Income Volatility and the PSID:
Past Research and New Results

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The Panel Study of Income Dynamics (PSID) has made more contributions to the study of income volatility than any other data set in the U.S. Its record of research is truly seminal. In this paper we accomplish three tasks. First, we present the reasons that the PSID has made such major contributions to research on the topic. Second, we review the major papers that have used the PSID to study income volatility and we compare their results to those using other data sets. Third, we present new results for male earnings volatility through 2014.

I. Why the PSID Has Been So Valuable for Studying Income Volatility

The reason the PSID was used for the study of income volatility so heavily in the 1970s and 1980s is simply that it was just about the only major panel data set available to study the topic. Today, there are many others, so the reason the PSID has continued to be used lies elsewhere. One reason is its extraordinary length, stretching from 1967 to the present. A second is its following rules, which follow children of the original sample families through adulthood, allowing the data to stay representative of the U.S. population aside from immigration. A third is the comprehensiveness of its variable collection on individual and family social and economic characteristics ((including hours of work). . Fourth, the PSID does have local area identifiers which allow it be used for area-specific analyses and spatial questions.

The data set is not without its weaknesses. Possible response error and attrition may affect the PSID as it might for any survey data set. However, PSID has maintained its cross-sectional validity (Fitzgerald et al., 1998) and even its measures of changes in earnings appear to be little affected by response error (Bound et al., 1994). A significant weakness of the PSID is its sample size, which often does not permit much subgroup analysis or distributional analyses (e.g., by detailed quantile), especially in comparison to administrative data sets. But most administrative data sets also have weaknesses, particularly the lack of other variables that the PSID has, and because administrative data sets also miss many types of earnings and workers that survey data sets have (Abowd and Stinson, 2013).

II. A Review of PSID Research on Income Volatility

While our review is focused on PSID research on income volatility, we wish to emphasize the enormous literature using the PSID to study other forms of economic volatility, including job mobility, migration, employment turnover, and related topics. It has also been used to study mobility, both intragenerational and intergenerational, between quantiles of income and occupational distributions, another area we will not cover. The PSID was used for all these topics in the early years of its existence, and an important collection of those studies published in 1984 (Duncan et al., 1984) was the first to reveal a startling high level of dynamism, mobility, but also instability and turbulence, among American families.

Its contributions to the specific study of income volatility, primarily that of individual earnings rather than family income, have been major. In the Online Appendix, we provide tables of the major studies that have been conducted and we present the findings of each. We first review studies using error components models to decompose income variances into permanent and transitory components. The most well-known early study in this line was that of Lillard and Willis (1978), who used newly developed methods for random effects panel data models to estimate a simple permanent-transitory model. The literature subsequent to that time has grown in volume and sophistication, with ever more refinements in the specification of the dynamic processes generating both permanent and transitory components of earnings. This literature has made major methodological contributions as well, developing methods which have been adopted for us in many other panel data sets.

Next we review studies using the PSID to study calendar time trends in volatility, a literature initiated by Gottschalk and Moffitt (1994). Those authors studied trends in the transitory variance of white men's earnings and found that it rose from the 1970s to the 1980s, and that its rise constituted about half the increase in cross sectional inequality over that period. About a dozen PSID studies followed that article, using different methods and extending the analysis further. Three of these studies examined only trends in "gross" volatility, defined as some measure of the dispersion of $y_{i,t-1}$-y_t, where y_{it} is earnings for individual i at time t. Trends in the dispersion of gross volatility combine trends in the dispersion of both permanent and transitory volatility and hence are not the same as the latter.

These PSID show male earnings volatility to have three phases: a rise in volatility from the 1970s to the mid-1980s, a middle phase from the 1980s to 2000 or the mid-2000s where volatility was either flat or slightly increasing or declining, and a third phase showing a rise in volatility, possibly associated with the Great Recession but sometimes appearing to begin before it. Two studies examined trends in female earnings volatility and found it to decline over the entire period since 1970 and three examined household income volatility, finding it to rise over time.

A number of studies have estimated models—usually only of trends in gross volatility—with the Current Population Survey (CPS), Survey of Income and Program Participation (SIPP), Unemployment Insurance (UI) earnings data, and Social Security (SS) earnings data. Our review shows that matched CPS data reveal the same three-phase trend in male earnings volatility as shown in the PSID. The one SIPP study showed declining volatility from 1984 to 2006, and with magnitudes which seem to exceed those found by PSID studies of the middle period finding slight declines. The one study using UI records found stable male volatility from 1992 to 2008, consistent with PSID studies of the middle period. Among studies using SS data, two only showed volatility combining men and women and are noncomparable to other work. One published study of male gross volatility alone showed a flat trend from 1987 to 2009 although also showing signs of an uptick at the end, from 2006 to 2009, while another showed declines over a longer period.

While many of the studies using data sets other than the PSID find trends consistent in a rough sense with the PSID, there are many differences as well, particularly for the studies using administrative data sets. Differences in composition, such as the inclusion of non-heads in the administrative data sets and their exclusion in the PSID studies, make comparisons difficult. More work resolving the differences is warranted.

III. Some New Results

We provide new PSID results on trends in male earnings gross volatility and transitory variances up through 2014, and using for the latter a new, more flexible model than used in past work. Our data set consists of male heads from 1970 to 2014 30-59 years old who were not full-time students, had positive weeks worked and wage and salary earnings and which excludes nonsample men and all in PSID oversamples. The unbalanced panel has 3,508 men and 36,403 person-year observations. We group the data into age categories 30-39, 40-49, and 50-59 to construct the autocovariance matrix of the data, with typical element equal to the covariance between earnings regression residuals for individuals in age group *a* in year *t* and the residuals for those individuals when they were age *a'* in year *t-(a-a')* and with a 1% top and bottom trim.

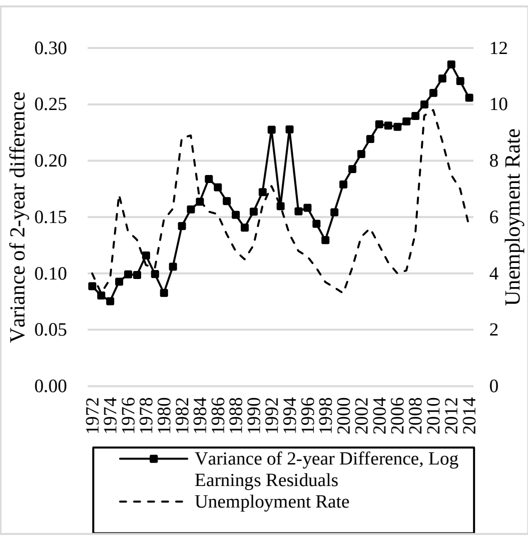

FIGURE 1: Variance of 2-Year Difference in Log Earnings Residuals

Figure 1 shows the trend in gross volatility (defined as the variance of the two-year change in log earnings regression residuals) to have followed the same three-phase pattern found in past work, rising from the 1970s to the mid-1980s, exhibiting a stable trend around significant fluctuations from the mid-1980s to the mid-2000s, and rising thereafter. The unemployment rate is also shown in the graph and shows volatility countercyclical with a slight lag, on average, but this pattern does not hold for all periods.

Error components models have been criticized for being excessively parametric. Our model maintains many of the restrictions in past work but innovates in two respects: it makes a clear identifying assumption for separating permanent from transitory components, and it is nonparametric on the dynamic evolution of the two components, albeit within a traditional linear framework. Our model is:

(1) $y_{iat} = \alpha_t \mu_{ia} + \beta_t \nu_{ia}$

(2) $\mu_{ia} = \mu_{i0} + \sum_{s=1}^{a} \omega_{is}$

(3) $\nu_{ia} = \varepsilon_{ia} + \sum_{s=1}^{a-1} \psi_{a,a-s} \varepsilon_{is}$ for $a \geq 2$

and with $\upsilon_{i1} = \varepsilon_{i1}$. The model retains the linear framework, restricts the permanent and transitory calendar year shifters (α_t and β_t) to be invariant w.r.t. age (but this could be easily relaxed), and we assume, as in past models, that the permanent shocks ω_{ia}, the transitory shocks ε_{ia}, and the initial permanent component μ_{i0} to be independently distributed with each other and over time. But we define a permanent shock, in accordance with the dictionary definition of the word, to be a shock that has a long-lasting effect which does not go away, even partially, implying $\partial\mu_{ia}/\partial\omega_{ia}=1$. The unit root process in (2) is the only function that satisfies this condition. Transitory shocks are identified as those which affect age-specific earnings with a coefficient different than 1. Finally, we allow the variances of ω_{ia} and ε_{ia} to be nonparametric in age and the transitory shock coefficients $\psi_{a,a-s}$ to be nonparametric in age and lag length (*s*). Allowing ω_{ia} to be nonparametric in age nests the heterogeneous growth rate model in the specification. ARMA specifications for the transitory component are clearly nested as well.

The online Appendix gives identification conditions for estimation of the model parameters and the second moments of the unobservables as well as the nonparametric estimation method, which consists of series estimation with a basis function expansion. A generalized cross-validation statistic with a penalty for the number of parameters is used to choose the order of the series. Traditional minimum distance is used for estimation, fitting the second moments implied by the model to the 1,417 unique elements of the age-year autocovariance matrix of the data. The Appendix shows the estimates of all parameters.

Figure 2 shows the estimation results for α_t and β_t, both normalized to 1 in the initial year. Both rose from the 1970s to the 1980s, with the transitory peaking in the mid-1980s and the permanent peaking in the late 1980s. Both fluctuated until the mid-2000s, after which they began to rise, with the trend line emerging close to the Great Recession. By 2014, both had risen by 80 percent, implying equal contributions to long term inequality since 1970.

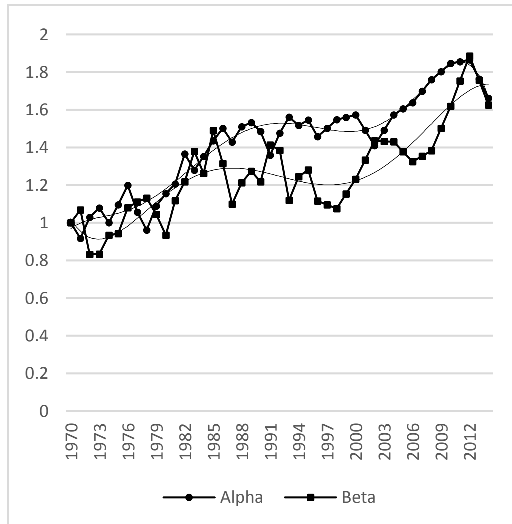

FIGURE 2: Estimates of Alpha and Beta

Figure 3 shows the predicted values of the total variance of male earnings residuals as well as that of the permanent and transitory components for men 40-49 (other ages have different levels but the same trend patterns). The three-phase trend appears here as well. The transitory variance is about two-thirds of the total and has risen much more during the Great Recession than has the permanent variance.

Using the model estimates to decompose the trends in gross volatility shown in Figure 1 into trends in permanent and transitory components shows that those two-year volatility measures are almost entirely the result of changes in the transitory variance, which is not surprising since the permanent variance does not change much over a two-year period.

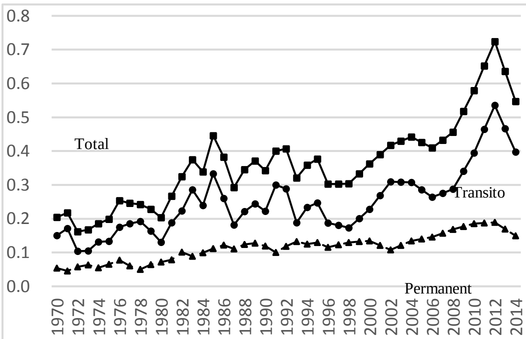

FIGURE 3: Fitted Permanent, Transitory, and Total Variance of Log Earnings Residuals, Age 40-49.

III. Summary

The PSID has made major contributions to the study of income volatility in the U.S. Most PSID studies show growing volatility from the 1970s to the mid-1980s, and a flat or declining trend after that, followed by a resumption of increasing volatility around the time of the Great Recession. New estimates using a more flexible model than used in past work confirms these general results. However, differences remain with findings from other data sets which deserve future attention.

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Online Appendix to

“Income Volatility and the PSID:

Past Research and New Results”

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This paper is an Online Appendix to "Income Volatility and the PSID: Past Research and New Results" (AER, May 2018). It expands on all three sections of the paper: the discussion of the usefulness of the PSID for the study of income volatility, the review of research using the PSID to study income volatility and a comparison with findings from other data sets, and the presentation of a new model of male earnings volatility with new results using PSID data through 2014.

The Michigan Panel Study of Income Dynamics (PSID), as its name implies, was intended from its origins to study the dynamics of income. The study of income volatility with the PSID began very quickly after its initiation in 1968, after only a few waves were available, and has continued since. Defining volatility generally as the degree of change in a variable from one time period to a later one, the PSID has permitted studies of a wide variety of other forms of economic volatility as well as family income, including studies of individual or family earnings, of job mobility and labor market turnover, and of turnover in welfare participation, for example. The studies in these areas have made major contributions to research and policy over the years. In addition, the studies have in many cases provided the initial impetus for research on volatility by researchers using other panel data sets in the U.S. and using panel data in other countries, and its influence consequently goes beyond those studies using the PSID itself.

As we noted in the first paragraph above, this Appendix expands on the three goals of the paper. First, we provide an expanded discussion of the reasons that the PSID has been so valuable for research on economic volatility, and we provide some comparisons with other data sets to emphasize the ways in which the PSID has a comparative advantage. However, over the past two decades other panel data sets have come into use for the study of U.S. economic volatility that were not available in the early years of the PSID, and some of those data sets have advantages in certain dimensions over the PSID. We discuss those disadvantages as well. Second, we expanded on our review of the research on income volatility using the PSID, providing a brief overview of the voluminous literature and then a detailed review of the literature specifically on models of individual earnings and family income volatility. We also compare findings using the PSID specifically on the question of trends in U.S. volatility to findings on trends using other data sets. Third, we expand on our estimates of male earnings volatility, updating prior estimates through 2014. To our knowledge, updates through this year have not appeared in the literature.

I. The Usefulness of the PSID in the Study of Income and Economic Volatility

The structure of the PSID is well known. It began with a sample of approximately 5,000 households in 1968, combining an oversample of low income households from a previous survey combined with a fresh random sample drawn from the U.S. population at that time. Households were interviewed annually thereafter, initially in person and later by telephone, asking a comprehensive set of socioeconomic questions. The low-income oversample was mostly dropped in 1997 and biennial interviewing began in 1998. An important feature of the PSID is its rules for following household members, which require that individuals who leave original PSID households and form new households (“splitoffs”) are retained in the sample and asked approximately the same comprehensive set of socioeconomic questions as the initial households, thereby allowing the PSID to stay broadly representative of the U.S. population, aside from immigration.

While there were few alternative panel data sets in 1968, many more have developed since that time. Survey data have been collected as part of the National Longitudinal Surveys (NLS), which consist of a series of birth cohorts of individuals who are interviewed annually for several years; the Health and Retirement Survey (HRS), a survey of older individuals in the U.S.; and the Survey of Income and Program Participation (SIPP), a set of short panels of no longer than 3 or 4 years whose respondents are interviewed every 4 months and a comprehensive set of socioeconomic data are obtained.[1] While the Current Population Survey (CPS) is primarily a cross-sectional survey, it can be used to construct a set of two year panels by matching families who appear in two surveys a year apart.

In addition to these surveys, the development of panel data from administrative records has increased substantially over the last two decades. Earnings data from the Social Security Administration, panel data on tax records from the Internal Revenue Service, and earnings data from state-level Unemployment Insurance (UI) records have all been used to study earnings volatility. These data are typically restricted in use and require application and licensing procedures for their analysis. In a few special cases, administrative data have been matched to one of the surveys mentioned in the previous paragraph (e.g., HRS, SIPP), but this is still the exception rather than the rule.[2]

<u>Strengths of the PSID</u>. While the panel nature of the PSID per se was its chief advantage relative to the available alternatives in its early years, its relative strength today does not rely on its panel nature per se given the existence of several alternatives. Instead, its strengths lie in the nature of the survey. First and foremost is its long length, with data from 1968 through the current time, covering almost a 50-year age span. Sample members who were

[1] The SIPP has now moved to an annual interviewing frame.
[2] This has become fairly common in Europe.

working adults in 1968 were either dead or retired 50 years later. For those born into PSID families after 1968, a similarly long age span is available. The 50-year period also allows a long period with which to examine business cycles, long term trends, and related calendar-time events. Aside from Social Security administrative earnings data, no other panel has this breadth in life cycle period covered or calendar years covered. The comprehensiveness of the life cycle coverage also makes it advantageous relative to panels like the HRS, which only cover part of the life span (but in much greater detail than the PSID for that part). The long period makes it advantageous for life cycle research relative to short panels like SIPP (although SIPP has advantages, too, as noted below).

The following rules of the PSID also make it advantageous relative to cohort panels like the NLS which are cohort-based. Cohort-based panels necessarily support research only on the cohorts selected for enrollment, and they also make it difficult to separate life cycle effects from calendar time effects. The PSID decision not merely to follow the families in the initial 1968 sample, but also the splitoff families, makes it superior for this purpose.

An important strength of the PSID relative to most administrative data sets is its comprehensive set of questions on variables related to earnings and employment, as well as its collection of information on other family members. Most administrative data sets used for earnings do not have information on hours of work and only sometimes on weeks or quarters of work, making it difficult to separate volatility in the amount of labor supplied and volatility in the earnings per unit of labor, an important distinction. While many administrative data sets have information on industry of work, few have information on occupation, while the PSID has both. Administrative data also rarely have information on job search and unemployment (UI data are a partial exception), which are often needed to estimate models of volatility that involve movements in and out of the labor force as well as in and out of employment.

The family context is also important, for it has been a long-standing finding of research on labor force and employment decisions that those decisions are closely intertwined within the family. Spousal decisions on whether and how much to work, and at what level of potential earnings, are affected by the other spouse's decisions and outcomes. A common hypothesis, for example, is that the volatilities of spouses are negatively correlated, with one of them increasing his or her earnings when the earnings of the other spouse declines. This implies that family earnings may be less volatile than the earnings of either spouse taken individually. Social Security and UI earnings data, because they are not easily linked within families, are not as well suited for these questions. Tax data do have some family information, although there are coverage differences with survey data. The PSID also has information on total earnings of others in the family who are not the head or spouse, even if not for those individuals individually.

Information on family composition permits controls for the presence and numbers of children, which many administrative data sets cannot do. Data collected on children in the PSID also allow the study of the effect of volatility on child outcomes, a research topic pursued more in sociology and child development than in economics (see Hill et al., 2013 for a review). The presence, number, and ages of children may also be determinants of volatility, especially for parents who are their caregivers. The availability of information on the presence or absence of a spouse or cohabiting partner permits the PSID to be used to study volatility among single mothers, a large and typically disadvantaged subgroup in the U.S. which is known to have high economic volatility.

Finally, the availability of state and county identifiers for PSID families permits geographic-level research. While the county level data are restricted use and sample sizes for individual areas are usually small, models that pool areas and use covariates measuring area-level characteristics can be estimated with the PSID. Many administrative and survey data sets do not have geographic level data beyond the state level. If they do have geographic data it is not as detailed as the PSID restricted use data.

Weaknesses of the PSID for economic volatility research. While the PSID has the major strengths just noted, it has some weaknesses and is not as strong as some other data sets in certain dimensions. One issue often noted in comparing any survey like the PSID to administrative data is that response error and attrition may affect PSID estimates relative to those in administrative data. In principle, this issue can be examined by comparing the PSID to administrative data and, if the latter are taken as truth, determining whether volatility patterns in the PSID match up to those in administrative data. This exercise is not completely straightforward because most administrative data sets also have error, and most exact matches between survey and administrative data sets find differences in both directions—that is, survey reports often have jobs and earnings reports that are missing from the administrative data as well as the other way around. In many cases, this seems to be because the administrative data are in error and do not, for a variety of reasons, pick up jobs and earnings that survey respondents report (Juhn and McCue, 2010; Abraham et al., 2013; Abowd and Stinson 2013; see also Abowd et al. (2018) for a discussion of fraudulent Social Security numbers). Relatedly, many administrative data sets (e.g., those from tax records) miss large fractions of the population (e.g., those who do not file taxes). Nevertheless, in the next section, we will review whether volatility as reported in the PSID appears to be the same or similar as in administrative data sets.

There have been a number of studies comparing cross-sectional distributions of earnings in the PSID to those in the CPS (Becketti et al., 1988; Fitzgerald, Gottschalk and Moffitt, 1998; Gouskova, Andreski and Schoeni, 2010). As a general rule, earnings data in the PSID line up reasonably well with the CPS, at least for all percentiles except those in the tails, where small sample sizes do not allow detailed comparisons. In addition, the PSID appears to have higher mean levels of earnings reports than the CPS. However, for the purpose of volatility, comparisons cannot be easily made with the CPS because it is primarily a cross-sectional data set.

Comparisons of the PSID volatility with other surveys also does not reveal which is the truth. One study which attempted to do so compared presumably accurate payroll records from a private company in two successive years to earnings reports in a PSID-worded survey given to the same workers (Bound et al., 1994). The study found a reliability ratio—the ratio of the variance of the true change in earnings in the payroll records to the variance of the change in earnings from the survey—was .75, a relatively high number. Pischke (1995) also showed that measurement error in the PSID has little effect on earnings covariances, and Gottschalk and Huynh (2010) show that this is a result of the non-classical structure of measurement error in earnings found in many surveys.[3] However, Fitzgerald et al. (1998) found that attrition rates seemed to be positively correlated with past income volatility, which might result in PSID having families who are more stable than the population at large.

[3]In fact, Gottschalk and Huynh find that the cross-sectional variance of true earnings is greater, rather than smaller, than that variance in survey data, contrary to expectations (this is because measurement error is negatively correlated with true earnings—high earners underreport and low earners overreport). Nevertheless, we do expect some measurement error in the PSID data and expect this to affect our estimates. However, since our focus is on how the various variance estimates have changed over time, this should be a problem for our work only if PSID measurement error has changed.

A variety of other aspects of the PSID make it somewhat weaker than other data sets for the study of volatility. One is that the PSID went to biennial interviewing after 1996 which prevents the study of volatility at the annual level, which most other data sets have. Some, like the SIPP, have historically permitted the study at the subannual level. While most surveys, including the PSID, attempt some retrospective reporting, most analysts do not believe that such reporting has a high degree of accuracy for earnings. Another aspect of the PSID which puts it at a disadvantage relative to some other panels is its lack of detailed earnings information for individuals in the household other than the head or spouse. Some other surveys obtain more detail on those types of individuals, and most administrative data sets (UI wage records, Social Security earnings data) have information on all working individuals, regardless of position within the family, although those data sets also have the disadvantage mentioned above that they usually cannot identify headship or spouse relations and hence cannot separately identify individuals who are not heads or spouses. This also makes comparisons of volatility between the PSID and those data sets more difficult (see below). A third weakness of the PSID is its relative lack of coverage of those who have immigrated to the U.S. since 1968, which constitutes more than 10 percent of the U.S. population. While attempts to incorporate that population into the PSID have been attempted, it is fair to say that these attempts have not been successful.

Finally, the PSID has smaller sample sizes in general than many other data sets. To take one example, examining of earnings volatility broken out by gender and by education level for prime-age workers runs into small samples if education has more than two categories. The sample size is also limiting for the study of volatility if percentile points of volatility are used, since percentile points in the tails typically have insufficient sizes for reliable calculation. Administrative data sets generally have the strength of much larger sample sizes and permit greater disaggregation as well, at least using the variables they have available. Data sets like the SIPP generally have somewhat larger sample sizes, and NLSY cohorts and the HRS have larger samples for the specific age and cohort groups they examine.

II. A Review of PSID Research on Income Volatility

As noted in the Introduction, economic volatility is, at the most general level, the measurement of the degree of change in an economic variability from one-time period to the next. We will use very specific definitions of volatility below when we review the literature in earnings and income volatility, but we begin by mentioning briefly some PSID studies of volatility in a broader sense. For example, the PSID was used for the study of economic mobility--most commonly studied by examining transition rates from one quantile of a distribution to other quantiles of the distribution between two time periods—in the early year of the Panel, with Smith and Morgan (1970) possibly representing the earliest. Smith and Morgan used the first two waves of the PSID, 1967-1968 to study family income mobility across deciles of the distribution. Their early study showed that, while remaining within the same decile was the most common transition rate, moving to a different decile was also very common. They found that the most important determinant of mobility was changes in male earnings within the family. They also found that, despite considerable mobility across deciles, very few of the movements moved families over the poverty line or on or off welfare, so that poverty and welfare transitions were much less common. These findings, familiar from many studies since that time, illustrate the contribution of the PSID from the early days of the literature. The PSID has been used heavily in the succeeding years for the study of mobility.[4]

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[4] The literature here is obviously massive. For a recent review, see Jäntti and Jenkins (2013). An important study which we also do not review here, although it focused mostly (but not exclusively) on mobility trends, is

A landmark 1984 volume edited by Duncan (1984) compiled a broad range of findings related to economic dynamics over the approximately first ten years of the PSID by a number of authors, changing the conclusions from some of the early analyses.[5] For example, the volume found a high degree of economic mobility, with less than half of families staying in the same relative position from one year to the next, combined with many large movements up and down. Another dramatic finding from this volume was that much of the dynamics of family income mobility was actually associated with changes in family composition. The findings on poverty mobility also changed, with the longer-term data showing that only one half of those in poverty in one year were also in poverty the next year, implying a very high level of poverty mobility. Mobility on and off welfare was also found to be very high many years later by Bane and Ellwood (1996) who, using even more years of PSID data, pointed out that, while the majority of families had only short periods of time on welfare, a small fraction had very long durations and spent many years on welfare, and that these two patterns were not inconsistent with one another. The Duncan volume also examined the dynamics of labor market status, hours of work, and differences in various aspects of dynamics by race and gender. Taken together, the findings from the PSID reported in the Duncan volume revealed a startling high level of dynamism and mobility, but also instability and turbulence, in the lives of American families.[6] This was a completely new picture of American society which was made possible only because of the PSID.[7]

Kopczuk et al. (2010).

[5] The volume drew heavily from a sequence of 10 unpublished volumes analyzing the early years of data from the PSID.

[6] We attach no normative values to these different concepts because their implications for well-being depend upon whether they are permanent or transitory as well as how well they can be smoothed.

[7] There is not space here to also discuss the methodological contributions of these studies to the study of dynamics and mobility of all kinds, as researchers began to confront the challenges posed by dealing with long panels like the PSID. Some illustrations of methodological advances with the PSID specifically on the earnings dynamics will be given below.

Studies of Earnings and Income Volatility. One of the many literatures on economic dynamics to which the PSID has made particularly strong contributions has been the literature on earnings volatility in the U.S. and how it has changed over time. This literature, primarily located within the discipline of economics, began in the discipline in the late 1950s, 1960s, and early 1970s with the development of econometric methods for the analysis of panel data. Much of the econometric work at that time developed so-called "error components" models, the simplest version of which assumed that each cross-sectional unit had an unobserved, time-invariant component in the error term along with a random term that varied independently across individuals and over time. This model was attractive because it corresponded to the theoretical model of permanent and transitory effects developed in the late 1940s and early 1950s in macroeconomics by Milton Friedman (for example, Friedman, 1957). In this structure, the variance of the transitory component is the measure of volatility.

Table 1 lists several of the leading papers in this literature using the PSID, running from papers in 1972 to papers in 2017.[8] An early paper by Benus and Morgan (1972), using the first four waves of the PSID, was the first to decompose earnings of the family head into several components in a simple version of an error components model. The first component was just average earnings over the four years, called the "permanent" component; the second was the trend in earnings over the years; and the third was the instability, or volatility, of earnings experienced by individuals around their trend. The authors found a pattern that has held up ever since. Heads with higher permanent earnings have both higher trends and lower instability. Benus (1974) and Mirer (1974) followed up with work that more formally calculated earnings

[8] In this Table and in Tables 2 and 3, we list only papers that have appeared in published journals or books.

instability as the variance of regression residuals around individual-specific means or trends, and analyzed the correlates of that instability.

The literature took a more technical and econometric turn in 1978 with a well-known paper by Lillard and Willis (1978), which applied the more formal methods and models that had then recently emerged from the econometrics literature on the estimation of error components models with panel data. The authors used PSID male earnings data from 1967 through 1973 to estimate log earnings as a function of observed covariates and an error term which had a time invariant permanent component and an AR(1) transitory component. About 73 percent of the residual earnings variance was a result of the permanent component and the AR(1) correlation coefficient was high. They used their estimates to analyze the dynamics of movements into and out of poverty, finding a high degree of mobility and that the probability of still being in poverty in 1973 conditional on having been in poverty in 1967 was quite low. Several important papers followed, including an analysis by MaCurdy (1982), using 1967-1976 PSID data on male earnings, but with a richer specification of the serial correlation of the transitory component. MaCurdy found that a MA specification fit better than an AR specification for the dynamics, implying much shorter lags than found by Lillard and Willis, with consequent lower dynamics and turnover. Hall and Mishkin (1982) argued more strongly for the presence of a unit root in the permanent component, implying an increasing variance of earnings over the life cycle, a feature subject to much reanalysis in the later literature. Abowd and Card (1989) and Carroll (1992) also found evidence for a unit root in male earnings and for a low-order transitory process. Carroll also emphasized the relative importance of permanent and transitory components, finding them to be approximately equal in variance.

The literature has since progressed significantly in various directions. Baker (1997), following an earlier suggestion by Hause (1980), argued in favor of what is called a heterogeneous growth component in earnings, which implies that different individuals not only have different average earnings over their lifetimes but also different trends (the early work by Benus and Morgan noted above found something similar). Geweke and Keane (2000) focused instead on the relative contributions of the permanent and transitory components to the distribution of lifetime earnings as opposed to annual earnings, finding that the transitory component was a greater contributor to the latter but the permanent component was the main contributor to the former. Meghir and Pistaferri (2004) proposed a different model of the transitory variance, allowing that variance to shift randomly over time, while Guvenen (2009) returned to the heterogeneous growth model of Baker, providing new evidence for its support. Bonhomme and Robin (2010) developed new methods for estimating the entire distribution of permanent and transitory components, finding them to be non-normal and to have fat tails, while Browning et al. (2010) focused on expanding the number of heterogeneous components in the error components model.

Low et al. (2010) attempted to incorporate job mobility into a model of earnings mobility, an important issue because most of the prior literature had examined only individuals with positive annual earnings, thereby ignoring mobility into and out of annual employment; and the literature mostly had not attempted to decompose annual earnings instability into within-year instability in job mobility and instability in wage rates on the job.[9] Among many other findings, the authors find that the variance of the permanent shock is lower when job mobility is

[9] There is an enormous literature on job mobility that is connected, but somewhat separate, from the earnings volatility literature we review here. But the PSID has been a major contributor to that literature as well. See the volume by Neumark (2000) which contains several studies using the PSID, Stevens (2001) for another example, the recent paper by Altonji et al. (2013) for an econometric treatment of job mobility with the PSID.

ignored.[10] In another paper, Hryshko (2012) argues that the unit root process in earnings does, in fact, fit the data better than the heterogeneous growth process analyzed by earlier authors. Arellano et al. (2017) allow a more flexible specification of the persistence of shocks to earnings, allowing those shocks to have a different level of persistence for workers at different points in the earnings distribution. They find strong persistence of shocks both among high-earnings individuals who experience positive shocks and low-earnings individuals who experience negative shocks.

Calendar Time Trends. The sampling design and long length of the PSID has also permitted a large number of studies of whether the structure of earnings volatility has changed over time in the U.S. The majority of these studies have followed the lead of the literature just discussed by estimating separate permanent and transitory components of earnings and determining whether either or both have shifted over time. The studies are listed in Table 2.

The first paper in this literature was that of Gottschalk and Moffitt (1994), who noted that the increase in U.S. cross-sectional inequality which had recently appeared had to be accompanied by an increase in the permanent variance, the transitory variance, or both. They used the PSID to ask this question of white male heads from 1969 to 1987 and found that both the permanent and transitory variance had grown over the period and that they had experienced about equal growth. Therefore, half of the increase in cross-sectional inequality could be attributed to an increase in volatility. A 1995 paper by the same authors (Moffitt and Gottschalk, 1995), using a more formal error components model yielded the same result, a finding reported again by Gittleman and Joyce (1999). The literature evolved by adding additional years to the

[10] See also Liu (forthcoming), who finds that individuals can partly insure themselves against firm-specific shocks by moving to a different firm, implying that the variance of shocks is larger than what is seen in realized earnings after mobility.

PSID and estimating different models for the decomposition into permanent and transitory effects.

Haider (2001) used a slightly different model that also showed increases in the variances of both components but a slowdown in transitory growth after 1982, while Hyslop (2001) estimated a simpler error components model of husband and wife earnings and found that both husband and wife transitory variances rose from 1979 to 1985. Moffitt and Gottschalk (2002) extended the data frame through 1996 and also found a slowdown in the growth of volatility but beginning at a later date than Haider had found. Keys (2008), using data through 2000, also found a slowdown in male transitory variance growth beginning around 1990. Keys was also the first to examine female earnings and total family income, finding much smaller increases in volatility for women but much larger increases in total family volatility, compared to that for men. Gottschalk and Moffitt (2009) used data through 2004 and also found that transitory variance growth had ceased in the late 1980s but detected a possible reemergence of growth in the late 1990s. Heathcote et al. (2010) found general increases in both permanent and transitory variances but pooled over men and women, making the results difficult to compare to other studies in the literature. Moffitt and Gottschalk (2012), using formal error components model methods on data through 2004, found once again that the transitory variance earnings for men had stopped growing after the late 1980s, and that their earlier suggestion of a reemergence of growth in the late 1990s had turned out to be only a business cycle effect.

Jensen and Shore (2015) were the first to attempt to identify and estimate heterogeneity across individuals in the growth of male earnings volatility, finding that different men have different levels of volatility and that almost all of the growth in volatility had occurred among men who had high long-run levels of volatility in the first place.

Other studies related to time trends in earnings volatility A small number of studies have not attempted to decompose earnings changes into permanent and transitory components. Instead, they simply estimate the variance or other measures of dispersion of the change in earnings from one period to the next. The results of these studies are noncomparable to those just reviewed because the variance of changes in earnings can arise from either a change in permanent earnings dispersion or transitory earnings dispersion. These studies are therefore labeled as studying "gross" volatility in Table 2 and must be interpreted as estimating a sum of changes in permanent and transitory variances.

In this category are studies by Dynarski and Gruber (1997), Shin and Solon (2011), and Dynan et al. (2012). Dynarski and Gruber examined the variances of residuals in a first-differenced male earnings regression and found those variances to have risen steadily from 1970 to 1991, although with a strong cyclical component visible as well. Shin and Solon found the variance of 2-year changes in male earnings to have risen from 1970 through the mid-1980s, to have declined after that until about 1997, and to have risen from 1997 to 2004. Dynan et al. found the variance of male earnings changes also to have risen through 1985, but to have fluctuated after that around a slowly rising trend through 2008.[11] Dynan et al. also examined female earnings gross volatility through 2008, finding it to have actually declined over the period, especially in the earlier years. The authors found that combined head and spouse earnings gross volatility rose on net, but at a slower rate than for male head earnings alone. Finally, the study examined gross volatility trends for household income, finding a significant upward trend over the entire 1970-2008 period but rising at different rates in different periods.

[11] Dynan et al. included observations with zero earnings at one of the two periods of the 2-year change. Shin and Solon (2011) argue that Dynan et al.'s turning points were affected by the inclusion of labor income and farm income in addition to wage and salary income.

Earnings volatility in data sets other than the PSID. Earnings volatility has also been estimated in a number of other data sets, some also household surveys but some instead drawn from administrative records. Table 3 lists the major studies that focused on calendar time trends in volatility.[12] Interestingly, most of the studies using data sets other than the PSID have focused on trends in gross volatility rather than making an attempt to do a decomposition into permanent and transitory components. This may be partly because an important initial question is whether even trends in gross volatility in other data sets match those in the PSID. For this reason, the studies examining gross volatility are listed first in the Table 3.

Two studies examined trends in gross volatility in the SIPP (Bania and Leete, 2009; Celik et al., 2012). Bania-Leete is somewhat noncomparable to other work because the authors calculated short-term monthly volatility within a calendar year, which may follow a different pattern than year-to-year volatility. In any case, the authors found that gross volatility of household income by this measure rose over the 1990s. This is consistent with the one PSID study that examined gross volatility of household income (Dynan et al., 2012). Celik et al. examine the more conventional year-to-year volatility of male earnings with the SIPP starting in 1984, finding that it declined from that year through 2006, although experiencing strong business cycle variation around the trend. This finding is inconsistent with the PSID study of Dynarski and Gruber (1997) and somewhat inconsistent with the PSID study of Dynan et al. (2012) who found that, after the mid-1980s, male volatility of biannual earnings rose slowly, around periods of decline, through 2008. But it is a bit more consistent with the PSID study of Shin and Solon (2011), who found that male gross volatility fell after the mid-1980s, at least through 1997.[13]

[12] As noted previously, only studies that have been published in journal or book form are listed. Also, almost all of this literature has focused on calendar time trends, so we omit the few studies that did not focus on that issue. We also only review U.S. studies, since our goal is to compare trends to those in the PSID.

[13] This may be the place to note again that attrition bias in the PSID could affect its findings and explain some of

Three studies examined matched year-to-year CPS records to obtain a measure of one-year-apart gross volatility, which are not strictly comparable to the PSID measures of gross volatility two years apart. Matched CPS files face a well-known problem that the CPS returns to housing units, not families or individuals, and hence only some families can be matched, which is likely to lead to an understatement of volatility. Ziliak et al. (2011) found that male earnings gross volatility rose sharply from the early 1970s to the mid-1980s, followed by a decline and a rise which left it at its mid-1980s level by the last year of the analysis, 2009, not inconsistent with the PSID. The authors also examined female earnings volatility and found it to decline over the entire period from the 1970s to 2009. This is consistent with the PSID study of Dynan et al. (2012). Celik et al. (2012) who also examined the CPS and found male earnings gross volatility to have risen strongly from the 1970s through the early 1980s, followed by a slow decline through 2006, followed by a rise through 2009. While the first period is consistent with the SIPP, the PSID, and the Ziliak et al. CPS findings, this finding of Celik et al. for the later periods is not consistent with the CPS findings of Ziliak et al. nor with the studies of Dynarski-Gruber or, to an extent, Dynan et al. for the PSID, all of whom found a stable or rising trend after the 1980s. Finally, Hardy and Ziliak (2014) focused on gross volatility in household income using the CPS, finding it to have risen strongly from 1980 to 2009.

Three studies of gross volatility used Social Security earnings data, and of these DeBacker et al. (2013) used data matched with IRS 1040 returns and hence only for the taxpaying population. DeBacker et al. saw no long-term trend in gross male earnings volatility from 1987 to 2009, although there were significant short-term trends up and down and an upturn

the differences here. However, the main concern with PSID attrition is that those individuals with high levels of volatility are more likely to attrite (Fitzgerald et al., 2008). This would tend to bias the time trend of volatility in the PSID downwards.

at the end of their data, from 2006 to 2009. Sabelhaus and Song (2010) find that gross earnings volatility fell steadily from 1980 to 2005 but the authors combined men with women. Given the survey evidence of a decline in volatility among the latter, it is difficult to compare these authors' results to those from the surveys examining only men. Indeed, Dynan et al. found that when men and women were combined, the net trend in the PSID gross volatility is negative. Also, as noted in the previous section, Social Security earnings data include non-heads, who are explicitly excluded from the PSID studies and from many of the SIPP and CPS studies. If trends in volatility among non-heads differ from those of heads, Social Security earnings data will not necessarily show the same trends as the survey data sets. Dahl et al. (2011) also pooled men and women, using Social Security earnings data from 1984 to 2005, finding a decline in gross volatility over the period (albeit at different rates), consistent with Sabelhaus and Song who also combined men and women[14]

Celik et al. (2012), alone among the studies, also examined male gross earnings volatility with UI wage records in the LEHD data set. The authors only had 12 states with complete data over the 1992-2008 period, and found no trend in volatility over the time frame. This also is not inconsistent with the several survey data sets that also found that the rise in male earnings volatility either stopped completely or grew or declined slowly in the middle period of the three periods demarcated above.[15]

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[14] In unpublished work, however, Dahl et al. (2008) found that male gross volatility in SSA data declined after 1984 but was essentially flat from 1984-2005 period when the sample was restricted to men employed at both periods. We also note that Guvenen et al. (2014), in a study focused on cyclical effects on volatility rather than trends, found a small trend decline in SSA male gross earnings volatility (Figure 5). Carr and Weimers (2018), using Social Security earnings data matched to the SIPP, found a rise in male gross volatility from 1978 to 1983, a decline from 1983 to either the late 1990s or mid-2000s (depending on a judgement of what is cycle and what is trend), and a rise in volatility thereafter. Thus, the various studies of male gross earnings volatility using Social Security data, including these three and those of DeBacker and that of Hryshko et al. noted below, are not consistent with one another.

[15] However, see Abowd et al. (2018) for a discussion of possible errors in the low-wage UI data.

Three non-PSID studies have attempted a decomposition of volatility into permanent and transitory components. Sabelhaus and Song (2010) used an approximate method for decomposition based on the work of Carroll (1992) listed in Table 1.[16] The authors found that the decline in gross volatility was shared by both permanent and transitory component declines. DeBacker et al. (2013) used W-2 data on male earnings matched to IRS 1040 records from 1987 to 2009, finding that the variance of the transitory component was stable over this period, which is consistent with several of the survey data set findings for the middle period. While it is inconsistent with the trends found for the two Social Security earnings studies just referenced, the fact that those two studies combined men and women and included non-heads make the results noncomparable.[17] DeBacker et al. also estimated the transitory variance of household income, finding it to have risen slightly. Finally, Hryshko et al. (2017) used Social Security earnings data matched to SIPP records with a focus on the differences in transitory variance levels and trends for husbands and wives, and for their joint earnings. The authors find that the male transitory variance fell from 1980 to 2000 but rose thereafter and that the variance for the couples' combined earnings fell over the entire period. The former finding is consistent with much of the rest of the literature, albeit less often for the period after 2000. Volatility among couples' combined earnings has been little examined in the literature. Dynan et al. (2012) also examined this earnings concept with the PSID, albeit only for gross volatility, and also found a decline after the late 1980s.

[16] See also Carroll and Samwick (1997).

[17] Another issue with the DeBacker et al. study is that the authors did not estimate a permanent-transitory model but rather a persistent-transitory model, allowing an autoregressive process to be located in the permanent rather than the transitory component. This is likely to yield different results than a model which restricts the permanent component to have a unit root and puts all autoregressive processes into the transitory component.

Summing up, the PSID studies of trends in male earnings volatility are consistent with a three-phase trend. In the first phase, virtually all show an increase, whether in gross volatility or in the transitory variance, from the 1970s to the mid-1980s, although the exact year of the turning point differs somewhat across studies. However, the PSID studies differ for periods in a second phase after the mid-1980s, with some finding a slowly rising trend, others showing a flat trend, and others showing a declining trend. But the trends in either direction are not large in magnitude, and it would not be surprising if differences in samples and volatility measures accounted for these differences. In a third phase, most PSID studies also show some increase in male earnings volatility in later years but with, again, differences in the turning points, with some showing the rise to have begun in the late 1990s while others show it to have begun later, sometimes close to the Great Recession.

Comparing these findings to those using other data sets, the PSID is consistent with trends in the CPS, where studies using gross volatility measures for men also show the three-phase trend of rises from the 1970s to the 1980s, followed by a flat or declining trend through sometime in the 2000s, and with one study showing an increase starting in 2006. The SIPP, however, shows an increase in the 1990s to 2000s in intrayear volatility but a decline in year-to-year volatility from 1984 to 2006. Published studies using SSA male earnings data which focus on long-term trends are sometimes consistent with the survey findings and sometimes not. Most consistent is the work of DeBacker et al., who find no trend in gross volatility for men from 1987-2009 but a small rise from 2006 to 2008, consistent with the PSID and the CPS. One study using SSA earnings data on married men found declines then increases in the transitory variance from 1980 to 2000, but ending in that final year slightly above what it was in 1980

(Hryshko et al., 2017).[18] The decline in the early 1980s is inconsistent with the PSID-CPS trend, but the small net increase from the mid-1980s to 2000 is consistent with them.

The volatility of female earnings has only been examined with the PSID and the CPS, both finding it to have declined over the periods examined, starting as early as 1967 and running through as late as 2009.[19] Household income volatility has been examined in only a few studies, mostly using the PSID or the CPS, where volatility has been found to exhibit a much smaller rise. Other data sets sometimes show a rise as well, but smaller in magnitude.

III. Some New Results on Trends in Male Earnings Volatility

The work examining trends in earnings volatility with the PSID reported in the previous section only used data through 2009. Data through 2014 are now available, so we provide new results through that year. The 2009-2014 period is particularly interesting because it encompasses the Great Recession. For our new results, we focus solely on male earnings, which has been the focus of the majority of the literature to date and which can be analyzed without special attention to selectivity of employment. We provide measures both of gross volatility and estimates of an error components model which allows us to decompose trends in gross volatility into trends in permanent and transitory volatility.

We use the data from interview year 1971 through interview year 2015.[20] Earnings are collected for the previous year, so our data cover the calendar years 1970 to 2014. The PSID skipped interviews every other year starting in interview year 1998, so our last observations are

[18] That study only included married men. In addition, it found an uptick in volatility toward the end of the period, just before 2009, consistent with the study by Debacker et al. (2013).
[19] Hyslop (2001) is an exception.
[20] We do not use earnings reported in 1969 or 1970 since wage and salary earnings, which is what we use, are reported only in bracketed form in those years.

for earnings years 1996, 1998, and so on, every other year through 2014. The sample is restricted to male heads of households. Only heads are included because the PSID earnings questions we use are only asked of heads of household. We take any year in which these male heads were between the ages of 30 and 59, not a student, and had positive annual wage and salary income and positive annual weeks of work. We include men in every year in which they appear in the data and satisfy these requirements. We therefore work with an unbalanced sample because a balanced sample would be greatly reduced in size because of aging into and out of the sample in different years, attrition, and movements in and out of employment. Fitzgerald et al. (1998) have found that attrition in the PSID has had little effect on its cross-sectional representativeness, although less is known about the effect of attrition on autocovariances. We exclude men in all PSID oversamples (SEO, Latino) and we exclude nonsample men. All earnings are put into 1996 CPI-U-RS dollars. The resulting data set has 3,508 men and 36,403 person-year observations, for an average of 10.4 year-observations per person. Means of the key variables are shown in Appendix Table 1.

As is common in the literature, we work with residuals from regressions of log earnings on education, a polynomial in age, and interactions between age and education variables, all estimated separately by calendar year (however, we will show gross volatility trends for log earnings itself as well). We use these residuals to form a variance-autocovariance matrix indexed by year, age, and lag length. A typical element of the matrix consists of the covariance between residual log earnings of men at ages a and a' between years t and t'. Because of sample size limitations, however, we cannot construct such covariances by single years of age. Instead, we group the observations into three age groups--30-39, 40-49, and 50-59--and then construct the variances for each age group in each year, as well as the autocovariances for each group at all possible lags back to 1970 or age 20, whichever comes first. We then compute the covariance between the residual log earnings of the group in the given year and each lagged year, using the individuals who are in common in the two years (when constructing these covariances, we trim the top and bottom one percent of the residuals within age group-year cells to eliminate outliers and top-coded observations[21]). The resulting autocovariance matrix represents every individual variance and covariance between every pair of years only once, and stratifies by age so that life cycle changes in the variances of permanent and transitory earnings can be estimated. The matrix has 1,417 unique elements.

Figure 1 shows the variance of 2-year differences in the residuals from the log earnings regression, the usual measure of gross volatility. Gross volatility rose from the 1970s to the mid-1980s and then exhibited no trend (albeit around significant instability) until around 2000, when it resumed its rise. Our results through 2014 show that gross volatility rose sharply during the Great Recession. As shown by the unemployment rate (also in the figure), volatility is correlated with the unemployment rate but with a slight lag. Our findings are consistent with Dynarski and Gruber (1997), who found rising (on average) gross volatility from 1970 to 1991, and with Shin and Solon (2011)'s results through 2005, although those authors found more of a decline in the middle period than a stable and flat trend. Our results for the early and late periods are similar to those of Dynan et al. (2012) although those authors found a slow rise in the middle period. The large number of extreme fluctuations in the middle period in our data may be responsible for these other authors' finding of a slight decline or rise.

[21]If top-coding were the only motivation for trimming, a preferable procedure would be to top-trim the earnings variable directly rather than the residuals. However, our motivation is more general, to avoid distortion of log variances from outliers. In prior work (Moffitt and Gottschalk, 2002), we tested trimming on the residuals versus trimming on earnings itself, and found no qualitative difference in the results.

Figure 2 shows trends in the percentile points of the distribution of the 2-year change, showing that the increasing volatility reflects a widening out at all percentile points but with the largest widening occurring at the top and bottom of the change distribution. Figure 3 shows the variance of 2-year changes of log earnings itself, not of residuals from a regression. The trend pattern and, in particular, the existence of three approximate periods of rise, then flat trend, then rise, is the same as for the residuals.

To decompose gross volatility into its permanent and transitory components, we adopt an error components model similar to those used in the past literature but with some of the more restrictive features of those models eliminated. Error components models have been criticized for being excessively parametric, so, while we maintain many of the restrictions in past work, we also reduce some of their parametric restrictions in two ways. First, we make a clear, non-arbitrary identification assumption to separate permanent from transitory components and, second, we are nonparametric for the evolution of their variances. Letting y_{iat} be the log earnings residual for individual *i* at age a in year *t*, our model is

$$y_{iat} = \alpha_t \mu_{ia} + \beta_t \upsilon_{ia} \tag{1}$$

where μ_{ia} is the permanent component for individual *i* at age a, ν_{ia} is the transitory component for individual *i* at age a, and α_t and β_t are calendar time shifters for the two components. We shall maintain the usual assumption in these models that the permanent and transitory components are additive and independently distributed, an assumption that can be partially relaxed. We also adopt the common specification that calendar effects do not vary with age, although this could be relaxed by allowing the calendar time shifts to vary with age (but we will not do that here).

The first question is how permanent and transitory components can be separately identified if both are allowed to be a function of age. We assume the dictionary definition of a permanent component, which is a component which has a literally permanent, lasting, and indefinite effect and does not fade away even partially. The transitory component can then be identified as consisting of any residual component whose impact on y does change over time. To make this definition operational, we will assume that the permanent component at the start of the life cycle is μ_0 and that an individual experiences independently distributed permanent shocks ω_1, ω_2,…,ω_T through the end of life at time *T*. We let the permanent component at age *a* be some function of these shocks: $\mu_{ia} = f(\omega_{i1}, \omega_{i2}, \dots, \omega_{ia}, \mu_0)$. We define a permanent shock ω_{is} to be one for which $\partial\mu_{ia}/\partial\omega_{ia} = 1$ and we assert that the only function *f* which satisfies this condition is the unit root process

$$\mu_{ia} = \mu_{i0} + \sum_{s=1}^{a} \omega_{is} \tag{2}$$

If we similarly define the transitory component to be a linear function of a series of independently distributed transitory shocks ε_{i1}, ε_{i2}, …, ε_{iT} but we put no restrictions on the impact of each of these shocks on ν_{ia}, then, as noted previously, the impact of transitory shocks can be identified as all shocks which do not have an impact coefficient of 1 on y.

Beyond this assumption, we attempt to make as few restrictive assumptions as possible. We let the distributions of the permanent and transitory shocks, ω_{ia} and ε_{ia}, respectively, be nonparametric functions of a.[22] We do assume that the transitory component is linear in the

[22] This assumption makes the unit root and heterogeneous growth models equivalent and both embedded in the model. The typical heterogeneous growth model assumes that the permanent component to have a subcomponent equal to age times a heterogeneous growth factor. That model is identified only because of the restrictive assumption that individual growth heterogeneity is linear in age. If the growth factor is allowed to be nonparametric in age, the model is not identified from a unit root model with shocks whose distribution varies freely with age.

transitory shocks (this could be relaxed) but we do not impose any ARMA form on the coefficients. Instead, we specify the transitory component to be

$$\nu_{ia} = \varepsilon_{ia} + \sum_{s=1}^{a-1} \psi_{a,a-s} \varepsilon_{i,a-s} \qquad (3)$$

and we allow the impact coefficients of transitory shocks, the T(T+1)/2 – T parameters $\psi_{a,a-s}$ to be unconstrained.[23] This model nests the linear models used in the literature but does not nest those which are nonlinear in the shocks and those which have heterogeneous transitory shock impacts (e.g., which allow the ψ parameters or the distributions of the shocks to be individual-specific).[24] We name our model the Extended Semiparametric (ESP) Model because it is a major extension of the semiparametric model proposed by Moffitt and Gottschalk (2012).

Following the majority of the literature, we restrict our attention to the explaining the second moments of y_{iat} by second moments of the permanent and transitory shocks. We therefore seek to estimate the variances of the permanent and transitory shocks, allowing them to be nonparametric in age. In the Appendix, we show conditions for identification of the parameters. We estimate the parameters with conventional minimum distance. The exact specification of the model and the estimates of the parameters and their standard errors are shown in the Appendix Table 2.

Figures 4 and 5 show the trends in α and β, respectively, which are the calendar time factors in the model. The results show that both permanent and transitory variances trended upward over time and both roughly followed the pattern exhibited by gross volatility, with an initial rise, followed by a middle period when the rise had stopped, and ending with a rising

[23] The coefficient on the contemporary shock, ε_{ia} is not identified and must be set equal to 1.

[24] We also make no attempt to identify measurement error in the model. It can be identified only by untestable parametric assumptions which make such error evolve in a different functional form than the other shocks. For present purposes, which is mainly to identify calendar time trends, measurement error should have no effect unless it has been changing over time.

trend. The turning points—with a necessary caution as to the difficulty of detecting them visually in the facing of considerable instability—are slightly different, however. The transitory variance appears to have stopped rising in the early 1980s whereas the permanent variance continued to rise through the late 1980s. The transitory variance exhibits a slight decline in the middle period whereas the permanent variance is mostly flat. However, both variances turned up toward the end of the period. One reading of the results is that neither variance substantially departed from a process with fluctuations around a stable trend until 2008, when its increase truly started to emerge. This would be consistent with an effect of the Great Recession. The variances also show signs in the last two years of starting to decline from their Recession peaks.

The implications of these trends for the variances of the permanent and transitory components themselves are shown in Figure 6 for those age 40-49 (variances differ by age, with older individuals having higher variances, but the trend is the same at all ages given the model specification). The now-familiar three-phase trend is still apparent. The transitory variance is about two-thirds of the total variance and has risen more than the permanent variance from beginning to end. Thus we find that a larger fraction of the increase in cross-sectional male earnings inequality is accounted for by increases in the transitory component.[25]

We use our estimates to decompose the trend in the variance of 2-year changes of log earnings residuals (see Figure 1) into trends in the 2-year changes in permanent and transitory variances. The variance of 2-year changes involves both the level of the variance at each of the two time points as well as the covariance between them. The results can be found in Appendix Table 4 and show that both the level of the variances and the covariances have trended upward over time, for both the permanent and transitory components. But, on net, the variance of the

[25] The exact numbers for these variables can be found in the Appendix Table 3.

total change is almost entirely the result of increases in the transitory variance. The permanent variance does not have the same volatility as the transitory variance and changes at a slower rate, and the permanent variance is also smaller in magnitude than the transitory variance.

IV. Sensitivity Tests: Imputation and Window Averaging

We conduct two sensitivity tests to our findings. The first estimates the sensitivity of our results to the inclusion of imputed earnings values in the PSID. The second presents estimates of time trends in the transitory variance using the Window Averaging (WA) method, which is a particularly intuitive method of estimating transitory variances that is used in many studies.

Like all survey data sets, a certain fraction of earnings values are imputed in the PSID because of don't know responses and refusals to answer, from implausible values indicating response error, and other reasons. The PSID has conducted imputations for all of these reasons and the exact method of using them has varied somewhat over time, generally with growing sophisticated and complexity. Current imputation procedures for income use a variety of imputation methods, depending on the type of income being imputed and using a different set of variables for each (Duffy, 2011). In our sample of male heads from 1970 to 2014, the percent of wage and salary income observations that are imputed ranges from a low of 0.30 to a high of 4.6, with the high value occurring in 1992, a period when the PSID changed its methodology and interviewing method.

The traditional primary issue with imputation is whether it is ignorable, i.e., whether those observations which are imputed have unobservable differences in earnings from those which are not, and whether the imputation process can adjust for any such differences. The common method of testing for non-ignorability and the accuracy of the process is simply to estimate models with and without imputed observations even though, if non-ignorability holds, both estimates are biased. Figure 7 shows the trend in gross volatility in our sample including and excluding the imputed observations. There is very little difference in the trends in either case, suggesting that the observations being imputed are ignorable or that the imputation process adequately corrects for any non-ignorability.

Moffitt and Gottschalk (2012) dubbed any method of estimating transitory variances based on taking an interval of annual observations and computing transitory components as the deviations from some (possibly trend-adjusted) mean as a Window Averaging (WA) method. This method has been used primarily in the literature on calendar time trends in volatility and was used by the initial paper in that literature, Gottschalk and Moffitt (1994) but has been used in modified form in several subsequent papers (see Table 2 and 3). A traditional ANOVA definition of the transitory variance within a window of T observations is

$$\frac{1}{N(T-1)}\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{it}-\bar{y}_i)^2 \tag{4}$$

However, because $y_{it}-\bar{y}_i=\frac{1}{T}\sum_{\tau\neq t}^{T}(y_{it}-y_{i\tau})$, the WA method is based on the variance of pairwise differences between each y and the others within the window. Hence it is closer to an extended version of gross volatility than a true measure of the transitory variance, combining changes in permanent and transitory variances. In addition, if any model like that in equation (1) above holds, the WA method produces some time average of α_t and β_t, weighted by the variances of the pairwise differences.

Figure 8 shows estimates of equation (4) using a 9-year window for our male head data set 1970-2014, plotted against the year in the center of the window. The levels of the estimated variances is quite a bit below those of the transitory variance in Figure 6 (exact numbers in

Appendix Table 3) which is to be expected since the WA method averages over years and hences damps down the year-to-year variances from the ESP model. But the three-phase pattern revealed previously for both gross volatility and the transitory variance continues to hold here, although the turning points are considerably more indistinct than in the ESP model because of the smoothing inherent in the use of a 9-year average.

Appendix
The Extended Semiparametric (ESP) Model

Letting y_{iat} be the earnings residual for individual i at age a in year t, the model is:

$$y_{iat} = \alpha_t \mu_{ia} + \beta_t \upsilon_{ia} \tag{1}$$

$$\mu_{ia} = \mu_{i0} + \sum_{s=1}^{a} \omega_{is} \tag{2}$$

$$\upsilon_{ia} = \varepsilon_{ia} + \sum_{s=1}^{a-1} \psi_{a,a-s} \varepsilon_{i,a-s} \text{ for } a \geq 2 \tag{3}$$

$$\upsilon_{i1} = \varepsilon_{i1} \text{ for } a = 1 \tag{4}$$

for $a = 1, ..., A$ and $t = 1, ..., T$ and where the shocks ω_{ia} and ε_{ia} are independently distributed from each other and over time. The autocovariances implied by this model, which will be fit to the autocovariances in the data, are:

$$Var(y_{iat}) = \alpha_t^2 Var(\mu_{ia}) + \beta_t^2 Var(\upsilon_{ia}) \tag{5}$$

$$Var(\mu_{ia}) = Var(\mu_{i0}) + \sum_{s=1}^{a} Var(\omega_{is}) \tag{6}$$

$$Var(\upsilon_{ia}) = Var(\varepsilon_{ia}) + \sum_{s=1}^{a-1} \psi_{a,a-s}^2 Var(\varepsilon_{i,a-s}), \text{ for } a \geq 2 \tag{7}$$

$$Var(\upsilon_{i1}) = Var(\varepsilon_{i1}), \text{ for } a = 1 \tag{8}$$

$$Cov(y_{iat}, y_{i,a-\tau,t-\tau}) = \alpha_t \alpha_{t-\tau} Cov(\mu_{ia}, \mu_{i,a-\tau}) + \beta_t \beta_{t-\tau} Cov(\upsilon_{ia}, \upsilon_{i,a-\tau}) \tag{9}$$

$$
\begin{aligned}
Cov(\mu_{ia}, \mu_{i,a-\tau}) &= Var(\mu_{i,a-\tau}) \\
&= Var(\mu_{i0}) + \sum_{s=1}^{a-\tau} Var(\omega_{is})
\end{aligned} \tag{10}
$$

$$
\begin{aligned}
Cov(\upsilon_{ia}, \upsilon_{i,a-\tau}) &= \psi_{a,a-\tau} Var(\varepsilon_{i,a-\tau}) \\
&+ \sum_{s=1}^{a-\tau-1} \psi_{a,a-\tau-s}\psi_{a-\tau,a-\tau-s} Var(\varepsilon_{i,a-\tau-s}), \text{ for } a \geq 3
\end{aligned} \tag{11}
$$

$$
\begin{aligned}
Cov(\upsilon_{ia}, \upsilon_{i,a-\tau}) &= \psi_{a,a-\tau} Var(\varepsilon_{i,a-\tau}) \\
&= \psi_{21} Var(\varepsilon_{i1}), \text{ for } a = 2, \tau = 1
\end{aligned} \tag{12}
$$

We allow the variances of the permanent and transitory shocks to be nonparametric functions of age and we allow the ψ parameters to be nonparametric functions of age and lag length (τ or $\tau + s$).

Identification. Considering first the identification of the parameters of the age-earnings process under the stationary model $\alpha_t = \beta_t = 1$, we note that a data set of age length $a = 1, ..., A$ has an autocovariance matrix of the y_{ia} with $A(A+1)/2$ elements. The unknown parameters in the model are $\sigma^2_{\mu_0}$, the A parameters $\sigma^2_{\omega a}$ ($a = 1, ..., A$), the $A(A-1)/2$ parameters $\psi_{a,a-r}$ ($r = 1, .., a-1$), and the A parameters $\sigma^2_{\varepsilon a}$ ($a = 1, ...A$), for a total of $[A(A+1)/2] + A + 1$ parameters. The stationary model is therefore nonparametrically not identified without $A+1$ restrictions.[1] We allow restrictions by imposing smoothness on the nonparametric functions σ^2_{ω},ψ, and σ^2_{ε} as described below. Our estimation shows that the number of parameters needed to fit the data allow the model to be heavily overidentified.[2] The α_t and β_t parameters are identified, subject to a normalization and conditional on the identification of the parameters of the age-earnings process, from the change in the

[1] Because the equations of the model are nonlinear in the parameters, we also require that the solutions for the parameters exist and are unique if the number of elements of the autocovariance matrix equals the number of unknowns.

[2] We note that the model is identified for a data set of length $A \geq 4$ under homoskedasticity of the permanent and transitory shocks, defined as the model with $\sigma^2_{\omega a} = \sigma^2_{\omega}$, $\sigma^2_{\varepsilon a} = \sigma^2_{\varepsilon}$ for $a = 2, , , A$, and with $\sigma^2_{\varepsilon 1}$ left as a free parameter for initial conditions purposes. We test for, and reject, homoskedasticity of the transitory variances.

autocovariance matrix elements at the same age and lag position but at different points in calendar time, which therefore requires multiple cohorts. Since α_t and β_t constitute two parameters, any two elements of the matrix observed at two calendar time points is sufficient for identification. For example, using the variances at ages a and a' observed at times t and $t+1$, we have

$$Var(y_{iat}) = \alpha_t^2 \sigma_{\mu a}^2 + \beta_t^2 \sigma_{\upsilon a}^2 \tag{13}$$

$$Var(y_{ia't}) = \alpha_t^2 \sigma_{\mu a'}^2 + \beta_t^2 \sigma_{\upsilon a'}^2 \tag{14}$$

$$Var(y_{ia,t+1}) = \alpha_t^2 r_\alpha^2 \sigma_{\mu a}^2 + \beta_t^2 r_\beta^2 \sigma_{\upsilon a}^2 \tag{15}$$

$$Var(y_{ia',t+1}) = \alpha_t^2 r_\alpha^2 \sigma_{\mu a'}^2 + \beta_t^2 r_\beta^2 \sigma_{\upsilon a'}^2 \tag{16}$$

where $r_\alpha = \alpha_{t+1}/\alpha_t$ and $r_\beta = \beta_{t+1}/\beta_t$. We normalize the calendar shifts at $t = 1$ by setting $\alpha_1 = \beta_1 = 1$. Equations (13)-(16) can be solved for α_t and β_t for $t = 2, ..., T$.

Nonparametric Estimation. To estimate the functions $\sigma_{\omega a}^2$, $\sigma_{\varepsilon a}^2$, and ψ, we specify the functions as series expansions in basis functions and use a generalized cross-validation (GCV) statistic, which has a penalty for the number of parameters, to choose the degree of the expansion. Our specific functional forms are:

$$Var(\omega_{ir}) = e^{\Sigma \delta_j (r-25)^j} \tag{17}$$

$$Var(\varepsilon_{ir}) = e^{\Sigma \gamma_j (r-25)^j}, \text{ for } r \geq 2 \tag{18}$$

$$Var(\varepsilon_{i1}) = k e^{\Sigma \gamma_j (1-25)^j}, \text{ for } r = 1 \tag{19}$$

$$\psi_{A,A-b} = [1 - \pi(A - 25)][\Sigma w_j e^{-\lambda_j b}] + \Sigma \eta_j D(b = j) \tag{20}$$

The variances use exponential functions of polynomial expansions in age minus 25 (the approximate minimum age), with the initial transitory variance allowed to differ by factor k for an initial conditions adjustment. The ψ parameters are allowed to expand in a weighted sum of exponentials, which force the parameters to asymptote to 0 as the lag length goes to infinity, and with a linear age-function factor in front of that weighted sum. Deviations from the smooth exponential expansions are allowed at each lag length. The unknown parameters in the model are $Var(\mu_{i0}), \delta_j, \gamma_j, k, \pi, \lambda_j, w_j$,and the η_j as well as the α_t and β_t. The parameters are fit to the second-moment matrix of the data using minimum distance.

Appendix Table A-2, column 1, reports the results of the estimation. As is often the case using the PSID, only a small number of basis functions in the expansion improve the parameter-adjusted fit. The initial variance of the permanent component is significant but the variances of the permanent shocks do not vary with age.[3] The transitory variance is also weakly positive in a linear function of age. The initial transitory variance is over twice the size as subsequent transitory shocks (as expected) but the transitory autocovariance curve is only weakly (and negatively) correlated with age and with only a single exponential. The λ parameter confirms that autocovariances decline with lag length and the η parameters indicate that the most recent three lags have a different impact on the current transitory component than the age-adjusted smooth exponential curve indicates. The estimates of the α and β parameters are also shown; the figures in the text are plots of these estimates. The second column in the Table shows the estimates of the parameters if a model stationary in calendar time is estimated (i.e., constraining $\alpha_t = \beta_t = 1$). The parameter estimates are quite different than those estimated when calendar time shifts are allowed.

The parameter estimates are inserted into equations (6)-(8) to compute the implied variances of the permanent and transitory components without calendar time effects, and then those estimated components are used in equation (5) to compute the total variance and the two components on the right-hand-side of that equation. The text reports plots of these three variances for those aged 40-49, and Appendix Table 3 reports the exact figures for all three age groups.

[3]The two δ parameters are insignificant but adding the second one lowered the GCV, so we retain both. The total transitory variance is positive and highly significant.

The text reports the implications of the fitted model for the sources of the variance of 2-year changes in y. The 2-year change is

$$\begin{aligned} y_{iat} - y_{i,a-2,t-2} &= (\alpha_t \mu_{ia} + \beta_t \upsilon_{ia}) - (\alpha_{t-2}\mu_{i,a-2} + \beta_{t-2}\upsilon_{i,a-2}) \\ &= \alpha_t \mu_{ia} - \alpha_{t-2}\mu_{i,a-2} + \beta_t \upsilon_{ia} - \beta_{t-2}\upsilon_{i,a-2} \end{aligned} \tag{21}$$

and its variance is

$$\begin{aligned} & Var(y_{iat} - y_{i,a-2,t-2}) \\ &= \alpha_t^2 Var(\mu_{ia}) + \alpha_{t-2}^2 Var(\mu_{i,a-2}) - 2\alpha_t \alpha_{t-2} Cov(\mu_{ia}, \mu_{i,a-2}) \\ &\quad + \beta_t^2 Var(\upsilon_{ia}) + \beta_{t-2}^2 Var(\upsilon_{i,a-2}) - 2\beta_t \beta_{t-2} Cov(\upsilon_{ia}, \upsilon_{i,a-2}) \end{aligned} \tag{22}$$

which contains variances and covariances which have been fitted by the model. Appendix Table 4 shows the exact components by year.

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Table 1
PSID Studies of Permanent-Transitory Volatility with No Calendar Time Trends

Study	Sample	Method	Findings
Benus and Morgan (1972)	Families in first four PSID waves, 1968-1971 with same family head who works in all years	Decomposition of head labor income into average, trend, and instability	Higher average income is correlated with higher trend and lower instability
Benus (1974)	Families in first five PSID waves, 1968-1972 with same family head who works in all years	Instability in head labor earnings and total family income measured as variance of deviation of trend from regression residuals	Instability higher for those with low permanent income, farmers and the self-employed, younger heads, and those in areas of high unemployment; instability of total family income largely driven by head labor income, little offset from other income sources except transfers
Mirer (1974)	Families in 1967-1969	Instability of total family income measured as standard deviation of residuals from a regression with a year trend	Instability negative related to expected income, instability largely driven by head labor income with spouse labor income playing little role
Lillard and Willis (1978)	Prime-age working male heads, 1967-1973	Error components model for earnings with random permanent effect and AR(1) transitory effect	Permanent component explains 73 percent of residual variable. Significant AR(1) component and high degree of mobility
Hall and Mishkin (1982)	Families 1969-1975	Error components model of total after-tax family income decomposed into deterministic portion, unit root, and stationary transitory component	Significant variances of unit root and transitory components with evidence for MA components of latter
MaCurdy (1982)	Prime-age white married working male heads, 1967-1976	Error components model for earnings with random permanent effect and ARMA transitory effect	Low-order ARMA fits the data
Abowd and Card (1989)	Prime-age working male heads, 1969-1979	Error components model for earnings with unit root permanent effect and MA(2) in transitory effect changes	Nonstationary unit root and MA(2) model fits the data best

Table 1
PSID Studies of Permanent-Transitory Volatility with No Calendar Time Trends (Continued)

Study	Sample	Method	Findings
Carroll (1992)	Families with prime-age heads, 1968-1985	Error components model for labor income with a unit root and a transitory error	Variances of permanent and transitory shocks approximately equal
Baker (1997)	Prime-age working male heads, 1967-1986	Error components model of earnings with tests for random growth versus random walk	Rejects random walk in favor of random growth
Geweke and Keane (2000)	Prime-age working male heads, 1968-1989	Error components model with non-Gaussian shocks for earnings with random permanent effect and autoregressive transitory effect	Most cross-sectional earnings differences are explained by transitory shocks but lifetime differences explained but individual heterogeneity
Meghir and Pistaferri (2004)	Prime-age working male heads, 1968-1993	Error components model for earnings allowing ARCH effects in permanent and transitory shocks	Strong evidence for ARCH effects
Guvenen (2009)	Prime-age working male heads, 1968-1993	Error components model for earnings with focus on testing for heterogeneous income profiles model	Finds support for heterogeneous income profiles
Bonhomme and Robin (2010)	Working male heads, 19787-1987	Nonparametric estimates of the density of permanent and transitory earnings in an error components model	Densities are non-Gaussian, with higher modes and fatter tails
Browning et al. (2010)	Prime-age white male working high school heads, 1968-1993	Error components model for earnings with features to incorporate additional types of heterogeneity	Data show more heterogeneity than that using simpler models
Hryshko (2012)	Prime-age working male heads, 1968-1997	Error components model for earnings with new tests for unit root process versus heterogeneous profile process	New tests provide support for the unit root process
Arellano et al. (2017)	All families 1999-2009	Allows nonparametric first-order Markov process for persistent component of total family earnings	Finds strongest persistence among high-earnings households experiencing large positive shocks and among low-earnings households experiencing large negative shocks.

Table 2
PSID Studies of Volatility with Focus on Calendar Time Trends

Study	Sample	Method	Findings
Permanent-Transitory Decomposition			
Gottschalk and Moffitt (1994)	White male heads, 1970-1987	WA method applied to earnings*	Equally large increases in the permanent and transitory variance from 1970-1978 to 1979-1987
Moffitt and Gottschalk (1995)	White male heads, 1970-1987	Error components model of individual earnings with unit root permanent effect and ARMA transitory effect	Same as 1994 paper
Gittleman and Joyce (1999)	Families, 1968-1991	WA method applied to total family income	Both permanent and transitory components grew (former slightly greater than latter), from 1967-1979 to 1980-1991
Haider (2001)	White male heads, 1967-1991	Error components model with heterogeneous growth component	Equal split of growth of permanent and transitory effects but transitory did not grow after 1982
Hyslop (2001)	Married couples, 1979-1985	Error components model allowing husband and wife permanent and transitory components to be correlated	Permanent and transitory variances of men rose equally over the period while permanent variances of women did not rise but transitory variances did
Moffitt and Gottschalk (2002)	Male heads, 1969-1996	Same error components model as Moffitt and Gottschalk (1995)	Permanent variance rose over the whole period but transitory variance declined in the 1990s
Keys (2008)	Male and female heads and families, 1970-2000	WA method applied to head earnings and family income	Permanent and transitory variances of male earnings rose from 1970 to 1990 but usually flattened out in the 2000s. Permanent variances for female heads fell and their transitory variances rose a small amount. Permanent and transitory variances of family income rose.
Gottschalk and Moffitt (2009)	Individual earnings and family income, 1970-2004	WA method for male earnings and family income, percentile point method for women,	Male transitory variance rose from the 1970s to the late 1980s, flattened out and rose starting in the late 1990s. No clear trend in variance for women. Strong upward trend for transitory variance of family income.

Table 2
PSID Studies of Volatility with Focus on Calendar Time Trends (Continued)

Study	Sample	Method	Findings
Heathcote et al. (2010)	Heads and spouses, 1967-2006	Error components model of earnings with unit root in permanent component	Upward trends in permanent and transitory variances, differ somewhat by estimation method
Moffitt and Gottschalk (2012)	Male heads, 1970-2005	Error components model of earnings together with WA and nonparametric method	Transitory variance increased from the 1970s to the mid-1980s, then remained at this level through 2005.
Jensen and Shore (2015)	Male heads,1968-2009	Error components model of earnings with evolving permanent effect and correlated transitory effect that captures heterogeneity in permanent and transitory variances	Variances have not risen for most of the population but have risen strongly for those with high past volatility levels
Gross Volatility			
Dynarski and Gruber (1997)	Male heads, 1970-1991	Variance of residuals from a first-difference regression of earnings	Variance rises over time, punctuated by business cycles
Shin and Solon (2011)	Male heads 1969-2006	Standard deviation of 2-year change in earnings residuals	Variance rose in the 1970s, peaked in 1983, declined through approximately 1997, rose thereafter
Dynan et al. (2012)	1967-2008	Standard deviation of 2-year arc percent change	
	Male heads	Labor earnings	Strong increase from 1970 to 1985, followed by slower trend upward punctuated by periods of decline
	Female heads and spouses	Labor earnings	Sharp decline through early 1990s, slower rate of decline thereafter
	Household	Combined Head and Spouse Labor Earnings and Income	Steady upward trend interrupted by decline in late 1980s and early 1990s (combined head and spouse labor earnings) and slow trend upward except for a large jump upward in the early 1990s (household income)

Note: WA method = Window Averaging Method. Within a fixed interval of years, the variance of the permanent component is calculated as the variance of average earnings and the variance of the transitory component is calculated as the variance of the deviations of actual earnings from average earnings

Table 3
Non-PSID Studies of U.S. Volatility with Focus on Calendar Time Trends

Study	Sample	Method	Findings
Gross Volatility			
Bania and Leete (2009)	SIPP Households from 1991-1992 and 2001 panels	Calculates coefficient of variation of monthly household income over 12-month periods	Volatility rose over time mostly for low income households
Sabelhaus and Song (2010)	Social Security individual earnings data, 1980-2005	Gross volatility calculated as the variance of changes in log earnings	Volatility fell over the period.
Dahl et al. (2011)*	Social Security individual earnings data, 1984-2005	Volatility measured as dispersion of arc earnings changes greater than 50 percent between years	Volatility declined in late 1980s and then more gradually through 2005
Ziliak et al. (2011)	Matched CPS data, 1973-2009	Volatility measured as standard deviation of arc earnings change	Male volatility rose from the early 1970s to the mid 1980s, was at same level by 2009. Female volatility declined over the entire period.
DeBacker et al. (2013)	Tax returns merged with male primary or secondary earner W-2 data, 1987-2009	Standard deviation of percent change in earnings for men	Fluctuations in several year intervals around a stable trend
Celik et al. (2012)	LEHD (UI earnings records) in 12 states,1992-2008, compared to CPS, SIPP, and PSID. Men only.	Standard deviation of change in log earnings residuals	LEHD shows little or no change in volatility, 1992-2008. PSID and CPS show rising volatility from 1970s to early 1980s, subsequent declines, and then resumption of increase starting in early 2000s (PSID) and 2006 (CPS). SIPP shows declines, 1984-2006.
Hardy and Ziliak (2014)	Matched CPS data, 1980-2009	Variance of arc percent change of household income	Volatility doubled over the time period, most pronounced among top incomes

Table 3
Non-PSID Studies of U.S. Volatility with Focus on Calendar Time Trends (Continued)

Study	**Sample**	**Method**	**Findings**
Permanent-Transitory Decomposition			
Sabelhaus and Song (2010)	Social Security individual earnings data, 1980-2005	Permanent variance identified change in variance of change in log earnings by lag length.	Both permanent and transitory variances fell over the period.
DeBacker et al. (2013)	Male primary or secondary earner W-2 data merged with IRS tax return data, 1987-2009	Two WA methods plus error components model applied to earnings and household income	Permanent variance of male earnings rose but transitory was stable around fluctuations. Transitory variance of household income rose by a modest degree.
Hryshko et al. (2017)	Married couples in matched SSA-SIPP data, 1980-2009	WA method for estimating transitory variance of earnings	Husband volatility fell 1980-2000 then rose, small net positive. Couple earnings volatility fell more, net decline.

*The authors also conducted an analysis of household income volatility using matched SIPP-SSA data from 1985 to 2005, finding stability over that period.

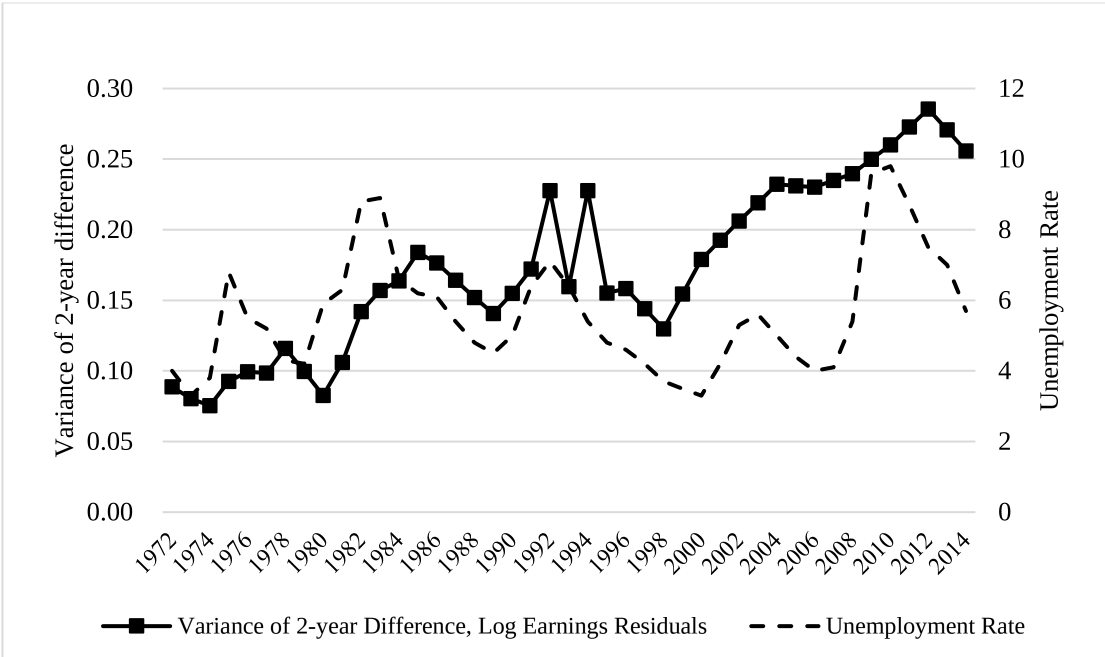

Figure 1
Variance of 2-Year Difference in Male Log Earnings Residuals

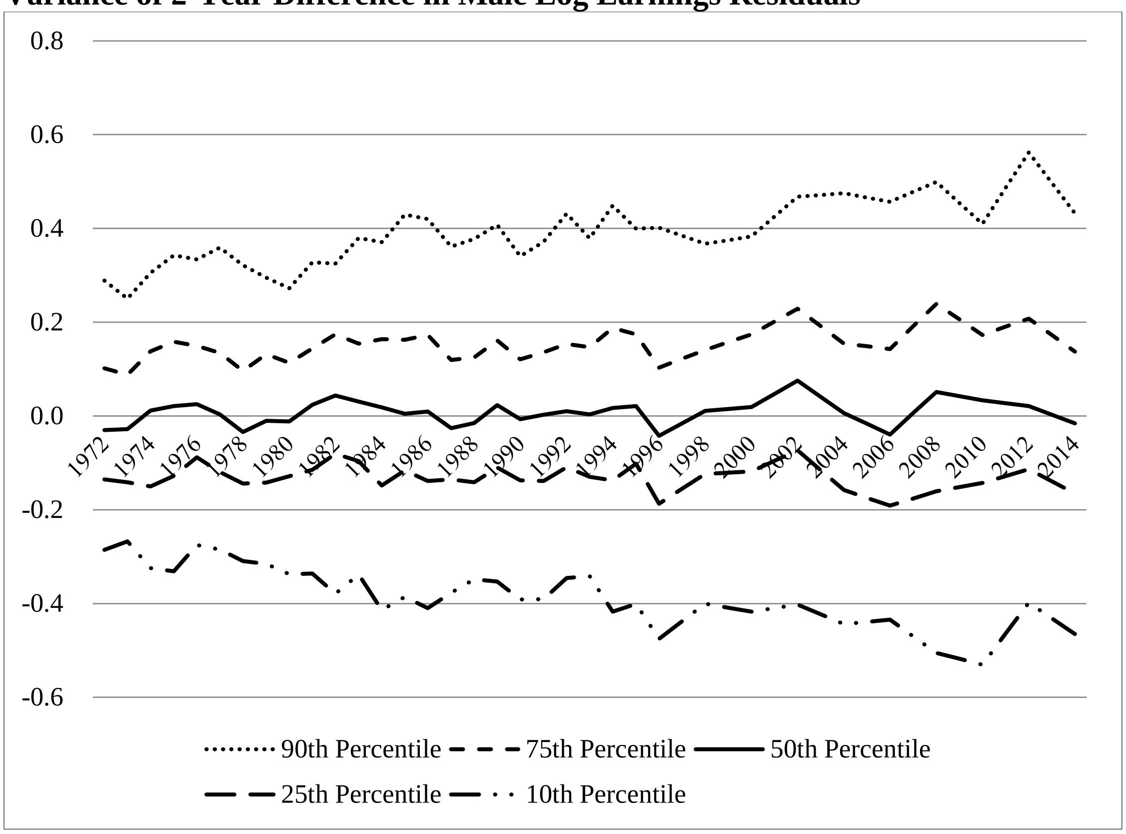

Figure 2
Percentiles of 2-Year Difference in Male Log Earnings Residuals

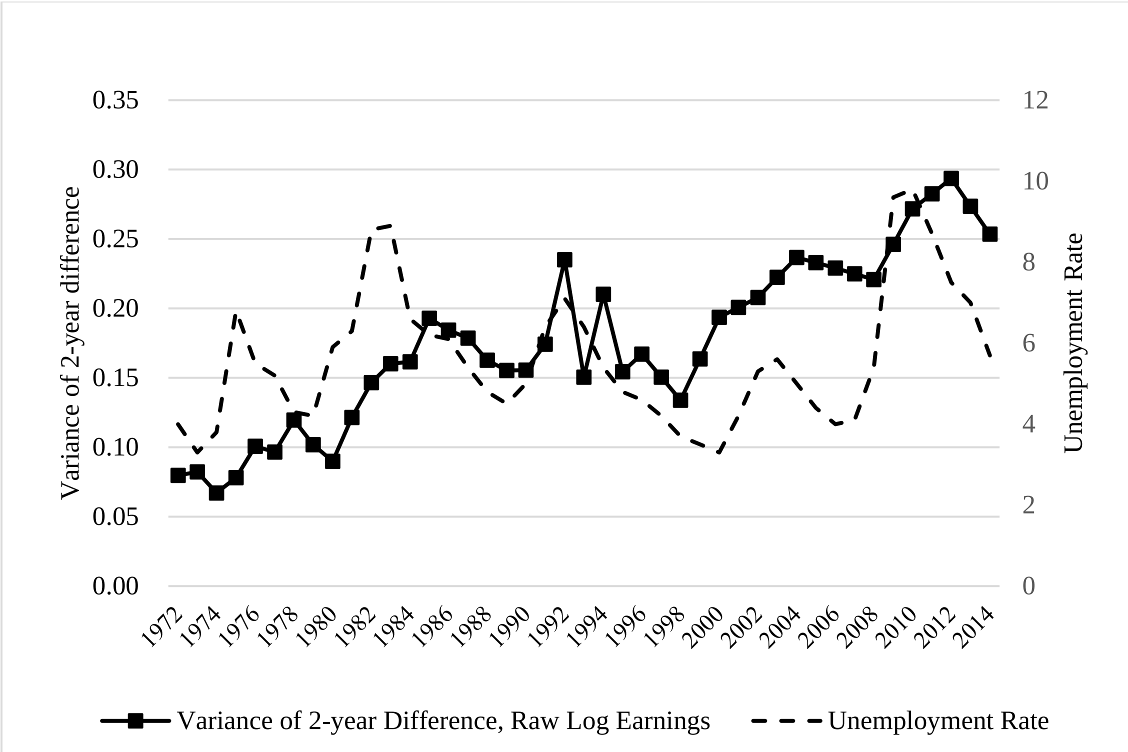

Figure 3
Variance of 2-Year Difference in Raw Male Log Earnings

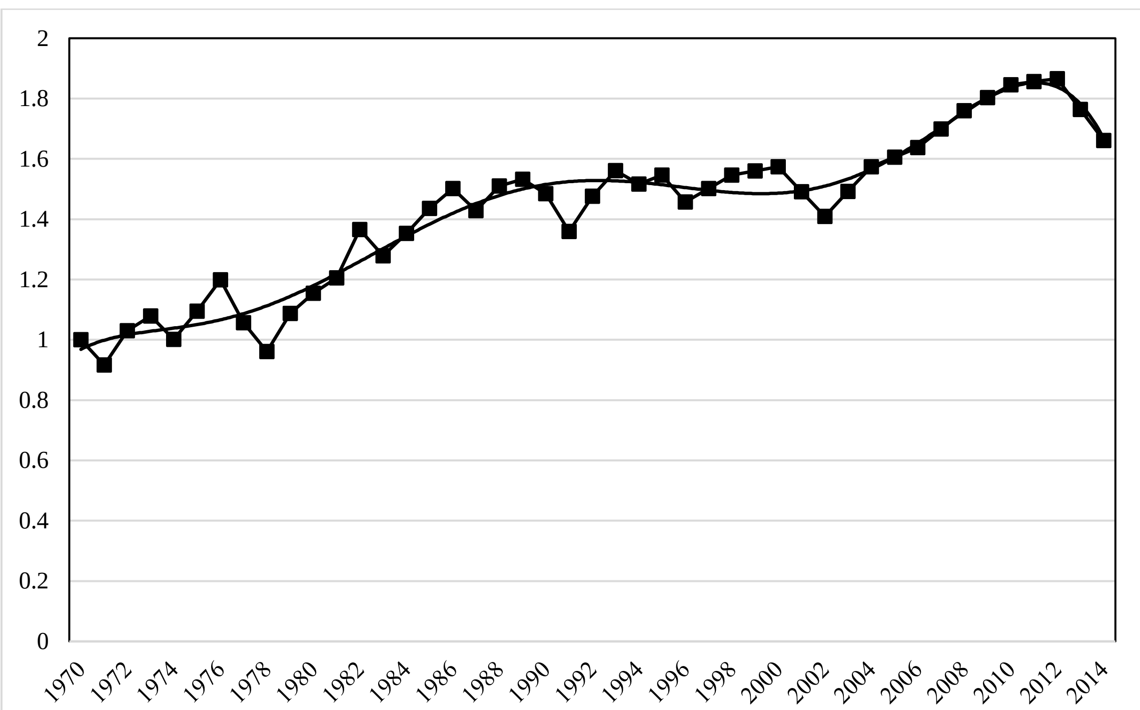

Figure 4
Extended Semiparametric (ESP) Model Estimates of Alpha

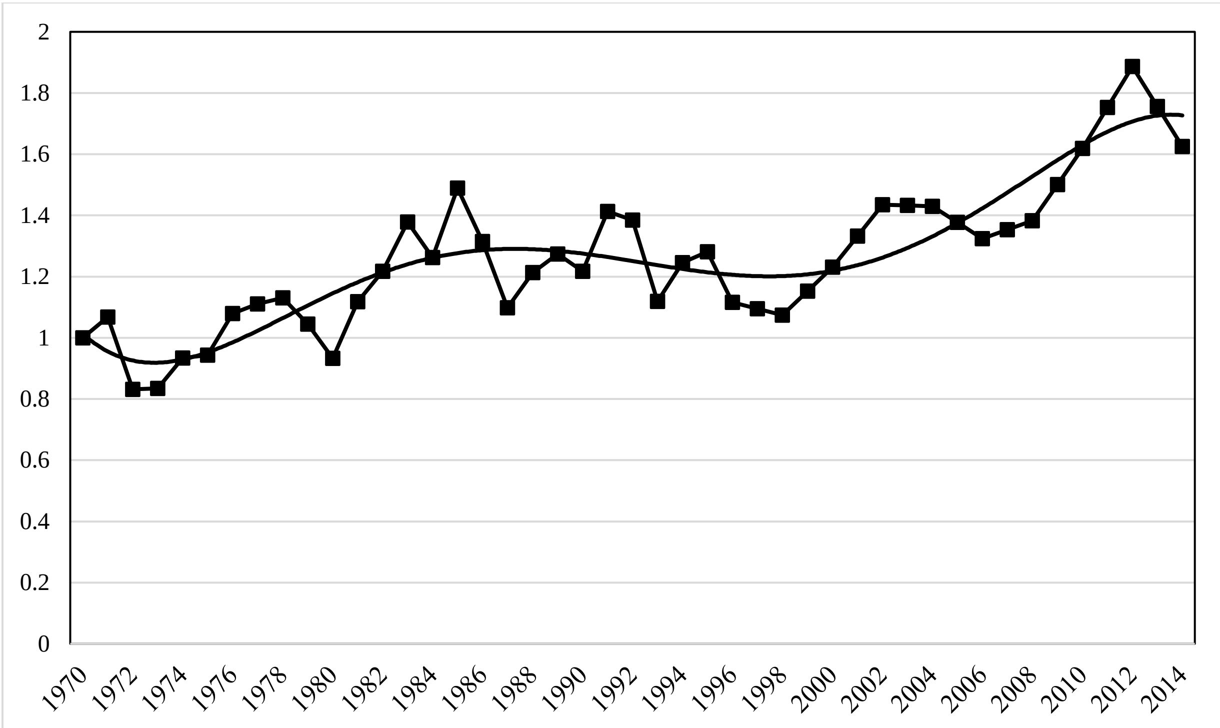

Figure 5
Extended Semiparametric (ESP) Model Estimates of Beta

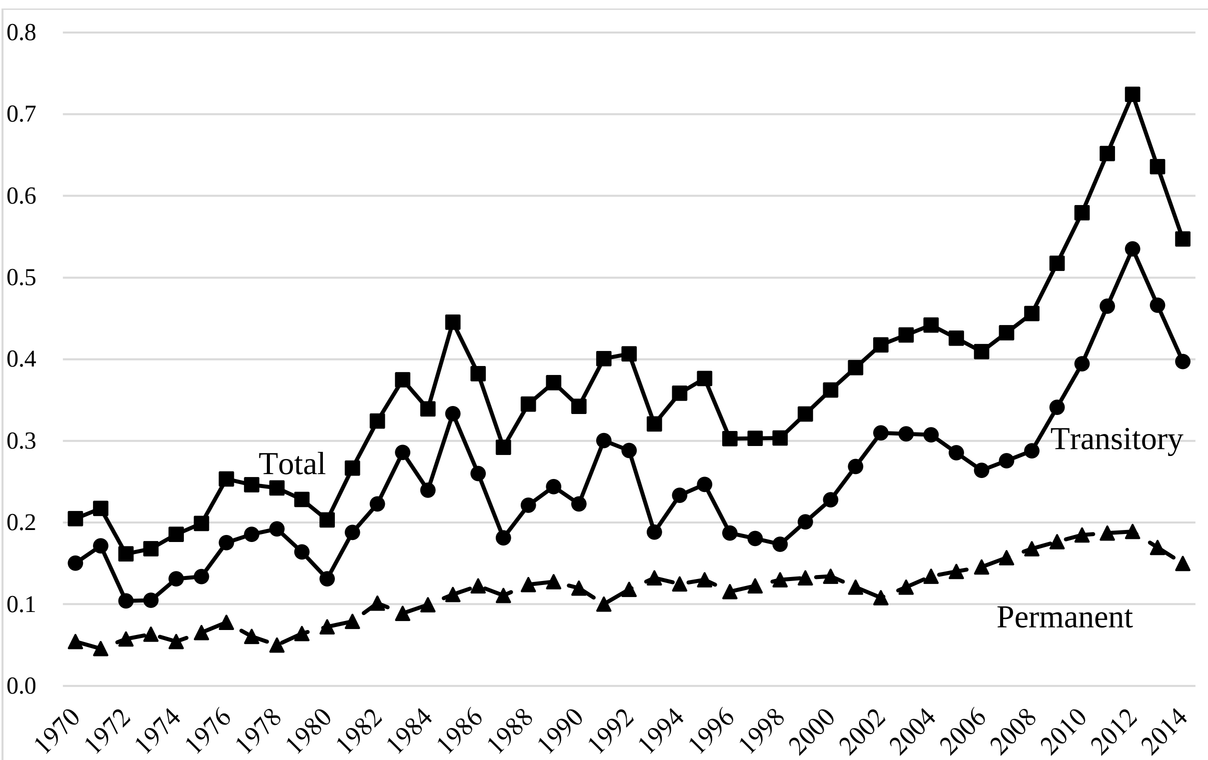

Figure 6
Fitted Permanent, Transitory, and Total Variance of Log Earnings Residuals, Age 40-49, ESP Model

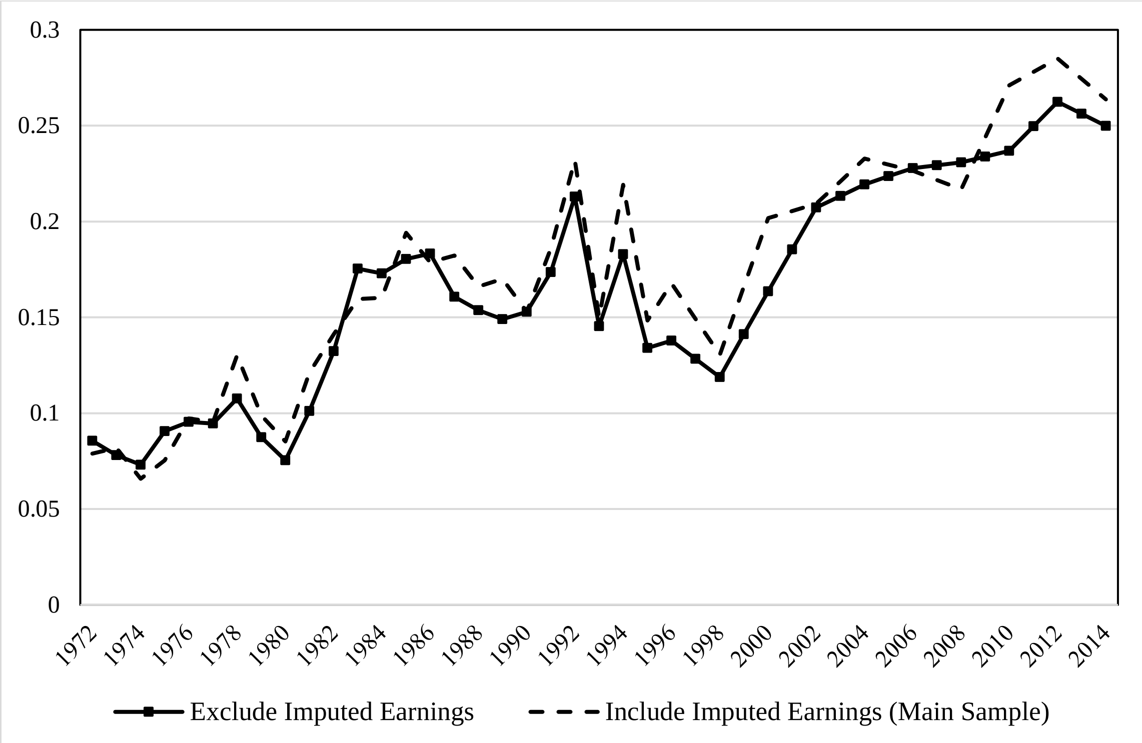

Figure 7
Variance of 2-Year Difference of Log Earnings Residuals, Including and Excluding Imputed Observations

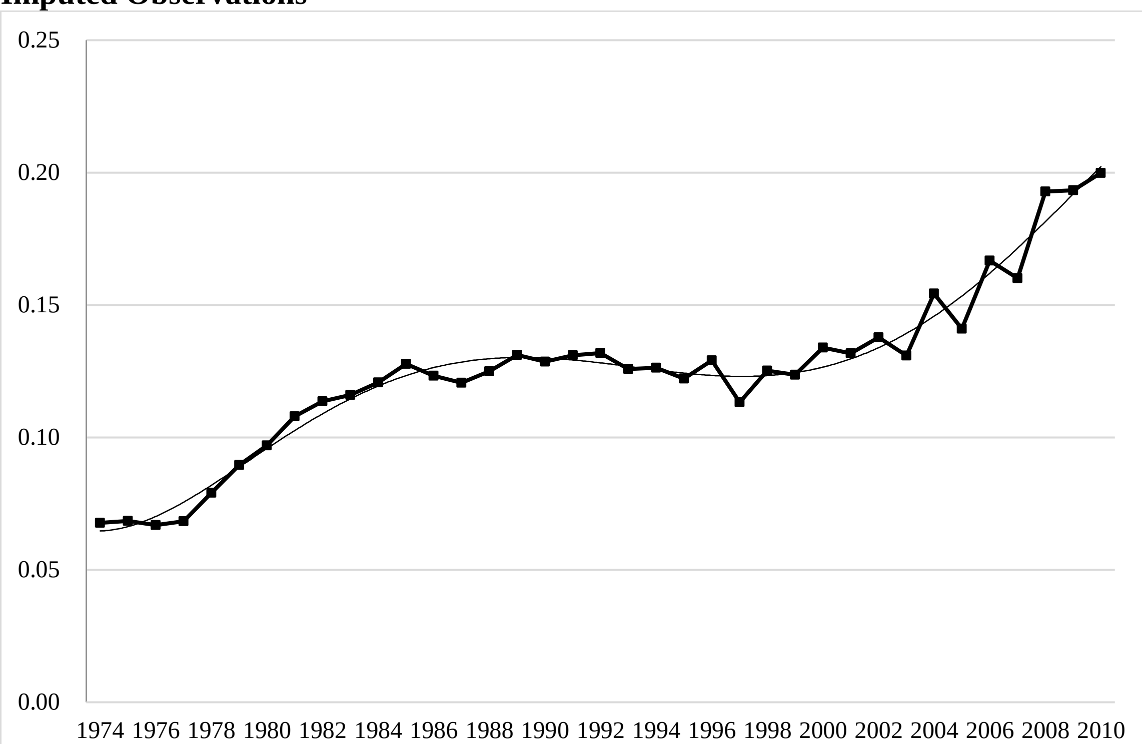

Figure 8
Window Averaging (WA) Estimate of Transitory Variance, 9-year Window

Appendix Table 1
Summary Statistics of Key Variables

Variable	No. of Obs	Mean	Standard Deviation	Minimum	Maximum
Person ID	36,403	1,524,646	826,882	1001	2,930,001
Age	36,403	42.9	8.4	30	59
Income Year	36,403	1989.4	12.4	1970	2014
Log Earnings Residual	36,403	0.020	0.589	-4.716	2.271

Appendix Table 2
Estimates of the ESP Model Parameters

Parameter	With Calendar Time Trends	Without Calendar Time Trends
Var(μ_{i0})	.054 (.010)	.104 (.006)
δ_0	-12.2 (11.7)	1.41 (.268)
δ_1	.681 (1.25)	-.842 (.104)
γ_0	-4.45 (0.30)	-6.06 (1.36)
γ_1	0.011 (.010)	.115 (.101)
k	2.21 (.38)	.004 (.024)
π	-0.010 (0.007)	3.97 (1.74)
λ_1	.094 (.021)	.070 (.024)
η_1	2.03 (0.41)	-4.97 (.752)
η_2	-.639 (.089)	.010 (.006)
η_3	.208 (.049)	.711 (.195)
α_{1971}	.916 (.096)	--
α_{1972}	1.03 (.103)	--
α_{1973}	1.08 (.101)	--
α_{1974}	1.00 (.106)	--

Appendix Table 2
Estimates of the ESP Model Parameters (continued)

Parameter	With Calendar Time Trends	Without Calendar Time Trends
α_{1975}	1.10 (.125)	--
α_{1976}	1.20 (.138)	--
α_{1977}	1.06 (.125)	--
α_{1978}	.961 (.110)	--
α_{1979}	1.09 (.135)	--
α_{1980}	1.15 (.138)	--
α_{1981}	1.21 (.143)	--
α_{1982}	1.37 (.167)	--
α_{1983}	1.28 (.161)	--
α_{1984}	1.35 (.167)	--
α_{1985}	1.14 (.173)	--
α_{1986}	1.15 (.183)	--
α_{1987}	1.43 (.171)	--
α_{1988}	1.51 (.176)	--
α_{1989}	1.53 (.176)	--
α_{1990}	1.48 (.174)	--
α_{1991}	1.36 (.168)	--
α_{1992}	1.48 (.176)	--
α_{1993}	1.56 (.181)	--
α_{1994}	1.52 (.177)	--
α_{1995}	1.55 (.182)	--

Appendix Table 2
Estimates of the ESP Model Parameters (continued)

Parameter	With Calendar Time Trends	Without Calendar Time Trends
α_{1996}	1.46 (.169)	--
α_{1998}	1.55 (.180)	--
α_{2000}	1.58 (.192)	--
α_{2002}	1.41 (.196)	--
α_{2004}	1.57 (.197)	--
α_{2006}	1.64 (.200)	--
α_{2008}	1.76 (.202)	--
α_{2010}	1.85 (.221)	--
α_{2012}	1.87 (.246)	--
α_{2014}	1.66 (.214)	--
β_{1971}	1.07 (.086)	--
β_{1972}	.832 (.071)	--
β_{1973}	.835 (.074)	--
β_{1974}	.934 (.075)	--
β_{1975}	.943 (.084)	--
β_{1976}	1.08 (.092)	--
β_{1977}	1.11 (.091)	--
β_{1978}	1.13 (.090)	--
β_{1979}	1.05 (.092)	--
β_{1980}	.933 (.092)	--
β_{1981}	1.12 (.104)	--

Appendix Table 2
Estimates of the ESP Model Parameters (continued)

Parameter	With Calendar Time Trends	Without Calendar Time Trends
β_{1982}	1.22 (.120)	--
β_{1983}	1.38 (.123)	--
β_{1984}	1.26 (.120)	--
β_{1985}	1.49 (.132)	--
β_{1986}	1.31 (.126)	--
β_{1987}	1.10 (.108)	--
β_{1988}	1.21 (.112)	--
β_{1989}	1.27 (.117)	--
β_{1990}	1.22 (.112)	--
β_{1991}	1.41 (.131)	--
β_{1992}	1.38 (.124)	--
β_{1993}	1.12 (.110)	--
β_{1994}	1.25 (.117)	--
β_{1995}	1.28 (.120)	--
β_{1996}	1.12 (.098)	--
β_{1998}	1.07 (.101)	--
β_{2000}	1.23 (.113)	--
β_{2002}	.143 (.126)	--
β_{2004}	1.43 (.119)	--
β_{2006}	1.32 (.113)	--

Appendix Table 2
Estimates of the ESP Model Parameters (continued)

Parameter	With Calendar Time Trends	Without Calendar Time Trends
β_{2008}	1.38 (.119)	--
β_{2010}	1.62 (.143)	--
β_{2012}	1.89 (.173)	--
β_{2014}	1.63 (1.43)	--

Notes:
Standard errors in parentheses.
Parameters α and β normalized to 1 in 1970.

Appendix Table 3
Estimated Permanent Variance, Transitory Variance, and Total Variance by Age Group, ESP Model

	Age 30-39			Age 40-49			Age 50-59		
	Permanent Variance	Transitory Variance	Total Variance	Permanent Variance	Transitory Variance	Total Variance	Permanent Variance	Transitory Variance	Total Variance
1970	0.054	0.122	0.176	0.054	0.150	0.205	0.082	0.183	0.266
1971	0.046	0.139	0.185	0.046	0.172	0.217	0.069	0.209	0.278
1972	0.058	0.084	0.142	0.058	0.104	0.162	0.087	0.127	0.214
1973	0.063	0.085	0.148	0.063	0.105	0.168	0.096	0.128	0.223
1974	0.054	0.106	0.161	0.054	0.131	0.186	0.082	0.160	0.242
1975	0.065	0.108	0.173	0.065	0.134	0.199	0.099	0.163	0.262
1976	0.078	0.142	0.220	0.078	0.175	0.253	0.118	0.214	0.332
1977	0.061	0.150	0.211	0.061	0.186	0.246	0.092	0.226	0.318
1978	0.050	0.156	0.206	0.050	0.192	0.243	0.076	0.235	0.311
1979	0.064	0.133	0.197	0.064	0.164	0.228	0.097	0.200	0.297
1980	0.072	0.106	0.178	0.072	0.131	0.203	0.109	0.160	0.269
1981	0.079	0.152	0.231	0.079	0.188	0.267	0.119	0.229	0.348
1982	0.101	0.181	0.282	0.101	0.223	0.324	0.153	0.272	0.425
1983	0.089	0.232	0.320	0.089	0.286	0.375	0.134	0.349	0.483
1984	0.099	0.194	0.293	0.099	0.240	0.339	0.150	0.292	0.443
1985	0.112	0.270	0.382	0.112	0.333	0.445	0.169	0.407	0.576
1986	0.122	0.211	0.333	0.122	0.260	0.382	0.185	0.317	0.502
1987	0.111	0.147	0.258	0.111	0.181	0.292	0.168	0.221	0.389
1988	0.124	0.179	0.303	0.124	0.221	0.345	0.187	0.270	0.457
1989	0.127	0.198	0.325	0.128	0.244	0.371	0.193	0.297	0.490
1990	0.120	0.180	0.300	0.120	0.223	0.342	0.181	0.272	0.453
1991	0.100	0.243	0.344	0.100	0.300	0.401	0.152	0.366	0.518
1992	0.118	0.234	0.352	0.118	0.288	0.407	0.179	0.352	0.531
1993	0.132	0.153	0.285	0.132	0.188	0.321	0.200	0.230	0.430
1994	0.125	0.189	0.314	0.125	0.233	0.358	0.189	0.285	0.474
1995	0.130	0.200	0.330	0.130	0.247	0.377	0.196	0.301	0.497

Appendix Table 3
Estimated Permanent Variance, Transitory Variance, and Total Variance by Age Group, ESP Model (continued)

	Age 30-39			Age 40-49			Age 50-59		
	Permanent Variance	Transitory Variance	Total Variance	Permanent Variance	Transitory Variance	Total Variance	Permanent Variance	Transitory Variance	Total Variance
1997	0.123	0.146	0.269	0.123	0.180	0.303	0.185	0.220	0.406
1998	0.130	0.141	0.270	0.130	0.174	0.303	0.196	0.212	0.408
1999	0.132	0.163	0.295	0.132	0.201	0.333	0.200	0.245	0.445
2000	0.134	0.185	0.319	0.134	0.228	0.362	0.203	0.278	0.481
2001	0.121	0.218	0.339	0.121	0.269	0.390	0.183	0.328	0.511
2002	0.108	0.251	0.359	0.108	0.310	0.417	0.163	0.378	0.541
2003	0.121	0.250	0.371	0.121	0.309	0.430	0.183	0.376	0.560
2004	0.134	0.249	0.384	0.134	0.308	0.442	0.203	0.375	0.579
2005	0.140	0.231	0.371	0.140	0.286	0.426	0.212	0.348	0.560
2006	0.145	0.214	0.359	0.146	0.264	0.409	0.220	0.322	0.542
2007	0.157	0.223	0.380	0.157	0.276	0.433	0.237	0.336	0.574
2008	0.168	0.233	0.401	0.168	0.288	0.456	0.254	0.351	0.605
2009	0.176	0.276	0.453	0.177	0.341	0.518	0.267	0.416	0.683
2010	0.185	0.319	0.504	0.185	0.394	0.579	0.280	0.481	0.761
2011	0.187	0.377	0.563	0.187	0.465	0.652	0.283	0.567	0.850
2012	0.189	0.434	0.622	0.189	0.535	0.724	0.286	0.653	0.939
2013	0.169	0.378	0.547	0.169	0.466	0.636	0.256	0.569	0.825
2014	0.150	0.322	0.472	0.150	0.397	0.547	0.227	0.485	0.711

Note: After income year 1996, we interpolate the variances between two years.

Appendix Table 4
Decomposition of the Variance of Two-year Changes in Log Earnings Residuals, Age 40-49, ESP Model

Second Year	Variance of Change in Permanent Component	Variance of Change in Transitory Component	Variance of Change in Total	$\alpha_t^2 Var(\mu_{ia})$	$\alpha_{t-2}^2 Var(\mu_{i,a-2})$	$-2\alpha_t\alpha_{t-2} * cov(\mu_{ia}, \mu_{i,a-2})$	$\beta_t^2 Var(\upsilon_{ia})$	$\beta_{t-2}^2 Var(\upsilon_{i,a-2})$	$-2\beta_t\beta_{t-2} * cov(\upsilon_{ia}, \upsilon_{i,a-2})$
1972	0.000	0.142	0.142	0.058	0.054	-0.112	0.104	0.144	-0.107
1973	0.001	0.155	0.157	0.063	0.046	-0.107	0.105	0.165	-0.114
1974	0.000	0.131	0.131	0.054	0.058	-0.112	0.131	0.100	-0.100
1975	0.000	0.133	0.133	0.065	0.063	-0.128	0.134	0.101	-0.101
1976	0.002	0.172	0.174	0.078	0.054	-0.130	0.175	0.126	-0.130
1977	0.000	0.179	0.180	0.061	0.065	-0.126	0.186	0.128	-0.135
1978	0.003	0.204	0.207	0.050	0.078	-0.125	0.192	0.168	-0.157
1979	0.000	0.193	0.193	0.064	0.061	-0.125	0.164	0.178	-0.149
1980	0.002	0.180	0.182	0.072	0.050	-0.120	0.131	0.185	-0.136
1981	0.001	0.196	0.196	0.079	0.064	-0.142	0.188	0.158	-0.150
1982	0.002	0.203	0.205	0.101	0.072	-0.171	0.223	0.126	-0.146
1983	0.000	0.268	0.269	0.089	0.079	-0.167	0.286	0.180	-0.198
1984	0.000	0.256	0.256	0.099	0.101	-0.201	0.240	0.214	-0.197
1985	0.001	0.344	0.346	0.112	0.089	-0.199	0.333	0.275	-0.264
1986	0.001	0.277	0.278	0.122	0.099	-0.220	0.260	0.230	-0.213
1987	0.000	0.292	0.292	0.111	0.112	-0.223	0.181	0.320	-0.210
1988	0.000	0.266	0.266	0.124	0.122	-0.246	0.221	0.250	-0.205
1989	0.001	0.238	0.239	0.128	0.111	-0.238	0.244	0.174	-0.180
1990	0.000	0.246	0.246	0.120	0.124	-0.243	0.223	0.212	-0.190
1991	0.002	0.303	0.305	0.100	0.127	-0.226	0.300	0.234	-0.231
1992	0.000	0.286	0.286	0.118	0.120	-0.238	0.288	0.214	-0.216
1993	0.002	0.274	0.276	0.132	0.100	-0.230	0.188	0.288	-0.203
1994	0.000	0.289	0.289	0.125	0.118	-0.243	0.233	0.277	-0.222
1995	0.000	0.244	0.244	0.130	0.132	-0.262	0.247	0.181	-0.184
1996	0.000	0.233	0.233	0.115	0.125	-0.240	0.187	0.224	-0.179
1997	0.000	0.216	0.217	0.123	0.120	-0.242	0.180	0.202	-0.166
1998	0.000	0.199	0.200	0.130	0.115	-0.245	0.174	0.180	-0.154
1999	0.000	0.212	0.212	0.132	0.123	-0.254	0.201	0.173	-0.162

Appendix Table 4

Decomposition of the Variance of Two-year Changes in Log Earnings Residuals, Age 40-49, ESP Model (continued)

Second Year	Variance of Change in Permanent Component	Variance of Change in Transitory Component	Variance of Change in Total	$\alpha_t^2 Var(\mu_{ia})$	$\alpha_{t-2}^2 Var(\mu_{i,a-2})$	$-2\alpha_t\alpha_{t-2} * cov(\mu_{ia}, \mu_{i,a-2})$	$\beta_t^2 Var(\upsilon_{ia})$	$\beta_{t-2}^2 Var(\upsilon_{i,a-2})$	$-2\beta_t\beta_{t-2} * cov(\upsilon_{ia}, \upsilon_{i,a-2})$
2000	0.000	0.225	0.225	0.134	0.130	-0.264	0.228	0.167	-0.170
2001	0.001	0.263	0.264	0.121	0.132	-0.252	0.269	0.193	-0.198
2002	0.002	0.302	0.303	0.108	0.134	-0.241	0.310	0.219	-0.227
2003	0.002	0.322	0.323	0.121	0.121	-0.241	0.309	0.258	-0.245
2004	0.002	0.341	0.343	0.134	0.108	-0.241	0.308	0.297	-0.263
2005	0.001	0.329	0.330	0.140	0.121	-0.260	0.286	0.296	-0.253
2006	0.000	0.316	0.316	0.146	0.134	-0.280	0.264	0.295	-0.243
2007	0.001	0.311	0.311	0.157	0.140	-0.296	0.276	0.274	-0.239
2008	0.001	0.306	0.307	0.168	0.146	-0.313	0.288	0.253	-0.235
2009	0.001	0.344	0.345	0.177	0.157	-0.333	0.341	0.265	-0.261
2010	0.000	0.383	0.383	0.185	0.168	-0.353	0.394	0.276	-0.288
2011	0.000	0.452	0.453	0.187	0.176	-0.363	0.465	0.327	-0.340
2012	0.000	0.522	0.522	0.189	0.185	-0.374	0.535	0.379	-0.392
2013	0.001	0.520	0.521	0.169	0.187	-0.355	0.466	0.446	-0.393
2014	0.002	0.517	0.520	0.150	0.189	-0.336	0.397	0.514	-0.394

Notes: See formula in Appendix.