Global Trends in Income Distribution across age groups?

Gabriele Guaitoli[*] Roberto Pancrazi[†]

University of Warwick University of Warwick

September 18, 2023

Abstract

We document the evolution of the income distribution across age groups using harmonised microdata from 28 countries at different stages of economic development. The average disposable income of late-career age group relative to early-career age group has increased by 20 per cent in richer countries, and it has declined by 15 per cent in poorer countries in the last 20 years. These opposite trends are strong and statistically significant. We highlight that the main contributors of those shifts relate to labour market dynamics. Specifically, in rich countries, employment rates and salaries are disproportionally augmenting the income of the old compared to the young, while in poorer economies, salaries are growing faster for the young. These results do not depend upon the composition of the workforce (gender and education). Through a panel regression, we suggest the relevance of three main forces related to ageing, education, and political economy factors.

Keywords: Age group income, growth decomposition, income distribution, cross-section.

JEL Classification: E24, J31, O57

[*]E-mail: g.guaitoli@warwick.ac.uk

[†]Corresponding author: Roberto Pancrazi, Department of Economics, University of Warwick, United Kingdom; E-mail address: R.Pancrazi@warwick.ac.uk. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. Declarations of interest: none.

1 Introduction

The increase in income differences between old and young, in favour of the former, has recently risen to prominence in many countries political and media debates. For example, policymakers such as the House of Lords in the UK or the European Commission in the EU have produced in-depth reports on this topic (House of Lords, 2019; Raitano et al., 2021), highlighting that *"the young are facing a future of low pay, high rent, and few incentives"* and that they are *"struggling to find secure, well-paid jobs"*. At the same time, more and more institutions have invested in studying this issue for specific countries (e.g. (Masson, 2021) for France, (Barra et al., 2021) for Ireland, (Berry and Sinclair, 2010), (Miller et al., 2020) for Australia, and (Henehan et al., 2021) for the UK). The topic has increasingly attracted attention also in the academic literature (see the Related Literature section below). Although issues related to the unequal distribution of income across age groups generate understandable concerns, many dimensions of this phenomenon still need to be well-understood and investigated. One of the main obstacles is its complexity and, consequently, the difficulties of assessing the magnitude of the phenomenon in different countries in a comparable and meaningful way. In this context, two questions still need to be answered. First, how globally widespread is the increase in income differences between old and young? And second, are there statistical regularities that might shed light on its drivers?

In this paper, we address these questions by conducting a *global*, *coherent*, and *in-depth* analysis of one specific dimension related to age group income inequality, which is how disposable income is distributed across different age groups in a given point in time and how that distribution has evolved. We leverage income microdata – which comes from income, labour force, or permanent population surveys – harmonised in the Luxembourg Income Study Database (LIS) to create a coherent dataset for 28 countries in the period 2004-2018. For this purpose, we define and analyse the *Age Group Income Ratio*, (henceforth, *AGIR*), which captures with a simple number the relative average disposable income of two age groups in any given period. There are three main advantages of using this statistic. First, it has a straightforward interpretation, as it highlights how resources are distributed, in a given period, among different segments of the population related to their age. Second, it allows for clear comparisons across both time and space. Third, it can be easily decomposed to highlight the contribution of individual income components toward the uneven evolution of the income distribution across-age groups. Therefore, we can quantify how much of its observed changes are due to labour remunerations, employment rates, transfers, or taxes.

We provide two main contributions. First, we establish novel stylized facts about the global income distribution trends across age group. We focus on two age groups: early-career individuals (aged 25-34) and late-career individuals (aged 50-64). We choose these two age groups because they reflect individuals that have already completed their education and are at opposite ends of their career paths, having recently started (25-34) or approaching retirement age (50-64). This choice allows us to highlight, in a coherent way, how labour market dynamics have had heterogeneous effects on the evolution of income, even between younger and older workers. We show that:

(i) in the last 20 years, the late-career/early-career $AGIR$, defined as the average disposable income of late-career individuals relative to early-career individuals, has evolved in opposite directions in richer and poorer countries. In the former, the $AGIR$ has steadily risen by almost 20 per cent, from 1.10 to 1.30; in the poorer economies, it has steadily declined by around 15 per cent, from 1.20 to 1.05.

(ii) in rich countries, the main contributor to the increased $AGIR$ is the divergence in employment rates (increasing for older individuals, stagnating for younger individuals), while in lower-income countries, the main contributor to the fall in $AGIR$ is the faster labour earning growth of the young with respect to the old.

Therefore, our paper highlights that the divergence path of average disposable income between late-career and early-career individuals is mainly driven by labour market forces rather than by changes in pensions or fiscal policies. In addition, we show that the stylised facts above also hold for different demographic subsets of the population, regardless of their gender or education level.

Our second contribution is to suggest possible channels for understanding the stylised fact above. Through a panel regression, we present suggested evidence – in terms of correlation, not causality – for three main forces: the first one is the role of ageing, the second one relates to the education boom experienced in the last decade in the industrialized countries, and the third one relates, broadly, to political economy factors. We show that these variables explain alone around 50 per cent of the time- and cross-country variation of $AGIR$ and they entirely absorb its link with GDP.

Related Literature Age group income dynamics have been discussed for decades. During the 1970s and 1980s, economists focused on the "baby-boom" generation's ingress in the labour market, which increased the relative supply of young, inexperienced labour (Welch, 1979; Levine and Mitchell, 1988). Since economists tried to explain the consequent wage trends with the imperfect substitutability of labour inputs with different tenure/experience, many concluded that the wages of the successive, smaller cohorts were set to grow faster once the ageing baby boomers created an excess of "experienced" labour supply. However, as (Bianchi and Paradisi, 2023) noted for Italy and as we document for most advanced economies, this does not seem to have been the case. Even if the price of experience is affected by its relative supply (Jeong et al., 2015), this channel appears to have been dominated by other opposing forces. We show that those opposing forces have even strengthened in the last two decades in all advanced economies, to the point that the disposable income of late-career individuals is now 30% higher (starting from 10% higher in the early 2000s) than the one of the early-career individuals. This trend has been analysed only for individuals countries by (Rosolia and Torrini, 2007) and (Naticchioni et al., 2016) for Italy, (Guvenen et al., 2022) for the U.S., and (Cribb, 2019) for Britain. (Bianchi and Paradisi, 2023) studies age-wage inequalities in a set of high-income countries (with administrative data for Italy and Germany), while (Freedman, 2017) uses a similar set to study cohort trends. We contribute by providing further international evidence. Since our data covers not only advanced economies, but also Eastern Europe, and South America, we are able to uncover the divergent trend in age inequalities across high and low-income countries.

Another important contribution of our paper to the existing literature is our focus on the income subcomponents. The majority of the papers mentioned above have focused on the relative earnings or wages of employed individuals (Bianchi et al., 2022; Bianchi and Paradisi, 2023; Bennett and Levinthal, 2017; Beaudry et al., 2014). However, we show that most of the shifts in the distribution of disposable income across age groups in rich countries have been determined by a faster rise in *employment* among older individuals than among younger ones, and not only by increasing differences in earnings conditional on being employed. Researchers should be careful when drawing generalised conclusions from the dynamics of the age-*wage* gap, as it may not reflect the dynamics of the overall age-*income* gap, nor that of sub-populations.

Finally, our reduced-form results provide suggestive evidence for the international importance of channels studied, causally but often for single events/countries, by other contributions such as (Bianchi et al., 2022), (Boeri et al., 2022) and (Ferrari et al., 2023) (changes in retirement age increase the income of the old, delay hiring of the young), (Adao et al., 2023) (skill-biased technical transitions in the '70s favoured the then-young, now-old cohorts), and (Guvenen et al., 2013) (taxes affect human capital accumulation).

Paper organisation. The rest of the paper is organised as follows. In Section 2, we present the data and define the underlying economic variable of interest. In Section 3, we derive two novel stylised facts about how disposable income is distributed across age groups across countries and how that distribution has evolved in the last 25 years. In Section 4, we propose possible explanations of the evidence presented in the previous sections. Section 5 sums up our results and discusses future avenues of research.

2 Data, income, and its subcomponents

In this section, we first describe the data and then carefully define the underlying economic variables of interest, i.e., disposable income and its subcomponents.

2.1 Data

We use harmonised microdata provided by the Luxembourg Income Study (LIS), a data archive and research centre that collects, harmonises and distributes microdata in order to *"enable, facilitate, promote, and conduct cross-national comparative research on socio-economic outcomes"* (Luxembourg Income Study (LIS) Database, 2021). These data are collected from national surveys or derived from administrative data. They are then harmonised following a framework that aims to create variables representing the same income and categorical concepts, as well as to clean the datasets' errors and inconsistencies. The LIS dataset contains information for 53 countries, with the number of available annual surveys for each country ranging from one (Palestine) to 45 (UK).

From the LIS database, we select all countries that satisfy the following four data availability and consistency criteria.

1. **Individual-level data**. We keep only country-year data points with individual-level income data. Since we aim to compare the income of young and old individuals, datasets that only report household-level income are unsuitable for our goals.

2. **Long time series**. To perform a coherent analysis on the, at least, medium-term trends in age inequalities, we need a long enough time series (for each country) located approximately within the same time frame (across countries). Thus, we discard all countries that do not have at least one survey between 2004 and 2006 and one between 2015 and 2018.

3. **Consistent income definition**. When a country changes its income reporting scheme (gross, net, or mixed) across data points, we only keep the surveys whose income reporting approach has the largest number of observations between 2004 and 2018. We always drop all data points using a "mixed" reporting approach.

4. **Further cleaning**. After step (3), we discard all countries with insufficient surveys to satisfy criterion (2). Finally, we drop Luxembourg, where a larger part of the workforce does not reside in the country, making it unsuitable for our analysis.

This procedure leaves us with 28 countries and 306 country-year surveys collected between 2004 and 2018. We transform all income variables into real terms (by CPI) and PPP, allowing for a cross-country and cross-period comparison.

Waves. The dataset composed of country-year observations is unbalanced because only some of the countries are surveyed in the same years. To overcome possible related issues, we group yearly surveys into five *waves*, i.e. 3-year windows starting from 2004 (i.e. 2004-2006, 2007-2009, 2010-2012, 2013-2015, 2016-2018). All our countries have at least one observation per wave, apart from Serbia and Slovenia, which are missing one wave each. We create country-wave data by merging all yearly surveys within a wave (if more than one exists), giving equal weight to each yearly survey. This procedure yields 138 country-wave surveys and composes an almost perfectly balanced panel.

TABLE I. Summary of the data

Country	**Observations**	**First Year**	**Last Year**	**Years**	**Waves**
Australia	160,050	2004	2018	6	5
Austria	167,497	2004	2018	15	5
Belgium	162,608	2004	2017	14	5
Brazil	1,466,602	2006	2016	5	5
Canada	802,049	2004	2018	15	5
Chile	1,091,258	2004	2017	6	5
Colombia	7,915,257	2004	2018	15	5
Czech Republic	80,831	2004	2016	5	5
Denmark	735,845	2004	2016	5	5
Finland	104,274	2004	2016	5	5
France	1,296,110	2004	2018	15	5
Germany	424,596	2004	2018	15	5
Ireland	148,980	2004	2018	15	5
Israel	252,068	2004	2018	15	5
Italy	84,472	2004	2016	5	5
Mexico	778,487	2004	2018	9	5
Norway	1,618,510	2004	2016	5	5
Paraguay	238,322	2004	2018	15	5
Peru	1,062,822	2004	2018	15	5
Poland	1,269,373	2004	2018	15	5
Serbia	50,526	2006	2016	4	4
Slovakia	123,090	2004	2018	9	5
Slovenia	47,700	2004	2015	5	4
Spain	590,594	2004	2015	15	5
Switzerland	182,877	2006	2018	13	5
United Kingdom	614,202	2004	2018	15	5
United States	2,187,365	2004	2018	15	5
Uruguay	1,455,840	2004	2018	15	5
Total	25,112,205			306	138

Note: countries are listed in alphabetical order. "Observations" refers to the number of individual observations after the data selection procedure described in the main text. "First Year" and "Last Year" refer to the first and last year of surveys considerd in our chosen sample. The first year will be denoted as T_i and the last year as $T_i + h_i$, where i is the country-specific index. "Years" illustrates the number of surveys available for each country in our sample. The maximum number of datapoints a country can have, given our sample selection, is 15. "Waves" indicates the number of waves, i.e. three-years intervals described in the main text, observed for each country. The maximum number of wave datapoints a country can have, given our sample selection, is 5.

Table I reports summary statistics for the dataset. In the first column, we list the 28 countries that satisfy the criteria described above. In the second column, we report the total number of individual observations available for each country; they vary from about 47 thousands for Slovenia to almost 8 millions for Colombia. The third and fourth column report the first and last year in our chosen sample. The fifth column reports the number of annual surveys years observed in our sample for each country. Finally, the sixth column reports the number of waves for each country. Table IV of Appendix A reports further details.

2.2 Income definition and its subcomponents

We now illustrate our observed variables of interest from the LIS dataset. Let us first define the theoretical disposable income of an individual q (in a given year/wave and a given country), denoted $\hat{y}_q$, as:

$$\hat{y}_q \equiv y_q^g + y_q^k + \hat{\Theta}_q^g - \hat{\tau}_q,$$

where y_q^g denotes gross labor income, y_q^k denotes gross capital income, $\hat{\Theta}_q^g$ denotes gross transfers, and $\hat{\tau}_q$ denotes taxes. Because all the variables in this subsection should be interpreted at a given time, we have omitted the time subscript for convenience.

The LIS dataset with observations at the individual level provides an approximated measure of the theoretical disposable income, i.e.:

$$y_q = y_q^g + \Theta_q^g - \tau_q, \tag{1}$$

where y_q^g denotes observed labour income, and Θ_q^g is an observed approximated measure of transfers, i.e. the payments received for a subset of transfers, namely: pension payments, unemployment benefits and (when available) scholarships and paid maternity/paternity leave. Notably, capital income is not available at the individual level. The lack of information about this income dimension does not present a critical problem for our analysis for two reasons. First, even omitting this channel, we will show that the data provide important insights into the role of the labour market for the age income distribution. Second, we believe that, if anything, excluding capital income from the analysis leads to underestimating the stylised facts presented in the next section since, at least in industrialised countries, wealth has become more concentrated towards the older age groups.[1]

[1] While statistics about wealth-age distribution are not homogenous across countries, there is evidence that, at least in industrialised countries, wealth has become more concentrated towards the older age groups. In the US, from 2003 to 2018, the age group 55-69 has increased their share of wealth from 36 to 44 per cent, while the age group under 40 has decreased from 8.1 to 5.6 per cent (source: Distributional financial account data, Board of Governors of the Federal Reserve system. In Italy, from 1991 to 2010, the share of the wealth of households whose head was in the age group 55-64 increased from 18 to 24 per cent, while the ones whose head was in the age group 35-44 decreased from 19 to 16 per cent (source:(Colombo et al., 2014)). In Australia, from 2003, the total wealth of the age group over 65 increased from 26 per cent higher than average to 34, while the total wealth of the age group under 35 decreased from 64 lower than average to 70 per cent (source: ABS Surveys of Income and Housing). In Canada, in 1999, the total net worth of the age group 55-64 relative to the age group under 35 was 2.7, while the same ratio was 4.4 in 2019 (source: Survey of Financial Security, Statistics Canada). For each of these countries the share shifts in wealth in favour of the older age group are sensibly larger than the observed share shift in the demogrographic composition.

Finally, notice that τ_q, the observed measure of taxes, does not include taxes on capital income and other transfers.

Some countries report only net income data.[2] In this case, the observed individual disposable income is:

$$y_q = y_q^n + \Theta_q^n, \tag{2}$$

where the over script n indicates that the data are net instead of gross.
In the LIS database, we observe y_q for each individual, as well as each component on the right-hand side of equations (1) or (2). Throughout the rest of the paper, we will refer to the variable y_q as *disposable income.*

Income Decomposition Starting from the observed individual disposable income, defined in equation (1) and (2), and ignoring time and country indices, we can specify what is the country *average* disposable income, y, at a given period. For the countries for which gross income and taxes are available, it is:

$$y = ey^g + p\Theta^g - \tau, \tag{3}$$

where y^g denotes average labour earning, i.e. gross labour income conditional on being employed, e is the share of employed individuals, p denotes the share of individuals receiving any transfer, Θ^g denotes the average amount of gross transfers conditional on receiving a non-zero value, and τ denotes taxes.

For the countries that do not have data on gross labour earnings and for which we cannot separately isolate the role of taxes, their measure of *average* disposable income is:

$$y = ey^n + p\Theta^n$$

where y^n denotes the average net labour earnings, conditional on employment, and Θ^n denotes the average net transfer amount conditional on receiving a non-zero value.

[2] See Table in Appendix A for the list.

3 Novel Stylized facts on the income distribution across age group

We use the LIS data presented above to draw a novel picture of how disposable income is distributed across age groups in each country and how that distribution has evolved in the last 20 years. We will derive two novel stylized facts.

3.1 Age Group Income Ratio

As a parsimonious statistic of the income distribution between age groups, we consider the ratio of the average disposable income between two age groups at a given period: we refer to this statistic as the *Age Group Income Ratio* or *AGIR*. For a given country, and ignoring the country index, define as $y_{j,t}$ its average disposable income for age group j at time t, that is:

$$y_{j,t} = \frac{1}{N_{j,t}} \sum_{q \in \mathcal{Q}_{j,t}} y_{q,t},$$

where the average is taken for the individuals q belonging to the age group j. The set of all individuals of age group j at time t is defined as $\mathcal{Q}_{j,t}$, and it contains $N_{j,t}$ elements.

For any two age groups j and j' with average disposable income $y_{j,t}$ at time t, we denote their *AGIR* as $R^j_{j'}(t)$:

$$R^j_{j'}(t) = \frac{y_{j,t}}{y_{j',t}}.$$

With a simple number, this statistic captures the income relation between two age groups in any given period. Moreover, since an age group includes all individuals of that age, regardless of employment status, this measure provides a broad picture of how *overall* income is distributed between age groups at a given time.

Our analysis will consider two benchmark age groups: individuals aged 50-64 (late-career working-age individuals, LC) and individuals aged 25-34 (early career, EC). We choose these two age groups because they reflect individuals that have already completed their education and are at opposite ends of their career paths, having recently started

(25-34) or approaching retirement age (50-64). We often refer to these two age groups as the old and the young.

As a preliminary illustrative step, in Figure 1 we plot the evolution of the $AGIR$ between late-career and early-career individuals for two sets of countries, richer and poorer. The two groups are defined by applying a k-means clustering, with $k = 2$, based on the first observation of the GDP (PPP-real, per-capita), which corresponds to the 2004 observation for all the countries, except for Serbia, whose first observation is in 2006. The resulting classification is consistent with the 2006 IMF classification (International Monetary Fund, 2006).[3] The reported statistics are the unweighted average of $AGIR$ across countries of each group. The left panel displays the average $AGIR$ among the two subsets of countries for the five waves of surveys between 2004 and 2018, as described in the previous section. The right panel displays the average $AGIR$ among the two sub-groups of countries at an annual frequency. The solid red line displays the average $AGIR$ among poorer countries, and the dashed blue line reports the one among richer countries.[4]

The figure reveals two facts. First, at the beginning of the 2000s, the $AGIR$ in poorer countries was slightly larger than in richer countries. In poorer countries, the late-career age group's disposable income was 20 per cent higher than the early-career age group, while in richer countries, it was 12 per cent higher. Second, and most importantly, the average disposable income of the older age group relative to the younger one displays diverging trends for the two subsets of countries. In richer countries, the $AGIR$ displays a solid upward trend, increasing by 20 percentage points; in poorer countries, the $AGIR$ displays a downward trend, decreasing by 15 percentage points. Notice that the pattern of the $AGIR$ in the two subsets of countries is relatively smooth and does not display sizeable cyclical fluctuations.[5] Therefore, it makes sense to interpret the observed pattern

[3]The two groups are defined as follows. Richer countries: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Norway, Slovenia, Spain, Switzerland, United Kingdom, United States. Poorer countries: Brazil, Chile, Colombia, Mexico, Paraguay, Peru, Poland, Serbia, Slovakia, Uruguay.

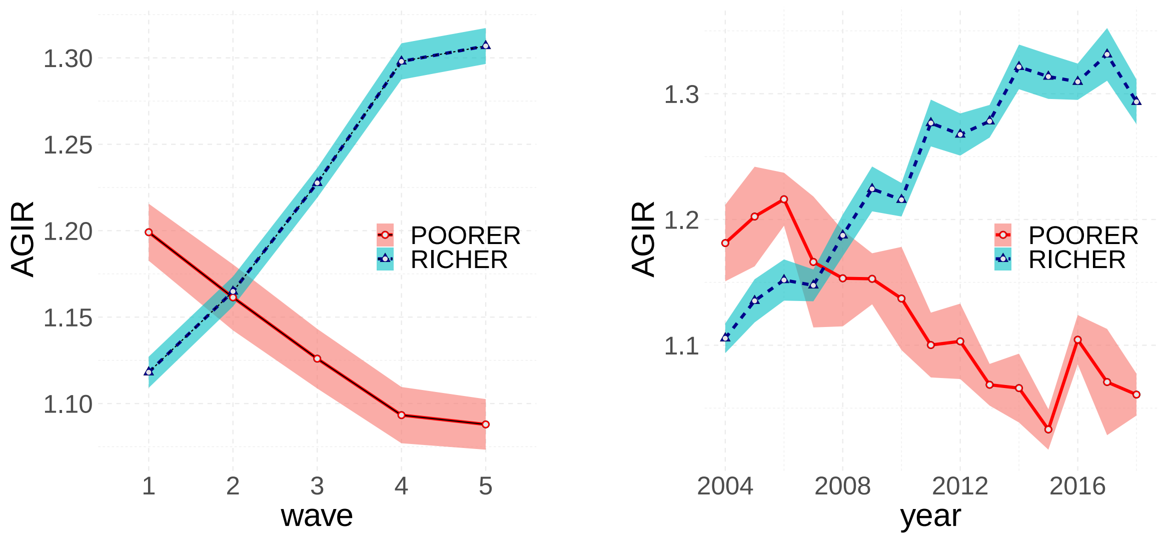
[4]The confidence bands represent the +2/-2 standard errors interval. Standard errors are computed with the delta method from the standard errors of the average income by age group for each country/year(wave) survey.

[5]Notice that the yearly plot is more volatile because, due to the unbalanced panel, countries might enter and exit the calculation from one year to another.

as a *trend* rather than as an outcome of cyclical fluctuations.

Figure 1. $AGIR$, 50-64 vs 25-34 years old

(a) Across five waves (b) Across years



Note: The figure depicts the Age Group Income Ratio ($AGIR$) between late-career individuals (50-64 years old) and early-career individuals (25-34 years old). The lines represent the simple average across countries of a given group (dashed blue for richer countries, solid red for poorer countries). The shaded area represents the 95% Confidence Interval of the mean of the two groups, calculated with the delta method from the standard errors of each average age group income mean. The countries used for these calculations are reported in Table I.

We now statistically corroborate the illustrative evidence of diverging trends in $AGIR$ between richer and poorer economies. Specifically, we first run the following regression:

$$log(R_{i,t}) = \alpha + \tilde{\alpha}\mathbb{1}_i^d + \beta t + \tilde{\beta}(\mathbb{1}_i^d \times t) + \varepsilon_{i,t}. \tag{4}$$

Here, $R_{i,t}$ denotes the $AGIR$ computed for the age group 50-64 and 25-34, i denotes the country index, $\mathbb{1}_i^d$ is a dummy variable that takes the value of 1 if country i belongs to the richer group and 0 otherwise, The time variable t takes values in $[0, 1, .., 4]$ when we consider wave observations and takes the value $[0, 1, .., 14]$ when we consider annual observations. Accordingly, α represents the average value of $\log(AGIR)$ at the beginning of the 2000s for the poorer countries, $\tilde{\alpha}$ is the additional initial average $\log(AGIR)$ for the richer countries, β is the average time trend for the poorer countries, and $\tilde{\beta}$ is the additional time-slope for richer countries.

Columns (1) and (6) of Table II report the results for years and waves, respectively.

At the beginning of the 2000s, the *AGIR* in the poorer countries is larger than in richer countries ($\tilde{\alpha} < 0$)- albeit significantly only for the wave-observations-, but the trends are quite different. In fact, in poorer countries, the *AGIR* time trend is negative (-2.4% per year) and turns strongly positive (4.1% per year) in richer countries. Notice that because each wave consists of three years, the magnitude of the trend coefficients in column (6) is similar to the one in column (1).

The above results do not depend on our classification of the countries in the "richer" and "poorer" subsets. To show that, we perform the same analysis while relaxing this rigid division. In particular, we estimate the effect of the initial log-GDP level on the magnitude of the *AGIR* trend. For this purpose, we run the following regression:

$$log(R_{i,t}) = \alpha + \theta\overline{GDP}_{i,0} + \beta t + \gamma(\overline{GDP}_{i,0} \times t) + \varepsilon_{i,t} \quad (5)$$

Here, $\overline{GDP}_{i,0}$ denotes the deviation of the initial log-GDP for each country from the cross-section sample mean. Accordingly, α should be interpreted as the beginning of the sample log($AGIR$) for a country with initial log-GDP equal to the cross-section mean, θ is the elasticity of *AGIR* to a change in initial GDP, β is the *AGIR* time-trend for a country with initial log-GDP equal to the cross-section mean, and γ is the additional slope of the time trend correlated to cross-country variation of initial GDP.

Columns (2) and (7) of Table II report the estimates for years and waves. The beginning of sample *AGIR* for a country with average initial GDP ($exp(\alpha)$) was around 1.13, and the correlation between initial *AGIR* and initial GDP level is negative (but not strongly significant), which confirms that richer countries had lower initial *AGIR*. In addition, the estimates of the time trend for a country with average initial GDP, β, is slightly positive, and the compounded trend effect of initial GDP deviation, γ is strongly positive. This fact implies that countries much poorer than average at the beginning of the 2000s (negative log-GDP in deviation from the mean) have experienced a decrease in *AGIR*. In contrast, countries much richer than average have experienced increased *AGIR*. The last four rows of the Table report the non-linear trend effects along the initial GDP distribution. When moving from the poorer to the richer countries, the time trend of *AGIR* grows monotonically from -4.4% per wave (or -1.5% per year) to 5.1% per wave (or +1.6% per year). These estimates were computed using OLS. In addition, one could account for the uncertainty derived by the fact that the dependent variable is computed as a non-linear function of country averages, i.e. the average income of late-career and early-career individuals in each country, which can be estimated more or less precisely depending on the underlying income distribution and the number of observations for each country-year(wave) survey. To account for the role of uncertainty, in columns (3) and (8), we estimate the model using a weighted least-square estimator, with the weights equal to the inverse of the standard errors of $\log(AGIR)$ computed with the delta method from the standard errors of each country-year(wave) estimated average age group income. The results are identical to the OLS ones. For completeness, columns (4) and (9) report the regression estimates with all second-order terms. They confirm the results already stated. Finally, we highlight that the time trends in the *AGIR* are not shared by similar trends in the second moments of the age group income distribution. For this purpose, in columns (5) and (10), we conduct the same regression as in equation (5) by considering, as the dependent variable, the ratio of the coefficient of variations of disposable income computed for the late-career and early career individuals. This measure, denoted by *AGcvR*, captures the relative variance of the two distributions that account for the mean changes.[6] The data do not display any time trend in the second moments, motivating our focus on AGIR.

These observations lead to the first stylized fact.

Stylized fact 1 In the last 25 years, the *AGIR* has evolved in opposite directions in richer and poorer countries: in the former, the *AGIR* has steadily risen by around 20 per cent, while in the latter economies, it has steadily declined by around 15 per cent. These trends are smooth and statistically different.

[6] The coefficient of variation of disposable income for an age group j is the ratio of the standard deviation of disposable income for that age group divided by its average. The *AGcvR* is the ratio of the coefficients of variation so computed for the late-career and early-career age groups.

TABLE II. Trend in AGIR

	Waves					Years				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent	log(AGIR)	log(AGIR)	log(AGIR)	log(AGIR)	log(AGcvR)	log(AGIR)	log(AGIR)	log(AGIR)	log(AGIR)	log(AGcvR)
[1] β: Trend	-0.024*	0.017**	0.009	0.025	0.024	-0.010***	0.005**	0.003*	0.010*	0.003
	(0.012)	(0.007)	(0.007)	(0.027)	(0.016)	(0.003)	(0.002)		(0.006)	(0.003)
[2] $\tilde{\beta}$: Trend × Richer	0.066***					0.023***				
	(0.015)					(0.003)				
[3] $\tilde{\alpha}$: Richer	-0.055					-0.063**				
	(0.039)					(0.027)				
[4] γ: Trend × Initial log-GDP(Dev)		0.044***	0.042***	0.044***	-0.027		0.015***	0.014***	0.015***	-0.002
		(0.012)	(0.011)	(0.012)	(0.026)		(0.002)	(0.002)	(0.002)	(0.005)
[5] θ: Initial log-GDP (Dev)		-0.032	-0.034	-0.008	0.053		-0.037*	-0.039*	-0.021	0.041
		(0.029)	(0.029)	(0.033)	(0.065)		(0.020)	(0.021)	(0.023)	(0.044)
[6] α: Constant	0.165***	0.130***	0.146***	0.104***	0.216***	0.174***	0.133***	0.145***	0.107**	0.261
	(0.031)	(0.018)	(0.018)	(0.026)	(0.041)	(0.022)	(0.013)	(0.013)	(0.020)	(0.029)
Weights	No	No	Yes	No	No	No	No	Yes	No	No
Second order terms		No	No	Yes	No		No	No	Yes	No
Observations	138	138	138	138	138	306	306	306	306	306
R^2	0.20	0.18	0.17	0.19	0.02	0.26	0.22	0.20	0.22	0.00
F-Test:[1]+[2]=0 or [1]+[4]=0	18.68***	18.55***	15.09***		0.00	44.18***	43.51***	34.86***		0.01
Trend effect at min GDP	-0.024*	-0.044**	-0.048***	-0.041**	0.06	-0.009***	-0.015***	-0.016***	-0.015***	0.007
Trend effect at 25% GDP	-0.024*	-0.003	-0.001	-0.000	0.037	-0.009***	-0.001	-0.003*	-0.002	0.005
Trend effect at 75% GDP	0.041***	0.037***	0.028***	0.040***	0.012	0.013***	0.011***	0.009***	0.011***	0.002
Trend effect at max GDP	0.041***	0.051***	0.042***	0.054***	0.003	0.013***	0.016***	0.014***	0.016***	0.001

Note: Columns (1) and (6) report the estimates of equation (4) for yearly and wave observations, respectively. The other columns report the estimates of equation (5). Columns (3) and (8) use a weighted-least-squared estimator, with the weights equal to the inverse of the standard error of each country-year(wave) observation computed with the delta-method. Columns (4) and (9) includes all of the second-order terms. Finally, columns (5) and (10) use the ratio of the coefficient of variations for the two age groups of interest as dependent variable.

3.2 Growth Rate Differentials

The evolution of the *AGIR* in the last two decades displays a clear time trend and does not display cyclical fluctuations. These facts allow us to introduce another statistic of interest: the difference between the growth rate of disposable income of different age groups from the beginning to the end of the sample. We label this statistic as *growth rate differentials*, *GRD*, and has three advantages. First, as a preliminary step, it allows us to investigate how income has changed for each age group; second, it directly relates to the evolution of the *AGIR*; and third, it can be easily decomposed to investigate the source of its evolution.

Consider the average disposable income for a specific age group j at a given period t, denoted by $y_{j,t}$. The country i's age group j's income growth rate, annualized, between period T_i and $T_i + h_i$ is:

$$g_i(y_j) = \frac{1}{h_i}\left(\frac{y_{j,T_i+h_i}}{y_{j,T_i}} - 1\right),$$

where $y_{j,T}$ denotes average income in period T for age group j. Let us drop the country index, i, for the sake of notation. Then, the *GRD* is simply the difference of the annualized growth rates for two different age groups, i.e. $g(y_j) - g(y_{j'})$. This statistic approximates the growth rate of the *AGIR*:[7]

$$GRD \equiv g(y_j) - g(y_{j'}) \approx \frac{\Delta R^j_{j'}}{R^j_{j'}(T)}. \tag{6}$$

Furthermore, the *GRD* has the desirable property that it can be easily decomposed in the contribution of different sub-components of income, allowing us to dig deeper into the causes of the changes in intergenerational inequalities. We will discuss this point in Section 3.3.

As a first illustrative step, we compute the age group-specific disposable income growth rates and their differential. For each country i, we consider the disposable income at two data points, T_i and $T_i + h_i$, between 2004 and 2018.[8] As in the previous section, we focus on the 50-64 (late-career) and the 25-34 (early-career) age groups.

[7] See Appendix B for the derivation.

[8] For each country, the first observation is set in Wave 1 (2004-2006), while the second observation is in Wave 5 (2016-2018). Since we do not have data available for each country at each year, the initial period T_i and the final period $T_i + h_i$ and, therefore, their gap h_i are country-specific.

In Figure 2a, we display the average growth rates for early-career individuals (green, left bar) and for late-career individuals (purple, right bar). The countries are ordered from left to right in descending order according to their initial PPP GDP per capita. The vast majority of richer countries have registered a stagnant income growth for the younger individuals and a positive, considerably larger income growth for the older ones. In contrast, the early-career age group has experienced a much larger income growth in the poorer economies.

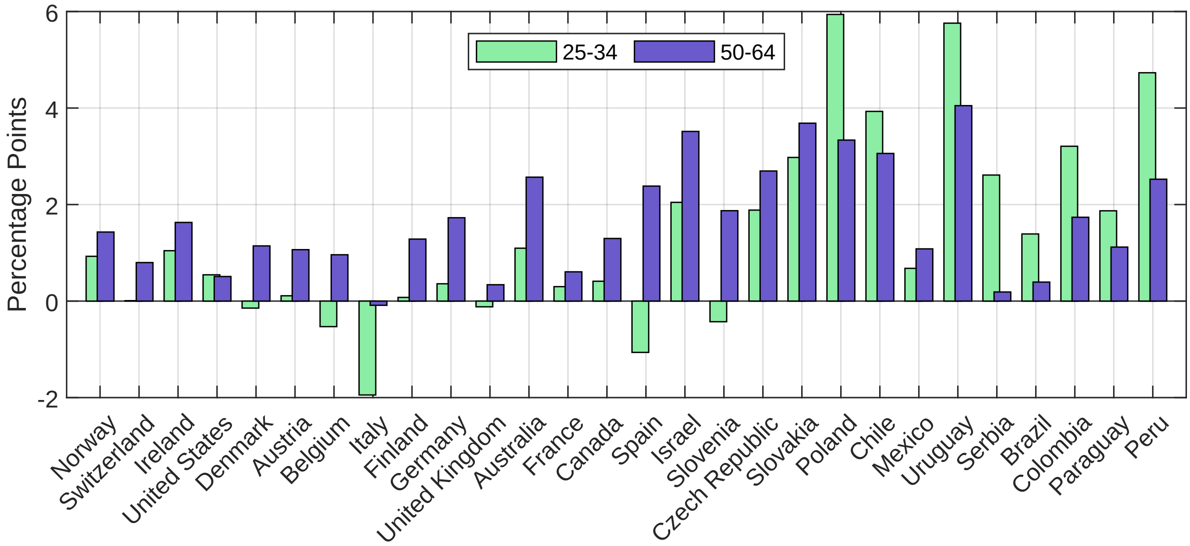
In Figure 2b we display the growth rate differentials, which are simply the difference between the two age groups' income growth rates. Consistently with the evidence provided about the evolution of the $AGIR$, the GRD are positive for all rich countries except for the US, while negative for most poorer economies. For 19 out of 29 countries, the GRD are statistically different from zero, with 95 per cent confidence.

This relationship between income groups and GRD can be better visualised in Figure 3, which plots the GRD against the GDP per capita, in log, of each country at the beginning of the sample. The GRD shows a strong positive correlation with the GDP level (Pearson = 0.69, Spearman = 0.60). The positive correlation is a natural consequence of the heterogeneous trends in $AGIR$ as a function of GDP levels, displayed in the previous section.

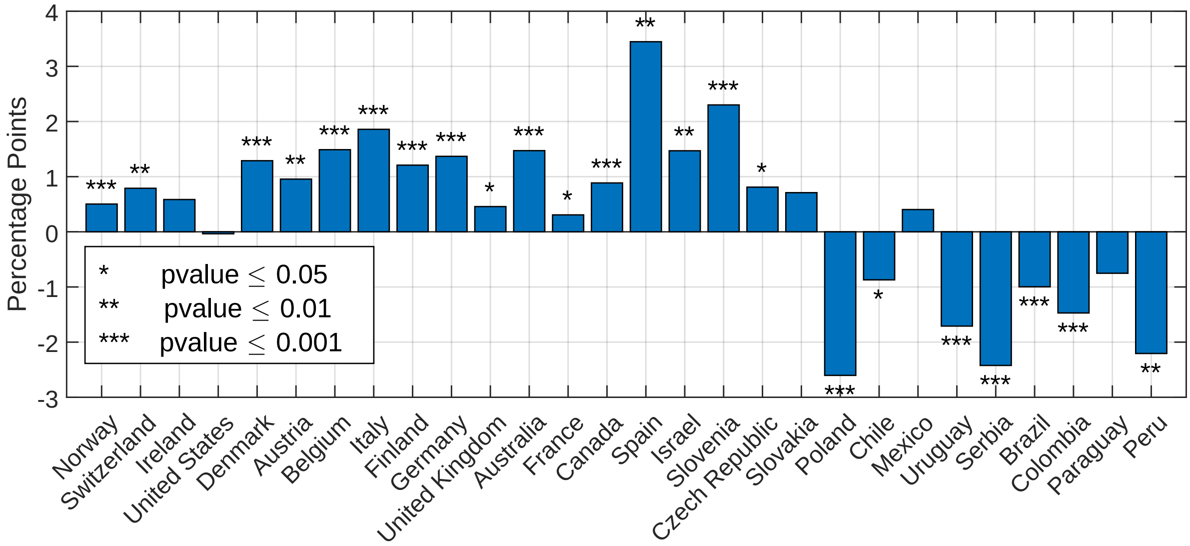
In the following sections, we continue to investigate the source of that relationship, isolating and analysing the possible channels for the age group income divergences.

Figure 2. Income growth rates and growth rate differentials: early-career and late-career

(a) Annualised income growth: early-career and late-career

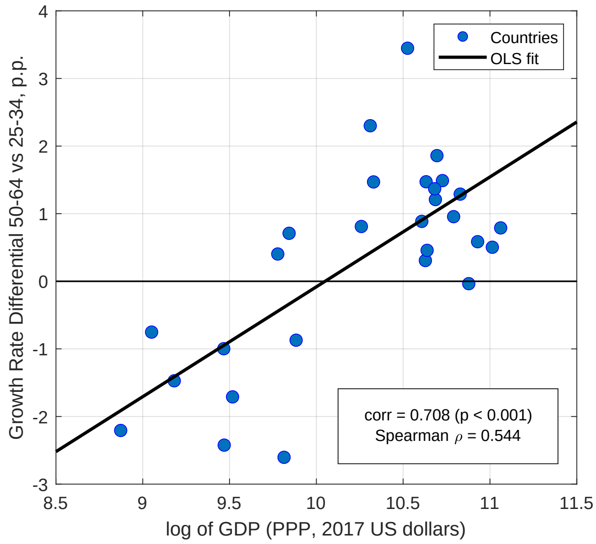


(b) Growth Rate Differentials between late-career and early-career



Note: Panel (a) displays the annualised disposable income growth for early-career individuals (25-35 y.o., green light bars on the left) and for late-career individuals (50-64 y.o., dark purple bar on the right). Panel (b) displays the resulting Growth Rate Differential (*GRD*). A positive value indicates that the income of the old has increased faster than the one of the young over the reference periods. We report statistical significance with respect to the null hypothesis $\text{GRD}_i = 0$. The dates between which the *GRD* and the growth rates are calculated are provided in Table I.

Figure 3. *GRD* and country income level



Note: The figure plots the Growth Rate Differential *GRD* comparing late-career individuals (50-64 y.o.) and early-career individuals (25-35 y.o.) against the log of PPP GDP calculated at the beginning of the period of analysis. The time interval for which the *GRD* are computed, are reported for each country in Table I. The black line shows the linear fit. In the box, we report the Pearson (ρ) and the Spearman correlation between the two variables.

3.3 Decomposing growht rate differentials

We now conduct a growth accounting decomposition to further investigate the sources of the growth rate differential between late- and early-career age groups and, consequently, of the trend of *AGIR*. Specifically, we exploit the degree of details of the LIS dataset to decompose the *GRD* into the contribution of different income subcomponents.

Using the approximation in equation (3), the *growth rate* of average disposable income of age group j between period T and $T+h$ is:

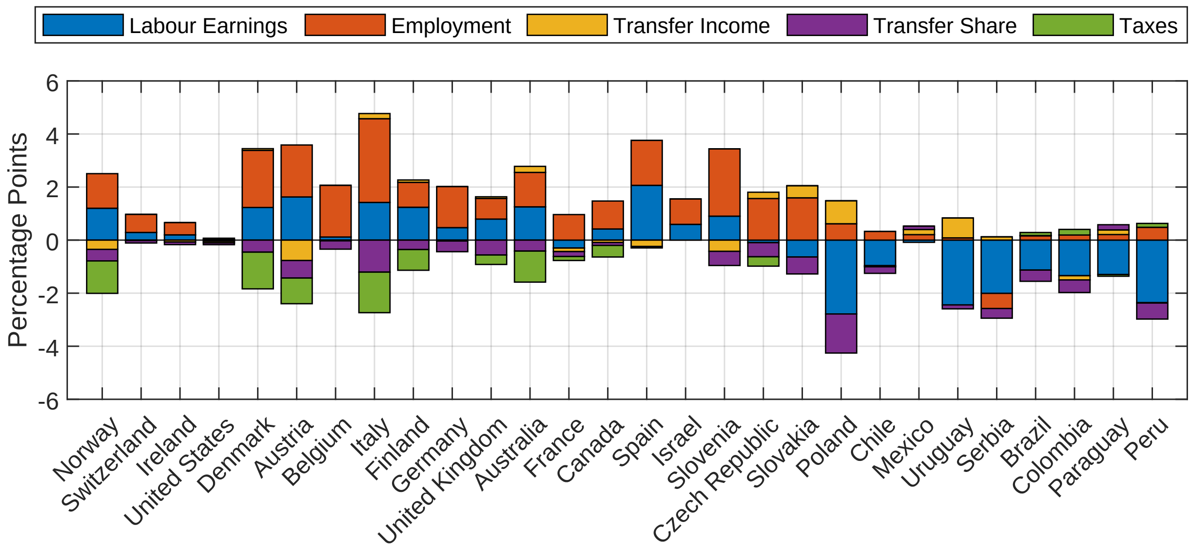
$$\frac{\Delta y_j}{y_{j,T}} = \underbrace{\frac{e_{j,T}\Delta y_j^g}{y_{j,T}}}_{\text{Labor Earnings}} + \underbrace{\frac{y^g_{j,T}\Delta e_j}{y_{j,T}}}_{\text{Employment}} + \underbrace{\frac{p_{j,T}\Delta\Theta^g_j}{y_{j,T}}}_{\text{Transfer Income}} + \underbrace{\frac{\Theta^g_{j,T}\Delta p_j}{y_{j,T}}}_{\text{Transfer Share}} - \underbrace{\frac{\Delta\tau_j}{y_{j,T}}}_{\text{Tax}}, \tag{7}$$

where Δx denotes the difference of variable x between periods T and $T+h$. For countries with only net income data, the tax component will be zero, and net components will substitute the gross ones.

By subtracting the right-hand side terms computed for the early-career age group from those computed for the late-career age group, we can decompose the overall *GRD* into the contributions of each income sub-component.

Figure 4 illustrates these contributions: a positive value means that the specific subcomponents grew faster for the 50-64 age group than for the 25-34 one. Recall that the components for each country sum up to that country's *GRD*, displayed in Figure 2b. We now describe the main findings focusing on each subcomponent at a time.

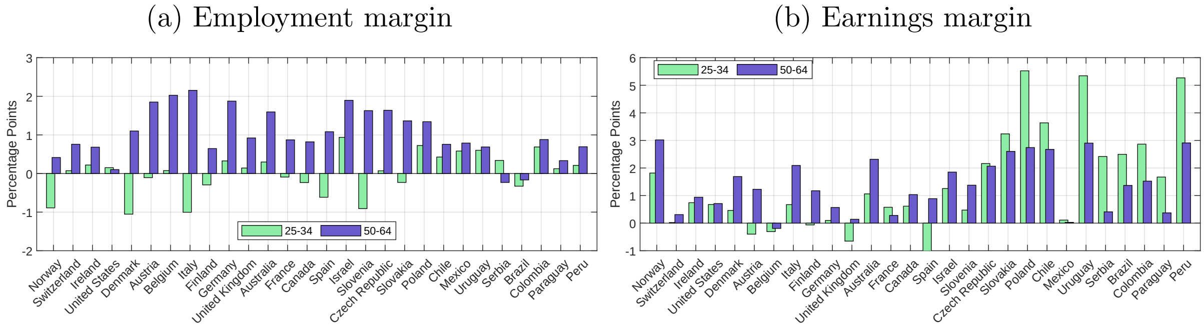
Figure 4. *GRD* Decomposition, by income components



Note: The figure depicts the decomposition of the Growth Rate Differential (*GRD*) calculated for disposable income, comparing late-career individuals (50-64 y.o.) with early-career individuals (25-34 y.o). "Labor earnings" refers to the contribution to the *GRD* of differences in growth of the average labor earnings received, conditional on being employed. "Employment" refers to the contribution toward the total *GRD* of differences in growth of the employment rate. "Transfer Income" refers to the contribution of differences in growth of the average transfer received, conditional on receiving one. "Transfer Share" refers to the contribution of differences in growth of the share of individuals receiving a transfer. "Taxes" refers to the contribution of differences in growth of the average amount of taxes paid on labor income and transfers. The five components sum to the total *GRD* plotted in Figure 2b. The dates between which the *GRD* and its components are calculated are provided in Table I.

Employment. In rich countries, the main contributor to the unequal income growth between early- and late-career individuals has been the increase in differences in employment rates. Panel (a) of Figure 5 displays the employment contribution to income, i.e. $\frac{y^g_{j,T}\Delta e_j}{y_{j,T}}$ for the two age groups of interest. It is evident that while the employment rate of early-career individuals has not risen substantially (and has even fell in some countries), the employment rate of late-career individuals has increased substantially, up to 1 to 2 per cent annually. The difference across age groups is much less evident in poorer countries.

Figure 5. Labor Income contributions to GRD



Note: panel (a) depicts the employment contribution to the average growth rate of disposable income, for late-career individuals (50-64 y.o., dark purple bar, on the right) and for early-career individuals (25-34 y.o, light green bar, on the left). It is equal to $\frac{y^g_{j,T}\Delta e_j}{y_{j,T}}$ for the two age groups of interest. Panel (b) depicts the labour earnings contribution, and it is equal to the difference of $\frac{e_{j,T}\Delta y^g_j}{y_{j,T}}$ for the two age groups of interest.

Labor Earnings. Focusing on labour earnings, our decomposition highlights how, in richer economies, also that component has favoured late-career workers. Although there is significant heterogeneity in the level, mostly reflecting the different countries' average growth in the last two decades, the labour earnings of the late-career age group have been larger than that of the early-career one in richer countries. This fact is displayed in panel (b) of Figure 5, which reports the labour earnings contribution to the GRD, i.e.$\frac{e_{j,T}\Delta y^g_j}{y_{j,T}}$. Notice that this component reflects the dynamics of the age-*wage* gap, which is studied by (Bianchi et al., 2022; Bianchi and Paradisi, 2023; Bennett and Levinthal, 2017; Beaudry et al., 2014) in the context of intergenerational inequality. Our results highlight that, particularly in richer countries, this component is only a fraction of the overall evolution of *income* age inequalities, and it cannot be considered in isolation if one would like to draw conclusions related to overall income distributions. Finally, the younger age group has experienced much faster labour-earning growth in poorer economies than the older age group. This margin explains virtually all the fall in $AGIR$ in low-income countries.

Pensions. The effect of later retirement for older workers, which rationalises the increased employment rates for late-career individuals, can be observed from the negative contribution of *"transfer share"*, indicating that fewer individuals receive pension payments. However, the contribution of the size of the transfer, *"transfer income"*, does not appear large for most countries.

We can further investigate the role of the pensions to the *GRD* with the following decomposition. By definition, the average disposable income of the age group j can be rewritten as the average disposable income of the non-retired and retired individuals of that age group, with weight equal to the share of retired individuals, denoted by p_j. Hence,

$$y_j \equiv y_j^{np} + (y_j^p - y_j^{np})p_j, \tag{8}$$

where y_j^{np} is the average earnings of non-retired (employed or unemployed) in the age group j, y_j^p is the average pension income of retired, and p_j is the share of retirees. The annualised hange of average income for age group j between T and $T+h$ is then:

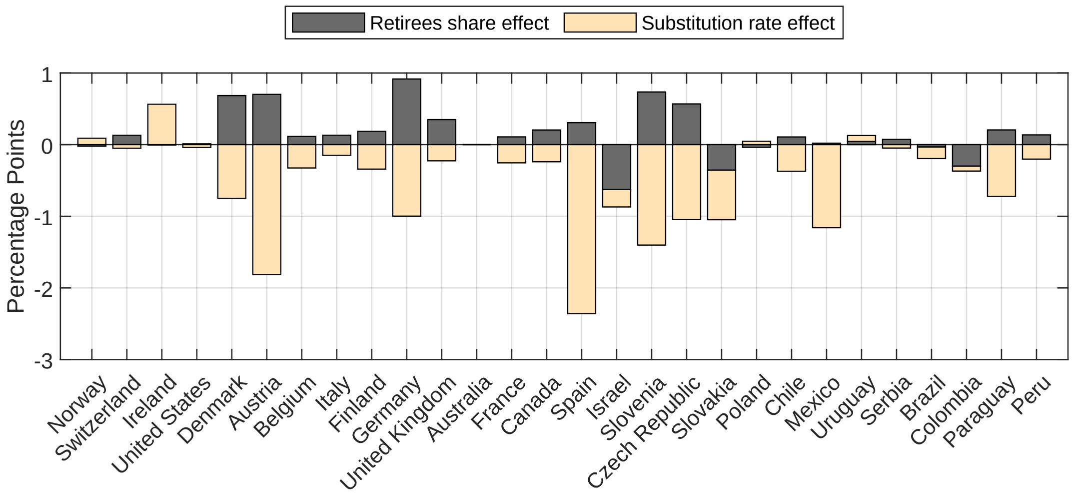
$$\Delta y_j = \frac{1}{hy_{j,T}} \left[\Delta y_j^{np} + \underbrace{(y_{j,T+h}^p - y_{j,T+h}^{np})\Delta p_j}_{\text{Retirees share effect}} + \underbrace{\Delta(y_j^p - y_j^{np})p_{j,T}}_{\text{Substitution rate effect}} . \right] \tag{9}$$

By subtracting the terms above for two age groups, we obtain their *GRD* (left-hand side) and the contribution of each of the three components on the right-hand side. We focus on the last two components, that is, the contribution to the *GRD* of the change of the share of retiree (keeping their substitution income fixed) and the contribution to the *GRD* of the change of the retiree substitution income (keeping their share fixed). Notice that because the share of retirees is very close to zero for early-career individuals, the two subcomponents of interest can be interpreted as the role of changes in retirement intensity and changes in substitution income for the older age group.

Figure 6 display the results. As expected, the change in retiree shares, displayed by the darker bars, contributes positively to the *GRD*, with a more substantial role in richer countries. Intuitively, because the substitution income rate is negative (the income of retirees is smaller than the income of non-retiree in a given age group, i.e. $y^p - y^{np} < 0$), lower retirement rates for older workers increase the average income of that age group. However, the substitution rate effect goes in the opposite direction: pension income did not grow as much as the earnings for workers of the same age group. In other words, the substitution rate $y^p - y^{np}$ has become more negative, ceteris paribus, thus dampening that group's average income. This strong effect explains why the transfer income and transfer share effect, combined, do not appear to be an important contributor to the evolution of the *GRD*.

As a result, one could safely rule out that the increased *AGIR* in the richer countries can be mainly attributed to more generous state transfers and pensions.

Figure 6. Pension margin contribution



Note: the dark bar displays the contribution of the retirees share effect to the *GRD* between late-career individuals (50-64 y.o.) and early-career individuals (25-34 y.o), defined as the difference of $(y^{p}_{j,T+h} - y^{np}_{j,T+h})\Delta p_j$ for the two age group of interest. The light bar displays the contribution of the substition rate effect, defined as the difference of $\Delta(y^{p}_{j} - y^{np}_{j})p_{j,T}$ for the two age group of interest.

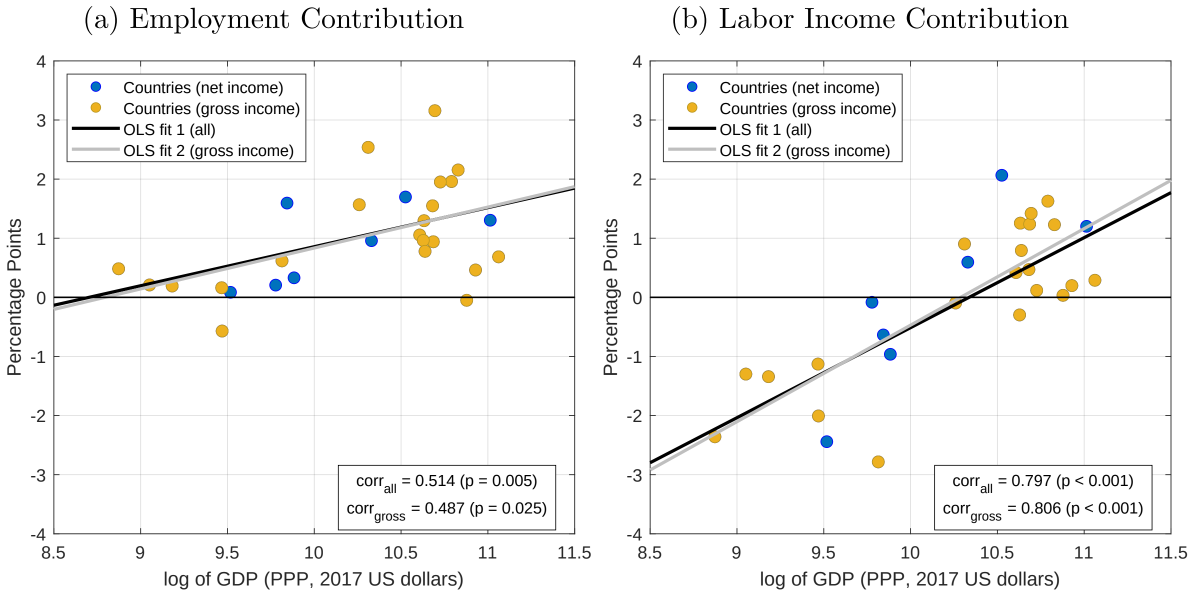
Taxes Finally, in rich countries, the role of taxes has played a role in reducing the gap between the increase in income of the old to the young, which might be seen as a reassuring mechanism of automatic redistribution (or differential tax burden), albeit it was not strong enough to equate the growth rates of the two age groups.

To take stock, we find that the main contributors to the *GRD* are related to labour market outcomes: in rich countries, the positive *GRD* mainly depend upon the two labour market margins- intensive and extensive- both increasing the income of the old relative to the young, while in the poorer economy, the intensive margin primarily benefits the young, thus generating negative *GRD*.

We provide visual evidence for the relationships between GDP levels and the two income contributions stemming from the labour market to *GRD* by plotting, in Figure 7, the per capita PPP GDP (in 2017 US dollars, in log) of each country at the beginning of the sample against the contribution of employment (panel a), and labour income (panel b) to the *GRD*. Using the same scale, a reader can immediately evaluate the relative contributions of the two components to the *GRD*. Notice that the extensive margin, i.e. the employment contribution, is basically positive for all countries: small for poorer and large for richer countries. On the contrary, the intensive margin, i.e. the labour income contribution, flips sign across the GDP level, being large and negative for poorer economies and large and positive for the richer ones. This counteracting effect strongly contributes to the negative or close to zero *GRD* in poorer countries. The results do not depend on whether the data available are net (blue darker dots) or gross (yellow lighter dots). These observations lead to our second stylized fact.

Stylized fact 2 In rich countries, the main contributor to the positive *GRD* is the divergence in employment rates between young and old. In lower-income countries, the main contributor to negative *GRD* is the faster increase in labour income, conditional on being employed, of the young with respect to the old.

Figure 7. Employment and Labor Income Contribution to GRD vs GDP level



Note: Panel (a) plots the employment contribution to the GRD against the log of PPP GDP (calculated at 2017 dollars, for the initial year of the reference period). In the box, we present the linear correlation (ρ) between the two variables. Panel (b) plots the labor earnings contribution to the GRD against the log of PPP GDP (calculated at 2017 dollars, for the initial year of the reference period). Other specifics are as in panel (a). The blue darker dots denote the countries for which net income data are available, while yellow lighter dots denote the countries for which gross income data are available. The two solid lines, almost overlapping, display the two linear fits for the two subsets of countries. The countries and the dates between which the GRD and its components are calculated are provided in Table I.

Take away These results are relevant for two reasons. First, we have highlighted that the channels that mostly affect the uneven disposable income growth of the older age group relative to the younger one differ between high-income and lower-income countries but are similar within countries of the same income groups. While employment trends are the leading cause of the rise in $AGIR$ in rich countries, faster-rising wages for young employed individuals lead to its fall in poorer countries. The existence of these patterns justifies our initial intention of providing a *global* analysis. Second, due to the fairly consistent results within rich/poorer country groups but diverging ones across, our findings suggest that the causes of the rise or fall in $AGIR$ should be explored by looking at phenomena connected to the long-run development path of each economy. In Setion 4 we conduct a panel-regression to detect what those phenomena could be.

3.3.1 The role of demographics

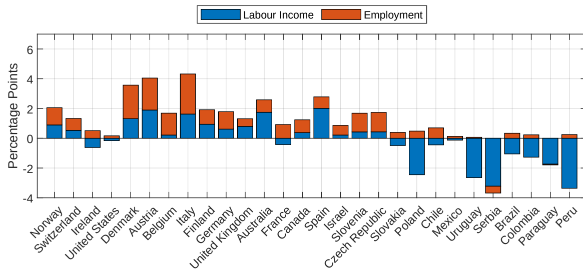
This section investigates whether the main stylized facts presented above are shared across different demographic subsets or whether specific characteristics drive them. Specifically, we focus on two characteristics: gender and education. The former will shed some light on whether the *GRD* could be related to the recent increase in female employment rates in industrialized countries, while the latter will shed some light on the role of the boom in education attainment.

We proceed in two steps. First, for the sake of clarity, we focus our analysis only on the two larger drivers of the *GRD*, the one related to the labour market, i.e. the labour earning contribution (intensive margin) and the employment contribution (extensive margin). We then divide our sample into male and female, and no-college and college education attainment. We then compute the overall labor income contribution to the *GRD* of each group for each country, i.e. $\frac{e_{j,T}\Delta y_j^g}{y_{j,T}} + \frac{y_{j,T}^g \Delta e_j}{y_{j,T}}$. Notice that because we focus on working-age individuals, education attainment rarely progresses further with age for a given individual in our samples.

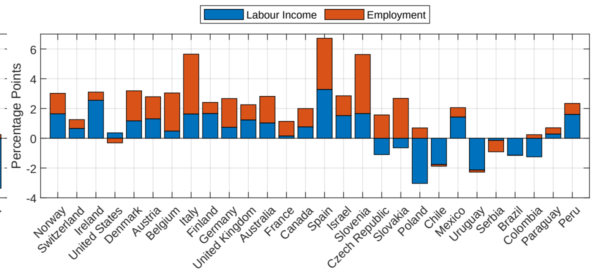
Figure 8 displays the two contributions for males and females. Stylized fact 1, highlighted in the previous section, hold for both men and women. Regardless of gender, in rich countries, both higher employment rates and higher wages contribute to higher income growth for late-career individuals, with respect to early-career ones; the employment margin is overall more important for women, thus highlighting the effect of their increased labour participation in richer countries reaching, over time, the older generations. In poorer countries, wages have increased more for all younger male workers, but with a couple of exceptions for women.

Figure 8. Labor income decomposition: Male and Female

(a) Male



(b) Female

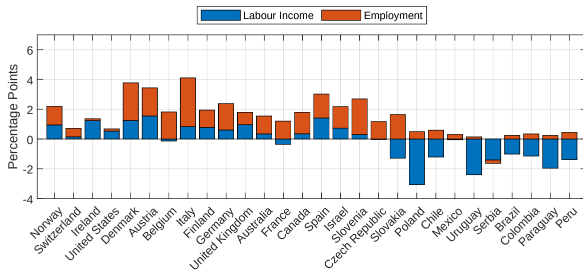


Note: panel (a) depicts the employment contribution (lighter red bar) to the *GRD*s for male late-career individuals (50-64 y.o.) and male early-career individuals (25-34 y.o), and the labour earnings contribution (darker blue bar). Panel (b) depicts the two contributions for female. The countries and the dates between which the components are calculated are provided in Table I.

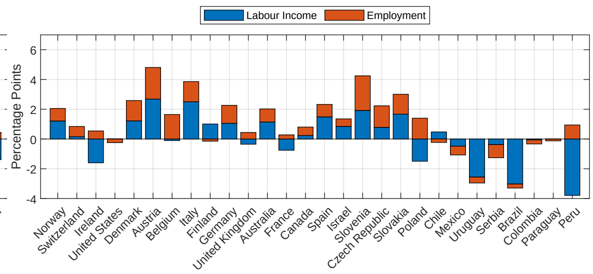
Figure 9 displays the *GRD* within the two education categories. Once again, stylized fact 1 holds regardless of educational attainment, with a more substantial contribution of the wage margin for college graduates and a larger contribution of the employment margin for no-college individuals.

Figure 9. Labor income decomposition: Non-College and College Educated

(a) No College



(b) College

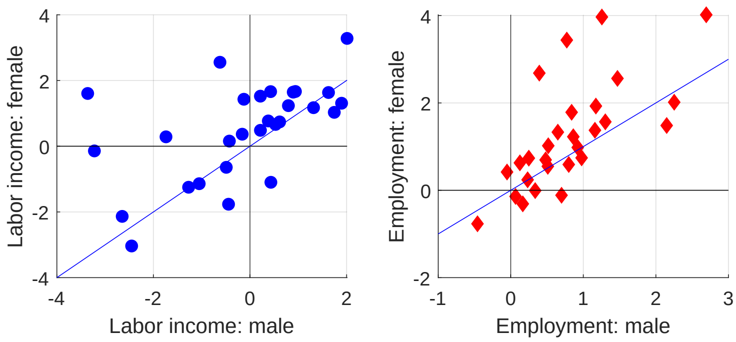


Note: panel (a) depicts the employment contribution (lighter red bar) to the *GRD*s for non college-educated late-career individuals (50-64 y.o.) and non college-educated early-career individuals (25-34 y.o), and the labour earning contribition (darker blue bar). Panel (b) depicts the two contributions for college-educated individuals. The countries and the dates between which the components are calculated are provided in Table I.

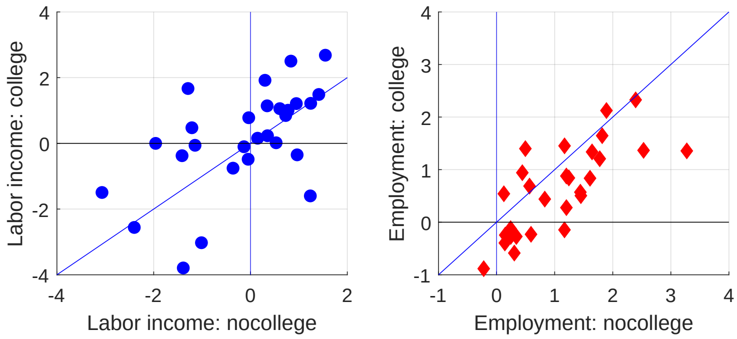
Figure 10 display the high degree of correlation of both labour income contributions between the different categories, with slightly more variation for labour earnings. Clearly, specific demographic characteristics do not drive the main stylized fact, but they are quite general and dependent on underlying more general labour market forces.

Figure 10. Labor income decomposition: Male and Female

(a) Gender



(b) Education



Note: panel (a) displays the labor earning contribution (left panel) and employment contribution (right panel) to the *GRD*s of late-career individuals (50-64 y.o.) and non college-educated early-career individuals (25-34 y.o). The x-axis reports the contribution for males and the y-axis for female. Panel (b) displays the two contributions for college and non-college educated individuals. The solid diagonal line is the 45 degree line. The countries and the dates between which the components are calculated are provided in Table I.

4 What drives AGIR?

The stylized facts presented in the previous sections state that the increased (decreased) income concentration in favour of the old (young) in richer (poorer) countries can be mainly attributed to the role played by the labour market, both in terms of unequal increase of employment rates and wages across different age groups. However, what are the channels that could lead to those outcomes? In this section, we present suggested evidence for three main forces: the first one is the role of ageing, the second one relates to the education boom experienced in the last decade in industrialized countries, and the third one relates broadly to policymaking. We explore the role of these three sets of variables in explaining the cross-section and time variation of the $AGIR$.

To provide suggesting - in the sense of correlation and not causality- evidence of the existence of those channels, we run the following regression:

$$log(R_{i,t}) = \alpha + \beta_e E_{i,t} + \beta_a A_{i,t} + \beta_p P_{i,t} + \theta X_{i,t} + \epsilon_{i,t}, \quad (10)$$

where $log(R_{i,t})$ represent the log-level of $AGIR$ for country i in year t; $E_{i,t}$ represents a vector of variables related to education attainment; $A_{i,t}$ represents a vector of variables related to ageing; $P_{i,t}$ represents a vector of political variables; $X_{i,t}$ are additional controls that we describe below; and $\epsilon_{i,t}$ are error terms. We now describe those variables, their sources, and the expected relationship with $AGIR$.[9]

The vector $A_{i,t}$ is composed of life expectancy (LE, source: Global Burden of Disease Study 2019, (Global Burden of Disease Collaborative Network, 2020)) and the age-dependency ratio (ADR, source: World Development Indicators, (World Bank, 2022)), measured as the ratio of dependents, i.e. people younger than 15 or older than 64, to the working-age population, i.e. those ages 15-64.[10] These two variables capture two different dimensions of the ageing process of a country, as signalled by their low correlation (0.176), and they should both be positively related to $AGIR$. Both life expectancy and the dependency ratio are likely connected to longer working lives, and thus higher labour revenue and AGIR, although for different reasons. Countries that face either forms of ageing may need to increase the incentives (or mandate) to work for longer in order to maintain a balanced budget. However, higher life expectancies can also represent individual incentives to remain in the workforce for longer.

The vector $P_{i,t}$ includes two political variables. The first one is the average age of people in government positions (AGP, source: The WhoGov Dataset, (Nyrup and Bramwell, 2020)), as we would like to explore whether political incentives related to the age of policymakers affect the evolution of $AGIR$. The second one is the average total tax rate, including social contributions (TR, source: ICTD/UNU-WIDER Government

[9]The choice of the regressors of interest was guided not only by subjective judgment but also by the Lasso variable selection method over a set of 115 variables.

[10]Notice that this measure of age dependency does not include directly individuals in the two age groups that define $AGIR$.

Revenue Dataset, (ICTD/UNU-WIDER, 2022)) to investigate whether higher tax burdens are associated with a higher $AGIR$. Once again, the correlation between these two variables is low (-0.179).

We explore two options regarding the education vector $E_{i,t}$. We first consider a direct measure of educational attainment of the early-career individuals, i.e. the average years of education in the age group 25-34 years (EDU_{EC}, source: Global Educational Attainment 1970-2015 dataset, (Institute for Health Metrics and Evaluation (IHME), 2015)), and a direct measure of the education gap between the late-career and early-career individuals, computed as the difference between the average years of education in the age group 55-64 and the one in the age group 25-34 years (EDU_{GAP}, same source). The correlation between these two variables is positive but not extremely high (0.63). Our prior is that higher education attainment for the young results in a lower $AGIR$, as education at the early career stage is directly related to the income of the young. However, a larger education gap, which means that the late-career individuals are catching up with the young ones regarding education level, should result in a larger $AGIR$. The source of those variables is Global Educational Attainment 1970-2015 dataset. However, unfortunately, this dataset does not have data for the period 2016-2018.

We also consider two proxies for the two variables of interest to overcome this issue. The first proxy is Human Capital Index (HCI, source: Penn World Table, (Feenstra et al., 2015)). This index is based on the average years of schooling from (Barro and Lee, 2013) and an assumed rate of return to education based on Mincer equation estimates around the world (Psacharopoulos, 1994). These two features make the HCI a good proxy for the average years of education in the age group 25-34 years. In fact, the correlation between the HCI and average years of education in the age group 25-34 years (EDU_{EC}) is 0.884. The second proxy is the Economic Complexity Index (ECI, source Growth Projections and Complexity Rankings, (The Growth Lab at Harvard University, 2019)). This index measures the number of capabilities and know-how of a given country determined by the diversity, ubiquity, and complexity of the products it exports, computed using SITC product classification. The index ranks countries based on how diversified and complex their export basket is. Because countries home to a great diversity of productive know-how - particularly complex specialized know-how - can produce a great diversity of sophisticated products, this variable is a good proxy for the level of education of a more senior labour force. In fact, the correlation between this index and the year of schooling gap is quite positive, 0.44. Also, the correlation between HCI and ECI is 0.57, not too dissimilar to one of the two direct education measures. The advantage of using these proxies is that they are available throughout the whole sample, and, therefore, we will use them as the benchmark variables for investigating the role of education. We will show the robustness of our results by using the more direct measures and, consequently, slightly reducing the sample size.

All the regressors display enough variation both in the time series and in the cross section, with no critical collinerarity that might undermine the validity of the estimates. In Appendix C we display the summary statistics of the covariates.

Table III reports the estimates. In column (1), we first regress log($AGIR$) on log(GDP) to recall their strong correlation. The goal of this section is to understand what could be the underlying forces that explain that correlation. Our strategy is to introduce sets of covariates of interest one by one. In column (2), we report the estimates of regressing log(AGIR) on the variables related to ageing. Both life expectancy (LE) and the age dependency ratio (ADR) are strongly correlated with *AGIR*, both in terms of statistical significance and of magnitude: an extra year of life expectancy at birth increases the *AGIR* by 1.9 percentage points, while an extra percentage of age-dependency ratio increase the *AGIR* by 0.6 percentage points. These two regressors related to ageing alone explain 19 per cent of the overall country-year variation of *AGIR*. Next, we add regressors related to education. As displayed in column (3), a higher Human-Capital-Index (HCI), a proxy for the education of the young, decreases the *AGIR* significantly, as younger workers are better educated and are likely to receive higher wages and employment opportunities. In contrast, higher economic complexity (ECI) - a proxy for the education of older workers when controlling for HCI - significantly increases *AGIR*, as expected. The regressors related to education attainment increase the linear fit (adjusted by the number of covariates) by 13 per cent. Finally, in column (4), we add the two political regressors. Both the average age of people in government positions (AGP) and average tax rate (TR) increase the $AGIR$ significantly and add an additional 15 per cent to the linear fit. Notice that the coefficients of the other regressors are quite stable when adding additional explanatory variables. Column (5) and column (6) display two robustness checks. In column (5), we include the direct education measures (instead of their proxies): the education of early career workers (EDU_{EC}), and the education gap between late and early career workers (EDU_{GAP}). The results regarding the effects of the two education variables on $AGIR$ and the stability of the other coefficients are unchanged. In column (6), we account for the role of sample uncertainty in estimating the dependent variable from survey data. We estimate the model using a weighted least-square estimator, with the weights equal to the inverse of the standard errors of $\log(AGIR)$, computed with the delta method from the standard errors of each country-year estimated average age group income. The results are identical to the OLS ones.

Finally, in column (7), we add again $\log(GDP)$ as an additional regressor: it is barely significant at 10 per cent of confidence, and all its explanatory power is almost entirely absorbed by the three sets of regressors of interest. One might wonder whether their correlation with GDP drives the statistical significance of the three sets of regressors of interest. To demonstrate that it is not the case, we conduct two exercises. First, we add in the regression three additional controls: CO2 emissions in tons per capita ($Co2$, source: World Development Indicators, (World Bank, 2022)), an estimate of Rule of Law (RoL, source: Worldwide Governance Indicators, (Kaufmann et al., 2010)), which measures the extent to which agents have confidence in and abide by the rules of society; and an estimate of Political Stability and Absence of Violence/Terrorism (PS, source: Worldwide Governance Indicators, (Kaufmann et al., 2010)), which measures perceptions of the likelihood of political instability and politically-motivated violence. These three variables are highly correlated with log(GDP), equal to 0.65, 0.91, and 0.68, respectively, and their pairwise correlations are: 0.64 between $Co2$ and RoL, 0.46 between $Co2$ and PS, and 0.74 between RoL and PS. Column (8) reports the results of adding these additional regressors. They are not significant; they reduce the importance of log(GDP) on $AGIR$; and, importantly, they do not alter the magnitude and the statistical significance of the three sets of regressors of interest. Finally, notice that adding these additional control highly correlated with log(GDP) reduces the overall goodness of fit of the linear model, as displayed by the lower adjusted-R^2. To further reassure that the main results of this section are not a spurious outcome from the degree of correlation between our regressors of interest and GDP, in Appendix D we also reports the details of a Montecarlo exercise in which we create synthetic regressors that are, by construction, highly correlated with log(GDP), (correlation around 0.75) and are orthogonal to $AGIR$. We find that the significance and the importance of the 6 variables of interest are not affected by including those synthetic placebos.

While the evidence we have provided cannot be interpreted in a causal way, they are closely related to other contributions which have looked at causal evidence of specific mechanisms within individual countries. (Bianchi et al., 2022) provides causal evidence for how a sudden reform of pension age in Italy caused a slowdown in the careers of young individuals. Similar results are derived in (Boeri et al., 2022), and by (Ferrari et al., 2023) for the Netherlands. This is indeed consistent with the positive coefficients we find for Life Expectancy and Age Dependency Ratio, which are - in turn - connected to having a older workforce, and a stronger need for longer working lives to ensure financial stability. (Adao et al., 2023) shows how, in the US, the income benefits of the slow ICT-related technical change, which began in the 1980s, went mainly to the educated young. These findings fit well with the positive correlation between AGIR and EDU$_{GAP}$, and the negative one with EDU$_{EC}$, suggesting that countries where the young are more educated, and more so than the old, have indeed seen a slower increase in AGIR. Moreover, this narrative fits well also with the overall diverging trends between richer and poorer countries. Similarly, (Guvenen et al., 2013) shows how countries that have reduced taxation since the 1980s may have fostered human capital accumulation due to lifetime incentives, fostering total income inequalities but - since education mainly regards the young - potentially reducing age-based ones.

TABLE III. The determinants of $AGIR$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\beta_{a,1}$: LE		0.019***	0.019***	0.014***	0.015***	0.011***	0.010***	0.012**
		(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
$\beta_{a,2}$: ADR		0.006***	0.007***	0.006***	0.004***	0.006***	0.006***	0.006***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{e,1}$: HCI			-0.103***	-0.097***		-0.064***	-0.110***	-0.107***
			(0.020)	(0.018)		(0.017)	(0.020)	(0.023)
$\beta_{e,2}$: ECI			0.081***	0.054***		0.040***	0.043***	0.044***
			(0.010)	(0.010)		(0.010)	(0.012)	(0.015)
$\beta_{e,1}$: EDU_{EC}					-0.026***			
					(0.006)			
$\beta_{e,2}$: EDU_{GAP}					0.016**			
					(0.008)			
$\beta_{p,1}$: AGP				0.015***	0.018***	0.016***	0.015***	0.015***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{p,2}$: TR				0.003***	0.004***	0.003***	0.002***	0.002***
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
θ_1: log(GDP)	0.065***						0.041*	0.047
	(0.012)						(0.024)	(0.043)
θ_2: Co2								0.000
								(0.002)
θ_3: RoL								-0.017
								(0.022)
θ_4: PS								0.010
								(0.013)
α: Intercept	-0.515***	-1.738***	-1.492***	-1.954***	-2.004***	-1.912***	-2.000***	-2.217***
	(0.134)	(0.272)	(0.242)	(0.226)	(0.268)	(0.236)	(0.227)	(0.377)
Weighted LS	NO	NO	NO	NO	NO	YES	NO	NO
Observations	306	306	306	305	244	306	305	305
R^2 (Adj)	0.07	0.19	0.32	0.47	0.43	0.48	0.48	0.46

Note: The table reports the estimate of regression 10. The six covariates of interest are: Life-expectancy (LE), age-dependency ratio (ADR), Average age of people in government position (AGP), average total tax rate (TR), human capital index (HCI), and Economic complexity index (ECI). Also, we include log(GDP) as an additional control in columns (1) and (7). In column (5), the human capital index and Economic complexity index are substituted by two more direct measures of education: the education of the early career workers (EDU_{EC}) and the education gap between late and early career workers (EDU_{GAP}). As discussed above, those data are available only until 2015, thus losing 62 observations. Column (6) reports the estimates using a weighted least-square estimator, with the weights equal to the inverse of the standard errors of $\log(AGIR)$ computed with the delta method from the standard errors of each country-year(wave) estimated average age group income.

5 Conclusions

The issue of income inequality is topical in the economic debate. Recently, one specific angle of this phenomenon has attracted the attention of policymakers and economists: how are resources distributed among different age groups? Are the young becoming poorer relative to the old? In this paper, we study how income distribution across age groups has evolved in 28 countries at different stages of their economic development. Our analysis's international dimension is crucial to uncover regularities and dissimilarities of the phenomenon's evolution and relate it to long-run economic trends. Our paper is the first one to provide a similar analysis.

Our first contribution is to establish two stylised facts. First, in the last 25 years, the late-career/early-career age group income ratio $AGIR$, defined as the average disposable income of late-career individuals (age 55-64) relative to early-career individuals (age 25-34), has evolved in opposite directions in richer and poorer countries. In the former, the $AGIR$ has steadily risen by around 20 per cent, from 1.10 to 1.30; in the poorer economies, it has steadily declined by around 15 per cent, from 1.20 to 1.05. This sharp increase is mainly due to the income of the younger age group falling or remaining stable and the one of the older age group increasing at sustained rates. Nevertheless, this trend is reverted in countries with lower GDP per capita. We document a second stylised fact by decomposing how income has grown in the last decades for each age group. In rich countries, the main contributor to the increased $AGIR$ is the divergence in employment rates (increasing for older individuals, stagnating for younger individuals). In contrast, in lower-income countries, the main contributor to decreased AGIR is the faster labour-earning growth of the young with respect to the old.

Our second contribution is to suggest possible channels for understanding the stylised fact above. Through a panel regression, we present suggested evidence- in terms of correlation, not causality- for three main forces: the first one is the role of ageing, the second one relates to the education boom experienced in the last decade in the industrialised countries, and the third one relates, broadly, to policymaking. We show that these variables alone explain around 50 per cent of the time- and cross-country variation of $AGIR$.

Our results are relevant for policymakers. First, our findings suggest that the upward trends in the income of older individuals relative to the younger ones in richer countries have resulted from decades-long economic and demographic dynamics. Nevertheless, they also suggest that tackling intergenerational inequalities may indeed *need* public policies aimed at ensuring intergenerational fairness, as it seems implausible that we will see, without policy intervention or any age-bias shock, a reverted trend, for which the younger age group regains a larger share of income.

Our results are also relevant for academics, as they open further research questions. First, because part of the shifts in the relative income distribution across age groups seems to be related to long-run economic and demographic trends, its welfare cost is unclear. For example, beyond the clear political and long-term public budgeting implications (for example, for the balance of pension funds), are those shifts economically inefficient, and what are their welfare costs? Also, since education convergence between age groups and ageing seems inevitable, which long-term generational policies should policymakers adopt to ensure intergenerational fairness? Our work and findings are relevant to setting the stage to address those questions.

References

Adao, R., M. Beraja, and N. Pandalai-Nayar (2023): "Fast and slow technological transitions," Tech. rep.

Barra, R., B. Maître, A. McTague, and I. Privalko (2021): "Intergenerational inequality: Chapter 4 in Poverty, Income Inequality and Living Standards in Ireland," Book/report chapter 202104, ESRI and The Community Foundation for Ireland.

Barro, R. J. and J. W. Lee (2013): "A new data set of educational attainment in the world, 1950–2010," *Journal of development economics*, 104, 184–198.

Beaudry, P., D. A. Green, and B. M. Sand (2014): "The Declining Fortunes of the Young since 2000," *American Economic Review*, 104, 381–86, doi:10.1257/aer.104.5.381.

Bennett, V. M. and D. A. Levinthal (2017): "Firm Lifecycles: Linking Employee Incentives and Firm Growth Dynamics," *Strategic Management Journal*, 38, 2005–2018, doi:10.1002/smj.2644.

Berry, C. and D. Sinclair (2010): "Intergenerational Fairness and the Spending Review 2010," Report, The International Longevity Centre - UK.

Bianchi, N., G. Bovini, J. Li, M. Paradisi, and M. L. Powell (2022): "Career spillovers in internal labor markets," *Review of Economic Studies, Forthcoming*, doi:10.3386/w28605.

Bianchi, N. and M. Paradisi (2023): "Countries for Old Men: An Analysis of the Age Wage Gap," Tech. rep.

Boeri, T., P. Garibaldi, and E. R. Moen (2022): "In medio stat victus: Labor Demand Effects of an Increase in the Retirement Age," *Journal of Population Economics*, 35, 519–556, doi:10.1007/s00148-021-00871-.

Colombo, F., P. Aroldi, and S. Carlo (2014): ""Stay tuned": The role of ICTs in elderly life," *Active Ageing and Healthy Living: A Human Centered Approach in*

Research and Innovation as Source of Quality of Life, 203, 145–156, doi:10.3233/978-1-61499-425-1-145.

Cribb, J. (2019): "Intergenerational Differences in Income and Wealth: Evidence from Britain," *Fiscal Studies*, 40, 275–299, doi:10.1111/1475-5890.12202.

Feenstra, R. C., R. Inklaar, and M. P. Timmer (2015): "The Next Generation of the Penn World Table," *The American Economic Review*, 105, 3150–3182.

Ferrari, I., J. Kabátek, and T. Morris (2023): "Longer careers: A barrier to hiring and coworker advancement?" *University Ca'Foscari of Venice, Dept. of Economics Research Paper Series No*, 6.

Freedman, M. (2017): "Are Recent Generations Catching Up or Falling Behind? Trends in Inter-Generational Inequality," LIS Working papers 689, LIS Cross-National Data Center in Luxembourg.

Global Burden of Disease Collaborative Network (2020): "Global Burden of Disease Study 2019 (GBD 2019) Results." .

Guvenen, F., G. Kaplan, J. Song, and J. Weidner (2022): "Lifetime Incomes in the United States over Six Decades," *The American Economic Review: Applied Economics, Forthcoming*.

Guvenen, F., B. Kuruscu, and S. Ozkan (2013): "Taxation of Human Capital and Wage Inequality: A Cross-Country Analysis," *The Review of Economic Studies*, 81, 818–850, doi:10.1093/restud/rdt042.

Henehan, K., M. Gustafsson, N. Cominetti, K. Handscomb, L. Judge, J. Leslie, and L.Try (2021): "An intergenerational audit for the UK : 2021," Report, London: Resolution Foundation.

House of Lords (2019): "Select Committee on Intergenerational Fairness and Provision: Tackling intergenerational unfairness," `https://publications.parliament.uk/pa/ld201719/ldselect/ldintfair/329/329.pdf`.

ICTD/UNU-WIDER (2022): "Government Revenue Dataset," Version 2022.

Institute for Health Metrics and Evaluation (IHME) (2015): "Global Educational Attainment 1970-2015," .

International Monetary Fund (2006): "World Economic Outlook September 2006," https://www.imf.org/external/np/exr/ib/2000/110300.htm.

Jeong, H., Y. Kim, and I. Manovskii (2015): "The Price of Experience," *American Economic Review*, 105, 784–815, doi:10.1257/aer.20080841.

Kaufmann, D., A. Kraay, and M. Mastruzzi (2010): "The worldwide governance indicators: a summary of methodology, data and analytical issues," *World Bank Policy Research Working Paper*, 5430.

Levine, P. B. and O. S. Mitchell (1988): "The Baby Boom's Legacy: Relative Wages in the Twenty-First Century," *The American Economic Review*, 78, 66–69.

Luxembourg Income Study (LIS) Database (2021): "http://www.lisdatacenter.org," (multiple countries; data runs: 20/12/2021-4/02/2022). Luxembourg: LIS.

Masson, A. (2021): "Intergenerational economic inequality in France. Insights and perspective," *Futuribles*, 441, 25–34, doi:10.1257/aer.99.2.45.

Miller, H., R. Meyricke, and L. Dixie (2020): "Mind the gap: the Australian Actuaries Intergenerational Equity Index-green paper," .

Naticchioni, P., M. Raitano, and C. Vittori (2016): "La Meglio Gioventù: earnings gaps across generations and skills in Italy," *Economia Politica: Journal of Analytical and Institutional Economics*, 33, 233–264, doi:10.1007/s40888-016-0034-2.

Nyrup, J. and S. Bramwell (2020): "Who Governs? A New Global Dataset on Members of Cabinets," *American Political Science Review*, 114, 1366–1374.

Psacharopoulos, G. (1994): "Returns to investment in education: A global update," *World development*, 22, 1325–1343.

RAITANO, M., E. KARAGIANNAKI, T. PREMROV, L. GEYER, M. FUCHS, F. BLOISE, J. COSTA-FONT, F. IUDICONE, AND B. DE MICHELI (2021): "Study on intergenerational fairness : final report," Brussels: European commission, doi:10.2767/26828.

ROSOLIA, A. AND R. TORRINI (2007): "The generation gap: relative earnings of young and old workers in Italy," Temi di discussione (Economic working papers) 639, Bank of Italy, Economic Research and International Relations Area.

THE GROWTH LAB AT HARVARD UNIVERSITY (2019): "Growth Projections and Complexity Rankings," doi:10.7910/DVN/XTAQMC.

WELCH, F. (1979): "Effects of Cohort Size on Earnings: The Baby Boom Babies' Financial Bust," *Journal of Political Economy*, 87, S65–S97, doi:10.1086/260823.

WORLD BANK (2022): "World Development Indicators," .

A Additional Information about the dataset

TABLE IV. Additional information on data availability

		Wave 1			Wave 2			Wave 3			Wave 4			Wave 5		
Country	Income	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Australia	Gross	✓				✓		✓				✓		✓		✓
Austria	Gross	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Belgium	Net	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Brazil	Gross			✓			✓		✓		✓			✓		
Canada	Gross	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Chile	Net			✓			✓		✓		✓		✓		✓	
Colombia	Gross	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Czech Republic	Gross	✓			✓			✓			✓			✓		
Denmark	Gross	✓			✓			✓			✓			✓		
Finland	Gross	✓			✓			✓			✓			✓		
France	Gross	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Germany	Net	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ireland	Net	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Israel	Net	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Italy	Gross	✓				✓		✓				✓		✓		
Mexico	Net	✓	✓	✓		✓		✓		✓		✓		✓		✓
Norway	Gross	✓			✓			✓			✓			✓		
Paraguay	Gross	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Peru	Gross	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Poland	Net	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Serbia	Net			✓				✓			✓			✓		
Slovakia	Net	✓			✓			✓			✓	✓	✓	✓	✓	✓
Slovenia	Net	✓			✓			✓		✓			✓			
Spain	Net	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Switzerland	Net			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
United Kingdom	Gross	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
United States	Gross	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Uruguay	Net	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: countries are listed in alphabetical order. The first column reports whether the income observations are gross or net. When a country changes its income reporting scheme (gross, net, or mixed) across surveys, we only keep the surveys whose income reporting approach has the largest number of observations between 2004 and 2018. We always drop all data points using a "mixed" reporting approach. The rest of the columns reports with a check mark the years available for each countries. Each vertical panel is a different wave.

B GRD and AGIR

To unravel the relationship between age group income growth and the evolution of the income ratio $R^j_{j'}(t)$, let us define the change in $AGIR$ between period T and $T+h$ as:

$$\Delta R^j_{j'} \equiv R^j_{j'}(T+h) - R^j_{j'}(T),$$

where $\Delta(x)$ denotes the change of a variable x from T to $T+h$.

Using the notion of age group income growth in (**??**),it becomes:

$$\begin{aligned}\Delta R^j_{j'} &= \frac{y_{j,T}(1+g(y_j))h}{y_{j',T}(1+g(y_{j'}))h} - \frac{y_{j,T}}{y_{j',T}} \\ &= R^j_{j'}(T)\left(\frac{1+g(y_j)}{1+g(y_{j'})} - 1\right).\end{aligned}$$

Rearranging, we have:

$$\frac{\Delta R^j_{j'}}{R^j_{j'}(T)} = \frac{g(y_j) - g(y_{j'})}{1+g(y_{j'})}.$$

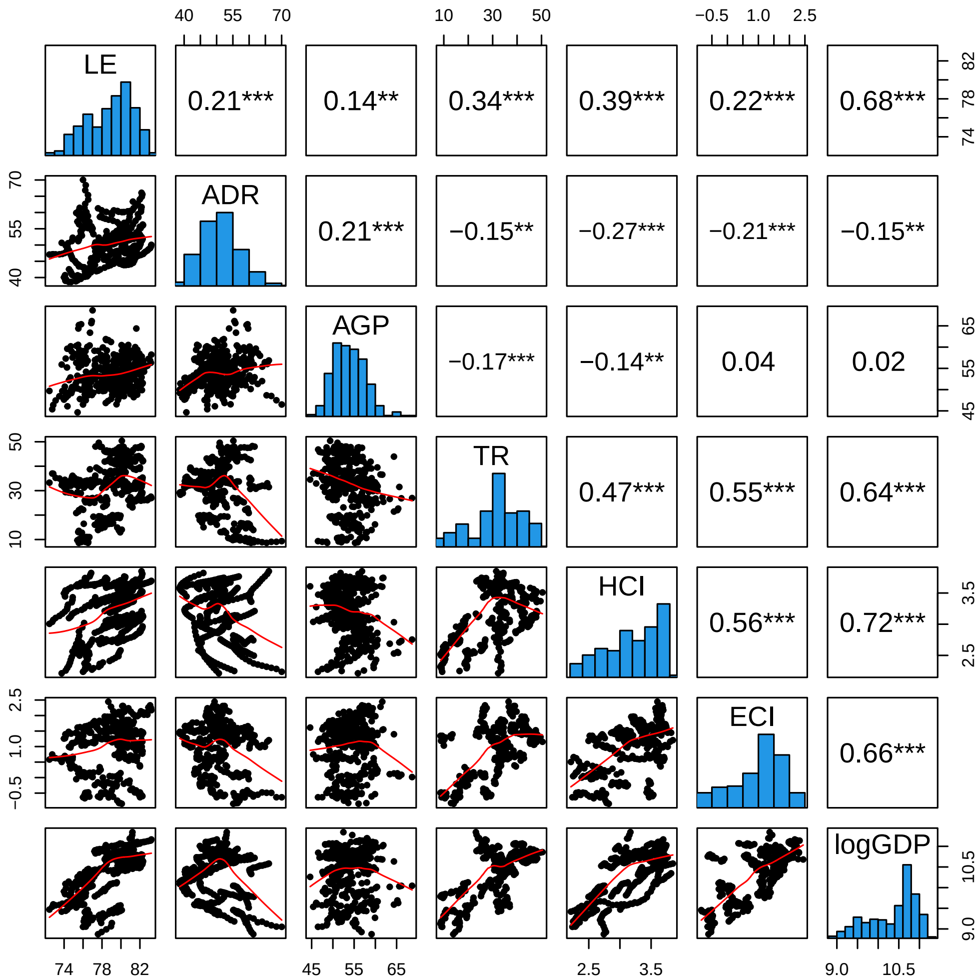
Then, for small $g(y_{j'})$, the annualised income growth rates differential $g(y_j) - g(y_{j'})$ approximates the growth rate of the income ratio $R^j_{j'}(T)$:

$$GRD \equiv g(y_j) - g(y_{j'}) \approx \frac{\Delta R^j_{j'}}{R^j_{j'}(T)}. \tag{11}$$

C Summary statistics of the regressors

Figure 11 summarises the relationship between the 6 covariates of interest and $log(GDP)$, displaying their distribution (in the diagonal), their pairwise correlation (upper triangle) and the pairwise scatter plot (lower triangle). The main takeaway is that the six variables are well-behaved, with enough variation and no critical collinearity that might undermine the validity of the estimates.

Figure 11. Summary statistics of regressors



Note: This figure summarises the relationship between the 6 covariates of interest: Life-expectancy (LE), age-dependency ratio (ADR), Average age of people in government position (AGP), average total tax rate (TR), human capital index (HCI), and Economic complexity index (ECI). The diagonal reports the distribution of the 306 country× year observations. The upper-triangle reports the pairwise correlation with the associated statistical significance (*=10 percent confidence, **=5 percent, ***=1 percent), and the lower-triangle reports the pairwise scatter plot with the best non-linear fit displayed with a solid line.

D Montecarlo: the role of regressors correlated with GDP

This Montecarlo exercise aims to verify that the significance of the 6 variables of interest in explaining the $log(AGIR)$, presented in regression (10), is not driven by their high correlation with GDP. Specifically, we ask the following questions. First, would a regressor that is highly correlated with GDP but orthogonal to the dependent variable be incorrectly picked up as one of its significant contributors? Second, would adding such a regressor alter the estimates of the coefficients on the variables of interest?

In the main text, we have provided evidence that adding in the regression three observed controls (namely, $Co2$,RoL, and PS) highly correlated with GDP do not alter the main results. While this check is reassuring, one cannot be certain about their independence from the dependent variable. To address this concern, we create synthetic regressors independent of $log(AGIR)$.

We assume three data-generating processes for $log(GDP)$: a time trend process, an AR(1), and a random walk with drift, i.e.:

$$log(GDP)_{i,t} = \mu_i^1 + \gamma_i t + \varepsilon_{i,t}^1 \tag{12}$$

$$log(GDP)_{i,t} = \mu_i^2 + \rho_i log(GDP)_{i,t-1} + \varepsilon_{i,t}^2 \tag{13}$$

$$log(GDP)_{i,t} = \mu_i^3 + log(GDP)_{i,t-1} + \varepsilon_{i,t}^3 \tag{14}$$

After estimating the parameters for each of the processes, we create three synthetic variables, denoted by $z_{i,t}$ composed of the fitted variables of the three regressions above and a random component drawn from an iid distribution with mean zero and standard deviation equal to the standard deviation of the corresponding estimated residuals from the three regressions above. Therefore, the synthetic regressors are:

$$z_{i,t}^1 = \hat{\mu}_i^1 + \hat{\gamma}_i t + \chi^1 \eta_{i,t}^1 \tag{15}$$

$$z_{i,t}^2 = \hat{\mu}_i^2 + \hat{\rho}_i z_{i,t-1}^2 + \chi^2 \eta_{i,t}^2 \tag{16}$$

$$z_{i,t}^3 = \hat{\mu}_i^3 + z_{i,t-1}^3 + \chi^3 \eta_{i,t}^3 \tag{17}$$

The parameters χ is a scale parameter that allows intensifying the role of the random noise and, therefore, drives the correlations between $log(GDP)$ and the synthetic variables. We calibrate those parameters such that each synthetic variable correlates with $log(GDP)$ around 0.75, a value similar to the correlation of the 6 variables of interest with

$log(GDP)$. Therefore, this procedure produces three regressors highly correlated with GDP but with no additional information content for the $AGIR$ by construction.

We repeat the process M=100000 times by drawing different sets of error terms and creating then M sets of synthetic variables.

For each repetition, we then run the regressions:

$$log(R_{i,t}) = \alpha + \beta_e E_{i,t} + \beta_a A_{i,t} + \beta_p P_{i,t} + \theta_1 log(GDP)_{i,t} + \theta_j z^j_{i,t} + \epsilon_{i,t}, \tag{18}$$

with $j = \{1, 2, 3\}$. We then store the estimates of the coefficient and their p-values.

The first question we answer is whether we alter the importance of the 6 covariates of interest, including the synthetic variable. To answer this question, we compute the share of the M repetitions in which the estimated coefficients are statistically significant at 5 per cent of confidence. The results are reported in Table V. For each of the three methods to construct the synthetic regressor, 5 of the 6 variables of interest are statistically significant in all repetitions; the average tax rate, TR, is significant in 99.30 per cent of the repetitions when creating the synthetic variable from a random walk model. Also, the synthetic variable z does not incorporate any relevant information to the dependent variable, as the frequency of its statistical significance is very close to 5 per cent, which is the correct theoretical variable. Finally, adding this additional synthetic regressor highly correlated with log(GDP) makes the coefficient of this variable significant, with frequency ranging from 15 to 45 per cent. This exercise confirms that including a regressor highly correlated with GDP does not improve explaining the $AGIR$. Therefore, we are confident that the importance of our 6 covariates of interest is not a mere consequence of their correlation with GDP.

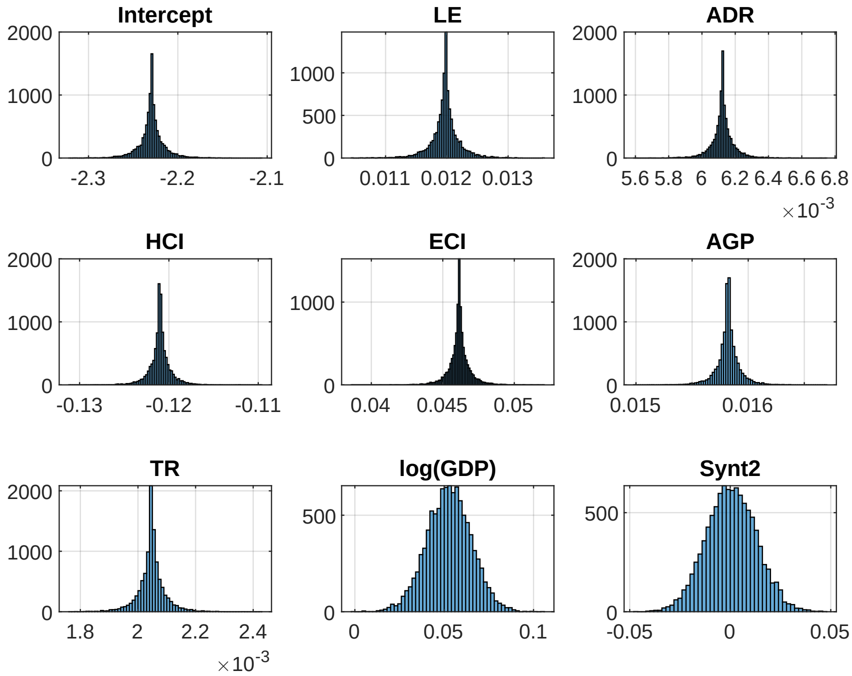
TABLE V. Significance of the regressors: Montecarlo

	time trend	**AR(1)**	**Random Walk**
Intercept	100.00	100.00	100.00
LE	100.00	100.00	100.00
ADR	100.00	100.00	100.00
HCI	100.00	100.00	100.00
ECI	100.00	100.00	100.00
AGP	100.00	100.00	100.00
TR	100.00	100.00	99.39
$log(GDP)$	15.31	45.09	43.34
z	4.88	4.80	4.77

Note: the table reports the share of simulations (in per cent) in which the estimates of the regressors in regression (18) are significant at 5 per cent of confidence. The covariates of interest are: Life-expectancy (LE), age-dependency ratio (ADR), Average age of people in government positions (AGP), average total tax rate (TR), human capital index (HCI), and Economic complexity index (ECI). As a control, we include log(GDP) and the synthetic variable z described above. Each column reports the results of constructing the synthetic variable z from three different DGP for log(GDP): time trend, AR(1), and Random Walk.

Finally, we show that including the synthetic regressors does not alter the magnitude of the other coefficients. We report the distribution of the M repetitions only for the AR(1) model, as the other two models deliver the same results. The estimates of the 6 covariates of interest, and the intercept, are very stable and are not affected by adding the synthetic regressor. In addition, the estimate of the synthetic regressor is very close to zero, as expected. Finally, the coefficient of log(GDP) has a relatively wider distribution, and it is statistically significant (at 5 per cent of confidence) in 45 per cent of the repetitions. This exercise should reassure a reader that the estimated importance of the 6 covariates of interest is not simply an artefact of their correlation with GDP per capita, meaning that they do not simply capture variation arising from being at a more advanced stage of economic development.

Figure 12. Estimated Parameters Montecarlo



Note: this figure reports the distribution of the estimated coefficient of regression (18) for the $M = 10000$ Montecarlo repetitions. The 6 covariates of interest are: Life-expectancy (LE), age-dependency ratio (ADR), Average age of people in government position (AGP), average total tax rate (TR), human capital index (HCI), and Economic complexity index (ECI). As a control, we include log(GDP) and the synthetic variable z computed from an AR(1) DGP process for log(GDP).