Age-Income Gaps: The Role of Skill Congestion

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Abstract

We study age-income gaps across 32 countries over 2004–2018 using harmonized microdata from the Luxembourg Income Study. We document a striking divergence: the ratio of disposable income of late-career workers (aged 55–64) relative to early-career workers (aged 25–34), which we name the Age Group Income Ratio (AGIR), rose by 18 percentage points in high-income countries but fell by 8 percentage points in middle-income economies. This divergence operates primarily through the employment margin, which accounts for two-thirds of rising AGIR in rich countries, a margin that conventional age-earnings measures miss entirely. To explain these patterns, we develop an overlapping generations model that discriminates among six competing mechanisms. In rich countries, skill congestion—late-career cohorts catching up with early-career workers in educational attainment and crowding them out of skilled labour markets—is the dominant driver (+36.1pp), amplified by general equilibrium wage and employment effects. Labour preferences constitute the second-largest contributor (+7.7pp), operating as a pure labour supply shift. In poor countries, productivity growth dominates and skill congestion reduces rather than raises inequality: late-career cohorts still lag substantially behind early-career workers educationally, making their upgrading complementary to rather than competitive with the young.

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 has become a defining concern in political and media discourse across industrialized countries. The House of Lords in the UK and the European Commission have published comprehensive reports warning 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). Country-specific studies from France (Masson, 2021), Ireland (Barra et al., 2021), Australia (Berry and Sinclair, 2010; Miller et al., 2020), and the UK (Henehan et al., 2021) echo these concerns, suggesting a widespread phenomenon rather than isolated national experiences.

Recent academic research lends empirical weight to these policy debates. Studies document widening earnings gaps favouring older cohorts in Italy (Bianchi and Paradisi, 2024) and across eight OECD countries (Freedman, 2024a), confirming that age-related inequality has grown substantially over recent decades. Yet this literature offers an incomplete picture. By focusing exclusively on employed individuals' labour earnings, existing work neglects two margins that may be equally or more important: differential changes in employment rates between age groups, and the role of public transfers in shaping disposable income. These margins may have evolved differently over time and across countries in ways that earnings-focused studies cannot capture, leaving open the question of how large age-income gaps truly are, whether they have widened or narrowed across the income distribution of countries, and what forces are driving them.

This paper addresses this gap through systematic analysis of age-income disparities across 32 countries over 2004–2018, examining disposable income from all sources rather than wages alone. We document a striking divergence: the ratio of disposable income of individuals aged 55–64 relative to those aged 25–34— which we term the Age Group Income Ratio (AGIR)—rose by 18 percentage points in high-income countries but *fell* by 8 percentage points in middle-income economies. We show that this divergence operates primarily through the employment margin rather than wages, a finding that conventional earnings-focused measures miss entirely. To explain these patterns, we develop a quantitative overlapping generations model that discriminates among six competing mechanisms. Our central finding is that skill congestion—older cohorts upgrading their education and crowding younger workers out of skilled labour markets—is the dominant driver of rising AGIR in rich countries, operating almost entirely through general equilibrium feedback that wage-focused analyses cannot capture.

Understanding which mechanism drives age-income gaps is paramount because, as we demonstrate, different mechanisms carry starkly different implications for the lifetime earnings of present and future generations. If gaps reflect productivity gains that raise older workers' wages, younger cohorts will eventually benefit as they age into the same high-earning roles, and the age-income gap would be transitory across the lifecycle. But if gaps reflect intergenerational competition in skill markets that depresses younger workers' employment, current young workers may face permanently lower lifetime earnings than their predecessors, creating a structural generational divide with no self-correcting mechanism. Discriminating between these explanations requires a framework that jointly measures all income margins and identifies the structural forces behind them.

Our analysis proceeds in three steps. First, using harmonized microdata from the Luxembourg Income Study (LIS), we construct a comprehensive measure of disposable income and decompose it into three constituent margins: wages, employment, and transfers. We establish that the *employment margin*—differential changes in employment rates between older and younger workers—accounts for two-thirds of rising age-income gap in high-income countries, contributing 1.2 percentage points annually compared to 0.5 points for wages. In middle-income countries, the pattern reverses: wage growth differentials drive a decline in AGIR of 1.3 percentage points annually, while the employment margin contributes a more modest +0.5 points.

Second, we develop a quantitative overlapping generations model to discriminate among six competing explanations for these patterns: skill-biased technological change (Acemoglu, 2002; GOLDIN and KATZ, 2008), rising experience premia (Jeong et al., 2015), demographic aging (Welch, 1979; Card and Lemieux, 2001), labor market institutional changes and preference shifts, transfer policies, and skill congestion. The first five mechanisms have well-understood empirical predictions and appear prominently in existing work. Skill congestion is the novel channel we introduce: as older workers' educational attainment catches up with that of the young, they crowd youth out of skilled occupations, depressing younger workers' wages and employment through general equilibrium feedback that reduced-form approaches cannot capture.[1]

Third, we bring the model to the data through a structural estimation strategy with exact identification. The model features five age groups, endogenous education choices

[1] Jeong et al. (2015) document a related puzzle in US data—younger cohorts did not experience the wage booms that baby boomers' aging might predict—which our skill congestion channel helps explain. GOLDIN and KATZ (2008) emphasise the "race between education and technology"; we identify a new dimension where educational expansion *within older cohorts* through adult education and lifelong learning exacerbates intergenerational inequality even as it reduces overall inequality.

(less than high school, high school, college), and skill-specific production with CES technology. Taking standard elasticity parameters from the literature as given, we match observed wage gaps, employment rates, education shares by age and skill, and transfers for each country type (representative high-income and middle-income) in 2004 and 2018. Because the number of free parameters equals the number of independent moments, the model reproduces these moments exactly and delivers a unique parameter vector. Exact identification ensures that counterfactual experiments, where we vary one mechanism at a time from its 2004 to its 2018 value, are disciplined by the data and isolate the contribution of each channel. We further decompose each effect into a partial equilibrium component (holding wages and education fixed) and a general equilibrium component (capturing endogenous adjustments), revealing which channels operate primarily through market interactions.

These three building blocks yield three main findings. In rich countries, skill congestion is the dominant driver of rising AGIR (+36.1pp), operating almost entirely through general equilibrium forces and contributing through both the wage margin (+17.7pp) and the employment margin (+14.0pp). The direct compositional effect is modest (+5.1pp), but general equilibrium responses amplify it dramatically (+32.4pp): as older cohorts crowd into skilled labour markets, equilibrium wages and employment rates for younger workers fall while those of older workers rise. Labour preferences constitute the second-largest contributor (+7.7pp), operating as a pure labour supply shift with negligible general equilibrium amplification, raising older workers' employment (+15.6pp) without significantly compressing the young's earnings. Skill-biased technical change, by contrast, *reduces* age-income gaps (−16.3pp) by disproportionately raising the productivity of younger, better-educated cohorts. In poor countries, the net decline in AGIR results from a tug-of-war between opposing forces: TFP growth and skill congestion both reduce inequality (the latter because the old still lag significantly behind the young in high-school attainment) while labour preferences raise it (+11.5pp) as older workers delay retirement. Beyond their effects on the old/young income ratio, these mechanisms carry fundamentally different lifetime income implications: skill congestion from older cohorts reduces the lifetime incomes of the young, while all other channels improve it.

Related Literature Our paper connects to three strands of literature. The first studies age-wage dynamics. During the 1970s and 1980s, economists focused on the entry of the baby-boom generation into the labour market, which increased the relative supply of young, inexperienced labour (Welch, 1979; Levine and Mitchell, 1988). Since economists tried to explain the consequent wage trends with the imperfect substitutability of labour inputs with different tenure and experience, many concluded that the wages of successive, smaller cohorts were set to grow faster once aging baby boomers created an excess supply of experienced labour (Jeong et al., 2015). We document that this prediction did not materialise in most advanced economies. Similar findings for individual countries have been reported 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 across a set of high-income countries, and Freedman (2024b) documents cohort trends in earnings using a comparable set of countries. We contribute to this literature by providing the first systematic cross-country evidence on *disposable* income gaps rather than wages, covering a broader set of countries spanning high-, middle-, and low-income economies.

The second strand examines employment and income margins in age inequality. The majority of existing papers focus 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), implicitly conditioning on employment and therefore missing a potentially important margin. We show that the employment margin—faster growth in employment rates among older workers relative to younger ones—accounts for two-thirds of rising age-income inequality in rich countries, substantially exceeding the contribution of wage gaps. Guvenen et al. (2022) considers lifetime labour earnings of US workers, which implicitly incorporates employment dynamics across cohorts, but does not disentangle the employment and wage margins explicitly. We are also the first to document that age-income inequalities have diverged sharply between high- and low-income countries, with the two groups following opposite trends—a pattern invisible to studies focused on advanced economies alone. Our findings suggest that researchers should exercise caution when drawing conclusions from age-wage gaps, as they may systematically mischaracterise the direction and magnitude of comprehensive age-income inequality.

The third strand examines the structural drivers of age-related labour market outcomes. We show that well-documented phenomena such as rising female participation (Maxwell, 1990; Costa, 2000; Acemoglu et al., 2004; Goldin, 2006; Olivetti and Petrongolo, 2016; Goldin and Katz, 2018b) and increases in retirement ages (Pilipiec et al., 2021; Staubli and Zweimüller, 2013) cannot fully account for the rise in AGIR in recent decades. Instead, our structural decomposition points to three main forces: trends in educational attainment (Goldin and Katz, 2007, 2018a), returns to experience (Jeong et al., 2015), and skill-specific technological change (Adão et al., 2024). Our key contribution to this strand is the identification of skill congestion as the dominant mechanism. GOLDIN and KATZ (2008) emphasise the race between education and technology as a driver of overall inequality; we identify a new dimension of this race operating *within* the age distribution, where educational upgrading among older cohorts crowds younger workers out of skilled labour markets through general equilibrium wage and employment effects. Jeong et al. (2015) document a related puzzle—younger US cohorts did not experience the wage booms that baby boomers' aging would predict under standard models—which our skill congestion channel explains. More broadly, our paper contributes to the literature on how long-run trends in human capital accumulation generate asymmetric effects across age groups (Adão et al., 2024; Lagakos et al., 2018), showing that the direction of these effects depends critically on the relative educational position of older versus younger cohorts across the development spectrum. Guaitoli et al. (2026) show that not enough young workers move to productive labour markets due how age differences in income and wealth interact with financial frictions to exacerbate the housing costs faced by the young.

Paper organisation. The rest of the paper is organized as follows. Section 2 describes the data and defines our comprehensive income measure. Section 3 documents two empirical patterns: divergence across development levels and margin asymmetry between employment and wages. Section 4 presents the overlapping generations model, discusses exact identification, and reports counterfactual decompositions. Section 5 sums up our results and discusses future avenues of research.

2 Data and Measurement

2.1 Sample Construction

We construct a cross-country dataset from harmonized microdata provided by the Luxembourg Income Study (LIS), a cross-national data archive covering household surveys from over 50 countries (Luxembourg Income Study (LIS) Database, 2024). To ensure cross-country comparability and data quality, our sample satisfies four criteria: individual-level income reporting (avoiding ambiguity in within-household allocation), temporal coverage spanning 2004–2018 with observations at both endpoints, consistent income definitions within countries, and data quality standards excluding countries with exceptional characteristics.[2] These restrictions yield 32 countries and 357 country-year observations spanning developed economies (Western Europe, North America, Australia), emerging markets (Eastern Europe, Latin America), and lower-income countries—providing variation across the development spectrum. All income variables are converted to real PPP terms (constant 2017 US dollars) for cross-country comparability.

Waves. Since countries are surveyed in different years, the raw country-year observations form an unbalanced panel. To address potential bias from uneven temporal coverage, we group yearly surveys into five three-year *waves*: 2004–2006, 2007–2009, 2010–2012, 2013–2015, and 2016–2018. Country-wave observations are constructed by merging all surveys within each wave, giving equal weight to each annual survey. This procedure yields 158 country-wave data points and creates a nearly balanced panel.[3] Table VI in Appendix A reports the data availability.

2.2 Measuring Disposable Income

We define disposable income as the sum of labour earnings and transfer income. For individual q in country c and year t:

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

where w_q^n denotes net labour income and Θ_q^n represents net transfers, including pension payments (public and private), unemployment benefits, scholarships, and paid maternity/paternity leave.[4] Since countries differ in whether they report gross or net income, we construct net income for gross-reporting countries by subtracting income taxes:

$$y_q = w_q^g + \Theta_q^g - \tau_q, \tag{2}$$

where τ_q excludes taxes on capital income. The list of countries and their reporting conventions is provided in Table VI of Appendix A.

LIS surveys do not provide individual-level capital income. Since wealth has become increasingly concentrated among older cohorts (Colombo et al., 2014), this omission likely *underestimates* age-income inequality in high-income countries.[5] Consequently, our esti-

[2]We exclude Luxembourg, where nearly 50% of workers commute internationally, making domestic age-income comparisons unrepresentative. When countries switch between gross and net income reporting, we retain only the definition with the most observations. See Appendix A for detailed sample construction and Table VI for country coverage.

[3]All countries have at least one observation per wave, except Serbia and Slovenia, which each lack one wave.

[4]Appendix B.4 shows that adding household-wide benefits (child allowances, housing benefits, general household transfers) yields quantitatively and qualitatively similar results.

[5]In the United States, households aged 55–69 increased their wealth share from 36% to 44% between 2003 and 2018, while those under 40 saw their share decline from 8.1% to 5.6% (Distributional Financial

mates provide a *lower bound* on the true rise in age-income inequality.

2.3 Age Groups and the AGIR Statistic

We divide the working-age population into five ten-year groups: 25–34, 35–44, 45–54, 55–64, and 65–74. While our framework accommodates analysis across all groups, we focus on individuals aged 25–34 (*young*, early career) and 55–64 (*old*, late career). This classification isolates workers who have completed education and stand at opposite ends of their working lives.[6]

As a parsimonious measure of income inequality between old and young, we use the ratio of their average disposable income, which we define as the *Age Group Income Ratio* (*AGIR*):

$$R_t = \frac{\bar{y}_{\text{old},t}}{\bar{y}_{\text{young},t}}, \tag{3}$$

where $\bar{y}_{j,t}$ denotes average disposable income for age group j in year t. When $R_t > 1$, older workers earn more than younger workers on average; rising R_t indicates widening inequality favoring the old.

The AGIR differs from the conventional *age-earnings gap* studied in prior work (Bianchi et al., 2022; Freedman, 2024b) along two dimensions. First, AGIR includes *all* individuals regardless of employment status, capturing variation in labour force participation—a margin we show dominates inequality dynamics in high-income countries. Second, AGIR incorporates transfer income (pensions, unemployment benefits) alongside market earnings, reflecting total resources available for consumption rather than labor market outcomes alone.

Finally, we preview our decomposition strategy. Average income for age group j can be written:

$$\bar{y}_j = e_j \bar{w}_j + p_j \bar{\Theta}_j, \tag{4}$$

where e_j is the employment rate, $\bar{w}_j$ is average labor income conditional on employment, p_j is the share receiving transfers, and $\bar{\Theta}_j$ is average transfer income conditional on receipt. This accounting identity decomposes income changes into four margins: employment rates, conditional wages, transfer incidence, and conditional transfer amounts. The decomposition reveals *which* economic forces drive age-income divergence—employment

Accounts, Federal Reserve). Similar patterns appear in Italy, Australia, and Canada—see Colombo et al. (2014).

[6] We exclude ages 16–24 (many still in education) and 75+ (predominantly retired). Results are robust to alternative classifications, including the UK Office for National Statistics' framework defining older workers as 50–64. We use 10-year intervals for equal group widths and cleaner lifecycle comparisons.

dynamics versus wage dynamics—and whether inequality reflects market outcomes or transfer policy.

3 Diverging Trends in Age-Income Gaps

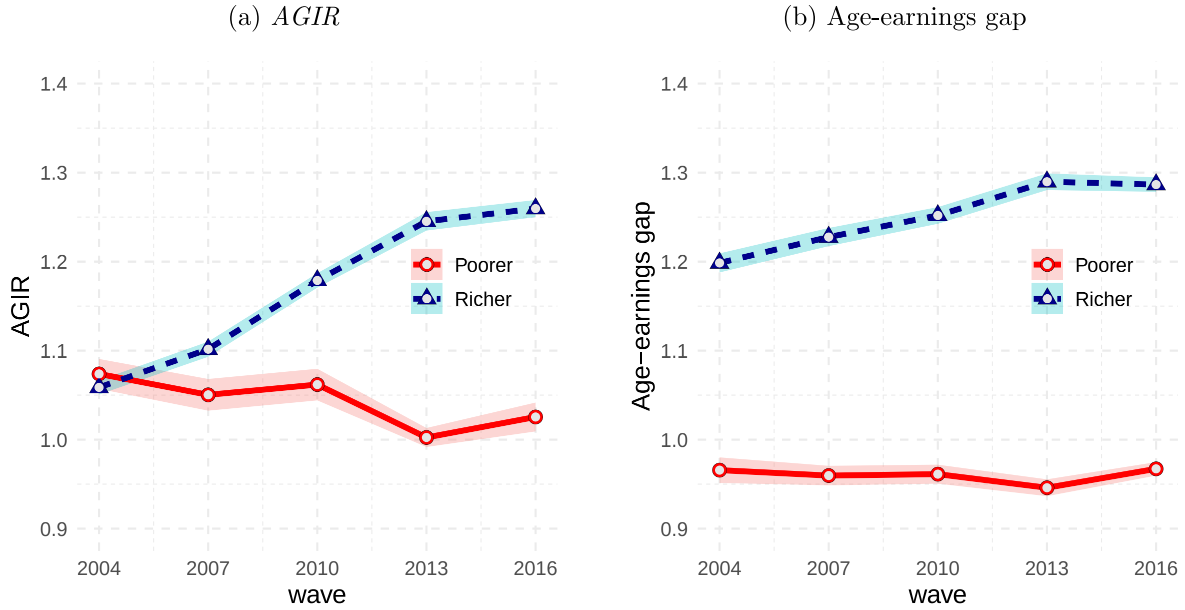
This section documents two empirical patterns that collectively pose the central puzzle of the paper. First, high-income countries experienced sharp increases in AGIR while middle-income countries saw substantial declines. Yet, both groups started from similar levels in 2004. Second, this divergence operates primarily through different economic margins: the employment rate gap between old and young drives AGIR growth in rich countries, while the conditional wage gap dominates in poor countries. Conventional measures focusing only on employed workers miss the employment margin entirely and understate inequality growth in high-income economies by approximately three times (see Table II).

3.1 Stylized Fact 1: Divergence Across Development Levels

We classify countries into high-income (20 countries from Western Europe, North America, Australia) and middle-income (12 countries from Eastern Europe and Latin America) based on 2004 per-capita GDP, using IMF income thresholds (International Monetary Fund, 2006).[7] Figure 1 shows that both groups started from similar AGIR levels in 2004 but followed sharply diverging trajectories over the subsequent fifteen years.

[7]High-income countries: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Netherlands, Norway, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States. Middle-income countries: Brazil, Chile, Colombia, Estonia, Mexico, Paraguay, Peru, Poland, Romania, Serbia, Slovakia, Uruguay. The threshold is $12,746 PPP (2004 dollars), corresponding to the IMF's high-income cutoff.

Figure 1. *AGIR*, 55–64 vs 25–34 years old



Notes: Left panel shows the Age Group Income Ratio (AGIR) comparing late-career (55–64 years) to early-career (25–34 years) individuals. Right panel shows the age-earnings gap—the ratio of average labor earnings among employed workers in the same age groups. Lines represent simple averages across countries within each income group (dashed blue: high-income; solid red: middle-income). Shaded areas show 95% confidence intervals calculated using the delta method.

The figure reveals three features of the data. First, AGIR levels were nearly identical in 2004: late-career workers earned 7% more in poorer countries and 6% more in richer countries. Second, trends diverged sharply: AGIR rose 20 percentage points in high-income countries but fell 5 percentage points in middle-income countries. This pattern does not depend on our binary country-group classification and is robust to using annual rather than wave-level data (See Appendix B.1.). Third, age-earnings gaps (Panel 1b) severely understate this divergence, rising only 9 percentage points in high-income countries, thus capturing less than half the true AGIR growth, and remaining flat in poorer countries.[8] This discrepancy between AGIR and the age-earnings gap foreshadows the second empirical pattern: the divergence operates through non-wage margins.

To establish statistical significance of these facts and test whether the AGIR divergence is a continuous function of income rather than a discrete rich/poor split, we estimate a difference-in-trends specification. For country i at time t, we regress log AGIR on a time trend, allowing both the intercept and slope to differ between richer and poorer countries:

$$\log(R_{i,t}) = \alpha + \tilde{\alpha}\mathbb{1}_i^d + \beta t + \tilde{\beta}(\mathbb{1}_i^d \times t) + \varepsilon_{i,t}, \tag{5}$$

where $R_{i,t}$ denotes AGIR for age groups 55–64 versus 25–34, $\mathbb{1}_i^d$ equals one for high-income

[8] See Appendix B.2 for the statistical evidence.

countries, and t measures years since 2004.[9] The parameters have natural interpretations: 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.

Table I, columns (1) and (3), formalises the visual patterns in Figure 1. Poorer countries experienced a slight AGIR downward trend (-0.3 percent annually for the waves regression), while the AGIR in richer countries increased sharply (+1.6 percent annually). The interaction term implies a close to 2 percent annual divergence in AGIR between the two groups.

The divergence does not depend on our binary classification of "richer" and "poorer" countries. To test this, we replace the income-group dummy with a continuous measure of initial development, estimating how both the level and trend of AGIR vary with initial (2004) GDP per capita:

$$\log(R_{i,t}) = \alpha + \theta\,\overline{\mathrm{GDP}}_{i,0} + \beta t + \gamma(\overline{\mathrm{GDP}}_{i,0} \times t) + \varepsilon_{i,t} \tag{6}$$

where $\overline{\mathrm{GDP}}_{i,0}$ denotes log GDP per capita in 2004, demeaned across countries. Demeaning allows α and β to capture the level and trend for a country at the cross-section sample mean, making coefficients more interpretable. The parameters have, therefore, a clear interpretation: α is the initial log(AGIR) for a country with initial mean GDP, θ is the elasticity of *AGIR* to a change in initial GDP, β is the AGIR time-trend for a country with initial mean GDP, 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 show that AGIR trends increase monotonically with initial development. The significant positive γ implies that richer countries experienced faster AGIR growth and poorer countries slower growth or decline. The bottom rows quantify this gradient. In the annual specification, the trend ranges from -1.5% per year at the poorest country to +1.9% per year at the richest, with the 25th percentile country experiencing essentially no trend (0.0%) and the 75th percentile a significant +1.4% annually. Over fourteen years, this implies a cumulative AGIR decline of around 21% at the bottom of the distribution and a 27% increase at the top—a monotonic gradient that confirms the divergence is a continuous function of development rather than an artefact of our binary country classification. In Appendix B.3 we provide additional

[9] We code $t \in \{0, 3, 6, 9, 12\}$ for wave observations (2004–06, 2007–09, ..., 2016–18) and $t \in \{0, 1, 2, \ldots, 14\}$ for annual observations, scaling wave coefficients by three to make estimates of the trend coefficient comparable.

robustness checks.

TABLE I. Trend in AGIR

	Wave		Year	
Dependent	ln(AGIR)			
	(1)	(2)	(3)	(4)
[0] α: Constant	0.036	0.050**	0.105***	0.067***
	(0.043)	(0.023)	(0.032)	(0.016)
[1] β: Trend	-0.003	0.008***	-0.007**	0.006***
	(0.005)	(0.003)	(0.004)	(0.002)
[2] $\tilde{\beta}$: Trend × Richer	0.019***		0.022***	
	(0.006)		(0.004)	
[3] $\tilde{\alpha}$: Richer	0.023		-0.060*	
	(0.049)		(0.036)	
[4] θ: Initial log-GDP (Dev)		0.004		-0.046**
		(0.023)		(0.022)
[5] γ: Trend × Initial log-GDP(Dev)		0.009***		0.015***
		(0.003)		(0.003)
Observations	159	159	388	388
R^2	0.245	0.178	0.180	0.152
F-Test:[1]+[2]=0 or [1]+[5]=0	22.18	19.86	50.42	60.98
Trend effect at min GDP		-0.004		-0.015**
Trend effect at 25% GDP		0.004		-0.000
Trend effect at 75% GDP		0.012***		0.014***
Trend effect at max GDP		0.015***		0.019***

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are heteroscedasticity-robust and corrected for the degrees of freedom. Columns (1) and (3) report the estimates of Equation (5) for wave and yearly observations, respectively. Columns (2) and (4) report the estimates of Equation (6). The bottom four rows report implied annual AGIR trends at the min, 25th, 75th percentiles and max of the 2004 GDP distribution, calculated as $\beta + \gamma \times \overline{\text{GDP}}_p$ where $\overline{\text{GDP}}_p$ is demeaned log GDP at the pth percentile.

3.2 Stylized Fact 2: Employment Drives Divergence in Rich Countries, Wages in Poor Countries

The AGIR divergence documented above could operate through multiple channels: older workers earning higher wages conditional on employment, maintaining employment while young workers drop out of the labor force, or receiving larger transfer payments. Each of these mechanisms would suggest the presence of different mechanisms at works, such as changes in skill accumulation or prices by cohort (wage margin), labour supply preferences (labor margin) or public policies (transfers). To discriminate among these channels, we decompose income growth into four constituent margins.

We measure inequality growth using the *Growth Rate Differential (GRD)*—the annualized difference in income growth rates between old and young workers:

$$\text{GRD} = \frac{1}{h}\left(\frac{\Delta\bar{y}_{\text{old}}}{\bar{y}_{\text{old},T}} - \frac{\Delta\bar{y}_{\text{young}}}{\bar{y}_{\text{young},T}}\right), \tag{7}$$

where $\Delta \bar{y}_j = \bar{y}_{j,T+h} - \bar{y}_{j,T}$ measures the change in average income for group j over h years. For small growth rates, GRD $\approx \frac{1}{h}\log(R_{T+h}/R_T)$, so the GRD approximates the annualized log change in AGIR (see Appendix C). A positive GRD indicates that older workers' incomes grew faster than younger workers'.

Recalling that $\bar{y}_j = e_j \bar{w}_j + p_j \bar{\Theta}_j$, we can decompose GRD into four components:

$$\mathrm{GRD} = \underbrace{\frac{1}{h}\left(\frac{e_{\text{old},T}\Delta\bar{w}_{\text{old}}}{\bar{y}_{\text{old},T}} - \frac{e_{\text{young},T}\Delta\bar{w}_{\text{young}}}{\bar{y}_{\text{young},T}}\right)}_{\text{Wage Margin}} + \underbrace{\frac{1}{h}\left(\frac{\bar{w}_{\text{old},T}\Delta e_{\text{old}}}{\bar{y}_{\text{old},T}} - \frac{\bar{w}_{\text{young},T}\Delta e_{\text{young}}}{\bar{y}_{\text{young},T}}\right)}_{\text{Employment Margin}}$$
$$+ \underbrace{\frac{1}{h}\left(\frac{p_{\text{old},T}\Delta\bar{\Theta}_{\text{old}}}{\bar{y}_{\text{old},T}} - \frac{p_{\text{young},T}\Delta\bar{\Theta}_{\text{young}}}{\bar{y}_{\text{young},T}}\right)}_{\text{Transfer Income Margin}} + \underbrace{\frac{1}{h}\left(\frac{\bar{\Theta}_{\text{old},T}\Delta p_{\text{old}}}{\bar{y}_{\text{old},T}} - \frac{\bar{\Theta}_{\text{young},T}\Delta p_{\text{young}}}{\bar{y}_{\text{young},T}}\right)}_{\text{Transfer Share Margin}}. \tag{8}$$

The wage margin captures earnings growth among employed workers—the conventional age-earnings gap. The employment margin captures changes in labour force participation. The transfer margins capture changes in pension and unemployment benefits. Positive values indicate that the component contributed to faster income growth for older workers relative to younger workers.

Figure 2 implements this decomposition for all 32 countries, ordered by initial GDP per capita. Table II summarizes average contributions within each income group. Three patterns emerge.

Figure 2. *GRD* Decomposition, by income components

Notes: The figure depicts the GRD decomposition for disposable income, comparing late-career (55–64) to early-career (25–34) individuals, ordered by 2004 GDP per capita. "Labour earnings" captures differences in average wage growth among employed workers. "Employment" captures differences in employment rate growth. "Transfer Income" captures differences in average transfer growth conditional on receipt. "Transfer Share" captures differences in the growth of the share receiving transfers. Positive values indicate faster income growth for older relative to younger workers.

TABLE II. Trend in AGIR and GRD

Country Group	AGIR 2004	AGIR 2018	GRD components				
			GRD (%)	Labour Earnings (%)	Employment (%)	Transfer Income (%)	Transfer Share (%)
Poorer	1.07	1.02	-0.62	-1.34	0.77	0.68	-0.73
Richer	1.06	1.26	1.35	0.43	1.58	-0.17	-0.50

Notes: The table reports unweighted averages for rich and poor countries. The first two columns report initial and final AGIR values, as displayed in Figure 1. The third column reports the average annualised GRD and its four subcomponents, as displayed in Figure 2. The GRD over 14 years does not exactly match the AGIR growth rate because the GRD is an approximation that holds accurately only when growth rates are close to zero.

(i) In high-income countries, the employment margin is the dominant contributor to GRD, averaging +1.58 percentage points per year compared to +0.43 pp for the wage margin. Older workers' employment rates rose sharply relative to younger workers', generating income divergence through labour market attachment rather than wage dynamics. This explains why AGIR grows approximately three times faster than what the conventional age-earnings gap would suggest: the main driver of income inequalities is differences in employment trends, rather than wages. As shown in Appendix D, young workers' employment contributed negligibly or even negatively to their income growth in most rich countries, while older workers experienced substantial employment gains of between 0.5 and 2 percentage points per year.[10] In Appendix D.1 we show that these patterns do not depend on young individuals switching from employment to education.

(ii) In middle-income countries, the pattern reverses: the wage margin contributes −1.34 pp per year to GRD while the employment margin contributes +0.77 pp. Faster wage growth among younger workers drives the AGIR decline, partially offset by employment gains for older workers. Appendix D decomposes the wage margin by age group, showing that younger workers in middle-income countries experienced substantially faster wage growth than their older counterparts—often 2–3 percentage points per year faster—accounting for most of the AGIR decline.

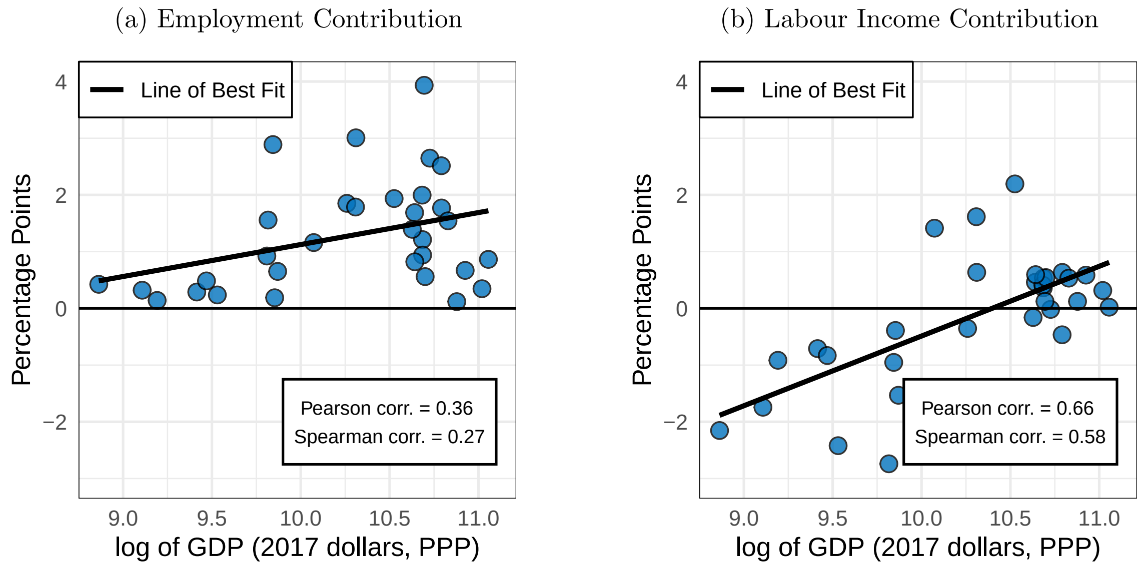
(iii) Transfers play a minor and largely offsetting role. The transfer share margin is negative in both country groups (average −0.50 pp in rich, −0.73 pp in poor), reflecting a declining share of older individuals receiving social transfers relative to the young. The transfer income margin is more heterogeneous: small and negative in rich countries (−0.17 pp) but positive and quantitatively meaningful in poor ones (+0.68 pp), where

[10] Our decomposition focuses on the employment-unemployment margin rather than variation in hours worked, 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). Appendix E confirms that hours worked contribute negligibly to AGIR dynamics across countries: the average GRD contribution of the hours margin is +0.02pp in rich countries and +0.12pp in poor countries, compared to +1.20pp and +0.47pp for the employment margin respectively.

falling transfer-to-wage ratios reduced older workers' non-labour income.

Figure 3 plots log per capita PPP GDP (in 2017 US dollars) at the beginning of the sample against the employment margin (panel a) and the labour earnings margin (panel b). Using the same scale across panels, the relative contributions of the two components to the GRD are immediately comparable. The employment margin is positive for almost all countries, although small for poorer and large for richer ones. The labour earnings margin, by contrast, flips sign across the GDP distribution: large and negative for poorer economies and positive but close to zero for most richer ones.

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



Notes: Panel (a) plots the employment margin of the GRD against log PPP GDP per capita in 2004, expressed in constant 2017 US dollars, with the linear correlation ρ reported in the box. Panel (b) plots the labour earnings margin of the GRD against the same measure of development.

Robustness to Demographics and Changes in Minimum Retirement Age Two concerns might complicate the interpretation of the two stylized facts. First, if high-income countries raised retirement ages faster than middle-income countries, the employment margin might simply reflect pension reforms rather than market forces. Second, if rising female labor force participation disproportionately benefited older women, the employment margin might confound gender and age effects. Appendix F shows that neither explanation accounts for the observed AGIR divergence.

Take-away Two lessons emerge from this section. First, the drivers of age-income divergence differ systematically across development levels: employment dynamics dominate in high-income countries while wage dynamics dominate in middle-income ones—a pattern that is robust within income groups and justifies the global scope of our analysis. Second, the rise in AGIR in rich countries is not driven by pension reforms or gender-specific trends, pointing instead to structural forces that affected older workers broadly and across both genders. Technology, demographics, education, and preferences all offer plausible explanations, but discriminating among them requires a structural framework capable of quantifying general equilibrium effects. Section 4 develops such a framework.

4 Model

To discriminate among competing explanations for AGIR divergence, we develop a quantitative overlapping generations model with endogenous education choices, skill-specific production, and labour supply decisions. The model is designed for exact identification: given standard elasticity parameters, it perfectly matches all observed moments—wage gaps, employment rates, education shares, and transfers—for each type of country and sub-period, recovering unique structural parameters. This allows us to conduct counterfactual experiments that vary each of six mechanisms independently—skill-biased technological change, experience premia, transfers, demographic aging, skill congestion, and labour preferences—and decompose each effect into partial equilibrium (direct compositional effects) and general equilibrium (endogenous wage, employment, and education responses).

General Environment Time is discrete, indexed by $t = 1, 2, 3, \ldots$. In each period t, a new cohort of measure N_t enters the economy. Each individual lives for 5 periods, corresponding to ages 25–34 (period 1), 35–44 (period 2), 45–54 (period 3), 55–64 (period 4), and 65–74 (period 5), after which they exit the model. We use superscript $a \in \mathbb{A} = \{1, 2, 3, 4, 5\}$ to denote age, with $A = 5$ representing the terminal period.

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 a share $(1 - \kappa(s)^{-1})$ of their income in each period. Young workers with skill s earn a wage $w_{s,t}$. In each subsequent period, they gain experience, earning a wage of $w_{s,t+1}(1 + g^a_{s,t+1})$, where $g^a_{s,t}$ captures the difference in efficient labour units between a worker of skill s at age 1 and age a, with $g^1_{s,t} = 0$ for all t, s. Education costs are assumed time-invariant, which is necessary for identification.[11]

[11] The assumption of time-invariant education costs is not unreasonable. In the U.S., institution-weighted real college prices net of scholarships and aid increased by 15.5%, driven by a doubling of public 4-year institution net fees from \$1,690/year to \$3,380/year, approximately constant fees for non-profit private institutions at \$12,800/year, and a fall of \$1,000 in 2-year public institution net fees (from −\$50

Labor Choice We model labour supply as an extensive margin, adopting Hansen's indivisible labour assumption, which convexifies labour supply and allows us to interpret employment as a zero-one decision while keeping the model tractable (Hansen, 1985). This is consistent with our empirical analysis, where variations in aggregate hours worked primarily reflect changes in the number of employed individuals rather than hours per worker—a pattern we confirm for all countries in our sample in Appendix E. Specifically, in each period a worker with skill s at age a chooses either to be unemployed ($l_{s,t}^a = 0$) or to work full-time ($l_{s,t}^a = 1$).

In line with the work of Adão et al. (2024), we assume that individuals gather into large households pooled by skill and age. These households decide on the proportion of individuals who are working ($l_{s,t}^a \in [0,1]$), then pool their income and consumption. Consequently, households can be viewed as type-specific mutualistic associations that provide unemployment insurance for non-workers.[12] Since the households consist of identical individuals, we refer to them by their age level a and skill level s.

Additionally, workers have access to an internationally traded risk-free asset with a return of r_t. We assume that $r_t = 0$ for all t, and that young workers do not discount future utility. We denote by $B_{s,t+1}^a$ the asset level chosen at time t by a household of age a and skill s, which matures at time $t+1$ when the household is age $a+1$. Young generations are born with no assets ($B_{s,t}^0 = 0$), and aged-A workers optimally choose zero assets, as in equilibrium it is not optimal to save and it is infeasible to borrow (since they will not repay). Finally, non-working agents of age a obtain a transfer $\tau_{s,t}^a(1 - l_{s,t}^a)$, which can be interpreted as a skill-specific pension payment when $a = A$ and unemployment transfers when $a < A$.

Household Problem Each period, households maximize their lifetime utility. Using a standard formulation of the instantaneous utility function with endogenous labor supply choice (see (Keane, 2011)), the problem of an old household at their terminal age A, with

to −\$1,080) (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.

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

skill s at time t is:

$$\max_{c^A_{s,t}, l^A_{s,t}} U^A_{s,t}(c^A_{s,t}, l^A_{s,t}) = c^A_{s,t} - \frac{1}{\alpha^A_{s,t}}(l^A_{s,t})^{1+b},$$

$$\text{s.t.} \begin{cases} c^A_{s,t} \leq B^{A-1}_{s,t} + \underbrace{w_{s,t}(1+g^A_{s,t})l^A_{s,t}\kappa(s)^{-1}}_{\text{Labor Income}} + \underbrace{\tau^A_{s,t}(1-l^A_{s,t})\kappa(s)^{-1}}_{\text{Transfer Income}}, \\ l^A_{s,t} \in [0,1], \ c^A_{s,t} \geq 0. \end{cases} \tag{9}$$

Here, $\alpha^A_{s,t}$ is the inverse of the utility cost of working, b is the curvature of the cost of effort, and $\kappa(s)$ is the cost of acquiring skill s (as a proportional salary sacrifice).[13]

Households of age $a \in \{2, 3, 4\}$ maximize lifetime utility, taking into account the cost $\kappa(s)$ of acquiring skill s:

$$\max_{\{c^{a+j}_{s,t+j}, l^{a+j}_{s,t+j}, B^{a+j}_{s,t+j+1}\}^{A-a}_{j=0}} U^a_{s,t}(c^a_{s,t}, l^a_{s,t}) + \sum_{j=1}^{A-a} \mathbb{E}_t \left(U^{a+j}_{s,t+j}(c^{a+j}_{s,t+j}, l^{a+j}_{s,t+j}) \right)$$

$$\text{s.t.} \begin{cases} c^{a+j}_{s,t+j} + B^{a+j}_{s,t+j+1} \leq B^{a+j-1}_{s,t+j} + w_{s,t+j}(1+g^{a+j}_{s,t+j})l^{a+j}_{s,t+j}\kappa(s)^{-1} \\ \qquad + \tau^{a+j}_{s,t+j}(1-l^{a+j}_{s,t+j})\kappa(s)^{-1}, \ \forall j \in \{0, \dots, A-a\} \\ l^{a+j}_{s,t+j} \in [0,1]; \ c^{a+j}_{s,t+j} \geq 0, \ \forall j \in \{0, \dots, A-a\}. \end{cases} \tag{10}$$

Finally, at age $a = 1$, the young are free to choose their skill level s to maximize their lifetime utility:

$$\max_{s, \{c^{1+j}_{s,t+j}, l^{1+j}_{s,t+j}, B^{1+j}_{s,t+j+1}\}^{A-2}_{j=0}} U^1_{s,t}(c^1_{s,t}, l^1_{s,t}) + \sum_{j=1}^{A-1} \mathbb{E}_t \left(U^{1+j}_{s,t+j}(c^{1+j}_{s,t+j}, l^{1+j}_{s,t+j}) \right)$$

$$\text{s.t.} \begin{cases} c^{1+j}_{s,t+j} + B^{1+j}_{s,t+j+1} \leq B^{j}_{s,t+j} + w_{s,t+j}(1+g^{1+j}_{s,t+j})l^{1+j}_{s,t+j}\kappa(s)^{-1} \\ \qquad + \tau^{1+j}_{s,t+j}(1-l^{1+j}_{s,t+j})\kappa(s)^{-1}, \ \forall j \in \{0, \dots, A-1\} \\ B^0_{s,t} = 0, \\ l^{1+j}_{s,t+j} \in [0,1]; \ c^{1+j}_{s,t+j} \geq 0, \ \forall j \in \{0, \dots, A-1\}. \end{cases} \tag{11}$$

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 choice, all combinations of saving and consumption across 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 assume that $B^a_{s,t+1} = 0$ for all a, s, and t throughout the remainder of this discussion. The optimal labour and education allocations derived under this assumption are therefore

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

not constrained by externally imposed borrowing limits but reflect unconstrained optimal choices.

To simplify notation, define $\tilde{\tau}^a_{s,t} = w^{-1}_{s,t}\tau^a_{s,t}$ as transfers expressed in units of the current wage, so that all income terms scale proportionally with $w_{s,t}$. Solving the old household problem for an interior solution of effort, we obtain the old household's indirect utility:

$$V^A_t(s) = \frac{\tau^A_{s,t}}{\kappa(s)} + \left(\frac{w_{s,t}(1+g^A_{s,t}-\tilde{\tau}^A_{s,t})}{\kappa(s)}\right)^{\frac{1+b}{b}} \left(\frac{\alpha^A_{s,t}}{1+b}\right)^{\frac{1}{b}} \frac{b}{1+b}. \tag{12}$$

For an interior solution of household employment rates in all periods, the indirect utility function of younger households of age $a < A$ that have chosen skill s is

$$V^a_t(s) = \frac{\tau^a_{s,t}}{\kappa(s)} + \left(\frac{w_{s,t}(1+g^a_{s,t}-\tilde{\tau}^a_{s,t})}{\kappa(s)}\right)^{\frac{1+b}{b}} \left(\frac{\alpha^a_{s,t}}{1+b}\right)^{\frac{1}{b}} \frac{b}{1+b} + \mathbb{E}_t\left(V^{a+1}_{t+1}(s)\right). \tag{13}$$

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

$$\pi^*_t = \max_{\{L_{s,t}\}_{s\in\mathbb{S}}} Y_t - \sum_{s\in\mathbb{S}} w_{s,t}L_{s,t}.$$

The solution to the firm's problem satisfies the first-order conditions:

$$\left(\sum_{s'} A_{s',t}\left(L_{s',t}\right)^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}-1} A_{s,t}L_{s,t}^{\frac{\theta-1}{\theta}-1} = w_{s,t},\ \forall s,t. \tag{14}$$

Appendix H.1 formally characterises the sequential competitive equilibrium.

4.1 Bringing the model to the data

A key property of the model is its tractability: all endogenous variables of interest—employment rates, labour income, and education shares by age—can be written in closed form as functions of the exogenous parameters: skill-specific TFP $A_{s,t}$, returns to experience $g^a_{s,t}$, cohort sizes $\Delta_{t,t'}N$, and labour preferences $\alpha^a_{s,t}$. This allows us to invert the model and recover unique structural parameters from observed data moments, taking the elasticity of substitution between skills, θ, and Frisch elasticity b^{-1} as calibrated from the literature, as described below.

Model limitations The tractability that allows exact identification comes at the cost of several simplifications, which we briefly acknowledge here. First, the model abstracts from within-period heterogeneity: workers within each age–skill cell are treated as identical, so the decomposition captures between-group dynamics but not changes in within-group wage or employment dispersion. Second, human capital accumulation is assumed to be complete at entry: the returns to experience $g^a_{s,t}$ are treated as exogenous shifters rather than outcomes of post-entry investment decisions. To the extent that on-the-job training and learning-by-doing differ systematically between age groups, our framework would attribute these effects to the experience-premium channel rather than isolating them separately. Third, retirement is modelled as an optimal extensive-margin labour supply decision within each period rather than as a dynamic stopping problem, so the model does not capture the option-value of delayed retirement or the effect of pension wealth on the timing of exit. Each of these extensions would enrich the analysis, and we view them as natural directions for future work.

Empirical strategy The endogenous variables have clear observable counterparts. We assume there are three skills characterized by education level: college-educated ($s = High$), high-school educated ($s = Med$), and less-than-high-school educated ($s = Low$). For a given country and year t, we observe: (i) relative wages across skills ($w_{s,t}/w_{s',t}$); (ii) employment rates by age and skill ($l^a_{s,t}$); (iii) education shares by age ($\rho^a_{s,t}$); (iv) relative size of generations (N^a_t/N^1_t); and (v) average transfers received by the non-employed, in proportion to wage per employee ($\tilde{\tau}^a_{s,t}$).

Since countries within-group (richer or poorer) experienced similar dynamics, our goal is to provide credible estimates for parameters of interest in 2004 and 2018 for two countries: a representative "rich" country and a representative "poor" country. The observable endogenous variables are the respective averages across all poor/rich countries. We estimate the model's parameters to perfectly match observed relative wages by skill, education shares by age, and employment rates by age and skill, taking as given the return to experience $g^a_{s,t}$ and aging $\Delta_{t,t'}N$.

Since we do not observe a full generation forward from 2004,[14] we assume that in 2004

[14] According to our definition of workers used in the empirical section, we track individuals across five age groups spanning from 25–74 years old. However, we only have a 15-year gap available in our sample between 2004 and 2018.

the future return to experience $g^a_{s,t+1}$ and wage growth $\Delta w_{s,t+1}$ equal their 2018 values. We perform three normalizations: (i) set the wage rate of low-skilled in 2004 to unity ($w_{L,2004} = 1$); (ii) normalize the 2018 less-than-high school wage to account for absolute productivity growth between periods; (iii) treat low-skill education as the outside option with zero cost ($\kappa(L) = 1$).

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 to $\theta = 3$. Following (Blundell et al., 2013), we set the (inverse) extensive-margin labor elasticity to $b = (0.3)^{-1}$.

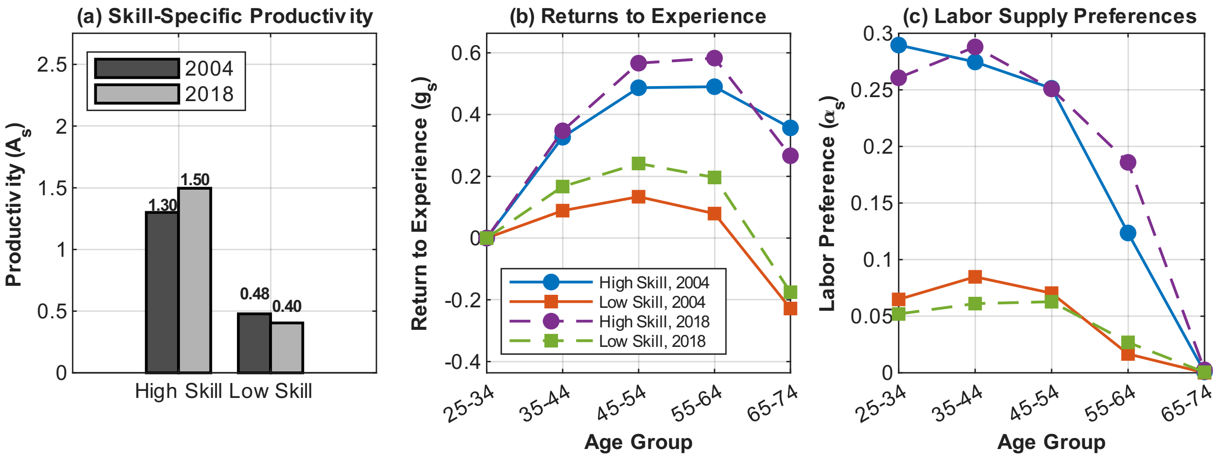
Given these assumptions, the model exactly replicates all observed moments—relative wages, employment rates, education shares, and transfers—for both country groups in 2004 and 2018, with no unexplained residual. Appendix H.2 details the estimation equations and Appendix H.3 the estimation procedure.

4.2 Estimates across the life-cycle

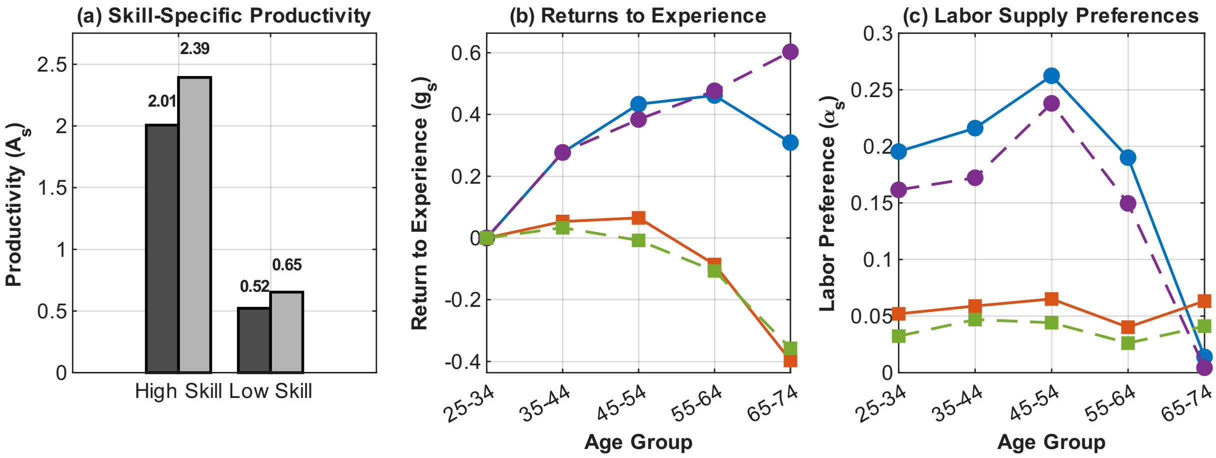
Our five age group framework allows us to estimate how returns to experience and labour preferences vary across the lifecycle. Figure 4 displays estimated parameters for high- and low-skilled workers; the full list of estimates appears in Appendix H.4. In rich countries, panel (a), skill-specific TFP—which does not depend on age—diverged sharply: high-skilled productivity rose substantially while low-skilled productivity declined, widening the skill premium. Returns to experience exhibit intuitive lifecycle patterns. Importantly, between 2004 and 2018, these returns increased for high-skilled workers only at older working ages (45–54 and 55–64), while low-skilled workers experienced increases across all ages. Labour supply preferences are systematically higher for high-skilled workers, reflecting stronger work attachment. Notably, preferences shifted markedly toward greater labour supply for high-skilled workers approaching pension age, consistent with delayed retirement trends. Recall that the preference parameter $\alpha^a_{s,t}$ serves as a reduced-form wedge that captures unmodelled forces—such as institutional changes or shifting norms around work and retirement—that affect workers' employment attachment across all age groups beyond what wages and experience premia alone can explain. Poor countries exhibit similar qualitative patterns but different magnitudes. Skill-specific TFP increased for both groups, though the skill premium widened even more due to faster high-skilled productivity growth. Returns to experience and labour preference follow comparable lifecycle gradient.

Figure 4. Lifecycle Profiles of Estimated Parameters

(a) Rich Countries



(b) Poor Countries



Notes: The figure displays estimated lifecycle profiles for high-skilled (circles) and low-skilled (squares) workers in 2004 (solid line) and 2018 (dashed line). Panels (a)–(c) show rich countries and panels (d)–(f) poor countries. Panel (a) shows skill-specific productivity (A_s), panel (b) returns to experience relative to the youngest age group (g_s^a), and panel (c) labour supply preferences (α_s^a). Medium-skilled parameters appear in Appendix H.4. Parameters are estimated using representative moments averaged across countries within each income group.

4.3 Decomposition of *AGIR* growth

Having established that our model successfully replicates the observed patterns in both rich and poor countries, we now use it as a laboratory to decompose the sources of AGIR changes. We construct counterfactual equilibria by varying one parameter or initial condition at a time while holding all others at their 2004 values. Then, we compare the resulting AGIR in 2018 to the 2004 baseline. This approach isolates the contribution of each mechanism through both direct effects and general equilibrium adjustments.

We consider six counterfactuals, each targeting a specific channel: (i) **Productivity** (A_s): set skill-specific TFP to 2018 values, capturing skill-biased technical change; (ii) **Returns to experience** (g_s^a): set age-skill-specific returns to 2018 values, capturing changes in the returns to accumulated human capital; (iii) **Transfers** (τ_s^a): set transfer rates to 2018 values, capturing changes in social insurance generosity; (iv) **Aging** (N_t^a): set cohort sizes to 2018 values, capturing demographic shifts; (v) **Skill congestion** ($\rho_{s,t}^a$ for $a > 1$): set the initial education distribution of older cohorts to 2018 values, capturing educational catch-up; (vi) **Labour preferences** (α_s^a): set preference parameters to 2018 values, capturing shifts in work attachment. Finally, we report the decomposition combining all channels simultaneously, which, by construction, replicates the observed AGIR growth exactly. Note, however, that the sum of the individual channels need not equal the total change, since the channels are not orthogonal.

The skill congestion counterfactual deserves further elaboration. The shares $\rho_{s,t}^a$ for $a > 1$ are initial conditions of the model: they record the educational composition of cohorts who are already in the market before time t and whose skill choices are therefore predetermined. Setting these shares to their 2018 values simulates a world in which the older cohorts present in 2004 had the educational composition of the older cohorts observed in 2018, that is, a more educated older workforce, and traces the consequences for equilibrium wages, employment rates, and the education choices of younger cohorts entering the labour market.

Table III summarises the AGIR growth contributions from each counterfactual.

TABLE III. Decomposition of AGIR Growth

	Rich Countries				Poor Countries			
	Total	Empl	Wage	Transfer	Total	Empl	Wage	Transfer
Data (2004-2018)	+19.7	+18.6	+7.1	-7.1	-8.0	+8.6	-15.9	-3.4
(i) Productivity	-16.7	-5.9	-11.1	-0.2	-5.2	+6.6	-3.1	-9.3
(ii) Returns to exp.	+3.5	+1.6	+4.2	-1.5	-1.8	-2.9	-0.7	+1.6
(iii) Transfers	+0.3	-1.3	-0.1	+1.7	-7.3	+7.9	-0.5	-13.9
(iv) Aging	-0.5	-0.3	-0.2	+0.0	-0.5	-0.2	-0.3	+0.0
(v) Skill congestion	+37.5	+12.1	+17.7	+0.0	-10.4	-1.7	-10.8	+2.1
(vi) Preferences	+7.8	+14.7	-0.4	-7.4	+11.9	+7.3	+2.7	-0.0
All channels	+19.7	+18.6	+7.1	-7.1	-8.0	+8.6	-15.9	-3.4

Notes: AGIR growth contributions in percentage points. Each counterfactual changes one parameter at a time to its 2018 value, holding all others at 2004 levels. "All channels" varies all mechanisms simultaneously and exactly replicates the observed AGIR growth by construction. Notice that the change in AGIR growth reported in this table is not identical to the one reported in Table II because in that table the statistics are computed as averages across country, while here we pool together all the observations for each country-type and then compute the statistics. Finally, the sum of the individual channels need not equal the total change, since the channels are not orthogonal.

Productivity changes reduced AGIR in both rich (-16.7pp) and poor (-5.2pp) countries. In rich countries, this operated primarily through the wage margin (-11.1pp), with a further employment contribution of −5.9pp. TFP growth was concentrated among high-skilled workers, who are disproportionately young, thus favouring younger cohorts' wages and reducing AGIR. In poor countries, productivity increased across all skills, creating incentives for older workers to remain in the labour force (+6.6pp through employment) while favouring younger workers' skill accumulation and high-skilled wages (−3.1pp through wages), with transfers absorbing the remaining effect (−9.3pp).

Skill congestion is the dominant driver of rising AGIR in rich countries (+37.5pp), operating through both employment (+12.1pp) and wages (+17.7pp). As older cohorts acquire more education, they compete more intensely with younger workers in skilled labour markets, depressing equilibrium wages and employment rates for the young while raising them for the old. General equilibrium responses amplify this mechanism: as older workers crowd into skilled markets, equilibrium wages for the young fall, further discouraging their labour market attachment. In stark contrast, this channel *reduces* AGIR in poor countries (−10.4pp, through both employment −1.7pp and wages −10.8pp), due to the fact that the education upgrading of the old was not as fast as the one desired by the young when looking at current skill prices and expectations.

Labour preferences constitute the second-largest contributor to rising AGIR in rich countries (+7.8pp), operating almost entirely through employment (+14.7pp). Older workers increasingly prefer continued work over retirement, directly raising their relative employment rates. A similar and quantitatively notable pattern is observed in poor countries, where this channel raises AGIR by +11.9pp (+7.3pp through employment).

Returns to experience contribute modestly in rich countries (+3.5pp) and are slightly negative in poor countries (−1.8pp), where the age premium of mid- and low-skilled workers declined between 2004 and 2018.

Transfers and aging play minor roles in rich countries (+0.3pp and −0.5pp respectively). In poor countries, transfers contributed substantially to a reduction in AGIR (−7.3pp): while the reduction in the transfer-to-wage ratio raised older workers' employment (+7.9pp), the net effect reduced older workers' income through both lower transfers per retiree and a smaller retiree base (transfer component −13.9pp).

Our decomposition reveals that improved skill-specific technology worldwide favoured younger workers' incomes through higher wages. This force dominates in poor countries, accounting for their entire AGIR decline. In rich countries, however, skill congestion—older workers becoming more educated and crowding out the young—more than counterbalances technology, raising older workers' incomes through both employment and wages. Additionally, stronger preferences for continued work among older workers further increased their relative employment. The divergence thus stems not from technological differences but from differential educational dynamics and labour supply responses across development stages.

4.4 General equilibrium effects

Table IV decomposes each channel's total effect into partial equilibrium (PE) and general equilibrium (GE) components, shedding further light on the two dominant drivers of rising AGIR in rich countries: skill congestion and labour preferences. In each counterfactual, the PE effect captures the direct impact of a parameter change on income composition, holding wages and education shares fixed at their 2004 values. The GE effect is defined as the residual between the total and PE effects, and reflects the endogenous responses of education choices, employment decisions, and equilibrium wages to the parameter change. By construction, mechanisms that operate primarily through labour market prices and human capital accumulation will generate large GE effects, while mechanisms that directly shift income through composition alone will be predominantly PE phenomena.

Despite being the largest contributor to AGIR growth, skill congestion operates almost entirely through general equilibrium forces. Its direct compositional effect is modest (+5.1pp PE), but endogenous labour market responses amplify this into a total effect of +37.5pp (+32.4pp GE). As older cohorts crowd into skilled labour markets, equilibrium wages for younger workers fall and their relative employment rates decline, generating a powerful feedback loop that would be entirely missed by a partial equilibrium or reduced-form approach.

Labour preferences, by contrast, operate almost entirely through a direct composition effect. As older workers increasingly prefer continued work over retirement, their relative employment rises mechanically, with only negligible general equilibrium feedback (+7.1pp PE vs +0.7pp GE). This makes the preferences channel essentially a reduced-form shift in labour supply, requiring no equilibrium amplification to generate its +7.8pp contribution to AGIR growth.

The remaining channels play secondary roles and are largely GE phenomena. Productivity generates its entire −16.7pp reduction in AGIR through general equilibrium forces (+0.0pp PE): TFP changes have no direct impact on income composition when wages are held fixed—their entire effect operates through endogenous wage adjustments.

Returns to experience show a partial PE/GE offset: a positive direct effect (+6.0pp PE) is partially reversed by endogenous responses (−2.4pp GE). Transfers and aging generate negligible effects through both channels. The bottom row confirms that while individual mechanisms trigger large and opposing GE responses, these largely cancel in aggregate, leaving overall AGIR growth of +19.7pp driven primarily by PE forces (+19.9pp).

Taken together, skill congestion and labour preferences account for +26.8pp of employment margin growth, partially offset by the −5.9pp employment effect of productivity—confirming that the employment margin dominance documented in Section 3 reflects the combined action of these two structural forces operating through fundamentally different channels: one almost entirely through general equilibrium feedback, the other through a direct labour supply shift.

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

Rich Countries

	Total			Employment			Wage		
	PE	GE	Total	PE	GE	Total	PE	GE	Total
(i) Productivity	+0.0	-16.7	-16.7	+0.0	-5.9	-5.9	+0.0	-11.1	-11.1
(ii) Returns to exp.	+6.0	-2.4	+3.5	+2.9	-1.3	+1.6	+5.2	-1.0	+4.2
(iii) Transfers	+0.5	-0.2	+0.3	-1.3	-0.0	-1.3	-0.1	-0.0	-0.1
(iv) Aging	+0.0	-0.5	-0.5	+0.0	-0.3	-0.3	+0.0	-0.2	-0.2
(v) Skill congestion	+5.1	+32.4	+37.5	+2.2	+9.9	+12.1	+2.6	+15.1	+17.7
(vi) Preferences	+7.1	+0.7	+7.8	+14.2	+0.5	+14.7	-0.5	+0.1	-0.4
All channels	+19.9	-0.2	+19.7	+18.7	-0.0	+18.6	+7.2	-0.1	+7.1

Notes: The table decomposes counterfactual AGIR growth contributions (percentage points) for a representative rich country, constructed by averaging moments across all rich countries. Partial equilibrium (PE) effects hold wages and education shares fixed at their 2004 values; general equilibrium (GE) effects are the residual. Each counterfactual sets one parameter to its 2018 value: (i) skill-specific TFP A_s; (ii) returns to experience g_s^a; (iii) transfer rates τ_s^a; (iv) relative cohort sizes; (v) skill congestion, i.e. initial education distribution of older cohorts; (vi) labour preference parameters α_s^a. "All channels" sets all parameters simultaneously and exactly replicates observed AGIR growth by construction.

4.5 *AGIR* and Lifetime Income Profile

Figure 5 complements the AGIR decomposition by examining how the four main channels (productivity, returns to experience, skill congestion, and labour preferences) shape the lifecycle income profile of the young alive when the shock happens. We calculate each lifetime income curve in two steps. First, we estimate the (general) equilibrium once at $t = 1$, similarly to the counterfactuals presented in the previous section. This yields a set of wages, employment rates and—most importantly—education levels of the young (age $a = 1$). Then, we iterate the model forward in time, yielding potentially different wages and employment rates by skill in each period, with the only constraint that the skill shares of each following cohort must be equal to those of the young at $t = 1$. This allows us to discipline the dynamics of the model.[15] Finally, we calculate the average lifetime income of the young as the average of the incomes perceived by the cohort born in period $t = 1$, between $t = 1$ and $t = 5$. Table V summarises how each counterfactual changes AGIR (in the first period), the lifetime income of the young and their average (across the lifecycle) wages and employment.

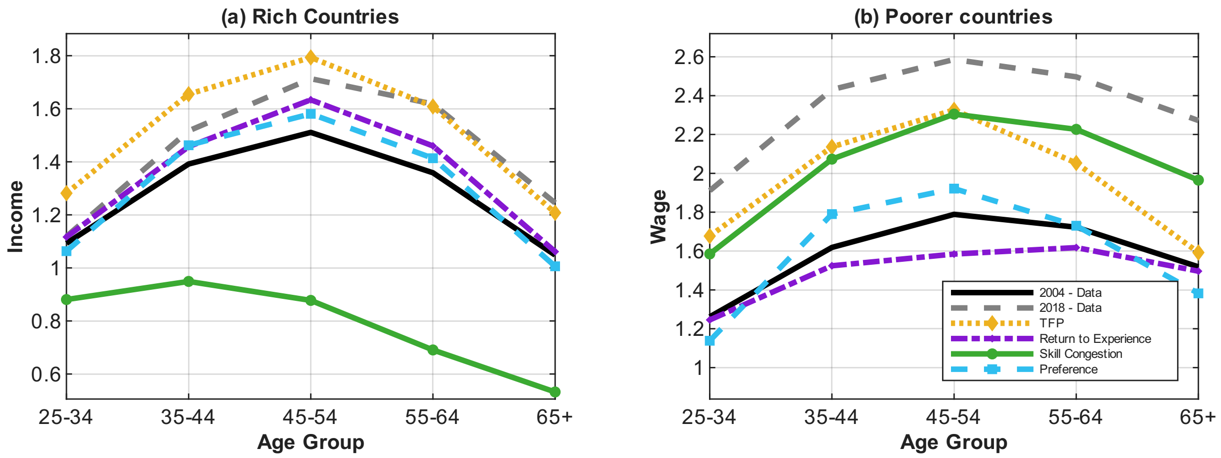
In rich countries, the two dominant drivers of a rising AGIR, skill congestion and labour preferences, have strikingly different distributional implications beyond their effect on the old/young income ratio. Skill congestion strongly depresses the present and future income of the young, increasing AGIR (1.46 vs 1.08) while reducing the young cohort's lifetime income (0.79 vs 1.28). The reason is that, without further skill-biased technical change, a higher level of education among the old, in particular at the college level, reduces the education incentives of the young. Changes in preferences for work increase both AGIR and lifetime income, since individuals work and earn higher wages for longer. This is consistent with the expected effects of a pure labour supply push. Similarly, an increase in the return to experience mechanically increases AGIR, but also lifts the lifetime income of future generations. A positive shock to TFP reduces AGIR and increases the lifetime income of the young as well (from 1.28 to 1.58).

The picture is strikingly different in poor countries, where an increase in the education level of the old *increases* the lifetime income of the young. This is because the shock mainly regards having less very-low educated old and more high-school graduates, with only a marginal increase in old college graduates. This strongly reduces congestion in the lowest-skilled labour market, while pushing the young towards even higher education levels, increasing their lifetime income (from 1.58 to 2.03) and reducing AGIR (from 1.12 to 1.02). In this sense, the education shocks is actually *decongesting* the low-skilled market while not congesting the college-level one. The remaining mechanisms work similarly to rich countries: TFP shocks increase lifetime income, and reduce AGIR since they are skill-biased in favour of college-educated workers. The fall in returns to experience in poorer countries between 2004 and 2018 reduced AGIR while also decreasing lifetime income. The increased preferences for work among older individuals, and a reduction among the

[15]This choice stems from the fact that our model yields, from the data, expectations over the future returns to education that do not necessarily match the simulated ones, since they cannot be disentangled agnostically. Fixing education allows us to preserve the direction of each mechanism relative to the initial case. Notice that this choice yields underestimates of the size of each mechanism relying heavily on skill acquisition choices, such as the TFP or skill congestion counterfactuals. For example, if a cohort ends up *below* the steady-state education share due to skill congestion, assuming that the following cohorts also have below-steady-state education shares understates the total skill congestion faced by the initial young cohort across its lifetime.

young, led to higher AGIR and approximately similar lifetime income.

Figure 5. Lifecycle Profiles and Inequality Metrics: Age-Increasing Counterfactuals



Notes: The figure displays lifecycle profiles under four counterfactual scenarios for rich countries (panel a) and poor countries (panel b). The plotted lifecycle profiles are the ones obtained by re-estimating the model's equilibrium forward, while keeping the education level of each following generation equal to the equilibrium one of the first-period young. These counterfactuals are: 2004 baseline (black), 2018 data (gray), productivity (orange), returns to experience (purple), skill congestion (green), and labour preferences (cyan). Each counterfactual changes only one mechanism from its 2004 to its 2018 value, holding all other parameters constant.

TABLE V. AGIR and Lifetime Income: Counterfactual Decomposition

	Rich Countries				Poor Countries			
	AGIR	Lifetime Income	Lifetime Wage	Lifetime Employment	AGIR	Lifetime Income	Lifetime Wage	Lifetime Employment
2004 - Data	1.08	1.28	1.51	0.61	1.12	1.58	1.87	0.58
2018 - Data	1.28	1.44	1.64	0.64	1.04	2.34	2.79	0.64
TFP	0.92	1.51	1.76	0.65	1.07	1.96	2.31	0.67
Return to Experience	1.12	1.35	1.57	0.62	1.10	1.49	1.78	0.57
Skill Congestion	1.46	0.79	0.97	0.51	1.02	2.03	2.36	0.63
Preference	1.16	1.31	1.53	0.64	1.24	1.59	1.94	0.57

Notes: The table reports AGIR (ratio of average disposable income of individuals aged 55–64 to those aged 25–34), average lifetime income, and its standard deviation across age groups, for representative rich and poor countries constructed by averaging moments within each income group. Each counterfactual row sets one mechanism to its 2018 value while holding all other parameters at 2004 levels.

5 Conclusions

The growing income divergence between older and younger workers has become a defining concern across industrialised economies, yet existing evidence relies almost exclusively on the wages of employed individuals in a small set of developed countries. This paper provides a more complete picture by analysing disposable income inequality across 32 countries over 2004–2018, introducing a structural framework capable of discriminating among competing explanations.

Our empirical analysis documents a striking divergence. The Age Group Income Ratio—the ratio of disposable income of individuals aged 55–64 to those aged 25–34—rose by 18 percentage points in high-income countries but fell by 8 percentage points in middle-income economies, starting from nearly identical levels in 2004. This divergence operates primarily through the employment margin: differential changes in employment rates between older and younger workers account for two-thirds of rising AGIR in rich countries, a margin that conventional age-earnings measures miss entirely.

To explain these patterns, we develop an overlapping generations model with endogenous education choices and skill-specific production, estimated through exact identification. Skill congestion—older cohorts becoming more educated and crowding younger workers out of skilled labour markets—is the dominant driver of rising AGIR in rich countries (+37.5pp), operating almost entirely through general equilibrium feedback: as older workers crowd into skilled markets, equilibrium wages and employment rates for the young fall while those of the old rise. Labour preferences constitute the second-largest contributor (+7.8pp), operating as a pure labour supply shift. Skill-biased technical change acts as a counterforce (−16.7pp), disproportionately raising younger cohorts' productivity. In poor countries, TFP growth dominates and skill congestion reduces rather than raises inequality, because older cohorts still lag substantially behind the young educationally.

Beyond their effects on the old/young income ratio, these mechanisms carry fundamentally different lifetime income implications. Skill congestion can decrease future generations' incomes, as it is the case in richer countries where the old are naturally converging to higher education levels. On the other hand, preferences for labor supply (which include pension reforms) and higher returns to experience raise both AGIR and lifetime incomes. Our results show that rising young-old inequalities in rich countries are also associated with very modest increases in lifetime incomes due to the prevalent skill congestion mechanism.

Our findings open several avenues for future research. Will new technologies such as artificial intelligence invert current trends by introducing age-biased technical change, or will continued educational convergence between old and young intensify skill congestion across both rich and poor countries? Do higher age-income gaps affect location choices and political preferences differently depending on whether they are driven by skill congestion or productivity growth? Addressing these questions requires extending the structural framework developed here—a natural next step given the urgency of intergenerational inequality as a policy challenge. For example, Guaitoli et al. (2026) show that, when high-income old and low-income young compete for space in productive labour markets, the presence of financial frictions on the housing market leads to too few young moving to cities to accumulate human capital, depressing long-run aggregate human capital, output and welfare.

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APPENDIX FOR ONLINE PUBLICATION

A Additional Information on Data Availability and Selection

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.[16]

2. **Long time series**. To coherently analyze the medium-term trends in age-income gaps, 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 applying criterion (3), we discard any remaining countries that no longer satisfy criterion (2) due to the reduction in available surveys. Finally, we drop Luxembourg, where almost 50 percent of workers do not reside in the country, making it unsuitable for our analysis.

[16] 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 young individuals, the selection may strengthen, making households with a young household head less representative of the average young person's income.

TABLE VI. 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	126602	✓				✓		✓				✓		✓		✓
Austria	Rich	Gross	131374	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Belgium	Rich	Gross	137874	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Brazil	Poorer	Gross	3655919	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓
Canada	Rich	Gross	636266	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Chile	Poorer	Net	915446			✓			✓		✓		✓		✓		✓	
Colombia	Poorer	Gross	7046752	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Czechia	Rich	Gross	187342	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Denmark	Rich	Gross	1902934	✓			✓			✓			✓		✓	✓	✓	✓
Estonia	Poorer	Gross	45266	✓			✓			✓			✓			✓		
Finland	Rich	Gross	86735	✓			✓			✓			✓			✓		
France	Rich	Gross	983724	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Germany	Rich	Gross	349293	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ireland	Rich	Gross	112052	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Israel	Rich	Gross	211407	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Italy	Rich	Net	85001	✓		✓		✓		✓		✓		✓		✓		
Mexico	Poorer	Net	695928	✓	✓	✓		✓		✓		✓		✓		✓		✓
Netherlands	Rich	Gross	249000	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Norway	Rich	Gross	1315064	✓			✓			✓			✓			✓		
Paraguay	Poorer	Gross	212886	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Peru	Poorer	Gross	924913	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Poland	Poorer	Net	1053175	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Romania	Poorer	Gross	152931			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Serbia	Poorer	Net	126953			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Slovakia	Poorer	Gross	99142	✓			✓			✓			✓	✓	✓	✓	✓	✓
Slovenia	Rich	Net	38930	✓			✓			✓		✓			✓			
Spain	Rich	Gross	339402	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sweden	Rich	Gross	265330	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Switzerland	Rich	Gross	142393			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
United Kingdom	Rich	Gross	470438	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
United States	Rich	Gross	1852568	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Uruguay	Poorer	Net	1163380	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table reports the data points included in our analysis. Countries are listed in alphabetical order. The second column reports whether the country is classified as "Rich" or "Poorer" according to the algorithm described in the main text. The third column indicates whether income variables are reported net or gross of taxes; for gross-reporting countries, we construct net income using the reported tax variables. Each remaining column indicates with a check mark whether a survey is available for a given country in that year; years are grouped by wave. Each country's first and last available survey years are used to calculate the *GRD*.

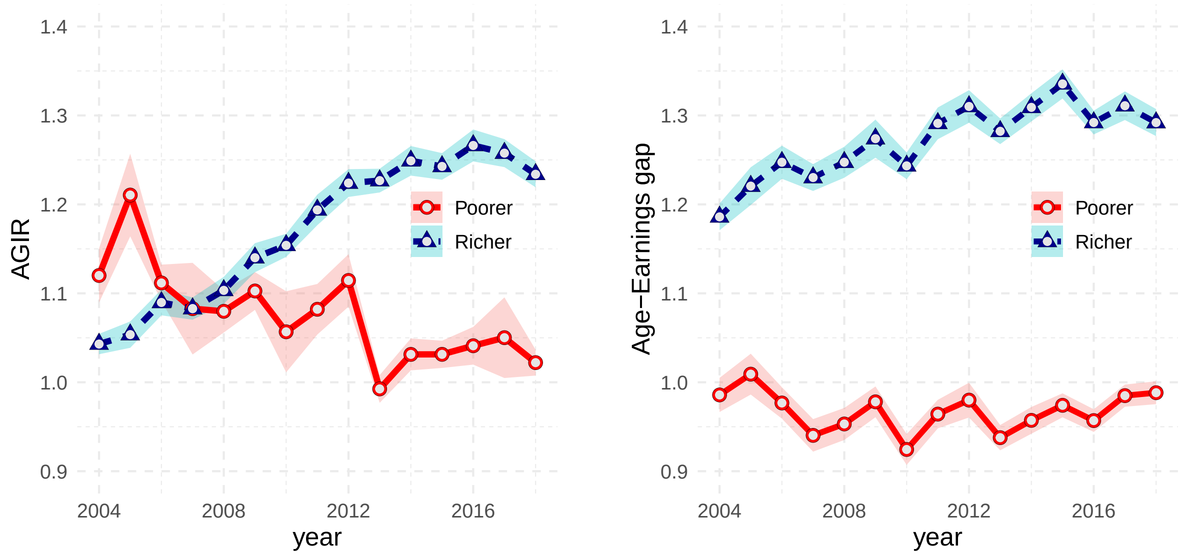
B AGIR Trends and Robustness Checks

B.1 AGIR with years as observation unit

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

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

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



Notes: The figure depicts the Age Group Income Ratio (*AGIR*) between late-career individuals (55-64 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.2 Trends in Age-Earnings Gaps

In Table VII, 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 for earning gap vs +1.5 percent for AGIR in rich countries). Even at the 75th percentile of GDP, the time trend of the age-earnings gap is small (+0.5 percent per year) and not statistically different from zero (p-value>0.10) for waves, less than half the trend in *AGIR* (+1.2 percent, p-value<0.001).

TABLE VII. Trend in Earnings gap

	Wave		Year	
Dependent	ln(earnings gap)			
	(1)	(2)	(3)	(4)
[1] β: Trend	0.0004	0.004	0.0007	0.004**
	(0.005)	(0.003)	(0.003)	(0.002)
[2] $\tilde{\beta}$: Trend $\times$ Richer	0.006		0.005	
	(0.006)		(0.004)	
[3] $\tilde{\alpha}$: Richer	0.223***		0.240***	
	(0.043)		(0.033)	
[4] θ: Initial log-GDP (Dev)		0.114***		0.164***
		(0.019)		(0.021)
[5] γ: Trend $\times$ Initial log-GDP(Dev)		0.002		0.004*
		(0.002)		(0.002)
Observations	159	159	387	387
R^2	0.470	0.403	0.491	0.412
F-Test:[1]+[2]=0 or [1]+[5]=0	4.55	2.79	10.87	9.05
Trend effect at min GDP		0.000		-0.002
Trend effect at 25% GDP		0.003		0.002
Trend effect at 75% GDP		0.005		0.006**
Trend effect at max GDP		0.006		0.007**

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are heteroscedasticity-robust and corrected for the degrees of freedom. Columns (1) and (3) report the estimates of Equation (5) for wave and yearly observations, respectively, when using the age-earnings gap, defined similarly to *AGIR* but comparing only the labor earnings of individuals in employment, as dependent variable. Columns (2) and (4) report the estimates of Equation (6). The bottom four rows report implied annual earning gaps trends at the min, 25th, 75th percentiles and max of the 2004 GDP distribution, calculated as $\beta + \gamma \times \overline{\text{GDP}}_p$ where $\overline{\text{GDP}}_p$ is demeaned log GDP at the pth percentile.

B.3 Robustness Checks

We perform several robustness checks, which corroborate the wave and annual specifications in Table I. Results are reported in Table VIII. 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 by using a weighted least-squares estimator, with 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, columns (3) and (6) show that the time trends in *AGIR* are not shared by the second moments of the income distribution, confirming that the phenomenon does not capture a different evolution of within-group inequality. For this purpose, we use as the dependent variable the ratio of the coefficients of variation of disposable income for late-career and early-career individuals, denoted *AGcvR*.[17] The data display no statistically significant time trend in this second-moment measure, motivating our focus on *AGIR*.

[17] The coefficient of variation for age group j is the ratio of the standard deviation of disposable income for that group to its mean. *AGcvR* is the ratio of these coefficients for late-career and early-career age groups.

TABLE VIII. Trend in AGIR

	Wave			Year		
Dependent	ln(AGIR)		ln(IGcvR)	ln(AGIR)		ln(IGcvR)
	(1)	(2)	(3)	(4)	(5)	(6)
[0] α: Constant	0.024	0.136***	0.205***	0.020	0.092***	0.248***
	(0.034)	(0.026)	(0.040)	(0.024)	(0.016)	(0.030)
[1] β: Trend	0.013	0.004	0.010	0.012*	0.005**	0.001
	(0.010)	(0.004)	(0.008)	(0.007)	(0.002)	(0.004)
[4] θ: Initial log-GDP (Dev)	0.014	-0.032	0.065	-0.007	-0.057**	0.056
	(0.025)	(0.028)	(0.051)	(0.026)	(0.026)	(0.053)
[5] γ: Trend $\times$ Initial log-GDP(Dev)	0.009***	0.009**	-0.004	0.015***	0.015***	-0.0008
	(0.003)	(0.004)	(0.009)	(0.003)	(0.003)	(0.007)
Observations	159	159	159	388	388	388
R^2	0.187	0.101	0.027	0.182	0.132	0.009
Weights	No	Yes	No	No	Yes	No
2nd order terms	Yes	No	No	Yes	No	No
F-Test:[1]+[2]=0 or [1]+[5]=0	16.60	14.76	0.27	16.60	42.08	42.08
Trend effect at min GDP	-0.005	-0.009	0.015	-0.014**	-0.016**	0.003
Trend effect at 25% GDP	0.003	-0.000	0.011	-0.000	-0.002	0.002
Trend effect at 75% GDP	0.012**	0.008**	0.008	0.014***	0.012***	0.001
Trend effect at max GDP	0.014***	0.011***	0.007	0.019***	0.017***	0.001

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are heteroscedasticity-robust and corrected for the degrees of freedom.. All columns report the estimates of equation (6). 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.4 *AGIR* and Household-level Benefits

Some benefits are paid at the household level rather than at the personal level and therefore do not enter our baseline personal income definition. In this section, we allocate these household-wide benefits to household 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).

Child benefits are allocated to individuals proportionally to the number of their own children living in the household. For example, in a household with two parents, one small child (who generates a child benefit) and one adult child (who does not), we allocate 50% of the child benefit to each parent and zero to the adult child. The reason is that if the adult child moved out, they would not receive any child benefit of their own. General assistance and housing benefits are split equally among all adults in the household. Since not all countries report all benefit types in each year, we exclude benefits that are not reported throughout the whole sample of a country.[18]

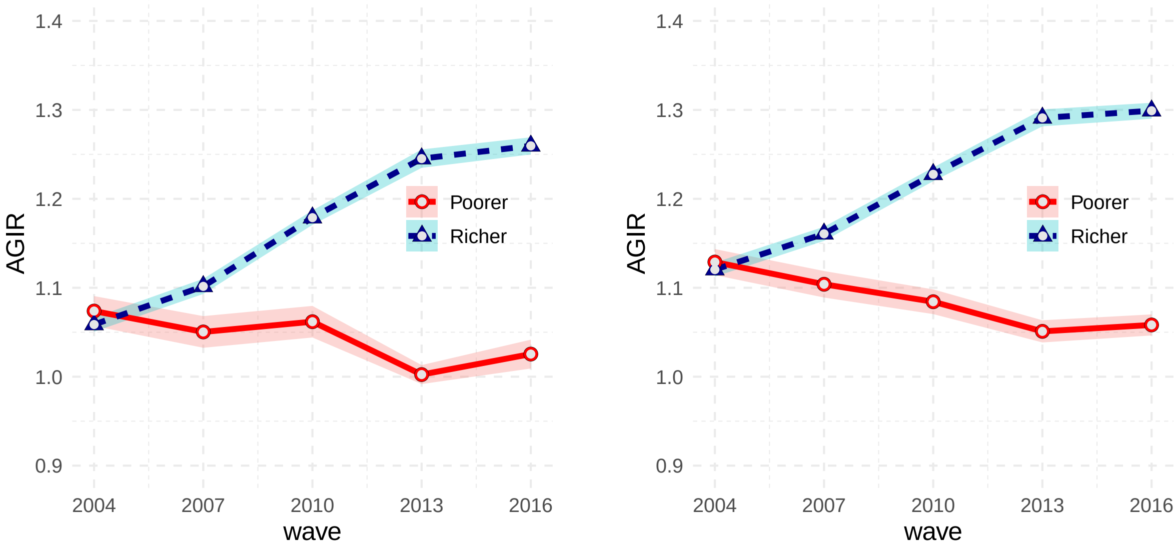
[18] These are child benefits for Australia, Belgium, Denmark, and Poland; housing benefits for Australia, Israel, Slovakia, and Switzerland; and general assistance for Denmark, France, Paraguay, and Uruguay.

We plot the two statistics side-by-side in Figure 7. Since more young individuals (aged 25–34) are renters and have children, a large share of household benefits accrues to younger 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, $AGIR$ with household benefits fell by 0.2 percentage points less than the baseline in poorer countries (out of 6.1) and 0.3 less in richer ones (out of 18.5).

We conclude that household-level benefits are, on average, only slightly age-biased in favour of the young,[19] and that this bias has not substantially changed over time.

Figure 7. $AGIR$, 55–64 vs 25–34 years old

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



Notes: The left panel depicts the Age Group Income Ratio ($AGIR$) comparing late-career (55–64 years) to early-career (25–34 years) individuals using our baseline personal income definition. The right panel shows the same statistic computed after allocating household-level benefit payments to individual members. Lines represent simple averages across countries within each income group (dashed blue: high-income; solid red: middle-income). Shaded areas show 95% confidence intervals calculated using the delta method.

C 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

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

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

Rearranging, we have:

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

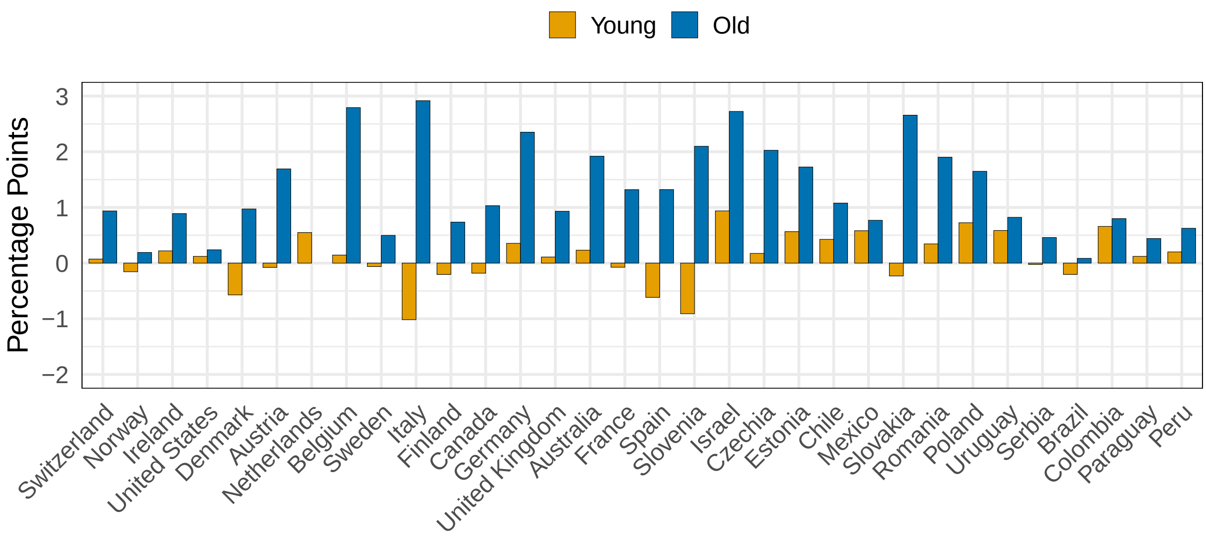
Then, for small $g(y_{\text{young}})$, the annualised income growth rates differential $g(y_{\text{old}}) - g(y_{\text{young}})$ approximates the annualised growth rate of the income ratio $R(T)$:

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

D Employment and Wage margin by age group

Figure 8 disaggregates the employment margin by age group.

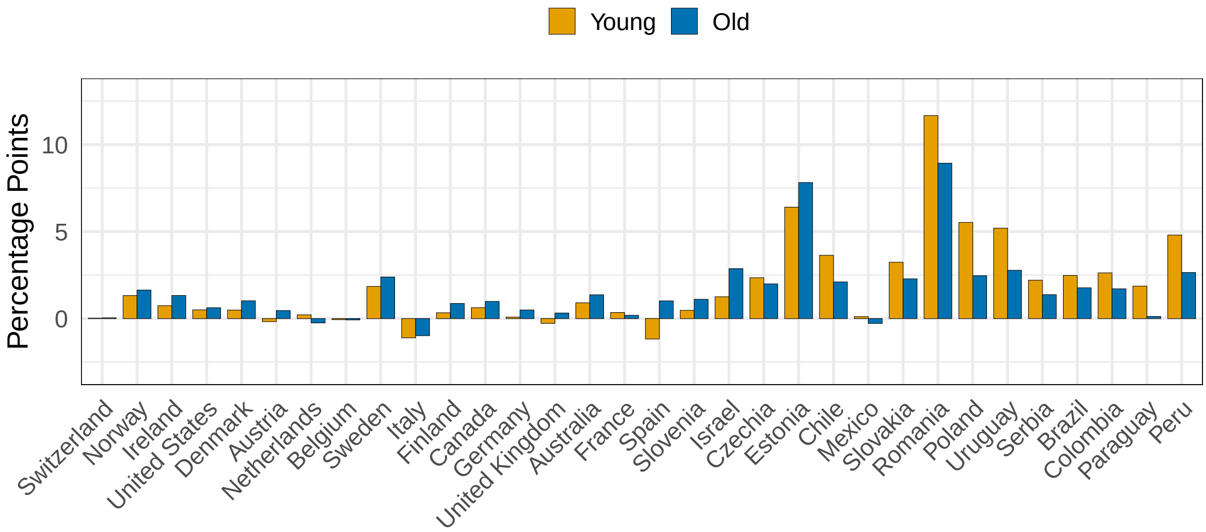
Figure 8. Employment margin of income growth rate



Notes: The figure depicts the employment margin of the Growth Rate Differential for late-career individuals (55–64 years old, "old") and early-career individuals (25–34, "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.

Figure 9 disaggregates the wage margin by age group.

Figure 9. Labor earnings margin of income growth rates



Notes: The figure depicts the earnings margin of the Growth Rate Differential for late-career individuals (55–64 years old, "old") and early-career individuals (25–34., "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.

D.1 The Role of Education Enrolment

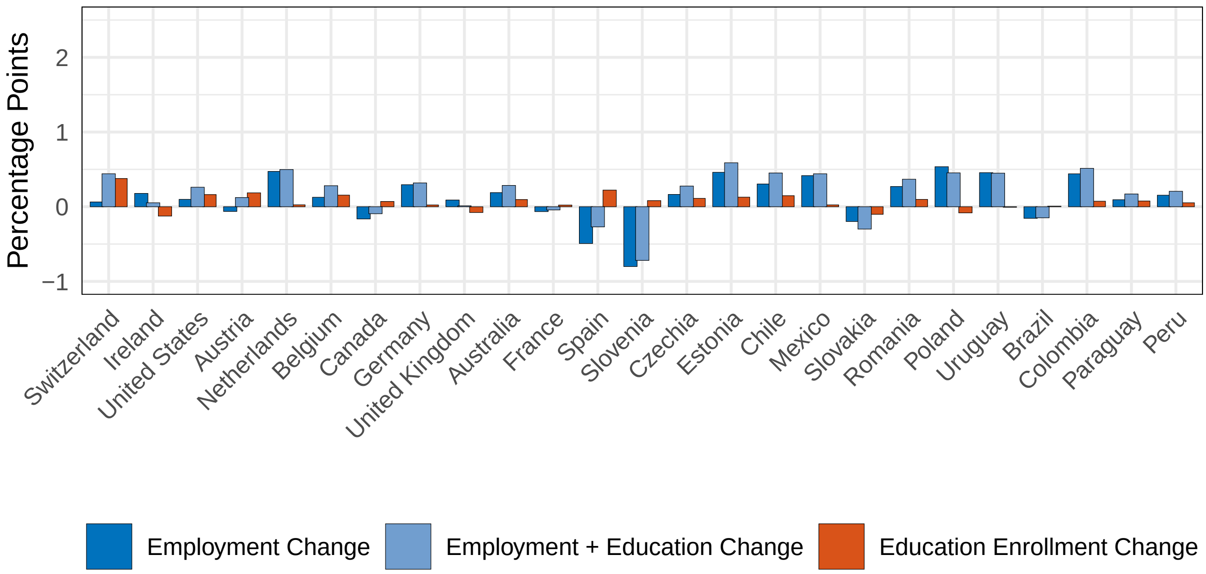
As shown in Figure 8, the positive employment margin of AGIR growth seen in most countries is mainly driven by a positive component for the old and a small, either positive or negative, component for the young. We now exclude that this latter phenomenon is due to an increase enrolment of the young into education, rather than work.

In Figure 10 we plot the 2004-2018 annualised changes in employment rates of the young (panel a) and old (panel b) together with changes in the share of individuals who are *only* enrolled in education and do not work and the sum of the two. Both panels are reported with the same scale to directly compare the different magnitudes of employment changes of young and old. As a reminder, the differential in employment rate changes is the main driver of the "employment margin of income growth" plotted in Figure 8.

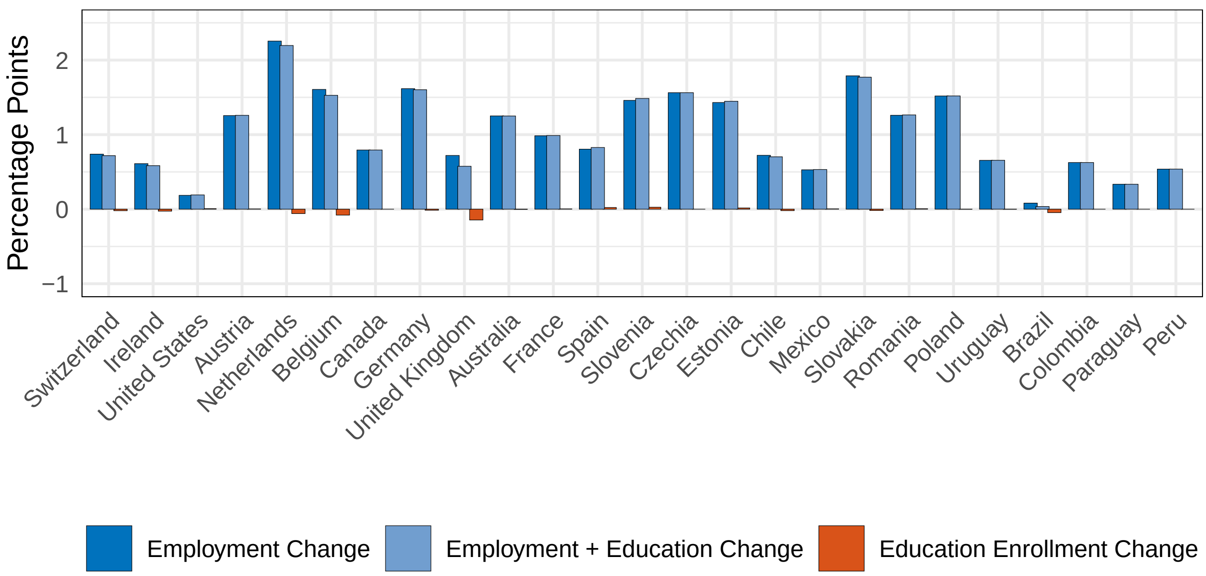
The figures suggest three considerations are in order. First, similarly to Figure 8, we see that the main action happens in the employment of the old, which grows rapidly between 2004 and 2018, rather than in the employment rate of the young, which is either stationary or slightly falling in most countries. Second, changes in enrolment rates among the young were marginal in most countries, with the exception of Switzerland. Third, the sum of changes in employment and enrolment is an upper bound of how much employment would have changed between 2014 and 2018, had some individuals not engaged in the education, since some of the increase in enrolment may be coming from individuals that would have otherwise been out of the labour force or unemployed. Hence, we can conclude that the effect of education choices of the young on the employment margin of income growth are small. Hence, education choices were not an important driver of either the employment margin of the GRD of AGIR, or the growth of AGIR itself.

Figure 10. Employment and education enrolment changes, 2004-2018, by age group

(a) Young



(b) Old



Note: The figure depicts the employment change, education enrolment change and the sum of the two for the young (25-34 y.o.) and the old (55-64 y.o.). Enrolment is defined as being enrolled in education without being employed. Hence, employment and enrolment are mutually exclusive categories.

E The Role of Hours Worked

In this section, we separately account for the intensive and extensive margins of labour in determining changes in $AGIR$—that is, we separately identify the roles of hours worked and employment.

To do so, we decompose the contribution of labour earnings to the Growth Rate Differential between old and young incomes into the contribution of hourly earnings growth and the contribution of hours worked growth. A few countries do not report hours worked at either or both endpoints of the sample and are therefore dropped from this analysis: Denmark, Finland, Norway, Poland, Serbia, Slovenia, and Sweden.

Table IX reports our findings aggregated by country group. The relative change in hours worked between old and young contributed negligibly to $AGIR$ dynamics in both country groups: 0.02 pp per year in high-income countries and 0.12 pp per year in middle-income countries. These contributions are substantially smaller than those arising from other components and account for less than 8% of the total labour earnings contribution to $AGIR$, with the remaining 92% explained by changes in the relative hourly earnings of old and young.

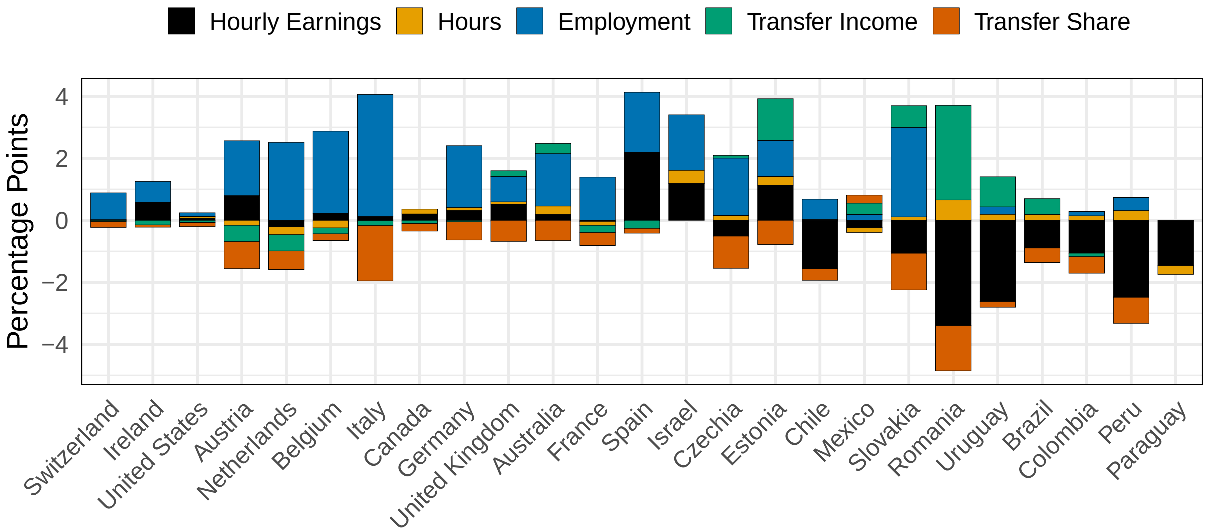
TABLE IX. Growth Rate Differential contributions, with hours decomposition

	GRD contribution (percentage points)				
Country Group	Hourly Earnings	Hours	Employment	Transfer Income	Transfer Share
Poorer	-1.135	0.123	0.474	0.568	-0.463
Richer	0.283	0.023	1.200	-0.087	-0.381

Notes: The table reports the average annualised GRD contributions (percentage points) for high-income and middle-income countries. Unlike Table II in the main text, the wage margin is further decomposed into hourly earnings and hours worked. The hours margin moved in the same direction as the employment margin in both country groups but contributed negligibly: +0.02pp in high-income and +0.12pp in middle-income countries.

Finally, Figure 11 reports the GRD decomposition by country under the extended margin breakdown. The hours margin (shown in pink) contributes negligibly in most countries.

Figure 11. *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 (55–64 years old) with early-career individuals (25-34). "Hourly earnings" refers to the contribution to the *GRD* of differences in growth of the average labor earnings per hours received, conditional on being employed. "Hours" refers to the contribution of differences in growth in average hours worked, 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.

F *AGIR* and *GRD* across Demographics

Two concerns might complicate interpretation. First, if high-income countries raised retirement ages faster than middle-income countries, the employment margin might simply reflect pension reforms rather than market forces. Second, if rising female labor force participation disproportionately benefited older women, the employment margin might confound gender and age effects.

Table X addresses both concerns by recomputing GRD and its components for restricted samples: (i) individuals below statutory retirement age, (ii) males only, (iii) females only. The employment margin persists across all specifications. Restricting to below-retirement-age workers reduces the employment margin slightly in high-income countries (from +1.2 pp to +1.0 pp) but leaves it dominant. Disaggregating by gender reveals positive employment margins for both males (+0.9 pp) and females (+1.5 pp) in high-income countries. The wage margin remains negative in middle-income countries (-1.3 pp) across all samples. The patterns documented above reflect general labor market dynamics, not specific demographic or policy shifts.

TABLE X. GRD for different demographics

	Rich Countries			**Poor Countries**		
	GRD	Employment	Wages	GRD	Employment	Wages
Full Sample	1.35	0.43	1.58	-0.62	-1.34	0.77
Men	1.05	0.45	1.23	-0.76	-1.32	0.61
Women	2.30	0.91	2.06	0.03	-0.91	0.87
Below retirement age†	1.13	0.43	1.23	-0.25	-0.45	0.48

†: Due to the official retirement age being equal or lower to lower bound of the old group (55 y.o.), this subsample excludes Italy, Australia, Romania, Serbia, Brazil, Paraguay and Peru from the sample. Hence, it is not directly comparable to the previous rows.
Notes: The table reports the GRD and its main components for the full sample and three subsamples: only men; only women; only individuals below the country's retirement age.

Next, we focus on the employment component, which is the novel contribution of the paper and the most important margin of AGIR in rich countries, and we present this margin for different demographic subsets in each country.

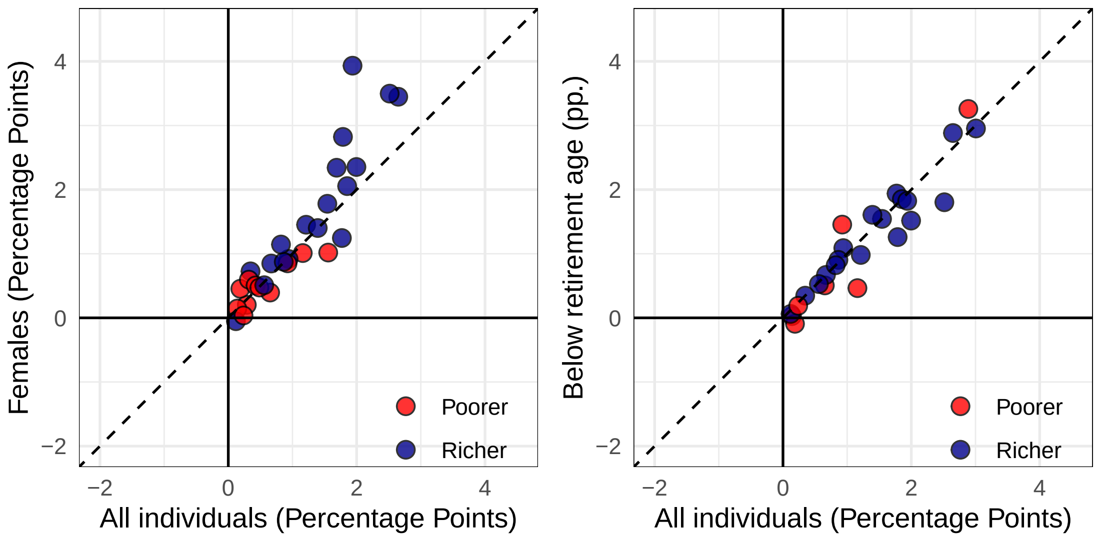
F.1 Employment margin decomposition by demographic

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 12a 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. [20] 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.

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 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).[21]. The employment margin of this alternative $AGIR$ measure (0.8 pp.) is similar to the headline figure (0.9 pp.), as displayed in Figure 12b. 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 12. Employment component of GRD across demographics subsets

(a) Sex (b) Pension age cutoff



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.

[20]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.

[21]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.

F.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 13, and for the definition of old that have age below the minimum pension age in Figure 14.

Figure 13. *GRD* decomposition: Male and Female

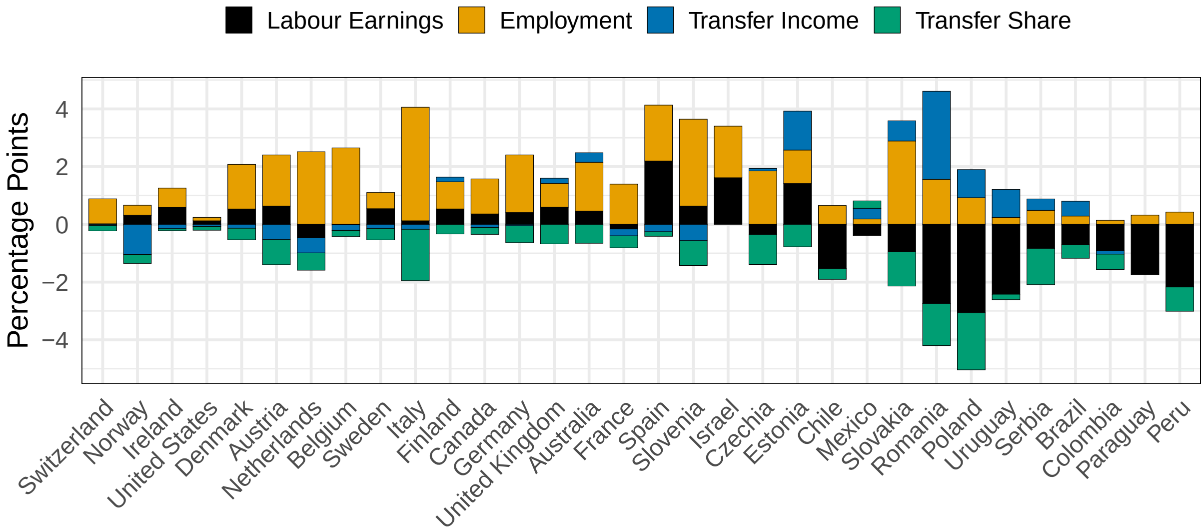
(a) Male

(b) Female

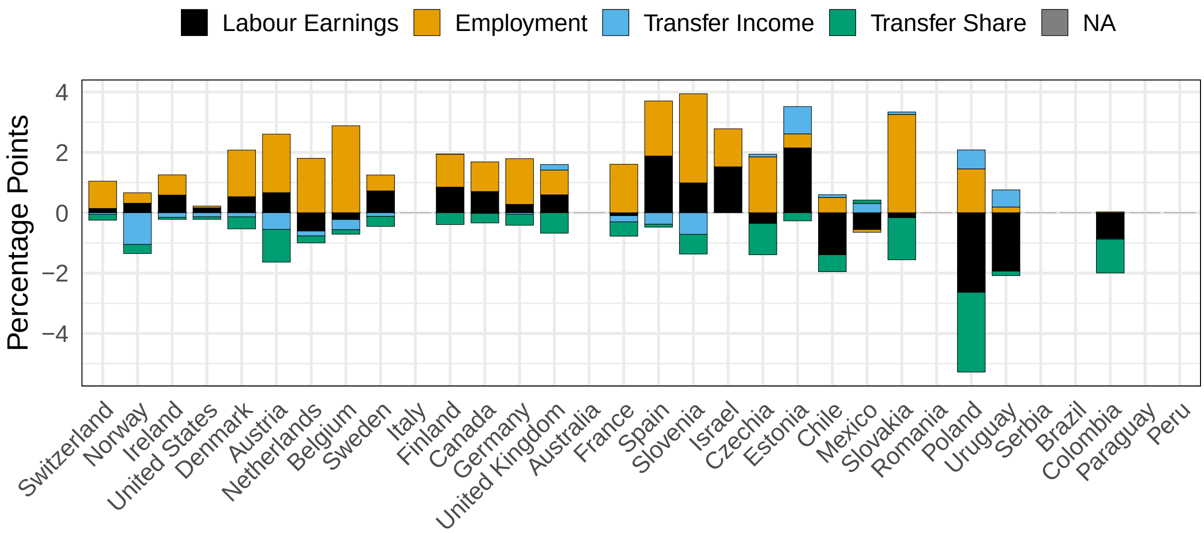
Notes: panel (a) depicts the employment contribution (lighter red bar) to the *GRD*s for male late-career individuals (50-64 y.o.) and male early-career individuals (25-34 y.o), and the labor earnings contribition (black bar). Panel (b) depicts the two contributions for female.

Figure 14. *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.3 Under-60 years old

Since the official retirement ages may not fully capture differences in retirement behaviour, we perform a further robustness check by restricting our definition of "old" individuals to individuals aged 50-59 years old.

In Table XI we replicate the GRD decomposition for richer and poorer countries. Restricting our definition of old does not qualitatively change our findings. Moreover, the quantitative differences with our baseline results are also small. The total GRD of richer countries is virtually unchanged (1.18 pp./year vs 1.21), similarly to labour earning (0.49 pp./year vs 0.44) while the employment component is just 0.13 pp. lower than the baseline (1.06 pp./year vs 1.18). The differences in poorer countries are larger, with the GRD being

-0.69 pp./year vs -0.84 of the baseline, but preserve the same initial intuition.

TABLE XI. Growth Rate Differential contributions, with a different definition of old

		GRD contribution (percentage points)				
Country Group	Old Definition	Labour Earnings	Employment	Transfer Income	Transfer Share	Total
Poorer	50-59 y.o.	-0.908	0.619	0.180	-0.579	-0.688
Poorer	Baseline	-1.280	0.465	0.445	-0.471	-0.841
Richer	50-59 y.o.	0.486	1.055	-0.125	-0.235	1.182
Richer	Baseline	0.440	1.184	-0.109	-0.309	1.207

Notes: The table reports the average contributions to the GRD for richer and poorer countries. We separately report our baseline results, already presented in the main text, and the results obtained when restricting the definition of "old" to individuals aged 50 to 59, rather than 50 to 64.

G 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 XII 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.[22] 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.

[22]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 XII. 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.

H Model Solution and Estimation

H.1 Equilibrium

Definition 1. Given the initial skill distribution $\{\rho_{s,2-a}\}_{a>1,s\in\mathbb{S}}$ and the sequence of cohort sizes $\{N_t\}_{t=-3}^{\infty}$, a sequential market equilibrium is a sequence of household allocations $\{\{\hat{c}^a_{s,t},\hat{l}^a_{s,t}\}_{t=1}^{\infty}\}_{a\in\mathbb{A},s\in\mathbb{S}}$, household education choices $\{\{\hat{s}_i\}_{i=0}^{N_t}\}_{t=-3}^{\infty}$, 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 $\{\{\hat{w}_{s,t}\}_{t=1}^{\infty}\}_{s\in\mathbb{S}}$, $\{\{\hat{c}^a_{s,t},\hat{l}^a_{s,t}\}_{t=1}^{\infty}\}_{a\in\mathbb{A},s\in\mathbb{S}}$ solve the household problems from Equations (9), (10), and (11).
2. $\forall\ t\geq 1$, education choices $\{\hat{s}_i\}_{i=0}^{N_t}$ satisfy

$$s_i \in \arg\max_{s,\{c^{1+j}_{s,t+j},l^{1+j}_{s,t+j},B^{1+j}_{s,t+j+1}\}_{j=0}^{A-2}} U^1_{s,t}(c^1_{s,t},l^1_{s,t})+\sum_{j=1}^{A-1}\mathbb{E}_t\left(U^{1+j}_{s,t+j}(c^{1+j}_{s,t+j},l^{1+j}_{s,t+j})\right)$$

$$\text{s.t.}\quad \begin{cases} c^{1+j}_{s,t+j}+B^{1+j}_{s,t+j+1}\leq B^{j}_{s,t+j}+w_{s,t+j}(1+g^{1+j}_{s,t+j})l^{1+j}_{s,t+j}\kappa(s)^{-1} \\ \qquad +\tau^{1+j}_{s,t+j}(1-l^{1+j}_{s,t+j})\kappa(s)^{-1},\ \forall j\in\{0,\dots,A-1\} \\ B^0_{s,t}=0, \\ l^{1+j}_{s,t+j}\in[0,1];\ c^{1+j}_{s,t+j}\geq 0,\ \forall j\in\{0,\dots,A-1\}. \end{cases}$$

3. For all $t\geq 1$,

   (a) (Goods Market Clears)

$$\sum_{s\in\mathbb{S}}\sum_{a\in\mathbb{A}}\rho_{s,t-a+1}N_{t-a+1}c^a_{s,t}=Y_t(\hat{L}_t),$$

   (b) (Labor Markets Clear)

$$\sum_{a\in\mathbb{A}}\rho_{s,t-a+1}N_{t-a+1}(1+g^a_{s,t})\hat{l}^a_{s,t}=\hat{L}_{s,t},\qquad \forall s\in\mathbb{S}, \tag{15}$$

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

$$V^1_t(s)=V^1_t(s'),\qquad \forall s,s'\in\mathbb{S}.$$

H.1.1 Equilibrium Characterization

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

$$l^a_{s,t}=\left[\frac{w_{s,t}(1+g^a_{s,t}-\tilde{\tau}^a_{s,t})}{\kappa(s)}(1+b)\alpha^a_{s,t}\right]^{\frac{1}{b}}. \tag{16}$$

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

$$\frac{l^a_{s,t}}{l^{a'}_{s,t}} = \left[\frac{\alpha^a_{s,t}}{\alpha^{a'}_{s,t}}\frac{(1+g^a_{s,t}-\tilde{\tau}^a_{s,t})}{(1+g^{a'}_{s,t}-\tilde{\tau}^{a'}_{s,t})}\right]^{\frac{1}{b}}. \tag{17}$$

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 15), we can express $L_{s,t}$ as:

$$\begin{aligned}
L_{s,t} &= \sum_{a\in\mathbb{A}} \rho_{s,t-a+1}N_{t-a+1}(1+g^a_{s,t})l^a_{s,t} \\
&= \sum_{a\in\mathbb{A}} \rho_{s,t-a+1}N_{t-a+1}(1+g^a_{s,t})\left[\frac{w_{s,t}(1+g^a_{s,t}-\tilde{\tau}^a_{s,t})}{\kappa(s)}(1+b)\alpha^a_{s,t}\right]^{\frac{1}{b}} \\
&= \left(\frac{w_{s,t}(1+b)}{\kappa(s)}\right)^{\frac{1}{b}} \sum_{a\in\mathbb{A}} \rho_{s,t-a+1}N_{t-a+1}(1+g^a_{s,t})(1+g^a_{s,t}-\tilde{\tau}^a_{s,t})^{\frac{1}{b}}\left(\alpha^a_{s,t}\right)^{\frac{1}{b}}.
\end{aligned} \tag{18}$$

Hence, the equilibrium wages satisfy:

$$w_{s,t} = \kappa(s)\frac{L^b_{s,t}}{(1+b)}\left(\sum_{a\in\mathbb{A}} \rho_{s,t-a+1}N_{t-a+1}(1+g^a_{s,t})(1+g^a_{s,t}-\tilde{\tau}^a_{s,t})^{\frac{1}{b}}\left(\alpha^a_{s,t}\right)^{\frac{1}{b}}\right)^{-b}. \tag{19}$$

Using the solution to the firm's problem (see Equation 14), we derive the relative equilibrium wages of skills s and s' as:

$$\frac{w_{s,t}}{w_{s',t}} = \left(\frac{A_{s,t}}{A_{s',t}}\right)^{1-\frac{1}{\theta}}\left(\frac{L_{s,t}}{L_{s',t}}\right)^{-\frac{1}{\theta}}. \tag{20}$$

Using Equations (19) and (20) 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:

$$\frac{w_{s,t}}{w_{s',t}} = \left(\frac{A_{s,t}}{A_{s',t}}\right)^{\frac{b(\theta-1)}{1+b\theta}}\left(\frac{\kappa(s)}{\kappa(s')}\right)^{\frac{1}{1+b\theta}}\left(\frac{X_{s',t}}{X_{s,t}}\right)^{\frac{b}{1+b\theta}}, \tag{21}$$

where $X_{s,t} = \sum_{a\in\mathbb{A}} \rho_{s,t-a+1}N_{t-a+1}(1+g^a_{s,t})(1+g^a_{s,t}-\tilde{\tau}^a_{s,t})^{\frac{1}{b}}\left(\alpha^a_{s,t}\right)^{\frac{1}{b}}$.

Skill Shares Finally, utility is equalized across all young workers of different skills, as they must be ex-ante indifferent between education choices. Hence, assuming perfect foresight,

$$\begin{aligned}
&\sum_{a\in\mathbb{A}}\left(\frac{w_{s,t+a-1}(1+g^a_{s,t+a-1}-\tilde{\tau}^a_{s,t+a-1})}{\kappa(s)}\right)^{\frac{1+b}{b}} C^a_{s,t+a-1} + \frac{\sum_{a\in\mathbb{A}}\tau^a_{s,t+a-1}}{\kappa(s)} = \\
&\sum_{a\in\mathbb{A}}\left(\frac{w_{s',t+a-1}(1+g^a_{s',t+a-1}-\tilde{\tau}^a_{s',t+a-1})}{\kappa(s')}\right)^{\frac{1+b}{b}} C^a_{s',t+a-1} + \frac{\sum_{a\in\mathbb{A}}\tau^a_{s',t+a-1}}{\kappa(s')},
\end{aligned} \tag{22}$$

where $C^a_{s,t+a-1} = \left(\frac{\alpha^a_{s,t+a-1}}{1+b}\right)^{\frac{1}{b}} \frac{b}{1+b}$.

Noting that $w_{s,t+k} = w_{s,t}(1 + \Delta_{t,t+k} w_s)$, we obtain the following expression for the relative education costs of different skills:

$$\frac{\kappa(s)}{\kappa(s')} = \frac{w_{s,t}}{w_{s',t}} \left[\underbrace{\frac{\sum_{a\in\mathbb{A}} \left(\alpha^a_{s,t+a-1}\right)^{\frac{1}{b}} \left((1+\Delta_{t,t+a-1}w_s)(1+g^a_{s,t+a-1}-\tilde{\tau}^a_{s,t+a-1})\right)^{\frac{1+b}{b}} + \frac{\kappa(s)^{\frac{1}{b}}}{w_{s,t}^{\frac{1}{b}}} \left(\sum_{a\in\mathbb{A}}(1+\Delta_{t,t+a-1}w_s)\tilde{\tau}^a_{s,t+a-1}\right)}{\sum_{a\in\mathbb{A}} \left(\alpha^a_{s',t+a-1}\right)^{\frac{1}{b}} \left((1+\Delta_{t,t+a-1}w_{s'})(1+g^a_{s',t+a-1}-\tilde{\tau}^a_{s',t+a-1})\right)^{\frac{1+b}{b}} + \frac{\kappa(s')^{\frac{1}{b}}}{w_{s',t}^{\frac{1}{b}}} \left(\sum_{a\in\mathbb{A}}(1+\Delta_{t,t+a-1}w_{s'})\tilde{\tau}^a_{s',t+a-1}\right)}}_{\Omega_t(s,s')} \right]^{\frac{b}{1+b}}. \tag{23}$$

Calling the bracketed term (excluding the exponent $\frac{b}{1+b}$) $\Omega_t(s,s')$, and substituting Equation (21), yields an expression for the relative education levels only as a function of parameters and the growth in education shares between different generations $\Delta_{t,t-a+1}\rho_s$:

$$\frac{\rho_{s,t}}{\rho_{s',t}} \left[\frac{\sum_{a\in\mathbb{A}} \frac{(1+g^a_{s,t})(1+g^a_{s,t}-\tilde{\tau}^a_{s,t})^{\frac{1}{b}}\left(\alpha^a_{s,t}\right)^{\frac{1}{b}}}{(1+\Delta_{t-a+1,t}\rho_s)(1+\Delta_{t-a+1,t}N)}}{\sum_{a\in\mathbb{A}} \frac{(1+g^a_{s',t})(1+g^a_{s',t}-\tilde{\tau}^a_{s',t})^{\frac{1}{b}}\left(\alpha^a_{s',t}\right)^{\frac{1}{b}}}{(1+\Delta_{t-a+1,t}\rho_{s'})(1+\Delta_{t-a+1,t}N)}} \right] = \left(\frac{\kappa(s')}{\kappa(s)}\right)^{\theta} \left(\frac{A_{s,t}}{A_{s',t}}\right)^{\theta-1} \Omega_t(s,s')^{\frac{1+b\theta}{1+b}}. \tag{24}$$

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

$$1 = \rho_{L,t} \sum_s \frac{\rho_{s,t}}{\rho_{L,t}}. \tag{25}$$

Finally, the wage level is pinned down by the system of equations given by (18), (24), (25), and the firm's first-order condition (14).

H.2 Estimation Equations

Using the characterization of the equilibrium conditions, we can write the following system of equations with as only unknowns the parameters $\alpha^a_{s,t}$, $\kappa(s)$, and $A_{s,t}$:[23]

$$\begin{cases} \ln\left(\dfrac{w_{s,t}}{w_{L,t}}\right) = \frac{1-\theta}{\theta}\ln\left(\dfrac{A_{s,t}}{A_{L,t}}\right) - \frac{1}{\theta}\ln\left(\dfrac{\sum_{a\in\mathbb{A}}(1+g^a_{s,t})(1+\Delta_{t-a+1,t}N)l^a_{s,t}\rho_{s,t-a+1}}{\sum_{a\in\mathbb{A}}(1+g^a_{L,t})(1+\Delta_{t-a+1,t}N)l^a_{L,t}\rho_{L,t-a+1}}\right) & \forall t, s\neq L \\ -\ln\left(\dfrac{\alpha^a_{s,t}}{\kappa(s)}\right) = \left[\ln(1+g^a_{s,t}-\tilde{\tau}_{s,t}) + \ln\left(\dfrac{w_{s,t}}{w_{L,t}}\right) + \ln(w_{L,t})\right] + \ln(1+b) - b\ln(l^a_{s,t}) & \forall a, s, t \\ \dfrac{\rho_{s',t}}{\rho_{s,t}} = \left(\dfrac{\kappa(s)}{\kappa(s')}\right)^{\theta}\left(\dfrac{A_{s,t}}{A_{s',t}}\right)^{1-\theta}\left[\dfrac{\sum_{a\in\mathbb{A}}\frac{(1+g^a_{s,t})(1+g^a_{s,t}-\tilde{\tau}^a_{s,t})^{\frac{1}{b}}\left(\alpha^a_{s,t}\right)^{\frac{1}{b}}}{(1+\Delta_{t-a+1,t}\rho_s)(1+\Delta_{t-a+1,t}N)}}{\sum_{a\in\mathbb{A}}\frac{(1+g^a_{s',t})(1+g^a_{s',t}-\tilde{\tau}^a_{s',t})^{\frac{1}{b}}\left(\alpha^a_{s',t}\right)^{\frac{1}{b}}}{(1+\Delta_{t-a+1,t}\rho_{s'})(1+\Delta_{t-a+1,t}N)}}\right]\Omega_t(s,s')^{-\frac{1+b\theta}{1+b}} & \forall s\neq L, t=1 \\ \left(\sum_{s'} A_{s',t}\left(L_{s',t}\right)^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}-1} A_{L,t}L_{L,t}^{\frac{\theta-1}{\theta}-1} = w_{L,t} \\ \ln(A_{s,t}) = \frac{\theta}{\theta-1}\left(\ln(w_{s,t}) + \theta^{-1}\ln(L_{s,t})\right) \\ \rho_{L,t} = \left(\sum_s \frac{\rho_{s,t}}{\rho_{L,t}}\right)^{-1} \end{cases} \tag{26}$$

H.3 Estimation Details

H.3.1 Moments

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

[23] Notice that $g^a_{s,t}$ is identified directly from the empirical moments.

TABLE XIII. Data moments used for the model estimation

			Ret. to experience			Transfers			Size
Country	Wave	Age	g College	g HS	g LHS	τ^a Co	τ^a HS	τ^a LHS	N
Poorer	2004	1	0.00	0.00	0.00	0.12	0.12	0.13	0.26
Poorer	2004	2	0.28	0.19	0.05	0.25	0.20	0.17	0.24
Poorer	2004	3	0.43	0.30	0.07	0.67	0.42	0.33	0.23
Poorer	2004	4	0.46	0.25	-0.09	1.12	0.84	0.62	0.16
Poorer	2004	5	0.31	-0.01	-0.40	1.11	0.95	0.77	0.12
Poorer	2018	1	0.00	0.00	0.00	0.13	0.13	0.14	0.24
Poorer	2018	2	0.28	0.12	0.03	0.24	0.18	0.17	0.24
Poorer	2018	3	0.38	0.16	-0.01	0.63	0.32	0.22	0.21
Poorer	2018	4	0.48	0.13	-0.11	0.94	0.66	0.46	0.18
Poorer	2018	5	0.60	-0.07	-0.36	1.02	0.87	0.67	0.13
Richer	2004	1	0.00	0.00	0.00	0.37	0.37	0.31	0.22
Richer	2004	2	0.33	0.16	0.09	0.50	0.42	0.38	0.24
Richer	2004	3	0.49	0.23	0.13	0.58	0.51	0.43	0.23
Richer	2004	4	0.49	0.20	0.08	0.90	0.73	0.58	0.18
Richer	2004	5	0.36	-0.13	-0.23	0.92	0.74	0.63	0.12
Richer	2018	1	0.00	0.00	0.00	0.34	0.37	0.31	0.21
Richer	2018	2	0.35	0.18	0.17	0.55	0.49	0.37	0.21
Richer	2018	3	0.57	0.27	0.24	0.64	0.52	0.43	0.23
Richer	2018	4	0.58	0.26	0.20	0.92	0.74	0.60	0.20
Richer	2018	5	0.27	-0.13	-0.18	1.02	0.86	0.77	0.15

			Relative Wage to LHS		Employment Rate			Education Shares		
Country	Wave	Age	w College	w HS	l College	l HS	l LHS	ρ College	ρ HS	ρ LHS
Poorer	2004	1	2.87	1.62	0.84	0.74	0.61	0.17	0.49	0.34
Poorer	2004	2	2.87	1.62	0.90	0.80	0.64	0.16	0.47	0.38
Poorer	2004	3	2.87	1.62	0.87	0.75	0.62	0.14	0.42	0.44
Poorer	2004	4	2.87	1.62	0.62	0.45	0.41	0.12	0.34	0.55
Poorer	2004	5	2.87	1.62	0.24	0.17	0.21	0.08	0.25	0.67
Poorer	2018	1	3.47	2.20	0.83	0.76	0.60	0.29	0.46	0.25
Poorer	2018	2	3.47	2.20	0.89	0.82	0.68	0.24	0.45	0.31
Poorer	2018	3	3.47	2.20	0.90	0.80	0.64	0.19	0.45	0.36
Poorer	2018	4	3.47	2.20	0.71	0.57	0.46	0.16	0.41	0.43
Poorer	2018	5	3.47	2.20	0.25	0.20	0.21	0.13	0.34	0.53
Richer	2004	1	1.51	1.18	0.83	0.78	0.61	0.37	0.47	0.16
Richer	2004	2	1.51	1.18	0.89	0.82	0.67	0.32	0.47	0.21
Richer	2004	3	1.51	1.18	0.89	0.80	0.63	0.28	0.44	0.28
Richer	2004	4	1.51	1.18	0.63	0.50	0.37	0.24	0.39	0.38
Richer	2004	5	1.51	1.18	0.13	0.08	0.05	0.16	0.32	0.51
Richer	2018	1	1.51	1.20	0.82	0.76	0.57	0.47	0.39	0.13
Richer	2018	2	1.51	1.20	0.89	0.82	0.63	0.47	0.39	0.15
Richer	2018	3	1.51	1.20	0.89	0.82	0.63	0.37	0.43	0.20
Richer	2018	4	1.51	1.20	0.74	0.62	0.45	0.32	0.41	0.27
Richer	2018	5	1.51	1.20	0.15	0.11	0.07	0.27	0.38	0.36

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.

H.3.2 Algorithm

We estimate the parameters of the model straightforwardly from the system of equations (26), according to the following algorithm:

1. Compute $g^a_{s,t}$ by taking the ratio of old and young wages in each period: $g^a_{s,t} = \frac{w^a_{s,t}}{w^1_{s,t}}$.
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 $A_{s,t}A^{-1}_{L,t}$ 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 $A_{s,t}A^{-1}_{L,t}$.
5. Recover $\alpha^a_{s,t}\kappa(s)^{-1}$ from wages and employment rates.
6. Use 2004 data to estimate $\Delta_{t-a+1,t}\rho_s = \frac{\rho^1_{s,2004}}{\rho^a_{s,2004}} - 1$ and $\Delta_{t-a+1,t}N = \frac{n^1_{2004}}{n^a_{2004}}$.
7. Use 2018 estimates for $\alpha^a_{s,t}\kappa(s)^{-1}$ from (5), return to age from (1), and the assumption $\Delta_{t,t+a-1}w_s = \frac{w_{s,2018}}{w_{s,2004}} - 1$ to compute the relative expectation term

$$\tilde{\Omega}_{2018}(s,s') = \left(\frac{\kappa(s)}{\kappa(s')}\right)^{-\frac{1}{b}} \Omega_{2018}(s,s').$$

   Notice that the value of $\tilde{\Omega}_{2018}(s,s')$ is known, since it depends on $\alpha^a_{s,t}\kappa(s)^{-1}$ but not on $\kappa(s)$.
8. Compute eduction costs $\kappa(s)$ by plugging in $\tilde{\Omega}_{2018}(s,s')$ in Equation (23) so that:

$$\frac{\kappa(s)}{\kappa(s')} = \left(\frac{w_s}{w_{s'}}\right)^{\frac{1+b}{b}} \tilde{\Omega}_{2018}(s,s')$$

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

H.4 Parameter Estimates

TABLE XIV. Parameter estimates

		Poor					Rich				
	Skill	a=1	a=2	a=3	a=4	a=5	a=1	a=2	a=3	a=4	a=5
	High	0.20	0.22	0.26	0.19	0.01	0.29	0.27	0.25	0.12	0.00
α_{2004}	Mid	0.11	0.13	0.12	0.05	0.02	0.20	0.20	0.19	0.06	0.00
	Low	0.05	0.06	0.07	0.04	0.06	0.06	0.08	0.07	0.02	0.00
	High	0.16	0.17	0.24	0.15	0.00	0.26	0.29	0.25	0.19	0.00
α_{2018}	Mid	0.09	0.11	0.11	0.06	0.02	0.17	0.21	0.19	0.11	0.01
	Low	0.03	0.05	0.04	0.03	0.04	0.05	0.06	0.06	0.03	0.00
	High	0.00	0.28	0.43	0.46	0.31	0.00	0.33	0.49	0.49	0.36
g_{2004}	Mid	0.00	0.19	0.30	0.25	-0.01	0.00	0.16	0.23	0.20	-0.13
	Low	0.00	0.05	0.07	-0.09	-0.40	0.00	0.09	0.13	0.08	-0.23
	High	0.00	0.28	0.38	0.48	0.60	0.00	0.35	0.57	0.58	0.27
g_{2004}	Mid	0.00	0.12	0.16	0.13	-0.07	0.00	0.18	0.27	0.26	-0.13
	Low	0.00	0.03	-0.01	-0.11	-0.36	0.00	0.17	0.24	0.20	-0.18
Δn		0.00	0.06	0.13	0.58	1.18	0.00	0.02	0.16	0.34	0.89

TABLE XV. Parameter estimates

		Poor		Rich	
	Skill	2004	2018	2004	2018
	High	2.01	2.39	1.30	1.50
A_s	Mid	1.30	1.50	0.96	0.93
	Low	0.52	0.65	0.48	0.40
	High	3.90	3.90	2.22	2.22
κ_s	Mid	1.90	1.90	1.45	1.45
	Low	1.00	1.00	1.00	1.00

I 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 **??** 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.

I.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

$$\begin{aligned} AGIR &= \frac{e_{\text{old}} y^n_{\text{old}} + p_{\text{old}} \Theta^n_{\text{old}}}{e_{\text{young}} y^n_{\text{young}} + p_{\text{young}} \Theta^n_{\text{young}}} \\ &= \frac{e_{\text{old}} y^n_{\text{old}}}{e_{\text{young}} y^n_{\text{young}}} \times \frac{1 + \tilde{p}_{\text{old}} \tilde{\Theta}^n_{\text{old}}}{1 + \tilde{p}_{\text{young}} \tilde{\Theta}^n_{\text{young}}} \\ &= \underbrace{\frac{y^n_{\text{old}}}{y^n_{\text{young}}}}_{\text{Age-earnings gap}} \times \underbrace{\frac{e_{\text{old}}}{e_{\text{young}}}}_{\text{Age-employment gap}} \times \underbrace{\frac{1 + \tilde{p}_{\text{old}} \tilde{\Theta}^n_{\text{old}}}{1 + \tilde{p}_{\text{young}} \tilde{\Theta}^n_{\text{young}}}}_{\text{Transfer multiplier}}. \end{aligned} \tag{27}$$

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 exact additive decomposition, we shift our focus to the natural logarithm of $AGIR$, $\ln(AGIR)$:[24]

$$\ln(\text{AGIR}) = \ln\left(\frac{y^n_{\text{old}}}{y^n_{\text{young}}}\right) + \ln\left(\frac{e_{\text{old}}}{e_{\text{young}}}\right) + \ln\left(\frac{1 + \tilde{p}_{\text{old}} \tilde{\Theta}^n_{\text{old}}}{1 + \tilde{p}_{\text{young}} \tilde{\Theta}^n_{\text{young}}}\right). \tag{28}$$

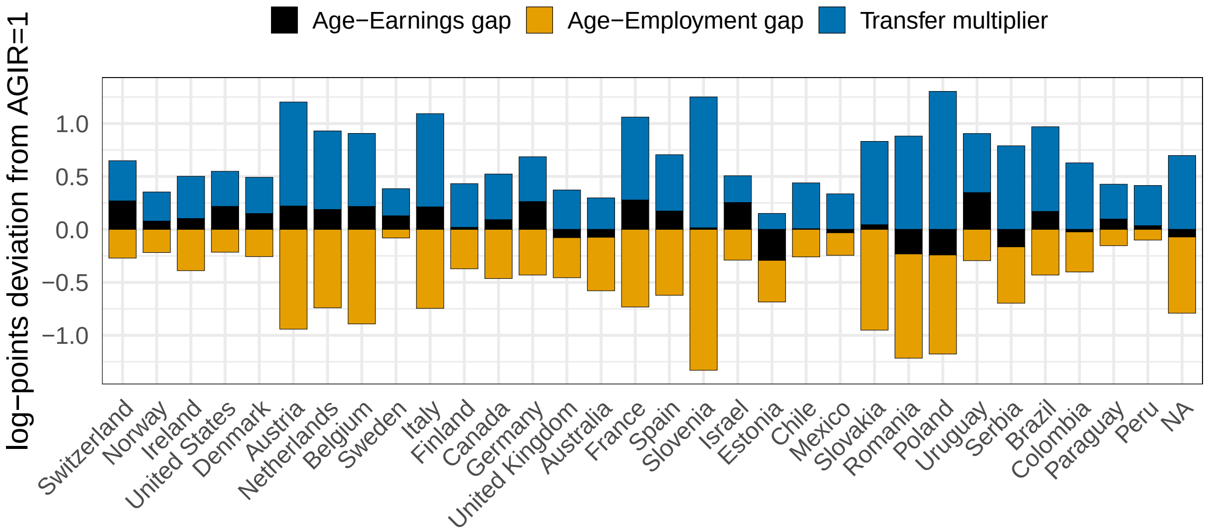
We show the results, separately for 2004 and 2018, in Figure 15. Recall that in 2004, high and lower-income countries had very similar $AGIR$ levels. In fact, their $AGIR$ present very similar compositions. Besides very high-GDP countries, both high- and lower-income countries have similar profiles. 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).

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

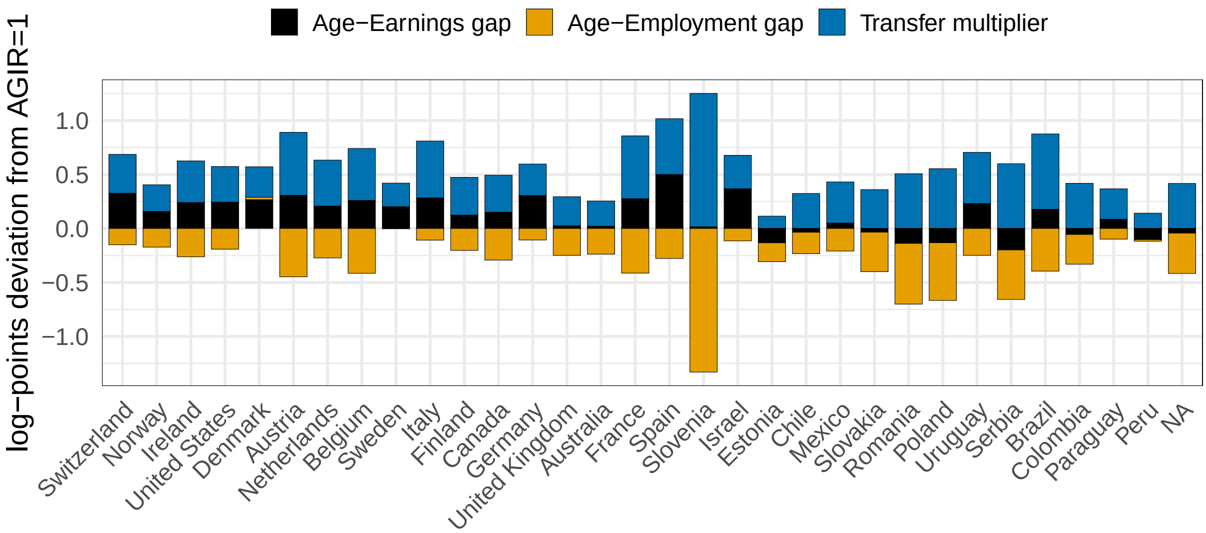
However, in 2018 presents a much clearer separation between high-income and lower-income countries, as well as less heterogeneity within group. $AGIR$ high in richer countries because of large increases in the age-earning gap, but also because of an increase in the age-employment gap, which reduced the 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 15. 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 $\left(\frac{1+\tilde{p}_{\text{old}}\tilde{\Theta}^n_{\text{old}}}{1+\tilde{p}_{\text{young}}\tilde{\Theta}^n_{\text{young}}}\right)$, the log-ratio of one plus transfers in proportion to labor earnings, for old and young.

I.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 XVI. 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 XVI. 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.

J Historical Trends

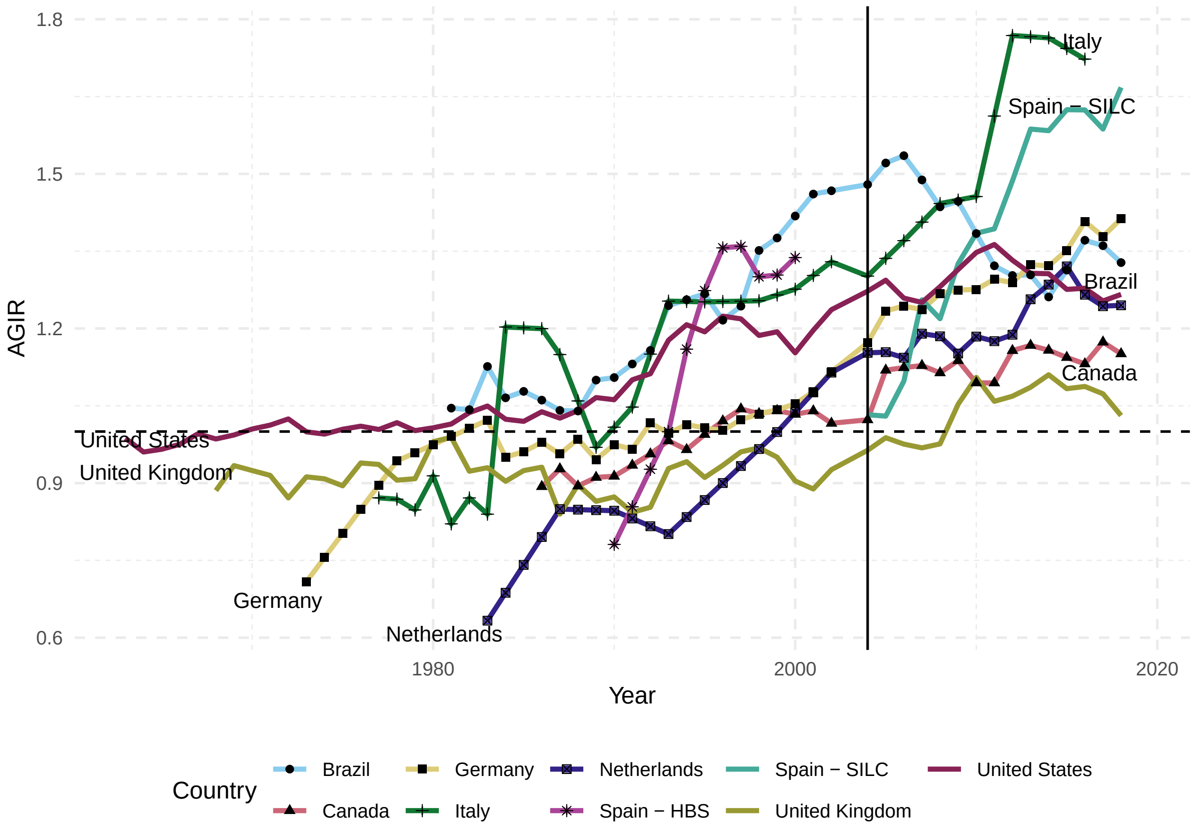
In this section, we leverage historical data for a few countries for which we have consistent time series for additional decades. In particular, we exclude countries which experienced changes in their survey methodology that gave rise to unreasonable changes in their AGIR statistic before 2004.

After this selection, we obtain time series for the United States (from 1963), United Kingdom (1968), Germany (1973), Italy (1977), Brazil (1981), Netherlands (1983), Canada (1986), and Spain (1990). In the case of Spain, a further change in methodology in 2004 does not allow for a direct comparison of pre- and post-2004 AGIR. Hence, we define the pre-2004 period as "Spain - Household Budget Survey (HBS)".

We plot the resulting time series for AGIR in Figure 16. Overall, we can observe a clear upward trend in all countries, besides Brazil (the only developing country) after 2006. The first most striking fact is that many countries had an AGIR *below* 1, meaning that young individuals had a higher income than older individuals, at the beginning of the sample and, for some, throughout the 1990s. This fact helps corroborate our theory that changes in AGIR have mainly arisen from shifts in the relative education achievement of old and young. Since returns to age (how income scales with age) are positive for all education groups, consistently with experience providing additional labour market value, an AGIR smaller than 1 can only arise from young workers being more skilled than older generations. The second striking fact is that even countries which have experienced small increases in AGIR after 2004 (Canada, US, UK) have experienced considerable increases in AGIR before then. Hence, our post-2004 facts capture fairly long-run trends that have affected *all* rich countries' age-income gaps in our sample, once we extend the time series back in time.

Overall, this historical evidence corroborates the long-run and composition-led interpretation of changes in AGIR in richer countries.

Figure 16. *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) for a selected number of countries for which consistent data are available before 2004. The horizontal dashed line represent the intercept at AGIR=1, indicating that the young and old incomes are identical for that given year and country. The vertical line indicates the date we choose as cutoff for our main analysis.