Interpreting Cohort Profiles of Life Cycle Earnings Volatility

Richard Blundell, *University College London and Institute for Fiscal Studies*

Christopher R. Bollinger, *University of Kentucky*

Charles Hokayem, *US Census Bureau*

James P. Ziliak, *University of Kentucky*

We present new estimates of earnings volatility over time and the life cycle for men and women by race and human capital, using Social Security earnings linked to the Current Population Survey. From the late 1970s to the mid-1990s, there is a strong negative trend in earnings volatility driven by a decline in transitory variance. From the mid-1990s, there is relative stability in trends of male earnings volatility due to an increase in the variance of permanent shocks. Cohort analyses indicate that earnings volatility is U-shaped, driven by large permanent shocks early and later in the life cycle.

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I. Introduction

Workers in the United States over the past five decades have experienced deep and protracted business cycle shocks, secular changes in the technology of work, and fundamental reforms of the tax and transfer systems. Whether and to what extent these economic and policy shocks have affected the volatility of earnings and how to properly model the earnings dynamics process to account for these forces have been the subject of extensive research in labor economics and macroeconomics (MaCurdy 1982; Abowd and Card 1989; Carroll 1992; Gottschalk and Moffitt 1994, 2009; Haider 2001; Stock and Watson 2003; Meghir and Pistaferri 2004; Blundell, Pistaferri, and Preston 2008; Bonhomme and Robin 2010; Sabelhaus and Song 2010; Shin and Solon 2011; Ziliak, Hardy, and Bollinger 2011; Dynan, Elmendorf, and Sichel 2012; Altonji, Smith, and Vidangos 2013; Bloom et al. 2018; Guvenen et al. 2021; McKinney, Abowd, and Janicki 2022; Moffitt et al. 2023). Some of this work has centered on how volatility ties into cross-sectional inequality, while other work attempts to distinguish whether volatility is temporary or permanent, the latter of which can have implications for economic mobility over time.

Much of the research on earnings instability over the past three decades is owed to the intellectual contributions of Robert Moffitt, who with his longtime collaborator Peter Gottschalk established the key result that the volatility of male earnings increased in the 1970s through the early 1980s, especially among the less educated, and while the instability of the 1970s was largely temporary in nature, that of the 1980s reflected more permanent shocks to earnings.

The aim of this paper is to use linked survey and administrative record data to provide new evidence over time and the life cycle on the volatility of earnings over the past five decades. We adopt two standard approaches to the measurement of volatility from the literature. The first provides a simple and transparent summary measure, defined alternatively as the variance of the arc percent change and the variance of the change in log earnings. The advantage of the arc percent change is that it permits one of the

financial support of the National Science Foundation (grant 1918828). The linked Annual Social and Economic Supplement–Detailed Earnings Record data used in this project were obtained as part of an internal-to-census project (DMS 7503840) and analyzed in a secure federal facility at the Kentucky Research Data Center in Lexington. Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the US Census Bureau. The Census Bureau has ensured appropriate access and use of confidential data and has reviewed these results for disclosure avoidance protection (project 7503840: CBDRB-FY22-CES010-021; CBDRB-FY22-CES004-046; CBDRB-FY23-081; CBDRB-FY24-0108). Contact the corresponding author, Richard W. Blundell, at r.blundell@ucl.ac.uk. Information concerning access to the data used in this paper is available as supplemental material online.

2 years to be a period of nonwork and thus includes labor market transitions that have historically been important for Black men and all women, as well as more recently important for less skilled White men (Ziliak, Hardy, and Bollinger 2011; Abraham and Kearney 2020). For completeness, instead of variance we also examine the difference of the 90th and 10th percentiles of the arc percent change (Bloom et al. 2018). While providing a more complete accounting of volatility with zero earnings, our summary volatility estimates indicate that both the time-series and the life cycle patterns are similar whether we use the arc percent or difference in log earnings measures (and 90/10 instead of variance). Based on this robustness of summary measures and the fact that the variance of log earnings is additively decomposable, our second approach decomposes the variance of the difference in log earnings into permanent and transitory components (see, e.g., Carroll 1992; Blundell, Pistaferri, and Preston 2008). In particular, we assume that the permanent component follows a unit root process and the transitory component follows a first-order moving-average (MA(1)) process. The generalized method of moments (GMM) estimation procedure allows for common aggregate shocks, as well as heterogeneous age profiles.

Our work builds on Moffitt's foundational research in this field. Most previous studies on volatility focus on trends in male earnings over time from survey data. While we provide updated time-series estimates here, any given period is composed of individuals of different ages from different birth cohorts, and thus we also examine whether the underlying time-series trends in volatility reflect changes across cohorts, changes across the life cycle for a given cohort, or both. Beyond understanding time-series patterns, estimating how permanent and transitory variance components vary over the life cycle is important, as it informs our understanding of how volatility affects intragenerational mobility.

We also move beyond men—and even White men as in early studies of Gottschalk and Moffitt (1994) and Haider (2001)—by providing a full set of time-series and life cycle estimates for both men and women by education attainment and race. We do so by using a restricted dataset that links individuals in the Current Population Survey (CPS) Annual Social and Economic Supplement (ASEC) over the 1996–2019 time period to their full history of administrative earnings records from the Social Security Administration. This provides much larger sample sizes for robust subgroup analyses by race and education than would be possible in common household surveys, such as the Panel Study of Income Dynamics (PSID) or Survey of Income and Program Participation. In addition, using the long panel of administrative records ameliorates the problem of missing earnings from nonresponse that plagues surveys such as the CPS (Bollinger et al. 2019).

We are not the first to estimate volatility and its variance components by cohort and gender or to use Social Security Administration earnings records. Sabelhaus and Song (2010) provide both time-series and cohort estimates of volatility from Social Security earnings but not separately by gender, race, or education. We extend their work by adopting a more flexible specification of transitory earnings and including more older and younger birth cohorts, and because we observe personal demographics with the link to the CPS, we also estimate volatility by race, education, and gender. Bloom et al. (2018) and Guvenen et al. (2021) study volatility by gender using Social Security records, but they do not have access to race and education in their administrative data as we do here. Still others have used survey data linked to administrative records to study volatility in the United States (Hryshko, Juhn, and McCue 2017; Carr, Moffitt, and Wiemers 2023; Ziliak, Hokayem, and Bollinger 2023). In related work, Ziliak, Hokayem, and Bollinger (2023) used the CPS linked to Social Security records as we do here, but our paper differs in several important ways—they used 2-year panels of the CPS linked to Social Security data whereas we use the full time series of Social Security earnings (up to 35 years); they did not examine life cycle volatility or separate by race; and they did not examine permanent and transitory components of variance.[1]

Our results for men suggest that from the late 1970s to the mid-1990s there is a strong negative trend in earnings volatility, followed by two decades of comparatively little trend but substantial business cycle sensitivity, especially in the years surrounding the Great Recession. The negative trend in the first half of the sample period aligns with results of Sabelhaus and Song (2010) and Bloom et al. (2018), while the latter two decades of relative stability align with the survey and administrative data studies covered in Moffitt et al. (2023) as well as McKinney, Abowd, and Janicki (2022). The distinction between transitory and permanent changes underlying the pattern of volatility turns out to produce a key insight. Both the trend decline and business cycle sensitivity stem from transitory variances, but after 1995 there is an "offsetting" upward trend in permanent shocks among workers without a college education, particularly Black men.

In addition, the cohort estimates demonstrate a strong U-shaped profile of earnings variance over the life cycle, especially among White college-educated men, but these profiles shifted downward and leftward in more recent cohorts. The U-shaped profile comes from permanent shocks across the life cycle, while declining volatility comes from reduced transitory variances among younger cohorts of men. The latter is less in evidence among Black men, keeping the volatility of earnings elevated compared with White men. These patterns are broadly similar for women as for men, with the notable difference that women's earnings exhibit little business cycle variation compared with men's and the life cycle U shape is more attenuated later in

[1] After starting this project, we learned of a paper by Braxton et al. (2023) using the same linked ASEC–Detailed Earnings Record (DER) data to examine earnings volatility. Our project differs in our focus on life cycle volatility and racial differences, as well as the methodological approach.

the life cycle. These differences appear more for White women than for Black women.

The rest of the paper is organized as follows. The next section outlines our approach to measuring volatility, both over time and over the life cycle, for summary measures and variance decompositions. Section III describes our panel of administrative earnings and the process of linking them to survey records. Section IV presents the results, with the full set of summary volatility estimates for men and women, followed by the corresponding permanent and transitory decompositions. Section V concludes.

II. Measuring Volatility

The literature on the measurement of volatility is bifurcated into two distinct strands, one that focuses on simple summary measures of volatility and another that focuses on the detailed decomposition of variance into permanent (persistent) and transitory components with often complicated time-series dynamics and sources of measurement error and unobserved heterogeneity.[2] The summary measures are useful for a transparent portrait of volatility trends over time, but they do not provide insights into the sources of the shocks, which could have vastly different welfare implications for households. In this section, we outline our approaches to both forms of volatility measurement over time and the life cycle.

A. Summary Volatility

We begin our analysis with an examination of basic patterns of earnings volatility. Specifically for our summary time-series measure, we use the variance of the arc percent change, defined as

$$V_t = \mathrm{var}\left(\frac{y_{i,t} - y_{i,t-1}}{\bar{y}_i}\right), \tag{1}$$

where $y_{i,t}$ represents real earnings of individual i in time t, $y_{i,t-1}$ represents 1-period-lagged earnings, and $\bar{y}_i$ represents the average of earnings across adjacent years, $\bar{y}_i = (y_{i,t} + y_{i,t-1})/2$ (Ziliak, Hardy, and Bollinger 2011; Dynan,

[2] For examples of summary volatility papers, see Cameron and Tracy (1998); Sabelhaus and Song (2010); Dahl, DeLeire, and Schwabish (2011); Shin and Solon (2011); Ziliak, Hardy, and Bollinger (2011); Celik et al. (2012); Dynan, Elmendorf, and Sichel (2012); Koo (2016); Bloom et al. (2018); and the papers in Moffitt et al. (2023). Examples of permanent and transitory decompositions include MaCurdy (1982); Carroll (1992); Gottschalk and Moffitt (1994, 2009); Haider (2001); Moffitt and Gottschalk (2002, 2012); Stock and Watson (2003); Meghir and Pistaferri (2004); Blundell, Pistaferri, and Preston (2008); Bonhomme and Robin (2010); Browning, Ejrnaes, and Alvarez (2010); Sabelhaus and Song (2010); Altonji, Smith, and Vidangos (2013); Guvenen and Smith (2014); Blundell, Graber, and Mogstad (2015); Jensen and Shore (2015); Arellano, Blundell, and Bonhomme (2017, 2018); Moffitt and Zhang (2018); Guvenen et al. (2021); and Braxton et al. (2023).

Elmendorf, and Sichel 2012; Koo 2016; Moffitt et al. 2023).[3] The advantage of the arc percent change is that it is still defined if earnings are zero in one of the 2 periods, thus capturing movements into and out of the labor force. This is a more inclusive measure of volatility than alternatives such as the variance of the change in log earnings, which removes zeros in both periods by construction (Shin and Solon 2011; Moffitt and Zhang 2018). Our baseline summary measures include these labor market transitions, but for robustness we also estimate summary volatility using the variance of the change in log earnings, as this is also the measure used in our variance decomposition to follow. We also report in the appendix (available online) the difference of the 90th to 10th percentiles of the arc percent change, which is the measure employed by Bloom et al. (2018) and also reported in Guvenen et al. (2021).

For summary volatility over the life cycle, we define real earnings of individual i of age a in birth-year cohort c as $y^c_{i,a}$, which leads to the modification of equation (1) as

$$V^c_a = \operatorname{var}\left(\frac{y^c_{i,a} - y^c_{i,a-1}}{\bar{y}^c_a}\right), \tag{2}$$

where $y^c_{i,a-1}$ represents earnings from 1-year-lagged age and $\bar{y}^c_a$ represents the cohort average of individual earnings across the two ages. Although we allocate individuals to single-year birth cohorts, for parsimony in reporting results we aggregate single-year cohorts to the decadal level. For example, this means anyone born from 1950 to 1959 will be allocated to the 1950 birth cohort, and likewise for other decadal birth cohorts.

B. Permanent and Transitory Variance

The literature on permanent and transitory decompositions of earnings is rich and, building on the seminal work of Gottschalk and Moffitt (1994), has expanded greatly to incorporate persistence in shocks of varying duration, dependence in the variance of shocks by time and age, and latent heterogeneity in profiles of shocks. To fix ideas, we focus our discussion on the life cycle permanent and transitory earnings process over cohorts using a specification that combines features found in Blundell, Pistaferri, and Preston (2008) and Blundell, Graber, and Mogstad (2015). The basic ideas are the same for the more familiar earnings decomposition over time, with the time subscript replacing the age subscript and suppressing cohort differences.

Define the natural log of real earnings for individual i at age a in cohort c as

[3] The arc percent change is bounded and symmetric between −2 and 2. In cases where earnings are negative from self-employment losses, earnings are then replaced by their absolute value at the loss of symmetry. Administrative earnings in our application are strictly nonnegative.

$$\ln y_{i,a}^c = \alpha_i^c + \sum_{k=1}^{K}\beta_{i,k}^c(a_i^c - 25)^k + \mu_{i,a}^c + \upsilon_{i,a}^c, \tag{3}$$

where α_i^c represents latent heterogeneity that varies across individuals in a cohort but not time, $\beta_{i,k}^c$ represents an idiosyncratic age profile of order k normalized around the (assumed) labor-market entry age of 25, $\mu_{i,a}^c$ is a permanent component allowed to vary by age, and $\upsilon_{i,a}^c$ is an age-varying transitory component. We define the permanent component as an autoregressive process

$$\mu_{i,a}^c = \rho^c\mu_{i,a-1}^c + \eta_{i,a}^c, \tag{4}$$

where $|\rho^c| \leq 1$ and $\eta_{i,a}^c$ is a mean-zero serially uncorrelated shock that is also uncorrelated with the lagged permanent component. The corresponding transitory component is assumed to follow an MA(1) process as

$$\upsilon_{i,a}^c = \varepsilon_{i,a}^c + \theta^c\varepsilon_{i,a-1}^c, \tag{5}$$

where $\varepsilon_{i,a}^c$ is a serially uncorrelated mean-zero shock that is uncorrelated with its lagged value and with any permanent component.

Equations (3)–(5) provide a fairly general system for the earnings process. Much of the extant literature on volatility over time assumes that the permanent component follows a random walk and imposes $\rho^c = 1$. Blundell, Graber, and Mogstad (2015) estimate ρ using administrative panel data from Norway, with estimates in the range of 0.98–1. Blundell, Pistaferri, and Preston (2008) use the PSID and find that a random walk on the permanent component coupled with an MA(1) in the transitory error captures the earnings process of men well, though they do find that an MA(0) in the transitory error yields similar results. We proceed by assuming a random walk in the permanent component but allow θ^c to differ from zero and thus permit an MA(1) transitory error. The appendix contains estimates where the transitory component has no memory ($\theta^c = 0$). In addition, we assume that the normalized age profiles vary across cohorts but are constant within a cohort ($\beta_i^c = \beta^c$) and that the age profile follows a quadratic ($k = 2$). With these assumptions, we then substitute equations (4) and (5) into (3) and take first differences, yielding

$$\Delta\ln y_{i,a}^c = \sum_{k=1}^{2}\beta_k^c\Delta(a_i^c - 25)^k + \eta_{i,a}^c + \varepsilon_{i,a}^c + (\theta^c - 1)\varepsilon_{i,a-1}^c - \theta^c\varepsilon_{i,a-2}^c. \tag{6}$$

Setting the age profile to zero for ease of presentation ($\beta^c = 0$), the variance of the change in log earnings at a given age and cohort is

$$\begin{aligned}\operatorname{var}\left(\Delta\ln y_{i,a}^c\right) = {} & \operatorname{var}(\eta_{i,a}^c) + \operatorname{var}(\varepsilon_{i,a}^c) + (\theta^c - 1)^2\operatorname{var}(\varepsilon_{i,a-1}^c)\\ & + (\theta^c)^2\operatorname{var}(\varepsilon_{i,a-2}^c).\end{aligned} \tag{7}$$

Following Blundell, Graber, and Mogstad (2015), we estimate the system implied above using a GMM approach. A key assumption is that the shocks are independent across age (or time in the time-series case). Equation (7) combined with covariances of two leads given as

$$\mathrm{cov}\left(\Delta \ln y_{i,a}^{c}, \Delta \ln y_{i,a+1}^{c}\right) = (\theta^{c} - 1)\mathrm{var}(\varepsilon_{i,a}^{c}) - (\theta^{c} - 1)(\theta^{c})\mathrm{var}(\varepsilon_{i,a-1}^{c}), \tag{8a}$$

$$\mathrm{cov}\left(\Delta \ln y_{i,a}^{c}, \Delta \ln y_{i,a+2}^{c}\right) = -(\theta^{c})^{2}\mathrm{var}(\varepsilon_{i,a}^{c}) \tag{8b}$$

identifies the permanent and transitory variances, as well as the persistence parameter θ^c. While this represents three equations in four unknowns, when an additional age (or year) is added, this rises to six equations while adding only two additional variance terms. With multiple ages (or years), the entire system is overidentified. The approach is greatly simplified if θ^c is assumed to be zero. We estimate this model (results are reported in the appendix) following Meghir and Pistaferri (2004) and Blundell, Pistaferri, and Preston (2008) using only three moments based on 1-period leads and lags

$$\mathrm{var}(\eta_{i,a}^{c}) = \mathrm{cov}\left(\Delta \ln y_{i,a}^{c}, \Delta \ln y_{i,a-1}^{c} + \Delta \ln y_{i,a}^{c} + \Delta \ln y_{i,a+1}^{c}\right), \tag{9a}$$

$$\mathrm{var}(\varepsilon_{i,a}^{c}) = -\mathrm{cov}\left(\Delta \ln y_{i,a}^{c}, \Delta \ln y_{i,a+1}^{c}\right), \tag{9b}$$

$$\mathrm{var}(\varepsilon_{i,a-1}^{c}) = -\mathrm{cov}\left(\Delta \ln y_{i,a}^{c}, \Delta \ln y_{i,a-1}^{c}\right). \tag{9c}$$

Moffitt and Gottschalk (2002, 2012) emphasize the importance of controlling for aggregate shocks in variance decompositions, which Blundell, Lopez, and Ziliak (2023) also found to be important in understanding life cycle wage profiles across cohorts. Thus, in lieu of using the change in log earnings to estimate the covariance structure, we first regress log earnings for each gender-race-education group on a full vector of year fixed effects and save the residuals. We then take those residuals and net out the age profile from equation (3) by regressing the first-stage residuals on a quadratic in age separately for each decadal cohort in each gender-race-education group. The residuals from this second step are then used for estimation of the variances and covariances in equations (7)–(8b).

III. Data

The data used in our analysis are a restricted-access panel of Social Security Administration Detailed Earnings Records (DERs) for tax years 1978–2019 linked to those individuals found in the CPS ASEC for survey years 1996–2020. The DER is an extract of Social Security's Master Earnings File and includes data on total earnings as reported on a worker's W-2 form, wages/salaries and income from (positive) self-employment subject to Federal Insurance Contributions Act and/or Self-Employment Contributions Act taxation reported on Form 1099, and deferred contributions to 401(k), 403(b), 408(k), 457(b), and 501(c) retirement and trust plans. We include all of these sources in our earnings measure. For workers with multiple W-2s or 1099s in a given year, we aggregate across all jobs to yield one annual earnings observation per worker. Wage earnings are uncapped in the DER, but self-employment earnings are capped at the Social Security taxable limit until 1993 and then uncapped thereafter. We convert nominal earnings to real values using the personal consumption expenditure deflator with 2019 base year.

The DER file contains no demographic information on the individual; however, this is obtained from the link to the ASEC using a unique identifier called a Protected Identification Key (PIK) that is available on each file. The PIK enables us to link each cross section of the ASEC from survey years 1996–2020 to the individual's full history of earnings in the DER. Individual PIKs through the 2004 tax year were based on Social Security numbers, but because refusal rates were high, in the 2005 tax year the Census Bureau switched to a model-based procedure to construct PIKs for data linkages (Wagner and Layne 2014). The change in procedure results in about 90% of individuals being linked to the DER, compared with about 70% in the period based on Social Security numbers. A possible concern with this change in linkage rate is that the distribution of earnings could change and possibly affect the trends in volatility. Appendix figure 1 (app. figs. 1–19 are available online) depicts ventiles of the real DER earnings distribution pooled across the 2002–4 and 2006–8 tax years, omitting the transition year 2005. This figure shows that there is no substantive change in the distribution after the switch to model-based linking. Bollinger et al. (2019) report that failure to link is more prevalent among low earners and in particular among the population of noncitizens of Hispanic ethnicity for whom either Social Security numbers do not exist or not enough information is known to construct a probabilistic estimate. As volatility tends to be higher among low earners, this failure to link is expected to reduce the level of volatility but not necessarily the trends.

From the linked ASEC-DER file, we select a sample of men and women aged 25–59, which captures most of the potential prime-age labor force after formal schooling is completed and before retirement. Based on age and year in the sample, each individual is assigned to a birth cohort, which we aggregate to the decadal level for the 1920s–1990s. Beyond age and gender, the real value added of the DER link to the ASEC is access to the individual's human capital and race. We focus on two education groups—some college or less and college or more—and two racial groups of White alone and Black alone.[4] While the split between college educated and not is not new in and of itself given the substantial evidence pointing to economic gains accruing mostly among the highly educated (Katz and Autor 1999; Card and DiNardo 2002), there has been much less work examining differences in volatility across education groups, especially in administrative earnings data. Moreover, the focus on Black-White differences is based on long-term interest in understanding

[4] Individuals reporting multiple races are omitted. However, each included racial group has individuals that self-identify as Hispanic or non-Hispanic ethnicity.

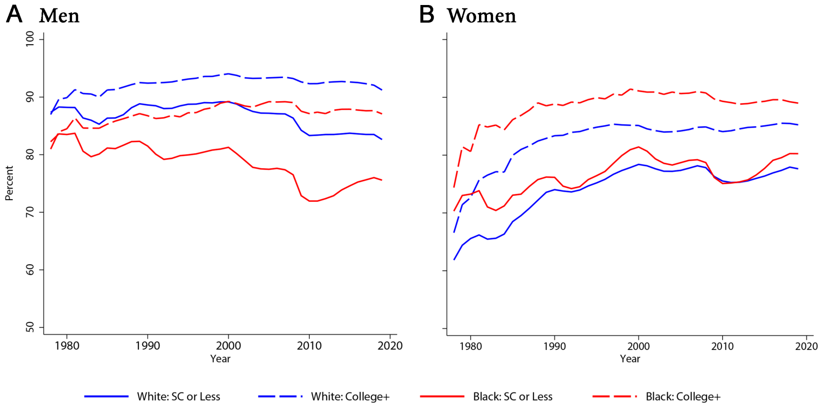

FIG. 1.—Trends in employment rates in the DER. Employment rates are the fraction of individuals with positive earnings from an employer or self-employment. The sample is individuals aged 25–59 in a given year. College+ = college or more; SC = some college. Source: US Census Bureau, CPS, 1996–2020 ASEC; Social Security Administration, DER, 1978–2019.

structural impediments to labor-market success of Black workers (Smith and Welch 1989; Donohue and Heckman 1991; Neal and Johnson 1996; Bayer and Charles 2019), where again little is known about volatility levels and trends across racial groups. In our case, we examine the intersection of race and education by gender. There are 1,680,000 individuals and 36,360,000 person years of DER earnings from the linked ASEC-DER sample.[5] Appendix table 1 (available online) presents the distribution of observations across gender, education, and race.

For our summary volatility measures described above, we do not require individuals to work in all years, and subsequently we treat missing DER values (among the population linked) as periods of nonwork. Figure 1 presents the fraction of the sample with nonzero DER earnings from 1978 to 2019 for each demographic group. The figure shows substantial employment cyclicality among both men and women with some college or less. This is particularly sharp for Black men in the years around the Great Recession of 2007–9 and among Black women in the late 1990s and again around the Great Recession. For men with less than college, there is also a secular decline in employment rates and a sizable racial gap that widened over time with Black men's employment falling relative to White men. Among women with less than a college education, however, employment rates increase until 2000 and then stabilize. Turning to the college educated, employment rates of both men and women are relatively stable, at least after 1990, as is the racial employment

[5] Numbers are rounded to four significant digits as per census disclosure avoidance rules.

gap. However, the gaps are reversed between men and women—White men have higher employment rates than Black men, but Black women have higher rates than White women.

To assess how closely the employment rates in figure 1 compare with a random cross section of 25–59-year-olds, in appendix figure 2 we depict annual employment rates from the public ASEC for the 1978–2019 calendar years for the same demographic groups.[6] The appendix figure shows broadly similar employment patterns for all eight groups. In the early years of the sample, DER employment falls below ASEC employment, and this reflects the fact that the DER sample is tilted toward younger workers at the start of the sample relative to a random cross section of the population. To be in the DER sample, the individual must appear in the ASEC at least once starting in 1996, and workers cannot be younger than 25 or older than 59, which means that the DER sample is younger at the beginning of the sample.

Finally, we note that some of these missing DER values may stem from earnings unreported to tax authorities and not nonwork, but we are not able to distinguish the reasons for missing data. Ziliak, Hokayem, and Bollinger (2023) use a more restrictive contemporaneously 2-year linked ASEC-DER sample than we do here and find that treating missing DER earnings as zero earnings aligns the time-series trends in summary volatility between the DER and the ASEC (with zeros included). As noted in the above section, the decompositions into permanent and transitory components are based on the log transform, and periods of zero earnings are dropped in that part of our analysis. Thus, we also estimate our summary volatility models using the variance of change in log real earnings, finding very similar patterns.

IV. Results

We organize this section by first presenting estimates of summary volatility over time (eq. [1]) and then the life cycle of cohorts (eq. [2]). This is then followed by variance components estimates of equations (7)–(8b) over time and the life cycle. Because a key contribution of our analysis is volatility by gender, race, and education, we present all estimates separately for these demographic groups. The first- and second-stage regressions to net out aggregate shocks and cohort-specific age profiles are estimated separately by gender, race, and education, allowing these macro and age profiles to differ by demographic group.

[6] The employment rates in app. fig. 2 are defined in the same way as in the main text—namely, a person is defined as employed if they have any earnings in the calendar year preceding the survey date. The employment rates in the appendix are weighted using the individual ASEC weight in each year, while those in the main text are unweighted.

A. Summary Volatility over Time and the Life Cycle

Figure 2 presents the time series of arc percent change volatility over 1978–2019. Figure 2*A* shows that earnings volatility of men with some college or less demonstrates considerable business cycle sensitivity, especially in the years surrounding the deep recession of 1981–82 and the Great Recession of 2007–9. The trend of male earnings instability is negative until the mid-1990s, notably among White college-educated men and to a lesser extent Black college-educated men, but then stabilizes among the college educated over the subsequent two decades and even reverses to become slightly positive for men with less than a college education. The latter suggests that increasing earnings risk shifted to the less skilled and coincided with increased employment risk as seen in figure 1. This risk is particularly pronounced among Black men lacking a college education, as both their employment has fallen more rapidly relative to White men over the last 20 years and the volatility of their earnings has increased.

Figure 2*B* shows that for women there is a sharp secular decline in earnings volatility again until the mid-1990s, which is then followed by a decade of relative stability, followed by another decade of decline. This pattern is broadly consistent across race and education. Unlike for men, there is a comparatively small business cycle component of earnings volatility for women, and in general the volatility of White women's earnings exceeds that of Black women, except for the last decade when they are of comparable levels within education group. Because of the secular decline in the earnings volatility of women,

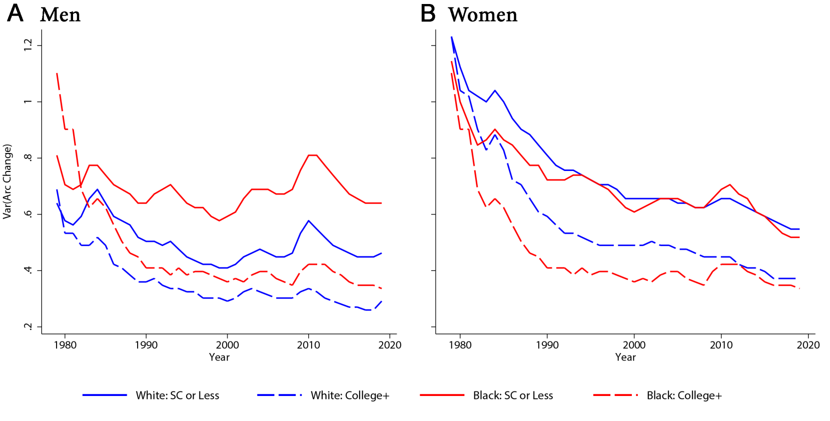

FIG. 2.—Summary volatility over time. Summary volatility is measured as the variance of the arc percent change. The sample is individuals aged 25–59 in a given year and includes those without earnings in one of the 2 years. College+ = college or more; SC = some college. Source: US Census Bureau, CPS, 1996–2020 ASEC; Social Security Administration, DER, 1978–2019.

the striking result is that over the last decade earnings volatility is highest among Black men with less than 4 years of college.

Figure 3 repeats the analysis of figure 2 but instead measures summary volatility using the variance of the difference in log earnings. In this case, periods of no earnings are dropped and are treated as missing at random. The time-series volatility patterns in figure 3 are broadly similar to those in figure 2 with the arc percent change, with a few differences. First, the secular decline in male earnings volatility before 1995, while still evident, is attenuated. Second, the volatility of Black men with college is the same as that of White men without college. Third, over much of the sample period, the volatility of Black women without college exceeds that of White women of the same education group. Most of these differences are small compared with overall patterns, and thus while allowing for periods of no earnings provides a more complete portrait of volatility, it does not have a substantive effect on time-series trends.

Figures 4 and 5, respectively, present arc percent life cycle earnings volatility of men and women across cohorts from the 1920s to the 1990s. Because birth cohorts age in and out of the sample, only the 1950 and 1960 cohorts provide data for every period over ages 25–59, and the remaining cohorts provide subsets of life cycle profiles. The figures show that there is a definitive U shape to life cycle earnings variability, especially pronounced among White men with a college education, and for both men and women there is a clear downward and leftward shift in volatility across successive cohorts. The implication of the downward shift across successive cohorts is falling cross-sectional volatility over time, while that of the leftward shift suggests that volatility is increasing

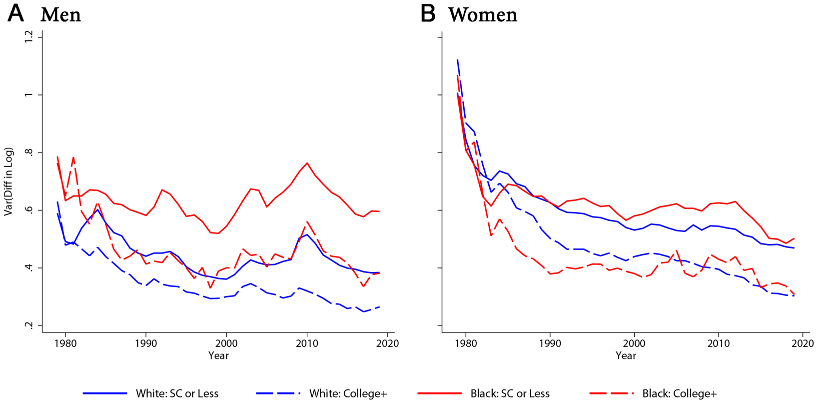

FIG. 3.—Summary volatility over time: difference in log earnings. Summary volatility is measured as the variance of the arc percent change. The sample is individuals aged 25–59 in a given year and drops those without earnings in both years. College+ = college or more; SC = some college. Source: US Census Bureau, CPS, 1996–2020 ASEC; Social Security Administration, DER, 1978–2019.

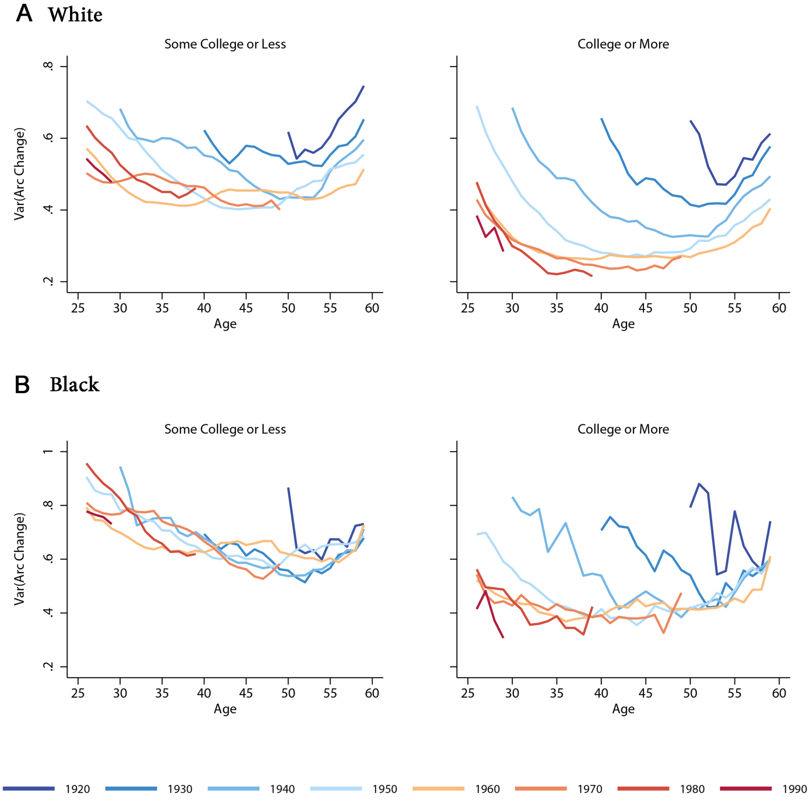

FIG. 4.—Summary volatility of men over cohorts and life cycle. Summary volatility is measured as the variance of the arc percent change. The sample is men aged 25–59 in a given year and includes those without earnings in one of the 2 years. Source: US Census Bureau, CPS, 1996–2020 ASEC; Social Security Administration, DER, 1978–2019.

at younger ages among more recent cohorts.[7] This is particularly pronounced among men with at least a college degree and women with or without a college degree. Again, the notable exception to these patterns is Black men without a college degree where there are few cohort differences in volatility across the

[7] Mincer (1974) presents the well-known result of the U shape of life cycle earnings variance. His result is for the level of earnings over the life cycle and not necessarily the growth rate. Equation (4.1) of his book relates growth in earnings to the return on postschool skill investment as $g_t = r_t k_t + (d/d_t)\ln(1 - k_t)$, where the left side represents earnings growth, r_t represents the return on postschool investment, k_t represents the fraction of time at work spent on skill investment, and the last term is a time derivative of the log of time spent in work. Following Mincer, if we assume that the return is constant over time and the time derivative term is negligible, then

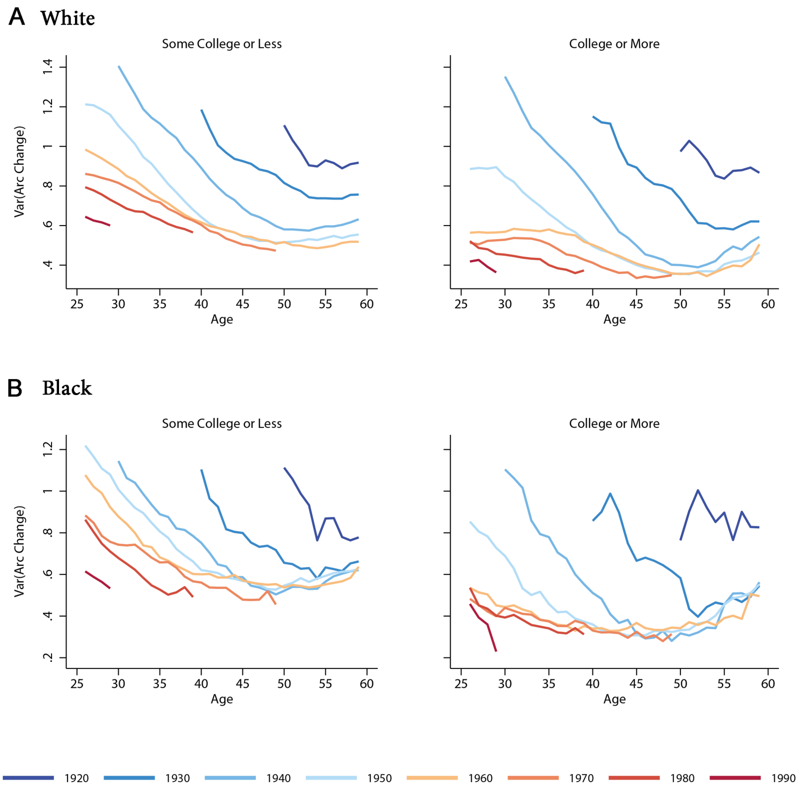

FIG. 5.—Summary volatility of women over cohorts and life cycle. Summary volatility is measured as the variance of the arc percent change. The sample is women aged 25–59 in a given year and includes those without earnings in one of the 2 years. Source: US Census Bureau, CPS, 1996–2020 ASEC; Social Security Administration, DER, 1978–2019.

life cycle. Appendix figures 3 and 4 repeat the exercise of figures 4 and 5 but instead use the variance of the difference in log earnings. These figures show similar life cycle profiles, albeit more noisy within cohorts given they measure a point percent change rather than an average change. We examine this further in the next section on the permanent and transitory decomposition.

the variance of earnings growth is $\text{var}(g_t) = r^2\text{var}(k_t)$. The U shape in earnings growth (volatility) in this case would stem from a U shape in the cross-sectional variance in time spent in productive work across the life cycle. Such a pattern seems quite plausible, even more so if the model is amended to be a function of net investment time defined as investment time less skill depreciation (see eqq. [1.20]–[1.23] of Mincer 1974).

In the appendix, we explore several sensitivity checks on the summary volatility estimates over time and the life cycle. One concern with the administrative data is that they contain many low-wage short-spell jobs and that this could skew the volatility estimates. Several authors, such as Sabelhaus and Song (2010), Bloom et al. (2018), and Guvenen et al. (2021), trim the earnings distribution to remove extreme values in the left tail. For example, Sabelhaus and Song require earnings to be in excess of the minimum earnings threshold to qualify for a year toward Social Security benefit eligibility, while Bloom et al. require earnings to be in excess of what one would earn working full time for a quarter of the year at half the minimum wage. Carr and Weimers (2021), however, caution against this practice of using real dollar trims because they can affect volatility trends if the trends in the left tail differ from other parts of the distribution or if the earnings levels in the tails are changing. Instead, if trimming is done it should be based on percentile points. Appendix figures 5, 6, 8, 9, 11, and 12 show how the time series and cohort summary volatility series change when trimming the top and bottom 1% of the group-by-year earnings distribution, respectively. As seen there, the percentile point trims attenuate only the level of volatility, not the patterns over time or the life cycle. Appendix figures 7, 10, and 13 replace the variance of the arc percent change with the 90/10 difference, and again this has no substantive effect on the patterns of summary volatility.

B. Permanent and Transitory Variance over Time and the Life Cycle

In this subsection, we present our estimates of the persistence parameter in the transitory error component, along with the permanent and transitory variances from equations (7)–(8b). Table 1 contains GMM estimates and standard errors of $\hat{\theta}$, the parameter governing the transitory error moving-average process from the time-series model. The estimates range from 0.18 to 0.21 for men and from 0.20 to 0.27 for women and are statistically significantly

Table 1
Estimates of MA(1) Parameter (θ) for Time-Series Permanent and Transitory Model

	Men		Women	
	White	Black	White	Black
Some college or less	.180	.183	.230	.203
	(.001)	(.003)	(.002)	(.003)
Observations	584,000	87,500	605,000	106,000
College or more	.196	.209	.265	.223
	(.003)	(.008)	(.003)	(.007)
Observations	182,000	14,500	188,000	21,000

Source.—US Census Bureau, CPS, 1996–2020 ASEC; Social Security Administration, DER, 1978–2019.

Note.—Model estimated via GMM with standard errors shown in parentheses. See the main text for details.

different from zero. The estimates for men lie slightly above those in Blundell, Pistaferri, and Preston (2008) in a sample of men from the PSID who find the MA(1) parameter to range between 0.11 and 0.17 and lie below those in Blundell, Graber, and Mogstad (2015) in a sample of Norwegian men where they estimate the MA(1) parameter to range between 0.24 and 0.29 depending on the education of the worker. To the best of our knowledge, these are the first estimates for women and thus there is no extant literature to compare with, though they are comparable with those of men.

Figure 6 presents the corresponding estimates and standard errors of the MA(1) parameter from the cohort life cycle model for men and women by race and education attainment. The model yields separate estimates for each birth cohort, and as the figure highlights, most are statistically greater than zero and tend to fall near 0.2. A notable increasing pattern is found among college-educated men and women across races among more recent cohorts of workers. For example, White men with at least college born in the 1920s have an estimated $\hat{\theta}$ of zero, while those born in the 1980s have the same parameter closer to 0.3. We see this same pattern among the other highly educated groups, albeit less pronounced. This suggests that 1-period-lagged

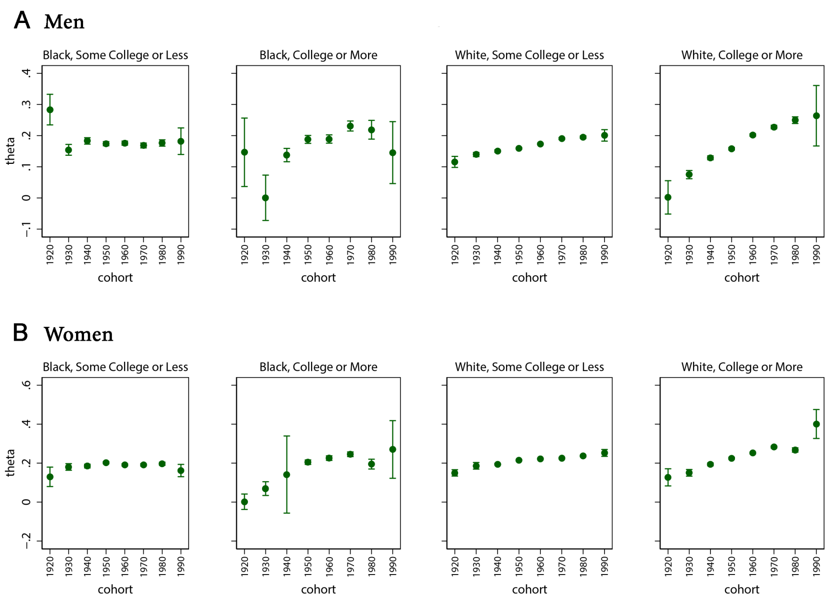

FIG. 6.—Cohort estimates of MA(1) parameter (θ^c). The moving average parameter (theta) is estimated by gender, education, and cohort group using GMM. The sample is men and women aged 25–59 in a given year. Source: US Census Bureau, CPS, 1996–2020 ASEC; Social Security Administration, DER, 1978–2019.

transitory shocks have a larger effect on current-period earnings among younger cohorts of skilled workers.

Figure 7 depicts the time-series permanent and transitory variances estimates for men, with figure 7*A* for White men and figure 7*B* for Black men. For the transitory variance, we present the total gender-race-education group variance—that is,

$$\mathrm{var}(\Delta \mathrm{var}(v_t)) = \mathrm{var}(\varepsilon_t) + (\hat{\theta} - 1)^2 \mathrm{var}(\varepsilon_{t-1}) + (\hat{\theta})^2 \mathrm{var}(\varepsilon_{t-2}), \qquad (10)$$

where $\hat{\theta}$ represents the gender-race-education group estimate from table 1. Within each education group, adding up the permanent variance and transitory

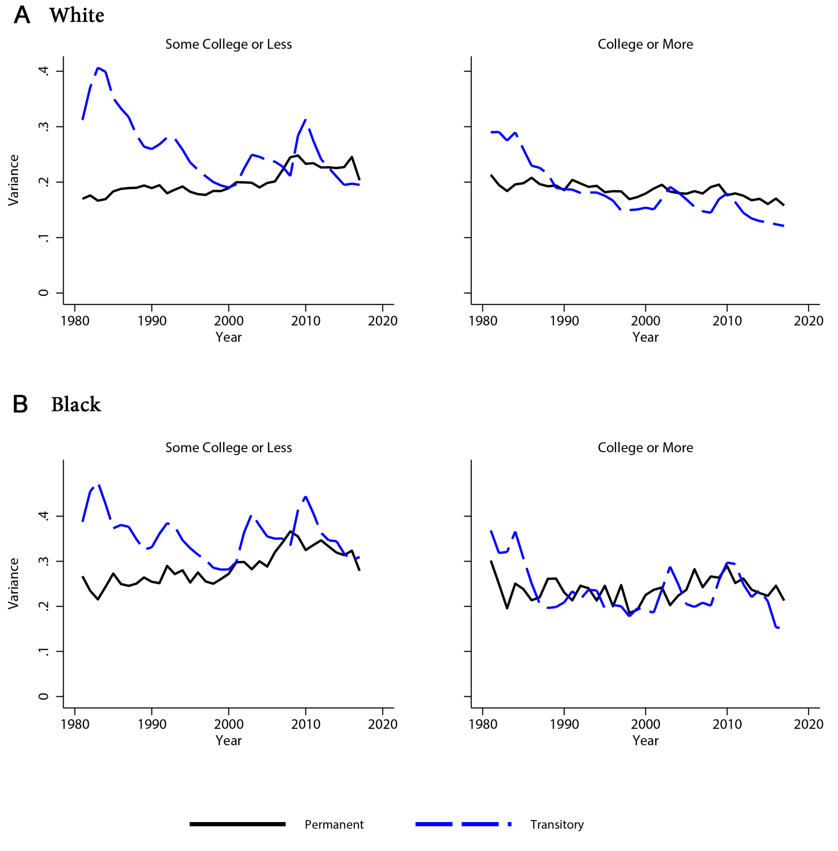

FIG. 7.—Permanent and transitory variance of men over time. Variance components are measured using the change in log earnings net of aggregate time effects and cohort-specific quadratic age profiles. The sample is men aged 25–59 in a given year and drops those without earnings. Source: US Census Bureau, CPS, 1996–2020 ASEC; Social Security Administration, DER, 1978–2019.

variance in (10) for any given year yields the corresponding estimate of volatility measured by the variance of the difference in log earnings. This is exactly the estimate of "summary volatility" as depicted in figure 3 (see app. figs. 3 and 4 for the cohort estimates below).

Figure 7 shows that permanent shocks facing men were stable from 1978 to 2000, while there was a sharp reduction in transitory variances, and thus the secular decline in volatility over that period seen previously in figures 2 and 3 stems from a decline in transitory variances. However, the substantial increase in variance around the Great Recession for White and Black men with less than college education and for Black men with college or more was an acute increase in both permanent and transitory variances. Indeed, across the whole sample period we see significant transitory variance associated with recessionary periods, but in a typical year since 2000 most volatility in earnings has been equally distributed across permanent and transitory shocks, while among White men with college or more has stemmed from permanent shocks.

In figure 8, we present the corresponding permanent and transitory time-series decomposition for women. Similar to men, there is a sharp reduction in transitory variances in the first two decades, but for the remaining two decades there are different trajectories for White and Black women. For White women, the transitory variance continued to decline, but perhaps more importantly, the variance in the permanent shock also declined (albeit much more slowly), meaning that White women's decline in earnings volatility after 2000 stemmed from reductions in both temporary and persistent shocks. For Black women, however, transitory and permanent variances were stable and more equal throughout most of the period after the 1980s, until the period after the Great Recession among the college educated, which helps account for the patterns depicted in figure 3. The other notable feature in figure 8 compared with men in figure 7 is the comparatively muted business cycle sensitivity in transitory variances (though this is more pronounced for Black women than for White women).

We return to life cycle volatility in figures 9–12, where we present persistent variances at the cohort level for men and women in figures 9 and 11, respectively, and the corresponding cohort transitory variances in figures 10 and 12.[8]

Figure 9 makes clear that the U shape of men's earnings volatility seen in figure 4, as well as appendix figure 3, stems from permanent shocks across the life cycle. To interpret this pattern, we can point to frequent job changes and promotions driving up volatility early in the working life as individuals

[8] Following from eq. (10), for the transitory variance we present the total cohort variance for each gender-race-education group—i.e., $\mathrm{var}(\Delta \mathrm{var}(\upsilon_a^c)) = \mathrm{var}(\varepsilon_a^c) + (\widehat{\theta}^c - 1)^2 \mathrm{var}(\varepsilon_{a-1}^c) + (\widehat{\theta}^c)^2 \mathrm{var}(\varepsilon_{a-2}^c)$, where $\widehat{\theta}^c$ represents the cohort-gender-race-education group estimate from fig. 6.

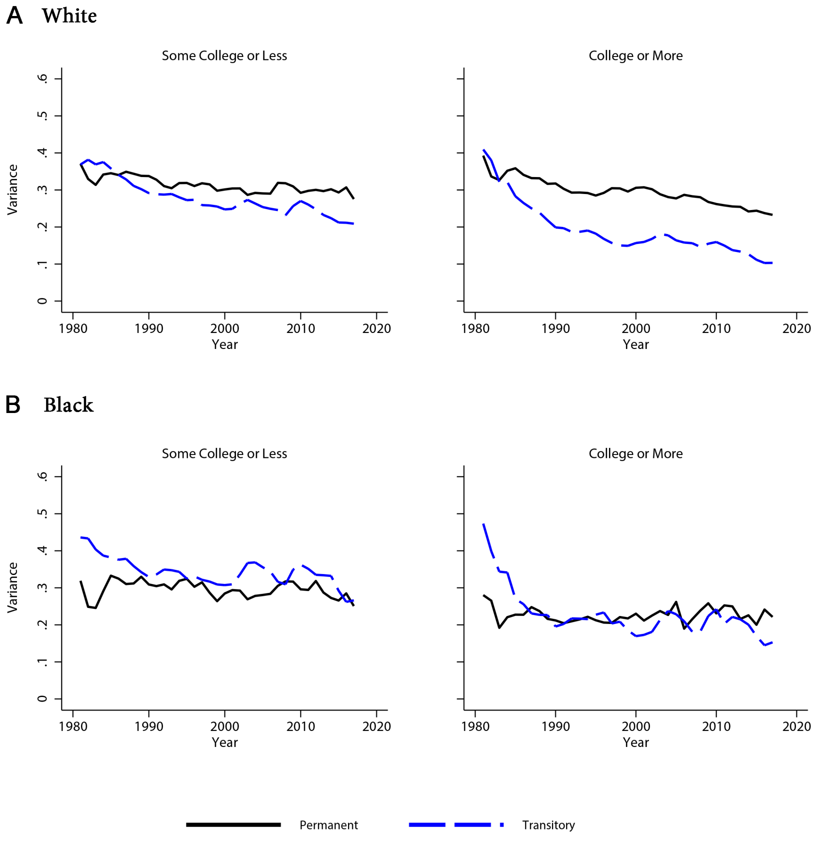

FIG. 8.—Permanent and transitory variance of women over time. Variance components are measured using the change in log earnings net of aggregate time effects and cohort-specific quadratic age profiles. The sample is women aged 25–59 in a given year and drops those without earnings. Source: US Census Bureau, CPS, 1996–2020 ASEC; Social Security Administration, DER, 1978–2019.

sort into their longer-run careers. This is followed by relative stability from ages 35 to 50, after which permanent shocks that are of equal or larger magnitude emerge.[9] The sources of these later working life changes could stem from health-related shocks but could also reflect permanent layoffs and restructuring. Figure 10 then shows that the fanning out across cohorts and

[9] Note that because we need at least four ages to construct the transitory variance, we expand the age range of the data to begin at age 23 and then present the permanent and transitory variances starting at age 27. For some cohorts, we can present variances starting at age 26, picking up the higher volatility at those early ages and yielding the sharp U shape.

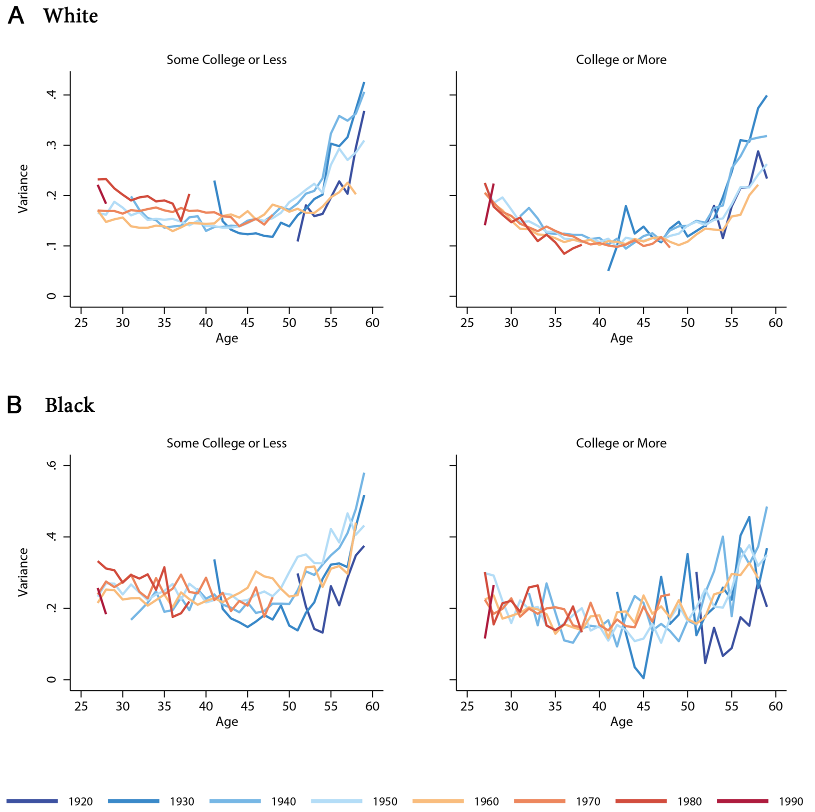

FIG. 9.—Permanent variance of men over cohorts and the life cycle. Variance components are measured using the change in log earnings net of aggregate time effects and cohort-specific quadratic age profiles. The sample is men aged 25–59 in a given year and drops those without earnings. Source: US Census Bureau, CPS, 1996–2020 ASEC; Social Security Administration, DER, 1978–2019.

decline in the Mincer overtaking age in figure 4 has been the result of reduced life cycle transitory shocks across cohorts. This is especially pronounced among White men, both with and without a 4-year college education, and to a lesser extent Black men with at least a college education. Transitory variance tends to be monotonically declining with age within cohorts of men, especially those with some college or less, although this decline emerges only among White men starting with the 1950s birth cohort. Among college-educated men of both races, these life cycle transitory variances tend to be more constant between ages 35 and 50 for cohorts after the 1940s.

The life cycle permanent earnings shocks of women in figure 11 have a similarly U-shaped profile as with the men but with two important differences.

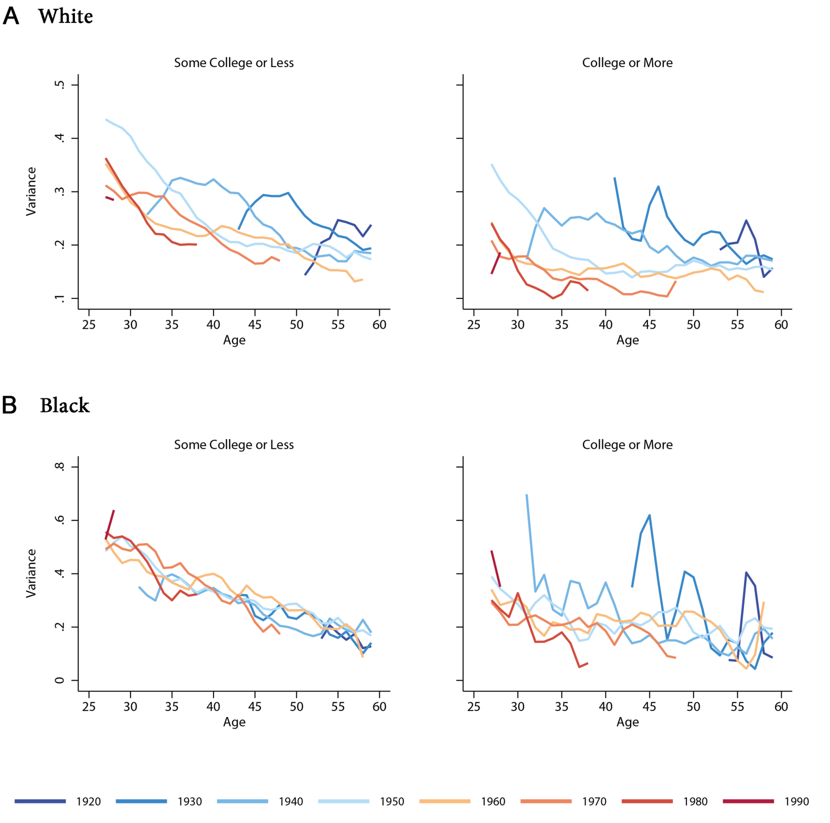

FIG. 10.—Transitory variance of men over cohorts and the life cycle. Variance components are measured using the change in log earnings net of aggregate time effects and cohort-specific quadratic age profiles. The sample is men aged 25–59 in a given year and drops those without earnings. Source: US Census Bureau, CPS, 1996–2020 ASEC; Social Security Administration, DER, 1978–2019.

First, there is a substantial decline in permanent variance among White women at younger ages in more recent cohorts, so that much of the across-cohort fanning out of summary volatility in figure 4 (and app. fig. 3) was a reduction in permanent shocks in more recent cohorts. Second, unlike White men, who have permanent shocks later in the working life of larger magnitude than those early in the life cycle, White women have more comparable-sized permanent shocks later in the working life relative to early ages. This is less so with Black women with a college education, who, like men, tend to have large permanent shocks later in the working life. The transitory shocks in figure 12 tell a story similar to what we saw with men in figure 10—there are significant reductions in transitory variances among younger cohorts pulling

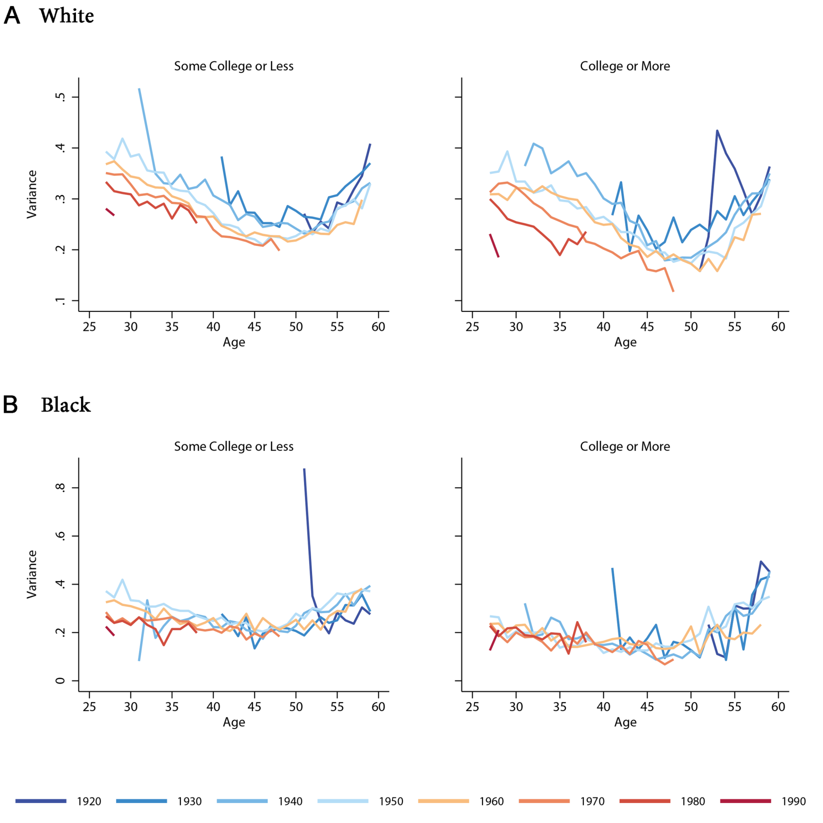

FIG. 11.—Permanent variance of women over cohorts and the life cycle. Variance components are measured using the change in log earnings net of aggregate time effects and cohort-specific quadratic age profiles. The sample is women aged 25–59 in a given year and drops those without earnings. Source: US Census Bureau, CPS, 1996–2020 ASEC; Social Security Administration, DER, 1978–2019.

down the overtaking age over the life cycle, especially among White and Black college-educated women. If anything, these transitory variances tend to decline across the working life with any given cohort even more sharply among women than among men.

In the appendix, we present the full set of time-series and life cycle cohort permanent and transitory variances under the simplifying assumption of no persistence in the transitory shock ($\theta = 0$) as described in equations (9a)–(9c). Appendix figures 14–19 demonstrate that the substantive pattern of permanent and transitory variances hold under the more restrictive model, with the notable difference in the time-series estimates with much more

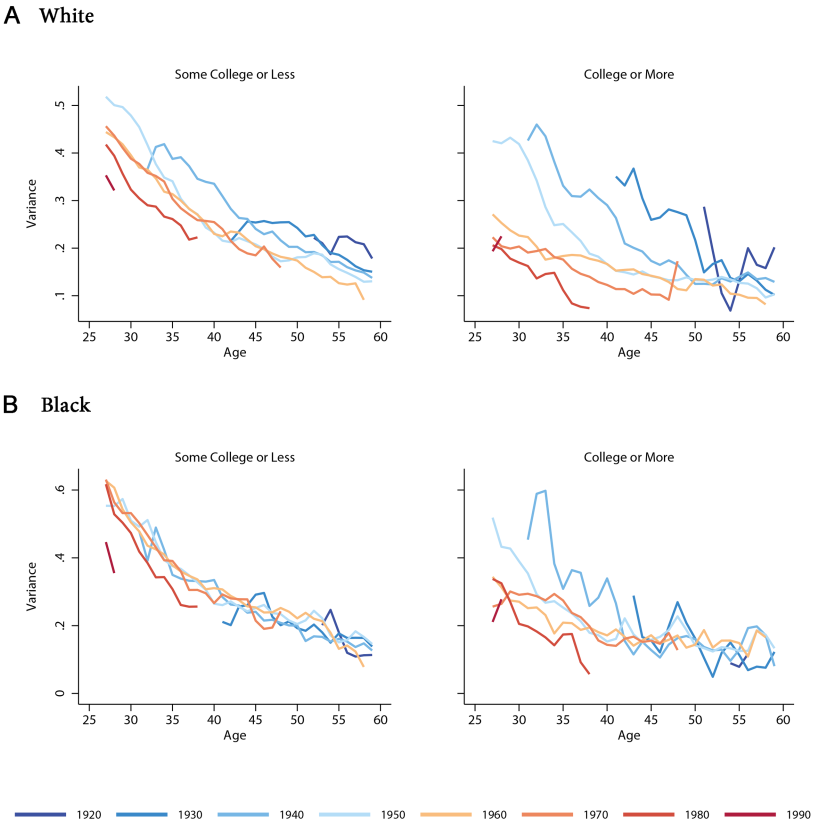

FIG. 12.—Transitory variance of women over cohorts and the life cycle. Variance components are measured using the change in log earnings net of aggregate time effects and cohort-specific quadratic age profiles. The sample is women aged 25–59 in a given year and drops those without earnings. Source: US Census Bureau, CPS, 1996–2020 ASEC; Social Security Administration, DER, 1978–2019.

weight given to the permanent component than the transitory, compared with the less restrictive model presented in figures 7 and 8.

V. Conclusion

In this paper, we presented new estimates of earnings volatility over time and the life cycle for men and women by race and human capital. Using a long panel of restricted-access administrative Social Security earnings linked to the CPS, we estimated volatility with both transparent summary measures, as well as decompositions into permanent and transitory variance components for both men and women separately by race and education attainment.

Our results for men suggested that from the late 1970s to the mid-1990s there was a strong negative trend in earnings volatility, followed by two decades of comparatively little trend but substantial business cycle sensitivity, especially in the years surrounding the Great Recession. Both the trend decline and business cycle sensitivity stemmed from transitory variances, but after 2000 there was an upward trend in the variance of permanent shocks among workers without a college education, particularly Black men. A rise in the variance of permanent shocks to earnings is likely to be much more costly in terms of household welfare. Consequently, an overall decline in earnings volatility accompanied by a rise in the variance of permanent shocks may not necessarily translate into a fall in key labor market risks or an improvement in welfare.

The cohort estimates demonstrated a strong U-shape profile of earnings variance over the life cycle, especially among White college-educated men, but these profiles shifted downward and leftward in more recent cohorts. The U-shape profile comes from permanent shocks across the life cycle, while declining volatility and the reduction in the age of minimum volatility came from reduced transitory variances among younger cohorts of men. The latter was less in evidence among Black men, keeping the volatility of earnings elevated compared with White men. These patterns were broadly similar for women and men, with the notable difference that women's earnings exhibited little business cycle variation compared with men's. These differences appeared more for White women than for Black women.

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