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INCOME MOBILITY AND INEQUALITY: ADULT-LEVEL MEASURES FROM THE US TAX DATA SINCE 1979

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A panel of tax returns shows that income mobility can explain between none and three-quarters of the increase in annual inequality since the 1980s. These estimates are sensitive to different measures of inequality, income definitions, and sample restrictions—mostly due to different treatments of mean-reverting income changes among those with temporarily low incomes. This range of results suggests that sensitivity analyses are crucial to understand the robustness of income inequality and mobility measures.

JEL Codes: D31, D63, H20, J60

Keywords: income inequality, income mobility, income variability

1. INTRODUCTION

US annual income inequality has increased in recent decades. Some reasons for this include skill-biased technological change (Acemoglu, 2002), falling rates of unionization (Farber *et al.*, 2018), and decreasing marriage and employment rates (Larrimore, 2014). However, annual income inequality may not be representative of incomes averaged over a number of years due to income mobility. This paper explores the extent to which intragenerational income mobility can explain the increase in annual inequality.

Mobility tends to equalize incomes over time. Specifically, income changes tend to be mean-reverting at both ends of the distribution: individuals move in and out of the workforce, temporarily pushing some to the bottom of the distribution, and volatile business profits and stock options can temporarily lift some to the top of the distribution. This mean reversion implies that incomes averaged over multiple years—multi-year incomes—are more equal than annual incomes. The resulting gap between annual and multi-year inequalities can serve as a measure of income mobility, referred to here as variability.

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This income variability can increase over time, contributing to increasing annual inequality. Previous studies find that variability explains between none and over half of the increase in annual inequality. Kopczuk *et al*. (2010, hereafter KSS) and DeBacker *et al*. (2013) estimate a low and constant level of variability of male earnings and tax-return income, after removing those with earnings or income below a low threshold in *any* year during each multi-year window. With this sample restriction, variability explains none of the increase in annual inequality. In contrast, after removing only the bottom and top 1 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 KSS truncation removes many more of these temporarily low-income observations.

This paper makes a number of contributions. First, it shows that the range of prior results can be replicated by changing a single sample restriction. Particularly, switching from removing the significant share of low-income adults with any *annual* incomes below \$3400 (2014 dollars) to removing the much smaller share with 11-year *average* incomes below \$3400, the fraction of increasing annual inequality due to variability can increase from nearly zero to half. This sensitivity shows the importance of retaining the bottom of the distribution for estimates of inequality and mobility.[1] Second, this paper explores the sensitivity of inequality and variability estimates to using different measures of inequality and definitions of income. Third, it provides insights into the income dynamics that cause high levels of income fluctuations in the bottom of the distribution, as documented in Gottschalk and Moffitt (2009) and Sabelhaus and Song (2009). These incomes are shown to form a V-shaped pattern over time: negative shocks temporarily push some into the bottom of the distribution, but their incomes tend to quickly recover. This pattern of mean-reverting income changes provides context for the Proctor *et al*. (2016) finding that 35 percent of individuals were in poverty for at least two months between 2009 and 2012 but only 3 percent over the entire four years. Fourth, this paper uses long-run administrative data to address a number of prior data limitations.

Previous studies of long-run trends in the US income mobility have often used survey data.[2] 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 paper 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

[1]Common sample restrictions can have first-order effects on inequality trends. When including relatively low-income single-quarter workers, Hyatt and Spletzer (2017) find that recent inequality increases become decreases. Abowd *et al*. (2018) also argue for retaining those with very low incomes.

[2]Dynan *et al*. (2012) review this literature. de Fontenay *et al*. (2002), Jenkins and Kerm (2006), and Berman (2019) present evidence of mean reversion. Celik *et al*. (2012) and Carr and Wiemers (2017) compare the permanent/transitory decompositions of male earnings in survey and administrative data. Comin *et al*. (2009) use survey data to suggest a link between increasing variability of firm-level sales and worker earnings.

data to study variability. 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 highest levels of mobility, excluding non-filers can bias results.[3] A number of studies use Social Security individual earnings data, such as Congressional Budget Office (2008), Sabelhaus and Song (2009), and KSS. These earnings data usually miss income from self-employment and always miss income from pensions and investments. I address these limitations of prior studies using administrative data by including non-filers and all market income sources reported on individual tax returns.

The next two sections describe the income variability measure and the tax return panel data. Section 4 presents the adult-level mobility estimates and evidence of large mean-reverting income changes in the bottom of the working-age distribution. Section 5 discusses the effects of variability on inequality, and Section 6 concludes.

2. Measuring Income Variability

Annual inequality can be decomposed into multi-year inequality, a more permanent source of inequality, and variability, a more transitory source of inequality. Following KSS, and similar to Shorrocks (1978), Maasoumi and Zandvakili (1990), and Fields (2010),

$$Ineq_{Annual} = Ineq_{Multi-year} + Variability. \tag{1}$$

With a simple rearrangement, variability can be defined as the gap between annual and multi-year inequalities.

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

For these Shorrocks variability measures, *Ineq* can be various dispersion measures, including the Gini coefficient and the variance in the natural logarithm of incomes. In this framework, relative mobility can be defined as a coefficient between 0 and 1, where $Mobility = Variability / Ineq_{Annual}$. Therefore, when this measure of mobility stays constant, variability and annual inequality both increase or decrease proportionally.

Annual inequality averages the dispersion of annual incomes y over a multi-year period of length T centered on year t:

$$Ineq_{Annual} = \frac{\sum_{s=t-(T-1)/2}^{t+(T-1)/2} Ineq(y_{i,s})}{T}. \tag{3}$$

[3]Auten and Gee (2009); Splinter *et al*. (2009); Dowd and Horowitz (2011); Auten *et al*. (2013); and Larrimore *et al*. (2016, 2020) 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 three studies listed, also exclude non-filers. Chetty *et al*. (2014) use tax data to measure *inter*generational income mobility, as opposed to the *intra*generational income mobility measured in these other studies and in this paper.

Multi-year inequality measures the dispersion of observation-level incomes averaged over the multi-year period[4]:

$$Ineq_{Multi-year} = Ineq\left[\frac{\sum_{s=t-(T-1)/2}^{t+(T-1)/2} y_{i,s}}{T}\right]. \tag{4}$$

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. While Shorrocks measures capture a distribution-wide picture, I also use observation-level income mobility measures to evaluate income changes in specific parts of the income distribution.

3. Data

3.1. *Source Data and Sample Selection*

Incomes are measured using the Continuous Work History Sample (CWHS), which tracks the US individual tax returns since 1979. This should not be confused with the Social Security Administration's individual earnings panel of the same name. The CWHS panel is embedded in confidential annual tax return files, often referred to as 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 observations enter when they start filing tax returns and exit upon death of the primary filer (Burman *et al*., 2005).

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, for example due to moving in and out of work with reported earnings or having a child for whom tax credits can be claimed. Exclusion of these individuals can downwardly bias estimates of income mobility. In addition, 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 paper takes steps to address these issues. By retaining all primaries filing at least a minimum number of times within a multi-year period, this paper includes the correct

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

number of non-filers. Using adult-level incomes, rather than tax-return incomes, the effect of marriage and divorce is attenuated.

The CWHS sampling rate has generally grown over time. To remove issues from taxpayers entering and leaving due to changes in sampling rates, I only include those 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. This means primary filers of sampled returns before 1987 had TINs with the same last four digits, resulting in a one in 9999 sample (as no TIN ends in all zeros). For 1987–1997, sampling is based on two TIN endings. For 1998–2004, 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.

The sample is limited to the working-age population to remove most income changes related to retirement. Primary filers must be between 20 and 62 years old and non-deceased throughout each multi-year period. Note that non-retirement life-cycle effects are intentionally included to capture the full effect of variability on annual inequality. To approximate the correct number of non-filers, those filing fewer than 3 years for the 11-year sample (and 1 year for the 5-year sample) are removed. Splinter (2019) applied similar restrictions to this panel. 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. Tax returns with a head of household or other non-joint status are treated as having one adult. This leaves the 11-year sample with 10,547 adult-level observations for 1988 and 65,889 for 2005. The growing number of observations is due to the larger sampling rate in recent years.

A final restriction limits the effect of tax units with persistently low or negative incomes, usually due to business losses. Each observation must have average income over each multi-year period of at least \$3400 (after indexing incomes to 2014 values and imputing non-filer incomes as described below). This removes about half a percent of the 11-year sample, leaving it with 10,494 observations for 1988 and 65,551 for 2005. KSS 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 non-randomly removes about 15 percent of the 11-year sample, an extremely large fraction. Using administrative data, Abowd *et al*. (2018) also find a large share of adults with very low annual earnings. They estimate average reported earnings of only \$1760 among the bottom fifth of eligible workers and emphasize the importance of retaining these individuals in the sample due to transitions in and out of work with reported earnings. For annual earnings volatility, Ziliak *et al*. (2020) also consider the impact of observations with zero earnings.

3.2. *Income Definitions*

The main 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—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 about 60 percent of national income in recent decades (Auten and Splinter, 2018; Piketty *et al*., 2018). Broader measures of income typically result in smaller inequality increases. Other income definitions are also considered. For individual-level mobility estimates, *fiscal income excluding capital gains* is used to limit sensitivity to business cycles. Pre-tax incomes are the standard focus of inequality and mobility studies, but taxes can also have effects. *After-tax income* is defined as fiscal income including capital gains, plus refundable earned income and child tax credits, less federal individual income taxes. Filer incomes are assigned by tax 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, income is set to 30 percent of average income of filers for that year, the underreporting-inclusive estimate based on information returns of non-filers (Auten and Splinter, 2018). Incomes are indexed 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 tax return incomes by two if married and filing jointly 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 inequality and variability because there is no income smoothing across spouses.

Unequal-split income provides a measure 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 are not available for most years of the sample; therefore, I account for these patterns by splitting wages between spouses based on the average for various AGI groups, 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 in recent years, as well as a sensitivity check of the non-filer income assumption, is discussed in the online appendix.

Size-adjusted income provides a measure that accounts for children and the sharing of resources. Incomes are size adjusted following the standard approach: divide incomes by the square-root of the number of individuals within the tax unit, including dependents, and set weights by the number of individuals. This follows Congressional Budget Office (2018) except for one difference—by only accounting for economies of scale within a tax unit, it does not capture sharing between separate tax units living in the same household, such as cohabiting couples (Larrimore *et al*., 2019).

4. Individual-Level Income Mobility

Individual-level income mobility estimates show the importance of income increases for adults starting with low incomes. Figure 1 (left side) shows average

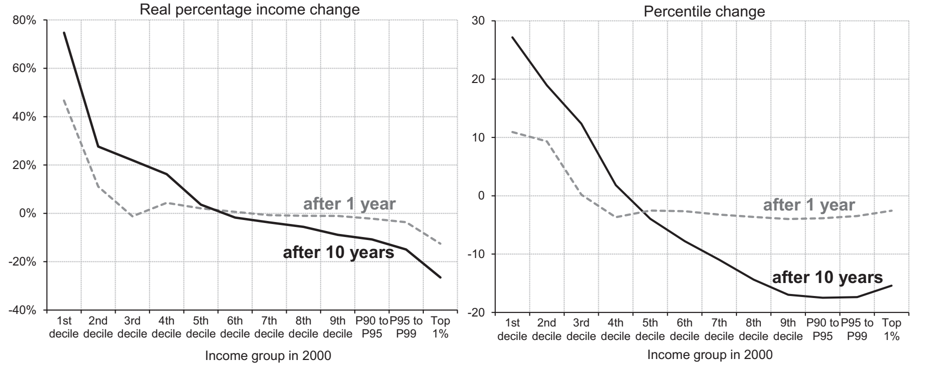

Figure 1. Individual-Level Income Mobility by 2000 Income Group.

Notes: "After 1 year" shows average income changes between 2000 and 2001 and "after 10 years" between 2000 and 2010. 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. Income is fiscal income excluding capital gains indexed with the CPI-U-RS. The unit of observation is adults, where income of married returns are divided by two. Sample includes tax units with non-deceased primaries aged 20–62 in all years that between 2000 and 2010 filed at least three tax returns and had adult-level average incomes of at least $3400.

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

percentage income changes over 1 and 10 years by initial income group. 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, whereas incomes of those starting in the top 1 percent fell by 13 percent.[5] Mean reversion of incomes becomes more pronounced over a decade. Between 2000 and 2010, incomes of adults starting in the bottom decile rose by 75 percent, whereas incomes of those starting in the top 1 percent fell by 27 percent.

This progressive pattern of income changes raises many questions: Are these income changes driven by outliers? Are they somehow mechanical? And do they persist for other years? First, the observed pattern is not driven by outliers because the 25th and 75th percentiles of within-income-group changes, as well as the median, show the same downward-sloping percentage income changes over the distribution. Second, income increases for those starting in the bottom of the distribution are neither mechanical nor a certainty. For example, more than a quarter of those in the second decile have income decreases, and incomes can even turn negative due to business losses. The progressive pattern is also observed for all age groups, although younger cohorts have slightly higher levels of income changes. Finally, the pattern of progressive income changes persists in other years, although high-income changes are sensitive to business cycles. For years starting between 1988 and 2004, real incomes of adults starting in the bottom decile rose an average of 81 percent over 10 years, whereas real incomes of those starting in the top 1 percent fell by 17 percent. See the online data for these estimates.

[5]For the same years, Splinter *et al.* (2009) estimated similar average annual wage changes among consistent tax return filers: a bottom quintile 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.

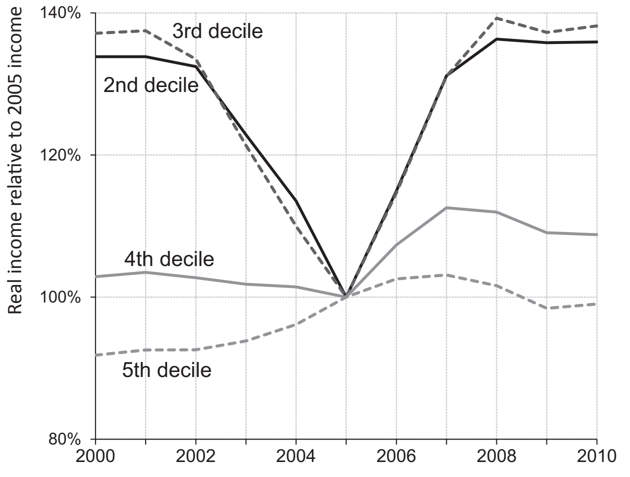

Figure 2. Mean Reversion: Average Real Incomes by Income Group Relative to 2005.
Notes: Income deciles are based on 2005 incomes. See Figure 1 for sample details.
Source: Author's calculations using the CWHS tax return panel.

Another concern is that percentage changes are asymmetric because they are bounded below by −100 percent and unbounded above. To deal with this asymmetry, observation-level percentage changes in Figure 1 (left side) are top-coded at 100 percent. With larger top-codes, mean reversion appears even more pronounced. For the bottom half of the distribution, increasing the top-code to 200 percent almost doubles the estimated increases and increasing the top-code to 300 percent almost triples them. Alternatively, the asymmetry of percentage changes can be addressed using a symmetric measure such as arc percentage changes, which show a nearly identical progressive pattern (see online appendix).

Income changes can also be measured with relative mobility, which is based on rank changes. Figure 1 (right side) presents average percentile changes over 1 and 10 years by initial income group. Adults starting in the bottom decile rose an average of 27 percentiles after 10 years and those starting in the top 1 percent fell an average of 15 percentiles. This suggests a high level of rank reversals. In summary, the pattern of progressive income changes, or mean reversion, is clearly observed for both absolute and relative mobility.

Mean reversion of incomes is caused in part by short-term fluctuations. Although these fluctuations temporarily push some toward the bottom of the distribution, many incomes tend to quickly rebound. To see these income dynamics, Figure 2 classifies adults into 2005 income groups and then for five prior and five subsequent years estimates real incomes as a share of 2005 income. This shows dramatic income increases among low-income working-age adults following negative income shocks. For example, adults in the second and third deciles in 2005 had far higher average incomes in both prior and subsequent years, such that their incomes form a distinct V-shape. This V-shaped pattern becomes muted by the fourth decile. For consistently married filers the V-shape pattern is muted by the third decile, and for consistently single filers not until the sixth decile (see online

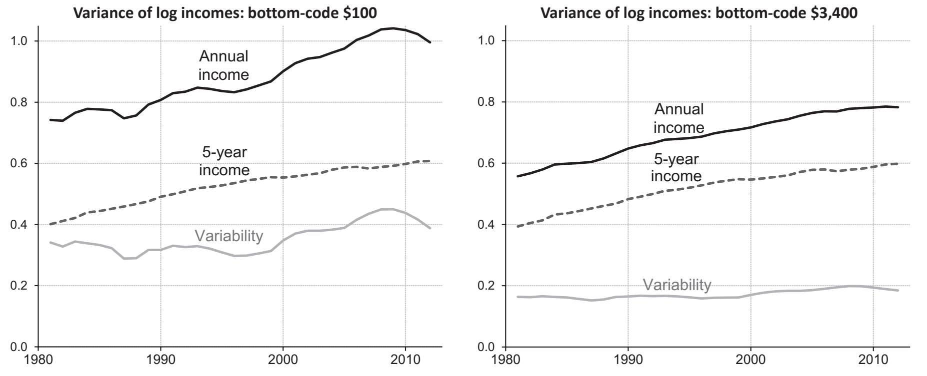

Figure 3. Annual and 5-Year Income Inequality and Variability.

Notes: 5-year periods are centered and include years $t-2$ to $t+2$. Income is adult-level fiscal income including capital gains indexed with the CPI-U-RS. Annual incomes have a bottom-code of \$100 in the left figure and \$3400 in the right figure. Sample includes tax units that throughout each 5-year period: had non-deceased primaries aged 20–62, filed a tax return at least once, and had adult-level average incomes of at least \$3400.

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

data). This suggests an important spousal income insurance effect. Finally, the first decile is not shown in Figure 2 because their average incomes decrease from about 300 percent of 2005 income followed by a symmetric increase, which would distort the scale.[6]

What might cause these large income fluctuations? Larrimore *et al.* (2016) estimate that size-adjusted tax-unit income decreases of 25 percent or more are most associated with one adult 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 2 could therefore be related to short-term movements in and out of work and divorce followed by remarriage.[7] Acs *et al.* (2009) and Western *et al.* (2016) also find mobility effects from employment and marriage patterns.

5. Income Variability and Inequality

Income variability can explain a significant fraction of the increase in annual income inequality since the 1980s. Recall that variability is defined as the gap between annual and multi-year inequality. Between 1981 and 2012, Figure 3 shows variability and inequalities of both annual and 5-year incomes. Recall from Equations 3 and 4 that annual and multi-year incomes are centered and based on

[6]Similar V-shaped patterns for 1985 and 1995 and within-decile heterogeneity are shown in the online data. Those in the second decile in 2005 can be subdivided into deciles based on 2000 income—most show decreases between 2000 and 2005 and all show increases between 2005 and 2010. Top income groups tend to have inverse V-shaped patterns, although these are sensitive to business cycles and changes in tax policy.

[7]In the bottom three deciles of working-age adults, two-thirds had equal-split wages under \$5000 in 2005. Among these, 61 percent had at least \$10,000 in wages 5 years earlier or later, suggesting that many in the bottom of the distribution in a given year are temporarily working less.

incomes from surrounding years. The figure's left panel shows a large gap between annual and 5-year inequalities, resulting in variability of about 0.4 in the 2000s, similar to transitory variance in Moffitt and Zhang (2018). However, variability estimates can be sensitive to different income restrictions. Whereas the left panel bottom-codes annual incomes at \$100, the right panel bottom-codes them at \$3400, meaning annual incomes are increased to at least that amount. The smaller gap between annual and 5-year inequalities implies variability of only about 0.2.

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 *et al.*, 2014). Specifically, 11-year periods are centered in 1988 and 2005, 2 years before business cycle peaks. When measured with variance of logs, income variability estimates are sensitive to low-income observations. To address this sensitivity, annual incomes are bottom-coded at \$100. 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 \$3400 affects a larger share of the sample—14 percent of working-age adults in the 2005 period, as compared to only 4 percent with the lower bottom-code—and variability only increases from 0.21 to 0.23.

Different inequality measures show different variability levels and trends. For 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 one-tenth of annual inequality. Mean log deviation variability increases by about one-fifth, and Gini coefficient variability is basically unchanged. These differences result from variance of log estimates being sensitive to low-income observations, whereas Gini coefficients emphasize the middle of the distribution, placing much less weight on low-income mobility.[8]

5.1. *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 \$3400. For other inequality measures, the effect is smaller. 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 \$3400.

Variability explains a larger share of the unequal-split income inequality increases. This is because relative to equal-split income, unequal-split income has a larger share of low incomes and the variance of log-incomes is sensitive to these low incomes. In addition, note that unequal-split incomes lead to higher levels of inequality and smaller inequality increases. This effect is similar to the findings by

[8]Incomes for Gini coefficients are not bottom-coded for this reason. Mean log deviations have a bottom-code of \$100. Recall that observations with multi-year incomes below \$3400 are removed for all measures of inequality.

TABLE 1
INCOME INEQUALITY AND VARIABILITY, 11-YEAR PERIODS

	Income Inequality						Annual Ineq. Change from Variability
	1988			2005			
	Annual	Multi-Yr	Var.	Annual	Multi-Yr	Var.	
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 $3400	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 $3400	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%
Panel C: Equal-split income, KSS truncation (drop if <$3400 any year)							
Var. log: bot-code $100	0.493	0.349	0.144	0.596	0.448	0.148	4%
Var. log: bot-code $3400	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 D: 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 $3400	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%
Panel E: After-tax income, size-adjusted (includes children)							
Var. log: bot-code $100	0.791	0.439	0.351	0.965	0.524	0.441	52%
Var. log: bot-code $3400	0.608	0.434	0.174	0.710	0.517	0.193	18%
Mean log deviation	0.342	0.246	0.096	0.462	0.350	0.113	14%
Gini coefficient	0.424	0.381	0.044	0.496	0.452	0.044	1%

Notes: 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. See Figure 1 for sample details.

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

Hyatt and Spletzer (2017) that inequality increases become *decreases* when adding single-quarter workers to their sample.

How should one interpret the range of results? If one wants to consider all individual-level changes, including the effect of very low incomes, then up to three-quarters of the increase in income inequality was from variability. These results also use measures corresponding to those that are standard in labor economics: log-variances at the individual level. Equally dividing incomes between spouses reduces the impact of variability on increasing inequality to half. A low bottom-code of \$100 captures important effects from stopping and starting work and volatile business income.[9] A higher bottom-code of \$3400 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, the Gini coefficient suggests that variability explains little of the increase in annual inequality because it emphasizes the middle of the distribution.

Relative to the 11-year periods discussed here, 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 (see online appendix). 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.

5.2. *Effects of Sample Restrictions and Taxes*

The effects of an alternative sample restriction and income definitions are explored. Table 1, Panel C shows that the KSS truncation—dropping observations with annual (rather than multi-year) incomes below \$3400 in any year of the multi-year period—lowers inequality levels and negates almost any variability increase or effect on the increase in inequality. Carr and Wiemers (2017) show similar results for male earnings. This comparison suggests that the KSS sample restriction, which drops a significant fraction of observations with high levels of variability, may explain the lower variability levels and modest variability changes estimated in both KSS and DeBacker *et al*. (2013).

Panel D considers after-tax income. Federal individual income taxes decrease inequality levels by about one-third and variability levels by about one-fifth, as expected, given income tax progressivity. The impact of variability on the increase in inequality, however, is slightly larger for after-tax income. This may be related to changes in tax policy over this period: decreases in marginal tax rates appear to increase income mobility (Alloza, 2020), and the growing generosity of refundable tax credits can exacerbate after-tax income changes relative to pre-tax changes in credit phase-in ranges (Larrimore *et al*., 2016).

[9]Incomes below \$100 are often due to business losses and a low bottom-code captures some of the effect of this volatile business income on annual inequality. For example, in the 2005 sample, half a percent of adults had annual incomes below \$100, of which two-thirds had current-year business losses (negative income from combined tax Schedules C and E) and over a 3-year period their median income fell from over \$10,000 to *negative* \$10,000 and then returned over positive \$10,000. However, a higher bottom-code seems more appropriate for less volatile measures such as consumption.

Panel E considers size-adjusted after-tax income. Accounting for children within tax units and for economies of scale, which are ignored with the other adult-level income definitions, results in higher inequality levels and slightly lower variability levels. The impact of variability on the increase in inequality is smaller with size-adjusted income. This likely results from re-ranking effects and the increased weight on tax units with children, as parents benefited from growing tax credits that can stabilize after-tax income changes relative to pre-tax changes in credit phase-out ranges. This size-adjusted approach and the resulting estimates are similar to those of Gottschalk and Moffitt (2009), although differences between households and tax units can influence variability trends given the rise of cohabitation over this period.

5.3. *Comparisons to Consumption Inequality Trends*

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, particularly when focusing on the bottom half of the distribution. Rather than the pre-tax/pre-transfer income definition used in this paper, these studies typically use an after-tax/transfer-inclusive definition of "disposable" income, for which inequality grew more slowly, making these comparisons even more striking.

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 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 *et al.* (2013) estimate that annual income inequality, measured with Gini coefficients, increased a bit more than consumption inequality. Between 1980 and 2010, Attanasio *et al.* (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. In comparison, Aguiar and Bils (2015) estimate similar increases in annual income and consumption inequality when using an alternative assumption to correct for measurement error. 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 paper.

6. Conclusion

Using a panel of tax returns, this paper considers how income mobility may have contributed to the increase in the US annual inequality. Relative to incomes averaged over multiple years, which controls for short-term mobility, measures of annual income appear to have increasingly overstated adult inequality. A range of plausible results is estimated for working-age adults, with income variability causing 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 a V-shaped income pattern over time.

This suggests a more nuanced interpretation of the increase in annual inequality. A significant share of the increase may be due to both larger wage-rate dispersion (associated with multi-year inequality) and less consistent labor force attachment (associated with income variability). These two effects may interact. For example, Bhagwati and Dehejia (1994) suggest a "rolling stones gathers no moss" mechanism, in which decreases in firm-specific human capital result from increasing labor turnover. Changes in labor force attachment may be related to other negative outcomes. Among white non-Hispanic men with less than a bachelor's degree, Case and Deaton (2017) suggest a correlation between cohort-specific rising mortality rates and falling labor force participation.

Income variability levels and trends, however, are extremely sensitive to different measures of inequality, definitions 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 show larger increases in variability than income definitions accounting for sharing between spouses, such as equal-split and size-adjusted incomes. This suggests an important role for family labor supply responses and sharing within a family as forms of individual income insurance (Blundell *et al.*, 2008; Hryshko *et al.*, 2017). Low bottom-coding of incomes results in high and increasing variability. Meanwhile, removing observations with temporarily low incomes results in low and stable variability. These 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 *et al.* (2018) argue that rather than dropping eligible workers in years when they have low incomes, inequality measures should include them even if temporarily inactive; otherwise inequality measures will understate the impact of the bottom of the distribution. This paper'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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