Trends in Men’s Earnings Volatility:  
What Does the Panel Study of Income Dynamics Show?

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Abstract
Using Panel Study of Income Dynamics data for 1969 through 2006, we examine movements in men’s earnings volatility. Like many previous studies, we find that earnings volatility is substantially countercyclical. As for secular trends, we find that men’s earnings volatility increased during the 1970s, but did not show a clear trend afterwards until a new upward trend appeared in the last few years.

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“… the volatility of family incomes has gone up – way, way up…. In fact, over the past generation the economic instability of American families has actually risen much faster than economic inequality….”
-- Hacker (2006, p. 2)

“… we find that the transitory variance [of male earnings in the U.S.] increased substantially in the 1980’s and then remained at this new higher level through 2004.”
-- Moffitt and Gottschalk (2008, p. 21)

“… we estimate that the volatility of household income – as measured by the standard deviation of two-year percent changes in income – increased one-third between the early 1970s and early 2000s…. The rise in volatility did not occur in a single period but represented an upward trend throughout the past thirty years…. Of the various components of income we study, household heads’ labor earnings experienced the largest increase in volatility.”
-- Dynan, Elmendorf, and Sichel (2008, pp. 3 and 24)

“CBO’s analysis of the CWHS administrative data indicates that, since 1980, the trend in year-to-year earnings variability has been roughly flat.”
-- Congressional Budget Office (2007, p. 3)

I. Introduction

The seminal study by Gottschalk and Moffitt (1994) used 1970-1987 data from the Panel Study of Income Dynamics (PSID) to suggest that the well-known increase in men’s earnings inequality during that period stemmed partly from an increase in transitory earnings variation. Several subsequent studies corroborated the general finding and filled in additional details about the trend.1 Haider (2001), for example, analyzed PSID data for 1967-1991 and concluded that “earnings instability increased dramatically

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1 Because the permanent component of earnings variation also increased, the rise in transitory earnings variation need not have reduced autocorrelations in earnings nor increased transition rates across quintiles of the earnings distribution. The evidence that transitory earnings variation increased therefore is altogether consistent with studies such as Kopczuk, Saez, and Song (2010) that have found relative stability in such measures of economic mobility.
during the sample period, with most of the increases occurring during the 1970s” (p. 829).²

Spurred by popular press accounts of a dramatic upsurge in income and earnings volatility during the 1990s and 2000s (such as the above-quoted book on The Great Risk Shift by political scientist Jacob Hacker), economic researchers have begun to extend the analysis of trends in men’s earnings volatility to more recent years. In section II, we will discuss in detail what is suggested by the series of quotations above – that the recent literature has been inconclusive, in large part because of seemingly discrepant findings from the PSID. The primary purpose of our study is to clarify matters by providing a transparent and accessible view of the patterns in the PSID data up through 2006, the most recent available year.

In section III, we discuss alternative ways of measuring trends in earnings volatility. Our discussion emphasizes serious flaws in some commonly used methods, highlights an important distinction between volatility and transitory variation, and notes the imperfect connection between measured volatility and true economic risk.

Section IV presents our analysis of PSID data. Like many previous studies, we find that earnings volatility is substantially countercyclical. As for secular trends, we find that men’s earnings volatility as measured in the PSID increased during the 1970s, but did not show as clear a trend afterwards until a new upward trend appeared after 1998. Section V summarizes and discusses our findings, with particular attention to remaining questions that call for further research.

II. The Recent Literature

Among studies that have extended the analysis of trends in men’s earnings variability beyond about 1990, two of the most influential have used data other than the PSID. Cameron and Tracy (1998) studied longitudinally matched Current Population Survey (CPS) data for 1967-1996. Relative to the PSID, the longitudinal match of the

² A series of PSID-based studies by Moffitt and Gottschalk (1995, 2002, 2008) has concluded instead that the increase was concentrated in the 1980s, but the PSID-based studies by Dynarski and Gruber (1997) and Dynan, Elmendorf, and Sichel (2008) – as well as the present study and the Current Population Survey study by Cameron and Tracy (1998) – agree with Haider that much or most of the increase occurred during the 1970s. This finding is economically important because it suggests that much of the increase in earnings volatility preceded the well-documented increase in long-run earnings inequality (such as the rise in returns to schooling) and therefore probably stemmed at least partly from different sources.
CPS has the advantage of much larger sample size, but also the disadvantage of systematically excluding individuals who changed residences, which must make the sample at least somewhat unrepresentative with respect to earnings changes. Measuring earnings variability with the variance of year-to-year change in log earnings (a method we will discuss in detail in section III), Cameron and Tracy replicated Haider’s PSID-based finding that men’s earnings instability trended upwards during the 1970s and, after a large cyclical increase during the recession of the early 1980s, came back down for the rest of the 1980s to about the same level as in the late 1970s. Cameron and Tracy also found that this relatively flat trend continued through the end of their sample period in 1996.

The Congressional Budget Office (CBO, 2007) study by Dahl, DeLeire, and Schwabish used Social Security earnings histories for 1980-2003. Relative to the PSID, these Social Security data have the advantages of vastly greater sample size and avoidance of survey response error. On the other hand, the version of the Social Security data used in the CBO study is not publicly available for replication and further analysis, and it includes only those earnings reported by employers on W-2 forms. In particular, it leaves out earnings from self-employment, earnings abroad, “under the table” earnings, and earnings of some government employees. The part of the CBO analysis most comparable to other research on men’s earnings volatility (shown in figure A-15 on page 37) plots the standard deviation of the difference between a worker’s current age-adjusted log earnings and that worker’s five-year average containing the current year and the previous four years. Because the CBO data do not begin until the 1980s, they do not speak to the 1970s trend, but for the 1980-1996 period that overlaps with Cameron and Tracy’s analysis, they show similar behavior. In addition, the data underlying figure A-

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3 In Congressional Budget Office (2008), the same authors extended their analysis to family income, but the analysis of individual earnings in the 2008 study is less detailed than the 2007 analysis and leaves out the years 1980-1983.

4 Note that this change variable dampens measured volatility by including current earnings in the benchmark average. The variable is numerically identical to taking 0.8 times the deviation of current age-adjusted log earnings from the average for the preceding four years.
15 (generously provided to us by the CBO authors) show a nine percent increase between 1998 and 2003 in the CBO measure of men’s earnings volatility.\(^5\)

Up to this point, the studies seem to describe a fairly robust pattern: Apart from cyclical fluctuations, men’s earnings volatility rose considerably during the 1970s, did not show as clear a trend during the 1980s and most of the 1990s, and then may have risen again since the late 1990s. But once one adds in recent studies based on the PSID, matters become more confusing.

In a series of recent papers (Moffitt and Gottschalk 2002, Gottschalk and Moffitt 2006, Moffitt and Gottschalk 2008), Moffitt and Gottschalk have updated their decompositions of men’s earnings variation into permanent and transitory components. They have used several methods (discussed below in section III), but their preferred approach is to estimate parametric models of earnings dynamics. Their paper published in 2002 analyzes 1969-1996 PSID data and concludes that the transitory variance of men’s log earnings “rose dramatically in the 1980s, levelled off in the late 1980s, and fell after 1991” (p. C70). Their most recent study, the 2008 manuscript, extends the analysis through 2004 and finds that “the transitory variance increased substantially in the 1980’s and then remained at this new higher level through 2004” (p. 21).

Hacker’s (2006) analysis of 1974-2002 PSID data on family income, rather than men’s earnings, used one of Moffitt and Gottschalk’s decomposition methods and also reported a volatility increase in the 1980s, but found an even larger increase in the early 1990s, followed by a decline later in the 1990s and another increase in the early 2000s.

The PSID analysis most comparable to our own is Dynan, Elmendorf, and Sichel’s (2008) study, written concurrently with ours. Like Hacker, Dynan et al. focus mainly on family income, but they also present results for various components of family income, and these include a panel in their figure 1 that plots a time series for men’s earnings volatility through 2004. Their volatility statistic is the standard deviation of the two-year percentage change in earnings, calculated as the difference between earnings in years \(t\) and \(t-2\) divided by the average of earnings in both years. Their plot shows the three-year rolling average of each year’s statistic combined with the statistics for the two

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\(^5\) The CBO conclusion about a “roughly flat” trend, quoted at the beginning of our paper, comes partly from pooling the different trends for men and women in many analyses and partly from starting the sample period in the early 1980s, when earnings volatility was unusually high because of a severe recession.
preceding years. As the quotation at the beginning of our paper suggests, the plot shows a long-running rise in men’s earnings volatility, with particularly steep increases during the 1970s and the early 2000s.

Virtually the entire literature agrees that men’s earnings volatility is greater today than it was 40 years ago, but the PSID-based studies disagree both with each other and with other studies with respect to how much of an increase occurred when. The main point of our paper is to provide a more transparent view of what the PSID data have to say on the subject. Our paper is complementary to the study by Dynan et al. in that our paper is narrower and deeper – it focuses only on men’s earnings, not on the rest of family income, but it does so in much greater detail than the one graph in Dynan et al. In particular, we will show how the estimated trends vary with alternative earnings variables, alternative ways of measuring the dispersion in earnings changes, alternative treatments of zero earnings and other outliers, and controls for life-cycle effects on earnings growth. In addition, by presenting our statistics for each year, instead of taking rolling averages, we obtain a clearer delineation of cyclical fluctuations vs. secular trends. Finally, by adding the most recent available data for 2006, we get a better sense of the extent to which the measured earnings volatility increase in the early 2000s has persisted beyond the recession of that time. Before presenting our detailed analyses in section IV, in section III we first discuss some key issues in the measurement of earnings volatility.

III. Measuring Earnings Volatility

One branch of the relevant literature – exemplified by Moffitt and Gottschalk (1995, 2002, 2008), Gottschalk and Moffitt (2006), Haider (2001), and Baker and Solon (2003) – has used complicated parametric models of earnings dynamics to decompose cross-sectional earnings inequality into permanent and transitory components. The main motivation for such decompositions has been to ascertain the extent to which measured increases in cross-sectional earnings inequality signify increases in long-run inequality. Later in this section, we will explain why such decompositions may not be well-targeted for answering the more recent research question of whether earnings volatility (including permanent shocks) has increased.
In any case, another limitation of this approach is that the parametric models used in the literature are arbitrary mechanical constructs and the resulting estimates of trends can be sensitive to arbitrary variations in model specification. For example, using a large sample of Canadian income tax records, which enabled more thorough specification checking than is possible with smaller U.S. data sets, Baker and Solon strongly rejected the restrictions of Moffitt and Gottschalk’s (1995, 2002) preferred model and found that imposing those restrictions substantially biased the estimation of Canadian trends in components of earnings variation.

We therefore sympathize with the inclination of several other researchers – such as Dynarski and Gruber (1997), Cameron and Tracy (1998), Congressional Budget Office (2007), and Dynan, Elmendorf, and Sichel (2008) – to eschew complex earnings dynamics models and focus instead on transparently simple statistics that might be reasonable indexes of earnings volatility under a wide range of data-generating processes. Dynarski and Gruber, for example, measured earnings volatility with the variance of year-to-year change in log earnings. The simple idea is that, if earnings volatility increases a lot, one might reasonably expect that development to be reflected in increased dispersion of earnings changes.

Similar concerns presumably are what motivated Moffitt and Gottschalk – in their 1995, 2002, 2006, and 2008 papers – to supplement their analyses based on earnings dynamics models with what, in the 2006 paper, is called their “descriptive” approach. The particular descriptive statistic they use to measure the transitory component of earnings variation in year $t$ is the variance of log earnings in that year minus the $s$-order autocovariance between years $t$ and $t-s$. The 2002 paper uses the fifth-order autocovariance, the 2006 paper uses the fourth-order autocovariance, and the 2008 paper uses the sixth- and tenth-order autocovariances. Although Moffitt and Gottschalk

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6 The 2008 paper also presents a complex extension of the descriptive approach, labeled as the “approximate nonparametric method.” The results based on that method (figure 7) show that the transitory variance component dropped by more from 2002 to 2004 than during any other two-year period since 1970. This is surprising because, based on the same survey, our study and the independent study by Dynan, Elmendorf, and Sichel (2008) show that the dispersion of earnings changes for men in the Panel Study of Income Dynamics increased substantially between 2002 and 2004. Moffitt and Gottschalk do not explain why the transitory variance is estimated to drop precipitously during a period when the sample’s earnings changes became more dispersed. More broadly, it is hard to see how the earnings changes observed in the last year of the sample period can be credibly identified as transitory vs. permanent. Only subsequent years of data can reveal whether those changes turned out to be transitory or permanent.
clearly express a preference for their analyses based on parametric earnings dynamics models, they also feature their descriptive approach in all four papers. Thanks to Moffitt and Gottschalk’s well-deserved stature in the field, their descriptive approach has been quite influential; for example, Hacker (2006) adopted it for his own analysis of trends in family income volatility. We therefore need to explain why we do not adopt it as well.

Although we do not wish to commit to any particular model of the earnings dynamics process, we will begin to illustrate our concerns in terms of a simple version of the often-used variance components model that splits log earnings (after adjustment for life-cycle/cohort effects) into orthogonal permanent and transitory components. Expressed in a way that allows for trends in the dispersion of either component, the model is

\[ y_{it} = p_t \alpha_i + \varepsilon_{it} \]

where \( y_{it} \) is the age-adjusted log earnings of individual \( i \) in year \( t \), \( \alpha_i \) is an individual-specific “fixed effect” with population variance \( \sigma^2_\alpha \), \( p_t \) is a year-specific factor loading (which might reflect, for example, year-specific returns to human capital), and \( \varepsilon_{it} \) is a transitory component with time-varying variance \( \sigma^2_t \) and negligible serial correlation.\(^7\)

Then cross-sectional earnings inequality in year \( t \), as measured by \( Var(y_{it}) \), is simply

\[ Var(y_{it}) = p_t^2 \sigma^2_\alpha + \sigma^2_t. \]

According to this model, an increase in earnings inequality could stem from an increase in either the permanent variance component (represented as an increase in \( p_t \)) or the transitory variance component \( \sigma^2_t \).

\(^7\) The first statement of this model of which we are aware is in Katz’s (1994) published discussion of Gottschalk and Moffitt (1994). Katz used the model to explain that Gottschalk and Moffitt’s (1994) method of separating permanent and transitory components of earnings variation assumed that \( p_t \) held constant through the entire period 1970-1978, jumped to a new level in 1979, and then held constant at that level through 1987. The same method recently reappeared as the “BPEA method” on pages 14-15 of Moffitt and Gottschalk (2008).
Later in this section, we will generalize the model to incorporate permanent shocks, but for now the only individual-specific earnings volatility in the model is represented by the transitory variance component $\sigma_t^2$. The question then becomes how well Moffitt and Gottschalk’s descriptive statistic measures $\sigma_t^2$. It is easy to show that

\begin{equation}
Var(y_{it}) - \text{Cov}(y_{it}, y_{i,t-\tau}) = \sigma_t^2 + p_i (p_{t} - p_{t-\tau})\sigma_a^2.
\end{equation}

Thus, Moffitt and Gottschalk’s descriptive statistic correctly identifies the transitory variance component $\sigma_t^2$ only when $p_t = p_{t-\tau}$; that is, only when the permanent component is unchanged and earnings inequality has changed solely because of a change in the transitory component. In the general case, when both variance components may be changing, their descriptive statistic conflates the two.

More importantly, their statistic can be way off the mark not only for estimating the level of the transitory variance, but also for estimating its change over time. Consider the version of the statistic that uses the tenth-order autocovariance, as in Moffitt and Gottschalk (2008). Suppose that, up through year $t-10$, $\sigma_{t-10}^2 = p_{t-10} = 1$. Then $Var(y_{i,t-10}) = 1 + 1 = 2$; that is, cross-sectional earnings inequality as of year $t-10$ divides evenly between permanent and transitory variation. Given stationarity up through time $t-10$, Moffitt and Gottschalk’s descriptive statistic would correctly identify $\sigma_{t-10}^2$ as 1.

But now suppose that, in every year from $t-10$ through $t$, the permanent factor loading $p$ increases at an annual rate of 0.04 while the transitory variance stays the same. This may be a good characterization of the 1980s. All researchers agree that, during that decade, the earnings gap between high- and low-skill workers widened substantially, but, as discussed in sections I and II, most researchers find less of a trend in earnings instability. Indeed, the numbers we are using here are in fairly close proportion to the estimates for the 1980s in Haider (2001). In our scenario, by year $t$, cross-sectional inequality has grown to $Var(y_{it}) = (1.4)^2 + 1 = 2.96$ with no increase whatsoever in the transitory variance component, which still equals 1. Nevertheless, if
one applies Moffitt and Gottschalk’s descriptive method for estimating $\sigma_t^2$, one overestimates it as 1.56. The method incorrectly concludes that the transitory variance has increased by 56 percent over the ten years, and it incorrectly ascribes 58 percent of the increase in inequality to change in the transitory component. The lesson is that, in a non-stationary environment (which, after all, is entirely what this trends literature is about), this descriptive statistic does not actually describe what anyone wants it to. And this is not an artifact of the simple illustrative model from equation (1). Readers can verify for themselves that adding complications – permanent shocks, heterogeneity in earnings growth, serial correlation of the transitory component, or whatever – does not set things right.

Accordingly, we look elsewhere for our descriptive statistics. In particular, we will use measures of the dispersion in year-to-year earnings changes, such as the standard deviation of change in log earnings. It seems reasonable to guess that trends in earnings volatility would be reflected in such measures, but we should check that guess. To begin with, consider the variance of the age-adjusted change in log earnings between years $t-2$ and $t$. Under the model in equation (1), this variance is

\[
Var(y_{it} - y_{i,t-2}) = (p_t - p_{t-2})^2 \sigma_a^2 + \sigma_t^2 + \sigma_{t-2}^2.
\]

As conjectured, this dispersion measure tends to be higher when the transitory variance is higher in years $t$ and $t-2$. The bad news is that, like Moffitt and Gottschalk’s statistic, this measure also is affected by changes in $p$. The good news is that, if $p$’s closer together in time tend to be more similar, this measure tends to be less distorted than the Moffitt-Gottschalk statistic in equation (3), which is contaminated by the $s$-year difference where $s$ is 6 or 10 years in Moffitt and Gottschalk’s most recent paper. Of course, this good news gets better still when one has access to a data set in which one can use the variance of one-year instead of two-year changes, as in the CPS data used by Cameron and Tracy (1998) and the Social Security data used in Congressional Budget Office (2007). Additional good news for the measure in equation (4) is that it squares the typically fractional change in the $p$’s, leading to a smaller fraction multiplying $\sigma_a^2$. 
For example, consider again the numerical illustration above. In year \( t - 10 \), our statistic in equation (4) correctly identifies \( \sigma_{t-10}^2 + \sigma_{t-12}^2 \) as \( 1 + 1 = 2 \). In year \( t \), our statistic estimates \( \sigma_t^2 + \sigma_{t-2}^2 \) as \((0.08)^2 + 1 = 2.0064\), instead of the correct value of 2. This illustrates our claim that, although our statistic is affected by changes in the permanent factor loading, it is much less sensitive to them than Moffitt and Gottschalk’s statistic is.

We can gain further insight into the behavior of our statistic by generalizing the earnings dynamics model in equation (1) to encompass permanent as well as transitory earnings shocks. The extended model is

\[
y_{it} = p_i (\alpha_i + u_{it}) + \epsilon_{it}
\]

where \( u_{it} \) follows a martingale process

\[
u_{it} = u_{i,t-1} + v_{it}.
\]

This extension makes the earnings dynamics model more realistic by allowing for long-lasting shocks such as the persistent earnings losses often suffered by workers displaced from their jobs. With this addition to the model, the variance measure in equation (4) now gets modified to

\[\sigma_t^2 = p_i^2 \alpha_i^2 + \sigma_i^2 + \sigma_{i-2}^2 + \sigma_{i-12}^2.
\]

Some readers of previous drafts have asked what happens if the transitory component is serially correlated. If the second-order autocorrelation is stable and denoted by \( \rho \), then the statistic in equation (4) would be \( 2(1 - \rho) \) instead of 2; that is, it would identify the level of the transitory variances rescaled by the factor \( 1 - \rho \). Thus, when comparing an era of high transitory variance to an era of low transitory variance, our statistic would do a good job of measuring the proportional change. Of course, if the serial correlation parameter changes over time, matters become much more complicated. Indeed, it would become less clear what we even mean by changes in earnings volatility. Another concern is how our statistic would be affected by persistent heterogeneity across individuals in their earnings growth rates. As shown by Baker (1997), although such heterogeneity does matter for lifetime earnings, it is practically invisible in high-frequency data such as one- or two-year earnings changes. As Baker explains, this is why the classic earlier studies of earnings dynamics by MaCurdy (1982) and Abowd and Card (1989) failed to detect heterogeneous growth rates. By the same token, growth heterogeneity of a plausible magnitude cannot have an appreciable impact on our statistic in equation (4).

where $\alpha_i + u_{i,t-2}$ might be thought of as worker $i$’s permanent human capital as of time $t-2$. The important change relative to equation (4) is the addition of the last term $p_t^2[Var(v_{it}) + Var(v_{i,t-1})]$, the component of the variance in earnings change that comes from permanent shocks.

The key lesson is that an earnings volatility measure based on dispersion in year-to-year earnings change reflects permanent shocks in addition to transitory ones. Thus, in contrast to the model-based studies that have attempted to isolate the transitory component of earnings inequality, our study and others using similar methods include permanent shocks in our measurement of earnings volatility. This makes sense when the purpose of the research is not to disaggregate cross-sectional inequality into long-run and transitory components, but rather to measure volatility trends. The recent interest in volatility trends stems in large part from a concern about whether earnings risk has increased. Because permanent shocks, such as those experienced by many displaced workers, are even more consequential than transitory ones, it makes good sense to include them in the measurement of earnings volatility.

Having said that, however, we should be very clear that measures like the standard deviation of change in log earnings not only lump together permanent and transitory shocks, but also leave open the extent to which the shocks translate into economic risk. As discussed by Blundell, Pistaferri, and Preston (2008) and Cunha, Heckman, and Navarro (2005), identifying the risk associated with earnings changes will require further information on whether the changes were or were not anticipated (or even purposively chosen) and whether the affected individuals were or were not insured against the changes (through such means as transfer programs, saving/borrowing, or family labor supply adjustments). Assessing the welfare implications of changes in measured earnings volatility ultimately will require answers to these difficult questions.

Our empirical analysis in the next section is just a step directed at the preliminary question of what are the basic facts regarding overall trends in men’s earnings variability.
We regard it, however, as a crucial step. If evidence from the PSID and other data sources ultimately shows that men’s earnings variability has increased substantially in recent years, research will then need to proceed to ascertaining whether that increase does constitute what Hacker (2006) has called a “great risk shift” and what the attendant welfare consequences are.\textsuperscript{10}

### IV. Evidence from the Panel Study of Income Dynamics

#### A. Data

Our data are from the Panel Study of Income Dynamics, a longitudinal survey administered by the University of Michigan’s Survey Research Center every year from 1968 through 1997 and every other year since then. We use the data from the nationally representative Survey Research Center component of the PSID sample.\textsuperscript{11}

Like some previous researchers, we first analyze the wage and salary income of male household heads because it is the earnings variable that the PSID has measured most consistently over time. We exclude imputations for missing values, the inclusion of which would distort measured earnings variability.\textsuperscript{12} The wage and salary income variable is available only in “bracketed” (i.e., interval) form for the PSID’s 1968 and 1969 interviews, so our data set begins with the 1970 survey, which collected income information for the 1969 calendar year. Because the PSID was administered annually through 1997 and every other year since, our earnings data are for every year from 1969.

\textsuperscript{10}Dynarski and Gruber (1997), Blundell, Pistaferri, and Preston (2008), and Gorbachev (forthcoming) have begun to tackle these difficult issues by analyzing PSID consumption data in conjunction with the income data. The consumption data typically used, however, pertain only to food expenditures, and the reference period for those data does not align well with the reference period for the income data.

\textsuperscript{11}We do not use the Survey of Economic Opportunity component (the so-called “poverty sample”) mainly because of the serious irregularities in that sample’s selection. The problems recounted in Brown (1996) are too numerous to repeat here in their entirety. The problem we find most disturbing is that, for reasons that remain unknown to this day, the computer consulting firm in Washington, DC that the Office of Economic Opportunity hired to select low-income households from the Census Bureau’s 1967 Survey of Economic Opportunity sample failed to include most of the eligible households in the lists it transmitted to the Survey Research Center. Worse yet, the omissions clearly were not random. Brown’s memo notes a racial pattern – the transmission rate was 55 percent for non-whites and 21 percent for whites. A passage he quotes from the Survey Research Center’s 1984 PSID User Guide also refers to “substantial” variation across geographic areas. That passage concludes, “By the time we realized that not all the addresses of the ‘signers’ had been forwarded, the Census personnel knowledgeable about the process had moved on to designing the 1970 Census, and OEO personnel were not able to provide us any information. Our repeated efforts to secure more information about the lost cases were not successful.”

\textsuperscript{12}On the advice of PSID staff, we interpret the several instances from 1994 on in which wage and salary income is coded as 1 as missing values that require imputation.

We restrict our sample of earnings observations to calendar years when the male head of household is between the ages of 25 and 59. For a two-year change to be included in our analysis, the worker must be within that age range in both years. At the outset of each analysis in section IV.B, we will provide information on the available sample sizes. Each of those analyses of earnings changes begins with a regression adjustment for mean effects of year (such as inflation in nominal wages), life-cycle stage, and cohort. In particular, we apply least squares (separately for each year) to a regression of the earnings change variable on age and age squared, and then use the residual as the object of the subsequent analysis of dispersion in earnings changes.13

B. Analyses of PSID Earnings Changes

We begin by looking at the trend in the standard deviation of change in log earnings, i.e., the square root of the variance measure discussed at length in section III. For this particular analysis, in addition to the sample restrictions listed above, we exclude observations of zero earnings. We also exclude the top and bottom 1 percent of positive observations in each year. Besides the usual reasons for excluding outliers (especially the sensitivity of estimated variances to extreme observations, many of which may be artifacts of measurement error), dropping the top 1 percent eliminates all the top-coded observations and thereby sidesteps the question of whether and how to adjust them. We recognize, however, that excluding zeros and other extreme observations in a study of earnings volatility is not entirely a good thing. Accordingly, in an alternative analysis described later in this section, we take a different approach to the extreme observations.

13 We stop at a quadratic because going to a cubic specification typically resulted in coefficient estimates for the cubed terms that were small and statistically insignificant. In any case, given the restricted age range in our sample, variations on our age controls (including using none at all) turn out to have very minor effects on our results concerning volatility trends. Controlling for years of education has even less effect.
In combination, all the sample restrictions applied in the present analysis leave us with a total of 45,295 observations over our 31 years of data on two-year differences. The average sample size per year is thus 1,461. The smallest sample size is 1,005 for 1969-1971, and the largest is 2,016 for 2000-2002.

Our preliminary regression of change in log earnings on a quadratic in age each year causes our residualized measure of change in log earnings to have zero sample mean in every year. Accordingly, we estimate the variance of each year’s change in log earnings with that year’s sample mean squared residual. The estimated standard deviation plotted in figure 1 is the square root of the estimated variance. The time axis in the figure labels observations by the second year in the two-year difference; e.g., the observation for 1969-1971 is labeled as 1971. To underscore that the last few observations in the series are only for every other year, we connect those observations with a broken line. The figure also marks the timing and severity of recessions by plotting the annual civilian unemployment rate.

Like many previous studies discussed in section II, figure 1 displays the familiar finding that earnings volatility is strongly countercyclical. We confidently predict that, when additional data become available from the current recession, they will show a particularly large jump in earnings volatility, much as figure 1 shows for the severe recessions of the mid 1970s and the early 1980s.

Like Haider (2001) and Cameron and Tracy (1998), we find that earnings volatility trended upwards during the 1970s. Like those studies and the Congressional Budget Office (2007) study, which began with 1980 data, we see less evidence of increasing volatility during the 1980s or most of the 1990s (apart from temporary bulges during the recessions of the early 1980s and early 1990s). This impression of the 1990s is all the stronger if one discounts the observations for 1990-1992 through 1993-1995, i.e., the observations that come at least partly from the 1993 and 1994 PSID interviews. Kim, Loup, Lupton, and Stafford (2000) explain that the data from those interviews should be viewed cautiously because the continuity of the PSID data in those years was disrupted by a major overhaul of the survey that included, among other things, a switch to

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14 The 95 percent confidence band drawn around the series is based on the textbook result on the asymptotic distribution of the sample mean squared residual under the classical regression assumptions (Schmidt, 1976).
computer-assisted telephone interviewing, a shift from human to automated editing of the
data, and changes in the structure of the income questions.

Finally, like the Congressional Budget Office results for men’s age-adjusted
earnings, our results suggest that men’s earnings volatility started to increase by 2000.
Unlike the CBO study, we track our series beyond 2003, which gives a better sense of
whether the most recent volatility rise is merely a recession effect. That the volatility
measure is still high even as of 2006 is suggestive of a trend.

In figure 2, we check the sensitivity of our results to several variations in the
analysis. First, one of the differences between our figure 1 and the figure on men’s
earnings volatility in Dynan, Elmendorf, and Sichel (2008) is that their earnings change
variable is not adjusted for age. Figure 2 plots a series with no age adjustment (the blue
line connecting the dashed data points) along with our series from figure 1 (shown in
figure 2 as red diamonds) and demonstrates that age adjustment makes virtually no
difference for the estimated trends. .

Second, several previous studies (e.g., Baker and Solon, 2003) have documented
greater year-to-year earnings variation for workers in their twenties and as they approach
retirement age. If the representation of those age groups in the population changed over
time, this could produce the appearance of a trend in earnings volatility even if the life-
cycle profile of earnings volatility did not shift at all. We therefore check what happens
if we restrict our sample’s age range to 30-54 instead of 25-59. As expected, the
resulting purple line connecting the triangular data points in figure 2 is lower, but it
displays a time pattern quite similar to that for the larger sample.

Third, another difference between our main analysis and the earnings analysis by
Dynan et al. is that they use a more comprehensive earnings measure, “total labor
income,” which includes bonuses, overtime, tips, commissions, and the labor parts of
business, farm, market gardening, and roomers/boarders income in addition to wage and
salary income. The difficulty is that the PSID’s treatment of business and farm income in
total labor income has varied over the years, and it is not possible to construct a
consistent series over time. One approach we have tried is to use total labor income
excluding business and farm income. The resulting series is shown in figure 2 as the
black line connecting the rectangular data points. This series starts with the 1975-1977
observation because, prior to 1975, business and farm income were measured in bracketed form. We also have followed Dynan et al.’s approach of using the PSID’s total labor income variable up through 1992, adding in the “labor part of business income” after 1992 (when the PSID stopped counting it in “total labor income”), and excluding all observations with positive farm income. (Unfortunately, this approach remains inconsistent over time because, starting with the 1993 survey’s measurement of 1992 income, the PSID changed the way it calculates the labor part of business income.) The resulting series is shown in figure 2 as the green line connecting the circular data points. The volatility measures for these more comprehensive earnings variables track quite similarly to our series for wage and salary income until the early 1990s, when they start diverging upwards, especially the series that includes business income. It is unclear how to interpret the divergence. On one hand, the pattern with the more comprehensive earnings variables may signify that earnings components besides wage and salary income really did contribute to rising earnings volatility throughout most of the 1990s. On the other hand, the divergence coincides with the timing of the major overhaul of the PSID’s data collection and editing procedures, and might be merely an artifact of the changes in survey procedures. In any case, all the alternative series show rising volatility in the early 2000s, long after the changes in the survey had occurred.

One limitation of all our analyses so far is that the standard deviation is just one arbitrary measure of dispersion in earnings changes. A second limitation is the exclusion of zeros and other extreme earnings observations. One way of addressing the first limitation is to present a more complete picture of changes in the distribution of log earnings changes by plotting various quantiles of the distribution. Returning to the wage-and-salary-income variable used in figure 1, figure 3 displays the 10th, 25th, 50th, 75th, and 90th sample percentiles of the log earnings changes for each year. The 50th percentiles are always close to zero because the preliminary regression adjustments force the sample means to be zero. In figure 3, the cyclical increases in the dispersion of earnings changes in the severe recessions of the mid 1970s and early 1980s are manifested mainly as a lowering of the relative position of the 10th percentile. In contrast, the secular increases in the spread of the distribution during the 1970s and after 1998 are more symmetric.
Figure 3 has the virtue of presenting a more complete picture of shifts in the distribution of earnings changes, but in figure 4 we compress that information into a single summary measure of dispersion, the difference between the 90th and 10th percentiles, which can be taken as an alternative to the standard deviation shown in figure 1. (When we get to adding zeros and other outliers to the sample, the 90-10 difference will have the advantages of being relatively robust to outliers and unaffected by top-coding.) The black line connecting the diamonds in figure 4 corresponds to the 90th and 10th percentiles shown in figure 3. Like the standard deviation shown in figure 1, this 90-10 difference shows rising volatility in the 1970s, followed by less of a trend until a new rise in the early 2000s.

Bringing the zeros into the analysis requires us to stop using logarithms and to measure relative dispersion in earnings changes in another way. We begin by taking two-year differences in the level (not log) of real earnings. We use the CPI-U-RS to put earnings into real terms. Again we account for mean effects of year, age, and cohort by estimating a separate regression in each year of the change in real earnings on a quadratic in age, and then we proceed to study the residualized version of the earnings change. We rescale the residualized real earnings change between years $t-2$ and $t$ into relative terms by dividing it by the simple average of the sample means of real earnings in the two years. Initially using the same sample as before, figure 5 plots the quantiles of this alternative measure of earnings change. A comparison to figure 3 shows that, holding the sample constant, the two alternative measures show qualitatively similar time patterns. The 90-10 difference from figure 5 is plotted in figure 4 as the red line connecting the rectangles. Again, this measure of dispersion rises in the 1970s and then shows no clear trend until rising again in the most recent years.

Next, using the new measure of earnings change, we repeat the entire procedure with an expanded sample that includes zeros and other extreme earnings observations. The new sample contains a total of 56,297 observations over our 31 years of data on two-year differences. The sample size per year averages 1,816 and ranges from a low of 1,230 in 1969-1971 to a high of 2,500 in 2000-2002. Figure 6 plots the quantiles of the measured earnings changes for the expanded sample, and the 90-10 difference is shown in figure 4 as the blue line connecting the triangles. Naturally, with outliers added to the
sample, dispersion is greater than in the previous figures. Again, however, the temporal patterns are greater dispersion in severe recession years and secularly increasing dispersion in the 1970s and after 1998. The most striking difference from the earlier figures is that the post-1998 increase in dispersion is even greater.  

Finally, as a check on our eyeball impressions of our figures, we apply least squares to regressions of the earnings volatility time series plotted in the figures on the unemployment rate and a piecewise linear time trend. In the first column of table 1, the dependent variable is the standard deviation series plotted in figure 1. The other three columns are for the 90-10 differences plotted in figure 4. Using \( Y_t \) to denote each measure of the dispersion of earnings changes between years \( t - 2 \) and \( t \), we estimate the regression of each \( Y_t \) on the civilian unemployment rates in years \( t \) and \( t - 2 \) (to account for business cycle effects) and a spline function in time that allows for distinct time trends in three parts of our sample period: 1969-1971 through 1979-1981, 1979-1981 through 1990-1992, and 1990-1992 through 2004-2006. As expected from our visual impressions of the figures, the coefficient estimates for the unemployment variables are almost always significantly positive, and the estimated time trends are significantly positive in the first and third time periods, but not in the second.

\[ \frac{(x_t - x_{t-2})}{[(x_t + x_{t-2})/2]} \]

where \( x_t \) is real earnings in year \( t \). This measure is particularly sensitive to low earnings observations because it divides the earnings change by the low earner’s own earnings level. We should add that we have found Dynan et al.’s concern about false zeros to be well founded. In the course of this project, we discovered about 60 cases in the early 2000s (mostly in 2002) with zeros reported for wage and salary income despite positive values for bonuses or overtime payments and for hours of work. Tecla Loup of the PSID staff corroborated that these were false zeros, and she generously provided us with corrected positive values. We found that, if we added the new positive observations to the analysis in figure 1, our volatility series hardly changed at all. The patterns in the additional observations differed too little from those in our initial sample to shift the series. In our analysis in figure 6, these cases had been included as zeros. Because these cases constitute a small fraction of the overall sample and because of the robustness of our quantile approach, changing the zeros to the corrected positive values had only moderate impact on the quantiles and did not undo the finding of substantially higher volatility in the 2000s. We have not presented these modified analyses as our main analyses because the corrected values have not been made publicly available, and other researchers therefore would be unable to replicate these analyses.
V. Summary and Discussion

Our reanalysis of the Panel Study of Income Dynamics has found that, apart from business cycle fluctuations, men’s earnings volatility trended upwards during the 1970s, but did not show a clear secular trend after that until climbing again after 1998. These patterns are broadly consistent with those that Cameron and Tracy (1998) found for 1967-1996 in the Current Population Survey and that the Congressional Budget Office (2007) found for 1980-2003 in Social Security administrative data.

We are well aware that our results raise more questions than they answer, and so we conclude with several suggestions for further research. First, we believe the PSID evidence that increasing earnings volatility for men has resumed in recent years is potentially very important, and we think it should be checked with other data. Indeed, a new manuscript by Celik, Juhn, McCue, and Thompson (2009), inspired partly by our work, has replicated our analysis with the longitudinally matched Current Population Survey, the Survey of Income and Program Participation, and the Longitudinal Employment and Household Dynamics data. The results are puzzling. The CPS and SIPP data do not show increased volatility in the 2000s while the LEHD data do (but the LEHD data Celik et al. use go only through 2002). In addition, our own preliminary analysis of the National Longitudinal Survey of Youth shows increased volatility in the 2000s. Obviously, a pressing goal for future research is to ascertain why the PSID, Social Security, LEHD and NLSY data seem to be telling a different story than the CPS and SIPP data.

Second, the growing literature on earnings volatility trends should be connected to the growing literature on trends in job tenure and turnover (see Farber, 2007, and the references therein). Further research along the lines of Stevens (2001) that explores the earnings implications of changing job stability would illuminate both literatures.

Third, results in Congressional Budget Office (2007) and Dynan, Elmendorf, and Sichel (2008) suggest that, at the same time that earnings volatility may have risen for men, it has decreased for women, which is not surprising in light of women’s increasingly stable attachment to the labor market. Future research should combine the patterns by gender into a more complete picture and should give particular attention to the covariation of spouses’ earnings.
Finally, we wish to reemphasize the point we made at the end of section III – that translating measured trends in dispersion of earnings change into conclusions about economic risk will require additional information about whether the observed earnings changes were or were not anticipated and whether the affected individuals were or were not insured against the earnings changes. That information will be crucial for assessing the welfare implications of any trends in earnings variability.
References


Brown, Charles. “Notes on the ‘SEO’ or ‘Census’ Component of the PSID.” 1996 (available at [http://psidonline.isr.umich.edu/Publications/Papers/SEO.pdf](http://psidonline.isr.umich.edu/Publications/Papers/SEO.pdf)).


Table 1. Estimated Coefficients (and Standard Errors) for Regressions of Measures of Dispersion in Earnings Changes, 1969-1971 to 2004-2006

<table>
<thead>
<tr>
<th></th>
<th>(1) Standard Deviation of Change in Log Earnings</th>
<th>(2) 90-10 Difference for Change in Log Earnings</th>
<th>(3) 90-10 Difference for Relative Change in Real Earnings (Zeros and Outliers Excluded)</th>
<th>(4) 90-10 Difference for Relative Change in Real Earnings (Zeros and Outliers Included)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.1681</td>
<td>0.3980</td>
<td>0.3952</td>
<td>0.4715</td>
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<tr>
<td></td>
<td>(0.0333)</td>
<td>(0.0418)</td>
<td>(0.0301)</td>
<td>(0.0523)</td>
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<tr>
<td>Piecewise-linear time trend:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1969-1971 to 1979-1981</td>
<td>0.0060</td>
<td>0.0094</td>
<td>0.0077</td>
<td>0.0092</td>
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<tr>
<td></td>
<td>(0.0027)</td>
<td>(0.0034)</td>
<td>(0.0024)</td>
<td>(0.0042)</td>
</tr>
<tr>
<td>1979-1981 to 1990-1992</td>
<td>0.0020</td>
<td>-0.0013</td>
<td>-0.0023</td>
<td>-0.0024</td>
</tr>
<tr>
<td></td>
<td>(0.0018)</td>
<td>(0.0022)</td>
<td>(0.0016)</td>
<td>(0.0028)</td>
</tr>
<tr>
<td>1990-1992 to 2004-2006</td>
<td>0.0055</td>
<td>0.0124</td>
<td>0.0081</td>
<td>0.0223</td>
</tr>
<tr>
<td></td>
<td>(0.0016)</td>
<td>(0.0020)</td>
<td>(0.0014)</td>
<td>(0.0025)</td>
</tr>
<tr>
<td>Unemployment rates:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year $t$</td>
<td>0.0152</td>
<td>0.0168</td>
<td>0.0153</td>
<td>0.0221</td>
</tr>
<tr>
<td></td>
<td>(0.0044)</td>
<td>(0.0055)</td>
<td>(0.0040)</td>
<td>(0.0070)</td>
</tr>
<tr>
<td>Year $t - 2$</td>
<td>0.0121</td>
<td>0.0129</td>
<td>0.0029</td>
<td>0.0096</td>
</tr>
<tr>
<td></td>
<td>(0.0041)</td>
<td>(0.0052)</td>
<td>(0.0037)</td>
<td>(0.0065)</td>
</tr>
<tr>
<td>Number of time-series observations</td>
<td>31</td>
<td>31</td>
<td>31</td>
<td>31</td>
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<tr>
<td>$\hat{\rho}_1$</td>
<td>0.5492</td>
<td>0.0826</td>
<td>0.0864</td>
<td>-0.1298</td>
</tr>
<tr>
<td>$\hat{\rho}_2$</td>
<td>0.3850</td>
<td>-0.1490</td>
<td>-0.3802</td>
<td>-0.3130</td>
</tr>
</tbody>
</table>

Note: $\hat{\rho}_1$ and $\hat{\rho}_2$, the estimates of the first- and second-order autocorrelations of the error term, are calculated from least squares estimation of autoregressions (without intercepts) of the residuals. The regressions to calculate $\hat{\rho}_1$ stop with the 1994-1996 observation because, after that, the PSID interviews occur every other year.
Figure 1. Standard Deviation of Age-Adjusted Change in Log Earnings, 1969-1971 to 2004-2006
Figure 2. Standard Deviation of Age-Adjusted Change in Log Earnings with Various Earnings Measures
Figure 3. Quantiles of Age-Adjusted Change in Log Earnings, 1969-1971 to 2004-2006
Figure 4. 90-10 Differences in Various Measures of Earnings Change
Figure 5. Quantiles of Relative Age-Adjusted Change in Real Earnings (Zeros and Outliers Excluded), 1969-1971 to 2004-2006
Figure 6. Quantiles of Relative Age-Adjusted Change in Real Earnings (Zeros and Outliers Included), 1969-1971 to 2004-2006