Trends in Earning Volatility for U.S. Men: 1979-2017

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Abstract

This article explores how U.S. male income has evolved, ranging from 1979 to 2017. The research aims to decompose the income volatility into the permanent component − the long-term average − and transitory component − the period-specific deviation from the average − since the two have different implications in practice. After constructing a pseudo panel using the Current Population Survey, we estimate the structure of income volatility using an extended semiparametric model proposed by Moffitt & Zhang (2018). The transitory variance fluctuated through the mid-1990s and declined until 2002. Since then, the transitory variance increased through 2013 and almost recovered to the level in the mid-1990s. Furthermore, we find a countercyclical pattern of gross volatility and transitory variance around the Great Recession.

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I. Introduction

This article explores how U.S. male income has evolved over time. Our goal is to better understand income dynamics by decomposing the unexplained variation in earnings into permanent and transitory components and then examine how those components change over time. The purpose of decomposition is that the *permanent component* − the long-term average − and *transitory component* − the period-specific deviation from the average − have different implications in practice. For example, possible determinants of the permanent component are skill-biased technological change and labor demand shift, whereas a secular change in worker-firm attachment, labor market competitiveness, regulation, and temporary employment are pertinent to the transitory component (Haider, 2001; Moffitt & Gottschalk, 2011, 2012). Our analysis is, to our knowledge, the first study that investigates a long-term covariance structure of earnings in the Current Population Survey (CPS) by constructing a pseudo panel.

The early literature on variance decomposition uses the simplest error component model, consisting of a fixed individual-specific component and a year-specific idiosyncratic random component.[1] However, this model does not depict income dynamics in the real world. First, the relative importance of the permanent and transitory components changes over calendar time. Second, transitory shocks eventually fade out but last longer than one year. Third, a random walk or a random growth model is an excellent way to accommodate the individually fixed permanent component that evolves over the life cycle (Jäntti & Jenkins, 2015). Therefore, studies have extended the nascent model and incorporated additional features (Baker, 1997; Lillard & Willis, 1978; MaCurdy, 1982; Meghir & Pistaferri, 2004; Moffitt & Gottschalk, 2012). This article builds on Moffitt & Zhang (2018,

[1] An error component model is equivalent to a random-effects model.

hereafter MZ), which measure earnings volatility based on a semi-parametric approach.[2] Our results show that the permanent variance grew by 1989 and displayed no persistent trend from 1990 to 2017 with a fluctuation surrounding the Great Recession; The Transitory variance oscillated from 1979-1997, decreased until 2002, and resumed to increase surrounding the Great Recession. The countercyclical pattern of transitory variance surrounding the Great Recession is consistent with MZ. However, the transitory variance in our analysis decreased from the late 1990s to the mid-2000s, unlike a relatively stable pattern found in MZ. As in MZ, most increase in total variance surrounding the Great Recession is attributed to the rise in transitory variance. Others that study the variance of permanent and transitory components with a focus on calendar time trends (Braxton et al., 2021; Debacker et al., 2013; Hryshko et al., 2017; Jensen & Shore, 2015; Moffitt & Gottschalk, 2012) are not fully comparable because differences exist in sample selection and estimation methods.

Some studies only examine gross volatility − the dispersion of income change or income growth − because it is transparent and does not require delicate model assumptions. We also examine the dynamics of gross volatility prior to the variance decomposition. The gross volatility analysis in this article contributes to the recent effort to reconcile discrepancies across studies (Moffitt et al., 2022). We find the countercyclical movement in the gross volatility after the late 1990s, a common finding in not only MZ but also in Moffitt et al. (2022). However, MZ report gross volatility increasing from the 1970s to the mid-1980s before fluctuating until the mid-2000s and then spiking. Thus, a key difference between our work and MZ's is the sharp downtrend in gross volatility that preceded the Great Recession. Researchers disagree with the trend in gross volatility from the mid-1980s to the

[2] Our references to Moffitt & Zhang (2018) refer to both their articles as well as the accompanying online appendix.

late 1990s. A trimming method (Carr & Wiemers, 2021) and a degree of heaviness in a low tail (Moffitt et al., 2022) can explain those differences.

However, trends in permanent and transitory variances provide more evident policy implications than changes in gross volatility. For example, since consumers do not thoroughly smooth their consumption in response to permanent shocks, unlike transitory shocks, tax and welfare systems that focus on permanent shocks can remedy the partial insurance problem (Blundell et al., 2008). Furthermore, temporary deviations (transitory variance) from the long-term average (permanent variance) involve the re-ranking of individuals by income. However, the uncertainty of transitory income flows may be undesirable for risk-averse individuals.

Income Volatility and Income Mobility —This article examines how earnings volatility has changed in the U.S. If broadly defined, volatility measures the degree of change in economic variability from one period to the next. The primary volatility examined here is the variance of the transitory component obtained from the variance decomposition. However, earnings volatility often refers to gross volatility, the variance of income change or income growth.

This article also falls into one of four categories of income mobility defined by Jäntti & Jenkins (2015), each of which takes a distinct perspective on income mobility. Income mobility measures how individuals' incomes change from one time to the next. First, positional change measures each person's position relative to others. Second, aggregate individual income change between two periods − individual income growth − is another way to quantify income mobility. Third, income is highly mobile if the variance of long-term income is far smaller than the variance of period-specific income. Finally, the fourth measure is income risk, the primary topic of this article. If each individual's period-specific income is a sum of permanent and transitory components, the transitory components are subject to unexpected random idiosyncratic shocks. In this regard, a larger transitory variance represents greater income risk. This measure is often not based on overall dispersion in incomes but rather on variation in residual income after controlling for observables.

II. Data Sources in the Literature

Several data sets are used to decompose income patterns, and each has its own strengths and weaknesses.[3] This section discusses different data sets in income volatility studies.

CPS—This article uses the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS), commonly referred to as March CPS. In the CPS, each household is surveyed for the same four months in two consecutive years. Because the CPS has a larger sample size than the PSID, researchers can study earning volatility at a subgroup level (Ziliak et al., 2011). In addition, the CPS contains comprehensive questionnaires including labor market behavior, family characteristics, education, health insurance status, immigration, income from all sources, work experience, noncash benefits, poverty status, participation in government programs, and geographic mobility.

However, there are some drawbacks to the CPS data. First, the missing at random (MAR) assumption may not hold for non-responded earnings (Bollinger & Hirsch, 2006; Ziliak et al., 2011). Dropping allocated earnings is the best remedy, but unfortunately, the current data set does not have information on allocated earnings. Instead, since the non-response rate is the highest in tails (Bollinger et al., 2019),

[3] For more details, see Celik et al. (2012), Moffitt & Zhang (2018), Moffitt et al. (2022), and Moffitt (2021).
[4] https://lehd.ces.census.gov/

the trimming procedure, introduced in section IV.A., lowers the risk of biases on coefficients. Second, the top-coding method change can also lead to the wrong interpretation of income inequality (Burkhauser et al., 2009; Larrimore et al., 2008), which validates trimming again. Finally, a short panel is insufficient to examine earnings patterns over a longer time frame. Constructing a pseudo panel can address the issue (See section IV.B).

Some researchers have exploited the CPS's repeated sampling strategy in order to examine gross volatility in earnings using the matched CPS (Celik et al., 2012; Ziliak et al., 2011). However, year-over-year sampling is insufficient for examining a covariance structure of earnings over a longer time frame.

PSID—The Panel Study of Income Dynamics (PSID) is a longitudinal survey that began in 1968 with a sample of 5,000 U.S. families and has obtained information on individuals and their descendants from the initial sample. Since the data has tracked individuals for almost 50 years, the PSID has been heavily used in income dynamics studies. The PSID also provides a rich set of variables covering earnings, employment, other family member information, and county-level identifiers. Furthermore, non-response rates are relatively lower than CPS or SIPP (Killewald & Schoeni, 2011; Moffitt & Zhang, 2020). However, participants were initially surveyed annually and have been surveyed biennially since 1998, which is less frequent than other data sets. No detailed earnings information on non-head or non-spouse members in households and no coverage of U.S. immigrants are also a weakness of the PSID (Moffitt & Zhang, 2018).

SIPP—Survey of Income and Program Participation (SIPP) is a set of short panels spanning three to four years where sample members are interviewed every four months. The SIPP covers various topics, including economic well-being, family dynamics, education, assets, health insurance, childcare, and food security. Unlike the CPS, individuals are still interviewed even if they move to a new address.

LEHD—The Longitudinal Employment and Household Dynamics (LEHD) is compiled data of Unemployment Insurance earnings data, Quarterly Census of Employment and Wages data, additional administrative data, and data from censuses and surveys.[4] The LEHD provides longitudinal information on worker demographics, earnings histories, and firm characteristics. Not only the sample size is large, but also LEHD covers almost the entire U.S. workforce, unlike surveys that only include those who agreed to participate. However, the dataset began in the 1990s and thus does not go back as far as many other data sets.

Administrative Datasets—Panel data from the Social Security Administration (SSA), the Internal Revenue Services (IRS), and Unemployment Insurance (UI) records have been used to complement studies of permanent-transitory volatility (Braxton et al., 2021; Debacker et al., 2013) and gross volatility (Bloom et al., 2017; Guvenen et al., 2014). In contrast to survey data, these data sets are relatively free from reporting errors and attrition bias. In addition, administrative datasets are generally much more extensive than survey data sets. However, such datasets may miss some parts of the population – e.g., nonfilers with tax data.

III. Major Findings in the Literature

If broadly defined, volatility measures the degree of change in an economic variability from one period to the next. The primary volatility examined here is the variance of the transitory component after decomposing earnings residuals. However, earnings volatility often refers to gross volatility, the variance of income

[4] https://lehd.ces.census.gov/

change or income growth. This section summarizes past literature on these two concepts.[5]

A. Permanent and Transitory Variances

Table 1 lists several recent papers that examine the variance of permanent and transitory components with a focus on calendar time trends. In the last decade, Moffitt & Gottschalk (2012), Jensen & Shore (2015) and MZ examine trends in permanent and transitory variances of male heads in households using the PSID. Jensen & Shore (2015) show that both means of permanent and transitory variances increased during the period 1968-2009. According to Moffitt & Gottschalk (2012), permanent variance rose from the early 1970s to the mid-1980s, was stable through the mid-1990s, and resumed to increase thereafter. Transitory variance rose from the early 1970s to the mid-1980s and was stable thereafter. MZ, which build on Moffitt & Gottschalk (2012) but allow variances to be a non-parametric function in age, find that both variances rose from the 1970s to the 1980s. In addition, permanent variance peaked in the mid-1980s, and transitory variance peaked in the late 1980s. Both fluctuated through the mid-2000s and rose before the Great Recession. Some studies (Braxton et al., 2021; Debacker et al., 2013; Hryshko et al., 2017) using administrative data sets find increasing permanent variance and decreasing or stable transitory variance. However, these results are not fully comparable because differences exist in sample selection and estimation methods.

[5] The modern literature on income volatility begins with Friedman (1957) and is quite rich. Here, we do not summarize the entire literature but rather focus on several more recent studies that are most relevant to our work. Furthremore, we only focus on earnings volatility for U.S. men unless noted otherwise.

B. Gross Volatility

There are primarily two methods to measure gross volatility: 1) variance of (1-year or 2-year) change in (residual) log earnings and 2) variance of arc percentage change in (residual) earnings.[6] The latter includes workers even though their earnings observation in one year is zero. However, researchers demonstrate that including movements into and out of work does not significantly affect the gross volatility trend (Moffitt & Zhang, 2020; Ziliak et al., 2021). Table 2 is a list of recent gross volatility studies.[7]

Studies of U.S. gross income volatility from survey data sets sometimes yield similar findings but not always. For example, most studies using the matched CPS (Celik et al., 2012; Koo, 2016; Ziliak et al., 2011) and the PSID (Carr & Wiemers, 2018; Celik et al., 2012; Moffitt & Zhang, 2018; Shin & Solon, 2011) find rising gross volatility over the 1970s and 1980s and then a flat or downward trend in the 1990s. On the other hand, the volatilities in the SIPP survey modestly declined from 1984 to the 2000s or the 2010s (Celik et al., 2012; McKinney & Abowd, 2020).

Gross volatility results from administrative data sets also are not consistent across studies. For example, Guvenen et al. (2014) and Bloom et al. (2017) use Social Security Earnings data to show that gross volatility has declined steadily since 1978, called the *Great Micro Moderation*. Dahl et al. (2011) compare the Continuous Work History (CWHS) sample from SSA records and SIPP linked to the administrative data, and show that both trended down over the sample period (1984-2005). Two studies using LEHD (Celik et al., 2012; McKinney & Abowd, 2020) show slightly declining trends with a spike surrounding the Great Recession. Debacker et al. (2013) use IRS tax data merged with SSA records and W-2 data

[6] Most studies control age to eliminate a life-cycle effect.
[7] Readers should be cautions that methodologies are not perferctly analogous.

and find that gross volatility was reasonably stable over their sample period, from 1987-2009, with fluctuations. Carr & Wiemers (2018), Carr & Wiemers (2021), and Carr et al. (2020) using the SIPP linked to administrative earnings histories – Detailed Earnings Records (DER) from the Social Security Administration – report gross volatility that increased in the early 1980s, declined through 2000, and rose through the mid-2000s, similar to what studies using the PSID and matched CPS find.

Due to these different findings, Moffitt et al. (2022) focus explicitly on reconciling gross volatility estimates across studies, which is a project paper that includes key results of Moffitt and Zhang (2020), McKinney & Abowd (2020), Carr et al. (2020) and Ziliak et al. (2021). The paper finds no average trend from the mid-1980s to the 1998-2002 period with the PSID, SIPP linked to SSA records and SIPP. After 1998, the matched CPS, CPS linked to SSA records, Survey of Income and Program Participation Gold Standard File (SIPP GSF), and PSID show increases surrounding the Great Recession, followed by declines.[8] Meanwhile, the SIPP and LEHD show little downtrend after 1998. However, they report that with identical sample selection methods (left-tail adjusted), no data set shows a significant overall volatility trend over the last 30 years, even though apparent countercyclicality exists. According to Carr & Wiemers (2021), real dollar trim in administrative data (Bloom et al., 2017; Guvenen et al., 2014) and trim at percentile points mostly done in survey data sets (Moffitt & Zhang, 2018) may also explain the differences.

[8] The Survey of Income and Program Participation Gold Standard File (SIPP GSF) links each individual in a SIPP household in SIPP panels to their whole IRS and SSA earnings and benefits records.

IV. Data

A. Current Population Survey

Our data are from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) (commonly referred to as March CPS), which the U.S. Census Bureau compiles in conjunction with the Bureau of Labor Statistics.[9] In addition to tracking labor market behavior, ASEC CPS includes detailed demographic information on family characteristics, including marital status, education, health insurance status, geographic and immigration information. With respect to labor market behavior and program participation, these data include income from all sources, work experience, noncash benefits, poverty status, participation, and benefits from government programs. Participants are surveyed for four consecutive months. They are not followed for the next eight months. Then, they are sampled again for another four consecutive months before leaving the sample permanently.[10] Thus, each household is surveyed for the same four months in two consecutive years. While the CPS includes data on respondents over two years, it is primarily a repeated cross-sectional survey and thus not suitable for modeling income over the life cycle, which requires longer-run autocovariances. Section IV.B elaborates on how we address this issue by constructing a pseudo panel.

Our data spans the survey years 1980 through 2018. Because earnings (and other variables) pertain to the year preceding the survey year, this article studies earnings

[9] We use the publicly available version of the data from the Center for Economic and Policy Research (CEPR, Center for Economic and Policy Research. 2019. March CPS Uniform Extracts, Version 1.1. Washington, DC.). The CEPR version makes some adjustments for definitional changes over time and links the March CPS with some information from other survey months.

[10] For additional details, visit https://www.census.gov/programs-surveys/cps/technical-documentation/methodology.html.

volatility trends over the years 1979 to 2017.[11] We use annual wages and salaries as the measure of earnings. We restrict our sample to men between ages 30 and 59, excluding full-time students and those without positive earned income.[12] Samples with zero weight are dropped.[13] Finally, earnings are converted to 2017 CPI-U-RS dollars.

To protect the confidentiality of respondents, incomes in the CPS are top coded. Prior to survey year 1996, incomes above a maximum ($50,000 in 1980-1981, $75,000 in 1982-1984, $99,999 in 1985-1987, and $199,998 in 1988-1995) are assigned the same top-coded value. For the survey years 1996-2010, a different approach was used where incomes above the maximum were replaced by the mean income of individuals with the same characteristics. Beginning with the survey year 2011, the Census Bureau introduced the rank proximity swapping method. In this system, all incomes above the threshold are ranked and replaced with a value for respondents with a similar income rank.[14] Both changes to the threshold for top coding and top-coding procedures can result in a misleading picture of the top of the income distribution and how it has changed over time. In addition, the percentage of individuals with censored household income in public March CPS has increased since 1980 (Burkhauser et al., 2011). Therefore, we trim the top four percent so as to eliminate top-coded incomes.[15] The sample is summarized in Table 3.

[11] Unless otherwise noted, we refer to the year the data represents and not the year in which it is collected.

[12] MZ only include heads of household while we also include non-heads.

[13] In the CPS, the base weight is the inverse probability of the person in the sample and roughly equal to the number of actual persons that the sample person represents. The final weight is obtained after the base weight is adjusted for noninterview and demographic characteristics. We dropped oberservations with zero final weight.

[14] https://cps.ipums.org/cps/topcodes_tables.shtml

[15] MZ trim the top and bottom one percent of residuals, whereas R. Moffitt & Zhang (2020) trim the top and bottom one percent of log earnings. However, Moffitt & Gottschalk (2002) do not find any significant difference in the results between trimming earnings variable and trimming residuals.

[Insert Table 3 Here]

[Insert Figure 1, Figure 2, and Figure 3 Here]

Figure 1 and Figure 2 plot the earning distribution in 1979, 1989, 2000, 2007, and 2017. The distributions in later years are wider, with more mass in the right tail than in the early years. The range for 2017 is from approximately $9,000 to $213,000. Real earnings below the bottom 10th percentiles have changed little over these years. However, we observe divergence as we move beyond the middle of the earnings distribution. Figure 1 and Figure 2 are consistent with Ziliak et al. (2021), who use restricted-access CPS ASEC data linked to the Social Security Administration's Detailed Earning Records (DER).[16] Song et al. (2019) also report more divergence among higher income groups with CPS data. However, they found that bottom percentiles also experienced positive income growth, a finding that may be sensitive to the sample construction.[17]

Figure 3 depicts trends in selected percentiles of the male earning distribution from 1979 to 2017. The figure again shows more rapid growth at the 90th percentile, especially since 1990. The rise in cross-sectional variance is a conventional view on U.S. income (Bloom et al., 2017). On the other hand, researchers disagree on trends in earnings volatility (see section III).

Researchers also disagree about the degree of cross-sectional income divergence, especially for those above the 90th percentile. Some claims that the top 1% income share has increased marginally (Auten & Splinter, 2019, 2020; Larrimore et al., 2021; Smith et al., 2020), whereas others show dramatic upsurges in top incomes

[16] The sample is restricted to people between the ages of 25-59 who have positive earnings, are linked to the DER, and are not full-time students. The data is not trimmed for outliers.

[17] Song et al. (2019) include those aged between 20 and 60 with non-zero wage and salary income, and who are not employed in education services, or public administration (see Figure A.3 in the paper). While we trim observations at 4%, Song et al. (2019) use real dollar trim where the sample is restricted to only those with strong labor market attachement.

(Piketty et al., 2018; Saez & Zucman, 2020). Such difference partially results from methodological choices for imputing income sources that are not directly observed (Auten & Splinter, 2019).

The increased cross-sectional variance of income is consistent with increasing earnings inequality. However, readers should be cautious that it does not capture the entire picture. Income data represents wage and salary earnings before taxes and other deductions and only includes overtime pay, commissions, or tips. Important income sources, such as Social Security benefits, in-kind transfers, and employer fringe benefits, are not accounted for here. Employer-provided fringe benefits, particularly health insurance, have represented a growing share of compensation over the period (Piketty et al., 2018). According to Elwell et al. (2019), narrowly defined income measures overestimate income inequality moreso than comprehensive measures such as Haig-Simons income (see Appendix Figure 1).

B. Pseudo Panel

Some researchers have exploited the CPS's repeated sampling strategy in order to examine year-over-year variation in earnings using the matched CPS (Celik et al., 2012; Ziliak et al., 2011). However, year-over-year sampling is insufficient for examining the covariance structure of earnings over a longer time frame.

To investigate the longer-term covariance structure of earnings, we construct a pseudo panel so as to follow "pseudo" individuals, or composites based on cohorts of individuals who share the same set of demographic characteristics. In place of individuals, cohort means are the unit of observation (Deaton, 1985). Pseudo panel data have some advantages over true panel data, such as Panel Study of Income Dynamics (PSID), in that it circumvents the problem of attrition bias. Furthermore, pseudo panels typically follow cohorts over a longer time horizon than true panels.

However, pseudo-panel data only identify cohort-level shocks and not within cohort variability occurring at the individual level (Meghir & Pistaferri, 2011).

Each individual is assigned to precisely one cohort where the characteristics for creating cohorts are exogenous and time-invariant (Guillerm, 2017). Following the criteria, we form a pseudo panel based on an individual's year of birth, education level, and race, as shown in Table 4. The average cohort size in our data is 39, and cohort-year observations are 22,861, with 586 pseudo observations per year on average. Since cohorts vary in size, our analysis weights regressions by the square root of the cohort size, as Deaton (1985) proposed. For more details, see section V.A.

[Insert Table 4 Here]

V. Methodology

A. Pseudo-Panel Estimation

Our goal is to decompose the unexplained variation in earnings into permanent and transitory components and then examine how those components change over time. The first step is to estimate the following earnings equation in order to capture the residuals

$$y_{ct} = \beta_{0t} + X'_{ct}\beta_{1t} + Y'_{ct}\beta_{2t} + Z'_{ct}\beta_{3t} + \epsilon_{ct}. \tag{1}$$

y is log earnings for cohort c at time t. X is a vector of five education dummy variables − less than high school, high school, some college, college, and advanced degree. Y is an age polynomial (cubic), and Z is the interaction between X and age. Calendar year dummies are not included since the regressions are run separately by year. The regressions are weighted by the square root of the cohort size to correct for heteroscedasticity (Guillerm, 2017). The residuals, $\hat{\epsilon}_{ct}$, are then used to build a variance-covariance matrix where each off-diagonal element is the autocovariance between residual log earnings of males at age a and a' between years t and t'. (Again, we weight variances and covariances by cohort size.) We follow MZ in constructing variance-covariance matrices across age groups (30-39, 40-49, and 50-59) and by year. As a result, there are 1,670 elements in our matrix. This procedure is a first step in estimating life-cycle changes in the variance of permanent and transitory earnings components.

The variance of first-differenced residuals from the log income in equation (1), defined as $var[\hat{\epsilon}_{it} - \hat{\epsilon}_{it-1}]$, is a standard measure of *gross volatility* (Jäntti & Jenkins, 2015; Moffitt & Zhang, 2018). Other studies use the arc percentage change in (residual) earnings, $var[\frac{\hat{\epsilon}_{it} - \hat{\epsilon}_{it-1}}{(\hat{\epsilon}_{it} + \hat{\epsilon}_{it-1})/2}]$, as a measure of gross volatility (Dynan et al., 2012; Hardy & Ziliak, 2014; Ziliak et al., 2011). Meanwhile, *cross-sectional inequality* is typically defined as the variance of (residual) log earnings variance, $var(\hat{\epsilon}_{it})$. Figure 4 presents the gross volatility by year (weighted by cohort size) and compares it with the male unemployment rate.[18] Like MZ, we present the average annual variance (of the first-differenced residuals), which are first computed separately by age group.[19]

Figure 4 shows that the gross year-over-year volatility fluctuated through the mid-1990s, but did not exhibit a clear trend, followed by a steep decline through 2002. Post-2006, the gross volatility increased, exceeding its previous peak by 2014, followed by a sharp drop from 2014 to 2015. We also observe a direct relationship between the unemployment rate and gross volatility during the Great

[18] The unemployment rate represents the number of unemployed as a percentage of the labor force, restricted to men 20 years old and older (source: Federal Reserve Bank of St. Louis).
[19] Note that the overall variance – calculated separately by year but with all age groups together – yields a similar pattern.

Recession, implying that the recent decade's volatility mainly follows a business cycle effect.

The countercyclical movement in the gross volatility after the late 1990s is a common finding in not only MZ but also in the recent study by Moffitt et al. (2022) that compare six data series – PSID, matched CPS, CPS linked to SSA records, SIPP Gold Standard File, SIPP, and LEHD. However, MZ report gross volatility increasing from the 1970s to the mid-1980s before fluctuating until the mid-2000s, then spiking. Thus, an essential difference between our work and MZ's is the decreasing trend in gross volatility that preceded the Great Recession. Researchers disagree with the trend in gross volatility from the mid-1980s to the late 1990s, with some showing a stable trend (Moffitt & Zhang, 2018; Ziliak et al., 2011), others finding an increasing trend (Dynan et al., 2012), and others showing a decreasing trend (Carr & Wiemers, 2018; Shin & Solon, 2011). The disagreement may be attributed to a characteristic of data set sets, such as a heaviness in a low tail (Moffitt et al., 2022). Real dollar trim may also explain a consistent decreasing trend in the gross volatility since 1980 shown in administrative data sets (Bloom et al., 2017; Guvenen et al., 2014), while the rest trim data at percentile points (Carr & Wiemers, 2021). [20] In addition, a recent update from Moffitt & Zhang (2020) shows that gross volatility fell from 2014-2016, nearly returning to the pre-recession levels. Figure 4 shows something similar, with gross volatility in 2017 returning to the level in the 1990s. For more details, refer to Table 2, which lists recent gross volatility studies.

[Insert Figure 4 Here]

[20] For example, Bloom et al. (2017) restrict the sample to have earnings above a time-varing threshold equal to the mount one would earn by working full time for a quarter of the year at half of the federal minimum wage.

Because pseudo panels use the average for each cohort, caution is warranted when comparing our gross volatility measure to those from other studies. As sample sizes increase and the demographic characteristics used in constructing cohorts become more granular, pseudo panel results should mirror those from a true panel more closely. With less granular data, variances are likely to be lower since the average income of the cohort is likely to be more stable than for any of the individuals making up the cohort. In this article, we focus moreso on the trends in volatility, as opposed to levels, which are more directly comparable across studies.

B. Extended Semiparametric Model

We employ a version of the extended semiparametric (ESP) model developed by MZ. The ESP model uses residuals from log earnings equations, $\hat{\epsilon}_{ct}$, to decompose total volatility into permanent and transitory components. The ESP model overcomes one criticism of the widely used error component (EC) model that the EC model estimates are often sensitive to parametric assumptions (Jäntti & Jenkins, 2015). The ESP model is non-parametric with respect to the dynamic evolution of permanent and transitory variances but maintains a traditional linear framework of the EC model. Therefore, the EC and ESP models have something in common: the permanent and transitory components are a simple linear sum of independent shocks. However, the shocks in the ESP model are non-parametric functions of age, unlike in the EC model, where shocks are constant or linear functions of age.

For studies relying on the Panel Study of Income Dynamics (PSID), such as MZ, the shortest volatility measure is over two-year intervals since the data is biennial. Because our pseudo-panel data are annual, we can estimate calendar shift effects – α_t and β_t – over one-year intervals.

Following MZ, we set out to estimate

(2) $$\epsilon_{cat} = \alpha_t \mu_{ca} + \beta_t v_{ca}$$

where ϵ is the log earnings residual for cohort c at age a and year t. μ is the permanent component with α_t representing the corresponding calendar time shift. v is the transitory component with β_t representing the corresponding calendar time shift. While μ and v only evolve with age, the calendar time shifts represent differences in levels across calendar years. For example, μ being a flow of human capital services, α_t shows changes in the average return to skill (Moffitt & Gottschalk, 2012). Equations (3) and (4) present the structure of the permanent and transitory components.

(3) $$\mu_{ca} = \mu_{c0} + \sum_{s=1}^{a} \omega_{cs}$$

(4) $$v_{ca} = \xi_{ca} + \sum_{s=1}^{a-1} \psi_{a,a-s} \xi_{c,a-s} \ \ for\ a \geq 2$$

(5) $$v_{c1} = \xi_{c1} \ \ for\ a = 1.$$

Equation (4) is approximated to $v_{ca} = \psi v_{c,a-1} + \xi_{ca}$ if $\psi_{a,a-s} \cong \psi$ for all s, which represent an $AR(1)$ process. Hence, transitory component, v_{ca}, depends on its one-period lag, $v_{c,a-1}$, and a transitory shock, ξ_{ca}. $AR(1)$ can also be presented as an infinite moving average process $-$ $MA(\infty)$ $-$ as in equation (4). In this formulation, the transitory component, v_{ca}, depends on past transitory shocks, $\xi_{c,a-s}$, but the effect of the shock, $\psi_{a,a-s}$, dims as distance between the present and the past, s, widens, with condition $|\psi_{a,a-s}|$<1. On the other hand, the effect of the permanent shock, ω_{cs}, "permanently" remained because its coefficient is always 1, as in equation (3). The permanent shock, ω, and the transitory shock, ξ, are independently distributed over cohorts and time.

Following MZ, the variances and autocovariances derived from our model are

(6) $$Var(\epsilon_{cat}) = \alpha_t^2 Var(\mu_{ca}) + \beta_t^2 Var(\upsilon_{ca})$$

(7) $$Var(\mu_{ca}) = Var(\mu_{c0}) + \sum_{s=1}^{a} Var(\omega_{cs})$$

(8) $$Var(\upsilon_{ca}) = Var(\xi_{ca}) + \sum_{s=1}^{a-1} \psi_{a,a-s}^2 Var(\xi_{c,a-s}) \;\; for\ a \geq 2$$

(9) $$Var(\upsilon_{c1}) = Var(\xi_{c1}) \; for\ a = 1$$

(10) $$\begin{aligned} &Cov\left(\epsilon_{cat}, \epsilon_{c,a-\tau,t-\tau}\right) \\ &= \alpha_t \alpha_{t-\tau} Cov\left(\mu_{ca}, \mu_{c,a-\tau}\right) + \beta_t \beta_{t-\tau} Cov(\upsilon_{ca}, \upsilon_{c,a-\tau}) \end{aligned}$$

(11) $$Cov\left(\mu_{ca}, \mu_{c,a-\tau}\right) = Var\left(\mu_{c,a-\tau}\right) = Var(\mu_{c0}) + \sum_{s=1}^{a-\tau} Var(\omega_{cs})$$

(12) $$\begin{aligned} &Cov\left(\upsilon_{ca}, \upsilon_{c,a-\tau}\right) = \psi_{a,a-\tau} Var\left(\xi_{c,a-\tau}\right) \\ &+ \sum_{s=1}^{a-\tau-1} \psi_{a,a-\tau-s} \psi_{a-\tau,a-\tau-s} Var(\xi_{c,a-\tau-s}) \;\; for\ a \geq 3 \end{aligned}$$

(13) $$\begin{aligned} &Cov\left(\upsilon_{ca}, \upsilon_{c,a-\tau}\right) = \psi_{a,a-\tau} Var\left(\xi_{c,a-\tau}\right) = \psi_{21} Var(\xi_{c1}) \\ &for\ a = 2, \tau = 1. \end{aligned}$$

Hence, using a generalized method of moments (GMM), the estimator finds close matches for population variances and autocovariances in equations (6)-(13) to their sample counterparts from log earning residuals, $\hat{\epsilon}_{ct}$, in equation (1). For more details, see section V.C.

The variances of the permanent and transitory shocks, ω and ξ, are non-parametric functions of age, and ψ parameters are also non-parametric functions of age and lag length, τ or $\tau + s$, as follows:

(14) $$Var(\omega_{ca}) = e^{\sum \delta_j (a-25)^j}$$

(15) $$Var(\xi_{ca}) = e^{\sum \gamma_j (a-25)^j} \; for\ a \geq 2$$

(16) $$Var(\xi_{c1}) = ke^{\sum \gamma_j (1-25)^j} \; for\ a = 1$$

(17) $$\psi_{a,a-b} = [1 - \pi(a-25)]\left[\sum \omega_j e^{-\lambda_j b}\right] + \sum \eta_j D(b=j).$$

The variances of permanent and transitory shocks, ω and ξ, are exponential functions of polynomial expansions of age minus 25. The initial transitory variance $Var(\xi_{c1})$ contains an initial adjustment k. The ψ parameters expand in a weighted sum of exponentials, and a linear age-function factor is in front of the weighted sum. The degree of expansion is chosen by generalized cross-validation (GCV). The chosen degree minimizes the objective function − the difference between empirical and predicted variances/autocovariances of residuals adjusted by some values (e.g., the number of parameters). Therefore, $Var(\mu_{c0}), \delta_j, \gamma_j, k, \pi,$ $\lambda_j, \omega_j, \eta_j, \alpha_t, \beta_t$ are parameters to be estimated and fit the variance-autocovariance matrix of the data using a minimum distance method.[21]

C. GMM Estimation of the Covariance Structure on Earnings

We use the generalized method of moments (GMM) to estimate the model. The parameter vector is denoted by $A = [Var(\mu_{c0}), \delta_j, \gamma_j, k, \pi, \lambda_j, \omega_j, \eta_j, \alpha_t, \beta_t]'$. The

[21] For more details on methodology, see the Appendix in MZ.

population moment is $m(A_0) = E[g(A_0)] = 0$ with an actual parameter vector A_0 and a vector-valued function $g(\bullet)$. The population moments are derived from equations (6)-(13) for all ages and times. GMM chooses the parameter vector which minimizes the criterion function

$$\bar{m}(A)' W_n \bar{m}(A) \tag{18}$$

where W_n is a semi-definite weighting matrix that does not depend on A, and $\bar{m}(A)$ is a vector of sample moments. The sample moments are variances and autocovariances of log earning residuals, $\hat{\epsilon}_{ct}$, in equation (1). However, since estimation with the weighing matrix can lead to biases in finite samples (Doris et al., 2011), an identity matrix can be chosen as an alternative (Altonji et al., 2013). This approach is widely adopted as standard practice when estimating earnings covariance (Doris et al., 2011; Moffitt & Gottschalk, 2012; Moffitt & Gottschalk, 2011; Moffitt & Zhang, 2018). Then, equation (18) becomes equivalent to

$$\bar{m}(A)' \bar{m}(A) \tag{19}$$

where $\hat{A}$ becomes a vector of minimum distance estimators. Thus, $\hat{A}$ minimizes the sum of squares of the distance between population variances-covariances from equations (6)-(13) and sample variances-covariances, from log earning residuals, $\hat{\epsilon}_{ct}$, in equation (1).

VI. Results

Early studies of income dynamics (Bound & Johnson, 1992; Levy & Murnane, 1992) in the 1990s suggest determinants of inequality are labor demand shift and skill-biased technological change, which implicitly assume that the permanent variance is responsible for income volatility over the 1970s and 1980s. Since then, the literature has shifted, focusing more on the transitory variance and the role of factors such as market competitiveness, deregulation, and temporary employment (Haider, 2001; Moffitt & Gottschalk, 2011, 2012). In this later literature, the focus on the transitory variance addresses earnings volatility resulting from temporary deviations from the long-term average, which is more likely to involve the re-ranking of individuals by income on an annual basis. While an increasing transitory variance implies more volatility or mobility, it also entails a loss in welfare due to uncertainty (Jäntti & Jenkins, 2015).

The importance of each of these effects is subject to caveats. To the extent people can smooth consumption over time, the random transitory shock becomes less important. If permanent income is not affected (and capital markets are efficient), then consumption should also be unaffected, implying little loss due to risk aversion. Likewise, temporary income rerankings are not too meaningful if they have little relationship to the distribution of permanent income. This also depends on individual perceptions. For example, in real-time, people may not be able to discern permanent from transitory shocks. To the extent this is the case, the utility will be lower since consumption should under-respond to permanent shocks and over-respond to transitory shocks – compared to a scenario where the nature of the income shocks is fully understood.

[Insert Figure 5 Here]

[Insert Table 5 Here]

Figure 5 presents calendar time factors α and β based on the income process from equation (2). α and β are normalized to one in 1979. The calendar time factor for the permanent component, α, grew to over 1.3 by 1989 and then displayed no persistent trend from 1990 to 2017 with a fluctuation surrounding the Great Recession. The increase of α in the 1980s corresponds to rises in the return to education and other indices of skill differentials (Moffitt & Gottschalk, 2012). The trend of α is consistent with MZ, but ours in the 2010s almost returned to the level in the early 1980s, but α estimates in MZ rose about 52% by 2014. The smallest and the largest estimates for α were recorded in the final two years – 0.96 in 2016 and 1.37 in 2017. The calendar time factor for the transitory component, β, oscillated between 0.95 and 1.2 from 1979-1997. From 1998-2012, our estimates of β were unusually low, averaging 0.86 and never reaching 1. For comparison, estimates of β from MZ rose from the 1970s to the mid-1980s, fluctuated until the mid-2000s, and increased since then. Our estimates of β resemble those from MZ in that they increased in years around the Great Recession, supporting evidence that countercyclicality explains a significant part of the trends in transitory variance. However, a downtrend in the 1990s is different from a stable trend from MZ. In addition, estimates of β from MZ rose 55% from 1979 to 2014, whereas our corresponding estimates exhibit no net trend over the entire sample period, similar to the estimates of α. Because Moffitt et al. (2022) update the PSID data up to 2018 and show an ongoing downtrend after the peak in 2012, estimates of α and β using PSID may eventually return to the level of the 1980s if more data are availabe. The full estimates for α and β are reported in Table 5.

[Insert Figure 6, Figure 7, and Figure 8 Here]

[Insert Table 6 Here]

The implications of these trends for the permanent and transitory variances are shown as the fitted variances of log earnings residuals by age groups in Figures FIGURE 6-FIGURE 8. The fitted permanent variance and fitted transitory variance are $\hat{\alpha}_t^2 Var(\hat{\mu}_{ca})$ and $\hat{\beta}_t^2 Var(\hat{v}_{ca})$, repectively, from equation (6). The fitted values are summarized in Table 6. Even though the levels of variances differ by age group, the permanent and transitory variance trends are nearly identical and emulate the movement of α and β. Again, the countercyclical pattern of transitory variance surrounding the Great Recession is consistent with MZ, but transitory variance decreased from the late 1990s to the mid-2000s, unlike a relatively stable pattern found in MZ. The transitory variance was about 74% of the total variance until the late 1990s, and its contribution to the total variance dropped to almost 52% in 2002. Then, the transitory variance resumed to increase and was about 70% of the total variance surrounding the Great Recession. As in MZ, the increase in total variance surrounding the Great Recession is attributed to the rise in transitory variance.

Other than MZ, Moffitt & Gottschalk (2012) and Jensen & Shore (2015) also examine the variance of permanent and transitory components with a focus on calendar time trends. Jensen & Shore (2015) show that both means of permanent and transitory variances increased during the period 1968-2009. According to Moffitt & Gottschalk (2012), permanent variance rose from the early 1970s to the mid-1980s, was stable through the mid-1990s, and resumed to increase thereafter. Transitory variance rose from the early 1970s to the mid-1980s and was stable thereafter. Some studies (Braxton et al., 2021; Debacker et al., 2013; Hryshko et al., 2017) using administrative data sets find increasing permanent variance and decreasing or stable transitory variance. However, these results are not fully comparable because differences exist in sample selection and estimation methods.

VII. Conclusion

This article explores how U.S. male income has evolved over time by decomposing the unexplained variation in earnings into permanent and transitory components. After constructing a pseudo panel using the Current Population

Survey, we estimate the structure of income volatility using an extended semiparametric model proposed by Moffitt & Zhang (2018).

The results show that the calendar time factor for the permanent component, α, grew by 1989 and then displayed no persistent trend from 1990 to 2017 with a fluctuation surrounding the Great Recession. The increase of α in the 1980s corresponds to rises in the return to education and other indices of skill differentials. The calendar time factor for the transitory component, β, oscillated from 1979-1997, was unusually low during the period 1998-2012, and increased in years around the Great Recession. The transitory variance was about 74% of the total variance until the late 1990s, and its contribution to the total variance dropped to almost 52% in 2002. Then, the transitory variance resumed to increase and was about 70% of the total variance surrounding the Great Recession. Furthermore, we find a countercyclical pattern of gross volatility and transitory variance around the Great Recession.

The article focuses on the income volatility of prime-age men, and extensions to other sub-demographic levels – such as females, immigrants, or minorities – are not explored yet. The heterogeneity of income volatility across different demographic groups would also be of interest and is left for future research.

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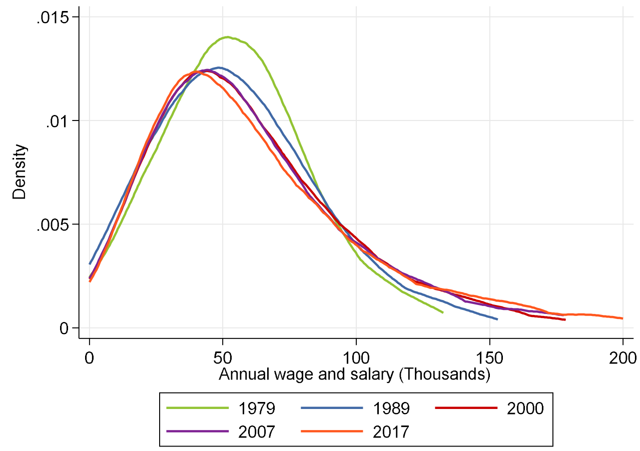


FIGURE 1. PROBABILITY DENSITY OF MALE EARNINGS

Notes: The statistics are based on kernel density estimates. All annual wage and salary earnings are adjusted for inflation to 2017 dollars using CPI-U-RS. The sample includes men between the ages of 30 and 59 who are not full-time students, and have positive earned income. The data is trimmed at 4%.

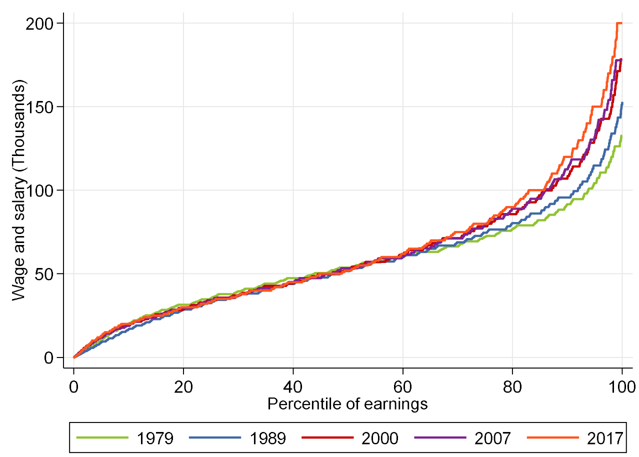


FIGURE 2. CUMULATIVE DISTRIBUTION OF MALE ANNUAL EARNINGS

Notes: All annual wage and salary earnings are adjusted for inflation to 2017 dollars using CPI-U-RS. The sample includes men between the ages of 30 and 59 who are not full-time students, and have positive earned income. The data is trimmed at 4%.

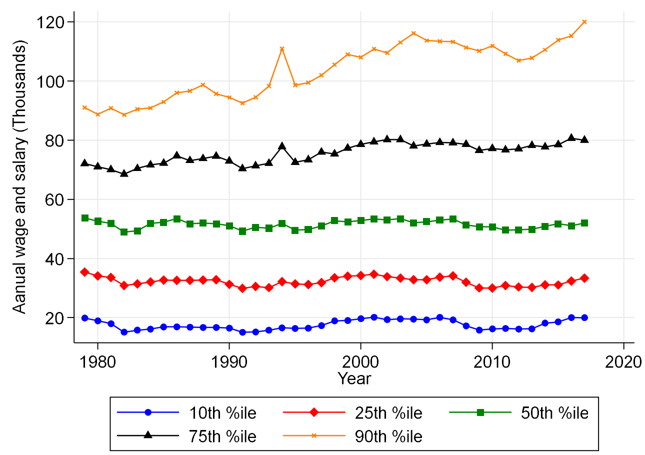


FIGURE 3. MALE EARNINGS BY PERCENTILES

Notes: All annual wage and salary earnings are adjusted for inflation to 2017 dollars using CPI-U-RS. The sample includes men between the ages of 30 and 59 who are not full-time students, and have positive earned income. The data is trimmed at 4%.

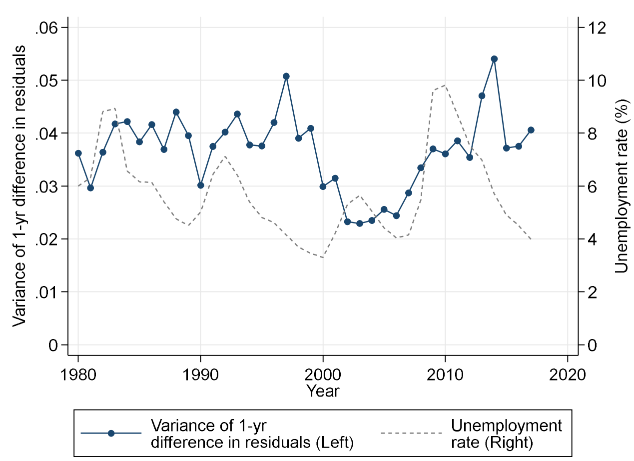


FIGURE 4. VARIANCE OF ONE-YEAR DIFFERENCE IN MALE LOG EARNINGS RESIDUALS

Note: The variance of one-year difference in log earning residuals is defined as $var(\hat{\epsilon}_{it} - \hat{\epsilon}_{it-1})$. To obtain residuals, we regress log earnings on education, a polynomial in age, and interaction between age and education variables, separately by calendar year, as described in equation (1). It is an average of variance among the different age groups where the variance is a weighted sum by cohort size. The unemployment rate represents the number of unemployed as a percentage of the labor force, restricted to men 20 years old and older (source: Federal Reserve Bank of St. Louis).

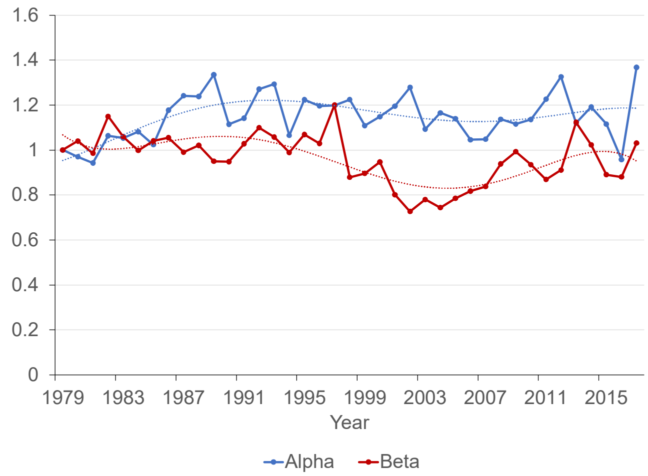


FIGURE 5. EXTENDED SEMIPARAMETRIC (ESP) MODEL ESTIMATES OF ALPHA AND BETA

Notes: α and β are the calendar time factors based on the income process in equation (2), normalized to 1 in 1979. The smoothed lines are fitted from fifth-order polynomials. The estimates are also in Table 3.

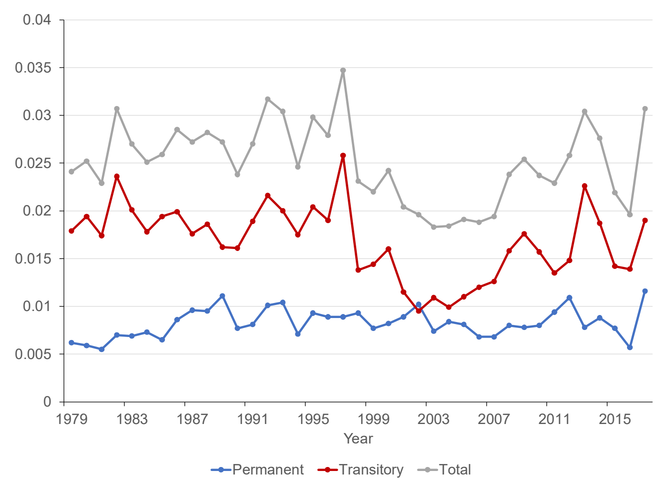


FIGURE 6. FITTED PERMANENT, TRANSITORY, AND TOTAL VARIANCE OF LOG EARNINGS RESIDUALS: AGES 30-39

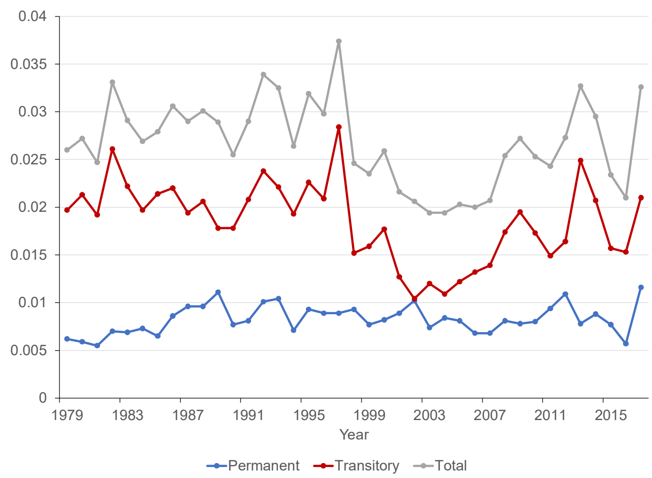


FIGURE 7. FITTED PERMANENT, TRANSITORY, AND TOTAL VARIANCE OF LOG EARNINGS RESIDUALS: AGES 40-49

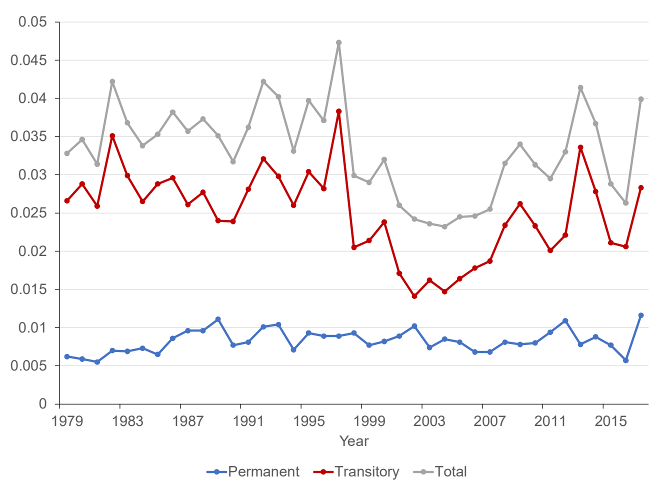


FIGURE 8. FITTED PERMANENT, TRANSITORY, AND TOTAL VARIANCE OF LOG EARNINGS RESIDUALS: AGES 50-59

TABLE 1. LITERATURE ON PERMANENT AND TRANSITORY VARIANCES WITH FOCUS ON CALENDAR TIME TRENDS

Study	**Sample**	**Method**	**Findings**
Moffitt & Gottschalk (2012)	PSID, Male heads, Ages 30-59, 1970-2004	Error components model: Random walk and random growth in permanent component and ARMA(1,1) process in transitory component	Permanent variance rose from the early 1970s to the mid-1980s, was stable through the mid-1990s, and resumed to increase thereafter. Transitory variance rose from the early 1970s to the mid-1980s and was stable thereafter.
DeBacker et al. (2013)[22]	Tax returns merged with SSA records and W-2 data, Males, Ages 25-60, 1987-2009	Two WA methods[23] Error components model: Random walk and random growth in permanent component and MA(2) process in transitory component	Permanent variance increased over the sample period, but transitory variance was stable.
Jensen & Shore (2015)	PSID, Males heads, Ages 22-60, 1968-2009	Error components model: Variance of permanent and transitory shocks are correlated and heterogeneous.	Both means of permanent and transitory variances increased over the sample period by the right tail.
Hryshko et al. (2017)[24]	SIPP-SSA, Males, Ages 25-59, 1980-2009	WA method	Permanent variance rose over the sample period, but transitory variance fluctuated with no trend.
Moffitt & Zhang (2018)	PSID, Males heads, Ages 30-59, 1970-2014	Error components model: Random walk process is in permanent component, and the evolution of variances is non-parametric.	Both variances rose from the 1970s to the 1980s. Permanent variance peaked in the mid-1980s, and transitory variance peaked in the late 1980s. Both fluctuated through the mid-2000s and rose before the Great Recession.
Braxton et al. (2021)	SSA-CPS, Men and women combined, Ages 25-60, 1982-2016	Heterogenous permanent and transitory components are conditional on labor market status and observables	Transitory variance declined, but permanent shocks increased since the 1980s.

Notes: The table summarizes results related to our analysis the most only.

[22] DeBacker et al. (2013) also include studies on household incomes.
[23] Moffitt & Zhang (2018) define Window Averaging (WA) method as "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." One example is to use a variance based on traditional Anaysis of Variance (ANOVA) as a transitory variance.
[24] Primary interest of Hryshko et al. (2017) is earnings volatility of married couples, but the table summarizes the male volatility only, which is comparable with our result.

TABLE 2. LITERATURE ON GROSS VOLATILITY

Study	Sample	Method	Findings
Shin & Solon (2011)	PSID, Male heads, Ages 25-59, 1969-2006	Standard deviation of 2-year change in log earnings residuals	Standard deviation trended upwards until 1983, declined through the late-1990s, and rose thereafter.
Dahl et al. (2011)	CWHS, All workers, Ages 25-55, 1984-2005 SIPP-SSA, All workers, Ages 25-55, 1984-2005	Dispersion of arc earnings changes greater than 50 percent between years	Volatility declined over the sample period
Ziliak et al. (2011)[25]	Matched CPS, Males, Ages 16-60, 1973-2009	Standard deviation of arc percentage change	Standard deviation increased sharply through the 1970s and into the mid-1980s and was stable thereafter.
Dynan et al. (2012)[26]	PSID, Male heads and spouses, Non-students and non-retirees, 1971-2008	Standard deviation of 2-year arc percentage change	Standard deviation strongly increased until 1985 and then showed a slower rate of increase
Celik et al. (2012)	PSID (Males, Ages 25-59, 1971-2006) Matched CPS (Males, Ages 25-59, 1967-2009) SIPP (Males, Ages 25-59, 1984-2006) LEHD (Males, Ages 25-59, 1992-2008)	Standard deviation of change in log earnings residuals	Both the CPS and the PSID estimates increased in the 1970s, peaked in the early 1980s, and declined in the 1990s. After stabilization, the CPS measure resumed the increase during the Great recession, while the PSID measure rose again before the Great Recession. LEHD showed a slightly declining trend from 1992 to 2008. SIPP estimates declined from 1984 to 2006.
DeBacker et al. (2013)[27]	Tax returns merged with SSA records and W-2 data, Males, Ages 25-60, 1987-2009	Standard deviation of the percentage change in log earnings residuals	Gross volatility fluctuates but shows no evidence of a trend.
Hardy & Ziliak (2014)	Matched CPS, Families, Ages 25-60, 1980-2009	Variance of arc percentage change in disposable family income	The volatility rose until 2001 and stabilized thereafter.
Guvenen et al. (2014)	SSA records, Males, Ages 25-60, 1978-2011	Standard deviation of change in log earnings	The standard deviation decreased over the sample period.
Koo (2016)[28]	Matched CPS, Males, Ages 25-59, 1979-2011	Standard deviation of the change in log earnings residuals	Standard deviation peaked in the early 1980s, was stable, and increased after the Great Recession.

[25] Ziliak et al. (2011) also measure female gross volatility, which declined over the entire period.
[26] Dynan et al. (2012) also conducted an analysis of gross volatility using female heads and spouses, and households
[27] DeBacker et al. (2013) also include studies on household incomes.
[28] Koo (2016) also include an analysis on females.

Study	Sample	Method	Findings
		Standard deviation of the arc percentage change in earnings residuals	
Bloom et al. (2017)[29]	SSA records, Males, Ages 25-64, 1978-2013	Variance of the change in log earnings	The standard deviation decreased over the sample period.
Carr & Wiemers (2018)	SIPP GSF[30], Males, Ages 25-59, 1978-2011 PSID, Male heads, Ages 25-59, 1978-2012	Standard deviation of 2-year change in log earnings residuals	The volatility from both rose during the early 1980s, declined through 2000 and rose through the mid-2000s.
Braxton et al. (2021)	SSA-CPS, Men and women combined, Ages 25-60, 1982-2016[31]	Standard deviation of change in log earnings residuals	A mild downward trend with countercyclical spikes in the late 1980s and the mid-2000s
Carr & Wiemers (2021)	SIPP GSF, Males, Ages 25-59, 1978-2014	Variance of change in log earnings residuals Variance of arc percentage change in earnings residuals	The volatility increased until 1982, declined between 1983 and 1999, and increased through the Great Recession.
Moffitt et al. (2022)[32]	PSID, Male heads, Ages 25-59, 1970-2018 Matched CPS, Males, Ages 25-59, 1995-2015 CPS-SSA, Males, Ages 25-59, 1995-2015 SIPP GSF, Males, 25-59, 1980-2014 SIPP, Males, 25-59, 1984-2012 LEHD, Males, 25-59, 1998-2016	Variance of 1-year or 2-year arc percentage change in earnings	There was no average trend from the mid-1980s to the 1998-2002 period with PSID, SIPP GSF, and SIPP. After 1998, matched CPS, CPS-SSA, SIPP GSF, and PSID show increases around the Great Recession, followed by declines. The volailtiy in the SIPP and LEHD modestly declined over the sample period.

Notes: The table summarizes results related to our analysis the most only.

[29] Bloom et al. (2017) also include an analysis on females and firm-level variance decomposition.
[30] The Survey of Income and Program Participation Gold Standard File (SIPP GSF) links each individual in a SIPP household in SIPP panels to their whole IRS and SSA earnings and benefits records.
[31] A main data source in Braxton et al. (2021) is the SSA records whose supplement is the CPS while the CPS-SSA in Ziliak et al. (2021) and Moffitt et al. (2022) are those men and women in both the CPS and the SSA data.
[32] Because Moffitt et al. (2022) include the main results of Moffitt and Zhang (2020), McKinney & Abowd (2020), Carr et al. (2020) and Ziliak et al. (2021), the four papers are not on the list.

TABLE 3. DESCRIPTIVE STATISTICS: CPS CROSS-SECTION

	Mean	Standard Deviation	Minimum	Maximum
Age	43	8.424	30	59
Married (%)	0.74	0.437	0	1
Race:				
White (%)	0.78	0.415	0	1
Black (%)	0.08	0.275	0	1
Hispanic (%)	0.09	0.283	0	1
Others (%)	0.05	0.219	0	1
Education:				
Less than high school (%)	0.12	0.329	0	1
High school (%)	0.33	0.472	0	1
Some college (%)	0.25	0.432	0	1
College (%)	0.19	0.391	0	1
Advanced (%)	0.11	0.308	0	1
Employment:				
Full time, full year (%)	0.82	0.385	0	1
Working hours per week	43.56	9.46	1	99
Working weeks	48.82	8.87	1	52
Wage and Salary (2017 Dollars)	56,584	33,668	1	200,000

Notes: The data ranges from 1979 to 2017. All annual wage and salary earnings are adjusted for inflation to 2017 dollars using CPI-U-RS. The sample includes men between the ages of 30 and 59 who are not full-time students and have positive earned income. The data is trimmed at 4%. The table is based on 890,159 observations.

TABLE 4. DESCRIPTIVE STATISTICS: A PSEUDO PANEL

	Mean	Standard Deviation	Minimum	Maximum
Wage and salary earnings (2017 Dollars)	45,615	21,326	90	187,370
Working weeks	48.32	4.340	1	52
Age	44.35	8.615	30	59
Married (%)	0.72	0.206	0	1
Race:				
White (%)	0.26	0.436	0	1
Black (%)	0.25	0.433	0	1
Hispanic (%)	0.25	0.430	0	1
Others (%)	0.25	0.432	0	1
Education:				
Less than high school (%)	0.20	0.401	0	1
High school (%)	0.20	0.403	0	1
Some college (%)	0.20	0.401	0	1
College (%)	0.20	0.400	0	1
Advanced (%)	0.19	0.395	0	1
Cell size	39	63.767	1	626

Notes: The data ranges from 1979 to 2017. All annual wage and salary earnings are adjusted for inflation to 2017 dollars using CPI-U-RS. The sample includes men between the ages of 30 and 59 who are not full-time students and have positive earned income. The data is trimmed at 4%. A pseudo-panel is constructed based on an individual's year of birth, education level, and race. The table is based on 22,861 observations.

Table 5. Estimates of the ESP Model Parameters

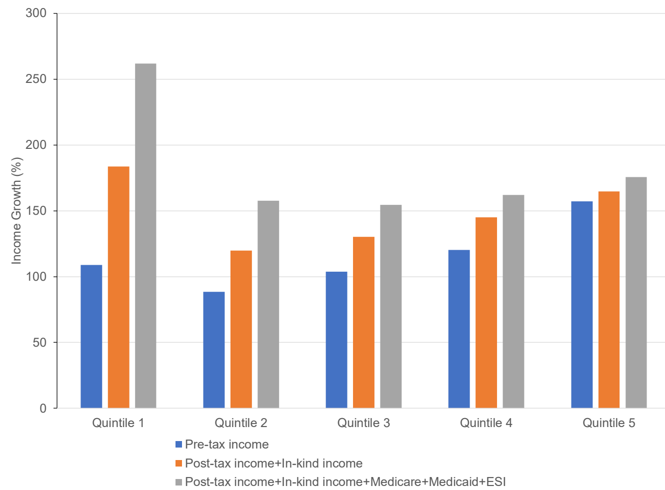
Alpha			Beta			Others		
	Coefficient	Standard Error		Coefficient	Standard Error		Coefficient	Standard Error
α_{1980}	0.9697	0.0080	β_{1980}	1.0400	0.0048	$Var(\mu_{i0})$	0.0062	0.0001
α_{1981}	0.9425	0.0073	β_{1981}	0.9859	0.0086	λ	0.0551	0.0029
α_{1982}	1.0633	0.0063	β_{1982}	1.1494	0.0047	η_0	-11.5137	0.4775
α_{1983}	1.0533	0.0102	β_{1983}	1.0595	0.0058	π	-0.1468	0.0048
α_{1984}	1.0817	0.0094	β_{1984}	0.9981	0.0046	k	1.5188	0.0997
α_{1985}	1.0240	0.0094	β_{1985}	1.0410	0.0054	η_1	-2.3291	0.0579
α_{1986}	1.1773	0.0104	β_{1986}	1.0547	0.0050	δ_0	-15.4304	29.0889
α_{1987}	1.2415	0.0106	β_{1987}	0.9907	0.0050	δ_1	-0.0074	2.1871
α_{1988}	1.2386	0.0144	β_{1988}	1.0206	0.0039	γ_0	-8.6724	0.0877
α_{1989}	1.3349	0.0134	β_{1989}	0.9502	0.0066	γ_1	0.0344	0.0005
α_{1990}	1.1146	0.0139	β_{1990}	0.9484	0.0038	η_2	-0.2634	0.0083
α_{1991}	1.1418	0.0100	β_{1991}	1.0277	0.0080			
α_{1992}	1.2708	0.0129	β_{1992}	1.0991	0.0081			
α_{1993}	1.2934	0.0133	β_{1993}	1.0578	0.0059			
α_{1994}	1.0651	0.0110	β_{1994}	0.9892	0.0057			
α_{1995}	1.2245	0.0132	β_{1995}	1.0690	0.0068			
α_{1996}	1.1960	0.0133	β_{1996}	1.0294	0.0047			
α_{1997}	1.1984	0.0139	β_{1997}	1.2002	0.0092			
α_{1998}	1.2243	0.0113	β_{1998}	0.8787	0.0047			
α_{1999}	1.1088	0.0101	β_{1999}	0.8963	0.0049			
α_{2000}	1.1483	0.0111	β_{2000}	0.9467	0.0064			
α_{2001}	1.1952	0.0133	β_{2001}	0.8013	0.0060			
α_{2002}	1.2785	0.0157	β_{2002}	0.7269	0.0041			
α_{2003}	1.0928	0.0121	β_{2003}	0.7797	0.0038			
α_{2004}	1.1649	0.0123	β_{2004}	0.7442	0.0039			
α_{2005}	1.1398	0.0120	β_{2005}	0.7851	0.0044			
α_{2006}	1.0461	0.0111	β_{2006}	0.8175	0.0048			
α_{2007}	1.0481	0.0114	β_{2007}	0.8379	0.0050			
α_{2008}	1.1372	0.0135	β_{2008}	0.9383	0.0044			
α_{2009}	1.1160	0.0125	β_{2009}	0.9931	0.0069			
α_{2010}	1.1357	0.0126	β_{2010}	0.9352	0.0062			
α_{2011}	1.2262	0.0143	β_{2011}	0.8695	0.0074			
α_{2012}	1.3259	0.0144	β_{2012}	0.9110	0.0040			
α_{2013}	1.1204	0.0114	β_{2013}	1.1234	0.0078			
α_{2014}	1.1915	0.0138	β_{2014}	1.0230	0.0048			
α_{2015}	1.1153	0.0115	β_{2015}	0.8906	0.0070			
α_{2016}	0.9575	0.0099	β_{2016}	0.8803	0.0045			
α_{2017}	1.3676	0.0203	β_{2017}	1.0310	0.0053			

Notes: Parameters α and β are normalized to 1 in 1979.

TABLE 6. ESTIMATED PERMANENT VARIANCE, TRANSITORY VARIANCE, AND TOTAL VARIANCE BY AGE GROUP

Year	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
1979	0.0062	0.0179	0.0241	0.0062	0.0197	0.0260	0.0062	0.0266	0.0328
1980	0.0059	0.0194	0.0252	0.0059	0.0213	0.0272	0.0059	0.0288	0.0346
1981	0.0055	0.0174	0.0229	0.0055	0.0192	0.0247	0.0055	0.0259	0.0314
1982	0.0070	0.0236	0.0307	0.0070	0.0261	0.0331	0.0070	0.0351	0.0422
1983	0.0069	0.0201	0.0270	0.0069	0.0222	0.0291	0.0069	0.0299	0.0368
1984	0.0073	0.0178	0.0251	0.0073	0.0197	0.0269	0.0073	0.0265	0.0338
1985	0.0065	0.0194	0.0259	0.0065	0.0214	0.0279	0.0065	0.0288	0.0353
1986	0.0086	0.0199	0.0285	0.0086	0.0220	0.0306	0.0086	0.0296	0.0382
1987	0.0096	0.0176	0.0272	0.0096	0.0194	0.0290	0.0096	0.0261	0.0357
1988	0.0095	0.0186	0.0282	0.0096	0.0206	0.0301	0.0096	0.0277	0.0373
1989	0.0111	0.0162	0.0272	0.0111	0.0178	0.0289	0.0111	0.0240	0.0351
1990	0.0077	0.0161	0.0238	0.0077	0.0178	0.0255	0.0077	0.0239	0.0317
1991	0.0081	0.0189	0.0270	0.0081	0.0208	0.0290	0.0081	0.0281	0.0362
1992	0.0101	0.0216	0.0317	0.0101	0.0238	0.0339	0.0101	0.0321	0.0422
1993	0.0104	0.0200	0.0304	0.0104	0.0221	0.0325	0.0104	0.0298	0.0402
1994	0.0071	0.0175	0.0246	0.0071	0.0193	0.0264	0.0071	0.0260	0.0331
1995	0.0093	0.0204	0.0298	0.0093	0.0226	0.0319	0.0093	0.0304	0.0397
1996	0.0089	0.0190	0.0279	0.0089	0.0209	0.0298	0.0089	0.0282	0.0371
1997	0.0089	0.0258	0.0347	0.0089	0.0284	0.0374	0.0089	0.0383	0.0473
1998	0.0093	0.0138	0.0231	0.0093	0.0152	0.0246	0.0093	0.0205	0.0299
1999	0.0077	0.0144	0.0220	0.0077	0.0159	0.0235	0.0077	0.0214	0.0290
2000	0.0082	0.0160	0.0242	0.0082	0.0177	0.0259	0.0082	0.0238	0.0320
2001	0.0089	0.0115	0.0204	0.0089	0.0127	0.0216	0.0089	0.0171	0.0260
2002	0.0102	0.0095	0.0196	0.0102	0.0104	0.0206	0.0102	0.0141	0.0242
2003	0.0074	0.0109	0.0183	0.0074	0.0120	0.0194	0.0074	0.0162	0.0236
2004	0.0084	0.0099	0.0184	0.0084	0.0109	0.0194	0.0085	0.0147	0.0232
2005	0.0081	0.0110	0.0191	0.0081	0.0122	0.0203	0.0081	0.0164	0.0245
2006	0.0068	0.0120	0.0188	0.0068	0.0132	0.0200	0.0068	0.0178	0.0246
2007	0.0068	0.0126	0.0194	0.0068	0.0139	0.0207	0.0068	0.0187	0.0255
2008	0.0080	0.0158	0.0238	0.0081	0.0174	0.0254	0.0081	0.0234	0.0315
2009	0.0078	0.0176	0.0254	0.0078	0.0195	0.0272	0.0078	0.0262	0.0340
2010	0.0080	0.0157	0.0237	0.0080	0.0173	0.0253	0.0080	0.0233	0.0313
2011	0.0094	0.0135	0.0229	0.0094	0.0149	0.0243	0.0094	0.0201	0.0295
2012	0.0109	0.0148	0.0258	0.0109	0.0164	0.0273	0.0109	0.0221	0.0330
2013	0.0078	0.0226	0.0304	0.0078	0.0249	0.0327	0.0078	0.0336	0.0414
2014	0.0088	0.0187	0.0276	0.0088	0.0207	0.0295	0.0088	0.0278	0.0367
2015	0.0077	0.0142	0.0219	0.0077	0.0157	0.0234	0.0077	0.0211	0.0288
2016	0.0057	0.0139	0.0196	0.0057	0.0153	0.0210	0.0057	0.0206	0.0263
2017	0.0116	0.0190	0.0307	0.0116	0.0210	0.0326	0.0116	0.0283	0.0399

APPENDIX FIGURE 1. INCOME GROWTH FOR 1959-2016 USING ALTERNATIVE MEASURES OF INCOME BY QUINTILES



Source: Elwell et al. (2019)

Note: Household income is adjusted using the square root of the number of people in the household and assumes equal sharing across household members. The first income measure includes gross income from wages and salaries, farm income, self-employment and business income, retirement income from pensions, dividends, interest, rent and alimony, and government cash transfers. The second measure adds federal and state taxes and liabilities, SNAP, housing subsidies, and school lunches to the first.