Inequality in an Equal Society

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A society in which everybody is the same at the same stage of the life-cycle will exhibit substantial income and wealth inequality. We use this idea to empirically quantify natural inequality - the share of observed inequality attributable to life-cycle profiles of income and wealth. We document that recent increases in inequality in the United States and other developed countries are larger than observed rates would suggest. Extrapolating our measures forward suggests that natural inequalities will fluctuate over the next 20 years before settling to a new higher level.

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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 a related contribution Paglin (1975) uses an argument similar to Atkinson’s to suggest that popular measures of inequality such as the Gini coefficient should be corrected for the age structure inherent in income and wealth profiles. While Paglin’s suggestion for a correction was not uncontroversial, the core of his argument – that inequality measures should be adjusted for the underlying life-cycle structure – still holds.

A powerful new body of evidence (particularly Piketty (2003), Piketty and Saez (2003) and more recently, Atkinson et al. (2011), Piketty and Saez (2014) and Saez and Zucman (2016)) 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 natural inequality due to changes in nations’ demographics. This paper addresses this need by taking the life-cycle argument to the data. The

1See the three rounds of comments and replies generated by his paper.
main contribution of this paper is descriptive. We assemble comparable
time-series describing the long-term evolution of the Paglin-Gini for a
number of countries. In doing so we document how much of the vari-
ation 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. We then study how future demographic changes, particu-
larly the ageing of the Baby Boom generation will impact upon inequality
over coming decades.

Firstly, with detailed micro-data for the United States and then moving
on to use harmonised micro-data for other developed countries (includ-
ing the US), we show that even in the absence of any inequality between
individuals of the same age group, societies exhibit substantial degrees of
income and wealth inequality. In particular, we show that the level due to
life-cycle effects only (natural inequality) accounts for around one third
of income inequality in the United States, with the remaining two-thirds
attributable to differences between individuals, the effects of institutions,
and so forth. Moreover, between the early 1970s and the early 1990s,
the level of natural inequality increased by around 2 percentage points
from just under 18 percent. The mid 1990s marks a turning point, nat-
ural inequality declined slightly, however this has been more than offset
by large increases in excess ‘inequality’, that is inequality attributable to
other sources. This is in contrast to the other countries we study where
the level of excess inequality is often lower and with a less pronounced
upwards trend. Taking into account the role of demographics suggests
that variations in inequality across countries are considerably larger than
otherwise measured and increasing. Results for wealth show that natu-
Cultural wealth inequality has varied little over the last 20 years in the US as observed inequality has increased rapidly. However, life-cycle effects can explain a considerable amount of the cross-country variation in wealth inequality.

We utilise harmonised micro data from the Luxembourg Income Study (LIS) and the Luxembourg Wealth Study (LWS) for our analysis. Importantly for our purpose, these studies contain data which have harmonised variable definitions to allow meaningful comparison across countries as well as over time.

Our aim of quantifying the effect of changes in demography on inequality is similar to that of the early work of Mookherjee and Shorrocks (1982). Like them we will use the Formby and Seaks (1980) modification of the Paglin-Gini. Despite 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 ‘natural’ inequality. A key advantage of the much improved quality and coverage of harmonised data now available, is that we can see this trend in its proper historical context – as a temporary phenomenon soon to be reversed.

There has been relatively little recent work looking at the role of demography in inequality. Thus, by documenting the relationship between the demographic structure and the natural rate of inequality we contribute to the important recent literature on trends in inequality. We assess the impact of the disproportionate size of the Baby Boom generation on natural inequality and study how natural inequality should be expected to change, ceteris paribus as the demographic structure converges.
to its long-run equilibrium. This exercise suggests that the bulge on the
demographic pyramid generated by the Baby Boom is depressing natu-
ral inequality. Hence, in the future, as the demographic pyramid settles
into its long-run equilibrium, wealth and income inequality will increase.
Perhaps worryingly, this process will accelerate further the trend of in-
creasing inequality documented by the seminal contributions of Piketty
(2003), Piketty and Saez (2003), Atkinson et al. (2011), Piketty and Saez
(2014), Saez and Zucman (2016). In that sense, our paper contributes
to the extant literature on inequality trends by highlighting that demo-
ographic forces will exacerbate the upward trends in inequality this litera-
ture has identified.\textsuperscript{2} This paper builds on an important literature follow-
ing Mookherjee and Shorrocks (1982) that focusses on how to attribute
inequality to multiple sources. This is a complication we avoid given
our focus on only on life-cycle effects and on the Gini coefficient. A no-
table feature of all of this work, particularly that of Lerman and Yitzhaki
(1985), Lambert and Aronson (1993), Cowell and Jenkins (1995), Bour-
guignon et al. (2008), is that they largely conclude that demographic fac-
tors are relatively unimportant.\textsuperscript{3} Yet we argue, that \textit{à la} Piketty and Saez

\textsuperscript{2}Other recent country-specific studies on trends in inequality include: Australia
and New Zealand Creedy et al. (2017), Germany Fuchs-Schündeln et al. (2010), Italy

\textsuperscript{3}Lerman and Yitzhaki (1985) introduce a method for decomposing the 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 in-
come and transfers. Lambert and Aronson (1993) clarified the meaning of the residual
term, identifying it as the extent to which there was a cross-over in incomes across age-
groups due to within age-group variations in earnings. Cowell and Jenkins (1995) pro-
vide 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 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 differ-
ences in the distribution of household incomes across countries maybe compared and
apportioned to different sources. Applying this method they are able to decompose the
(2003, 2014) that there is much to be gained by a considering variation over time and this paper demonstrates 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 total inequality.

Some other recent work has sought to decompose the sources and evolution of inequality over time. Brewer and Wren-Lewis (2016) who decompose trends in UK inequality by income source and demographic characteristics to show that increases in inequality amongst 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 OLG model. Almås et al. (2011a) uses register data to study the role of the Baby Boomer generation in the evolution of inequality of Norway.4

The paper proceeds as follows. The next section sketches the empirical argument for, and formalizes the notion of, natural inequality, and introduces the life-cycle adjusted Gini. Section II takes the notion of natural inequality to data. It focuses first on income inequality in the US, before considering a panel of countries. These results suggest, that particularly in the US, ignoring changes in natural rates of inequality over the last 20 years may mean underestimating increases in inequality. The last part of Section II shows that comparatively little of wealth inequality is due to natural inequality. Section III turns to the future and simulates the evolution sources of differences in inequality between Brazil and the USA, showing that these are driven by greater inequality in education levels (and the returns to education), and pension incomes. Like Cowell and Jenkins (1995) they conclude that little of the difference can be explained by demographic factors.

4This work links to the related literature on lifetime inequality, for example Blundell and Preston (1998), Blundell and Etheridge (2010) and Corneo (2015).
tion of natural inequality as countries return to their demographic steady states following the Baby Boom. The results suggest that in many countries there will be substantial increases in natural inequality over the next 20 years. We close with a brief conclusion. The Appendix summarises the data used and presents additional results.

I. Natural Rates of Inequality

Our focus on the level of inequality due solely to life-cycle factors is directly related to the prominent literature that studies the determinants of the distributions of earnings and wealth. For example, Huggett et al. (2011) consider how shocks received at different life stages affect lifetime income. The distribution of wealth is studied by Cagetti and De Nardi (2006) who study a quantitative model of occupational choice with the potential for entrepreneurship and study the role bequests and restrictions on investment play in determining wealth inequality. See also Neal and Rosen (2000) for a review and Huggett et al. (2006) for a more recent example attempting to match the extent to which more or less sophisticated life-cycle models can explain observed income-inequality. In this class of models life-cycle inequality is determined by the choice of parameters, often calibrated to US data, and the form of the model. As in Cagetti and De Nardi (2006), this approach allows for sophisticated analyses of the interaction of different features of an economy but any estimates depend on how well the model corresponds to reality and how precisely the parameters are chosen. Our approach is different, we use micro-data to study the empirical importance of life-cycle inequality for income and wealth without recourse to additional assumptions. One way
we contribute to this literature is by providing empirical evidence as to the extent to which income and wealth inequality should be attributed to life-cycle effects in this type of model.

To fix ideas we follow Atkinson (1971) and start with a stylized exposition of the levels of income and wealth inequality that would prevail if the only difference between individuals is that they are at a different stage of their life cycle. Starting with income inequality, consider the following process of labour income:

\[(1) \quad W(v,t) = E(t-v)w(t),\]

where \(W(v,t)\) is the income at time \(t\) of an individual born at time \(v\), \(w(t)\) is the economy wide wage rate and \(E(t-v)\) is an individual scaling factor that creates a life-cycle pattern in labour income. \(E(t-v)\) can be driven by many factors, which, for the sake of brevity we do not model separately. Indeed, for the current purpose it suffices to acknowledge that \(E(t-v)\) can contain experience effects by which more senior workers earn more than junior workers but also institutional factors such as a social security system that redistributes income from workers to retirees.

This makes clear the argument of Atkinson (1971) and Paglin (1975) 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. Thus, we refer to such innate earnings differences as the level of ‘natural’ inequality.

However, the degree of inequality is determined not only by how much richer the old are than the young, but their relative number. The demographic structure of the UK in 1969, as analysed by Atkinson (1971), is both quite different to that of today given improvements in longevity but is also different to that elsewhere, then and now. 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). The income profile, contained in the solid line of Figure 1, reflects the average income of men in each age group. There we see that income has the familiar hump-shaped profile. The bars in Figure 1 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

5The Paglin 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 index 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 micro-data 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 excess inequality internationally. We only need data on ages and income/wealth and not the detailed data used by Almås et al. (2011a). More similar to this paper is Almås et al. (2011b) who propose an alternative method of adjusting the Gini coefficient 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 micro-data normally not available such as parental earnings, that the effects of age and other factors may be precisely estimated.
Figure 1: Income and cohort size by age group United States, 2015

Source: ASEC Supplement of Current Population Survey
Notes: The left y-axis corresponds to the relative size of each age cohort for men in 2016, represented by the light blue bars. The right y-axis is the average labour income in $1000 dollars for each group. Thus the red line maps the average earnings profile. The bulge in the relative population size around ages 45 to 60 is the impact of the Baby Boom generation distorting the standard demographic pyramid.

decrease in cohort size as age increases, we notice the ragged structure of the triangle - due to, for instance, the Baby Boom. Importantly, we can combine the income profile and the size of the cohorts in Figure 1 to calculate a Gini coefficient. This simply involves using cohort averages, $\bar{x}_i$ and $\bar{x}_j$ for each pair of cohorts $i$ and $j$ in place of individual data, and weighting by cohort sizes $p_i$ and $p_j$, in an otherwise standard expression
for the Gini coefficient:

\[
\theta^{NR} = \frac{\sum_{i \neq j} p_i p_j |\bar{x}_i - \bar{x}_j|}{2 \bar{x}}.
\]

This provides a value of 0.16, thus attesting to the idea of a natural level of income inequality. For wealth we provide a similar analysis in Figure 2 where we sketch out the age profile of mean wealth for the United States using data from the Luxembourg Wealth Study. If anything, the wealth profile is more hump-shaped over the life-cycle. This translates into higher natural inequality with the Gini coefficient of wealth being 0.38.

For brevity, we formalize the reasoning developed above and summarize the main conclusions from the model in the following theorem.

**Theorem 1.** The Gini coefficient of income (wealth) is positive in the presence of a non-flat life-cycle income (wealth) profile.

**Corollary 1.1.** Perfect income (wealth) equality implies a flat income (wealth) profile over the life-cycle.

The proof works by writing the Gini coefficient as a product of the standardised variation of income, and the correlation of income with its rank, following Milanovic (1997), and noting that both of these terms are only zero when income is constant for all ages. The proof itself is in Appendix A.

Considering that observed inequality is generated by a host of factors, it seems appropriate to view natural inequality as a benchmark, deviations from which are useful as indicators of life-cycle adjusted measures of inequality. For expositional purposes we take a graphical approach,
Figure 2: Wealth and cohort size by age group United States, 2016

Source: Luxembourg Wealth Study (LWS), year 2016
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 weights.

but there is no conceptual or quantitative difference from the approach in equation (2). Figure 3 reproduces the conventional graph defining the Gini coefficient, but with an additional Lorenz curve. The thick curved line is the life-cycle Lorenz curve – the Lorenz curve associated with the natural rate – and the dashed line is the actual Lorenz curve. A indicates the area between the line of equality and the life-cycle Lorenz curve and B and B’ indicate the areas under the life-cycle and actual Lorenz curves, respectively. The natural rate Gini can be expressed as: $\theta^\text{NR} = 1 - 2B$, sim-
ilarly the non-adjusted or conventional Gini coefficient can be expressed as: \( \theta^U = 1 - 2B' \). Using the graph we can also define the life-cycle adjusted Gini as: \( \theta^{LA} = \frac{B - B'}{B} \). Which can be derived from the above Ginis as:

\[
(3) \quad \theta^{LA} = \frac{\theta^U - \theta^{NR}}{1 - \theta^{NR}}.
\]

Implying that a society with only natural inequality will have \( \theta^{LA} = 0 \), while a society exhibiting inequality in excess of natural inequality will take positive adjusted values. A useful measure we will employ below is excess inequality defined as the difference between actual and natural inequality \( \theta^E = \theta^U - \theta^{NR} \).

Focusing on the Paglin (1975) debate about how to properly correct for age factors in inequality, we can observe that what we call the natural rate comes closest to what he calls the A(ge)-Gini, which was not the source of controversy. In fact, it is equivalent to the Modified-Paglin Gini suggested by Formby and Seaks (1980) and also employed by Formby et al. (1989) to analyse trends in inequality.\(^7\) We seek to build on these earlier insights by exploiting vastly improved and harmonised data to obtain precise and comparable estimates of the inequality trends of multiple countries and, importantly, to predict the development of inequality into the future.

In taking this argument to the data one previously neglected, but important, subtlety in the computation of the Paglin Gini emerges. This

\(^6\)For comparison, sing the notation of (2), we can write the conventional Gini as

\[
\theta^U = \frac{\sum_i |x_i - \bar{x}|}{\sum_i x_i \sum \bar{x}}.
\]

\(^7\)Their modification of the Paglin (1975) measure amounts to redefining the denominator of \( \theta^{LA} \) as \( B \) and not \( A + B \).
Figure 3: 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 natural rate. The dashed curve is the actual Lorenz curve. A is the area between the two solid lines, and B is the area under the natural rate Lorenz Curve. B' is the area under the actual Lorenz curve. The natural rate Gini can be expressed as: $\theta^{NR} = 1 - 2B$, similarly the non-adjusted or conventional Gini coefficient can be expressed as: $\theta^U = 1 - 2B'$. 
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, as in Figure 1, our analysis to people aged 18-65 for the purposes of analysing labour income. This minimises concerns about endogenous selection in to full- or part-time employment once of retirement age. As per Figure 2 for wealth we consider the entire population, but to avoid having to split jointly held assets, choose households as the unit of analysis.

To address concerns about endogenous labour market participation at other ages our analysis will focus on natural inequality between men with positive earnings. Thus, at all ages we are comparing only those in work. 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 pa-

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8 Our findings are not sensitive to this choice of cutoff. Figure 6 discussed below shows that including older people does not impact the key qualitative and quantitative conclusions.

9 While, Men retire at different ages, and average retirement ages have varied, our results are robust to a range of alternative cutoffs.
per is to understand the relative importance of natural inequality over time, including those with zero earnings will also introduce into the calculation of natural inequality a component that is not ‘natural’. For example, if youth unemployment is high then including the unemployed will overstate the natural 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 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 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. These were 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, and 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
natural inequality amongst 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.

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. Moreover, we have seen that this measure can be used to calculate a life-cycle adjusted Gini coefficient.

II. Inequality in an Equal Society

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

A. 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 B. 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. Moreover we use the CPS in favour of the LIS to maintain comparability with other the majority of other recent studies, such as Heathcote et al. (2010). 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 IIB below.\footnote{We present in the same results for the United States in Appendix C, where Figure C.1 for total income and Figure C.2 for labour income.}

Consider first the solid red line in Figure 4. This shows the Gini coefficient of labour income for the period 1961 to 2015 while the blue dashed line shows the Gini coefficient of total income for the same period. The most striking feature is the pronounced and consistent upwards trend over the period. The 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 2015. 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. For both series, it is apparent that the biggest growth in inequality was experienced in the period 1974 to 1995. While the trend is clear, there is also a substantial cyclical component, as as shown more generally by Milanovic (2016). Finally, we can note that the growth in inequality is faster from 2000 onwards for both series.

We now analyse the extent to which these changes in inequality reflect demographic changes. Figure 5 plots, for labour income, both actual (green circles) and natural inequality (blue diamonds), as well as our
Figure 4: Actual Gini Coefficients for Labour and Total Income

Source: Authors’ calculations using ASEC Supplement of the Current Population Survey years 1962-2016
Notes: The graph shows trends over time in unadjusted 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.

two measures of the difference: excess (red squares) and adjusted (purple triangles). As outlined in Section I, the natural inequality (from which excess and adjusted inequality are derived) is calculated by determining the Gini coefficient of average incomes by age. We can see that natural inequality increased from 1961 to the late 1980’s by around 8 percentage points. Before falling slightly, by almost 3 percentage points over the rest of the period to 2015.
Considering actual, natural, excess, and adjusted Ginis in Figure 5 together it is clear that while inequality increased only modestly from 1960 to 1990, this was in spite of a substantial increase in natural inequality. Indeed over the period 1960-1980 excess inequality declined, by the late 1970s half on inequality was natural. On the other hand, the substantial increase in labour income inequality since the mid-1990s has been despite no increase in natural inequality. Excess 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 natural rate of inequality can lead us to overstate the increase in inequality over the last 25 years. Equally, it leads us to understate it for the previous 25, and thus also to understate the difference between the two periods.

Comparison with Figure 6 that these results are robust to alternatively considering inequality in total income (calculated over the male population aged 18-78). In both cases excess inequality accounts for around three quarters of prevailing inequality in the US – the adjusted Gini is around 0.35 for labour income and 0.40 for total income. Moreover, trends in the two have been similar over the period with a substantial increase since the 1960s, particularly in the period since 1990. One interesting feature of the data is that the frequency with which natural and excess inequality vary are noticeably different. Changes in natural inequality are of lower frequency than changes in excess inequality which is known to be cyclical (Milanovic, 2016), perhaps as expected given the gradual nature of demographic change. Thus, changes in the natural rate
are of most importance when analysing the evolution of inequality over substantial periods of time.

Figure 5: Actual, Natural, and Excess Gini Coefficients of Labour Income for the US 1961-2015

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. 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 7 summarises the cross country variation in wave IX of the LIS for all of the countries we consider.
Figure 6: Actual, Natural, and Excess Gini Coefficients of Total Income for the US 1961-2015

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.
Natural inequality is blue, and excess inequality is red. The sum of these gives actual inequality in labour income, reported to the right of each bar. The most obvious feature of the data is the substantial variation in actual inequality, between 0.49 for the US or Canada and 0.30 for Hungary or Italy. This variation is continuous, meaning that there are no obvious ‘groups’ in the data. Secondly, we note that there is similarly large variation in excess inequality. For example, actual inequality in Spain or Germany is similar, but excess inequality is much higher in Spain. Alternatively, if Spain had the same demographics as the US, it would be nearly as unequal. Conversely, while natural inequality in Slovenia is similar to that in Spain, excess inequality is around 7 percentage points lower. Thus, cross-country comparisons of actual inequality may be misleading. France and Finland have the same actual Gini, but excess inequality in France is higher, and thus perhaps more amenable to policy. This emphasises that as well as being important in understanding variation over time, separating natural and excess 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, as reported in Figure 7.\textsuperscript{11} As well as 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 prioritise countries for which gross income information

\textsuperscript{11}Data are for wave IX of the LIS data, with the exception of France and Ireland where the data is for wave IIX. Mexico is excluded as the last wave available is wave VI.
Figure 7: Cross Country Variation in Natural and Excess Inequality

Source: Authors’ calculations using LIS Wave IX, (circa 2013)

Notes: The number to the right of the bars for each country denotes the actual Gini, and the total length of the bar. Thus this graph shows the decomposition of the level of actual inequality into its natural component (Blue) and excess inequality (red). All data are for gross incomes, apart from for Israel and Slovenia which are net, and Italy and France which are mixed. Individual level weights are used in all cases. Sample includes men ages 18-65 with positive labour incomes.

is available. The countries which we discuss here are Canada, (West) 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 coun-

\[\text{References for Germany are for West Germany only throughout. Figures for Spain are for net incomes. Results for all other countries are for gross incomes. See Appendix B for more information.}\]
tries below. Figures describing the other countries are available in the appendix.

Figure 8: Adjusted and Unadjusted Gini of Labour Income: Selected Countries: 1969-2016

Source: Authors’ calculations using LIS data.

Notes: All results are calculated using data on gross incomes with the exception of Spain which are net incomes (with exception of wave IX). We consider those aged between 18-65 and who have positive earnings. Results are calculated using individual level weights.

We begin by considering labour income. Looking at the top left (green) panel of Figure 8, we can see that the actual Gini coefficient in the US 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 US 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 natural rates of inequality presented in the top-right (blue) panel of Figure 8. While natural inequality is stable on average, this masks comparatively notable increases for Spain, Germany and the Netherlands. This suggests that the similar trends in inequality have different sources in the US than elsewhere.

This difference is clearer when we consider adjusted inequality, displayed in Figure 8 in the bottom-right (purple) panel. Now we can see that the US has seen a substantial increase in adjusted inequality, both starting and finishing the period at a higher level of adjusted inequality than elsewhere. Taiwan is notable in that adjusted inequality has remained relatively stable over the sample period. Other countries, such as the UK and Canada, have seen rapid growth rates of adjusted inequality similar to those in the US, 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 excess inequality may be driven by technological and policy changes common across the developed nations.

To demonstrate that our results are not specific to the countries plotted, Table 1 reports the results of estimating a linear trend using a simple fixed-effects model.\textsuperscript{13} We report results for both total income and labour

\textsuperscript{13}Given the small number of observations, these simple estimators are preferred to more sophisticated alternatives.
income in the first and second rows respectively. Hence, the first column reports results for the actual 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.\(^{14}\) 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 adjusted inequality as the dependent variable suggest that, for total income, it is increasing at the same rate as actual inequality. This again highlights that the increasing importance of adjusted inequality in the US is an outlier. However, for labour income it is clear that adjusted inequality cannot explain all of the increase in actual inequality. There is a gap of between 5 (FE estimates) and 7 percentage points (MG), which suggests that around a quarter of increases in inequality have been due to demographic change.

C. 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. To understand the role of demographics in

\(^{14}\)These are reported in Table C.1 in the appendix.
Table 1: Time Trends in Inequality

<table>
<thead>
<tr>
<th></th>
<th>Actual</th>
<th>Adjusted</th>
</tr>
</thead>
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<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Labour Income</td>
<td>0.37***</td>
<td>0.39***</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Total Income</td>
<td>0.32***</td>
<td>0.34***</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.05)</td>
</tr>
</tbody>
</table>

Estimator FE MG FE MG
Countries 22 22 22 22
N 216 216 216 216

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

this pattern, we repeat our prior analysis for wealth using the Luxembourg Wealth Study (LWS). These data, like the LIS, are harmonised 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 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. Wealth data are measured by the household rather at the individual level, because of this we use the head of the household’s age as a proxy, in favour of attempting to divide assets within the household. Again, this assumption does not matter for our results.

Figure 9 shows the (actual) Gini coefficient of wealth inequality for the United States over the period 1995 – 2016. As expected wealth inequality is higher than income inequality over the same period. We can see that while inequality has been increasing, that changes in the natural Gini have contributed to this, although excess and life-cycle adjusted Gini have also increased. More precisely, the excess Gini of wealth has increased by around ten percentage points over the 20 year period, while natural inequality increased by four 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 amongst the moderately wealthy. It is clear, that whilst there is a substantial increase in the adjusted Gini that increases in natural wealth inequality have also played an important role.

Table 2 shows results for the ten countries for which wealth data are available. We can see that the wealth inequality varies substantially, between 0.53 in Slovenia and 0.82 in the US. However, the second and third columns suggest that this variation is in part driven by variations in the

\[16\text{We drop the top 1\% of the distribution to limit the effects of topcoding procedures in the original datasets. Similar results are obtained with the alternative of interpolating the true values of the topcoded observations assuming a Pareto distribution as in Heathcote et al. (2010).}\]
natural rate. This is 0.38 in the US but only 0.14 in Slovenia, and excess inequality is relatively consistent compared to actual inequality varying between 0.35 in Australia for the US to 0.45 in the US. Comparing the US and Canada is instructive as while the actual Gini coefficients are quite different (0.82 and 0.68 respectively) the excess Ginis are very similar (0.45 and 0.44). Thus, abstracting from life-cycle effects both societies (at least on this basis) are similarly unequal, and the US appears less of an outlier. Thus, natural 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 actual Gini alone may be misleading.

Table 2: Wealth Inequality

<table>
<thead>
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<th>Natural</th>
<th>Excess</th>
<th>Adjusted</th>
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</thead>
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<td>0.22</td>
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<td>0.38</td>
<td>0.50</td>
</tr>
<tr>
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<td>0.16</td>
<td>0.39</td>
<td>0.47</td>
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<tr>
<td>Norway</td>
<td>0.76</td>
<td>0.37</td>
<td>0.39</td>
<td>0.61</td>
</tr>
<tr>
<td>Slovenia</td>
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<td>0.14</td>
<td>0.40</td>
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<td>0.58</td>
<td>0.23</td>
<td>0.35</td>
<td>0.45</td>
</tr>
<tr>
<td>US</td>
<td>0.82</td>
<td>0.38</td>
<td>0.45</td>
<td>0.72</td>
</tr>
</tbody>
</table>

Actual is the conventional Gini coefficient. Natural, Excess, and Adjusted are the alternative measures of inequality defined in Section I. Results are rounded to two decimal points. Results for Austria and Australia refer to 2014, Canada and Germany refer to 2012, Italy and Slovenia refer to 2014, Finland and Norway refer to 2013, the US refer to 2016, and the UK to 2011.
III. Inequality and the Baby Boom

We have seen that individual life-cycles have a central role in understanding inequality. An implication of this is that demographic dynamics will lead to changes in the distributions of income and wealth. Economists have paid considerable attention recently to long-run trends in inequality, prominent studies include Piketty (2003), Piketty and Saez (2003), Piketty (2011), Piketty and Saez (2014) and Roine and Waldenström (2015). In this section we ask: what is going to happen to natural rates of inequality, over the next forty years as the Baby Boom generation passes, and
the demographic structure returns towards its long-run equilibrium? We find that this return *ceteris paribus* will increase the natural rate of inequality for most countries in our sample, and thus may lead to increases in overall inequality.

The Baby Boom generation, for the US commonly considered those born between 1946 and 1964, represented a temporary upwards deviation from developed countries’ otherwise stable demographic trajectories. This can be seen in Figure 10 which reports long-run fertility data for a selection of countries. A first observation is that the Baby Boom was a common feature across many developed countries.\(^{17}\) Although, there are variations in timing and magnitude these fail to mask the overall scale of the boom - nearly an extra child per woman for 18 years. Also, notable is the rapidity with which it began and ended. This large, sudden, and in demographic terms brief, rise in fertility has led to a one generation distortion in the demographic structure of the affected societies. This shock to the demographic pyramid provides an interesting natural experiment for us to study as the demographics return to their long run steady state following the departure of the Baby Boom generation. Our analysis suggests that recent increases in natural inequality will be permanent, and continue as the share of Baby Boomers in the labour market and overall population declines, with increases of up to 10 percent in inequality as societies return to the demographic steady-state.

\(^{17}\) All data are from the Human Fertility Database (2013). Germany refers to West Germany only, France excludes the overseas territories. The ‘Average’ series is the annual arithmetic mean of available observations.
Figure 10: The Baby Boom

Source: Authors’ calculations using data are from the Human Fertility Database (HFD), 2013.
Notes: The y-axis reports the number of children born per woman in a given year. The blue line is the (unweighted) mean fertility rate across the six countries reported. The red line highlights the USA for clarity but is otherwise identical in construction to those for other countries. The dotted vertical lines indicate the beginning and end of the baby-boom.

Future Levels of Inequality

In order to study the impact of the Baby Boomers we simulate future population cohort sizes using age specific data on birth rates, death rates, and population cohort size. We do this using a Leslie matrix, a standard approach in Demography, in which the birth and death rates define a transition matrix that projects the cohort sizes next period given the cur-
rent sizes. Then, because the natural rate of inequality only requires cohort or age-group specific income shares, we can then use the projected cohort sizes to scale these income shares, giving estimates of natural inequality under the new demographics. This process can be repeated to obtain projected demographics at any given time horizon.

We make two key assumptions for this exercise. Firstly, that the lifecycle earnings profile is be stationary. Secondly, we fix the relative size of the working cohort sizes. That is, we assume that the labour market participation and unemployment rates will remain fixed for each cohort over time. We are asking *ceteris paribus* what will happen to the level of natural rate inequality in a society in the future if all that is going to change is relative cohort sizes. In particular, we can expect to see the society returning to its normal demographic pyramid following the shock of the Baby Boom generation. This assumption entails also not making any inference regarding expected immigration. Thus we are assuming that this will be such that the relative size of the working cohort is fixed.

Thus, for the 15 countries for which suitable fertility and mortality data are available, and are part if the LIS data, we project expected levels of natural labour income inequality. Figure 11 plots projected natural inequality for the next forty years. We choose this horizon as by this point the children of the Baby Boomers have largely left the labour market and so the population will be approaching its steady-state. The key prediction is that in almost all countries natural inequality will remain at its current level or increase. A second prediction is that natural inequality

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18 The key difference between our approach and standard population forecasts is that, for simplicity, abstract from anticipated net migration and advances in life-expectancy.
Figure 11: Simulated Natural Rates of Income Inequality

Source: Simulations use data from the Human Mortality Database (2013) and Human Fertility Database (2013) and earnings profiles are taken from the most recent data available in the LIS database.

Notes: On the y-axis is the Natural Gini Coefficient and time (years in the future) is on the x-axis. We project the population distribution for up to 40 years in the future by which time all societies will be extremely close to their steady state.

will be much less volatile than in the past, although other than in the United States and Norway it will continue to fluctuate. Both of these results are consistent with our intuitions, as the Baby Boomers either have now retired or will do in the next few years. Seemingly, in the past the presence of the Baby Boomers reduced natural inequality, offsetting and thus masking increases in adjusted inequality. Any future rises in adjusted inequality will translate directly into increased overall inequality.
A second prediction concerns the timing of the fluctuations, which are expected to be largest around twenty years from now, when mortality rates for the Baby Boomers will be highest. This effect seems particularly pronounced for France, Germany, Spain and Britain. To further look at how these projections compare with the historical data, we plot them together in Figure 12 along with the line of best fit from a linear least-squares regression in red. The vertical red dashed line represents the point at which the simulation starts. To the left of this line are the historical results from LIS, and points to the right are the projected levels of inequality. Taken together it seems that future increases in natural inequality would represent a continuation of the historical trend. Historically, this presumably reflects the increased numbers of older people in the population due to improved health, and it is important to note that any continued improvements will likely increase natural inequality further. Most countries are forecast to experience a five to ten percentage points increase in the natural rate relative to the 1980’s by the 2040’s. This suggests that in the absence of more migration or changes in fertility patterns that there is unlikely to be any reduction in natural inequality, to offset trends in excess inequality, in the foreseeable future.

19The reduced set of countries reflects data availability.
Figure 12: Historical and Simulated Future Rates of Income Inequality

Source: Simulations use data from the Human Mortality Database (2013) and Human Fertility Database (2013). Historical data are taken from the LIS, the Earnings profiles for the projections are taken from the final wave of the LIS.

Notes: On the y-axis is the Natural Gini Coefficient and the x-axis plots the year. The dashed vertical red line signals the end of the historical LIS results and the beginning of the projected trend. The solid red line is the least-squares line of best fit for the entire time period.
IV. 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 natural inequality is a substantial component of actual inequality. Treating the natural rate as the benchmark, and thus analysing excess or adjusted inequality suggests that recent increases in income inequality in the US are both larger than the actual rate would suggest, and represent a distinct change from the period pre-1990. It is also clear that natural inequality is of first-order importance in understanding variation in other developed countries and the variation between them. A similar analysis for wealth inequality suggests that natural inequality is also important for understand trends in wealth inequality, although it accounts for a smaller component of actual wealth inequality. Allowing for differences in natural inequality suggests the USA is much less of an outlier compared to other countries. To home in on the role of the demographic structure for inequality we close our analysis by focusing on the impact of the bulge on the demographic pyramid generated by the Baby Boom generation. This shows that the as cohort shares transition back into their long-run equilibrium levels, natural inequalities of income will fluctuate and reach a new higher level of steady state natural rate inequality.
REFERENCES


Human Fertility Database (2013): “Human Fertility Database,” Available at www.humanfertility.org (data downloaded July 2013). Max Planck Institute for Demographic Research (Germany) and Vienna Institute of Demography (Austria).

Human Mortality Database (2013): “Human Mortality Database.” University of California, Berkeley (USA), and Max Planck Institute for Demographic Research (Germany) www.mortality.org or www.humanmortality.de (data downloaded July 2013).


A. Proof of Proposition 1

Proof of Proposition 1. Focusing on income inequality and following Milanovic (1997) we can write the Gini Coefficient of Income as:

\[ \theta(W) = \frac{1}{\sqrt{3}} \frac{\sigma_W}{\bar{W}} \rho(W, r_W) \frac{\sqrt{N^2 - 1}}{N} \approx \frac{1}{\sqrt{3}} \frac{\sigma_W}{\bar{W}} \rho(W, r_W), \]

where \( \bar{W}, \sigma_W \) are the mean and standard deviation of individual income \( W, r_W \) is the rank of a specific income level \( W \) and \( \rho(W, r_W) \) is the correlation of \( W \) with its rank \( r_W \). To proceed, observe that \( \rho(W, r_W) \in [0, 1] \) and that \( \rho(W, r_W) = 0 \) if and only if \( W = \bar{W} \forall W \), otherwise \( \rho(W, r_W) \in (0, 1] \). In combination with the fact that \( \sigma_W \geq 0 \) but also \( \sigma_W = 0 \) if and only if \( W = \bar{W} \forall W \), implies that as longs as the set \( W \neq \bar{W} \) is non-empty \( \theta(W) > 0 \). Results for the Gini Coefficient of Wealth can be established with the same arguments. □

B. Data Appendix

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 to 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)\textsuperscript{20} 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

\textsuperscript{20}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.
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.

**Luxembourg Income Study Database (LIS)**

The Luxembourg Income Study (LIS) provides a harmonised 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, where their individual observations regarding income and expendi-
tured to create the household aggregate information. For our purposes we use the individual level income data only.

The harmonisation 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 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 monetary and non-monetary income however not all data sets are as good as reporting non-monetary income so this component maybe under reported 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 which there is no information provided regarding taxes and other contributions. Finally, mixed datasets where that taxes and contribution data is not sufficiently available to be purely classified as either gross or net.

Luxembourg Wealth Study (LWS)

Our estimates of wealth inequality use data from the Luxembourg Wealth Study Database (LWS) . This combines representative national surveys on the basis of the same principles as the LIS, producing harmonised 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 natural and adjusted 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.
C. Additional Results

Figure C.1: Adjusted and Unadjusted Gini of Total Income for the United States using LIS: 1974 - 2016

Source: Authors’ calculations using LIS data.

Notes: We consider men who are aged 18-78 for total income and who have positive earnings. Results are calculated using individual level weights.
Figure C.2: Adjusted and Unadjusted Gini of Labour Income for the United States using LIS: 1974 - 2016

Source: Authors’ calculations using LIS data.

Notes: We consider men who are aged 18-65 for labour income and who have positive earnings. Results are calculated using individual level weights.
Figure C.3: Adjusted and Unadjusted Gini of Total Income: Selected Countries: 1969-2016

Source: Authors’ calculations using LIS data.

Notes: All results are calculated using data on gross incomes with the exception of Spain which are net incomes (with exception of wave IX). We consider ages 18-78 for total income and who have positive earnings. Results are calculated using individual level weights.
Table C.1: Country Specific Trend Estimates

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<th>Adjusted</th>
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Coefficients are country specific time trends obtained using the Mean Group estimator of Pesaran and Smith (1995). See Table 1 for further details.
Figure C.4: LIS Additional Countries, Total Income

[Graphs showing trends in Unadjusted Gini Coefficient, Natural Rate of Inequality, Excess Inequality, and Life-Cycle Adjusted Gini from 1980 to 2020 for various countries.

Source: Authors’ calculations using LIS data.

Notes: These are the countries for which a sufficient time series is available not reported in Figure 8. Note that, however, data for these other countries are not consistently classified as gross or net. Most datasets are classified as Gross. France is all classed as mixed and Slovenia is classed as Net. Austria, Belgium, Hungary, Israel, Italy, Luxembourg and Poland 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 weights.
Source: Authors’ calculations using LIS data.

Notes: These are the countries for which a sufficient time series is available not reported in Figure 8. Note that, however, data for these other countries are not consistently classified as gross or net. Most datasets are classified as Gross. France is all classed as mixed, and Slovenia is classed as Net. Austria, Belgium, Hungary, Israel, Italy, Luxembourg and Poland 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 weights.