Age-Income Gaps

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Abstract

This paper examines the growing income disparities between older and younger individuals. Using harmonized data from 32 countries with varying levels of economic development for the period 2004–2018, we introduce the Age Group Income Ratio ($AGIR$) to measure the relative disposable income of older individuals (aged 50–64) compared to younger individuals (aged 25–34). We establish two stylized facts. First, the age-income gap in favor of older individuals has significantly increased in richer countries and decreased in lower-income countries. Second, we show that conventional measures of age disparities, such as the age-earnings gap, underestimate income inequality, as employment rates among older individuals are the primary driver of rising $AGIR$ in high-income countries. Lastly, we develop an overlapping generations model incorporating endogenous education, skill accumulation, and employment decisions. Our model identifies rising skill-specific returns to age and, primarily, increasing education levels among older workers as the main contributors to the observed increase in $AGIR$ in rich countries. These trends have important implications for lifetime earnings, with younger generations facing potential long-term income stagnation. Our findings call for policy interventions to address structural labor market imbalances and mitigate the widening intergenerational income divide.

Keywords: Age group income, growth decomposition, income distribution, cross-country comparison, human capital, overlapping generation

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 garnered attention in academic literature, particularly regarding the analysis of the causes and extent of the earnings gap between older and younger workers. For instance, Bianchi and Paradisi (2024) examines the relative wage levels of young and older workers in Italy, while Freedman (2024) studies the labor earnings of various age groups across eight wealthy countries. However, these works are limited in their focus on employed individuals, neglecting other sources of income. While this approach is suitable for studying wage dynamics, it may not adequately address the broader evolution of age-income inequalities for several reasons. First, it is unclear whether wages are indeed the primary driver behind the widening income disparities observed between age groups. Second, alternative income sources — like employment rates and public transfers — may have evolved differently over time and across countries, rendering the age-earnings gap an insufficient indicator of global age-income disparity trends. Understanding the key factors that contribute to overall intergenerational income differences is paramount, as changes in different income margins can lead to different consequences for the lifetime earnings of present and future generations, as we show in the model section. Consequently, comprehensive analysis that considers all income sources is essential for fostering informed discussions and effective policies aimed at mitigating age-related 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 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 metric the relative average disposable income of the old and young in any given period. While the absence of a panel dimension in the income surveys within the LIS and the relatively short duration of the available sample prevents a full cohort analysis, our measure still provides valuable insights into income dynamics across cohorts. Specifically, the *AGIR* captures the relative distance between the final income of one cohort and the initial income of a new cohort that starts in the same period. Understanding this distance is crucial for analyzing the distribution of economic resources and living standards across age groups at a given point in time, a concept linked to generational conflicts over policy (vonWeizsacker, 1996) and social segregation (Sabater and Finney, 2023). Our comprehensive dataset enables us to uncover regularities in the international evolution of the age-income gap, to highlight how it differs from the more frequently studied age-earnings gap, and to produce a model-based quantification of its drivers.

Our study establish three new stylized facts. First, the age-income gap has followed different trends across countries: it has grown in favour of the old 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 that the faster increase in the employment rate of the old relative to the young explains alone two third of the increased *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' labor earnings has evolved in the opposite direction of the overall population's $AGIR$ between 2004 and 2018. Third, we show that this employment margin is large and positive in rich countries across several demographics, suggesting that it was not caused by increases in the minimum legal retirement age or female labor force participation trends.

Finally, as a second contribution, we develop an overlapping generation model that incorporates endogenous education choices, skill accumulation, and labor market participation decisions. Agents' decisions and income are influenced by exogenous skill-specific productivity, return to experience, and demographic trends such as ageing and (from the perspective of the young) the education level of the old generation. Our rich dataset allows us to precisely identify the model parameters. We use the model to achieve two main objectives. The first one is to decompose the observed increase in the $AGIR$ between 2004 and 2018 in rich countries and to determine the roles played by each contributing factor. Moreover, we decompose the effect of each of these factors into the direct partial equilibrium (PE) effects, which ignore changes in endogenous education decisions and labor market clearing conditions, and the general equilibrium (GE) effects, which do take these factors into account. The second objective is to demonstrate how the factors that contributed to the growth in $AGIR$ can have very different effects on the lifetime income of future generations.

Our first finding is that the rise in the age-income gap can largely be attributed to (i) the increasing skill-specific returns to age; and (ii) the higher education levels of the older generation (see (Goldin and Katz, 2007, 2018a)). In simple terms, the higher returns to age create a strong PE effect that benefits older workers, directly enhancing their wages. Additionally, the larger share of high-skilled older workers increases their income through a composition effect, as more skilled individuals tend to have higher wages and employment rates. General Equilibrium effects strongly exacerbate the PE ones, as a larger supply of high-skilled labor tends to lower the wages for high-skill positions relative to low-skill ones, which discourages younger workers from pursuing high-skilled education. While the increased return to experience alone accounts for 23 percent of the observed rise in $AGIR$, the convergence in education levels explains 85 percent.

Second, our model illustrates how these two channels influence the lifetime income and profiles of the younger cohort in different ways. Although the LIS data do not permit cross-cohort comparisons, the model predicts clear outcomes: the increase in returns to experience raises the lifetime income of the young cohort, as well as the steepness of their lifetime income profile. Instead, the education convergence of the older generation results in a lower lifetime income for young workers. Intuitively, when young individuals face competition from previous generations on the high-skilled labor market, they have lower incentives to acquire high-skilled education, leading to an overall decrease in their lifetime income and a flatter lifetime income profile.

Our findings have significant implications for the ongoing debate on intergenerational fairness. They reveal that the income gap between older and younger workers could continue to widen if current demographic and economic trends persist. Specifically, the increasing educational convergence of older workers with younger workers may worsen age-based income inequality, further intensifying disparities in disposable income across generations. This trend is particularly concerning in wealthy countries, where older workers are more likely to remain in the workforce longer and earn higher incomes, while younger workers face stiffer competition and often lack economic advantages. Our model predicts that the educational convergence among older workers is the main factor driving the observed increase in $AGIR$ in rich countries. As a result, the current generation is likely to experience reduced lifetime income. These projections highlight the urgent need for academics and policymakers to investigate the long-term effects of these trends on generational equity. Without intervention, the growing income divide may strain intergenerational solidarity and could lead to a situation where younger generations experience systematically reduced economic opportunities compared to their older counterparts.

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 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, with a more comprehensive income definition.

Our analysis focuses on disposable income gaps and their components. Since our data covers advanced economies, 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). 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. Guvenen et al. (2022) considers *lifetime* labor earnings of US workers, implicitly accounting for the employment margin of cohorts but without disentangling this margin explicitly. 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 of the age-earnings gap systematically underestimates the change of $AGIR$, whether positive (in richer countries) or negative (in poorer countries).

Finally, our work relates to the literature that has explored the differential evolution of wages and employment across different demographics. We show that phenomena such as the long-run increases in female participation (Maxwell, 1990; Costa, 2000; Acemoglu et al., 2004; Goldin, 2006; Olivetti and Petrongolo, 2016; Goldin and Katz, 2018b) and retirement age (Pilipiec et al., 2021; Staubli and Zweimüller, 2013) cannot fully explain the increase in $AGIR$ in the XXI Century. Instead, we find that trends in education achievement (Goldin and Katz, 2007, 2018a), the return to experience (Jeong et al., 2015), and technical change (Adão et al., 2024) are the main drivers of changes in $AGIR$. In particular, we focus on how these long-run trends had asymmetric effects on 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 introduces a structural OLG model of education and labor market choices, and discusses the different quantitative and qualitative effects of different channels of $AGIR$ growth. 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 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 *"en-*

able, 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 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 for two reasons. First, it is unclear how to attribute incomes within multi-generational households. Second, there is selection in household formation choices, and its effects can be time-varying.[1]

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.

[1]For example, consider how young individuals who do not exit their parents' household may do so because they cannot afford their own accommodation, or expect low returns from moving to better labor markets. If rent growth outpaces the income growth of lower-income individuals, the selection may strengthen, making households with a young household head less representative of the average young person's income.

Waves. Since not all countries are surveyed in the same year, the set of country-year observations is unbalanced. To overcome possible related issues, we group yearly surveys into five *waves*, each of three years, starting from 2004. Hence, the waves are 2004-2006, 2007-2009, 2010-2012, 2013-2015, 2016-2018. We create country-wave data by merging all yearly 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 dataset.[2] Table V 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:

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

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 (both public and private), unemployment benefits, scholarships and paid maternity/paternity leave.[3]

While some countries report the income components net of taxes, others report gross income.[4] In such a case, we construct net income as the difference between gross income and income taxes τ_q, i.e. $y_q = w_q^g + \Theta_q^g - \tau_q$.[5]

Remark. Notably, capital income is not available at the individual level. The lack of information about this income dimension does not represent 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 stylized facts presented in the next section since, at least in industrialised countries,

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

[3] In Appendix B.3 we add household-wide benefits, such as child allowance, housing benefits, and general benefits paid to the household as a whole. The results are both quantitatively and qualitatively similar.

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

[5] Notice that τ_q, the observed measure of taxes, does not include taxes on capital income.

wealth has become more concentrated towards the older age groups.[6]

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.

3.1 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 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, employed or not. Hence, this measure provides a broad picture of how *overall* income is distributed between age groups in a given year.

Remark. Notice that the income surveys in the LIS lack a panel dimension and has a relatively short duration of about two decades. Therefore, a full cross-cohort analysis

[6] 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 average wealth of the age group over 65 increased from 26% higher than average to 34%, while the average wealth of the age group under 35 decreased from 64% lower than average to 70% (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.

across time is not feasible. Nevertheless, our measure still offers valuable insights into income dynamics across cohorts. Specifically, the *AGIR* captures the relative gap between the ending income of one cohort and the starting income of a new cohort in the same period. Analyzing this difference is essential for understanding how economic resources and living standards are distributed across age groups at a specific point in time, a concept relevant to generational policy conflicts and social segregation (vonWeizsacker, 1996; Sabater and Finney, 2023). Also, in section 4, we demonstrate how the *AGIR* statistics relate to measures of lifetime incomes and the steepness of the lifetime income profile.

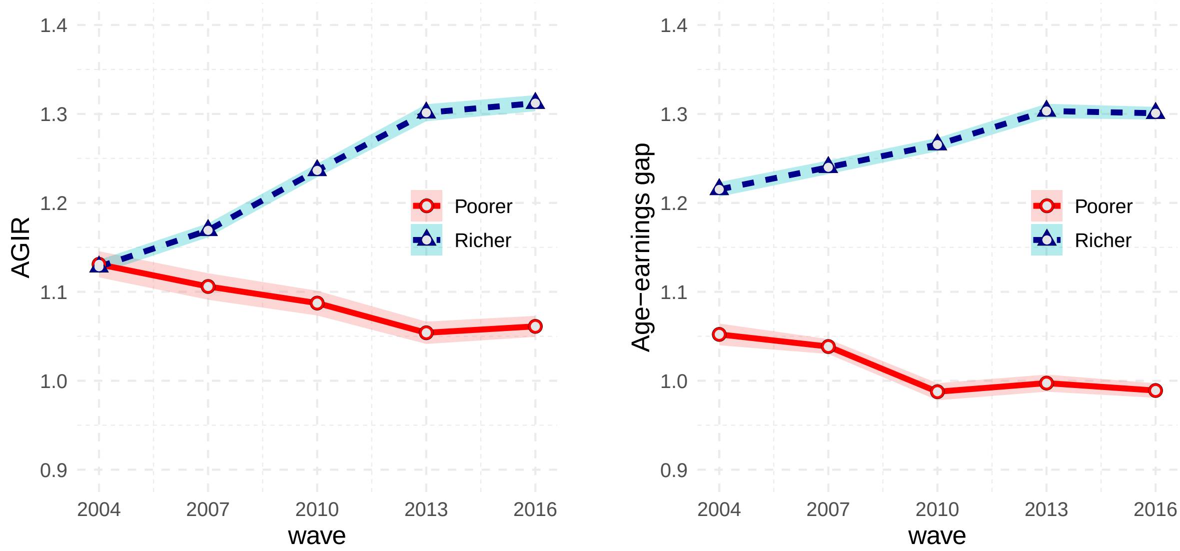
Our analysis focuses on two age groups: individuals aged 50-64 (late-career working-age individuals) and individuals aged 25-34 (early career). We choose these two age groups because they reflect individuals who have already completed their education and are at opposite ends of their work lives. We often 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. 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 matches the 2006 IMF classification (International Monetary Fund, 2006).[7] 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. The right panel displays the average age-earnings gap, defined similarly to our *AGIR* but comparing only employed individuals' net labor earnings.

[7] 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.

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

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



Notes: 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.

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 the next subsection, we show that our results (i) 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, and (ii) hold when considering the unbalanced dataset with years, rather than waves, as the unit of observation. Third, the age-earnings gap grew by only 8 pp in richer countries. Hence, the age-earnings gap grew considerably less than the overall age-income gap.[8] These findings lead to our first novel stylized fact.

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

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.

3.1.1 Trends: statistical significance

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

$$log(R_{i,t}) = \alpha + \tilde{\alpha}\mathbb{1}_i^d + \beta t + \tilde{\beta}(\mathbb{1}_i^d \times t) + \varepsilon_{i,t}. \quad (2)$$

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 $[0, 3, 6, 9, 12]$ when we consider wave observations and values in $[0, 1, 2, \ldots, 14]$ when we consider annual observations.[9] Accordingly, α represents the average value of $\log(AGIR)$ at the beginning of the 2000s in poorer countries, $\tilde{\alpha}$ is the additional initial average $\log(AGIR)$ for the richer countries, β is the average time trend in poorer countries, and $\tilde{\beta}$ is the additional time-slope for richer countries.

Columns (1) and (3) of Table I 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 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, estimating 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:

$$log(R_{i,t}) = \alpha + \theta\overline{GDP}_{i,0} + \beta t + \gamma(\overline{GDP}_{i,0} \times t) + \varepsilon_{i,t} \quad (3)$$

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

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 I 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 I. Trend in AGIR

Dependent	Wave		Year	
	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***	
	(0.005)		(0.004)	
[3] $\tilde{\alpha}$: Richer	0.031		-0.031	
	(0.043)		(0.032)	
[4] θ: Initial log-GDP (Dev)		0.007		-0.037**
		(0.019)		(0.018)
[5] γ: Trend $\times$ Initial log-GDP(Dev)		0.009***		0.015***
		(0.002)		(0.002)
Observations	159	159	378	378
R^2	0.277	0.202	0.255	0.190
F-Test:[1]+[2]=0 or [1]+[5]=0	22.77	21.58	57.23	73.11
Trend effect at min GDP		-0.006		-0.016***
Trend effect at 25% GDP		0.003		-0.002
Trend effect at 75% GDP		0.011***		0.012***
Trend effect at max GDP		0.013***		0.017***

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

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

3.2 Income determinants of age income dynamics

In this section, we examine which subcomponent of income played the primary role in shaping the dynamics of the $AGIR$. We focus on the changes in $AGIR$ between 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.[10]

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:

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

[10] In Appendix H.1 we compute a similar decomposition for the *level* of $AGIR$.

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 $AGIR$:[11]

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

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 margins of labor and non-labor income.

In Figure 2a, 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 it has not grown over the last 20 years.

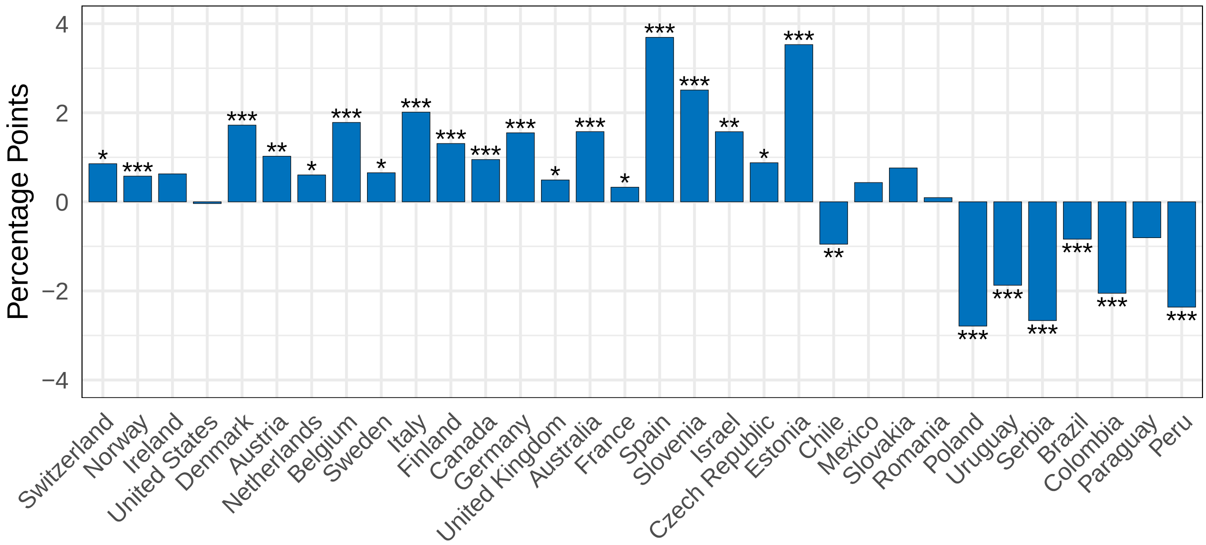
In Figure 2b we display the growth rates of income of young and old for each country. In most richer countries, the average income of young individuals has either fallen or remained approximately stationary between 2004 and 2018, while the income of the old grew at moderate rates. On the other hand, the negative GRD in poorer countries has arisen from a fast growth of income for both young and older individuals, although somewhat larger for the young.

We now turn to studying what income component caused these patterns in GRDs. 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,

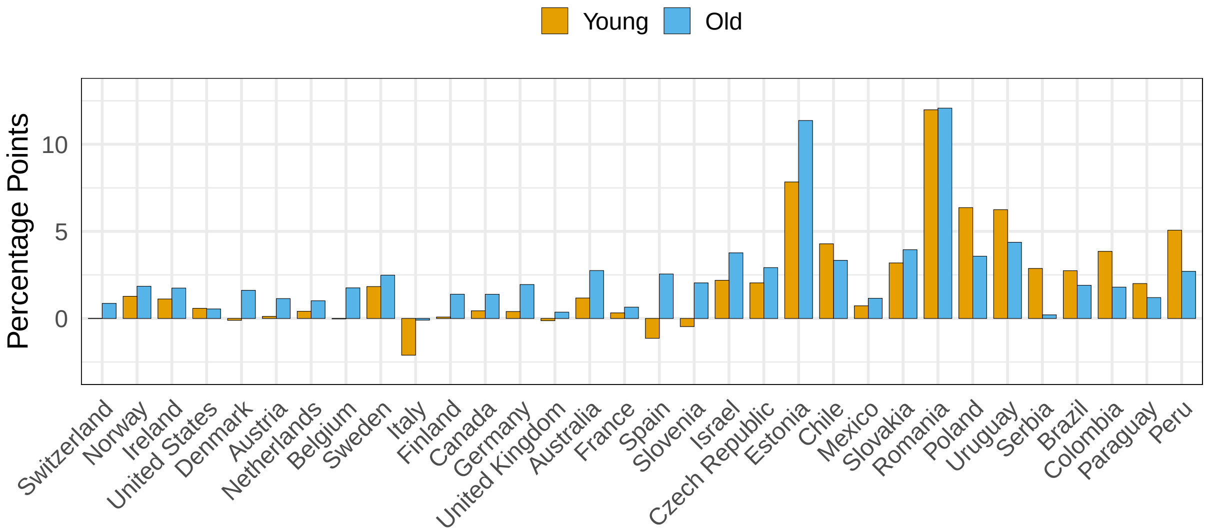
[11] See Appendix C.1 for the derivation.

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

(a) Growth Rate Differentials



(b) Growth Rate of Real Income, annualized



Notes: panel (a) depicts the Growth Rate Differentials (GRD), defined as the difference between the annualized income growth between 2004 and 2018 of late-career individuals (50-64 y.o., "old") and early-career individuals (25-34 y.o., "young"), by country. The stars indicate whether the GRD is statistically different from zero. Significance level: * = 0.05, ** = 0.01, *** = 0.001. Panel (b) plots the annualized income growth figures behind the calculation on the GRD, by country and age group.

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.

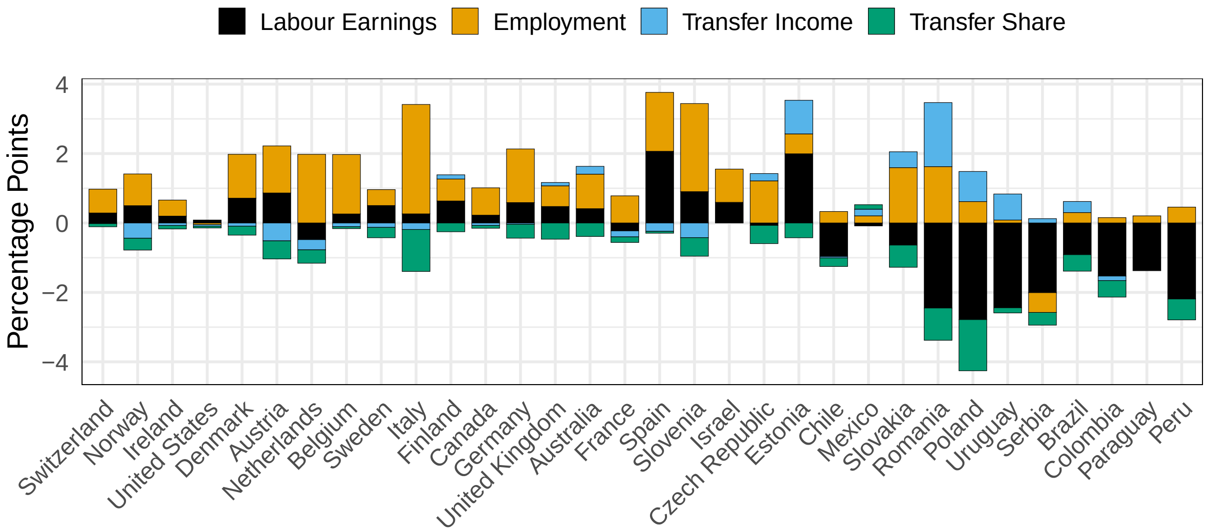
Then, the *growth rate* of average disposable income of age group j between period T and $T+h$ is:

$$\frac{\Delta y_j}{y_{j,T}} = \underbrace{\frac{e_{j,T}\Delta y_j^n}{y_{j,T}}}_{\text{Labor Earnings}} + \underbrace{\frac{y_{j,T}^n \Delta e_j}{y_{j,T}}}_{\text{Employment}} + \underbrace{\frac{p_{j,T}\Delta\Theta_j^n}{y_{j,T}}}_{\text{Transfer Income}} + \underbrace{\frac{\Theta_{j,T}^n \Delta p_j}{y_{j,T}}}_{\text{Transfer Share}}, \tag{4}$$

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 (4), by computing the four components of the difference $\frac{\Delta y_{old}}{y_{old,T}} - \frac{\Delta y_{young}}{y_{young,T}}$.

Figure 3 illustrates these contributions: a positive value means that the specific sub-components contributed to faster income growth for the 50-64 age group than for the 25-34 one. We now describe the main findings, focusing on each component at a time.

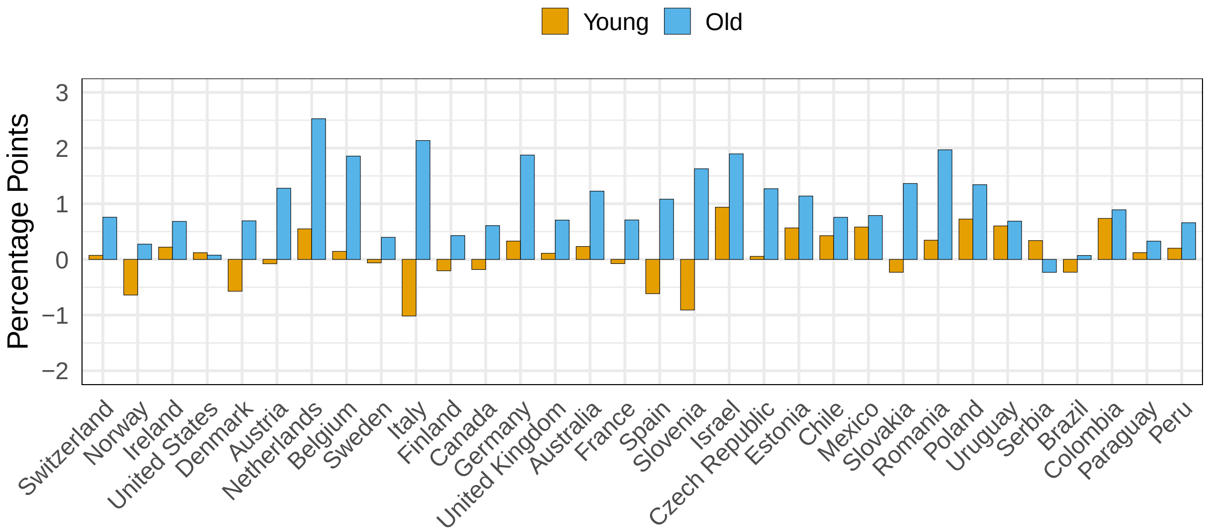
Figure 3. *GRD* Decomposition, by income components



Notes: 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, in Figure 4 we show that while the employment margin did not contribute to the growth the income of early-career individuals (or even negatively so for some countries), the employment margin of late-career individuals provided a substantial contribution to their income growth, between 0.5 and 2 percentage points 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 (average contribution of 0.5 pp). This is due to the young's employment margin component being positive and almost as large as the old's one.

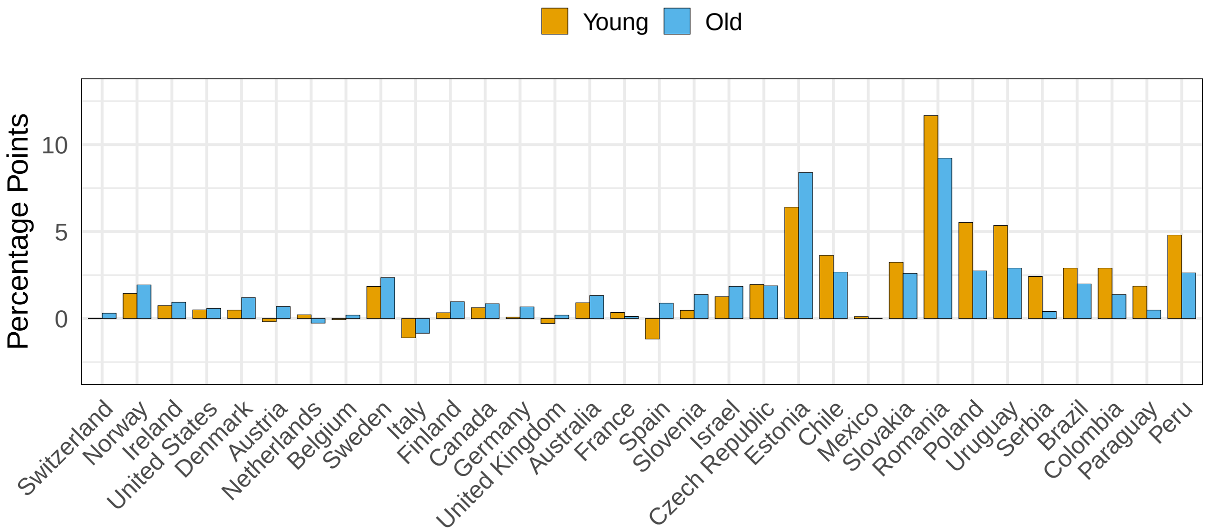
Figure 4. Employment margin of income growth rate



Notes: The figure depicts the employment margin of the Growth Rate Differential for late-career individuals (50-64 y.o., "old") and early-career individuals (25-34 y.o., "young"), by country. The employment margin captures the contribution to the (annualized) real income growth of an age group arising from changes in the average employment rate. Hence, an employment margin of 1% implies that changes in employment rates contributed towards total income growth by 1 percentage point per year between 2004 and 2018.

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 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 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). In Figure 5 we plot each age group's earnings component.

Figure 5. Labor earnings margin of income growth rates



Notes: The figure depicts the earnings margin of the Growth Rate Differential for late-career individuals (50-64 y.o., "old") and early-career individuals (25-34 y.o., "young"), by country. The earning margin captures the contribution to the (annualized) real income growth of an age group arising from changes in the average labor earnings of employed individuals. Hence, an earning margin of 1% implies that changes in average wages contributed towards total income growth by 1 percentage point per year between 2004 and 2018.

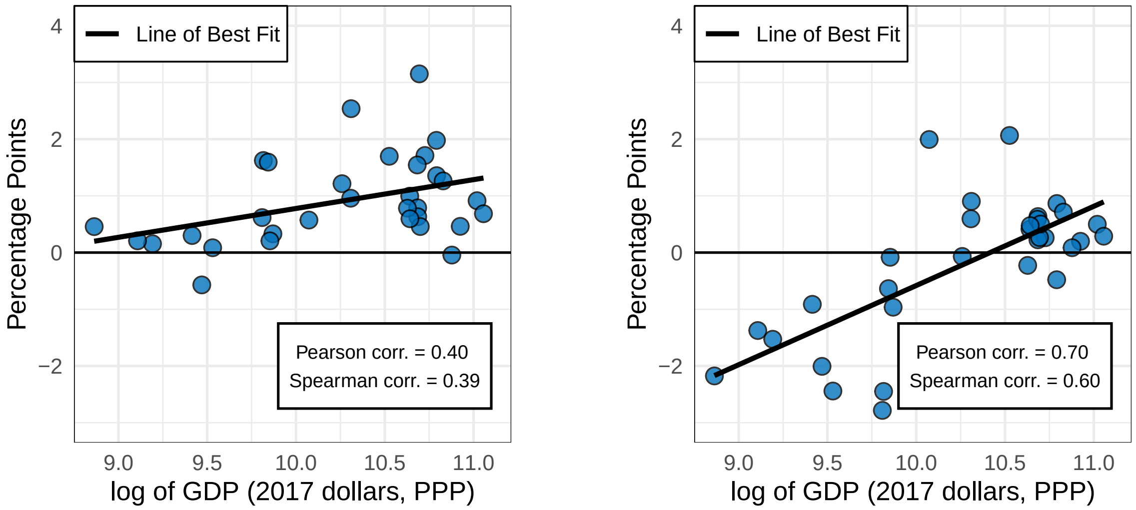
Pensions and Transfers. For most countries, pension and welfare payment changes had little impact on the *GRD*. However, we can observe some common patterns. In most countries, the share of old-age individuals receiving transfers has fallen slightly faster than the young, implying a negative transfer 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" margin) 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 6 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 6. Employment and Labor Income Contribution to *GRD* vs GDP level

(a) Employment Contribution (b) Labor Income Contribution



Notes: 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).

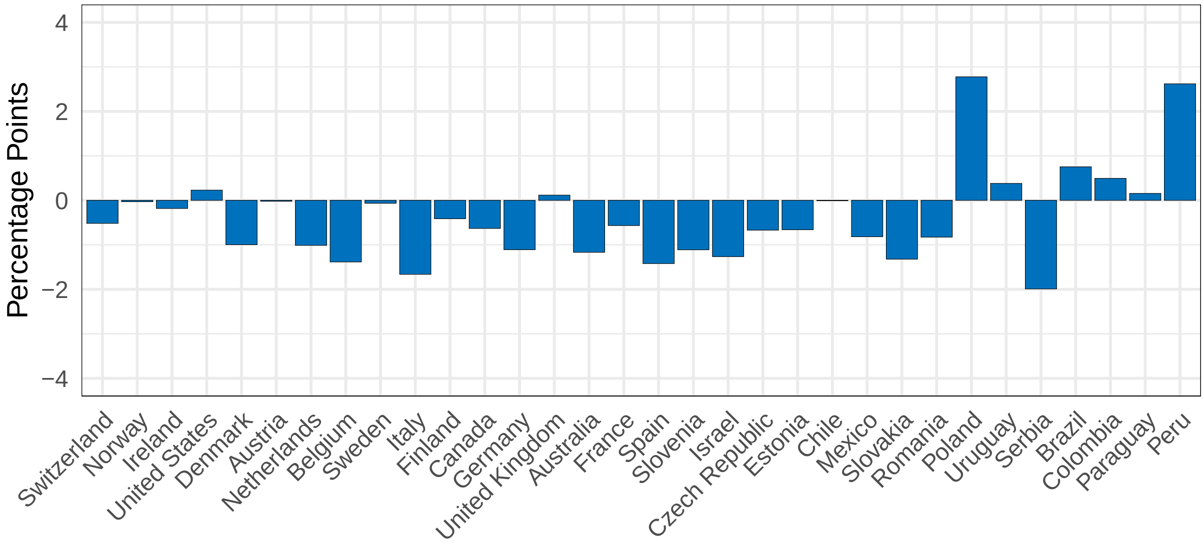
Stylized fact 2. In rich countries, the main contributor to the positive *GRD* is the divergence in employment rates between young and old. In lower-income countries, the main contributor to negative *GRD* is the faster increase in labor income, conditional on being employed, of the young relative to 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 *AGIR* 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.[12] Hence, *AGIR* fell more than the age-earnings gap. In Figure 7, we depict these differences between the *GRD* of the labor earnings (including both employees' wages and self-employed labor earnings) of employed individuals and the income of all individuals.

[12]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.

A negative number means that the *GRD* of income is larger than that one of earnings. The consistent negative bias in richer countries (where *GRD*s are positive) and positive bias in many poorer countries (where *GRD*s are negative) highlights how earning gaps have changed less than income gaps. In richer countries, the age-income gap has grown twice as fast as the age-earnings gap.

Figure 7. Difference between GRD of earnings and income



Notes: 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 labor earnings.

Demographics Finally, we demonstrate that our findings are not influenced by specific demographic characteristics. We focus on two key aspects. First, we recalculate the *GRD* along with its employment and wage margins for both males and females. We aim to determine whether the increase in female labor force participation (see (Costa, 2000; Olivetti and Petrongolo, 2016; Goldin and Katz, 2018b)) could solely explain the observed rise in the *AGIR* in rich countries. Second, we examine whether the significant employment margin of *GRD* is primarily a result of delays in retirement (see (Pilipiec et al., 2021; Staubli and Zweimüller, 2013)). To this end, we define an alternative age group for older individuals: this group includes all individuals older than 50 but younger than the minimum pension age for each country and gender within our sample. This specification aims to insulate our statistic from changes in the age threshold for old-age retirement and aging (insofar as it changes the relative composition of old individuals above or below the retirement age).[13]

Table II displays the overall GRD, and its employment and wage margin for the whole population, for males only, for females only, and when using the alternative measure of old described above.[14]

TABLE II. *GRD* by demographic

Country Group	Component	Full sample	Males	Females	Below retirement age
Poorer	Total	-0.84	-0.76	-0.25	-1.01
	Labor Earnings	-1.28	-1.15	-0.85	-1.15
	Employment	0.47	0.41	0.59	0.45
Richer	Total	1.21	0.94	1.99	1.19
	Labor Earnings	0.44	0.40	0.87	0.51
	Employment	1.18	0.95	1.50	1.03

Notes: The table reports the *GRD* and its labor and employment sub-components for different demographics. "Full sample" refers to the headline figures presented in the paper. "Males" and "Females" refer to the GRD of AGIR, as calculated within each gender group. "Below retirement age" refers to the *GRD* calculated by redefining the old group by excluding individuals above the minimum pension age in 2004, as defined in Table IX.

We find that the GRD in rich countries is fairly similar whether or not we include individuals above the minimum retirement age set in 2004 (as defined in Table IX). The GRD is 1.21 annualized percentage points when including this group and 1.19 percentage points when excluding them. The difference is somewhat larger in poorer countries, but qualitatively similar. Additionally, we observe larger differences between males and female, with women experiencing a larger GRD. However, since both the GRD and its sub-components show similar trends for both genders, we can conclude that gender-specific trends, such as the increase in female labor force participation in the late 20th century, cannot account alone for the rise in the $AGIR$ in wealthier countries or its decline in poorer countries. Appendix E reports additional statistics for those demographics.

Our analysis suggests following third stylized fact:

Stylized fact 3. The stylized facts 1 and 2 above are not influenced by changes in the minimum pension age that occurred between 2004 and 2018. Additionally, these stylised

[13]We consider the minimum pension age in 2004 because, in none of the countries in our sample, it has declined in the sample 2004-2018. See Appendix D for a detailed description.

[14]In Appendix E.1, we provide additional results on the country-level GRD across genders and for individuals above and below the minimum retirement age.

facts apply to both males and females. As a result, gender-specific trends are not the primary reason for the dynamics of $AGIR$.

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, the causes of the rise in $AGIR$ in richer economies are not strongly connected to a rise of (minimum) retirement age or gender-specific trends. These two stylized facts suggest that the causes of the disproportionate increase in employment and wage gap between old and young should be explored by looking at other long-run, structural trends in the economy that have affect old workers (and not only retirees) and both genders alike. We now explore the roles of those structural trends through the lens of a labor-market model.

4 Model

This section proposes a tractable overlapping generation model that incorporates endogenous education choices, skill accumulation, and labor decisions. This framework allows us to quantify the role of the various exogenous forces contributing to the observed changes in the labor income component of the $AGIR$. Specifically, our economy is driven by: (i) time-varying, skill-specific total factor productivity; (ii) time-varying, skill-specific returns to experience; (iii) aging; and (iv) the initial skill distribution among older workers. In line with the empirical evidence discussed earlier, we focus on the differences in labor income between older and younger workers, intentionally leaving out retirement decisions and related transfers.[15] Since countries within-group (richer or poorer) experienced similar dynamics, we calibrate the model to a representative rich and a representative poor

[15] Our benchmark model does not include transfers, as we have demonstrated that they constitute a very minor component of the $AGIR$. This simplification allows us to concentrate our analysis on the factors influencing employment and wage dynamics. However, in Appendix G.2, we propose an extension that incorporates transfers. The results from this extension are similar to those obtained from the benchmark model.

country.

General environment Time is discrete, with periods denoted as $t = 1, 2, 3, \ldots$. In each period t, a new generation of young workers (of measure N_t) is born. We index these young workers with a superscript y. In the following period, they become old workers, indicated by the superscript o, and then die. We use the superscript $a \in \{y, o\}$ to refer to their age. Therefore, our model is based on the standard timing of dynamic overlapping generation models pioneered by (Diamond, 1965) and (Samuelson, 1958).

Education choice and human capital accumulation Education choices are made when young. Young workers select a skill level s from a discrete set $\mathbb{S}$ and pay education costs equal to the inverse of a share $(1 - \kappa(s)^{-1})$ of their income in both periods.

Young workers with skill s earn a wage $w_{s,t}$. In the second period, they gain experience $g_{s,t}$, allowing them to earn an hourly wage rate of $w_{s,t+1}(1 + g_{s,t+1})$. Therefore, the parameters $g_{s,t}$ reflect the differences in wages that older workers receive compared to younger ones with the same skill level. It is important to note that we assume education costs are time-invariant; this assumption is necessary for identification.[16]

Labor choice In our empirical analysis, we concentrated on the extensive margin of labor supply, as variations in aggregate hours worked primarily result from changes in the number of employed individuals rather than fluctuations in hours worked per worker (Hansen, 1985). Consistently, we adopt Hansen's indivisible labor assumption, which convexifies the labor supply and allows us to interpret labor as an extensive margin (employment) rather than an intensive one (hours worked), while keeping the model tractable. Specifically, in each period, a worker chooses either to be unemployed ($l_t = 0$) or to work full-time ($l_t = 1$), thus sacrificing leisure. In line with the work of Adão et al. (2024),

[16] The assumption of time-invariant fixed education cost is not unreasonable. In the U.S., the institution-weighted real college prices net of scholarships and aid increased by 15.5%, given by a doubling of public 4-year institutions net fees from \$1690/year to \$3380/year, approximately constant fees for non-profit private institutions at \$12,800/year, and a fall of \$1000 in 2-year public institution net fees (from -\$50 to -\$1080) (Ma et al., 2015). In the same period, real college graduate earnings increased by around 8 percentage points more than high-school graduate earnings. Several European countries in our sample have always provided free (Finland, Sweden, Denmark) or near-free (Germany, France) public education. Moreover, our costs capture not only the *financial* cost of education, but also its utility effort.

we assume that individuals gather into large households. We assume that the pooling happens by skill and age. These households decide on the proportion of individuals who are working ($l_t \in [0,1]$). They then pool their income and consumption. Consequently, households can be viewed as type-specific mutualistic associations that provide unemployment insurance for non-workers.[17] Since the households consist of identical individuals, we will refer to them as "old" or "young" with skill level s.

Additionally, workers have access to an internationally traded risk-free asset, denoted by B_{t+1}, with a return of r_t. We assume that $r_t = 0$, for all t, and that young workers do not discount future utility. The young generations are born with no assets, and old workers will optimally choose zero assets, as in equilibrium it is not optimal for the old to save and it is infeasible to borrow because they will not repay. Therefore, we denote with B_{t+1} the asset level chosen by a young in period t.

Household problem Each period, households maximise their lifetime utility. Using a standard formulation of the instantaneous utility function with endogenous labour supply choice (see (Keane, 2011)), the problem of an old with skill s at time t is:

$$\max_{c_t, l_t} U^o_{s,t}(c_t, l_t) = c_t - \frac{1}{\alpha^o_{s,t}} l_t^{1+b},$$

$$\text{s.t.} \begin{cases} c_t \leq w_{s,t}(1+g_{s,t}) l_t \kappa(s)^{-1} + B_t, \\ l_t \in [0,1], c_t \geq 0. \end{cases}$$

Here, α^o_s the inverse of the utility cost of working, b the curvature of the cost of effort, and $\kappa(s)$ the cost of acquiring skill s (as a proportional salary sacrifice).[18]

The young households maximise lifetime utility, taking into account the cost $\kappa(s)$ of acquiring skill s:

$$\max_{c^y_t, c^o_{t+1}, l^y_t, l^o_{t+1}, s} U^y_{s,t}(c^y_t, l^y_t) + U^o_{s,t}(c^o_{t+1}, l^o_{t+1}) = c_t^{1-\nu} - \frac{1}{\alpha^y_{s,t}} l_t^{1+b} + E_t\left(U^o_{s,t}(c^o_{t+1}, l^o_{t+1})\right)$$

$$\text{s.t.} \begin{cases} c^y_t + B_{t+1} \leq w_{s,t} l^y_t \kappa(s)^{-1} \\ c^o_{t+1} \leq w_{s,t+1}(1+g_{s,t+1}) l^o_{t+1} \kappa(s)^{-1} + B_{t+1} \; l^y_t, l^o_{t+1} \in [0,1]; \; c^y_t, c^o_{t+1} \geq 0. \end{cases}$$

[17]This assumption has real-world ground in household formation and several countries' welfare and pension systems, which originate from occupation-specific mutualistic associations.

[18]In this formulation, the cost can be intended as financing education through a "graduate tax", or a student loan system with long repayment dates and maximum monthly payments, such as the UK.

Remark. The structure of education choice, the linearity of consumption in the utility function, and the alignment of the interest rate with the rate of intertemporal discounting imply that young workers' borrowing and lending do not affect the optimal decisions regarding labor and education. In fact, for any labor and education chice, all combinations of saving and consumption across the two periods that adhere to the intertemporal budget constraint yield the same maximum lifetime utility. Thus, the equilibrium with free borrowing is equivalent to the no-borrowing equilibrium. To simplify our analysis, we will assume that $B_{t+1} = 0$ for all t throughout the remainder of this discussion. However, it is essential to understand that the optimal allocations for labor and education derived from this assumption should not be viewed as being dictated by externally imposed borrowing constraints.

Solving the old household problem for an internal solution of effort, we can write the old workers' indirect utility as:

$$V_t^o(s) = \left(\frac{w_{s,t}(1+g_{s,t})}{\kappa(s)}\right)^{\frac{(1+b)}{b}} \left(\frac{\alpha_{s,t}^o}{1+b}\right)^{\frac{1}{b}} \frac{b}{1+b}.$$

Similarly for an internal solution of household employment rates in both periods, the indirect utility function of the young is:

$$V_t^y(s) = \left(\frac{w_{s,t}}{\kappa(s)}\right)^{\frac{1+b}{b}} \left(\frac{\alpha_{s,t}^y}{1+b}\right)^{\frac{1}{b}} \frac{b}{1+b} + V_{t+1}^o(s).$$

Production We assume there is perfect competition. Firms produce a final consumption good by combining labor from all skills, according to a CES production function:

$$Y_t = \left(\sum_{s\in\mathbb{S}} A_{s,t} \left(L_{s,t}\right)^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}},$$

where $L_{s,t}$ is the total supply of labor of skill s at time t, and $A_{s,t}$ is the productivity of a unit of labor provided by a skill s worker. The price of the good is the numeraire of the economy.

Firms maximise profits, given the skill-specific wage rates $\{w_{s,t}\}_{s\in\mathbb{S}}$, by choosing the optimal employment level for each skill:

$$\pi_t^* = \max_{\{L_{s,t}\}_{s\in\mathbb{S}}} \left(\sum_{s\in\mathbb{S}} A_{s,t} \left(L_{s,t}\right)^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}} - \sum_{s\in\mathbb{S}} w_{s,t} L_{s,t}.$$

The solution to the firm problem satisfies the first order conditions:

$$\left(\sum_{s'} A_{s',t}\left(L_{s',t}\right)^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}-1} A_{s,t} L_{s,t}^{\frac{\theta-1}{\theta}-1} = w_{s,t}, \ \forall s,t. \tag{5}$$

That is, the marginal revenue from hiring more labor of type s is equal to its marginal cost, given by the wage.

4.1 Bringing the model to the data

In Appendix F.1, we formally describe the sequential competitive equilibrium of the economy, and we characterize it. The model allows writing the endogenous variables of interest, i.e., employment levels, labor income, and education levels for each age as a function of the relevant exogenous parameters of the model, i.e., the age-neutral skill-specific total factor productivities, $A_{s,t}$, the age- and skill-specific return to experience, $g_{s,t}$, and aging $\frac{N_t}{N_{t-1}}$. In addition, the equilibrium variables will depend on the skill-specific cost of education $\kappa(s)$, the Frisch elasticity of labor supply, the inverse of b, and on the weight of the preference for leisure in the utility function, $\alpha^a_{s,t}$. The latter will be estimated and treated as a residual or a wedge, allowing the model to match the observables.

Importantly, the endogenous variables have clear observable counterparts. We assume there are three skills characterized by the education level of individuals: college-educated ($s = High$), high-school educated ($s = Med$), and less-than-high-school educated ($s = Low$). For a given country and a given year, t, we observe the following quantities:

1. Relative wages across skills, whose model counterpart is: $\dfrac{w_{s,t}}{w_{s',t}}$, with $s' \neq s$..
2. Employment rates of the old, by skill, whose model counterpart is: $l^o_{s,t}$
3. Employment rates of the young, by skill, whose model counterpart is: $l^y_{s,t}$
4. Education (skill) shares of the young at time t, whose model counterpart is: $\rho^y_{s,t}$,
5. Education (skill) shares of the old at time t, whose model counterpart is: $\rho^o_{s,t}$.
6. The relative size of young and old generations, whose model counterpart is: $\frac{N^o_t}{N^y_t}$

Our first goal is to provide credible estimates for the parameters of interest in 2004 and 2018 for two countries: a representative "rich" country and a representative "poorer" country. The observable endogenous variables are the respective averages across all the poor/rich countries. Since identifying a country's parameters is independent of the other, we ignore any country subscript to simplify notations.

Notice that we do not observe a full generation "forward" starting from 2004.[19] To bridge two consecutive periods in our model to the observable data for estimation purposes, we assume that in 2004 the future return to experience $g_{s,t+1}$ and wage growth $\Delta w_{s,t+1}$ are $g_{s,t+1} = g_{s,2018}$ and $\Delta w_{s,t+1} = \dfrac{w_{s,2018}}{w_{s,2004}}$.

Then, we perform three normalizations. First, we set the wage rate of the low-skilled in 2004 to 1, so that $w_{L,2004} = 1$. Second, we normalize the 2018 less-than-high school wage to $w_{L,2018} = 1 \times \dfrac{w_{L,2018}}{w_{L,2004}}$, to take into account the absolute productivity growth between periods. Third, we normalize the cost of low-skill education to zero, meaning that $\kappa(L) = 1$.

Finally, we calibrate two parameters from the literature. Following (Adão et al., 2024) and (Hsieh and Moretti, 2019), we set the elasticity of substitution between skills in the production function to $\theta = 3$. Following (Blundell et al., 2013), we set the (inverse) extensive-margin labor elasticity to $b = (0.3)^{-1}$.

Given these assumptions, our model can exactly replicate the observed variables (the labor income component of the *AGIR* and the wage and employment margins) for rich and poor countries in 2004 and 2018. Appendix F.2 details the estimation procedure and the empirical moments that we match.

Table III presents the estimates. As expected, the price of education, denoted as $\kappa(s)$, is higher for individuals with greater skill levels, and productivity A_s follows a similar trend. Our findings indicate that low-skilled workers experience nearly zero returns from age g, while high-skilled older workers earn approximately 50% more than their equally skilled younger counterparts. Between 2004 and 2018, returns to experience increased in rich countries but declined in poor ones. Additionally, the value of leisure is greater

[19] According to our definition of young and old workers used in the empirical section, the two "central" points of each generation are 27.5 years apart (30 y.o. vs 57.5 y.o.). However, we only have a 15-year gap available in our sample.

for older individuals (indicated by a smaller value of α) compared to younger ones. The parameter α represents all unexplained variation in employment rates l_s, given wages, returns to experience, and education costs. Nevertheless, estimates for α are fairly similar across countries and time.

TABLE III. Estimated Parameters

		Poor		Rich	
	Skill	2004	2018	2004	2018
α^Y	High	0.20	0.16	0.22	0.20
	Mid	0.11	0.08	0.14	0.12
	Low	0.05	0.03	0.04	0.03
α^O	High	0.08	0.08	0.10	0.12
	Mid	0.03	0.04	0.05	0.07
	Low	0.02	0.02	0.01	0.02
g	High	0.53	0.48	0.48	0.57
	Mid	0.32	0.18	0.21	0.25
	Low	-0.00	-0.05	0.09	0.20
A	High	2.05	2.36	1.30	1.47
	Mid	1.20	1.43	0.98	0.98
	Low	0.54	0.65	0.47	0.41
κ	High	4.48	4.48	2.69	2.69
	Mid	2.02	2.02	1.66	1.66
	Low	1.00	1.00	1.00	1.00
Δn		-0.09	-0.16	-0.22	-0.29

Notes: The table lists the identified parameters for richer and poorer countries, in each period (2004 and 2018 waves). Where necessary, the parameters are presented separately for each skill level. κ_s is equal across periods by assumption, and is estimated using 2004 data for present-period wages and 2018 data for next-period wages and return to experience. All figures are rounded to the second decimal digit for display in this table.

4.2 Decomposition of $AGIR$ growth

In this section, we conduct counterfactual exercises to quantify the role of four possible channels responsible for the observed dynamics of labor income $AGIR$ from 2004 to 2018. In each counterfactual scenario, we keep all parameters fixed at their 2004 levels (see Table III), which, as a reminder, perfectly fit the observed moments (education shares, employment, and within-skill and total $AGIR$) in that period. We then adjust one specific set of parameters to reflect their 2018 estimates in each counterfactual. This approach allows us to isolate the impact of each individual channel. We will present the results related to growth rate differentials, which are equivalent to the $AGIR$ growth rates.[20]

We decompose the impact of each channel into two types of effects: partial equilibrium (PE) effects and general equilibrium (GE) effects. The PE effect represents the outcome of a hypothetical scenario where both the wage rate (per unit of skill) and education shares remain at their values from the first period. Therefore, the PE effect reflects the direct income composition effect generated by each channel. In contrast, the GE effect is defined as the difference between the total effect and the partial equilibrium effect. This means that the GE effect accounts for the influence of endogenous education and employment choices as well as the market-clearing conditions in the labor market. In order to shed light on the forces that drive the increase in $AGIR$, we focus only on the results for rich countries in this section. Appendix G.1 presents the ones for poor countries. Figure 8 and Table IV present the results. Since some countries differ in term of the exact numbers of years between the first and last observation, we present the results as total changes over the 1st-5th wave period, rather than annualised.

First, we assume that the only parameters that change to their 2018 estimates in the second period are the TFPs, $A_{s,t+1}$. The estimated total factor productivity growth alone reduces the labor income $AGIR$ by 10 percentage points. The intuition is simple: the increase in TFP is estimated to be higher for high-skill workers compared to low-skill workers. In 2004, the older generation had a lower prevalence of high skills, which means that the increased TFP benefits younger workers. This occurs through a direct composition effect and by providing greater incentives for high-skill education. The benefits manifest in two ways: through employment, with a 5 percent advantage for the young, and through wages, with an 8 percent advantage for the young. Since the effect of TFP on workers is mediated solely through wages, all its impacts are considered General Equilibrium effects by construction.

Second, we assume that only the skill-specific returns to age change to their 2018 estimated values, $g_{s,t+1}$. This estimated increase in the return to age contributes to a 6 percentage point rise in labor $AGIR$. Unsurprisingly, the largest portion of this increase

[20] In Appendix H.2 we compute a similar decomposition for the model-implied *level* of $AGIR$.

comes from the wage component, as the return to age directly enhances labor income (PE effect). Interestingly, the general equilibrium (GE) effect benefits the young, as changes in the relative returns to experience across different skill levels encourage younger individuals to pursue more education. This allows them to seek higher returns, while older individuals cannot adjust their educational paths. It is important to note that although the increased return to experience could help explain the observed rise in *AGIR*, this channel accounts for only 23 percent of the total change.

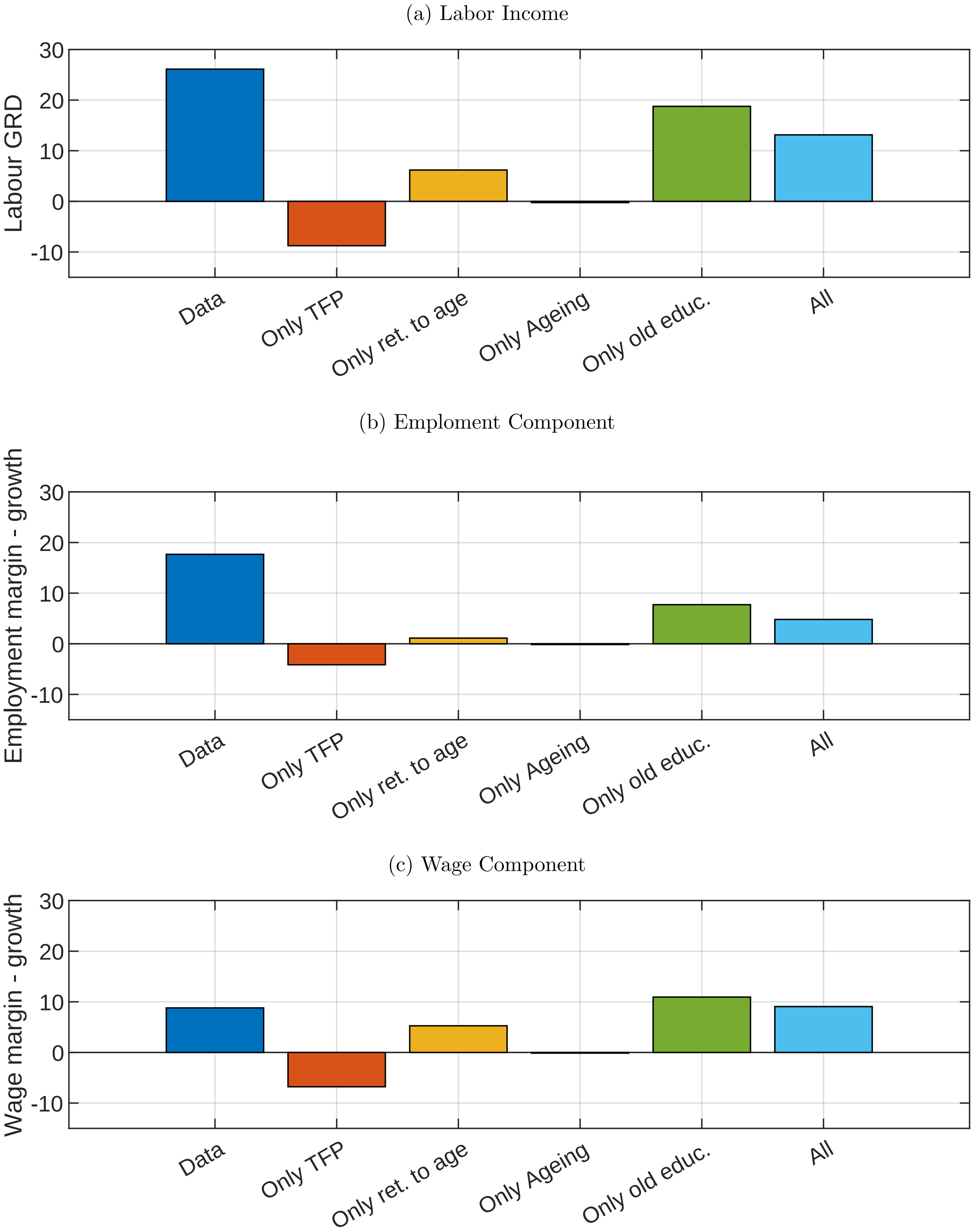
Third, we assume that only the relative number of young workers in the population, $\frac{N^o_{t+1}}{N^y_{t+1}}$, which captures aging, shifts to the 2018 value. The overall effect is almost null. The increased supply of old workers has only a slightly negative general equilibrium effect: since old workers are mainly unskilled in the first period, a larger supply of them reduces wages more for low skills than for high skills. As young people are more educated than older adults, the overall effects on employment and wages are in their favor, but minimal in size.

Fourth, we focus on the role of the share of old workers with high education, $\rho^o_{s,t+1}$. Recall that the skill distribution of the old worker is an initial condition of the model. In the last counterfactual scenario, we only change the old skill distribution to the observed 2018 value. The impact on *AGIR* is large and equal to 22 percentage points, which is 85 percent of the observed value alone. Slightly less than half of it is attributable to a direct PE effect: a higher share of high-skill old workers increase their income by simply a composition effect, as more skilled individuals have higher wages and employment rates. However, slightly more than half of the effect comes from a GE effect: skilled wages respond negatively to the increased supply of (old) skilled workers, and, conversely, they increase for low-skilled jobs. This incentivises the young to reduce the take-up of high-skilled education, relative to 2004. Therefore, a high share of old workers in the economy could be another strong channel that rationalizes the observed increased *AGIR* in rich countries.[21]

[21] Notice that in 2018 the education level of the young increases only as a consequence of the increase in TFP, which enhance the incentives to become high-skilled. In the counterfactual scenario, this channel is shut down.

Finally, these channels are not orthogonal but interact with each other. In the final scenario, we turn on all four channels at the same time. Together, they account for 50 percent of the observed change in labor income $AGIR$, with a strong explanatory power for the wage component and a weaker one for the employment margin. This result is explained by the substantial role played by the outside option of working, which is captured by the preference for leisure. While in this model we do not put structure on the outside option, future research could explore whether these changes are due to preferences, longer expected lives, or public policies that either discouraged employment for the young, or encouraged it for the old.

Figure 8. Contribution to Labor Income GRD and sub-components, by factor



Notes: the figures shows the change in the age-labor income gap between 2004 and 2018 ("Labor GRD") for a representative "richer" country (given by averaging across the moments of all rich countries in our dataset). The blue bar ("Data") is the GRD as seen in the data. The other bars represent counterfactual estimations from the model, estimated by taking all parameters at their 2004 level, besides the ones listed in each column. In "Only TFP", we set the productivity levels A_s to their 2018 value. In "Only ret. to age" we set the return to experience g_s to its 2018 level. In "Only transfer" we set the relative size of transfers to wages equal to their 2018 levels. In "Only Ageing" we set the relative size of the two generations to its 2018 level. In "Only old educ." we set the initial education level of the old generation to its 2018 level. In "All" we set all the aforementioned parameters and initial conditions to their 2018 level. Panels (b) and (c) provide similar counterfactuals for the employment and wage margins of the Labor GRD, respectively.

TABLE IV. Partial and General Equilibrium counterfactuals for LGRD (percentage points)

	Data	Only TFP	Only ret. to age	Only Ageing	Only old educ.	All
Total						
Partial EQ	0	0	0.069	0	0.102	0.177
GE effect	0	-0.088	-0.008	-0.002	0.086	-0.045
Total	0.261	-0.088	0.062	-0.002	0.188	0.131
Employment component						
	Data	Only TFP	Only ret. to age	Only Ageing	Only old educ.	All
Partial EQ	0	0	0.016	0	0.044	0.06
GE effect	0	-0.041	-0.005	-0.002	0.033	-0.012
Total	0.177	-0.041	0.011	-0.002	0.077	0.048
Wage component						
	Data	Only TFP	Only ret. to age	Only Ageing	Only old educ.	All
Partial EQ	0	0	0.056	0	0.063	0.119
GE effect	0	-0.068	-0.004	-0.001	0.047	-0.029
Total	0.088	-0.068	0.053	-0.001	0.109	0.091

Notes: The table decomposes the counterfactual growth in age-labor income gaps of a representative rich country "rich" country (given by averaging across the moments of all rich countries in our dataset). Partial equilibrium effects are calculate by fixing wages and education choices of the young to their 2004 value in each counterfactual. In "Only TFP", we set the productivity levels A_s to their 2018 value. In "Only ret. to age" we set the return to age g_s to its 2018 level. In "Only Ageing" we set the relative size of the two generations to its 2018 level. In "Only old educ." we set the initial education level of the old generation to its 2018 level. In "All" we set all the aforementioned parameters and initial conditions to their 2018 level.

4.3 *AGIR* and Lifetime Income profile

In the previous section, we showed that the increase in labor income $AGIR$ can be rationalized by an increase in the return to age and in the education level of the old generation. We now highlight how these channels have different implications for the lifetime income profile of a cohort, showing that higher $AGIR$ does not necessarily reflect steeper income profiles.

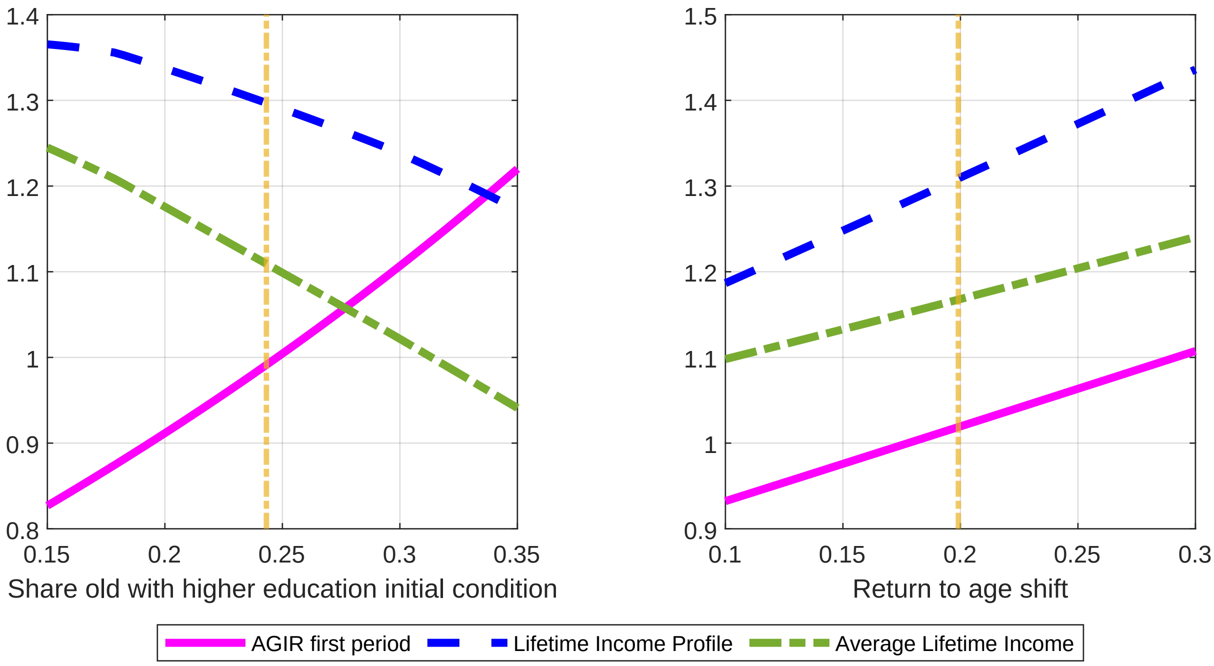
Using our model, we conduct two comparative static exercises, changing one parameter at a time. In the first exercise, we change the share of High skill workers, keeping the relative proportion of Low to Mid skill workers constant.[22] These shares represent the initial conditions of the model. In the second exercise, we change the return to age of Mid- and High-skilled workers: $g_{M,1}$ and $g_{H,1}$, respectively. We parametrize the skill for the second skill, $s = M$, in the interval $[0.1, 0.3]$. We also assume that the difference between the return to experience of high and medium skill, $g_{H,1} - g_{M,1}$ equals 0.27, its

[22]Hence, as we increase the share of High-skilled old from 0.15, we accordingly reduce the joint share of Low- and Mid- skilled old, while keeping the ratio $\rho^O_{\mathrm{M}}/\rho^O_{\mathrm{L}}$ fixed.

2004 estimated value. We run the model for two periods, assuming that all the rest of the parameters are as estimated in 2004 (see Table III).

We focus on three outcome variables, which are plotted in Figure 9; (i) the first-period labor income $AGIR$ (magenta solid line), which recall is $AGIR = \frac{Income_1^o}{Income_1^y}$ and measures the ratio between income of the old relative to the young; (ii) the lifetime income (dashed blue line), expressed in average income per period, of the young, defined as $LI = \frac{1}{2}(Income_1^y + Income_2^o)$; (iii), the lifetime income growth (dotted green line), LIG, which is defined as $LIG = \frac{Income_2^o}{Income_1^y}$ and measures the steepness of the lifetime income profile for a cohort. While both an increase in the share of old workers with high education and an increased return to age increase $AGIR$, the lifetime income of the young generation and its steepness ("lifetime income growth") follow different trends: having more educated old undermines the lifetime income of the young, while higher returns to age increase it.

Figure 9. Comparative statics for $AGIR$ and Lifetime Income Growth

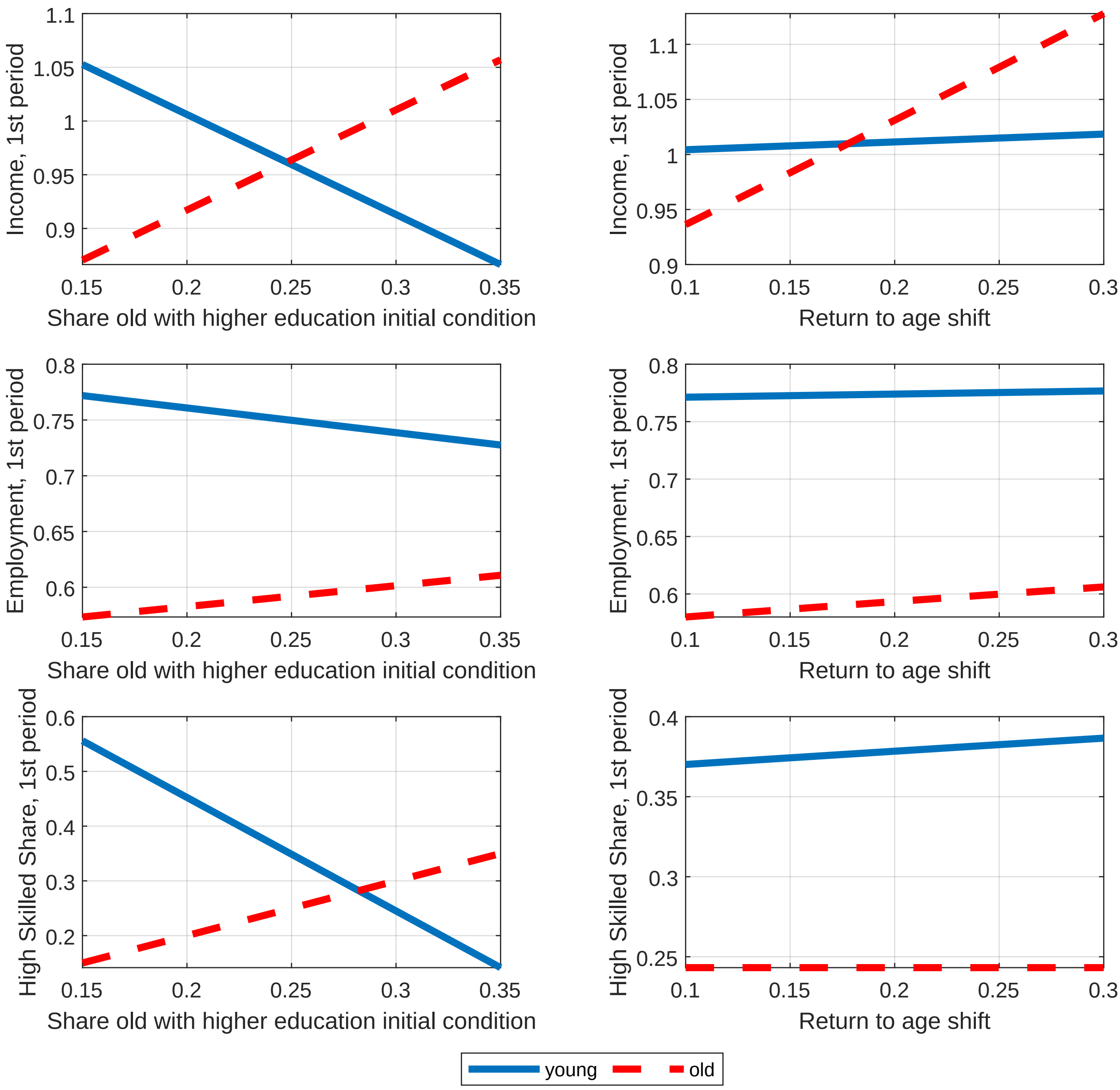


Notes: The figure plots the AGIR of the first simulated period (pink line), the average lifetime income of the young born in the first period (green line) and its ratio between first and second period (blue dotted line), resulting from simulating different initial conditions for the share of old with High skill, ρ_H (left panel), and the returns to skill g_s (right panel). The vertical dotted line corresponds to the initial condition in 2004.

Figure 10 rationalizes this finding. The upper panel plots the income of the young (solid blue line) and the old (dashed red line), the central panel plots the employment rates, and the bottom panel plots the share of highly skilled workers for the two comparative statics. Let us start with the increased return to age (right panels). An increase in the return to age directly increases the old's income. However, as the relative lifetime income of different skills changes, the young also increase their education achievement (third panel), and thus their average employment (second panel) and wage. Hence, both the first-period $AGIR$, the initial income, and the lifetime income growth of the young increases. Consider now an increase in the initial education of the old (left panels). As the old are more educated, their income increases as a direct effect of having access to higher wages and a higher equilibrium employment rate. However, the larger supply of skilled labor reduces skilled wages, and discourages the young from engaging in education. Hence, their average skill, wage and employment rate falls. Overall, an increase in the old's share of High-skilled increases $AGIR$ because the income of the old increases while the one of the young falls. The lifetime income of the young also becomes smaller and flatter, as the congestion in the high-skilled labor market incentivizes them to pick lower-pay, lower-return-to-age skills.

The results of this section are significant for two reasons. First, we demonstrate that the observed increase in $AGIR$ in rich countries is not necessarily associated with steeper income profiles, nor higher lifetime income. The specific direction of this relationship depends on the channels that contributed to the increase $AGIR$, and can be either positive or negative. Second, our estimation supports the view that the observed increase in $AGIR$ is largely driven by older workers converging to education levels that resemble those of younger workers. From the perspective of our model, this finding indicates that the current younger generation is likely to experience a flattening of their lifetime income profile and an overall decline in lifetime income compared to previous generations. Only time will reveal if the predictions of our model are reflected in real data. Nonetheless, our findings are insightful about the potential challenges that the current young generation faces and will face in the labor market. Any work on present and future intergenerational fairness could benefit from our analysis.

Figure 10. Relationship between fundamentals and endogenous variables



Notes: The figure plots three different variables, Income (top panels), Employment rate l (middle panels) and High-skill share ρ_H (bottom panel) as a function of changes: i) the share of old with High skill in the first period (left panels), and ii) the return to age (right panels). The blue line captures the value of the variable for the young alive in the first period, while the red line captures the value of the variable for the old alive in the first period.

5 Conclusions

The widening inequalities between young and old individuals has become a critical issue in several advanced economies, frequently covered in media and political discourse. Yet, most of the existing evidence has focused on the labor earnings of employed individuals and a small set of developed countries. This paper addresses these gaps by analyzing age inequalities in disposable income across 32 countries spanning different stages of economic development. Our findings reveal three key insights.

First, the age-income gap, measured by the Age Group Income Ratio, *AGIR*, has widened in richer countries (Western Europe, North America, and Oceania) but has narrowed in poorer countries (Eastern Europe and South America). Second, we identify distinct drivers behind these trends. In high-income countries, the rising employment rate of older individuals relative to younger workers is the primary force behind the growing income gap. In lower-income countries, the decline in age-income disparities stems from faster wage growth among younger workers compared to their older counterparts. This result explains why the trends in the age-earnings gap, the ratio of the labor earnings of employed individuals, consistently underestimates the increase in age-income gaps (our AGIR) in all high-income countries in our sample. Third, we show that long-term demographic trends, including rising female labor force participation and higher retirement ages, do not fully account for these patterns, indicating deeper structural shifts at play.

Using a model with endogenous education choice, we show that the main driver behind the increase in *AGIR* in richer countries is the educational convergence of older generations with younger ones. Directly, higher education achievements increase the income of the old by giving them access to better jobs. Indirectly, it creates congestion on the high-skilled labour market, reducing the young's incentives to acquire college education. This phenomenon drives most of the results, with a minor contribution from the increase in return to age. Moreover, increases in high-skilled labor productivity in the last two decades, relative to low-skilled labor, have moderated the increase in AGIR.

Finally, we discuss how our findings have important implications for the relationship between *AGIR* and lifetime income. While rising returns to age steepen the income profile over a lifetime, the congestion effect from better-educated older workers dampens earnings growth for younger generations. Given that education catch-up among the old explains much of the rising AGIR in rich countries, our results suggest that today's young workers may face a downward pressure on their lifetime incomes arising from the increasing age-income gap. If generational educational convergence continues, these challenges are likely to intensify.

Our results open new research questions. Will new technologies such as Artificial Intelligence invert the trend by introducing new age-biased technical change? Or will the convergence of skill achievements between young and old lead to higher age-income gaps in both high and lower-income countries? Finally, do higher age-income gaps affect welfare, location choice, and policymakers' electoral incentives? And do these consequences differ based on the underlying drivers of age-income inequality?

By shedding light on the structural forces shaping intergenerational income inequality, our work lays the foundation for future research to address these urgent questions.

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APPENDIX FOR ONLINE PUBLICATION

A Additional Information on Data Availability

TABLE V. Data availability

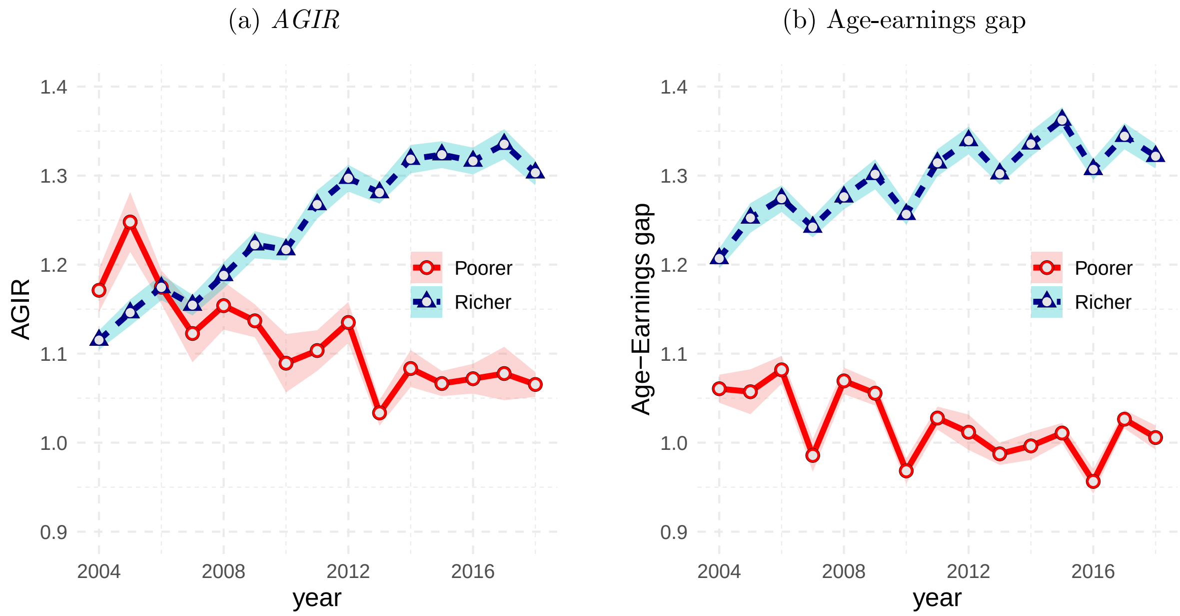
				Wave 1			Wave 2			Wave 3			Wave 4			Wave 5		
Country	Group	Income	obs	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Australia	Rich	Gross	160050	✓				✓		✓				✓		✓		✓
Austria	Rich	Gross	167497	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Belgium	Rich	Gross	175398	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Brazil	Poorer	Gross	4111572	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓
Canada	Rich	Gross	802049	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Chile	Poorer	Net	1091258			✓			✓		✓		✓		✓		✓	
Colombia	Poorer	Gross	7915257	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Czech Republic	Rich	Gross	80831	✓			✓			✓			✓			✓		
Denmark	Rich	Gross	2463597	✓			✓			✓			✓		✓	✓	✓	✓
Estonia	Poorer	Gross	57594	✓			✓			✓			✓			✓		
Finland	Rich	Gross	104274	✓			✓			✓			✓			✓		
France	Rich	Gross	1296110	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Germany	Rich	Gross	425094	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ireland	Rich	Gross	148980	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Israel	Rich	Gross	252068	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Italy	Rich	Net	118950	✓		✓		✓		✓		✓		✓		✓		
Mexico	Poorer	Net	778487	✓	✓	✓		✓		✓		✓		✓		✓		✓
Netherlands	Rich	Gross	305908	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Norway	Rich	Gross	1618510	✓			✓			✓			✓			✓		
Paraguay	Poorer	Gross	238322	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Peru	Poorer	Gross	1062822	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Poland	Poorer	Net	1269373	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Romania	Poorer	Gross	210042			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Serbia	Poorer	Net	170404			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Slovakia	Poorer	Gross	123090	✓			✓			✓			✓	✓	✓	✓	✓	✓
Slovenia	Rich	Net	47700	✓			✓			✓		✓			✓			
Spain	Rich	Gross	443364	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sweden	Rich	Gross	340992	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Switzerland	Rich	Gross	182877			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
United Kingdom	Rich	Gross	614202	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
United States	Rich	Gross	2187365	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Uruguay	Poorer	Net	1455840	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: 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 and Robustness Checks

For completeness, Figure 11 displays the AGIR and the Age-Earning Gaps when using years as the observation unit.

Figure 11. *AGIR*, 50-64 vs 25-34 years old



Notes: 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.

B.1 Trends in Age-Earnings Gaps

In Table VI, 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 VI. 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***

Notes: Significance level: * = 0.05, ** = 0.01, *** = 0.001. Columns (1) and (3) report the estimates of equation (2) for wave and yearly observations, respectively. Columns (2) and (4) report the estimates of Equation (3). 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 VII. 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 (3) 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.[23] 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 VIII provides similar robustness checks for the age-earning gap, which yields qualitatively identical results to the ones described for $AGIR$.

TABLE VII. 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	0.008	0.003*	0.002
	(0.009)	(0.003)	(0.007)	(0.006)	(0.002)	(0.004)
[4] θ: Initial log-GDP (Dev)	0.013	-0.029	0.064	-0.005	-0.051**	0.076*
	(0.021)	(0.024)	(0.041)	(0.022)	(0.022)	(0.045)
[5] γ: Trend $\times$ Initial log-GDP(Dev)	0.009***	0.010***	-0.004	0.015***	0.015***	-0.002
	(0.002)	(0.003)	(0.008)	(0.002)	(0.003)	(0.006)
Observations	159	159	159	378	378	378
R^2	0.207	0.132	0.029	0.214	0.173	0.015
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	15.95	14.40	0.28	15.95	48.42	48.42
Trend effect at min GDP	-0.006	-0.011	0.014	-0.016***	-0.017***	0.005
Trend effect at 25% GDP	0.002	-0.002	0.011	-0.002	-0.003	0.003
Trend effect at 75% GDP	0.010**	0.007*	0.007	0.012***	0.010***	0.001
Trend effect at max GDP	0.013***	0.010***	0.006	0.017***	0.015***	-0.000

Notes: Significance level: * = 0.05, ** = 0.01, *** = 0.001. All columns report the estimates of equation (3). 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].

[23] 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 VIII. Trend in age-earnings gaps

	Wave			Year		
Dependent	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*

Notes: Significance level: * = 0.05, ** = 0.01, *** = 0.001. All columns report the estimates of equation (3). 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].

B.3 *AGIR* and Household-level Benefits

Some benefits are paid at the household level, rather than at the personal level. Hence, they do not enter in our baseline personal income definition. In this section, we allocate these household-wide benefits to the households' members, and compare the resulting *AGIR* with our baseline figures.

We add three categories of household-wide benefits: i) child benefits, ii) general assistance (such as minimum income integrations, or universal benefit systems), and iii) housing benefits (such as rent subsidies).

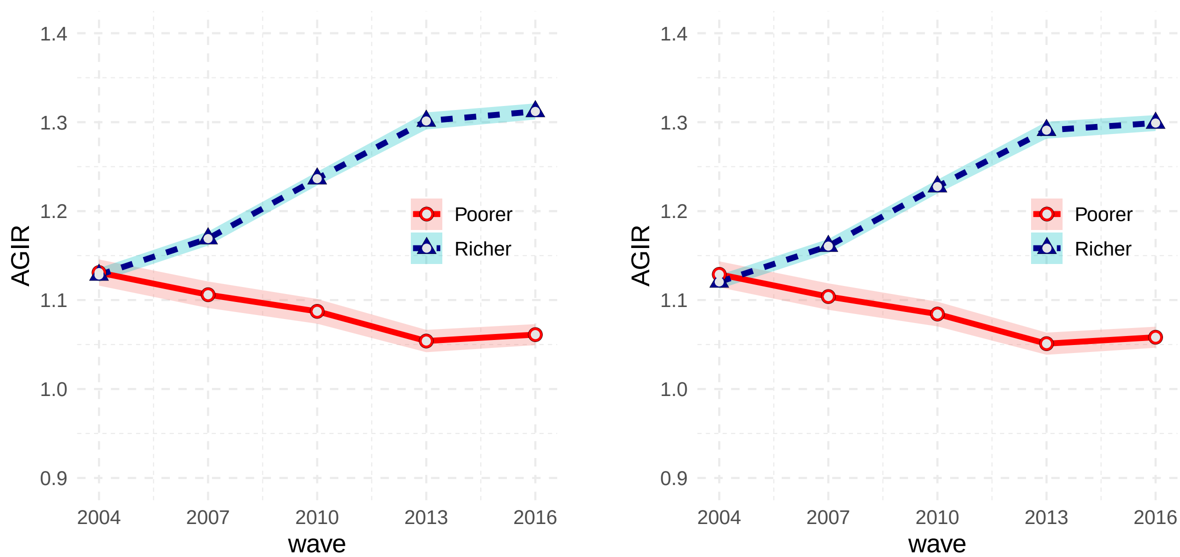
Children benefits are allocated to individuals proportionally to the number of own children who live in the household. For example, in an household with two parents with one small child (who generates a child benefit) and one adult child (who does not), we allocate 50% of the child benefit to each of the parent, and zero to the adult child. The reason is that if the adult child moved out of their household, they would not receive any child benefit of their own. General assistance and housing benefits are split among all adults in the household, with equal weight. Since not all countries report all benefits types in each year, we remove those benefits that are not resported throughout the whole sample of a country.[24]

We plot the two statistics side-by-side in Figure 12. Since more young individuals (25-34 years old) are renters and have children, a large share of household benefits accrues to young individuals. Hence, the level of *AGIR* is slightly smaller when accounting for these benefits (1 pp. smaller in richer countries in 2004). However, the trend is virtually unaffected: between 2004 and 2018, the *AGIR* with household benefits fell by 0.2 percentage points less than the baseline figure in poorer countries (out of 6.1), and 0.3 less in richer ones (out of 18.5).

Hence, we conclude that - on average - household-level benefits are only slightly age-biased in favour of the young,[25] and such bias had not substantially changed over time.

Figure 12. *AGIR*, 50-64 vs 25-34 years old

(a) *AGIR* (b) AGIR + Household Benefits



Notes: 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. The right panel displays a similar statistic, calculated by attributing to each individual household-level benefit payments. 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.

[24] These are child benefits for Australia, Belgium, Denmark and Poland. Housing benefits for Australia, Israel, Slovakia and Switzerland. General assistance for Denmark, France, Paraguay, and Uruguay.

[25] Exceptions are Denmark and Germany, where accounting for household-level benefits reduce *AGIR* by 4 to 5 percentage points. The trend remains unaffected.

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 $R(T)$:

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

D 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 IX 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.[26] Finally, recall that it is always possible to retire earlier than the legal minimum retirement age. The minimum retirement age defines the age at which it is possible to claim public pensions (and, in some cases, tax-free regimes on private pensions), but a worker may decide to retire earlier on private funds (or other non-old age benefits).

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 (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 Czech Republic set the minimum retirement age for women to 60, minus a discounts for each child. 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 over time, 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 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.

[26] For example, France provides some opportunities to retire at 56 y.o. for individuals who started working at age 17 and have a sufficiently long contribution history. Several countries, such as Italy, provide early retirement opportunities for individuals in physically-heavy occupations.

TABLE IX. Retirement Age

Country	Males	Females	Reference 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 Administration, SSPTW Americas 2004
Colombia	62	57	2004	Social Security Administration, 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 Administration, 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 Administration, 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 Administration, SSPTW Americas 2005
Peru	55	53	2005	Social Security Administration, SSPTW Americas 2005
Poland	65	60	2005	OECD, Pension at a glance 2005
Romania	55	55	2004	Social Security Administration, SSPTW Europe 2004
Serbia	53	53	2004	Social Security Administration, SSPTW Europe 2004
Slovakia	62	62	2005	OECD, Pension at a glance 2005
Slovenia	63	60	2004	Social Security Administration, 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 Administration, SSPTW Americas 2005

(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 some social security contribution gaps.

Notes: The table reports the retirement age used to limit the sample size in Section **??** 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.

E *AGIR* and *GRD* across Demographics

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

E.1 Employment margin decomposition by demographic

Increased Female 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 13a 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 female and 1.1 pp. for the whole population), while it disappear 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), which is a measure of agreement between two variables. [27] It is equal to 1 when the two measures alligns 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 excacerbated 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.[28]

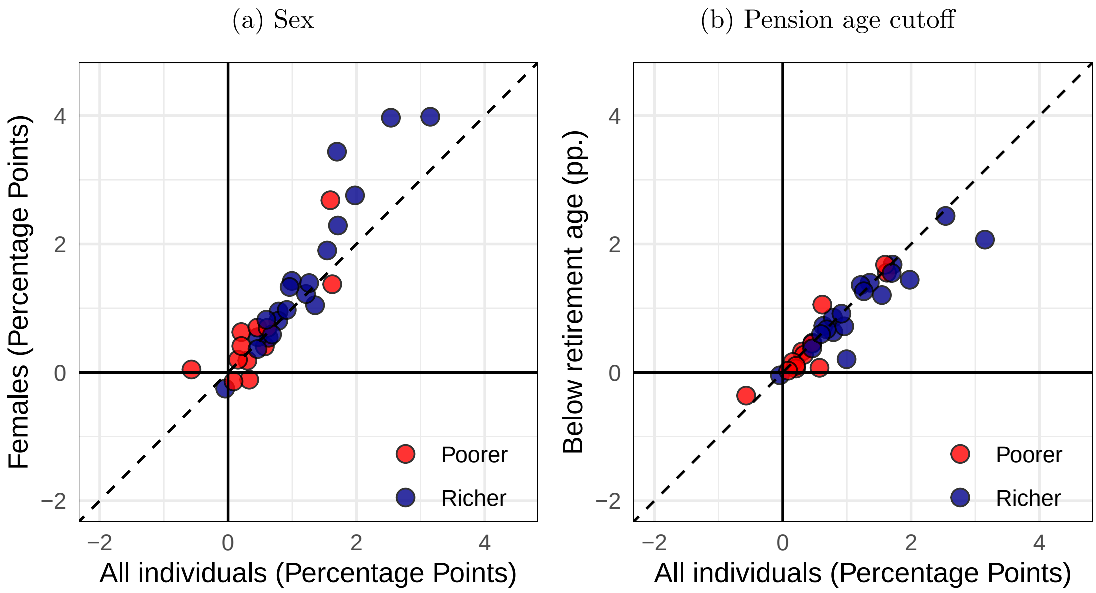
Increased Pension-Age Finally, we investigate whether the large employment margin of *AGIR* is mainly due to a delay in retirement (Pilipiec et al., 2021; Staubli and

[27]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.

[28]In Appendix E we report the GRD decomposition for all the subset of demographics considered in this section.

Zweimüller, 2013). We construct an alternative definition for the old age-group, defined as all individual older than 50 and younger than the minimum pension age for each country and gender within our sample. 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).[29]. The employment margin of this alternative $AGIR$ measure (0.8 pp.) is similar to the headline figure (0.9 pp.), as displayed in Figure 13b. Hence, the employment margin of $AGIR$ does not depend only on changes in the target age of retirement in each country. In this case the CCC is equal to 0.91.

Figure 13. 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 (c) the one calculated by including in the old age group only individuals below the minimum old-age retirement age in 2004.

E.2 *GRD* by demographic

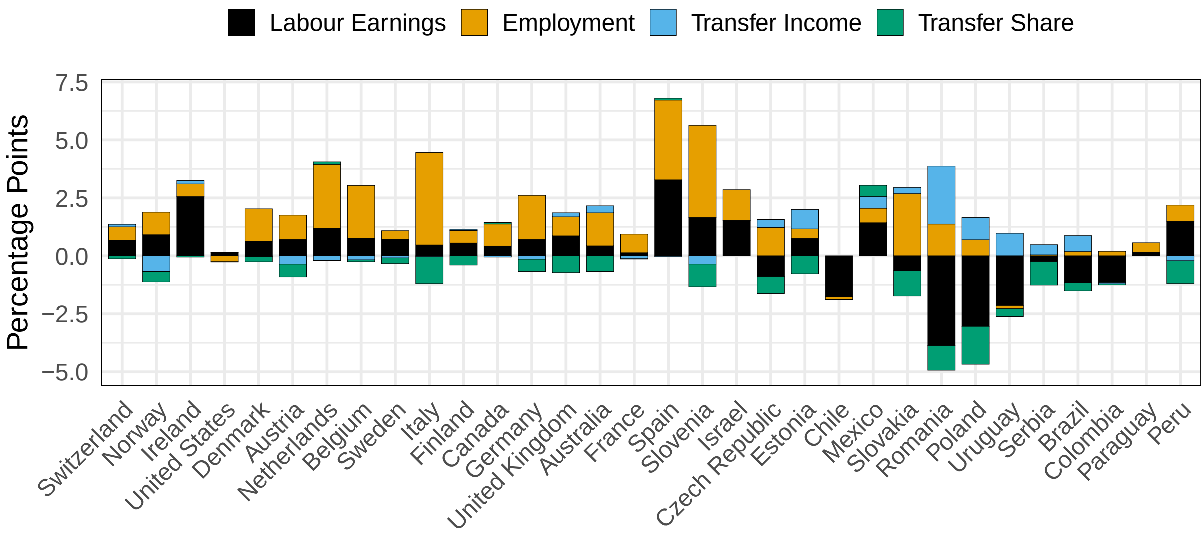
Below, we report the Growth Rate Differentials in each country splitting the sample in different demographic characteristics, specifically for female and male in Figure 14, and for the definition of old that have age below the minimum pension age in Figure 15.

[29] We consider the minum pension age in 2004 because in none of the countries in our sample it has declined in the sample 2004-2018.

Figure 14. *GRD* decomposition: Male and Female

(a) Male

(b) Female

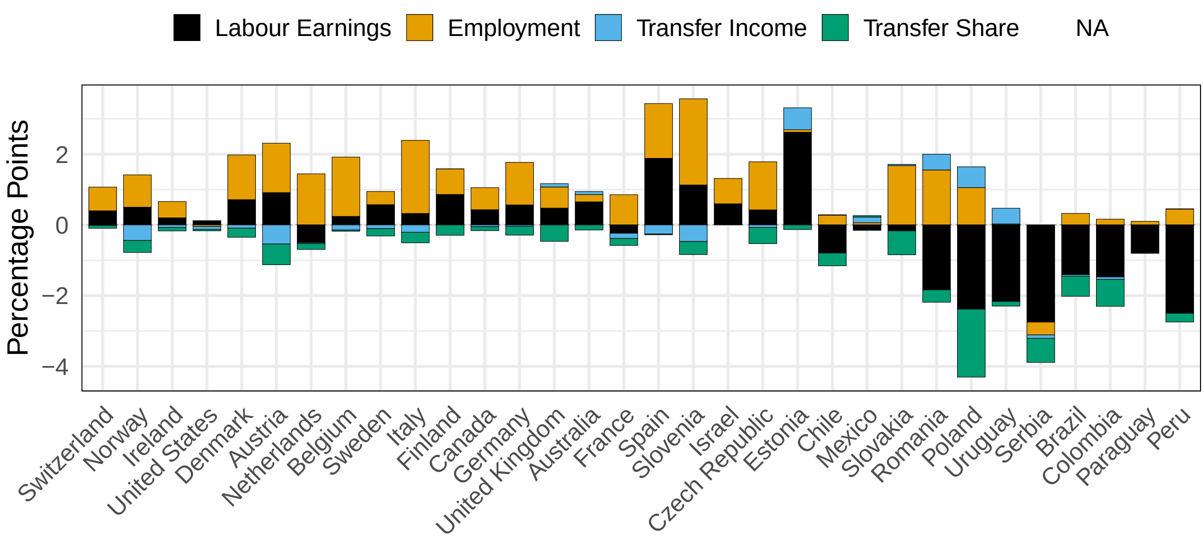


Notes: panel (a) depicts the employment contribution (lighter red bar) to the *GRD*s for male late-career individuals (50-64 y.o.) and male early-career individuals (25-34 y.o), and the labor earnings contribition (black bar). Panel (b) depicts the two contributions for female.

Figure 15. *GRD* decomposition: all individuals and below retirement age only

(a) All individuals

(b) Below retirement age



Notes: 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.

F Model

F.1 Equilibrium

Definition 1. Given the initial skill distribution $\{\rho_{s,1}\}_{s\in\mathbb{S}}$ and the sequence of cohort sizes $\{N_t\}_{t=0}^{\infty}$, a sequential market equilibrium is a sequence of household allocations $\{\hat{c}^o_{s,1}, \hat{l}^o_{s,1}, \{\hat{c}^y_{s,t}, \hat{c}^o_{s,t+1}, \hat{l}^y_{s,t}, \hat{l}^o_{s,t+1}\}_{t=1}^{\infty}\}_{s\in\mathbb{S}}$, household education choices $\{\{\hat{s}_i\}_{i=0}^{N_t}\}_{t=1}^{\infty}$, firm allocations $\{\{\hat{L}_{s,t}\}_{t=1}^{\infty}\}_{s\in\mathbb{S}}$ and prices $\{\{\hat{w}_{s,t}\}_{t=1}^{\infty}\}_{s\in\mathbb{S}}$ such that:

1. $\forall\, t \geq 1,\ s \in \mathbb{S}$, given $\{\hat{w}_{s,t}, \hat{w}_{s,t+1}\}_{s\in\mathbb{S}}$, $\{\hat{c}^y_{s,t}, \hat{c}^o_{s,t+1}, \hat{l}^y_{s,t}, \hat{l}^o_{s,t+1}, \hat{s}_t\}$ solves:

$$\max_{c^y_t, c^o_{t+1}, l^y_t, l^o_{t+1}, s} U^y_{s,t}(c^y_t, l^y_t) + \mathbb{E}_t\left(U^o_{s,t+1}(c^o_{t+1}, l^o_{t+1})\right)$$

$$\text{s.t.} \begin{cases} c^y_t \leq w_{s,t} l^y_t \kappa(s)^{-1}, \\ c^o_{t+1} \leq w_{s,t+1}(1+g_{s,t+1}) l^o_{t+1}\kappa(s)^{-1}, \\ l^y_t, l^o_{t+1} \in [0,1];\ c^y_t, c^o_{t+1} \geq 0. \end{cases}$$

2. For every $s \in \mathbb{S}$, given $\{\hat{w}_{s,1}\}$, $\{\hat{c}^o_{s,1}, \hat{l}^o_{s,1}\}$ solves:

$$\max_{c^o_1, l^o_1} U^o_{s,1}(c^y_1, l^o_1)$$

$$\text{s.t.} \begin{cases} c^o_1 \leq w_{s,1}(1+g_{s,1}) l^o_1 \kappa(s)^{-1}, \\ l^o_1 \in [0,1];\ c^o_1 \geq 0. \end{cases}$$

3. For all $t \geq 1$, $\hat{L}_t = \{\hat{L}_{s,t}\}_{s\in\mathbb{S}}$ solves:

$$\max_{\{L_{s,t}\}_{s\in\mathbb{S}} \geq 0} \left(\sum_s A_{s,t}\left(L_{s,t}\right)^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}} - \sum_s w_{st} L_{s,t}.$$

4. For all $t \geq 1$,

   (a) (Goods Market Clear)

$$\sum_{s\in\mathbb{S}} \left(\rho_{s,t} N_t \hat{c}^y_t + \rho_{s,t-1} N_{t-1} \hat{c}^o_t\right) = Y_t(\hat{L}_t),$$

   (b) (Labor Markets Clear)

$$\rho_{s,t} N_t \hat{l}^y_t + \rho_{s,t-1} N_{t-1}(1+g_{s,t})\hat{l}^o_t = \hat{L}_{s,t}, \qquad \forall s \in \mathbb{S},$$

   (c) (Education indifference) Given $\{\hat{w}_{s,t}, \hat{w}_{s,t+1}\}_{s\in\mathbb{S}}$, households are indifferent between all education options $s \in \mathbb{S}$:

$$V_t^y(s) = V_t^y(s'), \qquad \forall s, s' \in \mathbb{S}.$$

F.1.1 Equilibrium characterisation

Employment The solution to the households' maximisation problem yields an optimal employment rate for individuals of age a and skill s equal to:

$$\begin{aligned} l_{s,t}^y &= \left[\frac{w_{s,t}}{\kappa(s)}(1+b)\alpha_{s,t}^y\right]^{\frac{1}{b}}, \\ l_{s,t}^o &= \left[\frac{w_{s,t}(1+g_{s,t})}{\kappa(s)}(1+b)\alpha_{s,t}^o\right]^{\frac{1}{b}}. \end{aligned} \tag{6}$$

Relative Wages. The equilibrium aggregate supply of each skill satisfies the labor market clearing condition, for each skill $s \in \mathbb{S}$. Using the expression for the households' optimal employment rates (Equation 6), we can express L as:

$$\begin{aligned} L_{st} &= \rho_{s,t-1}N_{t-1}(1+g_{s,t})l_{s,t}^o + \rho_{s,t}N_t l_{s,t}^y \\ &= \rho_{s,t-1}N_{t-1}(1+g_{s,t})\left[(1+g_{s,t})w_{s,t}(1+b)\alpha_{s,t}^o\kappa(s)^{-1}\right]^{\frac{1}{b}} + \rho_{s,t}N_t\left[w_{s,t}(1+b)\alpha_{s,t}^y\kappa(s)^{-1}\right]^{\frac{1}{b}} \\ &= (w_{s,t})^{\frac{1}{b}}(1+b)^{\frac{1}{b}}\kappa(s)^{-\frac{1}{b}}\left(\rho_{s,t-1}N_{t-1}(1+g_{s,t})^{\frac{1+b}{b}}(\alpha_{s,t}^o)^{\frac{1}{b}} + \rho_{s,t}N_t(\alpha_{s,t}^y)^{\frac{1}{b}}\right). \end{aligned} \tag{7}$$

Hence, the equilibrium wages satisfy:

$$w_{s,t} = \kappa(s)\frac{L_{s,t}^b}{(1+b)}\left(\rho_{s,t-1}N_{t-1}(1+g_{s,t})^{\frac{1+b}{b}}(\alpha_{s,t}^o)^{\frac{1}{b}} + \rho_{s,t}N_t(\alpha_{s,t}^y)^{\frac{1}{b}}\right)^{-b}. \tag{8}$$

Using the solution to the problem of the firm (see Equation 5), derive the relative equilibrium wages of skills s and s' as:

$$\frac{w_{s,t}}{w_{s',t}} = \left(\frac{A_{s,t}}{A_{s',t}}\right)^{1-\frac{1}{\theta}}\left(\frac{L_{s,t}}{L_{s',t}}\right)^{-\frac{1}{\theta}}. \tag{9}$$

Using Equations (8) and (9) yields the following expression for relative wages, as a function of productivity A_s, education costs κ, and the determinants of skill supply ρ, N, g and α:

$$\frac{w_{st}}{w_{s't}} = \left(\frac{A_{s,t}}{A_{s',t}}\right)^{\frac{b(\theta-1)}{1+b\theta}}\left(\frac{\kappa(s)}{\kappa(s')}\right)^{\frac{1}{1+b\theta}}\left(\frac{X_{s',t}}{X_{s,t}}\right)^{\frac{b}{1+b\theta}}, \tag{10}$$

for $X_{s,t} = \left(\rho_{s,t-1}N_{t-1}(1+g_{s,t})^{\frac{1+b}{b}}(\alpha_{s,t}^o)^{\frac{1}{b}} + \rho_{s,t}N_t(\alpha_{s,t}^y)^{\frac{1}{b}}\right)$.

Skill shares. Finally, utility is equalised across all young of different skills, as they must be ex-ante indifferent between education choices. That is, for any skills $s, s' \in \mathbb{S}$, the following equation holds in equilibrium:

$$\left(\frac{w_{s,t}}{\kappa(s)}\right)^{\frac{1+b}{b}} C^y_{s,t} + \left(\frac{w_{s,t+1}(1+g_{s,t+1})}{\kappa(s)}\right)^{\frac{(1+b)}{b}} C^o_{s,t+1} =$$
$$\left(\frac{w_{s',t}}{\kappa(s')}\right)^{\frac{1+b}{b}} C^y_{s',t} + \left(\frac{w_{s',t+1}(1+g_{s',t+1})}{\kappa(s')}\right)^{\frac{(1+b)}{b}} C^o_{s',t+1}.$$

Collecting $\kappa(s)$, and calling $\Delta w_{s,t+1} = \frac{w_{s,t+1}}{w_{s,t}} - 1$ we obtain an expression for the relative education cost of different skills:

$$\frac{\kappa(s)}{\kappa(s')} = \frac{w_{s,t}}{w_{s',t}} \left[\frac{\left(\alpha^y_{s,t}\right)^{\frac{1}{b}} + ((1+\Delta_{t+1}w_s)(1+g_{s,t+1}))^{\frac{(1+b)}{b}} \left(\alpha^o_{s,t+1}\right)^{\frac{1}{b}}}{\left(\alpha^y_{s',t}\right)^{\frac{1}{b}} + ((1+\Delta_{t+1}w_{s'})(1+g_{s',t+1}))^{\frac{(1+b)}{b}} \left(\alpha^o_{s',t+1}\right)^{\frac{1}{b}}} \right]^{\frac{b}{1+b}}. \tag{11}$$

Substituting the value of relative wages from Equation (10) and calling $n_t = \frac{N_t}{N_{t-1}} - 1$ yields an expression for the relative education levels only as a function of parameters, and the growth in education shares relative to the previous period: $\Delta_t \rho_s = \frac{\rho_{s,t}}{\rho_{s,t-1}} - 1$,

$$\begin{aligned} &\frac{\rho_{s,t}}{\rho_{s',t}} \left[\frac{\frac{(1+g_{s,t})^{\frac{1+b}{b}} (\alpha^o_{s,t})^{\frac{1}{b}}}{(1+\Delta_t \rho_s)(1+n_t)} + (\alpha^y_{s,t})^{\frac{1}{b}}}{\frac{(1+g_{s',t})^{\frac{1+b}{b}} (\alpha^o_{s',t})^{\frac{1}{b}}}{(1+\Delta_t \rho_{s'})(1+n_t)} + (\alpha^y_{s',t})^{\frac{1}{b}}} \right] = \\ &\left(\frac{\kappa(s')}{\kappa(s)}\right)^{\theta} \left(\frac{A_{s,t}}{A_{s',t}}\right)^{\theta-1} \left[\frac{(\alpha^y_{s,t})^{\frac{1}{b}} + ((1+\Delta_{t+1}w_s)(1+g_{s,t+1}))^{\frac{(1+b)}{b}} \left(\alpha^o_{s,t+1}\right)^{\frac{1}{b}}}{\left(\alpha^y_{s',t}\right)^{\frac{1}{b}} + ((1+\Delta_{t+1}w_{s'})(1+g_{s',t+1}))^{\frac{(1+b)}{b}} \left(\alpha^o_{s',t+1}\right)^{\frac{1}{b}}} \right]^{\frac{1+b\theta}{1+b}}. \end{aligned} \tag{12}$$

Since the sum of education shares must be equal to 1, the education shares satisfy:

$$1 = \rho_{L,t} \sum_s \frac{\rho_{s,t}}{\rho_{L,t}}. \tag{13}$$

Finally, the wage level is pinned down by the system of equations given by (7), (12), (13), and the firm's first order condition (5).

F.2 Estimation equations

Using the equilibrium conditions, we can write the following system of equations with as only unknowns the parameters α^a_{st}, $\kappa(s)$ and A_{st}:[30]

$$
\begin{cases}
\ln\left(\frac{w_{s,t}}{w_{L,t}}\right) = \left(1-\frac{1}{\theta}\right)\ln\left(\frac{A_{st}}{A_{Lt}}\right) - \frac{1}{\theta}\ln\left(\frac{(1+g_{s,t})l^o_{H,t}\rho_{s,t-1} + l^y_{s,t}\rho_{s,t}(1+n_t)}{(1+g_{L,t})l^o_{L,t}\rho_{L,t-1} + l^y_{L,t}\rho_{L,t}(1+n_t)}\right) & \forall t, s\neq L \\
\ln\left(\frac{\alpha^o_{st}}{\kappa(s)}\right) = \left[\ln(1+g_{st}) + \ln\left(\frac{w_{s,t}}{w_{L,t}}\right) + \ln(w_{l,t})\right] + \ln(1+b) - b\ln(l^o_{st}) & \forall s,t \\
\ln\left(\frac{\alpha^y_{st}}{\kappa(s)}\right) = \ln\left(\frac{w_{s,t}}{w_{L,t}}\right) + \ln(w_{L,t}) + \ln(1+b) - b\ln(l^y_{st}) & \forall s,t \\
\frac{\rho_{s',t}}{\rho_{s,t}} = \left(\frac{\kappa(s)}{\kappa(s')}\right)^{\theta}\left(\frac{A_{s,t}}{A_{s',t}}\right)^{1-\theta}\left[\frac{\frac{(1+g_{s',t})^{\frac{1+b}{b}}(\alpha^o_{s',t})^{\frac{1}{b}}}{(1+\Delta_t\rho_{s'})(1+n_t)} + (\alpha^y_{s',t})^{\frac{1}{b}}}{\frac{(1+g_{s,t})^{\frac{1+b}{b}}(\alpha^o_{s,t})^{\frac{1}{b}}}{(1+\Delta_t\rho_{s})(1+n_t)} + (\alpha^y_{s,t})^{\frac{1}{b}}}\right]^{-1} & \\
\qquad \times\left[\frac{(\alpha^y_{s,t})^{\frac{1}{b}} + ((1+\Delta_{t+1}w_s)(1+g_{s,t+1}))^{\frac{(1+b)}{b}}\left(\alpha^o_{s,t+1}\right)^{\frac{1}{b}}}{\left(\alpha^y_{s',t}\right)^{\frac{1}{b}} + \left((1+\Delta_{t+1}w_{s'})(1+g_{s',t+1})\right)^{\frac{(1+b)}{b}}\left(\alpha^o_{s',t+1}\right)^{\frac{1}{b}}}\right]^{-\frac{1+b\theta}{1+b}} & \forall s\neq L, t=2004 \\
\left(\sum_{s'} A_{s',t}\left(L_{s',t}\right)^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}-1} A_{L,t}L_{L,t}^{\frac{\theta-1}{\theta}-1} = w_{L,t} & \\
\rho_{L,t} = \left(\sum_s \frac{\rho_{s,t}}{\rho_{L,t}}\right)^{-1} &
\end{cases}
\tag{14}
$$

F.3 Estimation Details

F.3.1 Moments

In Table X we report the moments used in the estimation of the model.

[30] Notice that g_{st} is identified directly from the empirical moments.

TABLE X. Model moments

Country	Wave	Wages			Ret. to experience			Size	
		w College	w HS	w LHS	g College	g HS	g LHS	N^y	N^o
Low Income	2004	2.94	1.64	1.00	0.48	0.29	-0.02	0.49	0.67
Low Income	2018	3.60	2.24	1.56	0.45	0.15	-0.07	0.47	0.69
High Income	2004	1.53	1.19	1.00	0.48	0.21	0.09	0.43	0.73
High Income	2018	1.54	1.22	1.01	0.57	0.25	0.20	0.40	0.75

Country	Wave	Employment Rate					
		l^y LHS	l^y HS	l^y Co	l^o LHS	l^o HS	l^o Co
Low Income	2004	0.62	0.74	0.84	0.49	0.57	0.72
Low Income	2018	0.61	0.76	0.84	0.53	0.64	0.77
High Income	2004	0.60	0.78	0.83	0.44	0.60	0.73
High Income	2018	0.56	0.75	0.81	0.49	0.69	0.80

Country	Wave	Skill					
		ρ^y LHS	ρ^o LHS	ρ^y HS	ρ^o HS	ρ^y Co	ρ^o Co
Low Income	2004	0.36	0.54	0.46	0.33	0.18	0.13
Low Income	2018	0.26	0.44	0.45	0.40	0.28	0.17
High Income	2004	0.16	0.34	0.49	0.42	0.36	0.24
High Income	2018	0.13	0.24	0.40	0.44	0.47	0.32

Notes: In this table, we list all the moments used in the estimation of the model. Each row reports a given country-year data point. Each other column lists, separating by skill when necessary, the estimated moments for w (wages), g (return to experience), N (population), l (employment rate) and ρ (educational achievement shares), which we use to identify the model parameters. All figures are rounded to the second decimal digit for display in this table.

F.3.2 Algorithm

We estimate the parameters of the model straightforwardly from the system of equations (14), according to the following algorithm:

1. Compute $g_{s,t}$ by taking the ratio of old and young wages in each period: $g_{s,t} = \frac{w^o_{s,t}}{w^y_{s,t}}$.
2. Compute skill-specific total labor supply $L_{s,t}$ from education shares, employment rates, return to age, and cohort size.
3. Recover relative productivities $A_{s,t}A_{L,t}^{-1}$ from wages and skill-specific total labor supply.
4. Recover the level of $A_{L,t}$ by matching minimum wage $w_{L,t}$; use this to recover the remaining $A_{s,t}$ from $A_{s,t}A_{L,t}^{-1}$.

5. Recover $\alpha^a_{s,t}\kappa(s)^{-1}$ from wages and employment rates.

6. Use 2004 data to estimate $\Delta\rho_s = \frac{\rho^y_{s,2004}}{\rho^o_{s,2004}} - 1$ and $\Delta n = \frac{n^y_{2004}}{n^o_{2004}}$.

7. Use 2018 estimates for $\alpha^a_{s,t}\kappa(s)^{-1}$ from (5), return to age from (1), and the assumption $\Delta_{2018}w_s = \frac{w_{s,2018}}{w_{s,2004}} - 1$ to compute the relative expectation term

$$\Omega_{2018}(s,s') = \left[\frac{\left(\alpha^y_{s,2018}\kappa(s)^{-1}\right)^{\frac{1}{b}} + ((1+\Delta_{t+1}w_s)(1+g_{s,t+1}))^{\frac{(1+b)}{b}}\left(\alpha^o_{s,t+1}\kappa(s)^{-1}\right)^{\frac{1}{b}}}{\left(\alpha^y_{s',t}\kappa(s')^{-1}\right)^{\frac{1}{b}} + ((1+\Delta_{t+1}w_{s'})(1+g_{s',t+1}))^{\frac{(1+b)}{b}}\left(\alpha^o_{s',t+1}\kappa(s')^{-1}\right)^{\frac{1}{b}}}\right]^{-\frac{1+b\theta}{1+b}}.$$

8. Compute eduction costs $\kappa(s)$ by inverting the education-ratio equation using the parameters estimated in (1), (4), (5) and (6), the estimate of $\Omega_{ss',2018}$ from (7) and the ratio of education shares $\frac{\rho_{s',t}}{\rho_{s,t}}$ from the moments:

$$\frac{\rho_{s',t}}{\rho_{s,t}} = \left(\frac{\kappa(s)}{\kappa(s')}\right)^{\frac{1+b\theta}{1+b}}\left(\frac{A_{s,t}}{A_{s',t}}\right)^{1-\theta}\left[\frac{\frac{(1+g_{s',t})^{\frac{1+b}{b}}(\alpha^o_{s',t}\kappa(s')^{-1})^{\frac{1}{b}}}{(1+\Delta_t\rho_{s'})(1+n_t)} + (\alpha^y_{s',t}\kappa(s')^{-1})^{\frac{1}{b}}}{\frac{(1+g_{s,t})^{\frac{1+b}{b}}(\alpha^o_{s,t}\kappa(s)^{-1})^{\frac{1}{b}}}{(1+\Delta_t\rho_s)(1+n_t)} + (\alpha^y_{s,t}\kappa(s)^{-1})^{\frac{1}{b}}}\right]^{-1}\Omega_{2018}(s,s')$$

9. Use the estimates from (5) and (8) to recover $\alpha^a_{s,t}$.

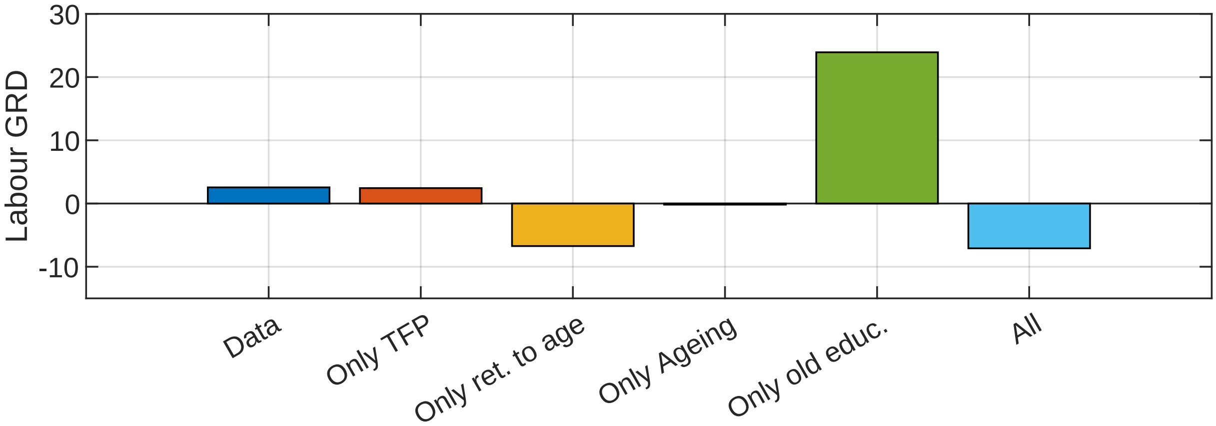
G Additional model results and extensions

G.1 Poorer countries

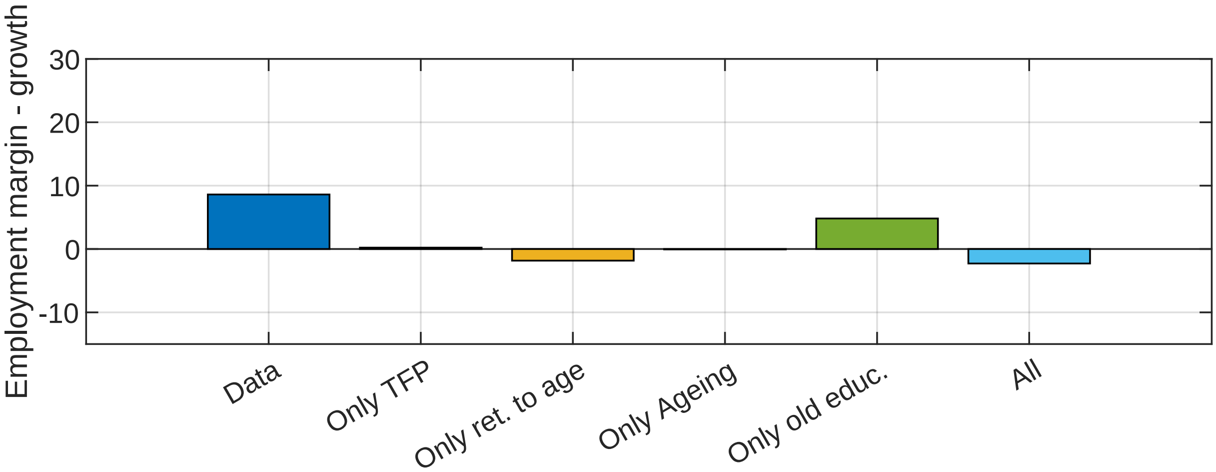
In poorer countries, the largest impact on the labor components of *GRD*)(employment and wage margins)came from the increase in the average education level of the old. The effect (+0.27 pp.) is particularly large because, due to general equilibrium effects, the increase in old education severely displaces the young from high education levels. However, once we account for other changes in fundamentals, we find that the total effect on changes in TFP, return to experience and old education on the labor *GRD* was negative. The reason is that changes in the relative productivity of different skills, and a fall in the experience premium for less-than-college educated, strongly encouraged the young to achieve higher education levels *despite* the higher congestion from old educated individuals. Hence, general equilibrium effects of wages on education achievements dominated the general equilibrium effects of the old's education on the young's education choices.

Figure 16. Components of Labor Income GRD and counterfactual scenarios, Poorer countries

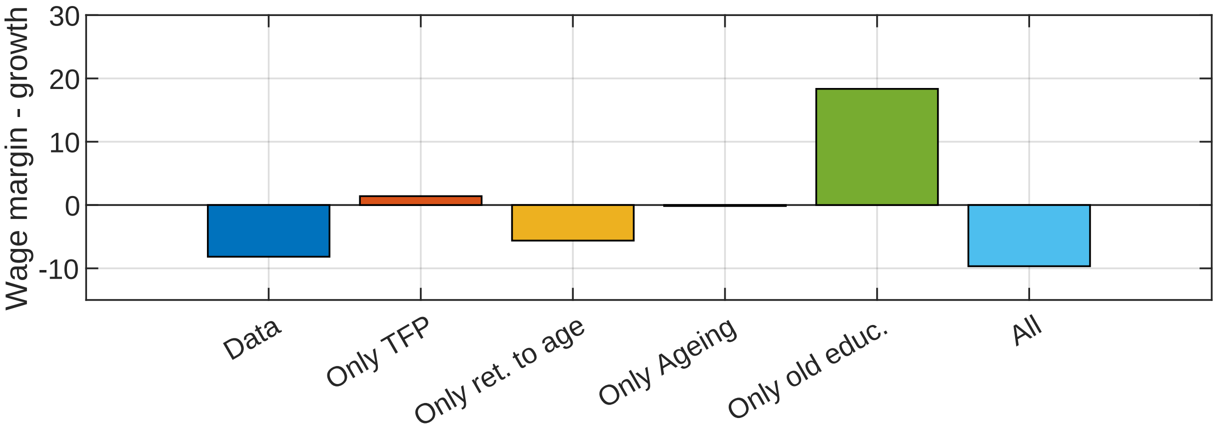
(a) All



(b) Employment



(c) Wages



Notes: the figures shows the change in the age-labor income gap between 2004 and 2018 ("Labor GRD") for a representative "poorer" country (given by averaging across the moments of all rich countries in our dataset). The blue bar ("Data") is the GRD as seen in the data. The other bars represent counterfactual estimations from the model, estimated by taking all parameters at their 2004 level, besides the ones listed in each column. In "Only TFP", we set the productivity levels A_s to their 2018 value. In "Only ret. to age" we set the return to experience g_s to its 2018 level. In "Only transfer" we set the relative size of transfers to wages equal to their 2018 levels. In "Only Ageing" we set the relative size of the two generations to its 2018 level. In "Only old educ." we set the initial education level of the old generation to its 2018 level. In "All" we set all the aforementioned parameters and initial conditions to their 2018 level. Panels (b) and (c) provide similar counterfactuals for the employment and wage margins of the Labor GRD, respectively.

G.2 Transfers

We now match the full *AGIR* statistics, rather than only its labor-income component, by adding transfers to the model. Since the main source of transfers are unemployment benefits and pensions, we treat transfers as being received only by non-employed individuals. We abstract from how pensions are accumulated over a worker's life for tractability reasons. However, this can be intended as a pay-as-you-go system where pension payments are set to "clear" the market, rather than as a capitalisation of actual contributions.

We assume that the transfers are financed through a lump-sum tax τ_t, which is always set so to achieve a balanced budget, and - for readability - will be omitted from the the notation henceforth.

We rewrite the problem of the old households as:

$$\max_{c_t, l_t} U^o_{s,t}(c_t, l_t) = c_t - \frac{1}{\alpha^o_{s,t}} l_t^{1+b},$$
$$\text{s.t.} \begin{cases} c_t \leq \underbrace{w_{s,t}(1+g_{s,t}) l_t \kappa(s)^{-1}}_{\text{Labor Income}} + \underbrace{\tau^o_{s,t}(1-l_t)\kappa(s)^{-1}}_{\text{Transfer Income}}, \\ l_t \in [0,1]. \end{cases} \tag{15}$$

Call $\tilde{\tau}^a_{s,t} = w^{-1}_{s,t}\tau^a_{s,t}$ the transfers expressed in current wage rate units. Then, for an internal solution of effort, we obtain the old's indirect utility:

$$V^o_t(s) = \frac{\tau^o_{s,t}}{\kappa(s)} + \left(\frac{w_{s,t}(1+g_{s,t}-\tilde{\tau}^o_{s,t})}{\kappa(s)}\right)^{\frac{(1+b)}{b}} \left(\frac{\alpha^o_{s,t}}{1+b}\right)^{\frac{1}{b}} \frac{b}{1+b}. \tag{16}$$

The young households maximise lifetime utility, taking into account the cost $\kappa_t(s)$ of acquiring skill s:

$$\max_{c^y_t, c^o_{t+1}, l^y_t, l^o_{t+1}, s} U^y_{s,t}(c^y_t, l^y_t) + \mathbb{E}_t\left(U^o_{s,t}(c^o_{t+1}, l^o_{t+1})\right) = c_t - \frac{1}{\alpha^y_{s,t}} l_t^{1+b} + \mathbb{E}_t\left(U^o_{s,t}(c^o_{t+1}, l^o_{t+1})\right)$$
$$\text{s.t.} \begin{cases} c^y_t \leq w_{s,t} l^y_t \kappa(s)^{-1} + \tau^y_{s,t}(1-l^y_t)\kappa(s)^{-1}, \\ c^o_{t+1} \leq w_{s,t+1}(1+g_{s,t+1}) l^o_{t+1}\kappa(s)^{-1} + \tau^o_{s,t+1}(1-l^o_{t+1})\kappa(s)^{-1}, \\ l^y_t, l^o_{t+1} \in [0,1];\ c^y_t, c^o_{t+1} \geq 0. \end{cases} \tag{17}$$

For an internal solution of household employment rates in both periods, the indirect utility function of the young is:

$$V_t^y(s) = \frac{\tau_{s,t}^y}{\kappa(s)} + \left(\frac{w_{s,t}(1-\tilde{\tau}_{s,t}^y)}{\kappa(s)}\right)^{\frac{1+b}{b}} \left(\frac{\alpha_{s,t}^y}{1+b}\right)^{\frac{1}{b}} \frac{b}{1+b} + V_{t+1}^o(s). \tag{18}$$

The rest of the model is unchanged.

G.2.1 Characterisation

The employment rate of individuals of age a and skill s is given by

$$\begin{aligned} l_{s,t}^y &= \left[\frac{w_{s,t}(1-\tilde{\tau}_{s,t}^y)}{\kappa(s)}(1+b)\alpha_{s,t}^y\right]^{\frac{1}{b}}, \\ l_{s,t}^o &= \left[\frac{w_{s,t}(1+g_{s,t}-\tilde{\tau}_{s,t}^o)}{\kappa(s)}(1+b)\alpha_{s,t}^o\right]^{\frac{1}{b}}. \end{aligned} \tag{19}$$

Hence, the relative employment rate across generations with the same skill s is

$$\frac{l_{s,t}^o}{l_{s,t}^y} = \left[w_s \frac{\alpha_{s,t}^o}{\alpha_{s,t}^y} \frac{(1+g_{s,t}-\tilde{\tau}_{s,t}^o)}{1-\tilde{\tau}_{s,t}^y}\right]^{\frac{1}{b}}. \tag{20}$$

Relative Wages. The equilibrium employment of each skill satisfies the market clearing condition:

$$\begin{aligned} L_{st} &= \rho_{s,t-1}N_{t-1}(1+g_{s,t})l_{s,t}^o + \rho_{s,t}N_t l_{s,t}^y \\ &= \rho_{s,t-1}N_{t-1}(1+g_{s,t})\left[(1+g_{s,t}-\tilde{\tau}_{s,t}^o)w_{s,t}(1+b)\alpha_{s,t}^o\kappa(s)^{-1}\right]^{\frac{1}{b}} + \rho_{s,t}N_t\left[(1-\tilde{\tau}_{s,t}^y)w_{s,t}(1+b)\alpha_{s,t}^y\kappa(s)^{-1}\right]^{\frac{1}{b}} \\ &= (w_{s,t})^{\frac{1}{b}}(1+b)^{\frac{1}{b}}\kappa(s)^{-\frac{1}{b}}\left(\rho_{s,t-1}N_{t-1}(1+g_{s,t})(1+g_{s,t}-\tilde{\tau}_{s,t}^o)^{\frac{1}{b}}(\alpha_{s,t}^o)^{\frac{1}{b}} + \rho_{s,t}N_t(1-\tilde{\tau}_{s,t}^y)^{\frac{1}{b}}(\alpha_{s,t}^y)^{\frac{1}{b}}\right). \end{aligned} \tag{21}$$

Hence, the equilibrium wage satisfies:

$$w_{s,t} = \kappa(s)\frac{L_{s,t}^b}{(1+b)}\left(\rho_{s,t-1}N_{t-1}(1+g_{s,t})(1+g_{s,t}-\tilde{\tau}_{s,t}^o)^{\frac{1}{b}}(\alpha_{s,t}^o)^{\frac{1}{b}} + \rho_{s,t}N_t(1-\tilde{\tau}_{s,t}^y)^{\frac{1}{b}}(\alpha_{s,t}^y)^{\frac{1}{b}}\right)^{-b}. \tag{22}$$

Using the solution to the problem of the firm, we know that the equilibrium relative wage of skills s and s' is:

$$\frac{w_{s,t}}{w_{s',t}} = \left(\frac{A_{s,t}}{A_{s',t}}\right)^{1-\frac{1}{\theta}}\left(\frac{L_{s,t}}{L_{s',t}}\right)^{-\frac{1}{\theta}}. \tag{23}$$

Relative employment is:

$$\frac{L_{s,t}}{L_{s',t}} = \left(\frac{A_{s,t}}{A_{s',t}}\right)^{\frac{\theta-1}{1+b\theta}}\left(\frac{\kappa(s')}{\kappa(s)}\right)^{\frac{\theta}{1+b\theta}}\left(\frac{X_{s',t}}{X_{s,t}}\right)^{-\frac{b\theta}{1+b\theta}}, \tag{24}$$

for $X_{s,t} = \left(\rho_{s,t-1}N_{t-1}(1+g_{s,t})(1+g_{s,t}-\tilde{\tau}_{s,t}^o)^{\frac{1}{b}}(\alpha_{s,t}^o)^{\frac{1}{b}} + \rho_{s,t}N_t(1-\tilde{\tau}_{s,t}^y)^{\frac{1}{b}}(\alpha_{s,t}^y)^{\frac{1}{b}}\right)$.

Hence, relative wages satisfy

$$\frac{w_{st}}{w_{s't}} = \left(\frac{A_{s,t}}{A_{s',t}}\right)^{\frac{b(\theta-1)}{1+b\theta}}\left(\frac{\kappa(s)}{\kappa(s')}\right)^{\frac{1}{1+b\theta}}\left(\frac{X_{s',t}}{X_{s,t}}\right)^{\frac{b}{1+b\theta}}. \tag{25}$$

Finally, utility is equivalised across all youngs of different skills, as they must be ex-ante indifferent between education choices. Hence,

$$\begin{aligned} &\left(\frac{w_{s,t}(1-\tilde{\tau}^y_{s,t})}{\kappa(s)}\right)^{\frac{1+b}{b}} C^y_{s,t} + \left(\frac{w_{s,t+1}(1+g_{s,t+1}-\tilde{\tau}^o_{s,t})}{\kappa(s)}\right)^{\frac{(1+b)}{b}} C^o_{s,t+1} + \frac{\tau^o_{s,t+1}+\tau^y_{s,t}}{\kappa(s)} = \\ &\left(\frac{w_{s',t}(1-\tilde{\tau}^y_{s',t})}{\kappa(s')}\right)^{\frac{1+b}{b}} C^y_{s',t} + \left(\frac{w_{s',t+1}(1+g_{s',t+1}-\tilde{\tau}^o_{s',t})}{\kappa(s')}\right)^{\frac{(1+b)}{b}} C^o_{s',t+1} + \frac{\tau^o_{s',t+1}+\tau^y_{s',t}}{\kappa(s')}. \end{aligned} \tag{26}$$

Collecting κ, we obtain an expression for the relative education cost of different skills:

$$\frac{\kappa(s)}{\kappa(s')} = \frac{w_{s,t}}{w_{s',t}} \left[\underbrace{\frac{(1-\tilde{\tau}^y_{s,t})^{\frac{1+b}{b}} \left(\alpha^y_{s,t}\right)^{\frac{1}{b}} + \left((1+\Delta_{t+1}w_s)(1+g_{s,t+1}-\tilde{\tau}^o_{s,t+1})\right)^{\frac{(1+b)}{b}} \left(\alpha^o_{s,t+1}\right)^{\frac{1}{b}} + \frac{\kappa(s)^{\frac{1}{b}}}{w_{s,t}^{\frac{1}{b}}} \left((1+\Delta_{t+1}w_s)\tilde{\tau}^o_{s,t+1} + \tilde{\tau}^y_{s,t}\right)}{(1-\tilde{\tau}^y_{s',t})^{\frac{1+b}{b}} \left(\alpha^y_{s',t}\right)^{\frac{1}{b}} + \left((1+\Delta_{t+1}w_{s'})(1+g_{s',t+1}-\tilde{\tau}^o_{s',t+1})\right)^{\frac{(1+b)}{b}} \left(\alpha^o_{s',t+1}\right)^{\frac{1}{b}} + \frac{\kappa(s')^{\frac{1}{b}}}{w_{s',t}^{\frac{1}{b}}} \left((1+\Delta_{t+1}w_{s'})\tilde{\tau}^o_{s',t+1} + \tilde{\tau}^y_{s',t}\right)}}_{\Omega_t(s,s')} \right]^{\frac{b}{1+b}}. \tag{27}$$

Calling the term within the parenthesis (and excluding the exponent) $\Omega_t(s,s')$, and substituting Equation (10) yields an expression for the relative education levels only as a function of parameters, and the same-period growth of the education level $\Delta_t p_s$.

$$\frac{\rho_{s,t}}{\rho_{s',t}} \left[\frac{\frac{(1+g_{s,t})(1+g_{s,t}-\tilde{\tau}^o_{s,t})^{\frac{1}{b}}(\alpha^o_{s,t})^{\frac{1}{b}}}{(1+\Delta_t\rho_s)(1+n_t)} + (1-\tilde{\tau}^y_{s,t})(\alpha^y_{s,t})^{\frac{1}{b}}}{\frac{(1+g_{s',t})(1+g_{s',t}-\tilde{\tau}^o_{s',t})^{\frac{1}{b}}(\alpha^o_{s',t})^{\frac{1}{b}}}{(1+\Delta_t\rho_{s'})(1+n_t)} + (1-\tilde{\tau}^y_{s',t})(\alpha^y_{s',t})^{\frac{1}{b}}} \right] = \left(\frac{\kappa(s')}{\kappa(s)}\right)^{\theta} \left(\frac{A_{s,t}}{A_{s',t}}\right)^{\theta-1} \Omega_t(s,s')^{\frac{1+b\theta}{1+b}}. \tag{28}$$

G.2.2 Results

We estimate the parameters using the same procedure as the one described in Appendix F.3. We report the estimated parameters in Table XI.

TABLE XI. Estimated Parameters, Transfer Model

	Skill	Poor 2004	Poor 2018	Rich 2004	Rich 2018
α^Y	High	0.22	0.18	0.26	0.24
	Mid	0.11	0.09	0.18	0.16
	Low	0.05	0.03	0.06	0.05
α^O	High	0.44	0.24	0.19	0.22
	Mid	0.09	0.09	0.10	0.14
	Low	0.05	0.04	0.03	0.03
g	High	0.48	0.45	0.48	0.57
	Mid	0.29	0.15	0.21	0.25
	Low	-0.02	-0.07	0.09	0.20
A	High	2.09	2.45	1.30	1.46
	Mid	1.23	1.48	0.97	0.97
	Low	0.55	0.68	0.48	0.42
κ	High	4.58	4.58	2.22	2.22
	Mid	1.99	1.99	1.45	1.45
	Low	1.00	1.00	1.00	1.00
Δn		-0.32	-0.36	-0.44	-0.49
τ^y/w	High	0.09	0.11	0.30	0.31
	Mid	0.08	0.09	0.33	0.35
	Low	0.11	0.12	0.28	0.32
τ^o/w	High	1.20	0.94	0.85	0.84
	Mid	0.80	0.60	0.67	0.67
	Low	0.56	0.46	0.51	0.54

Notes: The table lists the identified parameters for richer and poorer countries, in each period (2004 and 2018 waves). Where necessary, the parameters are presented separately for each skill level. κ_s is equal across periods by assumption, and is estimated using 2004 data for present-period wages and 2018 data for next-period wages and return to experience. All figures are rounded to the second decimal digit for display in this table.

Figure 17 illustrates the contribution of each factor in determining the increase in *AGIR* in the representative rich country. Notice that, unlike the model in the main text that considered only labor market income, this model fully matches the change in the headline *AGIR* (instead of the change in labor age-income gaps), as presented in the main empirical section.

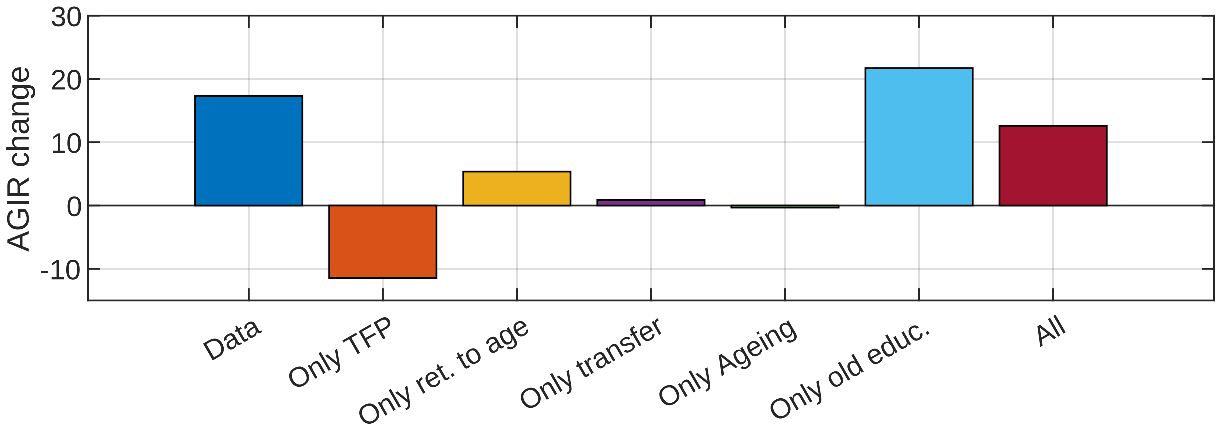
The main difference between the results with the model with transfers and the one without is that the old's education had a larger role in explaining the increase in *GRD* between 2004 and 2018 in the representative rich country. The old's education alone accounted for over 21 percentage points increase in *GRD*, over half of the employment component of the *GRD*, and most of the increase in wages. Similarly, we find that TFP alone reduced the growth of *GRD* by a substantial margin. The reason is that, once transfers are taken into account, the education choices of the young become more sensitive to the congestion on the labor market (since transfers are larger for low-skilled individuals, relative to wages, the incentives to acquire high education are smaller), but also to changes in the relative TFP levels.

Finally, transfers had a negligible role in increasing *GRD*, as they were mostly unchanged for both old and young (see Table XI), apart from a increase in transfers for low-skilled workers, which were overly represented in the 2004 old generation, relative to the 2004 young one. Hence, changes in transfers were not a major determinant of the increase in *GRD* in richer countries, both directly and through labor market GE effects.

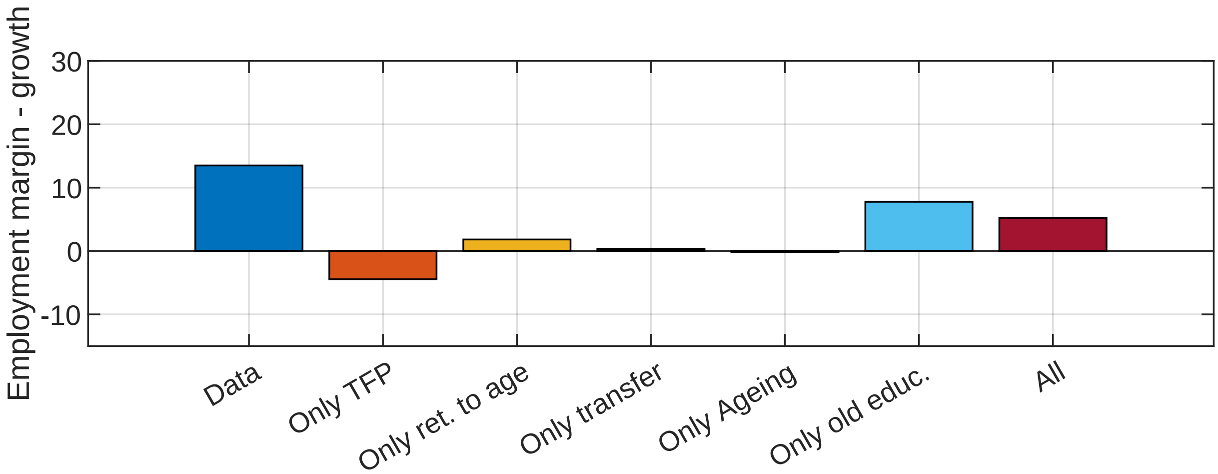
When looking at poorer countries (Figure 18), the model with transfers yields very different results from the one without transfers. We find that the two main determinants of the fall in AGIR in poorer countries were the fall in the return to age g and the increase in the education level of the young. The fall in transfers played a major role in reducing the fall in $AGIR$, mainly through the employment margin, as the average transfer size for the old was slashed by around 30% (relative to wages), but the (small) transfers for the young remained mostly untouched. This drove more old individuals to the labor market, as the outside option deteriorated, thus limiting the fall in $AGIR$. Interestingly, the increase in TFP contributed *positively* to $AGIR$ by motivating more low-skilled old to enter the labor market. Our model matches very well, even when ignoring changes in the price of leisure α, the overall $AGIR$ dynamic and the wage component dynamic of poorer countries.

Figure 17. Contribution to GRD and sub-components, by factor - Rich countries

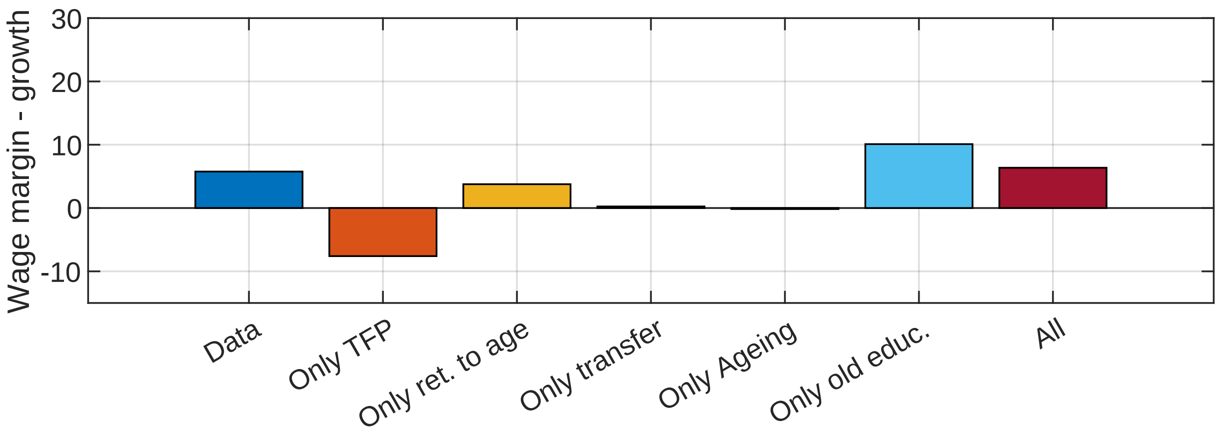
(a) All



(b) Employment



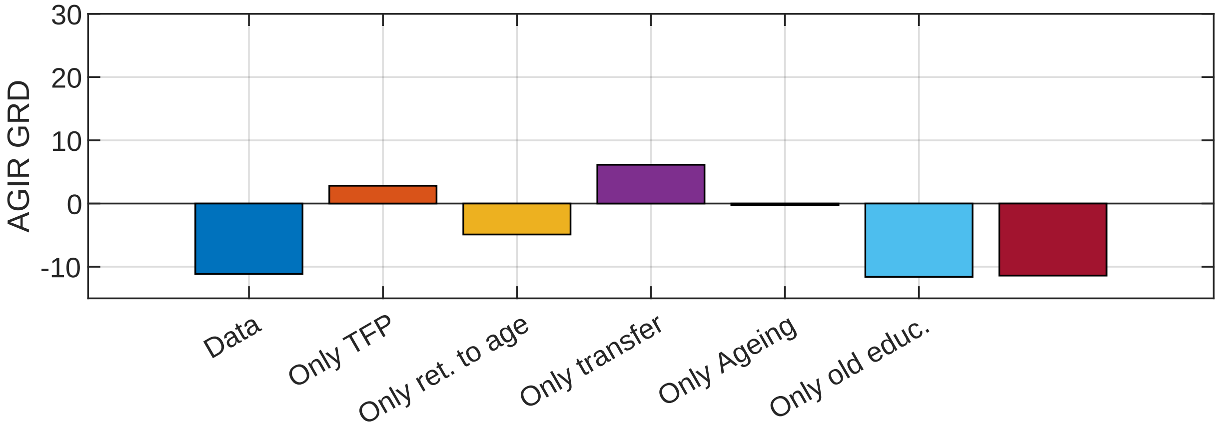
(c) Wages



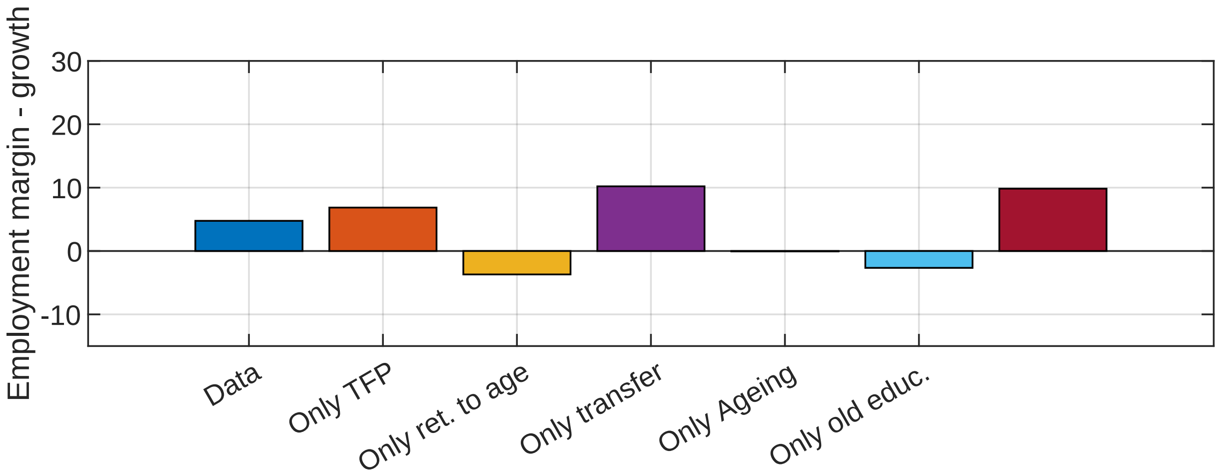
Notes: the figures shows the change in $AGIR$ between 2004 and 2018 for a representative "rich" country (given by averaging across the moments of all rich countries in our dataset). The blue bar ("Data") is the GRD as seen in the data. The other bars represent counterfactual estimations from the model, estimated by taking all parameters at their 2004 level, besides the ones listed in each column. In "Only TFP", we set the productivity levels A_s to their 2018 value. In "Only ret. to age" we set the return to experience g_s to its 2018 level. In "Only transfer" we set the relative size of transfers to wages equal to their 2018 levels. In "Only Ageing" we set the relative size of the two generations to its 2018 level. In "Only old educ." we set the initial education level of the old generation to its 2018 level. In "All" we set all the aforementioned parameters and initial conditions to their 2018 level. Panels (b) and (c) provide similar counterfactuals for the employment and wage margins of the Labor GRD, respectively.

Figure 18. Contribution to GRD and sub-components, by factor - Poorer countries

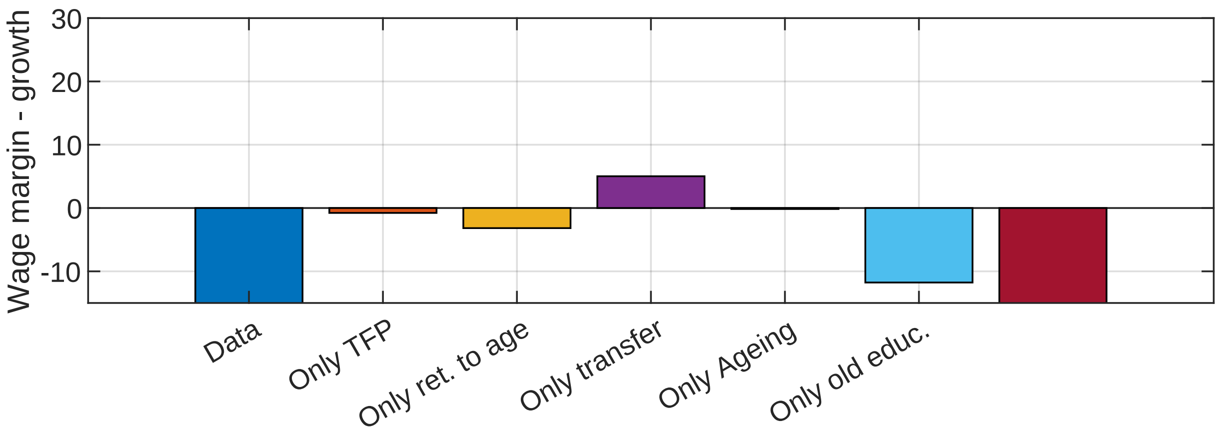
(a) All



(b) Employment



(c) Wages



Notes: the figures shows the change in $AGIR$ between 2004 and 2018 for a representative “poorer” country (given by averaging across the moments of all rich countries in our dataset). The blue bar (“Data”) is the GRD as seen in the data. The other bars represent counterfactual estimations from the model, estimated by taking all parameters at their 2004 level, besides the ones listed in each column. In “Only TFP”, we set the productivity levels A_s to their 2018 value. In “Only ret. to age” we set the return to experience g_s to its 2018 level. In “Only transfer” we set the relative size of transfers to wages equal to their 2018 levels. In “Only Ageing” we set the relative size of the two generations to its 2018 level. In “Only old educ.” we set the initial education level of the old generation to its 2018 level. In “All” we set all the aforementioned parameters and initial conditions to their 2018 level. Panels (b) and (c) provide similar counterfactuals for the employment and wage margins of the Labor GRD, respectively.

H Determinants of the *level* of *AGIR*

While in the rest of the paper we have studied the *evolution* of *AGIR*, in this section we study the determinants of its *level*. First, we perform an agnostic accounting exercise to decompose *AGIR* level in differences (between age groups) in the level of wages, employment, and transfers. Then, we use the model with transfers detailed in Appendix G.2 to account for how wages and employment are endogenously determined. Hence, we use the structural parameters to determine the causes of the age-income gap.

H.1 Accounting decomposition

Recall that *AGIR* is defined as:

$$\text{AGIR} = \frac{y_{\text{old}}}{y_{\text{young}}},$$

where we have ignored the time index for convenience of notation. Our income measure is composed of labor income ey^n and transfer income $p\Theta^n$, where y^n is the average earnings of the employed, e is the employment rate, Θ^n is the amount of transfers received by those who receive non-zero transfers, and p the share of transfer-receiving individuals. Calling $\tilde{p} = \frac{p}{e}$ and $\tilde{\Theta}^n = \frac{\Theta^n}{y^n}$, we decompose *AGIR* as

$$\begin{aligned} AGIR &= \frac{e_{\text{old}} y^n_{\text{old}} + p_{\text{old}} \Theta^n_{\text{old}}}{e_{\text{young}} y^n_{\text{young}} + p_{\text{young}} \Theta^n_{\text{young}}} \\ &= \frac{e_{\text{old}} y^n_{\text{old}}}{e_{\text{young}} y^n_{\text{young}}} \times \frac{1 + \tilde{p}_{\text{old}} \tilde{\Theta}^n_{\text{old}}}{1 + \tilde{p}_{\text{young}} \tilde{\Theta}^n_{\text{young}}} \\ &= \underbrace{\frac{y^n_{\text{old}}}{y^n_{\text{young}}}}_{\text{Age-earnings gap}} \times \underbrace{\frac{e_{\text{old}}}{e_{\text{young}}}}_{\text{Age-employment gap}} \times \underbrace{\frac{1 + \tilde{p}_{\text{old}} \tilde{\Theta}^n_{\text{old}}}{1 + \tilde{p}_{\text{young}} \tilde{\Theta}^n_{\text{young}}}}_{\text{Transfer multiplier}}. \end{aligned} \tag{29}$$

The first component is the age-earning gap, commonly studied in the rest of the literature. The second component is the age-employment gap, which scales the earnings gap according to the relative extensive margin of work between age groups. In order to obtain an additive decomposition, we shift our focus to the natural logarithm of *AGIR*, ln(*AGIR*):[31]

$$\ln(\text{AGIR}) = \ln\left(\frac{y^n_{\text{old}}}{y^n_{\text{young}}}\right) + \ln\left(\frac{e_{\text{old}}}{e_{\text{young}}}\right) + \ln\left(\frac{1 + \tilde{p}_{\text{old}} \tilde{\Theta}^n_{\text{old}}}{1 + \tilde{p}_{\text{young}} \tilde{\Theta}^n_{\text{young}}}\right). \tag{30}$$

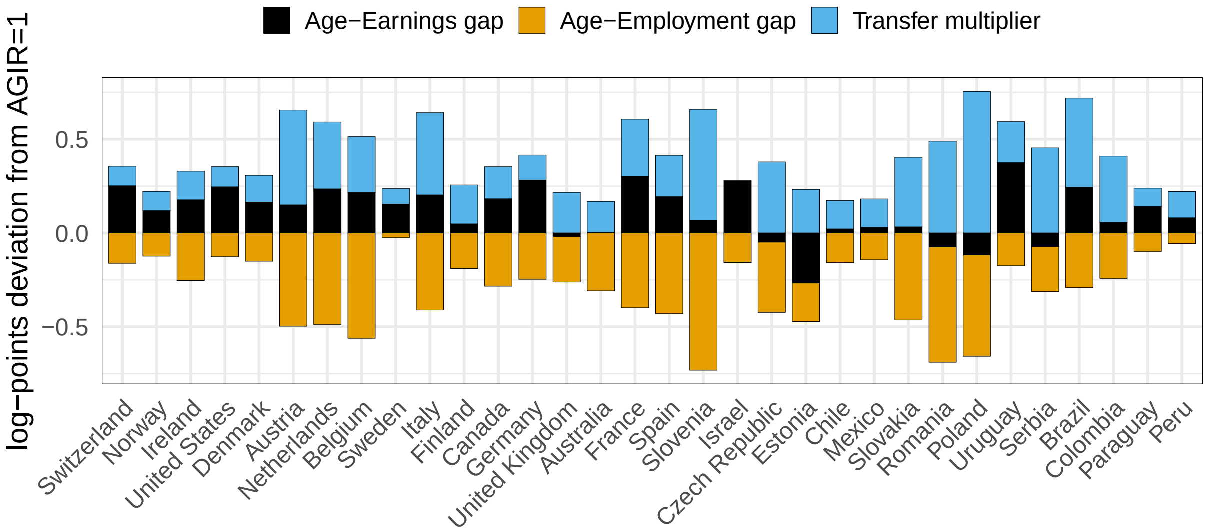
[31]Notice how log-*AGIR* approximates the sum of percentage deviation of wages, employment and transfer multiplier between old and young

We show the results, separately for 2004 and 2018, in Figure 19. Recall that in 2004, high and lower-income countries had very similar $AGIR$ levels. In fact, their $AGIR$ present very similar compositions. Besides very high-GDP countries, both high- and lower-income countries have similar profiles. However, we notice within-group heterogeneity in terms of whether similar gap levels are caused by large transfer multipliers in favour of the old, compensated by large employment gap in favour of the young, or by low levels of both gaps. The only clear, difference between high- and low-income countries was in the age-earnings gap, as already show in the main text (see Figure 1b).

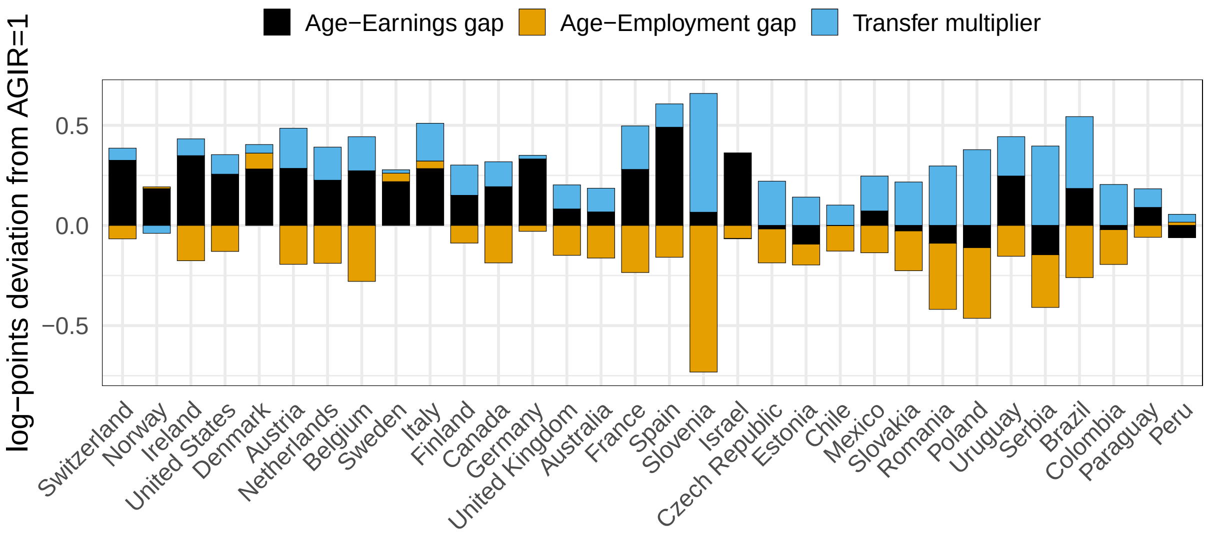
However, in 2018 presents a much clearer separation between high-income and lower-income countries, as well as less heterogeneity within group. $AGIR$ high in richer countries because of large increases in the age-earning gap, but also because of an increase in the age-employment gap, which reduced the advantage of the old. In countries such as Denmark, Sweden and Italy, the old are now slightly more likely to be in employment than the young. Conversely, lower-income countries saw further reductions in their age-earning gaps, as well as the transfer multiplier, but without a considerable reduction in the age-employment gap (unlike richer countries). The reason is that wages and employment among the young grew considerably faster than wages, employment and subsidies for the old. Hence, the low $AGIR$ in poorer countries in 2018 was clearly determined by an overall advantage of the young on the market. Conversely, the high $AGIR$ in poorer countries was mainly determined by a deterioration of this young's advantage. Interestingly, richer countries seem to have converged to similar profiles of $AGIR$ components between 2004 and 2018.

Figure 19. log-$AGIR$ decomposition

(a) Wave 1 (2004-2006)



(b) Wave 5 (2016-2018)



Notes: the figure plots the decomposition of $\ln(AGIR)$ for each country in our dataset, for wave 1 (panel a) and wave 5 (panel b), approximately corresponding to 2004 and 2018 data points. "Age-Earnings gap" corresponds to $\ln\left(\frac{y^n_{\text{old}}}{y^n_{\text{young}}}\right)$, the log-ratio of labor earnings of employed old and young. "Age-Employment gap" corresponds to $\ln\left(\frac{e_{\text{old}}}{e_{\text{young}}}\right)$, the log-ratio of employment rates of old and young. "Transfer multiplier" corresponds to $\left(\frac{1+\tilde{p}_{\text{old}}\bar{\Theta}^n_{\text{old}}}{1+\tilde{p}_{\text{young}}\bar{\Theta}^n_{\text{young}}}\right)$, the log-ratio of one plus transfers in proportion to labor earnings, for old and young.

H.2 Model-based AGIR decomposition

We now explore, through the lenses of our model, the fundamental determinants of the level of $AGIR$, and how they changed over time. In particular, we ask whether the level of $AGIR$ was caused by differences in: i) education, ii) returns to age, iii) transfers. To do so, we compare the realised $AGIR$ in the data with the $AGIR$ that would have realised in case:

1. The education of the old had been identical to the one of the young: $\rho_s^y = \rho_s^o,\ foralls$. This capture the composition and GE effects of different education levels between young and old.

2. The returns to age g_s were equal to zero. This captures how the return to age mechanically increases $AGIR$, by increasing the income of the old, as well as its GE effects on wages and supply.

3. The rate of transfer was identical and equal to zero for both generations: $\tau_s^y = \tau_s^o$.

Notice that the implied $AGIR$ of shutting down each of these three channels is not necessarily one, due to two factors. First, differences in the price of leisure. Second, the expectations of the young for the following period, which we take as fixed. We call the implied level of "neutral $AGIR$".

We present the results of the model-based decomposition of the level of $AGIR$ in Table XII. In 2004, the difference in education between old and young contributed negatively for -11 percentage points in rich countries, and -20 percentage points in poorer countries. While this number remained mostly unchanged for rich countries in 2018 (+1 percentage point in favour of the old), the (negative) contribution of the education gap to $AGIR$ increased by a further 4 percentage points in poorer countries tp -25 percentage points. Although the *total* contribution of the gap to $AGIR$ was stable between the two periods, we know - from the analysis performed in the previous section - that this was the result of a large increase in both the young and the old education levels between the two periods, meaning that the educational catch-up of the old more than compensated the larger incentives of new young generations to acquire high skill levels.

The largest determinant of $AGIR$ came from the return to age. However, while this increased over time in rich countries (from +32 to +45 percentage points), it decreased in poorer countries (from +35 pp. to +27 pp.). Returns to age are, taken in isolation, highly influential because they both increase income directly (due to the mechanical effect of supplying a larger amount of effective labor units) as well as indirectly (by increasing the incentives to work).

Transfers provide a smaller contribution to total $AGIR$, although similar between the two groups of countries (0.06 for richer countries and 0.09 for poorer countries). Moreover, their effect on $AGIR$ declined to approximately zero by 2018. While transfers have considerable direct effects on AGIR, they also reduce work incentives and thus have negative GE effects.

Finally, notice how the total effect of these three channels on the level of $AGIR$ is not equal to the sum due to second-order interaction between them. For example, the effects of increasing returns to age on $AGIR$ are inflated when the baseline assumption is - as in this case - that old and young have the same skill distribution.

TABLE XII. Determinants of $AGIR$, transfer model

	Poor		Rich	
	2004	2018	2004	2018
Neutral AGIR	1.03	1.03	0.91	0.97
Education gap effect	-0.20	-0.24	-0.11	-0.10
Return to age effect	0.35	0.27	0.31	0.45
Transfer gap effect	0.09	0.00	0.06	-0.00
Total	0.18	0.07	0.24	0.35

Notes: The table reports, for a representative poorer and richer country, the level of "neutral $AGIR$", as defined in the text, together with the additional effects of different counterfactuals, which reflect the first-order effect on $AGIR$ of the education gap between old and young, the return to age, and the difference in transfers. The "Total" row represents the joint effect of all these three channels. The sum of "Neutral $AGIR$" and "Total" yields the $AGIR$ level observed in the data.