Rising Inequality: Transitory or Permanent? New Evidence from a Panel of U.S. Tax Returns 1987-2006.\textsuperscript{1,2}

Jason DeBacker*, Bradley Heim*, Vasia Panousi**, and Ivan Vidangos**

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Abstract

Using a new, large, and confidential panel of tax returns from the Internal Revenue Service and a variety of methods, we analyze the role of permanent and transitory components in the evolution of inequality in male earnings and household income in the U.S. for the period 1987-2006. We find that the increase in male earnings inequality over this period was of a permanent nature, with permanent inequality accounting for almost two-thirds of the level, on average, and for essentially all of the increase in total inequality. By contrast, for (pre-tax) household income, we find that transitory inequality, though also nearly one-third of the total, increased by about 20-30 percent over our sample period and contributed 10-40 percent of the increase in total inequality. We provide evidence that the increase in transitory inequality for household income was driven by the non-labor income components of household income. Finally, we show that the trends in after-tax household income inequality are very similar to those in pre-tax household income inequality, but that the tax system reduces all variance components by about 15 percent, indicating that the U.S. tax system plays an important role in reducing income inequality, both transitory and permanent.
1 Introduction

An extensive literature has documented an increase in income inequality in the U.S. in recent decades. A smaller branch of the literature has then tried to determine whether this increase in inequality was permanent or transitory in nature.\textsuperscript{1} The distinction between permanent and transitory inequality is important because it has implications for the causal factors that may lie behind each component, and it also has implications for policy, for social mobility, for consumption and welfare, and for the trade-off between the private versus the public provision of insurance.

This paper uses a new, large, and confidential panel of tax returns from the Internal Revenue Service to analyze the role of permanent and transitory variance components in the evolution of inequality in individual (male) earnings and household income (both before and after taxes) in the United States over the period 1987-2006. Our panel contains detailed information from taxpayers’ Form 1040 and a number of related tax forms and schedules, and represents a one-in-5,000 random sample of tax units followed over 1987-2006. We have merged these data to individual-level W-2 forms and information on age and gender of the primary and secondary tax filers. Our baseline sample for individual male earnings has about 189,000 observations, and is therefore substantially larger than the typical PSID sample used to address related topics in the literature. Our baseline sample for household income has about 295,000 observations. Furthermore, our data is not subject to top-coding, and is less likely to be affected by measurement error than survey data, at least in the case of labor earnings. On the other hand, our tax data does not contain information on some demographics such as race and education.

We investigate the relative importance of permanent and transitory inequality for total inequality and its evolution, using a variety of tools including simple intuitive measures of volatility, approximate decompositions, nonparametric decompositions, and error-components models of earnings/income dynamics. Our paper is the first in the literature to use tax data to estimate models of earnings/income dynamics for the U.S. Other papers have either used the PSID, or tax data from other countries, or tax data from the U.S. but only for purposes of simple descriptive decompositions. The use of models of earnings/income dynamics is an important complement to simpler descriptive methods because it captures aspects of the structure and the evolution of earnings/income that have been documented in the literature but cannot be accounted for in simpler decompositions, which might therefore lead to erroneous conclusions about the contribution of the permanent or the transitory inequality components. For example, we provide evidence suggesting that some simple approximate decomposition methods tend to overstate the role of permanent inequality.

\textsuperscript{1}For instance, Gottschalk and Moffitt (1994, 2009), Moffitt and Gottschalk (1995, 2008), and Haider (2001). We discuss this literature in more detail below.
Findings.

For male earnings, our paper contributes to and is consistent with the previous literature on the relative importance of permanent versus transitory inequality in the most recent years.\textsuperscript{2} We find that most of the inequality in male earnings is due to permanent differences, and that the increase in inequality between 1987 and 2006 is basically entirely driven by an increase in its permanent component. In particular, our results indicate that permanent inequality comprises about two-thirds of total inequality, and that it is responsible for almost all of the 20 percent increase in male earnings inequality over our sample period.

Our paper also examines the evolution of household income inequality and explores the reasons for differences with the evolution of inequality in individual earnings.\textsuperscript{3} We find that, although the permanent component contributes about two-thirds to household income inequality (similar to the case of male earnings), the transitory component of household income increases by about 20 percent over the sample period, and thereby contributes about 10-40 percent of the increase in total inequality, in contrast to the case of male earnings. Furthermore, we provide evidence that the increase in transitory inequality for household income was driven by the non-labor income components of household income, including investment and business income.

Our paper also analyzes the differences in pre-tax and post-tax household income inequality, thereby providing evidence on the role of the tax system in reducing income inequality. The time trends in the evolution of the variance components are very similar for pre- and post-tax household income. However, all variance components of post-tax household income are about 15 lower than their pre-tax counterparts. Thus, the tax system has reduced the level of both transitory and permanent inequality.

Literature Review and Comparison.

An extensive literature has documented the increase in earnings inequality in the U.S. in recent decades. Kopczuk, Saez and Song (2010), for instance, using longitudinal earnings data from Social Security Administration (SSA) records, document that annual earnings inequality decreased sharply from the late 1930s to the early 1950s, but that it has increased steadily thereafter.

A smaller branch of the literature has attempted to determine whether this increase in inequality was permanent or transitory in nature. Examples include Gottschalk and Moffitt (1994, 2009), Moffitt and Gottschalk (1995, 2008), Haider (2001), and Heathcote, Perri, and Violante (2010).\textsuperscript{4} All of these studies use PSID data, and all except Gottschalk and Moffitt (1994), estimate

\textsuperscript{2}We compare our results to the existing literature below.

\textsuperscript{3}As we discuss below, Gottschalk and Moffitt (2009) is the only other study to provide some evidence on the role of permanent and transitory components for the evolution of inequality in household income.

\textsuperscript{4}Heathcote, Perri and Violante (2010) document the evolution of inequality in a number of variables at the individual and household level. Their decomposition of changes in the variance of earnings into transitory and permanent components is not the main focus of their paper.
error-components models of earnings dynamics. Kopczuk, Saez, and Song (2010) also provides permanent-transitory decompositions of the increase in inequality, but uses administrative earnings data and only a simple approximate decomposition method. To the best of our knowledge, our study is the first to combine the use of error-components models and tax data to analyze the contribution of permanent and transitory components to the increase in inequality.\footnote{We should also note that there is a very large literature in labor economics that has tried to explain the causes of the increase in inequality, especially for hourly or weekly earnings of male workers, using cross-sectional data. Our work is much less directly related to that literature. Katz and Autor (1999) and Autor, Katz, and Kearney (2008) provide thorough discussions of the "causal" literature.}

For male earnings, our findings are consistent with Moffitt and Gottschalk (2008) and Gottschalk and Moffitt (2009) for the period 1987-2004. Gottschalk and Moffitt find that the transitory component of male earnings increased steeply from the mid-1970s to the mid-1980s, but has remained about flat since, thereby contributing almost nothing to the increase of total inequality in the post-1985 period. For that period, they estimate that permanent inequality accounts for about half of total inequality, and that it is primarily responsible for the increase in the total. Contrary to our findings and to those of Gottschalk and Moffitt, Heathcote, Perri, and Violante (2010) find a more prominent role for the transitory variance post-1987. In particular, they find a large increase in the transitory variance in the early 1990s, and hence the transitory variance accounts for about 40 percent of the increase in total inequality in their post-1987 period. Our findings are also consistent with those in Kopczuk, Saez, and Song (2010), who use an approximate decomposition and find an overwhelming role of the permanent inequality in terms of contribution to total inequality. However, we will provide evidence suggesting that their decomposition method tends to overstate the importance of the permanent component for total inequality.

When it comes to household income, the only previous study to provide some evidence on decompositions of changes in inequality into permanent and transitory components (to the best of our knowledge) is Gottschalk and Moffitt (2009), who look at the evolution of the transitory variance for log annual (pre-tax) household income from the PSID, computed only using an approximate method. They find a large increase in the transitory variance of pre-tax household income in the post-1987 period, and only a slight increase in the pre-1987 period. In other words, the timing of the increase in the transitory component of household income is almost the exact opposite of the timing of the increase in the transitory component for male earnings. They also briefly suggest that the difference between individual and household income is due to the transfer and the nonlabor component of household income, both of which have overall been increasing since 1974. They conjecture that more volatile welfare receipts since the early 1990s and more volatile capital income are responsible for the difference, but they claim to lack sufficient disaggregate information to carry the analysis further. Heathcote, Perri, and Violante (2010), using the PSID and simple
descriptive measures of inequality, such as the variance and the Gini coefficient, find that household inequality increases less than earnings inequality for the main earner at the top of the distribution, but not at the bottom. Our results are also consistent with Heathcote, Perri, and Violante (2010) when it comes to the progressivity of the tax system and the role of taxes in reducing pre-tax income inequality in the US. They do not provide a decomposition of changes in household income inequality into permanent and transitory components.

As for earnings volatility trends, our findings are consistent with Shin and Solon (2008), who find that the volatility of male earnings did not increase between the 1980s and the early 2000s. They are also consistent with a CBO study (2008) that uses administrative records from the SSA and finds a slightly decreasing trend for the volatility of individual earnings, and with Sabelhaus and Song (2009), who use SSA data and find results similar to the CBO study. Our findings contrast with those of Dynan, Elmendorf, and Sichel (2007), who 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.

2 Data

This section describes our data, emphasizes two main points to which we will return later in the paper, and presents our sample selection.

2.1 Description

We use data from a twenty-year panel of tax returns spanning the period 1987-2006. To create this panel, we merged returns from an existing panel, known as the 1987-96 Family Panel, with returns from cross-sectional files from 1997-2006. We then cut the sample to returns for which the primary filer had a social security number (SSN) that ended in one of the two four-digit combinations. The resulting panel (with two exceptions noted below) is a one-in-5,000 random sample of tax units followed over 1987-2006, and is known as the Continuous Work History Subsample (CWHS). Each of the sources of data is described in turn.

The 1987-96 Family Panel was collected by the Statistics of Income (SOI) division of the Internal Revenue Service (IRS), starting with a stratified random sample of taxpayers who filed in 1987. The 1987 stratified random sample consisted of two parts: the CWHS subsample and a high income oversample. Over the following nine years, any return filed that reported any panel member as a primary or secondary taxpayer was incorporated in the sample, including tax returns filed by panel members who were dependents of another taxpayer. To keep the panel representative of the tax filing population in subsequent years, tax returns were added to the panel for those primary filers with social security number ending in one of the two four-digit CWHS endings and who filed at
least once between 1988 through 1996 but who were not filers in 1987. However, taxpayers with CWHS endings who filed as dependents or who were listed as a dependent or secondary filer in 1987 were not included in the sample. In addition to information from each taxpayer’s Form 1040, the data set includes information on age and gender of the primary and secondary filers, information on wages and contributions to employer-based retirement plans from W-2 forms, and information on contributions to tax-preferred savings accounts from Form 5498.

The 1997-2006 data come from yearly cross-sections collected by the SOI. Like the 1987 sample described above, a stratified random sample was collected in each of these years, consisting of a strictly random sample based on the last four digits of the primary filer’s SSN and a high income oversample. Over these years, the size of the strictly random sample grew, consisting of two four-digit endings in 1997, five endings in 1998-2005, and ten endings starting in 2006. Each cross-section contains information from the taxpayer’s Form 1040 and from a number of other forms and schedules. To these data, we merged information on age and gender of the primary and secondary filers, information on wages and contributions to employer-based retirement plans from W-2 forms, and information on contributions to tax-preferred savings accounts from Form 5498.

As noted above, in our estimation sample, we only include returns where the primary taxpayer’s SSN had one of the two original four-digit CWHS endings from either of these two data sources, resulting in a random sample that does not oversample high income taxpayers. The panel is not balanced, as some taxpayers drop out of the sample due to death, emigration, or falling below the tax filing thresholds, while others enter because of immigration or becoming filers.

The ideal measure of individual-level earnings for this study is gross labor income before any amounts are deducted for health insurance premiums or retirement account contributions. However, our data does not contain such a variable, and so we use a measure of labor income that is as close to gross labor income as is possible using tax data. For this, we take taxable wages reported in the “Wages, tips, other compensation” box of taxpayers’ W-2 forms, and we add to that 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, the measure of labor income will exclude those amounts. Our measure also does not include any income earned from self-employment.

Because of this sample frame, when we cut the sample to returns from CWHS taxpayers, we are missing two groups: dependent CWHS filers in 1987-96, and non-dependent CWHS 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. As a result, the effect of missing these returns is likely to be very small when we examine the labor income of males in their earning years, though it may be larger when examining household income. We will return to this issue in sections 2.2 and 5.3 of the paper.
For pre-tax total household income, we start with the “total income” amount that is reported on Form 1040. This variable includes wages and salaries, dividends, alimony, business income (including from sole proprietorships, partnerships, and 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 amount, 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 this measure, because the amount of capital gains realized in a particular year and reported on the tax form may include gains that were accrued in the past. As a result, it may make household income appear “lumpier” than it actually is, as income will be higher in years when gains from prior years are realized, and lower in years when gains were accrued but not realized. However, excluding capital gains will result in the measure of household income being too low for any taxpayer who had gains in that year (whether or not they were realized), and this downward bias in the measure of income will be quite large for taxpayers whose primary source of income is from investments. On balance, we feel that this concern is more important than the former, and therefore we include capital gains in our benchmark measure of household income.\(^7\)

For after-tax household income, we start with the measure of pre-tax household income described above and we subtract the amount of “total tax” reported on Form 1040. This amount captures total income taxes (including self-employment taxes) after non-refundable tax credits are taken into account. We then subtract off refundable tax credits (including the earned income tax credit (EITC) and the refundable portion of the child tax credit). Finally, we add to this amount the total amount of 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.

### 2.2 Issues Related to Sampling Changes and Demographics

As already mentioned in Section 2.1, 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 CWHS filers in 1987-96, and non-dependent CWHS 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. In other words, starting in 1997, our sample size increased, but in a non-random way. In particular, in the 1987-1996 period, the number of female primary filers increases at an average rate of about 1 percent a year. By contrast, in the 1997-2006 period the number of female primary filers increases at an average rate of about

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\(^7\)We plan to check the robustness of our results to the exclusion of capital gains.
5 percent a year (6 percent for women with kids, and 3 for women without kids). Furthermore, this difference is entirely due to the increase in the number of female filers from 1996 to 1997. The majority of these women are older than 40 years. The numbers for male primary filers do not exhibit any significant changes around 1996. In section 5.3 of the paper we show that our results are robust to this sampling change in 1996.

One additional point to be mentioned is that our tax data contains fewer socio-demographic variables relative to those of standard survey data like the PSID. Most importantly, though we have information on age and gender of the primary filer, we do not have information on education and race. As a result, when we perform decompositions of total inequality into a permanent and a transitory component, the part of the variation in income explained by race and education will be adding to the variation attributed to the permanent component. We also do not have information on hours of work, and hence our analysis will focus only on annual earnings, rather than on wage rates.

2.3 Sample Selection

We use slightly different benchmark sample restrictions for studying individual male earnings and for studying household income. For individual earnings, our sample includes all male primary filers aged 25-60. We restrict the sample to males in order to facilitate comparability with most previous studies estimating earnings dynamics models and also because females moving in and out of the labor force are likely to create difficulties for estimating such models. We restrict age to 25-60 because individuals in this group are likely to have completed most of their formal schooling and are sufficiently young not be too strongly affected by early retirement. For household income, our sample includes all tax returns where the primary filer is aged 25-60. In this case we include tax returns with either male or female primary filers.

For both male earnings and household income, we exclude earnings/income observations below a minimum threshold. We do this for the following reasons. First, in the case of male earnings, we are interested in the earnings of “working individuals”. Since tax records do not provide information on employment status or hours of work, we can exclude people who are not working only by dropping low-earnings observations. Second, in the case of household income, households with sufficiently low income are not required to file taxes, although many such households do. In order to treat low-income observations consistently, we exclude observations with reported household income below a minimum threshold. Third, changes in earnings/income at low levels of earnings/income can unduly affect estimates of variance components models because these models treat, for instance, a change from $50 to $100 similarly to a change from $50,000 to $100,000. Two commonly used approaches to address this problem are to either exclude low earnings/income observations or to left-censor
them. Given the issues discussed above, we choose to exclude them. We adopt the threshold used by Kopczuk, Saez, and Song (2010), which is defined as one-fourth of a full year-full time minimum wage in 2004 ($2575 in 2004), and is then indexed for other years by nominal average wage growth.8

Table 1 shows the number of observations, the mean, and the standard deviation for male earnings, and for before- and after-tax household income in our samples. Our benchmark sample for male earnings contains a total of about 189,000 observations, and our benchmark sample for household income contains about 295,000 observations.

2.4 The Evolution of Inequality in IRS Tax Returns, 1987-2006

We begin by documenting the evolution of inequality in male earnings and household income (before and after taxes) in our panel of IRS tax returns. Figure 1 shows the evolution over time of the cross-sectional variance and of the Gini coefficient for male earnings, before-tax household income, and after-tax household income, respectively. As has been demonstrated in other studies using a variety of data sets, time periods, and measures of income, we find an increase in the variance and in the Gini coefficient for all three measures of income in our data over the period 1987-2006.

As expected, inequality in individual earnings is generally lower than inequality in household income, which, in addition to the earnings of the primary male filer, might include earnings of a spouse and other household members, transfers, investment income, and business income. Similarly, inequality in after-tax household income is consistently lower than inequality in before-tax household income, reflecting the progressive structure of the U.S. tax system. It appears from the figures that this reduction in inequality has has been slightly more pronounced towards the end of our sample period. Finally, the figures show that the increase in inequality over the period 1987-2006 was significantly larger for household income (especially before taxes) than for individual earnings.

Figure 2 displays the share of income received by each quintile of the income distribution, by year, for male earnings, before-tax household income, and after-tax household income. The figure also shows a steady increase in inequality for all three measures of income over our sample period. The share of income received by the top quintile increased continuously, while the share received by the bottom four quintiles fell. That is, the top quintile gained (in relative terms) "at the expense" of the bottom four quintiles. Over the sample period, the share received by the top quintile increased by 13 percent for male earnings, by 20 percent for before-tax household income, and by 19 percent for after-tax household income. Once again, the increase in inequality was larger for household income than for male earnings.

These inequality trends in our data are consistent with trends that have been documented in

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8We believe that our results are not sensitive to setting a lower/higher minimum threshold, but we plan to check this formally.
many other U.S. studies using different data sets. In the remainder of the paper, we focus on the variance of earnings and household income as a measure of inequality, and we investigate the extent to which the increase in the cross-sectional variance shown here represented an increase in long-run inequality versus an increase in transitory inequality. In other words, we investigate whether the increase in the cross-sectional variance was permanent or transitory in nature.

3 Methodology

This section discusses the methodology we use to analyze the role of permanent and transitory variance components. In particular, we focus on an intuitive approximate decomposition, a model-based decomposition, and a volatility measure that provides supplementary evidence.

3.1 Approximate Methods

We begin our analysis of the permanent-versus-transitory nature of the evolution of individual male earnings and household income inequality by decomposing the total variance into permanent and transitory components using an intuitive, approximate method. The method defines permanent income (or earnings) as the P-year average of annual income, where we let P take each of the values 3, 5, 7, and 9. The transitory variance is then defined as the difference between the total variance and the variance of permanent income. In other words, permanent income is a long-run average of annual income observations, and transitory income is simply the remainder of the total variation.

More precisely, the permanent variance is calculated as the variance of P-year average income, $\text{var} \left( \frac{1}{P} \sum_{j=t-k}^{t+k} \xi_{ij} \right)$, where $\xi_{it}$ is the relevant measure of (log) income and $k = \frac{P-1}{2}$. We define our measure of $\xi_{it}$ more precisely in section 3.2 below. The transitory variance is defined as $\text{var} \left( \xi_{it} - \frac{1}{P} \sum_{j=t-k}^{t+k} \xi_{ij} \right)$, and the total variance is then calculated as the average (over the relevant P years) of the variance of $\xi_{it}$.

This decomposition has been used in Kopczuk, Saez, and Song (2010), and is also similar, but not identical, to the "BPEA" method described in Moffitt and Gottschalk (2008). Like Kopczuk, Saez, and Song (2010), we restrict observations to individuals who are present in all P years.

3.2 Error-Components Models of Earnings/Income Dynamics

Next, we examine the role of permanent and transitory variance components in the evolution of inequality over our sample period by estimating non-stationary error-components models of income dynamics.\(^9\) These models fully specify the process that determines the evolution of income and

\(^9\)For ease of exposition, we often refer to a general variable called "income" that we mean to capture either individual (male) earnings or total household income.
thus can be used to provide a precise decomposition of the income variance into permanent and transitory components.

An advantage of using error-components models in this context is that the decompositions are exact. A disadvantage is that the decompositions are necessarily model-dependent. However, there is a large literature that has formulated and estimated (univariate) error-components models of income dynamics, and much has been learned from this previous work. For instance, it has been shown that the evolution of the variance and of the autocovariances of the permanent income component over the lifecycle is well described by either a random walk or a random growth process, or both. Similarly, it has been shown that the transitory component is serially correlated and that its covariance structure is well captured by a low-order ARMA process. In this draft, we work with a relatively simple model specification that we believe captures the main aspects that previous work has shown to be important, and that provides a convenient decomposition of income into permanent and transitory components, where the relative importance of each component can change over time. Nonetheless, because the results from such decompositions are necessarily (somewhat) model-dependent, we are still experimenting with a number of different model specifications, and future versions of the paper will include an analysis using alternative specifications.

Our benchmark model has the following elements. Let $y_{ct}$ denote log income, where $i$ stands for individual, $t$ for calendar year, and $c$ for cohort (defined as the first year that individual $i$ is in the labor force). Log income is given by:

\[ y_{ct} = g(\gamma; X_{ct}) + \xi_{ct}, \]

where $X_{ct}$ is a vector of observable characteristics, $g(\cdot)$ is the part of log income that is common to all individuals (conditional on $X_{ct}$), $\gamma$ is a vector of parameters (possibly including parameters that depend on calendar year $t$), and $\xi_{ct}$ is the unobservable error term. We focus on modeling and estimating the process followed by $\xi_{ct}$, as is common in the literature.

We let $\xi_{ct}$ be given by:

\[ \xi_{ct} = \lambda_t \cdot (\alpha_i^c + r_{ct}^c) + \zeta_{ct}, \]

where

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12 That is, we focus on residual income. Note, however, that since our tax returns data do not include information on race or education, this residual variation is not exactly within-group variation in the same way as in studies that include these two variables in the set of observables.
\[ r_{it}^c = r_{i,t-1}^c + \epsilon_{it}^c \]

\[ z_{it}^c = \rho z_{i,t-1}^c + \pi_t \eta_{it}^c \]

and

\[ \alpha_i \sim iid(0, \sigma_\alpha^2), \epsilon_{it}^c \sim iid(0, \sigma_r^2), \eta_{it}^c \sim iid(0, \sigma_z^2) \]

Above, \((\alpha_i^c + r_{it}^c)\) is the permanent income component, which consists of an individual-specific, time-invariant component, \(\alpha_i^c\), and a random-walk component, \(r_{it}^c\). The year-specific factor loading, \(\lambda_t\), multiplies the permanent component and allows its relative importance to change over calendar time. Permanent shocks, i.e. innovations to the random walk process, \(r_{it}^c\), might reflect, for instance, disability shocks, (some types of) job losses, (some types of) job changes, promotions, and the arrival of new information about workers’ skills.

The component \(z_{it}^c\) is the transitory component. By definition, the effects of innovations to the transitory component eventually disappear, though they may last for several periods.\(^\text{13}\) Transitory shocks might capture variation in income that is due to shocks such as temporary illness, (some types of) job losses, year-to-year variation in bonuses, overtime pay, etc. Ultimately, the covariance structure of the data will determine how long the effect of shocks to this component persists. We specify that the transitory component follows an AR(1) process.\(^\text{14}\) The year-specific factor loadings, \(\pi_t\), multiply the innovations to the transitory component, \(\eta_{it}^c \sim iid(0, \sigma_z^2)\), allowing the variance of the innovation, and hence the relative importance of the transitory component, to vary by calendar year. The next section describes the estimation of our model.\(^\text{15}\)

\(^\text{13}\)In other words, the permanent component is defined as capturing shocks that are not mean-reverting, whereas the transitory component is defined as capturing mean-reverting shocks.

\(^\text{14}\)Note that, due to the presence of the random walk component, the estimated persistence of the AR(1) component will turn out to be relatively low.

\(^\text{15}\)There are several dimensions along which the model above can be enriched, and some of them have been shown to be potentially important for questions related to those addressed in this paper. Possible extensions include: (i) Using an ARMA(1,1) transitory error instead of the AR(1) error. (ii) Adding a random growth component to the permanent income component. (iii) Allowing the variances of the transitory shocks (and possibly the innovations to the random walk component) to be age-dependent. (iv) Allowing for cohort-specific initial variances in the AR(1) (and possibly in the random walk) component. Obviously, estimating a model that incorporates all of the elements above is very demanding of the data, and choices will need to be made. We are in the process of experimenting with the estimation of richer model specifications that include some of the above elements, and examining which of these dimensions improve the model’s description of the data. Future versions of the paper will include results from alternative specifications resulting from this examination.
3.2.1 Estimation

We begin by estimating the component \( g(\gamma; X_{it}^c) \) in equation (1), which can essentially be thought of as a regression of income, \( y_{it}^c \), against a vector of observables, \( X_{it}^c \). More precisely, in the case of male earnings, we estimate least squares regressions, separately for each year, of log earnings against a full set of age dummies. In the case of household income, we regress, separately for each year, log household income against a full set of age dummies, gender of the primary tax filer, and household size/composition indicators.\(^{16}\) Since we do not have information on race and education, the part of the variation in income explained by race and education will remain in the residuals and will add to the variation attributed to the permanent component. Using the estimated regression, we obtain residuals \( \hat{\xi}_{it}^c = y_{it}^c - g(\hat{\gamma}; X_{it}^c) \). Appendix A describes our first-stage regressions in more detail.

The error-components model of earnings/income dynamics described in equations (2)-(5) implies a specific parametric form for each variance and autocovariance of (residual) income, \( \xi_{it}^c \), given cohort \( c \), calendar year \( t \), and lead \( k \). Call these variances and autocovariances \( \text{cov}(c, t, k) \), where \( c = 1952, ..., 2006, t = 1987, ..., 2006, \) and \( k = 0, ..., 19 \).\(^{17}\) These theoretical variances and autocovariances are functions of the model parameters \( \sigma_\alpha^2, \sigma_r^2, \rho, \sigma_z^2, \) and \( \lambda_t, \pi_t \) for \( t = 1987, ..., 2006 \). We estimate these model parameters by minimizing the distance between the theoretical variances and autocovariances implied by the error-components model and their empirical counterparts, which we compute from our longitudinal tax returns data.\(^{18}\) Our estimator is then a minimum distance estimator, and we essentially use the identity matrix as the weighting matrix (rather than an optimal weighting matrix) for reasons discussed in Altonji and Segal (1996).\(^{19}\)

This estimation approach is standard in the literature that formulates and estimates models of earnings/income dynamics. The basic intuition for identification is that the contribution of the transitory component to the autocovariance of income between two periods vanishes once the distance between the two periods gets large. The long autocovariances in the data thus permit separating out the effects of the permanent and transitory components.\(^{20}\)

\(^{16}\)These include an indicator of whether the primary filer is married or single, and a full set of dummies for the number of children (up to ten) in the household.

\(^{17}\)These are the cohorts, years, and leads for which we can compute empirical variances and autocovariances from our tax returns data.

\(^{18}\)For identification, we impose the restrictions: \( \pi_{1987} = 1, \lambda_{1987} = 1, \pi_{2006} = \pi_{2005} \).

\(^{19}\)More precisely, we use a diagonal matrix by which we weight each variance and autocovariance by the number of observations used to compute it in the tax data.

\(^{20}\)For a detailed discussion of the intuition behind the estimation of these types of models, see for instance Moffitt and Gottschalk (2008).
3.3 Volatility

We also examine the evolution of income (or earnings) volatility, defined as the standard deviation of percentage changes in income. A measure of the dispersion (such as the standard deviation) of year-to-year income changes is a simple and natural measure of volatility, and a few recent studies have examined similar simple measures, instead of performing a formal decomposition of the income variance into permanent and transitory components. Although volatility does not in general correspond exactly to the transitory variance as measured in the previous two sections, the concepts are closely related. We therefore interpret the volatility measure as providing evidence complementary to that of the approximate and model-based decompositions.\textsuperscript{21} To facilitate comparison with previous studies, we look at percentage changes in income over one year and over two years.

4 Empirical Results: Male Earnings

This section presents and discusses our empirical results for male earnings. We first show the results from the approximate and model-based decompositions, and then we show the volatility trends. Next, we present some evidence suggesting that the approximate method tends to overstate the role of the permanent component, and we perform an additional permanent-transitory decomposition using a nonparametric method proposed by Moffitt and Gottschalk (2008). We conclude that the model-based decomposition and the nonparametric decomposition give quantitatively similar results (which are also qualitatively consistent with the results from the volatility measure), whereas the approximate decomposition tends to overstate the importance of the permanent component in total inequality.

4.1 Decomposition using Approximate Methods

Figure 3 presents decompositions of the total variance of male earnings into permanent and transitory variances using the approximate method described in section 3.1. The four panels in the figure refer to decompositions that define permanent earnings as the average of annual log (residual) earnings over three, five, seven, and nine years, respectively. Two main points emerge from Figure 3. First, this decomposition attributes 80-90 percent of the total variance to the permanent component, depending on the number of years used to define permanent earnings.\textsuperscript{22}

Second, the increase in the total variance of male earnings seems to be driven entirely by the permanent variance, which exhibits a distinct increase over our sample period. By contrast, the

\textsuperscript{21}Shin and Solon (2008) and Moffitt and Gottschalk (2008) discuss in more detail the relation between this measure of volatility and transitory variances such as the ones presented in the previous two sections.

\textsuperscript{22}Note as well that the relative importance of the permanent component appears to fall as the numbers of years used to define permanent earnings increases.
transitory variance appears largely flat. To see this more clearly, Figure 4 normalizes both the permanent and the transitory variance to equal 1 in the first year, and then plots the level of the variance components in subsequent years relative to the level in the initial year; that is, we normalize each year by dividing by the level in the first year. In this figure, the permanent variance shows a clear increasing trend, whereas the transitory variance does not. For example, the permanent variance increases by 16 percent from 1989 to 2004 when permanent earnings are defined as a five-year average.

Our results are in line with those reported in Kopczuk, Saez and Song (2010), both in terms of magnitudes and in terms of trends. In terms of trends, our results are also consistent with those of Moffitt and Gottschalk (2008), who find that after 1987 the transitory variance of male earnings has remained mostly flat, whereas the permanent variance has been consistently increasing, thereby contributing almost all of the increase of total earnings inequality. However, in terms of magnitudes, the approximate method used here attributes a larger fraction of the total variance to the permanent component, compared to the findings of Moffitt and Gottschalk (2008). We will present some evidence below suggesting that the approximate method tends to overstate the contribution of the permanent component to the total variance. In any case, the evidence here overall indicates that the increase in the total variance of male earnings over our sample period was driven by an increase in the permanent variance.

4.2 Decomposition using the Error-Components Model

We now move to decompositions based on the non-stationary error-components model introduced in section 3.2. We begin by presenting the parameter estimates in Table 2. Recall that in our specification the permanent component consists of a random effect, $\alpha_i$, and a random walk, $r_{it}$, both multiplied by the year-specific factor loading, $\lambda_t$, whereas the transitory component, $z_{it}$, follows an $AR(1)$ process with year-specific innovation variances. Columns 1a and 1b present parameter estimates and standard errors for male earnings. The parameter estimates we obtain (other than for the factor loadings $\pi_t$ and $\lambda_t$) are $\hat{\sigma}_\alpha^2 = .2099$, $\hat{\sigma}_r^2 = .0066$, $\hat{\rho} = .5195$, and $\hat{\sigma}_z^2 = .2022$.

Next, we use our estimated model to decompose the variance of male earnings into permanent and transitory components. Figure 5 presents decompositions for four different levels of age: 29, 39, 49, and 59 years. Several features become apparent from this figure. First, moving across panels, note that in any given calendar year, the total variance increases with age. This fanning-out

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23 In reading these panels, note that, as the number of years used to define permanent earnings increases, one observation on each end of the sample is lost (by construction).

24 Their analysis uses levels of (log) earnings, as opposed to residual (log) earnings. However, our results are essentially identical when we use levels instead of residuals from a first-stage regression.

25 We also reach the same conclusions when we use the permanent-transitory decompositions based on the similar, but not identical "BPEA" method described in Moffitt and Gottschalk (2008).
of the variance as a cohort ages is a well-documented feature of individual earnings data present in different data sets. Second, note that, for all ages, the permanent variance accounts for about 60-70 percent of the total variance. Most importantly, the increase in the total variance over the sample period appears to be driven entirely by the increase in the permanent variance.\(^{26}\) In other words, the model-based decomposition indicates that the transitory variance did not increase, on net, over the period 1987-2006.

Figure 6 presents a decomposition for all age levels.\(^{27}\) Again, we see that the permanent component contributes about 60 percent to the total. Furthermore, the 16 percent increase in the total variance over our sample period is solely due to the increase in the permanent variance, since the transitory variance exhibits no clear trend.\(^{28}\)

Combining the model-based evidence presented in this section with the approximate decomposition from the previous section, we conclude that the increase in the variance of male earnings over the period 1987-2006 was permanent in nature. The transitory variance of male earnings over this period exhibits no clear trend. Our results are consistent with Moffitt and Gottschalk (2008), who also find a predominant role of permanent inequality for the evolution of total inequality in recent years. In particular, using the PSID, they conclude that transitory inequality for male earnings increased substantially from the 1970s until about the mid-1980s, but levelled off thereafter. Our results here corroborate their conclusions. Contrary to our findings and to those of Moffitt and Gottschalk (2008), Heathcote, Perri, and Violante (2010) find a more prominent role for the transitory variance in the post-1987 period: they find that the transitory variance increased substantially in the early 1990s, and therefore that it accounts for about 40 percent of the increase in total inequality in the post-1987 PSID.\(^{29}\)

### 4.3 Volatility

Figure 7 presents the evolution of volatility, defined as the standard deviation of either one-year or two-year percent changes in (residual) male earnings. The upper and lower lines show the standard

\(^{26}\) The increase in the permanent variance over calendar time appears somewhat larger for higher age levels.

\(^{27}\) This decomposition is constructed in a way that reflects the age distribution of the pooled 1987-2006 sample in our data set.

\(^{28}\) Since the permanent-component decompositions depend on age, one possible concern is that changes over time in the decomposition are driven by changes in the distribution of age over time. To check for this, we simulated the persistent and transitory earnings components from our estimated model, where the simulation keeps the age distribution over time constant. The resulting decomposition is essentially identical to the one presented in Figure 6.

\(^{29}\) One possible reason for their results is the significant changes in the collection and treatment of survey data in the PSID, which were implemented exactly around that time. These included a switch to computer-assisted telephone interviewing and a shift from human to automated editing of the data. Additionally, there were some changes in the structure of the income questions. See the discussions in Shin and Solon (2008) and Dynan, Elmendorf, and Sichel (2007). However, this does not explain why Moffitt and Gottschalk (2008), who also work with PSID data, find different results.
deviation of two-year and one-year percentage changes, respectively. The important result from the figure is that there is no evidence of an increasing (or decreasing) trend in male earnings volatility over our sample period. Furthermore, the trends are essentially the same for one-year and two-year earnings changes.

The finding of no increase in male earnings volatility over 1987-2006 agrees with our result of a stable transitory variance of male earnings, although, as already noted, the two measures need not necessarily move together. By contrast, Dynan, Elmendorf, and Sichel (2007) find a continuous increase in the volatility of male earnings from 1967 to 2004. However, their measure of earnings is different from ours in that it includes self-employment income as reported in the PSID, and evidence presented by Sabelhaus and Song (2009) suggests that this might account for the difference. On the other hand, our findings agree with the evidence presented in Shin and Solon (2008), the CBO (2008) study using SSA data, and Sabelhaus and Song (2009) for our sample period.\footnote{Shin and Solon (2008) analyze the evolution of two-year changes in (residual) individual earnings in the PSID, because the survey has been conducted only every two years since 1997 (before that it was conducted annually). \footnote{Note that Dynan, Elmendorf and Sichel (2007), the CBO (2008) study, and Sabelhaus and Song (2009) use levels, as opposed to residuals, of (log) earnings. Our results when we use earnings levels are similar to those presented here for earnings residuals.} Our findings here reinforce our result from the previous sections that the increase in male earnings inequality over 1987-2006 was of a permanent nature: the transitory variance as well as the volatility of male earnings appear very stable over this period.

4.4 Robustness of the Results for Male Earnings

Our results above showed that the approximate decomposition attributes about 80-90 of the total variance to the permanent component, whereas the model-based decomposition attributes about two-thirds of the total to the permanent component.\footnote{However, both methods attribute the increase in the total variance to the permanent component alone.} In this section we present some evidence suggesting that the approximate method tends to overstate the role of the permanent variance, especially when the number of years used to define permanent earnings is relatively small. We also present an additional decomposition using a nonparametric method proposed by Moffitt and Gottschalk (2008), and we find results similar to the model-based decomposition.

4.4.1 Bias in the Approximate Method

This section provides some evidence suggesting that the approximate method tends to overstate the contribution of the permanent component in the total. We conduct the following experiment. We simulate data from our estimated error-components model to form a 50-year panel of simulated data. The exact permanent-transitory decomposition for the simulated data is essentially the decomposition we presented in Figure 6; that is, the permanent variance should account for
about 60 percent of the total variance, and the transitory variance for about 40 percent. We then use the approximate method to decompose the total variance of the simulated data. We perform decompositions that define permanent earnings as the average of 5, 9, 15, 25, and 35 years, respectively. The results are presented in Figure 8. Panel (a), where permanent earnings are defined as a five-year average, shows that the approximate method attributes over 80 percent of the total variance to the permanent component (as it did for the actual tax data), instead of the 60 percent that the data generating process implies. In addition, one can see that the smaller is the time window that defines permanent earnings, the larger is the bias of the approximate method. In fact, the approximate method approaches the correct decomposition only as the number of years used to define permanent earnings becomes at least as large as 15 years. In computing such a decomposition, however, one loses 14 years of data (7 at each end of the sample), so one would need a very long panel in order to be able to still study time trends for the years that remain available. These findings suggest that the results in Kopczuk, Saez, and Song (2010) are probably also subject to this bias, and that therefore their conclusion for an overwhelming role of the permanent inequality are likely an overstatement of the true extent of permanent inequality in the U.S. in recent decades.

We conclude that the approximate decomposition tends to overstate the contribution of the permanent component (and thus understate the contribution of the transitory component), unless the number of years used to define permanent earnings is very (in our case, prohibitively) large. This should be kept in mind when interpreting the results from the approximate method in the rest of this paper.

4.4.2 Moffitt and Gottschalk Nonparametric Method

The evidence presented in the previous section leads us to place more trust on the quantitative results from the model-based decompositions. However, because of the quantitative differences across the two methods, and because of concerns about model-dependency of the results, we turn for additional evidence to the nonparametric decomposition method introduced by Moffitt and Gottschalk (2008).33

The results of the nonparametric decomposition are presented in Figure 9. Here, the permanent component constitutes about two-thirds of the total variance, similar to the model-based decomposition. Furthermore, the permanent component increases by 20 percent over the sample period, and is responsible for about 80 percent of the increase in the total variance. Hence, the nonparametric method agrees with the model in attributing a large role to the permanent component for the increase in the total, but it still recognizes some role for the transitory component in this respect. As we will see in what follows, in the case of household income we also find that the

33See Moffitt and Gottschalk (2008) for a detailed description of this method.
nonparametric decomposition finds a somewhat larger increase in the transitory variance relative to the model-based decomposition. Nonetheless, the evidence from the model and the nonparametric method is qualitatively and quantitatively very similar.

Summarizing the results from this section, we conclude that, for the case of male earnings, permanent inequality accounts for about two-thirds of total inequality in our sample period, and is responsible for almost all of the increase of the total cross-sectional inequality. By contrast, transitory inequality has remained largely flat. These findings are consistent across the model-based and nonparametric decompositions, and they are in line with the evidence provided by the volatility measures. The approximate decomposition, though yielding qualitatively similar results, appears to overstate the quantitative contribution of the permanent component to the total and to the increase in the total variance.

5 Empirical Results: Pre-Tax Household Income

In this section we examine the evolution of the permanent and transitory components of inequality for pre-tax household income, we show that it differs from the case of individual male earnings, and we explore the reasons for this difference. We also look into the robustness of our results for household income.

5.1 Benchmark Household Income Sample Results

As discussed earlier, our benchmark sample for household income includes all tax returns where the primary filer is aged 25-60. That is, we include tax returns with either male or female primary filers, and in this respect our sample selection is somewhat different relative to the case of individual male earnings.\footnote{We will show below that this difference in sample definition does not account for the results that we present in what follows.}

Figure 10 presents the results for pre-tax household income using our different methods introduced above. Panel (a) shows the results from the approximate decomposition, using a five-year average to define permanent income, and normalizing the permanent and transitory variances to equal 1 in the first year. As in the case of individual male earnings, the permanent variance comprises about 85 percent of the total variance\footnote{This cannot be seen in the normalized figure.}. Contrary to the case of male earnings, however, two features emerge from the figure for pre-tax household income. First, the transitory component increases by 21 percent, instead of staying flat.\footnote{The permanent component also increases, and in fact more than the transitory component, by 31 percent.} Second, the transitory component now contributes about 10 percent to the increase in the total variance. Hence, although the permanent variance
is still the main contributor to the increase in the total, the transitory variance now also makes a contribution.

Based on the evidence presented in section 4.4.1, we expect the approximate decomposition to understate the role of the transitory component. This expectation is supported by the results of the model-based decomposition, which are presented next. The model estimation results for pre-tax household income are shown in columns 2a and 2b of Table 2. The model-based permanent-transitory decomposition is shown in panel (b) of Figure 10. First, the permanent component accounts for about 64 percent of the total variance, which is lower than the contribution indicated by the approximate method.37 Second, the transitory component increases by about 21 percent over the period, in contrast to the case of male earnings.38 As a result, the contribution of the transitory component to the increase of the total variance is about 28 percent for pre-tax household income, compared to essentially zero for the case of male earnings.

Further support for the finding that the transitory component plays a role for the increase in household income inequality can be gleaned from panel (c) in Figure 10. This panel shows that the volatility of pre-tax household income has continuously increased over our sample period, whereas it was basically flat for the case of male earnings.39

Finally, panel (d) of Figure 10 shows the results from the decomposition using the nonparametric method of Moffitt and Gottschalk (2008). This method finds that the transitory component makes up about 33 percent of the total, increases by 36 percent over the sample period, and contributes about 43 percent to the increase of the total variance. These estimates are comparable to those from the model decomposition, although, as previously noted, the nonparametric decomposition attributes a somewhat larger role to the transitory variance for the increase of the total, compared to the model (43 percent versus about 30 percent).

A final point to be noted from Figure 10 is that, regardless of the method used, transitory inequality appears to increase more steeply in the post-1996 period. In what follows, we investigate the reasons behind the increased role of the transitory variance for pre-tax household income, relative to the case of individual male earnings, with special emphasis on year 1996.

In going from individual male earnings to total household income, a number of components are added, in particular spousal earnings, transfer income, investment income, and business income.40 We can therefore start from individual male earnings and add each of the other categories of

37 The contribution of the permanent component here is similar to the case of male earnings.
38 The permanent component also increases, by about 37 percent.
39 We note that our finding of increasing pre-tax household income volatility is consistent with the findings of Dynan, Elmendorf and Sichel (2007).
40 On average over our period, male labor earnings account for about 50 percent of total household income, female labor earnings for 26 percent, retirement and transfer income for 5 percent, investment income for 7.4 percent, and business income for 11.7 percent.
income one at a time, to determine which is responsible for the difference between male earnings and household income.

Figure 11 shows the transitory variance from the model-based decomposition for each measure of income. Panel (a) shows the transitory variance for male earnings, i.e. the transitory variance from Section 4.2. As already explained, this transitory variance is about flat over our sample period. Panel (b) shows the transitory variance for a measure of income that sums the earnings of the husband and the wife. The transitory variance for this measure of income increases by just 1 percent over the sample period, and it contributes about 6 percent to the increase of the total. Panel (c) shows the transitory variance for a measure of income that sums spousal earnings and transfers. Transfers are defined here as the sum of alimony received, pensions and annuities, unemployment compensation, social security benefits, and tax refunds. This transitory variance increases by about 8 percent over the sample period, and it contributes about 20 percent to the increase of the total. Finally, Panel (d) shows the transitory variance for total household income, i.e. the transitory variance from Figure 10, panel (b). Total household income is defined as the sum of household earnings plus transfers plus investment income plus business income. Investment income includes interest, dividends and capital gains, and business income includes income from self-employment, from partnerships, and from S-corporations. As we have already seen, the transitory variance for total household income increases by about 21 percent over the sample period, and it contributes about 28 percent to the increase of the total. Figure 12 provides additional support for these results, by showing that the volatility of household income increases as we pass from household earnings to the sum of household earnings plus transfers, and increases even further when we add the sum of investment and business income. The results are also similar in the case of the approximate and the nonparametric decompositions, omitted here for brevity.

Therefore, it appears that the addition of transfer income, as well as of investment and business income, results in an increased role for the transitory variance in terms of its contribution to the increase of the total variance over our sample period. In parallel work (DeBacker, Heim, Panousi and Vidangos, 2010) we find that the volatility and the transitory variance of business income is indeed significantly higher than the volatility of labor income. In other words, we find that male earnings (and household earnings) exhibit a smaller transitory component than a measure of household income that includes transfers and/or investment and business income. We also note that the addition of investment and business income in particular results in a profile for the transitory variance that is less steep before 1996 and more steep after 1996, possibly because of increased

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41 To be precise, the transitory variance decreases by about 2 percent.
42 The transitory component becomes overall flatter with the addition of spousal earnings, suggesting that the wives’ earnings covary negatively with the husbands’.
43 This finding confirms conventional wisdom, but to the best of our knowledge we are the first to provide concrete evidence using panel data for the U.S.
volatility in the financial markets after 1996, although this claim requires further investigation.\footnote{We are in the process of investigating further the role of different income components for the trends in household income inequality and possible reasons for changes over time in the different components.}

Gottschalk and Moffitt (2009) is the only other paper in the literature that has taken a look, albeit a brief one, into the variance decompositions for household income versus individual earnings. Using a method similar to the approximate method we have outlined here, they find that the transitory variance of (pre-tax) family income rose dramatically after the mid-1980s, and that this increase seems to have been due primarily to an increase in the transitory component of transfer income of head and spouse from the late 1980s to the late 1990s.\footnote{They also find an increasing transitory component of other nonlabor income (which includes capital gains) of head and spouse, but this trend appears to be smooth and continuous over their period (1970-2000), with maybe only a slight upward tilt from the late 1980s on.} Since transfer income primarily arises from welfare program payments, they conjecture that the increase in instability could have resulted from welfare reforms which began in the early 1990s and led to considerable movements off welfare and to much shorter spells of welfare receipt.

To summarize, we find evidence that the transitory variance accounts for a larger fraction of the total variance increase in the case of pre-tax household income, compared to the case of individual male earnings. In particular, using the model-based decomposition, the transitory component does not contribute at all to the increase in the total variance for the case of male earnings, whereas it contributes about 30 percent of the increase in the total variance for the case of pre-tax household income. This difference is attributable to the non-labor income component of household income, which includes investment and business income.\footnote{It should be noted however, that, even in the case of household income, most of the increase in the total variance is still attributed to the permanent component.}

\section*{5.2 Robustness to Changes in Household Size and Composition}

We have found that while the transitory variance and volatility of male earnings did not change over our sample period, those of household income increased. One possible concern is whether our results for household income might be affected by changes in household size and composition over time. Recall that our measure of household income consists of residuals from a first-stage regression. The first-stage regression (described in Appendix A) includes as regressors indicators of whether the primary filer is married or single (as well as the primary filer’s gender) and a full set of dummies for the number of children. This treatment essentially controls for the effects of changes in household size and composition on the mean of household income, but it does not control for potential effects on the variance. In order to check whether changes in household size and composition might be affecting our results, we perform the following experiment. We define a new sample where households with different size/composition are treated as separate households.
That is, if person A is observed for five years, then person A marries person B and the couple is observed for five years, and then the couple splits and person A is observed for another five years, we treat these three different five-year spells for person A as observations on three different households. Thus, to the extent that household formation and dissolution patterns have changed over time, this treatment will control for those changes. Our results (not shown for brevity) are essentially unchanged, regardless of the method used. If anything, our finding about the contribution of the transitory variance to the increase of the total variance is strengthened quantitatively, relative to the benchmark household income treatment (and, hence, compared to the case of individual male earnings). We interpret this as evidence that our results are not driven by changes in household size and composition (or household formation and dissolution) over our sample period.

5.3 Robustness to Change in Sampling Frame in Tax Data

As already mentioned in Section 2.2, there was a change in the sampling frame of our data in 1996, as a result of which the number of female primary filers increased significantly between 1996 and 1997. In other words, starting in 1996, our sample size increased, but in a non-random way. The concern is then whether this change in the sample might be responsible for our trends for household income, especially since our analysis suggests that the increase in household income volatility and transitory variance started around 1996.

To address this concern, we repeat our analysis of household income restricting our sample to the sample we used in the analysis of male earnings. In other words, we restrict our analysis to a subsample that was not affected by this change in the sampling frame.

We find that all of our results are essentially unchanged, including the relative contribution of permanent and transitory variances to the total, the increasing trend in the transitory variance, and the patterns found when moving from male earnings to broader measures of household income. We conclude that our findings are not driven by the change in the sample. More generally, this exercise shows that the differences we uncover in the evolution of individual male earnings and household income are not the result of using a somewhat different sample for the analysis of the two measures of income.

47 Since we are concerned with household income (as opposed to, say, consumption), we focus on the formation and dissolution of couples, and abstract from changes in household size and composition having to do with children.

48 For example, in terms of the model decomposition, the transitory variance accounts for 36 percent of total inequality, it increases by about 37 percent over the sample period, and it contributes about 44 percent to the increase in the total variance.

49 For example, the model-based decomposition finds that the transitory component is 37 percent of the total, it increases by 30 percent over the sample period, and it contributes about 33 percent to the increase of the total.
6 Empirical Results: Post-Tax Household Income

The results for post-tax household income are overall quite similar to those of pre-tax household income. Here we will therefore discuss only the results from the model-based decomposition. The first difference between pre- and post-tax income is that the transitory variance plays an even more important role in the increase of the total variance for post-tax income, compared to pre-tax income. In particular, the transitory component accounts for about 36 percent of the total, it increases by about 25 percent over the sample period, and it contributes about 37 percent to the increase of the total variance. In other words, the transitory component increases by more than in the case of pre-tax household income (25 versus 21 percent). Therefore, although the transitory component constitutes as big a part of the total as in the case of pre-tax income, it ends up accounting for a larger part of the increase in the total variance (38 versus 30 percent). But overall, for both measures of household income, we find that approximately 30-40 percent of the increase in total inequality is due to increases in transitory inequality. This seems to imply that households, as opposed to individuals, can do a better job of insuring against shocks they face over time, possibly because they can use alternative income sources to buffer labor earnings shocks.

The second difference between pre- and post-tax income is that, although their variance decompositions exhibit similar trends over time, the magnitudes of the variances are smaller in post-tax income. In particular, both the permanent and the transitory variances are about 15 percent lower in post-tax income compared to pre-tax income, regardless of the decomposition method used. This is further evidence for the role of the tax system in reducing inequality, which was already noted in Section 2.4. Figure 13 illustrates this point by presenting the evolution of the transitory variance for pre- and post-tax household income across the different decomposition approaches, as well as the one-year volatility of pre- and post-tax income. From this figure, it is clear that the time trends for pre- and post-tax transitory variance are remarkably similar, and that the post-tax variance lies everywhere below the pre-tax variance.

7 Conclusions

We use a panel of tax returns from the Internal Revenue Service to analyze the role of permanent and transitory variance components in the evolution of inequality in male earnings and household income in the United States over the period 1987-2006.

First, we document an increase in various measures of inequality in male earnings and household income in our dataset during this period. This increase in inequality is largest for pre-tax household income, but it is also significant for post-tax household income and for the labor earnings of male

\footnote{On average over our sample period, taxes lower the level of household income by $12,353 or 22 percent.}
primary tax filers.

Second, we examine the role of permanent and transitory variance components in the increase in inequality (as measured by the cross-sectional variance), using approximate decomposition methods and non-stationary error-components models of earnings/income dynamics. We provide evidence suggesting that the approximate decomposition tends to overstate the role of the permanent component. We then show that our quantitative results from the model-based decomposition is similar to a nonparametric decomposition proposed by Moffitt and Gottschalk (2008). We find that both for male earnings and for household income (whether pre- or post-tax) the transitory variance accounts for about 30-40 percent of the total cross-sectional variance. However, in the case of male earnings, the transitory variance was flat and did not contribute to the increase in total inequality in the post-1987 period. By contrast, in the case of household income the transitory variance contributes about 10-40 percent of the increase in total inequality, where the higher fraction refers to post-tax income. We conclude that, in the period 1987-2006, the increase in the cross-sectional inequality for male earnings has been permanent in nature. However, 10-40 percent of the increase in the cross-sectional inequality of household income was due to an increase in transitory inequality. In addition, we find that this difference between male earnings and household income is due to the more transitory nature of the non-labor component of household income, which includes investment and business income. Finally, we find that the tax system plays an important role in reducing all components of inequality (by about 15 percent), although it does not alter the time trends in the evolution of the different variance components. Our analysis using volatility measures provides additional evidence supporting all of the above.
8 References


Appendix A: Creating the Residuals from First-Stage Regression

In this paper we focus on residual earnings/income variation, i.e. the part of earnings/income variance that is not explained by observable characteristics of the individual/household. Focusing on residual earnings/income allows comparison with previous studies that estimate models of earnings dynamics, since such studies typically estimate error-components models for the residuals from a first-stage earnings regression. This effectively controls for changes in the earnings/income distribution that are driven by changes in sample composition such as the age distribution or, in the case of family income, the distribution of family size and composition. We construct residual individual earnings by applying least squares (separately for each year) to a regression of log earnings against a full set of age dummies. This regression purges individual earnings from the effect (on the mean) of economy-wide factors (“year effects”), stage in the lifecycle, and cohort (“cohort effects”). Note that tax records generally do not contain information on race or educational attainment and thus we cannot control for variation explained by these variables in the first-stage regression. The effects of race and education is therefore part of the permanent variance component of the residual, as in other studies that use income information from tax returns (and often other administrative data sources). The regression equation for individual earnings, $y_{it}^{ind}$, is thus:

$$y_{it}^{ind} = f(c_t^1, D_{it}^a)$$

where $c_t^1$ is a year-specific constant and $D_{it}^a$ is a full set of age dummies.

Similarly, we construct residual household income by applying least squares (separately for each year) to a regression of log household income against a full set of age dummies (for the primary filer), gender, and indicators for household size and composition, including an indicator of whether the primary filer is married or single, and a full set of dummies for the number of children (up to ten) in the household. The regression equation for household income, $y_{it}^{hh}$, is thus:

$$y_{it}^{hh} = g(c_t^2, M_i, D_{it}^a, D_{it}^f)$$

where $c_t^2$ is a year-specific constant, $M_i$ is a dummy for male, $D_{it}^a$ is a full set of age dummies, and $D_{it}^f$ is a full set of family size/composition dummies.
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Note: The slightly different number of observations of household income before and after taxes is due to the minimum income threshold necessary to be included in the sample.
### Table 2

Estimates of Error-Components Model

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Estimates of Error-Components Model

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Figure 1a
Cross-Sectional Variance by Year

Figure 1b
Cross-Sectional Gini Coefficient by Year
Figure 2a
Quintile Shares, Male Earnings

Figure 2b
Quintile Shares, Pre-Tax Household Income

Figure 2c
Quintile Shares, After-Tax Household Income
Figure 3a
Approximate Decomposition, Male Earnings
Permanent is Three-Year Average

Figure 3b
Approximate Decomposition, Male Earnings
Permanent is Five-Year Average

Figure 3c
Approximate Decomposition, Male Earnings
Permanent is Seven-Year Average

Figure 3d
Approximate Decomposition, Male Earnings
Permanent is Nine-Year Average
Figure 4a
Approximate Decomposition, Male Earnings
Permanent is Three-Year Average
Normalized to 1 in First Year

Figure 4b
Approximate Decomposition, Male Earnings
Permanent is Five-Year Average
Normalized to 1 in First Year

Figure 4c
Approximate Decomposition, Male Earnings
Permanent is Seven-Year Average
Normalized to 1 in First Year

Figure 4d
Approximate Decomposition, Male Earnings
Permanent is Nine-Year Average
Normalized to 1 in First Year
Figure 5a
Model Decomposition
Male Earnings, Age = 29

Figure 5b
Model Decomposition
Male Earnings, Age = 39

Figure 5c
Model Decomposition
Male Earnings, Age = 49

Figure 5d
Model Decomposition
Male Earnings, Age = 59
Figure 6
Model Decomposition, All Ages
Male Earnings
Figure 7
Volatility: Standard Deviation of Percentage Changes
Male Earnings

Volatility: Standard Deviation of Percentage Changes
Male Earnings

One-Year
Two-Year
Figure 9
Moffitt-Gottschalk Nonparametric Method
Male Earnings
Figure 10a
Approximate Decomposition, Normalized to 1 in First Year, Permanent is Five-Year Average Pre-Tax Household Income

Figure 10b
Model Decomposition, All Ages Pre-Tax Household Income

Figure 10c
Volatility: Standard Deviation of Percentage Changes Pre-Tax Household Income

Figure 10d
Moffitt-Gottschalk Nonparametric Method Pre-Tax Household Income
Figure 11a: Transitory Variance, Model Decomposition
Male Earnings

Figure 11b: Transitory Variance, Model Decomposition
Household Earnings

Figure 11c: Transitory Variance, Model Decomposition
Household Earnings + Transfers

Figure 11d: Transitory Variance, Model Decomposition
Total Household Income
Figure 12a: Volatility, One-Year Male Earnings

Figure 12b: Volatility, One-Year Household Earnings

Figure 12c: Volatility, One-Year Household Earnings + Transfers

Figure 12d: Volatility, One-Year Total Household Income
Figure 13a: Transitory Variance
Approximate Decomposition, Permanent is Five-Year Average
Pre-Tax vs. Post-Tax Household Income

Figure 13b: Transitory Variance
Model Decomposition, All Ages
Pre-Tax vs. Post-Tax Household Income

Figure 13c: Volatility
Standard Deviation of One-Year Percentage Changes
Pre-Tax vs. Post-Tax Household Income

Figure 13d: Transitory Variance
Moffitt and Gottschalk Nonparametric Method
Pre-Tax vs. Post-Tax Household Income