

JASON DEBACKER
Middle Tennessee State University

BRADLEY HEIM
Indiana University

VASIA PANOUSI
*Board of Governors of the
Federal Reserve System*

SHANTHI RAMNATH
U.S. Department of the Treasury

IVAN VIDANGOS
*Board of Governors of the
Federal Reserve System*

Rising Inequality: Transitory or Persistent? New Evidence from a Panel of U.S. Tax Returns

ABSTRACT We use a new, large, and confidential panel of tax returns to study the persistent-versus-transitory nature of rising inequality in male labor earnings and in total household income, both before and after taxes, in the United States over the period 1987–2009. We apply various statistical decomposition methods that allow for different ways of characterizing persistent and transitory income components. For male labor earnings, we find that the entire increase in cross-sectional inequality over our sample period was driven by an increase in the dispersion of the persistent component of earnings. For total household income, we find that most of the increase in inequality reflects an increase in the dispersion of the persistent income component, but the transitory component also appears to have played some role. We also show that the tax system partly mitigated the increase in income inequality, but not sufficiently to alter its broadly increasing trend over the period.

An extensive literature has documented a large increase in income inequality in the United States in recent decades. In this paper we ask to what extent this observed increase reflects an increase in persistent or in transitory inequality. By persistent inequality we mean long-run inequality, or the dispersion across the population in those components of income that are more or less stable over periods of more than a few years. By transitory inequality we mean the dispersion arising from short-run variability

in incomes, as individuals move around within the income distribution at relatively short frequencies of one to a few years.¹

The distinction between persistent and transitory inequality is important for various reasons. First, it is useful in evaluating proposed explanations for the documented increase in annual cross-sectional inequality. For example, if rising inequality reflects solely an increase in persistent inequality, then explanations consistent with this rise would include skill-biased technical change and long-lasting changes in employers' compensation policies. By contrast, an increase in transitory inequality could reflect increases in income mobility, driven perhaps by greater flexibility among workers to switch jobs. Second, the distinction is useful because it informs the welfare evaluation of changes in inequality. Lifetime income captures an individual's (or a household's) long-term available resources, and hence an increase in persistent inequality would reduce welfare according to most social welfare functions. By contrast, increasing transitory inequality would have less of an effect on welfare, especially in the absence of liquidity constraints restricting consumption smoothing.

One important aspect of our contribution is the use of a new and superior data source to shed new light on the decomposition of inequality and of changes in inequality into persistent and transitory components. We use a new, large, and confidential panel of tax returns from the Internal Revenue Service (IRS) to study the persistent-versus-transitory nature of rising inequality in individual male labor earnings and in total household income, both before and after taxes, in the United States over the period 1987–2009.² Our panel constitutes a 1-in-5,000 random sample of the population of U.S. taxpayers. It contains individual-level labor earnings information from W-2 forms as well as household-level income information from Form 1040. It also includes information on the age and sex of the primary and secondary tax filers from matched Social Security Administration (SSA) records. Our broadest sample consists of roughly 350,000 observations on 35,000 households and is therefore substantially larger than the publicly

1. In this study our baseline measure of income inequality is the cross-sectional variance (that is, the variance across all individuals or households in our sample at a given time) in the logarithm of annual income. We use the terms “persistent inequality” and “persistent variance” to refer to the variance of the persistent component of income. Therefore, an increase in inequality is called “persistent” if it is driven by an increase in the variance of the persistent component of income. A similar interpretation will apply to “transitory inequality” and “transitory variance.”

2. The analysis was conducted at and approved by the U.S. Treasury Department to ensure that the strictest confidentiality is preserved.

available, survey-based panels typically used to address related questions in the literature. In addition, our data are not subject to top-coding and are less likely than the survey data to be affected by measurement error.

We analyze the persistent-versus-transitory nature of rising inequality by decomposing income into persistent and transitory parts and examining how much each of these parts contributed to the increase in the cross-sectional variance of income (our measure of income inequality; see footnote 1) over our sample period. In reality, incomes are subject to many different types of shocks. Some of these might be truly persistent (or even permanent), and some entirely transitory, but many are likely to exhibit some degree of persistence (that is, serial correlation) in between the two extremes. As a result, decomposing income into persistent and transitory components requires taking a stand on what degree of serial correlation in income shocks will be considered “persistent” and what degree will be considered “transitory.” This choice necessarily involves some arbitrariness.

Our analysis uses two sets of methods, each of which takes a somewhat different approach to separating income into persistent and transitory parts. First, we employ simple nonparametric decomposition methods that essentially separate income into a highly transitory piece that exhibits no serial correlation and one other piece, which we call “persistent.” These methods then ask how much of the rise in the variance of income is coming from changes in the variance of the transitory piece and how much from changes in the variance of the persistent piece. Second, we employ rich nonstationary error components models of income dynamics.³ These models fully specify the process that generates income over time and essentially decompose income into a highly persistent piece and another, transitory piece that allows for some (limited) degree of serial correlation. Here, too, we then ask how much of the rise in the variance of income is coming from changes in the variance of the persistent piece and of the transitory piece.

The two approaches can give somewhat different answers about the shares of income inequality at any given point in time that are attributed to the persistent and to the transitory income components. The more serial correlation that is allowed in the transitory income component, the larger the share of inequality at a given point in time that will be attributed to that component (because some of the short-duration persistence in the income data will be attributed to the transitory piece). The simple nonparametric

3. Throughout the paper, we refer to error components models as nonstationary if model parameters are allowed to change over calendar time so as to capture changes over time in the distribution of income (including its dispersion).

methods, which use a stricter definition of transitory income, attribute the vast majority of the variance to the broadly defined persistent income component. Our error components models, which, as noted, allow for some serial correlation in transitory income, assign a somewhat larger fraction of total inequality to this more broadly defined transitory income.

However, and most important, both approaches yield very similar results for our main object of interest: the increase in income inequality and its components over time. For male labor earnings, both approaches imply that the entire increase in cross-sectional inequality over the 1987–2009 period was driven by an increase in the variance of the persistent component of earnings. Specifically, we find that the variance of the persistent component of log male labor earnings increased over this period but the variance of the transitory component did not.

For total household income—which in addition to male labor earnings includes spousal labor earnings, transfer income, investment income, and business income—both approaches imply that the increase in inequality over our sample period was mostly (although not entirely) persistent. For this broader category of income, the variance of both the persistent and the transitory components of income increased, but the persistent component contributed the bulk of the increase in the total variance. Furthermore, the increase in the variance of the transitory component of total household income reflects increases in the transitory variance of spousal labor earnings and of investment income.

Next, we use our data from tax returns to examine the role of the federal tax system in the observed trend in income inequality. In particular, we investigate whether the increase in inequality for after-tax household income differs materially from that for pre-tax income. Our measure of after-tax household income accounts for all federal personal income taxes (obtained from Form 1040), including all refundable tax credits, as well as payroll taxes (calculated using information from W-2 forms). We find that the cross-sectional variance of after-tax income is on average 0.10 squared log point, or roughly 15 percent, smaller than the variance of pre-tax income, reflecting the overall progressivity of the federal tax system. In terms of the trend, we find that the tax system helped mitigate somewhat the increase in household income inequality over the sample period, but this attenuating effect was insufficient to significantly alter the broad trend toward rising inequality.

Finally, we note that our paper is the first to estimate error components models of income dynamics using U.S. administrative data, and that the quality and significant size of our data set allow us to obtain very precise

estimates of our models. Our paper is also among the first to apply non-stationary models to household-level income, which is arguably a more relevant income measure than individual earnings for questions regarding consumption and welfare. Additionally, our comparison of decompositions using different approaches should help clarify the connections as well as the differences that exist across the different methods.

The rest of the paper is organized as follows. Section I discusses the related literature and places our results in the context of existing studies. Section II describes our data set, our sample selection, and the trends in income inequality in our data. Section III outlines our methodological approach. Section IV introduces the simpler nonparametric methods and presents results for male earnings using those methods. Section V introduces our error components models, discusses their estimation, presents model estimates for male labor earnings, and uses the estimated model to decompose the cross-sectional variance of male earnings into persistent and transitory parts. Section VI presents results using our various methods for pre-tax total household income. Section VII investigates the role of the federal tax system in the increase in income inequality. Section VIII concludes.

I. Related Literature

An extensive literature has documented a large increase in labor earnings inequality in the United States in recent decades.⁴ A small branch of this literature has attempted to determine whether this documented increase in cross-sectional earnings inequality reflects an increase in persistent or in transitory inequality, as these are defined in footnote 1. The earlier studies, including Peter Gottschalk and Robert Moffitt (1994), Moffitt and Gottschalk (1995), and Steven Haider (2001), all use data from the Panel Study of Income Dynamics (PSID) and generally conclude that a substantial part (as much as one half) of the increase in cross-sectional earnings inequality in the 1970s and early 1980s was transitory.⁵

4. For instance, Kopczuk, Saez, and Song (2010) use longitudinal earnings data from SSA records to document that inequality in annual earnings among men has been rising since around 1970. See also the earlier contributions by Bound and Johnson (1992), Katz and Murphy (1992), Murphy and Welch (1992), Juhn, Murphy, and Pierce (1993), Katz and Autor (1999), and more recently, Autor, Katz, and Kearney (2008).

5. Baker and Solon (2003) find broadly similar results for Canada using administrative data.

Very few studies have analyzed the last two decades, although earnings inequality has continued to increase. Furthermore, the results across the more recent studies are not conclusive. For example, using the PSID, Moffitt and Gottschalk (2011) find that the transitory variance has not increased since the mid- to late 1980s, whereas Jonathan Heathcote, Fabrizio Perri, and Gianluca Violante (2010) conclude that the transitory variance rose substantially in the 1990s.⁶ Wojciech Kopczuk, Emmanuel Saez, and Jae Song (2010), using Social Security earnings data, find that the increase in inequality from the 1970s to the early 2000s was entirely driven by the persistent component of earnings. However, they use only a simple nonparametric decomposition method, and their findings contradict the more established results of the earlier literature for the 1970s and early 1980s, raising some doubts about the factors driving their results for the more recent period as well. In this paper, our data clearly show that the increase in male earnings inequality since the mid- to late 1980s has been entirely driven by the persistent component of earnings. We confirm this finding with a variety of methods, obtaining very robust results.⁷

Inequality in total household income has also increased in recent decades, as documented by, among others, Dirk Krueger and Perri (2006) and Heathcote, Perri, and Violante (2010). Studies that have in some way attempted to decompose the increase in household income inequality into persistent and transitory parts include Gottschalk and Moffitt (2009), Giorgio Primiceri and Thijs van Rens (2009), and Richard Blundell, Luigi Pistaferri, and Ian Preston (2008). Gottschalk and Moffitt (2009) use a simple nonparametric method and provide only suggestive evidence of an increase in the transitory variance starting in the mid-1980s, without conducting a full analysis. By contrast, Primiceri and van Rens (2009), using repeated cross sections on income and consumption from the Consumer Expenditure Survey (CE), find that all of the increase in household income inequality in the 1980s and 1990s reflects an increase in the persistent (or permanent) component of the variance. Our results indicate that, for the

6. Heathcote, Perri, and Violante (2010) document patterns in inequality over time in a number of variables at the individual and the household level. Their decomposition of changes in the variance of earnings into transitory and persistent components is not the main focus of their paper. Also, they use hourly wages, rather than annual earnings, and estimate a simpler error components model. Our approach is closer to that of Moffitt and Gottschalk (2011).

7. In our online appendix, however, we present some results suggesting that the transitory component might play more of a role in the PSID data than in administrative data. Online appendixes for papers in this volume may be found at the Brookings Papers website, www.brookings.edu/about/projects/bpea, under "Past Editions."

increase in the cross-sectional variance of household income, the transitory variance does play some role, although not as prominent a role as Gottschalk and Moffitt (2009) seem to suggest.⁸ Furthermore, we show that the (relatively small) increase in the transitory variance of household income reflects increases in the transitory variance of spousal labor earnings and of investment income.

Our paper is also related to a recent literature that has analyzed the trends in the dispersion of short-term income changes, or income volatility, where volatility is defined as the standard deviation of percentage changes in male earnings over, say, 1 year. The findings in this literature have been more consistent across different studies. For instance, Congressional Budget Office (2008), John Sabelhaus and Song (2009, 2010), Sule Celik and coauthors (2012), and Donggyun Shin and Gary Solon (2011) all find that the volatility of male earnings did not increase between the 1980s and the early 2000s.⁹ Our male labor earnings data are consistent with the findings in this literature, as we document no increase in male earnings volatility. However, we do find an increase in the volatility of total household income.

Finally, our study also relates to a literature that examines changes in the distribution of household consumption expenditure in the United States. Economic theory predicts that increases in the dispersion of the persistent components of income are likely to lead to increases in the dispersion of consumption. A few studies have examined whether the well-documented increase in U.S. income inequality has indeed been accompanied by an increase in consumption inequality of similar magnitude. Some of the earlier studies in this literature, including Daniel Slesnick (2001), Krueger and Perri (2006), Heathcote, Perri, and Violante (2010), and perhaps to a lesser extent Orazio Attanasio, Eric Battistin, and Hide Ichimura (2007) and Attanasio, Battistin, and Mario Padula (2011), find that consumption inequality increased by only a fraction of the increase in income inequality. However, these studies relied on data from the CE, and it has been increasingly recognized in the literature that these data are subject to potentially severe measurement error problems. More recent studies, such as Mark Aguiar and

8. Blundell, Pistaferri, and Preston (2008) find an increase in the variance of persistent income shocks in the early 1980s, followed by an increase in the variance of transitory shocks in the late 1980s. We cannot directly compare our results with theirs, as our sample periods barely overlap.

9. Dynan, Elmendorf, and Sichel (2012) find a continuous increase in the volatility of male earnings in the PSID over the 1967–2004 period. However, their measure of earnings includes income from self-employment and hence is not directly comparable to ours or to that of the studies mentioned above.

Mark Bilts (2012) and Attanasio, Erik Hurst, and Pistaferri (2012), attempt to control for these measurement problems and conclude that consumption inequality has increased by a similar magnitude as income inequality. Thus, the implications of our results of a significant increase in consumption inequality appear to be borne out by the most recent evidence based on consumption data.

II. Data

This section describes our panel of income data from tax returns, the main variables we use, our sample selection, and the trends in income inequality observed in our data over the period 1987–2009.

II.A. Panel

We use a 23-year panel of income data from tax returns spanning the period 1987–2009. Our sample is a 1-in-5,000 random sample of the U.S. tax-filing population (with two exceptions noted below),¹⁰ and inclusion of tax units in the sample is based on the last four digits of the Social Security number (SSN) of the primary tax filer.¹¹ The sample is kept representative of the tax-filing population by adding, each year, any new tax units that join the population of filers (for example, immigrants and young people entering the work force) and have an SSN with the sampled four-digit ending. Our panel is not subject to the usual attrition or nonresponse problems present in most survey-based panels. Tax units might leave the sample because of death, emigration, or income falling below the tax filing threshold, but these exits do not affect the representativeness of the sample. Additionally, the age distribution of our sample is representative, each year, of the age distribution in the population of tax filers in that year.

To create our 23-year panel, we started with tax returns from an existing panel, known as the 1987–96 Family Panel, constructed by the

10. The fraction of U.S. households filing tax returns is generally around 90 to 95 percent (see, for example, Piketty and Saez 2003). Most households who do not file taxes are low-income households. Therefore, our data might miss some changes in income inequality at the bottom of the income distribution. However, we do not view this as a first-order concern, because, as documented by Autor, Katz, and Kearney (2008) and Kopczuk, Saez, and Song (2010), changes in income inequality over our sample period have been concentrated in the upper part of the income distribution.

11. On tax returns in which a married couple is filing jointly, the primary filer is the individual listed first on Form 1040. This is usually, although not always, the husband. On tax returns of single filers, the primary filer is the individual who filed the return.

Statistics of Income (SOI) division of the IRS. We then extended this panel using returns contained in cross-sectional files from 1997 to 2009. From this extended sample we then selected those returns for which the primary filer had an SSN ending in one of two four-digit combinations. The resulting panel (again, with two exceptions noted below) is essentially a 1-in-5,000 random sample of tax units in each year of the period 1987–2009. Each of the original data sources is next described in turn.

The 1987–96 SOI panel started with a stratified random sample of taxpayers who filed in 1987, a subset of which was chosen based on the primary filer's SSN ending in one of two four-digit combinations.¹² All individuals represented on the tax return of a member of this cross section, including secondary taxpayers on joint returns and dependents, were considered to be members of the panel. Over the following 9 years, the SOI division included in the panel all returns that reported any panel member as a primary or secondary taxpayer, including returns filed by panel members who were dependents of another taxpayer. To keep the sample representative of the tax-filing population in subsequent years, returns from tax years 1988 through 1996 were added to the panel if the primary filer had an SSN ending in one of the two original four-digit combinations but did not file a return in 1987. In addition to information from each taxpayer's Form 1040, the data set includes information on the age and sex of the primary and secondary filers from matched SSA records, and information on wages and contributions to employer-based retirement plans from W-2 forms.

The 1997–2009 data come from yearly cross sections, also collected by the SOI division. As with the 1987 sample described above, a stratified random sample was collected in each of these years, consisting partly of a strictly random sample based on the last four digits of the primary filer's SSN. In each year the set of SSNs used for sampling included the original two four-digit endings from 1987, making it possible to extend the earlier panel using returns collected from the yearly cross sections. Each cross section contains information from the taxpayer's Form 1040 and from a number of other forms and schedules. Into these data we merged information on the age and sex of the primary and secondary filers from SSA records, and information on wages and contributions to employer-based retirement plans from W-2 forms.

12. The full 1987 stratified random sample actually consisted of two parts: the random sample mentioned in the text and a high-income oversample. We do not use the high-income oversample in our analysis in this paper.

We note, however, that there was a change in the sampling frame of our data in 1996. As a result of this change, we are missing two groups of filers in the pre-1996 period: dependent filers in 1987 over the period 1987–96, and nondependent primary filers in 1988–96 who were either dependent or secondary filers in 1987. These two groups primarily consist of young (in the case of dependents) or female (in the case of secondary) taxpayers. The effect of missing these returns is therefore likely to be very small when we examine the labor income of males in their earning years, although it may be larger when we examine household income.

II.B. Variable Description

The ideal measure of individual-level earnings for this study would be gross labor income before any amounts are deducted for health insurance premiums or retirement account contributions. However, our data do not contain such a variable, and hence we use a measure of labor income that is as close to gross labor income as is possible when using tax data. For this we start with taxable wages, as reported in the “Wages, tips, other compensation” box of taxpayers’ W-2 forms, and add the contributions to retirement savings accounts reported on the W-2 forms. This measure of labor income will include all income that a taxpayer’s employer has reported to the IRS, namely, wages, salaries, and tips, as well as the portion of these that is placed in a retirement account. Since our data do not include information on the health insurance premiums paid by the taxpayer and excluded from taxable wages, our measure of labor income will exclude those amounts. Our measure also excludes any income earned from self-employment.

For pre-tax total household income, we start with “total income” as reported on Form 1040. This variable includes wages and salaries; dividends; alimony; business income (from sole proprietorships, partnerships, or S corporations); income from rental real estate, royalties, and trusts; unemployment compensation; capital gains; and taxable amounts of interest, IRA distributions, pensions, and Social Security benefits. To this we add back nontaxable interest, IRA distributions, pensions, and Social Security benefits reported on Form 1040.

There is some debate as to whether capital gains should be included in the measure of household income. Capital gains realized and reported in a particular year may include gains that accrued in past years. Hence, including capital gains may make household income appear “lumpier” than it actually is, since income will be higher in years when gains from earlier years are realized, and lower in years when gains accrued but were not realized. However, excluding capital gains will result in the measure of house-

hold income being too low for any taxpayer who had gains in that year (whether or not they were realized), and this downward bias will be quite large for taxpayers whose primary source of income is from investments. On balance, we feel that this concern is more important, and therefore we include capital gains in our benchmark measure of household income. However, we have verified that our results are robust to the exclusion of capital gains.

For after-tax household income, we start with the measure of pre-tax household income described above. We then subtract the amount of “total tax” reported on Form 1040. This amount captures total income taxes (including self-employment taxes) after nonrefundable tax credits are taken into account. Next, we subtract the total amount of payroll (FICA) taxes owed on the earned income of the couple. This is done to ensure that all federal taxes (including income and payroll taxes) are included for all taxpayers, regardless of whether they are wage and salary workers or self-employed. Finally, we add refundable tax credits (including the earned income tax credit and the refundable portion of the child tax credit) to arrive at our measure of after-tax household income.

As is usually the case with administrative data, our data contain relatively few sociodemographic variables. Most important, although we have information on the age and sex of the primary and secondary filers, we do not have information on the education or race of either. We also lack information on hours of work, and hence our analysis will focus on annual earnings as opposed to hourly wage rates.

II.C. Sample Selection

For the case of individual earnings, we restrict our sample to males (whether they appear as the primary or the secondary filer in the tax form), as is standard in the literature, because the movements of females into and out of the labor force introduce discontinuities in the earnings process that are difficult for the statistical models of income to handle. For household income we carry out our analysis using two alternative samples. The first includes only households with a male primary or secondary filer and is thus similar to the sample we use to study male earnings. This avoids confounding the effects of moving to a broader measure of income (total household income) with the effects of moving to a broader sample of households. In addition, this sample is less likely to be affected by the change in sampling frame discussed in section II.A. In a slight abuse of terminology, we refer to this sample as our “male-headed households” sample. The second sample adds to this sample all other tax-filing households (that is, those

without a male primary or secondary filer), a group that consists largely of single females. We are also interested in this broader sample because it is representative of the population of U.S. taxpayers.

For both male earnings and household income, we restrict our sample to individuals aged 25 to 60. We impose this restriction because individuals in this age group are likely to have completed most of their formal schooling and are sufficiently young not to be too strongly affected by early retirement. We also exclude earnings (or income) observations below a minimum threshold. For male earnings, since tax records do not provide information on employment status or hours of work, we can exclude individuals with presumably weak labor force attachment only by dropping low-earnings observations. For household income, we cannot simply exploit the fact that households with sufficiently low income are not required to file taxes, because many actually do so to claim refundable tax credits such as the earned income tax credit. Therefore, in order to treat low-income observations consistently, we exclude observations with reported household income below a minimum threshold.¹³ We take the relevant threshold to be one-fourth of a full-year, full-time minimum wage.¹⁴

After imposing the restrictions above, we end up with a male earnings sample of 221,099 person-year observations on 20,859 individuals. For household income, our broader sample, which includes households without a male primary or secondary filer, contains 353,975 person-year observations on 33,730 households. We refer to this sample as our “all households” sample. Table 1 reports the number of observations and the mean and the standard deviation of the relevant income measure for our male earnings sample and for each of our household income samples.

II.D. Income Inequality Trends, 1987–2009

We begin by documenting the trends in inequality for male earnings and for household income, the latter before and after taxes, in our panel of tax returns. The top panel of figure 1 shows the cross-sectional variance of (the logs of) male earnings, pre-tax household income, and after-tax household

13. In addition, it is well known that changes in income at low levels of income can unduly affect estimates of models of the income process. Two commonly used approaches to address this issue are to exclude low-income observations or to left-censor them. Given the issues discussed above, we choose to exclude them.

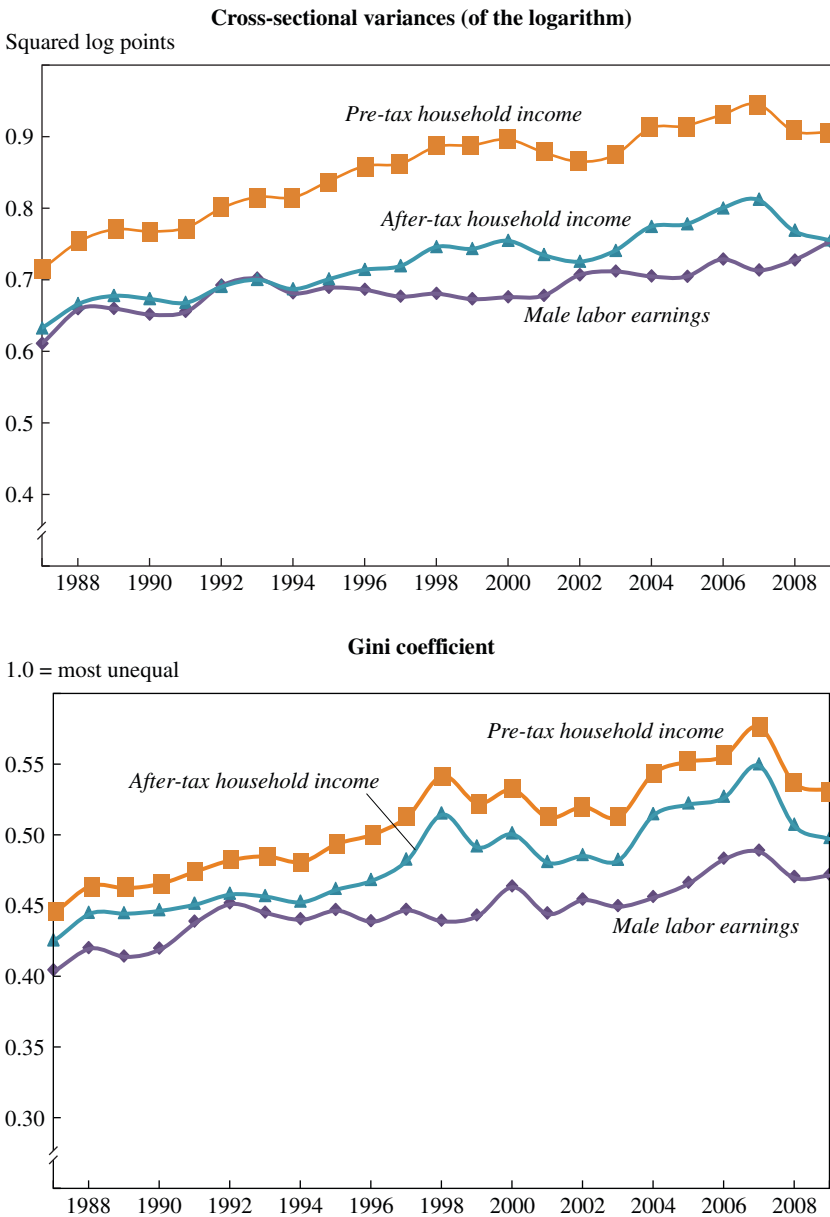
14. This is the same threshold as used by Kopczuk, Saez, and Song (2010). The threshold equals \$2,575 in 2004 and is indexed for other years by nominal average wage growth. In the online appendix we check the sensitivity of our results to setting lower and higher minimum thresholds.

Table 1. Descriptive Statistics for the Income Measures, 1987–2009^a

Year	Log of pre-tax household income						Log of after-tax household income								
	Log of male earnings			Male-headed households			All households			Male-headed households			All households		
	No. of obs.	Mean	SD	No. of obs.	Mean	SD	No. of obs.	Mean	SD	No. of obs.	Mean	SD	No. of obs.	Mean	SD
1987	8,180	10.38	0.78	8,161	10.65	0.78	12,789	10.45	0.85	8,155	10.48	0.73	12,783	10.29	0.80
1988	8,670	10.36	0.81	8,643	10.65	0.81	13,217	10.45	0.87	8,634	10.48	0.76	13,211	10.29	0.82
1989	9,019	10.33	0.81	8,991	10.63	0.83	13,625	10.43	0.88	8,982	10.46	0.78	13,616	10.27	0.82
1990	9,081	10.33	0.81	9,048	10.63	0.82	13,871	10.42	0.88	9,045	10.45	0.77	13,859	10.26	0.82
1991	8,891	10.32	0.81	8,858	10.60	0.83	14,058	10.40	0.88	8,849	10.43	0.77	14,045	10.25	0.82
1992	8,899	10.32	0.83	8,875	10.62	0.84	14,227	10.40	0.90	8,867	10.45	0.79	14,216	10.25	0.83
1993	9,240	10.29	0.84	9,215	10.61	0.85	14,461	10.39	0.90	9,209	10.44	0.79	14,457	10.24	0.84
1994	9,354	10.30	0.83	9,339	10.62	0.85	14,669	10.39	0.90	9,336	10.46	0.79	14,668	10.25	0.83
1995	9,522	10.32	0.83	9,494	10.64	0.85	14,980	10.40	0.92	9,487	10.47	0.79	14,987	10.26	0.84
1996	9,498	10.33	0.83	9,466	10.66	0.86	14,931	10.42	0.93	9,459	10.49	0.80	14,944	10.28	0.85
1997	9,608	10.37	0.82	9,588	10.69	0.87	15,253	10.45	0.93	9,582	10.52	0.80	15,252	10.31	0.85
1998	9,806	10.39	0.83	9,784	10.72	0.88	15,626	10.49	0.94	9,775	10.56	0.82	15,630	10.35	0.86
1999	9,865	10.43	0.82	9,830	10.77	0.88	15,772	10.52	0.94	9,826	10.60	0.82	15,773	10.38	0.86
2000	9,933	10.45	0.82	9,896	10.79	0.88	15,956	10.53	0.95	9,893	10.62	0.82	15,958	10.39	0.87
2001	9,978	10.46	0.82	9,939	10.78	0.87	16,114	10.53	0.94	9,936	10.62	0.81	16,117	10.39	0.86
2002	9,946	10.45	0.84	9,905	10.77	0.88	16,155	10.53	0.93	9,899	10.62	0.81	16,161	10.40	0.85
2003	9,895	10.42	0.84	9,848	10.76	0.87	16,198	10.51	0.94	9,843	10.62	0.82	16,198	10.39	0.86
2004	9,980	10.43	0.84	9,920	10.76	0.89	16,339	10.52	0.96	9,916	10.63	0.83	16,342	10.41	0.88
2005	10,048	10.43	0.84	10,001	10.75	0.90	16,540	10.51	0.96	9,995	10.62	0.84	16,541	10.40	0.88
2006	10,317	10.43	0.85	10,272	10.77	0.92	16,944	10.52	0.97	10,270	10.63	0.86	16,960	10.41	0.89
2007	10,574	10.44	0.84	10,516	10.77	0.92	17,469	10.51	0.97	10,511	10.63	0.87	17,474	10.40	0.90
2008	10,505	10.42	0.85	10,468	10.74	0.90	17,427	10.49	0.95	10,463	10.61	0.84	17,425	10.38	0.88
2009	10,290	10.39	0.87	10,247	10.72	0.91	17,354	10.45	0.95	10,241	10.59	0.84	17,355	10.36	0.87
Total or average	221,099	10.38	0.83	220,304	10.70	0.86	353,975	10.47	0.92	220,173	10.54	0.81	353,972	10.33	0.85

Source: Authors' calculations using data from the Statistics of Income Division (SOI) of the Internal Revenue Service.
a. See sections II.B and II.C in the text for definitions of the income measures and of the samples, respectively. SD = standard deviation.

Figure 1. Inequality in Male Labor Earnings and in Household Income, 1987–2009^a



Source: Authors' calculations using data from the Statistics of Income Division (SOI) of the Internal Revenue Service.

a. Household income is for the "all households" sample.

income annually over 1987–2009, and the bottom panel the Gini coefficient for the same three measures of income. The figures show an increase in both measures of inequality for all three measures of income over the period. For example, the cross-sectional variance increases by 0.14 squared log point for male earnings (from 0.61 in 1987 to 0.75 in 2009), by 0.19 squared log point for pre-tax household income, and by 0.12 squared log point for after-tax household income.¹⁵ In general, inequality in individual earnings is lower than inequality in household income. Furthermore, inequality in after-tax household income is lower than inequality in pre-tax household income, reflecting the progressivity of the federal tax system.

These inequality trends in our data are consistent with trends that have been documented in many other U.S. studies using different data sets. In the remainder of the paper, we focus on the cross-sectional variance of (the logs of) earnings and household income as our measure of inequality, because of its tractability for statistical decompositions, and we investigate to what extent the increase in the variance shown here represents an increase in the variance of the persistent or in the transitory component of income.

III. Methodological Approach

As discussed in the introduction, given that the degree of persistence (or serial correlation) of income shocks lies in a range between the two theoretical extremes, the choice of the dividing line between what degree of serial correlation will be considered “persistent” and what degree “transitory” is necessarily somewhat arbitrary. In our analysis we use two sets of methods, each of which takes a somewhat different approach to separating income into persistent and transitory parts.

First, in section IV we employ simple nonparametric decomposition methods that essentially decompose income into a highly transitory piece that exhibits no serial correlation and one other piece, which we call “persistent.” These methods then ask, for each of these two pieces, how much of the rise in the variance of income is coming from changes in the variance of that piece. Second, in section V we employ nonstationary error components models of income dynamics. These models fully specify the process that generates income over time and essentially decompose income

15. For household income the figures use our “all households” sample. In our “male-headed households” sample, the cross-sectional variance (of the log) increases by 0.22 squared log point for pre-tax and 0.17 squared log point for after-tax household income.

into a highly persistent piece and another, transitory piece that allows for some limited degree of serial correlation. Here, too, we then ask how much of the rise in the variance of income is coming from changes in the variances of the persistent and of the transitory piece. Note that neither approach is right or wrong: each is interesting in its own right. And as we show, both yield very similar qualitative results for the trends in inequality and its components.

Before turning to the specific methods and results, we note that throughout the paper we work with measures of income from which we have removed the predictable life-cycle variation in income, that is, the variation that can be explained by differences in age across individuals. For male earnings we work with residuals from least squares regressions (run separately for each calendar year) of log earnings against a full set of age dummy variables. For the two measures of household income, in addition to the age-related variation, we remove the income variation that is due to differences in household size and composition. We work with residuals from regressions (run separately for each calendar year) of log household income on a full set of age dummies for the primary tax filer, indicators of sex and marital status for the primary filer, and a full set of dummies for the number of children (up to 10) in the household. We have verified, however, that working directly with the raw measures of male earnings and total household income, rather than with these residuals, leads to qualitatively similar results.¹⁶

IV. Simple Nonparametric Methods

We begin our analysis using simple nonparametric methods. In this section we introduce the methods and present the corresponding decompositions for male labor earnings. The methods used in this section are largely descriptive and do not explicitly rely on any model of the income process. In section V we turn to our analysis using error components models and again present the resulting decompositions for male labor earnings. Results of both approaches for total household income are presented in section VI.

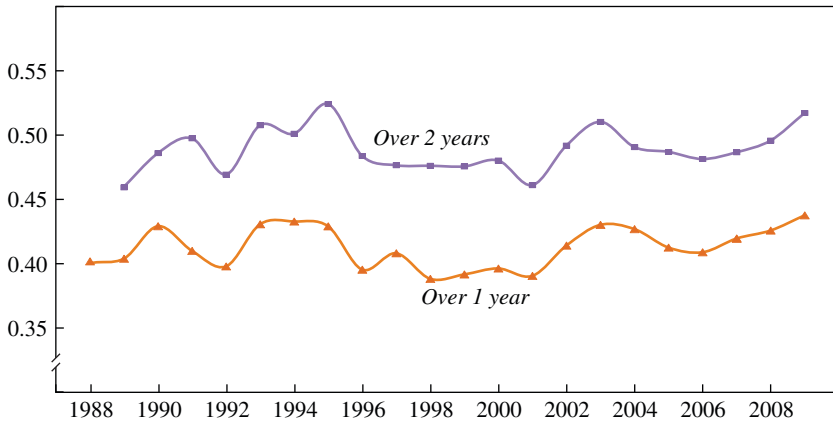
IV.A. Volatility

We start with a simple, purely descriptive measure of the dispersion in the cross-sectional distribution of income changes that occur over short

16. Furthermore, in the online appendix we examine the robustness of our results to alternative treatments of household size and composition.

Figure 2. Volatility of Male Labor Earnings, 1988–2009

Standard deviation of the
percentage change in earnings



Source: Authors' calculations using SOI data.

horizons, namely, the standard deviation of percentage changes in (residual) male earnings. Following Shin and Solon (2011), we refer to this measure as the “volatility” of earnings. This measure is closely related, although not equivalent, to the variance of the transitory component of income that we will discuss in the following sections.¹⁷ Figure 2 plots over the sample period the standard deviations of both 1-year and 2-year percentage changes in residual male earnings. The figure shows no clear increasing or decreasing trend in either series. Although volatility increased in the last 3 years of our sample, there is no indication that this represents the beginning of a rising trend. In fact, regressing each of the two volatility series shown on a constant and a linear time trend yields an estimated coefficient on the latter that is essentially zero.¹⁸ There is thus no evidence in our data of a trend in male earnings volatility for our sample period.

17. Indeed, for most specifications of an income process, volatility and the variance of transitory income changes tend to move closely together, although in many cases volatility also captures part of the variance of persistent income changes. See Shin and Solon (2011) for a detailed discussion.

18. For 1-year changes the estimated coefficient is 0.00037, with a standard error of 0.00050. This coefficient would imply an increase of less than 0.01 in the standard deviation over 23 years. For 2-year changes the coefficient is 0.00046, with a standard error of 0.00058.

IV.B. Simple Nonparametric Decomposition Methods

We next consider two simple nonparametric methods that decompose the cross-sectional variance of income (our measure of income inequality) into persistent and transitory parts. The methods in this section essentially define the persistent component of income as the average of annual income over a certain number of years, and transitory income as the deviations of annual income from that average.

The first method, which is used in Kopczuk, Saez, and Song (2010, hereafter KSS), defines person i 's persistent income component in year t as the average of person i 's annual log income (or residual log income) over a P -year period centered around t . Transitory income for person i in year t is then defined as the difference between person i 's current annual income at t and his or her persistent income in the same year. The persistent and transitory components of the variance are next calculated as the variances, across individuals, of persistent and transitory income, respectively.

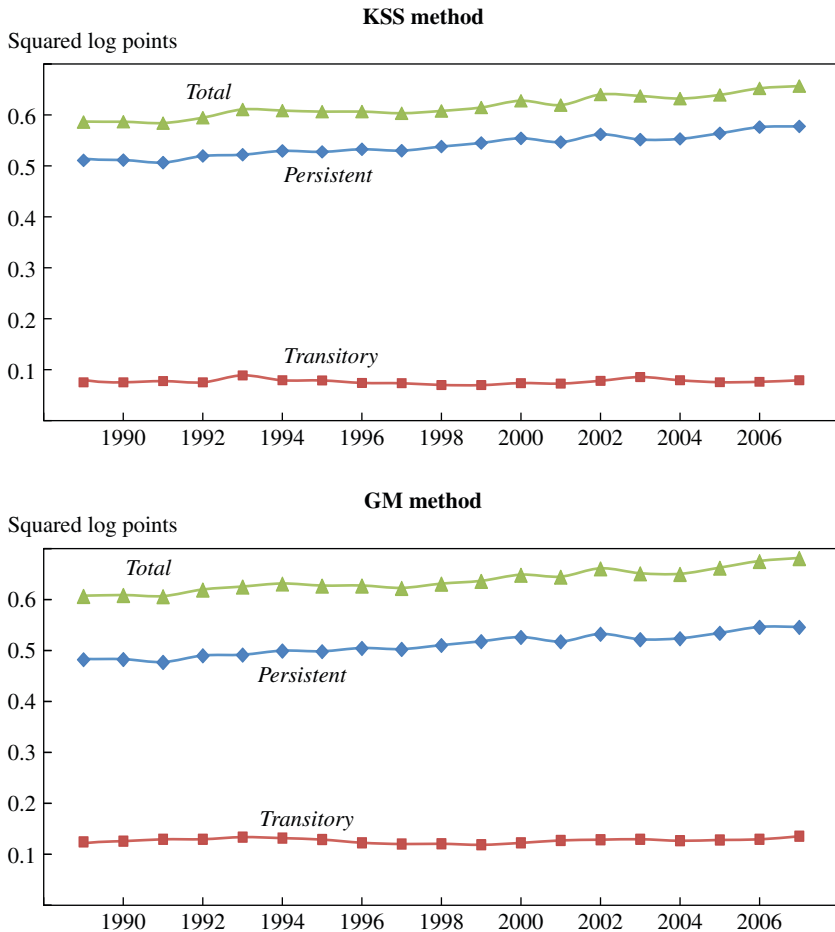
For our decomposition of the cross-sectional variance of (residual) male earnings into persistent and transitory parts using the KSS method, we set parameter $P = 5$, the same value used by KSS.¹⁹ Whereas they use raw (as opposed to residual) log earnings and restrict observations to individuals who are present in the sample for all 5 years, we use residual log earnings and do not require individuals to be present in the sample in all 5 years. However, the results are not materially different when we follow their treatment and restrictions.

The top panel of figure 3 presents the results of this decomposition, showing that the persistent component of the variance in male earnings increased over our sample period but the transitory component did not. Hence the increase in the total cross-sectional variance was entirely driven by the persistent component. Table 2 formalizes this result, reporting estimates from a regression that fits a linear time trend, separately, to the persistent variance series and to the transitory variance series.

The first column in each of the two panels of table 2 corresponds to the KSS decomposition from figure 3. The dependent variable is either the persistent (left panel) or the transitory (right panel) variance component, and the explanatory variables are a constant (not shown) and a linear time trend. The table shows a statistically significant rising linear trend in the persistent variance: the estimated linear trend coefficient is 0.0037 with a

19. Note that, by taking averages across periods, this method attenuates somewhat the increase in both persistent and transitory inequality, and thereby in total inequality, constructed here as the sum of its persistent and transitory parts.

Figure 3. Simple Nonparametric Decompositions of Cross-Sectional Variance in Male Labor Earnings, 1989–2007^a



Source: Authors' calculations using SOI data.

a. Series start in 1989 and end in 2007 because the use of multiyear averages in constructing the decomposition leads to the loss of two years at each endpoint of the sample.

standard error of 0.0002, implying an increase of 0.09 squared log point over 23 years. There is no trend in the transitory variance component (the estimated trend coefficient is 0.0000). That is, the entire increase in the total cross-sectional variance of (residual log) male earnings was driven by an increase in the variance of the persistent component of earnings, and thus reflects an increase in persistent inequality.

Table 2. Estimated Linear Time Trends of Persistent and Transitory Variance in Male Labor Earnings^a

	<i>Estimated component and decomposition method</i>					
	<i>Persistent component</i>			<i>Transitory component</i>		
	<i>KSS method</i>	<i>GM method</i>	<i>Error components model</i>	<i>KSS method</i>	<i>GM method</i>	<i>Error components model</i>
Coefficient on linear time trend	0.0037 (0.0002)	0.0037 (0.0002)	0.0038 (0.0003)	0.0000 (0.0002)	0.0001 (0.0002)	0.0001 (0.0004)
<i>p</i> value	0.000	0.000	0.000	0.947	0.610	0.746
<i>R</i> ²	0.95	0.94	0.89	0.00	0.02	0.01

Source: Authors' regressions using SOI data.

a. Each column reports results of an ordinary least squares regression of the persistent or the transitory component of the variance in male labor earnings, as calculated by the indicated decomposition method, on a constant (not reported) and a linear trend. Standard errors are in parentheses.

The second nonparametric decomposition method that we consider was introduced by Gottschalk and Moffitt (1994, hereafter GM). The GM method is similar, although not identical, to the KSS method, and we consider it separately because it relies (indirectly) on a simple model of income, which might provide a slightly more direct way of relating it to our error components models. The method is based on the simple specification of (residual) log earnings $\xi_{it} = \alpha_i + \varepsilon_{it}$, where α_i is purely permanent (time-invariant) and ε_{it} is purely transitory (i.i.d.). For a P -year window centered around each year t , the method uses the standard formulas implied by this simple “random effects model” to compute the persistent variance of ξ_{it} as the variance of the α_i component, and the transitory variance of ξ_{it} as the variance of the ε_{it} component.²⁰ To obtain a series of persistent and transitory variance estimates over time, this procedure is repeated for consecutive, overlapping P -year moving windows.²¹

The bottom panel of figure 3 presents the GM inequality decomposition. As with the KSS method, this decomposition implies that the persistent

20. That is, to compute the variance of α_i and ε_{it} in a given year t , the method treats the data in the P -year window centered around t as if they were the entire data set available.

21. The difference between the KSS and GM methods essentially reflects a “bias correction term” in the random effects formula upon which the GM decomposition is based. For the exact formulas used by the GM method, see appendix B. Also see the discussion of the method in Gottschalk and Moffitt (2009).

variance component increased over the sample period but the transitory component did not. This is confirmed in the second column in each panel in table 2. Here, too, the coefficient on the linear time trend is large and significant for the persistent variance component and is essentially zero for the transitory component. Both trend coefficients are quite precisely estimated. Thus, once again, the increase in the total cross-sectional variance was entirely driven by the increase in the variance of persistent earnings, constituting an increase in persistent inequality.

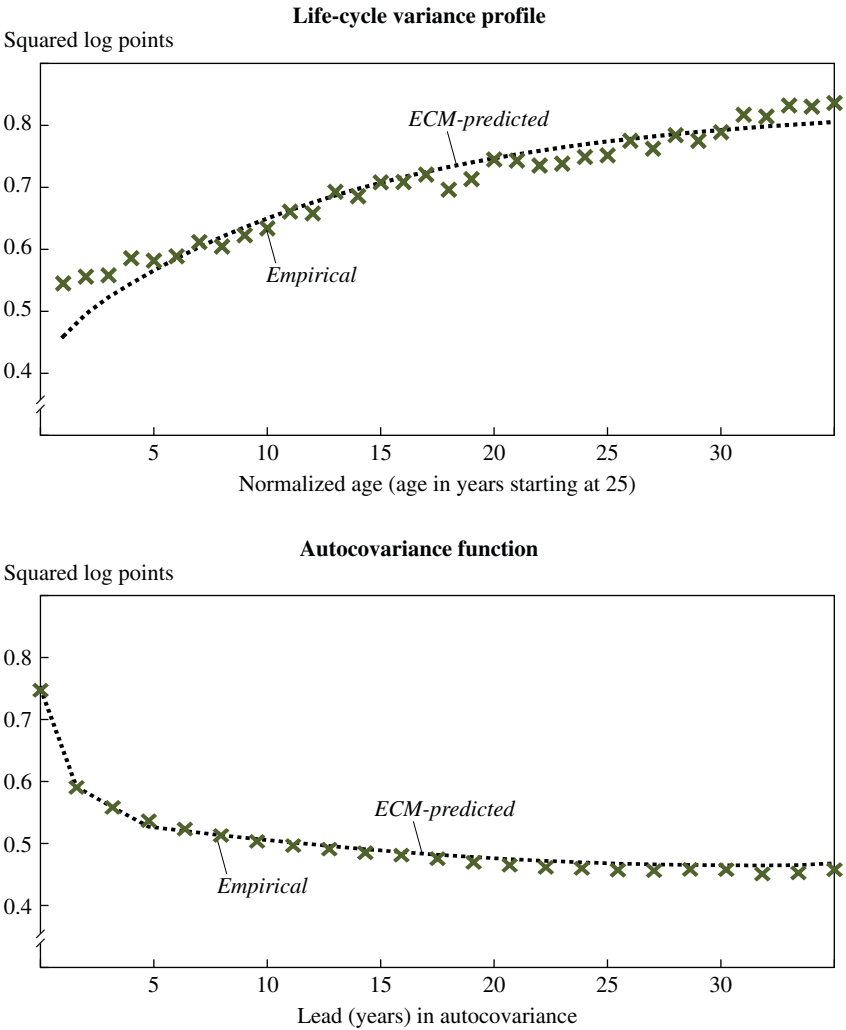
Note as well that both the KSS method and the GM method attribute a large fraction of the total variance (more than 80 percent on average across all years) to the persistent component. We will come back to this point below.

V. Error Components Models

In this section we turn to error components models (ECMs) of income dynamics to examine the role of persistent and transitory income components in determining the trend in inequality. These ECMs are statistical models (stochastic processes) that approximate the dynamic properties and the trajectory of income over time. Like the simpler nonparametric decomposition methods presented in section IV, ECMs typically specify income as consisting of a persistent component and a transitory component, and they can be used to decompose the variance of (log) income into persistent and transitory parts.

For example, the persistent component of income in the model will tend to capture differences in incomes across individuals that are due to differences in permanent characteristics such as education and unobserved ability. It will also capture income changes that have lasting effects on the path of the income process, such as the onset of a chronic illness or the permanent loss of a high-paying job. The transitory component will tend to capture changes in income that are less persistent but may have some serial correlation, such as a temporary illness or transitory unemployment. The model then essentially attributes variation in income to the persistent or the transitory component according to the strength in the correlations between individuals' current and future income in the data, and to how this strength changes as the periods move further apart. Statistically, the separate identification of the persistent and transitory components relies on the simple idea that the contribution of the transitory component to the autocovariance of income between two periods vanishes as the periods get further apart.

Figure 4. Life-Cycle Variance Profile and Autocovariance Function of Male Earnings, Empirical Estimates and ECM-Based Predictions



Source: Authors' calculations using SOI data.

Flexible specifications of the income process, such as the ones we consider in this paper, can match the entire autocovariance structure of income in the data, as well as its changes over the life cycle and over calendar time. To illustrate, figure 4 shows two particular aspects of the autocovariance structure of male labor earnings in our data. Here we focus on the series

labeled “empirical” in each of the two panels in the figure.²² The top panel displays the variance (calculated across all individuals of the same age) of residual log male earnings as a function of age. To construct the series, we computed the variance of (residual) male labor earnings in the data for each combination of age and calendar year and regressed this variance against a full set of year and age indicators. The figure displays the estimated coefficients on the age indicators (normalized so that $a = 1$ in the figure corresponds to age 25).

The corresponding series in the bottom panel displays the empirical autocovariance function for our male earnings data, that is, how the strength of the autocovariance between current earnings and future earnings changes as the periods get further apart. In other words, the figure shows how the empirical autocovariance (the autocovariance of earnings in the data for observations that are k years apart) depends on the “lead” k . To construct the series, we computed the autocovariance of male labor earnings for each combination of age, calendar year, and lead k and then regressed the autocovariance against a full set of age, year, and lead indicators. We then calculated the value of the autocovariance that is implied by the estimated regression for individuals aged 35 in base year 1990. The implied autocovariances for different ages or different years look very similar. For now, we simply note that the goal of the ECMs is to match aspects of the data such as these.²³ We will return to these figures below.

V.A. Stationary ECMs

We begin by presenting stationary models of the income process, that is, models in which the parameters are not allowed to change over calendar time.²⁴ In the next section we will present nonstationary ECMs, which allow certain parameters in the model to change over time, in order to capture changes in the distribution of income.

22. The lines in the figure labeled “ECM-predicted” correspond to predicted values from the nonstationary model that we introduce in the next section and are discussed in section V.D.

23. More precisely, and as we discuss below, the objective in estimation is to match the entire set of variances and autocovariances that can be computed from the data.

24. Stationary, univariate error components models have been estimated in a large number of papers. An incomplete list includes the early contributions of Lillard and Willis (1978), Lillard and Weiss (1979), and MaCurdy (1982). See also Carroll (1992), Baker (1997), Carroll and Samwick (1997), and more recently, Guvenen (2009) and Hryshko (2012). Richer, multivariate stationary models have recently been estimated in Low, Meghir, and Pistaferri (2010) and Altonji, Smith, and Vidangos (forthcoming).

Let $y_{a,t}^i$ denote log income, where i indexes individuals, a age, and t calendar years.²⁵ Log income is given by

$$(1) \quad y_{a,t}^i = g(\zeta; X_{a,t}^i) + \xi_{a,t}^i,$$

where $X_{a,t}^i$ is a vector of observable characteristics, $g(\cdot)$ is the part of log income that is common to all individuals conditional on $X_{a,t}^i$, ζ is a vector of parameters, and $\xi_{a,t}^i$ is the unobservable error term. As is common in the literature on income dynamics, we control for the income variation that is due to observables, $X_{a,t}^i$, and focus on the dynamics of the error term, $\xi_{a,t}^i$.²⁶

The error $\xi_{a,t}^i$ is modeled as consisting of a persistent and a transitory part:

$$(2) \quad \xi_{a,t}^i = \underbrace{\alpha^i}_{\text{persistent}} + \underbrace{p_{a,t}^i}_{\text{transitory}} + \tau_{a,t}^i, \text{ where}$$

$$(3) \quad p_{a,t}^i = \psi p_{a-1,t-1}^i + \eta_{a,t}^i$$

$$(4) \quad \tau_{a,t}^i = \varepsilon_{a,t}^i + \theta_1 \varepsilon_{a-1,t-1}^i + \theta_2 \varepsilon_{a-2,t-2}^i$$

$$(5) \quad \alpha^i \sim \text{i.i.d.}(0, \sigma_\alpha^2), \eta_{a,t}^i \sim \text{i.i.d.}(0, \sigma_\eta^2), \varepsilon_{a,t}^i \sim \text{i.i.d.}(0, \sigma_\varepsilon^2).$$

The persistent part of income includes, first, an individual-specific, time-invariant component, α^i , which captures differences in income across individuals due to factors that include education as well as unobserved ability or productivity. It also includes an autoregressive component, $p_{a,t}^i$, which captures other components of income that are highly persistent. As is common in such models, our estimates of ψ for the above specification will turn out to be quite close to 1, so it is appropriate to label component $p_{a,t}^i$ as “persistent.” These large values of ψ allow the model to match both the nearly linear increase in the variance of (residual) income in the data as a function of age seen in the top panel of figure 4, and the very gradual

25. The index a actually represents “normalized age” or “potential experience,” defined as $a = \text{age} - 25 + 1$, or years starting with age 25.

26. The covariates $X_{a,t}^i$ used for the $g(\cdot)$ component in these regressions correspond exactly to the discussion in section III. The residuals $\xi_{a,t}^i$ obtained from equation 1 are thus identical to the residuals discussed in section III, and equation 1 formalizes their definition. As noted in section III, the regressions are run separately by calendar year.

decline (after the first 1 to 2 years) in the empirical autocovariance function seen in the bottom panel.²⁷

We specify the transitory income component in the model, $\tau_{a,t}^i$, as an MA(2) process. Several studies of income processes have found evidence for the presence of either an MA(1) or an MA(2) transitory component.²⁸ We choose an MA(2) process to err on the side of allowing the transitory income component to exhibit more persistence, but we have verified that our results are not sensitive to this choice.

The top panel of table 3 presents point estimates and standard errors for the model in equations 2 through 5 for our various measures of income and our various samples.²⁹ For instance, the first column reports the following point estimates (with standard errors in parentheses) for residual male earnings: $\hat{\sigma}_\alpha^2 = 0.1968$ (0.0018), $\psi = 0.9623$ (0.0010), $\hat{\sigma}_\eta^2 = 0.0293$ (0.0007), $\hat{\sigma}_\varepsilon^2 = 0.1826$ (0.0034), $\hat{\theta}_1 = 0.2286$ (0.0144), and $\hat{\theta}_2 = 0.1231$ (0.0151). For (residual) pre-tax household income using the sample of all households (third column of the table), the estimates are $\hat{\sigma}_\alpha^2 = 0.1960$ (0.0016), $\psi = 0.9669$ (0.0007), $\hat{\sigma}_\eta^2 = 0.0269$ (0.0006), $\hat{\sigma}_\varepsilon^2 = 0.1577$ (0.0032), $\hat{\theta}_1 = 0.2766$ (0.0148), and $\hat{\theta}_2 = 0.1639$ (0.0154). These estimates are broadly comparable to those obtained by other studies that use similar specifications.³⁰ Also, the estimated models match the main features of the data, such as those presented in figure 4, quite well.³¹

The bottom panel of table 3 presents estimates for a version of the model that imposes the restriction that $\psi = 1$, that is, that $p_{a,t}^i$ follows a random walk, an assumption often made about the persistent component. Here we simply note that, in terms of matching the features of the data shown in figure 4, the random walk specification matches the nearly

27. For the variance profile, a value of ψ of exactly 1 would imply an exactly linear increase in the variance of $p_{a,t}^i$ as a function of age. For the autocovariance function, the decline in the covariances after the first couple of years in the model is entirely determined by the value of ψ . The slow gradual decline seen in the data requires a value of ψ that is close to, but smaller than, 1.

28. See, for example, Meghir and Pistaferri (2004), Baker (1997), MaCurdy (1982), and Abowd and Card (1989).

29. Our estimation methodology is discussed in the next section, in the more general context of our nonstationary model, which nests the stationary specifications presented here.

30. One difference is that, as should be expected, our estimate of parameter σ_α^2 is larger than the estimates typically found by studies using residuals that have removed the effects of education.

31. As already noted, the lines labeled “ECM-predicted” in figure 4 show the fit of the nonstationary version of this model and are discussed in section V.D.

Table 3. Estimates of Stationary Error Components Models^a

Parameter	Income measure and sample				
	Male labor earnings	Pre-tax household income		After-tax household income	
		Male-headed households	All households	Male-headed households	All households
<i>Unrestricted model</i>					
σ_{α}^2	0.1968 (0.0018)	0.1885 (0.0018)	0.1960 (0.0016)	0.1533 (0.0015)	0.1579 (0.0013)
ψ	0.9623 (0.0010)	0.9717 (0.0012)	0.9669 (0.0007)	0.9805 (0.0011)	0.9770 (0.0007)
σ_{η}^2	0.0293 (0.0007)	0.0183 (0.0006)	0.0269 (0.0006)	0.0135 (0.0005)	0.0187 (0.0004)
σ_{ε}^2	0.1826 (0.0034)	0.1405 (0.0038)	0.1577 (0.0032)	0.1199 (0.0031)	0.1387 (0.0026)
θ_1	0.2286 (0.0144)	0.3072 (0.0191)	0.2766 (0.0148)	0.3066 (0.0186)	0.2772 (0.0136)
θ_2	0.1231 (0.0151)	0.2131 (0.0206)	0.1639 (0.0154)	0.2185 (0.0203)	0.1734 (0.0142)
<i>Restricted model ($\psi = 1$)</i>					
σ_{α}^2	0.2431 (0.0014)	0.2162 (0.0014)	0.2391 (0.0013)	0.1713 (0.0012)	0.1854 (0.0011)
σ_{η}^2	0.0093 (0.0001)	0.0076 (0.0001)	0.0095 (0.0001)	0.0072 (0.0001)	0.0089 (0.0001)
σ_{ε}^2	0.2069 (0.0035)	0.1512 (0.0040)	0.1756 (0.0033)	0.1262 (0.0032)	0.1492 (0.0026)
θ_1	0.3477 (0.0116)	0.3830 (0.0168)	0.3875 (0.0127)	0.3608 (0.0168)	0.3528 (0.0119)
θ_2	0.2895 (0.0145)	0.3276 (0.0207)	0.3313 (0.0160)	0.2998 (0.0202)	0.2852 (0.0142)

Source: Authors' calculations using SOI data.

a. Estimates of equations 2 through 5 in the text using a minimum distance estimator (see section V.C). Asymptotic standard errors are in parentheses.

linear increase with age of the cross-sectional variance in the top panel of figure 4, but it does not match well the gradual decline in the autocovariance function shown in the bottom panel. By contrast, the unrestricted estimates of ψ (which generally lie around 0.96 to 0.98 for our various income measures and samples) allow the unrestricted model to match the increase in the variance with age fairly well and the pattern of the autocovariance function of male earnings quite closely. In the analysis that follows, we do not impose the restriction $\psi = 1$ on component $p_{a,r}^i$, in part to better match the autocovariance function of income.

V.B. Nonstationary ECMs

Stationary models, however, cannot be used to study changes in the distribution of income (such as income inequality) over calendar time. This question requires the use of nonstationary models, which allow certain features of the income process (and hence of the income distribution) to change over time. Such models can capture (in addition to those features of the autocovariance structure of the data shown in the previous section) trends in the cross-sectional variance of income, such as that seen in the top panel of figure 1.

Our baseline nonstationary ECM is as follows. We model residual income, $\xi_{a,t}^i$, as

$$(6) \quad \xi_{a,t}^i = \lambda_t (\underbrace{\alpha^i}_{\text{persistent}} + \underbrace{p_{a,t}^i}_{\text{transitory}}) + \tau_{a,t}^i, \text{ where}$$

$$(7) \quad p_{a,t}^i = \psi p_{a-1,t-1}^i + \eta_{a,t}^i$$

$$(8) \quad \tau_{a,t}^i = \pi_t \varepsilon_{a,t}^i + \theta_1 \pi_{t-1} \varepsilon_{a-1,t-1}^i + \theta_2 \pi_{t-2} \varepsilon_{a-2,t-2}^i$$

$$(9) \quad \alpha^i \sim \text{i.i.d.}(0, \sigma_\alpha^2), \eta_{a,t}^i \sim \text{i.i.d.}(0, \sigma_\eta^2), \varepsilon_{a,t}^i \sim \text{i.i.d.}(0, \sigma_\varepsilon^2).$$

In the equations above, both components of persistent income, α^i and $p_{a,t}^i$, are multiplied by the year-specific factor loadings λ_t , which allow the relative importance of the persistent components of income to vary over calendar time (note that the parameter λ_t can change from year to year). The transitory income component in the model, $\tau_{a,t}^i$, is specified as an MA(2) process in which the transitory innovations, $\varepsilon_{a,t}^i$, are multiplied by the year-specific factor loadings π_t , which allow the variance of the innovations, and hence the relative importance of the transitory component, to vary by calendar year.

A few words about the interpretation of the λ_t parameters are in order. Suppose, first, for simplicity that α^i represents solely education, and that $p_{a,t}^i$ represents human capital (which changes slowly over time and is highly persistent). Then, the λ_t parameters would represent the “price” that the economy attributes to these characteristics in year t . Note as well that the “price” of such characteristics can indeed change from year to year, as evidenced, for example, by the well-documented changes in the returns to education in recent decades. It seems reasonable to expect that the economy will assign a price not just to education, but also to other productive

characteristics of individuals (including, but not restricted to, those embedded in human capital).³² More generally, α^i will capture, in addition to education, other permanent characteristics of individuals (or households) such as unobserved ability or productivity, and $p_{a,t}^i$ will capture characteristics that are slow-moving and persistent, such as human capital and social connections. A similar modeling approach of nonstationarity in the persistent component of income is followed, for example, in Moffitt and Gottschalk (1995, 2011), Haider (2001), and Baker and Solon (2003).³³

A key element of the above specification is clearly the ability of the λ_t parameters to change over time. One potential concern that this raises, however, is that the λ_t parameters could in principle bounce around from year to year. Such transitory variation in λ_t could muddle the labeling of $\lambda_t(\alpha^i + p_{a,t}^i)$ in equation 6 as the “persistent” component of income. To address this concern, when estimating the above model, we impose some smoothness on the movements of λ_t over time by restricting λ_t to lie on a fourth-degree polynomial.³⁴

V.C. Estimation

Estimation of our ECMs proceeds in two stages. In the first stage we construct residuals from regressions of log earnings (or log income) against observables, $\hat{\xi}_{a,t}^i = y_{a,t}^i - g(\zeta; X_{a,t}^i)$, as discussed in section III. In the second stage we use those residuals to estimate all model parameters other than ζ , using a minimum distance estimator. The estimator matches all of the theoretical variances and autocovariances implied by the model in equations 6 through 9 to their empirical counterparts. The procedure matches 7,912 variances and autocovariances in total. All variances and autocovariances are specified in levels. Appendix C provides details on the minimum distance estimation procedure, and appendix D shows the theoretical moments that are implied by the model and that are matched in estimation.

32. Card and Lemieux (1996) provide evidence in support of this idea.

33. In appendix A we present results for an alternative nonstationary specification in which the λ_t parameters multiply the α^i component only, and in which the variances of the persistent shocks are allowed to vary over time. The results from that alternative specification are consistent with the results obtained with our baseline model.

34. Using a quadratic or a cubic polynomial instead yields similar results. In general, we have found that restricting the λ_t parameters to lie on a polynomial has little effect on the trend captured by the λ_t series. The restriction also has little effect on the model’s ability to match the trend in the total variance, since the π_t parameters pick up the transitory part of the variation in the (fully unrestricted) λ_t . Results for the unrestricted λ_t are presented in the online appendix and yield similar conclusions.

V.D. *ECM-Based Variance Decomposition for Male Earnings*

Table 4 presents parameter estimates of our baseline nonstationary ECM for our various measures of income and our various samples. Note that the estimates of parameters σ_ω^2 , ψ , σ_η^2 , σ_ε^2 , θ_1 , and θ_2 (those also present in the stationary version of the model) in table 4 are quite similar to the corresponding estimates in table 3 for the stationary model. The lines labeled “ECM-predicted” in figure 4 show the estimated nonstationary model’s predictions for the variance of male earnings as a function of age (top panel) and for the autocovariance function of male earnings (bottom panel).³⁵ As the figure shows, the estimated model fits the data quite well.

In this section we use our estimated nonstationary ECM to decompose the cross-sectional variance of log (residual) male earnings into its persistent and transitory parts. For each calendar year between 1987 and 2009, and given an age distribution, the ECM in equations 6 through 9 implies a specific value for the total cross-sectional variance, the variance of the persistent component, and the variance of the transitory component of log (residual) earnings, as a function of the model parameters. We compute these variances implied by the estimated model using the actual empirical age distribution for each year in our sample.³⁶ Note that the trends in the persistent and the transitory variance components in our baseline model are primarily determined by the estimates of the λ_i and π_i parameters, respectively.

The decomposition of inequality implied by our estimated baseline ECM is presented in figure 5. The top line, which shows the total cross-sectional variance implied by the estimated model for each calendar year, is essentially identical to the empirical cross-sectional variance of log (residual) male earnings in our data. That is, our estimated model matches the evolution of the cross-sectional variance over calendar time very closely.³⁷

35. The “ECM-predicted” series are constructed in the same way as the “empirical” series, but using the theoretical moments implied by the estimated model rather than the empirical moments.

36. We could also use the estimated model to compute similar decompositions for any age group, or for any age distribution. In the online appendix we perform the decomposition assuming a constant age distribution, and the results are essentially unchanged.

37. We do not show separately the empirical cross-sectional variance of log residual male earnings because it looks indistinguishable from the top line in figure 5. However, the latter differs somewhat from the variance of log male earnings shown in figure 1, because figure 5 uses residuals that have removed the variation in earnings that is due to age, whereas figure 1 uses the raw data.

Table 4. Estimates of Nonstationary Error Components Model^a

Parameter	Income measure and sample				
	Male labor earnings	Pre-tax household income		After-tax household income	
		Male-headed households	All households	Male-headed households	All households
<i>Persistent component</i>					
σ_{α}^2	0.1742 (0.0027)	0.1566 (0.0027)	0.1701 (0.0022)	0.1328 (0.0024)	0.1445 (0.0020)
ψ	0.9631 (0.0010)	0.9751 (0.0012)	0.9687 (0.0008)	0.9831 (0.0012)	0.9784 (0.0007)
σ_{η}^2	0.0246 (0.0008)	0.0129 (0.0005)	0.0209 (0.0005)	0.0103 (0.0004)	0.0158 (0.0004)
<i>λ_t polynomial^b</i>					
b_1	0.0226 (0.0048)	0.0275 (0.0055)	0.0132 (0.0039)	0.0269 (0.0056)	0.0126 (0.0040)
$b_2 (\times 10)$	-0.0273 (0.0089)	-0.0198 (0.0103)	0.0019 (0.0071)	-0.0279 (0.0106)	-0.0090 (0.0074)
$b_3 (\times 100)$	0.0151 (0.0061)	0.0073 (0.0071)	-0.0060 (0.0049)	0.0143 (0.0073)	0.0041 (0.0050)
$b_4 (\times 1000)$	-0.0029 (0.0014)	-0.0012 (0.0016)	0.0016 (0.0111)	-0.0029 (0.0017)	-0.0009 (0.0011)
<i>Transitory component</i>					
θ_1	0.2343 (0.0141)	0.3273 (0.0181)	0.2905 (0.0133)	0.3230 (0.0184)	0.2880 (0.0131)
θ_2	0.1262 (0.0148)	0.2306 (0.0198)	0.1762 (0.0140)	0.2316 (0.0202)	0.1827 (0.0139)
σ_{ε}^2	0.1834 (0.0119)	0.1354 (0.0101)	0.1493 (0.0100)	0.1123 (0.0089)	0.1264 (0.0086)
π_{87}^c	1.0000	1.0000	1.0000	1.0000	1.0000
π_{88}	1.0792 (0.0447)	1.0737 (0.0557)	1.0642 (0.0499)	1.0910 (0.0597)	1.0815 (0.0519)
π_{89}	1.0352 (0.0443)	1.0715 (0.0521)	1.0493 (0.0456)	1.0911 (0.0559)	1.0651 (0.0475)
π_{90}	0.9763 (0.0439)	0.9597 (0.0553)	1.0015 (0.0459)	0.9915 (0.0571)	1.0242 (0.0470)
π_{91}	0.9611 (0.0469)	0.9666 (0.0549)	0.9853 (0.0476)	0.9676 (0.0576)	0.9935 (0.0489)
π_{92}	1.0266 (0.0544)	1.0058 (0.0586)	1.0141 (0.0503)	1.0191 (0.0606)	1.0318 (0.0505)
π_{93}	1.0342 (0.0480)	0.9858 (0.0589)	1.0130 (0.0493)	0.9989 (0.0608)	1.0384 (0.0495)
π_{94}	0.9657 (0.0479)	0.9304 (0.0551)	0.9573 (0.0445)	0.9209 (0.0567)	0.9432 (0.0455)

Table 4. Estimates of Nonstationary Error Components Model^a (Continued)

Parameter	Income measure and sample				
	Male labor earnings	Pre-tax household income		After-tax household income	
		Male-headed households	All households	Male-headed households	All households
π_{95}	0.9925 (0.0449)	0.9584 (0.0553)	0.9997 (0.0466)	0.9273 (0.0572)	0.9869 (0.0475)
π_{96}	0.9798 (0.0430)	0.9604 (0.0516)	1.0039 (0.0441)	0.9409 (0.0536)	0.9974 (0.0449)
π_{97}	0.9628 (0.0447)	1.0012 (0.0559)	1.0126 (0.0457)	1.0140 (0.0578)	1.0197 (0.0475)
π_{98}	0.9684 (0.0438)	1.0396 (0.0574)	1.0584 (0.0466)	1.0503 (0.0595)	1.0764 (0.0485)
π_{99}	0.9548 (0.0442)	1.0224 (0.0488)	1.0226 (0.0405)	1.0430 (0.0510)	1.0331 (0.0419)
π_{00}	0.9785 (0.0497)	1.0029 (0.0556)	1.0217 (0.0443)	1.0320 (0.0584)	1.0374 (0.0457)
π_{01}	0.9665 (0.0466)	0.9652 (0.0581)	0.9760 (0.0453)	0.9653 (0.0605)	0.9743 (0.0461)
π_{02}	1.0284 (0.0496)	1.0175 (0.0543)	0.9769 (0.0435)	1.0059 (0.0556)	0.9835 (0.0445)
π_{03}	1.0155 (0.0457)	0.9576 (0.0548)	1.0044 (0.0455)	0.9712 (0.0569)	1.0222 (0.0471)
π_{04}	0.9909 (0.0503)	1.0385 (0.0623)	1.0872 (0.0476)	1.0560 (0.0641)	1.1077 (0.0490)
π_{05}	0.9810 (0.0497)	1.0941 (0.0612)	1.1010 (0.0482)	1.1173 (0.0642)	1.1317 (0.0493)
π_{06}	1.0379 (0.0513)	1.1863 (0.0624)	1.1457 (0.0507)	1.2276 (0.0664)	1.1971 (0.0511)
π_{07}	0.9854 (0.0521)	1.1695 (0.0645)	1.1512 (0.0520)	1.2034 (0.0688)	1.1978 (0.0534)
π_{08}	1.0335 (0.0483)	1.0562 (0.0613)	1.0522 (0.0489)	1.0700 (0.0646)	1.0815 (0.0506)
π_{09}	1.0763 (0.0479)	1.0989 (0.0625)	1.0555 (0.0500)	1.0909 (0.0641)	1.0707 (0.0510)

Source: Authors' calculations using SOI data.

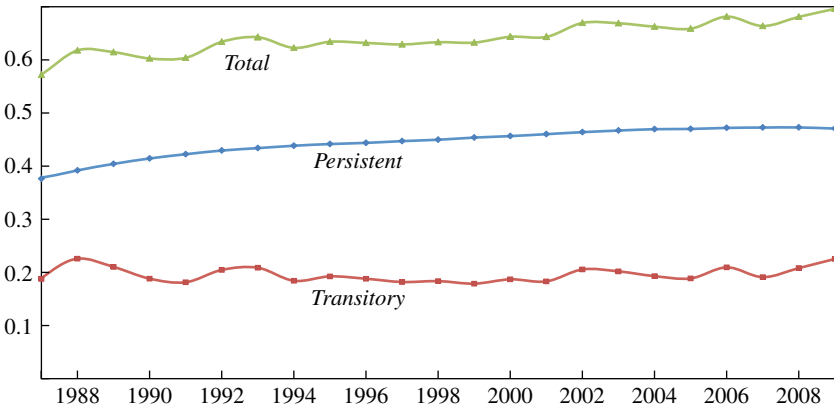
a. Estimates of equations 6 through 9 in the text using a minimum distance estimator (see section V.C). Asymptotic standard errors are in parentheses.

b. See appendix D for specification of the polynomial.

c. Parameters π_{97} through π_{09} correspond to the years of the sample period (1987–09) and are normalized to equal 1 in 1987 (see appendix D).

Figure 5. ECM Decomposition of Cross-Sectional Variance in Male Labor Earnings, 1987–2009

Squared log points



Source: Authors' calculations using SOI data.

The persistent component of the variance in figure 5 displays a clearly increasing trend, rising from 0.38 squared log point in 1987 to around 0.47 squared log point in 2009. The transitory component of the variance, by contrast, fluctuates over the 23-year period but does not exhibit any trend. The last column of table 2 shows that there is no trend for the transitory variance: the estimated trend coefficient is 0.0001 (with a standard error of 0.0004), which would imply a negligible increase of 0.003 squared log point over 23 years. In other words, the entire increase in the total cross-sectional variance of (residual log) male earnings as determined by the nonstationary ECM is driven by an increase in the variance of the persistent component of earnings, confirming the results obtained previously with the simpler nonparametric methods.

V.E. Comparison with Simple Nonparametric Decompositions

Here we briefly discuss the relationship between the model-based decomposition just presented and the simple nonparametric decompositions shown previously, in the hope of clarifying some of the connections and the differences that exist across the methods. So far we have shown that the different methods yield essentially the same answer regarding the trends in inequality, namely, that the rising trend in male earnings inequality over our sample period has been entirely driven by the persistent component

of earnings. However, the different decompositions presented above yield somewhat different relative shares of persistent and transitory inequality at a given point in time. Specifically, the KSS and GM methods attribute, on average, more than 80 percent of the total variance to the persistent component, whereas the ECM attributes slightly less than 70 percent.

This difference reflects the feature of the KSS and GM decompositions that transitory income is defined as deviations from multiyear averages of annual income, and therefore captures only purely transitory income (that is, income that has no serial correlation whatsoever). As a result, basically all the persistence in the income data is attributed to the persistent income component. This implies in turn that even shocks that dissipate in 1 to 2 years, and that would generally be viewed as transitory but are somewhat serially correlated, will tend to be attributed to the persistent income component. Consequently, the persistent component is assigned a larger role overall and accounts for a large fraction of total inequality at any given point in time. In the ECM, by contrast, transitory income is allowed to have some degree of serial correlation, so it captures some of the short-duration persistence in the data, and thus the transitory component is assigned a slightly larger share of the total variance. It is reassuring that despite some differences in the persistent and transitory shares of inequality, both approaches yield essentially the same answer for the trends in income inequality.³⁸

VI. Household Income

We next examine the trend in the variance of the persistent and transitory components of pre-tax total household income. As noted in the introduction, examining household income is important because it is a broader measure of a household's resources and therefore has a more direct bearing on household consumption and welfare. In going from individual male earnings to total household income, a number of income components are added. These can be grouped into four main categories: spousal labor earnings, transfer

38. Along the same lines, previous versions of this paper included specifications where the transitory component followed an ARMA(1, 1) process, which exhibited more persistence than the transitory component in the ECM model presented above (in those specifications, the $p_{a,t}^i$ component was restricted to a random walk). As suggested by the previous discussion, those specifications attributed a larger share of the total variance to the transitory component at any given point in time, but the results for the trends were essentially identical.

income, investment income, and business income. Transfers are defined here as the sum of alimony received, pensions and annuities, unemployment compensation, Social Security benefits, and tax refunds. Investment income includes interest, dividends, and capital gains. Business income includes income from sole proprietorships, partnerships, and S corporations.³⁹

As already mentioned in section II, we carry out the analysis of household income using two alternative samples. The first, our “male-headed households” sample, consists of households with a male primary or secondary filer aged 25 to 60 whose annual labor earnings are above the minimum threshold. Our second, broader sample of “all households” essentially adds single females to the previous sample.⁴⁰ As table 1 shows, for pre-tax household income the broader sample has about 133,000 observations more than the sample of male-headed households.

As described in section III, the analysis here is performed on residuals from a first-stage regression of log household income on the sex, age, and filing status of the primary filer, and on a full set of dummies for the number of children.⁴¹

VI.A. Volatility

Figure 6 plots the standard deviation of 1-year and 2-year percentage changes in total household income for our sample of all households over the sample period. (The corresponding figure for the sample of male-headed households is very similar and is not shown.) As the figure shows, household income volatility, as measured here, rose 9 percent for 1-year income changes and 11 percent for 2-year income changes over the sample period, and there appears to be a clear rising trend. In fact, fitting a linear time trend to each of these two series yields coefficients on the time trend of 0.0022 (0.0003) for 1-year changes, and 0.0020 (0.0003) for 2-year changes, each implying an increase of about 0.05, or more than 10 percent, over the 23-year period. Thus, in contrast to male earnings, household income volatility appears to have increased over the sample period, which

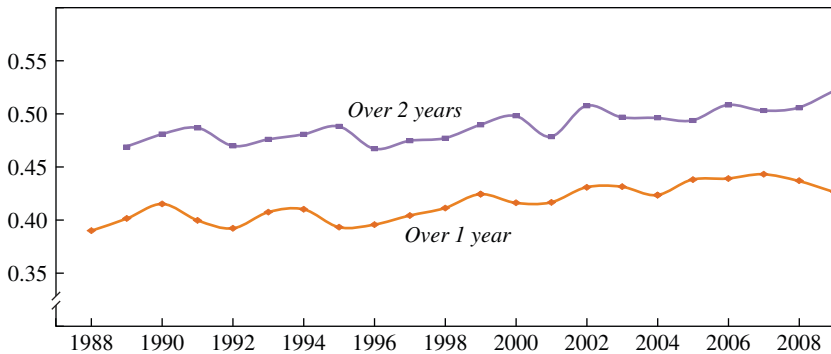
39. Using the sample of all households, on average over 1987–2009, male labor earnings account for about 54 percent of total household income, female labor earnings for 26 percent, retirement and transfer income for 5 percent, investment income for 8 percent, and business income for 7 percent.

40. It also adds some household observations for which labor earnings of the male filer are below the minimum threshold, but for which total household income is above the minimum threshold.

41. In the online appendix we investigate the robustness of our results to alternative treatments of household size and composition.

Figure 6. Volatility of Pre-Tax Household Income, All Households, 1988–2009

Standard deviation of the
percentage change in income



Source: Authors' calculations using SOI data.

suggests that the transitory component of the variance might have played a role in the increase in the cross-sectional inequality of household income.

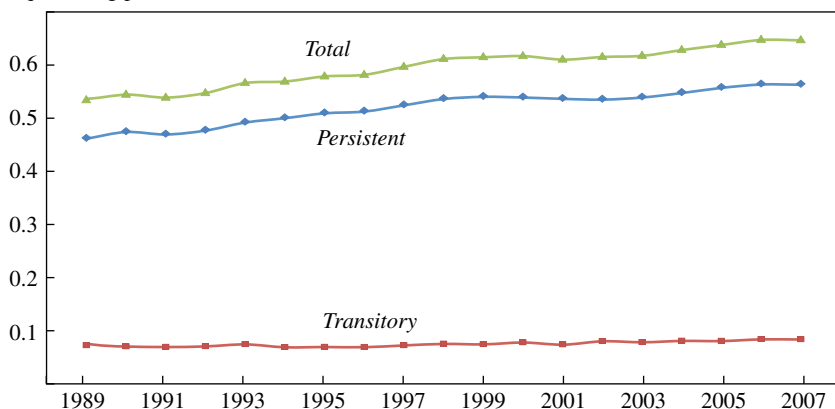
VI.B. Simple Nonparametric Variance Decompositions

Figure 7 shows the decomposition of the cross-sectional variance of (residual) pre-tax household income on the sample of all households, using the KSS method. (The decomposition using the GM method is very similar and is therefore not shown.) The figure shows a clear increase in the persistent part of the variance over the period of about 22 percent. The first column in the bottom panel of table 5 fits a linear time trend to the persistent variance. The estimated trend coefficient of 0.0056 (0.0004) is strongly significant and implies an increase in the variance of 0.13 squared log point over 23 years, explaining nearly the entire increase in the total variance shown in the figure.

However, the transitory variance component in the figure has also increased over the period, by about 15 percent. (This is somewhat hard to see in the figure because of the low level of the transitory variance.) The fourth column in the bottom panel of table 5 shows an estimated linear time trend coefficient of 0.0008 (0.0001) for the transitory variance, which is statistically significant but implies an increase in the variance of only 0.02 squared log point over 23 years. In other words, although the transitory component of the variance did increase, that increase had little effect on the total variance because the KSS method attributes only a very small fraction of the total variance to the transitory component (13 percent, on average, in this

Figure 7. Simple Nonparametric Decomposition of Cross-Sectional Variance in Pre-Tax Household Income, All Households, 1989–2007^a

Squared log points



Source: Authors' calculations using SOI data.

a. The KSS method is used for the decomposition.

decomposition). Thus, the increase in the total variance is again driven by the increase in the persistent component. However, under a decomposition that assigned a larger share of the total variance to the transitory component, the transitory variance would likely play a somewhat larger role.

VI.C. ECM-Based Variance Decomposition

We next examine the decomposition of the variance of pre-tax household income based on our nonstationary ECM. The second and third columns of table 4 present point estimates and standard errors for our baseline specification estimated on pre-tax household income, for both our sample of households with a male head (second column) and our broader sample of all households (third column). Figure 8 presents the corresponding variance decompositions.⁴²

The figure shows a clear increasing trend in the persistent component of the variance, which appears to have been concentrated in the first half of the 23-year sample period. The transitory component, by contrast, appears

42. Note that the total variance of household income in figure 8 is lower in any given year than the total variance of male earnings shown earlier. The reason is that these are variances of residuals, which in the case of household income have removed all variation explained by household size and composition. If we were to compare the raw data instead, the variance of household income would be larger than that of male earnings, as seen in figure 1.

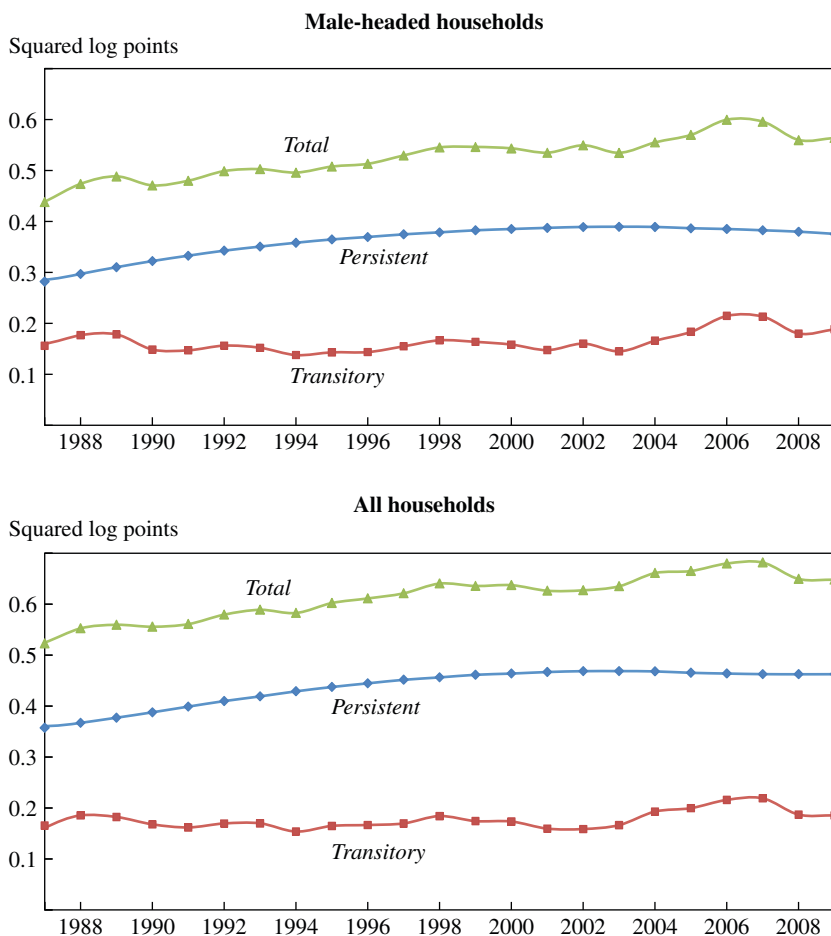
Table 5. Estimated Linear Time Trends of Persistent and Transitory Variance in Pre-Tax Household Income^a

Sample	Estimated component and decomposition method					
	Persistent component			Transitory component		
	KSS method	GM method	Error components model	KSS method	GM method	Error components model
<i>Male-headed households</i>						
Coefficient on linear time trend variable	0.0050 (0.0003)	0.0048 (0.0003)	0.0040 (0.0005)	0.0007 (0.0001)	0.0009 (0.0001)	0.0016 (0.0006)
<i>p</i> value	0.000	0.000	0.000	0.000	0.000	0.010
<i>R</i> ²	0.94	0.93	0.73	0.78	0.92	0.28
<i>All households</i>						
Coefficient on linear time trend variable	0.0056 (0.0004)	0.0054 (0.0004)	0.0048 (0.0005)	0.0008 (0.0001)	0.0010 (0.0001)	0.0013 (0.0005)
<i>p</i> value	0.000	0.000	0.000	0.000	0.000	0.010
<i>R</i> ²	0.94	0.93	0.80	0.77	0.85	0.28

Source: Authors' regressions using SOI data.

a. Each column in each panel reports results of an ordinary least squares regression of the persistent or the transitory component of the variance in household income, as calculated by the indicated decomposition method, on a constant (not reported) and a linear time trend. Standard errors are in parentheses.

Figure 8. ECM Decomposition of Cross-Sectional Variance in Pre-Tax Household Income, 1987–2009



Source: Authors' calculations using SOI data.

to have been relatively flat, although it increased somewhat in the last few years of the sample (the early to mid-2000s). The third and sixth columns of table 5 fit a linear time trend to the two variance components from figure 8 and confirm the rising trend for the persistent component of pre-tax household income. In the third column of the bottom panel, which corresponds to the sample of all households, the estimated linear trend coefficient of 0.0048 (0.0005) is strongly statistically significant and implies an increase of 0.11 squared log point over 23 years, accounting for roughly

80 percent of the increase in the total variance seen in the bottom panel of figure 8. The estimates in the sixth column of the bottom panel show a small rising trend in the transitory component of the variance, which has an estimated trend coefficient of 0.0013 (0.0005), implying an increase of 0.03 squared log point over 23 years and accounting for the remaining 20 percent of the increase in the total variance.

These results suggest that an increase in the variance of the persistent component of income accounted for the bulk of the increase in the cross-sectional variance of total pre-tax household income. The transitory component also contributed to the increase, but only a relatively small fraction, the precise contribution depending somewhat on the decomposition method used, on model specification in the case of the model-based decompositions, and on other factors such as the sample used. We conclude that the increase in household income inequality was mostly persistent.⁴³

VI.D. The Increase in the Transitory Variance of Household Income

We have shown that the increase in the total variance of household income was mostly persistent, but that unlike with male earnings, the transitory variance appears to have played some role. Here we explore which source or category of household income might account for the increase in the transitory variance of total household income. As previously discussed, household income can be decomposed into male labor earnings, spousal labor earnings, transfer income, investment income, and business income. In this section we take male earnings and then sequentially (and cumulatively) add each of spousal earnings, transfer income, investment income, and business income. For each of the resulting income aggregates, we estimate our ECM and decompose the cross-sectional variance into persistent and transitory parts.⁴⁴ We then fit a linear time trend to the transitory variance component and estimate the increase in the transitory variance over 1987–2009 that is implied by the estimated time trend. Here we report results from decompositions based on our baseline ECM and

43. As already noted in section I, in the online appendix we present estimates of our nonstationary ECM, and the corresponding variance decompositions, for a sample of male labor earnings and total household income from the PSID. In the PSID samples, the transitory variance component appears to have played more of a role for both male earnings and total household income.

44. We analyze increasingly broad income aggregates, rather than individual income categories separately, because for many households, income from at least some of these individual categories is zero. The large number of zero-income observations makes it difficult to estimate the ECM separately for each income category.

our male-headed households sample, but the other methods lead to similar conclusions.⁴⁵ Starting with male earnings and moving along the series of increasingly broad income aggregates, the implied increases in the transitory variance over 1987–2009 (in squared log points) are 0.003, 0.015, 0.016, 0.035, and 0.038, respectively. That is, the addition of spousal labor earnings and of investment income leads to a larger change in the implied increase in the transitory variance component over the sample period. We conclude that both spousal labor earnings and investment income contributed to the (relatively small) increase in the transitory variance of total household income.

VII. The Role of the Federal Tax System

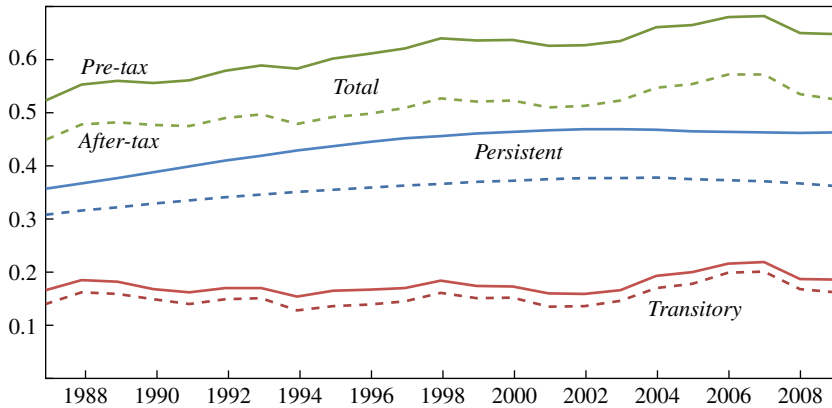
This section explores the role of the federal tax system in the increase in income inequality over our sample period. In particular, we examine whether the trend in inequality for after-tax household income differs materially from that for pre-tax income. As discussed in section II.B, our measure of after-tax household income reflects all federal personal income taxes (obtained from Form 1040), including all refundable tax credits such as the earned income tax credit and the child tax credit, as well as payroll taxes (calculated using information from W-2 forms).

The last two columns of table 4 present point estimates and standard errors for our ECM estimated on after-tax household income using both our male-headed households sample and our broader sample of all households. Figure 9 plots the total, persistent, and transitory variances of both pre-tax and after-tax household income for the sample of all households. As the figure shows, the total variance of after-tax income is on average 0.10 squared log point, or roughly 15 percent, smaller than the variance of pre-tax income, reflecting the overall progressivity of the federal tax system. The effect of the tax system in reducing income inequality appears relatively stable over the sample period, but for the period as a whole, pre-tax household income inequality increased by more than after-tax income inequality (0.13 versus 0.08 squared log point). That is, the tax system appears to have reduced the increase in household income inequality over the sample period. Nonetheless, as was already seen in figure 1, this attenuating effect was insufficient to alter the broad trend toward rising inequality for after-tax household income.

45. We use our male-headed households sample so as not to confound the effects of moving to broader measures of income with the effects of moving to broader samples.

Figure 9. ECM Decomposition of Cross-Sectional Variance in Pre-Tax and After-Tax Household Income, All Households, 1987–2009

Squared log points



Source: Authors' calculations using SOI data.

The relatively constant effect of the federal tax system on reducing the level of inequality during our sample period might appear surprising in light of the high-profile reductions in marginal tax rates, especially at the high end of the income distribution, in 2001 and 2003. However, the changes in top marginal tax rates were accompanied by (smaller) reductions in marginal tax rates for other income groups as well as by significant expansions of the earned income tax credit and the child tax credit. Our results suggest that the net effect on after-tax income inequality of all these changes to the federal tax system was relatively small.⁴⁶

VIII. Conclusions

We have used a confidential panel of tax returns from the Internal Revenue Service to analyze the role of persistent and transitory income components in changes in inequality in male labor earnings and total household income, both before and after taxes, in the United States over the period 1987–2009. We first documented an increase in inequality in male earnings and in

46. See, however, Piketty and Saez (2007), who find a decrease in progressivity between 1960 and 2004, which was driven primarily by changes in corporate taxes and in estate and gift taxes, which are not included in our analysis.

pre-tax and after-tax household income in our data during this period, consistent with what other studies have documented using different data sets. We then examined the contributions of persistent and transitory income components to this increase in inequality, as measured by the cross-sectional variance of log income.

We have used two broad sets of methods in our analysis. First, we employed a variety of simple nonparametric decomposition methods that use a strict definition of transitory income, which is not allowed to be serially correlated, and a broad definition of persistent income, which captures income with varying degrees of persistence. Second, we employed rich nonstationary error components models of income dynamics, which fully specify the process that generates income over time, and essentially decomposed income into a highly persistent piece and another transitory piece that allows for some limited degree of serial correlation. Our paper is the first to estimate rich nonstationary ECMs of income on U.S. administrative data, and among the first to apply nonstationary ECMs to household-level income. Here the quality and significant size of our data set allow us to obtain very precise estimates of our models.

Overall, our data yield very robust results for the trends in the variance of persistent and transitory income components. For male labor earnings, we find that the variance of the persistent component of earnings increased over the sample period, but the variance of the transitory component did not. Hence the increase in male earnings inequality was driven entirely by the increase in the persistent component, thus reflecting an increase in persistent inequality. For household income, both before and after taxes, the increase in inequality over this period derived mostly (although not entirely) from the persistent component. The increase in the variance of the transitory component of total household income reflects an increase in the transitory variance of spousal labor earnings and investment income. We also find evidence that the federal tax system helped reduce the increase in household income inequality, but this attenuating effect was insufficient to significantly alter the broad trend toward rising inequality.

Our findings, along with economic theory, suggest that the increase in income inequality observed in roughly the last two decades should translate into increases in consumption inequality and is therefore likely to be welfare-reducing, at least according to most social welfare functions. Although measurement problems with household consumption data in the United States have made it difficult to convincingly measure the increase in consumption inequality, some recent studies that attempt to control for these measurement issues, such as Aguiar and Bils (2012) and Attanasio,

Hurst, and Pistaferri (2012), suggest that it was indeed substantial. This is consistent with our findings of a large role of the persistent component of income in rising income inequality.

APPENDIX A

An Alternative Nonstationary ECM Specification

A few papers (for instance, Heathcote, Storesletten, and Violante 2010, Blundell, Pistaferri, and Preston 2008, and Heathcote, Perri, and Violante 2010) have estimated versions of an alternative nonstationary ECM specification, in which the variance of persistent shocks can change over calendar time, but which are simpler along other dimensions of the model. Here we present estimates for a version of this alternative specification in order to check the robustness of our results. The general model can be expressed as

$$(A.1) \quad \xi_{a,t}^i = \lambda_t \alpha^i + p_{a,t}^i + \tau_{a,t}^i, \text{ where}$$

persistent

transitory

$$(A.2) \quad p_{a,t}^i = \psi p_{a-1,t-1}^i + \phi_t \eta_{a,t}^i$$

$$(A.3) \quad \tau_{a,t}^i = \pi_t \varepsilon_{a,t}^i + \theta_1 \pi_{t-1} \varepsilon_{a-1,t-1}^i + \theta_2 \pi_{t-2} \varepsilon_{a-2,t-2}^i$$

$$(A.4) \quad \alpha^i \sim \text{i.i.d.}(0, \sigma_\alpha^2), \eta_{a,t}^i \sim \text{i.i.d.}(0, \sigma_\eta^2), \varepsilon_{a,t}^i \sim \text{i.i.d.}(0, \sigma_\varepsilon^2).$$

In this specification the $\tilde{\lambda}_t$ parameter multiplies the α^i component only, and a new set of parameters ϕ_t allow the variance of the persistent shocks $\eta_{a,t}^i$ to change over calendar time. (Note that parameters $\tilde{\lambda}_t$ are different from the λ_t in our baseline model, since $\tilde{\lambda}_t$ allow only the value of α^i to change over time, and not that of the persistent characteristics $p_{a,t}^i$.) The previous studies typically use a simpler version of this model that excludes the $\tilde{\lambda}_t \alpha^i$ from equation A.1. For our purposes the inclusion of the $\tilde{\lambda}_t \alpha^i$ component is necessary, because we cannot remove the income variation that is due to characteristics such as education, and in our context it is key to allow the prices of such characteristics to change over time.⁴⁷

47. The inclusion of the $\tilde{\lambda}_t \alpha^i$ component renders the estimation of the model more challenging. Indeed, we have found the estimation of this model to be much less numerically stable than that of our baseline ECM, and the estimates of the variance of the persistent innovations ($\hat{\sigma}_{\eta_t}^2 \equiv \hat{\phi}_t^2 \hat{\sigma}_\eta^2$) are very noisy. As in the case of our baseline ECM, we impose smoothness restrictions on the $\tilde{\lambda}_t$ series by restricting it to a fourth-degree polynomial, for the reasons discussed in section V.B. We thank Greg Kaplan for sharing computer code that helped with the estimation of this specification. Note also that in this specification the timing

Table A.1 presents point estimates and standard errors for the above model for male earnings and for total pre-tax household income, the latter using our sample of all households. Figure A.1 shows the corresponding decompositions of the cross-sectional variance of male earnings. Note that the component of the variance labeled “persistent” is the sum of the contributions of both $\tilde{\lambda}_i \alpha^i$ and $p_{a,t}^i$ to the cross-sectional variance. As in our baseline ECM, the persistent variance component displays a clearly increasing trend, rising from 0.39 squared log point in 1987 to 0.50 squared log point in 2009. Fitting a linear time trend to this series yields an estimated trend coefficient of 0.0041 (with a standard error of 0.0003), similar to that obtained with our baseline nonstationary specification. The transitory part of the variance, the lowest line in figure A.1, again exhibits no trend (an estimated linear time trend yields a coefficient of essentially zero).

Figure A.2 separates the persistent variance component in this model into the contributions of the terms $\tilde{\lambda}_i \alpha^i$ and $p_{a,t}^i$. As the figure shows, the increase in this component is driven by an increase in the variance of $\tilde{\lambda}_i \alpha^i$, whereas the variance of $p_{a,t}^i$ fluctuates but does not exhibit any clear trend. As the absence of a trend in $\text{var}(p_{a,t}^i)$ implies, the estimated variance of the persistent shocks ($\hat{\sigma}_{\eta,t}^2 \equiv \hat{\phi}_t^2 \hat{\sigma}_\eta^2$) in table A.2 varies substantially from year to year but has remained relatively stable on average over our sample

of the effects of changes in model parameters on changes in income inequality is different from that in our baseline model, because of the presence of the ϕ_t parameters (changes in the variance of persistent shocks). In particular, in the alternative ECM, changes in the variance of persistent shocks will have lagged effects on income inequality. To see this, suppose for simplicity that $\psi = 1$, so that $p_{a,t}^i$ is a random walk and the persistent shocks $\eta_{a,t}^i$ accumulate over time. Next, suppose, for example, that the variance of persistent shocks experiences a one-time permanent increase in year t (there is a one-time permanent jump in ϕ_t). Then, over time, as new cohorts enter the adult (ages 25–60) population, they will face the larger persistent shocks, and these shocks accumulate over time. Therefore, the one-time permanent increase in the variance of persistent shocks in year t would continue to lead to increases in inequality in future periods, as younger cohorts (facing larger persistent shocks) replace the older cohorts (which have accumulated smaller persistent shocks over their lifetime). One implication of this is that, if the model in equations A.1 through A.4 were the correct representation of the world (and especially if $\psi = 1$), and if it were the case that the variance of persistent shocks had increased permanently some time before 1987 (the beginning of our sample), then part of the increase in income inequality after 1987 would be the result of the increase in the variance of the persistent shocks before 1987. Our baseline ECM would likely attribute such changes in inequality to λ_t . We thank Greg Kaplan for making this observation.

Table A.1. Estimates of the Alternative Nonstationary Error Components Model^a

<i>Parameter</i>	<i>Male labor earnings</i>		<i>Pre-tax household income, all households</i>	
	<i>Persistent component</i>	<i>Transitory component</i>	<i>Persistent component</i>	<i>Transitory component</i>
σ_{α}^2	0.1458 (0.0235)		0.1313 (0.0187)	
$\tilde{\lambda}_t$ polynomial ^b				
b_1	0.0136 (0.0419)		0.0170 (0.0425)	
$b_2 (\times 10)$	0.0190 (0.0584)		0.0488 (0.0567)	
$b_3 (\times 100)$	-0.0175 (0.0337)		-0.0443 (0.0316)	
$b_4 (\times 1000)$	0.0038 (0.0069)		0.0097 (0.0064)	
Ψ	0.9619 (0.0058)		0.9693 (0.0041)	
σ_{η}^2	0.0296 (0.0040)		0.0248 (0.0025)	
θ_1		0.2396 (0.0163)		0.2877 (0.0114)
θ_2		0.1353 (0.0179)		0.1703 (0.0142)
σ_{ϵ}^2		0.1749 (0.0166)		0.1533 (0.0122)
ϕ or π^c				
1987	1.0000	1.0000	1.0000	1.0000
1988	1.1382 (0.3929)	1.0867 (0.0571)	1.3067 (0.2610)	1.0068 (0.0496)
1989	1.2149 (0.2613)	1.0160 (0.0584)	0.9528 (0.3390)	1.0198 (0.0443)
1990	0.8679 (0.3494)	0.9985 (0.0530)	0.9199 (0.3456)	0.9910 (0.0465)
1991	1.0022 (0.2808)	0.9845 (0.0536)	1.0393 (0.2798)	0.9619 (0.0418)
1992	0.7569 (0.3553)	1.0887 (0.0505)	0.0028 (0.3144)	1.0833 (0.0474)
1993	1.1759 (0.2280)	1.0444 (0.0483)	1.2418 (0.2059)	1.0038 (0.0492)
1994	0.0051 (0.2890)	1.0659 (0.0509)	0.1117 (0.2974)	1.0396 (0.0522)
1995	1.2536 (0.1737)	1.0071 (0.0580)	1.2674 (0.1697)	0.9879 (0.0520)

(continued)

Table A.1. Estimates of the Alternative Nonstationary Error Components Model^a
(Continued)

Parameter	Male labor earnings		Pre-tax household income, all households	
	Persistent component	Transitory component	Persistent component	Transitory component
1996	0.7085 (0.3096)	1.0319 (0.0567)	0.8273 (0.2178)	1.0129 (0.0525)
1997	1.0256 (0.1961)	0.9884 (0.0552)	0.8840 (0.1912)	1.0257 (0.0544)
1998	0.7510 (0.2669)	1.0236 (0.0599)	1.1198 (0.1457)	1.0285 (0.0550)
1999	0.9245 (0.2239)	1.0070 (0.0578)	0.4886 (0.2776)	1.0629 (0.0520)
2000	0.8369 (0.2959)	1.0463 (0.0654)	0.8887 (0.2519)	1.0652 (0.0555)
2001	1.1827 (0.1766)	0.9787 (0.0613)	1.2008 (0.1599)	0.9645 (0.0527)
2002	1.2415 (0.1344)	0.9859 (0.0538)	1.1278 (0.1612)	0.9388 (0.0502)
2003	0.7567 (0.1758)	1.0239 (0.0601)	1.1011 (0.1411)	0.9511 (0.0494)
2004	1.0366 (0.1428)	0.9898 (0.0534)	1.1579 (0.0958)	1.0118 (0.0470)
2005	0.7861 (0.2186)	1.0202 (0.0565)	0.9594 (0.1427)	1.0476 (0.0481)
2006	1.0178 (0.1622)	1.0685 (0.0582)	1.1553 (0.1235)	1.0720 (0.0478)
2007	0.7559 (0.2257)	1.0508 (0.0553)	0.7027 (0.1846)	1.1380 (0.0482)
2008	1.2584 (0.1457)	1.0277 (0.0544)	1.1606 (0.1313)	1.0100 (0.0474)
2009		1.0208 (0.0557)		0.9954 (0.0491)

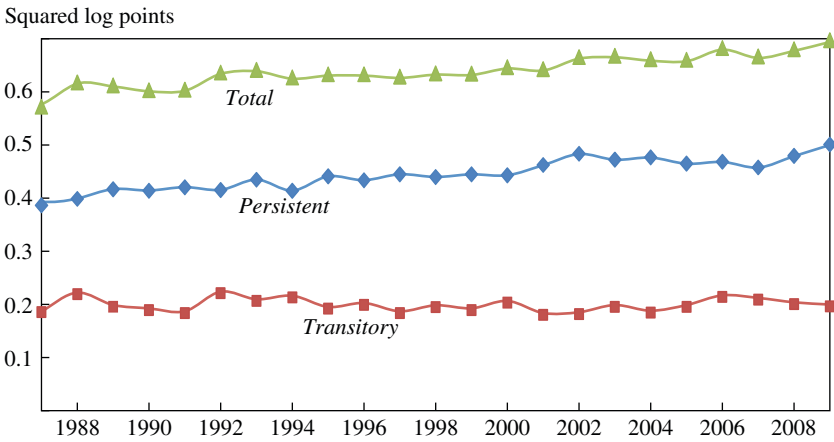
Source: Authors' calculations using SOI data.

a. Estimates of equations A.1 through A.4 using a minimum distance estimator (see section V.C). Bootstrap standard errors based on 200 replications are in parentheses.

b. See appendix D for specification of the polynomial.

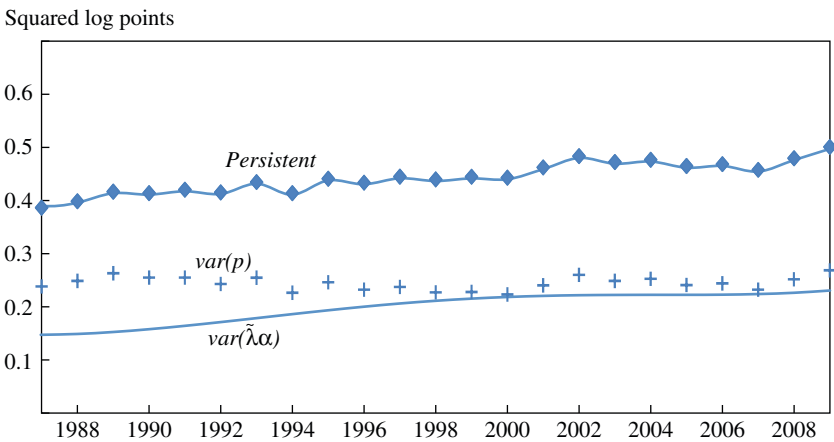
c. Panel reports estimates of parameters ϕ (for the persistent component) and π (for the transitory component) corresponding to each year of the sample period (1987–09); parameters are normalized to equal 1 in 1987 (see appendix D).

Figure A.1. Alternative ECM Decomposition of Cross-Sectional Variance in Male Labor Earnings, 1987–2009



Source: Authors' calculations using SOI data.

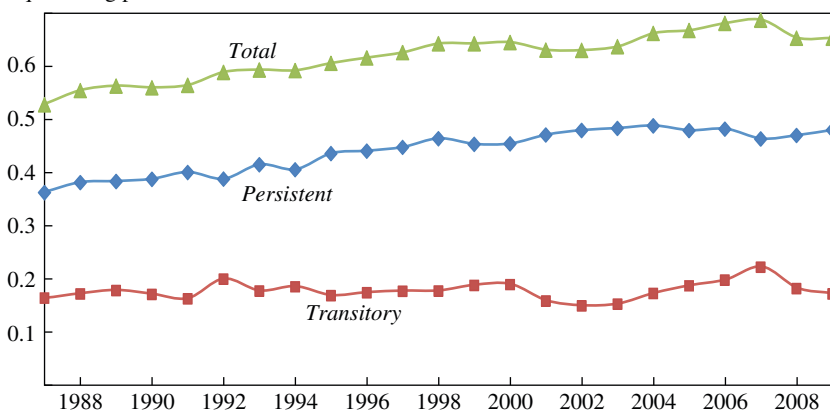
Figure A.2. Alternative ECM Decomposition of Persistent Variance in Male Labor Earnings, 1987–2009



Source: Authors' calculations using SOI data.

Figure A.3. Alternative ECM Decomposition of Cross-Sectional Variance in Pre-Tax Household Income, 1987–2009^a

Squared log points



Source: Authors' calculations using SOI data.

a. The decomposition is performed on the "all households" sample.

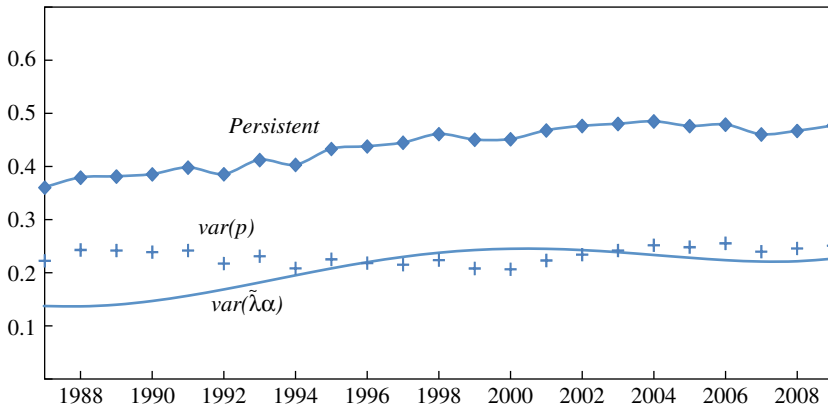
period.⁴⁸ For the question addressed in this paper, these results are very similar to those obtained with our baseline model.

Figure A.3 shows the decomposition, using the alternative model, of the cross-sectional variance of total pre-tax household income for our sample of all households. Here, too, the results are similar to those obtained with our baseline specification. There is a clear rising trend in the persistent component of the variance, and this increase is concentrated in the first half of the sample period. The transitory variance component fluctuates but overall is largely flat, except perhaps for a small increase in the last

48. According to this model specification (and our data), there has been no distinct trend in the variances of persistent or transitory shocks in our sample period. All the increase in the variance of the persistent component of earnings comes from an increase in the "price" of permanent characteristics. This is entirely consistent with our findings from our baseline ECM, where the rise in the variance comes from an increase in the price of permanent and persistent characteristics. One might ask, both in the context of this alternative model and in the context of our baseline ECM, to what extent this increase in the price of certain permanent or persistent characteristics represents increases in the returns to observable characteristics (such as education and experience) versus unobservable ones. The large causal literature on earnings and wage inequality in labor economics indicates that the answer is both, as it generally finds increases in inequality both between and within narrowly defined education and experience groups (see, for instance, Lemieux 2008).

Figure A.4. Alternative ECM Decomposition of Persistent Variance in Pre-Tax Household Income, 1987–2009^a

Squared log points



Source: Authors' calculations using SOI data.

a. The decomposition is performed on the "all households" sample.

few years of the period. Fitting a linear time trend to the persistent and transitory variance components yields trend coefficients of 0.0055 (0.0005) and 0.0005 (0.0005), respectively. Again, most of the increase in the cross-sectional variance of total pre-tax household income was driven by the variance of the persistent component of income. In fact, this specification implies that the transitory variance component played even less of a role than in our baseline model (compare the 0.0005 estimated trend coefficient on the transitory variance component with the 0.0013 coefficient shown in the bottom right panel of table 5).

Figure A.4 shows the contributions of $\text{var}(\tilde{\lambda}_t \alpha^i)$ and $\text{var}(p_{a,t}^i)$ to the persistent variance component in the same decomposition and indicates that, similar to the case of male earnings, the increase in the persistent variance component was driven by an increase in the variance of $\text{var}(\tilde{\lambda}_t \alpha^i)$, that is, by an increase in the $\tilde{\lambda}_t$. Fitting a linear time trend to the $\text{var}(p_{a,t}^i)$ series yields a trend coefficient of 0.0008 (0.0005), implying only a minor increase of about 0.02 squared log point over 23 years.

Overall, for the question asked in this paper, the results obtained with this alternative specification are very similar to those obtained with our baseline model.

APPENDIX B

KSS and GM Methods

Let ξ_t^i be residual log income, where t is the calendar year, and where the age index a is suppressed for convenience. In the KSS methodology, the persistent variance in year t is $\text{var}\left(\frac{1}{P}\sum_{j=t-k}^{t+k}\xi_j^i\right)$, where $k = (P - 1)/2$, and where the variance is computed across all individuals (or households) for whom $\frac{1}{P}\sum_{j=t-k}^{t+k}\xi_j^i$ is defined for a given t . The transitory variance at t is $\text{var}\left(\xi_{it} - \frac{1}{P}\sum_{j=t-k}^{t+k}\xi_j^i\right)$. Following Kopczuk, Saez, and Song (2010), we set $P = 5$.

In the GM methodology, let N be the number of individuals, $T_i \leq P$ the number of years (within the P -year window) that person i is observed, $\bar{\xi}_i$ the person-specific average residual log income over T_i years, $\bar{\xi}$ the mean of residual log income across the full sample, and \bar{T} the mean years covered by the window over the individuals in the sample. Then, the exact formula (within each fixed-size window) for the transitory variance is $\hat{\sigma}_v^2 = \frac{1}{N}\sum_{i=1}^N\left[\frac{1}{T_i-1}\sum_{t=1}^{T_i}(\xi_{it} - \bar{\xi}_i)^2\right]$ and for the persistent variance is $\frac{1}{N-1}\sum_{i=1}^N(\bar{\xi}_i - \bar{\xi})^2 - \frac{\hat{\sigma}_v^2}{\bar{T}}$.

The persistent and transitory variances from GM are similar, although not identical, to the KSS ones. The main difference lies in the presence of the term $-(\hat{\sigma}_v^2/\bar{T})$ in the persistent GM variance (see Gottschalk and Moffitt 2009, footnote 2).

Note that Gottschalk and Moffitt use $P = 9$ (rather than our $P = 5$ in the main text). This slightly reduces the share of the total variance attributed to the persistent component, and slightly increases the share attributed to the transitory component, but has no effect on the trends of the two components.

APPENDIX C

Estimation of the Error Components Model

This appendix provides details of our minimum distance estimator. As mentioned in the text, the estimator matches the model's theoretical variances and autocovariances (specified in levels) to their empirical counterparts. In particular, given any triplet (a, t, k) of normalized age a , calendar year t ,

and lead k , the error components model in equations 6 through 9 implies a specific parametric form for each autocovariance of residual income, such as $\text{cov}(\xi_{a,t}, \xi_{a+k,t+k})$. For instance, for $(a = 2, t = 1995, k = 0)$, this would be the variance (since $k = 0$) in the incomes across all individuals of age 26 in year 1995. These theoretical variances and autocovariances, denoted by $\text{cov}(a, t, k)$, are functions of the model parameters $\sigma_\alpha^2, \psi, \sigma_\eta^2, \sigma_\varepsilon^2, \theta_1$, and θ_2 , and λ_t and π_t for $t = 1987, \dots, 2009$. We estimate these model parameters by minimizing the distance between, on the one hand, the theoretical variances and autocovariances implied by the model, and on the other, their empirical counterparts, which we compute from our longitudinal tax return data for $a = 1, \dots, 36; t = 1987, \dots, 2009$; and $k = 0, \dots, 22$. This yields 7,912 variances and autocovariances that are matched in estimation. Our minimum distance estimator uses a diagonal matrix as the weighting matrix, with weights equal to the inverse of the number of observations used to compute each empirical statistical moment.⁴⁹ We do not use an optimal weighting matrix, for reasons discussed in Altonji and Segal (1996).

APPENDIX D

Moment Conditions

Let a be “normalized age” or “potential experience,” defined as $a = \text{age} - 25 + 1$, or years starting with age 25. Then, the theoretical moments implied by our baseline error components model in equations 6 through 9 are as follows:

$$\begin{aligned} \text{cov}(\xi_{a,t}^i, \xi_{a+k,t+k}^i) &= \lambda_t \times \lambda_{t+k} \times (\sigma_\alpha^2 + \psi^t \text{var}(p_{a,t}^i)) \\ &+ 1[k = 0] \times \sigma_\varepsilon^2 \times (\pi_t^2 + 1[a \geq 2] \pi_{t-1}^2 \theta_1^2 + 1[a \geq 3] \pi_{t-2}^2 \theta_2^2) \\ &+ 1[k = 1] \times \sigma_\varepsilon^2 \times (\pi_t^2 \theta_1 + 1[a \geq 2] \pi_{t-1}^2 \theta_1 \theta_2) \\ &+ 1[k = 2] \times \sigma_\varepsilon^2 \times \pi_t^2 \theta_2, \end{aligned}$$

where $1[\]$ is an indicator function equal to either zero or 1.

For $t = 1987, 2 \leq a \leq 36$,

$$\text{var}(p_{a,1987}) = \sigma_\eta^2 \frac{1 - \psi^{2a}}{1 - \psi^2}.$$

49. We have also estimated the model using the identity matrix as weighting matrix. The results (not reported) are very similar.

For $1987 \leq t \leq 2009$, $a = 1$,

$$\text{var}(p_{1,t}) = \sigma_{\eta}^2.$$

For $1988 \leq t \leq 2009$, $2 \leq a \leq 36$,

$$\text{var}(p_{a,t}) = \psi^2 \text{var}(p_{a-1,t-1}) + \sigma_{\eta}^2.$$

To obtain identification, we impose the normalization $\lambda_t = \pi_t = 1$ for all calendar years $t \leq 1987$, where 1987 is the first year in the sample. Parameter λ_t (normalized) is restricted to lie on a fourth-order polynomial of the following form: for $1988 \leq t \leq 2009$, $\lambda_t = \lambda_{1987} + b_1 \tilde{t} + b_2 \tilde{t}^2 + b_3 \tilde{t}^3 + b_4 \tilde{t}^4$, where $\tilde{t} = t - 1987$.⁵⁰

APPENDIX E

Sample Age Distribution by Calendar Year

Year	Age (years) ^a				Year	Age (years)			
	Male earnings sample		All households sample ^b			Male earnings sample		All households sample ^b	
	Mean	SD	Mean	SD		Mean	SD	Mean	SD
1987	39	9.9	39	10.0	1999	41	9.6	41	9.8
1988	39	9.8	39	10.0	2000	41	9.6	41	9.8
1989	39	9.8	39	9.9	2001	41	9.7	41	9.9
1990	39	9.7	40	9.8	2002	41	9.7	41	9.9
1991	39	9.6	40	9.8	2003	41	9.7	42	10.0
1992	40	9.7	40	9.8	2004	41	9.8	42	10.0
1993	40	9.6	40	9.7	2005	41	9.9	42	10.1
1994	40	9.6	40	9.7	2006	41	10.0	42	10.2
1995	40	9.6	40	9.8	2007	41	10.0	42	10.2
1996	40	9.6	40	9.8	2008	42	10.1	42	10.3
1997	40	9.6	41	9.8	2009	42	10.1	42	10.3
1998	41	9.7	41	9.8					

Source: Authors' calculations using SOI data.

a. SD = standard deviation.

b. Age is that of the primary filer.

50. When λ_t is unrestricted, we use the normalization $\pi_{2008} = \pi_{2009}$, since in that case λ_t and π_t cannot be identified separately in the last year of the sample, $t = 2009$. Results for the unrestricted version are presented in the online appendix.

ACKNOWLEDGMENTS We are grateful to the editors, to our discussants Greg Kaplan, Lindsay Owens, and David Grusky, and to Chris Carroll for extremely useful feedback and suggestions. We thank Joe Altonji, Eric Engen, Michael Golosov, Michael Palumbo, Emmanuel Saez, Dan Sichel, and Paul Smith for very helpful comments and discussions. We also thank the participants at the Brookings Panel and at numerous other seminars and conferences. The views presented here are solely those of the authors and do not necessarily represent those of the Treasury Department, the Board of Governors of the Federal Reserve System, or members of their staffs. The authors report no relevant conflicts of interest.

References

- Abowd, John, and David Card. 1989. "On the Covariance Structure of Hours and Earnings Changes." *Econometrica* 57, no. 2: 411–45.
- Aguiar, Mark, and Mark Bilts. 2012. "Has Consumption Inequality Mirrored Income Inequality?" Princeton University and University of Rochester (May).
- Altonji, Joseph, and Lewis M. Segal. 1996. "Small Sample Bias in GMM Estimation of Covariance Structure." *Journal of Business and Economic Statistics* 14, no. 3: 353–66.
- Altonji, Joseph, Anthony Smith, and Ivan Vidangos. Forthcoming. "Modeling Earnings Dynamics." *Econometrica*.
- Attanasio, Orazio, Eric Battistin, and Hide Ichimura. 2007. "What Really Happened to Consumption Inequality in the US?" In *Hard-to-Measure Goods and Services: Essays in Honor of Zvi Griliches*, edited by E. Berndt and C. Hulten. University of Chicago Press.
- Attanasio, Orazio, Eric Battistin, and Mario Padula. 2011. "Inequality in Living Standards since 1980: Income Tells Only a Small Part of the Story." Washington: American Enterprise Institute.
- Attanasio, Orazio, Erik Hurst, and Luigi Pistaferri. 2012. "The Evolution of Income, Consumption, and Leisure Inequality in the US, 1980–2010." Working Paper no. 17982. Cambridge, Mass.: National Bureau of Economic Research (April).
- Autor, David, Lawrence F. Katz, and Melissa S. Kearney. 2008. "Trends in U.S. Wage Inequality: Revising the Revisionists." *Review of Economics and Statistics* 90: 300–23.
- Baker, Michael. 1997. "Growth-Rate Heterogeneity and the Covariance Structure of Life-Cycle Earnings." *Journal of Labor Economics* 15: 338–75.
- Baker, Michael, and Gary Solon. 2003. "Earnings Dynamics and Inequality among Canadian Men, 1976–1992: Evidence from Longitudinal Income Tax Records." *Journal of Labor Economics* 21: 289–321.
- Blundell, Richard, Luigi Pistaferri, and Ian Preston. 2008. "Consumption Inequality and Partial Insurance." *American Economic Review* 98: 1887–1921.
- Bound, John, and George E. Johnson. 1992. "Changes in the Structure of Wages in the 1980s: An Evaluation of Alternative Explanations." *American Economic Review* 82: 371–92.
- Card, David, and Thomas Lemieux. 1996. "Wage Dispersion, Returns to Skill, and Black-White Wage Differentials." *Journal of Econometrics* 74, no. 2: 319–61.
- Carroll, Christopher. 1992. "The Buffer-Stock Theory of Saving: Some Macroeconomic Evidence." *BPEA*, no. 2: 61–135.
- Carroll, Christopher, and Andrew Samwick. 1997. "The Nature of Precautionary Wealth." *Journal of Monetary Economics* 40, no. 1: 41–71.
- Celik, Sule, Chinhui Juhn, Kristin McCue, and Jesse Thompson. 2012. "Recent Trends in Earnings Volatility: Evidence from Survey and Administrative Data." *B.E. Journal of Economic Analysis and Policy* 12, no. 2: article 1 (December).

- Congressional Budget Office. 2008. "Recent Trends in the Variability of Individual Earnings and Household Income." Washington. www.cbo.gov/ftpdocs/95xx/doc9507/06-30-Variability.pdf.
- Dynan, Karen E., Douglas W. Elmendorf, and Daniel E. Sichel. 2012. "The Evolution of Household Income Volatility." *B.E. Journal of Economic Analysis and Policy* 12, no. 2: article 3 (December).
- Gottschalk, Peter, and Robert Moffitt. 1994. "The Growth of Earnings Instability in the U.S. Labor Market." *BPEA*, no. 2: 217–72.
- . 2009. "The Rising Instability of U.S. Earnings." *Journal of Economic Perspectives* 23: 3–24.
- Guvenen, Fatih. 2009. "An Empirical Investigation of Labor Income Processes." *Review of Economic Dynamics* 12: 58–79.
- Haider, Steven J. 2001. "Earnings Instability and Earnings Inequality of Males in the United States, 1967–1991." *Journal of Labor Economics* 19: 799–836.
- Hause, John C. 1980. "The Fine Structure of Earnings and the On-the-Job Training Hypothesis." *Econometrica* 48: 1013–29.
- Heathcote, Jonathan, Fabrizio Perri, and Gianluca L. Violante. 2010. "Unequal We Stand: An Empirical Analysis of Economic Inequality in the United States, 1967–2006." *Review of Economic Dynamics* 13: 15–51.
- Heathcote, Jonathan, Kjetil Storesletten, and Gianluca L. Violante. 2010. "The Macroeconomic Implications of Rising Wage Inequality in the United States." *Journal of Political Economy* 118, no. 4: 681–722.
- Hryshko, Dmytro. 2012. "Labor Income Profiles Are Not Heterogeneous: Evidence from Income Growth Rates." *Quantitative Economics* 3: 177–209.
- Juhn, Chinhui J., Kevin M. Murphy, and Brooks Pierce. 1993. "Wage Inequality and the Rise in Returns to Skill." *Journal of Political Economy* 101: 410–42.
- Katz, Lawrence F., and David Autor. 1999. "Changes in the Wage Structure and Earnings Inequality." In *Handbook of Labor Economics*, vol. III, edited by Orley Ashenfelter and David Card. Amsterdam: North Holland.
- Katz, Lawrence F., and Kevin M. Murphy. 1992. "Changes in Relative Wages, 1963–87: Supply and Demand Factors." *Quarterly Journal of Economics* 107: 35–78.
- Kopczuk, Wojciech, Emmanuel Saez, and Jae Song. 2010. "Earnings Inequality and Mobility in the United States: Evidence from Social Security Data since 1937." *Quarterly Journal of Economics* 125: 91–128.
- Krueger, Dirk, and Fabrizio Perri. 2006. "Does Income Inequality Lead to Consumption Inequality? Evidence and Theory." *Review of Economic Studies* 73: 163–93.
- Lemieux, Thomas. 2008. "What Do We Really Know about Changes in Wage Inequality?" University of British Columbia.
- Lillard, Lee A., and Yoram Weiss. 1979. "Components of Variation in Panel Earnings Data: American Scientists 1960–1970." *Econometrica* 47: 437–54.
- Lillard, Lee A., and Robert J. Willis. 1978. "Dynamic Aspects of Earning Mobility." *Econometrica* 46: 985–1012.

- Low, Hamish, Costas Meghir, and Luigi Pistaferri. 2010. "Wage Risk and Employment Risk over the Life Cycle." *American Economic Review* 100, no. 4: 1432–67.
- MaCurdy, Thomas E. 1982. "The Use of Time Series Processes to Model the Error Structure of Earnings in a Longitudinal Data Analysis." *Journal of Econometrics* 18: 83–114.
- Meghir, Costas, and Luigi Pistaferri. 2004. "Income Variance Dynamics and Heterogeneity." *Econometrica* 72: 1–32.
- Moffitt, Robert, and Peter Gottschalk. 1995. "Trends in the Covariance Structure of Earnings in the U.S.: 1969–1987." Johns Hopkins University and Boston College.
- . 2011. "Trends in the Transitory Variance of Male Earnings in the U.S., 1970–2004." Working Paper no. 16833. Cambridge, Mass.: National Bureau of Economic Research.
- Murphy, Kevin M., and Finis Welch. 1992. "The Structure of Wages." *Quarterly Journal of Economics* 107: 285–326.
- Piketty, Thomas, and Emmanuel Saez. 2003. "Income Inequality in the United States, 1913–1998." *Quarterly Journal of Economics* 118: 1–39.
- . 2007. "How Progressive Is the U.S. Federal Tax System? A Historical and International Perspective." *Journal of Economic Perspectives* 21: 3–24.
- Primiceri, Giorgio, and Thijs van Rens. 2009. "Heterogeneous Life-Cycle Profiles, Income Risk and Consumption Inequality." *Journal of Monetary Economics* 56: 20–39.
- Sabelhaus, John, and Jae Song. 2009. "Earnings Volatility across Groups and Time." Working paper. University of Maryland and U.S. Social Security Administration.
- . 2010. "The Great Moderation in Micro Labor Earnings." *Journal of Monetary Economics* 57: 391–403.
- Shin, Donggyun, and Gary Solon. 2011. "Trends in Men's Earnings Volatility: What Does the Panel Study of Income Dynamics Show?" *Journal of Public Economics* 95: 973–82.
- Slesnick, Daniel T. 2001. "Consumption and Social Welfare: Living Standards and Their Distribution in the United States." Cambridge University Press.

Comments and Discussion

COMMENT BY

GREG KAPLAN This paper by Jason DeBacker and coauthors provides a new perspective on the much-documented rise in income inequality in the United States, by exploiting confidential data on labor earnings and household income from the Internal Revenue Service (IRS). The IRS data contain information from a large panel of tax returns over the period from 1987 to 2009. The authors use these data to ask whether the recent rise in inequality is mostly due to persistent or to transitory factors. Other authors have answered this question using survey data, predominantly from the Panel Study of Income Dynamics (PSID), and for earlier periods. But this paper breaks new ground in its use of high-quality administrative data to decompose the rise in inequality in the 1990s and 2000s.

DeBacker and his coauthors reach a stark conclusion: all of the recent rise in inequality in male earnings is due to persistent factors; transitory factors have made no contribution to the increase in inequality. Their findings for total household income are similar but less extreme. The authors reach these conclusions using two different approaches. First, they employ simple nonparametric methods, which effectively measure the persistent component of income as a rolling average of income in a given number of adjacent years, and the transitory component as the residual from this rolling average. Second, they estimate error components models (ECMs) for earnings. The ECM approach involves specifying and estimating the parameters of a time-varying stochastic process for income. The persistent and transitory components are then inferred from the estimated model. The authors' conclusions about the relative importance of persistent versus transitory factors are consistent across the two methods.

In this discussion I will elaborate on three issues that are related to these findings, focusing exclusively on the ECM analysis of male labor

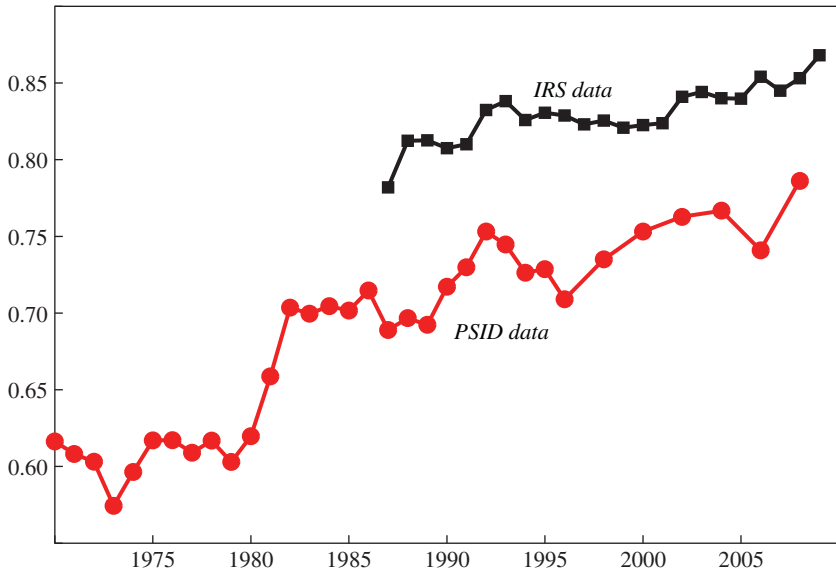
earnings. First, I will use data from the PSID to investigate how the particular choice of ECM framework may have influenced the authors' conclusions. In doing so I will distinguish between factors that are fixed at the time of entry into the labor market, and shocks that are realized after entry. I will attempt to shed light on which of these factors is responsible for the increase in the persistent variance. I will also explain how an increase in the variance of shocks that occurred before 1987 could be responsible for the observed increase in inequality from 1987 to 2009 even in the absence of any changes in the labor market during this period. Second, I will use the PSID data to investigate the importance of changes in the returns to education in accounting for the authors' findings. I will show that the findings are mostly consistent across the two data sets and are not substantially affected by controlling for education. Third, I will highlight an issue that the authors do not address, but that is a natural one to raise in light of their findings, and given their access to the IRS data: in which part of the income distribution is the recent rise in inequality concentrated? I will conduct a simple decomposition using the PSID data to investigate this issue.

How do the publicly available PSID data compare with the confidential IRS data used by the authors? The baseline sample of male earners from the IRS contains 221,099 person-year observations on 20,859 individuals over the period 1987–2009. In all of the analyses that follow, I use a sample of male heads of households from the PSID that imposes the same selection criteria for age and minimum annual earnings as the authors impose on the IRS data. The resulting sample contains 70,479 person-year observations on 6,778 individuals over the period 1970–2008 (the data are biennial after 1996). Thus, the IRS sample is about three times the size of the PSID sample, both in terms of individuals and in terms of individual-year observations.

My figure 1 plots inequality in male earnings, as measured by the standard deviation of the logarithm, in the two data sets over time. For the period over which the two samples overlap, the trends in inequality are very similar. The level of inequality is about 0.1 log point higher in the IRS data, likely because of undersampling of very high earners in the PSID. Moreover, the IRS series appears far less noisy than the PSID series, which reinforces the view that the IRS data are useful for reevaluating questions that have been addressed using PSID data in the existing literature, such as the cyclicity of idiosyncratic labor income risk (compare, for example, the difference in the increase in inequality during the 1990–91 recession in the two series in this figure).

Figure 1 also puts in perspective the magnitude of the rise in inequality that DeBacker and coauthors decompose. Although inequality has

Figure 1. Standard Deviation of Log Male Earnings in IRS and PSID Data



Source: Author's calculations.

undoubtedly increased between 1987 and 2009 in the IRS data, the magnitude of the increase is smaller (about 0.05 log point) than that in the 1970s and 1980s in the PSID data (about 0.15 log point). Both data sets have advantages and disadvantages. The IRS data set is cleaner and larger and has better coverage at the top of the earnings distribution. Yet it is confidential and lacks data on demographic information, such as education. The PSID data, on the other hand, are publicly available and contain many demographic and financial variables.

The ECM framework that DeBacker and his coauthors employ is one of many possible choices. Consider the following parametric model for residual log earnings of individual i in year t , ξ_t^i :

$$\begin{aligned}
 \xi_t^i &= \alpha^i + p_t^i + \tau_t^i \\
 p_t^i &= \psi p_{t-1}^i + \eta_t^i \\
 \tau_t^i &= \varepsilon_t^i + \theta \varepsilon_{t-1}^i,
 \end{aligned}
 \tag{1}$$

where ε_t^i and η_t^i are mean-zero i.i.d (over time) shocks with constant variances σ_ε^2 and σ_η^2 , and α^i is a mean-zero fixed effect with variance σ_α^2 . The authors refer to the component $(\alpha^i + p_t^i)$ as the persistent component and

to τ_t^i as the transitory component. I will adopt the same terminology. The process in equation 1 differs from the one in the paper only in that the transitory component is modeled as an MA(1) rather than an MA(2) process. This difference is not consequential and helps to simplify the analysis.

Decomposing changes over time in the variance of residual log earnings requires allowing some or all of the parameters in equation 1 to change over time. There are many ways to do this. One natural way, which I will refer to as version A, allows the variances of the two shocks to change over time, and the price of the fixed effect to change over time. Thus, in version A the variances of the two shocks become $\sigma_{\epsilon t}^2$ and $\sigma_{\eta t}^2$, and the first line in equation 1 is modified to read

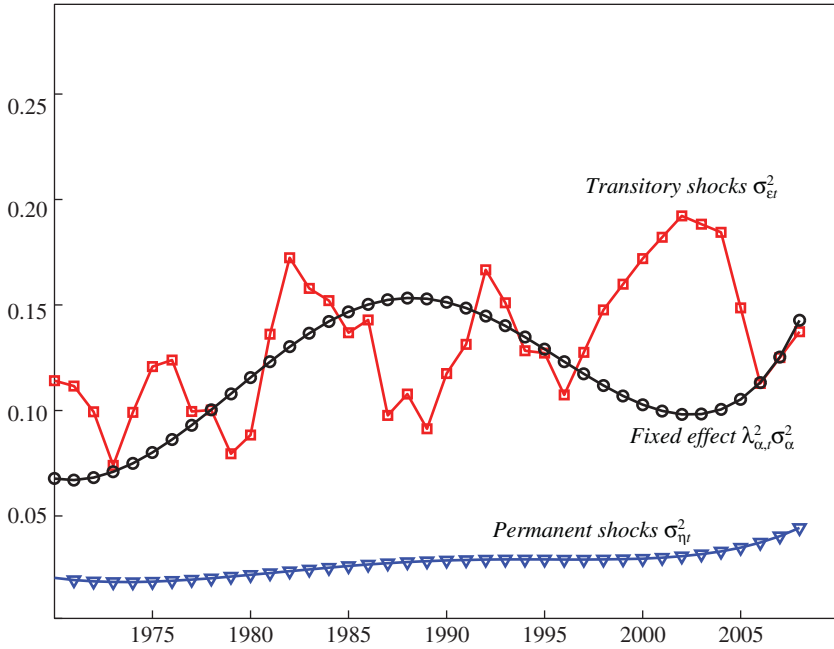
$$(2) \quad \xi_t^i = \lambda_{\alpha,t} \alpha^i + p_t^i + \tau_t^i,$$

where a normalization is imposed on $\lambda_{\alpha,0}$. In this interpretation the ECM changes over time for two reasons: individuals experience persistent and transitory shocks that are drawn from a more or less dispersed distribution, and the market price of an individual's fixed skills is changing over time.

Figure 2 shows the results from estimating ECM version A using the PSID data. The estimate of the autoregressive parameter, ψ , is 0.962, and the estimate of the moving average parameter, θ , is 0.215. To keep the procedure as close as possible to that in the paper, I have restricted the price of skills, $\lambda_{\alpha,t}$, and the variance of persistent shocks, $\sigma_{\eta t}^2$, to lie on fourth-degree polynomials in t . The variance of the transitory shock, $\sigma_{\epsilon t}^2$, is left unrestricted. Consistent with a large existing literature, the estimates reveal that the variance of persistent shocks increased from the late 1970s to the late 1980s, but was then constant until the mid-2000s before starting to rise again. The variance of the fixed component, $\lambda_{\alpha,t}^2 \sigma_{\alpha}^2$, also increased during the 1970s and 1980s, but then declined substantially in the 1990s and early 2000s.

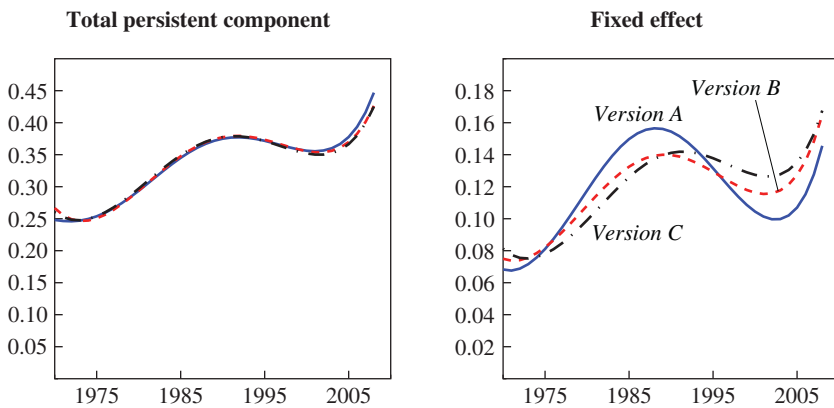
The implied variance of the total persistent component, $\lambda_{\alpha,t}^2 \sigma_{\alpha}^2 + \text{var}(p_t^i)$, is shown in the left-hand panel of figure 3. The PSID estimates of ECM version A suggest that the variance of the persistent component of income increased sharply from 1975 to 1990, but was flat (or declined slightly) between 1990 and 2005. After 2005 the variance began to increase again. The behavior of the variance of the persistent component in the 1990s contrasts with DeBacker and coauthors' finding of an increase in the 1990s in the IRS data. Yet given the estimated variances in figure 2, one might be

Figure 2. Estimated Decomposition of Variance in Earnings for ECM Version A



Source: Author's calculations using PSID data.

Figure 3. Estimated Variance of the Persistent Component of Earnings in Alternative ECM Versions^a



Source: Author's calculations using PSID data.

a. See the text for specifications of the different ECM versions.

surprised that the PSID estimates do not reveal an even larger decline in the variance of the persistent component: that graph shows that the 1990s were a period with no increase in the variance of persistent shocks, while the variance of the fixed component declined substantially. The reason why the variance of the total persistent component does not decline more is that even though there was no increase in the variance of persistent shocks during this period, the earlier increases in σ_{η_t} during the 1980s led to a continued increase in the variance of the persistence component, $\text{var}(p_t^i)$, well into the 1990s. This occurs because it takes time for the older cohorts who were subject to the small shocks of the 1970s to be replaced by the younger cohorts who were subject to large shocks for their entire working life.

The cohort effect that arises from changes in σ_{η_t} is something to bear in mind when interpreting the findings in this paper. The IRS data begin only in 1987, which is exactly when the variance of the persistent shocks levels off in the PSID data. Thus if, as one might expect, there was also an increase in σ_{η_t} before 1987 in the IRS data, one would expect to see an increase in the variance of the persistent component in the 1990s. This increase would not be due to changes that occurred after 1987, yet estimation using the authors' strategy with IRS data would necessarily attribute the increase to a change that occurred after 1987, since their framework cannot handle lagged effects of pre-1987 changes. Unfortunately, little can be done about this given the available data, and a similar criticism might apply to the PSID estimates regarding changes that occurred before 1970.

An alternative way to allow the parameters in equation 1 to change over time is to fix σ_{η} but modify the first line of the equation to read

$$(3) \quad \xi_t^i = \lambda_{\alpha,t} \alpha^i + \lambda_{p,t} p_t^i + \tau_t^i.$$

I will refer to this model as ECM version B. Here the interpretation is that the dispersion of the persistent shocks that hit individuals does not change over time. Instead the accumulation of these shocks, p_t^i , is interpreted as slow movement in a stock of individual-specific human capital or skills, which command a price in the labor market $\lambda_{p,t}$. The price of these skills is allowed to change over time, which leads to changes in the cross-sectional variance of residual earnings. The conceptual distinction between α^i and p_t^i in this interpretation is that α^i reflects skills that are determined at the time of entry into the labor market, whereas p_t^i reflects skills that continue to evolve stochastically after entry. Finally, one could

also impose the restriction that $\lambda_{\alpha,t} = \lambda_{p,t} = \lambda_t$, so that the first line of equation 1 reads

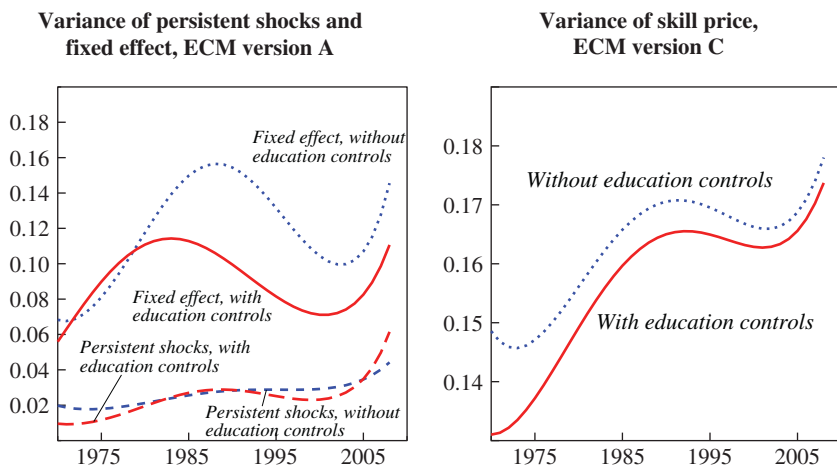
$$(4) \quad \xi_t^i = \lambda(\alpha^i + p^i) + \tau_t^i.$$

I will refer to this model as ECM version C. Here the interpretation is that the market does not distinguish between the value of skills obtained before entry into the labor market (such as formal education) and the value of skills acquired later in life (such as on-the-job training or job-specific human capital). This is the interpretation that the authors adopt, since version C is the specification that the authors estimate with the IRS data.

How does the choice of ECM affect one's conclusions about the rise in the persistent variance of earnings? My figure 3 attempts to answer this question by reporting estimates of versions B and C from the PSID as well as of version A. The left-hand panel shows that the variance of the total persistent component is essentially identical in all three versions (the three versions also deliver very similar estimates for the autoregressive and the moving-average parameters). Thus, to the extent that these findings carry over to the IRS data, it is unlikely that the authors' conclusions about the rise in the variance of the total persistent component would have been changed by adopting either version A or version B.

Although the three versions of the ECM yield the same estimates over time for the variance of the total persistent component, they yield very different estimates for how this variance is divided between factors that are fixed at the time of entry to the labor market, α^i , and factors that evolve stochastically over time, p_t^i . These differences are illustrated in the right-hand panel of figure 3, which shows the variance of the fixed effect, $\lambda_{\alpha,t}^2 \sigma_{\alpha,t}^2$, for each of the three versions. Version A, which allows for the size of persistent shocks to change over time, attributes a much bigger role to movements in the price of fixed skills in accounting for changes in the variance of the persistent component, compared with either version B or version C. The distinction between cross-sectional variation in earnings due to fixed factors and variation due to the realization of shocks is potentially important. First, the two views of the increase in earnings inequality may have different implications for the increase in consumption inequality (and thus welfare) in a structural life cycle model of intertemporal consumption choice, since the impact of the changes in λ_t depends crucially on the assumptions one makes about how these changes enter workers' information sets. Second, the appropriate policy interventions for influencing the earnings distribution are different: the latter view points to

Figure 4. Contribution of Returns to Education to the Components of Earnings Variance^a



Source: Author's calculations using PSID data.

a. See the text for a description of the specifications.

the importance of labor market interventions, whereas the former points to education interventions.

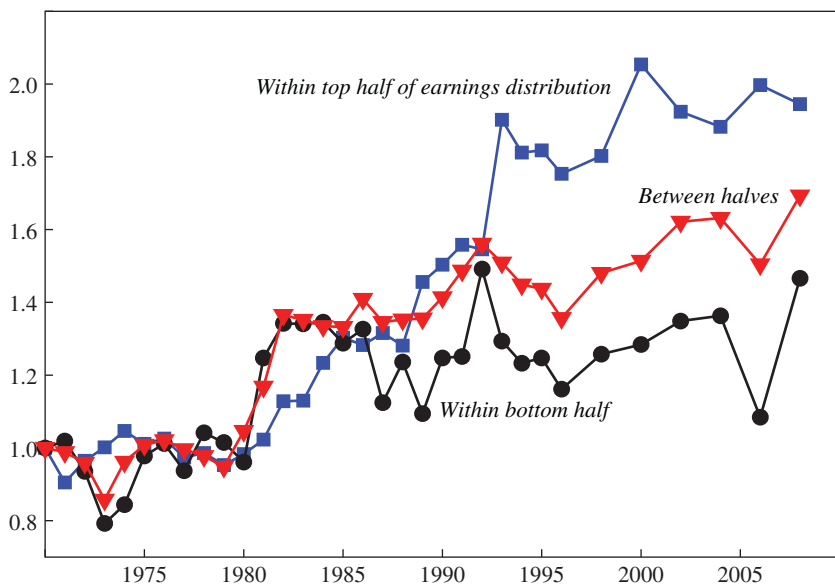
Cross-sectional variation in the fixed effect, α^i , is partly due to cross-sectional differences in observed education and partly due to cross-sectional differences in unobserved cognitive and noncognitive skills. Given the importance of changes in λ_t in accounting for the change in earnings inequality in the IRS data, it is natural to ask whether these changes reflect an increase in returns to traditional measures of education or an increase in returns to the unobserved components of skills. This question cannot be answered with the IRS data, but it can be answered with the PSID data. To address this, my figure 4 presents estimates using data on residual log earnings, ξ_t^i , that are constructed in two different ways. The lines labeled “without education controls” are estimates based on data where ξ_t^i is constructed as the residual from a regression of log earnings on a full set of age dummies in each year. This is the same approach followed by DeBacker and coauthors. The lines in figure 4 labeled “with education controls” are estimates based on data where ξ_t^i is constructed as the residual from a regression of log earnings on a full set of age dummies, education dummies, and education \times age interactions in each year.

The left-hand panel of figure 4 displays parameter estimates of ECM version A with and without education controls. Both the estimates of the variance of the fixed effects $\lambda_{\alpha_i}^2, \sigma_{\alpha}^2$ and the variance of persistent shocks $\sigma_{\eta_i}^2$ are affected by the education controls. At least half of the increase in the variance of the fixed effects and the subsequent decline between 1970 and 2000 is due to returns to education, but the increase in the variance in the 2000s is the same in both specifications. This result is useful in interpreting DeBacker and coauthors' findings, since they cannot control for education in the IRS data. Using the PSID findings as a guide, one might conclude that the recent increase in the market price of skills that the authors document would remain largely unchanged if they were able to control for education. It appears that the increase is driven by an increase in the returns to unobserved skills rather than returns to formal education.

The right-hand panel of figure 4 offers an alternative perspective on the likely effect of controlling for education on DeBacker and coauthors' findings, by estimating ECM version C (the authors' preferred specification) with and without education controls on the PSID data. These estimates also indicate that the biggest differences in trends under the two specifications occur before the 1990s, further reinforcing the view that the increase in the variance of the persistent component in the IRS data reflects an increase in returns to unobserved skills within education groups.

Before concluding, I will raise one additional issue that the authors do not tackle, but that could be addressed with their IRS data. The authors focus their analysis on determining whether the recent increase in earnings inequality has been persistent or transitory in nature, and conclude that it is entirely the former. In addition, one might ask which individuals have been most affected by this increase in the variance of the persistent component. Specifically, many researchers and policymakers are interested in understanding whether changes in inequality affect mostly high-earnings individuals, low-earnings individuals, or individuals in the middle of the income distribution. The IRS data set is well suited to address this issue, again because it is larger and cleaner than the PSID (particularly at the top of the distribution). One possible approach to answering this question is to decompose the cross-sectional variance of log earnings (or residual log earnings), y_t^i , in each year as follows:

$$(5) \quad \text{var}(y_t^i) = \frac{1}{2} \text{var}(y_t^i | r_t^i \leq 0.5) + \frac{1}{2} \text{var}(y_t^i | r_t^i > 0.5) + \frac{1}{4} [\text{E}(y_t^i | r_t^i > 0.5) - \text{E}(y_t^i | r_t^i \leq 0.5)]^2 .$$

Figure 5. Decomposition of Earnings Variance by Level of Earnings

Source: Author's calculations using PSID data.

where r_t^i is the rank of individual i in the year t earnings distribution. The first two terms in equation 5 are the variances of earnings within the bottom and the top half of the earnings distribution, respectively. The third term in equation 5 is the component of the variance of earnings that is due to the difference in average earnings between the top half and the bottom half. The decomposition here focuses on the overall cross-sectional variance, but the panel nature of the IRS data lends itself to a similar decomposition of only the persistent component of earnings, for example by first employing the authors' simple nonparametric methods.

My figure 5 displays the results from implementing this decomposition in the PSID. All three components are normalized to 1 in 1970. The figure shows that since the early 1980s, there has been essentially no increase in the variance of earnings in the bottom half of the distribution. By contrast, the variance within the top half of the distribution has increased steadily since 1980 and continues to rise. The gap between average earnings in the two halves of the distribution has also continued to widen in recent years. Thus, the PSID data suggest that there are important asymmetries in the earnings distribution and that the recent increase in inequality is a more

complicated phenomenon than just changes in dynamics of the first and second moments of the earnings process.

Given these asymmetries, a useful step forward for the literature would be to move toward richer, possibly nonlinear, models of earnings dynamics that can shed light on the complicated changes in the earnings distribution observed in recent years. This paper is a useful starting point. The IRS data set, a large panel of earnings data that is mostly free of measurement error and top-coding, is an ideal resource for such an investigation. Efforts to further improve this data set could lead to large benefits for researchers, policymakers, and ultimately the welfare of individuals. Such efforts might be focused on extending the sample back before 1987 or on making a suitably anonymized version of the data available for wider use.

COMMENT BY

LINDSAY A. OWENS and DAVID B. GRUSKY¹ It has long been argued that the ongoing increase in income and earnings inequality cannot be well understood until it is decomposed into persistent and transitory components. The persistent component pertains to the inequality generated by the permanent characteristics of individuals (their education, unobserved ability, and the like), whereas the transitory component pertains to the inequality generated by temporary shocks (such as a temporary illness, transitory unemployment, or a change in jobs). It is not implausible that the takeoff in income inequality partly reflects the emergence of a labor market that is increasingly subject to transitory shocks in the form of a growing risk of unemployment, underemployment, or job change. If this is indeed the case, it might change our understanding of both the sources of the takeoff and its implications for social welfare.

The key contribution of Jason DeBacker and his coauthors in this paper is to bring a large panel of tax returns to bear on this debate. The results reveal that the entire rise in inequality in male earnings, and most of that in household income, is attributable to an increase in the dispersion of the persistent component.

1. The Stanford Center on Poverty and Inequality is supported by grant number AE00101 from the U.S. Department of Health and Human Services, Office of the Assistant Secretary for Planning and Evaluation (awarded by the Substance Abuse Mental Health Service Administration). The contents of this comment are solely the responsibility of the authors and do not necessarily represent the official views of the U.S. Department of Health and Human Services, Office of the Assistant Secretary for Planning and Evaluation.

We leave it to others to comment on the models, the data, and other technical features of this analysis. It suffices for our purposes to stress that the analysis is noteworthy because of the extraordinary data upon which it rests. The confidential panel of Internal Revenue Service (IRS) tax returns delivers unusually high-quality earnings and income data for an unusually large sample. Moreover, the authors apply an impressive range of parametric and nonparametric approaches to the IRS data, with reassuringly similar results. The authors also supplement the more conventional and usual analyses of earnings data with revealing analyses of pre-tax and after-tax household income. For all of these reasons, the authors have contributed an important paper, and their results merit close attention.

We are so impressed with the paper that we are inclined to stipulate that it is a major contribution, forgo the usual internal critique, and instead take on the task of considering how the analyses might be usefully elaborated upon in light of the opportunities that the IRS data open up. We approach this question from the point of view of better understanding the welfare implications of inequality. The long-standing presumption in this regard is that, insofar as the takeoff in inequality is mainly generated by an increase in transitory shocks, it is less consequential for welfare because individuals can always borrow against future income and smooth out the effects of such shocks. The takeoff in inequality might therefore be understood from a welfarist stance as entailing little more than the nuisance of engaging in more smoothing than had before been necessary.

This comment will consider whether considerations of welfare are indeed adequately understood in these terms. We first suggest that a welfarist stance, if rigorously adopted, instead leads us to privilege the concept of lifetime income and to move toward IRS-based analyses of trends in lifetime income. We next argue for extending the characteristic focus on intraindividual transfers to a more encompassing consideration of inter-individual transfers.

THE CASE FOR A LIFETIME INCOME APPROACH The simple point with which we begin is that, insofar as one is willing to assume away liquidity constraints that prevent smoothing, it seems appropriate to do so wholeheartedly and move directly to analyzing data on lifetime income. The obvious virtue of this approach is that it obviates the need to parameterize the potentially complicated ways in which a shock may or may not have short-term or long-term effects. If, for example, a lottery winner decides to immediately exit the labor market, this decision will ultimately be revealed in his or her lifetime income. The same applies to such shocks as pregnancy, unemployment, job shifting, or receipt of program benefits (such as the

earned income tax credit, food stamps, or unemployment insurance). Although the authors very elegantly model how the income effects of such shocks tend to dissipate over time, an attractively nonparametric alternative is simply to examine trends in the inequality of lifetime income, an approach that is approximately equivalent to applying the method of Kopczuk, Saez, and Song (2010) with a *very* large P parameter (where P refers to the number of years over which income is averaged).

What makes this nonparametric approach attractive? If one cares about the welfare implications of inequality, surely the first cut at understanding those implications is to examine the first moment of each individual's own distribution of income across years. The presumption, in other words, is that individuals operating under a veil of ignorance about their own distribution of future annual earnings would, more than anything else, want to know how much they will make on average per year (as well as the number of years they will have earnings). It follows that the inequality of those lifetime averages, calculated separately for each birth cohort, would speak rather directly to matters of welfare, arguably more directly than any of the parametric or nonparametric approaches deployed in this paper. That said, we well appreciate that conventional parametric and nonparametric approaches are useful for a host of other objectives, including making inferences about consumption and consumption inequality. It must also be conceded that a lifetime income approach implies a rather delayed reading of trends, because each birth cohort enters the series only after its members complete their labor force participation. This is clearly a disadvantage insofar as real-time reporting is desired. We are merely suggesting that a lifetime income approach is but one additional tool that happens to be especially useful when one is making judgments about welfare.

It bears noting that such an approach entails a shift of emphasis from period analyses to cohort analyses of trends in income inequality. This shift is attractive because it allows one to better capture the effects of forces that operate in cohort-specific ways. For example, recessions have especially prominent effects on birth cohorts that come of age during the recession itself, and these effects in turn serve to suppress lifetime earnings (see Kahn 2010). Insofar as recessions are inequality enhancing (because they hit poorly credentialed workers the hardest), a cohort approach will reveal that effect especially clearly. There is good reason to believe that other important sources of the trend in inequality (such as changes in schooling institutions or early-childhood antipoverty interventions) likewise operate in cohort-targeted ways that will be obscured by the field's typical emphasis on period effects.

It is also attractive to focus on cohorts because the invidious comparisons that individuals make tend to feature their same-age peers. As life unfolds, individuals compete in schools and in the workplace with members of their own birth cohort, and the outcome of that age-specific competition is likely to affect self-assessments. We expect, for example, that individuals will be more troubled and jealous when they see their same-age peers benefiting disproportionately from the takeoff than when members of some distant birth cohort are the principal beneficiaries. It follows that a cohort approach is especially relevant to considerations of welfare insofar as social comparison processes and their subjective fallout are taken into account.

THE INEQUALITY-EXAGGERATING EFFECTS OF INTERINDIVIDUAL TRANSFERS For those interested in making judgments about welfare, lifetime income is of interest because it is assumed that, without any constraints on liquidity, individuals can freely borrow against their future income stream or freely draw on savings from past streams. This form of borrowing or saving may be understood as an *intraindividual transfer* from the past or future to the present. If the transitory variance has risen substantially, as some (Heathcote, Perri, and Violante 2010) have claimed, then the takeoff is presumably less troubling because such transfers can smooth out these transitory shocks. The literature has thus focused on the possibility that the usual cross-sectional analyses may overstate the welfare consequences of rising inequality.

The purpose of this section is to shift the focus to various types of *inter-individual transfers* that, if properly taken into account, may lead to the conclusion that the welfare consequences of the takeoff are in fact worse than is usually supposed. That is, whereas a consideration of intraindividual transfers may lead one to overstate the welfare costs of the takeoff in inequality, a consideration of interindividual transfers leads to precisely the opposite conclusion. We develop this argument by considering the welfare effects of interindividual transfers between spouses, among households within a neighborhood, and between parents and children.

Interspousal transfers To illustrate the argument, we begin by considering the well-known tendency of spouses to pool income, a type of interindividual transfer that motivates the field's long-standing interest in analyzing household or family income inequality. This pooling will increase inequality insofar as there is some amount of income-based "marital homogamy" in which high-income men tend to marry high-income women. In the United States, this form of homogamy is intensifying over time (Schwartz 2010, Mare and Schwartz 2006), a development that contributes to the takeoff in

inequality. As Schwartz (2010) reports, the correlation between the earnings of spouses almost tripled between 1967 and 2003, leading in turn to an approximately 25 percent rise in the earnings inequality of families (Schwartz 2010). Although conventional analyses of individual income inequality will not reflect this transfer-based source of rising inequality, there is, of course, a long tradition of analyzing family or household inequality (in which the effects of such homogamy are “built in”).

It is striking, however, that critics of conventional cross-sectional analyses of individual income inequality often complain about the possible inequality-exaggerating effects of ignoring intraindividual transfers without acknowledging the opposing inequality-suppressing effects of ignoring interindividual transfers (within households). If one type of transfer-induced bias is to be corrected, then surely the other, opposing bias should be corrected as well. This selective acknowledgment of “transfer bias” cannot be explained by differences in the reliability with which such transfers can be effected. To the contrary, spouses tend to pool income relatively freely on the basis of informal agreements (see Bennett 2013), whereas individuals typically have to engage more formally with friends, parents, or financial intermediaries when seeking to borrow from these sources against their future income. The resulting constraints on liquidity can be substantial (Blank and Barr 2009). This suggests that, if anything, the bias arising from ignoring interindividual transfers should be more troubling than that arising from ignoring intraindividual transfers.

Interneighbor transfers The example of transfers between spouses is, of course, well known. What is perhaps less appreciated is that residential neighbors also engage in pooling and that, by virtue of rising residential segregation, this pooling is leading to a more unequal distribution of valued goods (Reardon and Bischoff 2011). The key dynamic here is again a growth in segregation. That is, just as spouses have increasingly similar incomes (marital homogamy is rising), so too neighborhoods are becoming increasingly homogeneous by income (residential segregation is rising). This means that high-income families are increasingly likely to be living in high-income neighborhoods that give them indirect access to the considerable resources of their neighbors. Because neighborhood goods are often financed by property taxes, it is advantageous to live with high-income neighbors who will contribute substantially to schools, parks, police protection, fire protection, local government, and other public goods. The ongoing takeoff in residential segregation means that this particular advantage, like the advantage of marrying a high-income spouse, increasingly accrues to those with relatively high incomes themselves. This advantage

is concealed in conventional analyses of individual income inequality because the “income” takes the form of in-kind resources.

The analogy between these two types of interindividual transfers is by no means perfect. Most obviously, in the United States one makes no overt payment (no dowry) for the privilege of marrying a high-income spouse, whereas one does overtly pay for the privilege of living in a high-income neighborhood. It is accordingly possible that, as neighborhoods become increasingly income segregated, the resulting interneighborhood differences in public goods advantages come to be reflected in the purchase price of homes, thus complicating any effort to understand the effects of this rising segregation on inequality. The second main difference is that spouses typically engage in quite substantial income pooling, whereas residential neighbors are far less collectivist, in effect pooling their income only for a relatively small number of local public goods. The total effects of interneighbor transfers on inequality are, as a result, likely to be comparatively limited.

Intergenerational transfers The third type of interindividual transfer of interest occurs between generations of a family as well as between relatives of the same generation (such as siblings). This type of transfer is closely related to the previous two: it may be understood either as entailing transfers among members of a “virtual neighborhood” defined by kinship ties, or as entailing transfers among members of a “virtual household” that extends beyond those actually living together. Under either interpretation, the key force at work is again rising segregation, which now expresses itself as growing intergenerational elasticities of income. This force, if indeed it is at work, implies that the offspring of high-income families are increasingly likely to find themselves ensconced in virtual households that provide them with access to high-income parents, high-income grandparents, and high-income siblings. It is unclear, however, whether such elasticities are indeed increasing. In a recent review, Chul-In Lee and Gary Solon (2009) conclude that available estimates on trends in intergenerational elasticities are “highly imprecise” (p. 766), mainly because the available data sets (principally the Panel Study of Income Dynamics) are extremely small.

There is nonetheless good reason to worry that these elasticities are on the rise (see Krueger 2012). If indeed they are, what does it mean for our understanding of trends in income inequality? It suggests that high-income offspring may be more likely to receive gifts or substantial inheritances that then generate investment income. Because these income transfers are at least partly revealed as individual income (among the offspring), they will

not be concealed in conventional individual analyses of income inequality. However, many of the transfers again take an in-kind form, such as unreported gifts, access to lavish parental vacation homes, or “parental buffering” of children when they experience unemployment or other labor market difficulties. The provision of such goods will tend to increase inequality insofar as they are disproportionately available to high-income offspring.

CONCLUSION It is testimony to our high regard for the analysis in this paper that, rather than carry out the usual critique of its methods or conclusions, we have instead sought to consider various extensions of their analysis. We began by suggesting that the welfare implications of inequality might be better understood by supplementing the usual parametric approach with a nonparametric analysis of lifetime income inequality. The IRS tax data are well suited to the cohort analysis that such an approach implies.

We have also argued that an exclusive focus on intraindividual transfers may have distracted scholars from appreciating how various interindividual transfers may create inequalities that conventional individual analyses miss. Because high-income individuals are increasingly embedded in networks that provide access to income or in-kind benefits provided by others (spouses, parents, extended families, neighbors), existing models of individual income inequality may *understate* the welfare implications of rising inequality, a bias that is precisely the opposite of that emphasized by those who attend exclusively to intraindividual transfers. It is unclear why the field has been so captivated by intraindividual transfers when the countervailing effects of interindividual transfers may be more important. The IRS data provide an opportunity to develop models that can at once capture changes in inequality as well as these possible changes in income dependencies within households, neighborhoods, and extended families.

REFERENCES FOR THE OWENS AND GRUSKY COMMENT

- Bennett, Fran. 2013. “Researching Within-Household Distribution: Overview, Developments, Debates, and Methodological Challenges.” *Journal of Marriage and Family* 75, no. 3: 582–97.
- Blank, Rebecca M., and Michael S. Barr, eds. 2009. *Insufficient Funds: Savings, Assets, Credit and Banking among Low-Income Households*. New York: Russell Sage.
- Kahn, Lisa B. “The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy.” *Labor Economics* 17, no. 2: 303–16.

- Krueger, Alan B. 2012. "The Rise and Consequences of Inequality in the United States." Washington: Executive Office of the President. www.whitehouse.gov/sites/default/files/krueger_cap_speech_final_remarks.pdf.
- Lee, Chul-In, and Gary Solon. 2009. "Trends in Intergenerational Income Mobility." *Review of Economics and Statistics* 91: 766–72.
- Mare, Robert D., and Christine R. Schwartz. 2006. "Educational Assortative Mating and the Family Background of the Next Generation: A Formal Analysis." *Sociological Theory and Methods* 21: 253–77.
- Reardon, Sean, and Kendra Bischoff. 2011. "Growth in Residential Segregation of Families by Income, 1970 to 2009." US2010 Research Brief. New York: Russell Sage.
- Schwartz, Christine R. 2010. "Earnings Inequality and the Changing Association between Spouses' Earnings." *American Journal of Sociology* 115, no. 5: 1524–57.

GENERAL DISCUSSION John Haltiwanger noted that job destruction rates and unemployment inflow rates had declined over the authors' study period. If job flows and unemployment are treated in the model as transitory shocks to income, those trends should be driving the temporary component in income inequality downward, to the point where the permanent component alone might account for, or more than account for, the observed results.

William Brainard agreed with the discussants' suggestion that the authors address the differences between their tax data and other data sets in widespread use. He also pointed out that there is substantial heterogeneity in individuals' lifetime income profiles. Some occupations have a period of apprenticeship, which causes the profile for those workers to be flat initially; unionized workers, in contrast, have a very different pattern. Because the authors' model does not account for these individual differences, Brainard thought, all of them would show up in the permanent component, when in fact they are caused by interaction with the individual's education and other factors. Brainard suggested that the authors take the structural differences between individuals more thoroughly into account by including age and education covariates.

Justin Wolfers requested that the authors clarify how they distinguished between permanent and transitory shocks. In reply, Greg Kaplan described the method with reference to a random walk model. In each period a shock occurs that either increases or decreases the individual's income. The sum of these shocks over time was taken to be the permanent component for the individual, and a time-varying, universal weighting factor

was applied to that sum. The more traditional method, Kaplan noted, would be to apply the weighting factor to the individual shocks rather than to their sum.

Christopher Carroll called the authors' method an interesting innovation but observed that, since their data were also novel, it was difficult to determine what portion of the difference between their results and those of others working in this area was being driven by their modeling choice and what portion by their novel data set. He urged the authors to go back and apply the simplest standard model to their data, to serve as a benchmark, and from there do further analysis to see what cannot be explained by that simple model.

Carol Graham noticed an upward tick in permanent income inequality and a downward one in transitory inequality in the authors' data around 2007. She wondered whether those movements represented merely transient phenomena or whether what was happening in that period might explain some of the difference between permanent and transitory income.

Replying to a comment made by David Grusky in his formal discussion, Robert Gordon questioned whether the income homogeneity of neighborhoods is in fact increasing. His own impression was that demographic changes have been making income more heterogeneous as blacks move into the suburbs and back to the South while Hispanics and affluent whites move into the inner cities. New York's East Village, for example, was uniformly poor 30 years ago, but more recently the boom in the city's financial services and entertainment industries had brought some very wealthy people into the neighborhood, leading to a mix of incomes. Gordon also challenged Grusky's implication that a decline in intergenerational mobility was not yet in evidence. He cited recent findings that the United States today has one of the lowest levels of intergenerational mobility among developed economies. One can almost predict, Gordon added, that this trend will persist, as it is being reinforced by the behaviors of those at both the top and the bottom: the wealthy are taking pains to ensure that their children learn foreign languages (and economics), while the share of children in the poorest third of the white population living with both parents continues to decline.

Gita Gopinath commented that an increase in permanent income inequality will have implications for consumption inequality, and thus that looking at consumption decisions should make it easier to determine whether a given income shock is transitory or permanent. Gopinath was curious to know whether the paper's results were driven by the fixed effects or the random walk component of the income shock. The answer, she thought,

could help determine whether today's income inequality was caused by a widening difference in payoffs between high- and low-ability workers.

Richard Cooper agreed with Brainard that the authors' distinction between permanent and temporary income was highly suspect. He also thought it would be valuable to compare individuals' reported W-2 (wage) income with their income reported on Schedules C and D (business income and capital gains, respectively) of their IRS Form 1040. That information could help determine how much income inequality is due to proprietary income and how much to earnings from labor. Gordon remarked that a paper by Thomas Piketty and Emmanuel Saez had done just such an analysis and found that the increase in inequality came mainly from labor earnings. A caveat to that finding, however, was that stock options—an important contributor today to incomes at the top—are inappropriately reported as labor earnings.

Responding to the discussion, Ivan Vidangos argued that the distinction between permanent and transitory components was necessarily fairly arbitrary. In the real world shocks can be very transitory, very permanent, or anywhere in between, but one has to draw the line somewhere. Their strategy was to select two points near the ends of the continuum and see if the results differed dramatically. They had experimented with many different specifications, including one that indicated that permanent factors were capturing 87 percent of the variance and another that put it at 36 percent, but in all cases the trends showed that the rise in inequality was driven by the permanent component.