Inequality in an Equal Society

Laura A. Harvey — *University of East Anglia*

Jochen O. Mierau — *University of Groningen*

James Rockey — *University of Birmingham*

Abstract: A society in which everybody of a given age has the same income will exhibit substantial income and wealth inequality. We use this idea to empirically quantify *inter-cohort* inequality – the share of observed inequality attributable to life-cycle profiles of income and wealth – using data on male earnings and household wealth. We document that recent increases in income and wealth inequality in the United States and other developed countries are larger than observed rates would suggest due to favourable demographics. That is, while demographic change played a substantial role in the dynamics of income and wealth inequality until 1990, the stark increase in inequality in the US and elsewhere ever since is despite not because of demographic change. Moreover, we show that there is important variation across countries in the level and trends in the extent of inequality that is due to lifecycle effects, and that taking this into account gives a more nuanced view of cross-country comparisons.

Keywords: Income Inequality, Wealth Inequality, Demographic Structure

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1 Introduction

The most equal society will exhibit a substantial degree of income and wealth inequality. Even in the absence of differences in talent, individuals approaching retirement will be substantially wealthier than those who are younger. Moreover, experience and seniority mean that older workers will have higher wages than their younger colleagues. Jointly, such life-cycle aspects of income and wealth give rise to a degree of inequality that is natural in all societies – even if each individual over the course of the life-cycle is exactly the same as any other individual.

An early version of this argument was made by Atkinson (1971), who suggested that the distribution of wealth should be expected to be unequal solely due to differences in accumulated savings over the life-cycle. In another important contribution Paglin (1975) argued that standard Lorenz curves 'combine and thus confuse' life-cycle inequality with other sources of inequality and proposed that the Gini coefficient (hereinafter 'the Gini') should be corrected for the age structure inherent in income and wealth profiles.[1]

A powerful new body of evidence (particularly Piketty (2013, 2020) and the many references therein) has transformed our understanding, and highlighted the societal implications, of long-term trends in inequality. However, following Atkinson (1971) and Paglin (1975) it is important to understand the extent to which these trends reflect changes in inequality due to changes in nations' demographic structure. We refer to this component of inequality as *inter-cohort* inequality, since it considers variation in income or wealth over the life-cycle.[2]

We address the need to understand the role of demographic change for the dynamics of inequality by taking the life-cycle argument to the data. Therefore, the main contribution of this paper is descriptive. We assemble comparable time series describing the long-term evolution of *inter-cohort* inequality in male earnings and household wealth for a number of developed countries. In doing so we document how much of the variation in income and wealth inequality over time and between countries is due solely to life-cycle effects and by implication how much reflects other factors.

[1] The measure we will use is the refinement of Paglin's measure introduced by Formby and Seaks (1980) which can be interpreted in the same way as a normal Gini coefficient.

[2] We discuss this point further in Section 2.

We start with detailed microdata for the United States from the Current Population Survey (CPS) and then move on to use harmonized microdata from the Luxembourg Income Study (LIS) and Luxembourg Wealth Study (LWS) for other developed countries (including the United States). With these data in hand we analyse the degree to which even in the absence of any inequality between individuals of the same cohort, societies exhibit substantial degrees of income and wealth inequality.

We show that the level of inequality in male earnings due to life-cycle effects only (i.e., *inter-cohort* inequality) accounts for around one third of inequality in male earnings in the United States, with the remaining two-thirds attributable to differences between individuals (i.e., *intra-cohort* inequality). Moreover, between the early 1970s and the early 1990s, the level of *inter-cohort* inequality increased by around 2 percentage points from just under 18 percent.

Results for wealth show that in the United States *inter-cohort* wealth inequality has varied little over the last 20 years and can only explain around one third of the growth in overall inequality. This suggests a more modest role for life-cycle effects in understanding wealth inequality. However, a cross-country comparison suggests that life-cycle effects can explain a considerable amount of the cross-country variation in wealth inequality. That is, disparities in wealth inequality across countries are substantially smaller once we focus on *intra-cohort* effects and abstract from differences due to variations in demographics.

Our aim of quantifying the effect of changes in demography on inequality is similar to that of the work of Mookherjee and Shorrocks (1982). Like them, we will use the Formby and Seaks (1980) modification of the Paglin–Gini to calculate the *inter-cohort* inequality. Despite having access to only very limited aggregated data they were nevertheless able to provide evidence that rises in inequality in Great Britain over the period 1965–1980 could be almost entirely attributed to increasing *inter-cohort* inequality. A key advantage of the much improved quality and coverage (both in terms of years covered and countries considered) of harmonized data now available to us, is that we can see this trend in its proper historical context – as a temporary phenomenon soon to be reversed.

Our paper further relates to the important literature following, again, Mookherjee and Shorrocks (1982) that focuses on how to attribute inequality to multiple sources. This is a complication we avoid given our focus only on life-cycle effects and on the Gini. A notable feature of all of this work, particularly that of Lerman and Yitzhaki (1985), Lambert and Aronson (1993), Cowell and Jenkins (1995), Bourguignon et al. (2008), is that they largely conclude that demographic factors are relatively unimportant.[3] Yet we argue, that *à la* Piketty and Saez (2003, 2014) there is much to be gained by considering variation over time. Importantly, in this paper we demonstrate that there have been substantial differences in the relative importance of life-cycle effects both over time and across countries and that these can account for a meaningful share of overall inequality.[4]

Our analysis of the changing role of demography as a determinant of inequality also contributes to various recent strands of literature that build on a new body of evidence that documents increased concentration of income and wealth of the richest (Piketty and Saez, 2014, Piketty and Zucman, 2015, Saez and Zucman, 2016, Piketty et al., 2017, Zucman, 2019, Smith et al., 2022, Saez and Zucman, 2022).

One line of work has sought to understand *who* is getting richer – Gomez (2023) develops an accounting framework with which to understand changes in top income and wealth shares. He finds that around half of the increase in US top wealth shares is due to new, wealthier, entrants.

A second quantifies the role of differences in portfolio composition and asset returns. Kuhn et al. (2020) studies the joint distribution of US household income and wealth and shows how the fact that middle-class wealth is concentrated on housing, while a large

[3]Lerman and Yitzhaki (1985) introduce a method for decomposing the Gini by income source and use it to show, for U.S. data for 1981, the relative importance of the earnings of the head of household versus that of their spouse or property income and transfers. Lambert and Aronson (1993) clarified the meaning of the residual term, identifying it as the extent to which there was a crossover in incomes across age groups due to within-age-group variations in earnings. Cowell and Jenkins (1995) provide a method for computing the share of inequality that may be explained by within-group variation for the generalized-entropy class of inequality measures. Analysing one wave of the Panel Study of Income Dynamics (PSID) they conclude that 'not much' of inequality can be explained by race, age, and gender. Bourguignon et al. (2008) develop a method by which differences in the distribution of household incomes across countries maybe compared and apportioned to different sources. Applying this method they are able to decompose the sources of differences in inequality between Brazil and the USA, showing that these are driven by greater inequality in education levels (and the returns on education), and pension incomes. Like Cowell and Jenkins (1995) they conclude that little of the difference can be explained by demographic factors.

[4]Some other recent work has sought to decompose the sources and evolution of inequality over time. Brewer and Wren-Lewis (2016) decompose trends in UK inequality by income source and demographic characteristics to show that increases in inequality among those in employment have been ameliorated by relatively low unemployment and more generous pension provision. Yamada (2012) studies the role of individual risk, macroeconomic and demographic changes in Japan using an Overlapping Generations (OLG) model. Almås et al. (2011a) uses register data to study the role of the Baby Boom generation in the evolution of inequality of Norway. This work links to the related literature on lifetime inequality, for example Blundell and Preston (1998), Blundell and Etheridge (2010) and Corneo (2015).

share of the wealth of the richest households is equity means that there have been very different wealth dynamics across the wealth distribution. Garbinti et al. (2021) show that in France the wealthiest are increasingly those whose wealth is derived from capital rather than labour income. On the other hand Pfeffer and Waitkus (2021) argues that differences in housing equity is a key determinant of cross-national differences in the wealth distribution. Relatedly, Saez and Zucman (2020), using distributional accounts show, that the wealthiest 400 Americans pay a lower than average tax rate, contributing to this increasing concentration implying further differences in post-tax returns.

Chancel and Piketty (2021) provide a grand overview of the long run trends in global inequality, emphasizing differences between high and low income countries and the twin roles of between country and within country inequality. Ranaldi and Milanovi (2022) emphasize the role of the composition of income in driving these changes. Others (Heimberger, 2020, Nolan et al., 2019, Furceri and Ostry, 2019), point to globalization and technological change. Parallel work has sought to understand differences within the set of rich countries argue for the role of greater pre-distribution in Europe in explaining lower income inequality (Blanchet et al., 2022) and the role of this reduced income inequality and stronger relative house price growth in turn in explaining lower European wealth concentration (Blanchet and Martínez-Toledano, 2023).

The paper proceeds as follows. Section 2 sketches the empirical argument for, and formalizes, the notion of *inter-cohort* and *intra-cohort* inequality. Section 3 takes these definitions to data. It focuses first on income inequality in the United States, before considering a panel of developed countries. These results suggest, that particularly in the United States, ignoring changes in *inter-cohort* rates of income inequality over the last 20 years may mean underestimating increases in inequality. In Section 4 we shall see that the same is not true of wealth inequality. We close with a brief conclusion.

2 Inter-Cohort Rate of Inequality

The argument of Atkinson (1971) and Paglin (1975) was that the standard egalitarian view of complete income and wealth equality implies either substantial redistribution from old to young, or that there is no return to experience, etc. Indeed, a society in which one never accumulates assets or develops is quite alien. This implies, as argued by Paglin (1975), that the correct benchmark is the level of inequality due only to life-cycle effects. However, the Paglin–Gini was controversial, and we work with the measure of Formby and Seaks (1980), Formby et al. (1989) which does not have the same shortcomings.[5] Thus, we refer to such age-based earnings differences as the level of *inter-cohort* inequality.

This benchmark is shown graphically in Figure 1. This reproduces the conventional graph defining the Gini coefficient, but with an additional Lorenz curve. The thick curved line is the *inter-cohort* Lorenz curve, plotting the distribution of cohort averages – that is differences due only to life-cycle effects. The dashed line is the overall Lorenz curve, the distribution of income (or wealth) given variation between and within cohorts. A indicates the area between the line of equality and the inter-cohort Lorenz curve and B and B' indicate the areas under the inter-cohort and overall Lorenz curves, respectively. The *inter-cohort* Gini can be expressed as: $\theta^{IC} = 1 - 2B$, while the conventional, or overall, Gini coefficient can be expressed as: $\theta^{O} = 1 - 2B'$. The difference between these two is inequality due to other sources, what we term the *intra-cohort* Gini and is equal to $\theta^{O} - \theta^{IC} = B' - B$.[6]

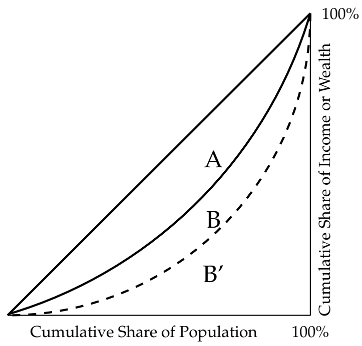
We calculate the Gini coefficient, θ^{O} as follows:

$$\theta^{O} = \frac{\sum_k \sum_l |x_l - x_k|}{2\,100^2\,\overline{x}}. \tag{1}$$

[5]The Paglin and Formby and Seaks (1980) Gini differs from other modifications of the Gini in that it maintains the same egalitarian benchmark. Other approaches include that of Almås et al. (2011a) who provide an alternative adjustment of the inequality measures, focusing on *unfair* inequality. This approach replaces the assumption incarnate in the standard Gini, or Lorenz curve, that fairness implies complete egalitarianism with a more general framework that better corresponds to intuitive and philosophical conceptions of a fair society. For example, *unfair* inequality may see as fair that those who work harder or who are better qualified earn more. In their empirical analysis Almås et al. (2011a) use rich microdata to study departures from the *fair* income distribution for Norway. Generalizing standard approaches to other definitions of inequality extends in important ways our toolkit but is quite different to the approach of our paper, which maintains the standard egalitarian definition of inequality. It is also quite different in practical terms, as a key advantage of our measure is that it can be derived without having recourse to registry data with variables such as IQ, thereby enabling us to compare *intra-cohort* inequality internationally. We only need data on ages and income/wealth and not the detailed data used by Almås et al. (2011a). More like the approach in this paper is Almås et al. (2011b) who propose an alternative method of adjusting the Gini for life-cycle effects, that can better account for correlations between, say age and education levels. This is a substantial advantage, but again necessitates detailed microdata normally not available, such as parental earnings, that the effects of age and other factors may be precisely estimated.

[6]There is a large literature concerned with decomposing inequality indices, and particularly the Gini coefficient. Mookherjee and Shorrocks (1982) and Lambert and Aronson (1993) note that the Gini coefficient can be decomposed into three components: variation between groups, here the *inter-cohort* component, variation within groups, and the extent to which variation within groups causes the group distributions to overlap. The distinction between the latter two is not important here, and like in Figure 1 and Paglin (1975) we conflate them.

Figure 1: The Life-Cycle Adjusted Gini Coefficient



The solid diagonal line is the conventional line of perfect equality. The solid curve is the Lorenz curve associated with the *inter-cohort* rate. The dashed curve is the overall Lorenz curve. A is the area between the two solid lines, and B is the area under the *inter-cohort* rate Lorenz Curve. B' is the area under the overall Lorenz curve. The *inter-cohort* rate Gini can be expressed as: $\theta^{IC} = 1 - 2B$, similarly the overall or conventional Gini can be expressed as: $\theta^{O} = 1 - 2B'$.

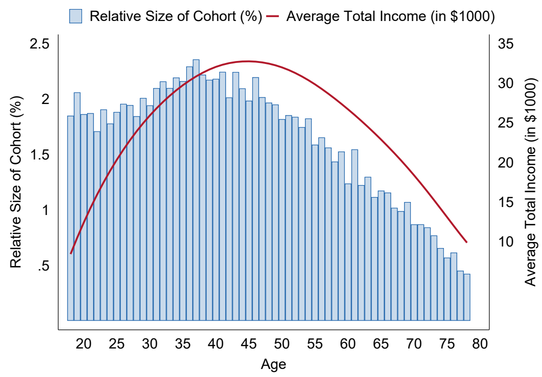
The *inter-cohort* Gini is obtained by replacing individual observations in eq. (1) with cohort averages thus eliminating any *intra-cohort* variation from the calculation. Thus, for each pair of cohorts i and j we use cohort means $\bar{x}_i$ and $\bar{x}_j$, which can be measures of income or wealth, in place of individual data weighting by cohort sizes p_i and p_j. Thus, we have:

$$\theta^{IC} = \frac{\sum_j p_j \sum_i p_i |\bar{x}_i - \bar{x}_j|}{2\overline{x}}. \tag{2}$$

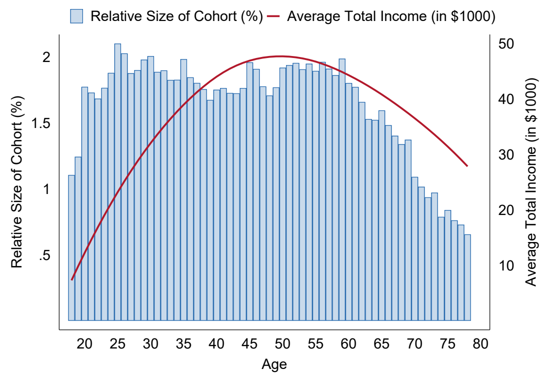
Thus, the degree of inequality is determined not only by how much richer the old are than the young as captured by the cohort means, but their relative number as captured by the cohort weights. We develop this intuition by sketching out the profile of income and cohort shares for the United States using data from the Current Population Survey (CPS) in the top row of Figure 2. The income profile, contained in the solid red line, reflects the average income of men in each age group. There we see that income has the familiar hump-shaped profile. The bars in Figures 2a and 2b trace out the associated cohort sizes by age. This provides the relatively uniform demographic pyramid associated with high income countries. However, in contrast to a steady-state demographic structure, where we would expect a smooth decrease in cohort size as age increases, we notice the ragged structure of the triangle – due to, for instance, the Baby Boom. Combining the income

Figure 2: Cohort size, Income, and Wealth by age group.

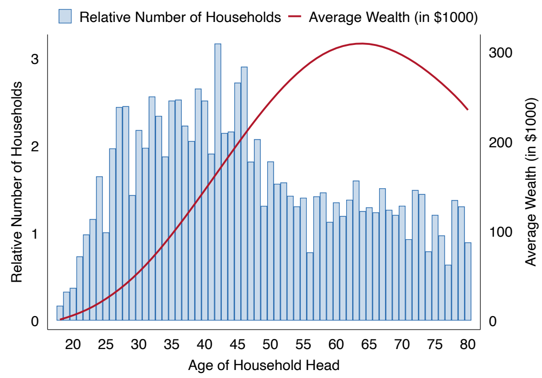
(a) Total Income and cohort size by age group United States: 1961



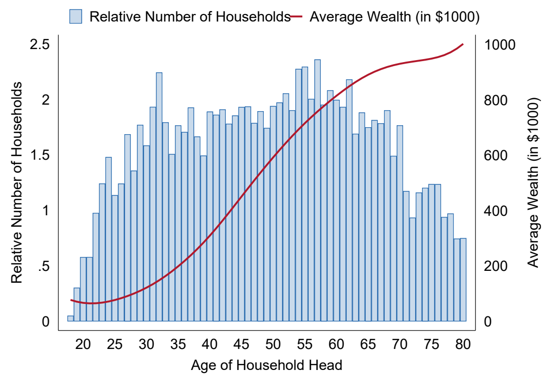
(b) Total Income and cohort size by age group United States: 2015



(c) Wealth and cohort size by age group United States: 1995



(d) Wealth and cohort size by age group United States: 2016



Source: Panel (a) and (b) are from the March CPS. Panels (c) and (d) Luxembourg Wealth Study (LWS).
Notes: The left y-axis corresponds to the relative number of households with a household head at a given age cohort, expressed by the blue bars. The right y-axis is the average wealth of each household in $1000. Hence, the red line maps the average wealth accumulation of households over the age profile of the household head. Results are produced using the household level sampling weights.

profile data and the size of the cohorts in Figures 2a, 2b we can calculate the *inter-cohort* Gini as per Equation 2, obtaining $\theta^{IC} = 0.16$, thus attesting to the idea of an *inter-cohort* level of income inequality.

For wealth, we provide a similar analysis in Figures 2c and 2d, where we sketch out the age profile of mean wealth for the United States using data from the Luxembourg Wealth Study. Since we are unable to observe wealth at the individual level, we trace out the relative number of households, using the age of the household head. If anything, the wealth profile is more hump-shaped over the life-cycle than income. This translates into higher *inter-cohort* inequality with the Gini coefficient of wealth being 0.38. We can also see strikingly, the impact of demographic change. In particular, the marked growth in households whose head is aged 50 or more.

2.1 Inequality Metrics

Two issues emerge in taking this argument to the data if we are to make meaningful comparisons over time and across countries. The first is the sample used to calculate the metrics introduced above so that sensible comparison can be ensured. The second is the extent to which we can regard the demographic structure of a society as separable from other factors. We address these in turn.

The first issue is the choice of the relevant population, given both unemployment and endogenous labour market participation. If one includes the entire population as is implicit in the work of Paglin (1975) and Formby and Seaks (1980), then the income attributed to those unemployed, or not in the labour market, becomes important. How the income from shared assets (e.g. a joint savings account between a married couple) is attributed also becomes important. This is true, a fortiori, for our purposes since we are making comparisons over a period in which dispersion in retirement ages has increased within as well as across countries. To minimize concerns about endogenous labour market participation decisions we focus on labour income inequality among men with positive earnings aged 18–65. Likewise, for wealth we consider the entire population but with households as the level of analysis so that we avoid having to make judgements about the ownership of assets within households. To show our results are not sensitive to this choice we also report results for total income for men aged 18–78. The rationale for these choices is outlined in Appendix A.1.

One way of capturing the contribution of changes in the age-structure of earnings to θ^{IC} is to employ ideas from index number theory, treating the income distribution as akin to prices, and the age distribution as akin to quantities.[7] Then, the Laspeyres index $\theta_t^{IC,L}$ is given by:

$$\theta_t^{IC,L} = \frac{\frac{\sum_j p_{j,t-1} \sum_i p_{i,t-1} |\overline{x}_{i,t} - \overline{x}_{j,t}|}{2\overline{x}_t}}{\theta_{t-1}^{IC}}. \tag{3}$$

That is, the ratio of θ_t^{IC}, but computed using the population structure of the previous period, to θ_{t-1}^{IC}. The Paasche index $\theta_t^{IC,P}$ is given by the ratio of $\frac{\theta_t^{IC}}{\theta_{t-1}^{IC}}$. We can then define a Fisher ideal index in the usual way as $\theta_t^{IC,F} = \sqrt{\theta_t^{IC,L}\theta_t^{IC,P}}$.

Because we are interested in the substantive value of θ_t^{IC} and $\theta_t^{IC,F}$, we focus on the numerator of the Fisher ideal index (and thus of the Laspeyres and Paasche indices), rather than on the ratio to some arbitrary base year. We can then compute the absolute difference θ_t^{IC} - $\theta_t^{IC,F}$. If this is large, relative to θ_t^{IC}, then the age-structure of earnings is a large contributor to the inequality of income. As Figures B.1a and B.1b makes clear, in practice the difference is very small suggesting that the age-structure of earnings is not a large contributor to the inequality of income. However, to obviate such concerns we focus hereinafter on $\theta^{IC,F}$.

In sum, taking inspiration from Atkinson (1971), Paglin (1975) and Formby and Seaks (1980) this section has sought to reinvigorate the argument that a stylized economy populated by individuals who are equal to each other at every stage of the life-cycle displays a substantial degree of income and wealth inequality, and demonstrated how this inequality can be measured.

3 Inequality in an Equal Society

This section empirically assesses the quantitative importance of *inter-cohort* inequality. First for the United States and then for a cross-section of developed countries.

[7]We are extremely grateful to an anonymous referee for this suggestion.

3.1 Inequality in the United States

For clarity, and in line with much of the focus of the literature, e.g. Piketty and Saez (2003), Saez and Zucman (2016), we begin our analysis by focusing on the United States, using the Current Population Survey (CPS), the details of which may be found in Appendix A. We use these data in preference to the World Income Database (Alvaredo et al., 2016) because they contain the necessary detailed microdata. Similarly, using register data such as that used by Almås et al. (2011a) is infeasible because we wish to study a range of countries for a sufficiently long period. The results are similar if instead we use the harmonized data of the LIS, as we will in our comparison of trends across countries in Section 3.2 below.[8]

As explained above we focus on male earnings throughout our analysis of income inequality. The definitions of income which we use throughout are similar in both datasets. For the CPS, labour income is the total pre-tax income from employment. Similarly, the corresponding variable from LIS is defined as any monetary payments received from employment. Total income is the total pre-tax personal income or losses from all sources for the CPS and in LIS is described as income from labour and transfers.[9]

Consider first the lines with interconnected green circles in Figures 3a and 3b. These plot the overall Gini coefficient for the period 1961–2021 for labour income (calculated for males with positive earnings aged 18–65) and total income (calculated over the male population aged 18–78), respectively. The most striking feature is the pronounced and consistent upwards trend over the period. The overall Gini was 0.36 for labour income and just above 0.40 for total income in 1961 and 0.47 and 0.50 respectively in 2021. Also clear, is that inequality in labour income has increased more than that of total income, with total income experiencing a less steep upward trend.[10] For both series, it is apparent that the biggest growth in inequality was experienced in the period 1974–1995. While the trend is clear, there is also a substantial cyclical component, as shown more generally by

[8] We present in the same results for the United States in Appendix B, where Figure B.3a for total income and Figure B.3b for labour income.

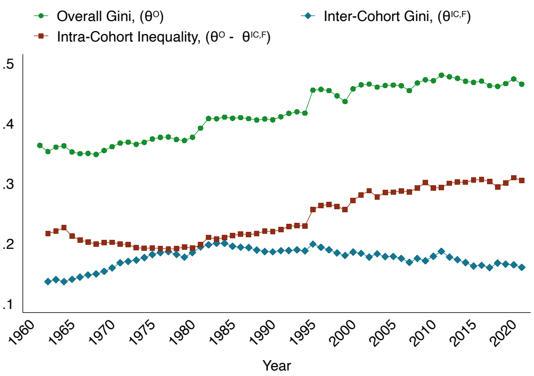
[9] A more complete description of all the data used is given in Appendix A.

[10] These changes in trend are more apparent if we plot the different Gini series by themselves as in Figure B.2 in the Appendix.

Milanovic (2016). Finally, we can note that the growth in inequality is faster from 2000 onwards for both series.

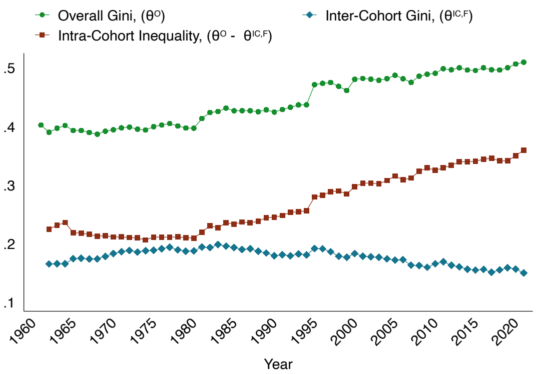
Figure 3: Overall, Inter-Cohort, and Intra-Cohort Gini Coefficients for the United States 1961–2021

(a) Labour Income



Source: Authors' calculations using ASEC Supplement of the Current Population Survey.
Notes: Sample includes men with positive income and are aged 18–65. Results are calculated using individual weights.

(b) Total Income



Source: Authors' calculations using ASEC Supplement of the Current Population Survey.
Notes: Sample includes men aged 18–78. We exclude individuals with a zero or negative income. Results are calculated using individual weights.

We now analyse the extent to which these changes in inequality reflect demographic changes. Figures 3a and 3b also report *inter-cohort* inequality, $\theta^{IC,F}$, (blue diamonds) and the difference, *intra-cohort* inequality, $\theta^O - \theta^{IC,F}$ (red squares).

Considering overall, *inter-cohort* and *intra-cohort* Ginis in Figures 3a and 3b together it is clear that while inequality increased only modestly from 1960 to 1990, this was in spite of a substantial increase in *inter-cohort* inequality. Over the period 1960–1980 *intra-cohort* inequality declined, by the late 1970s half of inequality was *inter-cohort*. On the other hand, the substantial increase in labour income inequality since the mid-1990s has been despite no increase in *inter-cohort* inequality. *Intra-cohort* inequality has rapidly increased. The difference between these two periods is important as it makes plain the quantitative importance of our argument. Ignoring the role of demographic change in generating variations in the *inter-cohort* rate of inequality can lead us to understate the increase in inequality over the last 25 years. Equally, it leads us to overstate it for the previous 25 years, and thus also to understate the difference between the two periods.[11]

3.2 Cross-Sectional Time-Series Analysis

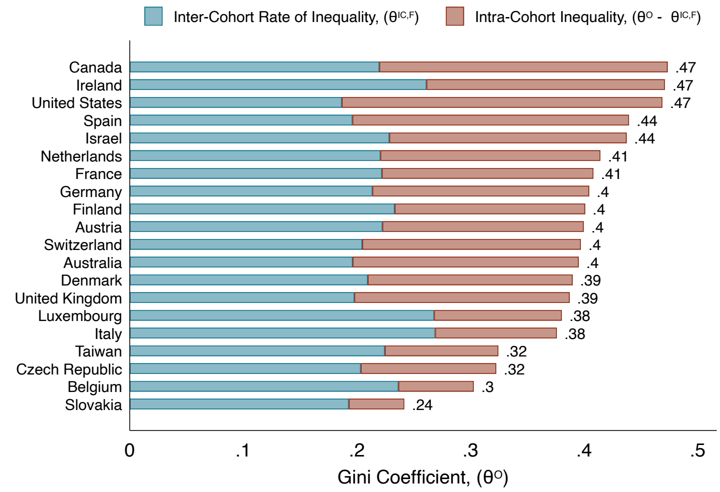
We now broaden the discussion to a sample of countries with sufficient time series available from LIS to conduct a meaningful study of trends over time. Figure 4 summarizes the cross-country variation in wave X of the LIS for all the countries we consider.

Inter-cohort inequality is blue, and *intra-cohort* inequality is red. The sum of these gives overall inequality in labour income, reported to the right of each bar. The most obvious feature of the data is the substantial variation in overall inequality, between 0.47 for the United States or Canada and 0.3 for Belgium. This variation is continuous, meaning that there are no obvious 'groups' in the data. Secondly, we note that there is similarly large variation in *intra-cohort* inequality. For example, overall inequality in Spain or Ireland is similar, but *intra-cohort* inequality is much higher in Ireland. Alternatively, if Spain had the same demographic structure as the United States, it would be nearly as unequal. Conversely, while *inter-cohort* inequality in Germany is similar to that in Spain, *intra-cohort* inequality is around 5 percentage points higher. Thus, cross-country comparisons of overall inequality may be misleading. Australia and Finland have the same overall Gini, but *intra-cohort* inequality in Australia is higher, and thus perhaps more amenable to policy. This emphasizes that as well as being important in understanding variation over time, separating *inter-cohort* and *intra-cohort* inequality is crucial to a nuanced understanding of cross-country variation in income inequality.

In moving on to consider both cross-sectional and time-series variation we, initially, restrict our attention to a subset of the countries for which sufficient data are available in the LIS, focusing on those for which the data provide for a sufficient time series to look at the trends in inequality, we also limit our sample to a group of countries designed to be representative while ensuring clarity. To ensure comparability we prioritize countries for which gross income information is available. The countries which we discuss here

[11] An interesting feature of the data is that the frequency with which *inter-cohort* and *intra-cohort* inequality vary are noticeably different. Changes in *inter-cohort* inequality are of lower frequency than changes in *intra-cohort* inequality which is known to be cyclical (Milanovic, 2016), perhaps as expected given the gradual nature of demographic change. Thus, changes in the *inter-cohort* rate are of most importance when analysing the evolution of inequality over substantial periods of time.

Figure 4: Cross-Country Variation in Inter- and Intra-Cohort Inequality



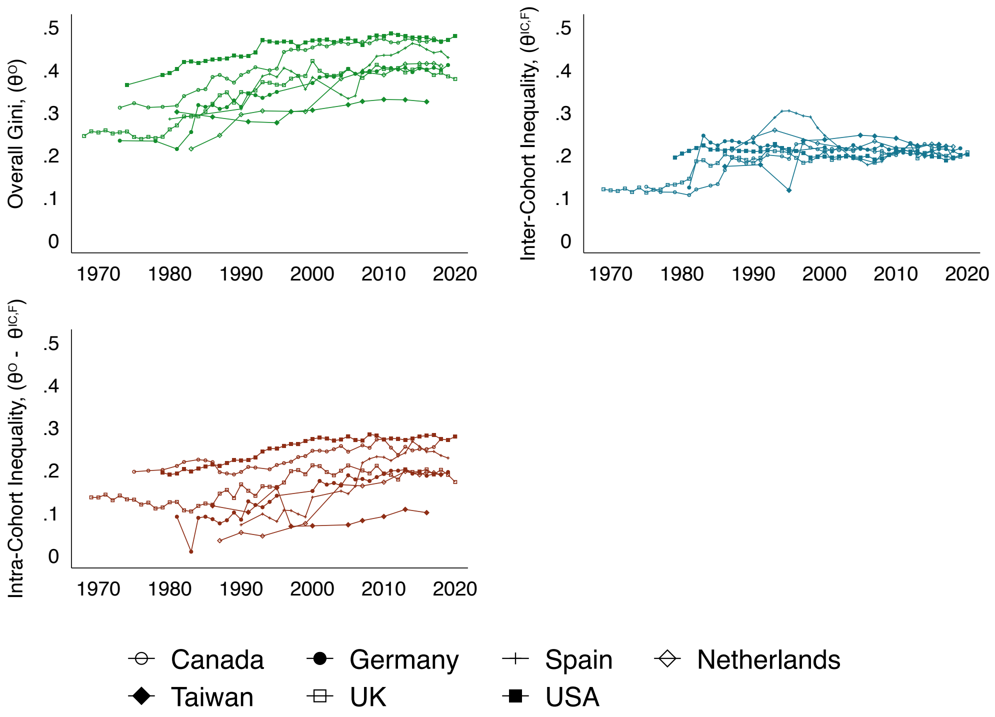
Source: Authors' calculations using LIS Wave X, (circa 2016)
*Notes:*The number to the right of the bars for each country denotes the *overall* Gini, and the total length of the bar. Thus, this graph shows the decomposition of the level of *overall* inequality into its *Inter-cohort* component (Blue) and *Intra-cohort* inequality (red). All data are for gross incomes. Individual level sampling weights are used in all cases. Sample includes men ages 18–65 with positive labour incomes.

are Canada, Germany, Netherlands, Taiwan, United Kingdom and Spain. The United States is presented again in order to make a comparison with other countries. We discuss regression analyses of the trends for the full set of countries below. Figures describing the other countries are available in the appendix, as well as a detailed discussion of the data.

We begin by considering labour income. Looking at the top left (green) panel of Figure 5, we can see that the overall Gini coefficient in the United States is high compared to the other countries we consider, particularly at the beginning of our sample period. However, the gap has narrowed, and all countries have experienced rising inequality. Looking closer, it is clear that the biggest changes have been in Spain, the Netherlands, and Germany. In comparison, the United States and Taiwan seem to have experienced relatively stable levels of inequality in labour income.

This finding is cast in new light when we consider the *inter-cohort* rates of inequality presented in the top-right (blue) panel of Figure 5. While *inter-cohort* inequality is stable on average, this masks comparatively notable increases for Spain, Germany and the

Figure 5: Overall and Intra-Cohort Gini of Labour Income – Selected Countries: 1968–2020



Source: Authors' calculations using LIS data.
*Notes:*All results are calculated using data on gross incomes except for Spain, which are net incomes for the period 1980-2000. We consider those aged between 18–65 and who have positive earnings. Results are calculated using individual level sampling weights.

Netherlands. This suggests that the similar trends in inequality have different sources in the United States than elsewhere.

This difference is clearer when we consider *intra-cohort* inequality, displayed in Figure 5. Now we can see that the United States has seen a substantial increase in *intra-cohort* inequality, both starting and finishing the period at a higher level of *intra-cohort* inequality than elsewhere. Taiwan is notable in that *intra-cohort* inequality has remained relatively stable over the sample period. Other countries, such as the UK and Canada, have seen rapid growth rates of *intra-cohort* inequality similar to those in the United States, albeit from lower initial levels. In general, the rate of increase was relatively slow everywhere until the mid 1980s after which it accelerated. The similarities in these trends, allowing for different starting points, suggests that rises in *intra-cohort* inequality may be driven by technological and policy changes common across the developed nations.

To demonstrate that our finding that *intra-cohort* cohort inequality has driven recent increases in overall inequality are not specific to the countries plotted, in Appendix Table B.1 and discussion we report the results of estimating a linear trend using a simple fixed-effects model, and the mean group estimator of Pesaran and Smith (1995).

4 Wealth Inequality

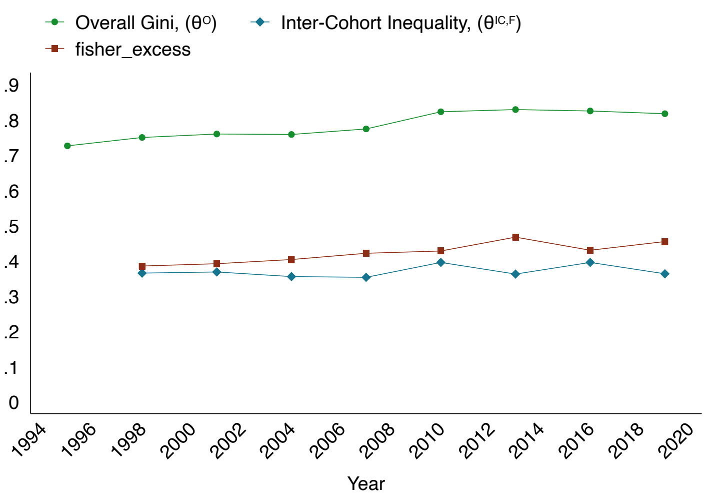
As well as increases in income inequality, the prior literature has shown that increases in wealth inequality have tended to be even larger than those in income inequality (Saez and Zucman, 2016). To understand the role of demographics in this pattern, we repeat our prior analysis for wealth using the Luxembourg Wealth Study (LWS). Now our analysis is at the household level and thus describes the entire population rather than just working-age men.[12] These data, like the LIS, are harmonized cross-country data. Although the LWS does not have the coverage of the LIS we are able to construct a limited time series for the United States and make cross-sectional comparisons for a number of other countries, which we have discussed with respect to income inequality and are available in the LWS data. The choice of data is a delicate one: the LWS data are top-coded, unfortunately

[12] Luxembourg Wealth Study (LWS) Database, http://www.lisdatacenter.org (multiple countries; 1995–2016). Luxembourg: LIS. Refer to Appendix A.4 for a data description.

the WID data (Alvaredo et al., 2016) which contain much better information on the very wealthy do not contain sufficient age data.

We choose disposable net worth (non-financial assets plus financial assets (excluding pensions) minus total liabilities) as our measure of wealth, but this choice is not important for our results.[13] As the wealth data are measured at the household rather than at the individual level, we use the head of the household's age as a proxy, in favour of attempting to divide assets within the household. Again, we obtain similar results under alternative assumptions.

Figure 6: Wealth Inequality over Time (United States)



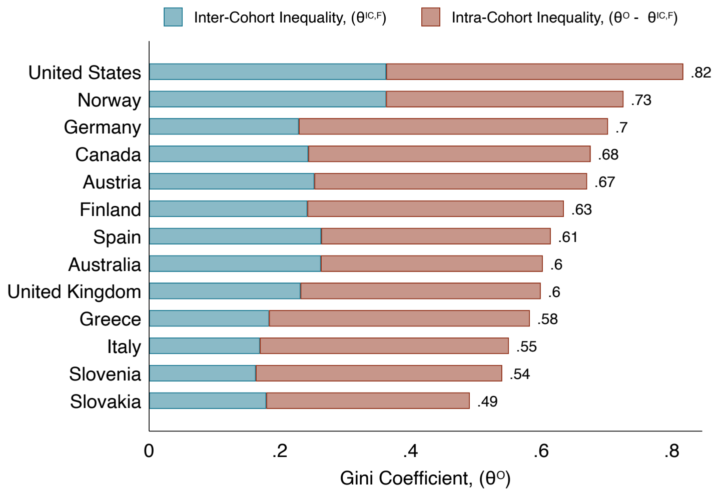
Source: Authors' calculations using Luxembourg Wealth Study (LWS).
Notes: Time series for the United States, the underlying data are from the Survey of Consumer Finances and the wealth measure used is disposable net worth. The sample includes all households who have a head who is aged 18–78 including those who are recorded as having zero or negative net worth. Household level sampling weights are used to produce results.

Figure 6 shows the (overall) Gini coefficient of wealth inequality for the United States over the period 1995–2019. As expected, wealth inequality is higher than income inequality over the same period. We can see that while inequality has been increasing, changes in the *inter-cohort* Gini have contributed to this, although *intra-cohort* inequality has also increased. More precisely, the *intra-cohort* Gini of wealth has increased by around ten percentage points over the 20-year period, while *inter-cohort* inequality increased by four

[13]We drop the top 1% of the distribution to limit the effects of top-coding procedures in the original datasets. Similar results are obtained with the alternative of interpolating the true values of the top-coded observations assuming a Pareto distribution as in Heathcote et al. (2010). This measure is preferred over others, as pension data is not as comparable across countries and for some it's not available.

percentage points. Of course, our focus on the Gini coefficient is in contrast to much of the literature which uses concentration indices such as the share of the top 1% or 0.1%. We would not expect demographics to affect these concentration indices, but our approach here will capture changes among the moderately wealthy. It is clear, that whilst there has been a substantial increase in *intra-cohort* inequality that increases in *inter-cohort* wealth inequality have also played an important role.

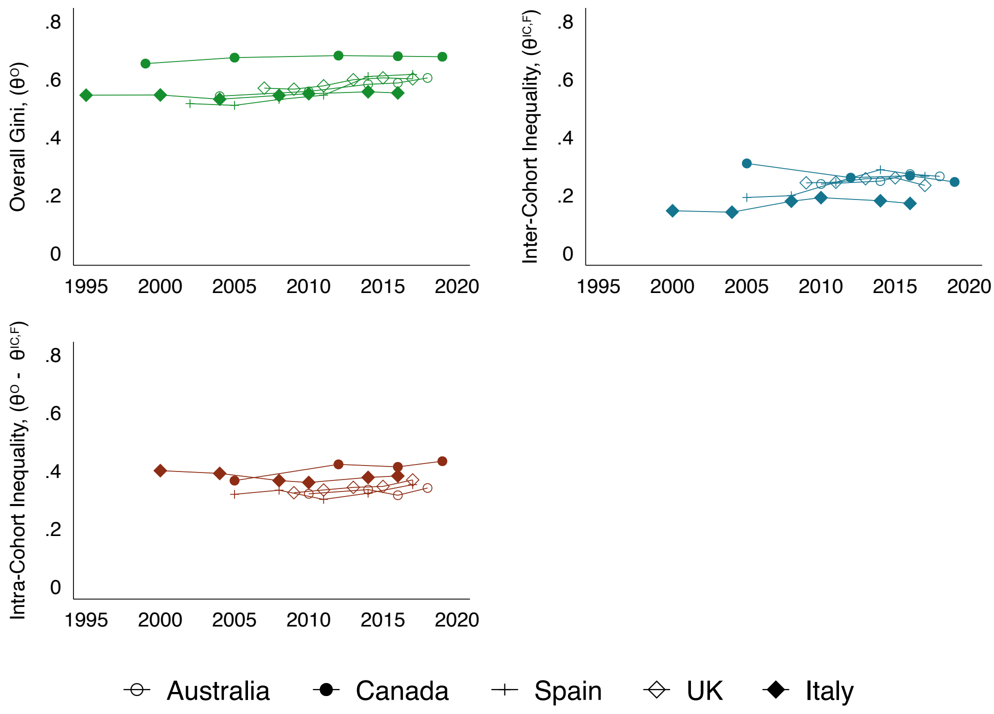
Figure 7: Cross-Country Variation in Inter- and Intra-Cohort Inequality



Source: Authors' calculations using Luxembourg Wealth Study (LWS).
Notes: Overall is the conventional Gini coefficient. Inter and intra refer to *inter-cohort* and *intra-cohort* inequality defined in Section 2. Results are rounded to two decimal points. Results for Finland and Italy refer to 2016, Austria, Germany, Spain, Slovenia, Slovakia and the United Kingdom refer to 2017, Australia and Greece refer to 2018, Canada and the United States refer to 2019 and Norway to 2020.

Figure 7 shows results for the ten countries for which wealth data are available. We can see that the wealth inequality varies substantially, between 0.54 in Slovenia and 0.82 in the United States. However, the second and third columns suggest that this variation is in part driven by variations in the *inter-cohort* rate. This is 0.38 in the United States but only 0.16 in Slovenia, and *intra-cohort* inequality is relatively consistent compared to overall inequality varying between 0.34 in Australia to 0.45 in the United States. Comparing the United States and Canada is instructive as while the overall Gini coefficients are quite different (0.82 and 0.68 respectively) the *intra-cohort* Ginis are very similar (0.45 and 0.43). Thus, abstracting from life-cycle effects both societies (at least on this basis) are similarly unequal, and the United States appears less of an outlier. Thus, *inter-cohort* inequality is arguably as or more important in understanding the cross-sectional variation in wealth inequality than it is for the time-series variation. This highlights, again, that considering the overall Gini alone may be misleading.

Figure 8: Wealth Inequality over Time (Cross-country comparison)



Source: Authors' calculations using Luxembourg Wealth Study (LWS).
Notes: Wealth measure used is disposable net wealth. The sample includes all households who have a head who is aged 18–78 including those who are recorded as having zero or negative net worth. Household level sampling weights are used to produce results.

Finally, we study changes in wealth inequality overtime for those countries for which adequate data are available. Figure 8 plots overall inequality, θ^{O}, *inter-cohort* inequality, $\theta^{IC,F}$, and *intra-cohort* inequality, $\theta^{O} - \theta^{IC,F}$ for Australia, Canada, Spain, the UK, and Italy. Focusing initially on overall inequality in the top left panel we see that wealth inequality has remained stable over the time period, although there is some evidence of an upwards trend post-2005. Comparison with the trends in $\theta^{IC,F}$ in the top-right panel suggest that while inter-cohort inequality is a growing source of inequality, there is substantial heterogeneity across countries. For example, there is a decline in Canada, but an increase in Australia and the UK. This again highlights the importance of considering demographics when making cross-country, and intertemporal, comparisons of wealth inequality.

5 Conclusion

Even a society in which everybody is the same at the same stage of the life-cycle will exhibit a substantial degree of income and wealth inequality. In this paper we take this notion to the data in order to quantify the share of observed income and wealth inequality that is attributable to life-cycle profiles of income and wealth. The data reveal that *inter-cohort* inequality is a substantial component of overall inequality.

Treating the *inter-cohort* rate as the benchmark, and focusing on *intra-cohort* inequality suggests that recent increases in income inequality in the United States are both larger than the overall rate would suggest, and represent a distinct change from the period pre-1990. It is also clear that *inter-cohort* inequality is of first order importance in understanding variation in other developed countries and the variation between them. However, while demographic changes played a substantial role in the dynamics of income and wealth inequality until 1990, the stark increase in inequality ever since cannot be attributed to demographic changes.

A similar analysis for wealth inequality suggests that *inter-cohort* inequality is also important to understand trends in wealth inequality, although it accounts for a smaller component of overall wealth inequality. Allowing for differences in *inter-cohort* inequality suggests that the United States is much less of an outlier compared to other countries.

This paper has not disaggregated individuals except by age and gender. It would be interesting in future work to build on the findings of differences in income inequality across racial groups in the United States (Akee et al., 2019) to better understand how these are driven by and will change due to demographic factors. This paper has focused on individuals' income, but it would be interesting to extend our approach to study household inequality and the role of changing rates of female labour force participation in determining (*inter-cohort*) inequality, as discussed by Chevan and Stokes (2000).

Declarations

The authors declare that they have no conflict of interest.

The datasets analysed during the current study are available from IPUMS [https://cps.ipums.org/cps/] and the LIS Data Center, [https://www.lisdatacenter.org/].

References

Akee, Randall, Maggie R. Jones, and Sonya R. Porter, "Race Matters: Income Shares, Income Inequality, and Income Mobility for All U.S. Races," *Demography*, 2019, *56* (3), 999–1021.

Almås, Ingvild, Alexander W. Cappelen, Jo Thori Lind, Erik Sørensen, and Bertil Tungodden, "Measuring unfair (in)equality," *Journal of Public Economics*, 2011, *95* (7-8), 488–499.

_ , Tarjei Havnes, and Magne Mogstad, "Baby booming inequality? Demographic change and earnings inequality in Norway, 1967-2000," *Journal of Economic Inequality*, 2011, *9* (4), 629–650.

Alvaredo, Facundo, Anthony B Atkinson, Lucas Chancel, Thomas Piketty, Emmanuel Saez, Gabriel Zucman et al., "Distributional National Accounts (DINA) Guidelines: Concepts and Methods used in WID. world," *WID.World Working Paper*, 2016, *2.*

Atkinson, Anthony B., "The distribution of wealth and the individual life-cycle," *Oxford Economic Papers*, 1971, *23* (2), 239–254.

Blanchet, Thomas and Clara Martínez-Toledano, "Wealth inequality dynamics in europe and the united states: Understanding the determinants," *Journal of Monetary Economics*, January 2023, *133*, 25–43.

_ , Lucas Chancel, and Amory Gethin, "Why Is Europe More Equal than the United States?," *American Economic Journal: Applied Economics*, October 2022, *14* (4), 480–518.

Blundell, Richard and Ben Etheridge, "Consumption, income and earnings inequality in Britain," *Review of Economic Dynamics*, 2010, *13* (1), 76–102.

_ and Ian Preston, "Consumption inequality and income uncertainty," *The Quarterly Journal of Economics*, 1998, *113* (2), 603–640.

Bourguignon, François, Francisco H.G. Ferreira, and Phillippe G. Leite, "Beyond Oaxaca-Blinder: Accounting for differences in household income distributions," *Journal of Economic Inequality*, 2008, *6* (2), 117–148.

Brewer, Mike and Liam Wren-Lewis, "Accounting for Changes in Income Inequality: Decomposition Analyses for the UK, 1978-2008," *Oxford Bulletin of Economics and Statistics*, 2016, *78* (3), 289–322.

Chancel, Lucas and Thomas Piketty, "Global Income Inequality, 18202020: the Persistence and Mutation of Extreme Inequality," *Journal of the European Economic Association*, 10 2021, *19* (6), 3025–3062.

Chevan, Albert and Randall Stokes, "Restructuring and Demographic Change," *Demography*, 2000, *37* (3), 365–380.

Corneo, Giacomo, "Income inequality from a lifetime perspective," *Empirica*, 2015, *42* (2), 225–239.

Cowell, Frank A. and Stephen P. Jenkins, "How Much Inequality Can we Explain ? A Methodology and an Application to the United States," *Economic Journal*, 1995, *105* (429), 421–430.

Database, Luxembourg Income Study (LIS), July http://www.lisdatacenter.org. multiple countries; Accessed February 2017 to May 2023. Luxembourg: LIS.

Database, Luxembourg Wealth Study (LWS), http://www.lisdatacenter.org. multiple countries; Accessed February 2017 to May 2023. Luxembourg: LWS.

Formby, John P and Terry G Seaks, "Paglin's Gini measure of inequality: A modification," *American Economic Review*, 1980, pp. 479–482.

Formby, J.P., T.G. Seaks, and W.J. Smith, "On the measurement and trend of inequality: a reconsideration," *American Economic Review*, 1989, *79* (1), 256–264.

Furceri, Davide and Jonathan D Ostry, "Robust determinants of income inequality," *Oxford Review of Economic Policy*, 07 2019, *35* (3), 490–517.

Garbinti, Bertrand, Jonathan Goupille-Lebret, and Thomas Piketty, "Accounting for wealth-inequality dynamics: Methods, estimates, and simulations for france," *Journal of the European Economic Association*, 2021, *19* (1), 620–663.

Gomez, Matthieu, "Decomposing the Growth of Top Wealth Shares," *Econometrica*, 2023, *91* (3), 979–1024.

Heathcote, Jonathan, Fabrizio Perri, and Giovanni L Violante, "Unequal we stand: An empirical analysis of economic inequality in the United States, 1967–2006," *Review of Economic Dynamics*, 2010, *13* (1), 15–51.

Heimberger, Philipp, "Does economic globalisation affect income inequality? A meta-analysis," *The World Economy*, 2020, *43* (11), 2960–2982.

Kuhn, Moritz, Moritz Schularick, and Ulrike I Steins, "Income and wealth inequality in america, 19492016," *Journal of Political Economy*, 2020, *128* (9), 3469–3519.

Lambert, Peter J and J Richard Aronson, "Inequality decomposition analysis and the Gini coefficient revisited," *Economic Journal*, 1993, pp. 1221–1227.

Lerman, Robert I . and Shlomo Yitzhaki, "Income Inequality Effects by Income Source : A New Approach and Applications to the United States," *The Review of Economics and Statistics*, 1985, *67* (1), 151–156.

Milanovic, Branko, "Income inequality is cyclical," *Nature*, 2016, *537* (7621), 479–482.

Mookherjee, Dilip and Anthony Shorrocks, "A decomposition analysis of the trend in UK income inequality," *Economic Journal*, 1982, pp. 886–902.

Nolan, Brian, Matteo G. Richiardi, and Luis Valenzuela, "The Drivers of Income Inequality in Rich Countries," *Journal of Economic Surveys*, June 2019, *33* (4), 1285–1324.

Paglin, Morton, "The measurement and trend of inequality: a basic revision," *American Economic Review*, 1975, pp. 598–609.

Pesaran, M. Hashem and Ron Smith, "Estimating long-run relationships from dynamic heterogeneous panels," *Journal of Econometrics*, 1995, *68* (1), 79–113.

Pfeffer, Fabian T. and Nora Waitkus, "The Wealth Inequality of Nations," *American Sociological Review*, 2021, *86* (4), 567–602.

Piketty, Thomas, *Capital in the 21st Century*, Harvard University Press, 2013.

_ , *Capital and ideology*, Harvard University Press, 2020.

_ **and Emmanuel Saez**, "Income Inequality in the United States, 1913–1998," *The Quarterly Journal of Economics*, 2003, *118* (1), 1–39.

_ **and** _ , "Inequality in the long run," *Science*, 2014, *344* (6186), 838–843.

_ **and Gabriel Zucman**, "Wealth and Inheritance in the Long Run," in "Handbook of Income Distribution," Vol. 2 2015, pp. 1303–1368.

_ **, Emmanuel Saez, and Gabriel Zucman**, "Distributional National Accounts: Methods and Estimates for the United States," *The Quarterly Journal of Economics*, October 2017, *133* (2), 553–609.

Ranaldi, Marco and Branko Milanovi, "Capitalist systems and income inequality," *Journal of Comparative Economics*, 2022, *50* (1), 20–32.

Saez, Emmanuel and Gabriel Zucman, "Wealth Inequality in the United States since 1913: Evidence from Capitalized Income Tax Data," *The Quarterly Journal of Economics*, may 2016, *131* (2), 519–578.

_ **and** _ , "The Rise of Income and Wealth Inequality in America: Evidence from Distributional Macroeconomic Accounts," *Journal of Economic Perspectives*, November 2020, *34* (4), 3–26.

_ **and** _ , "Top Wealth in America: A Reexamination," Working Paper 30396, National Bureau of Economic Research August 2022.

Smith, Matthew, Owen Zidar, and Eric Zwick, "Top Wealth in America: New Estimates Under Heterogeneous Returns*," *The Quarterly Journal of Economics*, 08 2022, *138* (1), 515–573.

Yamada, Tomoaki, "Income risk, macroeconomic and demographic change, and economic inequality in Japan," *Journal of Economic Dynamics and Control*, 2012, *36* (1), 63–84.

Zucman, Gabriel, "Global Wealth Inequality," *Annual Review of Economics*, 2019, *11* (1), 109–138.

A Data Appendix

A.1 Choice of Sample

A primary issue to be addressed before taking this argument to the data is a previously neglected, but important, subtlety in the computation of the *inter-cohort* Gini. This is the choice of the relevant population, given both unemployment and endogenous labour market participation. If one includes the entire population as is implicit in the work of Paglin (1975) and Formby and Seaks (1980) then the income attributed to those unemployed, or not in the labour market becomes important. As is how the income from shared assets is attributed. This is true, a fortiori, for our purposes since we are making comparisons across countries and over a period in which dispersion in retirement ages has increased.

More concretely, the decision to retire embodies choices that are endogenous with respect to earning potentials as well as societal mores and institutions. For this reason, we restrict our analysis to people aged 18–65 for the purposes of analysing labour income. This minimizes concerns about endogenous selection in to full- or part-time employment once of retirement age. As per Figure 2d for wealth we consider the entire population, but to avoid having to split jointly held assets, choose households as the unit of analysis.[14]

To address concerns about endogenous labour market participation at other ages our analysis will focus on *inter-cohort* inequality between men with positive earnings.[15] Thus, at all ages we are comparing only those in work (including the self-employed). While, it might be reasonable to presume that those who do not have positive earnings are mostly unemployed, attributing to them earnings of zero leads to estimates of income inequality substantially higher than conventional estimates. More importantly, given the purpose of this paper is to understand the relative importance of *inter-cohort* inequality over time, including those with zero earnings will also introduce into the calculation of *inter-cohort* inequality a component that is not *typical*. For example, if youth unemployment is high then including the unemployed will overstate the *inter-cohort* rate of unemployment by conflating the lower human capital of younger workers with the effects of other factors that are driving unemployment. Whilst potentially difficult policy challenges, such factors are not inescapable in the same way as the accumulation of skills and experience over the life-cycle is. The data suggest that very few men of this 18–65 age range work part-time. The issue is more complicated for women as an assumption that zero earnings reflects unemployment is patently untrue. Changes in female labour market participation rates have been the largest

[14] A related issue is how to define age-groups. In results available upon request we document that the bias of the Gini coefficient is decreasing in the number of groups, and negligible if we work with individual years. The large sample surveyed by the CPS means that sample size concerns that might have motivated pooling into coarser cohorts in previous work can be ignored.

[15] While, Men retire at different ages, and average retirement ages have varied, our results are robust to a range of alternative cut-offs.

change in the labour market over the period we study but still vary markedly across developed countries, and are changing within them, limiting what may be reasonably inferred. By focusing on the subpopulation of prime aged men we are able to abstract from this and the other key labour market changes of the period, such as the increase in the share of university graduates and skill-biased technological change. We include students in our sample, as to exclude them would potentially bias our estimates as it would increase the average income of the young since they are more likely to be students. Thus, changes in student numbers might alter the average life-cycle income depressing average incomes in the first few years of adulthood and raising them in later years. We note however, that there do not seem to be substantial changes in the life-cycle earnings profile over the period.

There is of course a trade-off incarnate in restricting the sample we consider. By excluding the elderly we restrict our attention to total and *inter-cohort* inequality among those of working age, ignoring the important consequences for total inequality of longer lifespans and changes in pension provision. By excluding women we exclude the important impact that women's increased participation and equality in the labour market will have had. We argue that this is the necessary cost of ruling out the effects of endogenous responses to other changes in society. As well as highlighting the challenges in taking a longitudinal approach, we argue that this also highlights the importance of not relying on a cross-sectional snapshot to infer the relative importance of demographic characteristics in explaining inequality.

A.2 Current Population Survey

The Current Population Survey (CPS) has been conducted monthly by the U.S. Census Bureau, since 1962. In what follows we outline the nature of the survey and our treatment of the data. This treatment has been closely informed by those of Heathcote et al. (2010), and where possible we have done exactly as they did. Indeed, one important contribution of their paper was to establish a treatment of the data that provided estimates that could be cross-validated against those from the Panel Study of Income Dynamics (PSID) and the Consumer Expenditure Survey (CEX).

The CPS surveys a representative sample of each state population restricted to those over the age of 15 and who are not in the armed forces nor any kind of institution such as a prison or hospice. In total, it surveys around 60,000 households each month. Households are sampled using a 4–8–4 sampling scheme, in which households are interviewed for four consecutive months, not visited for eight months, and then surveyed again for four more consecutive months at the same time the following year. Most important for our purposes is the data collected in the March Annual Social and Economic Supplement (ASEC). This cross-sectional annual supplement contains detailed data relating to income and employment.

All of our estimates are produced using the March ASEC weights which correspond to individual level observations. We first restrict our sample by dropping the small number of observations for which 'bad', i.e. negative weights are recorded, although this does not affect our results. Secondly, we remove individuals younger than age 18 and older than age 78 when using total income measures. When we consider labour income inequality the age range included is 18–65.

The CPS data are top-coded and this might lead us to understate inequality. In our preferred results we do not use any correction for top-coding, but we obtain the same results if we instead apply the Pareto-interpolation correction suggested by Heathcote et al. (2010).[16] More important for our analysis is the slight discrepancy between the survey year and the year to which the survey refers. Given the retrospective nature of the survey we assign values from the survey in year t to calendar year $t-1$. That is, for example, results for 2002, are based on the 2003 survey which was conducted in March that year.

The two income variables we are interested in are, again like Heathcote et al. (2010), labour income and total income. Our labour income variable is each respondent's total pre-tax wage income from employment. The total income variable records the total, pre-tax, personal income or losses from all sources. Both variables are adjusted for inflation using the CPI-U series of the Bureau of Labor Statistics.

Perhaps the most substantive decision is how to handle missing data. Data can be missing either because a household did not respond, or because a particular question was not answered. Weights are used to address the former problem, and "hot-deck" imputation (assigning the response from a randomly chosen statistically similar household). We, again, follow Heathcote et al. (2010) and retain these imputed values and use the CPS provided survey weights.

A.3 Luxembourg Income Study Database (LIS)

The Luxembourg Income Study (LIS) provides a harmonized data set of microdata recording a broad range of economic and demographic characteristics drawn from various nationally representative surveys. Data are compiled at both the individual and household levels. For each wave, from each country, LIS takes data for the individual and the household level, with variables relating to socio-demographics, household characteristics, labour market and flow variables. The individual file is made up of the members of the households included in the household level files,

[16] This correction assumes that underlying distribution of income has a Pareto distribution. By estimating the parameter of this Pareto distribution from the non-top-coded upper end of the distribution, allows estimation of the true mean of the top-coded incomes.

where their individual observations regarding income and expenditure are summed to create the household aggregate information. For our purposes we use the individual level income data only.

The harmonization procedure involves two main components. Firstly, ensuring the variables are comparable in terms of their definitions and in the coding convention applied, for example with respect to categorical variables. Secondly, missing values are processed to ensure both a consistent coding across countries and waves, but also given the differing questions asked by each national survey wave where possible missing data are derived from the available data. For example, if the underlying survey does not contain information about unemployment but does contain sufficient employment data then unemployment data is derived appropriately.

The datasets produced by LIS are representative of the total population of that country for the given year. To this end the most appropriate weights provided by the original surveys are selected, and where necessary missing individual or household level sampling weights are derived using the provided weighting data. The key criteria for the choice of weight variable, is that they deliver nationally representative results and in the cases where there is a choice of these priority is given to those which are designed to accurately capture the population income distribution.

We consider two main income variables from the LIS datasets taken from the individual level data files. These values are corrected for inflation by LIS using the Consumer Price Index (CPI).

Personal Monetary Income: This is the total monetary income that an individual receives from labour and transfers. As such it is akin to the pre-tax total income in the CPS, and we will refer to it as Total Income.

Labour Monetary Income: Labour income includes any monetary payments received from employment, in addition any profits or losses accruing from self-employment.

We can additionally consider both the value of monetary and non-monetary income, however not all data sets are as good as reporting non-monetary income, so this component maybe underreported in many cases. Regardless of this difference we can find similar results for both monetary and non-monetary incomes. We limit the age range consider to 18–78 when using personal monetary income, and to 18–65 for labour monetary income.

The LIS classifies each data set depending on the kind of income that the host data provider report. These groups are either *gross*, *net*, or *mixed*. A majority of the datasets are *gross*, that is the income amounts reported are gross of income taxes and social security employer contributions. This is contrasted to the *net* datasets where there is no information provided regarding taxes and other contributions. Finally, *mixed* datasets where taxes and contribution data are not sufficiently available to be purely classified as either *gross* or *net*.

A.4 Luxembourg Wealth Study (LWS)

Our estimates of wealth inequality use data from the Luxembourg Wealth Study Database (LWS). This combines representative national surveys on same principles as the LIS, producing harmonized cross-country data. A key difference is that wealth variables are measured at the level of the household unit. Therefore, we need to assign an 'age' to each household to calculate *inter-cohort* and *intra-cohort* inequality. To do so, we use the age of the head of household. This choice is unimportant for our results. All of our estimates are produced using the weights provided by LWS, and we allow net wealth to be negative. Wealth data are often top-coded and the wealthy are often oversampled due to higher rates of non-response. This can mean, given the small number of very wealth individuals, that results may not be truly representative. To address bias due to this we drop the top 1% of wealth observations in each country. Data for the United States are drawn from the Survey of Consumer Finances (SCF) and so we follow the approach of Heathcote et al. (2010) who trim the SCF so that the mean income is consistent across all their datasets.

We choose disposable net worth (non-financial assets plus financial assets (excluding pensions) minus total liabilities) as our measure of wealth. A driving factor in this choice is the inconsistent way in which pension wealth is measured across countries and in some cases not available in the LWS dataset. So for this reason we have decided not to use the measure of wealth which includes pensions.

B Additional Results

B.1 Econometric Analysis

To demonstrate that our finding that *intra-cohort* cohort inequality has driven recent increases in overall inequality are not specific to the countries plotted, Table B.1 reports the results of estimating a linear trend using a simple fixed-effects model.[17] We report results for both total income and labour income in the first and second rows respectively. Hence, the first column reports results for the overall Gini in a model in which the trends are assumed to be homogenous across countries: $y_{it} = \tau \times t + \mu_i + \epsilon_{it}$. For both income and labour income the slope is positive and precisely estimated, reflecting the secular upwards trend in inequality. The second column reports estimates from the mean group estimator of Pesaran and Smith (1995) in which the reported coefficients are the averages of the coefficients from separate regressions for each country: $y_{it} = \tau_i \times t + \mu_i + \epsilon_{it}$. The results are qualitatively unchanged. Inspection of the individual slopes makes clear that virtually all countries exhibit positive and significant trends.[18] This provides broader support for the previous finding of consistent upwards trends. However, as above, there are differences between labour and total income.

Using both estimators, the results using *intra-cohort* inequality as the dependent variable suggest that, for total income, it is increasing at a similar rate as overall inequality. This again highlights that the increasing importance of *intra-cohort* inequality in the United States is an outlier. However, for labour income it is clear that *intra-cohort* inequality cannot explain all the increase in overall inequality. There is a gap of between 8 (FE estimates) and 7 percentage points (MG), which suggests that around a quarter of increases in inequality have been due to demographic change. Put differently, we find that around 75% of the increase in income inequality can be attributed to increases in *intra-cohort* inequality.

[17] Given the small number of observations, these simple estimators are preferred to more sophisticated alternatives.

[18] These are reported in Table B.2 in the appendix.

Table B.1: Time Trends in Inequality

	Overall		*Intra-Cohort*	
	(1)	(2)	(3)	(4)
Labour Income	0.32***	0.29***	0.24***	0.22***
	(0.03)	(0.04)	(0.03)	(0.05)
N	506	506	473	473
Total Income	0.30***	0.25***	0.26***	0.20***
	(0.03)	(0.04)	(0.02)	(0.05)
N	498	498	471	471
Estimator	FE	MG	FE	MG
Countries	26	26	26	26

FE Estimator denotes the standard fixed-effects estimator with a homogenous time trend, with robust standard errors in parentheses. MG denotes the mean-group estimator of Pesaran and Smith (1995) using the outlier-robust mean of coefficients, with standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Country Specific Trend Estimates

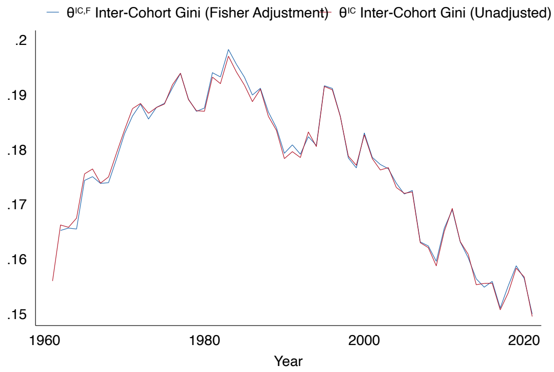
	Overall			
Country	Total	*N*	Labour	*N*
Austria	0.25***	22	0.35***	22
	(0.04)		(0.05)	
Australia	0.43***	12	0.39***	12
	(0.06)		(0.04)	
Belgium	0.28***	21	0.23***	21
	(0.06)		(0.07)	
Canada	0.26***	31	0.41***	39
	(0.03)		(0.02)	
Switzerland	0.30***	14	0.35***	14
	(0.02)		(0.02)	
Czech Republic	0.28**	8	0.31 ***	8
	(0.11)		(0.09)	
Germany	0.37***	36	0.40***	36
	(0.03)		(0.03)	
Denmark	0.27***	9	0.24***	9
	(0.04)		(0.05)	
Spain	0.33***	26	0.38***	26
	(0.05)		(0.06)	
Finland	0.10***	9	0.07	9
	(0.04)		(0.05)	
France	-0.02	20	0.08***	20
	(0.02)		(0.01)	
Hungary	-0.26***	8	-0.39***	8
	(0.10)		(0.08)	
Ireland	0.53***	21	0.52***	21
	(0.06)		(0.05)	
Israel	0.36***	22	0.36***	22
	(0.05)		(0.05)	
Italy	0.42***	13	0.45***	13
	(0.08)		(0.09)	
Luxembourg	0.36***	34	0.36***	34
	(0.03)		(0.03)	
Mexico	0.15**	17	0.14**	17
	(0.06)		(0.06)	
Netherlands	0.52***	13	0.56***	13
	(0.04)		(0.04)	
Norway	0.13***	11	0.21***	11
	(0.04)		(0.04)	
Poland	0.20**	20	0.15	20
	(0.08)		(0.09)	
Sweden	-0.06	8	0.08	8
	(0.08)		(0.09)	
Slovenia	0.30**	7	0.48	7
	(0.12)		(0.19)	
Slovakia	-0.03	10	-0.04	10
	(0.16)		(0.17)	
Taiwan	0.04	11	0.14***	11
	(0.12)		(0.04)	
United Kingdom	0.40***	52	0.37***	52
	(0.03)		(0.02)	
United States	0.22***	43	0.21***	43
	(0.02)		(0.02)	

Coefficients are country specific time trends obtained using the Mean Group estimator of Pesaran and Smith (1995). See Table B.1 for further details.

B.2 Additional Figures

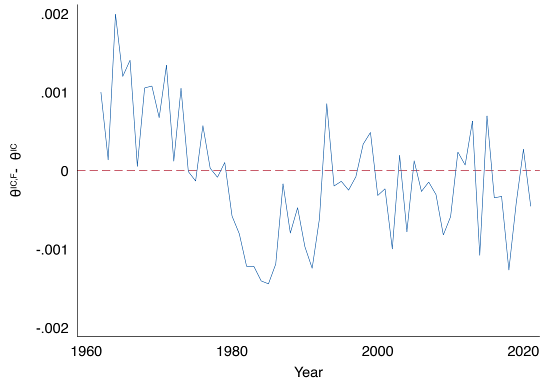
Figure B.1: Adjusted and Unadjusted θ^{IC} are similar.

(a) Comparison of $\theta^{IC,F}$ and θ^{IC}



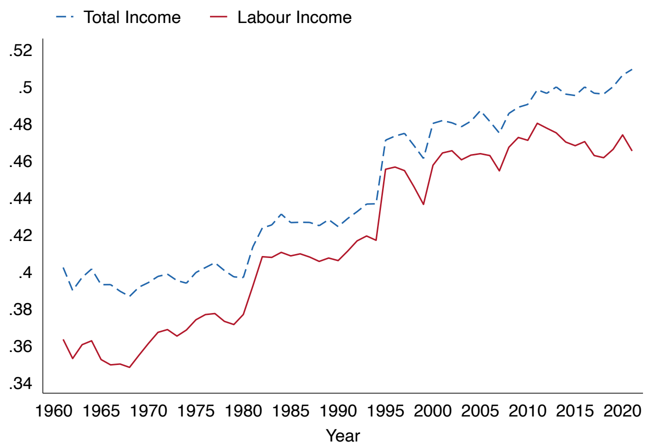
Source: Authors' calculations using ASEC Supplement of the Current Population Survey.
Notes: Sample includes men with positive income and are aged 18–65. Results are calculated using individual weights.

(b) $\theta^{IC,F} - \theta^{IC}$



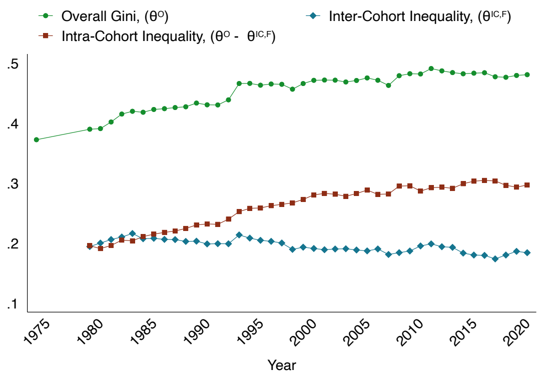
Source: Authors' calculations using ASEC Supplement of the Current Population Survey.
Notes: Sample includes men aged 18–78. We exclude individuals with a zero or negative income. Results are calculated using individual weights.

Figure B.2: Actual Gini Coefficients for Labour and Total Income



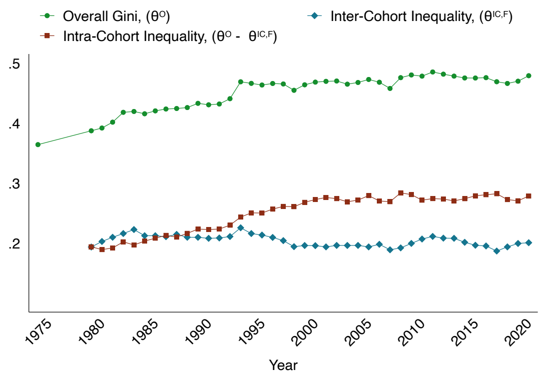
Source: Authors' calculations using ASEC Supplement of the Current Population Survey years 1961–2021
Notes: The graph shows trends over time in the overall Gini. Labour Income (solid line) includes those aged 18–65 and total income (dashed line) includes those aged 18–78. For both time series we exclude individuals with a zero or negative income. Results are calculated using individual weights.

(a) Actual and Life-Cycle-Adjusted Gini of Total Income for the United States using LIS: 1974–2020



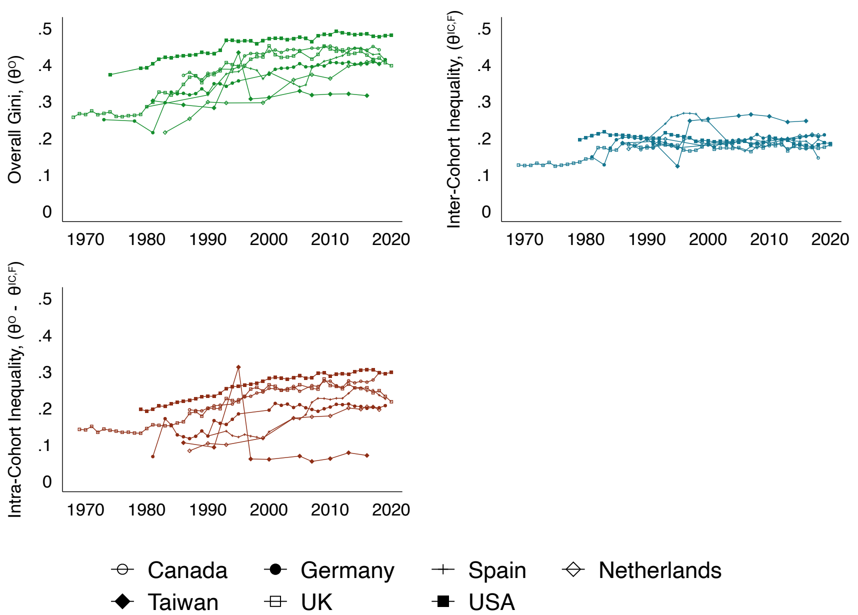
Notes: Results are for men who are aged 18–78 for total income and who have positive earnings. Results are calculated using individual level sampling weights.

(b) Actual and Lifecycle-Adjusted Gini of Labour Income for the United States using LIS: 1974–2020



Results are for who are aged 18–65 for labour income and who have positive earnings. Results are calculated using individual level sampling weights.

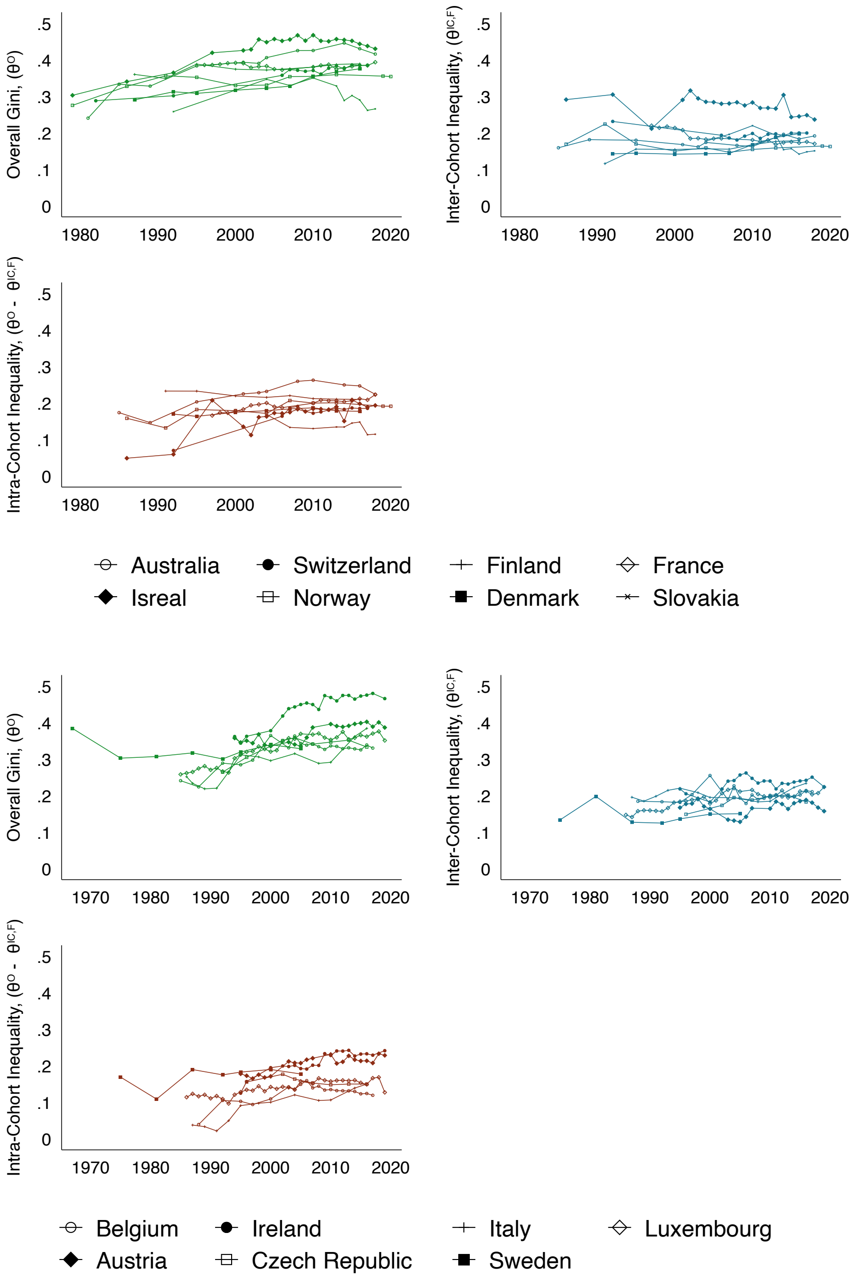
Figure B.4: Actual and Life-Cycle-Adjusted Gini of Total Income: Selected Countries: 1968–2020



Source: Authors' calculations using LIS data.

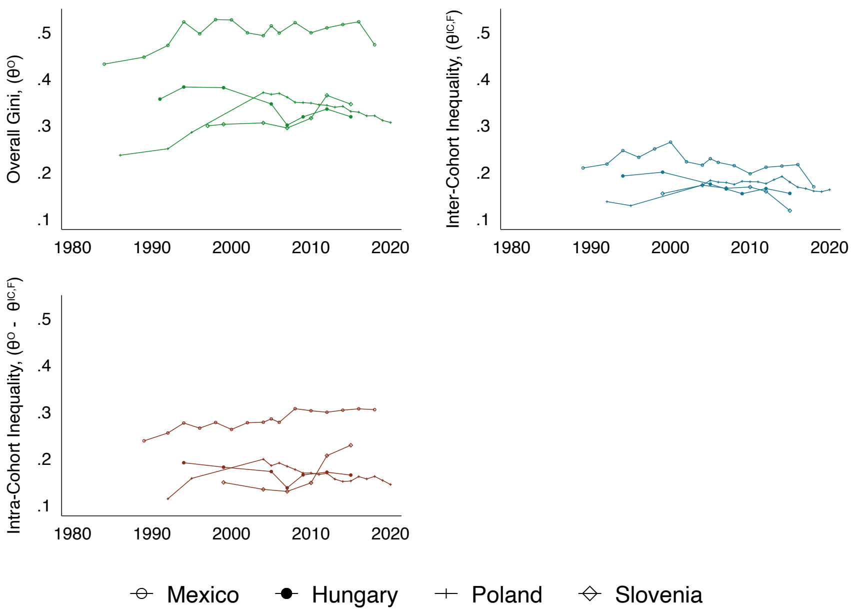
Notes: All results are calculated using data on gross incomes except for Spain which are net incomes for 1980-2000. We consider ages 18–78 for total income and who have positive earnings. Results are calculated using individual level sampling weights.

Figure B.5: LIS Additional Countries, Total Income



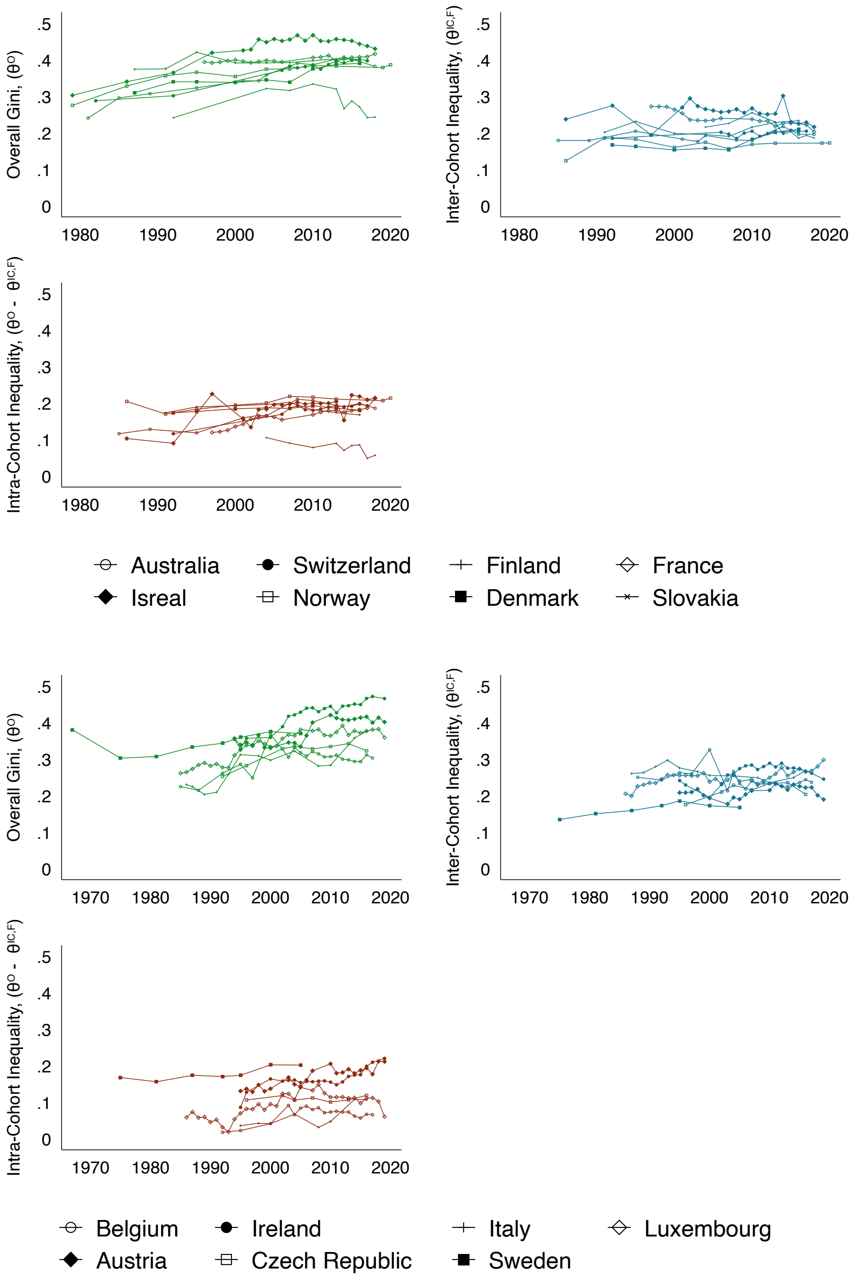
Source: Authors' calculations using LIS data.
Notes: These are the countries for which a sufficient time series is available not reported in Figure 5. Note that, however, in many cases data for these other countries are not consistently classified as gross or net. Most datasets are classified as Gross. Slovenia is classed as Net with the exception if 1992 which is mixed. Austria, Belgium, Czech Republic, Israel, Italy, and Luxembourg do not have a consistent classification over the time series. All others are for gross income. We consider Men aged between 18–78 and who have positive income. Results are calculated using individual level sampling weights.

Figure B.6: LIS Additional Countries, Total Income



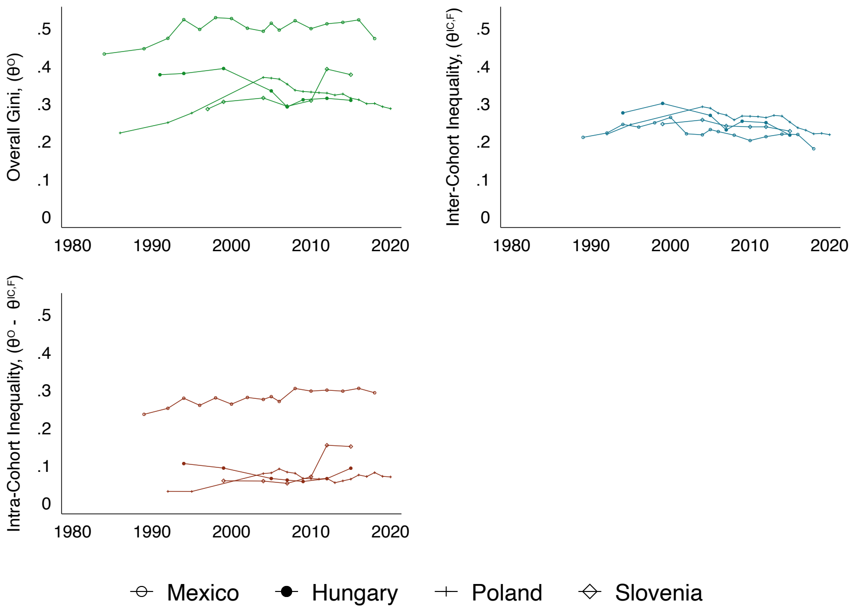
Source: Authors' calculations using LIS data.
Notes: These are the countries for which a sufficient time series is available not reported in Figure 5. Mexico and Hungary are Net incomes. Poland and Slovenia do not have a consistent classification over the time series. All others are for gross income. We consider Men aged between 18–78 and who have positive income. Results are calculated using individual level sampling weights.

Figure B.7: LIS Additional Countries, Labour Income



Source: Authors' calculations using LIS data.
Notes: These are the countries for which a sufficient time series is available not reported in Figure 5. Note that, however, data for these other countries are not consistently classified as gross or net. Most datasets are classified as Gross. Slovenia is classed as Net with the exception if 1992 which is mixed. Austria, Belgium, Czech Republic, Israel, Italy, and Luxembourg do not have a consistent classification over the time series. All others are for gross income. We consider Men aged between 18–65 and who have positive income. Results are calculated using individual level sampling weights.

Figure B.8: LIS Additional Countries, Labour Income



Source: Authors' calculations using LIS data.
Notes: These are the countries for which a sufficient time series is available not reported in Figure 5. Mexico and Hungary are Net incomes. Poland and Slovenia do not have a consistent classification over the time series. All others are for gross income. We consider Men aged between 18–78 and who have positive income. Results are calculated using individual level sampling weights.