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The great moderation in micro labor earnings ☆

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ABSTRACT

Between 1980 and the early 1990s the variability of labor earnings growth rates across the prime-age working population fell significantly. This decline and timing are consistent with other macro and micro observations about growth variability that are collectively referred to as the "Great Moderation." The variability of earnings growth is negatively correlated with age at any point in time, and the U.S. working age population got older during this period because the Baby Boom was aging. However, the decrease in variability was roughly uniform across all age groups, so population aging is not the source of the overall decline. The variance of log changes also declined at multi-year frequencies in such a way as to suggest that both permanent and transitory components of earnings shocks became more moderate. A simple identification strategy for separating age and cohort effects shows a very intuitive pattern of permanent and transitory shocks over the life cycle, and confirms that a shift over time in the stochastic process occurred even after controlling for age effects.

1. Introduction

One of the apparent mysteries associated with the so-called "Great Moderation" literature is a lack of evidence that individual earnings growth has become less variable in recent decades (Davis and Kahn, 2008). Although there is significant evidence that aggregate earnings growth became more stable and major labor market shocks like involuntary unemployment became less frequent, some studies have concluded that individual labor earnings growth rates actually became more variable during the last several decades (Gottschalk and Moffitt, 1994; Moffitt and Gottschalk, 2002, 2008; Dynan et al., 2007).[1] However, Social Security earnings data show that (1) the average variance of earnings growth rates fell in line with the aggregate volatility measures, (2) the profile of earnings growth variability shifted uniformly for the entire working-age population, and (3) different approaches to decomposing earnings growth into permanent and transitory components agree that the decline in variability involved moderation in both types of shocks.

There are both positive and normative reasons to investigate changes in the stochastic process underlying individual labor earnings growth. On the positive front, predictions from models of consumption behavior with labor income

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[1] A notable exception that is generally consistent with the results presented here is Congressional Budget Office (2008). One important commonality between the results here and the CBO study is the use of administrative earnings data instead of self-reported earnings from household surveys.

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uncertainty are very sensitive to the presumed level and nature of the uncertainty about future earnings growth. If labor income becomes more volatile than one would expect consumption to become more volatile, though different types of shocks to labor earnings have different implications for consumption behavior.[2] In particular, transitory earnings shocks affect the level of precautionary savings generally because consumers can accumulate wealth to insure against those fluctuations, while permanent shocks impact the target wealth to income ratios in "buffer-stock" consumption models.[3,4]

The normative basis for investigating changes in earnings growth variability is also important. As Davis and Kahn (2008) point out, there is evidence of moderating fluctuations in aggregate output and income growth, firm-level gross employment flows, unwanted job loss, and inventories. If it is true that person- or household-level incomes actually became more volatile during this period while these other volatility measures fell, then the Great Moderation may have come with an important downside. Indeed, one could speculate that some forms of risk were simply shifted onto workers, which raises the important normative question about the type of economic environment that is preferable.

The divergence between the general decline in volatility associated with the Great Moderation and individual earnings growth is intuitively difficult to explain, but the analysis here suggests that there is no great mystery to be explained in any event. The purported divergence between macro and micro earnings volatility may leave one wondering how direct inputs to individual labor earning outcomes such as overall unemployment and unwanted job loss could decrease, while earnings growth variability increased. The evidence presented here shows that there is no discrepancy, because the measures of earnings growth variability all show that the decline at the micro level is consistent with the aggregate patterns. Further, the finding that some of the decrease in earnings growth variability occurred at longer (permanent) frequencies could actually help explain other trends observed during the Great Moderation, such as the decline in personal saving.

The data used here to analyze earnings growth variability over time is a one percent sample of Social Security Administration earnings records for ages 25–55 between 1980 and 2005. Focusing first on annual changes in log earnings, the administrative data show a clear drop in the average variance of log changes over the time period.[5] One important feature of the one-year variance measures is that conditioning on a positive earnings threshold when computing person-level changes matters a great deal for the estimated level of the variance of log changes, but not the time pattern. In particular, limiting the sample to people with enough earnings to qualify for credit towards Social Security benefit eligibility – a fairly modest amount – lowers the log change variance by half. However, the pattern of decline over time is the same whether or not the threshold is applied.

The second set of results – again based on simple one-year earnings growth rates – focuses on variability across age groups and time. The administrative earnings data show a negative relationship between age and the variance of log-changes in earnings at any point in time, and the U.S population did get older over this period as the Baby Boom entered and moved through their prime working years. However, a comparison of the age-variance profile for the first half of the sample (1980–1992) with the second half (1993–2005) also indicates a uniform drop in the variability of growth rates at all ages, and the magnitude of the decline at every age is similar to the overall change. This suggests that the simple combination of population aging and declining earnings growth variability with age cannot explain the overall trend.

The observed patterns in earnings growth variability by time and age is in some ways just the starting point for this analysis. The main issue explored here is whether the decline in earnings growth variability occurred at all frequencies, or just in the annual measures. Analyzing variances of changes across multiple frequencies is the key to separating transitory from permanent earnings shocks, and the empirical strategy for making that distinction involves first measuring the variance of log earnings changes at multiple frequencies and then investigating whether there is a systematic change in the variance as the time-gap over which earnings growth is measured is increased. If the variance rises with the length of the gap, the increased component of earnings growth variance is permanent. Using a few different approaches, the data show a very clear and systematic decline over time in the variance of log earnings change at all observed frequencies, which suggests that both transitory and permanent variances changed.[6]

[2] Along these lines, Davis and Kahn (2008) present evidence that micro consumption growth variability failed to decline after 1990, which would be consistent with a lack of decline in micro earnings volatility. This could reflect a divergence between individual-level earnings and household-level income volatility, or it might just indicate that the available spending data for the U.S. is not well-suited for testing whether or not consumption volatility changed.

[3] The idea that a permanent income shock affects consumption more than transitory shocks goes back as least to Friedman (1957). Carroll (1992) quantifies the difference between the predicted effects of permanent and transitory shocks in the context of a buffer-stock consumption model.

[4] Another positive and closely related reason for investigating stochastic labor earnings processes is building dynamic microsimulation models for policy evaluation. In those models one is trying to simulate realistic longitudinal earnings trajectories and evaluate the distributional and aggregate impacts of changes in programs (like Social Security) where idiosyncratic differences across the population matter a great deal. See, for example, Harris et al. (2006).

[5] Sabelhaus and Song (2009) use this same one percent file, but also linked administrative plus Survey of Income and Program Participation (SIPP) data, and another administrative-only data set that adds self-employment earnings (only available for 1994 and later). None of the basic results presented here are affected by the choice of which administrative data set is used.

[6] It should be noted that the estimated stochastic processes presented here and in similar papers are not perfect measures of uncertainty about future labor earnings, though they are often treated as such in consumption models. One reason is that decisions like schooling choices reveal information about earnings potential (Cunha et al., 2005; Cunha and Heckman, 2007). A second reason is that the analysis here and elsewhere is based on total earnings, which obviously depends on both potential earnings and labor supply intensity. Recent work has focused on separating changes in earnings over time into component sources such as labor market entry and exit, voluntary versus involuntary separations and change in hours worked. See, for example, Low et al. (2008) and Altonji et al. (2009). Our approach is limited to the more traditional approach using total earnings variability, because of a lack of data on

The first approach to discerning permanent and transitory components is basically visual and intuitive, and very much in the spirit of seminal work by Carroll (1992) and Carroll and Samwick (1997). The idea is to look at variances across multiple periods – generally 1 to 12 year gaps – and the slope of the change in variance as the gap increases as the key to identifying the permanent component. The innovation here involves splitting the sample several different ways to show how the stochastic process evolved over time and across groups. The approach is to compare the first and second half of the time periods for the entire sample, and then again for the younger- and older-half sub-samples. In all cases there is a clear decline in both the levels and slope of the variance across year-gap frequencies. Because the slope is the key to identifying permanent shocks, and the levels the key to transitory shocks, there is evidence of a decline in both.

The second approach involves imposing just enough structure on the stochastic process to identify age and cohort effects.[7] The structure adopted identifies point estimates for permanent and transitory shock variances at every age, while imposing the same shift at every age across cohorts. One advantage of this approach is that it generates values for permanent and transitory shocks by age that are consistent with basic intuition about life cycle earnings uncertainty and useful for modeling.[8] For example, while both types of shocks decline with age, the patterns are somewhat different. The second outcome is that the residual cohort effects confirm the findings of the visual sample-splitting exercise that focused directly on the levels and slopes of the variances across multiple year-gaps. That is, the stochastic process for earnings changed in a way that is basically consistent with the Great Moderation.

In addition to providing evidence of consistency between micro labor earnings variability and other features of the Great Moderation, there is new information in the estimated patterns of earnings growth variability by age that may also help reconcile some outstanding issues in life cycle modeling. First, there is evidence in the literature that a model of heterogeneous earnings profiles (Guvenen, 2007a, 2007b) fits the data better than a more traditional model of fixed permanent and transitory shocks around expected earnings over the life cycle. However, the benchmark for that evidence is a model with fixed permanent and transitory shocks, which the results here seem to repudiate, because permanent shocks are much larger earlier in the life cycle. Second, there is also evidence that the relationship between earnings and consumption growth varies systematically over the life cycle (Deaton and Paxson, 1994; Carroll, 1992; Gourinchas and Parker, 2002; Scholz and Seshadri, 2007). The estimates of earnings growth variability by age presented here are consistent with these observations, because the data suggest that permanent shocks drop dramatically with age. Essentially, the data confirm the (perhaps obvious) intuition that much of the uncertainty about potential lifetime earnings is resolved fairly early in the life cycle.

2. The decline in micro labor earnings growth variability

The starting point for this study is documenting the decline in the average variance of changes in log earnings since 1980. This section begins with a simple measure of labor earnings growth variability over time using an administrative data set with two different earnings threshold criteria, and confirms findings from some earlier research about the decline in variability since 1980.[9] The data also indicate significant differences in the variability of labor earnings growth by age, and shows that there was a uniform decline in variability across age groups over time. Finally, a look at the variance of log earnings levels since 1970 for a particular group (males, ages 30 to 39) helps put the period since 1980 in perspective, and shows how the sample inclusion criteria may be important for some of the results in the remainder of the paper.

The concept of earnings growth variability used throughout is the average variance of the annual change in log earnings (in later sections the focus shifts to average variances across multiple-year frequencies). The variance is a convenient statistic to use for a couple reasons: the extent of variability is summarized in one number, and it is useful for distinguishing between permanent and transitory earnings shocks. There are also drawbacks, however, because the

(*footnote continued*)
labor supply intensity. However, limiting the sample to earnings above the Social Security qualifying threshold does help to mitigate the effects of change in labor supply intensity. Finally, even within the class of earnings changes that can rightly be classified as shocks, it is important to discern what kind of shock a person experiences if one is trying to implement a model of earnings uncertainty for use in predicting life-cycle consumption. For example, a health-related earnings shock may have very different implications for consumption than a shock to potential earnings. This is a specific example of the general idea that different sources of earnings changes will lead to different types of consumption responses over the life cycle (Aguiar and Hurst, 2008).

[7] Given panel data, one can arbitrarily choose between a structure that identifies age and cohort effects or one that identifies age and time effects, and it's really just a question of how one interprets the results.

[8] Differences in the values of shock variances by age are also easily incorporated into the typical life cycle dynamic programming framework, because they do not involve increasing the number of state variables, just varying the parameters of the stochastic process across an existing state variable (age).

[9] Sabelhaus and Song (2009) show the same basic pattern using both this one percent Master Earnings File and a data set that links Survey of Income and Program participation (SIPP) data to administrative earnings records for the 1940 to 1960 birth cohorts. The Congressional Budget Office (2008) focuses on the period after the mid-1980s, and their conclusion of "no change" in earnings growth variability is basically consistent with the patterns here, because most of the decline occurs in the early period. One crucial difference between these and earlier studies is the use of administrative data, but more recent analysis of household surveys also provides some evidence that the way in which the sample is selected and specific time period studied could also help reconcile these differences. In particular, Gottschalk and Moffitt (2009) show that earnings growth variability is much higher for low earners at every point in time, so a sampling strategy focused on head of household males may not capture the same trends as in a broader population. Also, when viewed in a longer-run context, the significant increases in variability over time occurred before 1980, so they are not observed in our data.

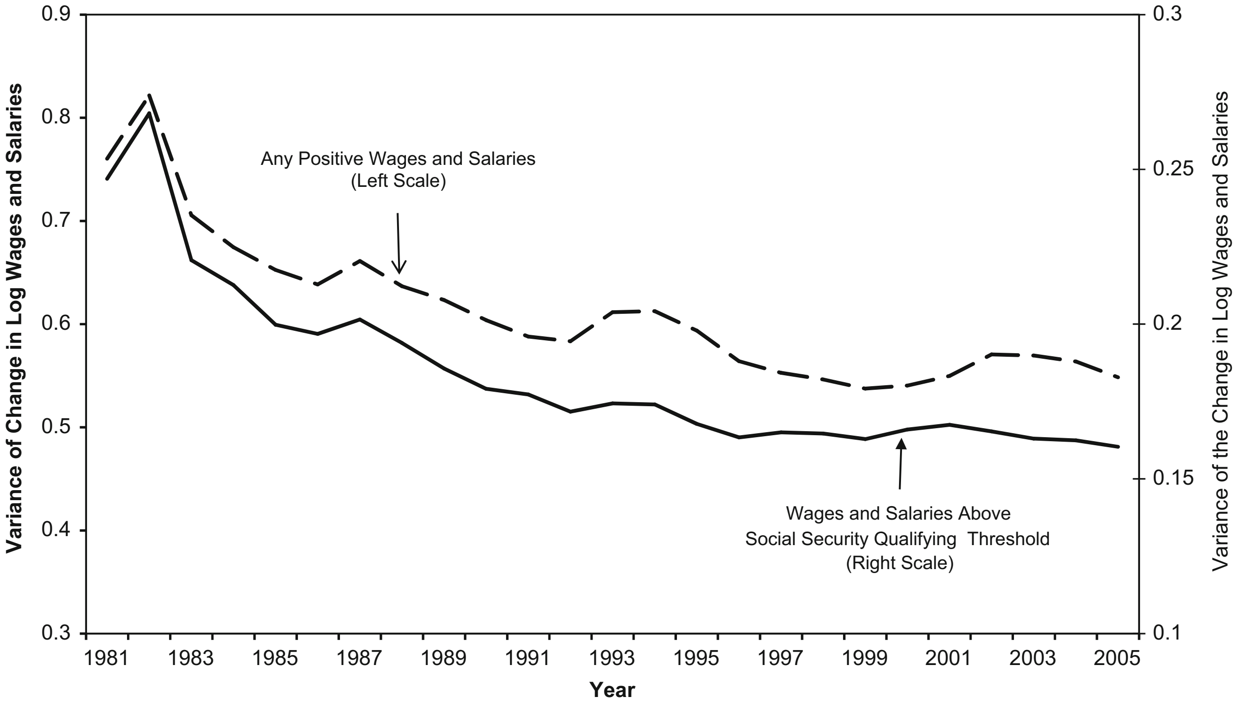

Fig. 1. Variability of changes in log annual wage and salary earnings, 1980–2005 (all earners ages 25–55).

average variance may be hiding important information about population heterogeneity over time.[10] Another implication is that a large percentage change at very low earnings may not have much economic meaning for the distribution of consumption, but the average variance measure will give that observation the same weight as an identical percentage change at higher earnings levels.

Fig. 1 shows the variance of the annual change in log earnings for wage and salary earners ages 25–55 between 1980 and 2005. The first (dashed) line is based on the entire Social Security Administration Continuous Work History Sample (CWHS) one percent Master Earnings File (MEF) sample.[11] The estimated variance of the annual change in log earnings falls by one-third between 1982 and 2005, from 0.82 log points to just over 0.55 log points (see the left axis). Note that most of the decline (29 percent out of the 33 percent total drop) took place between 1982 and 1992.

The one percent sample used to construct the dashed line in Fig. 1 includes anyone with positive earnings in both of the years for which the change is being calculated. This can lead to the problem noted above that some relatively small dollar changes may dominate the estimates if those changes are relative to very low initial earnings. There are a number of ways to deal with that issue. For example, many studies restrict analysis of earnings growth variability to employed heads of household. The approach taken here is more direct—people with earnings below the amount needed to qualify for a year towards Social Security eligibility are excluded. That threshold value was $3680 in 2005. As with several other key Social Security parameters the threshold grows over time with average wages, and year-specific values are used to set the inclusion criteria.[12]

[10] For example, Jensen and Shore (2008) focused on changes in the distribution of volatility over time, and find that the overall average increase in the PSID has been dominated by changes in variability for the most volatile households.

[11] The CWHS is a one percent random sample based on the last four digits of individuals' Social Security numbers. The MEF contains most of the information one finds on the annual W2 information return. For more details about the MEF see Panis et al. (2000) or Kopczuk et al. (2007). Our measure of labor earnings used throughout is total wage and salary compensation, which is reported without any limitations (in particular, the Social Security or Medicare taxable maximums) for every year in our sample. This analysis excludes self-employment earnings because (until 1994) the values from the Form SE information return were limited to the taxable maximum—only after Medicare began taxing all self-employment is non-topcoded data available. Sabelhaus and Song (2009) show that including self-employment after 1994 does not change conclusions about earnings variability from that time forward, though one does not observe the decline in variability before 1994 that is the focus here. Finally, all of the calculations here involve variances of changes in log earnings, and the sample used for any given estimate is every observation with earnings in the two time periods for which the change is being measured.

[12] This threshold is consistent with the approach used in Kopczuk et al. (2007). One way to think about the Social Security coverage threshold is this: a person crossed the coverage threshold if they worked 715 h at the federal minimum wage, which was $5.15 in 2005. That is either about 14 h per week for a full year, or 18 weeks full time. One alternative involved estimating the variance trend using a threshold consistent with a minimum wage/full time/full year salary, which (in 2000 dollars) works out to $10,494. The estimated variance of earnings growth above this threshold shows the same relative decline as in the two measures reported in Fig. 1, which is just over a 20 percent decrease between 1980 and 1991. However, the much higher threshold

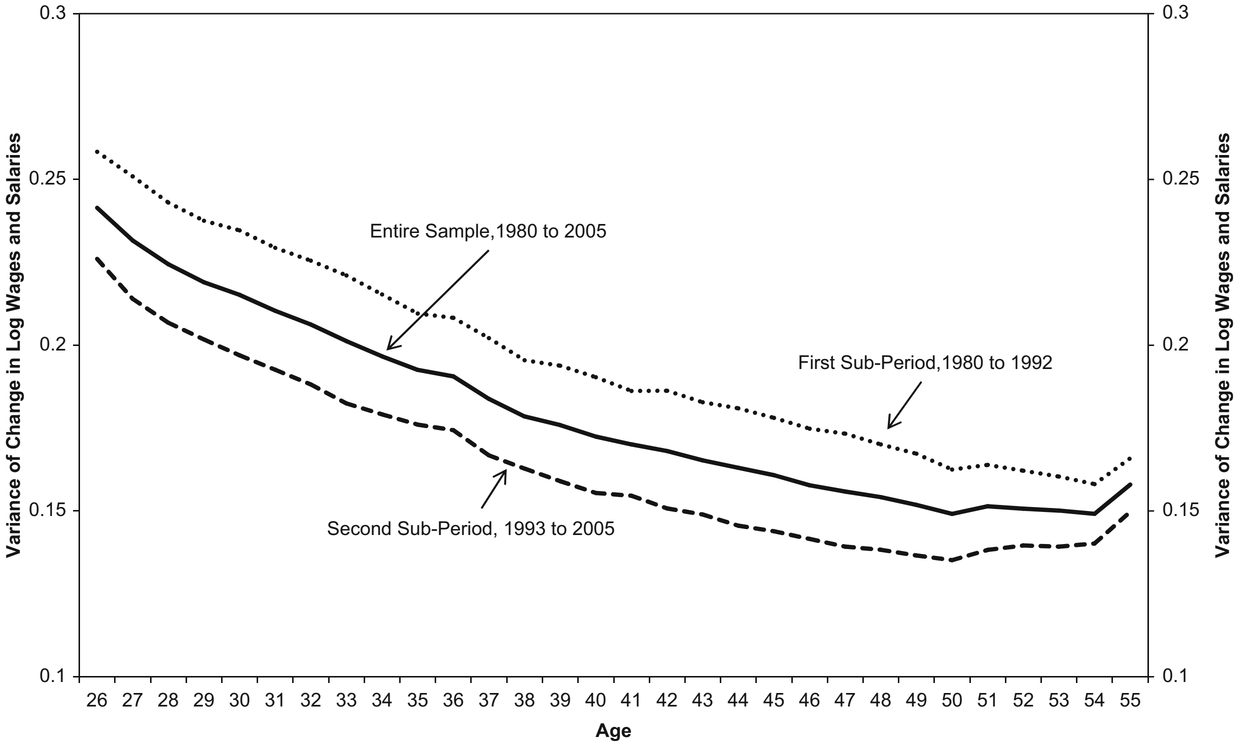

Fig. 2. Variability of changes in log annual wage and salary earnings by age (wages and salaries above social security qualifying amount).

Excluding people with earnings below the Social Security eligibility threshold has a big impact on the estimated level of the standard deviation of log earnings change, but it does not change the relative magnitude or timing of the decline. The solid line in Fig. 1, which excludes individuals with earnings below the qualifying threshold, is about half the height of the dashed line in every year. The overall decline and timing are the same, however, as the variance of log earnings changes fell about 41percent between 1982 and 2005, with most (a 36 percent drop) occurring between 1982 and 1992.

In any given year, just under ten percent of the observations in the administrative data with positive earnings are below the qualifying threshold, and there is no trend in that ratio over time. However, including those observations doubles the estimated variance at every point in time. Virtually all of the work done on stochastic earnings processes is based on analyzing some combination of variances and covariances across different lags, and Fig. 1 provides a useful cautionary tale about sample selection. A change from $100 to $200 of earnings has the same impact on the average variance as a change from $10,000 to $20,000.

The finding that earnings growth variability fell between 1980 and 2005 is in some ways just the starting point for the analysis here. The first question to investigate is whether the decline can be explained by changes in the age composition of the labor force. Fig. 2 shows variances of log earnings changes (above the Social Security qualifying threshold) by age for the entire period, the first sub-period (1980–1992), and the second sub-period (1993–2005). The prominent message of Fig. 2 is that the variability of earnings growth rates declines significantly between ages 25 and 55, and this is true of averages by age for the entire period and both sub-periods. However, the other message of Fig. 2 is that the decline was uniform across ages, with variances falling about 15 percent between the first and second sub-periods.[13] The overall average variance fell by something like 19 percent between the (averages for) the two sub-periods, so age effects do not explain much of the overall drop.

The last step in this preliminary look at the data involves analyzing the variances of log earnings levels over time, as opposed to the variance of changes in log earnings over time. Fig. 3 is motivated by the discussion (and a similar chart) in Moffitt and Gottschalk (2008). The idea is that looking at trends in the variance of log earnings for a particular group at a particular point in the life cycle (here, it is males ages 30–39) provides some clues about what is happening to the stochastic process underlying the evolution of earnings over time. In particular, the canonical labor earnings model implies

(*footnote continued*)
has a big impact on the sample (excluding 20–25 percent in any given year, as opposed to a steady 9 percent in the Social Security qualifying case) and (given the goal of capturing unemployment-related transitory shocks) the higher threshold is excluding observations that should be in the sample.

[13] The same patterns across age and time hold for men and women separately.

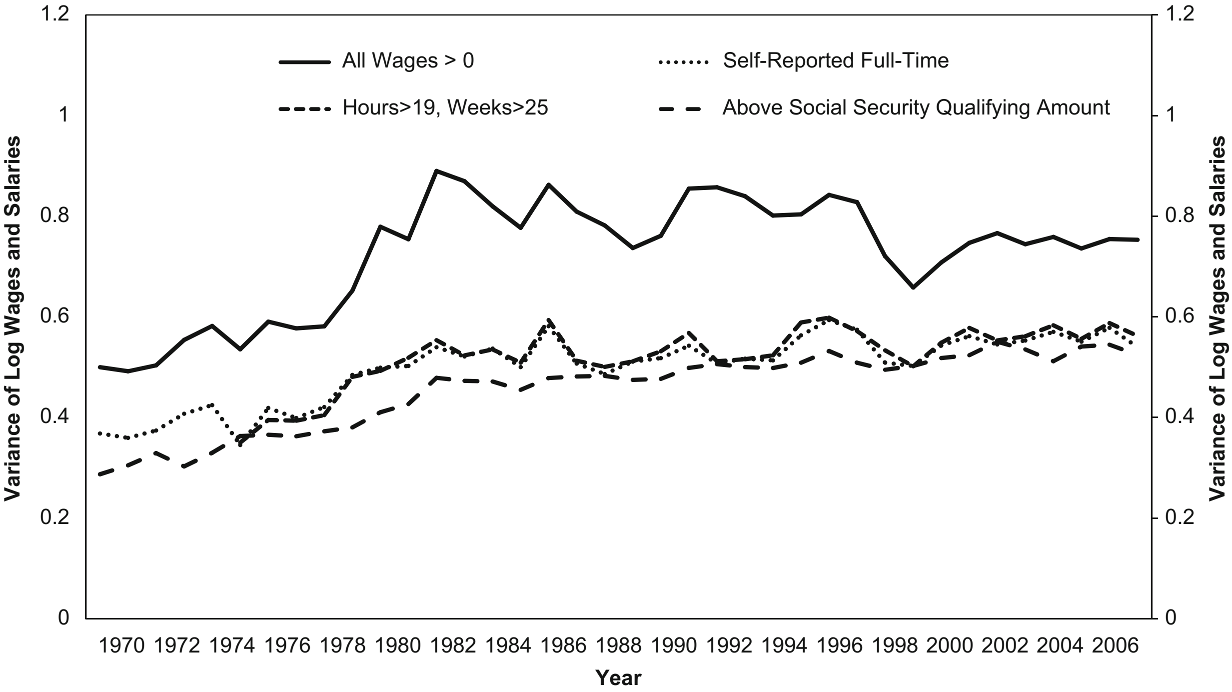

Fig. 3. Variance of real log annual wage and salary earnings (males ages 30–39).

that the level of variance at any point in time depends on that group's initial earnings dispersion, the current transitory shock, and cumulated permanent shocks.

Fig. 3 makes a few important points about trends in earnings variability over time.[14] First, most analysis of changes in earnings growth variability has rightly focused attention on the period 1970 through the early to mid-1980s, because that is when the variance of earnings levels was rising fastest. Second, there is a big difference between using the entire sample of positive earnings versus a restricted subset with stronger labor force attachment, even for males 30 to 39 who are very likely to work full-time. Third, the two variance measures based on restricting the sample using reported labor supply intensity (either self-reported usually "full-time" or usual hours greater than or equal to 20 and weeks worked greater than or equal to 26) give basically the same answer about the level of variance as the Social Security qualifying threshold applied to the administrative data.

The more fundamental message from the two figures for our purpose is the time-path of earnings variances after the early 1980s. The unadjusted log earnings variances in Fig. 3 suggest a slight upward trend, but nothing like the changes that occurred between 1970 and 1982.[15] The slight upward trend in cross-section variance after 1982 can be reconciled with stable or declining earnings shocks variances because the initial dispersion of earnings for any given cohort reflects other well-known trends, like increasing returns to education.[16] In any event, the prima facie evidence that earnings volatility increased after 1982 is not particularly evident in the CPS cross-section earnings data (as it was before 1982) but the specific details about how various underlying stochastic processes might have changed await the decomposition in the next section.

3. Was the decline in variability at transitory or permanent frequencies?

The second phase of this analysis involves decomposing the variation in earnings growth over time into permanent and transitory components. Permanent shocks are distinguished from transitory using variances of earnings growth rates over

[14] The March CPS data used here were downloaded from the CPS-IPUMS site at the Minnesota Population Center. See King et al. (2004).

[15] Also, to the extent that the variance of earnings levels increased at all after 1980, it had more to do with the between-group increase in earnings due to changes in returns to education and other factors. A version of Fig. 3 where variances are measured using deviations from means by age and education shows the same basic patterns, but there is no discernible trend after the early 1980s. The distinction between within- and across-group earnings is a possible key to understanding the level of residual earnings inequality over time (Lemieux, 2006, 2008). In particular, if the variance of unexplained earnings is larger for the highly educated, an increase in the highly educated share of the labor force will increase the overall residual earnings variance. There is some dispute as to whether that effect can explain trends in the level of U.S. earnings inequality (Autor et al., 2008).

[16] Sabelhaus and Song (2009) present cohort-by-age measures of log earnings variances based on the CPS. Cohorts born after 1950 had much higher earnings variances at younger ages, but the gap between them and older cohorts decreased with age. That suggests an increase in initial dispersion of earnings that was offset by declining permanent and/or transitory shocks, which the formal variance decomposition in the next section confirms.

multiple frequencies; in this section the focus is on log earnings change over one and 12 year gaps. Building on the annual frequency results in the last section, the data show a clear decline in earnings growth variability over time at all frequencies – with more decline at longer frequencies – implying that the variance of both permanent and transitory shocks decreased.

The decomposition of labor earnings changes into permanent and transitory components begins with the canonical model for log earnings

$$y_{it} = \beta x_{it} + \mu_{it} + \varepsilon_{it} \tag{1}$$

where x_{it} is observables like age and sex, μ_{it} the slowly evolving permanent component of earnings, and ε_{it} the transitory shock. The permanent component evolves over time according to

$$\mu_{it} = \mu_{it-1} + \eta_{it} \tag{2}$$

The usual assumption is that ε_{it} and η_{it} are distributed normally with variances σ_ε^2 and σ_η^2, respectively.

Ignoring the observables, the variance of the change in log earnings is given by

$$\text{var}(y_t - y_{t-1}) = \text{var}(\varepsilon_t - \varepsilon_{t-1}) + \text{var}(\mu_t - \mu_{t-1}) = \text{var}(\varepsilon_t) + \text{var}(\varepsilon_{t-1}) \text{-} 2{*}\text{cov}(\varepsilon_t, \varepsilon_{t-1}) + \text{var}(\eta_t) \tag{3}$$

In the simplest case where the variances for the permanent shocks are constant across groups and time, this becomes

$$\text{var}(y_t - y_{t-1}) = 2{*}\sigma_\varepsilon^2 \text{-} 2{*}\text{cov}(\varepsilon_t, \varepsilon_{t-1}) + \sigma_\eta^2 \tag{4}$$

This relationship is the starting point for the variance decomposition implemented below.

The key insight from Carroll (1992) and Carroll and Samwick (1997) is that every expansion of the "gap" over which the variance of the log earnings change is measured adds one permanent component, but the number of transitory components is unchanged. For example, the variance of the two-year change is given by

$$\text{var}(y_t - y_{t-2}) = \text{var}(\varepsilon_t - \varepsilon_{t-2}) + \text{var}(\mu_t - \mu_{t-2}) = \text{var}(\varepsilon_t) + \text{var}(\varepsilon_{t-2}) \text{-} 2{*}\text{cov}(\varepsilon_t, \varepsilon_{t-2}) + \text{var}(\eta_t) + \text{var}(\eta_{t-1}) \tag{5}$$

Again, in the simplest case where the variances for the permanent shocks are constant across groups and time, this becomes

$$\text{var}(y_t - y_{t-2}) = 2{*}\sigma_\varepsilon^2 \text{-} 2{*}\text{cov}(\varepsilon_t, \varepsilon_{t-2}) + 2{*}\sigma_\eta^2 \tag{6}$$

Extending the logic to the rth gap and assuming that the covariance term becomes zero

$$\text{var}(\Delta^r y_t) = 2{*}\sigma_\varepsilon^2 + r\sigma_\eta^2 \tag{7}$$

Carroll (1992) decomposition strategy involves assuming (based on results from autocovariance studies) that the covariance for gaps greater than r=2 are zero. Thus, one can run a regression of the variance at each frequency on the length of the gap for observations where $r>2$, and the slope is the estimate of the permanent shock variance, while the intercept is two-times the transitory shock variance.

The variance decomposition described above is implemented here using the CWHS one percent sample for ages 25–55 and over the years 1980–2005. The benefits of having a very large sample that covers a wide range of ages and years is that one can split the sample several different ways to get some sense of how the stochastic process differs across age groups and time. The data indicate that both types of differences are significant.

Fig. 4 shows the first such disaggregation, focusing on the relationship between the log change variances by frequency for the entire sample, then the first (1980–1992) and second (1993–2005) sub-periods. The results for all three time periods confirm three expectations about these variance profile based on the canonical model: the variance rises with the length of the gap, which suggests permanent shocks have a positive variance, the relationship is much steeper over the first two gaps, which suggests that covariances are important for the first two years, and the slope is fairly linear for r=3 and above, which suggests that the permanent shock variances are well identified.[17]

For the specific purposes of this analysis, the more important observation involves the shift in the variance profile between the first and second sub-periods. The profile for the earlier period is higher at all values for r, which suggests the variance of transitory shocks was higher before 1992. The profile for the first half of the period is also steeper for $r>3$, which suggests the variance of permanent shocks were also larger before 1992. Thus, the visual impression is that both types of shocks decreased over time.

Table 1 takes the decomposition from the visual to the numerical. The table shows the results of estimating the Carroll (1992) regressions on log earnings changes between r=3 and r=12, for the entire sample and first and second sub-periods. The estimated parameters are (not surprisingly, given the pictures) highly significant, and confirm the visual impression that both intercept and slope decreased.

[17] As the length of the r gap increases, the sample size will decrease because people exit the paid labor force. In this data set that decrease in sample size is very modest, which can be seen by tracking any given cohort across the possible r gap combinations. For example, among the 40 year olds who had a measured earnings change at r=1, over 80 percent had a measured change at r=12 (when they were 52). More importantly (because the variance decomposition is based on r=3 through r=12) the relevant survival rate is the ratio of the r=12 sample to the r=3 sample, which is 88 percent. The ratios are even higher at younger ages, with survival rates for 25 year old from r=3 to r=12 well over 90 percent.

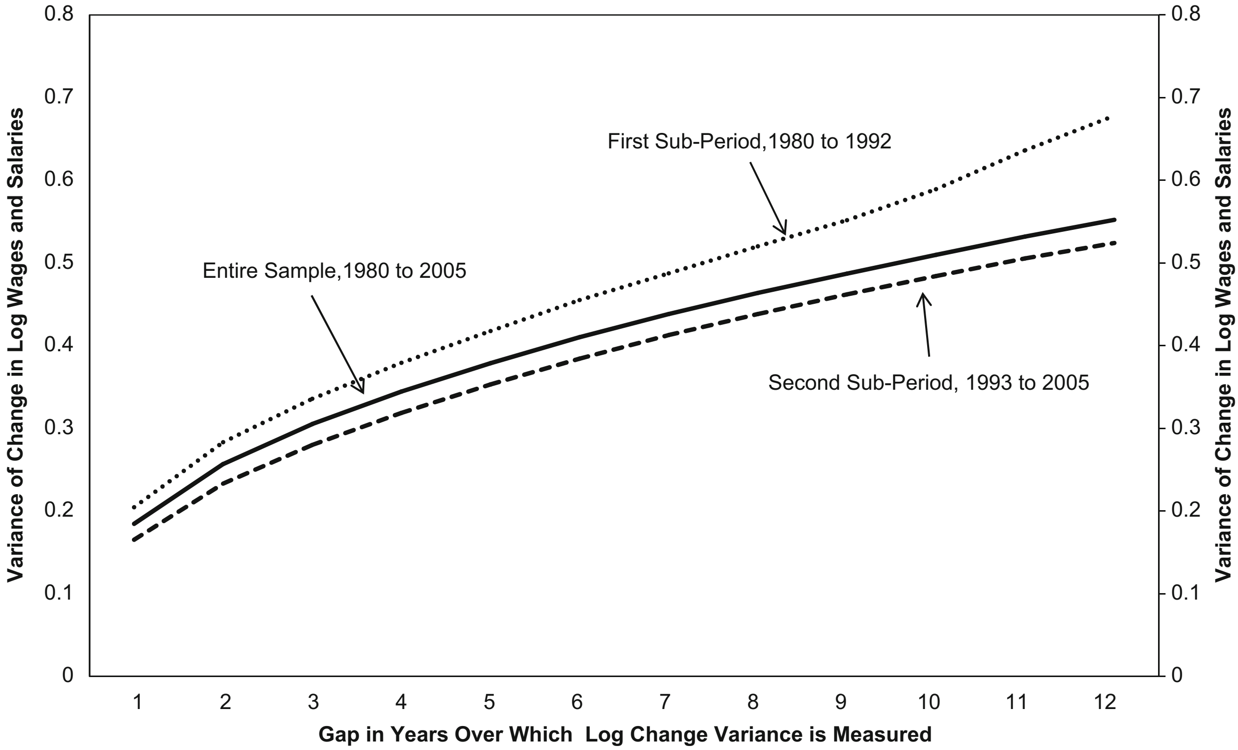

Fig. 4. Variance of change in log wages and salaries across year-gaps (all earners ages 25–55).

Table 1
Log wage and salary growth variance regressions, all ages 25–55 (wages and salaries above Social Security qualifying threshold).
Source: Social Security CWHS 1 Percent MEF.

	Regressions estimated on variance of change in log levels			
	Estimated intercept	**Estimated slope**	**Number of observations**	**Adjusted R-squared**
Entire period, 1980–2005	0.2372 (0.0083)	0.0273 (0.0011)	185	0.7729
First sub-period, 1980–1992	0.2317 (0.0126)	0.0364 (0.0011)	55	0.8661
Second sub-period, 1993–2005	0.2042 (0.0035)	0.0286 (0.0005)	55	0.9814

Note: All equations are estimated using variances between year gaps three to twelve.
Standard errors are in parenthesis.

Table 2
Log wage and salary growth variance decomposition by time, all ages 25–55 (wages and salaries above Social Security qualifying threshold).
Source: Social Security CWHS 1 Percent MEF.

	Entire period 1980–2005	**1st sub-period 1980–1992**	**2nd sub-period 1993–2005**	**Change 1st to 2nd sub-periods**
	Decomposition based on log earnings levels			
Estimated transitory variance	0.119	0.116	0.102	−0.014
Estimated permanent variance	0.027	0.036	0.029	−0.008
Variance of one-period (Δy)	0.184	0.205	0.165	−0.039
Variance of two-period (Δy)	0.257	0.283	0.233	−0.050
Implied covariance t, $t-1$	0.040	0.032	0.034	0.002
Implied covariance t, $t-2$	0.018	0.011	0.014	0.004

Note: Estimated shock variances are from Table 1.

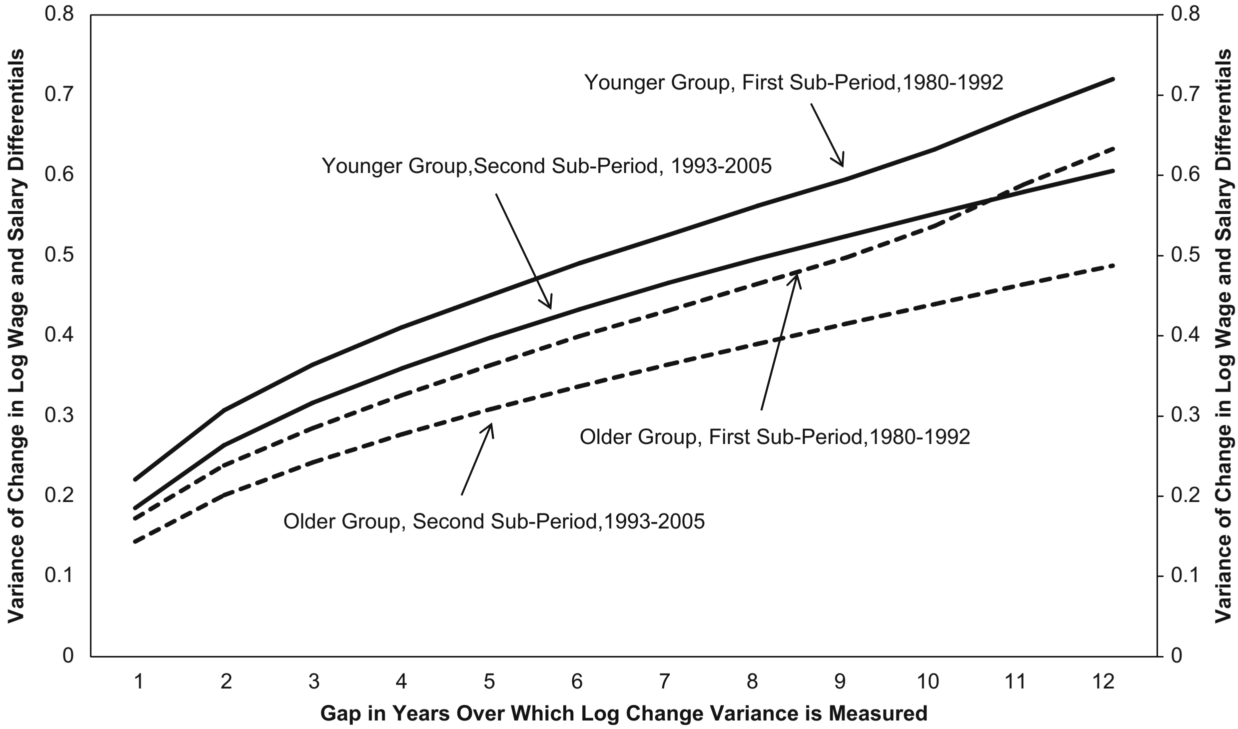

Fig. 5. Variance of change in log earnings differentials across age groups (younger group is ages 25–40, older group is ages 40–55).

The implied values for permanent and transitory shock variances are shown in Table 2, along with underlying sample statistics (the variances of one- and two-year log earnings changes) and the implied covariances at $r=1$ and $r=2$ (solved for using Eqs. 4 and 6 above, and plugging in the actual sample variances and estimated shock variances). The numerical decomposition confirms the visual impression that the variances of both permanent and transitory shocks fell over time, and also shows that the covariances at $r=1$ and $r=2$ are of an expected order of magnitude.[18]

The same combination of visual and numerical decomposition for log earnings differentials is reproduced for the younger (25–40) and older (40–55) halves of the sample, and again for the two sub-periods. Fig. 5 shows that the profile of variances for log earnings change are always higher and steeper for the young than they are for the old, though both sets of variance profiles show similar shifts (getting lower and flatter) over time. Tables 3 and 4 show the regression results and numerical decompositions for the two age groups and the two sub-periods. The results confirm the visual impression that the observed changes in estimated variances for the entire population also hold within the two age groups.

4. Separating age and cohort effects

The variance decompositions across sub-samples in the previous section provide strong evidence that the (average) stochastic process underlying labor earnings growth varies by age, and it has changed over time. Further identification of differences in shock variances across groups and times is subject to the usual constraint one faces with panel data—it is not possible to separate age, cohort, and time effects, because birth cohort (bc) is exactly time (t) minus age (a). The strategy in this section is to separate age and cohort effects. The results reinforce the basic conclusions from the variance decompositions in the last section, while also providing point estimates of the variances for permanent and transitory shocks across age groups.

The first step is to generalize the specification for the transitory and permanent shock variances, allowing them to vary by birth cohort (bc) and age (a). The transitory variance is now denoted more generally as $\sigma_{\varepsilon}^2(bc,a)$ and the permanent shock is $\sigma_{\eta}^2(bc,a)$. Now, the variance of the change in log earnings at time t for any given year-gap r varies across

[18] For example, in the latest Moffitt and Gottschalk (2008) estimates with an ARMA process, they find an autocorrelation term of 0.85 and a moving average term of -0.57, which implies a one-year covariance to variance ratio of 0.28. The corresponding value here (for the whole time period) is 0.04/0.119=0.34. One reason to explicitly consider the covariance terms is that Moffitt and Gottschalk (2008) argue that one might observe no change or a decrease in observed earnings growth variability – even if the transitory shock variance is rising – if there is an offsetting movement in the covariance term. There is some evidence of that here, as the covariances rise over time (though only slightly).

Table 3
Log wage and salary differentials growth variance regressions, younger versus older ages (wages and salaries above Social Security qualifying threshold). *Source*: Social Security CWHS 1 Percent MEF.

	Estimated intercept	Estimated slope	Number of observations	Adjusted R-squared
	Regressions estimated for ages 25–40			
Entire period, 1980–2005	0.2544 (0.0033)	0.0312 (0.0005)	1655	0.7118
First sub-period, 1980–1992	0.2532 (0.0056)	0.0387 (0.0010)	550	0.7482
Second sub-period, 1993–2005	0.2219 (0.0045)	0.0340 (0.0008)	550	0.7781
	Regressions estimated for ages 40–55			
Entire period, 1980–2005	0.1855 (0.0021)	0.0264 (0.0003)	1655	0.8085
First sub-period, 1980–1992	0.1842 (0.0056)	0.0326 (0.0005)	550	0.8406
Second sub-period, 1993–2005	0.1662 (0.0019)	0.0258 (0.0003)	550	0.9552

Note: All equations are estimated using variances between year gaps three to twelve.
Standard errors are in parenthesis.

Table 4
Log wage and salary differentials variance decomposition by age group and time (wages and salaries above Social Security qualifying threshold). Source: Social Security CWHS 1 Percent MEF.

	Entire period 1980–2005	1st period 1980–1992	2nd period 1993–2005	Change 1st to 2nd
	Younger ages (age 25–40)			
Estimated transitory variance	0.127	0.127	0.111	−0.016
Estimated permanent variance	0.031	0.039	0.034	−0.005
Variance of one-period (Δy)	0.203	0.221	0.185	−0.035
Variance of two-period (Δy)	0.284	0.307	0.264	−0.044
Implied covariance t, $t-1$	0.041	0.036	0.035	0.000
Implied covariance t, $t-2$	0.016	0.012	0.013	0.001
	Older ages (age 40–55)			
Estimated transitory variance	0.093	0.092	0.083	−0.009
Estimated permanent variance	0.026	0.033	0.026	−0.007
Variance of one-period (Δy)	0.157	0.172	0.144	−0.029
Variance of two-period (Δy)	0.216	0.239	0.201	−0.037
Implied covariance t, $t-1$	0.028	0.022	0.024	0.002
Implied covariance t, $t-2$	0.011	0.005	0.008	0.003

Note: Estimated shock variances are from Table 3.

birth cohorts

$$\mathrm{var}(y_{bc,t}\text{-}y_{bc,t-r}) = \sigma^2_{\varepsilon}(bc,t-bc-r) + \sigma^2_{\varepsilon}(bc,t-bc) + \Sigma_{s=t-r+1,t}\sigma^2_{\eta}(bc,s-bc) \tag{8}$$

because $a=t-bc$.

The second step is to impose some structure on the transitory and permanent shocks. The structure imposed here allows us to separately identify estimates of permanent and transitory variances at each age, but with a fairly simple linear specification for the trends in those variances across cohorts. That is, the approach effectively imposes a shift across age groups in the profiles of transitory and permanent shocks over time. This structure for both transitory and permanent shocks is implemented using a series of dummies for each age and type of shock, along with linear trends across cohorts.[19] That is

$$\sigma^2_{\varepsilon}(bc,a) = \Sigma_{a=25,55} D^{\varepsilon}_a 1_{a=\mathrm{age}} + \beta_{\varepsilon} bc \tag{9}$$

[19] In an earlier version a quadratic structure in age was imposed for the two types of shocks, and the result were qualitatively the same in terms of patterns by age and time. We are grateful to Stephen Shore for suggesting the dummies plus linear cohort trend approach used here.

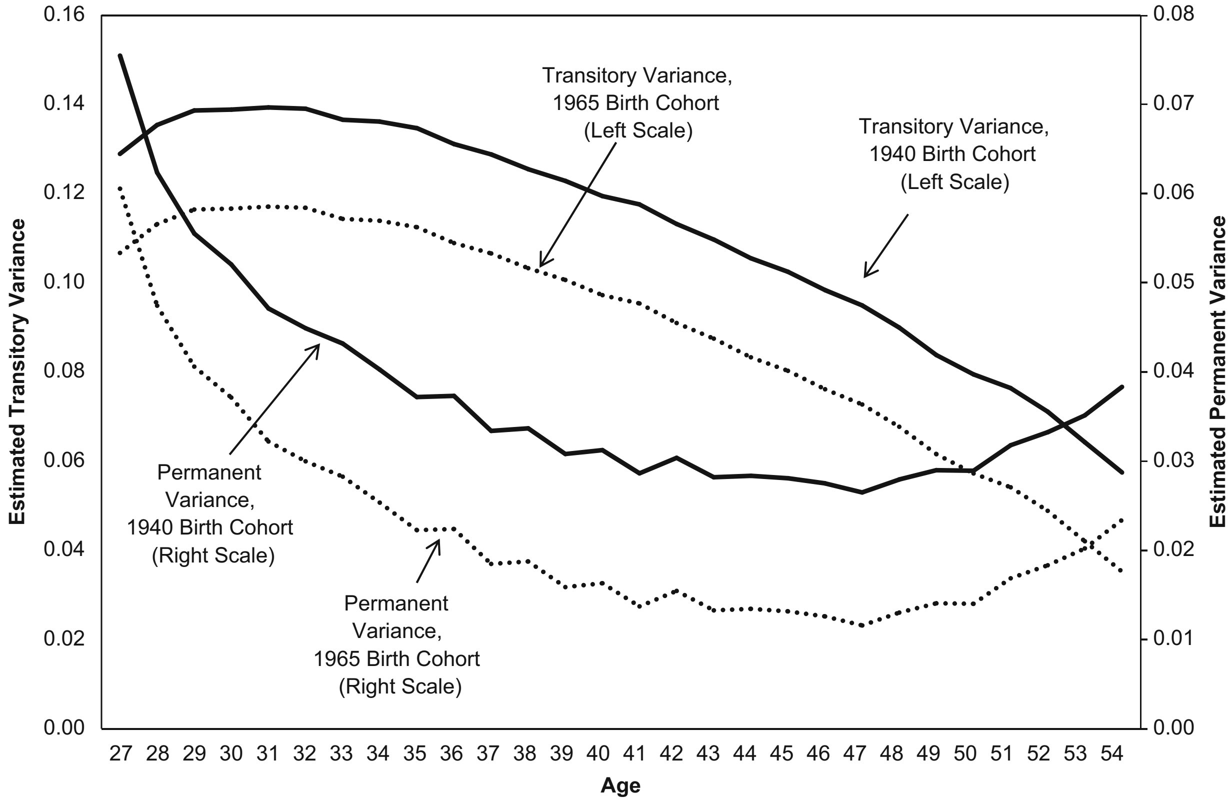

Fig. 6. Estimated variances of permanent and transitory shocks by age.

$$\sigma_\eta^2(bc,a) = \Sigma_{a=25,55} D_a^\eta 1_{a=\text{age}} + \beta_\eta bc \tag{10}$$

where D_a^ε and D_a^η are dummies, and $1_{a=\text{age}}$ is an indicator equal to one when the observation is at that particular age.

The advantage of this parsimonious specification is ease of implementation and evaluation. In particular, the estimation just involves creating variance measures across birth cohorts, time, and the possible r-gaps, then fitting

$$\text{var}(y_{bc,t}\text{-}y_{bc,t-r}) = D_{t-bc-r}^\varepsilon + D_{t-bc}^\varepsilon + \Sigma_{s=t-r+1,t} D_{s-bc}^\eta + 2\beta_\varepsilon bc + r\beta_\eta bc \tag{11}$$

This is effectively a regression of the variances across r-gaps on transitory shock dummies for the first and last age for the r-gap over which the log-change is measured, permanent shock dummies for every age within the particular r-gap, a birth cohort trend, and a birth cohort trend interacted with the length of the gap.

The results of estimating the specification above are very intuitive, and indicate the same sort of shifts over time (actually, across cohorts) as the sample-splitting exercises in the last section.[20] The estimated parameters effectively identify age-variance profiles of transitory and permanent shocks for any given cohort, and these are displayed in Fig. 6.

The pattern of transitory shocks by age shown in Fig. 6 is intuitive. The implication of the declining pattern is that short-term earnings fluctuations become smaller with age, in fact falling by about half between ages 27 and 54. Likewise, the pattern of permanent shocks by age in Fig. 6 also make sense, because they decrease quickly until about age 40, then spike up again after age 50. This pattern suggests that much of the lifetime uncertainty about (relative) earnings is resolved early in the life cycle, which is consistent with individuals moving along particular career trajectories. Towards the end of the working age range (which is set to 55) permanent shocks become relatively more important once again, almost certainly due to early retirements, health shocks, or other life-changing events.

In addition to an intuitive pattern by age, the cohort trend terms identify the same sorts of decrease over time that the sample-splitting exercises above revealed. The variances of both permanent and transitory shocks decreased, as indicated by comparing the estimates for the (arbitrarily chosen) 1940 birth cohort with those for the 1965 birth cohort. Although

[20] The coefficients on the transitory and permanent shock dummies in (9) are shown in Fig. 6, and all are highly significant. The coefficient on the cohort trend is −0.0017764 with t-statistic of −14.7, and the coefficient on the cohort trend interacted with r is −0.0005966 with a t-statistic of −30.5. Complete results are available from the authors.

there are a number of different ways to use these data to separate age and time/cohort effects, controlling for age effects in permanent and transitory shocks does not alter the conclusion that micro earnings growth moderated.[21]

5. Conclusions

The main findings from this analysis of Social Security earnings records are (1) there was a significant decline in the variance of micro labor earnings growth rates in the U.S. between 1980 and the early 1990s, (2) there is a negative relationship between the variance of earnings growth and age, but that cannot explain the decline in overall variability, (3) the decline over time occurred at multiple frequencies and in such a way that suggests both permanent and transitory variances fell, and controlling for age effects reinforces that. Taken together, these findings suggest that earnings growth variability per se is not a new or increasing problem in public policy, and that the changes in micro earnings variability are consistent with the macro Great Moderation. This is not meant to suggest that earnings inequality is not an important problem; indeed, one way to interpret the numbers is that low earners are now more certain their earnings are going to stay that way (Kopczuk et al., 2007).

The approach implemented here for separating age and cohort effects can and should be generalized to estimate more complicated stochastic processes for micro labor earnings growth.[22] The approach here was focused on isolating changes over time using the most parsimonious specifications. However, the results here also suggest that the stochastic processes being used to calibrate consumption models can and should be improved by introducing age effects. Those models can be used to evaluate the quantitative implications (for both consumption and economic well-being) of the sorts of shifts in variances over time that the data suggest took place.

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[21] For example, one alternative also explored involved estimating a version of (9) for the first and second sub-periods without cohort trends. Although the point estimates for the transitory and permanent shock variances change, the relative sizes, patterns with age, and decrease over time in both sets of variances are still very clear.

[22] In particular, the types of stochastic processes described in and Meghir and Pistaferri (2004).

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