Age-Income Gaps

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Abstract

The widening income gap between older and younger individuals is a key topic in political and academic discussions. Research often focuses on labor earnings, neglecting other income sources and cross-country comparisons. This paper fills these gaps by analyzing disposable income trends in 2004-2018 across 32 countries using the Luxembourg Income Study Database. Key findings: (1) The age-income gap has increased in richer countries but decreased in poorer ones; (2) Higher employment rates among older individuals drive this disparity in richer countries; (3) Increased female labor market participation mildly affected the employment margin, while rising education and later retirement did not.

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

JEL Classification: E24, J31, O57

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1 Introduction

The growing income divergence between older and younger individuals, favoring the former, has become a prominent topic in many industrialized countries' political and media discourse. For instance, the House of Lords in the UK and the European Commission in the EU have published comprehensive reports on this issue, highlighting that "the young are facing a future of low pay, high rent, and few incentives" and are "struggling to find secure, well-paid jobs" (House of Lords, 2019; Raitano et al., 2021). Additionally, other institutions have conducted studies on this topic focusing on specific countries such as France (Masson, 2021), Ireland (Barra et al., 2021), Australia (Berry and Sinclair, 2010; Miller et al., 2020), and the UK (Henehan et al., 2021).

This phenomenon has also gathered attention in the academic literature, particularly in analyzing the extent and sources of the (labor) earnings gap between older and younger workers. Examples include Bianchi and Paradisi (2024), which examines the relative wage levels of young and older workers in Italy, and Freedman (2024), which studies the labor earnings of different age groups in eight rich countries.

However, these works solely focus on individuals in employment and overlook other sources of income. While this approach is suitable for studying wage dynamics, it may have limitations when it aims to analyze the overall evolution of age-income inequalities. Firstly, it is unclear whether wages are the main factor contributing to the increase in age-income disparities among different age groups. Secondly, other income margins, such as employment rates and public transfers, may have evolved differently than wages over time and across countries, thus making the age-earnings gap an inadequate proxy for comparing the global evolution of age-income disparities.

This paper addresses these shortcomings by analyzing the evolution of the disposable income - and its components - of older and younger individuals across 32 countries at different ends of the economic development spectrum. We leverage income microdata harmonized in the Luxembourg Income Study Database (LIS) to create a panel dataset covering the period 2004-2018. For this purpose, we define and analyze the *Age Group*

Income Ratio, (henceforth, *AGIR*), which captures with a simple number the relative average disposable income of the old and young in any given period. Our rich dataset allows us to uncover regularities in the international evolution of the age-income gap and to highlight how it differs from the more commonly studied age-earnings gap.

Our study reveals three primary findings. First, the age-income gap has followed different trends across countries: it has grown in richer countries (Western Europe, North America), but it has fallen in poorer ones (Eastern Europe, South America). In fact, the *AGIR*, i.e., the ratio between the average income of 50-64 years old individuals (henceforth, the "old") and 25-34 years old ones (henceforth, the"young"), has increased by 18 percentage points (pp), from 1.13 to 1.31, in richer countries. In contrast, it has fallen by 8 pp in poorer countries, from 1.14 to 1.06.

Second, the evolution of the conventionally studied age-earnings gap is not the main driver of the growth in age-income gaps in richer countries. By decomposing income growth into its components (labor earnings, employment, and size of transfers and the share of individuals receiving them), we find the faster increase in the employment rate of the old relative to the young explains 69 percent of all components that have contributed to the increase in AGIR in rich countries. We label this channel as the *employment margin*. In contrast, most of the reduction in income inequalities in poorer countries has been driven by the stronger wage growth of young workers (*earnings margin*). As a result, we provide evidence that estimates of age inequalities that focus on labor income (such as the "age-earnings gap") severely underestimate the increase of age-income gaps in rich countries and their reduction in poorer countries. In one-third of the countries in our sample, the ratio of employees' earnings has evolved in the opposite direction of our *AGIR* between 2004 and 2018. Additionally, our work identifies countries (such as the US) where the two approaches yield similar results, providing valuable insights for researchers and policymakers.

Third, we investigate the role of long-run structural changes in explaining the employment margin of the growth AGIR in developed economies. To isolate the role of the increased late-career female labor market participation (Costa, 2000; Olivetti and

Petrongolo, 2016; Goldin and Katz, 2018b), we first compare the employment margins for the female population to the ones of the overall population. Women's employment margins are only slightly larger (average 1.1 pp) than in the whole population (average 0.9 pp). This difference is completely driven by rich countries (1.5 pp for females and 1.1 for the whole population), and it disappears in poorer countries (0.5 percent for both women and the whole population). Therefore, the increased late-career female labor market participation has exacerbated the income gap between old and young workers in rich countries but is not the only cause of the large contribution of the employment margin to *AGIR*. Then, we isolate the role of increased high-school attainments among the old by comparing the employment margins for the high-school graduates to the ones of the overall population, thus analyzing whether the education convergence occurring in richer countries - with older cohorts becoming progressively more educated - is the primary explanation for our findings (Goldin and Katz, 2007, 2018a). The data do not support this hypothesis because the employment component is identical for high-school graduates and the whole population (equal to 0.9 pp). In richer countries, the employment margin for high-school graduates is even slightly lower (1.0 pp) than the population's (1.2 pp).[1] Finally, we investigate the role of retirement age policies (Pilipiec et al., 2021; Staubli and Zweimüller, 2013). We construct an alternative *AGIR* measure by redefining the "old" as individuals below a country's 2004 minimum pension age. The employment margin of this alternative *AGIR* measure is almost identical to the original one (0.8 vs 0.9 pp), thus showing that it does not depend on changes in the old-age retirement thresholds in each country within our sample.

Related Literature Age group wage dynamics have been discussed for decades. During the 1970s and 1980s, economists focused on the "baby-boom" generation's ingress in the labor market, which increased the relative supply of young, inexperienced labor (Welch, 1979; Levine and Mitchell, 1988). Since economists tried to explain the consequent wage trends with the imperfect substitutability of labor inputs with different tenure/experience, many concluded that the wages of the successive, smaller cohorts were set to grow faster

[1] We obtain similar results when focusing only on college graduates.

once the aging baby boomers created an excess supply of "experienced" labor (Jeong et al., 2015). We document that this is not the case in most advanced economies. Similar trends have been shown for individual countries by Rosolia and Torrini (2007) and Naticchioni et al. (2016) for Italy, Guvenen et al. (2022) for the US, and Cribb (2019) for Britain. Bianchi and Paradisi (2024) reach similar conclusions when studying age-wage inequalities in a set of high-income countries (with administrative data for Italy and Germany). Also, Freedman (2024) uses a similar set of countries to study cohort trends in earnings. We contribute by providing further international evidence.

Our analysis extends to overall disposable income gaps and their components. Since our data covers advanced economies and Eastern Europe and South America, we are the first to document that age-income inequalities have been diverging between high- and low-income countries, with the two groups following opposite trends. The majority of papers have focused on the relative earnings or wages of employed individuals (Bianchi et al., 2022; Bianchi and Paradisi, 2024; Bennett and Levinthal, 2017; Beaudry et al., 2014; OECD, 2024). Guvenen et al. (2022) considers *lifetime* earnings of US workers, implicitly accounting for the employment margin of cohorts but without disentangling these margins explicitly. However, we show that the biggest contribution to the increase in age inequalities in rich countries came from the faster rise in *employment* among older individuals and not from the faster wage growth of older employees. Researchers should be careful when drawing generalized conclusions from the dynamics of the age-*wage* gap, as it may not reflect the dynamics of the overall age-*income* gap. The growth rates of the age-earnings gap systematically underestimate the change in $AGIR$, whether positive (in richer countries) or negative (in poorer countries).

Finally, we show that these concerns are valid also when looking at sub-populations that may have experienced different labor market dynamics. Therefore, our paper connects to the literature that analyzes the labor market consequences of the increased female participation (Maxwell, 1990; Costa, 2000; Acemoglu et al., 2004; Goldin, 2006; Olivetti and Petrongolo, 2016; Goldin and Katz, 2018b), the increased education level (Goldin and Katz, 2007, 2018a) and the increased retirement age (Pilipiec et al., 2021; Staubli and Zweimüller, 2013). In particular, we focus on the asymmetric effects for old and young workers related to the work of Adão et al. (2024) and Lagakos et al. (2018), among others.

Paper organization. The rest of the paper is organized as follows. In Section 2, we present the data and define the underlying economic variable of interest. In Section 3, we derive three novel stylized facts about how disposable income is distributed across age groups across countries and how that distribution has evolved in the last 25 years. Section 4 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 economic variables of interest, i.e., disposable income and its subcomponents.

2.1 Data

We use harmonized microdata provided by the Luxembourg Income Study (LIS), a data archive and research center that collects, harmonizes and distributes microdata to *"enable, facilitate, promote, and conduct cross-national comparative research"* (Luxembourg Income Study (LIS) Database, 2024). The data is derived from surveys or administrative datasets. Each dataset is then harmonized following a framework that aims to create variables representing the same income and categorical concepts and to remove errors and inconsistencies.

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

1. **Individual-level data**. We keep only country-year data points with individual-level income data. Household-level income data are unsuitable for comparing the income of young and old individuals.

2. **Long time series**. To coherently analyze the medium-term trends in age inequalities,

we need a long enough time series (for each country) located within the same time frame (across countries). Thus, we discard all countries not surveyed at least once between 2004 and 2006 and once between 2015 and 2018.

3. **Consistent income definition**. When a country changes its income reporting approach (gross, net, or mixed) across surveys, we only keep the surveys whose reporting approach has the largest number of observations between 2004 and 2018. We drop all data points with 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 almost 50 percent of workers do not reside in the country, making it unsuitable for our analysis.

This procedure yields a sample of 32 countries and 357 country-year surveys collected between 2004 and 2018. We transform all income variables into real terms and PPP, allowing cross-country and cross-period comparisons.

Waves. Since not all countries are surveyed in the same year, the panel of country-year observations is unbalanced. To overcome possible related issues, we group yearly surveys into five *waves*, i.e. 3-year windows starting from 2004 (2004-2006, 2007-2009, 2010-2012, 2013-2015, 2016-2018). We create country-wave data by merging all surveys within a wave, giving equal weight to each yearly survey. This procedure yields 158 country-wave data points and composes an almost perfectly balanced panel.[2] Table I in Appendix A reports the data availability.

2.2 Income definition and its subcomponents

We now illustrate our variables of interest from the LIS dataset. The observed disposable income of an individual q (in a given year/wave and a given country), denoted y_q, is:

$$y_q = w_q^n + \Theta_q^n \tag{1}$$

[2] All our countries have at least one observation per wave, apart from Serbia and Slovenia, which are missing one wave each.

where w_q^n denotes net labor income, and Θ_q^n is the net income derived from a subset of transfers, namely pension payments, unemployment benefits, and (when available) scholarships and paid maternity/paternity leave.[3]

While some countries report net income data components directly, others report gross income.[4] In such a case, we construct net income as the difference between gross income and income taxes, i.e. $y_q = w_q^g + \Theta_q^g - \tau_q$. Notice that τ_q, the observed measure of taxes, does not include taxes on capital income.

Remark. 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 labor market for the age income distribution. Second, we believe that, if anything, excluding capital income 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.[5]

3 Age-income gaps in the XXI Century

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 three novel stylized facts.

[3] We only include these additional benefits if present in all the country's surveys within our dataset.

[4] See Table I in Appendix A for the list.

[5] While statistics about wealth-age distribution are not homogenous across countries, there is evidence that, at least in industrialized 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 percent, while the age group under 40 has decreased from 8.1 to 5.6 percent (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 heads were in the age group 55-64 increased from 18 to 24 percent, while the ones whose heads were in the age group 35-44 decreased from 19 to 16 percent (source:(Colombo et al., 2014)). In Australia, from 2003, the total wealth of the age group over 65 increased from 26 percent higher than average to 34, while the total wealth of the age group under 35 decreased from 64 lower than average to 70 percent (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 favor of the older age group are sensibly larger than the observed share shift in the demographic composition.

3.1 Age Group Income Ratio

As a parsimonious statistic of the income gap between age groups, we consider the ratio of their average disposable income at a given period: we refer to this statistic as the *Age Group Income Ratio* (*AGIR*). For a given country, and ignoring the country index, let us define with $y_{j,t}$ its average disposable income for a given age group j at time t. Then, we denote the *AGIR* of a country as $R(t)$:

$$R(t) = \frac{y_{\text{old},t}}{y_{\text{young},t}}.$$

With a simple number, this statistic captures the relative income between two age groups in any given period, similar to the "age-earnings gap". Importantly, unlike the age-earnings gap, the average income is calculated across all individuals, not only employed ones. Hence, this measure provides a broad picture of how *overall* income is distributed between age groups in a given year.

Our analysis focuses on two age groups: individuals aged 50-64 (late-career working-age individuals) and individuals aged 25-34 (early career). We chose these two age groups because they reflect individuals who have already completed their education and are at opposite ends of their work lives. We often refer to these two age groups as the old and the young, respectively.

As an illustrative step, in Figure 1, we plot the evolution of age income and earnings inequalities between old and young for the two sets of countries. We divide countries into a "richer" or a "poorer" group. The two groups are defined by applying a k-means clustering algorithm, with $k = 2$, on their 2004 GDP (PPP, constant 2017 dollars, per capita) at the beginning of our dataset. The resulting classification is consistent with the 2006 IMF classification (International Monetary Fund, 2006).[6] The left panel displays the simple average of the *AGIR* of all countries comprising the "richer" or "poorer" group for the five waves of surveys starting in 2004. The solid red line reports the average *AGIR* among poorer countries, and the dashed blue line reports the one among richer countries.

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

The right panel displays the average age-earnings gap, defined similarly to our $AGIR$ but including only employed individuals' net labor income.

The figure reveals three facts. First, in the early 2000s, the mean $AGIR$ of poorer and richer countries was similar. In poorer countries, the late-career age group's disposable income was, on average, 14 percent higher than the early-career age group's. In richer countries, it was 13 percent higher.

Second, and most importantly, the average disposable income of the old relative to the young displays diverging trends for the two groups of countries. In richer countries, the $AGIR$ displays an upward trend (+18 pp in 14 years); in poorer countries, the $AGIR$ displays a downward trend (-8 pp). In Appendix B, we show that (i) our results do not depend on our binary country-group classification but that there is a statistically significant trend component that varies with the initial country-specific GDP level; (ii) our results hold when considering the unbalanced panel with years, rather than waves, as the unit of observation.

Third, the age-earnings gap grew by only 8 pp in richer countries, meaning that the age-earnings gap grew less than the overall age-income gap.[7]

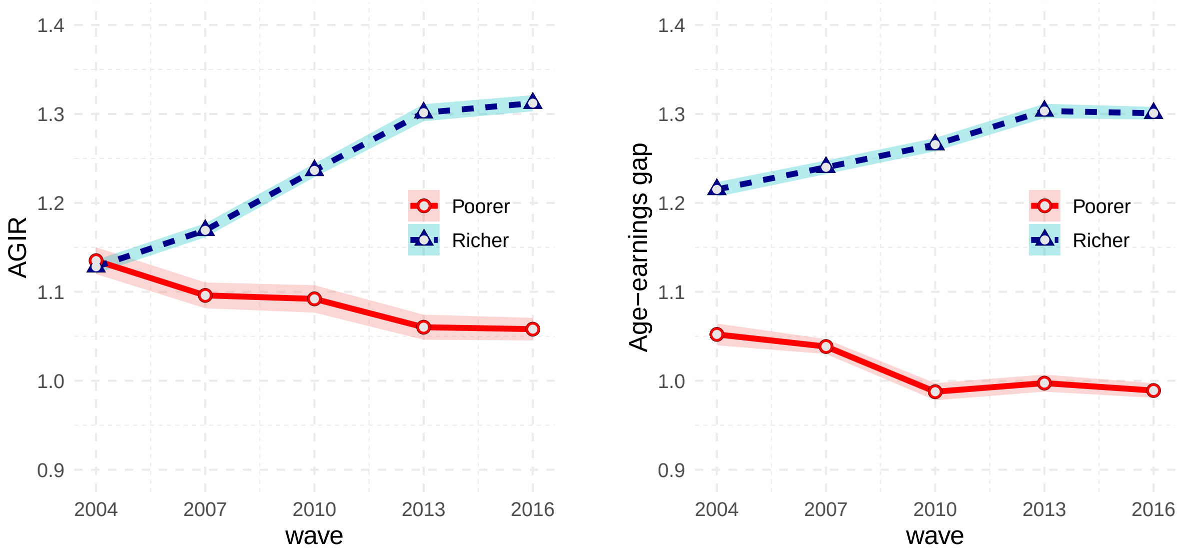
These findings lead to our first novel stylized fact.

Stylized fact 1 In the last 20 years, the $AGIR$ has evolved in opposite directions in richer and poorer countries: in the former, the $AGIR$ has risen by around 18 percent, while in the latter economies, it has declined by around 8 percent. Also, those trends for the $AGIR$ are more divergent than for the age-earnings gap.

[7]See Appendix B.1 for the statistical evidence.

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

(a) *AGIR* (b) Age-earnings gap



Note: The figure depicts the Age Group Income Ratio (*AGIR*) of late-career individuals (50-64 years old) and early-career individuals (25-34 years old) in the left panel, and the age-earnings gap, the ratio between the labor earnings of similarly defined categories of employed old and young, in the right panel. The data points 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 percent confidence interval calculated with the delta method.

In the next sections, we study the determinants of the growth in *AGIR* and why its dynamics differ from those of statistics based on the earnings of employees.

3.2 Income determinants of age inequalities

In this section, we examine which subcomponent of income played the primary role in the dynamics of the *AGIR*. We focus on the changes in *AGIR* from the beginning to the end of the sample period, as it displays a clear overall trend over the last two decades with no cyclical fluctuations.

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 between period T_i and $T_i + h_i$ is:

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

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, we define as Growth Rate Differential (GRD) the difference of the annualized growth rates of the income of old and young individuals, i.e. $g(y_{\text{old}}) - g(y_{\text{young}})$. This statistic has two advantages. First, it approximates the growth rate of the $AGIR$:[8]

$$GRD \equiv \frac{1}{h}\left(g(y_{\text{old}}) - g(y_{\text{young}})\right) \approx \frac{1}{h}\frac{R(T+h) - R(T)}{R(T)}.$$

Second, it allows us to perform an exact growth accounting to investigate the sources of these growth rate differentials 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 the intensive and extensive margin of different income subcomponents.

Starting from the observed individual disposable income, defined in Equation (1), and ignoring time and country indices, we can write the country *average* disposable income, y as:

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

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

Then, the *growth rate* of average disposable income of age group j between period T and $T+h$ is:

$$\frac{\Delta y_j}{y_{j,T}} = \underbrace{\frac{e_{j,T}\Delta y_j^n}{y_{j,T}}}_{\text{Labor Earnings}} + \underbrace{\frac{y_{j,T}^n \Delta e_j}{y_{j,T}}}_{\text{Employment}} + \underbrace{\frac{p_{j,T}\Delta\Theta_j^n}{y_{j,T}}}_{\text{Transfer Income}} + \underbrace{\frac{\Theta_{j,T}^n \Delta p_j}{y_{j,T}}}_{\text{Transfer Share}}, \tag{2}$$

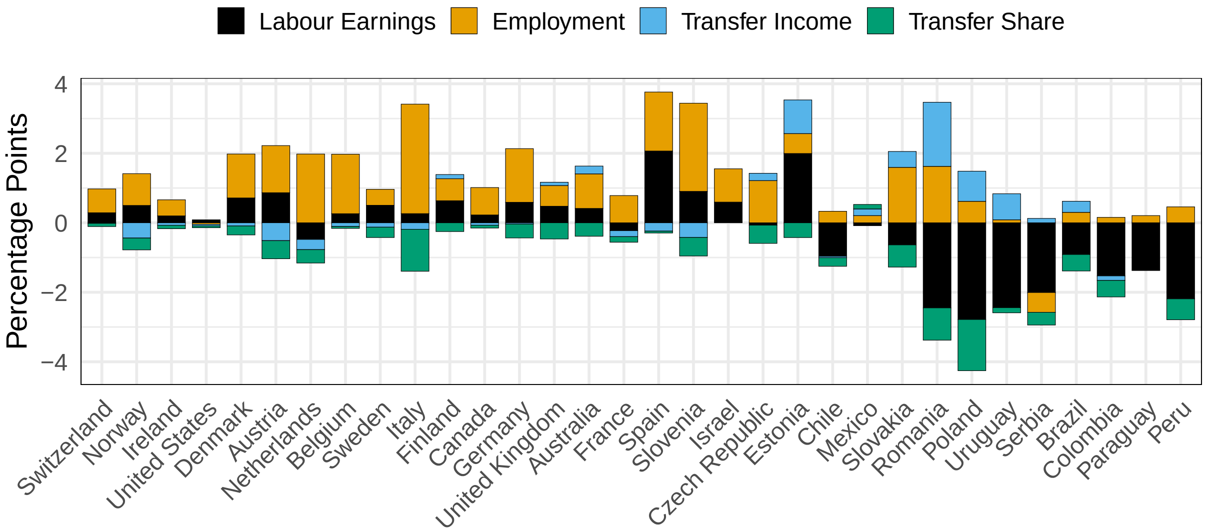
where Δx denotes the difference of variable x between periods T and $T+h$. All income components are considered net of taxes. Then, we can decompose the GRD into the contributions of the difference, between old and young, of each of the income growth margins depicted in equation (2), by computing the four components of the difference $\frac{\Delta y_{old}}{y_{old,T}} - \frac{\Delta y_{young}}{y_{young,T}}$.

Figure 2 illustrates these contributions: a positive value means that the specific sub-

[8]See Appendix C.1 for the derivation.

components contributed to faster income growth for the 50-64 age group than for the 25-34 one.[9] We now describe the main findings, focusing on each component at a time.

Figure 2. *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 employment rate growth. "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 the growth of the share of individuals receiving a transfer.

Employment. In rich countries, the main contributor to the unequal income growth between late- and early-career individuals is the employment margin, a consequence of the divergence in employment rates across the two age groups. In fact, while the employment rate of early-career individuals has not increased over the period (and has even fallen in some countries), the employment rate of late-career individuals has increased substantially, between 1 and 2 percent per year. As a result, the contribution of the employment margin to the *GRD* in rich countries is 1.2 pp. On the contrary, the employment margin is sensibly smaller in poorer countries (an average of 0.5 pp).

Labor Earnings. Labor earnings also contributed positively to the faster rise in the income of late-career workers in most richer countries, implying that the wage growth of late-career workers has outperformed that of early-career workers. Notice that this

[9]In Appendix C.2, we plot the overall *GRD* for each country and their statistical significance.

component reflects the dynamics of the age-*earnings* gap, which is studied by (Bianchi et al., 2022; Bianchi and Paradisi, 2024; Bennett and Levinthal, 2017; Beaudry et al., 2014). However, unlike the age-earnings gap, its relative size across countries is also affected by the employment rates and by the importance of labor income for the overall disposable income of an age group. Our decomposition highlights that, in richer countries, the earnings margin is not the main driver of the overall evolution of the $AGIR$(average of 0.5 pp across rich countries). On the contrary, in poorer economies, the younger age group has experienced much faster earnings growth than the older age group (average contribution to GDR equal to -1.3 pp). This margin explains virtually all the fall in $AGIR$ in low-income countries and contributed negatively also in countries with an overall positive GRD (such as Mexico, Slovakia, and Romania).

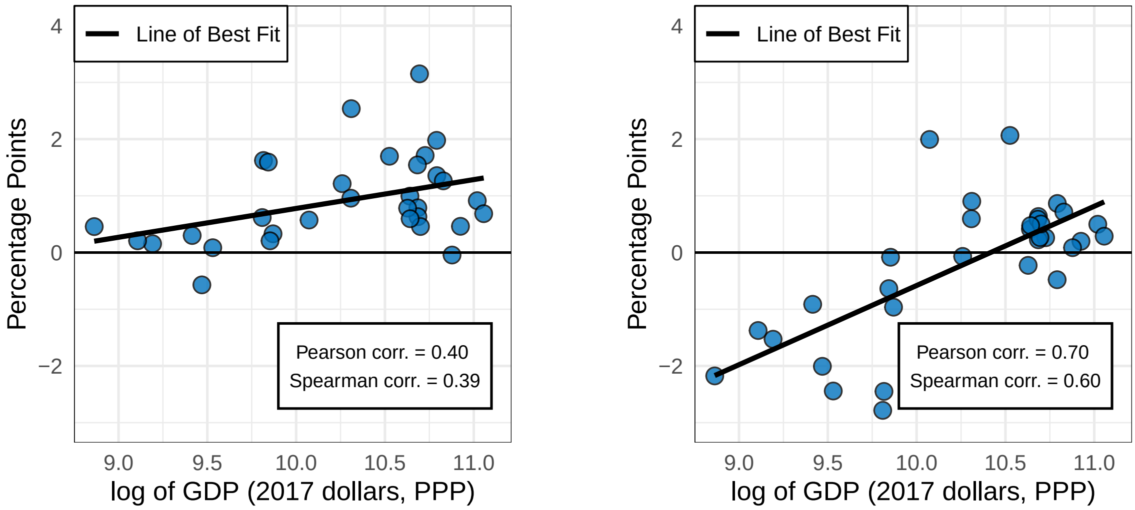
Pensions and Transfers. For most countries, pension and welfare payment changes had little impact on the GRD. However, we can observe some common patterns. In most countries, the share of old-age individuals receiving transfers has fallen slightly faster than the young, implying a negative transfer share margin (average -0.4 pp; -0.3 in the richer countries and -0.5 in the poorer ones.). The contribution of changes in the transfers' size ("Transfer Income" component) is more heterogeneous, being mostly small and negative in richer countries (average of -0.1 pp) but fairly large and positive for the poorer ones (average of 0.5 pp).

We provide visual evidence for the relationships between GDP levels and the two labor market margins of the GRD (employment and labor earnings). In Figure 3 we plot the per capita PPP GDP (in 2017 US dollars, in log) of each country at the beginning of the sample against the employment margin (panel a), and labor earning margin (panel b). Using the same scale, a reader can immediately evaluate the relative contributions of the two components to the GRD. Notice that the employment margin is positive for almost all countries, although small for poorer and large for richer countries. On the contrary, the labor earnings margin flips sign across the GDP distribution, being large and negative for poorer economies and positive but close to zero for most richer ones.

These observations lead to our main stylized fact.

Figure 3. Employment and Labor Income Contribution to *GRD* vs GDP level

(a) Employment Contribution (b) Labor Income Contribution



Note: Panel (a) plots the employment margin of the *GRD* against the log of PPP GDP (calculated at 2017 dollars in 2004). In the box, we present the two variables' linear correlation (ρ). Panel (b) plots the labor earnings margin of the *GRD* against the log of PPP GDP (calculated at 2017 dollars in 2004). Other specifics are as in panel (a).

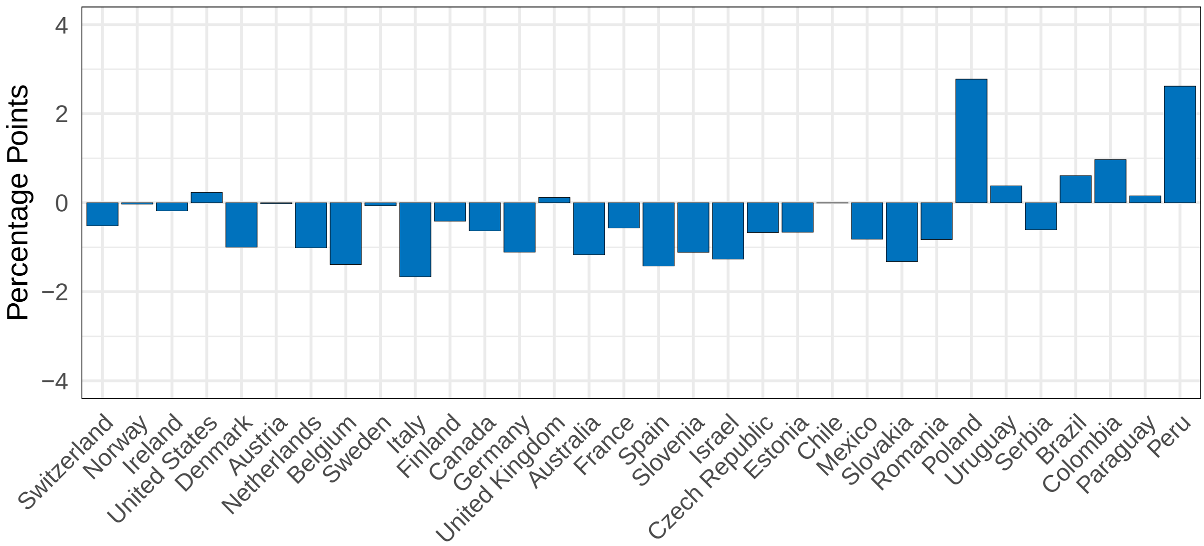
Stylized fact 2. In rich countries, the main contributor to the positive *GRD* is the divergence in employment rates between young and old. In lower-income countries, the main contributor to negative *GRD* is the faster increase in labor income, conditional on being employed, of the young relative to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

This stylized result can also help understand why the age-earnings gap has grown, in absolute terms, less than the age-income gap. Although the earnings of the old have increased faster than those of the young in rich countries, the employment margin provided a larger contribution. Hence, the age-income gap has increased faster than the age-earnings gap in rich countries. Conversely, the considerably higher employment rate among the young (relative to the old) in poorer countries amplified the effects of changes in the earnings margin.[10] Hence, the fall in *AGIR* is larger than in the age-earnings gap. In Figure 4, we depict these differences between the *GRD* of the labor earnings of employed individuals and the income of all individuals. A negative number means that

[10]Consider how even with an identical wage growth across age groups, the overall disposable income would increase more for the age group with more employed individuals, everything else equal.

the GRD of income is larger than that one of earnings. The consistent negative bias in richer countries (where GRDs are positive) and positive bias in many poorer countries (where GRDs are negative) highlights how earning gaps have changed less than income gaps.

Figure 4. Difference between GRD of earnings and income



Note: the figure depicts, for each country, the difference between the annualized GRD of the labor earnings of employed individuals and the annualized GRD of disposable income of all individuals. A negative value means that the latter was larger than the former, implying that age inequalities grew faster (or fell less) for disposable income than labour earnings.

Take away These results are relevant for two reasons. First, we have highlighted that the drivers of changes in the age-income gap differ between high-income and lower-income countries but are similar within income groups (employment rates in the former, earnings in the latter). These patterns justify the global scope of our analysis and uncover the rise in age-income gaps as a common problem in most high-income countries. Second, these patterns suggest that the causes of the rise in $AGIR$ in richer economies should be explored by looking at phenomena connected to the long-run trends that might have affected labor force participation at the later stage of the working career. We investigate this intuition in the next section.

3.3 Demographic trends and age-income gaps

Could the large employment margin in richer countries be attributed to specific long-run trends occurred in recent decades? This section investigates this question by isolating the employment margin for different demographic subsets.

Increased Female Labor Force Participation First we compute the employment component of the *GRD* for females only, so to investigate the role of the increased female labor force participation during the entire lifecycle (Costa, 2000; Olivetti and Petrongolo, 2016; Goldin and Katz, 2018b). Figure 5a reports the size of the employment margins for females (y-axis) and, as a reference, for the whole population (x-axis). On average, women's employment margins are only slightly larger (average 1.1 pp) than in the whole population (average 0.9 pp). This difference is driven by rich countries (1.5 pp. for females and 1.1 pp for the whole population), while it disappears in poorer countries (0.5 pp for both women and the whole population). As a measure of statistical similarity between the magnitudes of the employment margins of women and the population as a whole, we consider the concordance correlation coefficient (CCC), a measure of agreement between two variables.[11] It is equal to 1 when the two measures align in the 45-degree line. The CCC for females and the whole population is equal to 0.85, an *excellent* match according to (Altman, 1990)'s interpretation. Therefore, the increase in late-career female labor market participation appears to have exacerbated the income gap between old and young workers in rich countries. Nevertheless, the employment margin contributed to an increase in the income gap also among males. As a result, albeit quite important, the increased female participation alone cannot explain the overall large contribution of increased employment for the old.[12]

Education Second, we compute the size of the employment margin for high-school graduates. In this way, we can explore whether the education convergence occurring in richer countries - with older cohorts becoming progressively more educated - is the main

[11] The CCC for two variables x and y, denoted with ρ_c is defined as: $\rho_c = \frac{2s_{x,y}}{s_x^2+s_y^2+(\bar{x}-\bar{y})^2}$, where $s_{x,y}$ is the sample covariance between x and y, s_x^2 is the sample variance of x, and $\bar{x}$ is its sample mean.

[12] In Appendix D, we report the *GRD* decomposition for all the subset of demographics considered in this section.

explanation for that effect (Goldin and Katz, 2007, 2018a; Barro and Lee, 2013). As displayed in Figure 5b, the data do not support that evidence because the employment margin is identical for high-school graduates and for the entire population (equal to 0.9 pp), suggesting that it is a phenomenon that affected education groups in similar ways. In richer countries, the employment margin for high-school graduates is even slightly lower (1.0 pp) than for the entire population (1.2 pp).[13] Also in this case, the CCC is very high and equal to 0.86.

Increased Retirement Age Finally, we investigate whether the large employment margin of *AGIR* is mainly due to a delay in retirement (Pilipiec et al., 2021; Staubli and Zweimüller, 2013). We construct an alternative definition for the old age group: all individuals older than 50 and younger than the minimum pension age for each country and gender within our sample.[14] This specification aims to insulate our statistic from changes in the age threshold for old-age retirement, as well from aging (insofar it changes the relative composition of old individuals above or below the retirement age).[15] The employment margin of this alternative *AGIR* measure (0.8 pp) is similar to the headline figure (0.9 pp), as displayed in Figure 5c. Hence, the employment margin of *AGIR* does not depend only on changes in each country's target retirement age. In this case, the CCC is equal to 0.91.

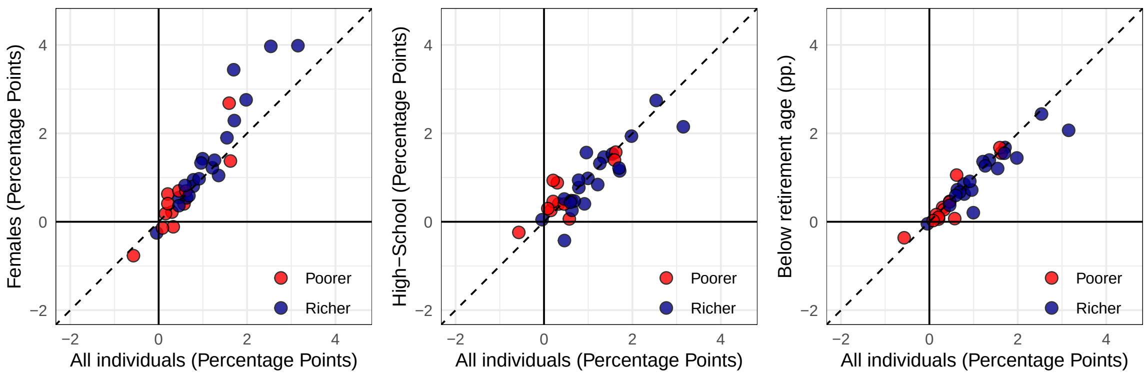
While in this section we focus on within-group contributions, in Appendix E we consider the combined effect of the female labour force participation, education trends, and changes to the retirement age. We corroborate the above results by using a decomposition to recover the composition effects of education trends on the *GRD* for males and females below the legal retirement age.

[13] We obtain similar results when focusing only on college graduates: in rich countries, the employment margin is, on average, 0.8 pp for college graduates.

[14] See Appendix D.1 for the full description and data source.

[15] We consider the minimum retirement age in 2004 because, in none of the countries in our sample, it has declined between 2004 and 2018.

Figure 5. Employment component of GRD across demographics subsets



Note: The figure depicts the employment component of the Growth Rate Differential (GRD), comparing late-career individuals (50-64 y.o.) with early-career individuals (25-34 y.o) of different sub-populations. Panel (a) compares females' employment margin to the whole population's. Panel (b) focuses on high-school graduates's employment margins. Panel (c) compares the employment margins calculated by including in the old age group only individuals below the minimum old-age retirement age in 2004.

Our analysis suggests the following third stylized fact:

Stylized fact 3. The large employment margin of the $AGIR$ in rich countries is not driven by the education composition or changes in the minimum pension age. Also, the employment margin in those countries is substantially larger among females than males but positive for both genders.

4 Conclusions

The growth of inequalities between young and old individuals has become a prominent topic in several advanced economies' media and political discourse. Yet, most of the existing evidence has focused on labor earnings of people in employment (rather than the income of all individuals) and a small set of developed countries.

In this paper, we overcome these limitations by studying the evolution of age inequalities in disposable income (thus covering all individuals and non-labor income sources) for 32 countries at different ends of the development spectrum. We uncover three novel results.

First, the age-income gap has increased in richer countries (Western Europe, North America, Oceania) but has fallen in poorer countries (Eastern Europe, South America).

Second, we find that the main driver of the increase in $AGIR$ in richer countries is the change in the relative employment rate of old and young individuals in favor of the former. In contrast, the fall in $AGIR$ in poorer countries came from the faster increase in labor earnings of the young relative to the old.

Finally, we show that accounting for some of the most important long-run demographic trends of recent decades (increase in female labor force participation, increase in the education level of older generations, stricter retirement policies as an answer to population aging) is not sufficient to account for the whole size of the employment margin that caused the growth of $AGIR$ in richer countries, although the trends in female labor force participation have had a relevant role.

Our results open new research questions. Commonly studied demographic trends cannot fully explain the role of the employment margin. Does this imply there have been *other* age-biased structural changes in the organization of labor and demand for skills in favor of the old? Or is it due to friction in firms' internal labor markets? And why have some countries been affected more than others? Finally, what are the implications of the age-income gaps regarding welfare, location choice, and political economy? Our work and findings are relevant to setting the stage to address those questions.

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APPENDIX FOR ONLINE PUBLICATION

A Additional Information on Data and Cleaning

TABLE I. Data availability

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

Note: The table reports the data points we include in our analysis. Countries are listed in alphabetical order. According to the algorithm described in the main text, the second column reports whether the country is classified as "richer" or "poorer". The third column provides information on whether income variables are reported as net or gross of taxes. We always calculate net income components using the reported tax variables for countries that report gross income. Each other column reports with a check mark whether the year is available for a given country. Years are grouped by wave. Each country's first and last available year are used to calculate the *GRD*.

B AGIR Trends: Statistical Significance

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

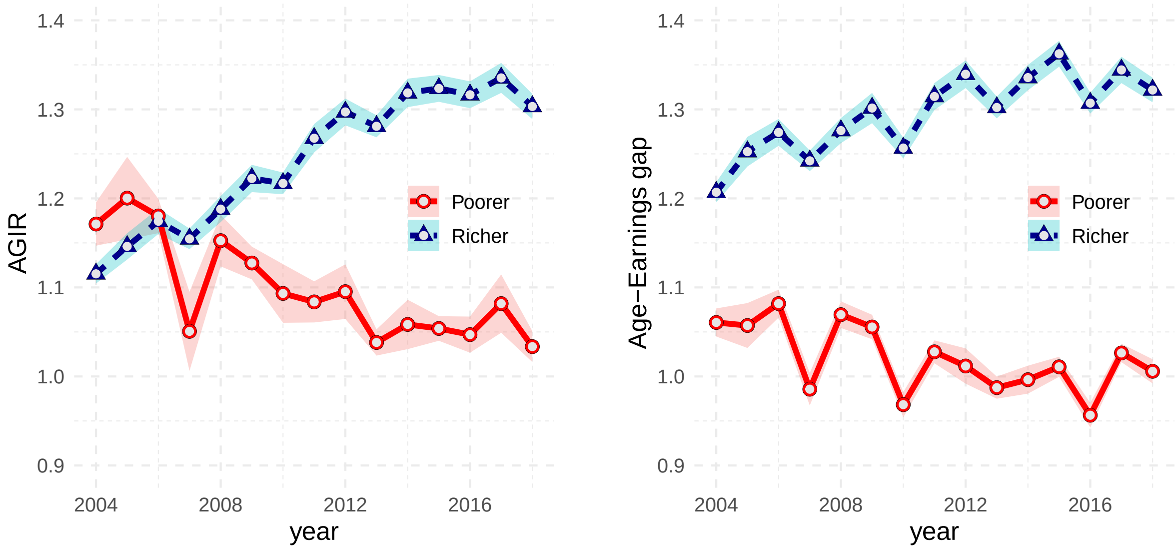
$$log(R_{i,t}) = \alpha + \tilde{\alpha}\mathbb{1}_i^d + \beta t + \tilde{\beta}(\mathbb{1}_i^d \times t) + \varepsilon_{i,t}. \quad (3)$$

Here, $R_{i,t}$ denotes the $AGIR$ computed for the age groups 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 $[0, 3, \ldots, 12]$ when we consider wave observations and takes the value $[0, 1, \ldots, 14]$ when we consider annual observations.[16] 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.

For completeness, Figure 6 displays the AGIR and the Age-Earning Gaps when using years as the observation unit.

Figure 6. *AGIR*, 50-64 vs 25-34 years old

(a) *AGIR* (b) Age-earnings gap



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) in the left panel, and the age-earnings gap, the ratio between the labor earnings of similarly defined categories of employed old and young, in the right panel. The data points 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 percent confidence interval of the mean of the two groups, calculated with the delta method.

Columns (1) and (3) of Table II report the results of our regressions for waves and years, respectively. The *AGIR* in the poorer and richer countries are not statistically different at the beginning of the sample but follow opposite trends. In fact, in poorer

[16]This allows the coefficients on the time trends to be comparable across wave and year specifications.

countries, the *AGIR* time trend is negative (-0.4 percent per year) but not significant, while it is strongly positive (1.4 percent per year) in richer countries.

These results do not depend on our binary classification of "richer" and "poorer" countries. We perform the same analysis while relaxing this rigid division. In particular, we estimate the relationship between the initial log-GDP level and the magnitude of the *AGIR*'s initial level and trend. For this purpose, we run the following regression:

$$log(R_{i,t}) = \alpha + \theta\overline{GDP}_{i,0} + \beta t + \gamma(\overline{GDP}_{i,0} \times t) + \varepsilon_{i,t} \qquad (4)$$

Here, $\overline{GDP}_{i,0}$ denotes the deviation of the log-GDP for each country in 2004 from the cross-section sample mean. Accordingly, α represents the beginning-of-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 (4) of Table II report the estimates for waves and years. The beginning of sample *AGIR* for a country with average initial GDP was around 1.13, and the correlation between initial *AGIR* and initial GDP level is slightly positive but not significant. Looking at the time trend, we find that a country with average GDP experienced a small increase in *AGIR* over the period (β). The trend was stronger for countries with higher GDP than the mean and weaker, or even negative, for those poorer than the mean (positive γ). The last four rows of the Table report the estimated time trend at different points of the GDP distribution. When moving from the poorest to the richest countries in our dataset, the time trend of *AGIR* grows monotonically from -0.6 percent per year to +1.3 percent per year.

TABLE II. Trend in AGIR

	Wave		Year	
Dependent	ln(AGIR)			
	(1)	(2)	(3)	(4)
[1] β: Trend	-0.004	0.006**	-0.008**	0.005***
	(0.005)	(0.003)	(0.003)	(0.002)
[2] $\tilde{\beta}$: Trend $\times$ Richer	0.018***		0.021***	
	(0.006)		(0.004)	
[3] $\tilde{\alpha}$: Richer	0.031		-0.017	
	(0.044)		(0.034)	
[4] θ: Initial log-GDP (Dev)		0.007		-0.027
		(0.020)		(0.020)
[5] γ: Trend $\times$ Initial log-GDP(Dev)		0.009***		0.015***
		(0.003)		(0.002)
Observations	158	158	357	357
R^2	0.274	0.200	0.281	0.206
F-Test:[1]+[2]=0 or [1]+[5]=0	22.77	21.55	57.19	71.39
Trend effect at min GDP		-0.006		-0.016***
Trend effect at 25% GDP		0.002		-0.002
Trend effect at 75% GDP		0.010***		0.012***
Trend effect at max GDP		0.013***		0.017***

Note: Significance level: * = 0.05, ** = 0.01, *** = 0.001. Columns (1) and (3) report the estimates of Equation (3) for wave and yearly observations, respectively. Columns (2) and (4) report the estimates of Equation (4). The last four rows illustrate the implied trend effect at different quantiles of GDP.

B.1 Trends in Age-Earnings Gaps

In Table III, we report the same regressions using as a dependent variable the age-earnings gap. Relative to *AGIR*, the fitted trend effect of GDP on the age-earnings gap (column 2) is smaller at the top of the GDP distribution (+0.6 percent vs +1.3 percent for the richest country). Even at the 75th percentile of GDP, the time trend of the age-earnings gap is not statistically different from zero and small (+0.4 percent per year, p-value>0.05), less than half the trend in *AGIR* (+1.0 percent, p-value<0.001).

TABLE III. Trend in Earnings gap

	Wave		Year	
Dependent	ln(earnings gap)			
	(1)	(2)	(3)	(4)
[1] β: Trend	-0.004	0.002	-0.004	0.002
	(0.004)	(0.002)	(0.003)	(0.002)
[2] $\tilde{\beta}$: Trend $\times$ Richer	0.011**		0.011***	
	(0.005)		(0.004)	
[3] $\tilde{\alpha}$: Richer	0.173***		0.167***	
	(0.038)		(0.032)	
[4] θ: Initial log-GDP (Dev)		0.079***		0.108***
		(0.016)		(0.019)
[5] γ: Trend $\times$ Initial log-GDP(Dev)		0.006***		0.008***
		(0.002)		(0.002)
Observations	158	158	356	356
R^2	0.492	0.394	0.482	0.384
F-Test:[1]+[2]=0 or [1]+[5]=0	6.24	5.83	14.92	20.37
Trend effect at min GDP		-0.006		-0.009*
Trend effect at 25% GDP		-0.001		-0.002
Trend effect at 75% GDP		0.004		0.006***
Trend effect at max GDP		0.006*		0.008***

Note: Significance level: * = 0.05, ** = 0.01, *** = 0.001. Columns (1) and (3) report the estimates of equation (3) for wave and yearly observations, respectively. Columns (2) and (4) report the estimates of Equation (4). The dependent variable is the age-earnings gap, defined similarly to *AGIR* but comparing only the labor earnings of individuals in employment. The last four rows illustrate the implied trend effect at different quantiles of GDP.

B.2 Robustness Checks

We perform several robustness checks, which corroborate the results of the first two sets of estimates. We report the results in Table IV. In columns (1) and (4), we introduce second-order terms for the initial GDP relationship, time trend, and their interaction. In columns (2) and (5), we account for the uncertainty in our estimates of the dependent variable. To do so, 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) average age group income. Finally, we show that the time trends in the $AGIR$ are not shared by the second moments of the income distribution, meaning that the phenomenon is not capturing a different evolution of within-group inequality. For this purpose, in columns (3) and (6), we conduct the same regression as in equation (4) 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 dispersion of the two distributions that account for the mean changes.[17] The data do not display any time trend in the second moments, motivating our focus on $AGIR$ rather than other measures of in-group inequalities.

Table V provides similar robustness checks for the age-earning gap, which yields qualitatively identical results to the ones described for $AGIR$.

TABLE IV. Trend in AGIR

	Wave			Year		
Dependent	ln(AGIR)		ln(IGcvR)	ln(AGIR)		ln(IGcvR)
	(1)	(2)	(3)	(4)	(5)	(6)
[1] β: Trend	0.009	0.002	0.009	0.010	0.004**	0.002
	(0.009)	(0.003)	(0.007)	(0.006)	(0.002)	(0.004)
[4] θ: Initial log-GDP (Dev)	0.013	-0.026	0.058	0.014	-0.040	0.078
	(0.022)	(0.024)	(0.043)	(0.025)	(0.025)	(0.048)
[5] γ: Trend $\times$ Initial log-GDP(Dev)	0.009***	0.010***	-0.003	0.015***	0.015***	-0.003
	(0.003)	(0.003)	(0.007)	(0.002)	(0.003)	(0.007)
Observations	158	158	158	357	357	357
R^2	0.204	0.140	0.027	0.234	0.193	0.014
Weights	No	Yes	No	No	Yes	No
2nd order terms	Yes	No	No	Yes	No	No
F-Test:[1]+[2]=0 or [1]+[5]=0	16.69	14.31	0.34	16.69	46.26	46.26
Trend effect at min GDP	-0.007	-0.012	0.012	-0.016***	-0.018***	0.007
Trend effect at 25% GDP	0.002	-0.002	0.010	-0.002	-0.004	0.004
Trend effect at 75% GDP	0.010**	0.006*	0.008	0.012***	0.010***	0.001
Trend effect at max GDP	0.013***	0.010***	0.007	0.017***	0.015***	-0.000

Note: Significance level: * = 0.05, ** = 0.01, *** = 0.001. All columns report the estimates of equation (4). Columns (1) and (4) 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 (2) and (5) include the second-order terms. Finally, columns (3) and (6) use the ratio of the coefficient of variations for the two age groups of interest as the dependent variable. The last four rows illustrate the implied trend effect at different quantiles of GDP. “Weights” refers to whether observations are weighted so to give less importance to data points where the dependent variable has a large standard error. “2nd order terms” refers to whether the specification includes the squared terms of the independent variables [4] and [5].

[17] 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 V. Trend in age-earnings gaps

Dependent	Wave			Year		
	ln(earnings gap)		ln(EGcvR)	ln(earnings gap)		ln(EGcvR)
	(1)	(2)	(3)	(4)	(5)	(6)
[1] β: Trend	0.001	-0.0002	-0.003	0.004	0.001	-0.006**
	(0.009)	(0.003)	(0.004)	(0.006)	(0.002)	(0.003)
[4] θ: Initial log-GDP (Dev)	0.063***	0.043**	0.079**	0.117***	0.076***	0.088***
	(0.019)	(0.021)	(0.032)	(0.025)	(0.023)	(0.028)
[5] γ: Trend $\times$ Initial log-GDP(Dev)	0.006***	0.006**	-0.005	0.008***	0.008***	-0.006*
	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)
Observations	158	158	158	356	356	356
R^2	0.414	0.255	0.053	0.386	0.331	0.039
Weights	No	Yes	No	No	Yes	No
2nd order terms	Yes	No	No	Yes	No	No
F-Test:[1]+[2]=0 or [1]+[5]=0	4.13	3.28	1.46	4.13	15.89	15.89
Trend effect at min GDP	-0.006	-0.008	0.004	-0.009*	-0.010*	0.003
Trend effect at 25% GDP	-0.001	-0.003	-0.001	-0.002	-0.003	-0.003
Trend effect at 75% GDP	0.004	0.002	-0.006	0.006***	0.005**	-0.009*
Trend effect at max GDP	0.006*	0.004	-0.007	0.008***	0.007***	-0.011*

Note: Significance level: * = 0.05, ** = 0.01, *** = 0.001. All columns report the estimates of equation (4). Columns (1) and (4) 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 (2) and (5) include the second-order terms. Finally, columns (3) and (6) use the ratio of the coefficient of variations for the two age groups of interest as the dependent variable. The last four rows illustrate the implied trend effect at different quantiles of GDP. "Weights" refers to whether observations are weighted so to give less importance to data points where the dependent variable has a large standard error. "2nd order terms" refers to whether the specification includes the squared terms of the independent variables [4] and [5].

C Growth Rate Differentials

C.1 GRD and AGIR

To unravel the relationship between age group income growth and the evolution of the income ratio $R(t)$, let us define the change in $AGIR$ between period T and $T+h$ as:

$$\Delta R \equiv R(T+h) - R(T).$$

Using the notion of age group income growth, we obtain

$$\begin{aligned}\Delta R &= \frac{y_{\text{old},T}(1+g(y_{\text{old}}))}{y_{\text{young},T}(1+g(y_{\text{young}}))} - \frac{y_{\text{old},T}}{y_{\text{young},T}} \\ &= R(T)\left(\frac{1+g(y_{\text{old}})}{1+g(y_{\text{young}})} - 1\right).\end{aligned}$$

Rearranging, we have:

$$\frac{\Delta R}{R(T)} = \frac{g(y_{\text{old}}) - g(y_{\text{young}})}{1+g(y_{\text{young}})}.$$

Then, for small $g(y_{\text{young}})$, the annualised income growth rates differential $g(y_{\text{old}})$ −

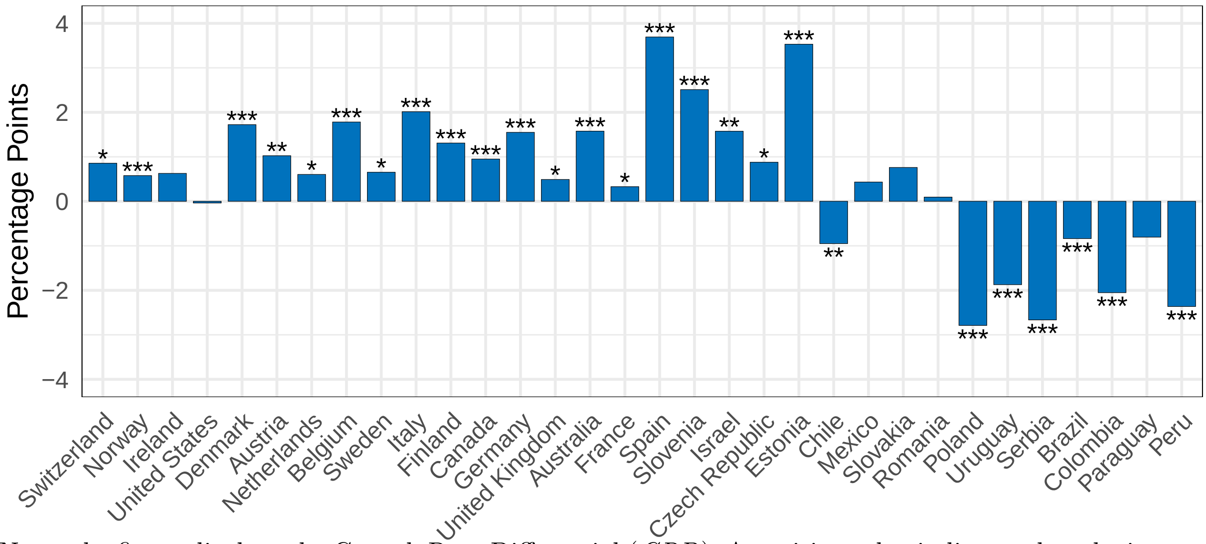
$g(y_{\text{young}})$ approximates the annualised growth rate of the income ratio $R(T)$:

$$GRD \equiv \frac{1}{h}\left(g(y_{\text{old}}) - g(y_{\text{young}})\right) \approx \frac{1}{h}\frac{\Delta R}{R(T)}.$$

C.2 GRD by Country

In Figure 7, we display the annualized 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 and negative for most poorer economies. For 27 out of 32 countries, the GRD are statistically different from zero. Notably, the US has one of the highest $AGIR$ in our sample but has not grown over the last 20 years.

Figure 7. Income growth rate differentials: early-career and late-career



Note: the figure displays the Growth Rate Differential (GRD). A positive value indicates that the income of the old has increased faster than the income of the young over the reference periods. We report statistical significance for the null hypothesis $\text{GRD}_i = 0$. Significance level: * = 0.05, ** = 0.01, *** = 0.001.

D GRD Across Demographics

In this section, we display the overall *GRD* decomposition of the different demographic subsets considered in section 3.3.

D.1 Retirement Age definition

First, we describe the data sources for our definition of retirement age at the beginning of the sample. The thresholds, for males and females when different, are presented in Table VI together with a link to the source datasets. All the retirement ages are based on either OECD's Pension at a Glance 2005 report or the U.S. Social Security Administration "Social Security Programs Throughout the World" publication closest to 2004 (2004 for Europe and Asia, 2005 for Americas). Where available, we pick the "early" retirement age. This represents the minimum retirement age for individuals with a long enough contribution history, or willing to accept lower replacement rates. This aims to capture the retirement age generally attainable by any individual. For this reason, we do not account for special regimes for particular occupations or exceptions for very early career starts.[18]

We make four minor discretionary adjustments. First, we set the minimum retirement age in our sample to 53 years old to avoid reducing our sample size for the old group (which is normally defined as 50-64 years old) too much. This choice affects only the female retirement ages for Serbia and Peru, where the female minimum retirement age was 50 in 2004. Second, in the Czech Republic, the minimum retirement age for females is 60, but women are entitled to discounts according to the number of children they have. Thus, we set the female retirement age at 58, the approximate retirement age for women with two children. Third, Israel introduced a pension reform in late 2004. Since most individuals surveyed in 2004 retired under the previous regime, and the new regime only slowly increased the retirement age, we take as reference the early-2004 regime (65 years for men, 60 for women). Finally, Brazil had no minimum retirement age in 2004 but a

[18]For example, France provides some opportunities to retire at 56 y.o. for individuals who started working at age 17 and have a long contribution history. Several countries provide discounts for individuals with a long employment history in heavy occupations.

minimum social security payment record (35 years for men, 30 for women). We thus pick 55 and 53 years old as reasonable early retirement ages for individuals who started working at around 18 years old and experienced a few employment/contribution gaps.

TABLE VI. Retirement Age

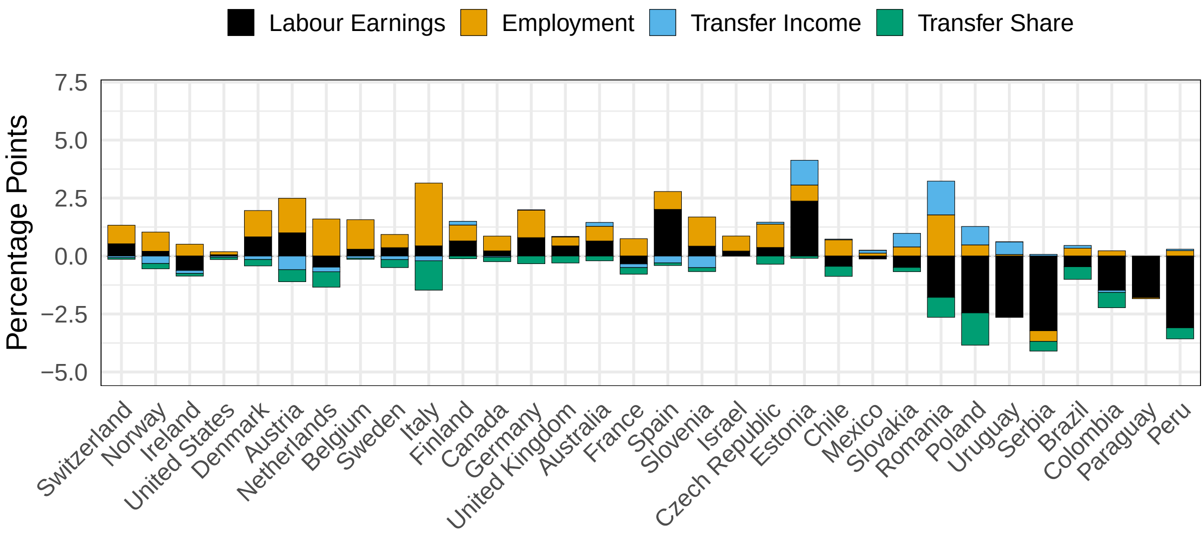
Country	Males	Females	Year	Source
Australia	55	55	2005	OECD, Pension at a glance 2005
Austria	65	60	2005	OECD, Pension at a glance 2005
Belgium	60	60	2005	OECD, Pension at a glance 2005
Brazil	55	53	2004	(a)
Canada	60	60	2005	OECD, Pension at a glance 2005
Chile	65	60	2008	Social Security Adm., SSPTW Americas 2004
Colombia	62	57	2004	Social Security Adm., SSPTW Americas 2004
Czech Republic	60	58	2005	OECD, Pension at a glance 2005
Denmark	65	65	2005	OECD, Pension at a glance 2005
Estonia	63	59	2004	Social Security Adm., SSPTW Europe 2004
Finland	60	60	2005	OECD, Pension at a glance 2005
France	60	60	2005	OECD, Pension at a glance 2005
Germany	65	63	2005	OECD, Pension at a glance 2005
Ireland	65	65	2005	OECD, Pension at a glance 2005
Israel	65	60	2004	Social Security Adm., SSPTW Asia 2004
Italy	60	60	2005	OECD, Pension at a glance 2005
Mexico	65	60	2005	OECD, Pension at a glance 2005
Netherlands	60	60	2005	OECD, Pension at a glance 2005
Norway	67	67	2005	OECD, Pension at a glance 2005
Paraguay	55	55	2005	Social Security Adm., SSPTW Americas 2005
Peru	55	53	2005	Social Security Adm., SSPTW Americas 2005
Poland	65	60	2005	OECD, Pension at a glance 2005
Romania	55	55	2004	Social Security Adm., SSPTW Europe 2004
Serbia	53	53	2004	Social Security Adm., SSPTW Europe 2004
Slovakia	62	62	2005	OECD, Pension at a glance 2005
Slovenia	63	60	2004	Social Security Adm., SSPTW Europe 2004
Spain	60	60	2005	OECD, Pension at a glance 2005
Sweden	61	61	2005	OECD, Pension at a glance 2005
Switzerland	63	62	2005	OECD, Pension at a glance 2005
United Kingdom	65	65	2005	OECD, Pension at a glance 2005
United States	62	62	2005	OECD, Pension at a glance 2005
Uruguay	60	60	2005	Social Security Adm., SSPTW Americas 2005

Note: (a) Brazil had no minimum retirement age in 2004, but anybody with 35 (males) or 30 (females) years of contribution was allowed to retire. We pick 55 (males) and 53 (females) to reflect a reasonable working life of non-college workers with a few social security contribution gaps. The table reports the retirement age used to limit the sample size in Section 3.3 in the main text and other results in this Appendix. The retirement age is intended, where available, as the "early" retirement option, as listed by either the OECD or the U.S. Department of Social Security in their reports. The "Reference Year" column indicates the year the data have been collected. This means all the retirement ages are correct for that year but may have been in place for longer. In the final column, we link the sources we used to compile the table. We set a minimum retirement age of 53 to have enough observations in our old (50+) age group.

D.2 GRD decomposition by demographic

Figure 8. GRD decomposition: Male and Female

(a) Male

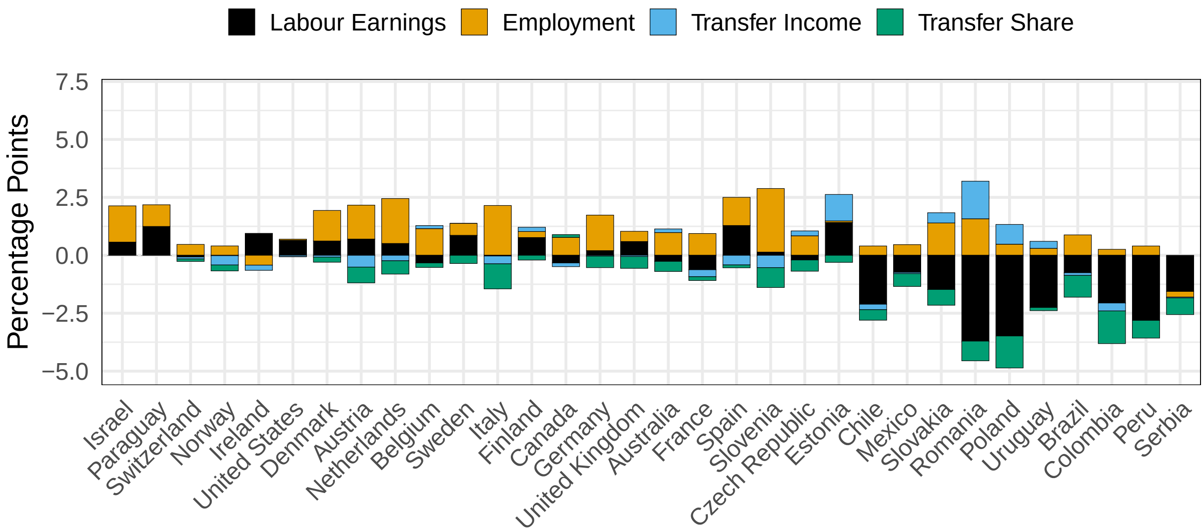


(b) Female

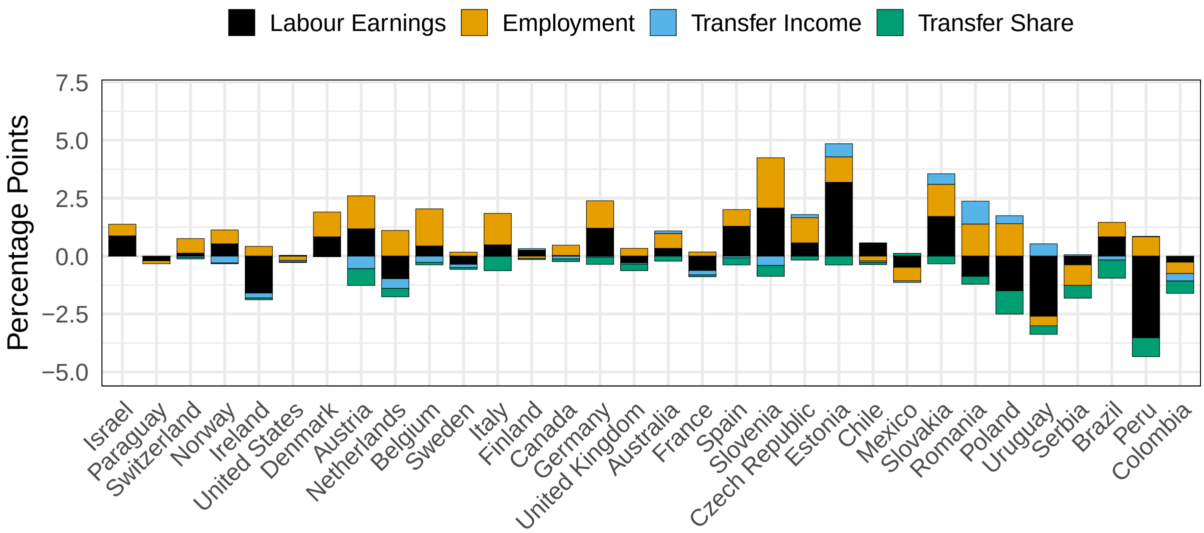
Note: panel (a) depicts the employment contribution (lighter red bar) to the *GRD*s for male late-career individuals (50-64 y.o.) and male early-career individuals (25-34 y.o), and the labor earnings contribition (black bar). Panel (b) depicts the two contributions for female.

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

(a) No College



(b) College graduates

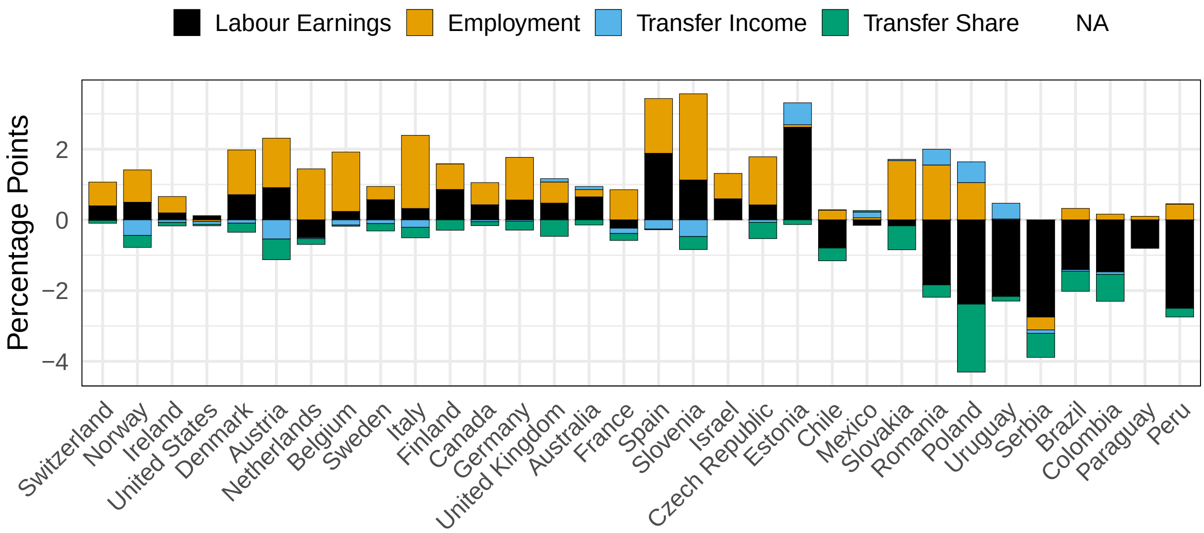


Note: panel (a) depicts the employment contribution (lighter red bar) to the *GRD*s for non-college-educated late-career individuals (50-64 y.o.) and non-college-educated early-career individuals (25-34 y.o) and the labor earning contribution (black bar). Panel (b) depicts the two contributions for college-educated individuals.

Figure 10. GRD decomposition: all individuals and below retirement age only

(a) All individuals

(b) Below retirement age



Note: panel (a) depicts the employment contribution (lighter red bar) to the *GRD*s for all late-career individuals (50-64 y.o.) and early-career individuals (25-34 y.o), and the labor earning contribution (black bar). Panel (b) depicts the two contributions for individuals below the minimum old-age pension retirement age. Retirement age is defined according to the prevailing legislation at the beginning of our sample, differentiation between countries, and - where necessary - gender.

E The role of between-education shifts

To account for changes in the composition of the working force, we adopt a comprehensive approach by considering the combined effect of the gender, education, and pension age margins. The income of the old below retirement age holding education level k can be expressed as the income of the young in the same education level, times an average age premium, r_t^k. That is: $y_{o,t}^k = y_{y,t}^k r_t^k$. Let us denote with $e_{j,t}^k$ the employment rate of k-educated individuals of group j at time t, and with $w_{j,t}^k$ the share of k-educated individuals in group j at time t. Notice that $y_{o,t}^k = y_{y,t}^k \left(r_{e,t}^k e_{j,t}^k + r_{u,t}^k (1 - e_{j,t}^k) \right)$, for $r_{e,t}^k$ and $r_{u,t}^k$ being the age premium of employed old and non-employed old, respectively. Then, we can express the differential in growth rates as:

$$
\begin{aligned}
g(y_o) - g(y_y) = & \underbrace{\sum_{k \in O} \left(\Delta w_o^k \frac{r_{T+h}^k}{r_T} - \Delta w_y^k \right) \frac{y_{y,T+h}^k}{y_{y,T}}}_{\text{Between-education component}} + \underbrace{\sum_{k \in O} \left(w_{o,T}^k \frac{r_{e,T+h}^k - r_{u,T+h}^k}{r_T} \Delta e_o^k \right) \frac{y_{y,T+h}^k}{y_{y,T}}}_{\text{Employment component}} \\
& + \underbrace{\sum_{k \in O} \left(w_{o,T}^k \frac{\Delta r_e^k e_{o,T}^k + \Delta r_u^k (1 - e_{o,T}^k)}{r_T} \right) \frac{y_{y,T+h}^k}{y_{y,T}}}_{\text{Age premium growth}} + \underbrace{\sum_{k \in O} \left(w_{o,T}^k \frac{r_T^k}{r_T} - w_{y,T}^k \right) \frac{\Delta y_y^k}{y_{y,T}}}_{\text{Income growth exposure}}
\end{aligned}
\tag{5}
$$

The first term captures differentials in income growth given by whether the old are moving faster than the young towards high-paying, high-age premium education levels. The second component captures changes in the employment rates of the old in different occupations. The third component captures the growth of age premium relative to the average income of the young. The last component captures how the initial education composition allowed each generation to benefit from within-education income growth.

To provide an example of what the between-education component measures, consider how in Germany, the 2004 *AGIR* was 1.36 for college graduates, 1.07 for high-school graduates, and 0.91 for individuals with less than high school. An increase in college graduates of 1 pp among both old and young would - ceteris paribus - increase the aggregate *AGIR*, as old college graduates benefit, on average, from a higher age premium relative to young college graduates than the one of non-college graduates, relative to their corresponding young group.[19]

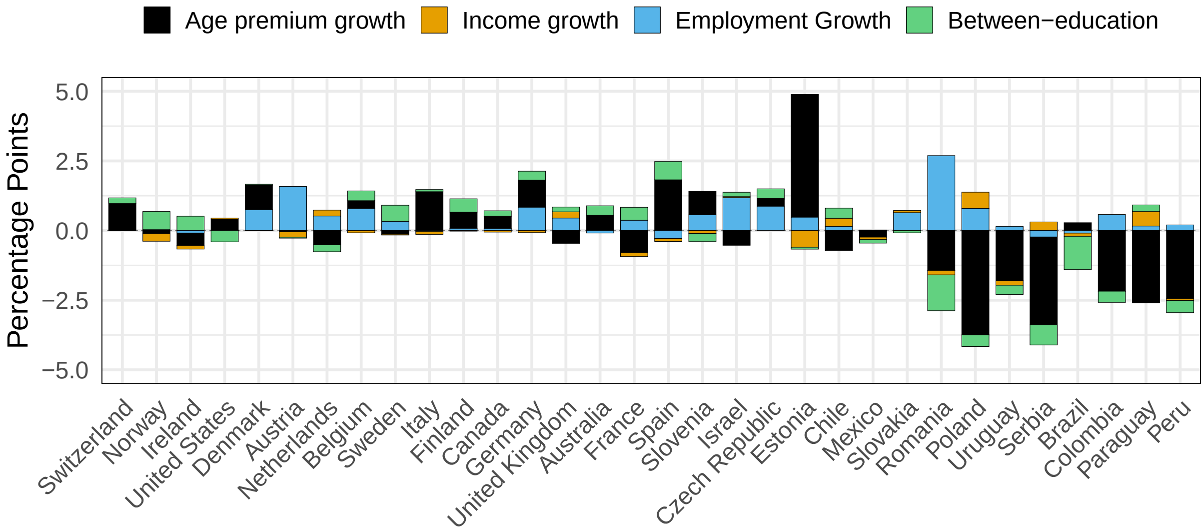
We plot the results of this decomposition in Figure 11a for males and 11b for females.

[19] In this example, a 1 pp. increase in college graduates among both young and old due to a fall of 1 pp. in high-school graduates would increase *AGIR* by approximately $(0.01 \times 1.31 - 0.01) \times \frac{33{,}000}{22{,}000} + ((-0.01) \times 1.02 - (-0.01)) \times \frac{23{,}000}{22{,}000} = 0.4\%$.

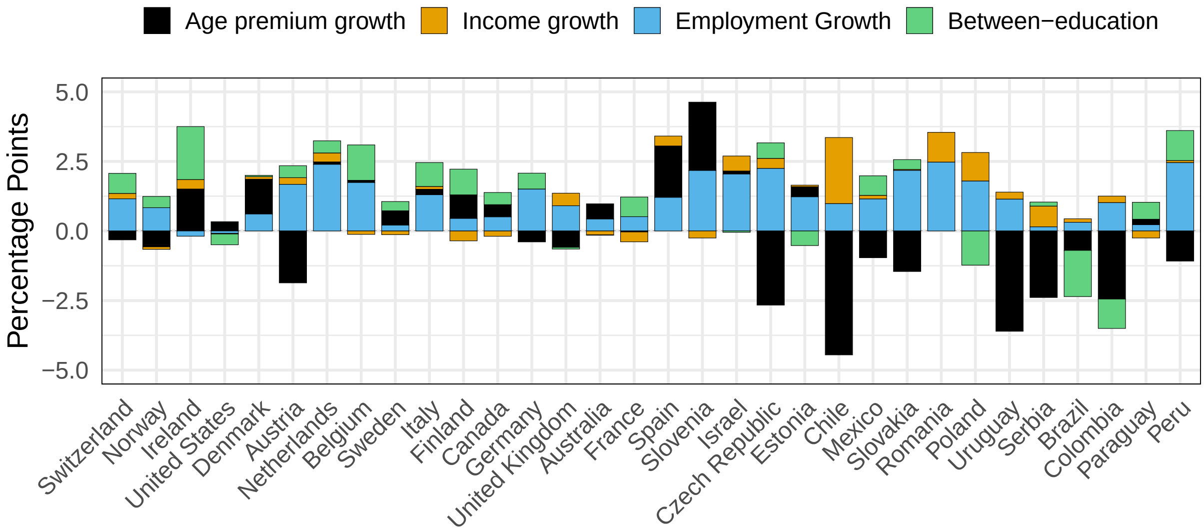
Even considering the shift in weights between education, the employment margin remains the largest contribution to the *GRD* of income (panel a) in rich countries. This component alone accounted for 59 percent of all GRD. Nevertheless, of the remaining 41 pp, 36 are explained by the educational catch-up of older generations (between-education component). On the other hand, we find different results in poorer countries. Although the divergence in educational attainment between the young and the old explains a large share of the fall in inequalities in Brazil and Serbia, the largest contribution comes from a fall in the age premium *within* education levels. These results are confirmed when focusing on the earnings of employed individuals (panel b), with the education catch-up explaining one-third of the total growth in the age-earnings gap of richer countries.

Figure 11. Age growth differential decomposition

(a) Males



(b) Females



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).