Absolute Intragenerational Mobility in the United States, 1962–2014

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Abstract

This paper combines historical cross-sectional and longitudinal data in the United States to study the evolution of absolute intragenerational mobility over periods of four years. Absolute intragenerational mobility over such periods is procyclical and is largely confined within 45%–55%. We also find that absolute mobility decreases with income. Individuals and families occupying the lower ranks of the income distribution have a higher probability of increasing their income over short time periods than those occupying higher ranks. This also occurs during periods of increasing inequality. Our findings stem from the importance of the changes in the composition of income ranks. These changes are over and above mechanical labor market dynamics, such as entering and exiting the labor force, and life cycle effects. We offer a simplified model to mathematically describe these findings.

Keywords: intragenerational mobility, income inequality, growth
JEL Codes: D31, H00, J62

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1 Introduction

Economic booms and busts, recessions and recoveries, all describe periods of economic prosperity or decline, either short or extended, abrupt or gradual. Such periods shape our world and sometimes lead to deep societal and political changes. A common feature of all is a major change in economic output, either positive or negative. Describing such periods using only aggregate measures has clear limitations. In particular, it does not enable answering which individuals or households and how many of them were better or worse off following such periods and to what extent.

Such changes can occur amidst the substantial growth of few and the decrease or the stagnation of many others. In particular, this scenario is the one that might have occurred during periods of increasing income inequality. For example, Figure 1 shows that during the recovery periods that followed the recessions of the 2000s, wages did not recover as fast as total income in the United States. This seemingly suggests that the fruits of economic recovery were predominantly enjoyed by the already better off. Since 1970, the average adult total income increased faster than the median adult labor income (*i.e.*, including only wages and self-employment income). This is particularly visible for the period 2010–2014, in which the average national income recovered to pre-recession levels. At the same time median incomes did not recover.

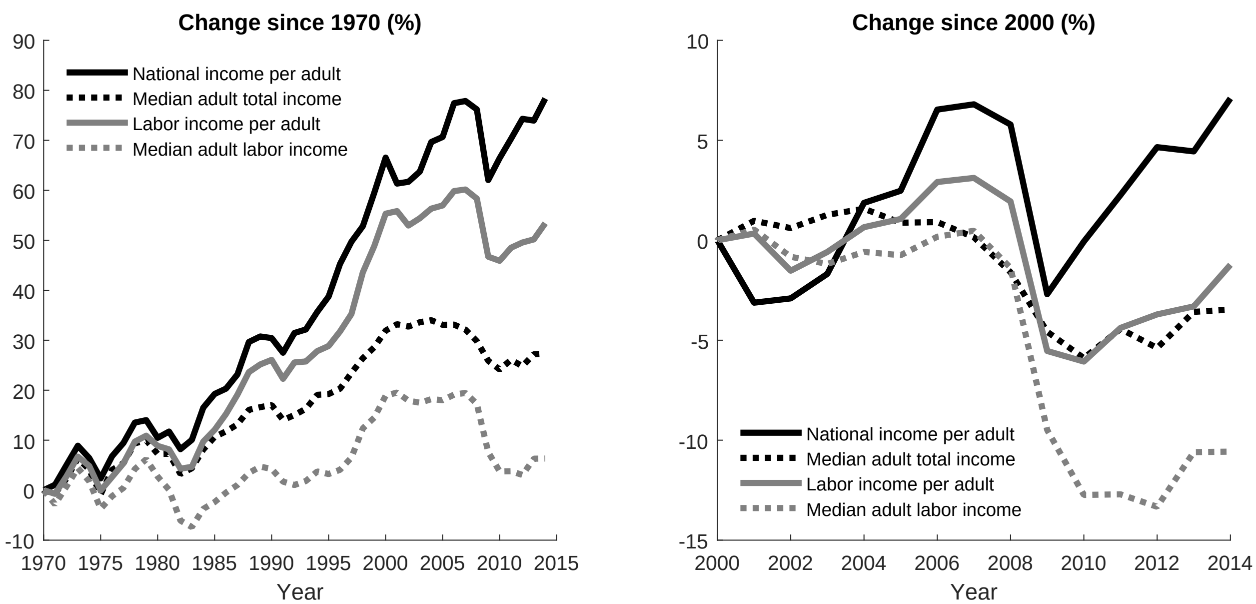

Figure 1: The evolution of real mean and median total national income and labor income in the United States, 1970–2014. Source: The World Inequality Database (WID, 2018).

Thus, it is necessary to track the incomes of individuals or families over time to describe in full the patterns of income growth in the short run. This paper aims to describe these patterns for the United States from 1962 to 2014 over periods of 4 years. It does this by studying the evolution of *absolute intragenerational mobility*, the fraction of individuals or families with higher real incomes at the end of a time period compared to the beginning of this period.[1]

Combining cross-sectional and longitudinal data, we find that for 4-year periods, trends of absolute intragenerational mobility closely follow the business cycle. Over all the phases of the business cycle, absolute intragenerational income mobility is confined within the range 43%–67% and averages at 53%. *I.e.*, over a period of 4 years, 43%–67% of the population will have higher real incomes, for all aggregate-level changes observed.[2]

This seemingly contradicts the picture that arises when changes in the composition of income ranks are not taken into account. Since such changes are generally small over periods of several years, they are usually not considered. Yet, in practice, it is necessary to test whether the changes in the income rank composition are indeed negligible. We find the little relative (rank) mobility in short time periods to be large enough to create a substantial effect on the estimates of absolute intragenerational mobility.

We start by describing a methodology for estimating absolute intragenerational mobility using cross-sectional data. We discuss its sensitivity to changes in relative intragenerational mobility. We find that this sensitivity is practically low, enabling the estimation of absolute intragenerational mobility with cross-sectional income data only. Using cross-sectional data from the US distributional national accounts (DINA) (Piketty, Saez and Zucman, 2018) we then estimate absolute intragenerational mobility of income in the United States from 1962 onward. For comparison, we also estimate absolute intragenerational mobility using the Panel Study of Income Dynamics (PSID) (PSID, 2018), where available. We decompose the evolution of absolute intragenerational mobility into the contribution of changes in income inequality and average income growth. While income growth has a bigger effect on absolute mobility than changes in inequality, we find that the increase of income inequality had a negative impact on absolute intragenerational mobility. Between 1962 to 2014 it led to an average decrease of 1.9 percentage points in absolute mobility over 4-year periods.

We then use panel data to study in detail absolute intragenerational mobility along the income distribution. We find that the likelihood of families and individuals to be better off by the end of a time period decreases with their income rank at the beginning of the period. Families at the bottom of the distribution are significantly more likely to see their incomes increase than families at the top of the distribution over periods of 4 years. Specifically, the probability of a family to increase its total income over a period of 4 years decreases by 2.4 percentage points per income decile. This occurs even in periods during which income inequality increases. Using micro panel data we find that these results are robust to the mechanical dynamics of the labor market. That is, the results are not driven by effects such as workers entering and exiting the labor force, life

[1] The literature abounds with mobility measures defined as "absolute" (see, *e.g.*, Fields and Ok (1996); Jäntti and Jenkins (2015); Chetty et al. (2017)). Our definition follows Chetty et al. (2017). We note that this measure of absolute mobility is specifically a measure of upward mobility.

[2] The choice in 4-year periods is meant to reflect a period that is long enough for the economy to go through events such as long recession or recovery periods, but not too long so that the relevant population in the end of the period is too different from at the beginning of the period. We also study periods of 2 years in Appendix A for robustness.

cycle effects (*i.e.*, younger adults are more likely to see their income increase than older ones, see Appendices B and C), or changes in family structure and marital status.[3]

The results are mainly driven by small changes in the composition of income ranks. Individuals who change their income rank following a certain period can be laid-off workers, who stay unemployed or underemployed at the end of the period, people taking leave, young adults joining the labor force and retirees. Yet, as explained, our results do not qualitatively change if we control for such effects. This implies that the income rank composition changes are over and above such labor market mechanical dynamics.

Our results indicate, therefore, that it would be misleading to compare the incomes of the same percentile at the beginning and the end of short time periods. They would not represent the same households or individuals. Thus, relative intragenerational mobility, even if much lower than in the intergenerational case, may play an important role in the interpretation of changes in the income distribution.

Finally, we present a simplified model for the dynamics of incomes based on Gibrat's law (Gibrat, 1931). It asserts that log-incomes grow over time at a rate that is independent on incomes, similarly to the model of Lillard and Willis (1978). The model results are consistent with the empirical evidence, and provide theoretical support to the finding that absolute intragenerational mobility can be adequately estimated with cross-sectional income data only. The model also shows that more inequality leads to lower absolute intragenerational mobility and that faster growth leads to higher absolute mobility, as already identified in the intergenerational case (Chetty et al., 2017; Berman, 2021).

This paper is related to several strands of literature. It contributes primarily to the literature on intragenerational mobility. Jenkins (2011) and Jäntti and Jenkins (2015) provide a thorough literature review of this literature. They survey conceptual issues with intragenerational mobility such as the nature of the data used and its limitations, the relevant income definitions, and the plethora of mobility measures discussed in the literature. Specifically, in the United States, a lot of attention was given to intragenerational mobility in earnings (Atkinson, Bourguignon and Morrisson, 1988; Gottschalk and Moffitt, 2009; Kopczuk, Saez and Song, 2010; Shin and Solon, 2011). More recently, mobility in income, based on panel tax records, was also studied (Auten and Gee, 2009; Splinter, Diamond and Bryant, 2009; Auten, Gee and Turner, 2013; Larrimore, Mortenson and Splinter, 2020; Splinter, 2021). These studies mostly focus on estimating the likelihood of families or individuals to change their income rank, particularly at the top of the income distribution. They also discuss how this likelihood has evolved over the years. Kopczuk, Saez and Song (2010) find that "short-term earnings mobility measures are stable [. . .]," findings that were recently confirmed

[3]The finding that the likelihood of families and individuals to be better off by the end of a time period decreases with their income rank is a manifestation of regression to the mean. The regression to the mean is a result of economic forces that lead to it, and the purpose of making a distinction between mechanical and non-mechanical effects, albeit imperfect, and potentially controlling for the former, is to "distill" from the observed regression to the mean as much as possible. The residual is what cannot be simply explained as mechanical effects (such as life cycle effects, moves in- and out-of-work, *etc.*. This is discussed in more detail in Section 4.

by Carr, Moffitt and Wiemers (2020); Splinter (2021) using different data. Intragenerational mobility was also given attention in the sociological literature, most notably in the context of racial division and class in the United States (see, for example, Sørensen (1975); Pomer (1986)). Yet, the vast majority of these studies focus on relative mobility, quantified using rank-based measures, the intragenerational elasticity of income, or other measures, rather than on absolute mobility. The existing economic literature on absolute mobility is mostly focused on the intergenerational case. See, *e.g.*, Chetty et al. (2017); Manduca et al. (2020); Berman (2021).[4]

There are a few limitations to the existing literature (Jäntti and Jenkins, 2015). First, focusing on earnings does not allow taking into account a large fraction of families whose income is based on other sources. Second, using panel surveys suffers from large measurement errors and limited coverage of the top of the distribution. Third, the estimated growth rates by income rank have high uncertainty and high sensitivity to income definition and unit of measurement specification (see also Splinter (2021)).

Another related strand of literature is that of income volatility. Growing income volatility may indicate simply growing inequality, but can also imply higher relative mobility or higher growth. Changes in income volatility, interpreted as changes in risks for workers and firms, are thus also related to changes in absolute mobility. Yet, current evidence on whether earnings volatility increased or not in recent decades, amidst the increase of income inequality, is mixed (Gottschalk and Moffitt, 2009; Shin and Solon, 2011; Moffitt and Gottschalk, 2012; Guvenen et al., 2021).

The main contribution of this paper is to provide new series on the evolution of absolute intragenerational mobility in the United States, and to quantify the dependence of absolute intragenerational mobility along the income distribution. The decline of absolute mobility with income rank is over and above the mechanical dynamics of the labor market.

This paper makes two additional contributions. First, we emphasize the importance of incorporating relative mobility when interpreting changes in inequality. In particular, as described above, we find that relative mobility over short time periods is large enough to have a substantial effect on absolute mobility. This has clear implications on the way changes in inequality are interpreted.

Second, we extend a methodology that can be easily applied for studying absolute intragenerational mobility in other periods of time and other countries. Following Chetty et al. (2017), our approach combines the marginal income distributions at the beginning and the end of a time period and their copula, *i.e.*, the joint distribution of income ranks. It provides an alternative to detailed panel data or synthetic matching approaches.

The paper is organized as follows. Section 2 lays out our methodology, addressing the necessity of panel data for producing reliable estimates of absolute intragenerational mobility. In Section 3 we specify our data sources. Section 4 presents the main results. It describes the evolution of

[4]See additional relevant papers on intragenerational mobility: Sawhill and Condon (1992); Gottschalk (1997); Fields and Ok (1999); Aaberge et al. (2002); Jenkins and Van Kerm (2006); Bonhomme and Robin (2009); Dynan, Elmendorf and Sichel (2012); Bourguignon and Moreno M. (2018).

absolute intragenerational income mobility in the United States. Section 5 discusses a simplified model, which allows estimating absolute intragenerational mobility without needing any panel data, consistent with the previous results. We conclude in Section 6.

2 Methodology

In an ideal setting, in which the income of every individual is known for any given year, measuring absolute intragenerational mobility – the fraction of individuals with higher real income at the end of a given period than at its beginning – is trivial. For N individuals (or families), we denote by Y_{ti} and $Y_{t'i}$ their initial and terminal real incomes, respectively (where $i = 1 \ldots N$). We define absolute mobility as

$$A = \frac{\sum_{i=1}^{N} \mathbf{1}_{Y_{t'i} > Y_{ti}}}{N} \,. \tag{2.1}$$

In practice, however, the data required for estimating A using Eq. (2.1) are usually available for small samples and do not cover the entire distribution, or available for a limited range of years. A way to overcome this limitation is by combining data on the marginal income distributions at t and t' with a copula, the joint income rank distribution at t and t'. It follows that the measure of absolute mobility A is

$$A = \int \mathbf{1}_{\{Q^{t'}\left(r^{t'}\right) \geq Q^{t}\left(r^{t}\right)\}} C\left(r^{t'}, r^{t}\right) dr^{t'} dr^{t} \,, \tag{2.2}$$

where r^t and $r^{t'}$ are the initial and terminal income ranks, respectively; Q^t and $Q^{t'}$ are the respective quantile functions; C is the copula. This decomposition into copula and marginal distributions is exact and follows from Sklar's theorem (Sklar, 1959).

It is possible to provide reliable estimates of absolute intragenerational mobility with narrow confidence intervals nevertheless, even in the absence of historical detailed panel data. The reason is twofold. First, the structure of realistic intragenerational copulas can be well approximated by a Plackett copula (Plackett, 1965).[5] This implies that collapsing the copula into a single representative measure of relative mobility, such as Spearman's rank correlation (or the rank-rank slope) is empirically justified. Second, the sensitivity of the absolute mobility estimates to the rank correlation changes in a highly non-linear fashion. Absolute mobility is very sensitive to the rank correlation for extremely low levels of relative mobility (namely when the rank correlation is very close to 1). Such levels are lower than realistic mobility, even for time periods as short as two years. For higher levels of relative mobility, changes in the rank correlation have a very small effect on absolute mobility. In particular, plausible uncertainties in relative mobility measures lead to only small uncertainties in the absolute mobility estimates.

[5] For income ranks u and v, and given a parameter θ, the Plackett copula is

$$C\left(u, v\right) = \frac{1}{2}\theta^{-1}\left(1 + \theta\left(u + v\right) - \left[\left(1 + \theta\left(u + v\right)\right)^2 - 4\theta\left(\theta + 1\right)uv\right]^{1/2}\right) \,. \tag{2.3}$$

The high similarity between empirical and Plackett modeled copulas was already identified by Bonhomme and Robin (2009) for earnings data in France. It is also demonstrated in Figure 2. We consider the copulas as transition (bistochastic) matrices $P \in \mathscr{P}(N)$, where p_{ij} represents the probability of transferring to quantile j (at t') for those starting in quantile i (at t) and N is the number of quantiles. We find that for all 4-year periods from 1967 onward, the transition matrices, estimated from the PSID total family income data (see more details in the next section), are well approximated by a Plackett copula with a single parameter. This parameter is uniquely mapped onto the rank correlation between the income distributions in the initial and final years of the period (Plackett, 1965; Trivedi and Zimmer, 2007). This enables using the rank correlation as a single measure of relative mobility for our purposes.[6]

A thorough analysis of the similarity between empirical and modeled copulas, and a comparison of different copula models are detailed in Appendix D.

2.1 The sensitivity of absolute intragenerational mobility to the rank correlation

We established that for estimating absolute intragenerational mobility the copula can be practically characterized by its rank correlation. We now wish to test to what extent absolute intragenerational mobility estimates are sensitive to the rank correlation. For that purpose we use microdata from the US distributional national accounts (Piketty, Saez and Zucman, 2018) and consider the US pre-tax income distribution on 2006, 2010 and 2014. We estimate the absolute intragenerational income mobility assuming a Plackett copula with rank correlation changing from 0 (perfect mobility) to 1 (perfect immobility). The copula is used to match incomes between two given marginal distributions. This allows estimating absolute mobility using Eq. (2.2), following the method used in Chetty et al. (2017); Berman (2021).

Apart from the absolute mobility estimate resulting from this calculation we produced an additional estimate in which it is assumed that for the top 5% of the distribution the rank correlation was 1, *i.e.*, assuming that within the top 5%, the richest at the beginning was necessarily the richest at the end, the second richest at the beginning was the second richest at the end, and so on. For the bottom 95% the rank correlation was changing from 0 to 1. This is a conservative estimate which takes into account the problematic handling of the top of the distribution in the PSID data and the measurement error. Kopczuk, Saez and Song (2010) have shown that over a period of 3 years, roughly 30% of top 1% earners are no longer in the top percentile. Similarly, Auten, Gee and Turner (2013) find that about one-third of tax units in the top 1% of incomes drop out after one year and more than two-thirds after five years. This clarifies that assuming perfect immobility within the top 5% of income earners is indeed conservative, as it is an underestimation of relative intragenerational mobility (otherwise, the bad coverage of top incomes in survey data may also bias

[6] Berman and Bourguignon (2021) show that Plackett copulas also provide a good approximation for real copulas over longer time periods, such as 10 years.

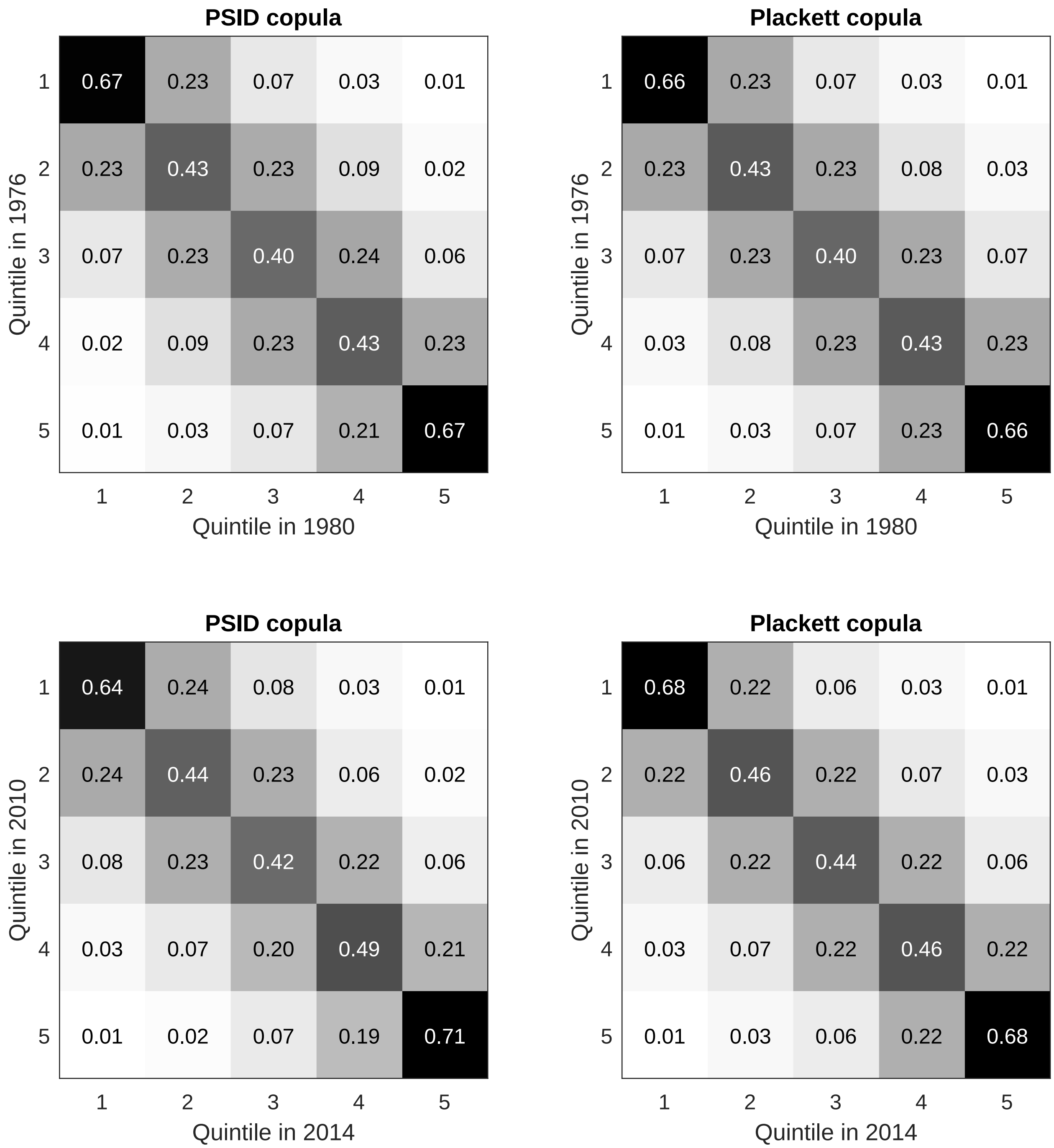

Figure 2: Transition matrices for 1976–1980 (top) and 2010–2014 (bottom) for total family income estimated using the PSID dataset (left) and approximated using a Plackett copula. The numbers refer to the transition matrix elements and the color map is scaled between 0 (white) and 1 (black).

the rank correlation estimates).

For both specifications we estimated the absolute intragenerational mobility during 2006–2010 and 2010–2014. We also estimated the share of adults which increased their real income by at least 3%. Figure 3 presents the results. It illustrates our key methodological finding. Within the plausible values of rank correlation (see Section 4.1), absolute intragenerational mobility is insensitive to the rank correlation. It becomes sensitive to the rank correlation as it approaches 1. Rank correlation of 1, *i.e.*, perfect immobility, is, however, unrealistic. These observations remain unchanged even with perfect mobility at the top (rigid top 5%).

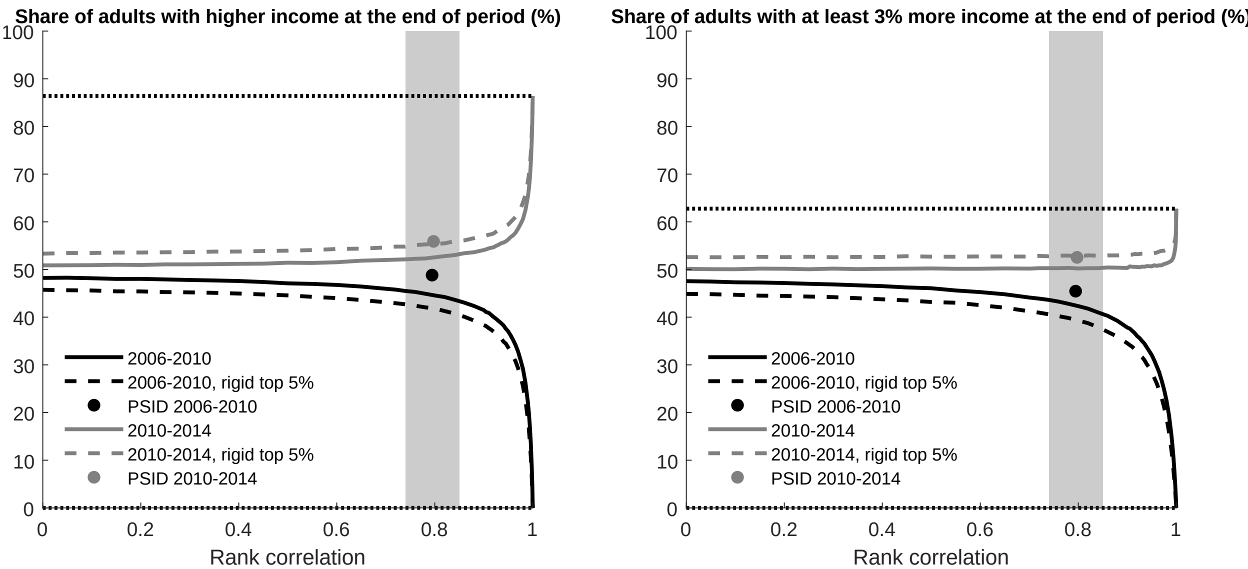

Figure 3: Sensitivity of absolute intragenerational mobility to the rank correlation. We calculate the absolute intragenerational mobility in the United States between 2006–2010 (black) and 2010–2014 (gray) assuming Plackett copulas with changing rank correlation. The dashed lines are the absolute intragenerational mobility values assuming the top 5% of income earners are perfectly immobile and the mobility taken into account is only within the bottom 95%. The marginal distributions used are taken from the US DINA (Piketty, Saez and Zucman, 2018). The shaded areas stand for the actual range of estimated 4-year rank correlation values (see Section 4). The dotted black curves stand for the level of absolute mobility for perfect rank correlation (no relative mobility).

The results show that even without good coverage of the top of the income distribution, it is possible to accurately estimate absolute intragenerational mobility. This enables the estimation of absolute intragenerational mobility in income in the United States, for which the marginal distributions are well known and the rank correlation lies within a narrow enough band of values, as we discuss below.

3 Data

Our estimations rely on two data sources. The first is the US Distributional National Accounts (DINA) (Piketty, Saez and Zucman, 2018). This database includes comprehensive estimates of the income distribution in the United States for the years 1962, 1964 and 1966–2014, combining tax data, survey data and national accounts.

The second data source is the Panel Study of Income Dynamics (PSID) (PSID, 2018). This is a longitudinal panel survey of US families conducted annually or biennially since 1967. We use the total family income variable in the survey. The sample sizes differ in each wave due to methodology changes in the survey, attrition, and since the survey tracks the descendants of past surveyed individuals. Overall, approximately 6000 families were surveyed in each wave. We use this database primarily for the purpose of estimating the intragenerational copula of income over 4-year periods. These data can also be used to estimate directly absolute mobility. However, due to measurement error, small sample size and top-coding issues, the DINA are preferable over survey data. They are also preferable over tax data only, as the latter are usually not reconciled with the national accounts. The PSID also includes detailed microdata, which we use for studying absolute intragenerational mobility along the distribution.

We note that estimating the intragenerational copulas using the PSID has clear limitations. Specifically, the total family income definition is not exactly the same as in the DINA. In addition, the small sample sizes, the limited coverage of the top of the distribution and the measurement errors may all lead to an overestimation of relative mobility. Yet, the fact that the copula is well approximated by a Plackett model is not affected by these limitations.

It is also important to note that the basic unit of observation for the income data in the DINA is an adult under the "equal-split" assumption.[7] In the PSID data the basic unit of observation is a family. Thus, the estimated family-based mobility may lead to overestimation of the rank correlation (compared to the adult-level rank correlation). In our estimations we also consider lower and upper bounds for the rank correlation to take into account this uncertainty and the potential biases measurement errors may create.

As we show below, estimating family level absolute mobility directly using the PSID data yields results that are higher in 5 percentage points on average than those estimated using the DINA. This difference might originate in the difference between the units of observation and income definitions. We focus on the DINA estimates for the reasons specified above. For robustness, we also use individual income data from PSID, showing only very small discrepancies from the baseline estimates.

Due to possible measurement errors, many studies of inequality and of intergenerational mobility consider incomes averaged over several years to smooth out transitory shocks. For intragenerational mobility such averaging may smooth out the effects one wishes to measure, if the averaging is over a long enough period. Appendix E presents a comparison with and without income averaging over 3 years, showing a very small effect on the absolute intragenerational income mobility.

We restrict our analysis to pre-tax income. The main reason is that for external validity, pre-tax income is more relevant – post-tax income may be influenced by differences in policy at different time periods. In addition, post-tax incomes are not as well documented as pre-tax incomes. Also,

[7]Individuals in tax units that are composed of more than one income-contributing individuals are assumed to contribute each an equal part to the total income. See Alvaredo et al. (2016); Larrimore, Mortenson and Splinter (2021) for a detailed discussion on this assumption.

the total family income PSID data, on which we rely in the estimation of the rank correlation, is only pre-tax. Yet, it is possible to make a basic comparison between absolute mobility of pre-tax and post-tax incomes, using data from Piketty, Saez and Zucman (2018) (where post-tax incomes are also post-transfer). Such a comparison is presented in Appendix F. We find that absolute mobility of post-tax income is generally higher than for pre-tax income. On average it is higher by 1.9 percentage points, and follows a very similar path in time.

The DINA data are adjusted for inflation using the national income price index (based on the GDP deflator, see WID (2018)). We ensured that our results are robust to different inflation adjustments. We used the Consumer Price Index Research Series (CPI-U-RS) and the Personal Consumption Expenditures Price Index (PCEPI) for comparison. Such adjustments had a small effect on the estimates of absolute mobility (see Appendix G for an analysis of the impact of different adjustments for inflation).

We also note that it is possible to estimate absolute intragenerational mobility defining mobility with a certain threshold. Instead of estimating the share of families with higher income at the end of a certain period, we estimate the share of families with income higher by a certain percentage. Such estimates are presented in Appendix H. Since applying a threshold does not change the qualitative behavior of absolute mobility, we focus on the standard definition, in which the threshold is any real increase.

4 Results

4.1 Intragenerational rank correlation

Using the PSID data we first estimate the 4-year intragenerational rank correlation for income in the United States (by a period of 4 years we mean that $t' = t + 4$ years). These estimates are shown in Figure 4. We present two different estimates for the correlation:

- A baseline estimate, for which we include in the sample only families surveyed in both the beginning and the end of the 4-year period
- A conservative estimate assuming that families surveyed in the beginning but not in the end had not changed their income by the end of the period (these rank correlation estimates are higher than the baseline estimate by design).

We also included an unweighted estimate of the 4-year period income rank correlation from 1967 onward. The minimum and maximum of all the estimates would serve as lower and upper bounds for the rank correlation in our absolute mobility analysis.

Figure 4 shows that the 4-year period rank correlation lies within the range $(0.74, 0.85)$. As demonstrated in Figure 3, such mobility values would be enough for the absolute mobility to be plausibly insensitive to the copula. Therefore, the rank correlation estimation error and the Plackett copula

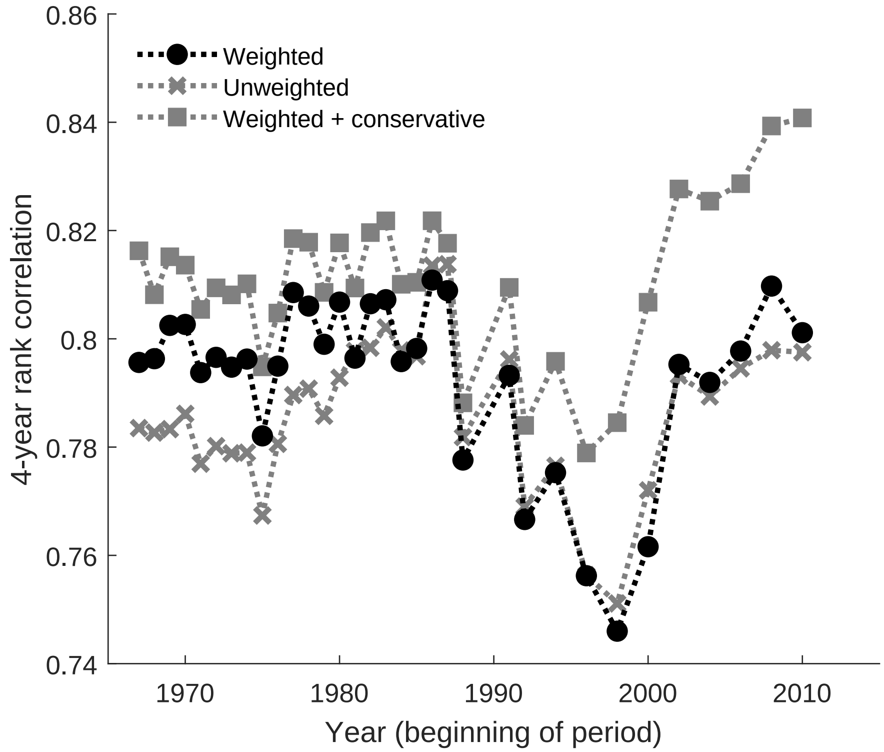

Figure 4: Spearman's rank correlation of income in the United States over 4-year periods. The results are based on PSID data. In the conservative estimates it is assumed that families surveyed in the beginning but not in the end of each period had not changed their income by the end of the period.

model would lead to a small uncertainty when estimating the absolute intragenerational mobility in income. For robustness we also compare the absolute mobility results to the estimates when using the PSID directly, without using the methodology that combines the copula with marginal distributions. The differences between the baseline absolute mobility estimates to these estimates are small for all specifications (see Appendix I).

We note that substantial changes were made in the PSID survey design in 1997 (Heeringa and Connor, 1999). These changes may have lead to the apparent dip in the results for the few years preceding the year 2000 in Figure 4, meaning that it is possible that 4-year period rank correlation are even more stable over time than presented.

4.2 The evolution of absolute intragenerational mobility

Based on the above it is now possible to estimate income absolute intragenerational mobility in the United States. We use the detailed data on income distributions from 1962 onward from the US DINA as described. For each 4-year period (in a rolling window) we produce 4 estimates, presented in Figure 5:

- A baseline estimate, using the baseline estimate of the rank correlation
- A baseline estimate with rigid top 5%, in which the composition and internal ranking of the top 5% remains unchanged for each period and the rest of the distribution changes according to the baseline rank correlation
- Two estimates produced using the lower and upper bounds for the rank correlation – 0.74 and 0.85

We also include an estimate based on the PSID data directly for the applicable years.

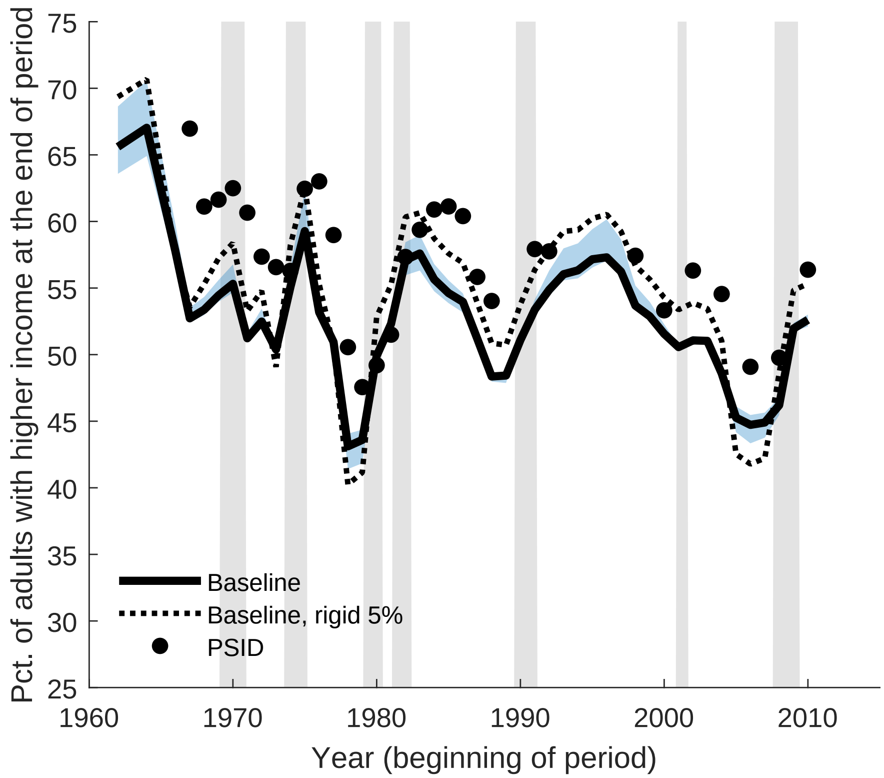

Figure 5: Absolute intragenerational mobility of income in the United States since 1962. The shaded blue area is the area covered by the absolute mobility estimates between the lower and upper bounds for the rank correlation – 0.74 and 0.85. The shaded gray areas are recession periods.

The uncertainty on the baseline estimates is limited to ±2.5 percentage points, based on the lower and upper bounds of the rank correlation. The results demonstrate that for 4-year periods, over all the phases of the business cycle, absolute intragenerational mobility in income is confined within the range 43%–67%, *i.e.*, that over a period of 4 years, 43%–67% of the population will enjoy higher living standards, for all aggregate-level changes observed. It averages 53%.

The results show that absolute mobility is procyclical. The evolution of absolute mobility follows the business cycles and its trend follows income growth trends. This is not at all surprising, as earnings and incomes are known to be procyclical (Solon, Barsky and Parker, 1994; Devereux, 2001). Yet, Figure 5 demonstrates how narrow is the band within which the absolute mobility values change during the business cycles. Since 1965, only in 15 out of 45 4-year periods, the baseline estimate was not within the range 45%–55%.

The absolute intragenerational mobility estimated directly using the PSID samples follows a similar trend to the DINA-based estimates. Yet, the PSID estimates are higher than the baseline estimates. The average discrepancy is 5 percentage points. The main source of this discrepancy is the small differences in income definition between the PSID and the DINA (see also Appendix J).

These findings are robust also when considering labor income (*i.e.*, including only wages and self-employment income) rather than total income (see Appendix K). This is particularly important since labor income is more accurately measured in surveys than capital income (Moore, Stinson and Welniak, 2000; Meyer and Sullivan, 2003; Yonzan et al., 2021). The similarity of the labor and total income results supports the findings on total income, which better reflects wellbeing than labor income alone.

Our results may also be indicative of strong structural changes related to demographic changes and labor market changes. Intentionally, we did not control for such effects in our baseline estimates. Appendix C presents a breakdown of the rank correlation and absolute mobility by age group. For young adults, absolute mobility is generally higher than for the rest of the adult population and for adults over 65, absolute mobility is lower than for the rest of the adult population. For families with head of family who was 35–55 years old at the beginning of the 4-year periods, the results are almost identical to those obtained for the entire population. This may mechanically lead to a small decrease in absolute mobility in the near future, due to the retirement of many "baby-boomers" along with lower family sizes and later entry to workforce of young adults.

We note that the choice in 4-year periods is meant to reflect a period that is long enough for the economy to go through events such as long recession or recovery periods, but not too long so that the relevant population in the end of the period is too different from at the beginning of the period (longer periods would include substantial changes which are due to life cycle effects). We also estimate absolute mobility over 2-year periods in Appendix A for robustness. These results are found to be very similar to those obtained for 4-year periods. The 2-year absolute intragenerational income mobility is confined within the range 43%–63% and averages 52%.

4.3 Absolute mobility decomposition

Figure 5 presented the evolution of absolute intragenerational mobility in the United States. It is possible to decompose this evolution for understanding the sources of its long run trend. Such a decomposition allows quantifying the contribution of income growth and changes in inequality to absolute mobility.

For that purpose, we produce, in addition to the baseline estimate, two counterfactual calculations:

- We keep the shape of the income distribution constant during each 4-year period, but not the average income. In each period we assume that the second (the later) marginal distribution in the period has the shape of the earlier marginal distribution. But, we let the average income change according to its real historical value. This controls for the contribution of income inequality changes.

- The distribution shape changes according to historical data, but we assume there was no real growth during each 4-year period. This controls for the contribution of income growth.

The results are presented in Figure 6. They show that without income inequality changes, the evolution of absolute intragenerational mobility would have been similar to the baseline estimate, but 1.9 percentage points higher, on average. Conversely, not taking income growth into account leads to different evolution that is almost constant in time, which no longer follows business cycles. On average, this leads to absolute mobility that is 4.6 percentage points lower than the baseline. These results show that growth is more important to the evolution of absolute intragenerational mobility than inequality. Yet, inequality changes still have a non-negligible negative effect on absolute mobility. This point is further discussed in Section 5.

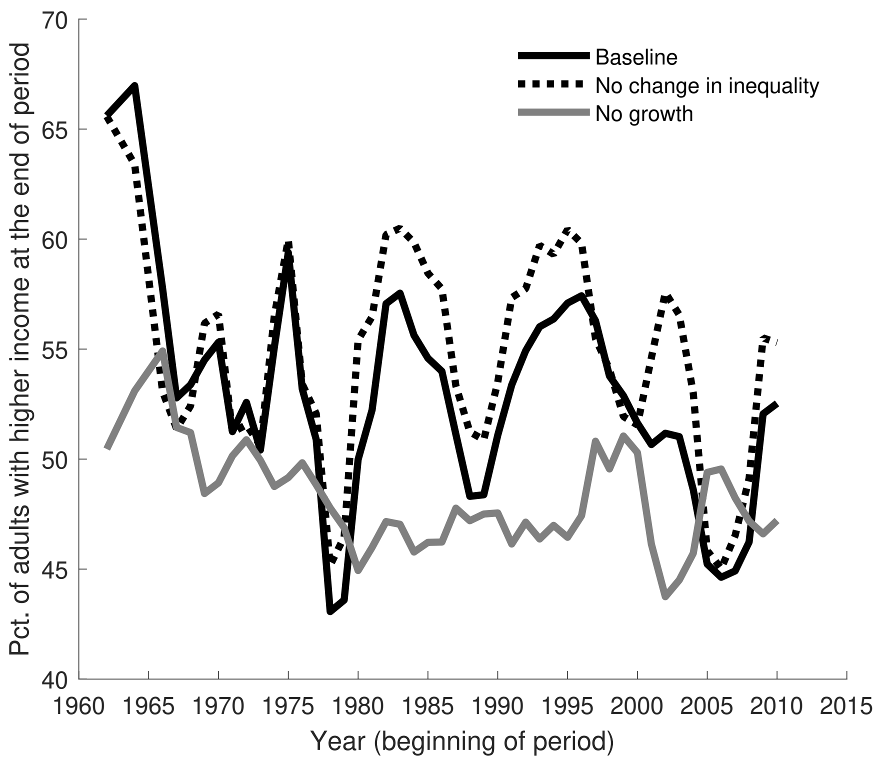

Figure 6: Counterfactual evolutions of absolute intragenerational income mobility in the United States (based on US DINA data (Piketty, Saez and Zucman, 2018)).

4.4 Absolute intragenerational mobility by percentile

The baseline estimates also allow calculating mobility not over the entire population, but for each percentile separately. For every adult belonging to a certain percentile at the beginning of the

4-year period considered, we ask whether they have been better off at the end of the period in terms of real income. The fraction of the adults which had higher income at the end of the period is defined as the absolute intragenerational mobility of this specific percentile. To demonstrate how absolute mobility depends on the income rank, we look at four time periods, which constitute two recessions and two recovery periods: 1978–1982 and 1982–1986; 2006–2010 and 2010–2014.

Figure 7 shows that absolute intragenerational mobility is generally decreasing with income rank. This pattern was also identified in the intergenerational case by Chetty et al. (2017). This pattern reflects potential regression to the mean, characterizing mainly the bottom and the top of the income distributions (Saez, 2003). Yet, even if the bottom 10% or the top 10% were excluded, the results in Figure 7 show clear downward sloping absolute mobility percentile profiles. Similar results were also found by Splinter (2021) over longer time periods.

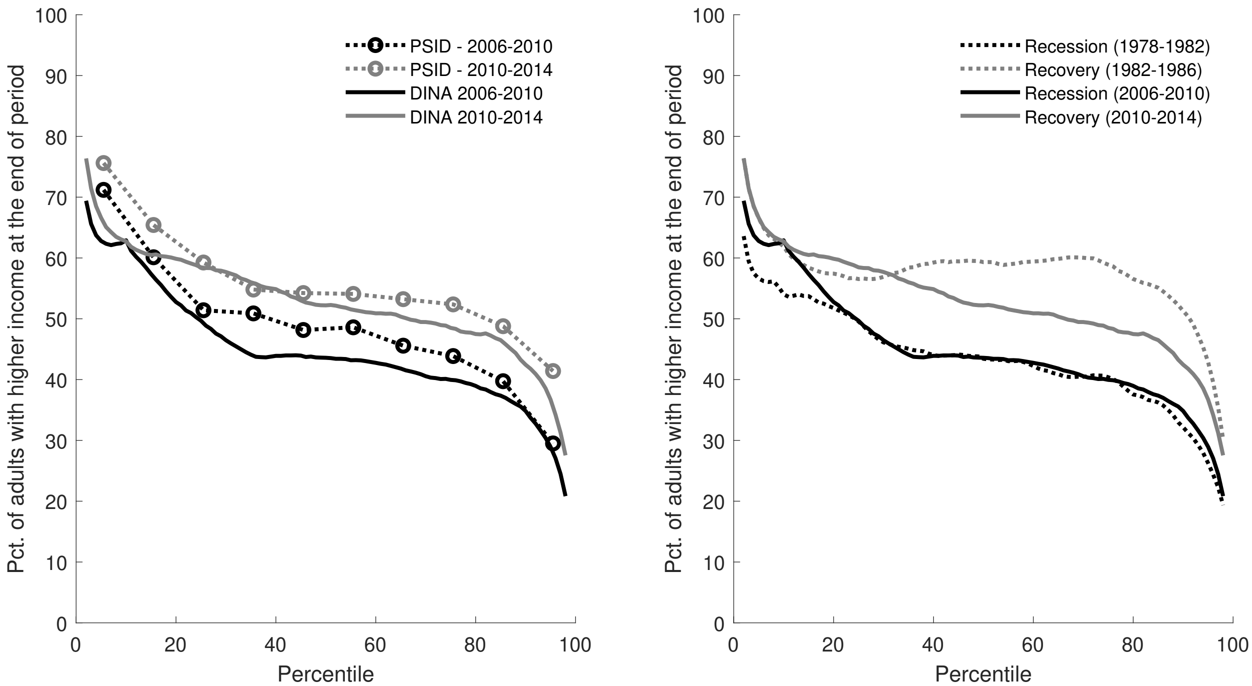

Figure 7: Absolute intragenerational mobility percentile profiles in the United States. Left) Absolute mobility in the periods 2006–2010 and 2010–2014 using PSID and the US DINA; Right) Absolute intragenerational mobility in income in the periods 2006–2010 and 2010–2014 (solid) and 1978–1982 and 1982–1986 (dotted), using the US DINA.

Figure 7 also shows that for 1978–1982 the absolute mobility percentile profile is similar to 2006–2010 for percentiles 20–100. The two periods are also similar in mobility in the aggregate level (see Figure 5). However, absolute mobility was higher following 2006–2010 for the poor – percentiles 1–20. During the recovery that followed these two recessions, absolute mobility differed. It was higher following 1982–1986 than following 2010–2014, particularly for percentiles 40–95. It was similar for the poorer and for the top 5%. Our results also demonstrate that the general pattern of absolute mobility percentile profiles is independent on whether inequality increased or decreased during the given period. Even in periods of substantial increase in inequality, such as 2010–2014, rates of absolute mobility were lower at the highest income levels.

The negative slope of absolute mobility percentile profiles is an indication of regression to the mean. It is a result of economic forces that lead to it. We would like to find out to what extent this negative slope is the outcome of mechanical effects, such as entering and exiting the labor force, life cycle changes and changes in family structure (Appendix B illustrates the strong life cycle effects on absolute mobility). We would also like to learn whether the negative slope of absolute mobility percentile profiles is over and above such mechanical effects.

The PSID allows using microdata to control for some effects. We first look at the absolute mobility percentile profiles for different specifications. These are presented in Figure 8 for different income definitions. We consider income per family member accounting for changes in family size (as opposed to income per adult in the US DINA). We also restrict the sample in two of the cases to full time workers only, aged 35–55, thus excluding some of the labor market mechanical effects. Here we calculate absolute mobility with respect to that of the entire population (*i.e.*, $x\%$ represents a probability that is $x\%$ higher for income increase over a 4-year period than of the entire population). This enables averaging over 35 4-year time periods without introducing significant age-cohort size effects.

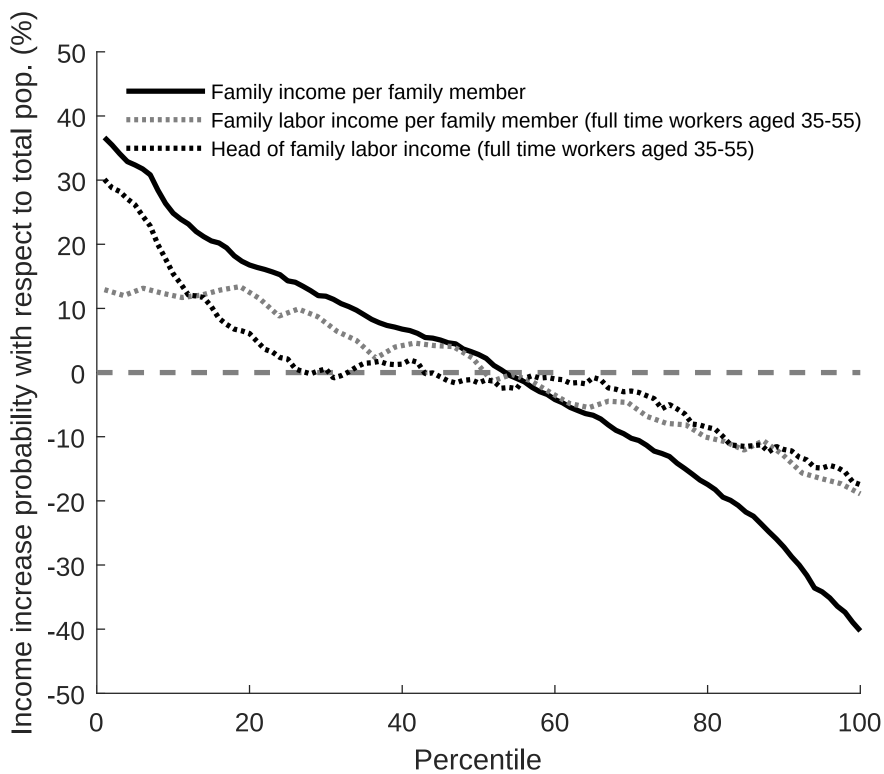

Figure 8: Average absolute intragenerational mobility in the United States by percentile for different income definitions and sample specifications.

Figure 8 demonstrates that the negative slope of the absolute mobility percentile profiles is robust and not mechanical. To further test this observation we consider

$$Y_{iat} = \alpha + \beta D_{iat} + \gamma_c c_{iat} + \delta_a + \theta_t + \epsilon_{iat} \, , \tag{4.1}$$

where:

- $Y_{iat} = 1$ if adult/family i, of age a, had higher income in year $t+4$ than in year t, 0 otherwise
- D_{iat} – decile of adult/family i, of age a, at year t
- c_{iat} – control variables
- δ_a – age fixed effects
- θ_t – year fixed effects

The baseline specification uses family head labor income for full time workers. We control for family size, change in family size between years t and $t+4$, number of hours worked, marital status and for the labor income decile of the spouse. We also consider year fixed effects and age fixed effects, accounting for across-the-board income growth and life cycle effects. Using labor income is affected less by measurement error in the survey. It also allows testing whether the observed effect is indeed over and above the mechanical short run labor market dynamics. We repeat this estimate using family head hourly wages for full time workers and for total family income without restricting our sample to full time workers, for comparison.

We note that measurement errors can lead to mechanical regression to the mean (Bound and Kruger, 1991; Fields et al., 2003) in practice. Appendix E shows that the results in the case of absolute mobility and their dependence on income ranks, which does not necessarily indicate the existence of mean reversion of incomes, are robust to such measurement errors.

The regression results are presented in Tab. 1. It shows a statistically significant negative relationship between absolute mobility and income decile. Being one decile higher decreases the probability of an adult to increase her income during a 4-year period by 2.4 percentage points.

The results also show that other variables have a significant effect on absolute mobility, however the effect is small for most control variables. Changes in family size have a large positive effect on absolute mobility for total family income (of about 6.5 percentage points). Yet, this may be mechanically driven by the increase of child benefits, included in total family income but not in labor income. The results also show that being married has a significant positive contribution to absolute mobility, especially for total family income.

Appendix H presents a similar regression considering a threshold of 30% (rather than any increase) for absolute mobility. It shows no substantial difference from the baseline results.

The negative relationship between absolute mobility and income decile is persistent over time. If we perform the regression for each 4-year period separately, we obtain a time dependent coefficient

Table 1: The dependence of absolute mobility on income decile

	Family head labor income			Family head hourly wages			Total family income		
Income decile	−0.0278***	−0.0278***	−0.0238***	−0.0305***	−0.0305***	−0.0260***	−0.0243***	−0.0275***	−0.0381***
	(0.0007)	(0.0007)	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0004)	(0.0004)	(0.0005)
Hours worked			−0.00006***			0.00008***			0.00003***
			(0.000004)			(0.000004)			(0.000001)
Family size			−0.0119***			−0.0109***			0.0102***
			(0.0017)			(0.0016)			(0.0009)
Change in family size			0.0074***			0.0066*			0.0652***
			(0.0020)			(0.0041)			(0.0011)
Marital status			0.0420***			0.0142**			0.1027***
			(0.0007)			(0.0007)			(0.0032)
Spouse's labor income decile			0.0013**			0.0032***			
			(0.0007)			(0.0007)			
Year and age FE		×	×		×	×		×	×
Observations	54431	54431	54431	54431	54431	54431	174622	174622	174622

Stars indicate statistical significance, at the *10% level, **5% level and ***1% level.

β_t (see Eq. (4.1)). Figure 9 presents β_t, showing it fluctuates between -1.5 to -3.5 percentage points in absolute mobility per one decile increase. These results further imply that the mechanical labor market and life cycle effects are not the main drivers of the narrow band of absolute mobility values.

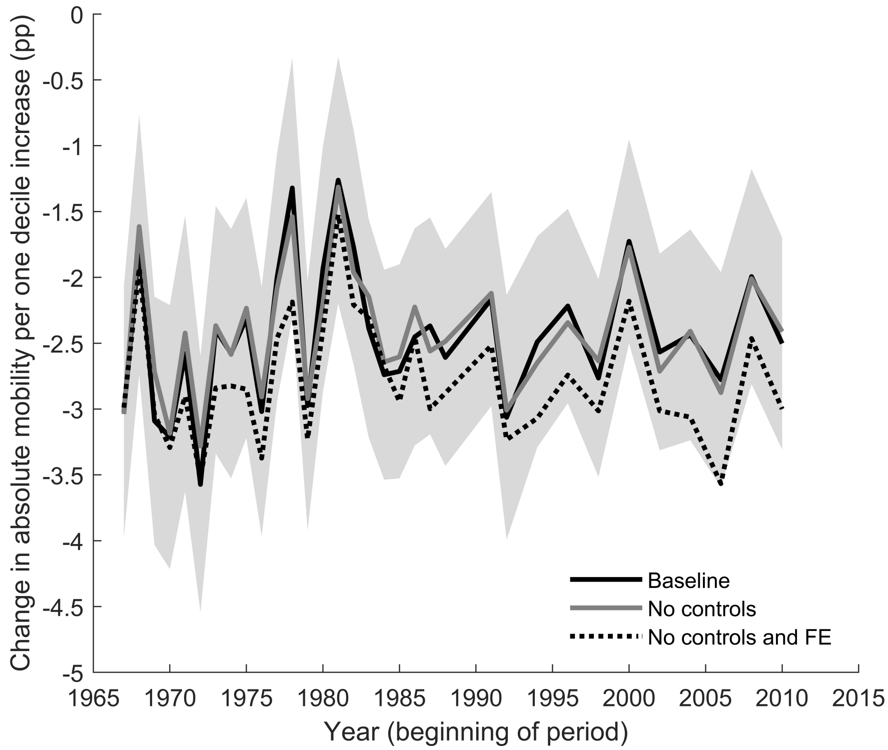

Figure 9: The change in absolute mobility per one decile increase. The shaded gray area stands for the 95% confidence interval of the baseline estimates. The estimates are based on the PSID data, using family head labor income, similarly to Tab. 1.

5 Dynamic model

The results so far emphasized the importance of changes in the composition of income ranks. This hints that the rank correlation has a primary role in determining absolute intragenerational mobility. Yet, as described above, relative mobility only plays a small role in determining absolute mobility, in practice. It is high enough, even in the intragenerational case, and lies within a narrow range of values.

We present a simple model which enables estimating absolute intragenerational mobility without needing external information on relative mobility. We assume that income follows Gibrat's law (Gibrat, 1931), *i.e.*, it follows a stochastic proportional growth process, a standard simplified model for income dynamics. It is similar to the basic longitudinal earnings model discussed by Lillard and Willis (1978).

The starting point of the model is an income distribution Y_t, which is assumed to be log-normal (the incomes Y_t are assumed positive). The log-income distribution $X_t = \log(Y_t)$ follows therefore $\mathcal{N}(\mu_1, \sigma_1^2)$. We assume that after a given time period Δt (say, several years) the log-income distribution is

$$X_{t+\Delta t} = X_t + g + \epsilon_t\,, \tag{5.1}$$

where g is an average growth rate and ϵ_t is a stochastic term which follows $\mathcal{N}(0, s^2)$ and is independent of X_t.

The distribution of $X_{t+\Delta t}$ is $\mathcal{N}(\mu_1 + g, \sigma_1^2 + s^2)$. We also denote $\sigma_2^2 = \sigma_1^2 + s^2$.

The absolute mobility over the period Δt is the probability that $Y_{t+\Delta t} - Y_t > 0$, which is the same as the probability that $X_{t+\Delta t} - X_t > 0$. $X_{t+\Delta t} - X_t = g + \epsilon_t$ and therefore the absolute mobility is

$$A = \Phi\left(\frac{g}{s}\right)\,. \tag{5.2}$$

It follows that assuming the multiplicative dynamics of Gibrat's law, the absolute mobility does not depend explicitly on the correlation or the rank correlation between X_t and $X_{t+\Delta t}$, but only on the marginal distributions.

It is also possible to derive the resulting correlation and rank correlation between X_t and $X_{t+\Delta t}$ based on the model parameters, *i.e.*, based on the marginal distributions only. The correlation between X_t and $X_{t+\Delta t}$ is

$$\rho = \frac{E[X_t X_{t+\Delta t}] - E[X_t]\,E[X_{t+\Delta t}]}{\sigma_1\sqrt{\sigma_1^2 + s^2}} = \frac{\sigma_1}{\sqrt{\sigma_1^2 + s^2}} = \frac{\sigma_1}{\sigma_2}\,. \tag{5.3}$$

Since the joint distribution of X_t and $X_{t+\Delta t}$ is a bivariate normal distribution, the copula between them is Gaussian and their rank correlation would be (Trivedi and Zimmer, 2007)

$$\rho_s = \frac{6\arcsin\left(\frac{\sigma_1}{2\sqrt{\sigma_1^2+s^2}}\right)}{\pi} = \frac{6\arcsin\left(\frac{\sigma_1}{2\sigma_2}\right)}{\pi}\,. \tag{5.4}$$

5.1 Comparison of model predictions to empirical evidence

We now test whether the absolute mobility predicted by the model is similar to the empirical evidence discussed above. We first estimate g and s based on the parameters σ_1, σ_2, μ_1 and μ_2, which are directly estimated from the US DINA microdata.

After setting σ as the log-income standard deviation for each year, we can also determine μ based on the average income. The mean of a log-normal distribution is $e^{\mu+\sigma^2/2}$, so $\mu = \log m - \sigma^2/2$, where m is the mean income as taken from data. This way, we obtain σ_1, σ_2, μ_1 and μ_2 for every 4-year period.

It is not necessary to externally estimate ρ_s or ρ in order to determine the absolute mobility. There is, however, one major limitation to this model: if $\sigma_2 < \sigma_1$, *i.e.*, when inequality decreases between t and $t + \Delta t$, s is undefined. Therefore, in those cases, the model cannot be used for estimating A.

The results of this estimation are presented in Figure 10 along with the baseline estimates of absolute intragenerational income mobility presented above. We also add estimates of absolute mobility in which the parameters σ_1, σ_2, μ_1 and μ_2 are used for estimating the marginal income distributions, while assuming explicitly that the rank correlation between X_t and $X_{t+\Delta t}$ is the same as assumed in the baseline estimate and not the resulting "endogenous" rank correlation in the model.

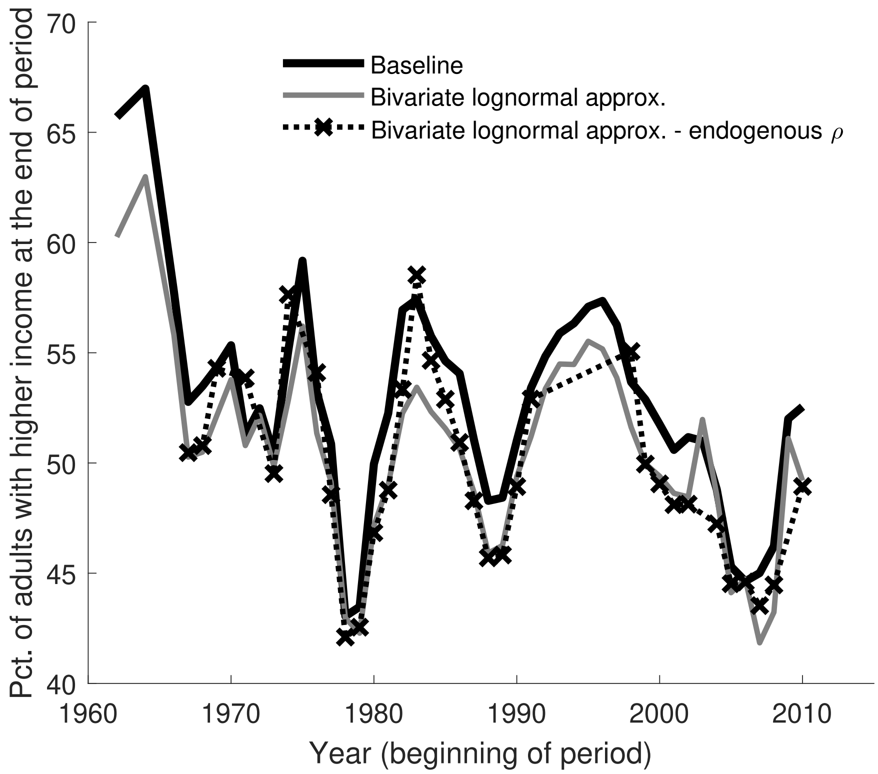

Figure 10: Income intragenerational mobility in the United States since 1962 using the dynamic model.

The model estimates are generally lower than the baseline estimates, but the difference is small – 1 percentage point on average – lower than the statistical uncertainty. This highlights, as hypothesized, that using a version of Gibrat's law it is possible to estimate intragenerational mobility without estimating the copula between the distributions.

Equation (5.2) also shows that the elasticities of absolute mobility to growth and to changes of inequality (quantified by s) are equal. A relative change in either g or s will have the same effect on A. In this model, income inequality in the beginning of the period does not affect absolute mobility, but only the inequality in the end of the period. Greater inequality at the end of the period will lead to lower absolute mobility, as reflected in Eq. (5.2). Therefore, if inequality increases substantially during a period of time, it would attenuate the positive effect of income growth on absolute mobility. In addition, as long as growth is positive, the lower bound of absolute mobility is 50%, even if inequality increases dramatically. This is, of course, inline with the empirical evidence, in which absolute mobility that is lower than 50% only occurred during periods of negative growth.

6 Conclusion

In this paper, we combined historical cross-sectional and longitudinal data to estimate absolute intragenerational mobility of income in the United States over the period 1962–2014. Absolute intragenerational mobility quantifies the probability of a family or an individual to have a higher income at the end of a given period, compared to the beginning of the period.

The contribution is both methodological and substantive. At the methodological level, we have shown that it is possible to reconcile micro-level and macro-level concepts and data sources in order to estimate the profile of absolute intragenerational mobility by income ranks, and its evolution in time. We hope that this work will contribute to stimulate similar work in other countries.

In particular, our findings highlight the importance of relative intragenerational mobility to absolute intragenerational mobility. Relative mobility is low for periods of 2 or 4 years. The changes in the composition of income percentiles are seemingly minor. Yet, we find that they are large enough to create a sizable effect on absolute mobility. Without taking into account these changes, absolute intragenerational mobility will be dramatically misestimated. We find this observation to be consistent with both empirical evidence and a standard simplified model for income dynamics.

At a more substantive level, we document the changes in absolute intragenerational mobility over time and over different phases of the business cycle. For 4-year periods absolute intragenerational income mobility is within the range 43%–67% and averages 53%. Hence, over a period of 4 years, 43%–67% of the population will have higher real incomes. In the vast majority of time periods absolute mobility was between 48% and 56%.

We also find that the likelihood of families at the bottom of the distribution to be better off by the end of a period is higher than that of families at the top of the distribution. This occurs even in periods in which income inequality increased substantially. This regression to the mean is over and above mechanical effects, such as entering and exiting the labor force, life cycle changes and changes in family structure. Even when such effects are controlled for, we find a persistent and significant regression to the mean.

Inequality has become a key issue in the public debate across the globe, and specifically in the United States. Our findings imply that taking the changes in the composition of income ranks into account is needed to better track economic growth and its inclusiveness. A detailed cross-sectional, in that sense, is insufficient. This is also politically important. Economic growth, opportunity and the chances of people across the distribution to achieve better living standards in the future have come to the forefront of the political debate. Absolute mobility quantifies these chances.

We note that our findings are mostly relevant for periods of several years only. Long run changes, such as described in Piketty, Saez and Zucman (2018); Splinter (2021), are different in nature. Long run changes in the income distribution reflect changes in the economic, demographic, societal and political structures of a country. This is fundamentally different from the individual trajectories of income we consider. Over very long time periods, life cycle effects make the analysis of intra-generational mobility uninformative. For example, over 35 years, almost the entire work force will retire. The very young low earners in the beginning will likely be the high earners in the end.

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A Absolute intragenerational mobility over 2-year periods

Our analysis is focusing on 4-year periods, however, since the PSID (2018) surveys are done every 2 years, it is also possible to perform the analysis for 2-year periods. First we estimate the rank correlations in such periods. These are presented in Figure 11. They show that naturally, the rank correlation over 2-year periods are higher than for 4-year periods.

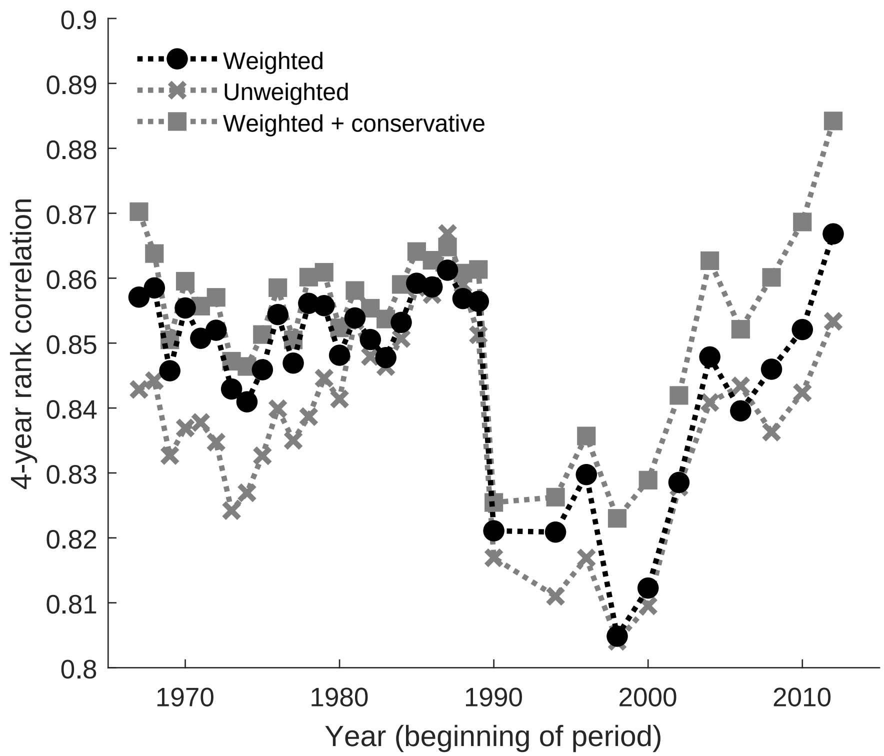


Figure 11: Spearman's rank correlation of income in the United States over 2-year periods.

Following these results, we assume that the 2-year rank correlation is within the range $(0.8, 0.9)$ and then estimate the absolute mobility similarly to what was done for the 4-year periods. The results are presented in Figure 12. They are found to be very similar to those obtained for 4-year periods (see Figure 5). The 2-year absolute intragenerational income mobility is confined within the range 43%–63% and averages 52%.

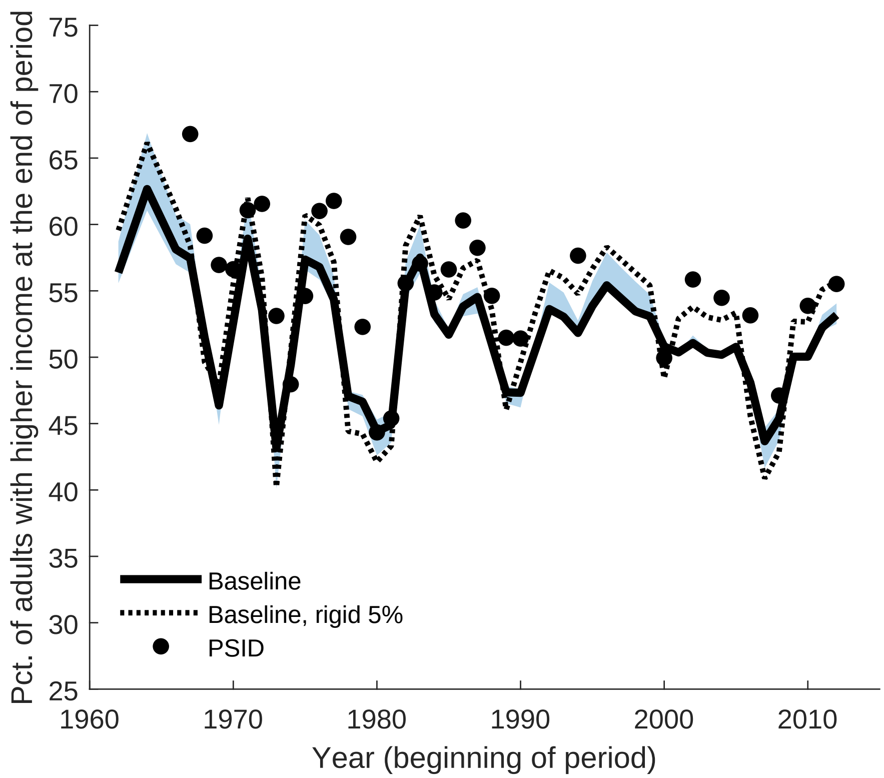


Figure 12: Absolute intragenerational mobility of income in the United States since 1962 for 2-year periods. The shaded blue area is the area covered by the absolute mobility estimates between the lower and upper bounds for the rank correlation – 0.8 and 0.9.

B Absolute mobility age profile

The probability of an individual's income to increase within a period of 4 years changes with age. Income tends to increase with age and peaks around the age of 50. It then tends to decline, especially after the retirement age. For this reason, it is expected that absolute mobility will tend to be high for young adults and decrease with age. This is presented in Figure 13. Indeed, 30 year olds have chances that are higher by 20 percentage points to see their incomes increase than for the entire population. 50 year olds have chances that are similar to those of the entire population and 60 year olds are much less likely to see their incomes increase compared to the rest of the population. The strong effect indicates that when describing how absolute mobility changes with income, age is an important factor that one needs to control for (see Section 4.4).

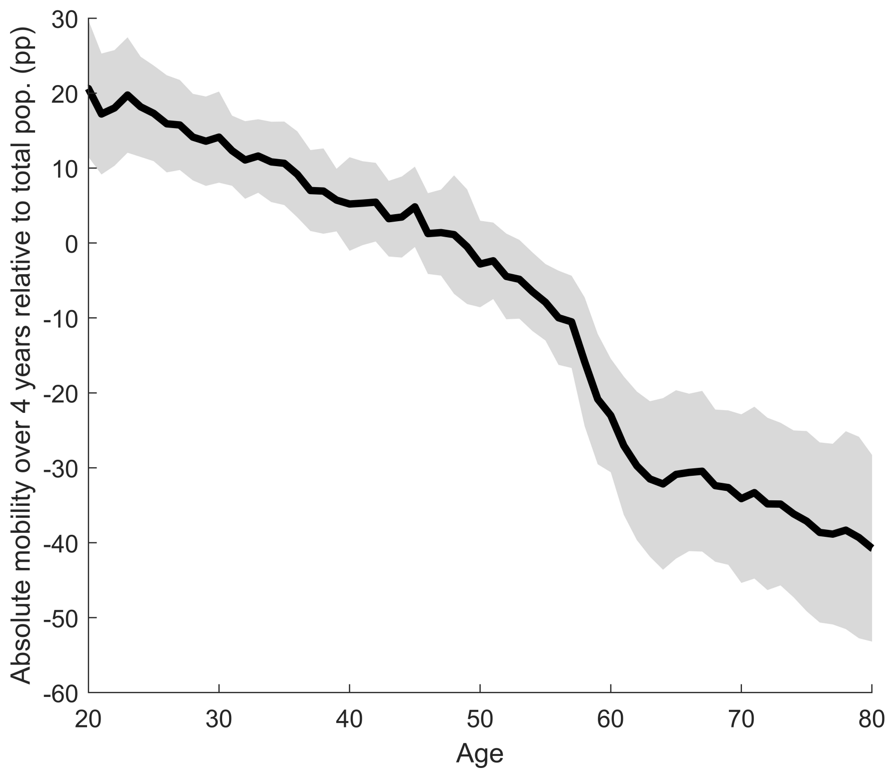


Figure 13: Absolute mobility over 4 years for ages 20–80 (the age refers to the age at the beginning of each 4 year period). The results are based on the PSID. The probability for each age was subtracted by the probability for the entire population. We then averaged over all 4 year periods available. The shaded gray area stands for the 95% confidence interval of these estimates.

We also estimated absolute mobility decile profiles for each age separately. For each time period t and each age a between 30 and 55, we estimate an absolute mobility decile profile $A_{t,a}(D)$ (where A is absolute mobility and D is the income decile relevant for the specific income and unit of observation definitions). In order to obtain plausible statistics, we average over all time periods and all ages. The results, presented in Figure 14, support the negative slope of absolute mobility with respect to income after considering age effects.

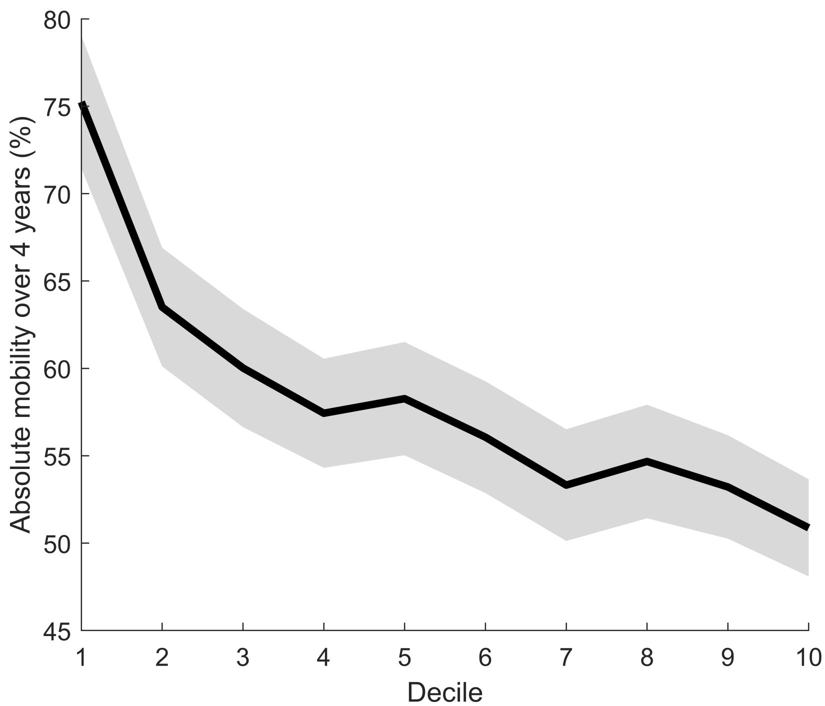


Figure 14: Absolute mobility decile profile over 4 years estimated for all ages 30–55 separately and then averaged. The results are based on PSID labor income data of family heads. The shaded gray area stands for the 95% confidence interval of these estimates.

C Absolute intragenerational mobility in different age groups

A possible mechanical explanation to our findings may be found in life cycle effects – since every year a large share of the adult population joins the labor market and leaves it, this may potentially dominate the results. We test this hypothesis by estimating separately the absolute intragenerational mobility for 3 age groups (of the head of family) using the PSID (2018) – 18–25; 35–55; 65–100. We find that indeed, the youngest group has substantially higher absolute mobility than the other groups and from the baseline estimates for the entire population. Similarly, the eldest group has substantially lower absolute mobility than the baseline estimate. However, the group of prime-age workers has mobility that is almost the same as the baseline estimate. Therefore, even if we reduce our entire discussion to this group, which is much less affected by life cycle shocks (such as retirement, or high-school/college graduation) our results would remain largely the same. The results are presented in Figure 15 and Figure 16.

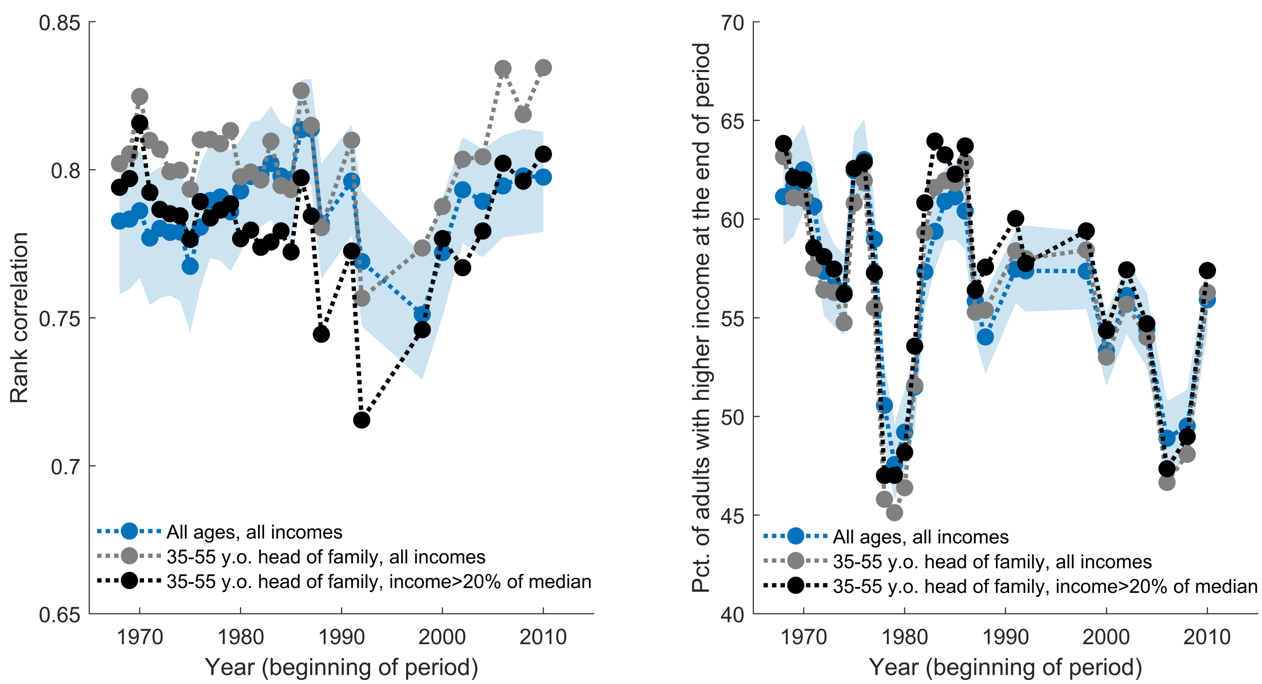


Figure 15: 4-year rank correlation and absolute intragenerational income mobility in the United States for the entire sample and for families with a 35–55 year-old head of family. We consider two specifications for the 35–55 age group – one in which all incomes are considered (including zero incomes) and one in which only incomes of at least 20% of the median family income are considered. The shaded areas stand for 95% confidence intervals produced by bootstrapping.

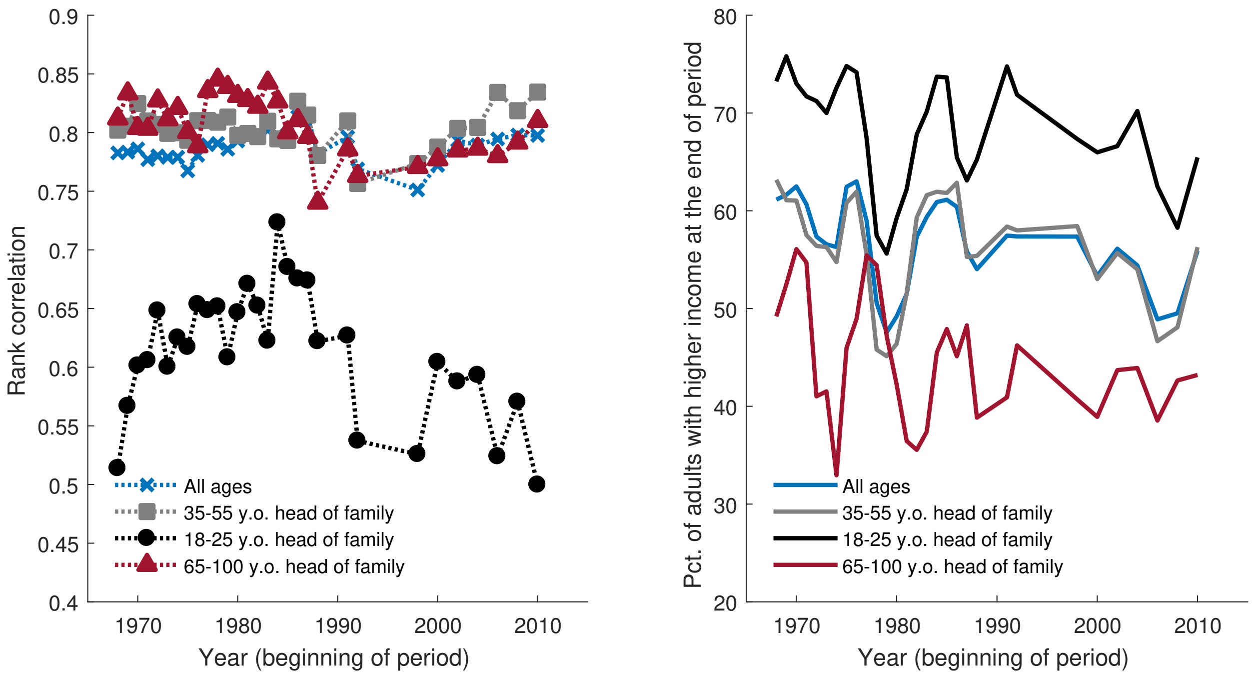


Figure 16: 4-year rank correlation and absolute intragenerational income mobility in the United States for different age groups.

D Intragenerational copula models

We estimate the empirical copulas for the joint income rank distributions over rolling 4-year periods between 1967 and 2014 from the PSID dataset. For each 4-year period we considered the sample of families surveyed in the beginning of the period and the end of the period.

For each case we also fit 5 copula models – Gaussian, Gumbel, Clayton, Frank and Plackett models (Plackett, 1965; Trivedi and Zimmer, 2007). In order to compare between the empirical copulas and the fitted modeled copulas we consider the copulas as transition (bistochastic) matrices $P \in \mathscr{P}(N)$, where p_{ij} represents the probability of transferring to quantile j (final year) for those starting in quantile i (initial year) and N is the number of quantiles.

This comparison was done for $N = 5$, 10, 50 and 100. In all cases the Plackett copula was found as the best model to fit the empirical copulas, as presented in Tab. 2 and demonstrated in Figure 17. This was already identified by Bonhomme and Robin (2009) for earnings data in France. When N increases the difference between the models becomes smaller, as is also demonstrated by the results in Tab. 2.

Table 2: Normalized Frobenius distance between the empirical and modeled copulas averaged over all 4-year periods during 1967–2014

Copula model	Number of quantiles			
	5	10	50	100
Plackett	0.01 (0.0038)	0.01 (0.0022)	0.01 (0.0012)	0.009 (0.0013)
Gumbel	0.027 (0.0077)	0.018 (0.0033)	0.013 (0.0017)	0.009 (0.0014)
Frank	0.027 (0.0077)	0.018 (0.0046)	0.013 (0.0018)	0.009 (0.0014)
Gaussian	0.027 (0.0084)	0.021 (0.0053)	0.015 (0.0026)	0.01 (0.0014)
Clayton	0.048 (0.0083)	0.032 (0.0044)	0.02 (0.0024)	0.01 (0.0012)

In practice, the absolute intragenerational mobility is not very sensitive to the copula model and for the same rank correlation we obtain similar estimates if different models are used. We use the US income data for 2006, 2010 and 2014, and estimate the absolute intragenerational mobility in the periods 2006–2010 and 2010–2014 assuming a rank correlation of 0.8, for each of the 5 copula models. The results are presented in Tab. 3.

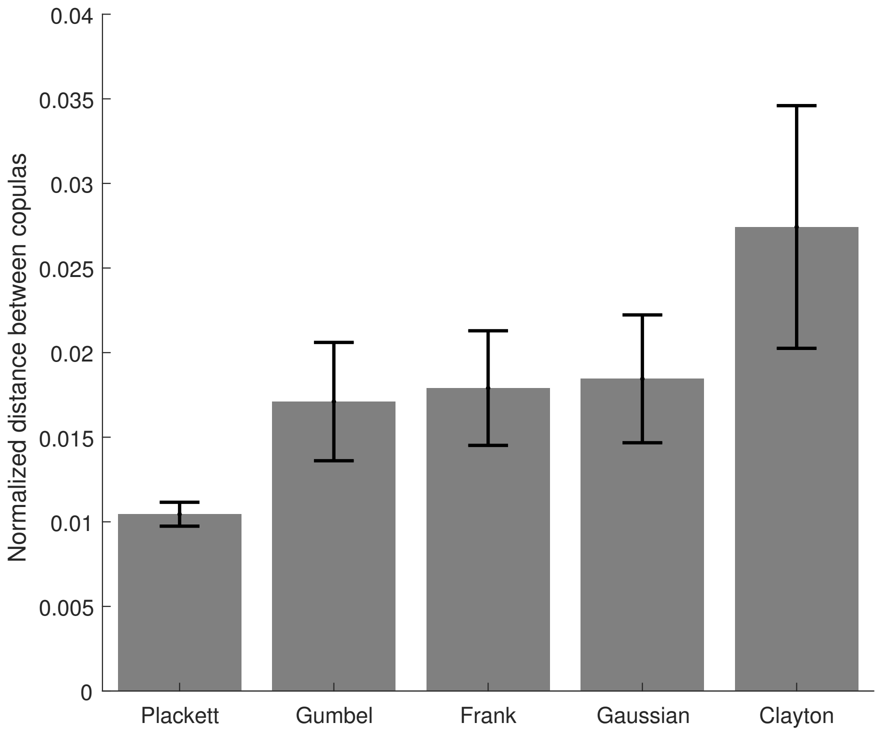


Figure 17: Average normalized Frobenius distance between empirical copulas and different copula models.

Table 3: Absolute intragenerational mobility sensitivity to copula model (standard errors produced by bootstrapping)

Copula model	Time period 2006–2010 (%)	Time period 2010–2014 (%)
Plackett	44.68 (0.13)	52.53 (0.12)
Gumbel	45.44 (0.11)	52.67 (0.11)
Frank	45.92 (0.1)	51.98 (0.1)
Gaussian	45.85 (0.1)	51.77 (0.09)
Clayton	43.86 (0.1)	50.79 (0.11)

E Absolute intragenerational mobility for time-averaged income

In order to reduce measurement errors, most notably when using survey data, it is possible to consider incomes averaged over several years. This smooths out potential transitory shocks. For intragenerational mobility such averaging may smooth out the effects one wishes to measure, if the averaging is over a long enough period. Since we are interested in 4-year periods, we compare the baseline estimates to estimates produced with incomes that are centered-averaged over 3 years. Figure 18 demonstrates that such averaging has a very small effect on the estimated absolute intragenerational income mobility. We conclude that in our baseline estimates and our estimates of rank correlation, based on PSID (2018), the measurement error has a small effect on the results.

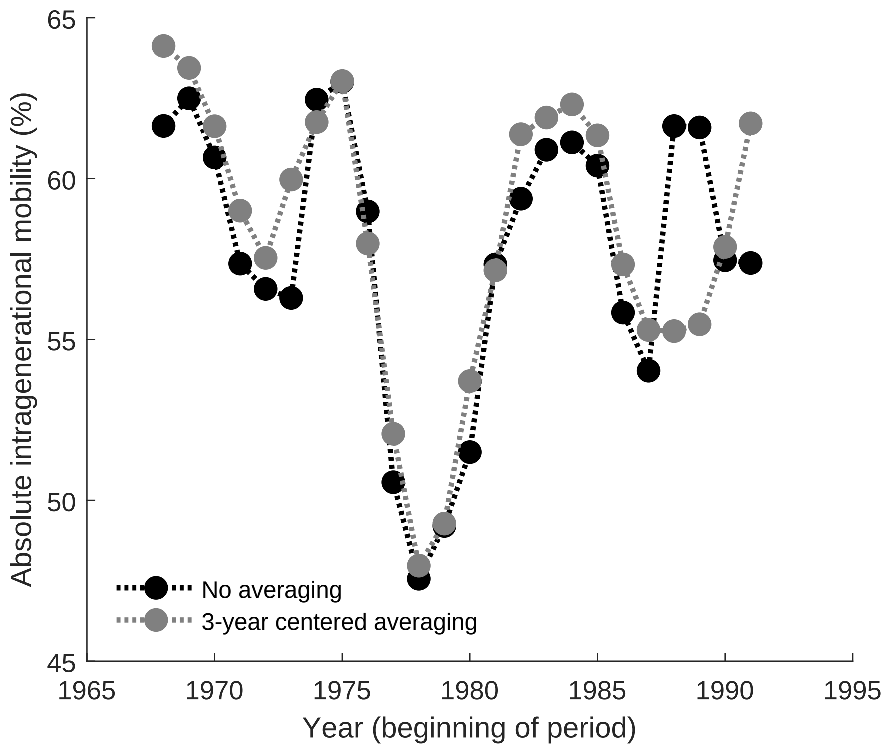


Figure 18: 4-year absolute intragenerational income mobility in the United States assuming non-averaged and 3-year centered-averaged income samples. Source: The Panel Study of Income Dynamics (PSID, 2018).

We also tested the effect of averaging on the negative slope of the absolute mobility percentile profiles. We find that after averaging these tend to be slightly higher than without averaging, however their slope remains negative. This is demonstrated in Figure 19 for the period 2000–2004 for individual labor income of full time workers.

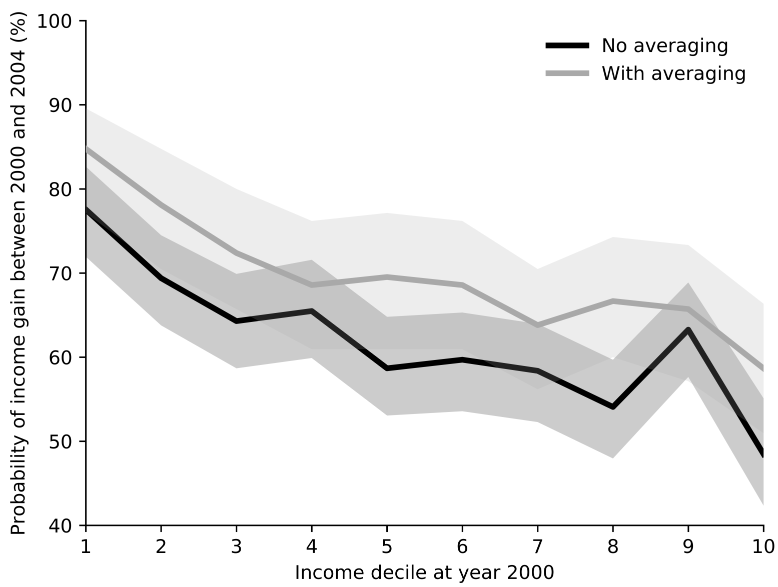


Figure 19: Absolute mobility decile profile over 4 years for full time workers, 2000–2004.

F Comparison of pre- and post-tax incomes

The results presented in this paper focus on pre-tax income. The main reason is that for external validity, pre-tax income is more relevant. Post-tax income may be heavily influenced by differences in fiscal and welfare policies in different countries. In addition, post-tax incomes are not as well documented as pre-tax income in most countries. Also, the PSID data, on which we rely in the estimation of the rank correlation, includes only pre-tax income.

Yet, the work of Piketty, Saez and Zucman (2018) allows comparing absolute mobility between pre- and post-tax incomes. We assume the same rank correlation in both cases. The results are presented in Figure 20. It shows that post-tax mobility over 4-year periods is generally higher than for pre-tax income. Yet, it is slightly lower during recessions. On average it is higher by 1.9 percentage points. In addition, like pre-tax income, absolute mobility by percentile decreases with the income rank.

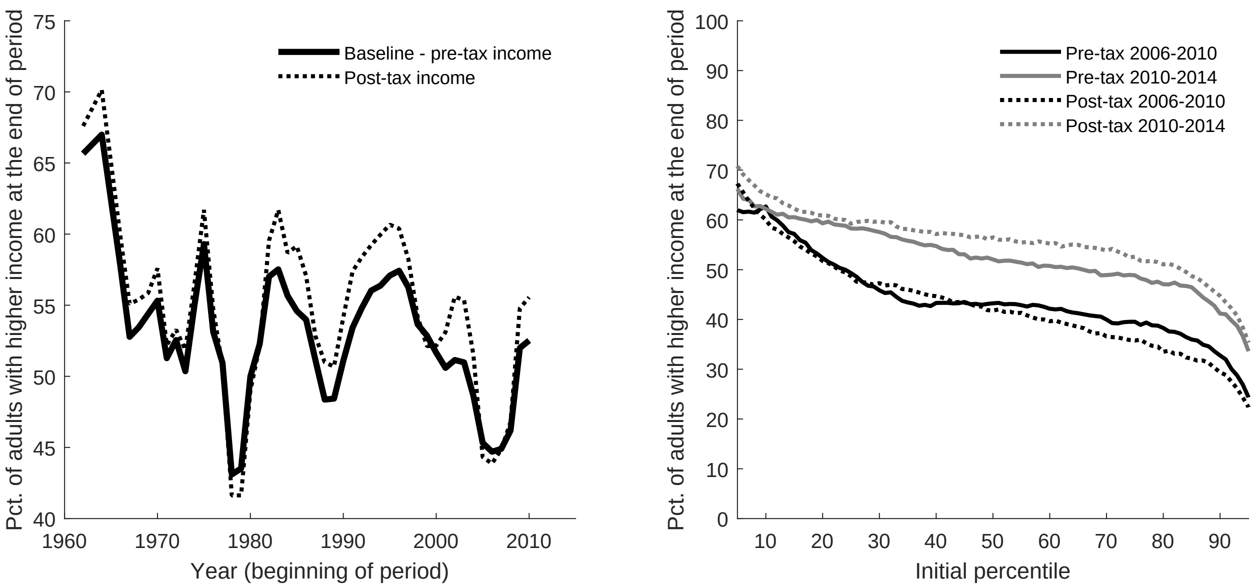


Figure 20: Comparison of absolute mobility between pre- and post-tax incomes in the United States. Left) Absolute intragenerational mobility in the United States since 1962 in 4-year periods for pre-tax (solid) and post-tax (dotted) incomes; Right) Absolute intragenerational mobility in the United States by percentile for pre-tax (solid) and post-tax (dotted) incomes.

G Sensitivity to inflation adjustments

The baseline estimates of absolute intragenerational income mobility are based on income adjusted for inflation using the national income price index (based on the GDP deflator, see WID (2018)). We test the robustness of our results to different price deflators. Specifically, we use the commonly used Consumer Price Index Research Series (CPI-U-RS) and the Personal Consumption Expenditures Price Index (PCEPI). The data for these deflators were retrieved from U.S. Bureau of Labor Statistics (2018) and U.S. Bureau of Economic Analysis (2018), respectively. The adjustments had a very small effect on the estimates of absolute mobility for all periods, except for during the late 1970s, in which using the CPI-U-RS led to substantially lower absolute mobility. It is important since the CPI-U-RS "may overstate inflation by failing to account adequately for improvements in product quality and the introduction of new goods" (Chetty et al., 2017) and "it is well known that the CPI tends to overstate inflation" (Piketty, Saez and Zucman, 2018). Figure 21 presents the results.

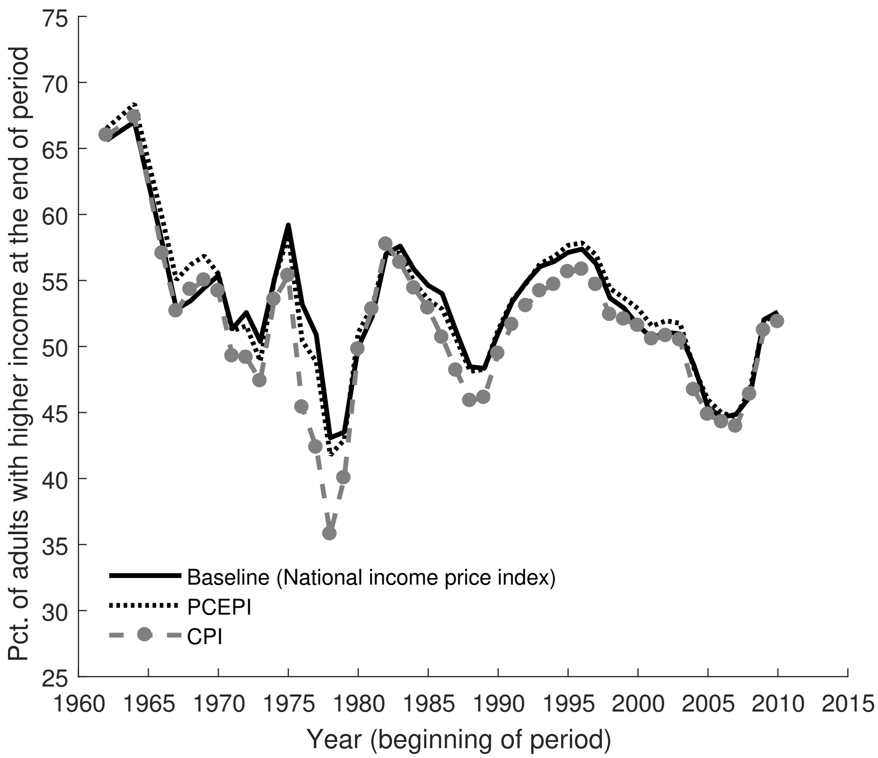
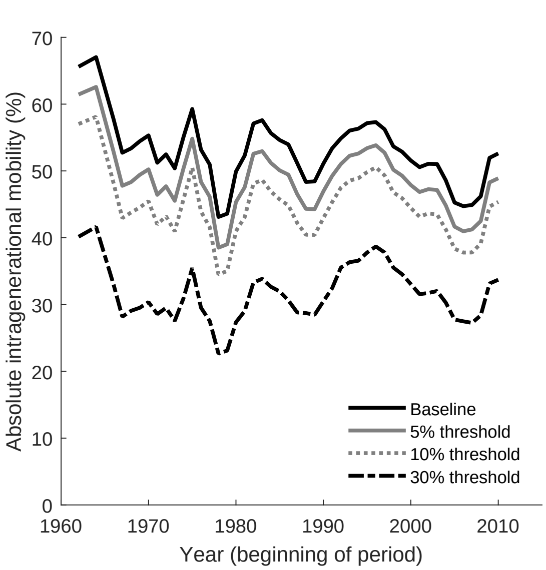


Figure 21: Income intragenerational mobility in the United States since 1962 assuming different inflation deflators.

H Absolute intragenerational mobility with threshold

We consider an alternative definition of absolute intragenerational mobility in which we estimate the share of families or individuals with income that is higher at the end of a given period by x percent relative to the beginning of the period. When $x = 0$ this definition trivially coincides with the standard definition.

Considering a threshold decreases mobility by design. We estimate the evolution of absolute intragenerational mobility over 4-year periods assuming thresholds of 5%, 10% and 30%. We also estimate how absolute mobility changes along the distribution, similar to Figure 8, given a threshold of 30%. The results show that while the threshold reduces the level of absolute mobility, the trend over time and the profile along the distribution remain similar to the baseline results.



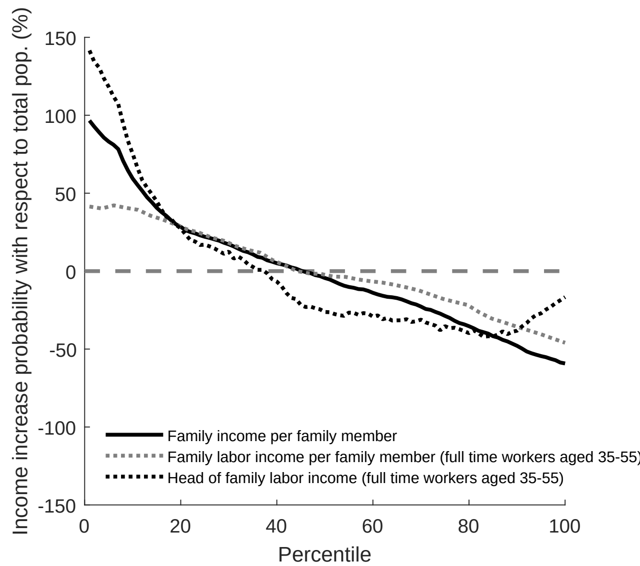


Figure 22: Income intragenerational mobility in the United States since 1962 assuming alternative thresholds (left) and mobility percentile profiles assuming a threshold of 30% (right).

For robustness, we also repeat the regression of absolute mobility on labor income decile and on total family income decile, considering a threshold of 30%. We compute the regression

$$Y_{iat} = \alpha + \beta D_{iat} + \gamma_c c_{iat} + \delta_a + \theta_t + \epsilon_{iat}\,, \tag{H.1}$$

where:

- $Y_{iat} = 1$ if individual/family i, of age a, had higher income in year $t + 4$ than in year t by at least 30%, 0 otherwise
- D_{iat} – decile of individual/family i, of age a, at year t
- c_{iat} – control variables

- δ_a – age fixed effects
- θ_t – year fixed effects

The results, presented in Tab. 4 are very similar to Tab. 1, showing a statistically significant negative relationship between absolute mobility and income decile.

Table 4: The dependence of absolute mobility with threshold of 30% on income decile

	Family head labor income			Family head hourly wages			Total family income		
Income decile	-0.0411^{***}	-0.0411^{***}	-0.0390^{***}	-0.0456^{***}	-0.0456^{***}	-0.0373^{***}	-0.0417^{***}	-0.0455^{***}	-0.0455^{***}
	(0.0007)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0007)	(0.0007)
Hours worked			0.00003^{***}			0.00014^{***}			0.00003^{***}
			(0.000004)			(0.000004)			(0.000004)
Family size			-0.0102^{***}			-0.0123^{***}			0.0071^{***}
			(0.0012)			(0.0014)			(0.0012)
Change in family size			-0.0038^{***}			0.0130^{***}			-0.0022^{***}
			(0.0001)			(0.0038)			(0.0001)
Marital status			0.0314^{***}			0.0337^{***}			0.0662^{***}
			(0.0005)			(0.0065)			(0.0007)
Spouse's labor income decile			0.0011^{***}			0.0016^{***}			
			(0.0006)			(0.0006)			
Year and age FE		×	×		×	×		×	×
Observations	54431	54431	54431	54431	54431	54431	174622	174622	174622

Stars indicate statistical significance, at the *10% level, **5% level and ***1% level.

I Absolute mobility estimates using PSID data

The baseline absolute mobility estimates use Plackett copulas with a parameter that fits the rank correlation, *i.e.*, the relative mobility, over the periods considered, as explained above. These copulas are then used to match between marginal distributions from the US DINA. Another possible way to produce such estimates is taking the copula as directly estimated for each period in the PSID (2018) and then matching the same marginal distributions. The downside of this option, albeit closer to the data and does not require using a fitted model (the Plackett copula), is the large uncertainty that would result from the small sample sizes in the PSID data.

We test the robustness of the baseline estimates to the different ways of matching the marginal distributions. The results are presented in Figure 23, demonstrating that the differences between the baseline estimates to the estimates produced when directly using the PSID copula are small compared to the associated large uncertainty.

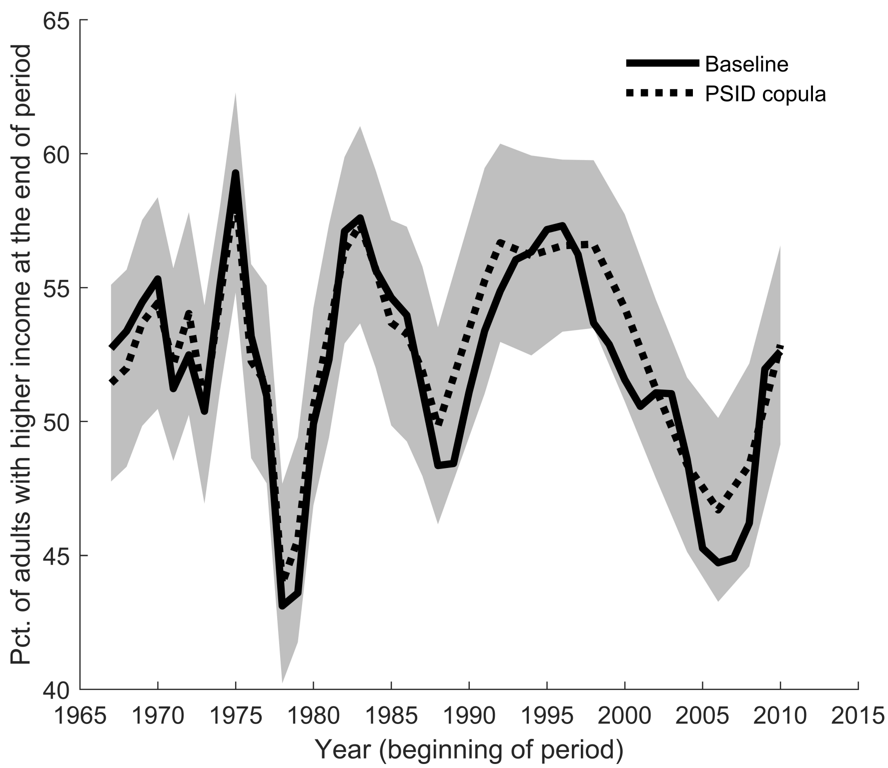


Figure 23: Income intragenerational mobility in the United States since 1967, assuming fitted Plackett copula (solid) and directly estimated copulas from the PSID (2018) surveys (dotted). The shaded gray area stands for the 95% confidence interval of the estimates based on the PSID copulas and is produced by bootstrapping.

J Income growth rate comparison

Absolute mobility generally follows the business cycle. This stems from its high sensitivity to the growth rate (see Section 5). This sensitivity can explain, in part, the discrepancy between the income absolute mobility estimates based on the PSID and the US DINA (see Figure 5). Figure 24 shows that 4-year income growth is indeed higher in the PSID than in the DINA (due to differences in income definitions between the sources).

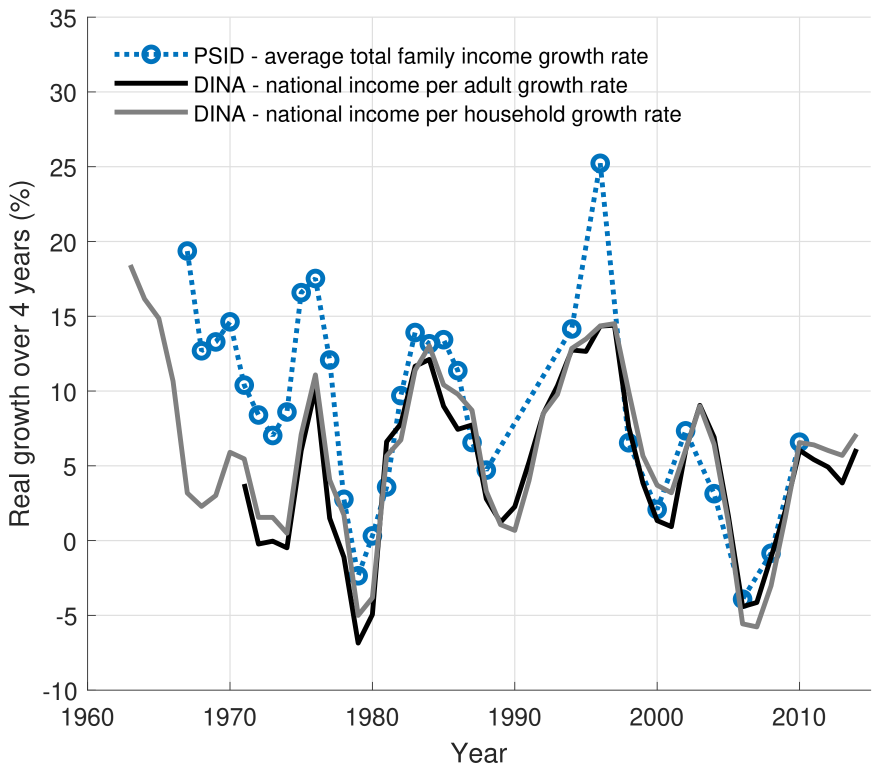


Figure 24: 4-year income growth rate comparison between the PSID and the US DINA. The US DINA time series are based on growth rates that were calculated once when the national income is divided by the number of adults (black) and once when it is divided by the number of households (gray).

K Absolute intragenerational labor income mobility

In addition to total income, which we use as the income concept in the baseline estimates, it is possible to estimate absolute intragenerational mobility for labor income only. This type of income is expected to be more sensitive to changes that are specifically related to the labor market, such as periods of massive job loss or creation. The relative mobility for labor incomes is also different from that of total income. Using the PSID (2018) data we find that the average 4-year rank correlation of labor income is 0.76, and similarly to the estimation done for total family income, we produce conservative bounds, which correspond in the labor income case to the range $(0.7, 0.81)$.

Figure 25 presents the evolution of absolute intragenerational mobility of labor income in comparison to the baseline estimates. Both specifications result in very similar estimates, with the labor income estimates being on average 0.5 percentage point lower than the total income estimates. The difference is more pronounced (1.5–2 percentage points lower) through the late 1970s and early 1980s recessions, which were accompanied by severe job losses, and through the Great Recession.

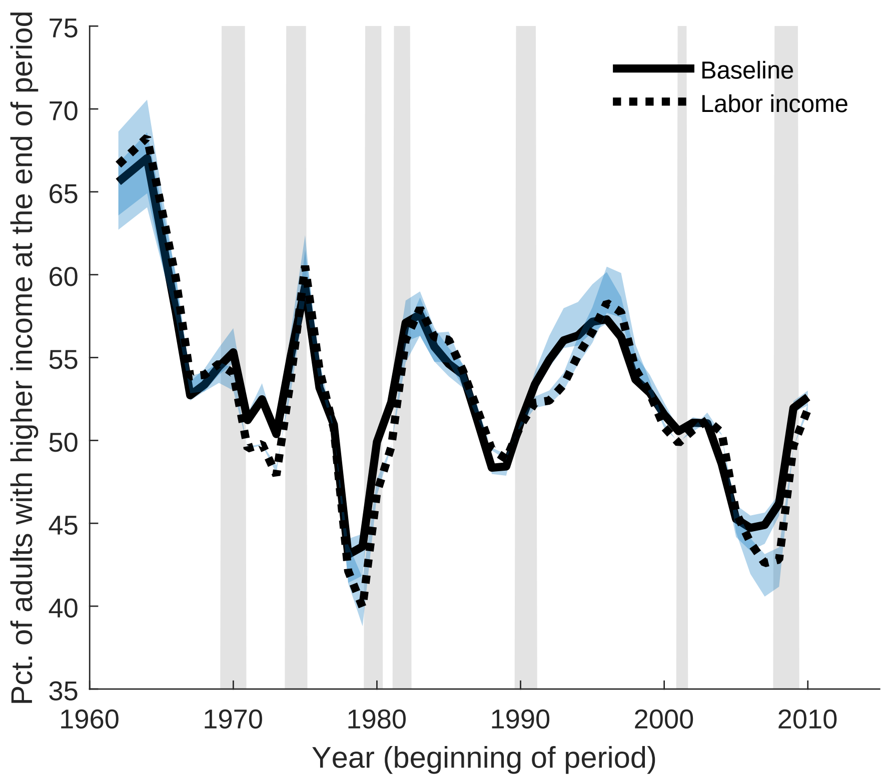


Figure 25: Income intragenerational mobility in the United States since 1962 for total income (solid) and labor income (dotted). The shaded blue areas are the areas covered by the absolute mobility estimates between the lower and upper bounds for the rank correlation in both specifications. The shaded gray areas are recession periods.