Rising Inequality: Transitory or Permanent? New Evidence from a Panel of U.S. Tax Returns 1987-2006.[1]

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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. For male earnings, we find that the permanent variance increased over the sample period, while the transitory variance did not increase, on net. As a result, the increase in male earnings inequality between 1987 and 2006 was entirely of a permanent nature. By contrast, for household income, we find that the transitory component contributed about 30-40 percent of the increase in inequality. A number of sources of household income (including spousal earnings, transfers, investment income, and business income) contributed to the increase in the transitory variance of household income. Finally, we find that the tax system played an important role in reducing all components of inequality, but it did not alter the broad trends in the evolution of the different variance components.

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.[1] The distinction between permanent and transitory inequality is important because it has implications for the causal factors that may lie behind inequality trends, as well as for mobility, consumption and welfare, and the trade-off between the private versus public provision of insurance.

This paper uses a new, large, and confidential panel of tax returns from the Internal Revenue Service (IRS) to study the role of permanent and transitory income components in the evolution of inequality in individual (male) earnings and in total household income (both before and after taxes) in the United States over the period 1987-2006. Our panel constitutes a one-in-5,000 random sample of U.S. taxpayers. It contains individual-level labor earnings information from W2 forms and household-level income information from Form 1040. It also contains information on the age and gender of the primary and secondary tax filers from matched Social Security Administration (SSA) records.[2] Our broadest sample contains nearly 300,000 observations on 30,000 households, and is therefore substantially larger than the typical Panel Study of Income Dynamics (PSID) sample used to address related questions in the literature. Furthermore, our data are not subject to top-coding, and it is less likely to be affected by measurement error compared to survey data.

Our preferred approach for investigating the role of permanent and transitory income components in the evolution of inequality uses nonstationary error-components models of income dynamics. These models fully specify the process that determines the evolution of income and can be used to provide a precise decomposition of the cross-sectional variance of income (our measure of income inequality) in any given year into permanent and transitory components. Our paper is the first to use administrative data to estimate models of income dynamics for the U.S. Other papers have used the PSID, or administrative data from other countries, or tax data from the U.S. but only for purposes of simple descriptive decompositions. We prefer the decompositions based on error-components models of income dynamics because the models capture aspects of the structure and the evolution of income that have been found to be important in the literature but that cannot be accounted for by simpler decompositions.

Nonetheless, we complement our model-based analysis with simpler or approximate decomposition methods that have been used elsewhere in the literature. We do this in order to investigate the robustness of the analysis to the use of alternative methods, to shed some light on the differences

[1] For instance, Gottschalk and Moffitt (1994, 2009), Moffitt and Gottschalk (1995, 2008), and Haider (2001). We discuss this literature in more detail below.

[2] As usual with data based on tax records, our data does not contain information on race and education.

across different methods, and to facilitate comparison with other studies. In particular, we use the variance decomposition employed by Kopczuk, Saez, and Song (2010), as well as a related approximate method introduced by Gottschalk and Moffitt (1994) and used in a number of subsequent studies. We show that, when the true data generating process is relatively rich, the simpler decomposition methods understate the role of the transitory component. Additionally, we explore the evolution of the standard deviation of year-to-year income changes (which has been called earnings *volatility* in this literature), a measure related to the concept of transitory variance.

Finally, we investigate the role of the federal tax system for the evolution of income inequality over our sample period, by comparing inequality trends for both pre-tax and after-tax household income.

Findings

Overall, the results for the *trends* of the permanent and transitory variance components are very robust to alternative model specifications and decomposition methods. For male earnings, we find that the permanent variance increased over our sample period, while the transitory variance did not increase, on net. As a result, the rise in male earnings inequality between 1987 and 2006 was driven entirely by the permanent component, thus constituting an increase in permanent inequality. Along the same lines, we find no increase in male earnings volatility over our sample period.

By contrast, for household income we find that both the permanent and the transitory variance contributed to the increase in inequality. For instance, using pre-tax household income for households with a male primary filer, we find that the transitory variance increased 34 percent between 1987 and 2006, while the permanent variance increased 43 percent. As a result, the transitory variance contributed 40 percent of the *increase* in the total cross-sectional variance over our sample period. For households with a male *or* female primary filer, the contribution of the transitory variance to the increase in the total variance of household income was 33 percent. We also show that a number of sources of household income (including spousal earnings, transfers, investment income, and business income) all contributed to the increase in the transitory variance of household income.

In contrast to the *trends*, we find that the *shares* of the total cross-sectional variance attributed to the permanent and transitory income components are sensitive to the model specification or the decomposition method used. For instance, the share of the cross-sectional variance of male earnings attributed to the transitory component ranges between about 15 and 60 percent, depending on the method used. We argue that these shares depend on how persistent transitory income is allowed to be (relative to permanent income). We show that, when the true data generating process is relatively rich (allowing transitory income to be relatively persistent), the simpler decomposition methods understate the role of the transitory component. Using our preferred model specification,

we find that for male earnings, the transitory variance accounts on average for 60 percent of the total variance, with the permanent variance accounting for the remaining 40 percent. For pre-tax household income, using our sample of households with a male primary filer, the transitory variance accounts on average for 40 percent of the total variance of household income. For our sample of households with a male or female primary filer, the transitory variance accounts for about 60 percent of the total variance of household income.

As for the importance of the federal tax system for the evolution of income inequality over our sample period, we find that the tax system played a substantial role in reducing all components of inequality, but it did not alter the broad trends we find in our analysis of pre-tax household income.

Literature Review and Comparison

An extensive literature has documented an increase in earnings inequality in the U.S. in recent decades. For instance, Kopczuk, Saez, and Song (2010) use longitudinal earnings data from Social Security Administration (SSA) records to document that annual earnings inequality fell sharply from the late 1930s to the early 1950s, but that it has increased steadily thereafter.[3]

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).[4] All of these studies use PSID data, and all except Gottschalk and Moffitt (1994) estimate error-components models of earnings dynamics. Kopczuk, Saez, and Song (2010) use their administrative earnings data to also provide permanent-transitory decompositions but they employ only a simple approximate decomposition method.

Our findings for male earnings are consistent with Moffitt and Gottschalk (2008) and Gottschalk and Moffitt (2009), who find that the transitory variance of male earnings increased steeply from the mid-1970s to the mid-1980s, but has remained about flat since. For the post-1985 period, they estimate that *permanent* inequality accounts for about half of total cross-sectional inequality, and that it is responsible for essentially the entire increase in the total. Contrary to our findings and to those of Gottschalk and Moffitt, Heathcote, Perri, and Violante (2010) find a more significant role for the transitory variance after 1987. In particular, they find a large increase in the transitory variance in the early 1990s, with the transitory variance accounting for about 40 percent of the increase in total inequality in their post-1987 sample period. One possible reason for this difference in findings is that Heathcote, Perri, and Violante use hourly wages, rather than annual earnings.

[3] See also the early 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).

[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.

Our findings are also consistent with Kopczuk, Saez, and Song (2010), who find an overwhelming role for permanent inequality in terms of contribution to the increase in total inequality.[5]

Inequality in *total household income* has also increased in recent decades. See, for instance, Krueger and Perri (2006) and Heathcote, Perri, and Violante (2010). The only studies that have attempted to decompose the increase in total household income inequality into permanent and transitory components are Gottschalk and Moffitt (2009), Primiceri and van Rens (2009), and Blundell, Pistaferri, and Preston (2008).

Our results for household income are consistent with Gottschalk and Moffitt (2009), who use the PSID to examine the evolution of the transitory variance of pre-tax household income (computed using only an approximate method), and find a substantial increase in the transitory variance starting in the mid-1980s.[6] Our results (and those of Gottschalk and Moffitt) differ from Primiceri and van Rens (2009), who find, using repeated cross-sections on income and consumption from the Consumer Expenditure Survey (CEX), that essentially all of the increase in household income inequality in the 1980s and 1990s was driven by an increase in the permanent variance. Blundell, Pistaferri, and Preston (2008) use panel data on income and consumption from the PSID[7], and find a large increase in the variance of permanent income shocks in the early 1980s, followed by a large increase in the variance of transitory shocks in the late 1980s. Unfortunately, we cannot directly compare our results against theirs because their decomposition essentially covers only the 1980s, so our sample periods barely overlap.

Finally, regarding the trends in the standard deviation of year-to-year income changes, our findings are consistent with Shin and Solon (2008), who find that the volatility of male earnings in the PSID 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, as well as with Sabelhaus and Song (2009), who use SSA data and find results similar to the CBO study. Our findings differ from 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.

The rest of the paper is organized as follows. Section 2 describes the data and sample selection.

[5] In particular, when we use their decomposition method, our results are very similar to theirs. As mentioned above, however, some aspects of the results are sensitive to the decomposition method used. It should also be noted that their results differ from Gottschalk and Moffitt for the pre-1985 period (which is not covered by our data).

[6] They also present some evidence suggesting that the transitory variance of family income was driven by an increase in the transitory dispersion of transfer income and other nonlabor income. One difference between our results and theirs is that we find that spousal (female) labor earnings did contribute to the increase in the transitory variance of household income.

[7] They create panel data on consumption for the PSID using an imputation procedure based on food demand estimates from the Consumer Expenditure Survey.

Section 3 presents our error-components models and discusses their estimation. Section 4 presents the results for individual male earnings using a variety of methods and discusses the reasons for differences across the various decompositions. Section 5 presents the results for before-tax household income, and Section 6 the results for after-tax household income. Section 7 describes several robustness tests. Section 8 concludes.

2 Data

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 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 next 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 Continuous Work History Subsample is the strictly random part of the 1987 stratified random sample.[8] Over the following nine years, any CWHS 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 SSN 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.[9] 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 (obtained from matched Social Security Administation records), 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 partly of a strictly random sample based on the last four digits of the primary filer's SSN. Each cross-

[8] The 1987 stratified random sample consisted of two parts: the CWHS and a high-income oversample. We do not use the high-income oversample in our analysis in this paper.

[9] 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. We discuss this issue in section 2.2.

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 one-in-5,000 random sample. 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.

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 (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 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 of household income, because the amount of capital gains realized in a particular year and reported on the tax form may include gains that 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 accrued but were 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 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.[10]

For after-tax household income, we start with the measure of pre-tax household income described above. We first 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 (i.e., after non-refundable credits have been subtracted from taxes owed). Next we subtract off 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. Finally, we add in 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.

2.2 Issues Related to Sampling Changes and Demographics

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 5 percent a year (6 percent for women with kids, and 3 percent 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. 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.

To address potential issues introduced by this sampling change, we carry out our analysis of household income using two alternative samples. First, we analyze household income using the same sample of households that we use to analyze male earnings, i.e. male-headed households, because this sample was essentially not affected by the change in sampling frame. Second, we analyze household income using a sample with either male or female primary filer.[11] We are interested in this broader sample because it represents the entire population of tax units in the U.S., not just

[10] We have, however, verified that our results are robust to the exclusion of capital gains from our measure of household income.

[11] See section 2.3.

those with a male primary filer.[12]

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 and secondary 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 lack information on hours of work, and hence our analysis will focus only on annual earnings as opposed to wage rates.

2.3 Sample Selection

When working with individual earnings, we restrict our sample to male primary filers. We restrict the sample to males because females moving in and out of the labor force introduce discontinuities in the earnings process that can create difficulties for estimating our error-components models of earnings dynamics.[13] When working with household income, we carry out our analysis using two alternative samples. The first sample includes households with a male primary filer only. The second sample includes households with either a male or a female primary filer.[14]

For both male earnings and household income, we restrict our sample to households with a primary filer aged between 25 and 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 to not be too strongly affected by early retirement.

For both male earnings and household income, we exclude earnings/household income observations that fall 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 individuals with weak labor force attachment 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 the minimum threshold. Third, changes in

[12] It should be kept in mind, however, that the sampling change discussed here could have some effect on the results for the broader household income sample.

[13] Restricting our sample to males also facilitates comparability with most previous studies that have estimated earnings dynamics models.

[14] We analyze household income using both samples for the following reasons. We are interested in the first of these samples because (i) it avoids confounding the effects of using a broader measure of income (total household income) with the effect of using a broader sample of households; and (ii) it was not affected by the change in sampling frame discussed in section 2.2. We are also interested in the second, broader sample, because it is representative of the population of U.S. taxpayers.

income at low levels of 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 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. We use the same threshold for male earnings and household income.[15]

After imposing the above restrictions, we end up with a male earnings sample with 189,424 person-year observations. We refer to this sample as our "male earnings" sample.[16] We use this sample to analyze not only male earnings, but also household income, both before and after taxes. Our broader sample for household income, which includes households with either a male or female primary filer, contains 294,910 person-year observations. We refer to this sample as our "full household income" sample.

Table 1 shows the number of observations, the mean, and the standard deviation for male earnings, before-tax household income, and after-tax household income. For household income (before and after taxes) the table shows the sample statistics for both our "male earnings" sample and our "full household income" sample.

2.4 Evolution of Inequality in 1987-2006 Panel of Tax Returns

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. Figures 1a and 1b show the evolution over time of the cross-sectional variance (of the log) and the Gini coefficient, respectively, for male earnings, before-tax household income, and after-tax household income.[17] The figures show an increase in the variance and in the Gini coefficient for all three measures of income in our data over the period 1987-2006.[18]

[15] In Section 7 we check the sensitivity of our results to setting a lower/higher minimum threshold.

[16] Note as well that in order to be included in our male earnings sample, a worker must have filed taxes and an employer must have filed a W2 form for that worker.

[17] Figures 1a and 1b use the raw data (as opposed to residuals from a first-stage regression) for each income measure. For before-tax and after-tax household income, the figures use our "full household income" sample, which includes households with a male or female primary filer.

[18] In the figure, the cross-sectional variance (of the log) increases, between 1987 and 2006, by 0.11 points (or 18 percent) for male earnings, by 0.23 points (or 33 percent) for before-tax household income, and by 0.17 points (or 28 percent) for after-tax household income. The Gini coefficient increases by 0.07 (or 18 percent) for male earnings, 0.10 (or 23 percent) for before-tax household income, and 0.09 (or 22 percent) for after-tax household income. Restricting the sample to our male earnings sample (not shown), the cross-sectional variance of the log increases by 0.24 points (or 40 percent) for before-tax household income, and by 0.20 points (or 38 percent) for after-tax household income. The Gini coefficient in the male earnings sample increases by 0.11 (or 27 percent) for both before-tax and after-tax household income.

As the figures show, 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 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 only 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 male earnings.

These inequality trends in our data are consistent with trends that have been documented in many other U.S. studies.[19] In the remainder of the paper, we focus on the cross-sectional variance (of the log) of earnings and household income as our measure of inequality, and we investigate the extent to which the increase in the variance shown here represented an increase in permanent inequality versus an increase in transitory inequality.

3 Error-Components Models of Income Dynamics

We use non-stationary error-components models of income dynamics to examine the role of permanent and transitory income components in the evolution of inequality over our sample period.[20] These models fully specify the process that determines the evolution of income and thus can be used to provide a precise decomposition of the income variance in any given year 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 error-components models of income dynamics, and much has been learned from this previous work.[21] 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.[22] 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. Our preferred specification includes the main elements that previous work has shown to be important, and pro-

[19] See, for instance, Kopczuk, Saez, and Song (2010) for annual individual earnings, and Krueger and Perri (2006) for annual household income.

[20] 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.

[21] Early contributions include Lillard and Willis (1978), Lillard and Weiss (1979), Hause (1980), and MaCurdy (1982). More recent contributions include Baker (1997), Haider (2001), Baker and Solon (2003), Meghir and Pistaferri (2004), Moffitt and Gottschalk (2008), and Guvenen (2009).

[22] See, for intance, Baker and Solon (2003).

vides a convenient decomposition of income into permanent and transitory components, allowing the relative importance of each component to change over time.

Our baseline model is as follows. Let $y^i_{a,t}$ denote log income, where i stands for individual, a for age, and t for calendar year. Log income is given by:

$$y^i_{a,t} = g(\gamma_t; X^i_{a,t}) + \xi^i_{a,t} \ , \tag{1}$$

where $X^i_{a,t}$ is a vector of observable characteristics, $g(.)$ is the part of log income that is common to all individuals (conditional on $X^i_{a,t}$), γ_t is a vector of parameters (possibly including parameters that depend on calendar year t), and $\xi^i_{a,t}$ is the unobservable error term. We focus on modeling and estimating the process followed by $\xi^i_{a,t}$, as is common in the literature.[23]

We let $\xi^i_{a,t}$ be given by:

$$\xi^i_{a,t} = \lambda_t \cdot (\alpha^i + r^i_{a,t}) + z^i_{a,t} \tag{2}$$

where

$$r^i_{a,t} = r^i_{a-1,t-1} + \epsilon^i_{a,t} \tag{3}$$

$$z^i_{a,t} = \rho z^i_{a-1,t-1} + \pi_t \cdot \eta^i_{a,t} + \theta \cdot \pi_{t-1} \cdot \eta^i_{a-1,t-1} \tag{4}$$

and

$$\alpha^i \sim iid(0, \sigma^2_\alpha), \epsilon^i_{a,t} \sim iid(0, \sigma^2_r), \eta^i_{a,t} \sim iid(0, \sigma^2_z) \tag{5}$$

Here, $(\alpha^i + r^i_{a,t})$ is the permanent income component, which consists of an individual-specific, time-invariant component, α^i, and a random-walk component, $r^i_{a,t}$. The year-specific factor loading, λ_t, multiplies the permanent component, allowing its relative importance to change over calendar time. Permanent shocks $\epsilon^i_{a,t}$, i.e. innovations to the random walk process, $r^i_{a,t}$, might reflect, for

[23] 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.

instance, disability shocks, (some types of) job losses, (some types of) job changes, promotions, and the arrival of new information about a worker's skills.[24]

Next, $z^i_{a,t}$ is the transitory component. By definition, the effects of innovations to the transitory component eventually disappear, though they may last for several periods.[25] 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 $ARMA(1,1)$ process. The year-specific factor loadings, π_t, multiply the innovations to the transitory component, $\eta^i_{a,t} \sim iid(0, \sigma^2_z)$, 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.[26]

3.1 Estimation

We begin by estimating the component $g(\gamma_t; X^i_{a,t})$ in equation (1), which can essentially be thought of as a regression of income, $y^i_{a,t}$, against a vector of observables, $X^i_{a,t}$. 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.[27] In Section 7 we examine the robustness of our results to alternative treatments of household size and composition. 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

[24] We have also experimented with two alternative specifications of the permanent income component that include a random growth component. In the first alternative specification, the permanent component is $\lambda_t \cdot (\alpha^i + \beta^i a + r^i_{a,t})$, where β^i is an individual-specific, random growth rate with $\beta^i \sim iid(0, \sigma^2_\beta)$, which is possibly correlated with α^i, with $cov(\alpha^i, \beta^i) = \sigma_{\alpha\beta}$ (here λ_t and $r^i_{a,t}$ are defined as before). A similar specification of random growth rates is used, for instance, in Baker (1997), Baker and Solon (2003), and Guvenen (2009). The estimation of this specification in our data yields $\hat{\sigma}^2_\beta = 0$. Therefore, we reject the random growth specification in our data. In the second alternative specification, the permanent income component is $\mu^i_{a,t}$, which follows a random walk with person-specific drift, i.e., $\mu^i_{a,t} = \delta^i + \mu^i_{a-1,t-1} + \epsilon^i_{a,t}$, where $\delta^i \sim iid(0, \sigma^2_\delta)$. This specification of random growth rates is used, for instance, by Moffitt and Gottschalk (2008). Under this specification, we obtain $\hat{\sigma}^2_\delta = 0$. In other words, in our data, we do not find evidence for random growth rates using either specification. Therefore, we opt for our specification of the permanent component in equations (2) and (3).

[25] 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.

[26] One possible extension of this model is to allow the initial variances of the transitory component (i.e., the variances of the transitory component in calendar year 1987), which are age-dependent, or equivalently, cohort-specific, to be estimated as free parameters, either for each cohort, or for groups of cohorts, as in Baker and Solon (2003). However, in doing so we found that we do not have the statistical power to identify the initial variances with sufficient precision.

[27] 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.

the estimated regressions, we obtain residuals $\hat{\xi}^i_{a,t} = y^i_{a,t} - g(\hat{\gamma}_t; X^i_{a,t})$. Appendix A describes our first-stage regressions in more detail.

The error-components model of income dynamics described in equations (2)-(5) implies a specific parametric form for each variance and autocovariance of (residual) income, $\xi^i_{a,t}$, given age a, calendar year t, and lead k. Let these variances and autocovariances be denoted by $cov(a, t, k)$, where $a = 25, ..., 60$, $t = 1987, ..., 2006$, and $k = 0, ..., 19$.[28] These theoretical variances and autocovariances are functions of the model parameters $\sigma^2_\alpha, \sigma^2_r, \rho, \theta, \sigma^2_z$, and λ_t, π_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.[29] Our estimator is then a minimum distance estimator, and we use the identity matrix as the weighting matrix (rather than an optimal weighting matrix) for reasons discussed in Altonji and Segal (1996).

This estimation approach is standard in the literature that formulates and estimates models of 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.[30,31]

4 Empirical Results: Male Earnings

This section presents our decompositions of the cross-sectional variance of male earnings into permanent and transitory components. We begin by presenting the results from our baseline error-components model. We then present results from an alternative model specification, in which the transitory component follows an $AR(1)$ process, rather than an $ARMA(1, 1)$ (that is, we impose the restriction $\theta = 0$ in our baseline model). We consider this alternative specification of the transitory component because it has been used in some previous influential studies (for instance, Baker and Solon (2003)).

Next, we compute permanent-transitory variance decompositions using alternative methods that have been employed by other studies. We do this because the variety of methods used in the literature complicates the comparison of results across the different studies: when results differ, it is

[28] These are the ages, years, and leads for which we can compute empirical variances and autocovariances from our tax returns data.

[29] We match 6,230 variances and autocovariances in our estimation procedure. See Appendix C.

[30] For a detailed discussion of the intuition behind the estimation of these types of models see for instance Moffitt and Gottschalk (2008).

[31] To obtain identification, we impose $\lambda_t = \pi_t = 1$ for all calendar years $t \leq 1987$, where 1987 is the first year in our sample. Additionally, we impose $\pi_{2005} = \pi_{2006}$, since λ_t and π_t cannot be identified separately in the last year of the sample, $t = 2006$.

unclear if this is due, for example, to the different methods or the different datasets. In particular, we present decompositions using a method utilized in Kopczuk, Saez, and Song (2010), as well as a method introduced by Gottschalk and Moffitt (1994) and used in a number of subsequent studies. We also examine the evolution of the standard deviation of year-to-year percent changes in earnings, otherwise known as earnings volatility, a measure that is related to the concept of transitory variance. We compare the results of the various decompositions to those of our baseline model as we go along. At the end of the section, we sum up and discuss our overall results for male earnings.

4.1 Baseline Model

Table 2 presents parameter estimates for our error-components models. Columns 1a and 1b report point estimates and standard errors for our baseline model in equations (2)-(5), estimated on male earnings data. The parameter estimates (other than those for the factor loadings π_t and λ_t) are $\hat{\sigma}_\alpha^2 = .1430$, $\hat{\sigma}_r^2 = .0031$, $\hat{\rho} = .9218$, $\hat{\theta} = -.5866$, and $\hat{\sigma}_z^2 = .2596$.[32]

We use our estimated model to decompose the cross-sectional variance of male earnings, each year, into permanent and transitory components. For any given pair of calendar year and age, (t, a), our estimated model implies a specific value for (i) the variance of log earnings (across all individuals of age a in year t), (ii) the permanent component of this variance (i.e., the variance of the permanent component of earnings), and (iii) the transitory component of this variance (i.e., the variance of the transitory component of earnings). For each calendar year $t = 1987, ..., 2006$, we compute the total, permanent, and transitory variance across all ages a, assuming, for each t, an age distribution equal to the empirical age distribution for that year in our sample. The resulting total, permanent, and transitory variances (that is, the variance decomposition by calendar year) are presented in Figure 2.

The total variance in the figure (which is constructed from our estimated model, as described in the previous paragraph) matches almost exactly the empirical variances of residual male earnings in our data for each calendar year. The transitory variance accounts for about 60 percent of the total variance (on average, across all years), and the permanent variance accounts for the remaining 40 percent. Furthermore, the transitory variance did not increase, on net, over our sample period. (In fact, the transitory variance in 2006 was 7% lower than in 1987.) The permanent variance, by contrast, increased by nearly 60 percent. It follows that the increase in the cross-sectional variance of male earnings over the sample period was entirely driven by the permanent income component. The increase in the permanent variance appears quite steady over the sample period. The transitory variance seems to have fallen slightly in the early-to-mid 1990s, and then to have

[32] These estimates are broadly comparable to those of other studies using $ARMA(1,1)$ specifications.

increased slightly in the early 2000s, roughly around the time of the 2001 recession. Below we explore the sensitivity of our results to the use of an alternative model specification and to the use of alternative permanent-transitory variance decomposition methods.

4.2 Alternative Model: AR(1) Transitory Component

In this section we present results for an alternative model specification, in which the transitory component follows an $AR(1)$, rather than $ARMA(1,1)$, process. Columns 2a and 2b in Table 2 present point estimates and standard errors for the restricted model (with the restriction $\theta = 0$).

Figure 3 shows the permanent-transitory variance decomposition for the restricted model. In terms of the *trends* over time of the two variance components, the results are very similar across models: the transitory variance did not increase, on net, over our sample period, while the permanent variance increased. Hence, as with our baseline model, the increase in the cross-sectional variance of male earnings over the sample period is entirely driven by the permanent earnings component. The time pattern of the evolution of the permanent and transitory variance components is also very similar across the two model specifications.

In terms of the *shares* of the total variance attributed to the permanent and transitory components, however, the results are different from our baseline model: the transitory variance now accounts for about 40 percent of the total cross-sectional variance (on average, across all years), compared to 60 percent in our baseline specification. Next, we investigate the source of the difference in the share of the total variance attributed to the permanent and transitory components between the two models.

4.2.1 Comparing the two models

This section examines why the two models attribute different shares of the total variance to the permanent and transitory components. As we will see below, the answer has to do with the degree of persistence of the transitory income component. Note first that imposing the restriction $\theta = 0$ leads to the following changes in some of the key parameter estimates in Table 2, relative to the baseline model: (i) the autoregressive coefficient $\hat{\rho}$ falls from .9218 to .5195 (we will see below that this, along with the estimate of θ, implies lower persistence of the transitory component); (ii) the variance of the transitory innovation $\hat{\sigma}_z^2$ falls from .2596 to .2022; (iii) the variance of the random walk component increases from .0031 to .0066. That is, setting $\theta = 0$ leads to a smaller and less persistent transitory component. As a result, the variances of the permanent income component $\hat{\sigma}_\alpha^2$ and $\hat{\sigma}_r^2$ both increase (with $\hat{\sigma}_r^2$ more than doubling), in order to match the evolution of the total variance.

Table 3 compares the persistence of *transitory* earnings across our estimated $ARMA(1,1)$ and

$AR(1)$ specifications. We simulate 35 years of data (i.e., an entire career) for each of 10,000 individuals from our estimated $ARMA(1,1)$ and $AR(1)$ processes (that is, we simulate the transitory component of earnings only), and then estimate autoregressions of simulated transitory earnings with one, two, and three lags. The (pooled) autoregression results are shown in Table 3. Columns 1a-1c show the regressions for the $ARMA(1,1)$ process and columns 2a-2c for the $AR(1)$ process. The last row in the table displays the sum of the autoregressive coefficients for the corresponding regression. As the table shows, the estimated $ARMA(1,1)$ is noticeably more persistent than the estimated $AR(1)$. For instance, comparing columns 1c and 2c, the sum of the estimated coefficients on the first, second, and third lag is .7443 for the $ARMA(1,1)$ but only .5175 for the $AR(1)$.

To see the effects of these differences across the baseline and restricted models on the variance decomposition more precisely, we next conduct the following experiment: For each of the two models, we set $\pi_t = \lambda_t = 1$ for all t, simulate a single cohort of $10,000$ individuals using the resulting (stationary) model, and examine the evolution of the permanent, transitory, and total cross-sectional variance over the lifecycle. (Note that this time we simulate both permanent and transitory earnings components). That is, we abstract from nonstationarity and focus on the implications of the two models for the evolution of the variance of earnings over the lifecycle.

Figure 4 presents the resulting decompositions of the cross-sectional variance (over the lifecycle) for the two models. The evolution of the total variance is fairly similar across the two specifications. The relative contributions of the permanent and transitory variances, however, are quite different. Under the restricted model (dashed lines), the variance of the transitory component increases relatively modestly over the lifecycle, and it also accounts for a much smaller share of the total variance than under the baseline model (solid lines). The permanent variance, on the other hand, rises faster and makes up a much larger share of the total variance, relative to the unrestricted model.

This example illustrates a more general point. The permanent-transitory variance decomposition will generally depend on how persistent the transitory component is, which in turn, depends on model specification, as well as on the persistence of earnings in the data. When the estimated transitory component is less persistent, more of the persistence in the data is picked up by the permanent component, which then makes up a larger part of the total variance. Our estimated $ARMA(1,1)$ process implies that about 30 percent of a transitory shock remains after 1 year, 25 percent remains after 5 years, and 15 percent remains after 10 years. This is, arguably, a fairly large degree of persistence. Is it then correct to call this component "transitory"? There is, of course, no single right answer to this question. As discussed above, the effects of innovations to the transitory component in our model eventually disappear (by definition). It is generally agreed that transitory earnings are serially correlated, but there is no agreement in the literature as to how persistent they can be.

We prefer the $ARMA(1,1)$ specification over the $AR(1)$ specification of the transitory earnings component because (i) this specification is supported by a large body of previous research on earnings dynamics; and (ii) our baseline model nests the restricted model, with the restriction $\theta = 0$ strongly rejected by the data (the small standard error for $\hat{\theta}$ in Table 2 yields a t-statistic of -76.71). However, we acknowledge that the choice of model is to some extent a matter of preference. We do, however, find reassuring that both model specifications yield very similar results in terms of the *trends* in each variance component, which is our main object of interest.

4.3 Alternative Decomposition Methods

This section presents permanent-transitory variance decompositions using alternative methods that have been used in other studies. As already discussed, we present these results because we want to investigate the robustness of our analysis to the use of alternative methods, as well as to shed some light on the sources of the differences across different methods and to facilitate comparison of our analysis with other studies.

4.3.1 Kopczuk, Saez, Song (2010)

The first alternative method we look at is a method used by Kopczuk, Saez, and Song (2010). We refer to this method as "KSS". The method decomposes the cross-sectional variance of annual earnings into permanent and transitory components in a simple, intuitive way that does not explicitly rely on any model of the evolution of earnings. For each person, permanent earnings are defined as the P-year average of annual earnings. Transitory earnings are defined as the difference between current annual earnings and permanent earnings. The permanent and transitory variances are then defined as the variance, across individuals, of permanent and transitory earnings, respectively. That is, the permanent variance in year t is $var(\frac{1}{P}\sum_{j=t-k}^{t+k}\xi_{ij})$, where ξ_{it} is the relevant measure of (log) earnings and $k = \frac{P-1}{2}$, and the transitory variance is $var(\xi_{it} - \frac{1}{P}\sum_{j=t-k}^{t+k}\xi_{ij})$. Following Kopczuk, Saez, and Song (2010), we set $P = 5$.[33]

Figure 5 shows the decomposition of the cross-sectional variance of male earnings into permanent and transitory components using the KSS method. The decomposition displayed in the figure is very similar, both in terms of shares and trends, to the decomposition presented in Kopczuk, Saez, and Song (2010). Two points in the figure are worth noting. First, in terms of the trends, the increase in the cross-sectional variance of male earnings is entirely driven by the permanent component,

[33] Kopczuk, Saez, and Song (2010) also restrict observations to individuals who are present in all P years. We present results without imposing this restriction. However, we have also computed the decomposition with this restriction, which reduces the total variance, but it turns out not to affect the decomposition, i.e. the relative roles and trends of the permanent and transitory variance components. In addition, we perform the decomposition using residuals from first-stage regressions, whereas Kopczuk, Saez, and Song use the raw annual (log) earnings data. We have verified that our results are also robust to using the raw data.

similar to our model-based results. Second, in terms of the relative shares, this method attributes on average about 85 percent of the cross-sectional variance to the permanent component, and only about 15 percent to the transitory component; rather than the 40 and 60 percent, respectively, from our baseline model decomposition.

To investigate the difference across the two methods in the shares of the total variance attributed to the permanent and transitory components, we conduct the following experiment. We simulate a panel of earnings data from our estimated error-components baseline model. The exact permanent-transitory decomposition for the simulated data is then essentially the decomposition presented earlier in Figure 2; that is, the transitory variance should account for about 60 percent of the total variance. We then apply the KSS method to decompose the variance of the simulated data. The results are presented in Figure 6.

As the figure shows, the KSS decomposition attributes less than 25 percent of the total variance to the transitory component, rather than the 60 percent that the true data generating process implies. Thus, for a relatively rich data generating processes such as our baseline model (which has a relatively persistent transitory component), the KSS method significantly understates the role of the transitory component. We defer the discussion of the relative merits of an approximate method like KSS versus a model-based decomposition to the next section, which presents results for another closely related approximate method. We do find reassuring, however, that the results for the trends, which are the main focus of our investigation, are similar across the two different methods.

4.3.2 Gottschalk and Moffitt "BPEA" Method

The second approximate method we look at is the method introduced by Gottschalk and Moffitt (1994) in their seminal work published in the Brookings Papers on Economic Activity. Following Moffitt and Gottschalk (2008), we refer to this method as "BPEA". The method is based on a simple error-components specification of (residual) log earnings:

$$\xi_{it} = \alpha_i + \varepsilon_{it}, \tag{6}$$

where α_i is purely permanent (time-invariant) and ε_{it} is purely transitory (iid).

To obtain the decomposition of the variance of ξ_{it} for year t, Gottschalk and Moffitt define a P-year window around year t, and compute the permanent variance of ξ_{it} as the variance of α_i, and the transitory variance of ξ_{it} as the variance of ε_{it}, as implied by the simple model above.[34]

[34] The exact formulas (within each fixed-size window) are $\hat{\sigma}^2_\varepsilon = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{1}{T_i-1}\sum_{t=1}^{T_i}(\xi_{it}-\bar{\xi}_i)^2\right]$ for the transitory variance, and $\hat{\sigma}^2_\alpha = \frac{1}{N-1}\sum_{i=1}^{N}(\bar{\xi}_i-\tilde{\xi})^2 - \frac{\hat{\sigma}^2_\varepsilon}{\bar{T}}$ for the permanent variance, where ξ_{it} is residual log earnings, N is the

To obtain a series of permanent and transitory variances over time, they repeat this procedure for each year t, using overlapping P-year windows centered around each t. The permanent and transitory variance components turn out to be very similar, though not identical, to those obtained with the KSS method.[35] Figure 7 shows the BPEA decomposition for P=5. Not surprisingly, this decomposition looks quite similar to the KSS decomposition. BPEA attributes 80 percent of the total cross-sectional variance to the permanent component and the remaining 20 percent to the transitory component.[36] In terms of time trends, we find again that the entire increase in the cross-sectional variance is driven by an increase in the permanent variance, whereas the transitory variance does not increase, on net, over the sample period.[37]

So, should we prefer a model-based decomposition or a simple, approximate decomposition such as KSS or BPEA? Our view favors the use of a carefully specified error-components model. First, recall that the BPEA decomposition is based on the simple random-effects model in equation (6), and note that our baseline model nests that simpler model. Specifically, we would obtain the random effects model in (6) by imposing, in our baseline model, $\sigma_r^2 = \rho = \theta = 0$ and $\lambda_t = \pi_t = 1$ for $t = 1987, ..., 2006$. However, these restrictions are strongly rejected in the data.[38] Second, and related, as Moffitt and Gottschalk (2008) discuss, although the BPEA method produces consistent estimates under the standard random effects model, it is problematic in more general models, particularly those with serial correlation in the transitory component.[39] Third, our baseline model captures well the covariance structure of earnings and is supported by a large body of previous research on earnings dynamics. In light of this, we maintain our model-based decomposition as our preferred method. We do, however, view the use of alternative decomposition methods as complementary and valuable. And, again, we find reassuring that the results for the trends of permanent and transitory variance components are robust to the use of different methods.

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number of individuals, $T_i \leq P$ is the number of years (within the P-year window) that person i is observed, $\bar{\xi}_i$ is the person-specific average earnings over T_i years, $\tilde{\xi}$ is the mean of log earnings across the full sample, and $\bar{T}$ is the mean years covered by the window over the individuals in the sample. See Gottschalk and Moffitt (2009).

[35] The main difference lies in the presence of the term $-\frac{\sigma_\varepsilon^2}{\bar{T}}$ in the permanent variance implied by the simple error-components specification used by BPEA. See Gottschalk and Moffitt (2009), footnote 2.

[36] Gottschalk and Moffitt use P=9, which slightly increases the share of the total variance attributed to the permanent component, and slightly reduces the share attributed to the transitory component, but has no effect on the trends of the two components.

[37] Appendix Figure A1 repeats the KSS experiment of Figure 6, using the BPEA method.

[38] As we discussed above, the KSS decomposition turns out to be very similar to the BPEA decomposition, although its motivation is not explicitly based on a model for the evolution of earnings

[39] In particular, they note that under a serially correlated transitory component, the variance of the deviations of the residuals from individual means (permanent earnings) includes the transitory autocovariances with a negative sign. Therefore, if these autocovariances are rising, the trend in the estimated transitory variance will be too small.

4.3.3 Volatility

Next, we examine the evolution of the standard deviation of percentage changes in earnings. Following Shin and Solon (2008), we refer to this measure as earnings *volatility*. This measure of dispersion in the cross-sectional distribution of year-to-year income changes is related, though not equivalent, to the concept of transitory variance.[40] A number of recent studies have examined similar simple measures, rather than performing a formal decomposition of the income variance into permanent and transitory components.[41]

Figure 8 presents the evolution of the standard deviation of one-year (the lower line) and two-year (the upper line) percent changes in (residual) male earnings.[42] As the figure shows, there is no clear increasing or decreasing trend in male earnings volatility over our sample period. This is consistent with the stable transitory variance of male earnings found in all the decompositions presented above. This finding thus reinforces the result 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 Summary and Discussion of Results for Male Earnings

To summarize, we find that the increase in the cross-sectional variance of male earnings (our measure of inequality) over the period 1987-2006 was permanent in nature. The permanent variance of male earnings increased over this period, while the transitory variance did not increase, on net. This result on the *trends* of the permanent and transitory variance components is robust to the alternative model specification we considered as well as to alternative variance decomposition methods. The share of the total variance attributed to permanent and transitory income components, however, is sensitive to model specification and to the decomposition method used. We have argued in favor of our baseline error-components model over alternative decomposition methods.

Focusing on the *trends*, our results are consistent with Moffitt and Gottschalk (2008), Gottschalk and Moffitt (2009), and Kopczuk, Saez, and Song (2010), who also find that the increase in male earnings inequality since the mid-1980s was driven by the permanent component of earnings. Our results differ from Heathcote, Perri, and Violante (2010), who find that the transitory variance increased substantially in the early 1990s, accounting for about 40 percent of the increase in total

[40] In particular, for many different specifications of the data generating process for earnings, the transitory variance and volatility (as defined above), which in general are not equivalent, do tend to move together. 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 above.

[41] See, for instance, Shin and Solon (2008), CBO (2008), Dynan, Elmendorf, and Sichel (2007), and Sabelhaus and Song (2009).

[42] We look at percentage changes in income over one year and over two years to facilitate comparison, since both measures have been used in previous studies.

inequality in the post-1987 PSID. One possible reason for this difference is that Heathcote, Perri, and Violante (2010) use hourly wages, rather than annual earnings. Our finding that the standard deviation of percentage changes in earnings was stable over our sample period, which is consistent with a stable transitory variance, agrees with the evidence presented in Shin and Solon (2008), CBO (2008), and Sabelhaus and Song (2009). On the other hand, our findings differ from Dynan, Elmendorf, and Sichel (2007), who find a continuous increase in the volatility of male earnings in the PSID from 1967 to 2004. However, their measure of earnings differs from ours in that it includes self-employment income. Evidence presented by Sabelhaus and Song (2009) suggests that this might account for the difference in results.[43]

5 Empirical Results: Pre-Tax Household Income

In this section we examine the evolution of the cross-sectional variance, and its permanent and transitory components, for pre-tax household income. Recall that in going from individual male earnings to total household income, a number of components are added. We group these components into four main categories: spousal labor earnings, transfer income, investment income, and business income.[44] We carry out the analysis for two alternative samples. First, we analyze household income using the same sample of households that we used to analyze male earnings. These are then households with a male primary filer aged 25-60, for whom a W2 form was filed, and whose annual labor earnings are above the minimum threshold. We refer to this sample as our "male earnings" sample. There are two advantages of analyzing this sample first: (i) This sample avoids confounding the effects of using a broader measure of income with the effect of using a broader sample of households. (ii) This sample was not affected by the change in sampling frame discussed in section 2.2. Second, we analyze household income using our "full household income" sample. This sample includes all tax returns where the primary filer, male or female, is aged 25-60, and whose total annual household income is above our minimum threshold. In moving from the male earnings sample to the full household income sample we mostly add households with a female primary filer (typically single females).[45] As Table 1 shows, the full sample has 294,968 person-year

[43] 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 for earnings residuals presented here.

[44] 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 self-employement, from partnerships, and from S-corporations. On average over our sample period, using our "full household income" sample, 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.

[45] However, we also add some households for which labor earnings of the male primary filer is below the minimum threshold, but for which total household income is above the minimum threshold, because they receive income from sources other than the earnings of the male primary filer.

observations, or 105,544 more observations than our male earnings sample.

The analysis is performed on residuals from a first-stage regression of log household income against a full set of age dummies (for the primary filer), gender, and indicators for household size and composition. See Appendix A for details. In section 7 we investigate the robustness of our household income results to alternative treatments of household size and composition.

5.1 Pre-Tax Household Income Results: Male Earnings Sample

Columns 3a and 3b of Table 2 present point estimates and standard errors for our baseline model estimated on pre-tax household income data, using our male earnings sample. The parameter estimates (other than those for the factor loadings π_t and λ_t) are $\hat{\sigma}_\alpha^2 = .1556$, $\hat{\sigma}_r^2 = .0047$, $\hat{\rho} = .7899$, $\hat{\theta} = -.4171$, and $\hat{\sigma}_z^2 = .1472$. As before, we use our estimated model to decompose the cross-sectional variance of household income into permanent and transitory components. The decomposition is presented in Figure 9.[46]

The transitory variance of pre-tax household income accounts on average for 40 percent of the total variance, which is less than in the case of male earnings (60 percent). The permanent variance of household income accounts for the remaining 60 percent. One possible reason for the result that the permanent share is higher for household income than for male earnings is insurance. For instance, for married couples, if spousal earnings rise when male earnings fall (the "added worker effect"), then the earnings of the couple will be smoother than male earnings and will thus be preceived as "more permanent" by the statistical decomposition.

Regarding the *trends* of the variance components over time, Figure 9 shows that the transitory variance increased by 34 percent between 1987 and 2006, while the permanent variance increased by 43 percent. As a result, the transitory variance contributed 40 percent of the *increase* in the total cross-sectional variance over our sample period. That is, in contrast to the case of male earnings, the transitory variance did play a role in the increase in household income inequality over our sample period. We show below that a number of sources of household income (including spousal earnings, transfers, investment income, and business income) all contributed to the increase in the transitory variance of household income.

Note as well the time pattern in the evolution of the two variance components. The transitory variance appears to have increased mainly in the early 2000s. The permanent variance appears to have increased relatively steadily until around 2000, and then declined somewhat.

[46] The total variance of household income in Figure 9 is lower in any given year than the total variance of male earnings from Figure 2. Note that these are variances of residuals. The household income residuals have removed the variation due to household size/composition (in addition to the predictable variation due to age). See Appendix A. If we were to compare instead the raw data, the variance of household income would be larger than the variance of male earnings, as seen in Figure 1.

5.2 Contribution of Sources of Household Income to Increase in Transitory Variance

We have seen that the transitory variance of male earnings did not increase over our sample period, but that the transitory variance of total household income did. Here we examine which category (or source) of household income–other than male earnings–is responsible for the increase in its transitory variance. The categories we consider are spousal labor earnings, transfer income, investment income, and business income. For many households, income from some of these sources is zero, which makes it difficult to separately estimate error-components models for each income category. For this reason, we analyze the contribution of each income category to the increase in the transitory variance of total household income by starting with male earnings, and then sequentially adding each of the other categories of income, one at a time. That is, we add income categories to build up to the broadest measure of income, total household income. For each of the resulting income aggregates, we estimate our baseline error-components model and decompose the cross-sectional variance into permanent and transitory components. We perform this exercise using our male earnings sample, in order to isolate the effect of adding income sources from the effect of moving to a broader sample.[47] Starting with male earnings, and moving along the series of increasingly broad income aggregates, the percent changes in the transitory variance between the first and last year in the sample (1987 and 2006) are: -7%, 6%, 15%, 29%, and 34%. That is, the addition of each income category leads to a larger increase in the transitory variance between 1987 and 2006. This takes us from the slight decrease in the transitory variance of male earnings, to the 34% increase in the transitory variance of total household income, when using our male earnings sample. We conclude that each income category contributed to the increase in the transitory variance of total household income, with no single category standing out.[48]

5.3 Pre-Tax Household Income Results: Full Sample

We now move to the full household income sample. Columns 4a and 4b of Table 2 present point estimates and standard errors for our baseline model estimated on pre-tax household income data, using our full sample. The variance decomposition is presented in Figure 10. As the figure shows, the transitory variance accounts on average for 60 percent of the total variance of household income, compared to 40 percent when restricting the sample to the male earnings sample. The

[47] The decompositions are presented in Appendix Figure A2. In the figure, panel (a) shows our baseline-model variance decomposition for male earnings, and is thus identical to Figure 2. Moving down the panels shows the decompositions using income aggregates that add sequentially (and cumulatively) sources of income in the following order: spousal earnings, transfer income, investment income, and business income.

[48] Note that investment income includes capital gains (in addition to interest and dividend income). We have repeated this exercise excluding capital gains from all income measures, and reach similar conclusions. Thus, our results do not depend on the inclusion or exclusion of capital gains.

trends for the permanent and transitory components are very similar to those obtained with the male earnings sample. In particular, the transitory variance increased over the sample period, thereby contributing 33 percent of the increase in the total cross-sectional variance, although, as before, it contributes less than the the permanent component does (67 percent).

We have also computed decompositions of the household income variance (on both our male earnings sample and our full household income sample) using our restricted model, the KSS method, and the BPEA method, and we have examined the evolution of the standard deviation of percent changes in household income (volatility). The results are shown in Appendix Figure A3 (for our males earnings sample) and Appendix Figure A4 (for our full household income sample). These figures corroborate our finding that the transitory variance did in fact contribute to the increase in the cross-sectional variance in the case of household income.

As with our male earnings sample, we have also explored (but do not show) the role of a number of sources of household income for the increase in the transitory variance in our full household income sample. Here, too, we find that a number of sources contributed to the increase, with no single source standing out.[49]

5.4 Summary and Discussion of Results for Pre-Tax Household Income

To summarize, we find that in the case of pre-tax household income, the transitory variance contributes about 30-40 percent to the increase in the total cross-sectional variance over our sample period. This stands in contrast to the case of male earnings, where the entire increase in the cross-sectional variance was due to the permanent component. The increase in the transitory variance of household income is driven by a number of sources of total household income, including spousal (female) earnings, transfers, investment income, and business income.

Our results for household income broadly agree with Gottschalk and Moffitt (2009), who, using the BPEA method and PSID data, find that the transitory variance of (pre-tax) family income rose substantially starting in the mid-1980s and through the end of their sample in 2004.[50] Our results differ from Primiceri and van Rens (2009), who use the Consumer Expenditure Survey (CEX) and find that essentially all of the increase in household income inequality in the 1980s and 1990s was due to an increase in the cross-sectional variance of permanent shocks to income.

[49] The results are available upon request.

[50] They also present some evidence that the transitory dispersion (in this part of their analysis they look at the the 90-10 percentile gap rather than the variance) of labor earnings of the head and spouse, and of the labor income of other household members, did not increase over their period. Thus, the increase in the transitory variance of family income appears to be driven by an increase in the transitory dispersion of transfer income and other nonlabor income (which includes investment income and business income). This is slightly different from our results in section 5.2, where we find that although the transitory variance of labor earnings of males did not increase, all other broad categories of household income contributed to the increase in the transitory variance of household income, including spousal (female) earnings.

6 Empirical Results: After-Tax Household Income

This section explores the role of the federal tax system in the evolution of income inequality. Specifically, we compare the evolution of the total, permanent, and transitory variance of household income, both before and after taxes. As discussed in Section 2.1, our measure of after-tax income adjusts household income for federal income taxes (including refundable tax credits) as well as for payroll taxes. Figure 11 shows the total, permanent, and transitory variance of pre-tax household income (the solid lines, which are identical to those in Figure 9), along with the corresponding variances of after-tax income (the dashed lines), for our male earnings sample. The figure reveals the following: (i) The variance of after-tax income is on average 15 percent smaller than the variance of pre-tax income, reflecting the progressivity of the U.S. tax system. (ii) The tax system reduced the transitory variance (transitory inequality) and the permanent variance (permanent inequality) by about equal amounts. (iii) The effect of the tax system in reducing income inequality (the total variance) appears fairly stable over the sample period, although it might have increased marginally around 1996. (iv) The tax system did not affect the increase in inequality over the sample period: the variance of pre-tax income increased by 39 percent over the sample period, while the variance of after-tax income increased by 38 percent. Overall, we interpret this evidence as indicating that the tax system played a substantial role in reducing all components of inequality, but it did not materially affect the broad trends we find in our analysis of before-tax income measures.[51]

7 Robustness Checks

In this section we discuss a number of tests we have performed to check the robustness of our results. In what follows we only discuss the main conclusions from these tests. The detailed results are available upon request.

7.1 Changes Over Time in the Age Distribution

Our error-components model implies that the decomposition of the cross-sectional variance of income into permanent and transitory components depends on age. For example, as seen in Figure 4, the variance of the ARMA(1,1) transitory earnings component stays flat after about 15 years of a career, while the variance of the permanent component continues to rise linearly with age. This implies that the permanent-transitory variance decomposition in a given calendar year will depend on the age distribution in that year. Therefore, one possible concern is that changes over time in the age distribution might affect the decomposition, masking the effects of "true" changes in the variance of

[51] We reach similar conclusions when we use the full household income sample.

permanent and transitory income components.[52] To check that our results are not simply reflecting changes in the age distribution, we repeat our analysis but now reweight the moments matched in our EWMD estimation procedure so as to keep the age distribution constant over time. We use an extension of the methodology introduced by DiNardo, Fortin, and Lemieux (1996), and used in a number of subsequent papers including Lemieux (2006) and Altonji, Bharadwaj, and Lange (2010). Appendix B describes the procedure for constructing the weights in detail. Overall, our results under this reweighting procedure are essentially unchanged both for male earnings and for household income. (Appendix Figure A5(a) shows our model-based decomposition for male earnings.) We conclude that our findings are not simply reflecting changes over time in the age distribution of the taxpayer population.

7.2 Changes Over Time in the Distribution of Household Composition

In the case of household income, an additional possible concern is that our results might be affected by changes in the distribution of household composition over time. For instance, if total income were more variable for married households than for single households, then changes in the married-vs-single composition of the taxpayer population over time could affect trends in the variances. 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 an indicator 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 composition on the mean of household income, but it does not control for potential effects on the variance. In order to check that our results for household income are not just capturing changes in the distribution of household composition, we have performed three different tests.

First, following the approach described in section 7.1, we reweight the moments matched in estimation in such a way as to keep the distribution of household composition unchanged. In other words, we apply the moment reweighting procedure introduced above in a way that keeps not only the age distribution, but also the distribution of household composition, constant over time. That is, in the description in Appendix B, the demographic characteristics used in creating the weights include not only a full set of age dummies, but also indicator variables for being a single male, a single female, and for the number of children of the taxpayer (up to ten). Once the weights are created in this way, the rest of the procedure is identical to that described in section 7.1.

In the second test, we restrict the household income sample to married households only, and repeat our analysis on this restricted sample. In the third test, we treat observations as coming from different households whenever a household (couple) forms or splits. That is, we define a new

[52] See, for instance, Lemieux (2006).

sample where households with different size/composition are treated as separate households. For instance, 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.[53]

In all three tests described above, our main results remain essentially unchanged. In particular, we continue to find that the increase in male earnings inequality over our sample period was entirely driven by an increase in permanent inequality, while the increase in household income inequality reflected an increase in both permanent and transitory inequality. (Appendix Figure A5(b) shows our model-based variance decomposition for pre-tax household income, using the reweighting procedure described above, on our male earnings sample.)

7.3 Changing the Minimum Threshold in the Sample Selection

We have also checked the sensitivity of our results to setting our minimum threshold for earnings (or household income) to alternative values. Recall that our analysis thus far excluded person-year observations where annual earnings or household income were below a full-year, full-time minimum wage in year 2004, indexed for other years by nominal average wage growth. We have experimented with both lower (up to one-fourth of the original threshold) and higher (up to four times the original threshold) minimum thresholds. In all cases, our main results are mostly unchanged. In particular, the increase in male earnings inequality is still entirely driven by an increase in permanent inequality, while the increase in household income inequality reflects an increase in both permanent and transitory inequality. The shares of the total variance attributed to the permanent and transitory components, however, are somewhat sensitive to setting the minimum threshold to a larger value than in our main treatment.[54]

8 Conclusions

We use a confidential panel of tax returns from the Internal Revenue Service to analyze the role of permanent and transitory income components in the evolution of inequality in male earnings and household income in the United States over the period 1987-2006. We first document an increase in inequality in male earnings and household income in our dataset during this period. This increase

[53] 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.

[54] Appendix Figures A6(a) and A6(b) show the permanent-transitory variance decomposition for male earnings and household income (on the male earnings sample), respectively, setting the minimum threshold to a full-year, full-time minimum wage (four times our original threshold).

in inequality is largest for pre-tax household income, but it is also significant for after-tax household income and for the labor earnings of male primary tax filers.

Next, we examine the role of permanent and transitory income components for the increase in inequality, as measured by the cross-sectional variance of income. Our preferred decomposition is based on our baseline non-stationary error-components model of income dynamics. However, we also provide decompositions using an alternative model specification, as well as approximate or simpler methods that have been used in other studies.

Overall, we find that the results for the *trends* of the permanent and transitory variance components are very robust to alternative variance decomposition methods. For male earnings, we find that the permanent variance increased over the sample period, while the transitory variance did not increase, on net. As a result, the increase in male earnings inequality over our sample period was driven entirely by the permanent component. By contrast, for household income (both before and after taxes), we find that both the permanent and the transitory variance contributed to the increase in inequality. For example, using pre-tax household income for a sample of households with a male primary filer, we find that the transitory variance increased by 34 percent between 1987 and 2006, while the permanent variance increased by 43 percent. As a result, the transitory variance contributed 40 percent of the increase in the total cross-sectional variance over our sample period. If we don't restrict the primary filer to be male, the contribution of the transitory variance to the increase in the total variance of household income was 33 percent. A number of sources of household income contributed to the increase in the transitory variance of household income, including spousal earnings, transfers, investment income, and business income.

In contrast to the *trends,* the *shares* of the total cross-sectional variance attributed to the permanent and transitory income components are sensitive to the decomposition method used. We have argued in favor of model-based decompositions over approximate methods, and we have shown that the latter can produce wrong decompositions when the true underlying data generating process is rich. We have also explored the mechanics underlying the differences in the decompositions generated by two alternative empirically relevant models for transitory income, and we have proposed the $ARMA(1,1)$ specification as our preferred model over the $AR(1)$ specification. Using out preferred model, we find that, for male earnings, the transitory variance accounts on average for 60 percent of the total variance. For pre-tax household income, using our male earnings sample, the transitory variance accounts for about 40 percent of the total variance of household income, whereas using our full sample, the transitory variance accounts for about 60 percent of the total variance.

Finally, we find evidence that the tax system plays an important role in reducing the level of all components of inequality, but that it does not alter the broad trends in the evolution of the different variance components.

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10 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") and stage in the lifecyle. 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 effect 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 adminstrative data sources). The regression equation for individual earnings, $y^i_{a,t}$, is thus:

$$y^i_{a,t} \;=\; f(c^1_t, A^i_{a,t})$$

where c^1_t is a year-specific constant and $A^i_{a,t}$ 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, $y^h_{a,t}$, is thus:

$$y^h_{a,t} \;=\; g(c^2_t, M^h, A^h_{a,t}, F^h_{a,t})$$

where c^2_t is a year-specific constant, M^h is a dummy for male (for the primary filer), $A^h_{a,t}$ is a full set of age dummies (for the primary filer), and $F^h_{a,t}$ is a full set of family size/composition dummies.

11 Appendix B: Reweighting the Moments in EWMD Estimation

This Appendix describes the procedure by which we reweight the moments used in our EWMD estimation so as to keep the distribution of age (for both male earnings and household income) and of household composition (for household income) constant over time. This is an extension of the methodologies used in DiNardo, Fortin, and Lemieux (1996), Lemieux (2006), and Altonji, Bharadwaj, and Lange (2010). The methodology involves calculating weights so that the sample characteristics, when the sample is reweighted, are similar to those in a set of base years. For this, we choose 1999 through 2001 to be the base years to which we wish to reweight each of the individual years. The method proceeds as follows. We first estimate a logit equation, where the dependent variable is an indicator variable for the observation coming from one of the base years, and the independent variables are a full set of age dummies (for household income, we also include indicator variables for being a single male, a single female, and for the number of children of the taxpayer (up to ten)). We then estimate twenty separate logits, one for each year of the sample, where the dependent variable is an indicator for the observation coming from that year, and the independent variables are the same as in the first logit. Using the results from these logits, we then calculate the predicted probability that the observation came from one of the base years given the demographic characteristics of the observation (denoted p(base years|z)), and the predicted probability that the observation came from the year that it actually came from given demographics (denoted p(year=t|z)). Given the unconditional probabilities in the sample that an observation came from a base year (denoted p(base years)) or from a particular year (p(year=t)), the weight for an observation from year t is calculated as

$$\Psi(z) = \frac{p(base\ years \mid z) \cdot p(year = t)}{p(year = t \mid z) \cdot p(base\ years)} \ .$$

12 Appendix C: Moment Conditions

The theoretical moments implied by our baseline error-components model (2)-(5), and which we match to their empirical counterparts in our estimation procedure, are as follows:

$$cov(\xi^i_{a,t}, \xi^i_{a+k,t+k}) = \lambda_t \cdot \lambda_{t+k} \cdot (\sigma^2_\alpha + a \cdot \sigma^2_r) + \rho^k var(z_{a,t}) + 1[k > 0] \cdot \rho^{k-1} \cdot \theta \cdot \pi^2_t \cdot \sigma^2_z \ .$$

Above,

for $t = 1987$, $26 \leq a \leq 60$,

$$Var(z_{a,1987}) = \pi^2_{1987}\sigma^2_z + (\rho + \theta)^2\sigma^2_z \frac{1 - \rho^{2(a-1)}}{1 - \rho^2} \ ,$$

for $1987 \leq t \leq 2006$, $a = 25$,

$$Var(z_{25,t}) = \pi^2_t \cdot \sigma^2_z \ ,$$

for $1988 \leq t \leq 2006$, $26 \leq a \leq 60$,

$$var(z_{a,t}) = \rho^2 var(z_{a-1,t-1}) + \sigma^2_z \cdot (\pi^2_t + \theta^2 \cdot \pi^2_{t-1} + 2 \cdot \rho \cdot \theta \cdot \pi^2_{t-1}) \ .$$

Table 1

Descriptive Statistics by Calendar Year - Various Income Measures

Year	Male Earnings			Before-Tax Household Income						After-Tax Household Income					
				Male Earnings Sample			Full Household Income Sample			Male Earnings Sample			Full Household Income Sample		
	Obs.	Mean	St Dev	Obs.	Mean	St Dev	Obs.	Mean	St Dev	Obs.	Mean	St Dev	Obs.	Mean	St Dev
1987	8,177	10.38	0.78	8,177	10.66	0.77	12,767	10.46	0.84	8,177	10.48	0.73	12,764	10.30	0.78
1988	8,681	10.35	0.81	8,681	10.66	0.80	12,991	10.47	0.86	8,681	10.48	0.76	12,978	10.30	0.80
1989	9,021	10.33	0.81	9,021	10.64	0.82	13,242	10.46	0.86	9,021	10.46	0.77	13,227	10.29	0.81
1990	9,092	10.33	0.81	9,092	10.63	0.81	13,353	10.45	0.86	9,092	10.45	0.77	13,341	10.29	0.81
1991	8,905	10.31	0.81	8,905	10.61	0.82	13,395	10.43	0.87	8,905	10.43	0.77	13,377	10.27	0.81
1992	8,923	10.32	0.83	8,923	10.62	0.84	13,480	10.44	0.88	8,923	10.45	0.79	13,464	10.28	0.83
1993	9,273	10.29	0.84	9,273	10.61	0.84	13,654	10.43	0.89	9,273	10.45	0.79	13,650	10.27	0.83
1994	9,387	10.30	0.83	9,387	10.63	0.84	13,838	10.43	0.89	9,387	10.45	0.80	13,821	10.26	0.84
1995	9,575	10.31	0.83	9,575	10.64	0.85	14,148	10.44	0.91	9,575	10.46	0.80	14,125	10.27	0.85
1996	9,624	10.33	0.83	9,624	10.66	0.86	14,257	10.45	0.92	9,624	10.48	0.81	14,233	10.29	0.86
1997	9,534	10.35	0.82	9,534	10.67	0.87	15,150	10.42	0.93	9,534	10.50	0.80	15,149	10.28	0.84
1998	9,762	10.38	0.82	9,762	10.70	0.88	15,515	10.46	0.94	9,762	10.54	0.82	15,525	10.32	0.86
1999	9,877	10.41	0.82	9,877	10.74	0.88	15,721	10.49	0.95	9,877	10.58	0.82	15,730	10.35	0.86
2000	9,904	10.43	0.82	9,904	10.76	0.88	15,918	10.51	0.95	9,904	10.59	0.82	15,923	10.37	0.87
2001	9,950	10.44	0.82	9,950	10.76	0.87	16,114	10.50	0.94	9,950	10.60	0.81	16,119	10.37	0.85
2002	9,860	10.43	0.84	9,860	10.76	0.88	16,095	10.50	0.94	9,860	10.61	0.81	16,104	10.38	0.85
2003	9,802	10.41	0.84	9,802	10.74	0.88	16,111	10.48	0.94	9,802	10.60	0.82	16,121	10.37	0.86
2004	9,956	10.42	0.84	9,956	10.74	0.89	16,296	10.49	0.96	9,956	10.61	0.83	16,310	10.38	0.88
2005	9,998	10.41	0.84	9,998	10.74	0.90	16,397	10.49	0.96	9,998	10.60	0.84	16,403	10.38	0.88
2006	10,123	10.42	0.85	10,123	10.76	0.91	16,526	10.51	0.96	10,123	10.62	0.85	16,546	10.40	0.89
Total (or Average)	**189,424**	**10.37**	**0.83**	**189,424**	**10.69**	**0.86**	**294,968**	**10.46**	**0.91**	**189,424**	**10.52**	**0.80**	**294,910**	**10.32**	**0.84**

Note: The slightly different number of observations of household income before and after taxes (in Full Household Income Sample) is due to the minimum income threshold in our sample selection criteria. This threshold is applied (separately) to both before- and after-tax income.

Table 2
Estimates of Error-Components Models

Column	1a	1b	2a	2b	3a	3b	4a	4b	5a	5b
	Male Earnings, Baseline Model		Male Earnings, Restricted Model		Pre-Tax Household Income, Baseline Model (Male Earnings Sample)		Pre-Tax Household Income, Baseline Model (Full Household Income Sample)		After-Tax Household Income, Baseline Model (Full Household Income Sample)	
Parameter	Estimate	*S.E.*	Estimate	*S.E.*	Estimate	*S.E.*	Estimate	*S.E.*	Estimate	*S.E.*
Permanent Component										
σ^2_α	0.1430	*0.0076*	0.2099	*0.0047*	0.1556	*0.0046*	0.1204	*0.0064*	0.0933	*0.0057*
σ^2_r	0.0031	*0.0003*	0.0066	*0.0002*	0.0047	*0.0002*	0.0022	*0.0003*	0.0024	*0.0003*
λ_{87}	1.0000		1.0000		1.0000		1.0000		1.0000	
λ_{88}	1.0542	*0.0329*	1.0264	*0.0150*	1.0717	*0.0218*	1.0975	*0.0372*	1.1458	*0.0402*
λ_{89}	1.0987	*0.0352*	1.0527	*0.0159*	1.0920	*0.0218*	1.0926	*0.0353*	1.1459	*0.0390*
λ_{90}	1.0790	*0.0331*	1.0594	*0.0153*	1.0826	*0.0214*	1.0873	*0.0354*	1.1474	*0.0391*
λ_{91}	1.0897	*0.0358*	1.0782	*0.0162*	1.1135	*0.0219*	1.0982	*0.0361*	1.1514	*0.0394*
λ_{92}	1.1223	*0.0378*	1.1112	*0.0167*	1.1279	*0.0220*	1.1249	*0.0368*	1.1798	*0.0408*
λ_{93}	1.1236	*0.0361*	1.1091	*0.0155*	1.1145	*0.0222*	1.1192	*0.0370*	1.1616	*0.0407*
λ_{94}	1.1257	*0.0367*	1.1069	*0.0156*	1.1305	*0.0224*	1.1483	*0.0363*	1.2193	*0.0419*
λ_{95}	1.1593	*0.0382*	1.1267	*0.0158*	1.1488	*0.0231*	1.1954	*0.0391*	1.2633	*0.0450*
λ_{96}	1.1844	*0.0388*	1.1412	*0.0158*	1.1844	*0.0227*	1.2617	*0.0409*	1.3276	*0.0476*
λ_{97}	1.1844	*0.0394*	1.1351	*0.0157*	1.2221	*0.0234*	1.3714	*0.0442*	1.3586	*0.0490*
λ_{98}	1.1711	*0.0386*	1.1336	*0.0156*	1.1842	*0.0228*	1.3936	*0.0454*	1.3581	*0.0491*
λ_{99}	1.2182	*0.0401*	1.1512	*0.0155*	1.2364	*0.0228*	1.3982	*0.0454*	1.3894	*0.0503*
λ_{00}	1.2170	*0.0410*	1.1449	*0.0158*	1.2147	*0.0232*	1.3862	*0.0454*	1.3833	*0.0507*
λ_{01}	1.2214	*0.0411*	1.1356	*0.0155*	1.1514	*0.0215*	1.2852	*0.0427*	1.2640	*0.0464*
λ_{02}	1.2413	*0.0415*	1.1417	*0.0157*	1.1611	*0.0213*	1.2732	*0.0424*	1.2827	*0.0471*
λ_{03}	1.1744	*0.0396*	1.0934	*0.0154*	1.1155	*0.0209*	1.2335	*0.0413*	1.2413	*0.0455*
λ_{04}	1.1950	*0.0397*	1.0905	*0.0150*	1.1233	*0.0205*	1.2964	*0.0436*	1.3005	*0.0479*
λ_{05}	1.2238	*0.0400*	1.1025	*0.0148*	1.1285	*0.0200*	1.2930	*0.0434*	1.2958	*0.0476*
λ_{06}	1.2484	*0.0404*	1.1258	*0.0151*	1.1723	*0.0206*	1.2869	*0.0434*	1.2903	*0.0475*
Transitory Component										
ρ	0.9218	*0.0040*	0.5195	*0.0088*	0.7899	*0.0152*	0.9438	*0.0028*	0.9429	*0.0034*
θ	-0.5866	*0.0076*			-0.4171	*0.0244*	-0.5960	*0.0064*	-0.6247	*0.0065*
σ^2_z	0.2596	*0.0131*	0.2022	*0.0103*	0.1472	*0.0116*	0.1996	*0.0096*	0.1925	*0.0100*
π_{87}	1.0000		1.0000		1.0000		1.0000		1.0000	
π_{88}	1.0122	*0.0453*	1.0471	*0.0446*	0.9781	*0.0758*	0.9749	*0.0570*	0.9161	*0.0570*
π_{89}	0.9627	*0.0459*	0.9779	*0.0418*	0.9898	*0.0669*	0.9900	*0.0480*	0.9274	*0.0487*
π_{90}	0.9794	*0.0398*	0.9672	*0.0402*	0.9655	*0.0632*	1.0098	*0.0444*	0.9503	*0.0450*
π_{91}	0.9805	*0.0426*	0.9423	*0.0455*	0.9450	*0.0656*	0.9975	*0.0450*	0.9272	*0.0445*
π_{92}	0.9826	*0.0476*	0.9352	*0.0512*	0.9893	*0.0648*	0.9871	*0.0482*	0.9283	*0.0471*
π_{93}	1.0029	*0.0399*	0.9688	*0.0409*	1.0165	*0.0641*	1.0290	*0.0456*	0.9560	*0.0450*
π_{94}	0.9659	*0.0410*	0.9268	*0.0439*	0.9470	*0.0650*	0.9535	*0.0421*	0.9080	*0.0429*
π_{95}	0.9443	*0.0394*	0.9166	*0.0388*	0.9490	*0.0659*	0.9537	*0.0464*	0.8972	*0.0474*
π_{96}	0.9185	*0.0393*	0.8895	*0.0392*	0.8879	*0.0629*	0.9037	*0.0423*	0.8375	*0.0433*
π_{97}	0.8941	*0.0401*	0.8586	*0.0412*	0.9238	*0.0643*	0.8760	*0.0428*	0.8145	*0.0424*
π_{98}	0.9340	*0.0351*	0.9000	*0.0384*	1.0515	*0.0606*	0.9254	*0.0407*	0.8832	*0.0391*
π_{99}	0.8882	*0.0355*	0.8627	*0.0377*	0.9678	*0.0543*	0.9297	*0.0356*	0.8618	*0.0351*
π_{00}	0.9182	*0.0399*	0.8968	*0.0413*	1.0127	*0.0608*	0.9843	*0.0357*	0.8988	*0.0370*
π_{01}	0.9119	*0.0378*	0.9062	*0.0398*	1.1055	*0.0579*	1.0792	*0.0341*	1.0034	*0.0345*
π_{02}	0.9685	*0.0385*	0.9781	*0.0407*	1.1306	*0.0555*	1.0964	*0.0331*	1.0065	*0.0338*
π_{03}	1.0372	*0.0354*	1.0492	*0.0378*	1.1471	*0.0555*	1.1121	*0.0332*	1.0388	*0.0338*
π_{04}	0.9856	*0.0370*	1.0041	*0.0392*	1.1569	*0.0592*	1.1017	*0.0360*	1.0303	*0.0356*
π_{05}	0.9517	*0.0315*	0.9873	*0.0325*	1.1566	*0.0521*	1.0833	*0.0320*	1.0272	*0.0312*
π_{06}	0.9517		0.9873		1.1566		1.0833		1.0272	

The table shows point estimates and standard errors of our error-components models in equations (2)-(5). The estimates were obtained by Equally Weighted Minimum Distance (EWMD). See section 3.1.

Table 3

Persistence of Transitory Earnings: ARMA(1,1) vs. AR(1)

Autoregressions of Simulated Transitory Earnings

	ARMA(1,1)			AR(1)		
	1a	1b	1c	2a	2b	2c
Variable	y_{it}	y_{it}	y_{it}	y_{it}	y_{it}	y_{it}
Constant	0.0020	0.0014	0.0015	0.0011	0.0010	0.0013
	(0.0009)	*(0.0009)*	*(0.0009)*	*(0.0008)*	*(0.0008)*	*(0.0008)*
$y_{i,t-1}$	0.5564	0.4015	0.3567	0.5200	0.5187	0.5193
	(0.0014)	*(0.0017)*	*(0.0017)*	*(0.0015)*	*(0.0017)*	*(0.0018)*
$y_{i,t-2}$		0.2899	0.2277		0.0021	0.0013
		(0.0017)	*(0.0018)*		*(0.0017)*	*(0.0020)*
$y_{i,t-3}$			0.1634			0.0006
			(0.0018)			*(0.0018)*
Number of observations	340,000	330,000	320,000	340,000	330,000	320,000
R^2	0.31	0.37	0.39	0.27	0.27	0.27
Sum of lag coefficients	0.5550	0.6880	0.7443	0.5185	0.5173	0.5175

The table shows the results of (pooled) autoregressions of simulated transitory earnings. Earnings were simulated for a single cohort of 10,000 individuals (35 years for each individual) using our estimated ARMA(1,1) and AR(1) specifications for the transitory component of individual (male) earnings.

Figure 1a
Cross-Sectional Variance by Year

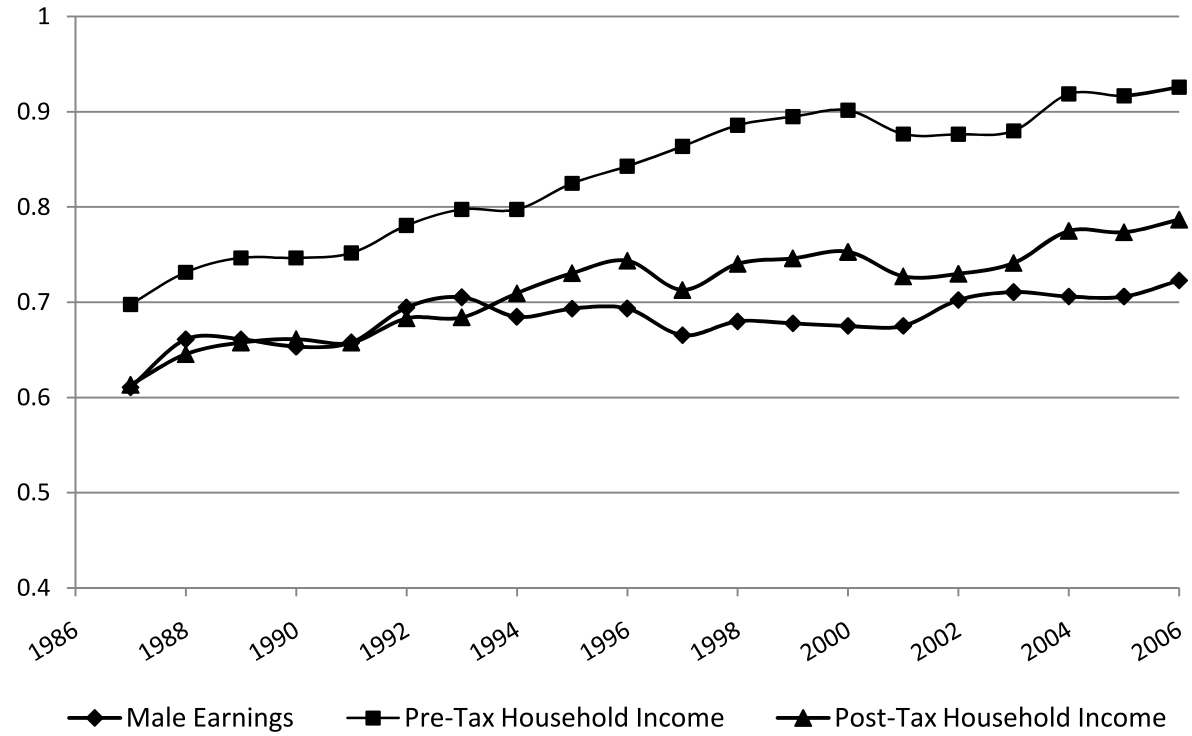


Figure 1b
Cross-Sectional Gini Coefficient by Year

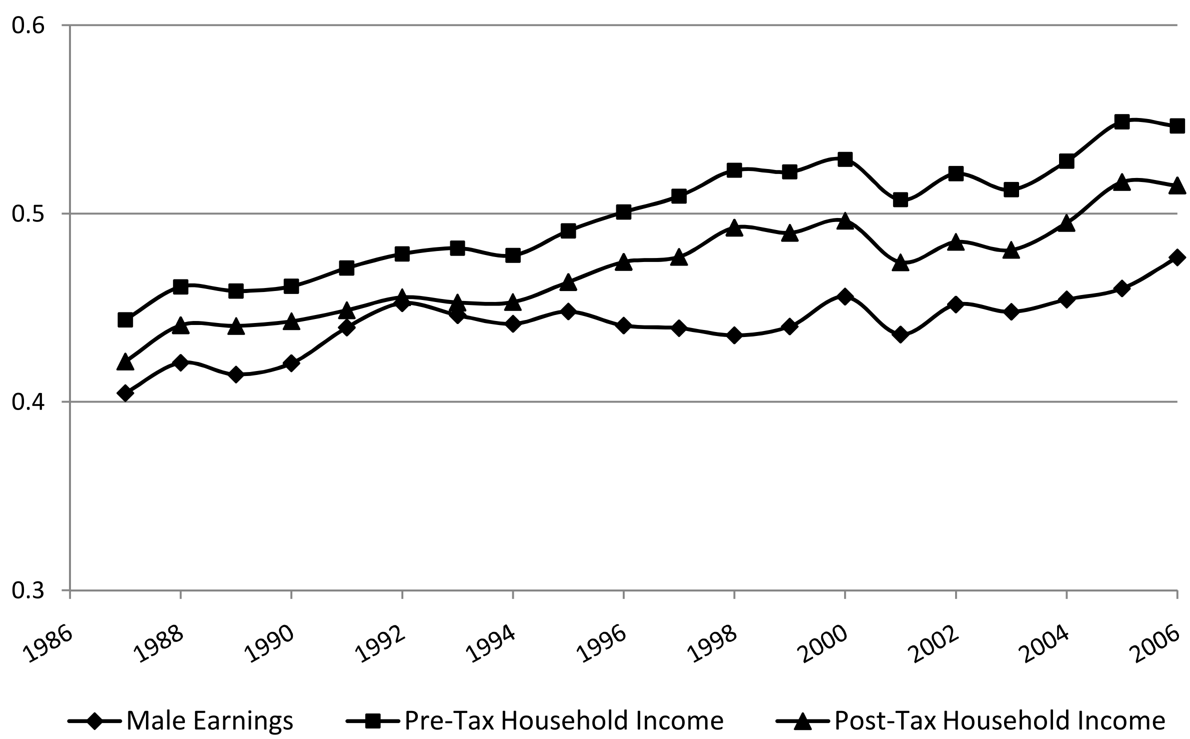


Figure 2
Decomposition of Cross-Sectional Variance
Male Earnings, Baseline Model

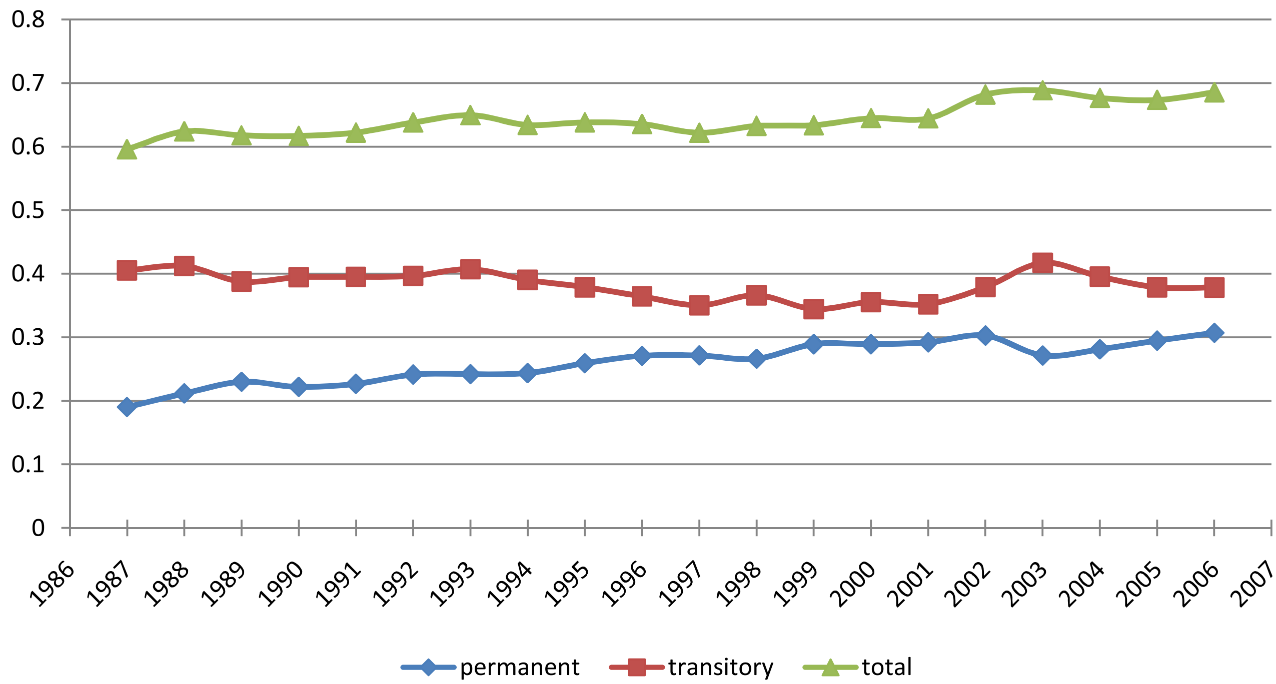


Figure 3
Decomposition of Cross-Sectional Variance
Male Earnings, Restricted Model

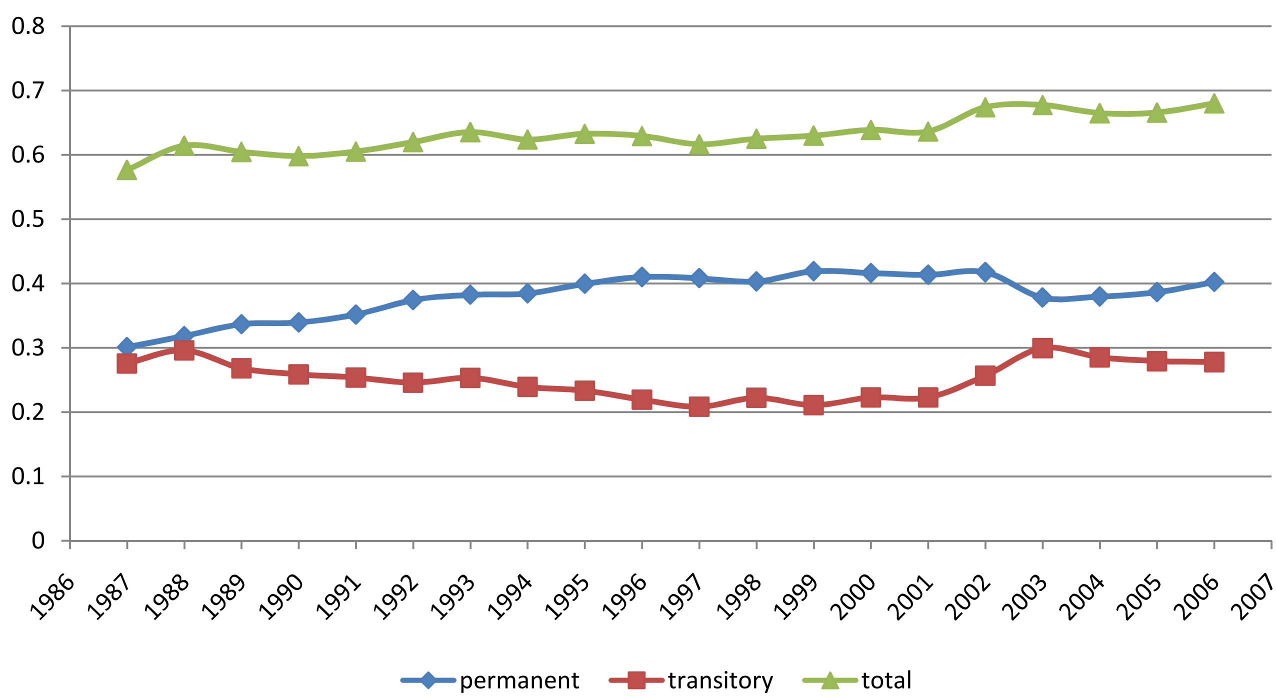


Figure 4
Decomposition of Cross-Sectional Variance over Lifecycle
Baseline Model and Restricted Model

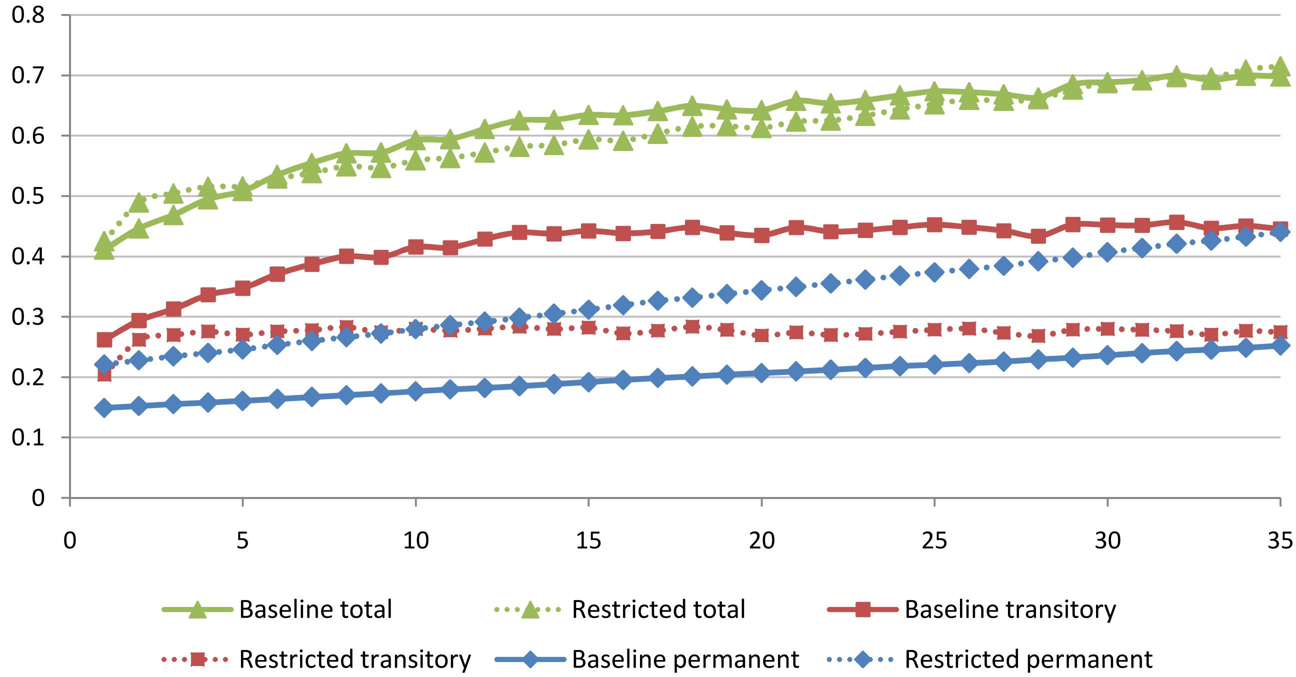


Figure 5
KSS Decomposition of Cross-Sectional Variance
Male Earnings

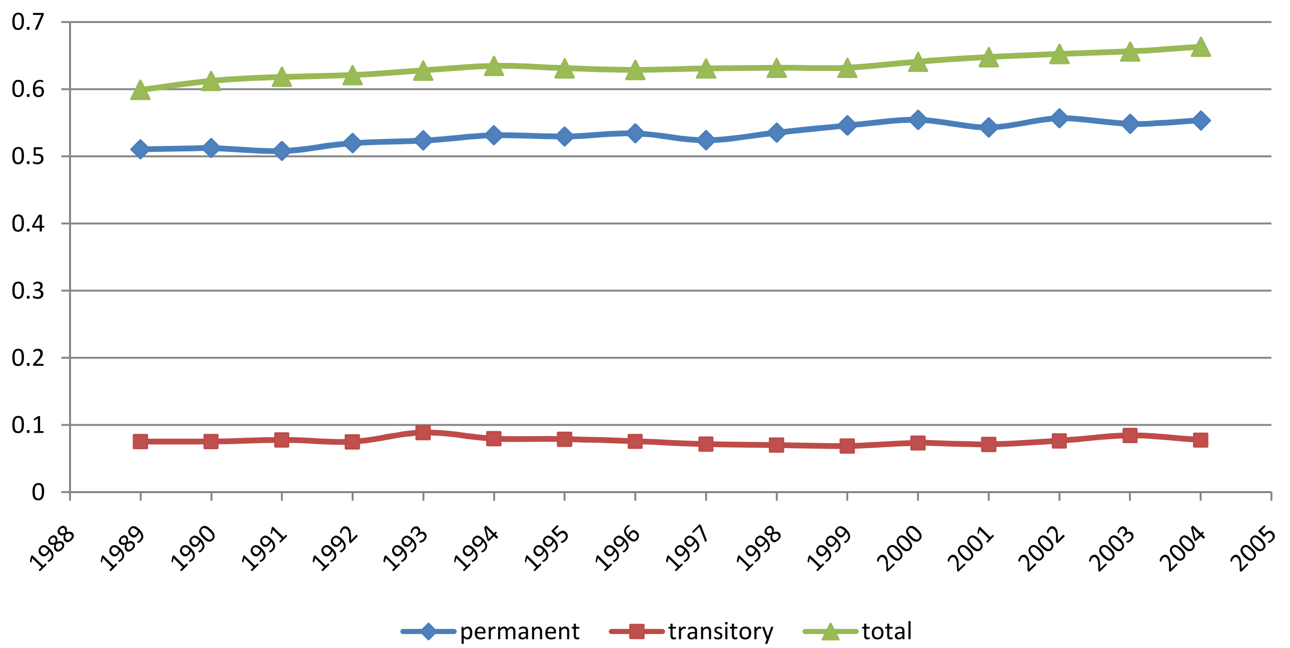


Figure 6
KSS Decomposition of Cross-Sectional Variance
Simulated Male Earnings

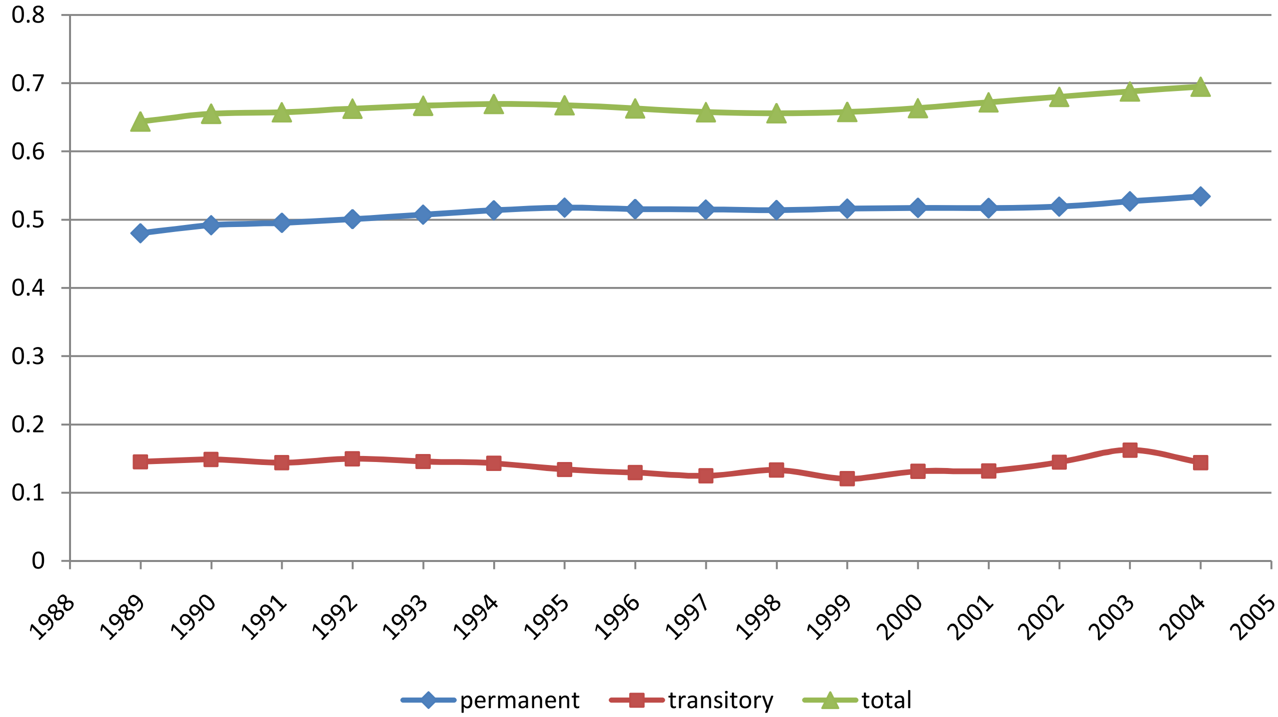


Figure 7
BPEA Decomposition of Cross-Sectional Variance
Male Earnings

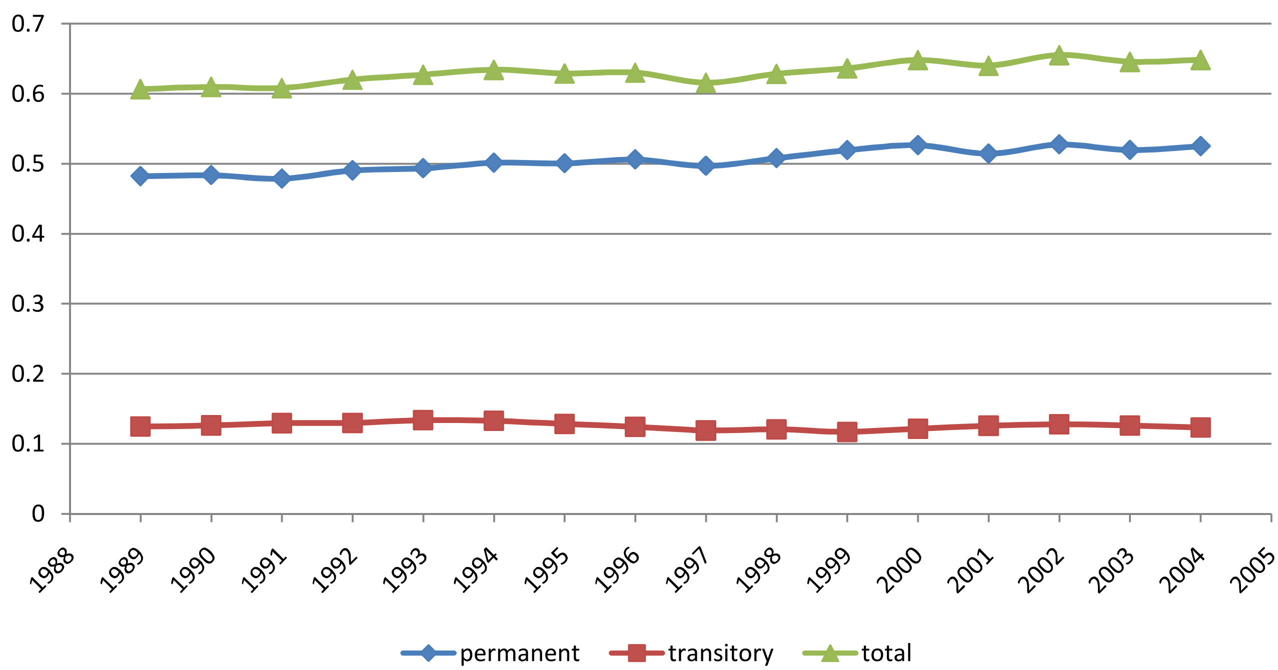


Figure 8
Standard Deviation of One-Year and Two-Year Percentage Changes (Volatility)
Male Earnings

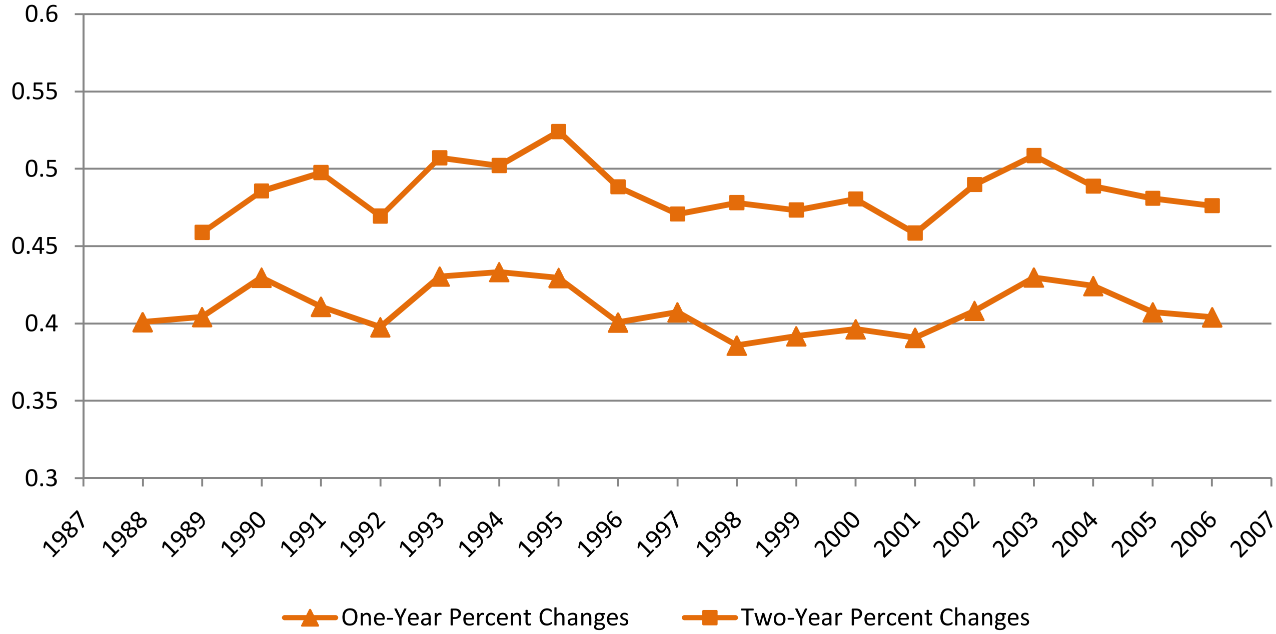


Figure 9
Decomposition of Cross-Sectional Variance
Pre-Tax Household Income; Baseline Model, Male Earnings Sample

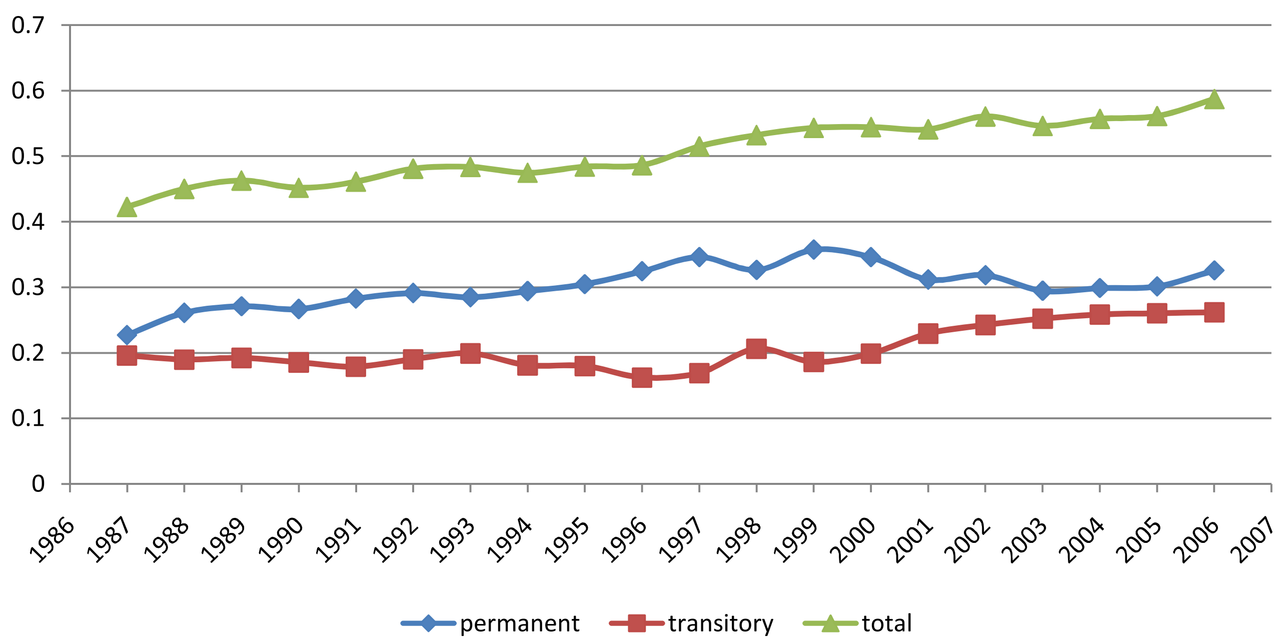


Figure 10
Decomposition of Cross-Sectional Variance
Pre-Tax Household Income; Baseline Model, Full Household Income Sample

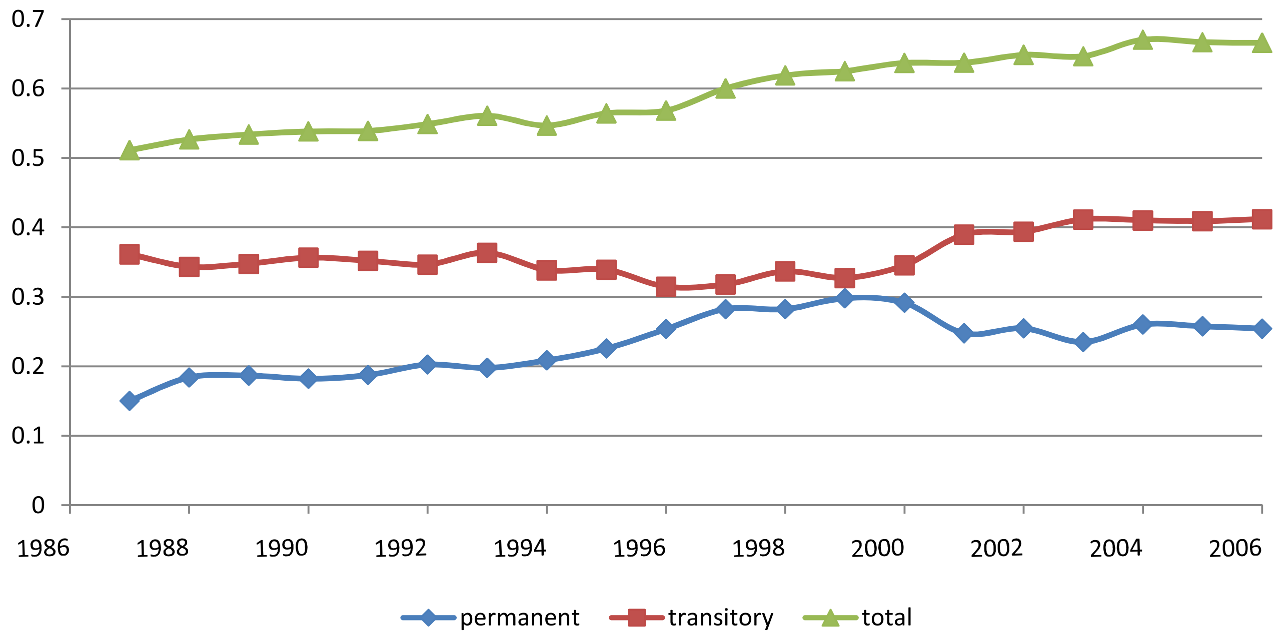
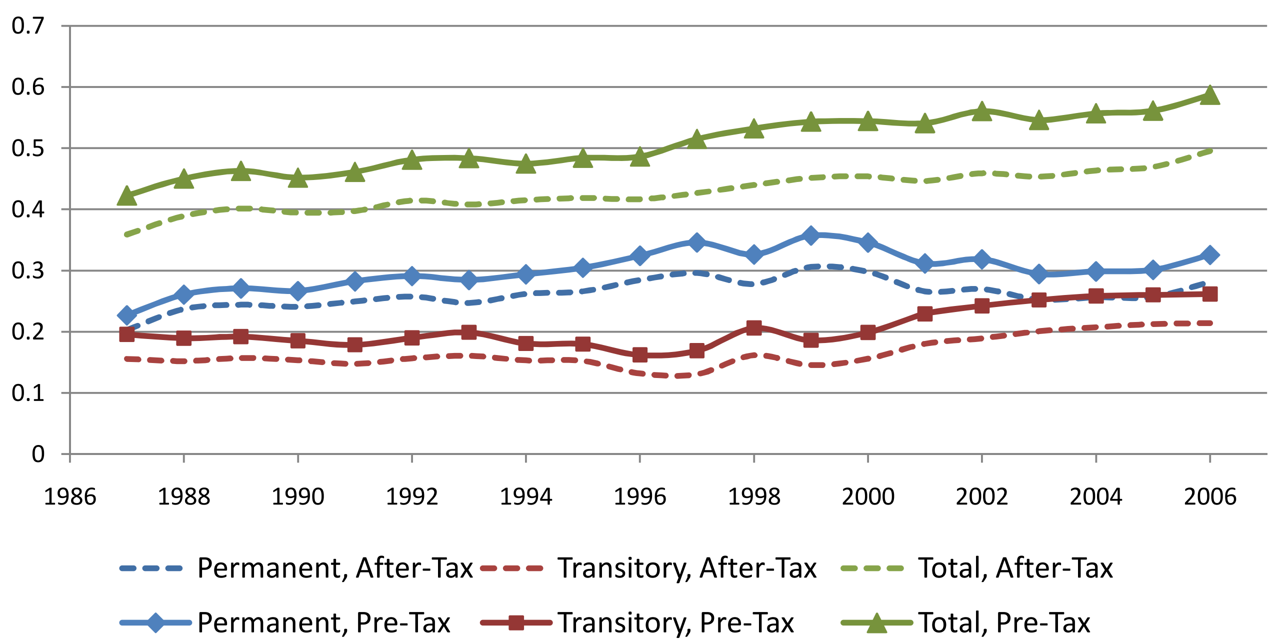
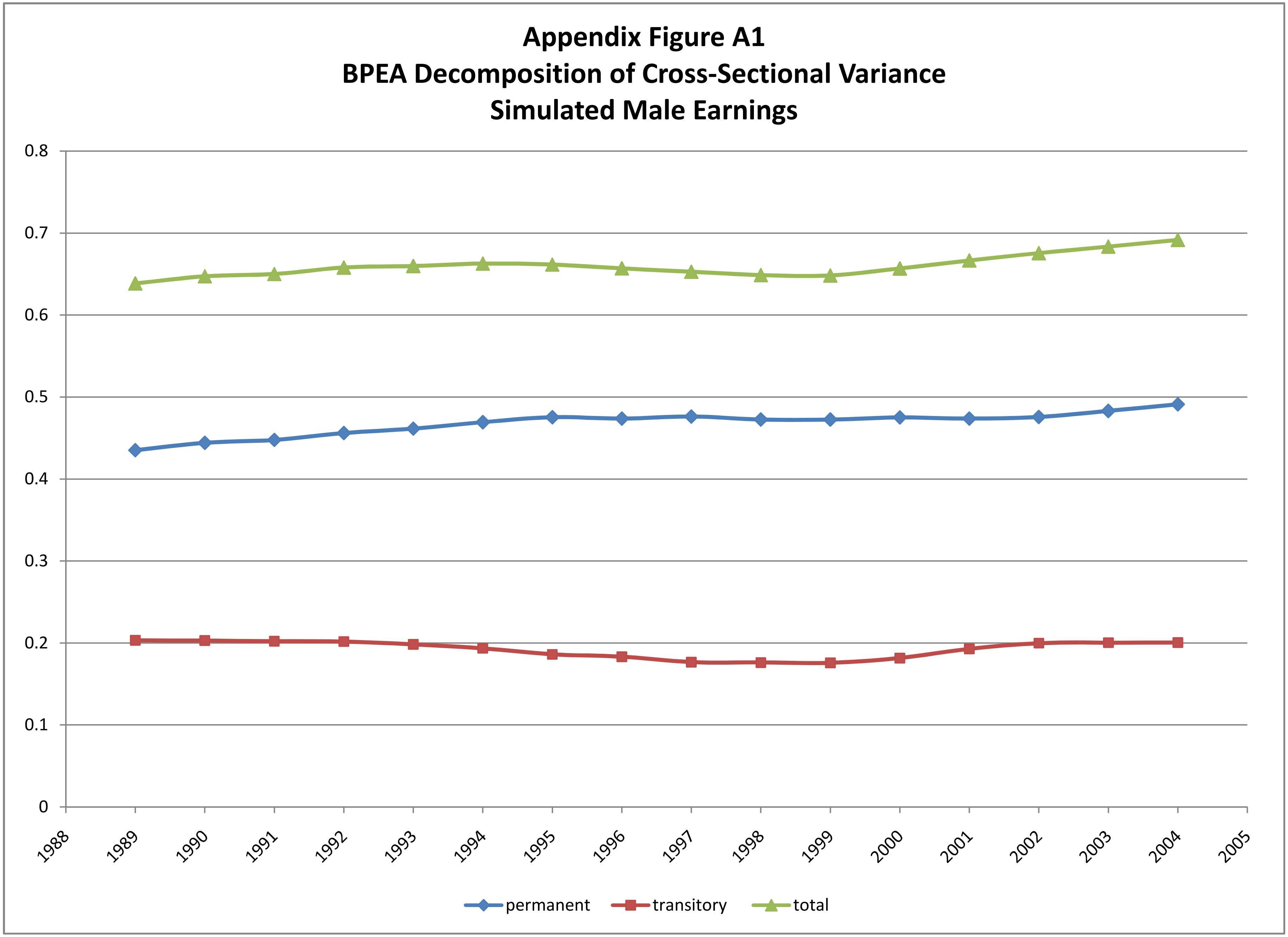


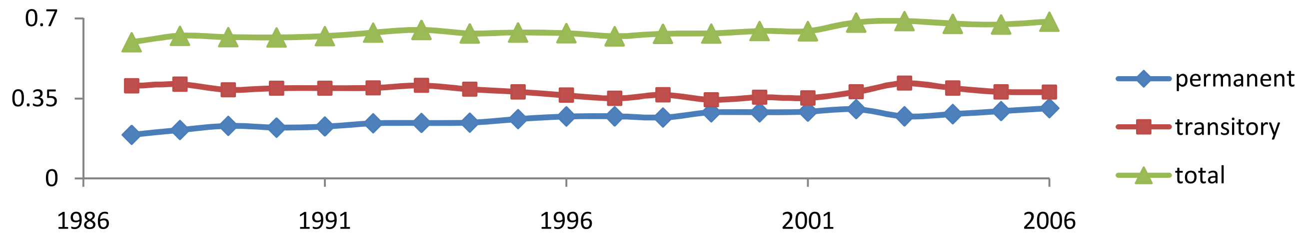
Figure 11
Decomposition of Cross-Sectional Variance
Pre-Tax and After-Tax Household Income, Baseline Model, Male Earnings Sample



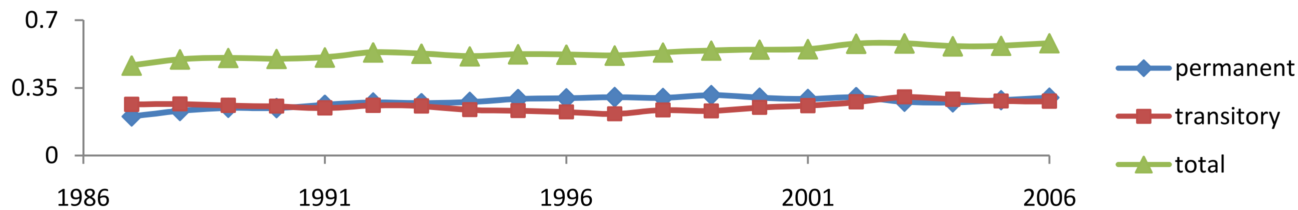


Appendix Figure A1
BPEA Decomposition of Cross-Sectional Variance
Simulated Male Earnings
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
permanent
transitory
total

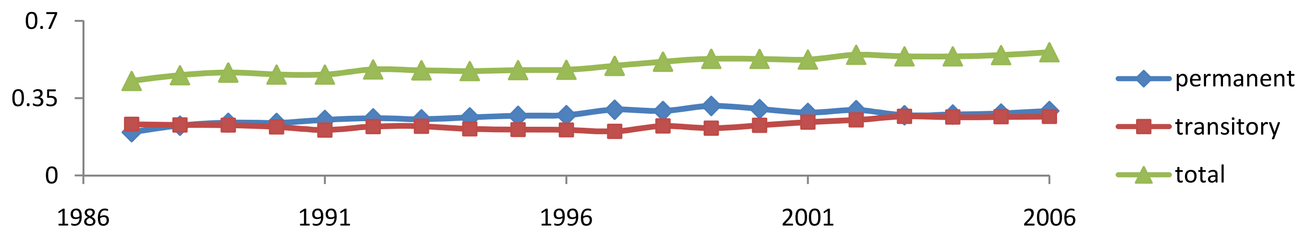
Appendix Figure A2 (a): Baseline Model Variance Decomposition
Male Earnings



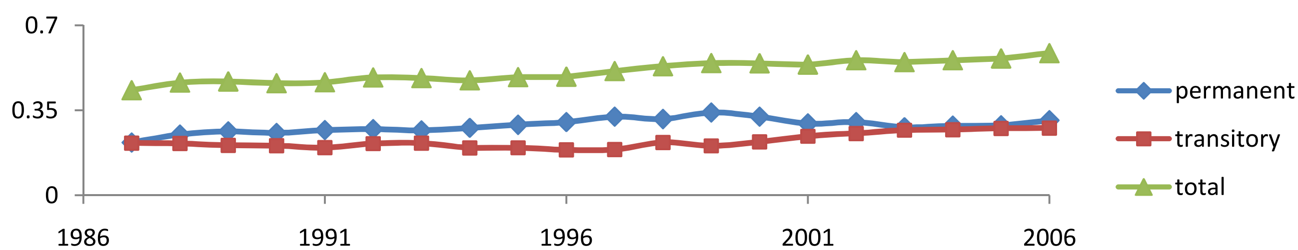
Appendix Figure A2 (b): Baseline Model Variance Decomposition
Male Earnings + Spousal Earnings



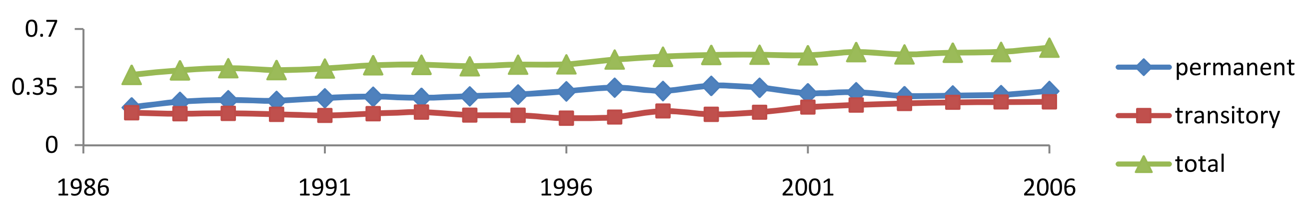
Appendix Figure A2 (c): Baseline Model Variance Decomposition
Male Earnings + Spousal Earnings + Transfers



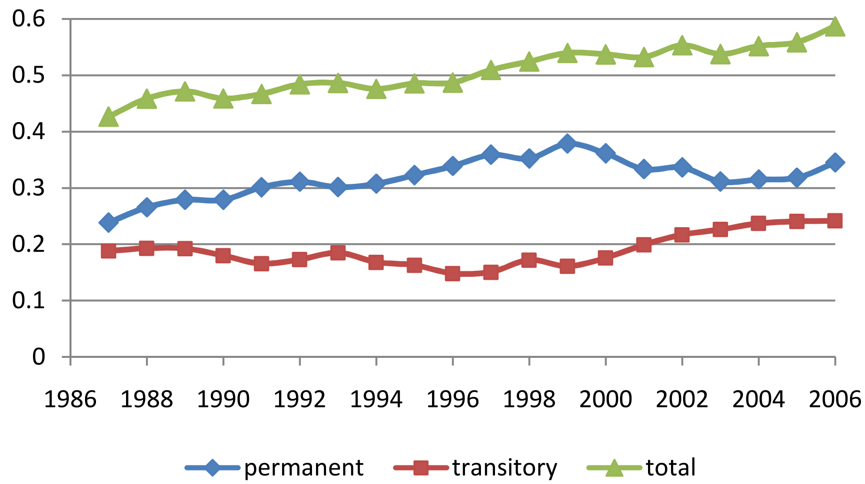
Appendix Figure A2 (d): Baseline Model Variance Decomposition
Male Earnings + Spousal Earnings + Transfers + Investment Income



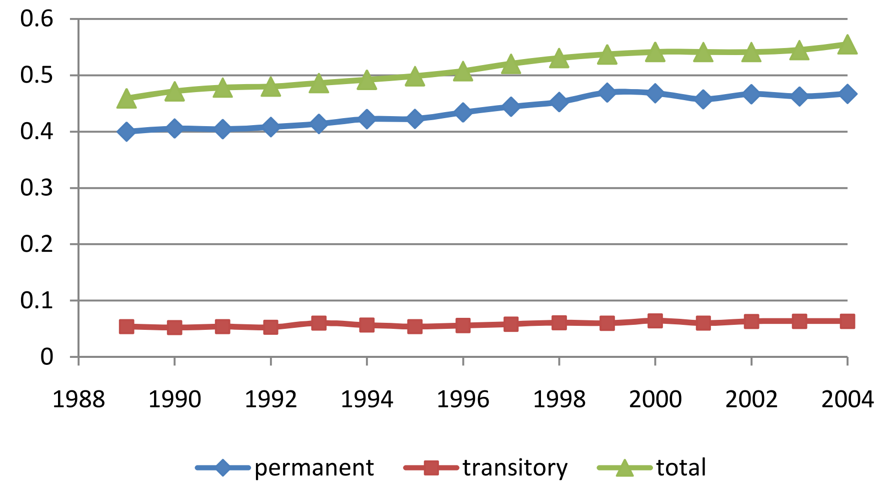
Appendix Figure A2 (e): Baseline Model Variance Decomposition
Total Household Income



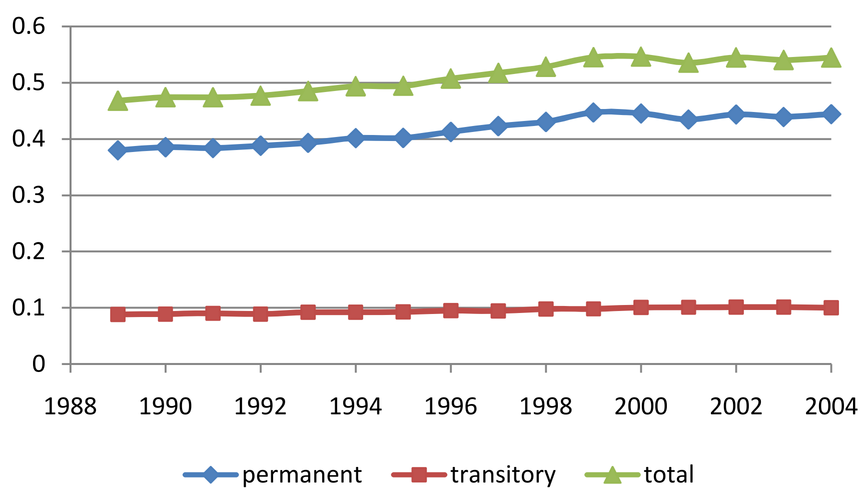
Appendix Figure A3 (a)
Variance Decomposition, Restricted Model
Pre-Tax Household Income, Male Earnings Sample



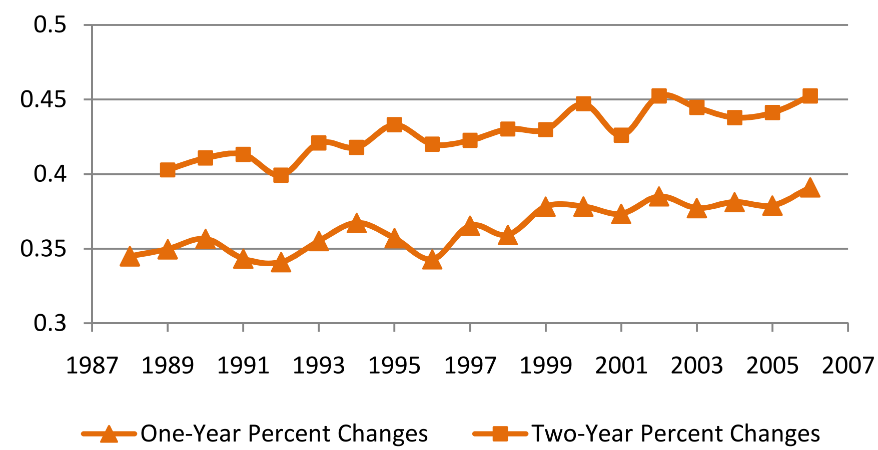
Appendix Figure A3 (b)
KSS Variance Decomposition
Pre-Tax Household Income, Male Earnings Sample



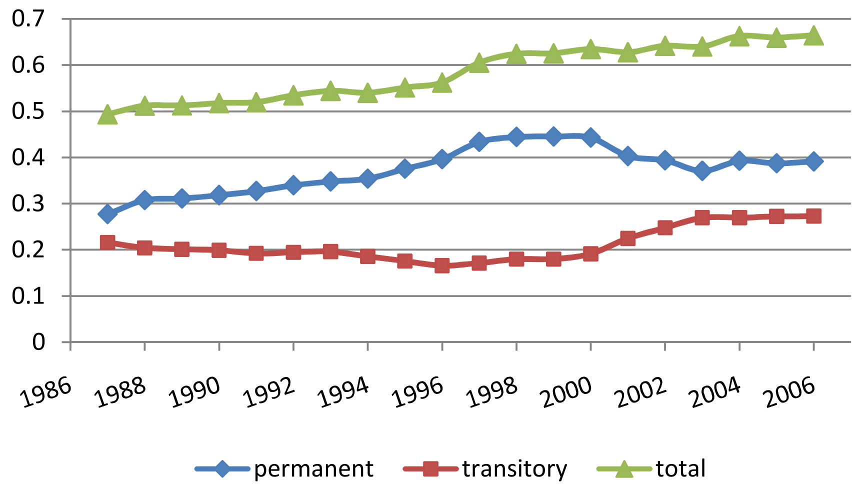
Appendix Figure A3 (c)
BPEA Variance Decomposition
Pre-Tax Household Income, Male Earnings Sample



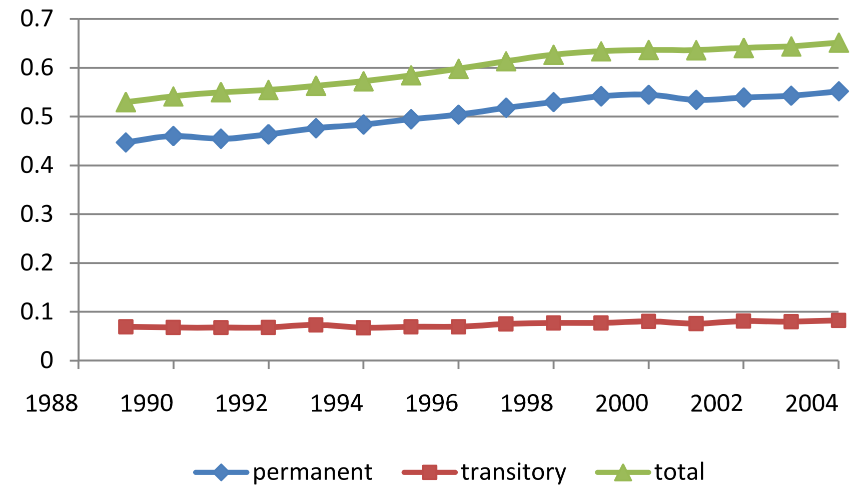
Appendix Figure A3 (d)
Standard Deviation of One-Year and Two-Year
Percentage Changes
Pre-Tax Household Income, Male Earnings Sample



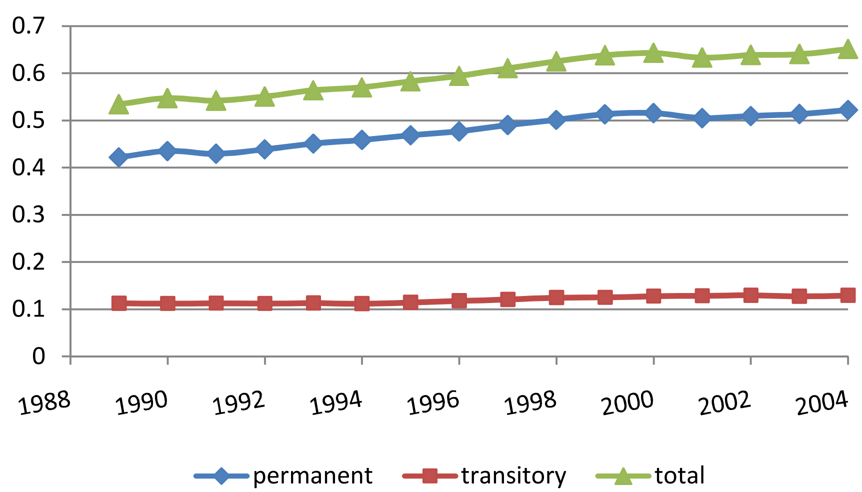
Appendix Figure A4 (a)
Variance Decomposition, Restricted Model
Pre-Tax Household Income, Full Sample



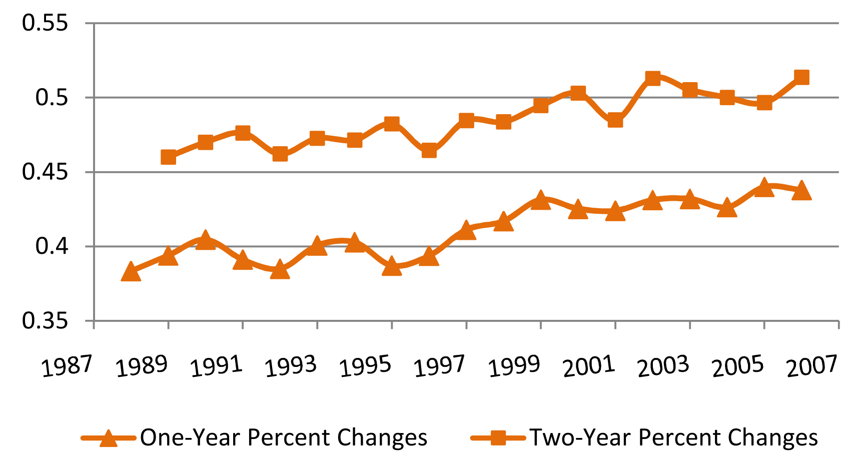
Appendix Figure A4 (b)
KSS Variance Decomposition
Pre-Tax Household Income, Full Sample



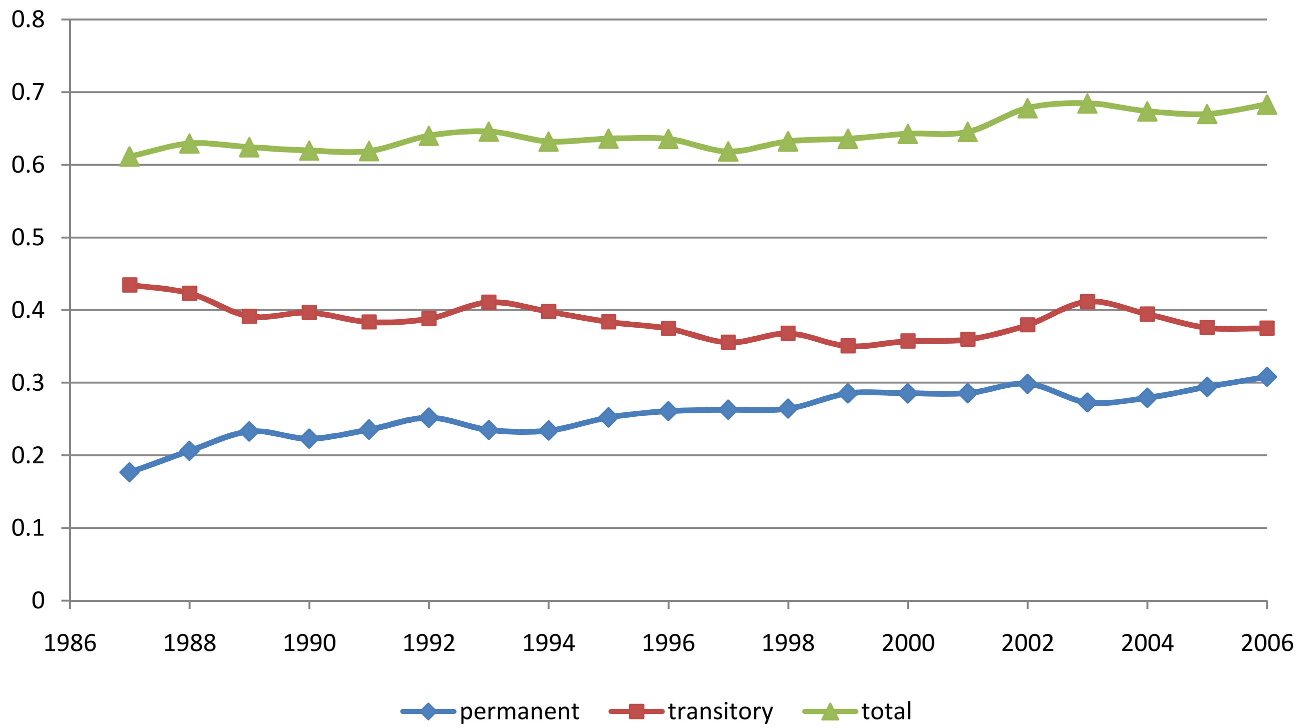
Appendix Figure A4 (c)
BPEA Variance Decomposition
Pre-Tax Household Income, Full Sample



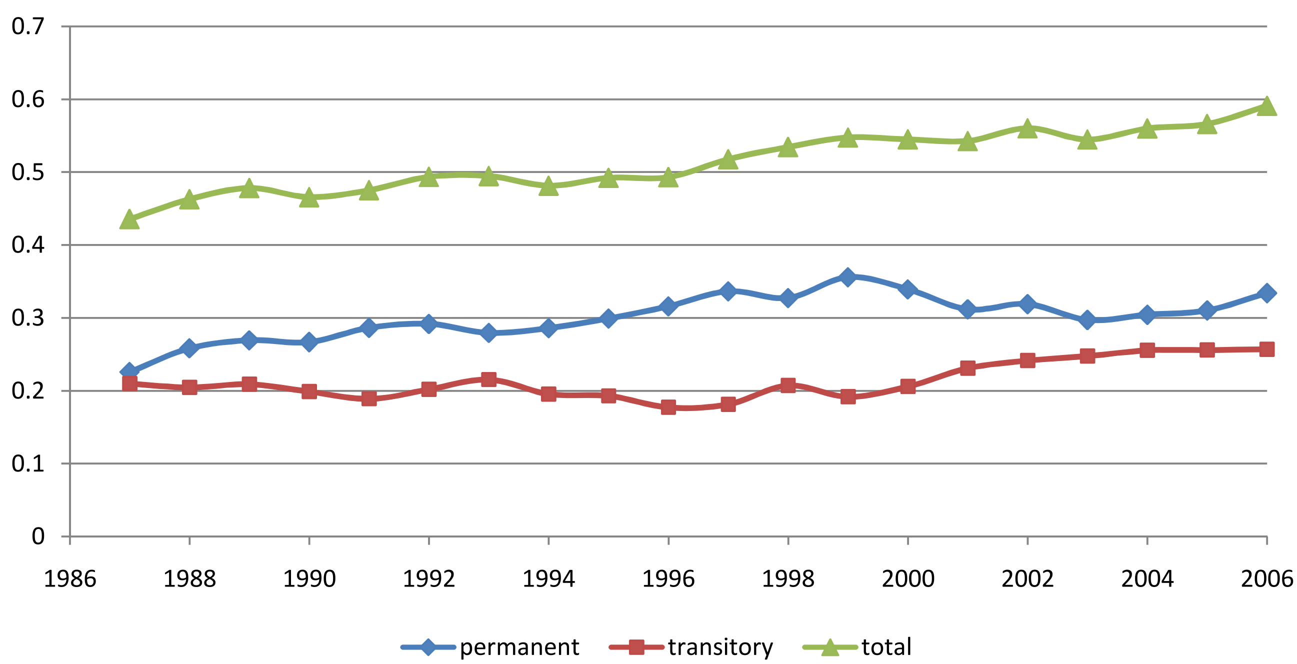
Appendix Figure A4 (d)
Standard Deviation of One-Year and Two-Year Percentage Changes
Pre-Tax Household Income, Full Sample



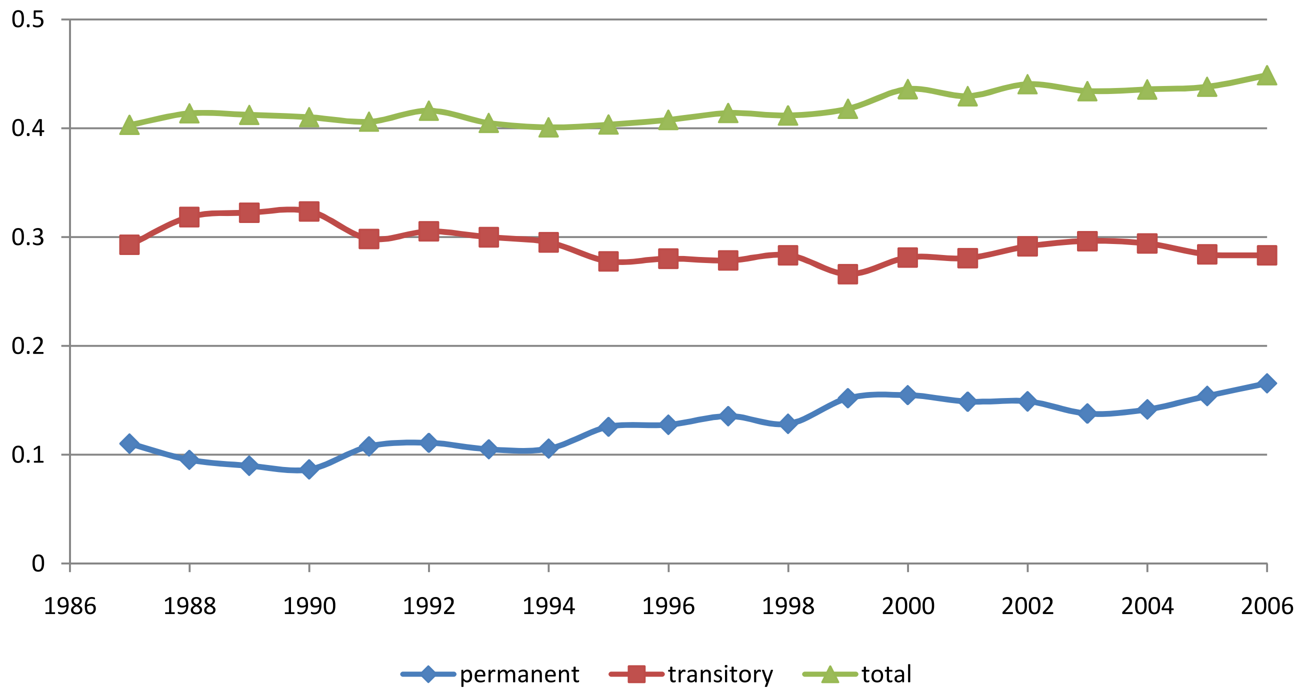
Appendix Figure A5 (a)
Variance Decomposition, Baseline Model
Male Earnings
DiNardo-Fortin-Lemieux reweighting



Appendix Figure A5 (b)
Variance Decomposition, Baseline Model
Pre-Tax Household Income, Male Earnings Sample
DiNardo-Fortin-Lemieux reweighting



Appendix Figure A6 (a)
Variance Decomposition, Baseline Model
Male Earnings
Minimum Threshold: Full-Year Full-Time Minimum Wage



Appendix Figure A6 (b)
Variance Decomposition, Baseline Model
Pre-Tax Household Income, Male Earnings Sample
Minimum Threshold: Full-Year Full-Time Minimum Wage