LWS
Working Paper Series

No. 26

Inequality in an Equal Society

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November 2017

CROSS-NATIONAL
DATA CENTER
in Luxembourg

Luxembourg Income Study (LIS), asbl

Inequality in an Equal Society

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November 2017

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 both larger than observed rates would suggest, and represent a distinct change from the period 1960-1980. Extrapolating our measures forward suggests that natural inequalities will fluctuate over the next 20 years before settling to a new higher level.

JEL: D31, J10

Keywords: Income Inequality, Wealth Inequality, Demographic Structure

* We thank Viola Angelini, Tony Atkinson, Gianni De Fraja, David de la Croix, Martin Jensen, Melanie Krause, Mariacristina De Nardi, David Rojo-Arjona, Richard Suen, Jonathan Temple, Timo Trimborn and Chris Wallace as well as conference participants at the Royal Economic Society Annual Meeting, at the Annual Meeting of the European Economic Association and the Association for Southern European Economic Theorists for useful comments. Any errors are ours alone. Email: lah39@le.ac.uk, j.o.mierau@rug.nl and james.rockey@le.ac.uk. This paper updates and replaces Leicester DP 15/23 'Inequality in an Equal Society: Theory and Evidence'. First Version April 2015.Harvey: University of Leicester, University Road, Leicester, LE1 7RH, UK, lah39@le.ac.uk. Mierau: University of Groningen, Nettelbosje 2, 9747 AE, Groningen, NL, j.o.mierau@rug.nl, Rockey: University of Leicester, University Road, Leicester, LE1 7RH, UK, jcr12@le.ac.uk.

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,[1] 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 most 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, versus changes in

[1] See the three rounds of comments and replies generated by his paper.

the technology of production and the distribution of rents. This paper addresses this need by taking the life-cycle argument to the data.

In doing so we document how much of the variation in income and wealth inequality is due solely to life-cycle effects and by implication how much reflects other factors. Using micro-data for the United States and 19 other developed countries, 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 1960s and the early 1980s, the level of natural inequality increased by around 8 percentage points. Adjusting for this, by considering the difference between natural inequality and actual inequality reveals that excess inequality fell from the early 1960s until the early 1980s, while actual inequality was relatively stable. This pattern has since reversed, while in the last 30 years natural inequality has declined slightly, this has been more than offset by large increases in excess inequality. 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. Results for wealth show that natural 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.

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 nethertheless able to provide evidence that 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 the data now available, is that we can see this trend in its proper historical context – as a temporary phenomenon soon to be reversed. Moreover, as we use microdata we are able to disaggregate by age and gender and to ensure consistent and comparable estimates over time despite changing labour markets.[2]

There has been relatively little recent work of this type and 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. From a policy perspective, it is as important to know where societies are headed as where they have been. To this end, 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 natural inequality. Hence, in the future, as the demographic pyramid settles into its long-run equilibrium, wealth and income inequality

[2]Related is the work of 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.

will increase. Perhaps worryingly, this process will accelerate further the trend of increasing 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 demographic forces will exacerbate the upward trends in 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.

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, that 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 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 contains a model that formalizes, and expands on the discussion in Section I as well collecting details of the data and simulations.

I. Natural Rates of Inequality

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:

$$W(v,t) = E(t-v)w(t), \tag{1}$$

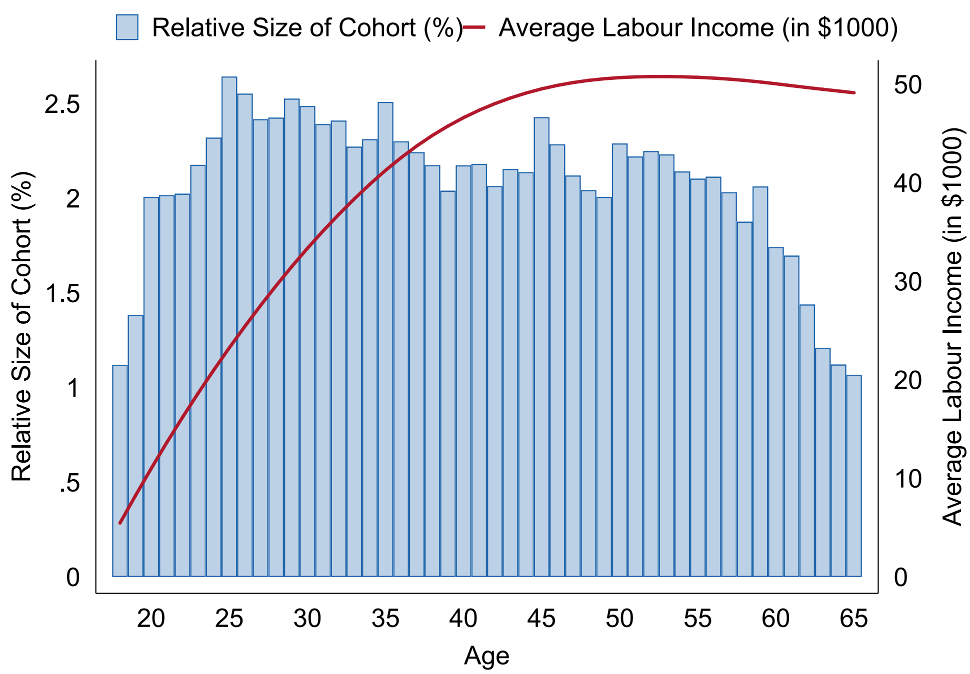
where $W(v,t)$ is the income at time t of an individual born at time v, $w(t)$ is the economy wide wage rate and $E(t-v)$ is an individual scaling factor that creates a life-cycle pattern in labour income. $E(t-v)$ can be driven by many factors, which, for the sake of brevity we do not model separately. 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.[3] However, the degree of inequality is determined not only by how much richer the old are than the young, but

[3]The 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) uses 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 detailed microdata 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 microdata such that the effects of age and other factors may be precisely estimated.

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.

Figure 1 : Income and cohort size by age group United States (Men), 2015



Source: ASEC supplement of the Current Population Survey, survey year 2016
Notes: The left y-axis corresponds to the relative size of each age cohort for men in 2015, represented by the light blue bars. The right y-axis in 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.

We develop the above 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

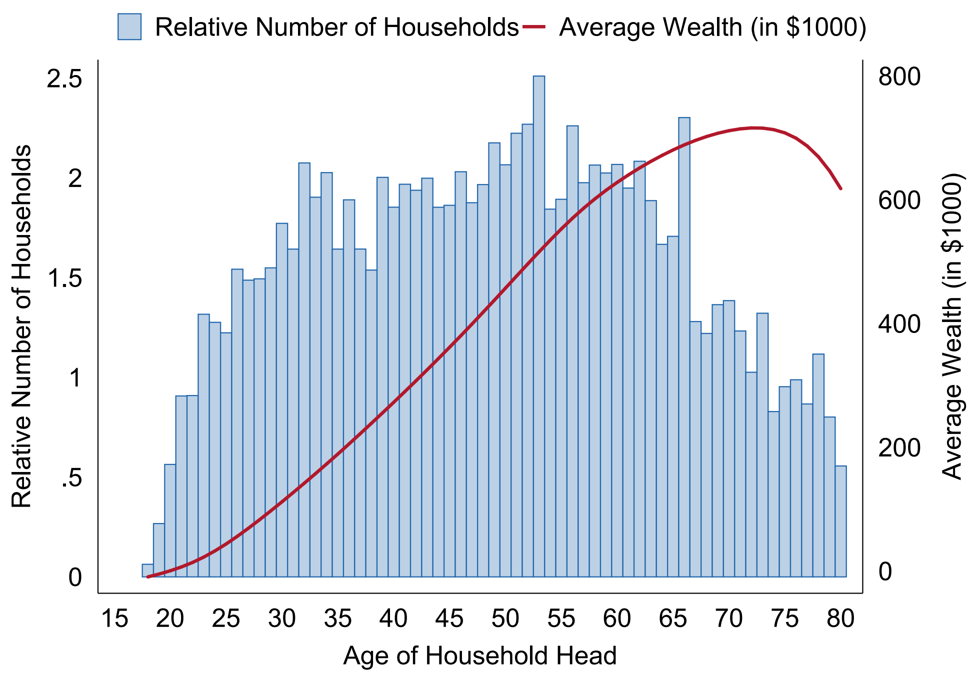
Figure 1, reflects the average income of men in each age group. There we see that income has the familiar hump-shaped profile. The bars in Figure 1 trace out the associated cohort sizes by age. This provides the relatively uniform demographic pyramid associated with high income countries. However, in contrast to a steady-state demographic structure, where we would expect a smooth 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 $\bar{x}_j$in place of individual data, and weighting by cohort sizes p_i and p_j, in an otherwise standard expression for the Gini coefficient:

$$\theta^{NR} = \frac{\sum\limits_{i \neq j} p_i p_j |\bar{x}_i - \bar{x}_j|}{2\bar{\bar{x}}}. \tag{2}$$

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 0.34.

A comparison of our results with the model in Appendix A shows that an earnings process of the form of (1) is sufficient to deliver the qualitative features of the empirical income distribution in Figure 1. This is

Figure 2 : Wealth and cohort size by age group United States, 2013



Source: 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 weights.

important because it suggests that, for our purposes, one need not appeal to additional explanations for differences in earnings between cohorts.[4]

[4]This is less true for wealth, particularly the right-hand tail of its distribution. An important series of papers, including Cagetti and De Nardi (2006, 2009), develop models that more fully explain the wealth distribution. See Cagetti and De Nardi (2006) for an anthology of such attempts to match life-cycle models to wealth inequality data. Closer to this paper is Mierau and Turnovsky (2014) who analysed life-cycle argument to establish the theoretical value of wealth inequality that would prevail in a society where differences in wealth holdings are solely generated by different ages. They show that, in simulations for the United States, the Gini coefficient describing the natural rate is substantial – around 0.35.

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 B.

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. 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: $\theta^{NR} = 1-2B$, similarly 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:

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

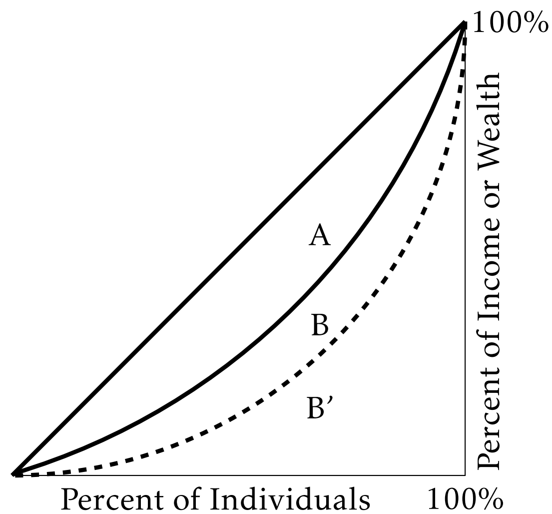
Implying that a society with only natural inequality will have $\theta^{LA} = 0$, while a society exhibiting inequality in excess of natural inequality will take positive adjusted values.

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.[5] We seek to build on these earlier insights by exploiting vastly improved and harmonized 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 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 labour

[5]Their modification of the Paglin (1975) measure amounts to redefining the denominator of θ^{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: $\theta^{U} = 1 - 2B'$.

market participation by women and dispersion in retirement ages have both increased.

More concretely, the decision to retire and women's decision to enter the labour market, both embody choices that are endogenous with respect to earning potentials as well as societal mores and institutions. For this reason we analyse the natural rate of inequality for men and women separately. We also 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.

Our analysis will focus disproportionately, but far from exclusively, on natural inequality amongst males. This is because it is reasonable to assume, as an approximation, that all (or a constant fraction of) men aged 18-65 over the entire period, and all the countries we study are in the labour market and thus that earnings of zero reflect unemployment. This is patently untrue for women, and female labour market participation rates still vary markedly across developed countries, and are changing within them, limiting what may be reasonably inferred.

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. We use data from the Current Population Survey (CPS), the details of which may be found in Appendix C. Consider first the solid red line in Figure 4, this shows the Gini coefficient of labour income (of men) 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 0.48 and 0.50 respectively in 2015. Also clear, is that inequality in labour income has increased more than that of total income; total income appears comparatively stable for the period of 1961 – 1980, before it then begins a strong upward trend. 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.

Figure 5 reports income inequality amongst women, and again plots the Gini coefficient of labour and total income over the period 1961 to 2015. The qualitative features of the data are clearly quite different to those for men reported in Figure 4. While inequality in total income is

Figure 4 : Actual Gini Coefficients for Labour and Total Income (Men)

Source: Authors' calculations using ASEC supplement of the Current Population Survey, 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.

again higher, the relationship between the two series is looser. However, both show that inequality in 2015 is approximately the same as in 1961. But, this consistency masks large declines of around 4 percentage points in inequality over the period 1961-1980 and subsequent increases. In the case of total income this increase was concentrated on the early 1980s with subsequent stability at around 0.49. While for labour income there was a consistent, upwards trend between 1980 and 2015. Notably, there is, as for men, a clear cyclical component of labour income inequality.

Figure 5 : Actual Gini Coefficients for Labour and Total Income (Women)

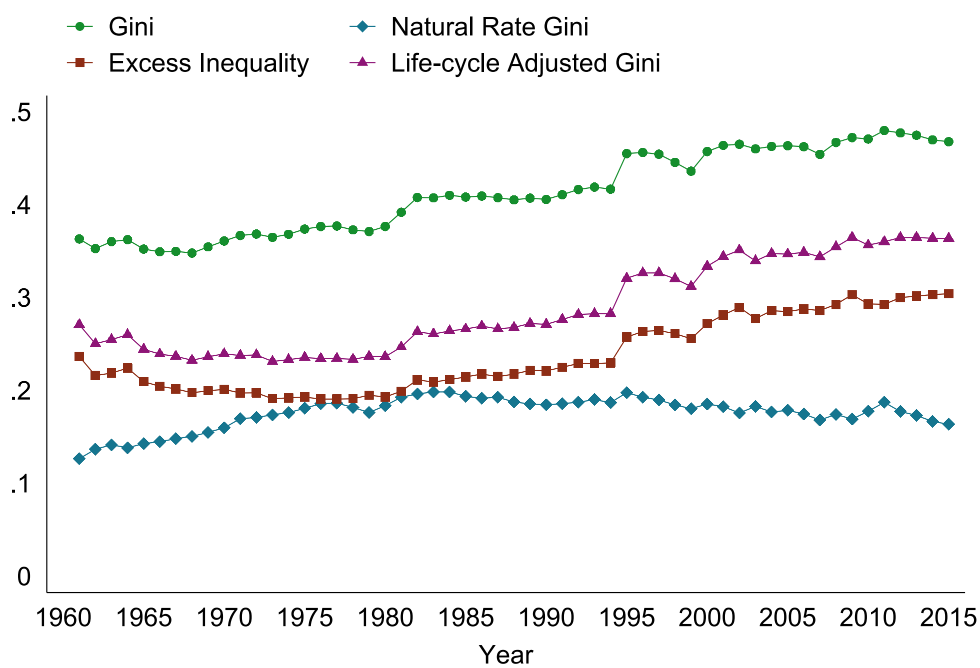
Source: Authors' calculations using ASEC supplement of the Current Population Survey, survey years 1962-2016
Notes: Sample includes those with positive income and are aged 18-65. Results are calculated using individual weights.

As noted above these results are harder to interpret than they are for men – in particular women's labour force participation increased dramatically over the period meaning that the subset of the population described by the 1961 gini coefficient is very different to that in 1981, or 2015. It is possible that once this changing participation were accounted for the trends would look similar to those of men. But, regardless, without being able to perform such an adjustment conflating trends in inequality amongst men and women will obscure a great deal of important variation.

We now analyse the extent to which these changes in inequality reflect demographic changes. Figure 6 plots, for labour income (men only), both actual (green circles) and natural inequality (blue diamonds), as well as our 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 6 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.

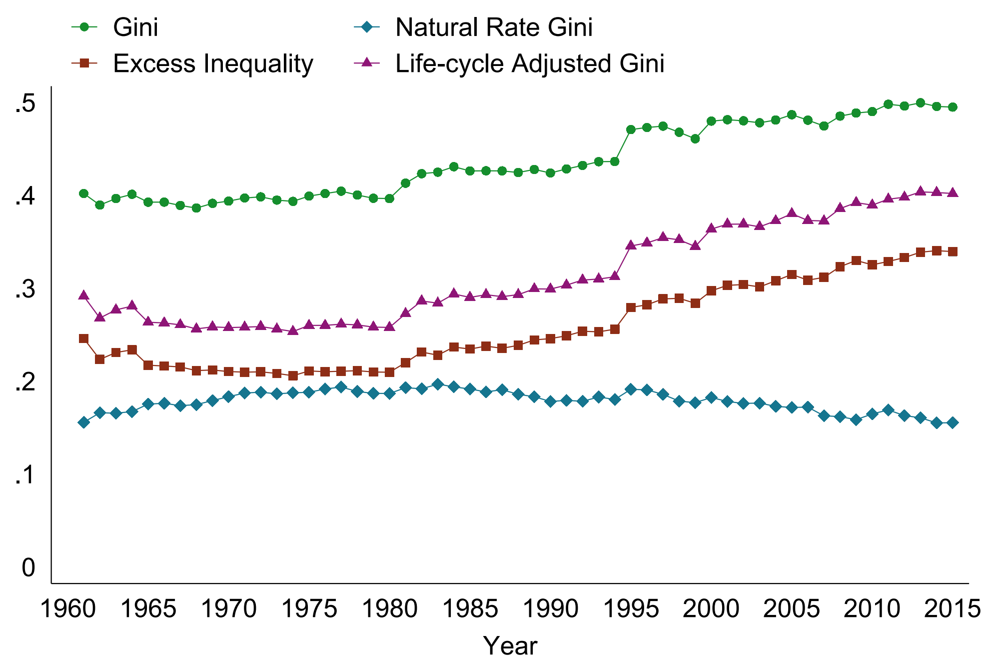
Figure 6 : Actual, Natural, and Excess Gini Coefficients of Labour Income for the US 1961-2015 (Men)



Source: Authors' calculations using ASEC supplement of the Current Population Survey, survey years 1962-2016
Notes: Sample includes Men with positive income and are aged 18-65. Results are calculated using individual weights.

Comparison with Figure 7 shows 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 natu-

Figure 7 : Actual, Natural, and Excess Gini Coefficients of Total Income for the US 1961-2015 (Men)

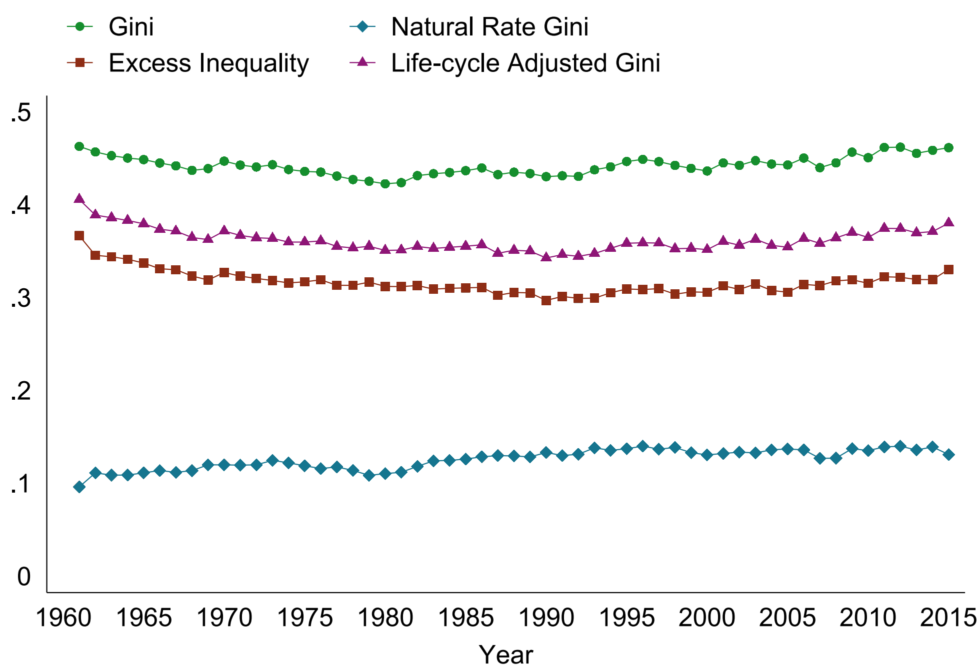


Source: Authors' calculations using ASEC supplement of the Current Population Survey, survey years 1962-2016
Notes: Sample includes Men aged 18-78. We exclude individuals with a zero or negative income. Results are calculated using individual weights.

ral 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.

Figures 8 and 9 show that the natural rate of inequality is lower for women. This may be because of the endogenous selection effects dis-

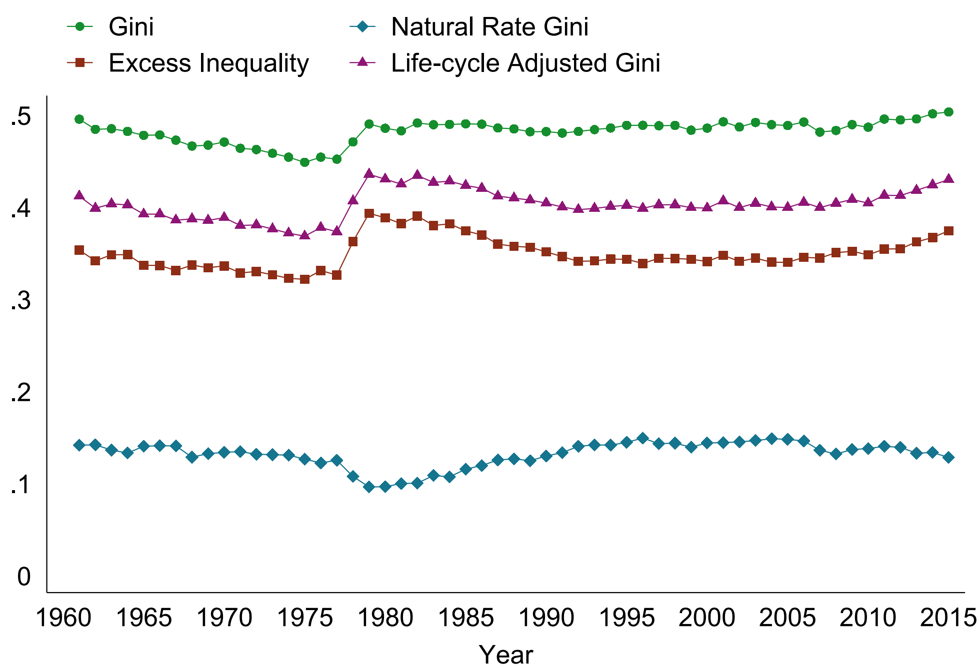
Figure 8 : Actual, Natural, and Excess Gini Coefficients of Labour Income for the US 1961-2015 (Women)



Source: Authors' calculations using ASEC supplement of the Current Population Survey, survey years 1962-2016
Notes: Sample includes Women with positive incomes and are aged 18-65. Results are calculated using individual weights.

cussed above, and notably there is comparatively little variation in its level over the period. For this reason, the trends in *adjusted*, *excess*, and *actual* inequality are similar. Given that there is little reason other than gender differences in labour force participation rates, especially amongst parents, to expect human capital accumulation to differ between men and women we are led to conclude that changes in inequality due to changes in demography have been muted by changes due to changes in participation rates.

Figure 9 : Actual, Natural, and Excess Gini Coefficients of Total Income for the US 1961-2015 (Women)



Source: Authors' calculations using ASEC supplement of the Current Population Survey, survey years 1962-2016
Notes: Sample includes Women aged 18-78. We exclude individuals with a zero or negative income. Results are calculated using individual weights.

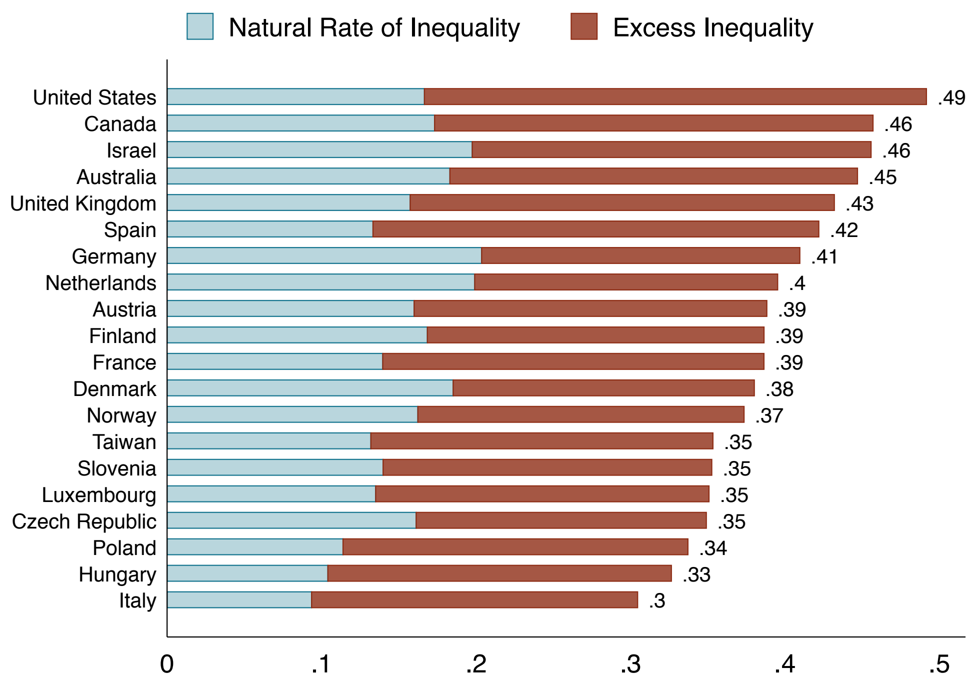
B. Cross Sectional Time Series Analysis

We now broaden the discussion to a sample of countries, using data from the Luxembourg Income Study Database (LIS), the details of which are again in Section C of the Online Appendix. Figure 10 summarizes the cross country variation in the final wave of the LIS for all of the countries we consider. 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 0.3 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 10. 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 is available. The countries which we discuss here are Canada, (West) Germany, Netherlands, Taiwan, United States, United Kingdom and Spain.[6]

[6] All results are for West Germany only throughout. Figures for Spain are for net incomes. Results for all other countries are for gross incomes. See Appendix C for more information.

Figure 10 : Cross Country Variation in Natural and Excess Inequality

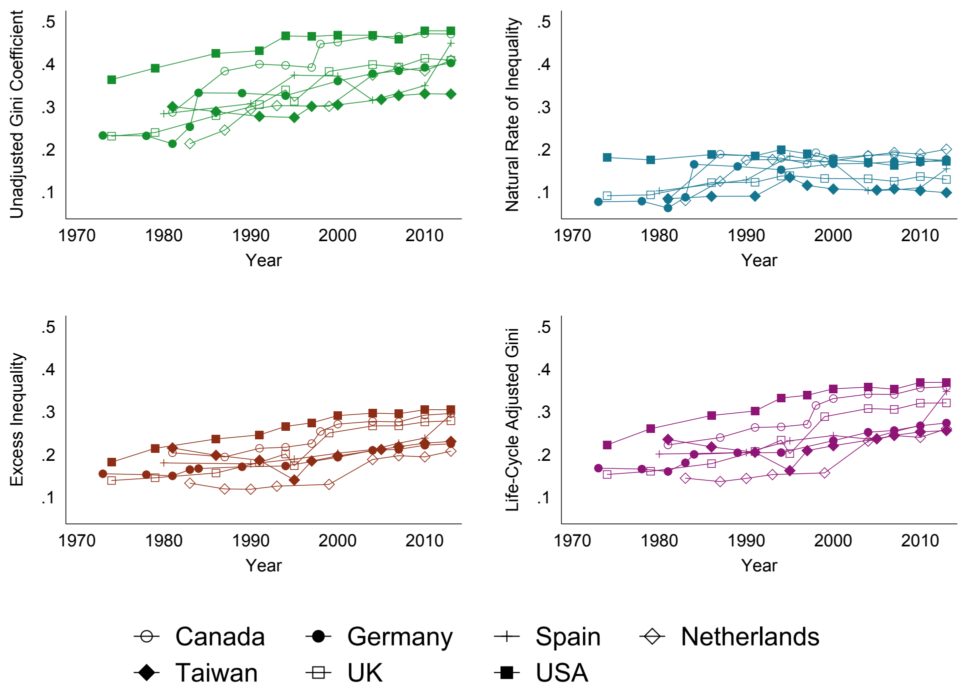


Source: Authors' calculations using LIS Wave IX, (circa 2013)
Notes: The number to the right of the bars for each country denotes the *actual* Gini, and the total length of the bar. Thus this graph shows the decomposition of the level of *actual* inequality into its *natural* component (Blue) and *excess* 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.

We discuss regression analyses of the trends for the full set of countries below. Figures describing the other countries are in Online Appendix I.

We begin by considering labour income. Looking at the top left (green) panel of Figure 11, 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

Figure 11 : Adjusted and Unadjusted Gini of Labour Income: Selected Countries: 1973-2014



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.

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 11. 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 11 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 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, for men and women, of estimating a linear trend using a simple fixed-effects model.[7] We report results for both total income and labour income in the first and second rows respectively. Columns (1) – (4) contain results for men and columns (5)–(8) for women. Hence, the first column reports results for the actual Gini of the male population 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

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

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.[8] 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 7 (FE estimates) and 10 percentage points (MG), which suggests that around a quarter of increases in inequality have been due to demographic change.

Turning now to the results for women in columns (5) – (8) we see that the again all the coefficients are positive and significant. The coefficients are larger for *actual* than for *adjusted* implying that not all of the increase is due to increases in excess inequality, although the difference is relatively small in the case of the estimates from the fixed-effect model. This is contrary to our results for the US described in Figures 8 and 9, and suggests that elsewhere there is an upwards trend in natural inequality amongst women. One possibility is that this reflects cross country differences in changes in women's labour market participation.

[8]These are reported in Table I.1 in the Online Appendix.

Table 1: Time Trends in Inequality

	Men				Women			
	Actual		*Adjusted*		*Actual*		*Adjusted*	
	(1)	2)	(3)	(4)	(5)	(6)	(7)	(8)
Labour Income	0.37***	0.39***	0.30***	0.29***	0.22***	0.26***	0.16***	0.17***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.06)	(0.04)	(0.06)
Total Income	0.18***	0.24***	0.18***	0.22***	0.16***	0.24***	0.16**	0.18***
	(0.04)	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Estimator	FE	MG	FE	MG	FE	MG	FE	MG
Countries	23	23	23	23	23	23	23	23
N	197	197	197	197	197	197	197	197

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 this pattern, we repeat our prior analysis for wealth using the Luxembourg Wealth Study (LWS).[9] 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.

We choose disposable net worth (non-financial assets plus financial assets (excluding pensions) minus total liabilities) as our measure of wealth

[9]Luxembourg Wealth Study (LWS) Database, http://www.lisdatacenter.org (multiple countries; 1995-2013). Luxembourg: LIS.

but this choice is not important for our results.[10] Wealth data are measured by the household rather at the individual level, and we use the head of the household's age as a proxy. Again, this assumption does not matter for our results.

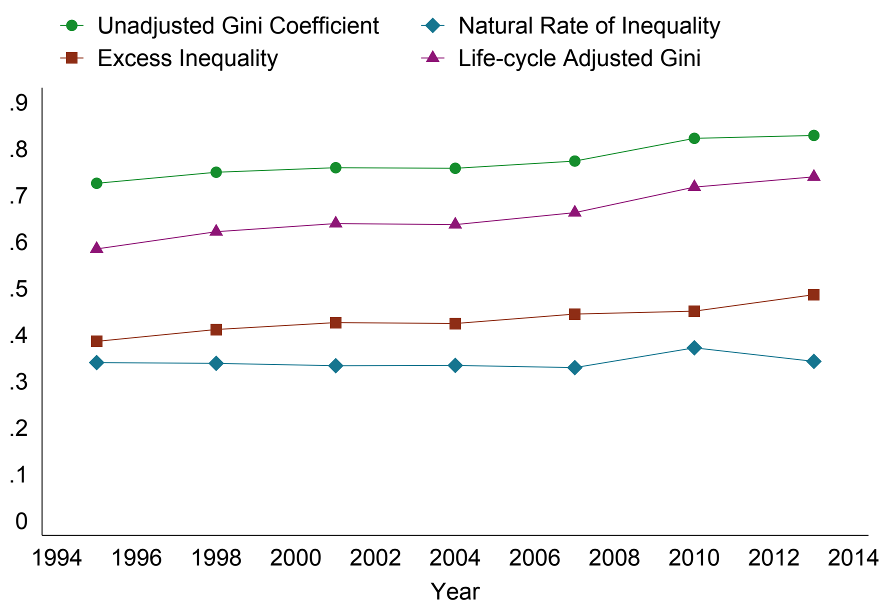
Figure 12 shows the (actual) Gini coefficient of wealth inequality for the United States over the period 1995 – 2015. As expected wealth inequality is higher than income inequality over the same period. We can see that while inequality has been increasing, that the natural Gini increased only marginally, and that consequently excess and life-cycle adjusted Gini have risen more markedly. More precisely, the excess Gini of wealth has increased by around ten percentage points over the 20 year period. 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%. Unlike those measures, our approach here will fail to capture much of the changes at the top end of the income distribution. But, importantly it is more sensitive to changes amongst the moderately wealthy. However, it is clear that while demographics can account for a substantial fraction of changes in income inequality they are comparatively unimportant for wealth. Changing demography cannot explain the stark increase in wealth inequality over the last few decades.

Table 2 shows results for the eight countries for which adequate data are available. We can see that the wealth inequality varies substantially, between 0.53 in Slovenia and 0.83 in the US. However, the second and third rows suggest that this variation is in part driven by variations in the

[10]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 0.34 in the US but only 0.14 in Slovenia, and excess inequality is relatively consistent compared to actual inequality varying between 0.33 in Australia for the US to 0.49 in the US. Comparing the US and Canada is instructive as while the actual Gini coefficients are quite different (0.83 and 0.68 respectively) the excess Ginis are very similar (0.49 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. This highlights, again, that considering the actual Gini alone may be misleading.

Figure 12 : Wealth Inequality over Time (United States)



Source: Authors' calculations using Luxembourg Wealth Study (LWS)
Notes: Time series for 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 weights are used to produce results.

Table 2: Wealth Inequality

	Australia	Canada	Finland	Italy	Norway	Slovenia	UK	US
Actual	0.56	0.68	0.62	0.55	0.76	0.53	0.58	0.83
Natural	0.22	0.24	0.24	0.16	0.37	0.14	0.23	0.34
Excess	0.33	0.44	0.38	0.39	0.39	0.40	0.35	0.49
Adjusted	0.43	0.58	0.50	0.47	0.61	0.46	0.45	0.74

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 Austrialia refer to 2010, Canada 2012, Italy and Slovenia refer to 2014, Finland, Norway and the US refer to 2013, 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 13 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.[11] 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.

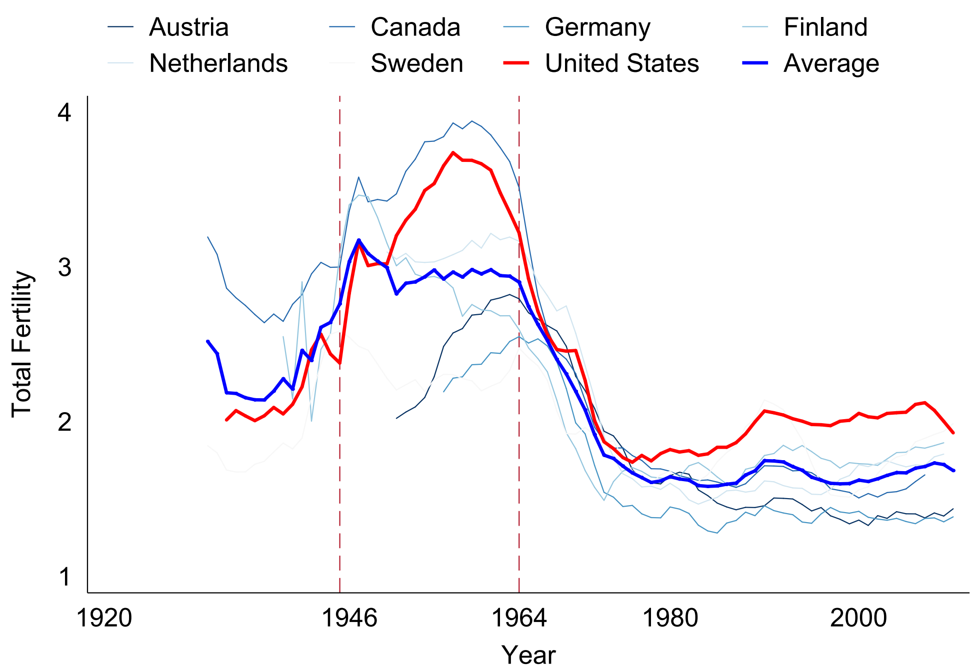
Future Levels of Inequality

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 the standard Leslie matrix approach, in which the birth and death rates define a transition matrix that projects the cohort sizes next period given the current sizes.[12] 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

[11] 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.

[12] Details of the simulation procedure can be found in Appendix F.

Figure 13 : 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.

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.

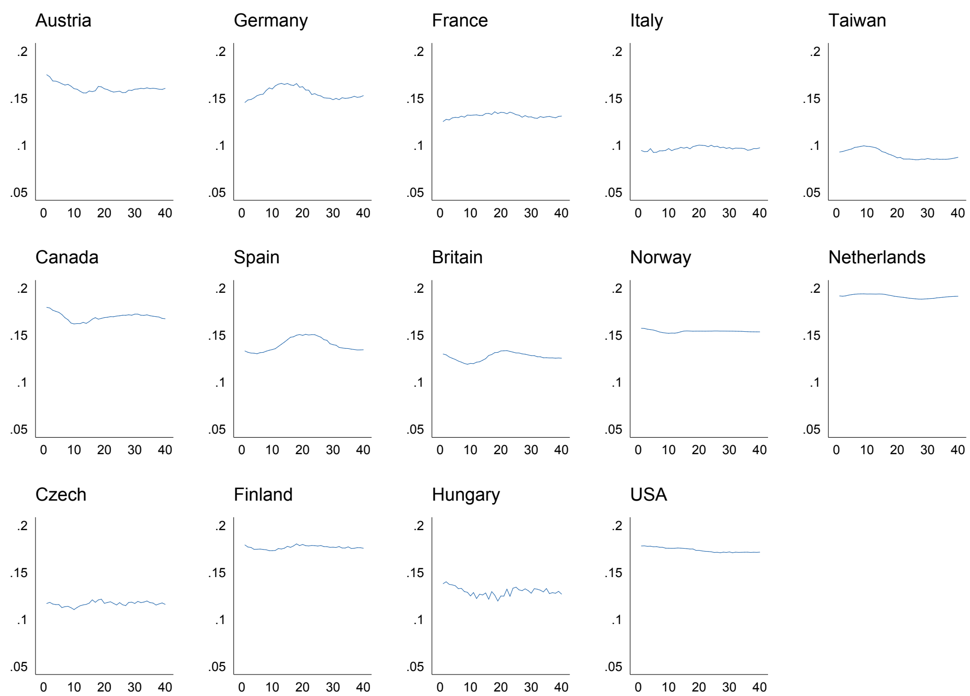
Thus, for the 15 countries for which suitable fertility and mortality data are available we project expected levels of natural labour income inequality. Figure 14 plots projected natural inequality for the next forty years. We choose this horizon as by this point the children of the Baby Boomers have 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 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 15 along with a line of best fit denoted by the red line.[13]

[13]The reduced set of countries reflects data availability, see Appendix F.

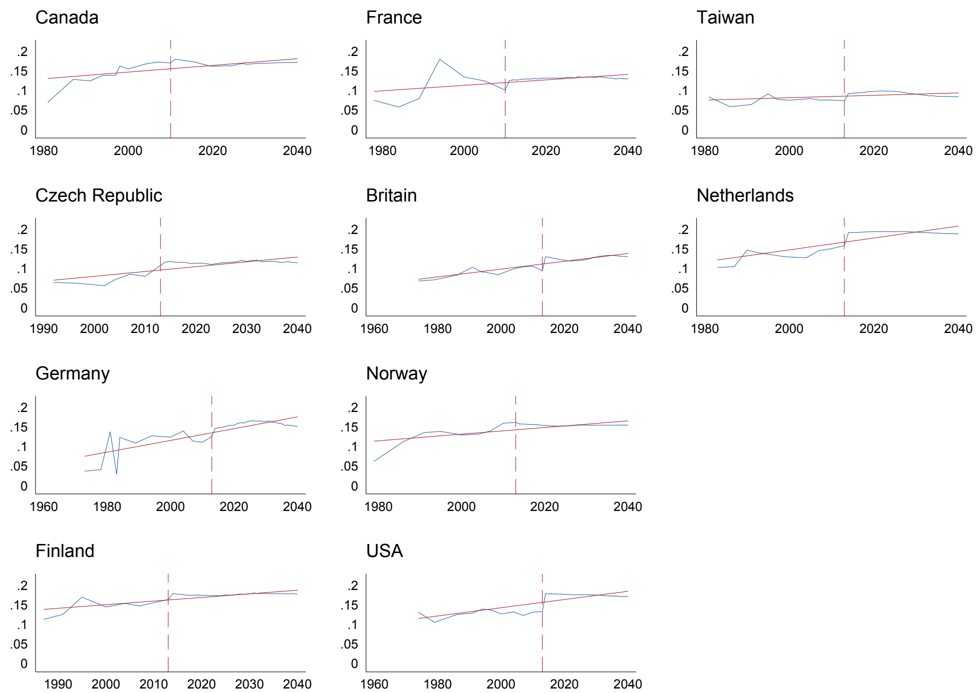
The vertical red dashed line represents the point at which the simulation starts. To the left of this line are the historical results from LIS, and points to the right are the projected levels of inequality. Taken together it seems that future increases in natural inequality would represent a continuation 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.

Figure 14 : Simulated Natural Rates of Income Inequality



Source: Cohort sizes are simulated used the procedure outlined in Section F of the Online Appendix, using data from the Human Mortality Database Human Mortality Database (2013)and Human Fertility Database Human Fertility Database (2013) and Earnings profiles are taken from the most recent data availaible 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. Cohort sizes are simulated used the procedure outlined in Section F of the Online Appendix, using data from the Human Mortality Database Human Mortality Database (2013)and Human Fertility Database 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.

Figure 15 : Historical and Simulated Future Rates of Income Inequality



Source: Cohort sizes are simulated used the procedure outlined in Section F of the Online Appendix, using data from the Human Mortality Database Human Mortality Database (2013)and Human Fertility Database 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 vertical line is the 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 1960-1980. 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 less important a determinant than it is for income, and a much smaller component of actual wealth inequality. It similarly explains less of the cross country variation. 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.

While the results for women are less easy to interpret due to endogenous changes in labour market participation rates, they do suggest that increases in participation rates over the period have partially offset changes in the natural rate. One speculative reading of this finding is that as participation rates stabilise, we may expect natural inequality among women to increase.

Our analysis speaks mainly to two literatures. First of all, by building on the work of Atkinson (1971) and Paglin (1975) we re-emphasize the central role that demographic structure has for the determination of inequality. Importantly, we add to this literature by quantifying the magnitude of life-cycle inequality for a collection of countries around the world. Second, we advance on the literature dealing with long-run trends in inequality initiated by Atkinson and Harrison (1978) and reinvigorated by Piketty (2003), Piketty and Saez (2014), Roine and Waldenström (2015), and Milanovic (2016). In this regard we show that an additional factor contributing to any future rise in income and wealth inequality is that comparatively high levels of natural inequality are forecast to remain, and indeed increase, from their historically high level. Given the current rapid increases in excess inequality in the US and elsewhere this suggests that, other things equal, actual inequality should be expected to rise substantially over the next 20 years.

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A. Model

Here, we make explicit how any earnings process of the form of (1) in Section I gives rise to substantial levels of inequality. To fix ideas we 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 a different stage of their life-cycle.

Starting with income inequality, as in the main text we consider the following process of non-asset income:

$$W(v,t) = E(t-v)w(t), \tag{A.1}$$

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 non-asset 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.

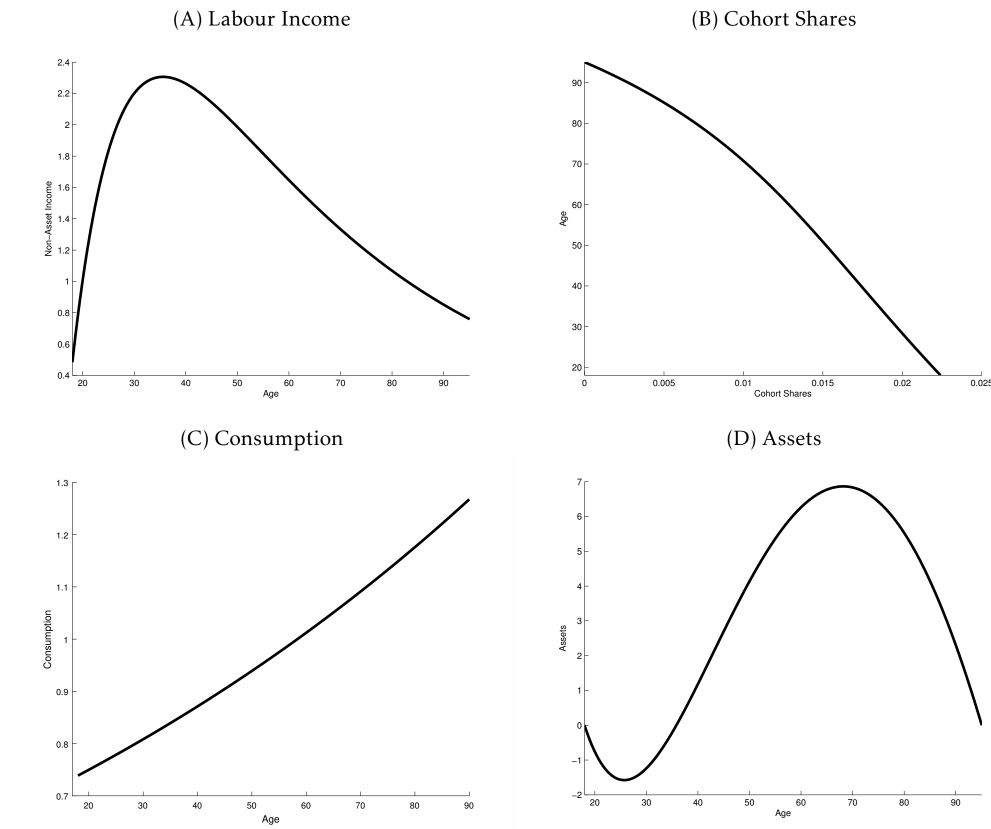
Panel A of Figure A.1 exhibits a typical life-cycle pattern of non-asset income.[14]Panel B of Figure A.1 displays the relative size of each cohort for a demographic structure that is in its steady state (see, Lotka, 1998).[15]

[14]The graph is a smoothed version of the life-cycle human capital pattern of Hansen (1993), which has been extrapolated to create a stylized social security benefit in old age. See Online Appendix H in for details.

[15]The cohort shares are based on the mortality structure of the 2006 United States cohort under the assumption of constant fertility. See Online Appendix H for more details.

This provides the triangular shape that makes up the typical population pyramid.

Figure A.1 : Life-cycle Profiles



Notes: Panel (A) displays the life-cycle profile of non-asset income. Panel (B) shows the relative size of each age group. Panel (C) exhibits the life-cycle consumption profile generated by the model in Section I. Panel (D) displays the associated asset profile as also derived from the model.

Combining the life-cycle pattern of income of Panel A with the structure of cohort shares in Panel B implies that even if each individual has the same income at the same age, the fact that individuals of different ages coexist impose a level of income inequality into the economy. The particular example given above, for instance, implies a Gini coefficient of

0.11. While not large, it certainly vitiates the idea of a natural level of income inequality.

In keeping with the reasoning set out by Atkinson (1971) we express the arguments in the current section in terms of the life-cycle of an individual. But, when on the economic and demographic equilibrium paths, age and cohort levels of income and wealth are equivalent. That is, in equilibrium every cohort, say aged 37, is equivalent to any other cohort when aged 37. This means, that the trajectories in Figure A.1 can be equivalently interpreted as describing an individual cohort's life-cycle or as a cross-sectional snap shot of the income and wealth levels of different cohorts.

Wealth Inequality

To analyse how life-cycle impacts affect wealth inequality we need to add more structure to our model. In particular, following the typical text-book life-cycle model, let the discounted life-time utility of an individual born at time v be given by:[16]

$$\Lambda(v) = \int_{v}^{v+D} U(C(v,t))e^{-\rho(t-v)-M(t-v)}\,dt, \tag{A.2}$$

where $C(v,t)$ is consumption at time t of an individual born at time v, ρ is the pure rate of time preference, $M(t-v)$ is the cumulative mortality rate and D is the maximum attainable age. While D is the maximum age, an individual has an increasing probability of death, $\mu(t-v) = M'(t-v)$, at any age before D. We assume an iso-elastic utility function $U(C(v,t))$,

[16] In principle D can also be infinite, for instance if the specified survivial function is of the Gompertz-Makeham form.

specifically:

$$U(C(v,t)) = \frac{C(v,t)^{1-1/\sigma} - 1}{1 - 1/\sigma}, \tag{A.3}$$

where σ is the intertemporal elasticity of substitution. The budget constraint of the individual is:

$$\dot{A}(v,t) = r^A(t)A(v,t) - C(v,t) + W(v,t), \tag{A.4}$$

where $A(v,t)$ is the stock of financial assets, $\dot{A}(v,t) = \frac{\partial A(v,t)}{\partial t}$, $W(v,t)$ is non-asset income and $r^A(v,t)$ is the interest rate received, both of which depend on age.

Following Yaari (1965), we assume that individuals have recourse to a perfect annuity market. Hence, the return on assets becomes a composite of the market rate of interest ($r(t)$) and the annuity premium - which, due to competition between annuity firms, equals the probability of death ($\mu(t-v)$):[17]

$$r^A(v,t) = r(t) + \mu(t-v). \tag{A.5}$$

Individuals maximize A.2 subject to A.4, which provides the familiar consumption Euler equation:

$$\frac{\dot{C}(v,t)}{C(v,t)} = \sigma(r-\rho), \tag{A.6}$$

[17]In practice life-insurance markets need not be perfect, leading to a load factor on the annuity premium (see, Mitchell et al. (1999)). This can easily be accommodated in the current framework by following Hansen and İmrohoroğlu (2008) and Heijdra and Mierau (2012) and letting the life-insurance premium equal $(1-\lambda)\mu(t-v)$, where $\lambda \in [0,1]$ is the load factor. For sake of argument we focus on the case that $\lambda = 0$.

where we have assumed that the economy is in its steady-state as is indicated by the absence of a time index on r.[18] Solving A.6 forward from time v allows us to write consumption at time t as:

$$C(v,t) = C(v,v)e^{\sigma(r-\rho)(t-v)}. \tag{A.7}$$

To obtain $C(v,v)$ (i.e., consumption of a new-born individual) we substitute A.7 into A.4 and solve the ensuing differential equation, which provides:

$$\tilde{C}(v,v) = w\frac{\int_v^{v+D} E(t-v)e^{-r(t-v)+M(t-v)}dt}{\int_v^{v+D} e^{-((1-\sigma)r+\sigma\rho)(t-v)+M(t-v)}dt}, \tag{A.8}$$

where $\tilde{C}(v,v)$ indicates the equilibrium value of $C(v,v)$, which we can then use to trace out the life-cycle consumption profile in Panel C of Figure A.1. With $\tilde{C}(v,v)$ in hand we can solve A.4 from any point in time forward to obtain the life-time path of assets:

$$\begin{aligned} A(v,t) = e^{r(t-v)+M(t-v)}\Bigg(&w\int_v^t E(t-v)e^{-r(t-v)+M(t-v)}dt \\ &-\tilde{C}(v,v)\int_v^t e^{-((1-\sigma)r+\sigma\rho)(t-v)+M(t-v)}dt\Bigg). \end{aligned} \tag{A.9}$$

For the special case that income is constant over the life-cycle (i.e., $E(t-v) = E$) it is straightforward to prove that $A(v,t)$ follows a hump-shape (see, Mierau and Turnovsky, 2014). For more elaborate income profiles, a proof is more involved, but the fact that $A(v,t)$ differs over the life-cycle is unambiguous. Using the parametrisation set out in Appendix H, we

[18] Details of the derivation are contained in Appendix G.

display the life-cycle profile of assets in Panel D of Figure A.1. As can be seen it exhibits the commonly documented hump-shaped structure.

As above we can combine the life-cycle asset profile with the cohort shares to derive a measure of inequality that is natural to the society. In the case of wealth the Gini coefficient equals 0.54, which is reasonably large given that observed values in developed countries range from 0.55 in Japan and 0.80 in Denmark (see, Davies et al., 2011). In any case, the current argument clearly suggests the need for inequality measures to be corrected for the life-cycle structure of income and wealth – as suggested by Atkinson (1971) and Paglin (1975).

B. *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:

$$\theta(W) = \frac{1}{\sqrt{3}} \frac{\sigma_W}{\overline{W}} \rho(W, r_W) \frac{\sqrt{N^2 - 1}}{N} \approxeq \frac{1}{\sqrt{3}} \frac{\sigma_W}{\overline{W}} \rho(W, r_W),$$

where $\overline{W}$, σ_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 $W = \overline{W} \, \forall \, W$, 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 $W = \overline{W} \, \forall \, W$, implies that as longs as the set $W \neq \overline{W}$ is non-empty $\theta(W) > 0$. Results for the Gini Coefficient of Wealth can be established with the same arguments. □

Not For Publication Appendices

C. 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 Annusal 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)[19] 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,

[19]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.

follow Heathcote et al. (2010) and retain these imputed values and use the CPS provided survey weights.

D. 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 expenditure are summed 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.

As with the CPS data, 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*.

E. Wealth Inequality

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.

F. Future Cohorts Simulation Procedure

In order to simulate the future cohort shares we create a Leslie Matrix (Leslie, 1945, 1948), a form of projection matrix that is a standard tool in Mathematical Demography. We have information regarding the population cohort sizes for time t, but we are interested in forecasting the population for time $t+s$. Given we have data, for each age i on age specific fertility rates β_i and death rates μ_i we can construct the Leslie matrix, $\mathbf{L}$ which has age specific fertility on its top row, and age specific survival rates on the first subdiagonal. Multiplying the vector of cohort population shares (ordered by age) for year t P_t by $\mathbf{L}$ gives the vector of population shares for the subsequent year P_{t+1}. That is $P_{t+1} = \mathbf{L}P_t$, where:

$$\mathbf{L} = \begin{bmatrix} \beta_0 & \beta_1 & \beta_2 & \dots & \beta_w \\ 1-\mu_0 & 0 & 0 & \dots & 0 \\ 0 & 1-\mu_1 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 0 \end{bmatrix}. \tag{F.1}$$

Where subscript w denotes the maximum possible attainable age. P_t is the vector of the current population cohort sizes ordered by age. Thus the population in year $t+s$ is obtained by calculating:

$$P_{t+s} = \mathbf{L}^s P_t. \tag{F.2}$$

Performing this procedure for each horizon $s \in 1,\ldots,40$ us our population forecasts and maps the transition of the population returning to its long run steady-state following the shock constituted by the Baby Boom.[20] Figure 18 excludes Austria, Spain, Italy and Hungary as the data sets used for the simulations are all *gross*, unlike the available historical data for these countries.

G. Detailed Model Derivation

Individuals maximize lifetime utility:

$$\Lambda(v) = \int_{v}^{v+D} \frac{C(v,t)^{1-1/\sigma}-1}{1-1/\sigma} e^{-\rho(t-v)-M(t-v)}\,\mathrm{d}t, \tag{G.1}$$

subject to the budget constraint:

$$A_t(v,t) = (r+\mu(t-v))A(v,t) - C(v,t) + E(t-v)w, \tag{G.2}$$

where we have imposed that the economy is in its steady-state throughout the life-cycle of the individual, as is indicated by the omission of the time indices on r and w. Defining the present value Hamiltonian for an agent born at time v:

$$\begin{aligned} \mathcal{H} \equiv e^{-\rho(t-v)-M(t-v)} \Bigg\{ & \frac{C(v,t)^{1-1/\sigma}-1}{1-1/\sigma} + \\ & \lambda(v,t)\left[(r+\mu(t-v))A(v,t) - C(v,t) + E(t-v)w\right] \Bigg\}, \end{aligned} \tag{G.3}$$

[20]We are grateful to Timo Trimborn for sharing his code for this procedure.

and optimizing with respect to $C(v,t)$ and $A(v,t)$ we obtain:

(G.4a) $$C(v,t)^{-1/\sigma} = \lambda(v,t),$$

(G.4b) $$\rho - \frac{\dot{\lambda}(v,t)}{\lambda(v,t)} = r.$$

Combining the equations in G.4a gives the consumption Euler equation:

(G.5) $$\frac{\dot{C}(v,t)}{C(v,t)} = \sigma(r-\rho).$$

Solving G.5 forward in time from v onward allows us to write consumption at time t as:

(G.6) $$C(v,t) = C(v,v)e^{\sigma(r-\rho)(t-v)}.$$

Solving G.2 forward from v provides:

(G.7)
$$w\int_v^{v+D} E(t-v)e^{-r(\tau-v)+M(\tau-v)}d\tau = \int_v^{v+D} C(v,\tau)e^{-r(\tau-v)+M(\tau-v)}\,\mathrm{d}\tau,$$

where we have used the initial and terminal assets (i.e., transversality) condition $A(v,v) = A(v,v+D) = 0$. Substituting G.5 into G.7 provides:

(G.8) $$C(v,v) = \frac{w\int_v^{v+D} E(t-v)e^{-r(\tau-v)+M(\tau-v)}d\tau}{\int_v^{v+D} e^{-((1-\sigma)r+\sigma\rho)(\tau-v)+M(\tau-v)}\,\mathrm{d}\tau},$$

which, in combination with G.6, allows us to draw out a path for consumption. Alternatively, solving G.2 forward from any other time t provides:

(G.9)

$$A(v,t) = e^{r(t-v)+M(t-v)} w \Bigg(\int_v^t E(t-v) e^{-r(\tau-v)+M(\tau-v)} \,\mathrm{d}\tau - \frac{\int_v^{v+D} E(t-v) e^{-r(\tau-v)+M(\tau-v)} \,\mathrm{d}\tau}{\int_v^{v+D} e^{-((1-\sigma)r+\sigma\rho)(\tau-v)+M(\tau-v)} \,\mathrm{d}\tau} \int_v^t e^{-((1-\sigma)r+\sigma\rho)(\tau-v)+M(\tau-v)} \,\mathrm{d}\tau \Bigg),$$

which is the asset path traced out in the figures of the main text.

H. Simulations

To simulate the model we need to associate values to the parameters and choose functional forms for the life-cycle income profile and the survival functions. For the parameters we follow Guvenen (2006) and set $\sigma = 0.5$. Not much is known is about the values of ρ so we set it equal to 0.01, which, in combination $r = 0.025$ assures that individuals are patient in the sense that they opt for an upward sloping consumption profile. We normalize $w = 1$.

As regards the demographic structure, we use the survival function suggested by Boucekkine et al. (2002):

$$S(t-v) \equiv e^{-M(t-v)} = \frac{\mu_0 - e^{\mu_1(t-v)}}{\mu_0 - 1}, \tag{H.1}$$

with $\mu_0 > 1$, $\mu_1 > 0$ and $D = \ln \mu_0 / \mu_1$. To estimate the parameters in H.1 we follow Mierau and Turnovsky (2014) and employ non-linear least squares in combination with survival data from Human Mortality Database

(2013). To this end we rewrite H.1 as:

$$S(u) = I(u \leq D)\frac{\mu_0 - e^{\mu_1 u}}{\mu_0 - 1} + \epsilon, \tag{H.2}$$

where $\epsilon \sim i.i.d(0, \sigma^2)$ is the error term, $S(u)$ is the fraction of individuals surviving to age u and $I(u \leq D)$ is an indicator function which takes the term between brackets as logical input. Performing this estimation procedure for the United States 2006 cohort provides $\mu_0 = 78.3618$, $\mu_1 = 0.0566$ and a tight fit ($R^2 = 0.9961$).

Assuming that the demographic structure is in its steady state (see, Lotka (1998)) cohort shares $p(t-v)$ are given by:

$$p(t-v) = \beta e^{\pi(t-v) - M(t-v)}, \tag{H.3}$$

where β is the crude birth rate and π is the population growth rate. For the figures and calculations in the main text we draw population growth rates from the World Bank, which for the US equals $\pi = 1\%$. Through the demographic steady state this implies a crude birth rate of 2.24%. For all other countries we follow the same procedure and the various estimates of the demographic parameters are available on request.

For the life-cycle income profile we follow Blanchard (1985) and employ the sum of two exponential functions:

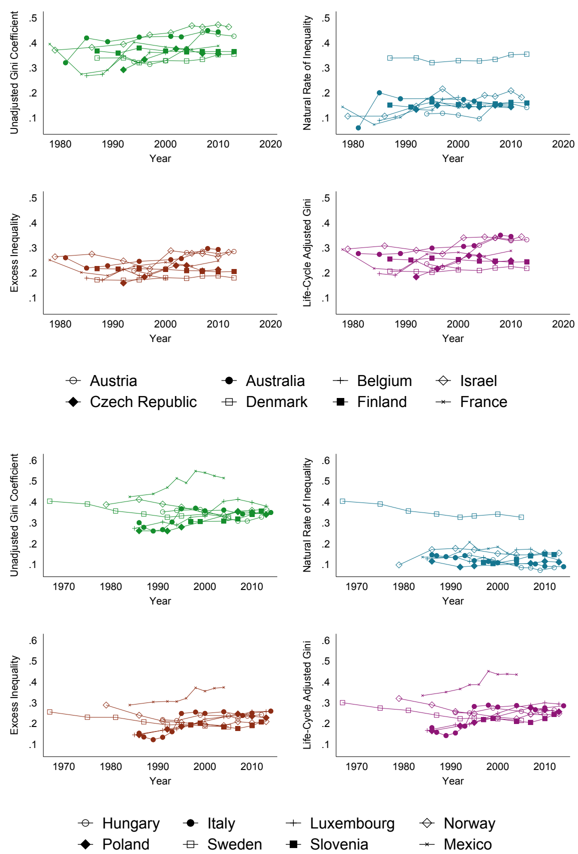
$$E(t-v) = \alpha_0 e^{-\gamma_0 u(t-v)} - \alpha_1 e^{-\gamma_1 u(t-v)}, \tag{H.4}$$

which, under the assumptions $\alpha_0 > \alpha_1 > 0$, $\gamma_0 > \gamma_1 > 0$ and $\alpha_1\gamma_1 > \alpha_0\gamma_0$, leads a hump-shaped income profile. We estimate the underlying parameters of H.4 using non-linear least squares using data from Hansen (1993). This provides $\alpha_0 = 4.494$, $\alpha_1 = 4.010$, $\gamma_0 = 0.0231$, $\gamma = 0.050$ and $R^2 = 0.80$.[21] Extrapolating the income profile up to D then provides the life-cycle income trajectory displayed in the Appendix G.

[21] See, Heijdra and Mierau (2012) for details on the estimation procedure.

I. Additional Results

Figure I.1 : LIS Additional Countries, Total Income (Men)



Source: Authors' calculations using LIS data.

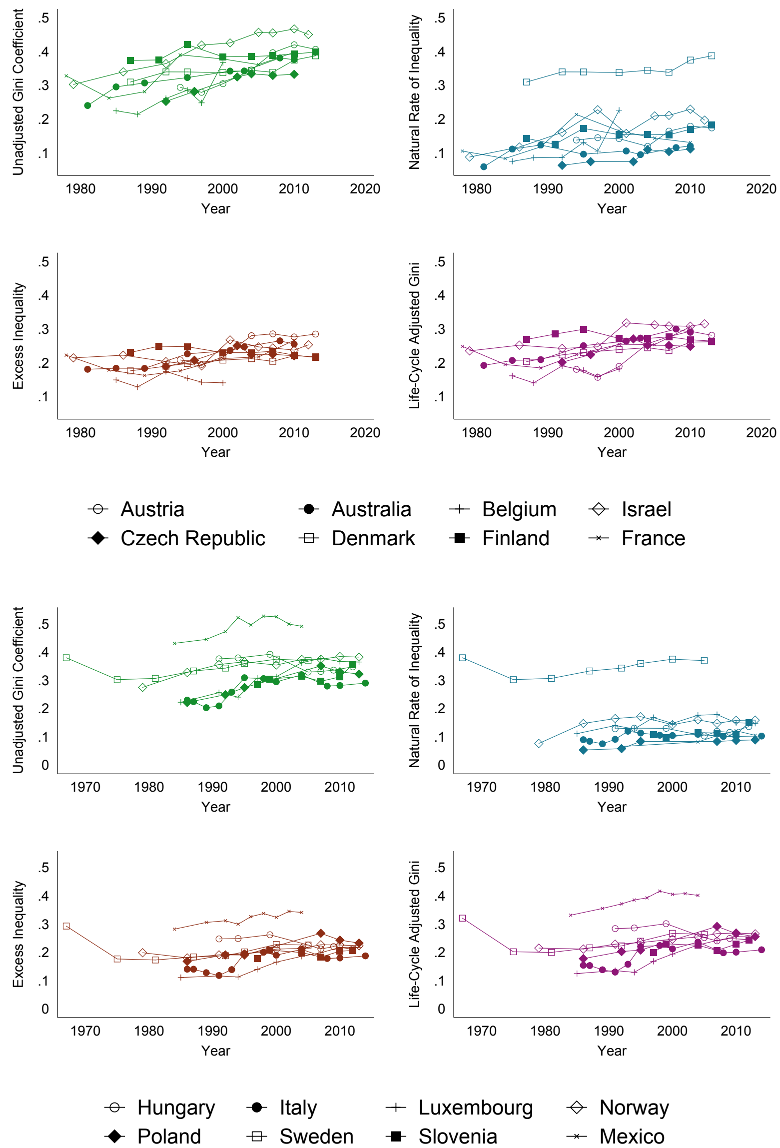
Notes: These are the countries for which a sufficient time series is available not reported in Figure 11. Note that, however, data for these other countries are not consistently classified as gross or net. Most datasets are classified as Gross. France is all classed as mixed and Slovenia is classed as 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.

Table I.1: Country Specific Trend Estimates

	Men				**Women**				
	Actual		*Adjusted*		*Actual*		*Adjusted*		
Country	Total	Labour	Total	Labour	Total	Labour	Total	Labour	*N*
Austria	0.74***	0.80***	0.67***	0.75***	0.76***	0.87***	0.63***	0.77***	7
	(0.13)	(0.13)	(0.12)	(0.14)	(0.15)	(0.13)	(0.11)	(0.10)	
Australia	0.29*	0.41***	0.26***	0.37***	0.07	-0.07	0.02	-0.14**	8
	(0.13)	(0.06)	(0.04)	(0.03)	(0.07)	(0.04)	(0.09)	(0.05)	
Belgium	0.67***	0.8**	0.20	0.16	0.49	0.50**	0.13	0.22	6
	(0.10)	(0.32)	(0.10)	(0.10)	(0.33)	(0.12)	(0.20)	(0.17)	
Canada	0.27***	0.52***	0.24***	0.48***	0.15***	0.23***	0.08	0.06	11
	(0.06)	(0.10)	(0.06)	(0.03)	(0.03)	(0.04)	(0.08)	(0.03)	
Czech Republic	0.35*	0.47 ***	0.37*	0.27**	0.33*	0.44***	0.43**	0.39**	6
	(0.15)	(0.09)	(0.14)	(0.10)	(0.14)	(0.09)	(0.13)	(0.12)	
Germany	0.16**	0.47***	0.00	0.30***	0.20***	0.31***	0.14**	0.21***	12
	(0.06)	(0.05)	(0.04)	(0.02)	(0.03)	(0.04)	(0.06)	(0.06)	
Denmark	0.06	0.23***	0.07**	0.20***	-0.02	0.08	-0.02	-0.05	8
	(0.05)	(0.05)	(0.02)	(0.03)	(0.05)	(0.05)	(0.04)	(0.04)	
Spain	0.32**	0.31**	0.39***	0.34**	0.30***	0.32**	0.44***	0.43***	8
	(0.09)	(0.13)	(0.07)	(0.12)	(0.07)	(0.12)	(0.08)	(0.09)	
Finland	-0.01	0.05	-0.05***	-0.06	-0.06*	0.13	-0.11***	0.03	8
	(0.02)	(0.05)	(0.01)	(0.05)	(0.03)	(0.07)	(0.01)	(0.04)	
France	0.17	0.33**	0.10	0.24	0.30	0.40**	0.20	0.30**	7
	(0.19)	(0.13)	(0.14)	(0.15)	(0.23)	(0.11)	(0.19)	(0.11)	
Hungary	-0.24**	-0.25**	0.01	-0.26***	-0.10	-0.20*	0.19***	-0.26**	7
	(0.07)	(0.07)	(0.04)	(0.05)	(0.07)	(0.09)	(0.04)	(0.10)	
Israel	0.34***	0.51***	0.17***	0.28***	0.33***	0.32***	0.18***	0.17***	9
	(0.03)	(0.04)	(0.04)	(0.03)	(0.06)	(0.06)	(0.04)	(0.03)	
Italy	0.29***	0.29***	0.52***	0.27***	0.40***	0.33***	0.63***	0.28***	12
	(0.08)	(0.08)	(0.09)	(0.07)	(0.06)	(0.07)	(0.08)	(0.07)	
Luxembourg	0.51***	0.61***	0.53***	0.57***	0.52***	0.39***	0.45***	0.43***	9
	(0.09)	(0.07)	(0.04)	(0.06)	(0.08)	(0.08)	(0.06)	(0.08)	
Mexico	0.59***	0.40**	0.62***	0.40***	0.88***	0.93***	0.97***	1.01***	9
	(0.12)	(0.13)	(0.07)	(0.07)	(0.12)	(0.13)	(0.09)	(0.10)	
Netherlands	0.36***	0.62***	0.35***	0.45***	0.17***	0.27***	0.12	0.19***	9
	(0.09)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.07)	(0.05)	
Norway	-0.15**	0.27***	-0.21**	0.19***	-0.32***	-0.03	-0.43***	-0.21***	9
	(0.05)	(0.06)	(0.07)	(0.02)	(0.05)	(0.04)	(0.08)	(0.08)	
Poland	0.39***	0.43***	0.40***	0.36***	0.42***	0.49***	0.52***	0.56***	6
	(0.06)	(0.08)	(0.06)	(0.08)	(0.05)	(0.09)	(0.06)	(0.10)	
Sweden	-0.21***	0.08	-0.23***	-0.02	-0.18**	0.02	-0.16	0.00	8
	(0.03)	(0.12)	(0.02)	(0.18)	(0.06)	(0.04)	(0.17)	(0.14)	
Slovenia	0.32**	0.30*	0.08	0.16	0.36***	0.35**	0.12	0.12	6
	(0.07)	(0.14)	0.10	0.10	(0.04)	(0.12)	(0.09)	(0.09)	
Taiwan	0.07	0.15**	0.02	0.13	0.07*	0.02	0.02	0.01	10
	(0.05)	(0.05)	(0.04)	(0.08)	(0.03)	(0.04)	(0.02)	(0.04)	
United Kingdom	0.14**	0.52***	0.28***	0.51***	0.13*	0.22***	0.25***	0.18***	11
	(0.06)	(0.03)	(0.03)	(0.04)	(0.06)	(0.02)	(0.03)	(0.02)	
United States	0.07**	0.28***	0.18**	0.37***	0.04	0.04***	0.05	0.03**	11
	(0.03)	(0.04)	(0.07)	(0.04)	(0.05)	(0.01)	(0.11)	(0.01)	

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

Figure I.2 : LIS Additional Countries, Labour Income (Men)

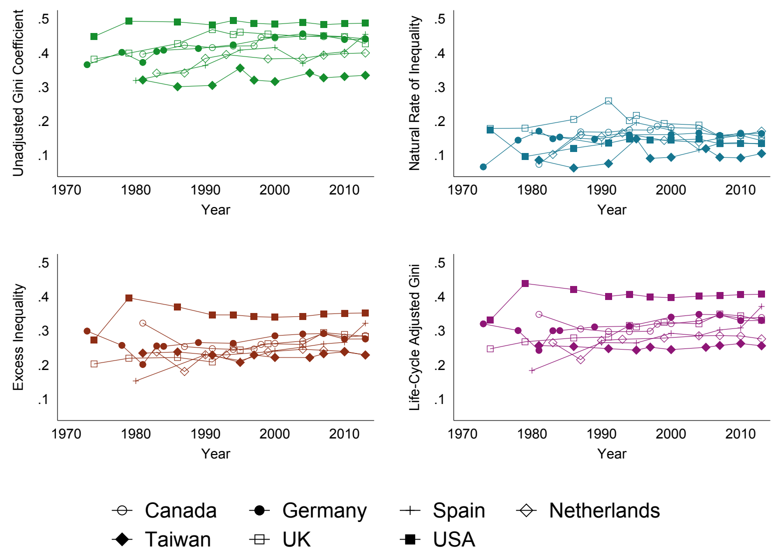


Source: Authors' calculations using LIS data.

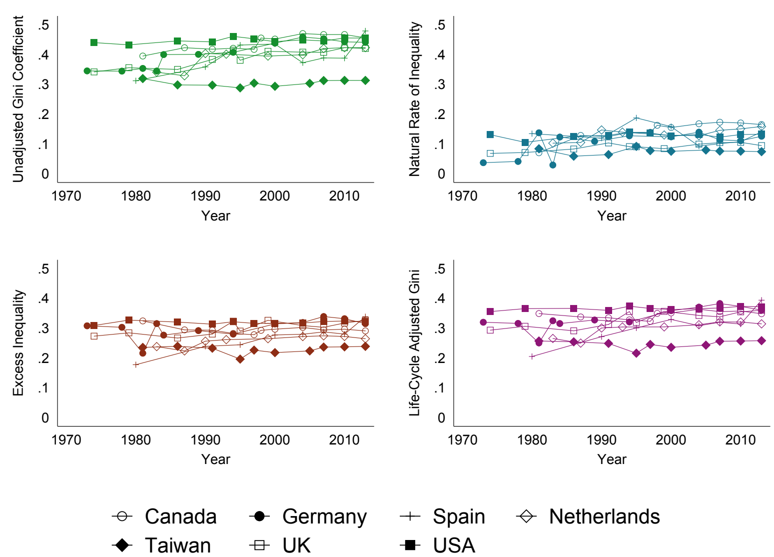
Notes: These are the countries for which a sufficient time series is available not reported in Figure 11. Note that, however, data for these other countries are not consistently classified as gross or net. Most datasets are classified as Gross. France is all classed as mixed and Slovenia is classed as 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.

Figure I.3 : LIS Selected Countries (Women)

(a) Adjusted and Unadjusted Gini of Total Income: Selected Countries: 1973-2014 (Women)



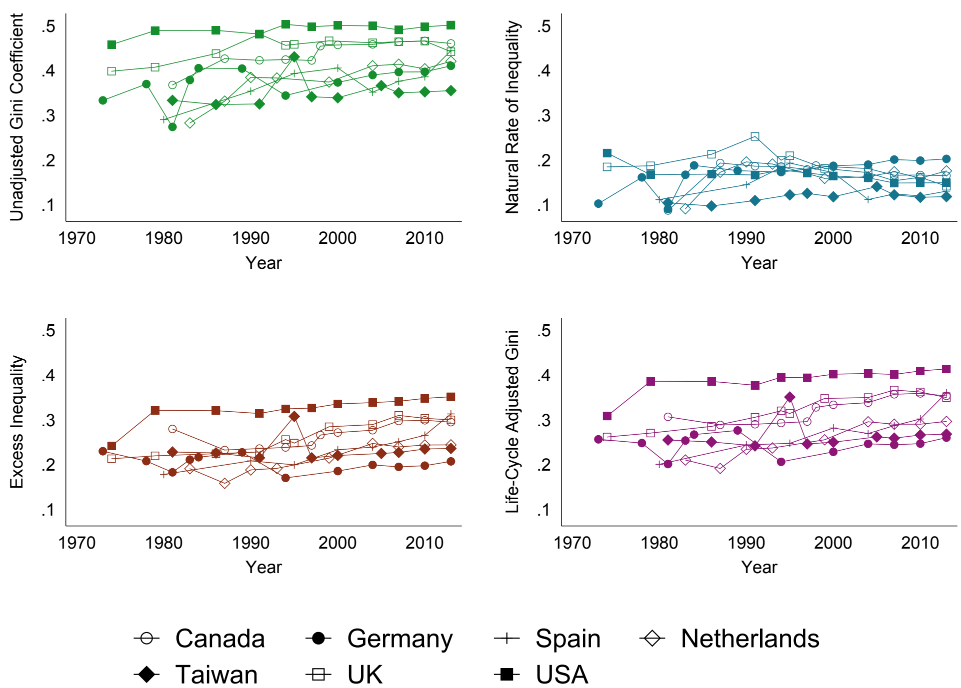
(b) Adjusted and Unadjusted Gini of Labour Income: Selected Countries: 1973-2014 (Women)



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 for Labour Income which is in panel (b) and ages 18-78 for total income in panel (a), and who have positive earnings for both graphs. Results are calculated using individual level weights.

Figure I.4 : Adjusted and Unadjusted Gini of Total Income: Selected Countries: 1973-2014 (Men)



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.