Income Mobility and Inequality in the United States: Evidence from Tax Data since 1979

By David Splinter*

Draft: September 13, 2018

How does income mobility affect estimates of the distribution of economic growth and inequality? A tax return panel reveals that the bottom of the distribution earned the largest percentage gains, while the top had the largest losses—implying economic growth was earned disproportionately by those with lower incomes. Estimates of how mobility affects annual income inequality are sensitive to measures of inequality, income definitions, and sample restrictions. This sensitivity results from mean-reverting income changes among those with temporarily low incomes in a given year. Income variability is estimated to explain between none and three-quarters of the increase in annual inequality.

JEL: D31, D63, H20

Keywords: Income Inequality, Income Mobility, Income Variability

* David Splinter (david.splinter@jct.gov) is an economist at the Joint Committee on Taxation, U.S. Congress. For helpful comments, I thank Gerald Auten, Tyler Cowen, Jason DeBacker, Tim Dowd, Nick Gutmann, Jeff Larrimore, Joseph LeCates, Borghan Narajabad, Andreas Peichl, Russ Roberts, and George Zodrow. This paper embodies work undertaken for the staff of the Joint Committee on Taxation, but as members of both parties and both houses of Congress comprise the Joint Committee on Taxation, this work should not be construed to represent the position of any member of the Committee. Online data are available at www.davidsplinter.com.

Common measures of U.S. annual income inequality have increased in recent decades. Some reasons for increased household-level income inequality include skill-biased technological change (Acemoglu, 2002), decreased marriage and employment rates (Larrimore, 2014), and the exclusion of employee benefits and government transfers from most income definitions (Burkhauser, Larrimore, and Simon, 2012; Auten and Splinter, 2018). Annual income inequality, however, may not be representative of longer-run income inequality. Tax return panel data show that since the 1980s income mobility has caused a widening gap between annual and multi-year income inequality. This effect can explain up to three-quarters of the increase in annual income inequality.

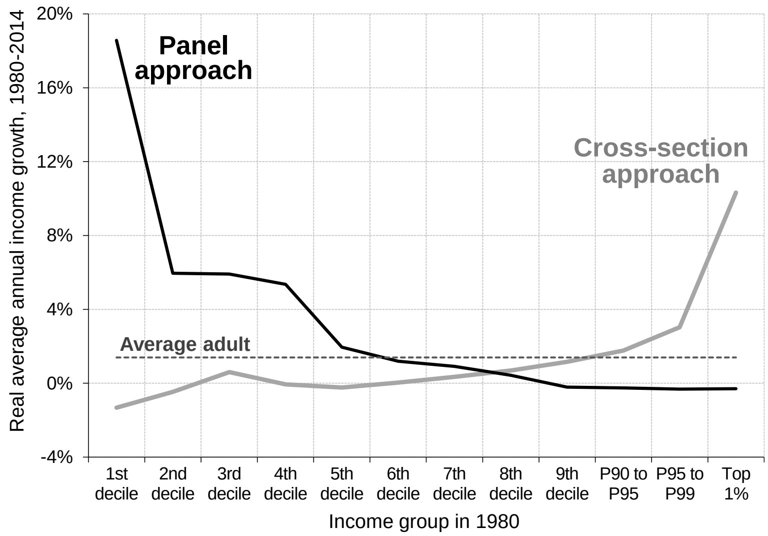
Income mobility effects are also essential for correctly estimating the distribution of economic growth. Figure 1 shows that when comparing changes between 1980 and 2014 cross-sectional income shares, the top of the distribution appears to have had the largest income growth rates. Piketty, Saez, and Zucman (2018) apply this cross-section approach for the same years and unit of observation and argue that the top of the distribution has earned a disproportionate share of economic growth. But mobility reshuffles adults across income groups, meaning cross-sectional comparisons provide inaccurate measures of income growth across the distribution.[1]

A panel approach corrects for this reshuffling. The pattern reverses and the bottom of the distribution has the largest growth rates and the top the largest losses. Hence, a panel approach suggests that economic growth was earned disproportionately by the those with lower incomes.[2] This mean reversion of income implies that the position of an individual in the income distribution in a given year may differ from their longer-run economic experience. Moreover, mean reversion equalizes multi-year incomes relative to annual incomes and can make annual inequality trends differ from multi-year trends. When inequality measures increase more for annual incomes than multi-year incomes, then variability explains a portion of the annual inequality increase.

[1] Dew-Becker and Gordon (2005) and Saez (2016) present similar estimates using tax data that disregard mobility. The "elephant curve" for worldwide incomes also relies on this cross-section approach, resulting in a similar spike for estimated top one percent annualized income changes. Lakner and Milanovic (2016) show that top changes decrease when using a country-based panel approach, but this still fails to account for individual-level mobility within each country. In quantitative models with heterogeneous agents, keeping the identity of observations fixed to account for mobility appears standard when estimating growth rates (Krueger, Mitman, and Perri, 2016).

[2] Other panel studies, such as de Fontenay, Gorgens, and Liu (2002) and Auten and Gee (2009), estimate a similar pattern of income changes over the distribution. Accounting for income sources excluded from tax returns, such as employee benefits and corporate income excluded from individual tax returns, should increase middle income growth rates and decrease estimated top growth rates. See the online data for similar estimates in more recent decades.

Figure 1. Real average annual income growth rates and changes, 1980–2014



Note: Income growth rates (panel approach) and changes (cross-section approach) are the average annual change in total real income of each income group. The same tax returns are used for both approaches, where 1980 income groups are used in 2014 for panel growth rates and 2014 income groups for cross-sectional changes. The sample is restricted to those on tax returns filing in either 1980 or 2014, where primary filers must be at least 20 years old in 1980 and alive at the end of 2014. The unit of observation is adults, where the income of married filing jointly tax returns is divided by two and assigned to each adult. Non-filer incomes are set to 30 percent of average filer income. Income is fiscal income excluding capital gains, as defined in Piketty and Saez (2003), with values bottom-coded to zero and indexed with the CPI-U-RS.
Source: Author's calculations using the CWHS tax return panel.

Previous studies find that variability explains between none and over half of the increase in annual inequality. Kopczuk, Saez, and Song (2010) and DeBacker et al. (2013) estimate a low and constant level of variability of male earnings and tax unit income,[3] after removing those with earnings or income below a threshold of about \$3,400 (2014 dollars) in *any* year during each multi-year window. With this data restriction, variability explains none of the increase in annual inequality. In contrast, after removing only the bottom and top one percent of the distribution, Gottschalk and Moffitt (2009) and Carr and Wiemers (2017) find that the transitory component of male earnings explains at least half of the increase in annual inequality. These different results appear to arise because income mobility is greatest at the bottom of the distribution, and the Kopczuk, Saez, and Song (2010) truncation removes many more of these temporarily low-income observations. This study shows that these two extreme results can both be replicated in tax data by changing this single sample restriction. Specifically, switching from removing adults with any *annual* incomes below \$3,400 to

[3]Tax units include all individuals filing a tax return together or who would file together in the case of non-filers.

removing those with 11-year *average* incomes below $3,400, the fraction of increasing annual inequality due to variability can increase from nearly zero to half.[4]

The importance of accounting for mobility in the bottom of the distribution has been shown by numerous studies. Gottschalk and Moffitt (2009) estimate that male earnings instability—the dispersion of the transitory component—was about three times larger in the bottom quarter of the distribution. Sabelhaus and Song (2009) estimate that volatility—the dispersion of earnings changes—doubles when adding the bottom ten percent of prime-age workers. The U.S. Census Bureau (2016) documents high levels of mobility in the bottom of the distribution between 2009 and 2012, with 35 percent of the population being in poverty for at least two months but only 3 percent over the entire four years. Elasticity of taxable income studies also acknowledge that mean reversion is most pronounced in the bottom of the distribution (Giertz, 2007). For example, Gruber and Saez (2002) remove tax units with incomes below $10,000 to limit the effect of mean reversion. This study provides additional insight into the dynamics of this mean reversion: negative shocks temporarily push many into the bottom of the distribution, but their incomes tend to quickly recover.

Previous studies of long-run trends in U.S. income mobility have often used survey data.[5] These surveys have a number of problems: small and sometimes non-representative samples, biannual sampling or limited coverage over time, top-coding of incomes, and other sources of measurement error (Bound et al., 1994). Instead, this study uses a large panel of administrative tax return data over nearly four decades, which is nationally representative, has no top-coding of incomes, and should have less measurement error.

Some recent studies also use administrative data to study mobility. DeBacker et al. (2013) use tax return panel data to study whether income inequality is permanent or transitory, but only over two decades and excluding non-filers. As those in the bottom of the distribution have the largest mobility, excluding non-filers could impact their results.[6] A number of studies use Social Security individual earnings

[4]Estimates from Carr and Wiemers (2017) similarly imply that when switching from the Kopczuk, Saez, and Song (2010) truncation to dropping the bottom and top one percent of observations, the transitory component of male earnings goes from explaining about none to two-thirds of the increase in annual inequality.

[5]Dynan, Elmendorf, and Sichel (2012) review this literature. Celik et al. (2012) and Carr and Wiemers (2017) compare permanent/transitory decompositions of male earnings in survey and administrative data.

[6]Auten and Gee (2009); Splinter, Diamond, and Bryant (2009); Dowd and Horowitz (2011); Auten, Gee, and Turner (2013); and Larrimore, Mortenson, and Splinter (2016) also use tax return panel data to study income mobility and find evidence of mean reversion, but do not link mobility to inequality and, except for the last two studies listed, also exclude non-filers. Chetty et al. (2014) use tax data to measure intergenerational income mobility, as opposed to the intragenerational income mobility measured in this study.

data, including Congressional Budget Office (2008), Sabelhaus and Song (2009), and Kopczuk, Saez, and Song (2010). These earnings data usually miss income from self-employment, pensions, and investments. This study addresses these limitations by including non-filers and all market income sources reported on individual tax returns. Tax data, however, has limited coverage of government transfers, many of which are means-tested and therefore target those with short-term income losses. Moreover, it does not account for private transfers or the substantial amount of market income missing from tax returns. Accounting for these income sources would result in higher income levels and likely less variability in the bottom of the distribution.

The next two sections describe how income mobility and variability are measured and the tax return panel data. Section III presents absolute mobility estimates and evidence of mean reversion. Section IV presents effects on inequality. Section V concludes.

I. Measuring Income Mobility and Variability

Absolute income mobility is based on the independent income changes of each observation i. Specifically, it is estimated as real income changes between years t_1 and t_2 in percentage terms.

$$AbsoluteMobility = (y_{i,t_2} - y_{i,t_1})/y_{i,t_1} \tag{1}$$

Mobility acts to equalize longer-term incomes relative to annual incomes. This implies that when incomes are averaged over multiple years, this multi-year inequality is lower than annual inequality. Following Kopczuk, Saez, and Song (2010)—and similar to Shorrocks (1978), Maasoumi and Zandvakili (1990), and Fields (2010)—Equation 2 decomposes annual inequality into multi-year inequality, a more permanent source of inequality, and variability, a more transitory source of inequality.

$$Ineq_{Annual} = Ineq_{Multi-year} + Variability \tag{2}$$

With a simple rearrangement, Equation 3 shows that variability can be defined as the gap between annual and multi-year inequalities.[7]

[7]In this framework, relative mobility can be defined as a coefficient between zero and one, where $RelativeMobility = Variability/Ineq_{Annual}$. Hence, when this measure of mobility stays constant, annual inequality and variability both increase or decrease proportionally.

$$Variability = Ineq_{Annual} - Ineq_{Multi-year} \tag{3}$$

For these Shorrocks variability measures, *Ineq* can be any dispersion measure satisfying a number of conditions, including the Gini coefficient and the variance in the natural logarithm of incomes. Annual inequality averages the dispersion of annual incomes y over a multi-year period of length T centered on year t:

$$Ineq_{Annual} = \frac{\sum_{s=t-(T-1)/2}^{t+(T-1)/2} Ineq(y_{i,s})}{T}. \tag{4}$$

Multi-year inequality measures the dispersion of observation level incomes averaged over the multi-year period:[8]

$$Ineq_{Multi-year} = Ineq\left[\frac{\sum_{s=t-(T-1)/2}^{t+(T-1)/2} y_{i,s}}{T}\right]. \tag{5}$$

Parametric decompositions must impose substantial structure to decide the amount of serial correlation in income shocks that is considered permanent or transitory. Shorrocks measures, in contrast, embed this decision in the length of time considered, where longer periods tend to have smaller multi-year inequality and hence more variability. To show the effect of different lengths of time, I consider income changes over 5-, 11-, and 21-year periods.

II. Data

A. *Source Data and Sample Selection*

Incomes are measured using the Continuous Work History Sample (CWHS), which tracks U.S. individual tax returns between 1979 and 2014.[9] The panel is embedded in confidential annual tax return (INSOLE) files from the Statistics of Income of the Internal Revenue Service (IRS). Tax returns are randomly selected for the CWHS based on the last four digits of primary filers' Taxpayer Identification Numbers (TINs, usually Social Security numbers). This sampling method keeps the sample representative, as tax units exit upon death of the primary filer and new tax units enter when they start filing tax returns (Burman et al., 2005).

[8] Multi-year incomes are averaged before taking logs to account for negative incomes: var$[\log(\sum_{s=t-(T-1)/2}^{t+(T-1)/2} y_{i,s}/T)]$. In comparison, Kopczuk, Saez, and Song (2010) estimate transitory log-earnings variances with individual level residuals: var$[log(y_{i,t}) - (\sum_{s=t-2}^{t+2} log(y_{i,s}))/5]$.

[9] This CHWS should not be confused with the Social Security Administration's individual earnings panel of the same name.

The CWHS has a number of limitations. It is a panel of tax returns and therefore has no data for years in which an individual did not file. Studies using the CWHS often limit the sample to those filing every year, but this drops anyone failing to consistently file. Also, by following primary filers—the individual listed first on Form 1040—marriage and divorce cause some secondary taxpayers to enter or leave the sample. This study takes steps to address these issues. By retaining all observations filing at least a minimum number of times within a multi-year period, this study includes the correct number of non-filers. By using adult-level incomes, rather than tax unit incomes, the effect of marriage and divorce is attenuated.

The CWHS sampling rate has generally grown over time. To limit issues arising from taxpayers entering and leaving due to changes in sampling rates, I restrict the sample to tax units that were planned to be sampled every year of each multi-year period. For annual incomes, continuous sampling before 1987 is based on a single TIN last four-digit ending.[10] This means primary filers of all sampled returns before 1987 had TINs with the same last four digits, resulting in a one in 9,999 sample (as no TIN ends in all zeros). For 1987 to 1997, sampling is based on two TIN endings. For 1998 to 2004, sampling is based on five TIN endings. For years after 2004, sampling is based on ten TIN endings, or about a one in a thousand sample.

A number of restrictions are made to the sample. The minimum age of primary filers is set at 20 years old. This is a common restriction to remove a large number of young, often dependent tax filers. Primary filers who die during a multi-year period are removed to prevent distorted estimates of income mobility. To approximate the correct number of non-filers, tax units who file fewer than a minimum number of years are removed. The minimum number of filing years required is set such that, after removing filers who are younger than 20 years old or deceased in any year of the multi-year period, the percent of years filing is similar to that of the annual sample, which includes non-filing tax units (shown in Table A1, Panel A).[11] To help control for declining marriage rates, the unit of observation is changed from tax units to adults by doubling the weight of observations who file joint returns in the center year of each multi-year period. This leaves the 11-year sample with 13,502 adult-level observations for 1988 and 86,249 for 2005 (Table A1, Panel C). The larger sampling rate in recent

[10] Before 1982, five TIN endings were sampled, and afterwards the sampling rate decreased. For Figure 1 sampling only, these additional tax returns are included, allowing for about 30 thousand tax units after the various restrictions.

[11] Splinter (Forthcoming) applies similar restrictions to this panel and explains that the minimum number of filing years requirement allows the inclusion of non-filers while preventing an excess number of non-filers.

years explains the growing number of observations in more recent years.

Additional restrictions are applied to the main sample. To remove most retirement-related income changes, I provide estimates of the working-age population. Specifically, primary filers are required to be aged 62 or younger at the end of each multi-year period.[12] Also, each observation must have an average income over each multi-year period of at least $3,400 (after indexing incomes to 2014 values and imputing non-filer incomes as described below). This leaves the 11-year sample with 10,494 observations for 1988 and 65,551 for 2005. The average income truncation limits the effect of tax units with persistently low or negative incomes, usually due to business losses, removing about half a percent of the sample. Kopczuk, Saez, and Song (2010) and DeBacker et al. (2013) use a more restrictive truncation, removing observations with annual—rather than average multi-year—earnings or incomes below a similar threshold. That restriction removes about 15 percent of the 11-year sample (Table A1, bottom row of Panel C). Using administrative data, Abowd, McKinney, and Zhao (2018) also find a large share of adults with very low annual earnings. They estimate average earnings of only $1,760 among the bottom fifth of eligible workers and emphasize the importance of retaining these individuals in the sample.

B. Income Definitions

The first income definition is *fiscal income including capital gains.* This is defined the same as tax return-based market income in Piketty and Saez (2003)—adjusted gross income (AGI), plus adjustments and excluded Schedule D capital gains before 1987, less government transfers in AGI (unemployment and taxable Social Security benefits)—but capital losses reported on Form 1040 are replaced with losses before limitations. Unfortunately, fiscal income is limited to income reported on tax returns, and therefore only captures 60 percent of national income in recent decades (Auten and Splinter, 2018; Piketty, Saez, and Zucman, 2018). Broader measures of income typically result in smaller inequality levels and increases (Burkhauser, Larrimore, and Simon, 2012). Other income definitions are also considered. For absolute mobility estimates, *fiscal income excluding capital gains* is used to limit sensitivity to business cycles. *After-tax income* is fiscal income including capital gains, plus refundable earned income and child tax credits, less federal taxes.[13] Filer incomes are assigned by tax

[12]Non-retirement life-cycle effects are intentionally included to capture the full effect of variability on annual inequality.

[13]Individual earnings are not considered in this study because wages reported on joint returns cannot be divided between spouses before 1999, when individual Form W-2 data generally became available.

year, so that correct incomes are used even if returns are filed late. Some tax units remaining in the sample do not file tax returns in certain years. For these non-filer observations, their income for that year is set to 30 percent of average filer income, the amount used by Piketty and Saez (2001) and the underreporting-inclusive non-filer income estimate of Auten and Splinter (2018). Incomes are indexed to 2014 dollars with the CPI-U-RS.

Income changes at the tax unit level can result from marriage or divorce. To limit this effect, individual adults are used as the unit of observation. *Equal-split income* is calculated by dividing joint return fiscal incomes by two if married in a given year. This equal-split conversion of married incomes is a simple approach that results in annual inequality levels and increases that are similar to those based on male earnings or tax unit incomes in other studies. Note that even though the unit of observation of equal-split income is separate adults, one should think of this as adjusted tax unit income, not individual income, which has higher levels of variability because there is no income smoothing across spouses. Individual income would also have higher levels of inequality and be less biased by falling marriage rates, which can exaggerate the long-run increase in equal-split income inequality.[14] To address these concerns, unequal-split incomes are also estimated.

Unequal-split income should provide measures closer to individual income. Over the years studied, IRS Statistics of Income data show that male wages on joint returns averaged about 75 percent of combined male and female wages. This fraction, however, tends to increase with income and has fallen over time. Data on individual wages from Form W-2 is not available for most of the sample, therefore I account for these facts by splitting wages between spouses based on the average for each AGI group, linearly interpolating male wage shares using 1979 and 2009 shares. Non-wage fiscal income sources are still split equally. A comparison of this approach to true individual income, as well as the non-filer income assumption, are discussed further in the appendix.

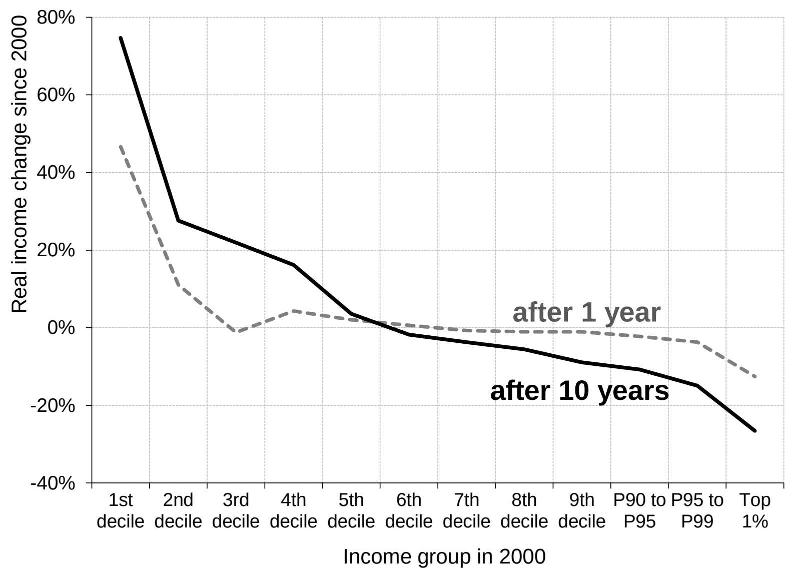
III. Absolute Income Mobility

Absolute income mobility trends across the distribution suggest that much mobility is due to mean-reverting changes in the bottom of the distribution. While the panel approach estimates in Figure 1 show this mean-reverting pattern, its long-run

[14]For example, consider a married couple with only wages, $15 for the primary and $5 for the secondary. An equal-split approach would reduce inequality by assigning both $10, and can be thought of as accounting for sharing within a tax unit or spousal income insurance.

analysis conceals the short-run nature of income changes. Figure 2, instead, shows 1-year and 10-year income changes. As seen before, adults starting in the bottom of the distribution had the largest percentage income increases, and adults starting higher in the distribution had the largest losses. Between 2000 and 2001, incomes of those starting in the bottom decile rose by 47 percent, while incomes of those starting in the top one percent fell by 13 percent.[15] Mean reversion becomes more pronounced over a decade. Between 2000 and 2010, incomes of adults starting in the bottom decile rose by 75 percent, while incomes of those starting in the top one percent fell by 27 percent. This pattern of income changes is similar when the initial year is 1980 or 1990 (see online data), suggesting a persistent pattern of income mean reversion. Next, we consider the robustness of these estimates and then explore the dynamics of mean reversion.

Figure 2. absolute income mobility by income group since 2000

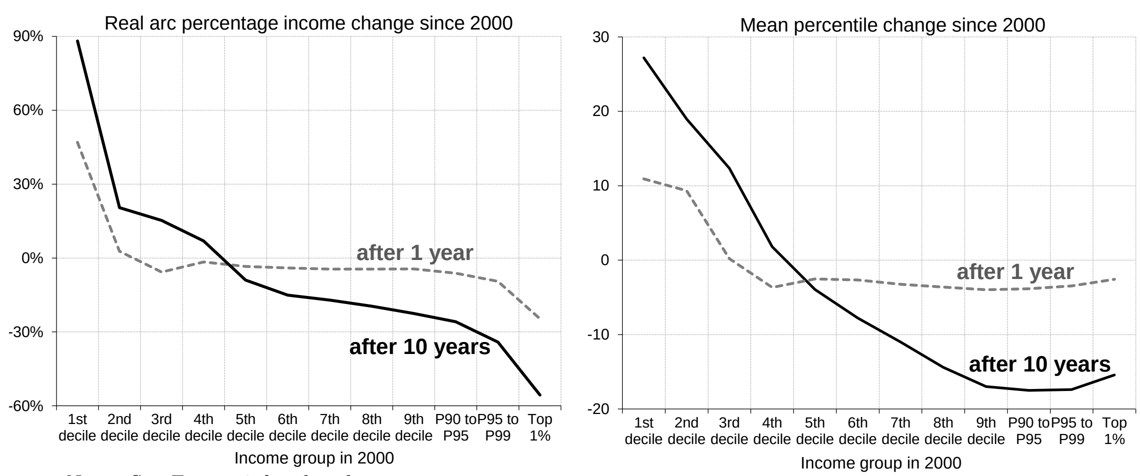


Note: Absolute income mobility is the percentage change in real annual adult-level fiscal incomes averaged across each income group. Percentage changes are set to 100 (−100) percent for incomes switching from non-positive to positive (positive to non-positive) and top-coded at 100 percent. "After 1 year" is for income changes between 2000 and 2001 and "after 10 years" between 2000 and 2010. Income groups are based on 2000 annual fiscal income excluding capital gains. Sample includes tax units with non-deceased primaries 20 to 62 years old between 2000 and 2010. The unit of observation is adults, where income of married filing jointly returns is divided by two. Non-filer incomes are set to 30 percent of average filer income. Adults with average incomes between 2000 and 2010 below $3,400 are dropped. Incomes indexed to 2014 values with the CPI-U-RS.
Source: Author's calculations using the CWHS tax return panel.

[15]For the same years, Splinter, Diamond, and Bryant (2009) estimate similar annual wage changes among consistent tax return filers: a bottom quintile annual wage gain of 32 percent, a top one percent (P99–P99.99) loss of 9 percent, and a top one-hundredth of one percent loss of 56 percent.

Percentage changes are asymmetric because losses are bounded by −100 percent while gains are unbounded. To deal with this asymmetry, observation-level percentage changes in Figure 2 are top-coded at 100 percent. With larger top-codes, mean reversion appears even more pronounced. For example, increasing the top-code to 200 percent almost doubles the bottom decile increase (see online data). Two alternative approaches to deal with the asymmetry of percentage changes are explored. First, arc percentage change is a symmetric measure bounded by −200 and 200 arc percent.[16] Figure 3 (left side) illustrates that arc percentage changes over ten years show similar gains in the bottom decile (88 arc percent) and losses in the top one percent (−56 arc percent). Second, income changes can be measured with relative mobility. Figure 3 (right side) shows a similar pattern for relative mobility over ten years, with adults starting in the bottom decile rising an average of 27 percentiles and those starting in the top one percent falling an average of 15 percentiles. Across these various approaches, the pattern of mean reversion is clearly observed, especially at the bottom of the distribution.

FIGURE 3. MEAN REVERSION: AVERAGE REAL INCOMES BY INCOME GROUP



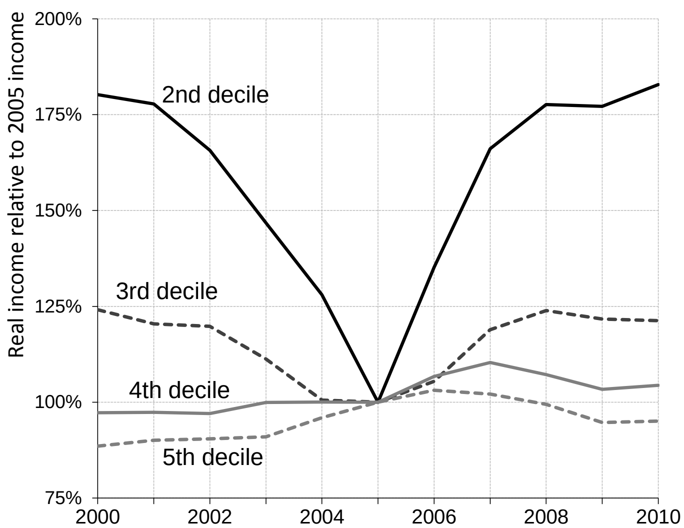
Note: See Figure 2 for details.
Source: Author's calculations using the CWHS tax return panel.

Mean reversion of incomes is caused in part by short-term fluctuations. Although these fluctuations temporarily push incomes toward the bottom of the distribution, incomes tend to quickly rebound. Figure 4 shows dramatic mean reversion among low-income working-age adults following negative income shocks. For example, adults

[16] Arc percentage change equals $2 \cdot (x_{final} - x_{initial})/(|x_{final}| + |x_{initial}|)$. For example, a doubling and halving of income results in asymmetric changes of 100 and −50 percent, but symmetric changes of 67 and −67 arc percent.

in the second decile in 2005 had far higher average incomes in both previous and subsequent years, such that their incomes form a distinct V-shape. Over a 5-year period centered on 2005, average incomes decreased one-third before increasing two-thirds—returning to about the same real income. Over a 9-year period, they decreased almost one-half before returning to the same real income.[17] This V-shaped income pattern is also seen for the third decile, although less pronounced, and becomes muted by the fourth decile. The first decile is not shown because their average incomes decrease from about 500 percent of 2005 income (followed by a symmetric increase), which would distort the scale. Again, this demonstrates that mean-reverting income mobility is most pronounced in the bottom of the distribution.

Figure 4. mean reversion: average real incomes by income group relative to 2005

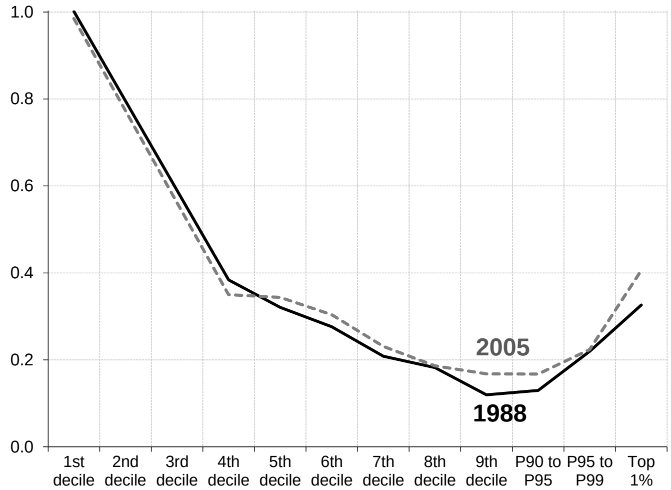


Note: Income deciles are based on 2005 incomes. See text and Figure 2 for sample details.
Source: Author's calculations using the CWHS tax return panel.

What might cause these large income fluctuations? Larrimore, Mortenson, and Splinter (2016) estimate that size-adjusted tax unit income decreases of 25 percent or more are most associated with one worker stopping work, adding a first child, and divorce. Conversely, large increases are associated with adding a worker, adding an additional child after the first child, and marriage. The V-shaped income patterns in Figure 4 could therefore be related to workers stopping and starting work and divorce followed by remarriage.

[17]Similar V-shaped patterns are observed for 1985 and 1995. These averages mask within-decile heterogeneity (see online data).

Figure 5. Variance of absolute income changes by income group



Note: Absolute income changes are three-year (t to t+2) arc percentage changes in real adult-level fiscal income excluding capital gains. To control for short-term fluctuations, income groups are set by 3-year average real incomes for each period: 1987–89 and 2004–06. Second and third deciles are interpolated due to large fractions of non-filers. Adults with 3-year average incomes below $3,400 are dropped. See text and Figure 2 for sample details.
Source: Author's calculations using the CWHS tax return panel.

The extent of mean reversion and reshuffling within each income group can be summarized by the dispersion of short-term income changes—a measure referred to as *volatility*. Figure 5 shows the variance of three-year arc percentage income changes. This volatility measure follows a reverse-J shape over the income distribution, with the highest levels at the bottom of the distribution, low levels in the top half of the distribution, and slightly higher levels in the top five percent. These estimates increased slightly between 1988 and 2005, the business cycle expansions explored in the next section.[18]

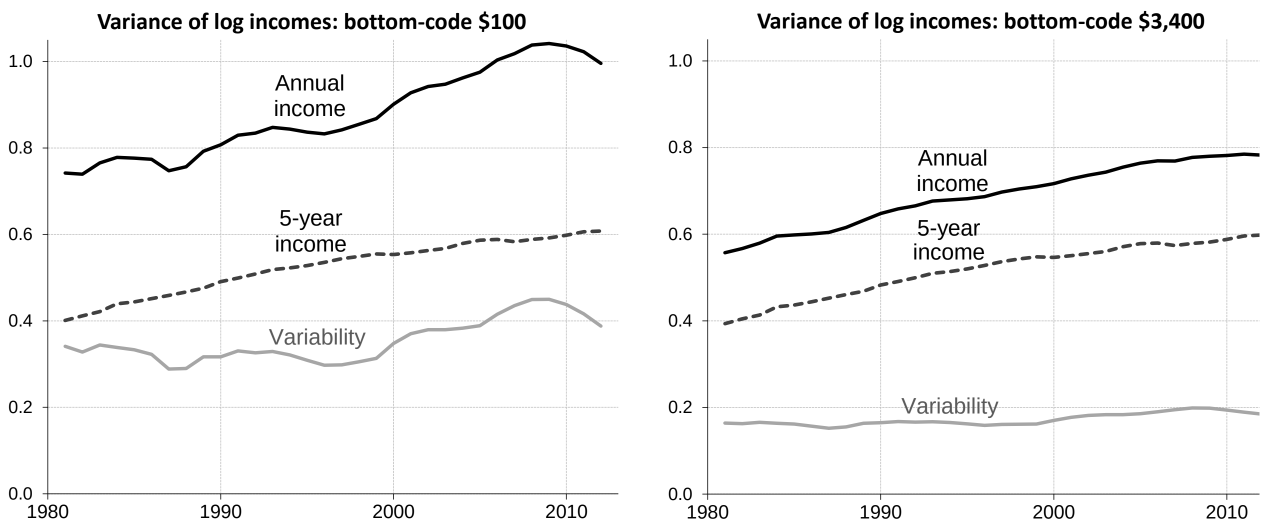
IV. Income Variability and Inequality

Income variability levels are sensitive to different income restrictions and sample selection criteria. Figure 6 shows annual and 5-year income inequality, as measured by variance of log incomes. In the left panel, annual incomes are bottom-coded at $100 before taking natural logarithms and calculating 5-year average incomes. Bottom-coding retains all observations and increases low incomes up to a minimum value. The large gap between annual and 5-year inequalities implies high variability of about

[18]Similar measures for the entire sample, rather than income groups, are shown in Dahl, DeLeire, and Schwabish (2011). Note that mean reversion can attenuate volatility measures, which means volatility can appear constant even as variability increases (Gottschalk and Moffitt, 2009).

0.4 in the 2000s. In the right panel, incomes are bottom-coded at $3,400. The smaller gap between annual and 5-year inequalities implies lower variability of about 0.2.[19] A further sample restriction used in a number of other studies is to truncate, rather than bottom-code, observations with incomes below $3,400 in any single year during each multi-year period. As discussed later, this further decreases variability.

Figure 6. annual and 5-year income inequality and variability



Note: 5-year periods are centered and include years t-2 to t+2. Income is adult-level fiscal income including capital gains. Annual incomes have a bottom-code of $100 in the left figure and $3,400 in the right figure. Adults with 5-year average incomes below $3,400 are dropped. See text and Figure 2 for sample details.
Source: Author's calculations using the CWHS tax return panel.

Table 1 compares changes in income inequality and variability. Starting and ending periods are set at similar points in the business cycle to help control for cyclical effects (Guvenen, Ozkan, and Song, 2014). Specifically, 11-year periods are centered in 1988 and 2005, two years before business cycle peaks. When measured with variance of logs, income variability estimates are sensitive to low-income observations. In order to address this sensitivity, annual incomes are bottom-coded at $100.[20] Panel A, shows that this results in a large variability increase for equal-split incomes from 0.39 to 0.49. Increasing the annual income bottom-code to $3,400 leads to a smaller variability increase from 0.21 to 0.23.

Different inequality measures show different variability levels and trends. For

[19]Increasing the bottom-code from $100 to $3,400 also causes 2010 annual income inequality to decrease from about 1.0 to 0.8. This is similar to the Hyatt and Spletzer (2017) estimated decrease in quarterly earnings inequality from about 1.3 to 1.0 when removing single-quarter workers.

[20]This is also applied to mean log deviations and is similar to U.S. Census bottom-coding at $1. Also, recall that observations with multi-year incomes below $3,400 are truncated for all measures of inequality.

variance of log income bottom-coded at \$100, variability is about one-half of annual inequality. For mean log deviations and Gini coefficients, variability is about one-fourth and on-tenth of annual inequality. Mean log deviation variability increases by about one-fifth and Gini coefficient variability is basically unchanged. These differences exist because variance of log estimates are sensitive to low-income observations, whereas Gini coefficients emphasize the middle of the distribution where income mobility tends to be lower.

Table 1—Income Inequality and Variability, 11-year periods

	Income inequality						**Annual ineq.**
	1988			**2005**			**change from**
	Annual	**Multi-Yr**	**Var.**	**Annual**	**Multi-Yr**	**Var.**	**variability**
Panel A: Equal-split income							
Var. log: bot-code \$100	0.808	0.414	0.394	1.009	0.517	0.492	49%
Var. log: bot-code \$3,400	0.615	0.409	0.206	0.745	0.511	0.234	22%
Mean log deviation	0.352	0.244	0.108	0.483	0.355	0.128	15%
Gini coefficient	0.428	0.378	0.050	0.503	0.454	0.049	−1%
Panel B: Unequal-split income							
Var. log: bot-code \$100	0.967	0.536	0.430	1.066	0.557	0.509	79%
Var. log: bot-code \$3,400	0.741	0.524	0.217	0.790	0.550	0.239	46%
Mean log deviation	0.441	0.321	0.119	0.524	0.391	0.133	16%
Gini coefficient	0.488	0.437	0.051	0.527	0.477	0.051	−1%

Note: For equal-split income, the fiscal income of married filing jointly tax returns is divided by two and assigned to each adult. For unequal-split income, spousal wages are split according to income-level specific average male/female wage splits and non-wage fiscal income is still split equally. Observations are only dropped if average multi-year income is less than \$3,400. See text and Figure 2 for details.
Source: Author's calculations using the CWHS tax return panel.

A. *Annual Inequality Increases and Variability*

What fraction of the increase in annual inequality was caused by variability? The final column of Table 1 divides changes in variability by changes in annual inequality. For equal-split incomes, this shows that 49 percent of the increase in annual inequality was caused by variability—but only when measured by the variance of log incomes bottom-coded at \$100. It falls to 22 percent when incomes are bottom-coded at \$3,400. For other inequality measures the effect is less. Panel B considers unequal-split incomes, for which 79 percent of the increase in inequality was explained by variability for log-variances bottom-coded at \$100, and 46 percent for log-variances bottom-coded at \$3,400.

Why does variability explain a larger share of the unequal-split income inequality increases? This income definition has a larger share of low incomes, and variance of log-income changes are more sensitive to changes from small initial incomes because all changes are proportional, hence an increase from \$1,000 to \$2,000 is considered equivalent to an increase from \$10,000 to \$20,000. Also, note that unequal-split incomes lead to higher levels of inequality and smaller inequality increases. This effect on inequality changes from increasing the low-income share is similar to the Hyatt and Spletzer (2017) finding that inequality increases become *decreases* when adding single-quarter workers to the sample.

How should one interpret this range of results? If one wants to consider all individual-level changes proportionally, including the effect of very low incomes, then up to three-quarters of the increase in income inequality was from variability. Equally dividing incomes between spouses reduces this to half. While a low bottom-code of \$100 captures important effects from stopping and starting work and volatile business income, from a welfare perspective it seems less clear how to weight income changes among those starting with very low annual incomes.[21] A higher bottom-code of \$3,400 reduces the share of increasing annual inequality from variability to about one-half for unequal-split incomes and one-fifth for equal-split incomes. Putting less emphasis on the bottom of the distribution, mean log deviations reduce this to one-seventh. Finally, focusing on the middle of the distribution, Gini coefficients suggest that variability explains little of the increase in annual inequality.

Relative to the 11-year periods discussed above, the effect of variability on inequality is slightly smaller over 5-year periods, as fewer income changes are captured, and slightly larger over 21-year periods (Table A2). Across various inequality measures, 5-year variability accounts for about two-thirds of 21-year variability. This suggests that some variability results from long-term income changes, but the majority results from short-term mean reversion.

Rather than relying only on income, some inequality studies instead consider consumption, which may serve as a better proxy of longer-run incomes and welfare. These studies typically find that annual income inequality increased more than consumption inequality, especially when focusing on the bottom half of the distribution.[22] Meyer and Sullivan (2017) estimate that despite increasing annual income inequality, when measured by 90/10 or 50/10 percentile ratios, consumption inequality has been flat. Between 1980 and 2004, Krueger and Perri (2006) estimate that

[21]Incomes below \$100 are often due to business losses and a low bottom-code captures the effect of this volatile business income on annual inequality. For example, in the 2005 sample, about two-thirds of annual incomes below \$100 had business losses (negative income from combined tax schedules C and E). A higher bottom-code, however, seems more appropriate for less volatile measures closer to welfare, such as consumption or transfer-inclusive measures of after-tax income.

[22]These studies typically use an after-tax transfer-inclusive income definition of "disposable" income, which is more comparable to potential consumption, but can differ from the pre-tax pre-transfer income definition used in this study.

annual income inequality increased four times more than consumption inequality when estimated with variance of logs, and about twice as much with Gini coefficients. Between 1985 and 2010, Fisher, Johnson, and Smeeding (2013) also estimate that with Gini coefficients annual income inequality increased at twice the rate of consumption inequality. Between 1980 and 2010, Attanasio, Hurst, and Pistaferri (2015) estimate that annual income inequality, measured by the standard deviation of logs, increased up to twice as much as consumption inequality, but due to measurement concerns, likely only up to one-third more. Using strong assumptions to correct for measurement error, Aguiar and Bils (2015) estimate a similar increase in annual income and consumption inequality. As consumption inequality should be similar to multi-year income inequality due to partial insurance (Guvenen and Smith, 2014), the range of these findings appears roughly consistent with the range of results in this study.

Also, social distance appears unchanged on a number of margins. For example, the probability of predicting whether an individual is in the bottom or top quartile of annual income based on products or brands consumed is unchanged since 1990 (Bertrand and Kamenica, 2018). If consumption patterns are correlated with longer-run incomes, this observation would also be consistent with relatively slower increases in multi-year income inequality as compared to annual income inequality.

B. Effects of Sample Restrictions and Taxes

The effects of an alternative sample restrictions and income definitions are explored in Table 2. Panel A shows that the Kopczuk, Saez, and Song (2010, hereafter KSS) truncation—dropping observations with annual (rather than multi-year) incomes below $3,400 in any year of the multi-year period—lowers inequality levels and negates almost any variability increase or effect on the increase in inequality. This comparison suggests that the KSS sample restriction, which drops a significant fraction of observations with high levels of variability, may explain the lower and steady levels of variability estimated in both KSS and DeBacker et al. (2013).

Panel B considers after-tax income. Federal individual incomes taxes decrease inequality levels by about one-third and variability levels by about one-fifth (relative to Table 1, Panel A). This is expected given the progressivity of income taxes. The impact of variability on the increase in inequality, however, is slightly larger for after-tax income. This may be related to the growing generosity of refundable tax credits, which can exacerbate after-tax income changes relative to pre-tax changes in credit phase-in ranges (Larrimore, Mortenson, and Splinter, 2016).

Table 2—Income Inequality and Variability, 11-year Periods: Sample Restrictions and Income Definitions

	Income inequality						Annual ineq. change from variability
	1988			2005			
	Annual	**Multi-Yr**	**Var.**	**Annual**	**Multi-Yr**	**Var.**	
Panel A: Equal-split income (KSS truncation, drop if <$3,400 any year)							
Var. log: bot-code $100	0.493	0.349	0.144	0.596	0.448	0.148	4%
Var. log: bot-code $3,400	0.493	0.349	0.144	0.596	0.448	0.148	4%
Mean log deviation	0.269	0.204	0.065	0.382	0.316	0.066	1%
Gini coefficient	0.392	0.349	0.043	0.465	0.430	0.035	−11%
Panel B: After-tax income, equal-split							
Var. log: bot-code $100	0.711	0.346	0.365	0.895	0.416	0.479	62%
Var. log: bot-code $3,400	0.522	0.342	0.180	0.622	0.411	0.211	31%
Mean log deviation	0.300	0.203	0.097	0.402	0.284	0.118	21%
Gini coefficient	0.395	0.346	0.049	0.456	0.407	0.049	0%

Note: See text and Figure 2 for details.
Source: Author's calculations using the CWHS tax return panel.

V. Conclusion

Using a panel of tax returns, this study shows that income mobility can have large impacts on measures of the distribution of economic growth and annual inequality. Relative to cross-sectional comparisons, the pattern of income growth over the distribution reverses when considering mobility. The largest income growth shifts from the top of the distribution to the bottom. That is, those starting with low incomes in a given year tend to have the largest percentage income gains in later years, while those starting with very high incomes tend to have the largest losses in later years. Despite providing clear evidence of the importance of using a panel approach, the estimates presented here are limited to only considering fiscal income (i.e., market income reported on tax returns) and therefore miss substantial amounts of lower- and middle-income growth from tax-excluded health benefits and government transfers (Burkhauser, Larrimore, and Simon, 2012).

Relative to longer-run incomes that account for mobility, measures of annual income have increasingly overstated inequality. I estimate that income variability caused up to three-quarters of the increase in annual inequality since the late 1980s. To a large degree, this effect is due to mean-reverting income changes in the bottom of the distribution. Low annual incomes tend to be understated relative to multi-year incomes, as losses pushing people to the bottom of the distribution are often followed by gains, resulting in V-shaped income patterns over time.

Income variability levels and trends are sensitive to the measure of inequality, the definition of income, and sample restrictions. Inequality measures emphasizing the bottom of the distribution, such as the variance of log incomes, show much larger variability than measures emphasizing the middle of the distribution, such as Gini coefficients. Individual incomes appear to have larger increases in variability than income definitions accounting for sharing between spouses, such as equal-split incomes. This suggests an important role for family labor supply responses and sharing within a family as forms of individual income insurance (Blundell, Pistaferri, and Preston, 2008; Hryshko, Juhn, and McCue, 2017). Low bottom-coding of incomes results in high and increasing variability. Meanwhile, truncating observations with temporarily low incomes results in low and stable variability. Different sample restrictions could explain diverging results in other studies and suggest that care should be taken when bottom-coding incomes or dropping observations. Abowd, McKinney, and Zhao (2018) argue that rather than dropping adults in years when they have low incomes, inequality measures should include eligible workers even if they are temporarily inactive, otherwise earnings inequality measures will understate the impact of the bottom of the distribution. This study's findings suggest that sensitivity analyses along these different margins can be crucial to understand the robustness of income inequality and mobility measures.

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APPENDIX

Additional sensitivity estimates are performed to compare results for unequal-split income to those for true individual income and to check the non-filer income imputation (see online data for details). *Individual income* is estimated like unequal-split income, but the wage of married primary filers is set to their individual Form W-2 wage amount (instead of the AGI group average) and secondary filer wages to the remaining amount of wages reported on the tax return. Form W-2 data is available since 1999, therefore I only consider 2005-centered 11-year estimates. Also, I restrict the fraction of primary wages to range between 10 and 90 percent to prevent outliers due to non-working spouses. For individual income, annual inequalities and variabilities increase relative to the unequal-split income estimates in Table 1, Panel B. For variances of log incomes, they increase by about one-third, for mean log deviations by one-quarter, and for Gini coefficients inequality increases by one-tenth while variability is relatively unchanged. This comparison suggests that relative to individual income, the unequal-split wage imputation moderately underestimates the level of variability.

When starting with individual income and also setting non-filer incomes to actual non-filer incomes (based on wages, dividends, interest, self-employment income, etc., reported on information returns and top-coded at $100,000), annual inequalities and variabilities increase relative to the individual income estimates discussed above. For variances of log incomes bottom-coded at $100, they increase by an additional one-fifth, for those bottom-coded at $3,400 and mean log deviations by about one-tenth, and for Gini coefficients they are unchanged. This suggests that the assignment of equal incomes to all non-filers works well, but slightly understates variability.

As an additional sensitivity check of the uniform non-filer income imputation, I estimate the effect of replacing non-filer incomes with each observation's surrounding-year tax return filer incomes. The concern is that the imputed non-filer incomes may sometimes be too large, therefore surrounding-year incomes are only used if lower than the original imputed non-filer income, and if the taxpayer also has no Schedule C or E business income (which can be significantly underreported) in the 11-year period. In both 1988 and 2005, and for both annual and multi-year inequalities of unequal-split income, variance of log incomes increase only about six percent, mean log deviations three percent, and Gini coefficients one percent. This comparison suggests that there is little impact from imputing excessive non-filer incomes.

Table A1—CWHS Tax Return Panel Summary Statistics

	Fraction years filing		Average age		Mean income ($2014)		Number of observations	
	1988	**2005**	**1988**	**2005**	**1988**	**2005**	**1988**	**2005**
Panel A: Single year (tax units)								
20+yrs old/not dec.	0.832	0.862	42.4	44.8	48,266	64,443	9,054	62,846
Panel B: 11-years (tax units)								
Filed at least 3 yrs	0.754	0.777	39.1	42.1	45,883	57,594	13,429	84,594
20+ years old	0.814	0.824	46.1	48.1	56,482	68,609	9,991	72,188
Not deceased	0.833	0.843	44.2	46.2	58,489	70,886	9,884	69,600
20–62 years old	0.827	0.834	37.9	40.1	60,214	68,101	8,193	57,432
Avg. inc. <$3,400	0.827	0.834	37.8	40.1	60,834	68,770	8,138	57,056
Ann. inc. <$3,400	0.844	0.847	38.2	40.3	64,875	73,337	7,447	51,794
Panel C: 11-years (adults, equal-split incomes)								
Filed at least 3 yrs	0.802	0.816	41.0	43.9	34,033	44,054	18,105	110,513
20+ years old	0.854	0.858	46.4	48.7	38,977	49,684	14,478	92,278
Not deceased	0.871	0.876	44.8	47.1	40,049	51,031	13,502	86,249
20–62 years old	0.866	0.866	38.5	40.7	41,608	50,070	10,547	65,889
Avg. inc. <$3,400	0.866	0.866	38.5	40.7	42,053	50,554	10,494	65,551
Ann. inc. <$3,400	0.883	0.878	38.7	40.9	44,253	53,256	9,093	55,696

Note: Years are the center year of each multi-year period. For example, in Panels B and C, 2005 encompasses 2000 to 2010. Sample restrictions apply to primary filers and each restrictions includes those above. The not deceased restriction means the primary filer must not have died by the end of the annual or multi-year period. Age restrictions apply to all years within each multi-year period. Tax return filer income is fiscal income including capital gains, and non-filer income is 30 percent of average filer income. For Panel A only, the total number of tax units is from the website of Emmanuel Saez.

Source: Author's calculations using the CWHS tax return panel.

Table A2—Income Inequality and Variability, 5- and 21-year periods

	Income inequality						Annual ineq. change from mobility
	1980s			2000s			
	Annual	Multi-Yr	Var.	Annual	Multi-Yr	Var.	
Panel A: 5-years, Equal-split income							
Var. log: bot-code $100	0.774	0.451	0.323	0.996	0.608	0.388	29%
Var. log: bot-code $3,400	0.601	0.444	0.157	0.783	0.598	0.185	15%
Mean log deviation	0.342	0.259	0.083	0.500	0.403	0.097	9%
Gini coefficient	0.421	0.387	0.034	0.514	0.484	0.030	-4%
Panel B: 5-years, Unequal-split income							
Var. log: bot-code $100	0.943	0.589	0.354	1.028	0.63	0.398	52%
Var. log: bot-code $3,400	0.733	0.571	0.162	0.804	0.618	0.186	34%
Mean log deviation	0.435	0.347	0.088	0.528	0.428	0.100	13%
Gini coefficient	0.485	0.449	0.036	0.528	0.498	0.030	-14%
Panel C: 21-years, Equal-split income							
Var. log: bot-code $100	0.833	0.404	0.429	0.971	0.475	0.496	49%
Var. log: bot-code $3,400	0.632	0.401	0.231	0.719	0.471	0.248	20%
Mean log deviation	0.363	0.242	0.121	0.478	0.342	0.136	13%
Gini coefficient	0.434	0.378	0.056	0.500	0.445	0.055	-2%
Panel D: 21-years, Unequal-split income							
Var. log: bot-code $100	1.000	0.518	0.482	1.036	0.519	0.517	96%
Var. log: bot-code $3,400	0.766	0.513	0.252	0.772	0.515	0.257	79%
Mean log deviation	0.453	0.317	0.136	0.522	0.379	0.143	10%
Gini coefficient	0.493	0.434	0.059	0.528	0.469	0.058	-1%

Note: For equal-split income, the income of married filing jointly tax returns is divided by two and assigned to each adult. For unequal-split income, spousal wages are split according to income-level specific average male/female wage splits and non-wage income is still split equally. 5-year periods are centered five years after business cycle peaks at 1986 and 2012. 21-year periods range from their earliest to latest years available, with centered years of 1989 and 2004. Adults with average incomes over each multi-year period below $3,400 are dropped. See text and Figure 2 for details.
Source: Author's calculations using the CWHS tax return panel.