Inclusive Growth and Absolute Intragenerational Mobility in the United States, 1962-2014

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18 October 2018

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First version: August 26, 2018 Last revised: October 16, 2018

Abstract

This paper combines historical cross-sectional and longitudinal income and wealth data in the United States to present the evolution of absolute intragenerational mobility from the 1960s onward. That is, the fraction of families with higher income or wealth over a given period. We find that the rates of absolute mobility over periods of two to four years are largely confined within 45%–55%. This occurs over all the phases of the business cycle. Absolute mobility is higher for lower percentiles, also during periods of increasing inequality. These results stem from the importance of the changes in the composition of income and wealth percentiles even over short time periods. We offer a simplified model to mathematically describe these findings.

Keywords: Mobility, inequality, copula modeling
JEL Codes: C2, D3, E2, H0, J6

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†I wish to thank Alex Adamou, François Bourguignon, Jonathan Goupille-Lebret, Cem Özgüzel, David Splinter and Daniel Waldenström; and numerous seminar and conference participants for helpful discussions and comments.

1 Introduction

Economic booms and busts, crises 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 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.

Income growth can occur amidst the substantial growth of few and the decrease or the stagnation of many others. In particular, in periods of increasing income inequality, this is a potential scenario that is thought to have occurred. Yet, this was not necessarily the case. It is necessary to track the incomes of every individual or household over time to describe the patterns of income growth among the US population in the short run. This paper aims to describe these patterns for the United States from 1962 to 2014.

The rising economic inequality in the past several decades raised the need for distributional national accounts (Piketty, Saez and Zucman, 2018; Auten and Splinter, 2018). Distributional national accounts consider not only aggregate measures such as per capita income, but also their distribution within the population. For example, they show that during the recovery periods that followed the recessions of the 2000s, wages did not recover as fast as total income in the US. This seemingly means that the fruits of economic recovery were predominantly enjoyed by the already better off, as illustrated in Fig. 1. Since 1970, the average adult total income increased faster than the median adult labor 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.

Yet, distributional national accounts do not allow answering who benefits and who loses during recessions and recoveries. They cannot answer what fraction of households or individuals is better or worse off following such periods. This measure is called *absolute intragenerational mobility*.[1] This paper studies absolute intragenerational mobility in the United States from the early 1960s onward, combining

[1] *i.e.* absolute intragenerational mobility is the probability of a family or an individual to have higher income (or wealth) at the end of a given period, compared to the beginning of the period.

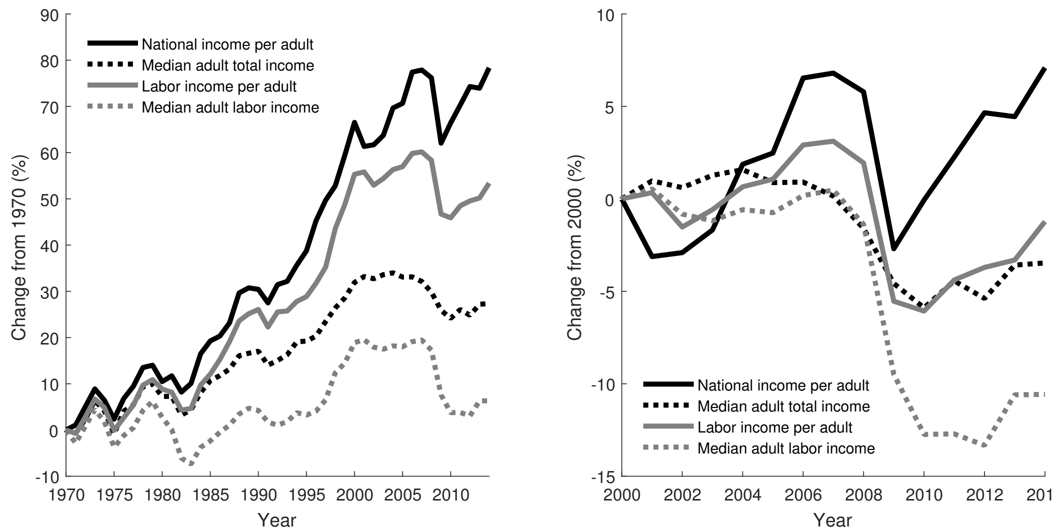

Figure 1: The evolution of real mean and median total national income and labor income in the US, 1970–2014. Source: The World Inequality Database (WID, 2017).

cross-sectional and longitudinal data. We find that following periods of economic slowdown and recessions, 40%–50% of families are still better off in terms of their real income. Similarly, following economic booms or recovery periods, 40%–50% of families would be worse off.

This seemingly contradicts the picture that arises when changes in the composition of income and wealth ranks are not taken into account. Since such changes are generally small over periods of several years, they are usually not considered. In such cases, it is useful to quantify income changes for different parts of the income distribution using *growth incidence curves* (Ravallion and Chen, 2003) (GIC). A GIC indicates the growth rate in income between two points in time at each percentile of the distribution. Fig. 2 presents GICs for the periods 2006–2010 and 2010–2014 in the United States.

GICs would allow measuring absolute intragenerational mobility had the changes in the composition of income ranks been negligible. For example, during 2006–2010 the real income per adult in the United States fell by almost 6%. Assuming no change in income ranks during this period, the entire adult population of the United States would have been worse off (in terms of income). This is illustrated in Fig. 2. Yet, in practice, it is necessary to test whether the changes in the income rank composition are indeed negligible.

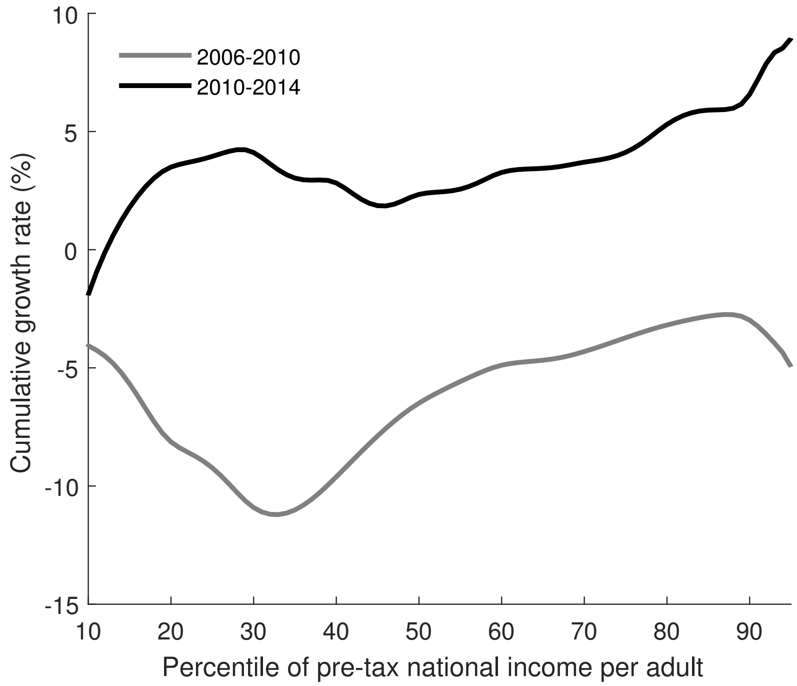

Figure 2: The cumulative income growth rate by pre-tax income percentile in the United States during 2006–2010 and 2010–2014 periods. Source: The World Inequality Database (WID, 2017). The x-axis is cropped to 10%–95% for display purposes.

The Panel Study of Income Dynamics (PSID, 2017) is a longitudinal dataset. It is based on surveys of national representative samples of US families. The PSID allows taking into account mobility of families between income ranks. For the period 2006–2010 the PSID shows that 48.8% of US families had a higher income in 2010 than in 2006 (in real terms).

This paper reconciles these different data sources. It emphasizes the importance of changes in the composition of income and wealth ranks. First, we describe a methodology of calculating absolute intragenerational mobility and discuss its sensitivity to changes in relative intragenerational mobility. We find that when relative mobility is very low, this sensitivity is high. Yet, the sensitivity becomes low when relative mobility is higher. This enables estimating absolute intragenerational mobility for any period for which cross-sectional income or wealth data are available. Using the World Inequality Database (WID, 2017) we then estimate absolute intragenerational mobility in income and in wealth for the United States from 1962 onward.[2]

We find that for 2- and 4-year periods, trends of absolute 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%. Over a period of 4 years, 43%–67% of the population will enjoy higher living standards, for all aggregate-level changes observed. For wealth we find this range to be 40%–60% apart from during the great recession, after which only 30%–35% of US families had more wealth than at its beginning.

We also find that the likelihood of families at the bottom of the distribution to be better off by the end of the period is higher than that of families at the top of the distribution. This occurs even in periods during which income inequality increases. Yet, we find that increasing income inequality had a negative effect on absolute mobility. Between 1962 to 2014 it led to an average decrease of 1.9 percentage points in absolute mobility over 4-year periods.

We present a simplified model for the dynamics of incomes based on Gibrat's law (Gibrat, 1931). It allows estimating absolute intragenerational mobility without needing panel data. The model results are consistent with the empirical evidence. They show that inequality reduces absolute intragenerational mobility and that higher growth leads to higher absolute mobility.

The main explanation for our results is the importance of changes in the composition of income and wealth ranks. Individuals who are worse off following a certain period are, generally-speaking, laid-off workers, who stay unemployed or underemployed at the end of the period, and retirees. Such individuals are very likely to change their income rank during the same period. At the same time, some unemployed or underemployed at the beginning of the period, as well as many young adults that join the labor force, have higher income at the end of it. Thus, they are very likely to have changed their income rank as well. In such a case, it would be misleading to compare the incomes of the same percentile at the beginning and the end of such period. They would not represent the same households or individuals. Therefore, relative intragenerational mobility, even if much lower than in the intergenerational case, may play an important role in the proper interpretation of GICs.

[2] When we refer to data from the World Inequality Database, we practically refer to the income data described in Piketty, Saez and Zucman (2018) and the wealth data described in Saez and Zucman (2016). The US entries in the World Inequality Database were derived from these papers.

Our results imply that framing the increasing inequality as "the rich really are hoarding economic growth" (Matthews, 2017) is inaccurate. They are consistent with the differences between mean and median income or wage growth in recent decades. In addition, the results stress the importance of obtaining a deeper understanding of how growth is distributed in the short run.

Relative intergenerational mobility has been studied for decades.[3] Yet, investigations of absolute intergenerational mobility remain "scarce, mainly because of the lack of large, high-quality panel data sets linking children to their parents" (Chetty et al., 2017, p. 398). Chetty et al. (2017) studied the historical evolution of absolute intergenerational mobility in the United States. They found that it has fallen from around 90% for children born in 1940 to 50% for children born in the 1980s. Berman (2018) showed a similar trend in other countries, also establishing the robustness of the estimation methodology of absolute mobility.

Relative intragenerational mobility of wealth and income was also studied in many countries.[4] Yet, it did not receive as large attention as in the intergenerational case. Intragenerational mobility was also given attention by the sociological literature, most notably in the context of racial division and class in the United States (see, for example, Sørensen (1975); Pomer (1986)).

This paper aims to be among the first to study absolute intragenerational mobility. Previous related studies focus on relative mobility measures and on short term mobility at the top of the distribution (Kopczuk, Saez and Song, 2010; Auten, Gee and Turner, 2013; Martínez, 2017), on earnings (Kopczuk, Saez and Song, 2010; Shin and Solon, 2011; Dynan, Elmendorf and Sichel, 2012), on income variability and growth (Splinter, 2018) and on limited subgroups of the population or limited time periods (Fontenay, Gørgens and Liu, 2002). Thus, the primary contribution of this paper is to provide new series on the evolution of absolute intragenerational mobility in the United States.

This paper has two additional main contributions. First, we emphasize the impor-

[3] See, for example, Becker and Tomes (1979); Borjas (1992); Piketty (2000); Mazumder (2005); Aaronson and Mazumder (2008); Lee and Solon (2009); Hauser (2010); Corak (2013); Chetty et al. (2014); Berman (2017).

[4] See, for example, Gottschalk (1997); Fields and Ok (1999); Aaberge et al. (2002); Jenkins and Van Kerm (2006); Bonhomme and Robin (2009); Kopczuk, Saez and Song (2010); Shin and Solon (2011); Dynan, Elmendorf and Sichel (2012); Auten, Gee and Turner (2013); Bourguignon and Moreno (2017).

tance of incorporating relative mobility when interpreting growth incidence curves. This has been suggested already in the form of non-anonymous growth incidence curves (Bourguignon, 2011) and cumulative mobility profiles (Jenkins and Van Kerm, 2016), but in different contexts and without quantifying absolute mobility. In particular, we find the little relative mobility documented for short time periods to be large enough to create a substantial effect on the estimates of absolute mobility, as described above. This has clear implications on the way changes in inequality are interpreted.

Second, we establish a methodology that is general, which 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 eliminates the need for detailed panel data or synthetic matching approaches. Unlike absolute intergenerational mobility, which is found as insensitive to the copula (Berman, 2018), we find that absolute mobility is very sensitive to changes in the copula when there is very little relative mobility. Our methodology also allows overcoming limitations related to the nature of the available data. Specifically, top-coding issues and removing low incomes[5] have a limited effect on our results.

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 and for interpreting GICs. In Section 3 we specify our data sources. Section 4 presents the main results. It describes the evolution of absolute intragenerational income and wealth mobilities in the United States. Section 5 discusses a simplified model based on Gibrat's law, 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 (and wealth) of all households is known for any given year, measuring the absolute intragenerational mobility – the fraction of

[5] See, for example, Gottschalk and Moffitt (2009); Kopczuk, Saez and Song (2010); DeBacker et al. (2013); Splinter (2018).

households with higher real income (or wealth) at the end of a given period than at its beginning – is trivial. However, such data are usually available for small samples and do not cover the entire distribution or available for a limited range of years. Notably, in many developing countries, such data are rare.

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 double. First, the structure of realistic intragenerational copulas can be well approximated by a Plackett copula (Plackett, 1965). 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 much 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 uncertainty in relative mobility measures leads to only a small uncertainty in the absolute mobility estimates.

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 Fig. 3. We consider the copulas as transition (doubly stochastic) 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. We find that for all 4-year periods from 1967 onward, the transition matrices, estimated from the PSID total family income data, 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.

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

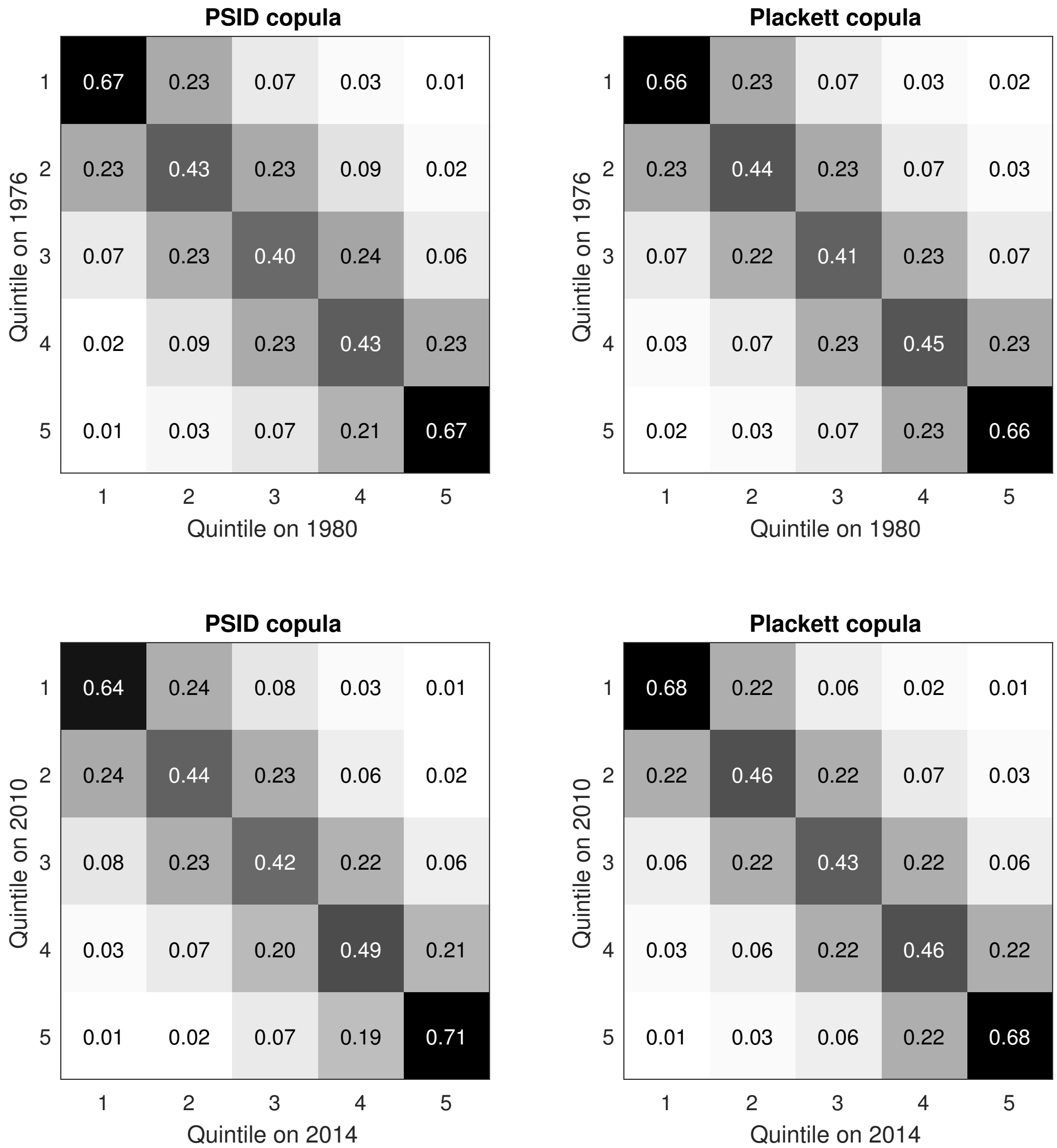

Figure 3: Transition matrices for 1976–1980 (top) and 2010–2014 (bottom) for total family income estimated using the PSID dataset (left) and approximated using a Plackett copula. The numbers refer to the transition matrix elements and the color map is scaled between 0 (white) and 1 (black).

2.1 The sensitivity of absolute intragenerational mobility to the rank correlation

We established that for estimating absolute intragenerational mobility the copula can be 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 used the WID (WID, 2017) and considered the US pre-tax income distribution on 2006, 2010 and 2014. We estimated 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 – $P(X_1)$ and $P(X_2)$ (where X_1 and X_2 are the incomes in the initial and final years of a given period, respectively) – to obtain a joint income distribution – $P(X_1, X_2)$. This allows estimating the absolute mobility, which is equal to $P(X_2 > X_1)$. This follows the method used in Chetty et al. (2017); Berman (2018).

Apart from the absolute mobility estimate resulting from this calculation we produced an additional estimate in which we 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 rest 95% of the population 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.

For both specifications we estimated the absolute intragenerational mobility during 2006–2010 and 2010–2014. We also estimated the share of families which increased their income by at least 3%. Fig. 4 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, which is, however, unrealistic.

When the rank correlation is 1, *i.e.* in the case of perfect immobility, the estimated mobility becomes identical to the interpretation of growth incidence curves as described above. These observations remain unchanged even with perfect mobility at the top (rigid top 5%).

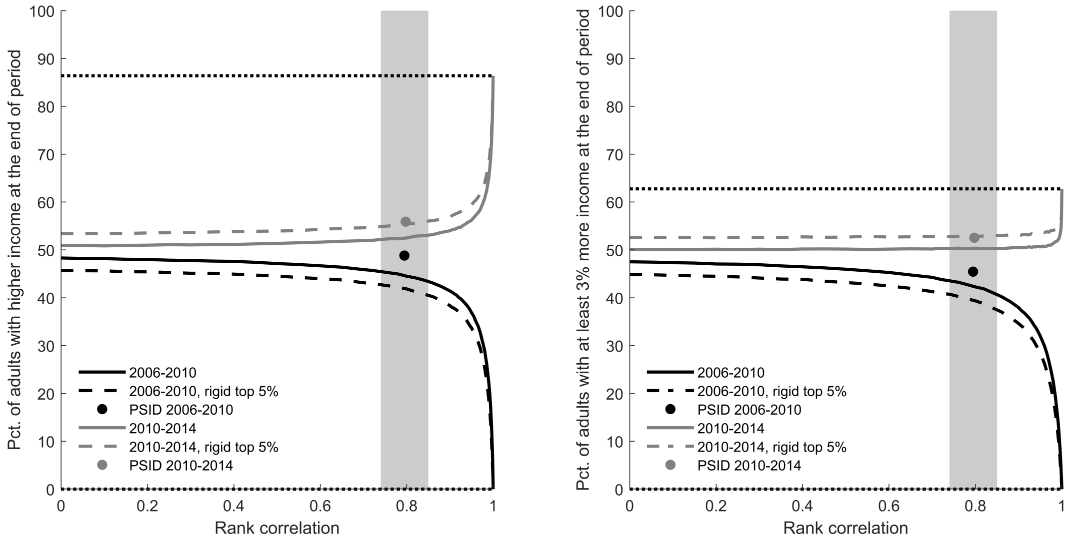

Figure 4: Sensitivity of absolute intragenerational mobility to the rank correlation. We calculate the absolute intragenerational mobility in the United States between 2006–2010 (black) and 2010–2014 (gray) assuming Plackett copulas with changing rank correlation. The dashed lines are the absolute intragenerational 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 WID (WID, 2017). 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 and wealth distributions, it is possible to estimate absolute intragenerational mobility with low uncertainty. This enables the estimation of absolute intragenerational mobility in income and in wealth in the United States, for which the marginal distributions are well known and the rank correlation lies within a narrow band of values, as we discuss below.

3 Data

Our estimations rely on two data sources. The first is the World Inequality Database (WID, 2017). This database includes comprehensive estimates of the income and wealth distributions in the United States for the years 1962, 1964 and 1966–2014, combining tax data, survey data and national accounts. The wealth distributions are based on the capitalization of income tax and reconciled with national accounts and surveys (Saez and Zucman, 2016; Piketty, Saez and Zucman, 2018).

To obtain the income and wealth samples for the absolute mobility estimates we use the generalized Pareto interpolation technique (Blanchet, Fournier and Piketty, 2017). It allows creating samples while accurately preserving the distribution. We use a sample size of $N = 5 \cdot 10^5$, for which the statistical uncertainty due to the sampling method is negligible. This way, for every year (1962, 1964 and 1966–2014) we possess a large sample representing the income distribution and the wealth distribution of individual adults in the United States.

The second data source is The Panel Study of Income Dynamics (PSID, 2017). This is a longitudinal panel survey of US families conducted annually or biennially from 1967 to 2015. We use the total family income and wealth variables in the survey. The sample sizes differ in each wave due to methodology changes in the survey and since the survey tracks the descendants of past surveyed individuals. Overall, approximately 6000 families were surveyed in each wave. The total income of each surveyed family is available from 1967 onward, whereas total wealth is available from 1999 onward. We use this database primarily for the purpose of estimating the intragenerational copula of income and of wealth 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 WID is preferable over survey data.

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 WID. In addition, the small sample sizes, the limited coverage of the top of the distribution and the measurement error 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. Furthermore, even if the PSID indeed overestimates relative mobility, it has a very small effect on the absolute mobility estimates, as demonstrated above.

It is also important to note that the basic unit of measurement for the income and wealth data in the WID is an adult under the "equal-split" assumption.[6] In the PSID data the basic unit is a family. Thus, the estimated family-based mobility may lead to overestimation of the rank correlation (compared to the individual-level rank correlation). But, the bad coverage of top incomes in the survey data, may lead to downward bias of the rank correlation, since the top of the distribution is characterized by lower relative mobility (Bourguignon, 2011; Corak, 2013). In our estimations we also consider lower and upper bounds for the rank correlation, to take into account this uncertainty and the additional potential biases. The PSID also includes individual-based data, but wealth is only measured for families. For consistency we only use the family-level data. 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 that those estimated using the WID. This difference might originate in the difference between the units of observation. We focus on the WID for the reasons specified above.

Due to possible measurement error, many studies of inequality and of intergenerational mobility consider incomes averaged over several years in order 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 B 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 and wealth. The main reason is that for external validity, pre-tax income is more relevant – post-tax income may be influenced by differences in fiscal and welfare policies in different countries. In addition, post-tax incomes are not 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, it is possible to make a basic comparison between absolute mobility of pre-tax and post-tax incomes, using new findings from Piketty, Saez and Zucman (2018). Such a comparison is presented in Appendix C. We find that absolute mobility of post-tax income is generally higher than for pre-tax income.

[6] 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) for a detailed discussion on this assumption.

On average it is higher by 1.9 percentage points, but follows a very similar evolution in time.

We also discuss absolute mobility among billionaires in the United States using the billionaires lists based on Forbes data, listing all billionaires in the US from 2001 to 2017 (Forbes Magazine, 2001).

4 Results

4.1 Intragenerational rank correlation

Using the PSID data we first estimate the 4-year intragenerational rank correlation for income and wealth in the United States. These estimates are presented in Fig. 5. 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/wealth by the end of the period. The latter estimate would be higher than the baseline estimate by design. While it is upward biased, this bias may overcome some of the measurement error (especially since the PSID does not capture well the top of the distribution, which is also known to be characterized by lower mobility (Bourguignon, 2011; Corak, 2013)). These estimates are given from 1997 onward. The reason is the substantial changes made in the PSID survey design in 1997, which particularly affect the sample weights (Heeringa and Connor, 1999). We also include 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.

The 4-year period rank correlation lies within the range $(0.74, 0.85)$. As demonstrated in Fig. 4, even such low 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 model would lead to a small uncertainty when estimating the absolute intragenerational mobility both in income and in wealth.

For robustness we also compare the results to the absolute mobility estimates when using the copula as estimated directly in the PSID data. The main downside of using

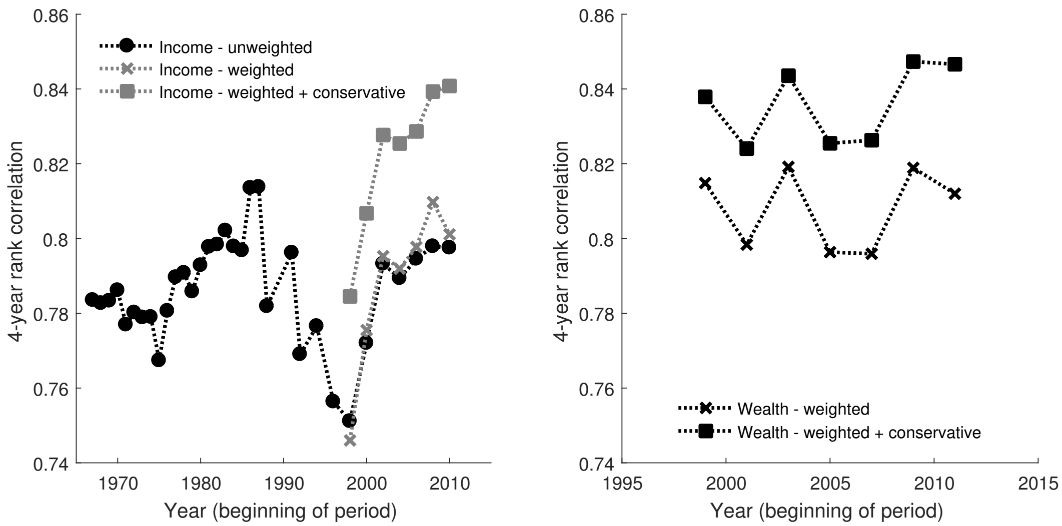

Figure 5: Spearman's rank correlation of income (left) and wealth (right) in the United States.

this copula explicitly is the small size of the PSID samples and the measurement error associated with it. This creates some uncertainty in the resulting absolute mobility estimates. Yet, the differences between the baseline estimates to these estimates of absolute mobility are small for all specifications (see Appendix D).

4.2 The evolution of absolute intragenerational mobility

Based on the above it is now possible to estimate income and wealth absolute intragenerational mobility in the US. We use the detailed data on wealth and income distributions from 1962 onward from the WID (WID, 2017), as described. For each 4-year period (in a rolling window) we produce 4 estimates, presented in Fig. 6:

- 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, when available.

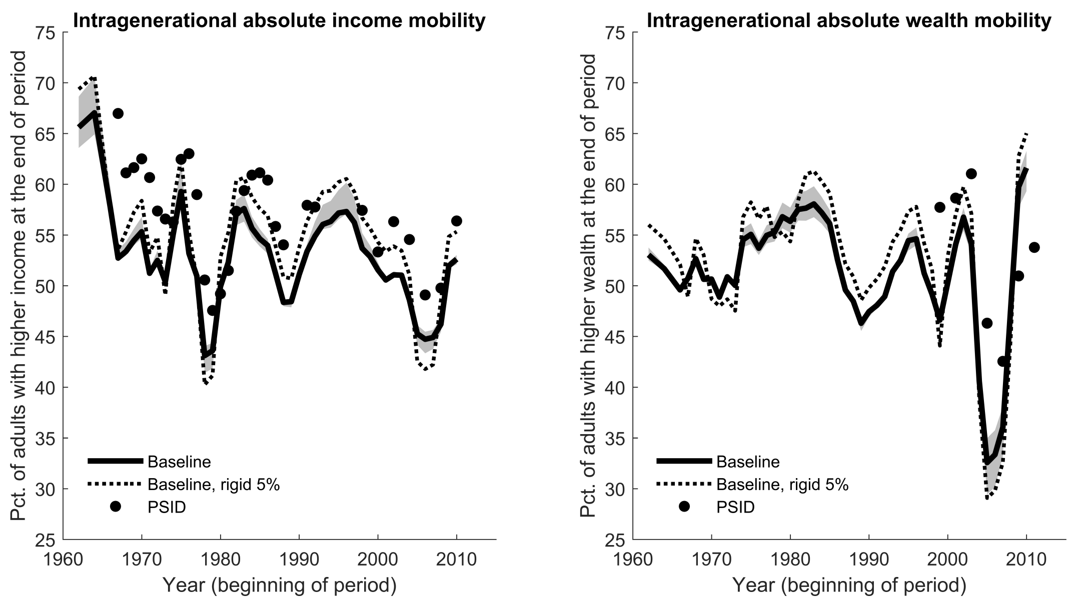

Figure 6: Income (left) and wealth (right) absolute intragenerational mobility in the United States since 1962. The shaded gray area is the area covered by the absolute mobility estimates between the lower and upper bounds for the rank correlation – 0.74 and 0.85.

The 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%. It averages at 53%, *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. For wealth this range is 40%–60% apart from during the great recession, after which 30%–35% of US families had more wealth than at its beginning.

The results demonstrate that the evolution of absolute mobility follows the business cycles. Its trend follows income and wealth growth trends. This is not at all surprising. Yet, an important finding is the width of 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% in either income or wealth.

The absolute intragenerational mobility estimated directly using the PSID samples follows a similar trend to the WID-based estimates. Yet, the PSID estimates are higher than the baseline estimates. The average discrepancy is 5 percentage points. The source of this discrepancy is the overestimation of income growth in the PSID data compared to the WID (see Appendix E). Since absolute mobility generally follows the business cycle, this has a sizable effect on the absolute mobility estimates. This indicates that the PSID absolute mobility estimates are slightly overestimated.

These findings are robust also when considering labor income rather than total income (see Appendix F). This is particularly important since it is well known that labor income is more accurately measured in surveys than capital income (Moore, Stinson and Welniak, 2000; Meyer and Sullivan, 2003). The similarity of the labor and total income results supports the findings on total income, which better reflects well-being than labor income only.

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 G presents a breakdown of the rank correlation and absolute mobility by age groups. 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.

Appendix H presents a similar breakdown of absolute mobility by education groups. We consider two groups: families in which at least one adult has 16 years of education or more, and families in which none of the adults has more than 12 years of education. In both cases the evolution of absolute mobility is similar to that of the whole population. Absolute mobility is slightly higher among the more educated and the difference is somewhat larger since the year 2000. This finding is inline with the recent evidence on the skill premium and how it is affected by trade and technological advances (Helpman, Itskhoki and Redding, 2010; Acemoglu and Autor, 2011; Autor et al., 2014; Beaudry, Green and Sand, 2016; Burstein and Vogel, 2017; Graetz and Michaels, 2017). Yet, though absolute mobility is lower among the less educated, the differences in comparison to the highly educated are small in magnitude. They are close to the baseline estimates and stay within the uncertainty bounds described above.

We note that the choice in 4-year periods is not arbitrary. The PSID (2017) surveys are conducted every two years, so the period length has to be an even number. Two years are usually too short to fully include dramatic events such as long crises or recovery periods. Longer periods would include substantial changes which are due to life-cycle effects. We also estimate absolute mobility over 2-year periods in Appendix I 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 at 52%. The 2-year absolute intragenerational wealth mobility is largely confined within the range 45%–60% and averages at 51%.

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 J. They show that absolute mobility in income decreases when considering such thresholds. Yet, even for a threshold as high as 10%, mobility over 4-year periods is largely confined between 40% and 55% and averages at 44.5%. In a typical 4-year period, 44.5% of the population will increase their income by at least 10%. At the same time, 38.5% of the population will see their incomes decrease by at least 10%. Since applying a threshold does not change the qualitative behavior of absolute mobility, we focus on the standard definition, in which no threshold is considered.

4.3 Absolute mobility decomposition

Figure 6 presents the evolution of absolute intragenerational mobility in the United States. It is possible to decompose this evolution to understand 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:

- The shape of the income distribution remains 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 assume that the average income changes according to its real historical values. This disables 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 disables the contribution of income growth.

The results are presented in Fig. 7. They show that without considering income inequality changes, the evolution of absolute intragenerational mobility remains similar to the baseline estimate. Yet, not taking inequality changes into account over 4-year periods would lead to absolute mobility that is higher by 1.9 percentage points than the baseline, on average.

Not taking income growth into account leads to different evolution that is almost constant in time. Naturally, this evolution no longer follows the 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.

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/family belonging to a certain percentile at the beginning of the 4-year period considered, we ask whether it has been better off at the end of the period in terms of income or of wealth. The fraction of the individuals/families which had higher income or wealth at the end of the period is defined as the absolute intragenerational mobility of this specific percentile. The results are presented in Fig. 8. They are based on the baseline

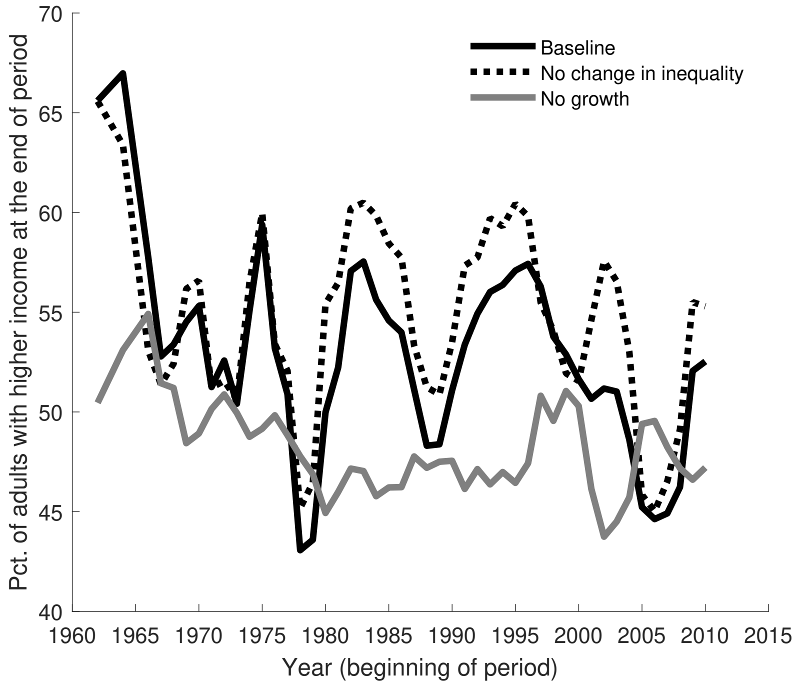

Figure 7: Counterfactual evolutions of absolute intragenerational income mobility in the United States.

estimates (considering the WID(WID, 2017)), as well as directly on the PSID data for income.

Similarly to the same analysis done in the intergenerational level by Chetty et al. (2017), we find that "the rates of absolute mobility were lower at the highest [...] income levels", since one has less scope to do better at the end of the period if one had a very high income at the beginning of the period. The same pattern is found for both income and wealth.

Figure 8 also shows that for 1978–1982 absolute mobility by percentile is similar to 2006–2010 for percentiles 20–100. The two periods are also similar in mobility in the aggregate level (see Fig. 6). However, absolute mobility was higher following 2006–2010 for the poor – percentiles 1–20. During the recovery that followed these two recession periods, 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 with percentile is independent on whether inequality increased

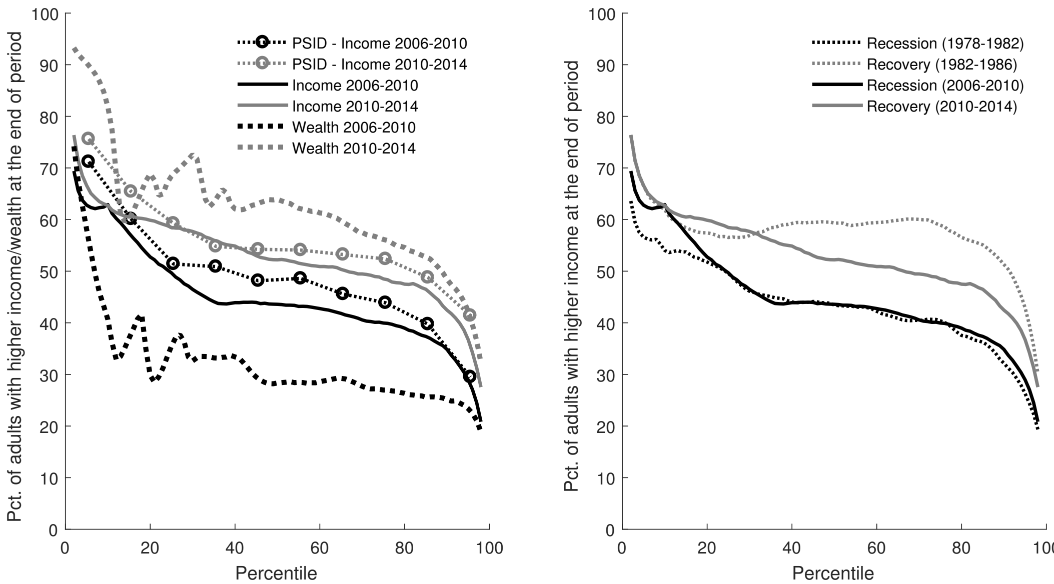

Figure 8: Absolute intragenerational mobility in the United States by percentile. Left) Absolute mobility in income and wealth in the periods 2006–2010 and 2010–2014; Right) Absolute intragenerational mobility in income in the periods 2006–2010 and 2010–2014 (solid) and 1978–1982 and 1982–1986 (dotted).

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.

If only the very wealthy are considered, their levels of absolute mobility for 4-year periods can be as high as 85%. We use the Forbes billionaires list (Forbes Magazine, 2001) to estimate absolute intragenerational wealth mobility over 4-year periods from 2001 to 2011 among billionaires only. The results are presented in Fig. 9. We note, however, that billionaires account for only 0.0002%–0.00025% of the United States adult population and therefore their contribution to absolute mobility for the entire population is negligible.

5 Dynamic model

The large discrepancy between absolute mobility estimates with and without taking relative mobility into account is driven by the importance of changes in the com-

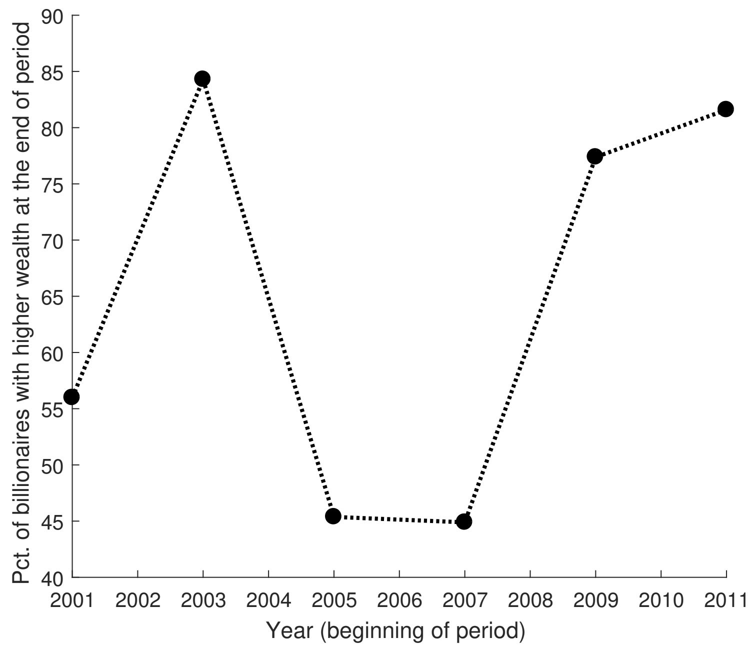

Figure 9: Absolute intragenerational wealth mobility among billionaires in the United States.

position of income percentiles and the nonlinear effect of relative mobility. 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 (or wealth) follows Gibrat's law (Gibrat, 1931), *i.e.* it follows a stochastic proportional growth process, a standard simplified model for income dynamics.

The starting point of the model is an income (or wealth) distribution Y_t, which is assumed to be log normal (Y_t is assumed positive). The log-income distribution $X_t = \log(Y_t)$ follows therefore $\mathcal{N}\left(\mu_1, \sigma_1^2\right)$. 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 $\mathcal{N}\left(0, s^2\right)$.

The distribution of $X_{t+\Delta t}$ is $\mathcal{N}\left(\mu_1 + g, \sigma_1^2 + s^2\right)$. 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

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

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)

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

In order to test the derived expressions it is possible to estimate g and s based on the parameters σ_1, σ_2, μ_1 and μ_2. For every year we use 14 income shares[7] given by the WID to fit (using OLS) the Lorenz curve of the income distribution. The Lorenz curve of a log-normal income distribution follows

[7] The top 90%, 80%, 70%, 60%, 50%, 40%, 30%, 20%, 10%, 5%, 1%, 0.1%, 0.01%, 0.001%.

$$L(p) = \Phi\left(\Phi^{-1}(p) - \sigma\right) , \tag{5.5}$$

where p is the cumulative share of the population and σ^2 is the variance of the log-income distribution.

After fitting σ for each year based on the income share data, 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 Fig. 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.

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 the multiplicative random walk, 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

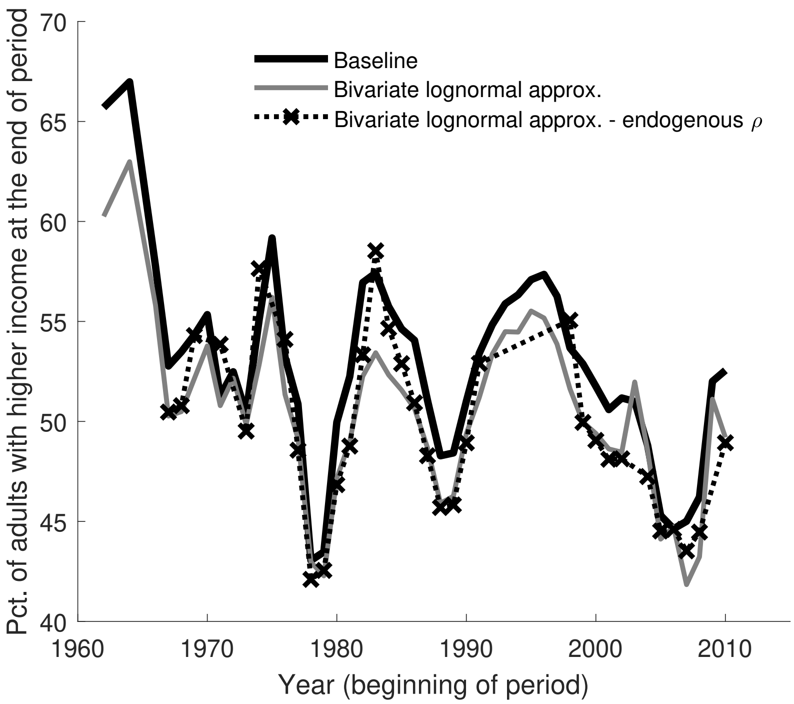

Figure 10: Income intragenerational mobility in the United States since 1962.

course, inline with the empirical evidence, in which absolute mobility that lower than 50% only occurred during periods of negative growth.

Multiplicative income dynamics as in Eq. (5.2) trivially result in flat non-anonymous growth incidence curves. The income growth rate of each percentile would be similar under such dynamics. The high similarity between the model results and the empirical evidence may hint that in practice non-anonymous growth incidence curves are not upward sloping, even in periods of increasing inequality. This, of course, stands in contrast to anonymous growth incidence curves, which are upward sloping for such periods (see Fig. 2). See Appendix K for a discussion on the differences between anonymous and non-anonymous growth incidence curves.

6 Conclusion

In this paper, we have combined historical cross-sectional and longitudinal data in order to estimate absolute intragenerational mobility of income and wealth in the United States over the period 1962–2014. Absolute intragenerational mobility quantifies the probability of a family or an individual to have higher income (or wealth) 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 absolute intragenerational mobility trends. We hope that this work will contribute to stimulate similar work in other countries.

In particular, our findings highlight the importance of relative mobility in the short run to absolute 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 at 53%. Hence, over a period of 4 years, 43%–67% of the population will enjoy higher living standards. For wealth this range is 40%–60% apart from during the great recession, after which 30%–35% of US families had more wealth than at its beginning. As illustrated in Fig. 11, for both income and wealth, 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 and wealth inequalities increased substantially. Thus, the changes in the composition of income and wealth ranks during such periods are important when interpreting the evolution of the distribution. In particular, this is relevant for interpreting growth incidence curves (see Appendix K for a discussion on the differences between anonymous and non-anonymous growth incidence curves).

Inequality has become a key issue in the public debate across the globe, and specifically in United States. Our findings imply that taking the changes in the composition

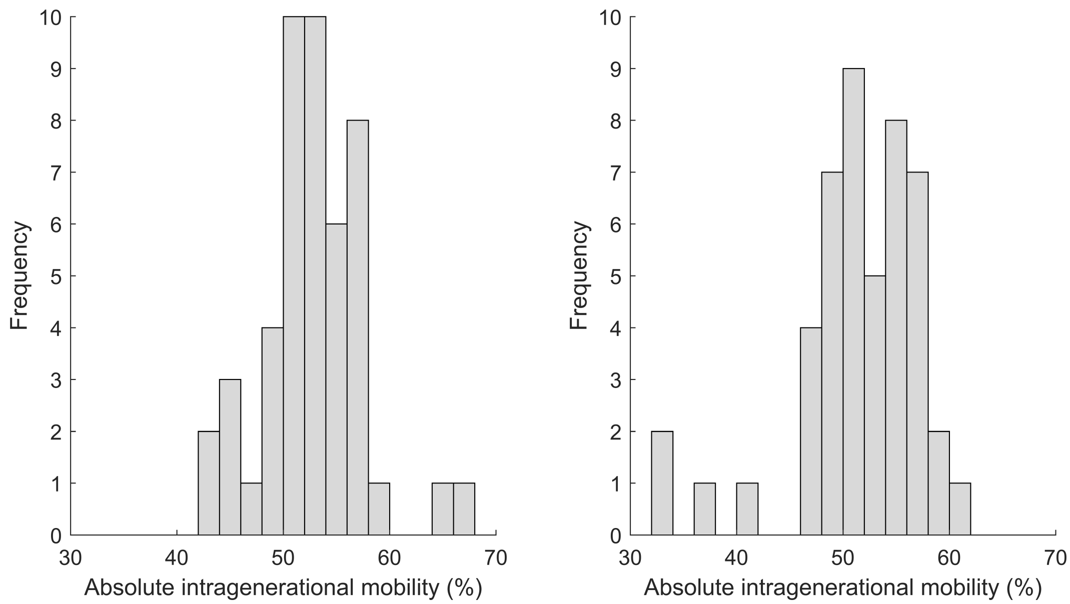

Figure 11: The distribution of income (left) and wealth (right) absolute intragenerational mobility values in the United States since 1962, for 4-year periods.

of income and wealth ranks into account is needed to better track economic growth and its inclusiveness. The detailed picture of distributional national accounts, in that sense, is insufficient.

We also note that our findings is mostly relevant for periods of several years only. Long run changes, such as described in Piketty, Saez and Zucman (2018), are different in nature. Long run changes in income and wealth distributions reflect changes in the economic, demographic, societal and political structures of a country. This is fundamentally different from the individual trajectories of income and wealth we consider. Over very long time periods, life-cycle effects make the analysis of intragenerational 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. Also, lifetime relative mobility has been stable in the long run (see Kopczuk, Saez and Song (2010)). Therefore, "it seems unlikely that the increase in cross-sectional income inequality—and the collapse in the bottom 50% income share—could be offset by rising lifetime mobility out of the bottom 50%" (Piketty, Saez and Zucman, 2018). Yet, we emphasize the importance of precisely interpreting short-run GICs. These need not be mistakenly seen as non-anonymous growth incidence curves (Bourguignon, 2011). This is also pertinent for the recent attempt for changing the way income growth is measured in the United States (see Schumer and Heinrich (2018)).

An additional relevant context is that of global inequality. The so-called "elephant curve" is a GIC in the global scale (Lakner and Milanovic, 2016; Anand and Segal, 2017; Alvaredo et al., 2018). It demonstrates that the incomes of the global top 1% of income earners and of the middle classes in developing countries increased during the past several decades, but stagnated for the global poor and for the middle classes in developed countries. This interpretation assumes quasi-anonymity.[8] In the global scale it is much harder to consider mobility as we do in this paper due to lack of sufficient data. Yet, a recent attempt has shown that taking mobility into account and using "quasi-non-anonymous growth incidence curves" may lead to different conclusions. Kharas and Seidel (2018) argue that the actual non-anonymous global growth incidence curve is flat compared to previous findings.

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[8] Assuming that the different income quantiles in different countries did not change their ranking in the global income distribution.

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A Intragenerational copula models

We estimate the empirical copulas for the joint income and wealth 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 (doubly stochastic) 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. 1 and demonstrated in Fig. 12. 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. 1.

Table 1: 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

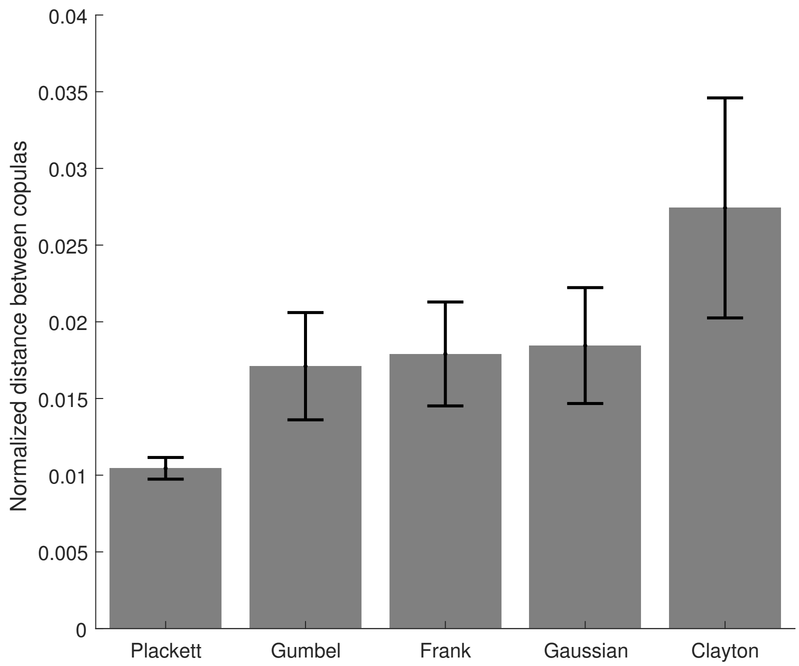

Figure 12: Average normalized Frobenius distance between empirical copulas and different copula models.

model and for the same rank correlation we obtain similar estimates if different models are used. We use the US income data from the WID in 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. 2.

Table 2: Absolute intragenerational mobility sensitivity to copula model (standard errors produced by bootstrapping)

Copula model	Time period	
	2006–2010 (%)	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)

B Absolute intragenerational mobility for time-averaged income

In order to reduce measurement errors, most notably when using survey data, many studies of inequality and of intergenerational mobility 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. Fig. 13 demonstrates that such averaging has a very small effect on the estimated absolute intragenerational income mobility. We therefore conclude that in our baseline estimates and our estimates of rank correlation, based on PSID (2017), the measurement error has an insignificant effect on the results.

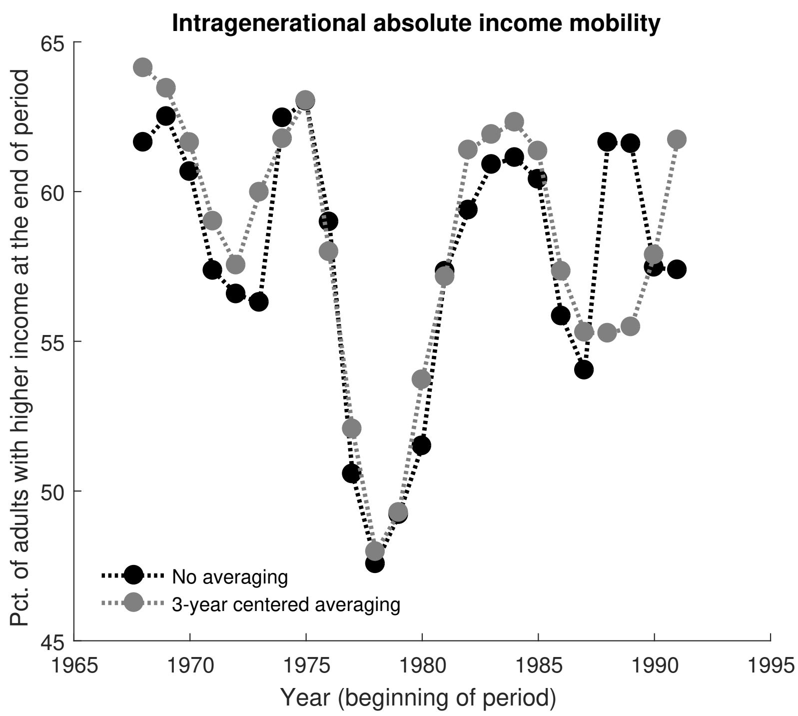

Figure 13: 4-year absolute intragenerational income mobility in the United States assuming non-averaged and 3-year centered-averaged income samples. Source: The Panel Study of Income Dynamics (PSID, 2017).

C 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 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 Fig. 14. It shows that post-tax mobility over 4-year periods is generally higher than for pre-tax income. Yet, it is slightly lower during crises. 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.

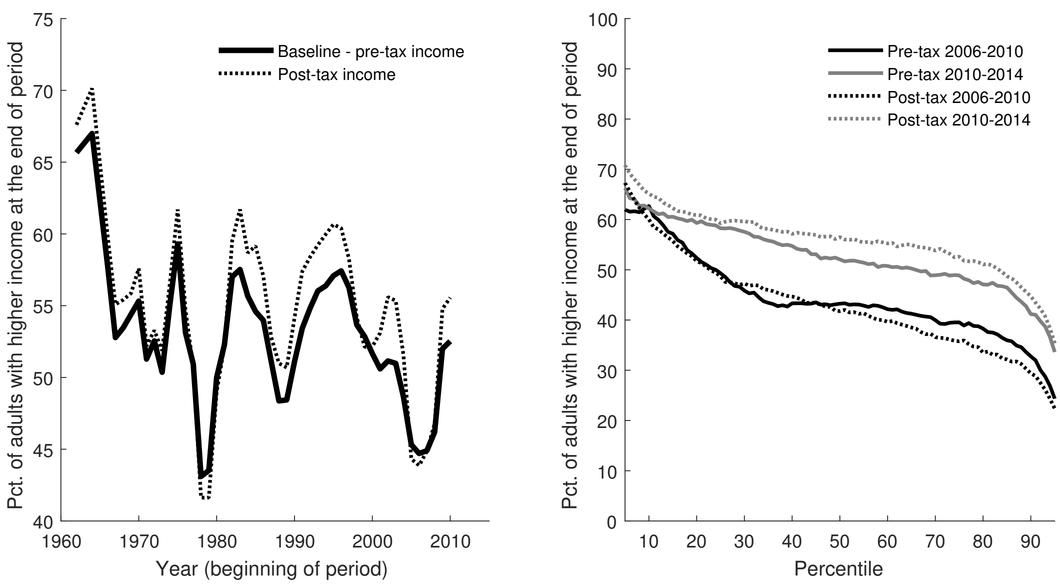

Figure 14: Comparison of absolute mobility between pre- and post-tax incomes in the United States. Left) Absolute intragenerational mobility in the United States since 1962 in 4-year periods for pre-tax (solid) and post-tax (dotted) incomes; Right) Absolute intragenerational mobility in the United States by percentile for pre-tax (solid) and post-tax (dotted) incomes.

D Absolute mobility for direct PSID copula estimates

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 – large samples created using WID (2017) data. Another possible way to produce such estimates is taking the copula as directly estimated for each period in the PSID (2017) 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 Fig. 15, 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.

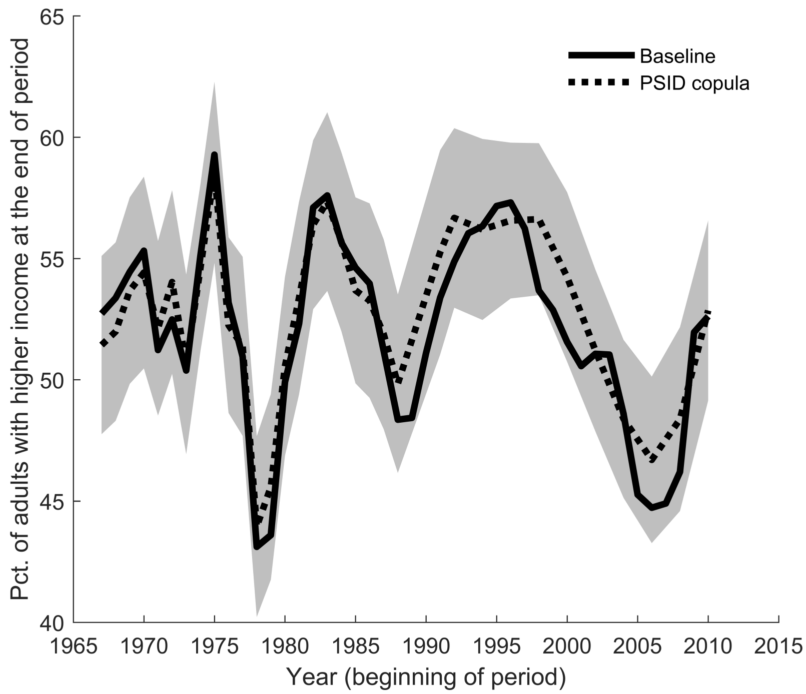

Figure 15: Income intragenerational mobility in the United States since 1967, assuming fitted Plackett copula (solid) and directly estimated copulas from the PSID (2017) surveys (dotted). The shaded gray area stands for the 95% confidence interval of the estimates based on the PSID copulas and is produced by bootstrapping.

E Income growth rate comparison

Absolute mobility generally follows the business cycle. This stems from its sensitivity to the growth rate (see Section 5). This sensitivity can explain part of the discrepancy between the income absolute mobility estimates based on the PSID and on the WID (see Fig. 6). Fig. 16 shows that income growth is indeed higher in the PSID than in the WID. The WID is a more reliable source for estimating growth rates, as it reconciles national accounts, surveys and tax data (see Piketty, Saez and Zucman (2018)). We conclude that the baseline absolute mobility estimates, using the WID, are more reliable.

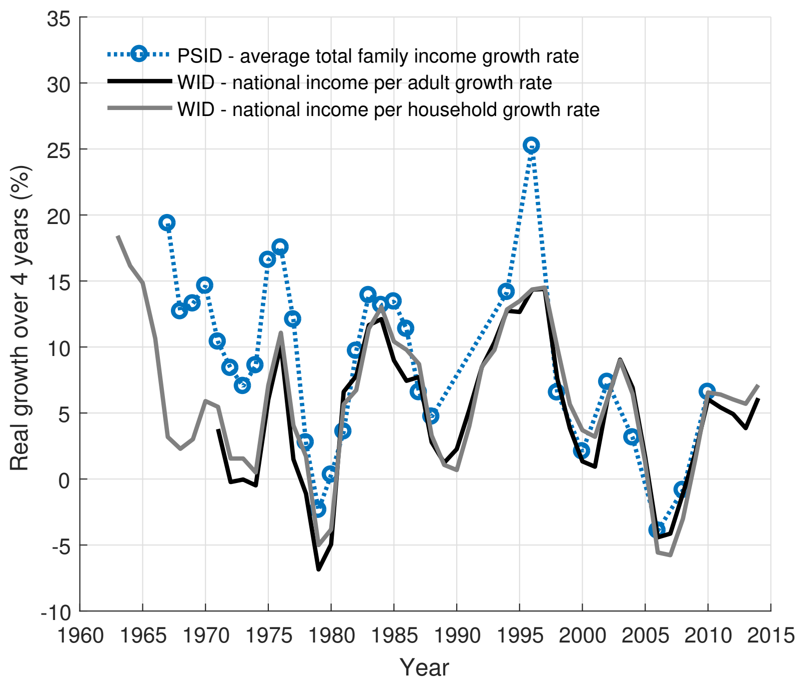

Figure 16: 4-year income growth rate comparison between the PSID and the WID.

F 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 use the data in WID (2017) and in PSID (2017) to estimate absolute intragenerational mobility for labor income only. This type of income is expected to be more sensitive to changes that are specifically in 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 (2017) 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 17 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 early 1980 recession, which was accompanied by severe job losses and the Great Recession.

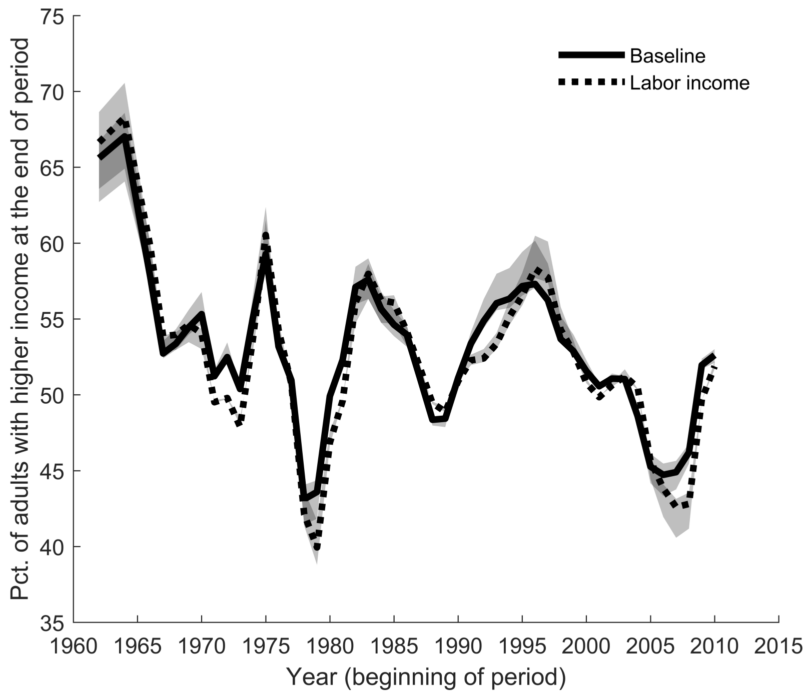

Figure 17: Income intragenerational mobility in the United States since 1962 for total income (solid) and labor income (dotted). The shaded gray areas are the areas covered by the absolute mobility estimates between the lower and upper bounds for the rank correlation in both specifications.

G 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 (2017) – 18–25; 35–55; 65–100. We find that indeed, the youngest group has substantially higher mobility than the other groups and from the baseline estimates for the entire population. Similarly, the eldest group has substantially lower 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 the same. We therefore conclude that our results are robust when controlling for age in the way described. The results are presented in Fig. 18 and Fig. 19.

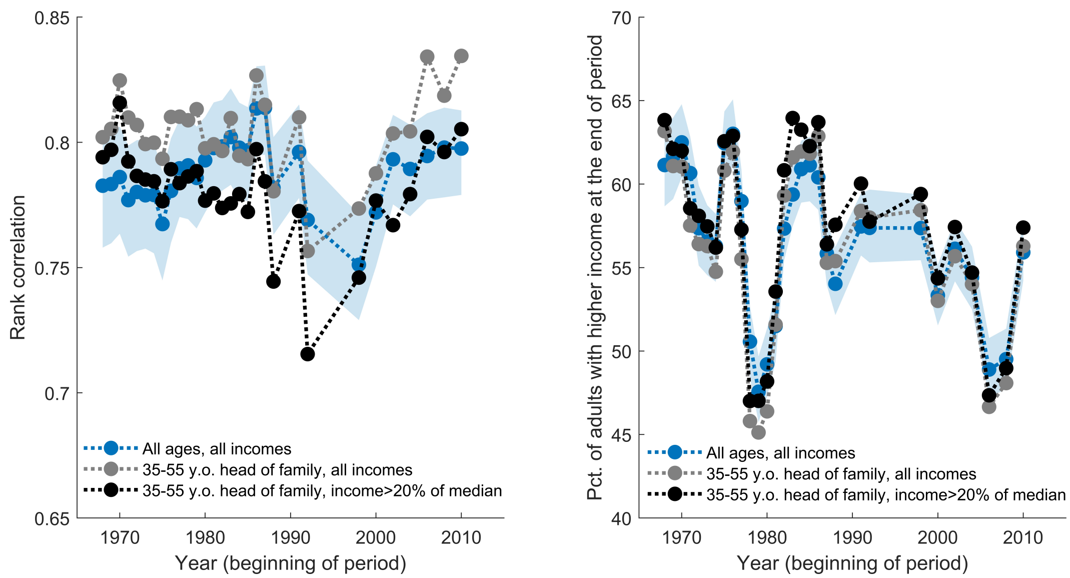

Figure 18: 4-year rank correlation and absolute intragenerational income mobility in the United States for the entire sample and for families with a 35–55 y.o. head of family. We consider two specifications for the 35–55 age group – one in which all incomes are considered (including zero incomes) and 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.

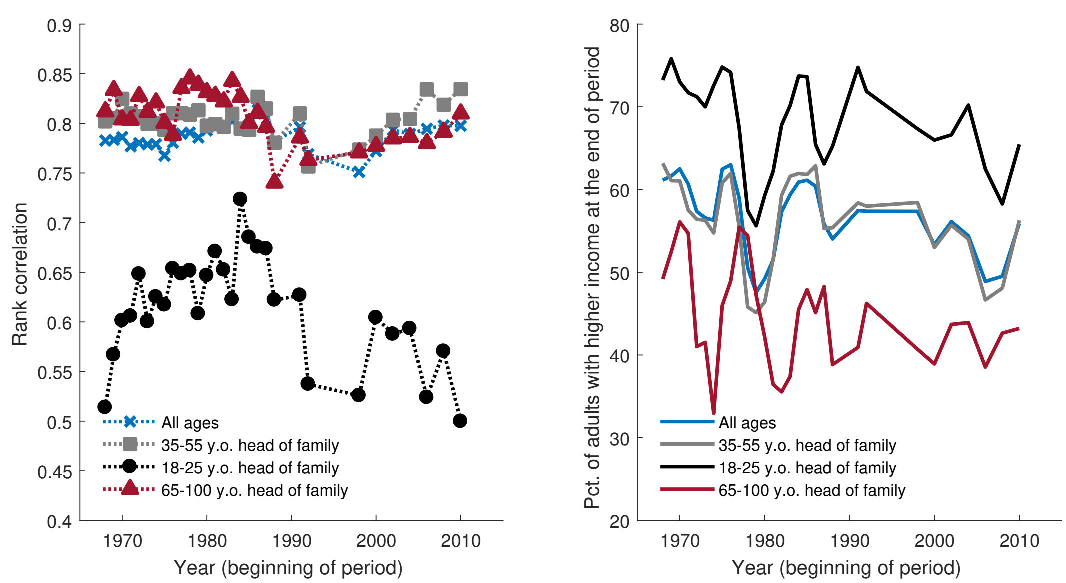

Figure 19: 4-year rank correlation and absolute intragenerational income mobility in the United States for different age groups.

H Absolute intragenerational mobility by education level

An important test for the presented analysis is whether the observed evolution of absolute mobility is different within education or skill groups. There is a reason to believe that the increasing skill premium in recent decades would translate into higher absolute mobility among the skilled and educated.

Figure 20 presents the evolution of absolute intragenerational mobility for two different education groups. In both groups mobility follows a similar trend to the baseline estimate (for the entire population). Specifically, the differences between these estimates and the baseline estimate fall within the statistical uncertainty discussed in Section 4.2. Yet, as expected, the highly-educated group displays consistently higher mobility than the less educated group. The gap between the groups has become larger after 2000, which is inline with the recent evidence on the skill premium and how it is affected by trade and technological advances (Helpman, Itskhoki and Redding, 2010; Acemoglu and Autor, 2011; Autor et al., 2014; Beaudry, Green and Sand, 2016; Burstein and Vogel, 2017; Graetz and Michaels, 2017).

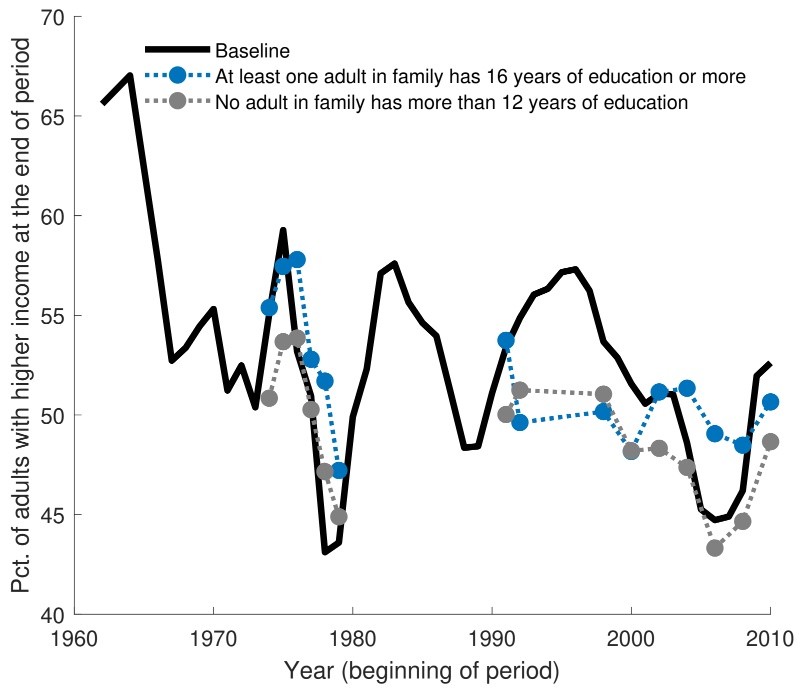

Figure 20: 4-year rank correlation and absolute intragenerational income mobility in the United States for the entire sample (based on WID (2017)) and for highly and low educated families (based on the PSID (2017)).

I Absolute intragenerational mobility over 2-year periods

Our analysis is focusing on 4-year periods, however, since the PSID (2017) 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 Fig. 21. They show that naturally, the rank correlation over 2-year periods are higher than for 4-year periods both in income and in wealth.

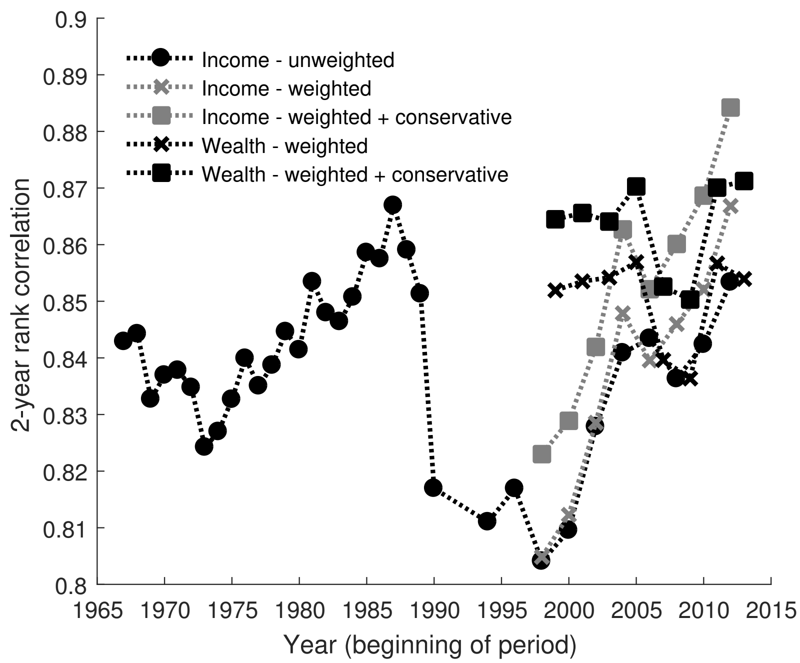

Figure 21: Spearman's rank correlation of income and wealth in the United States over 2-year periods.

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 Fig. 22. They are found to be very similar to those obtained for 4-year periods (see Fig. 6). The 2-year absolute intragenerational income mobility is confined within the range 43%–63% and averages at 52%. The 2-year absolute intragenerational wealth mobility is largely confined within the range 45%–60% and averages at 51%.

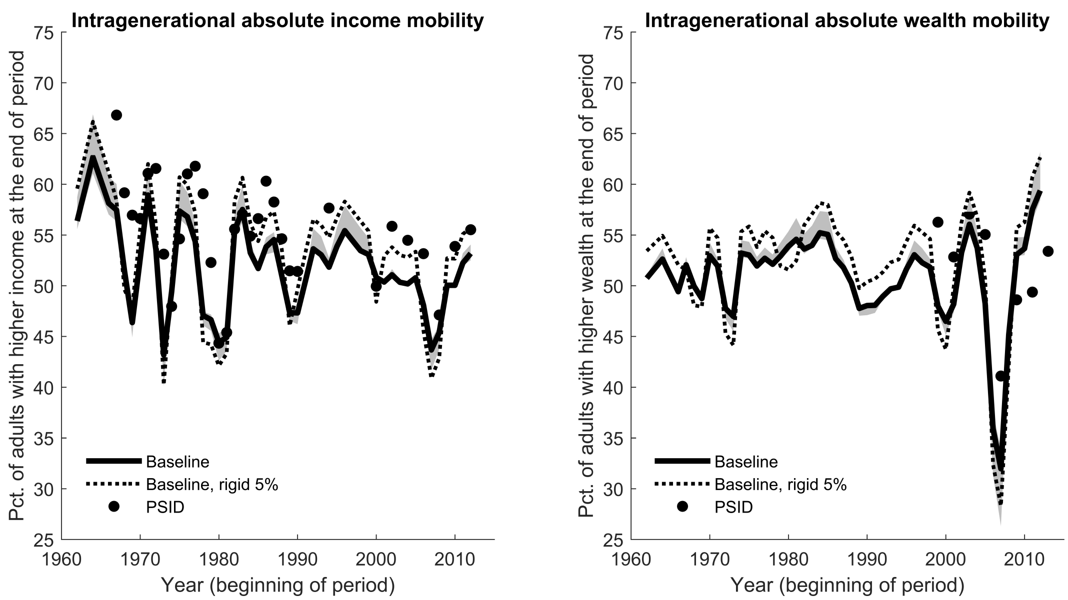

Figure 22: Income (left) and wealth (right) absolute intragenerational mobility in the United States since 1962 for 2-year periods. The shaded gray area is the area covered by the absolute mobility estimates between the lower and upper bounds for the rank correlation – 0.8 and 0.9.

J 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 by design decreases mobility. We estimate the evolution of absolute intragenerational mobility over 4-year periods assuming thresholds of 5% and 10%.

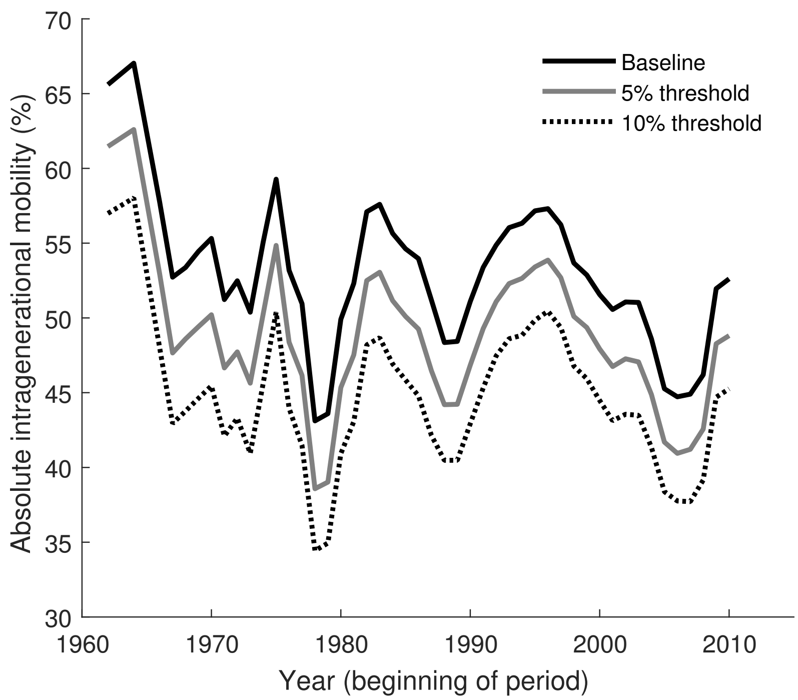

Figure 23: Income intragenerational mobility in the United States since 1962 assuming different thresholds.

K Anonymous and non-anonymous growth incidence curves

Absolute intragenerational mobility is related to the way growth incidence curves (GICs) can be interpreted. Since relative intragenerational mobility is small over short periods of time (compared to intergenerational mobility, for example), it is sometimes not considered and it is useful to quantify income changes for different parts of the income distribution using GICs (Ravallion and Chen, 2003). A GIC indicates the growth rate in income between two points in time at each percentile of the distribution. It would allow measuring absolute intragenerational mobility under the assumption that the changes in the composition of income ranks can be neglected.

The cross-sectional data in WID (2017) allow calculating GICs in the United States for different periods, for example for 2006–2010 and 2010–2014, representing crisis and recovery periods, respectively, as depicted in Fig. 2. We can also use the PSID (2017) surveys in order to produce non-anonymous GICs for the same periods. In non-anonymous GICs (Bourguignon, 2011), the average income of a given percentile in the beginning of the period is not compared to the average income of the same percentile at the end of the period, as done in an anonymous GIC, but to the average income at the end of the period of the individuals or families that this percentile consisted of at the beginning of the period. Without any mobility, the composition of percentiles will not change between the beginning and the end and the non-anonymous and anonymous GICs will be identical.

However, if mobility is considered, there might be a difference between the two. This is presented in Fig. 24. It shows that allowing for mobility changes substantially the GIC. In particular, during periods of increasing income inequality, such as both 2006–2010 and 2010–2014, the anonymous GIC will have a generally increasing trend with percentile. However, as seen in Fig. 24 this is not necessarily the case in the non-anonymous GIC, at least up to the top 5% of the distribution.

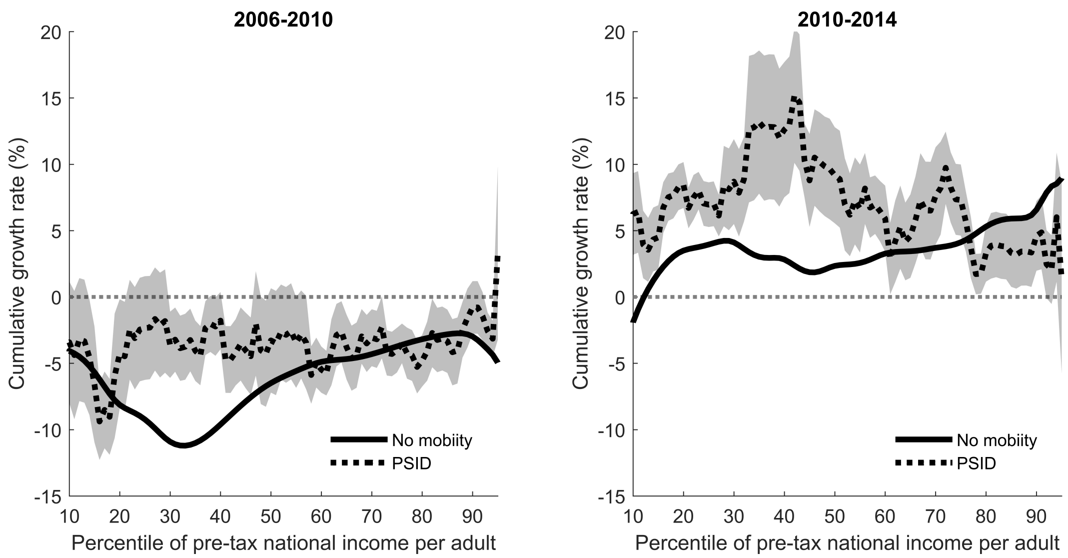

Figure 24: Anonymous (solid) and non-anonymous (dotted) growth incidence curves for the United States, 2006–2010 (left) and 2010–2014 (right). The data for the anonymous GIC are based on WID (2017) data and the data for the non-anonymous GIC are based on PSID (2017). The shaded areas stand for the standard error of the non-anonymous GIC values produced by bootstrapping. The x-axis is cropped to 10%–95% for display purposes.