The Long Run Evolution of Absolute Intergenerational Mobility

By Yonatan Berman*

This paper combines cross-sectional and longitudinal income data to present the evolution of absolute intergenerational income mobility in ten advanced economies in the 20th century. Absolute mobility decreased during the second half of the 20th century in all these countries. Increasing income inequality and decreasing growth rates have both contributed to the decrease. Yet, growth is the dominant contributor in most countries. We show that detailed panel data are effectively unnecessary for estimating absolute mobility over the long run.
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The question whether next generations will be better off than previous ones is central in the recent public and economic debate. Chetty et al. (2014b, p. 141) discuss a "growing public perception that intergenerational income mobility [...] is declining in the United States." Others argue that "people's frustrations [...are] rooted in the fear that their kids won't be better off than they were." (Obama, 2013) This can be quantified as absolute intergenerational mobility – the fraction of children with higher real incomes than their parents at the same age. This measure captures the chances of children to have a higher standard of living than their parents.

Chetty et al. (2017) studied the historical evolution of absolute mobility in the United States. They showed that it fell from around 90% for children born in 1940 to 50% for children born in 1980. They found that two-thirds of that decline are due to changes in the income distribution. A third of the decline is due to slower growth over the past thirty years relative to the 1940s and 1950s. Yet, there is little evidence on the experience in other countries and more cohorts. Thus, it is crucial to test how general these findings are in terms of absolute mobility levels, historical trends, and sources.

This paper presents the long run evolution of absolute intergenerational mobility in income in a large group of advanced economies. In France, Sweden and the United States it was possible to estimate absolute mobility going back to the early 20th century. This is

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well beyond the existing literature on absolute mobility.

With fast income growth we would expect absolute intergenerational mobility to be high. However, absolute mobility is not simply a proxy for long run income growth. This paper shows that it is affected by a combination of growth, inequality, and relative mobility, while the role played by each of these factors in determining absolute mobility differs among countries and over time.[1] Thus, absolute mobility can be viewed as an inequality-weighted measure of growth (while also incorporating information on relative mobility). From a normative perspective, it is therefore theoretically related to the inequality deflator approach, in which the distortionary cost of redistribution across income levels is accounted for when measuring economic efficiency (Hendren, 2020).

In addition, while the emphasis in the mobility literature across disciplines is on relative mobility, it is possible that absolute mobility is a more pervasive concept in the public debate. This is exemplified by polling questions and in the media in the United States (Gallup, 1951; Money Magazine, 1983; Roper Center, 1993) and internationally (Stokes, 2017).[2]

Estimating absolute intergenerational mobility for long time periods and across countries poses challenges. First, matching parents and children requires historical panel data. These are usually rare, do not cover the entire income distribution, or are available for a limited range of cohorts. Second, reliable income data are many times disjoint from microdata such as age and gender. This complicates the identification of parents and children. These issues are of particular importance when considering early 20th century, or earlier, cohorts. In such cases, the existing data sources on income are limited.

Our approach combines the marginal income distributions for the parent and child generations and their copula – the joint distribution of parent and child income ranks. We find that historical panel data are effectively unnecessary for estimating absolute mobility. Estimates of absolute mobility depend mainly on the marginal income distributions, and their copula plays a minor role in determining absolute mobility. We also find that changes in the copula cannot explain the long run trends of absolute mobility, and only changes in the marginal distributions can. In short, we provide robust evidence that absolute mobility is driven primarily by economic growth, secondarily by changes in inequality, and thirdly (and weakly) by relative mobility.

These observations make the estimation of absolute mobility possible even for countries in which panel data are scarce. We show that very limited data are enough for capturing the long run evolution of absolute mobility. We then combine available data on intergenerational copulas and historical income distributions to provide absolute mobility estimates in ten countries over the course of the 20th century.

[1] Intergenerational mobility is typically divided into two classes: relative and absolute. Relative measures gauge children's propensity to occupy a different position in the income distribution than their parents. The copula fully encodes relative mobility. Absolute measures gauge their propensity to have higher incomes than their parents in real terms.

[2] It is demonstrated in questions such as: Compared with your father when he was about your age, are you better or worse off in your income and standard of living generally? (International Social Survey Program, 1992); When children today grow up they will be worse off / better off financially than their parents? (Stokes, 2017)

We find a large and nearly monotonic decrease in the absolute intergenerational mobility estimates in all studied countries during the post-war period, from 80%–95% to 50%–70%. This decrease followed a rapid increase in absolute mobility from the early 1900s until World War II, reflecting the economic boom and the decreasing income inequality during the three decades that followed the end of the war. Our results thus confirm the findings of Chetty et al. (2017) for the United States and extend them. They show that levels of absolute mobility were high even before the war. They peaked during the 1930s (reflecting high absolute mobility for adults during the 1960s with respect to adults in the 1930s).

The factors driving the decrease in absolute mobility differ among countries. In Australia and the United States the decrease is mainly due to increasing income inequality. Yet, in other countries, notably Denmark, France and Japan, the slow economic growth of the past several decades is the key contributor to a similar decrease. Despite higher growth rates and regardless of the "American Dream" ethos, the absolute intergenerational mobility in the United States in recent years is among the lowest within the group of countries we studied.

To inform and interpret the empirical findings, we study a simple model. The model provides a relationship between absolute mobility, income growth, income inequality and relative mobility. It describes well the long run evolution of absolute mobility, even when only limited information on income distributions is taken into account. For example, the knowledge of historical income growth rates and Gini coefficients is satisfactory for reliable absolute mobility estimation. We also show that in this model, ceteris paribus, absolute and relative mobility are inversely related. In practice, despite this relationship, countries characterized by high relative mobility, such as the Nordic countries, are also characterized by high absolute mobility. As described, the effects of growth and inequality on absolute mobility are more important than the effect of relative mobility.

Relative mobility has been studied for decades.[3] Yet, investigations of absolute mobility in income remain scarce. Absolute mobility has been studied so far mainly in the context of class, education, and occupation, which are central in the sociological mobility literature.[4] In fact, absolute mobility can be seen as a unified approach to structural and exchange mobility (Sobel, Hout and Duncan, 1985), as it incorporates data on relative mobility (akin to exchange mobility) with structural changes in the income distribution. The differences in outcome variables and the different nature of measures used make the results in this literature difficult to compare to this paper. Yet, we note that Lipset and Zetterberg (1959, p. 13) had already identified that "the overall pattern of social mobility appears to be much the same in the industrial societies of various Western countries."

Our contribution is thus threefold. First, from an empirical perspective, the primary contribution of this paper is to provide new series on absolute intergenerational mobility in a large group of advanced economies. In particular, we provide evidence on absolute

[3]See, for example, Becker and Tomes (1979); Borjas (1992); Mazumder (2005); Aaronson and Mazumder (2008); Lee and Solon (2009); Corak (2013); Chetty et al. (2014b); Berman (2019).

[4]See, for example, Lipset and Rogoff (1954); Lipset and Zetterberg (1959); Erikson, Goldthorpe and Portocarero (1979); Goldthorpe (1987); Sobel, Hout and Duncan (1985); Erikson and Goldthorpe (1992); Breen and Jonsson (2005); Breen and Rottman (2014).

intergenerational mobility since the early 20th century. We find that in all studied countries absolute mobility decreased during the second half of the 20th century.

We also describe the effect of income growth and income inequality on absolute mobility and decompose the changes in absolute mobility into the contribution of each. We show that the decrease of income growth rates is the main determinant of changes in absolute mobility in most countries. In Australia and the United States, and to a much lesser extent in Finland and the United Kingdom, increasing inequality was more important for the long run trend of absolute mobility than growth.

Second, from a methodological perspective, we describe in detail the low sensitivity of absolute intergenerational mobility estimates to measurement error and incomplete data. This allows estimating absolute mobility in the long run without the necessity for detailed panel data. Notably, we show that copulas of different countries share a similar form. Together with the low sensitivity of absolute mobility to changes in the copula, this enables characterizing copulas with a single parameter, such as the rank correlation, when estimating absolute mobility. The same methodology could be applied to other countries in the years ahead. Also, since household surveys are a common practice in most countries today, it will be possible to continue tracking absolute mobility even without detailed panel data, which are still much less common.

Third, from a theoretical perspective, we derive a mathematical relationship between absolute mobility, income growth, income inequality changes and relative mobility. It proves as a powerful way for estimating absolute mobility with very limited data. Namely, total income growth between generations and the Gini coefficients are enough for reliable absolute mobility estimation. This relationship also allows studying properties of absolute mobility previously uncovered.

The paper is organized as follows. Section I defines absolute mobility and discusses a simplified model for the relationship between absolute mobility, income growth, income inequality and relative intergenerational mobility. Section II lays out our empirical methodology, addressing the necessity of panel data for producing reliable estimates of absolute mobility. Section III specifies our data sources and presents the results. We conclude in Section IV.

I. Growth, Inequality, Relative Mobility and Absolute Mobility

Absolute intergenerational mobility is defined as the fraction of children with higher real incomes than their parents at the same age. For N parent-child pairs, we denote by Y_{pi} and Y_{ci} the parents' and children's real incomes (at the same age) in family $i = 1 \ldots N$, respectively. We define absolute mobility as[5]

$$A = \frac{\sum_{i=1}^{N} \mathbf{1}_{Y_{ci} > Y_{pi}}}{N} . \tag{1}$$

[5]Following Chetty et al. (2017), our measure of absolute mobility is a measure of upward mobility. Clearly, the complement of the fraction of children with higher real incomes than their parents at the same age is a measure of downward mobility (assuming no children have the exact same real incomes as their parents).

Our first goal is to clarify the relationship between absolute mobility and its determinants: income growth, changes in income inequality and relative mobility. Figure 1 presents three hypothetical scenarios that summarize the intuition for the effects of these determinants – absolute mobility increases with income growth, but decreases with increasing inequality and relative mobility.

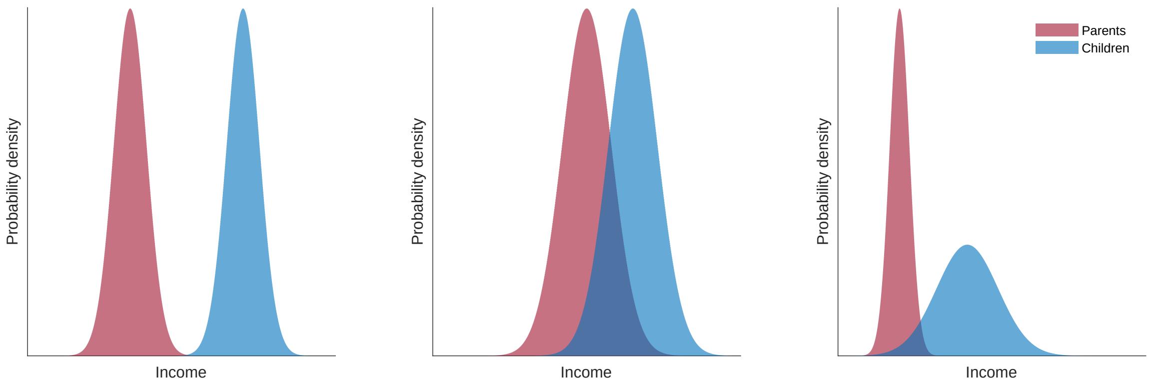

Figure 1. Descriptive scenarios of intergenerational changes in the income distribution.

Note: Left) No change in inequality between the two generations; growth is high enough so there is no overlap between the distributions, *i.e.* the poorest child is still richer than the richest parent. In this case absolute mobility will be 100% regardless of relative mobility; Middle) Inequality is still unchanged between the generations; growth is not as high as in the previous scenario. In this case the level of absolute mobility depends on relative mobility. In the extreme case of no relative mobility, absolute mobility will still be 100%, since the richest parent is mapped into the richest child and so do the second richest parent and child and so on. Realistically, because relative mobility exists, absolute mobility will be lower than 100%, and as relative mobility increases, absolute mobility decreases; Right) Growth is as high as in the left panel, but inequality is higher among the children. This case is similar to the middle one – absolute mobility will be lower than 100% and as relative mobility increases, absolute mobility decreases.

To formalize the intuition, we can use a simplified model for intergenerational mobility. In the previous notation, we assume that the incomes are positive and define the log-incomes $X_{pi} = \log Y_{pi}$ and $X_{ci} = \log Y_{ci}$. A standard model for the intergenerational relationship between log-incomes is the following linear regression, in which the slope (β) is the intergenerational earnings elasticity (IGE):

$$X_{ci} = \alpha + \beta X_{pi} + \epsilon_i \,. \tag{2}$$

Assuming that ϵ_i and X_{pi} are normally distributed, so are X_{ci}. The marginal income distributions are then log-normal ($Y_{pi} \sim \log \mathcal{N}\left(\mu_p, \sigma_p^2\right)$ and $Y_{ci} \sim \log \mathcal{N}\left(\mu_c, \sigma_c^2\right)$). The joint parent-child log-income distribution is a bivariate normal distribution, with correlation $\rho = \beta\sigma_p/\sigma_c$. The joint distribution is therefore fully specified by five parameters: μ_p, σ_p, μ_c, σ_c and ρ.

These assumptions are standard (Pinkovskiy and Sala-i-Martin, 2009), and "the lognormal is a good approximation of empirical income distributions, leads to tractable results, and allows for an unambiguous definition of inequality." (Bénabou, 2000, p. 98) As we demonstrate later in Section III, this model is also satisfactory for estimating the long run trend of absolute mobility.

The absolute mobility, A, is equal to the probability $P(X_{ci} - X_{pi} > 0)$. We can now derive a closed-form expression for absolute mobility in terms of the model parameters:

PROPOSITION 1: *For a bivariate log-normal distribution with parameters μ_p, σ_p (for the parents' marginal distribution), μ_c, σ_c (for the children's marginal distribution) and correlation ρ, the absolute mobility is*

$$A = \Phi\left(\frac{\mu_c - \mu_p}{\sqrt{\sigma_p^2 - 2\rho\sigma_p\sigma_c + \sigma_c^2}}\right), \tag{3}$$

where Φ is the cumulative distribution function of the standard normal distribution. Provided $\mu_c > \mu_p$ and $\sigma_c > \sigma_p$ it follows that

$$\frac{\partial A}{\partial \rho} > 0; \tag{4}$$

$$\frac{\partial A}{\partial\left(\frac{\sigma_c}{\sigma_p}\right)} < 0. \tag{5}$$

(See proof in Appendix A)

Proposition 1 clarifies the intuition demonstrated in Figure 1. Absolute mobility increases with the difference $\mu_c - \mu_p$, *i.e.* with growth, and decreases with increasing inequality and with relative mobility, which is inversely proportional to ρ. This intuition will be used in Section III to better understand the roles played by the determinants of absolute mobility in different countries.

We note that Katz and Krueger (2017) discuss an alternative measure of absolute mobility (which does not require panel data) – the share of children earning more than the median parent. Based on Chetty et al. (2017), they find that this measure moves almost identically to the standard absolute mobility measure across birth cohorts in the United States. Using the simplified model we are able to show that this measure will be close to the measure of absolute mobility only if the IGE is close to 1/2 (see Appendix B). Thus, it is no surprise that for the United States these measures are similar. Aaronson and Mazumder (2008) estimate the IGE for 1950–1970 birth cohorts in the United States at 0.46–0.58.[6] In countries such as Canada or Denmark, in which the IGE is substantially lower than 0.5

[6] We also note that Solon (1992); Aaronson and Mazumder (2008); Mazumder (2015) all estimate rank correlations that are higher (> 0.4) than reported in Chetty et al. (2014b) (0.3), which we use in our analysis. The important debate on the most accurate estimate for the intergenerational rank correlation in the United States exceeds the scope of this paper. As will be discussed in the next sections, the absolute mobility estimates are insensitive to differences in the rank correlation of the relevant magnitude.

(Corak, 2013), the Katz-Krueger measure of absolute mobility will lead to overestimation of absolute mobility. For example, in Denmark, the average estimated absolute mobility between 1950 and 1980 is 78.5% (see Section III). For the Katz-Krueger mobility the average value is 87.2%. In the United States this difference is much smaller: 62.2% and 63.7%, respectively. Thus, the Katz-Krueger mobility cannot be used as a proxy for absolute mobility unless the IGE is close to 1/2.

II. Methodology

In an ideal setting, measuring absolute intergenerational mobility is simple. For every birth cohort of children we would trace back their parents and compare their individual or household incomes at a certain age. However, such data are usually available for small samples, do not cover the entire income distribution, or available for a very limited range of birth cohorts. In many countries, such data are rare and may suffer from large measurement errors (Solon, 1992; Chetty et al., 2014a). Using such data for estimating typical measures of relative income mobility over a long period of time may be challenging and unreliable.

Yet, in the case of absolute intergenerational mobility, one is able to provide reliable estimates, even in the absence of historical detailed panel data. Our methodology builds on the approach of Chetty et al. (2017). We use repeated cross-sections and combine them using a copula, the joint distribution of parent and child income ranks. It follows that the measure of absolute mobility A is

$$A = \int \mathbf{1}_{\{Q^c(r^c) \geq Q^p(r^p)\}} C\left(r^c, r^p\right) dr^c dr^p \,, \tag{6}$$

where r^c and r^p are the child and parent income ranks, respectively; Q^c and Q^p are the respective quantile functions; C is the copula. This decomposition of absolute mobility into copula and marginal distributions is exact (*c.f.* Eq. (1)), and follows immediately from Sklar's theorem (Sklar, 1959). Copulas are typically estimated in discrete form, leading to a small bias in practice, which is inconsequential for our analysis (see Appendix C.1).

Using copulas estimated for different countries and birth cohorts we identify two crucial points.

First, the basic structure of realistic copulas is similar – when two realistic copulas differ in a measure of relative mobility, they differ proportionally in other relative mobility measures. This observation implies that using a single measure of relative mobility provides a good approximation for intergenerational copulas. In order to validate this point we use 28 different copulas measured for different cohorts, different countries, and for pre- and post-tax incomes (Jäntti et al., 2006; Eberharter, 2014; Chetty et al., 2017). We then compare them in terms of different measures of relative mobility. Each copula is considered as a bi-stochastic matrix $\mathbf{P} \in \mathscr{P}(N)$, where p_{ij} represents the probability of transferring to quantile j (child) for those starting in quantile i (parent) and N is the number of income quantiles.

We consider four standard measures of relative mobility, which are defined on $\mathbf{P}$: Spearman's rank correlation (Spearman, 1904); Bartholomew's index (Bartholomew, 1967); Average absolute non-zero jump (measured in income ranks); Shorrocks' trace index (Shorrocks, 1978) (their definitions are given in Appendix D). The different measures are mathematically related, however they are not linearly dependent. Specifically, it is possible to construct matrices which have the same trace index, but very different rank correlation, average absolute non-zero jump measure or Bartholomew's index and vice versa (see example in Appendix C.2, in addition to Bartholomew (1967); Shorrocks (1978); Atkinson and Bourguignon (1982); Atkinson (1983)).

We find that the correlation between each two measures across the 28 copulas is between 0.93 and 1. In other words, the different measures are, in fact, almost linearly related across time and countries, for pre- and post-tax incomes. Figure 2 presents the comparison of the different relative mobility measures.

We conclude, therefore, that the shape of the copulas is similar and they can be practically summarized by a single parameter. We use the rank correlation since in many countries relative mobility is reported using the rank correlation or the intergenerational elasticity, from which the rank correlation can be approximated. The entire copula is only rarely reported. Also, the rank correlation is more empirically robust than other – not rank-based – measures, such as the intergenerational elasticity (Nybom and Stuhler, 2017).

The second crucial point is that the sensitivity of the absolute mobility estimates to plausible changes in the copula is low. In particular, plausible changes in relative mobility measures cannot explain long term changes in absolute mobility. Therefore, assuming a fixed copula in time will provide meaningful and reliable estimates of absolute mobility, in terms of both levels and trends. Together with the observation on the copula structure, it allows arguing that the marginal income distributions and a single observation of a relative mobility measure, such as the rank correlation, can provide reliable estimates of absolute mobility for various countries.

Figure 2 demonstrates that estimating the absolute mobility in the United States with different copulas, some of which are very different from the one characterizing the United States (Appendix D illustrates the wide range of copulas), results in a similar evolution in time. The estimates obtained using the various copulas differ from the benchmark estimates of Chetty et al. (2017) by 0.79 percentage points on average. We conclude that letting the copula change in time within the boundaries defined by realistic copulas, cannot explain more than a change of several percentage points in absolute mobility over a long period of time. This is demonstrated by the shaded area in Figure 2. Thus, only changes in marginal distributions can possibly explain the long run absolute mobility trend observed.

To further demonstrate the low sensitivity of absolute mobility estimates to the copula in terms of levels, we use a series of simulations based on the bivariate log-normal model (Section I). The model allows controlling all three determinants of absolute mobility (income growth, differences in inequality and relative mobility) at the same time in a systematic manner. This way we can test the sensitivity of absolute mobility to the rank correlation, *i.e.* to the copula, in various regions of the space of income growth and differences in inequality.

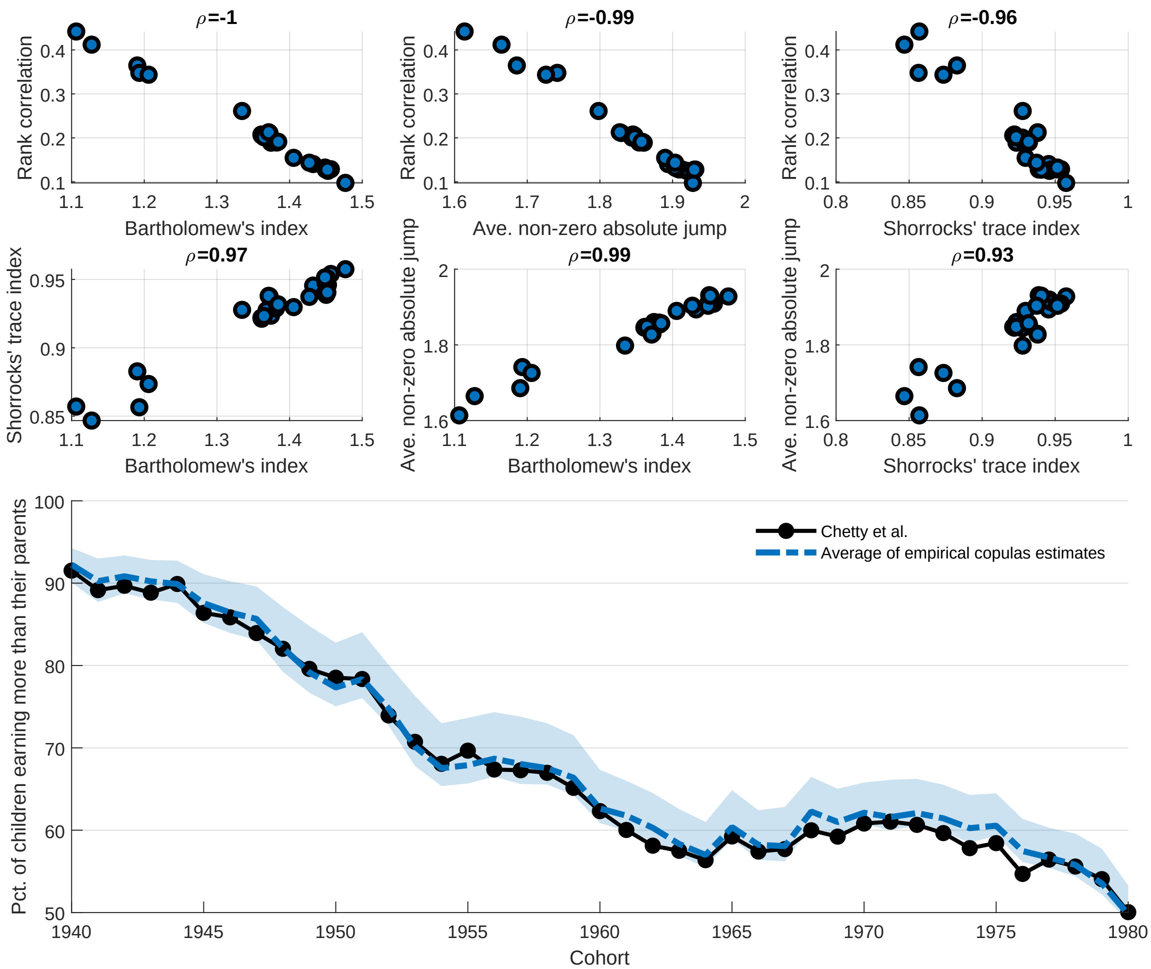

Figure 2. The effect of changes in copula on absolute intergenerational mobility in the United States.

Note: Top) A comparison between relative mobility measures in 28 empirical copulas (ρ is the Pearson correlation between each two relative mobility measures; the standard error on the correlation values was less than 0.01 in all cases); Bottom) Absolute mobility was estimated using the marginal distributions used in Chetty et al. (2017) and 28 empirical copulas for Denmark, Finland, Germany, Norway, Sweden, the United Kingdom and the United States. The shaded blue area is the area covered by the various absolute mobility estimates. The blue curve is the arithmetic mean of all 28 estimates in each year. The black circles are the estimates reported in Chetty et al. (2017).

Figure 3 presents the results of such simulations. We consider four scenarios of intergenerational income growth (*i.e.* relative change in average income between generations): 10%, 50%, 100%, and 400%; and four scenarios of inequality changes between generations, quantified as changes in the top 10% income share: from 50% to 30% (Sharp decrease in inequality), from 30% to 30% (No change in inequality), from 30% to 35% (Mild increase in inequality), from 30% to 45% (Sharp increase in inequality). The combination of these gives 16 scenarios, which represent a wide variety of realistic circumstances in different countries at different time periods. In each case we let the rank correlation change from 0 to 1. These specifications allow using the bivariate log-normal model (Eq. (3)) to calculate absolute mobility levels.

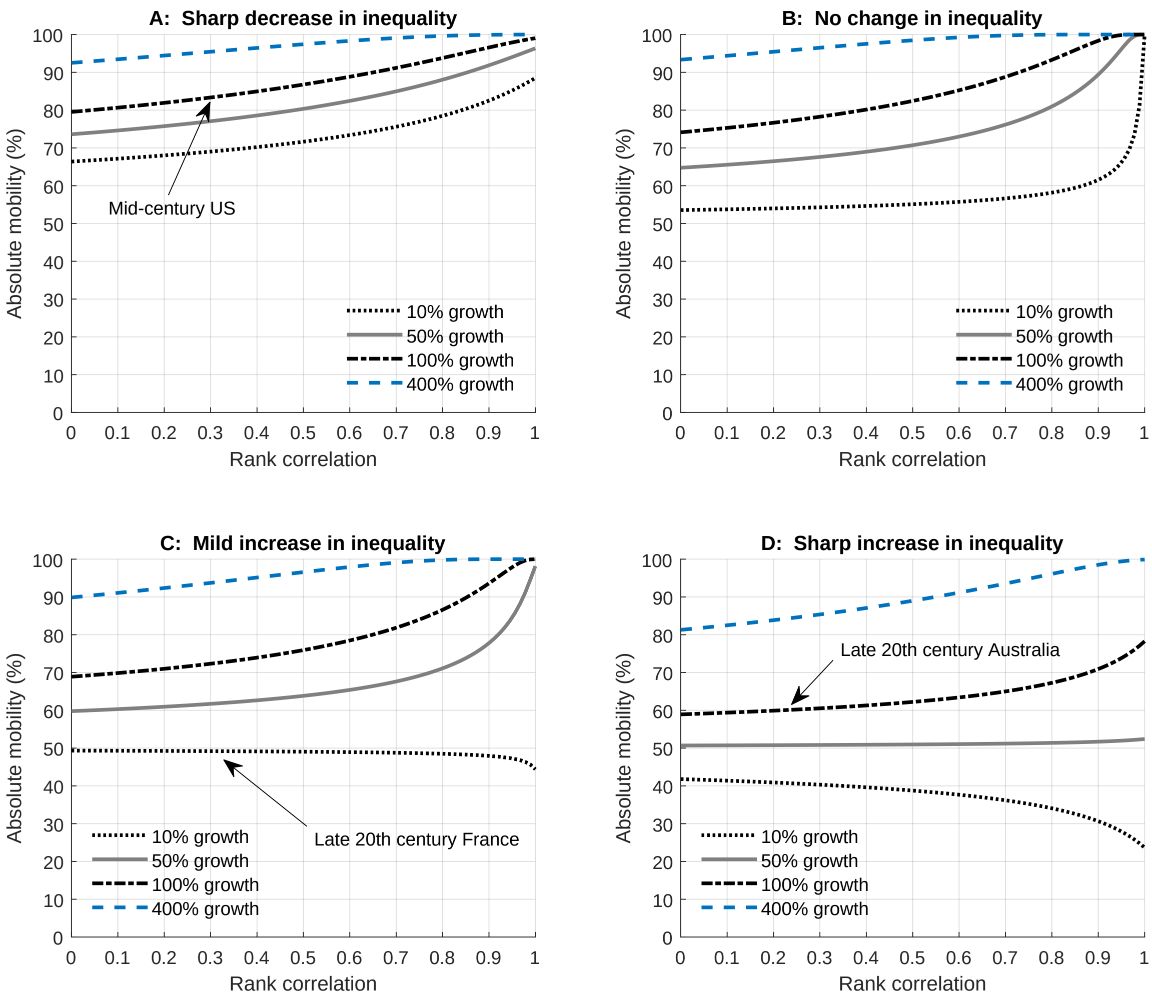

Figure 3. The sensitivity of absolute mobility to the rank correlation in various simulated scenarios.

Note: We consider 16 scenarios consisting of intergenerational income growth of 10%, 50%, 100%, and 400%, and intergenerational changes in the top 10% income share from 50% to 30% (Sharp decrease in inequality), from 30% to 30% (No change in inequality), from 30% to 35% (Mild increase in inequality), from 30% to 45% (Sharp increase in inequality). In each case we let the rank correlation change from 0 to 1 and use Eq. (3) to compute the resulting absolute mobility. The arrows are used to represent relevant circumstances for specific countries at specific time periods.

The simulations show that the sensitivity of absolute mobility to the rank correlation increases with the rank correlation unless absolute mobility is close to 100%, where it saturates. In most cases, a difference between a rank correlation of 0.1 and 0.5, which spans a realistic range of intergenerational rank correlations, leads to absolute mobility estimates that are different from one another in less than 5 percentage points. The sensitivity seems to be high for rank correlation values above 0.7.

Figure 3 also shows that with very high and very low intergenerational income growth (400% and 10%, for example), absolute mobility is very insensitive to changes in the rank correlation, unless the change in inequality is also sharp. Specifically, in the cases which can be considered as realistic and resemble specific countries and specific time periods, the absolute mobility estimates are insensitive to the rank correlation. We note that it is possible that less relative mobility leads to less absolute mobility, unlike the more usual case. Yet, this happens only when income growth is very slow and inequality increases (see also Proposition 1).

We also note that conceptually, the same rank correlation (for given marginal distributions) could result in different absolute mobility estimates. Yet, the similar shape of empirical copulas discussed above makes this practically implausible. In short, we find the estimates of absolute mobility insensitive to plausible changes in the copula both in terms of levels and in trends (see additional tests in Appendix C).

III. Results

A. *Data*

The previous section demonstrated that absolute intergenerational mobility mainly depends on the income distributions of parents and children, rather than on their copula. Following the steps of Chetty et al. (2017) requires such distributions for 30-year-olds only, in years that are 30 years apart. Namely, for estimating absolute mobility for children born in 1980, we would need to possess the marginal income distribution of 30-year-olds in 1980 and in 2010. In the United States this became possible combining census, tax, and survey data for 1940–1984 birth cohorts. In France this has also become possible for 1970–1984 birth cohorts, using the tax data studied in Garbinti, Goupille-Lebret and Piketty (2018). However, we have good knowledge of the income distribution of the entire adult population in these countries in earlier years, based on tax data, surveys and national accounts.[7]

Such data, in different levels of accuracy and detail, are available from The World Inequality Database (2017). When available, we use pre-tax annual total income data in

[7]In fact, estimating absolute mobility for 30-year-olds born in 1980, for example, would ideally require looking at their parents' incomes at the same age, which is not the cohort of 30-year-olds in 1980 (not everyone born in 1980 had parents born in 1950, and not everyone born in 1950 had the same number of children). Yet, Chetty et al. (2017, Fig. S8) showed that the results for the United States are insensitive to the sample choice in the parents generation in various relevant specifications. Moreover, fertility patterns changed over time endogenously with income during the 20th century (Duncan et al., 1965; Duncan, 2018) (although the negative relationship between income and fertility has considerably flattened in recent decades in the United States (Bar et al., 2018)). These patterns could be important for the analysis of relative mobility (Duncan, 2018), and this information is encoded in the copula. Thus, due to the low sensitivity of absolute mobility to changes in the copula, this would not have a large impact on absolute mobility.

the equal-split assumption: 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. The equal-split assumption is compatible with the income specification in Chetty et al. (2017), using family income rather than individual income (see Alvaredo et al. (2016) for more details on the equal-split assumption). When the incomes of equal-split adults are not available we use tax units as the unit of observation and when these are not available we use individual incomes. Appendix E.1 discusses the potential effect the differences in unit of observation may have on estimates of absolute mobility. In some cases these differences may lead to sizable effects in both levels and trends.

The income concept used (pre-tax total income data) "is the sum of all pre-tax personal income flows accruing to the owners of the production factors, labor and capital, before taking into account the operation of the tax/transfer system, but after taking into account the operation of pension system." (The World Inequality Database, 2017) In the case of Denmark, Norway, and Sweden we use fiscal income, "defined as the sum of all income items reported on income tax returns, before any deduction." (The World Inequality Database, 2017) The main difference between total income and fiscal income is that some income sources included in total income may not be taxed or reported to the tax authorities. This makes fiscal income somewhat sensitive to tax policies that may change over time, and can potentially have a sizable impact on the results in terms of level. However, it is unlikely to have a major impact on the long run trends of absolute mobility. These are driven by the generally increasing income inequality and generally decreasing income growth rates over the past 50 years, which are common features of any income concept used. Appendix E details multiple sensitivity tests to address the impact of possible mis-estimation of income growth and income inequality on absolute mobility (which can inform the impact of differences between income concepts). It shows that the main results are robust to such mis-estimation.

For comparability, using pre-tax incomes is usually preferred to post-tax incomes. The latter depend crucially on tax and welfare policy, which may change over time and differs from country to country. Using post-tax incomes instead may have substantial impact on absolute mobility estimates, as discussed in Appendix E.3. Yet, despite having a sizable impact on absolute mobility levels, redistribution is still quite far from overturning the long run trend we find (see Section III.B and Appendix E.3).

Data for the rank correlation were taken from different studies. The rank correlation values and their sources, and the cohorts covered by the data are detailed in Appendix F.[8] While we use fixed rank correlations, in practice they may have changed over time. As demonstrated for the United States in Figure 2, this has only a small impact on the estimates. Appendix C details additional sensitivity tests to this assumption, addressing both levels and trends.

[8]For the countries in which the intergenerational elasticity was reported, rather than the rank correlation, we use the relationship $\rho = \beta\sigma_p/\sigma_c$, where σ_p and σ_c are the standard deviations of the parent and child marginal log-income distributions and β is the estimated intergenerational income elasticity. The rank correlation is approximated by $\rho_S \approx (6 \arcsin(\rho/2))/\pi$ (see Trivedi and Zimmer (2007)).

B. *Absolute Intergenerational Mobility in Advanced Economies*

We estimate long run absolute intergenerational mobility series in 10 countries from 4 continents: Australia, Canada, Denmark, Finland, France, Japan, Norway, Sweden, the United Kingdom and the United States. As explained, we assume that the rank correlation in each country is stable over time. To get the marginal income distributions we use the generalized Pareto curve interpolation method (Blanchet, Fournier and Piketty, 2021). We use this method to generate large simulated samples of the pre-tax income distribution. In some country-years the data cover only the top 10% of the distribution. The generalized Pareto curve interpolation method might not be able to describe well the income distribution within the bottom 90% in such cases. In the next section we demonstrate, using the bivariate log-normal model, that such data limitations would have a small impact on the absolute mobility estimates in terms of levels, and virtually no impact on absolute mobility trends. This leads to a powerful conclusion: In the absence of detailed panel data and with limited information on the income distribution shape, it is possible to estimate the evolution of absolute mobility in the long run.

The analysis requires addressing an additional key data limitation. The available historical data in The World Inequality Database (2017) include all adult population and it is not possible to restrict the data to 30-year-olds only (or specific marital status, family size, *etc.*). It is necessary to address the potential impact of this limitation on our results. It would only have a small impact on the results if income growth and inequality among 30-year-olds evolve similarly to that of the entire adult population. Moreover, in the case the dominant factor in determining absolute mobility is either one of the factors – income growth or changes in inequality – it is enough to have similarity in one and not necessarily in the other, to obtain comparable estimates using specific birth cohorts or full adult populations. For simplicity, we call these full adult income populations 'cohorts', rather than birth cohorts, as they do not include necessarily people born in a specific year.[9]

In the United States, for example, the differences between our estimates of absolute mobility and those of Chetty et al. (2017) are small. They are always less than 2 percentage points, excluding several cohorts in the mid 1940s. Similarly, in France, "[…inequality] is almost as large within each age group as for the population taken as a whole." (Garbinti, Goupille-Lebret and Piketty, 2018, p. 73) This cancels out with the lower growth among 30-year-olds compared to the whole population (see Appendix E.2).

The difference between 'cohort' and 'birth-cohort' based absolute mobility estimates may be large in some country-years. Yet, with additional data available in some cases, it is possible to test how sensitive the estimates are to this limitation. In France, detailed tax

[9]While using the term cohort to represent these populations, it is important to note that there can be a large overlap between two cohorts. For example, the 1975 and 1980 cohorts would consist of the adult population in two years that are five years apart, and clearly have a large overlap between them. Also, note that when estimating absolute mobility for cohort X, we are considering the joint income distribution of adults in years X and $X + 30$, similarly to what is done for birth cohorts in Chetty et al. (2017). While the differences we find between 'cohort' and 'birth-cohort' based absolute mobility estimates do not qualitatively change our main results (as discussed in this section and demonstrated in Appendix E), it is crucial to recognize the fundamental difference between them when interpreting this analysis results.

data from 1970 onward (Garbinti, Goupille-Lebret and Piketty, 2018) allow testing the robustness of the estimates to this assumption for three cohorts (see Appendix E.2). We also find that our results closely match the existing empirical evidence for Canada (Ostrovsky, 2017). The results also accord well with recent working papers on other countries (Blanden, Machin and Rahman, 2019; Liss, Korpi and Wennberg, 2019; Manduca et al., 2020) (see Appendix G for a comparison with these papers).

A more systematic sensitivity test is done for the United States in Appendix E.2. It compares absolute mobility estimates in which the marginal distributions are taken from the Current Population Survey (CPS) in various specifications. This allows restricting the marginal distributions to certain age groups. It also enables considering individual income and family income separately. It shows that in multiple relevant specifications the absolute mobility results are close in terms of both levels and even more so in trends. Additional robustness checks are detailed in Appendix C and Appendix E.[10]

Figure 4 presents the main results. It shows that absolute mobility decreased in all countries studied during the second half of the 20th century. In some countries, especially France, Japan and the United States, the decrease is very dramatic. In these countries absolute mobility decreased from more than 90% for 1940s cohorts to less than 60% for 1980s cohorts. The Nordic countries, characterized by low income inequality and high relative mobility (Corak, 2013), also stand out in high absolute mobility.

We find that absolute mobility in France, Sweden and the United States increased for the 1910s–1940s cohorts. These are the direct beneficiaries of the *Trente Glorieuses* in France and the *Rekordåren* in Sweden. These findings also extend those of Chetty et al. (2017). They indicate that the levels of absolute mobility were high even before World War II in the United States, and peaked around the 1940 cohort. This is inline with Song et al. (2020, p. 252), who find that "upward mobility increased for birth cohorts prior to 1900 but has fallen for those born after 1940," in the context of occupational mobility in the United States.[11]

[10] We note that one specification in Appendix E.2 leads to somewhat higher estimates of absolute mobility when using the CPS data. This is obtained when comparing 40 year old 'children' compared to 30 year old 'parents' (*i.e.* considering the populations of 30 year olds at year X and of 40 year olds at year $X + 30$). This specification aims to address the fact that age-30 income was closer to permanent income in the past than it is nowadays, while age-40 income is currently closer (*e.g.* because increasing shares of people are completing post-secondary education (Bloome, Dyer and Zhou, 2018)). While this specification leads to estimates that are consistently higher than the baseline by about 6 percentage points, the trend remains similar.

[11] Despite the qualitative similarities, it is difficult to compare the results of Song et al. (2020) on the United States to this paper. First, Song et al. (2020) use occupational data for white males only. Second, the major increase in mobility they find is between the birth cohort of 1910 to that of 1920, a period which the data used in this paper only partially cover.

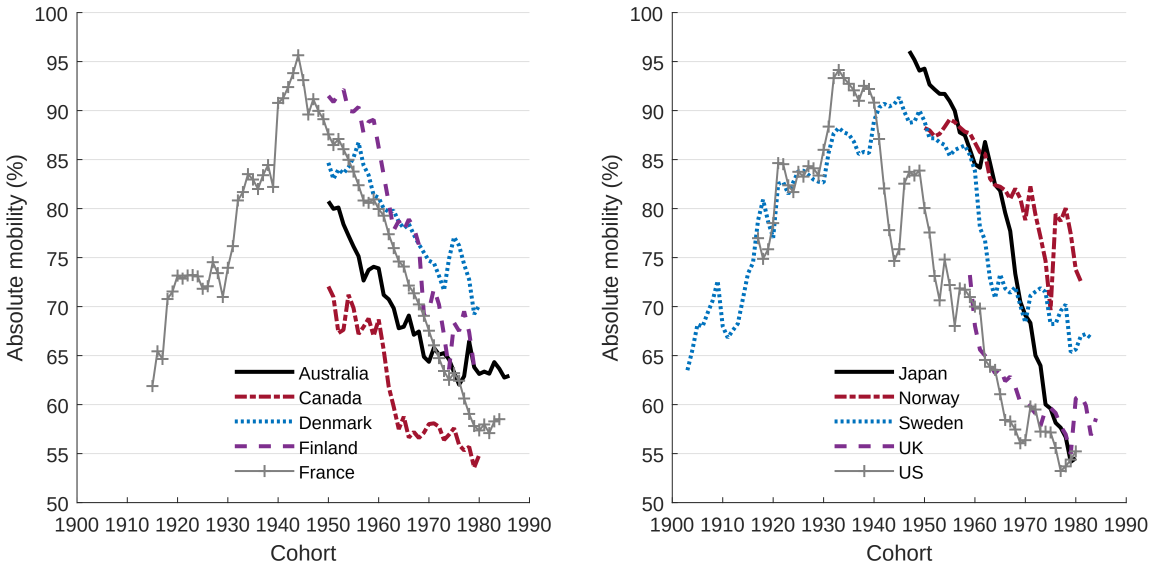

FIGURE 4. THE EVOLUTION OF ABSOLUTE INTERGENERATIONAL MOBILITY IN ADVANCED ECONOMIES.

Note: See Appendix H for the baseline estimates values.

C. *Absolute Mobility Decomposition*

Figure 4 shows that in all countries studied absolute mobility decreased during the second half of the 20th century. The size of the decrease differs between country to country. Yet, Figure 4 cannot answer whether the drivers leading to the decrease are similar or not. Chetty et al. (2017) showed that two-thirds of the decline in absolute mobility in the United States are due to changes in the income distribution. A third of the decline is due to slower growth over the past thirty years relative to the 1940s and 1950s.

How does this experience compare to the experience in other countries? To answer this question we decompose the absolute mobility trends into contributions of different factors. As noted, we assume that relative mobility is stable over time, so it cannot be the source of long run changes in absolute mobility in our results (and more generally, absolute mobility is insensitive to plausible changes in relative mobility, as discussed above). Thus, the observed trend is due to two factors – the generally decreasing income growth rates and the generally increasing income inequality (see Section I).

For each country we estimate the contribution of those factors to the absolute intergenerational mobility trend. For that purpose we produce two counterfactual calculations, in addition to the baseline estimate in each country: one in which the shape of the income distribution is kept constant in time and similar to the earliest distribution in the data (or 1940 in the case of France, Sweden and the United States), but with the average income changing according to its real historical values; and another, in which the distribution shape changes according to historical data, but the annual income growth rate is fixed in time and equal to the average annualized real income growth rate over the entire period considered.[12]

Figure 5 presents these calculations for France, Japan, Australia and the United States. The ten countries studied can be generally divided into two groups – such that the fixed inequality counterfactual scenario follows the baseline estimate (most notably Denmark, France and Japan), and such that the baseline estimate is similar to the fixed income growth scenario (like Australia and the United States). In the former case the decrease in absolute mobility is mainly due to the decrease in income growth rates, since fixing inequality has only a small effect. In the latter case, the effect of inequality is more dominant.

In most of the countries considered, the decreasing income growth rates account for most of the decrease in absolute mobility. Particularly in Canada, France, Japan and the Nordic countries. In Australia, the United Kingdom and the United States the role of increasing income inequality is more important. Despite the similarity in the evolution of absolute mobility in various countries, Australia and the United States are the only countries in which the increasing income inequality played such a dominant role in the decreasing mobility.

We note that this decomposition ignores the interaction between growth and changes in inequality (and also possible interactions with relative mobility). Yet, evidence for such an interaction are debatable and inconclusive (Bourguignon, 2004; Ostry, Berg and Tsangarides, 2014).

Figure 6 shows a similar calculation for earlier cohorts in the United States. Unlike the results in Figure 5, where the evolution of absolute mobility in the United States was mainly driven by changes in inequality, for earlier cohorts absolute mobility was mainly driven by fast income growth. Figure 6 shows that the increase in absolute mobility prior to the 1940 cohort closely follows the counterfactual scenario in which income inequality does not change.

[12] In the first counterfactual calculation, with fixed inequality, we take the initial distribution in the data for each cohort, while adjusting its average value so that the historical average income is recovered. This is done by multiplying all incomes by a common appropriate factor in each year. In the second counterfactual calculation, with fixed income growth, we first calculate the total income growth rate over the entire period considered for each country. This growth rate is then annualized. We then multiply the incomes in every year by an appropriate common factor which would make the average income equal to its value had the annual growth rate been fixed in time and equal to the annualized one.

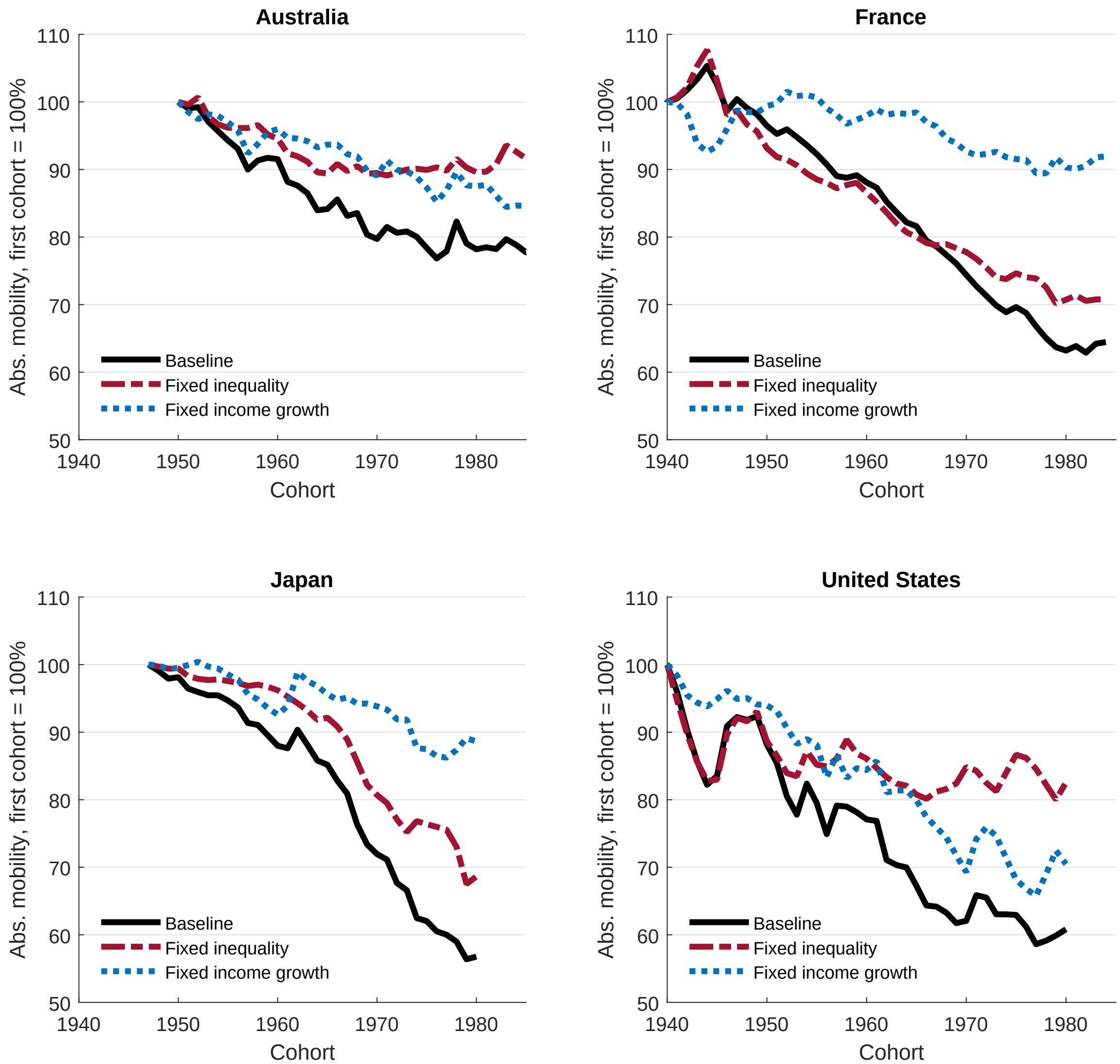

Figure 5. Counterfactual calculations of absolute mobility in Australia, France, Japan, and the United States after 1940.

Note: For comparability, we set the absolute mobility to 100% in the earliest cohort. See Appendix H for similar results in all ten countries and for the contribution of each factor to the overall decrease in mobility in all countries.

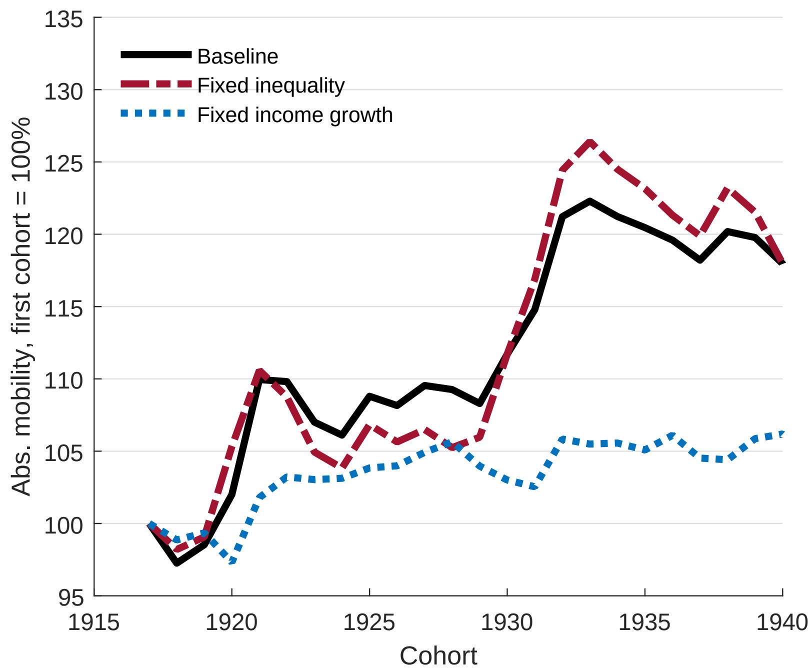

Figure 6. Counterfactual calculations of absolute mobility in the United States before 1940.

Note: For comparability, we set the absolute mobility to 100% in the earliest cohort.

D. Bivariate Log-normal Model Comparison

In Section I we saw that using a bivariate log-normal approximation we obtain an analytic expression for absolute intergenerational mobility:

$$A = \Phi\left(\frac{\mu_c - \mu_p}{\sqrt{\sigma_p^2 - 2\rho\sigma_p\sigma_c + \sigma_c^2}}\right), \tag{7}$$

for a bivariate log-normal distribution with parameters μ_p, σ_p (for the parents' marginal distribution), μ_c, σ_c (for the children's marginal distribution) and correlation ρ, where Φ is the cumulative distribution function of the standard normal distribution.

To demonstrate that the model is empirically sound we use pre-tax national income per adult data in France to obtain μ_p, σ_p, μ_c and σ_c for every cohort and compare the baseline estimates in Section III.B to Eq. (7). We use France specifically for the fine-grained distributional data available since the early 20th century (Garbinti, Goupille-Lebret and Piketty, 2018).

In a log-normal distribution, income shares are uniquely determined by σ, so we estimate σ for every year in four ways: based on the bottom 50% income share; the top 10% income share; the top 1% income share; the Gini coefficient. After obtaining σ, μ is given by $\mu = \log(m) - \sigma^2/2$, where m is the per-adult pre-tax income in the data. The different ways to determine the value of σ would correspond to four different series approximating the evolution of absolute mobility using Eq. (7).[13]

Figure 7 presents a comparison between the baseline absolute mobility estimates for France and the log-normal approximations. For the same rank correlation used in Section III.B, the differences between the baseline estimate and the model are small. They average between −1.4 to 1.6 percentage points across the different approximations. Moreover, the long run trends in all cases are nearly identical, and the pairwise correlations between the series are all above 0.91. Figure 7 demonstrates that despite its methodological naïvety, the bivariate log-normal model describes well the long run evolution of absolute mobility. Thus, it is also useful when very limited information on the evolution of the income distributions is available. Specifically, the knowledge of historical income growth rates and of either Gini coefficients or top 10% income shares is satisfactory for estimating absolute mobility.

The bivariate log-normal model predicts an inverse relationship between absolute and relative mobility (assuming positive income growth between generations) – absolute mobility (A) increases with the log-incomes correlation (ρ). This inverse relationship repeats the intuition illustrated in Figure 1 and seemingly stands in contrast to the findings about absolute intergenerational mobility in Figure 4 – the order of countries by either absolute

[13] The income share of the top quantile q in a log-normal distribution is $1-\Phi\left(\Phi^{-1}(1-q)-\sigma\right)$ and the Gini coefficient is $\mathrm{erf}(\sigma/2)$ (Cowell, 2011), where Φ is the cumulative distribution function of the standard normal distribution, and erf is the Gauss error function.

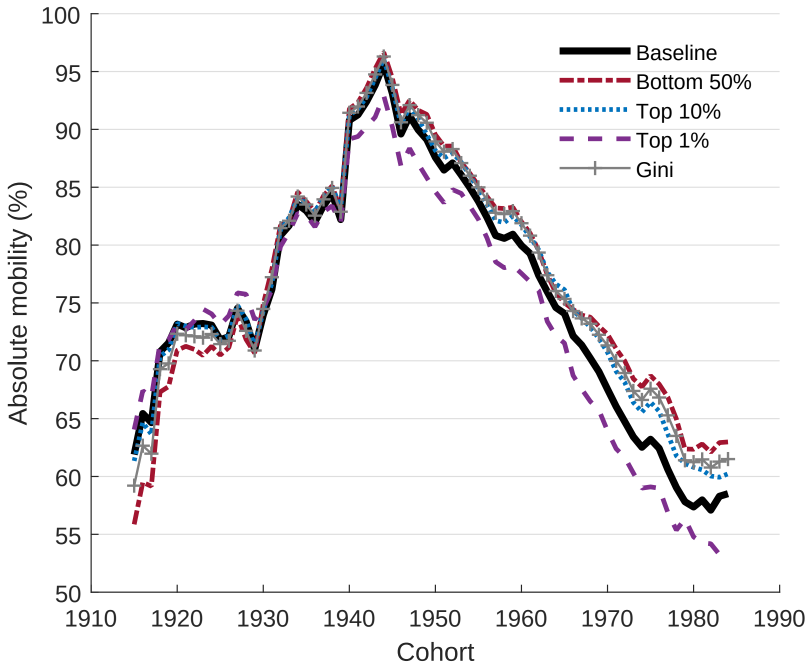

Figure 7. Absolute mobility in France under the bivariate log-normal approximation.

Note: The baseline estimates (solid black curve) are the same as in Figure 4. In the other estimates each case is based on the bivariate log-normal approximation, with the value of σ determined by different inequality measures – the bottom 50% income share (dash-dotted red); the top 10% income share (dotted blue); the top 1% income share (dashed purple); the Gini coefficient (gray crosses). The rank correlation was assumed as 0.3 in all cases.

or relative mobility is similar. Yet, as shown above, absolute mobility is driven primarily by economic growth, secondarily by changes in inequality, and only weakly by relative mobility.

IV. Conclusion

Absolute intergenerational mobility measures the fraction of children with higher real incomes than their parents at the same age. It aims to capture the chances of children to have a higher standard of living than their parents. We initially clarify the relationship between absolute mobility and its determinants: income growth, changes in income inequality and relative mobility and show that absolute intergenerational mobility increases with income growth, but decreases with increasing inequality and relative mobility. Thus, absolute intergenerational mobility can be viewed as an inequality-weighted measure of growth (while also incorporating information on relative mobility).

This paper highlights a decreasing absolute mobility trend in a group of ten advanced economies for post-World War II cohorts. The sources of this trend differ from country to country. In Australia and the United States, and to a lesser extent in Finland and the United Kingdom, the rising income inequality is the main contributor for decreasing absolute mobility. In other countries, a similar historical evolution of absolute mobility is predominantly explained by the decrease of income growth rates.

We were also able to detect an increase in absolute intergenerational mobility in France, Sweden and the United States for pre-World War II cohorts. These findings extend those of Chetty et al. (2017) for the United States. They indicate that the levels of absolute mobility were high even before the war, and peaked around the 1940 cohort. These high levels are mainly driven by the fast income growth rates in the United States after World War II.

Our findings also imply that it is possible to produce estimates of absolute intergenerational mobility without the need for high-quality panel data sets. The basic structure of realistic copulas is similar, and therefore different measures of relative mobility are effectively interchangeable. This means that collapsing the copula into a single representative measure of relative mobility is empirically justified for estimating absolute mobility. Furthermore, the sensitivity of absolute mobility to relative mobility is low in terms of both levels and trends over time. Thus, realistic changes in relative mobility cannot explain the evolution of absolute mobility. We found that a bivariate log-normal model is satisfactory for describing the long run dynamics of absolute mobility. This allows to further study absolute mobility in more countries and additional cohorts in the absence of detailed historical panel data.

The low sensitivity of absolute mobility estimates to relative mobility is a robust result. Yet, more caution is required when considering different adjustments to the income concept and unit of measurement used. For example, it matters for absolute mobility whether pre-tax or post-tax incomes are used, as taxes and transfers affect inequality. Furthermore, as tax and welfare policies evolve, producing consistent post-tax measures of income over time is challenging (see discussion in (Piketty, Saez and Zucman, 2018)). Considering individual or family income may also matter for absolute mobility estimates. Such adjustments may have a substantial quantitative impact on the observed trends of absolute mobility. This is especially important when comparing between countries. At the same time, the main qualitative picture we find – the decrease in absolute mobility over the second half of the 20th century – remains largely unchanged even when various adjustments are made.

Our methodology can be used to estimate not only absolute intergenerational mobility, but also intragenerational mobility. Many countries have gone through major economic crises and recoveries during the past two decades. These have hit or benefited the majority of the population in those countries, but not the entire population. In the United States, for example, national income per adult increased by 13% between 2009 and 2016. Yet, only about 55% of the adult population had enjoyed a higher standard of living in 2016 than in 2009 (Berman and Bourguignon, 2020). The changing age-income profile may also play a role when studying absolute intragenerational mobility trends (Bloome, Dyer and Zhou, 2018) and it is important for the interpretation of such trends. Yet, the general approach to studying absolute intragenerational mobility would remain similar to the methodology described in this paper. A thorough analysis of absolute intragenerational mobility is left for future work.

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