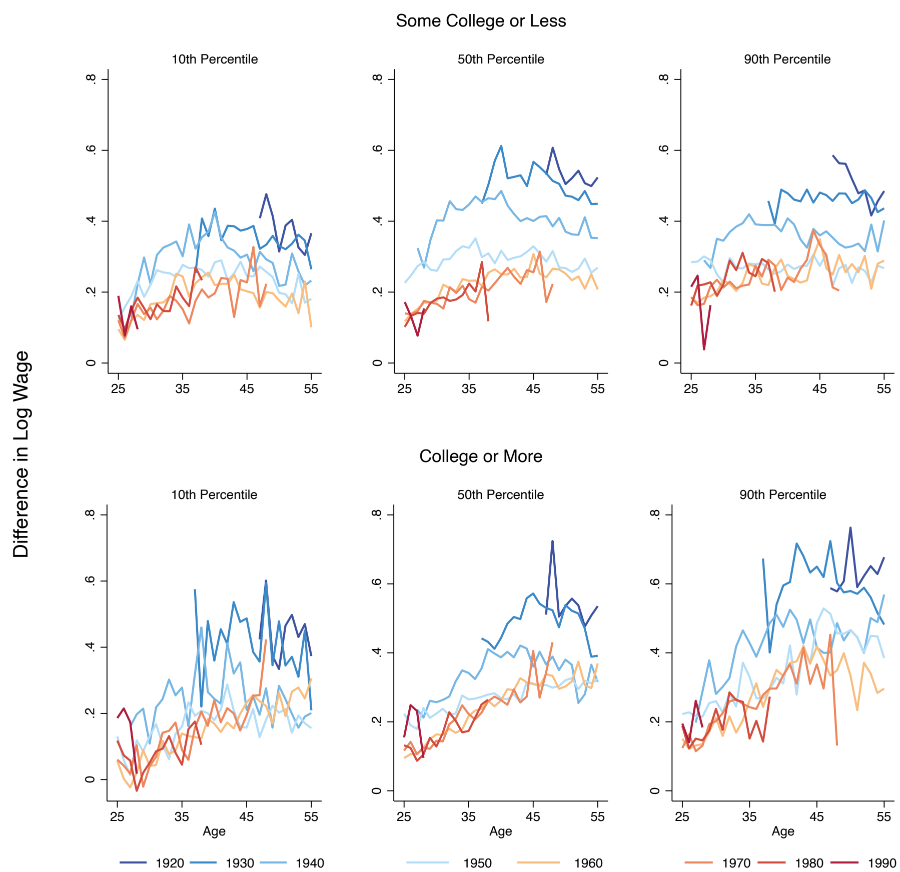
Appendix Figure A6. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers



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

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

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*)

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[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.

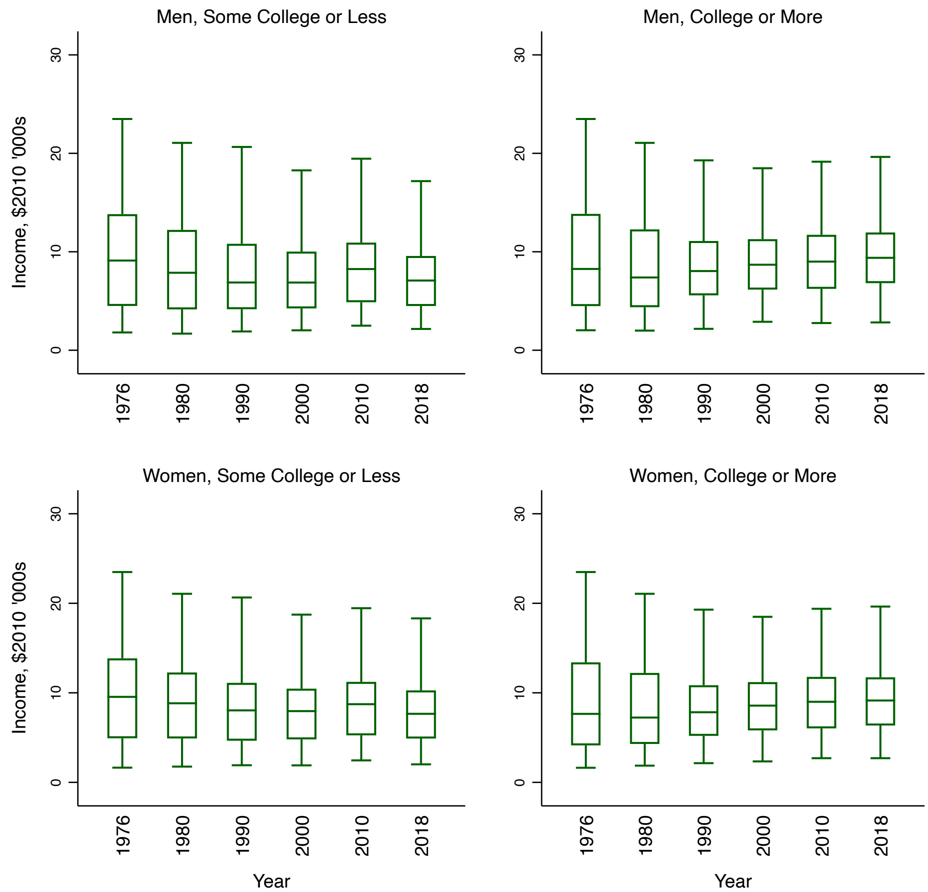
We then identify the selection equation from the wage equation by including in the selection model the two simulated disposable income instruments and the state unemployment rate described above. The unobservables in the log wage equation are assumed to be independent of these excluded 'instruments' 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.

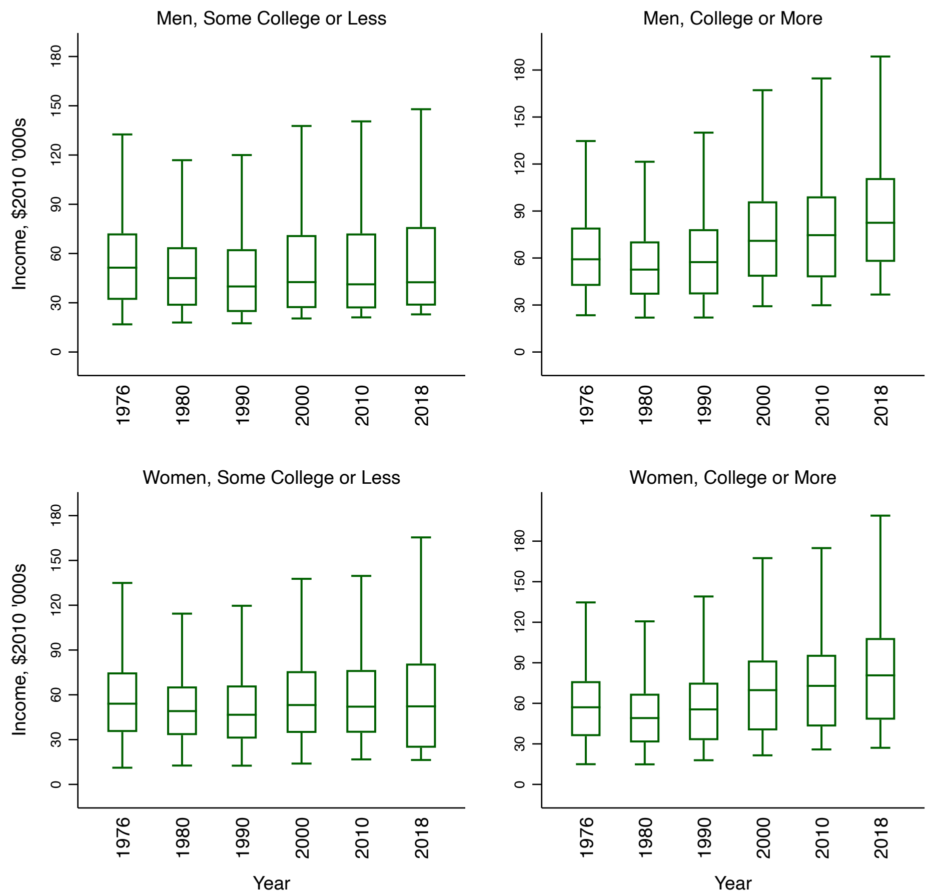
Appendix Figure B1. Simulated Disposable Income Instrument-No Work, Over Time



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.

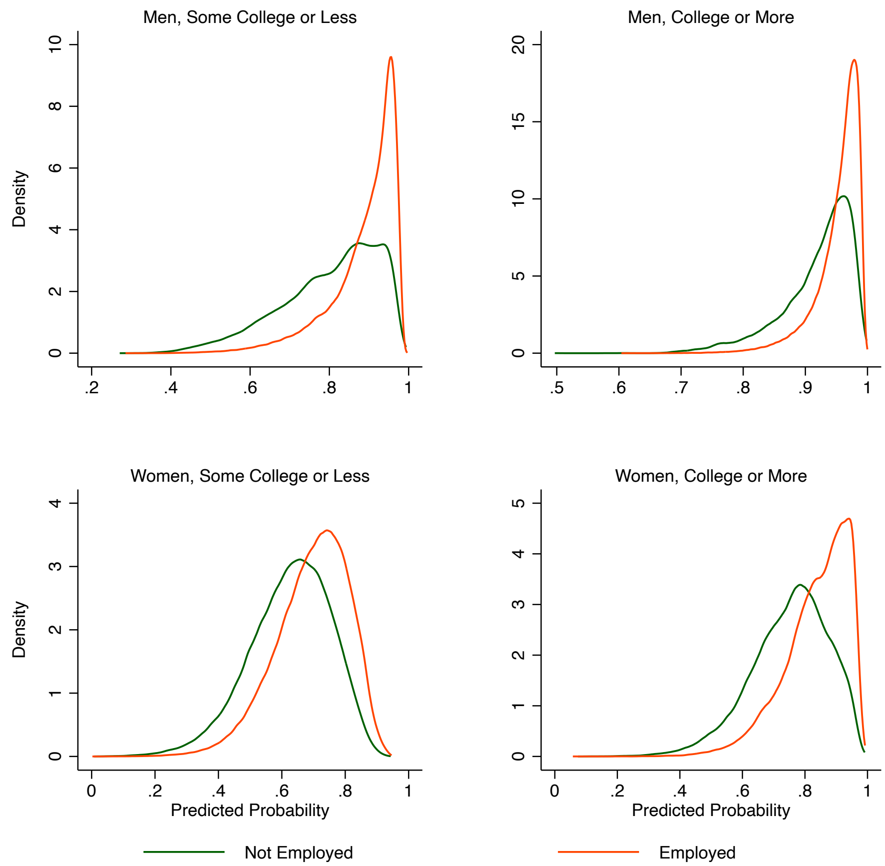
Appendix Figure B2. Simulated Weighted Disposable Income Instrument-Work, Over Time



Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: The figure is a box and whisker plot depicting the 25th, 50th, and 75th 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.

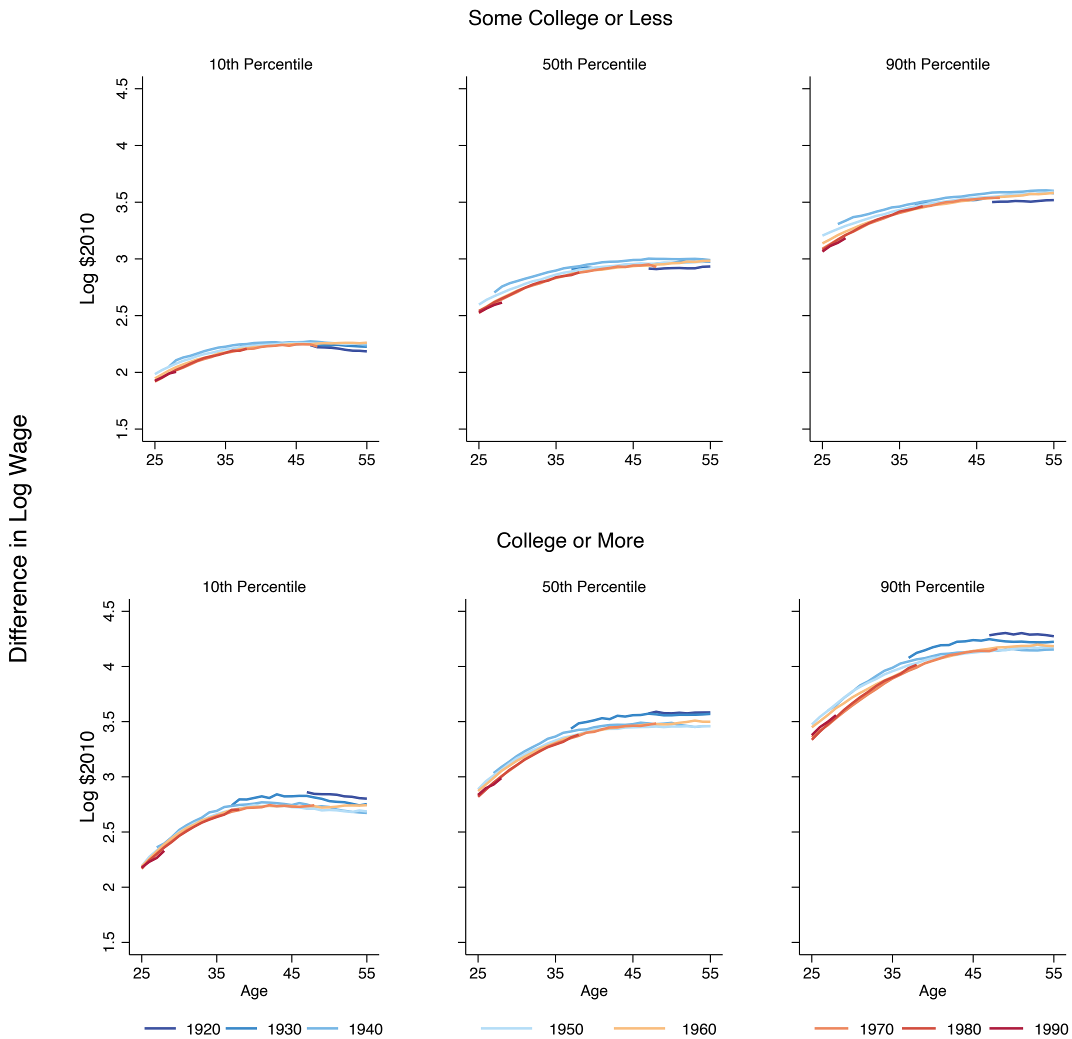
Tables 1-4 with all workers in the main text and Appendix Tables D1-D4 for full-time workers demonstrate that the three exclusion restrictions individually and jointly affect the decision to work. Across men and women in each education group higher levels of Simulated Disposable Income at No Work reduce 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 10th, 50th, and 90th 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 90th percentiles. Moreover, there is

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

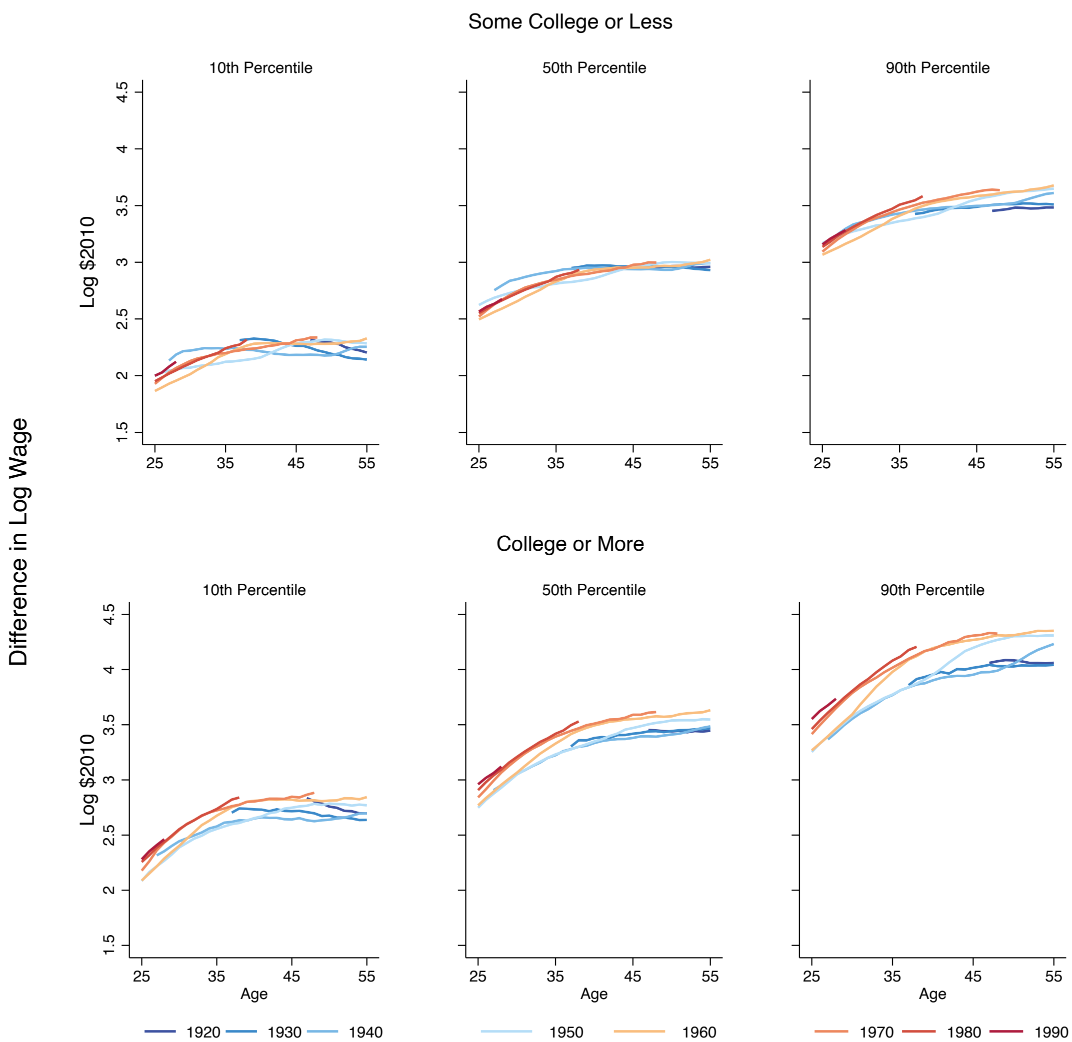


Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are based on counterfactual offer wage distributions based on coefficients from the quantile selection model net of gender- and education-specific time effects. See text for additional details.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



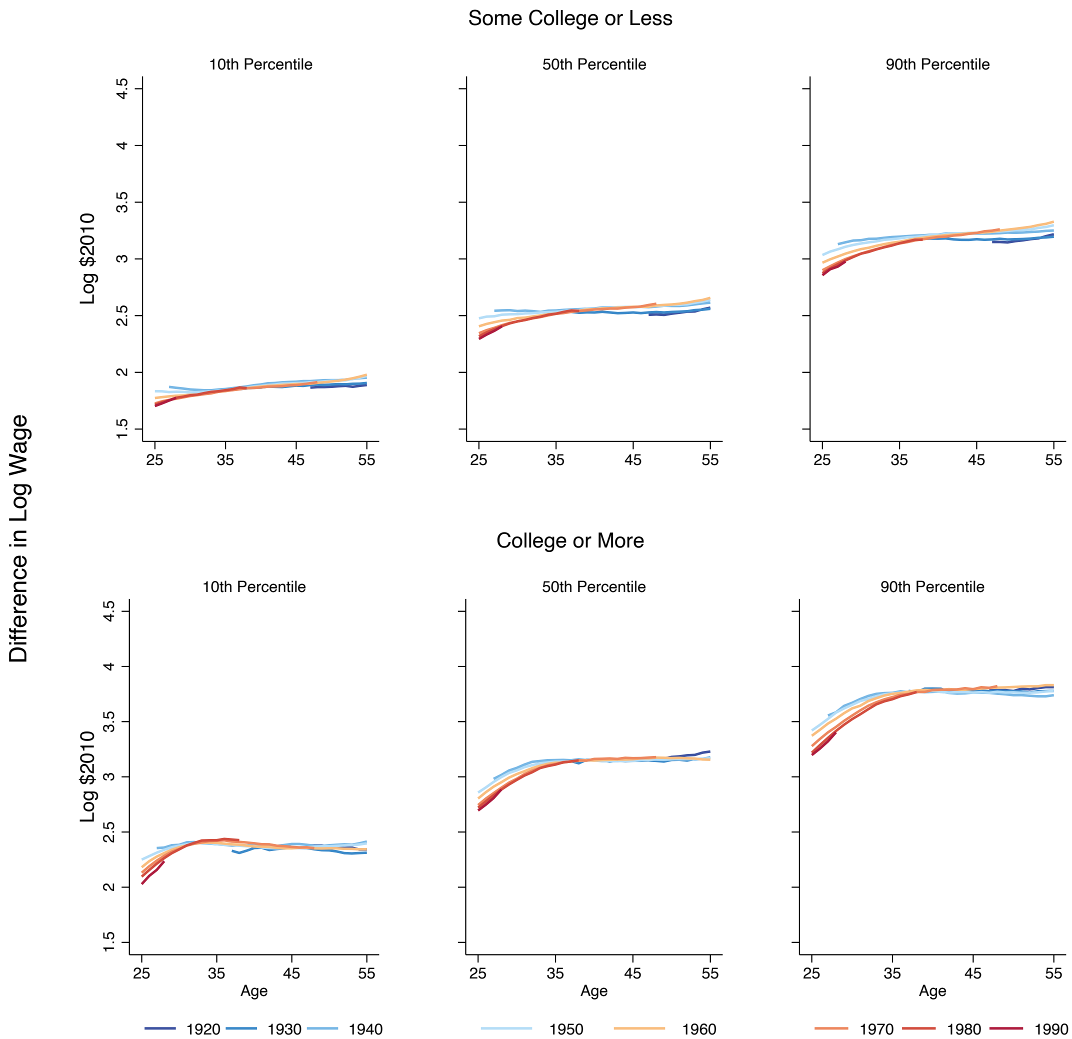
Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are based on counterfactual offer wage distributions based on coefficients from the quantile selection model inclusive of gender- and education-specific time effects. See text for additional details. 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 1^{st} 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 90^{th} 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.

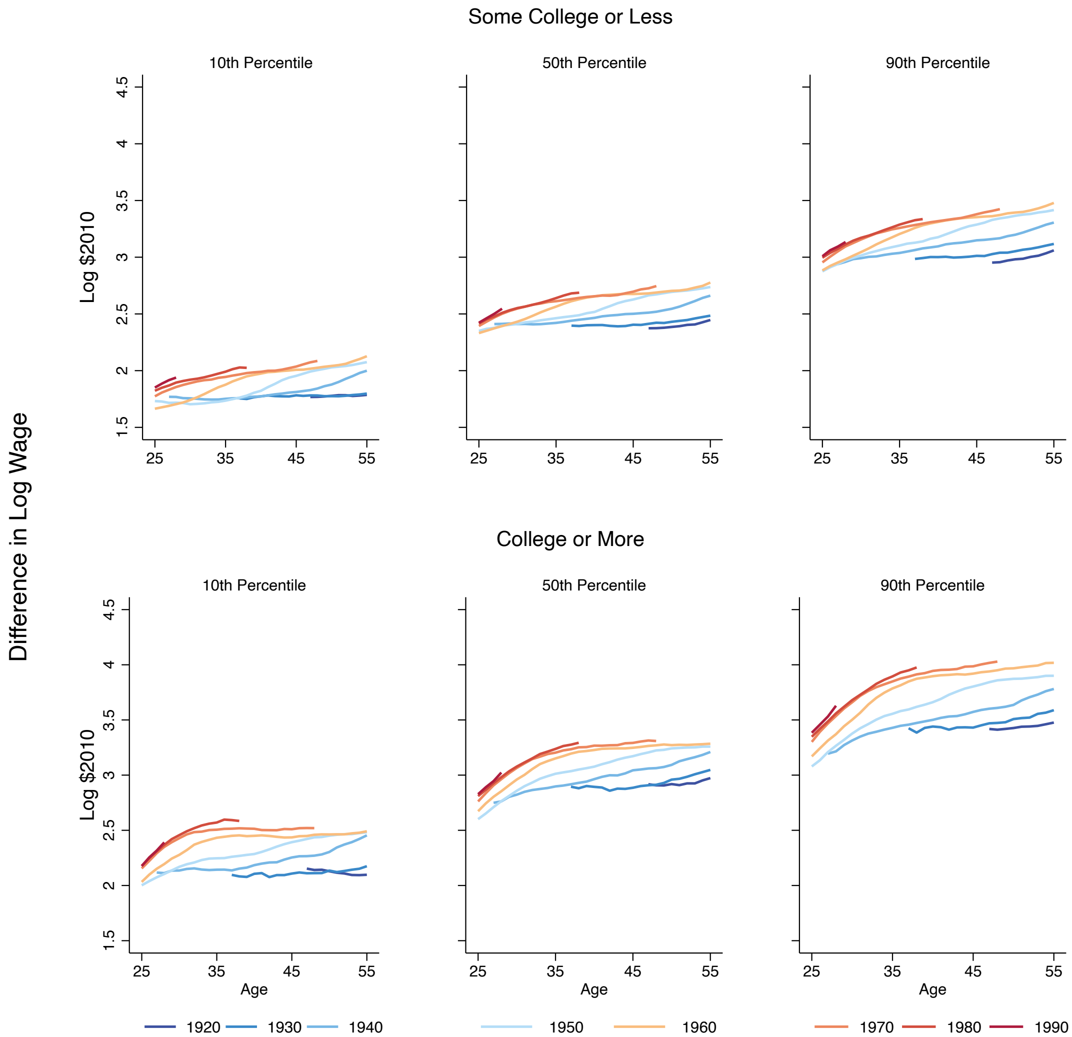
Figure C3 suggests that net of time effects, pseudo life cycle age-wage profiles of women are quite flat across the distribution, whereas inclusive of common time effects in Figure C4 more recent cohorts of women start out their working life with offer wages higher than older cohorts across both education 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 10^{th}, 50^{th}, and 90^{th} quantiles. This is a similar age as men at the 10^{th} quantile, but is a full decade earlier compared to men at the median and 90^{th} 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.

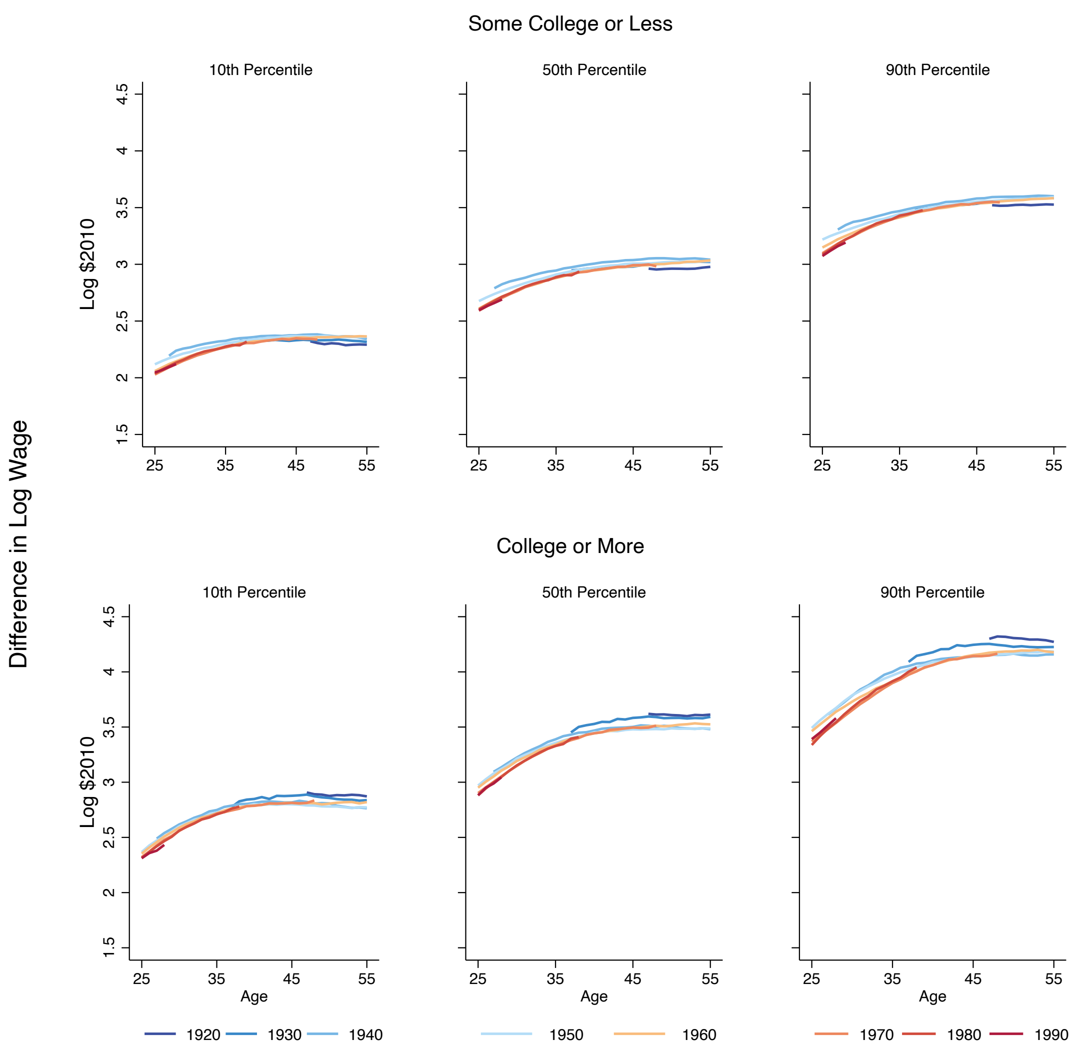
Appendix Table D4. Quantile Selection Estimates of Log Wages for Women with College or More, Full-Employment Model

	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.

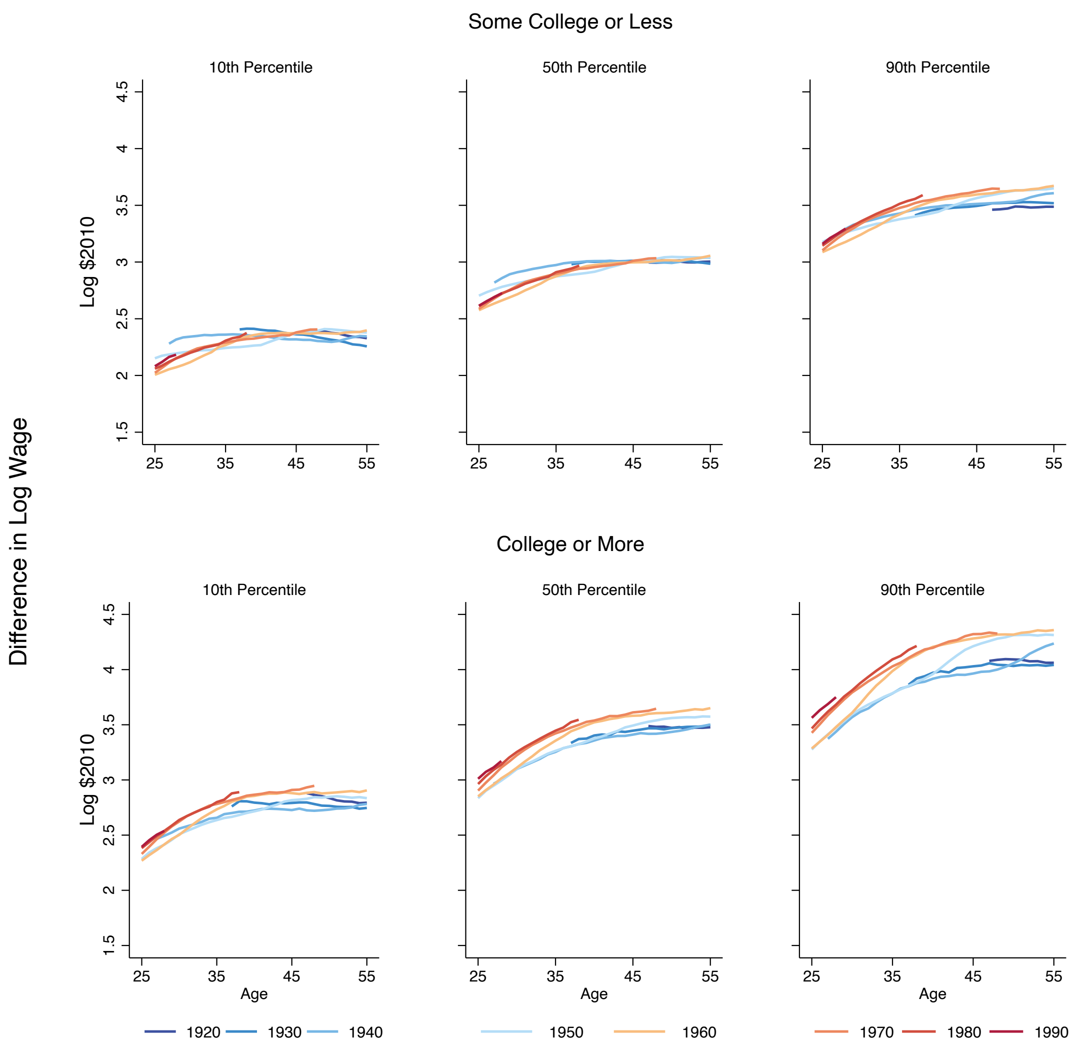
Appendix Figure D1. Quantile Selection Pseudo Life Cycle Age-Offer Wage Profiles of Full-Time Working Men Net of Time Effects



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

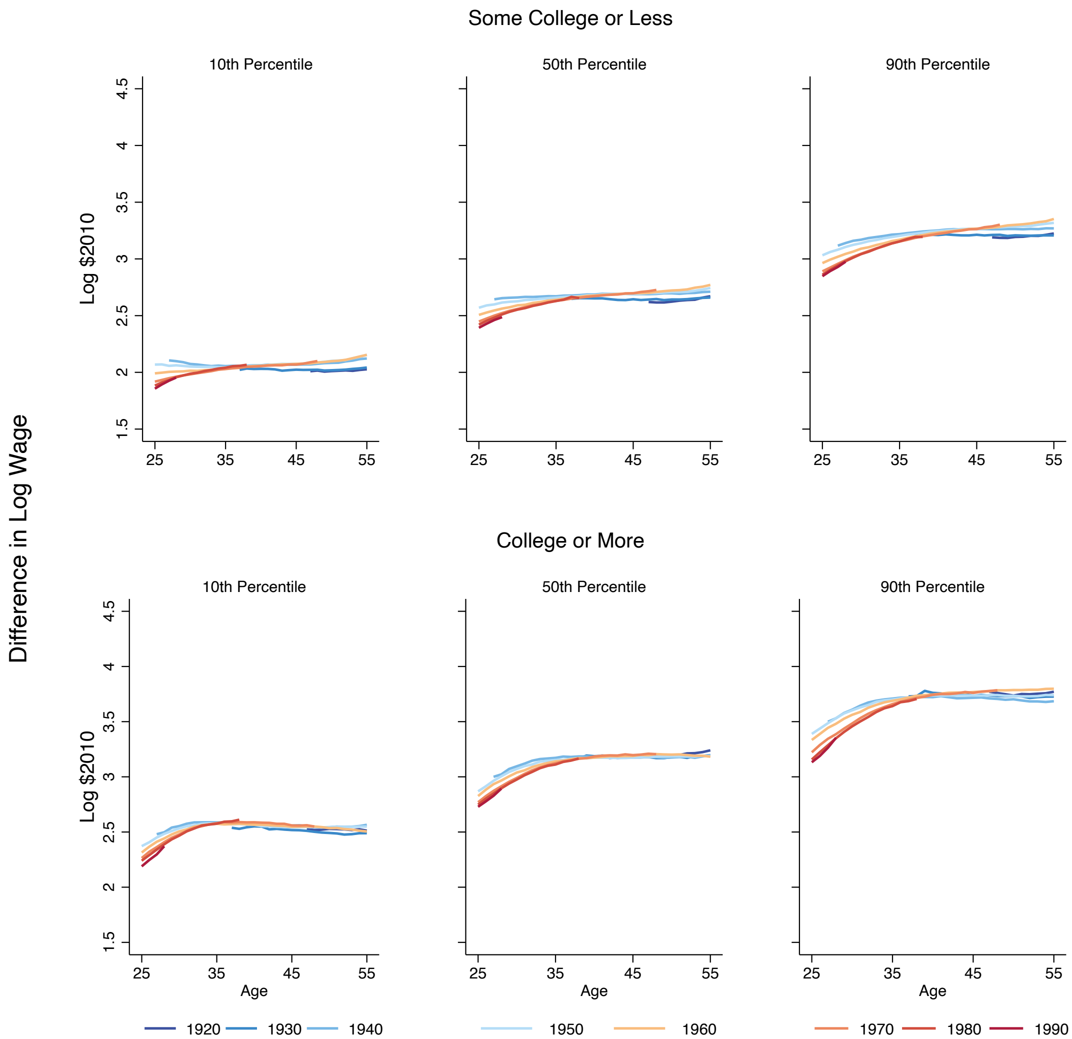
Note: Wages are based on counterfactual offer wage distributions based on coefficients from the quantile selection model of full-time workers net of gender- and education-specific time effects. See text for additional details. Sample consists of working and nonworking men aged 25-55. Workers with imputed 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



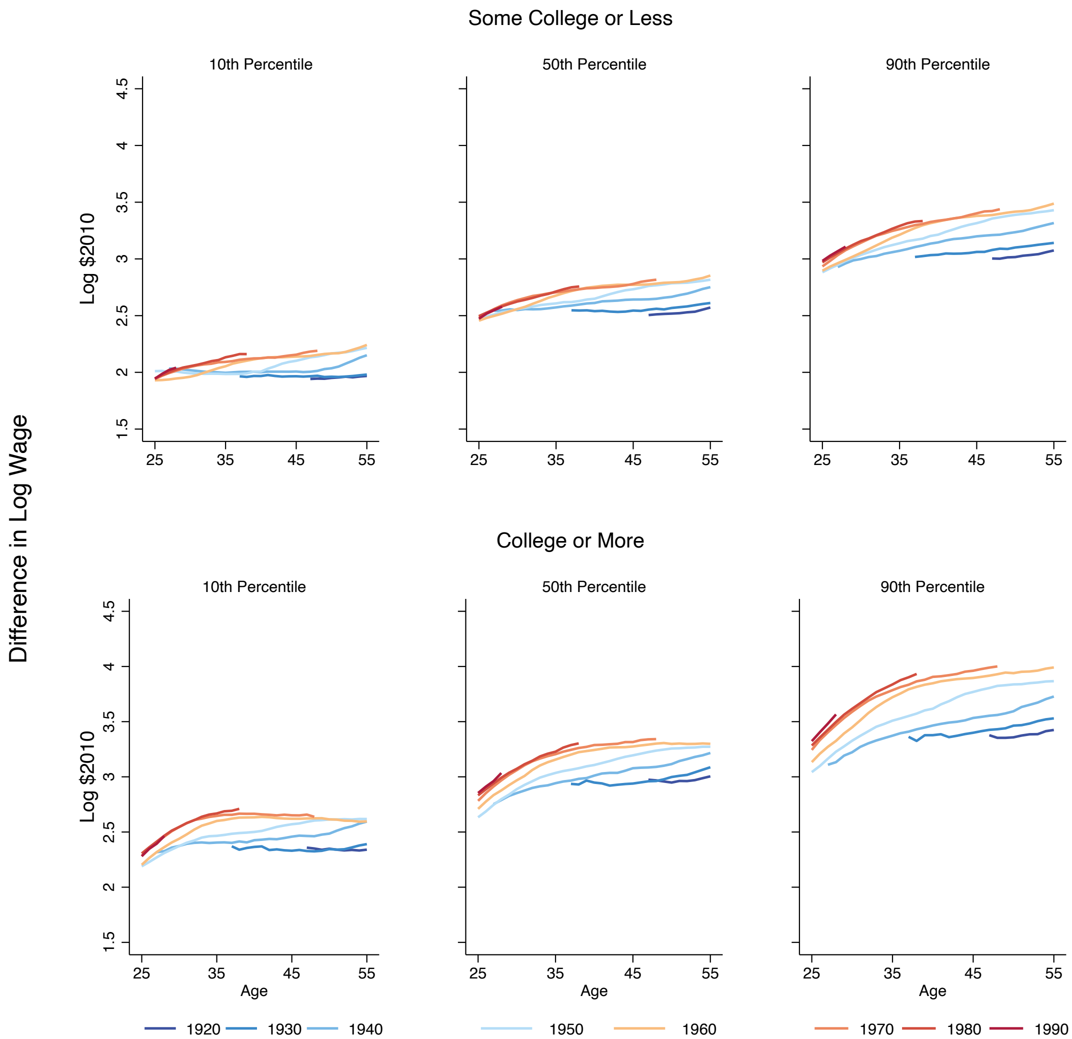
Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are based on counterfactual offer wage distributions based on coefficients from the quantile selection model of full-time workers inclusive of gender- and education-specific time effects. See text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



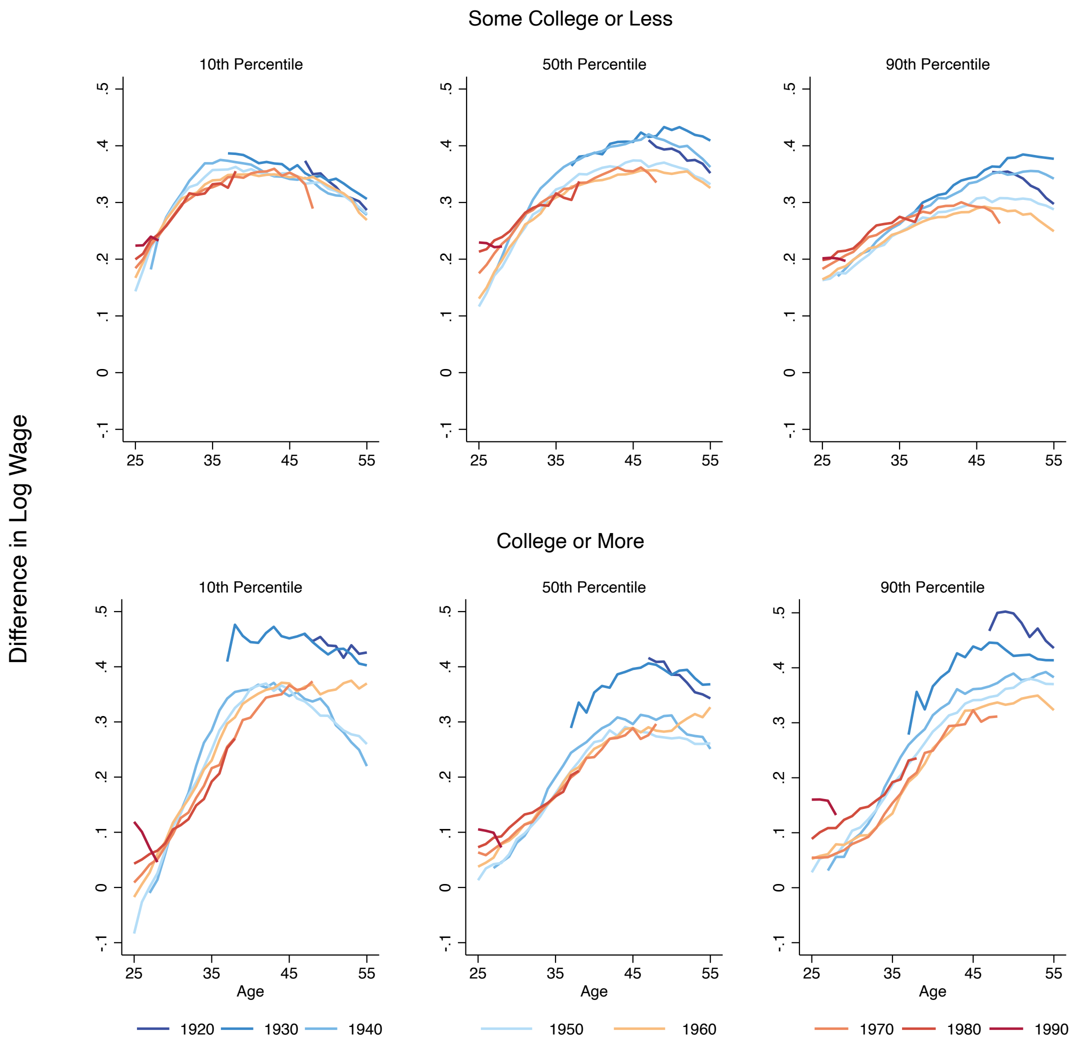
Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Wages are based on counterfactual offer wage distributions based on coefficients from the quantile selection model of full-time workers inclusive of gender- and education-specific time effects. See text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

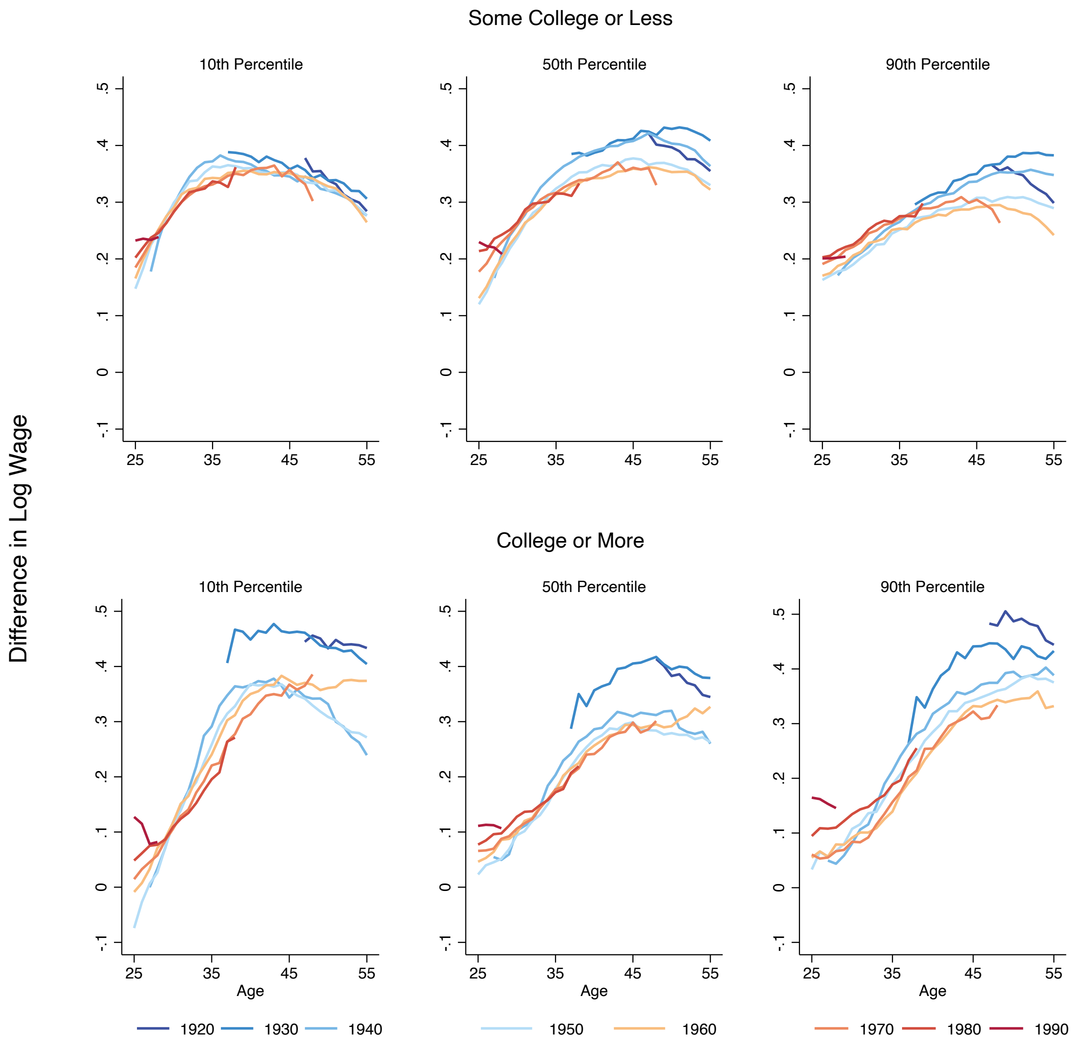
Appendix Figure E1. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Excluding Simulated Instrument from Work in Selection Equation



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.

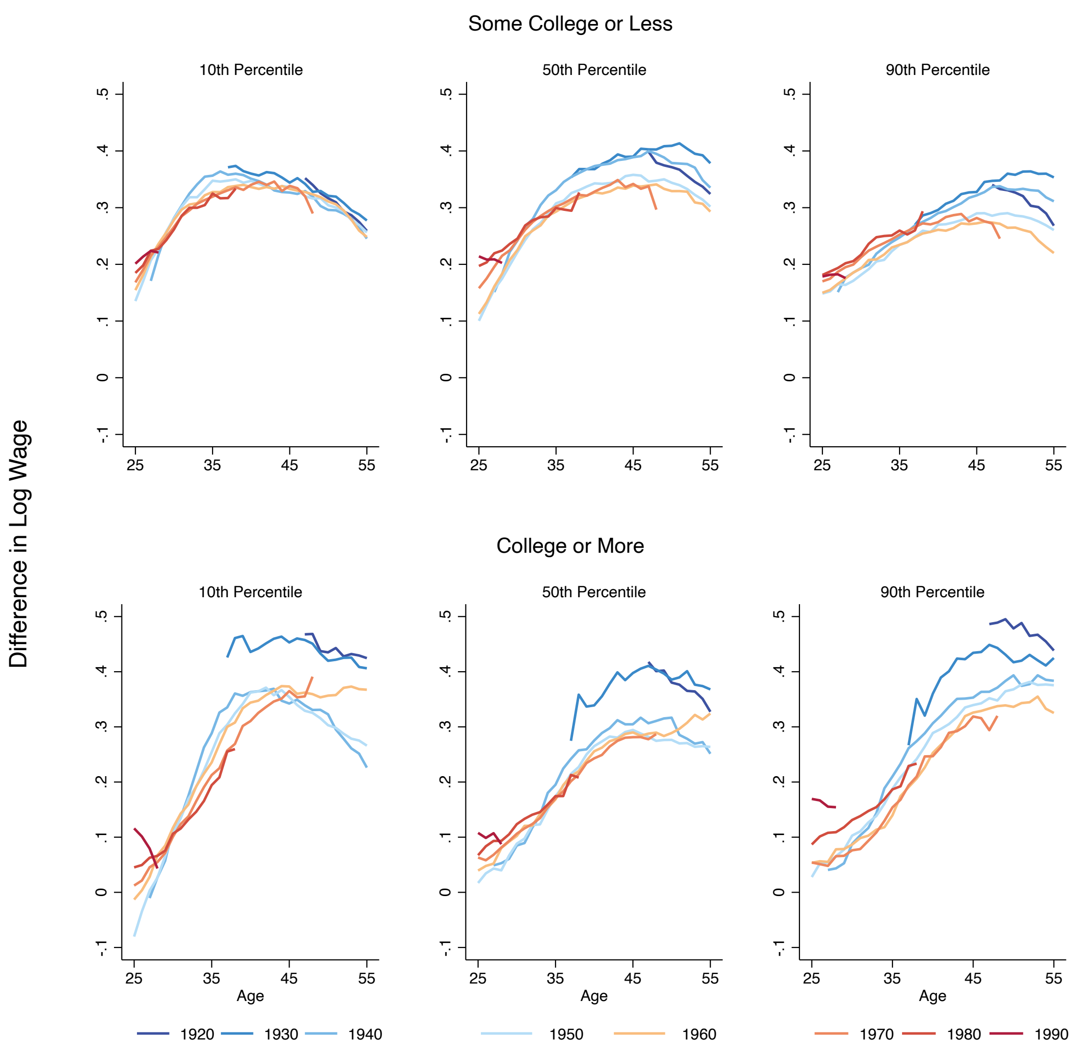
Appendix Figure E2. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: SNAP and TANF Maximum Benefits as Exclusion Restrictions in Selection Equation



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.

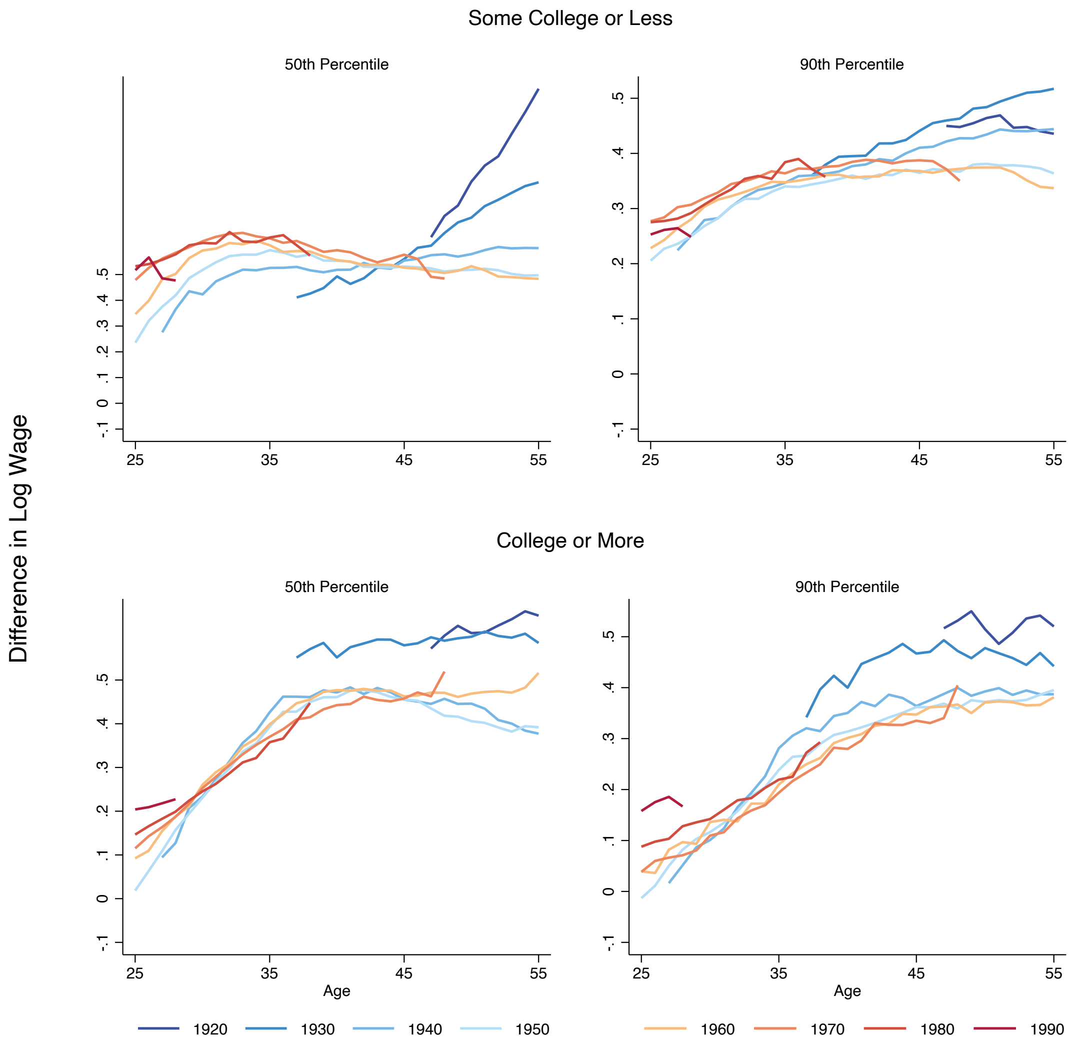
Appendix Figure E3. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: No Exclusion Restrictions in Selection Equation



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

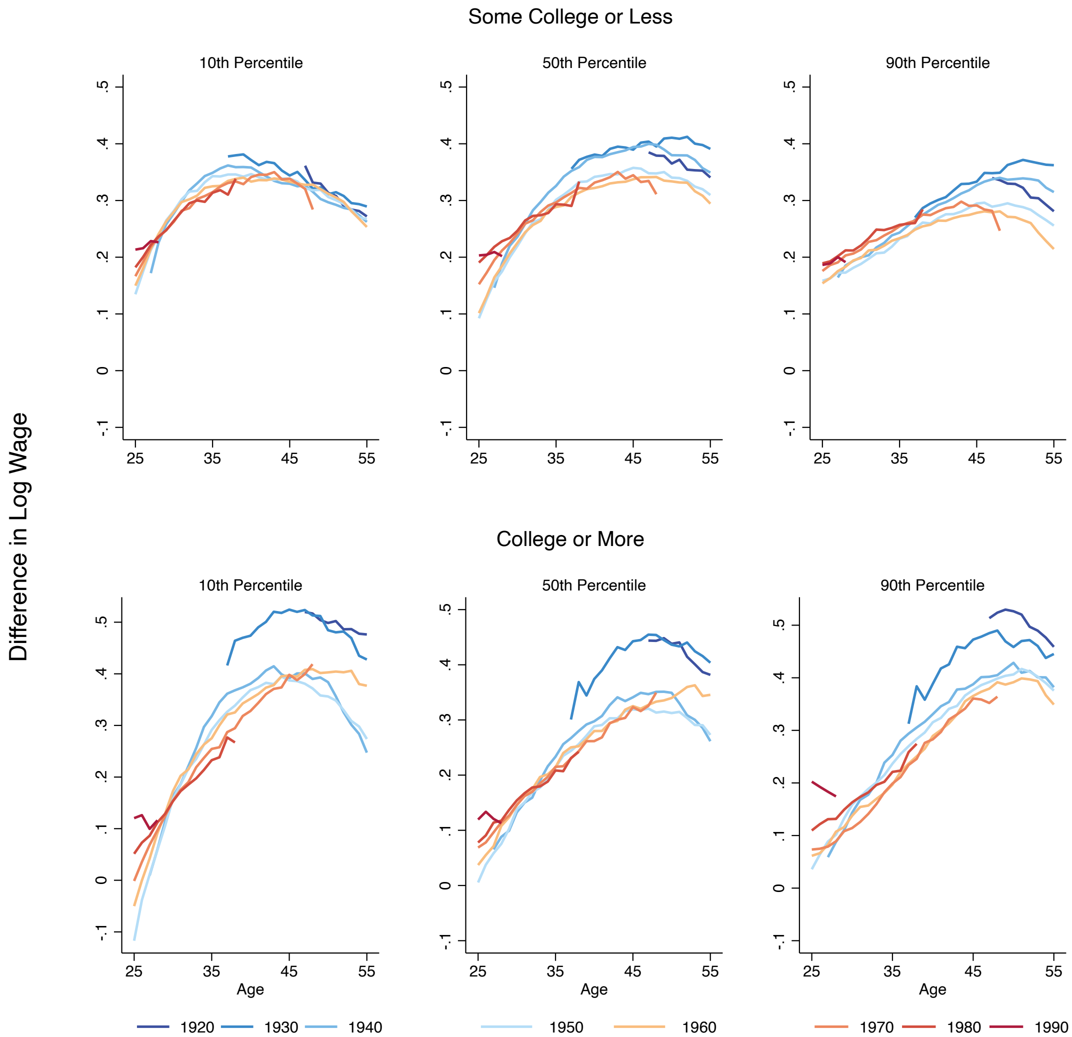


Source: Current Population Survey Annual Social and Economic Supplement, Survey Years 1977-2019
Note: Gender gaps are based on counterfactual offer wage distributions based on coefficients from the quantile median selection model net of gender- and education-specific time effects. See text for additional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

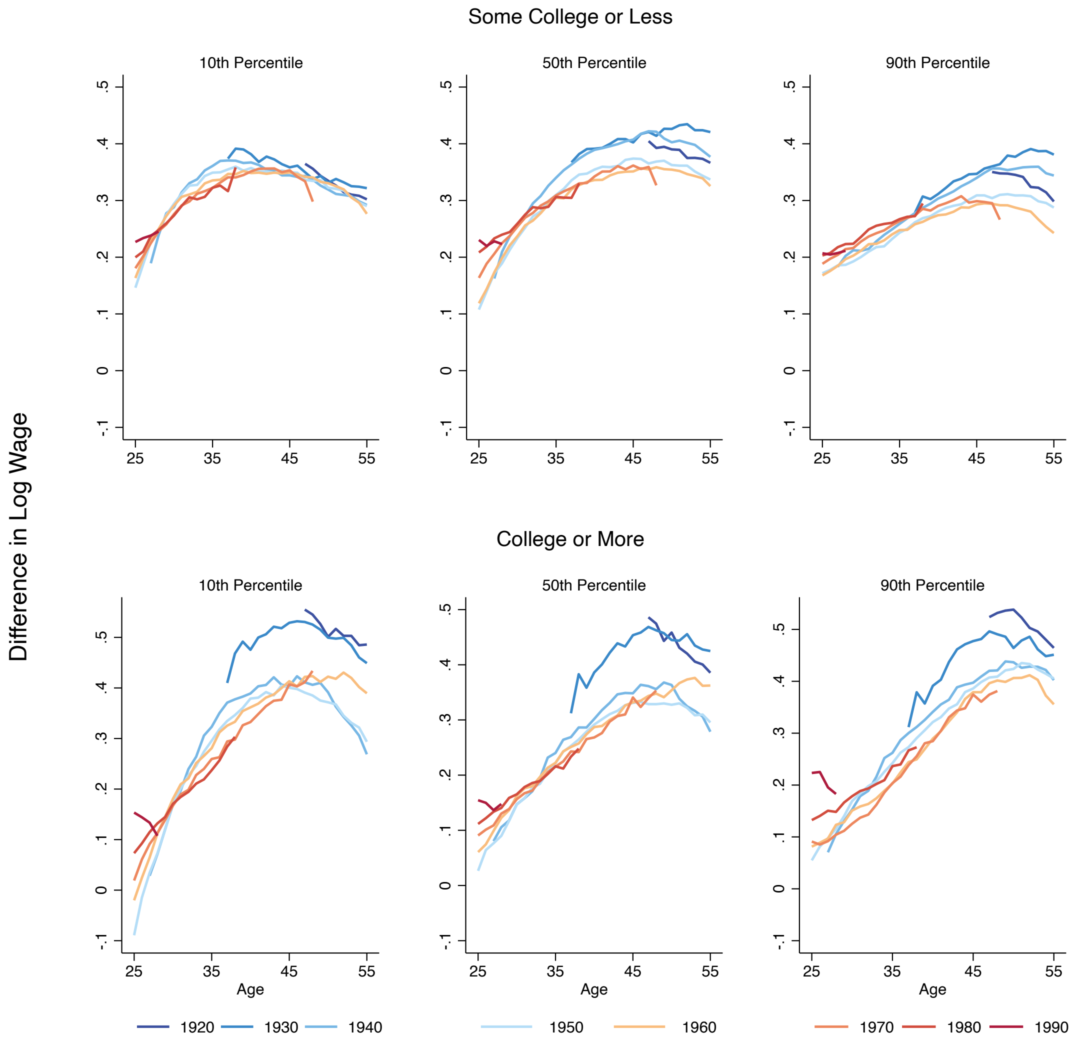
To assess how much this is due to omitting the three instruments from the selection equation, as opposed to omitting the age composition of children from the wage equation, in Appendix Figure E6 we repeat our baseline estimates from Figure V of the paper, but in this case we drop the age composition 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.

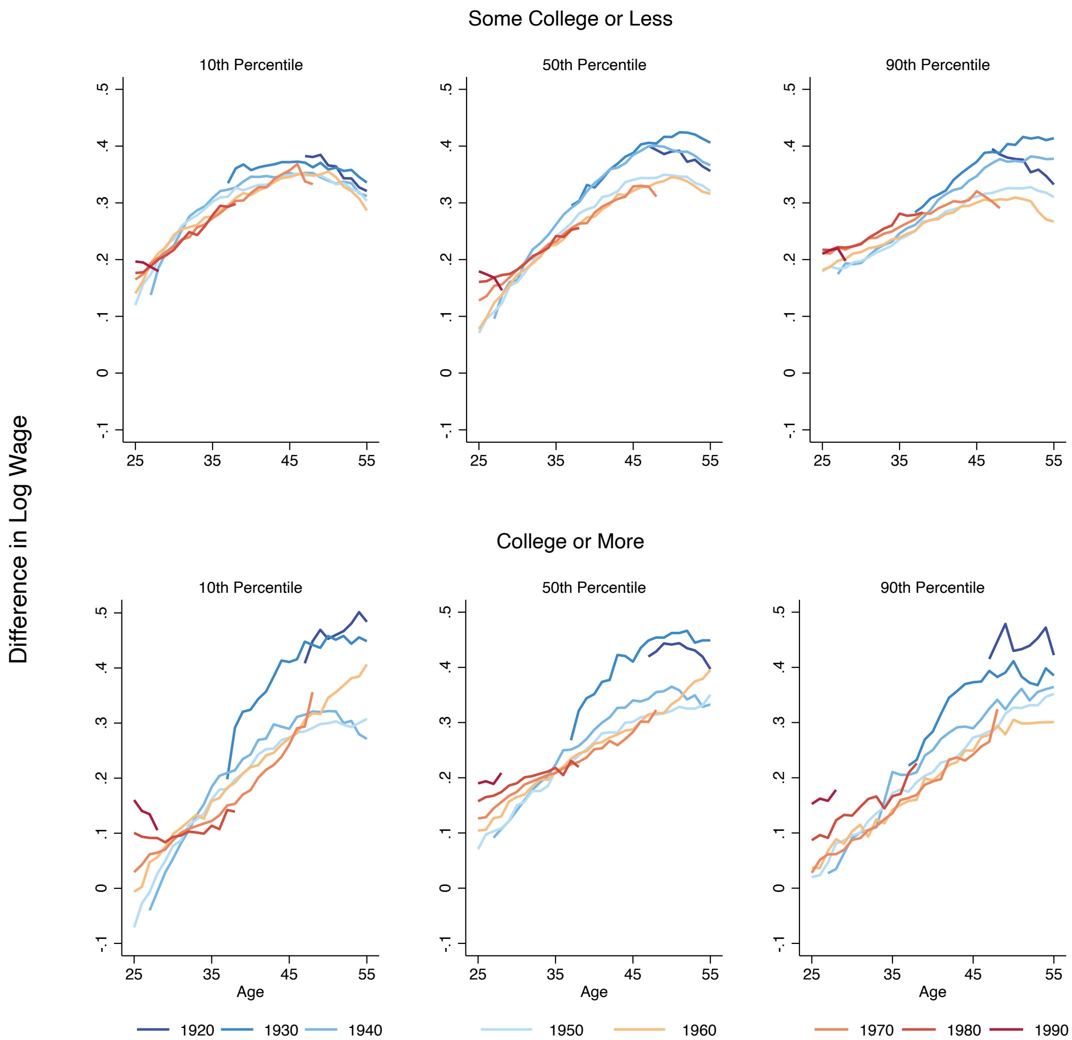
Appendix Figure E6. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Exclude Children Variables from Baseline Wage Equation



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.

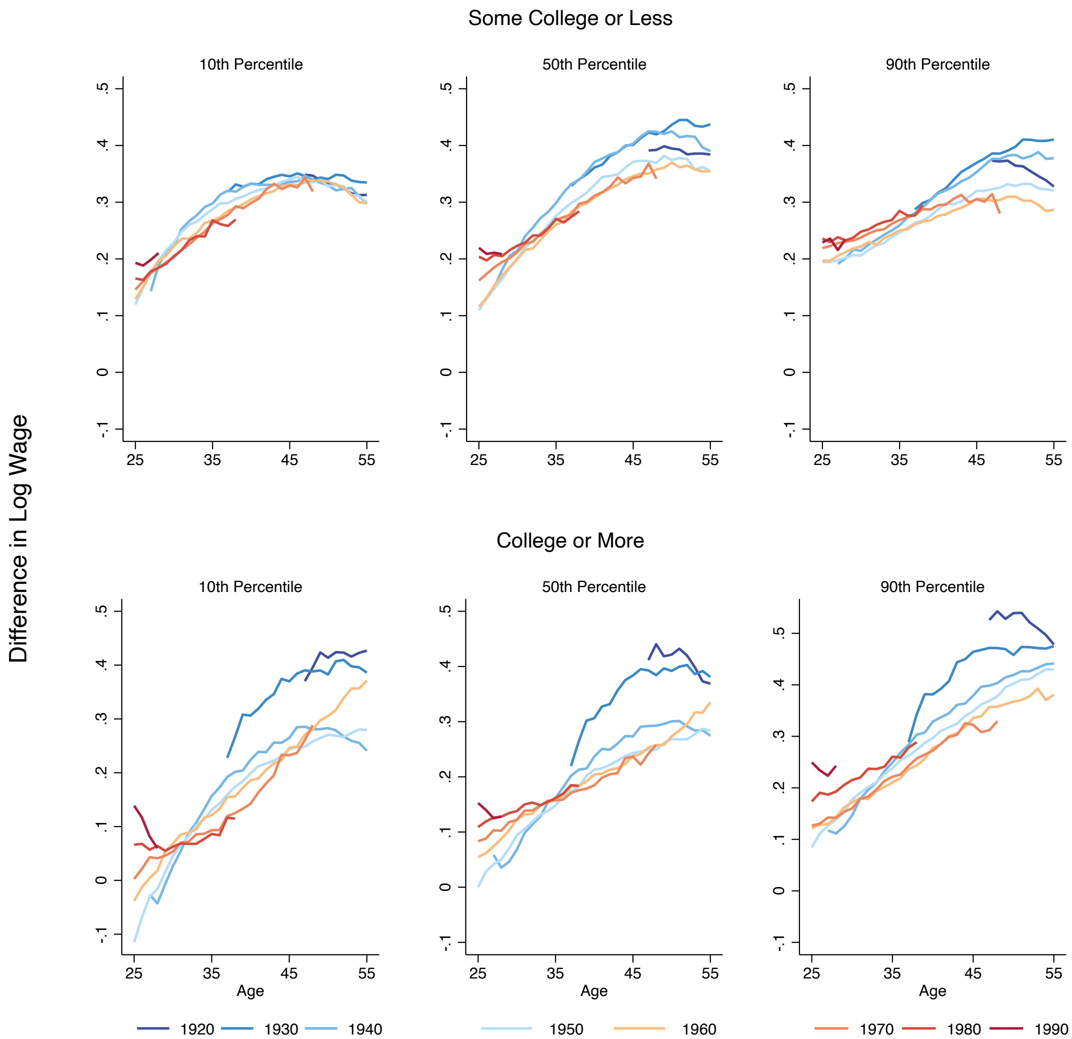
Appendix Figure E7. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: No Nonrandom Selection into Employment



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.

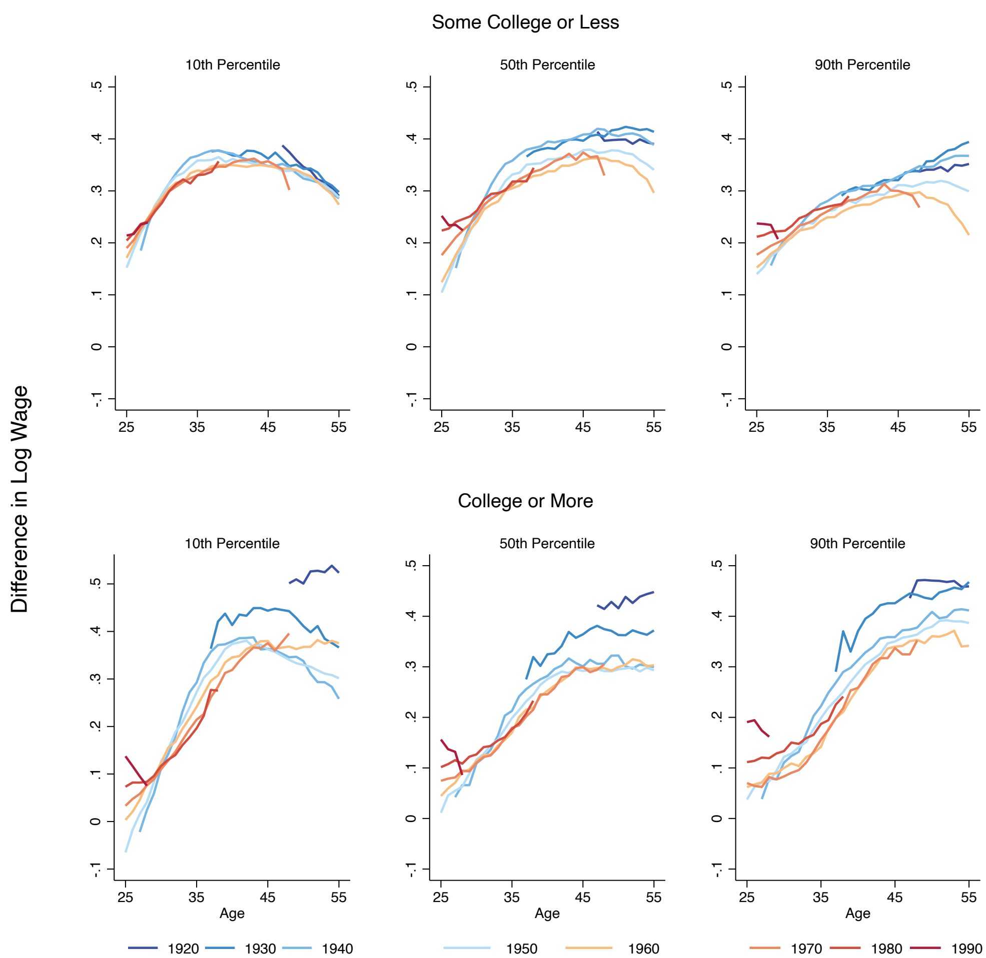
Appendix Figure E8. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Samples Split by Quartiles of Education Attainment



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.

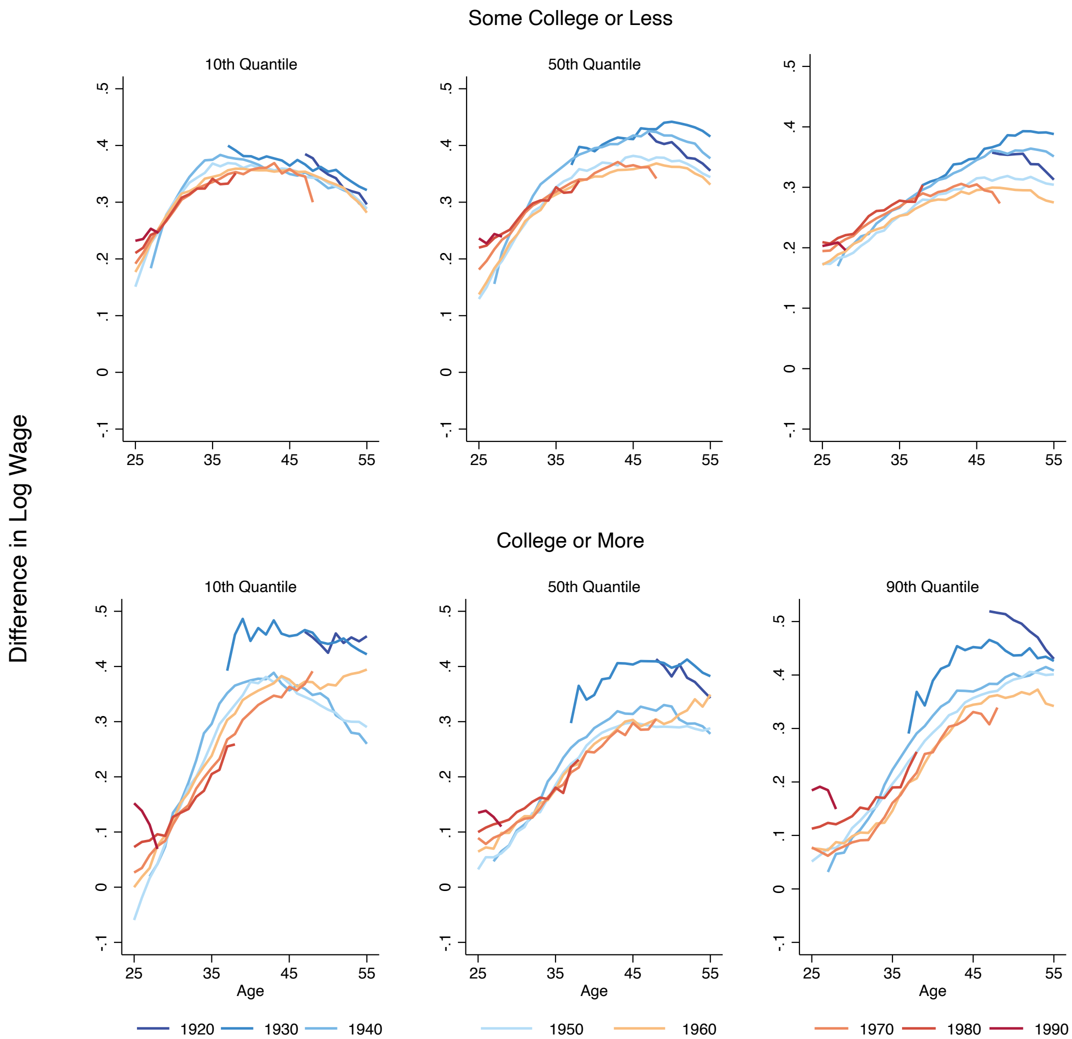
Appendix Figure E9. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Wage Model Based on Quadratic in Age, Time, and Cohort



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.

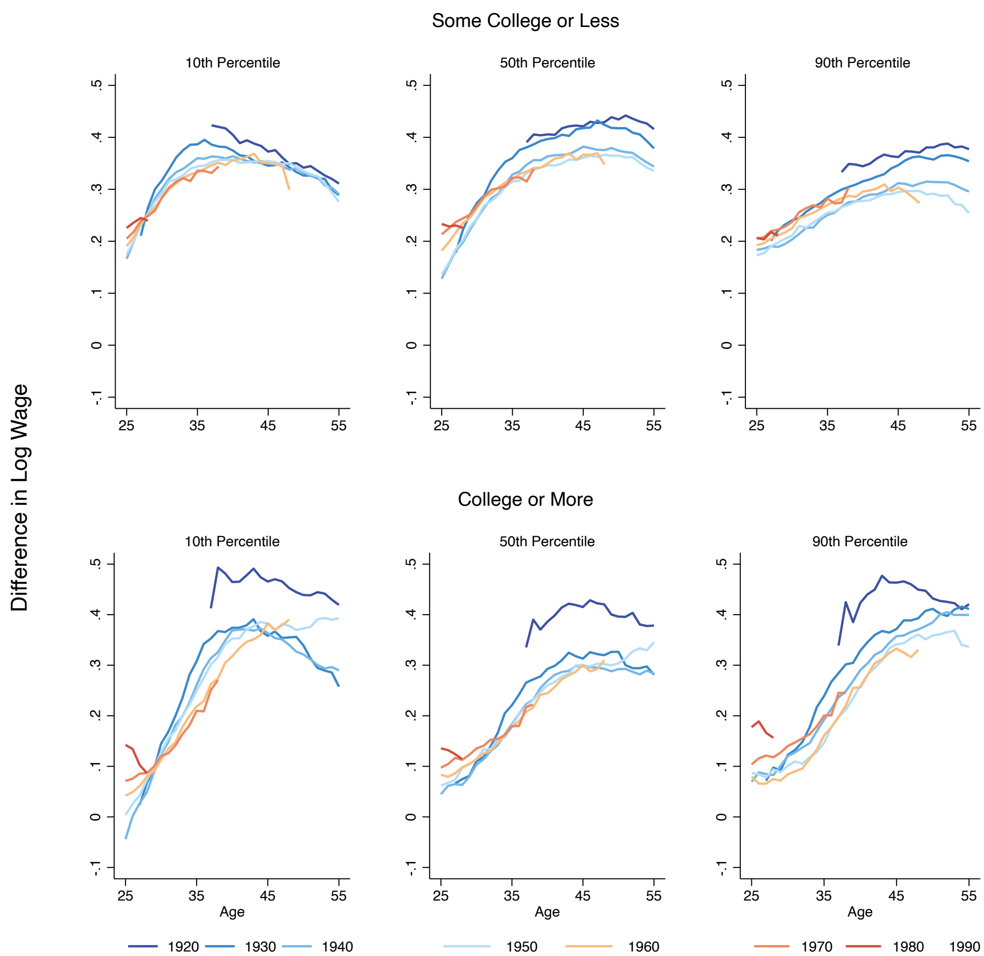
Appendix Figure E10. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Model With State-Specific Linear Time Trends



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.

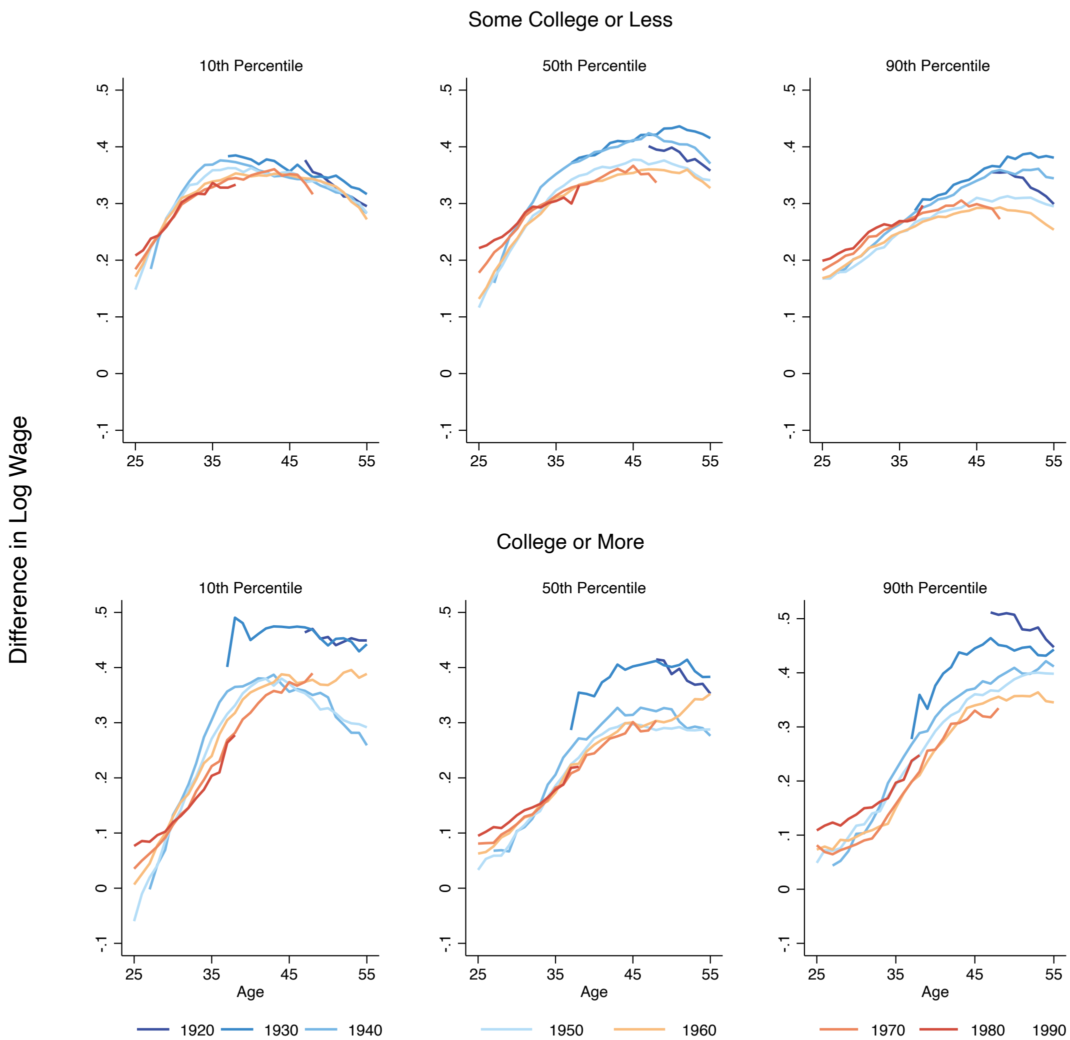
Appendix Figure E11. Within-Education Group Gender Wage Gaps over the Life Cycle Among Workers: Model Without 1920s Birth Cohort



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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