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Global Trends in Intergenerational Income Inequality?

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Global Trends in Intergenerational Income Inequality?

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Abstract

We document the evolution of intergenerational income (*IGI*) inequality, measured as the relative income between old and young individuals, using harmonised microdata from 42 countries at different stages of economic development. In the last 20 years, *IGI* inequality has increased (in favour of the old) in *all* rich countries, while it fell or remained constant in lower-income countries. We show that these diverging trends are due to different channels. In rich countries, the main contributor to the increased *IGI* inequality is the divergence in employment rates between young and old. Instead, in lower-income countries, we observe a strong counteracting force driven by a faster increase in labor income, conditional on being employed, of the young with respect to the old. We propose some possible explanations for the observed stylized facts, focusing on the role played by long-run trends in economic fundamentals. We find that changes in the differential in education achievement and high-skill occupation employment between young and old are strongly connected to the changes in income intergenerational inequalities but in non-obvious ways. In high-income countries, old individuals are catching up with younger ones in educational achievement: this share shift can explain half of the rise of the *IGI* inequality in the last two decades. Instead, the faster shift of young workers into better-paid occupations is at the centre of the fall of *IGI* inequality in lower-income countries, where it explains 40 percent of the average fall.

Keywords: Intergenerational inequality, income inequality, growth decomposition, cross-section, education gap, high-skilled occupation gap

JEL Classification: E24, J31, O57

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1 Introduction

The increase in income differences between young and old, the so-called intergenerational income (*IGI*, henceforth) inequalities, has recently risen to prominence in many countries’ political and media debates. For example, policymakers such as the House of Lords in the UK or the European Commission in the EU have produced in-depth reports regarding intergenerational inequality (House of Lords, 2019; Raitano et al., 2021). At the same time, more and more institutions have invested in studying this issue for specific countries (e.g. Masson (2021) for France, Barra et al. (2021) for Ireland, Berry and Sinclair (2010), Miller et al. (2020) for Australia, and Henahan et al. (2021) for the UK). The topic is also trending in the media for a broader audience as displayed by the large number of hits, 6515, we find for newspapers articles about “intergenerational inequalities” or similar terms, when querying the newspaper repository Lexis Nexis for the period 2015-2022. The same queries generate only 1513 hits in the period 2000-2015, showing a sharp increase in the interest for this topic in the last decade.¹ Finally, the topic has attracted attention also in the academic literature (see the Related Literature section below).

Although intergenerational inequalities generate understandable concerns, many dimensions of this phenomenon are still not well-understood or are under-investigated. Specifically, (i) there are no objective measures of *IGI* inequality that allow assessing, in a comparable meaningful way, the magnitude of the phenomenon in different countries; (ii) it is unclear whether different countries share similar trends regarding the evolution of *IGI* inequality; (iii) because most of the previous studies focus solely on labor income, the role of other dimensions of income, such as employment, transfers, or taxes, on *IGI* inequality, remains unknown; and thus (iv) the available analyses do not thoroughly investigate what the likely economic drivers of the *global* phenomenon are.

In this paper, we address these shortcomings by conducting a *global*, *coherent*, and *in-depth*

¹We use the following query, for the period spanning between 1/1/2000 and 03/02/2022: “*intergenerational inequality*” OR “*inter-generational inequality*” OR “*intergenerational inequalities*” OR “*inter-generational inequality*” OR “*intergenerational conflict*” OR “*inter-generational conflict*” OR “*intergenerational fairness*” OR “*inter-generational fairness*” OR “*generational inequality*”. The rise in the number of hits between 2000-2015 and 2015-2022 is robust to controlling for the increased number of articles published overall.

analysis of intergenerational income inequality. We leverage income microdata, harmonised in the Luxembourg Income Study Database (LIS) for 46 countries, which we group into Rich countries, Transition Economies, and Developing Economies. These microdata, which come from income, labor force, or permanent population surveys, cover up to 46 years per country (1974 to 2019) and provide harmonised variables for individual income and its components. We construct two measures of *IGI* inequality. The first one is the *Intergenerational Income Ratio*, *IGIR*. With a simple number, it captures the relative income of two age groups in any given period. Since an age group includes all individuals of that age, regardless of employment status, this measure provides a broad picture of overall income inequalities between generations. Notice that our measure differs from comparing changes in income of a given cohort at different points in time. Nevertheless, investigating how age group-specific income inequality has evolved is interesting for several reasons. First, it highlights how resources are distributed, in a given period, among different segments of the population related to their age. Second, our approach, together with the data available, allows us to relate intergenerational income inequality to long-run economic trends. The second measure is the *Growth Rate Differentials*, *GRD*, and measures the gap in income growth rates between two different age groups. The *GRD* not only directly relates to the *IGIR*, but also can be easily decomposed to highlight the contribution of individual income components toward the evolution of intergenerational income inequalities. Therefore, we can quantify how much of the observed changes in intergenerational income inequality are due to changes in labor remuneration, employment rate, transfers, or taxes. Finally, we formally investigate how several recent economic forces, such as the educational expansion, technical and structural changes, increased female participation, and exposure to severe recessions, relate to the observed trends of intergenerational income inequality.

Our analysis is *global* because it provides evidence of the recent intergenerational income inequality trends for several countries at different stages of economic growth and development. To our knowledge, no other study on *IGI* inequalities provides an overall view of the phenomenon for this many countries with such heterogeneous GDP-per-capita profiles. This feature of our analysis is relevant because it allows us to establish whether high- and low-

income countries display divergent or common trends in intergenerational inequality. Our analysis is *coherent* because using representative and harmonised datasets allows us to compute statistics over similar income definitions across time and space. This feature is paramount to assess and compare the magnitude of *IGI* inequalities across countries and periods. Finally, our analysis is *in-depth* because our dataset and our proposed measures of inequality permit a detailed decomposition of the role of the sub-components of income for the evolution of intergenerational income inequality.

We provide two main contributions. First, our approach allows us to establish novel stylized facts about the global trends of *IGI* inequalities. In the last 20 years, inequality increased in *all* advanced economies. Individuals aged 50-64 went from earning on average, in a given year, around the same income as young ones (aged 25-34) to earning almost 28 percent more than them.² This sharp increase is mainly due to the average income of the young falling or remaining stable, while the one of the old increased at sustained rates. Nevertheless, this trend is absent or even reverted in countries with lower GDP per capita. The analysis of the growth rate differential allows us to investigate the sources of this discrepancy. In rich countries, the main contributor to the increased *IGI* inequalities is the divergence in employment rates between young and old. Instead, in lower-income countries, we observe a strong counteracting force driven by a faster increase in labor income, conditional on being employed, of the young with respect to the old. This force is strong enough to reduce *IGI* inequality in those poorer countries. On the other hand, we also find that - in rich countries - individuals aged 50-65 pay more taxes and receive less transfers than in the past, possibly due to working longer (instead of retiring), and thus earning higher wages than the average pension payment.

Our second contribution is to propose some possible explanations for the observed stylized facts, focusing on the role played by long-run trends in economic fundamentals. We find that changes in the differential in education achievement and high-skill occupation employment between young and old are strongly connected to the changes in income intergenerational

²These aggregate figures can be reconciled with the bell-shape of individual lifetime earnings by considering generational differences in education, skills, employment rate, and culture.

inequalities but in non-obvious ways. In high-income countries, old individuals are catching up with younger ones in educational achievement: this share shift can explain half of the rise in *IGI* inequalities between 1997 and 2019 in rich countries. Instead, the faster shift of young workers into better-paid occupations is at the centre of the fall in *IGI* inequalities in lower-income countries, where it explains 40 percent of the average fall. We also investigate the role of increased female labor force participation and exposure to recession. However, these two phenomena do not seem to explain the observed trends.

How can we interpret these findings? Overall, our results suggest that the rise in *IGI* inequalities in high-income countries is, at least in part, a natural consequence of long-run trends in economic developments. Similarly, the fall (or stability) in lower-income countries appears to be a transitory phenomenon led by fast transformations of the economy, with current young generations strongly benefitting from higher education levels and structural/technical change. Nevertheless, local policies and economic factors are still likely to explain the residual part of these trends and influence both education and training. In this sense, our results offer both positive and negative news for policymakers and stakeholders interested in tackling intergenerational inequalities. On the one hand, the low level of inequality observed in the early 1990s and the following upward trends seem to have been the effect of decades-long transition dynamics. On the other, this means that tackling intergenerational inequalities may indeed *need* public policies aimed at ensuring intergenerational fairness, as it seems implausible that we will see, without policy intervention, a reduction in *IGI* inequalities in rich countries.

Our results open further research questions. The first set relates to welfare analysis. First, should policymakers care about *IGI* inequalities per-se? Or are they just consequences of other economic issues? In addition to the clear political and long-term public budgeting implications (for example, for the balance of pension funds), are *IGI* inequalities economically inefficient, and what is their welfare costs? Second, is there a trade-off between the intensive (wage) and extensive (employment) margins of *IGI* inequalities? Moreover, if yes, what outcome is the most desirable? The second set relates to predicted trends. Since education and technical change seem inevitable - and desirable - sources of long-term economic development, are

IGI inequalities in lower-income countries set to experience the same trajectory as the ones observed already in higher-income ones? Furthermore, if so, what does it imply for long-term generational policies that policymakers should adopt in order to ensure intergenerational fairness? We believe that our work and findings are relevant to setting the stage to address those questions.

Related Literature Intergenerational income inequalities have been discussed for decades. During the 1970s and 1980s, economists focused on the “baby-boom” generation’s ingress in the labor market, which increased the relative supply of young, inexperienced labor (Welch, 1979; Levine and Mitchell, 1988). Since economists tried to explain the consequent wage trends with the imperfect substitutability of labor inputs with different tenure/experience, many concluded that the wages of the successive, smaller cohorts were set to grow faster once the ageing baby boomers created an excess of “experienced” labor supply. However, as Bianchi and Paradisi (2021) noted for Italy, and as we document for most advanced economies, this does not seem to have been the case. Even if the price of experience is affected by its relative supply (Jeong et al., 2015), this channel appears to have been dominated by other, opposing forces.

We show that *IGI* inequalities have kept increasing in all advanced economies, to the point that the disposable income of the old surpassed the one of the young in all such countries by 2010. This trend has been analysed for individuals countries by Rosolia and Torrini (2007) for Italy, Bianchi and Paradisi (2021) for Italy and Germany, Guvenen et al. (2022) for the U.S., and Cribb (2019) for Britain. Freedman (2017) studies cohort trends for several advanced economies. We contribute by providing further international evidence for the trends in *IGI* inequalities. Our data covers almost all advanced economies, Eastern Europe and South America, and a few African and Asian developing countries.

Several papers studying *IGI* inequalities through various lenses have focused on the relative earnings or wages of employed individuals (Bianchi et al., 2021; Bianchi and Paradisi, 2021; Bennett and Levinthal, 2017; Beaudry et al., 2014). However, we show that most of the increase in *IGI* inequality in net income in high-income countries has been determined by a

faster rise in *employment* among older individuals than among younger ones, and not only by increasing differences in earnings conditional on being employed. Researchers should be careful when drawing generalised conclusions about the population as a whole from the dynamics of the age-*wage* gap, as it may not reflect the dynamics of the overall age-*income* gap, nor that of sub-populations. In fact, we find that estimates of the growth of the age-wage gap *underestimate* the absolute value of the changes in overall *IGI* inequalities by 0.4 annualised percentage points (out of an average of 1.5 annualised p.p., or 28 percent of the total), despite usually pointing in the same direction (correlation 0.88).³

The rest of the paper is organised as follow: in Section 2 we present the data, our measures of *IGI* inequality, and pin down a few stylised facts regarding their global distribution and trends. In Section 3 we decompose *IGI* inequalities trends into trends of individual components of income. In Section 4 we propose possible explanations of the evidence presented in the previous sections. Section 5 sums up our results and discusses future avenues of research.

2 Inter-generational Inequality: Stylized facts

Our first contribution is to provide several stylized facts and regularities about intergenerational income inequality across different countries. After describing the data, we propose two valuable statistics to measure this type of inequality, for which we state and discuss the findings.

2.1 Data

LIS Database. We leverage income microdata, harmonised in the Luxembourg Income Study Database (LIS) for several countries.⁴ These microdata come from income, labor force, or permanent census surveys that cover up to 46 years per country (1974 to 2019). The advantage of the LIS database is that it provides harmonised variables for individual income (and its components) and detailed demographic and job characteristics. We transform all

³See Appendix A.1 for a discussion of how our results relate to the age-wage gap and other similar concepts of *wage* intergenerational inequalities.

⁴Luxembourg Income Study (LIS) Database (2021).

income variables into real terms (by CPI) and PPP, allowing for a cross country and cross-period comparison.⁵

Table I reports summary statistics for the dataset. In the first column we report the number of data points (surveys) available in the whole LIS database. The next three columns report the number of observations in each country for (i) the whole dataset (second column); (ii) for the years after 1997, which will be the main focus of our analysis in this section (third column); (iii) the computation of the growth rate differentials, a key feature of our analysis presented in the next subsection (fourth column). For this analysis, we select 30 countries (out of 46 available in the LIS) for which: (i) we have sufficiently long time series; (ii) the first/last observation does not fall between 2007 and 2009, included;⁶ (iii) have consistently collected net (or gross plus taxes) income data across years; and (iv) have all the necessary income variables available at the individual level. Our final sample includes most of the European Economic Area, the UK, North America, Mexico, most South American countries, Australia, and India. The last two columns of the table display the selected initial and final year for each country.

⁵Source: Latest World Bank Development Indicators, made available by LIS.

⁶This to avoid comparing “normal” years to the years of deeper recession during and after the Great Recession.

TABLE I. Summary of the data

	Individual Observations				Growth Rate window	
	Surveys	All years	Since 1997	Growth Rate window	First, T_i	Last, $T_i + h_i$
<i>Rich Countries</i>						
01 Australia	12	319,978	201,318	39,821	2001	2018
02 Austria	22	274,847	192,787	21,197	2004	2019
03 Belgium	21	225,940	178,369	21,614	2003	2017
04 Canada	18	1,090,171	606,151	74,965	1997	2017
05 Denmark	9	1,059,527	876,925	294,961	2000	2016
06 Finland	9	192,566	125,773	41,438	2000	2016
07 France	7	160,934	70,389	0	.	.
08 Germany	39	1,017,372	561,008	35,871	1997	2018
09 Greece	7	126,146	114,311	61,291	2007	2016
10 Iceland	3	20,266	20,266	0	.	.
11 Ireland	21	199,799	164,977	14,854	2002	2017
12 Israel	22	348,024	295,078	0	.	.
13 Italy	13	243,215	120,894	34,754	1998	2010
14 Luxembourg	9	58,563	39,700	0	.	.
15 Netherlands	13	225,514	183,553	44,897	2007	2018
16 Norway	10	1,723,191	1,645,547	449,673	2000	2016
17 Spain	10	305,431	159,230	59,808	2007	2016
18 Sweden	7	165,839	56,788	0	.	.
19 Switzerland	18	232,990	203,207	26,879	2006	2018
20 United Kingdom	30	1,162,398	895,399	76,144	1998	2018
21 United States	32	4,165,547	3,135,972	122,032	1997	2019
<i>Transition Economies</i>						
22 Czech Republic	8	189,434	96,514	24,914	2004	2016
23 Estonia	6	71,492	71,492	23,773	2007	2016
24 Hungary	8	36,343	27,301	10,092	1999	2015
25 Lithuania	10	103,870	103,870	0	.	.
26 Poland	20	1,536,669	1,421,291	154,796	2004	2019
27 Russia	12	978,065	978,065	0	.	.
28 Serbia	4	50,526	50,526	0	.	.
29 Slovakia	11	207,676	123,090	25,876	2004	2018
30 Slovenia	7	65,496	58,347	9,130	1997	2015
<i>Developing Economies</i>						
31 Brazil	5	1,466,602	1,466,602	635,366	2006	2016
32 Chile	13	1,967,124	1,583,727	302,846	1998	2017
33 Colombia	19	9,401,811	9,401,811	751,716	2001	2019
34 Guatemala	3	110,297	110,297	0	.	.
35 India	2	285,496	285,496	285,496	2004	2011
36 Ivory Coast	3	94,127	94,127	0	.	.
37 Mexico	17	1,034,127	881,569	221,710	1998	2018
38 Panama	4	125,986	125,986	0	.	.
39 Paraguay	21	334,512	322,999	33,788	2004	2019
40 Peru	5	350,470	350,470	147,473	2004	2016
41 South Africa	5	108,169	108,169	0	.	.
42 Uruguay	5	442,422	442,422	135,856	2004	2016
Total	520	32,278,972	27,951,813	4,183,031		

Note: Countries are organised according to socio-economic region, as defined in the main text. “Surveys” refers to the number of datapoints available in the whole LIS database. Such datapoints are not necessarily contiguous years. The following three columns (“Individual Observations”) refer to the number of individual-level observations, and are organised as follows: i) “All years” refers to the observations available for that country across all datapoints; ii) “Since 1997” refers to the observations available for that country from 1997 onwards. Further into the paper, we will use this cutoff several times; iii) “Growth Rate window” refers to the observations used for the calculations of the Growth Rate Differentials. Finally, the last two columns specify the time interval used for the calculation of the Growth Rate Differential. The first year will be denoted as T_i and the last year as $T_i + h_i$, where i is the country-specific index.

Income definition. We now illustrate the observed variables that define income in the LIS dataset. Let us first define the theoretical disposable income of an individual q , denoted \hat{y}_q , as:

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

where y_q^g denotes gross labor income, y_q^k denotes gross capital income, $\hat{\Theta}_q^g$ denotes gross transfers, and $\hat{\tau}_q$ denotes taxes.

The LIS dataset defines as income an approximated measure of the theoretical disposable income, i.e.:

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

where y_q denotes observed labor income and Θ_q^g is an observed approximated measure of transfers, i.e. the payments received for a subset of transfers, namely: pension payments, unemployment benefits and (when available) scholarships and paid maternity/paternity leave. Importantly, capital income is not available at the individual level. However, this issue does not present a problem for our analysis because, as we will argue in the next section and we provide evidence for in Appendix A.4, at worst, excluding capital income from the analysis seems to lead to underestimating the inter-generational inequality. Finally, notice that τ_q , which is the observed measure of taxes, does not include taxes on capital income and other transfers.

Some countries report only net income data. In this case, we observe instead:

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

where the overscript n indicates that the data are net, instead of gross.

In the LIS database, we observe y_q for each individual, as well as each component on the right-hand side of equations (1) or (2). Throughout the rest of the paper, we will refer to the variable y as *disposable income*.

2.2 Intergenerational Income Ratio (IGIR)

As a measure of intergenerational inequalities, we consider the ratio in disposable income between two demographics at a given period: we refer to this statistics as *Intergenerational*

Income Ratio or *IGIR*. Define as $y_{j,t}$ the average disposable income for age group j at time t , that is:

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

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

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

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

This statistic captures, with a simple number, the income relation between two age groups in any given period. Since an age group includes all individuals of that age, regardless of employment status, this measure provides a broad picture of *overall* income inequalities between generations. This differentiates this statistic from other similar measures such as the “age-wage gap” proposed by [Bianchi and Paradisi \(2021\)](#). Also, the use of net income allows our statistics to take into account the effects of fiscal redistribution, which may contain age-related (or age-correlated) incentives and taxes. In [Appendix A.1](#) we discuss the comparison between income and wage intergenerational inequalities.

Remark (Age group statistics vs Cohort statistics). As evident by our definition of *IGIR*, our measure of intergenerational income inequality concerns the relationship between income of different age groups in a given period. This measure, therefore, differs from comparing changes in income of a given cohort at different points in time. Nevertheless, investigating how age group-specific income inequality has evolved is interesting for several reasons. First, it highlights how resources are distributed, in a given period, among different segments of the population related to their age. Second, our approach, together with the data available, allows us to relate intergenerational income inequality to long-run economic trends.

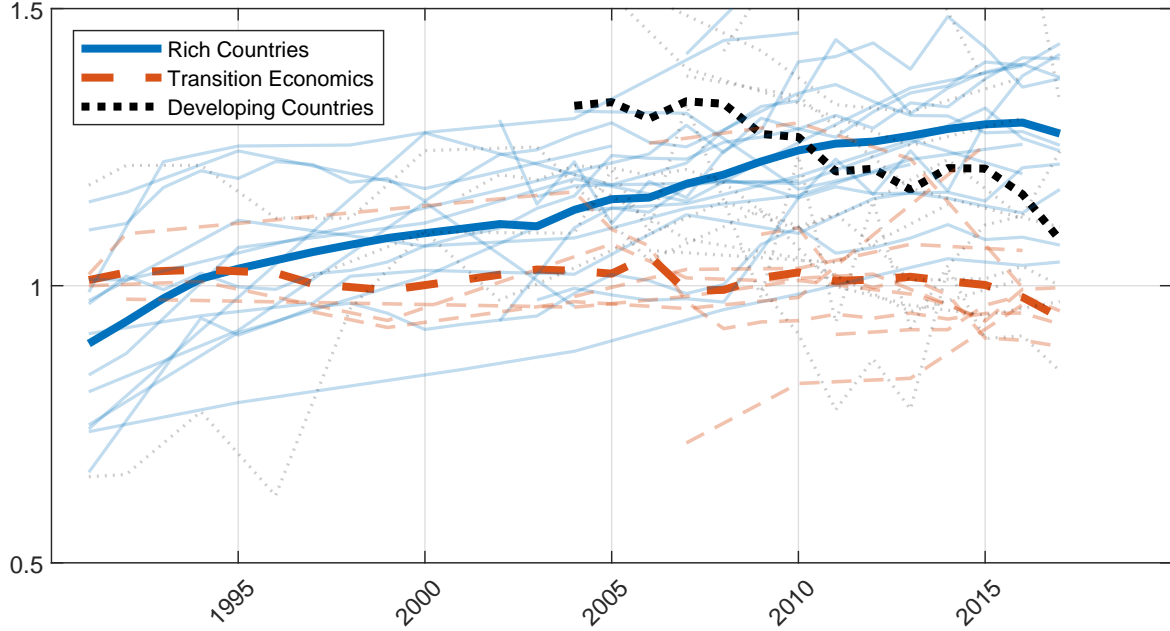
In [Figure 1](#) we plot the evolution of the *IGIR* between individuals aged 50-64 (late-career, working-age individuals) and individuals aged 25-34 (early career, post higher education). We

choose these two age groups because they reflect individuals that have already completed their education and are at opposite ends of their career paths, having recently started (25-34), or approaching retirement age (50-64). In Appendix A.2, we report the results of comparing the age group 65+ to the age group 16-24 instead. The results of this paper hold for this more extreme alternative definition of young and old. Finally, to facilitate the visual inspection of the results, we have divided the countries into three sub-groups: rich countries, transition economies, and developing economies.⁷ The simple average *IGIR* of each sub-group is displayed by the three thicker lines (solid blue for rich countries, dashed red for transition economies, and dotted black for developing countries), while the *IGIR* of each country is displayed with thinner lines of the corresponding colour. The developing economies aggregate plot starts in 2004, and all plots end in 2017, to average over a consistent and approximately constant number of countries.⁸

⁷The groups include: Rich countries, as defined in [Uribe and Schmitt-Grohé \(2017\)](#): France, Greece, Ireland, Italy, Spain, Austria, Belgium, Germany, Luxembourg, Netherlands, Switzerland, United Kingdom, Denmark, Finland, Iceland, Norway Sweden, Israel. Transition economies, as defined in [International Monetary Fund \(2000\)](#): Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Russia, Serbia, Slovakia, Slovenia. Developing Economies: Chile, Colombia, Guatemala, Mexico, Panama, Paraguay, Peru, Uruguay, Ivory Coast, South Africa, India.

⁸Before 2004, only two of these countries are available; after 2017, the data availability falls considerably.

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



Note: The figure depicts the Intergenerational Income Ratio (*IGIR*) between 50-64 years old individuals and 25-34 years old ones. The thicker lines represent the simple average across countries of a given group (solid blue for Rich Countries, dashed red for Transition Economies, and dotted black for Developing Economies). Thinner lines of corresponding style represent individual countries. We do not plot dates after 2017, and before 2004 for Developing Economies, due to limited data availability. The countries used for these calculations are reported in Table I. For this figure, we use all the available countries.

First, notice that the pattern of the *IGIR* in the three subsets of countries is quite smooth and does not display large cyclical fluctuations. Therefore, we interpret the observed pattern as a *trend*, rather than as an outcome of cyclical fluctuations. Next, while at the end of the 1980s the young were earning more than the old (*IGIR* less than one) in all rich countries but Italy and the USA, by 2010 the old were earning more than the young in *all* the rich countries in our sample. The *IGIR* upward trend appears to have continued in the last decade for most rich countries, with very few exceptions. On the other hand, most lower-income countries experienced stationary or downward-trending *IGIR*, as shown by the Transition and Developing economies time-series. We provide further evidence for the size of these diverging trends in Table II by reporting unweighted means⁹ of the *IGIR* across different geographical regions and a few individual countries.

These observations lead to the first stylized fact.

⁹That is, we do not weight each country by its population.

Stylized fact 1 In rich countries, the intergenerational income ratio has steadily risen in the last 25 years by around 20 percent, while in the transition economies it has been constant and around one. Finally, in developing economies that ratio has been declining since at least 2005.

TABLE II. *IGIR* by region and by decade, 50-64 vs 25-34 years old

	1980s	1990s	2000s	2010s	Δ 1990s-2010s
<i>Rich Countries</i>					
Southern Europe and France	0.80	1.09	1.25	1.42	0.20
Central Europe and UK	0.95	1.00	1.21	1.28	0.27
Scandinavia and Iceland	0.85	1.09	1.19	1.31	0.25
US, Canada, Australia	0.88	1.00	1.13	1.17	0.17
Israel	.	.	1.28	1.43	0.15 [†]
<i>Transition Economies</i>					
Eastern Europe and Russia	0.66	0.98	1.00	1.01	0.06
<i>Developing Economies</i>					
Central/South America	0.65	1.03	1.19	1.11	-0.03
South Africa	.	.	1.42	1.33	-0.09 [†]
India	.	.	1.21	1.11	-0.11 [†]

Note: [†]: difference calculated over 2000s-2010s interval. Geographical regions are as follows. Southern Europe and France: France, Greece, Italy, Spain; Central Europe and UK: Austria, Belgium, Germany, Ireland, Luxembourg, Netherlands, Switzerland, United Kingdom; Scandinavia and Iceland: Denmark, Finland, Iceland, Norway Sweden; Eastern Europe and Russia: Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Russia, Serbia, Slovakia, Slovenia; Central/South America: Chile, Colombia, Guatemala, Mexico, Panama, Paraguay, Peru, Uruguay. The graph shows the simple mean of the *IGIR* for the countries within the geographical aggregation. Each country's *IGIR* is computed at the last available observation of the decade in the LIS database. Not all observations for each geographical region contain the same countries, based on the availability of each country's data. The last column is the average of the country-level changes in *IGIR* between the 1990s and 2010s observations; hence it may differ from the difference between columns 4 and 2, if some countries are not available in either periods.

The results are relevant for at least two reasons. The first reason relates to the *level* of the *IGIR* between old and young working-age individuals, which has been steadily close to one in transition economies and was close to one in the 1990s in rich countries. An *IGIR* close to one implies that the old and young earned roughly the same income. However, one might wonder: how can this fact coexist with the well-known evidence of the hump-shaped individual life-cycle earning profile? Recall that the *IGIR* at a given time t measures the relative average income of the old and young at a given time. The average is computed across individuals with potentially very different shapes of income profiles, for example due to different shares of non-employed or college-educated individuals. Therefore, one should expect the pattern of our statistic to

differ from the international evidence of life-cycle incomes regarding full-time male employees (Lagakos et al., 2018).¹⁰ Also, economic forces might lead to dissimilar income growth across different age groups, which can reduce the observed *IGIR*, even below one. For example, skill-biased technical change can create a wedge between the skillset of the young and the old, leading to faster income growth of the former (Adão et al., 2021), leading to a lower *IGIR*. Phenomena of this type may rationalize the observed flat or even decreasing “cross-sectional” income profile, while being perfectly consistent with the hump-shaped income profile of a given generation across time. The second reason relates to the *trend* of the *IGIR*, which, in the last 20 years, has been diverging between rich countries and lower-income countries. This fact suggests that the economic and demographic forces that were keeping the ratio around one in rich countries started losing importance during the 1990s. However, this is not a global phenomenon, suggesting that some of the relevant economic forces are acting in the opposite direction in lower-income countries.

The investigation of these two topics will be the focus of the rest of this paper.

2.3 Income Growth Rates and Growth Rate Differentials (GRD)

While the increasing *IGIR* for rich countries signals a disproportional increase of the income of the old relative to the one of the young, it does not provide information on the direction of the change of each age group. One might argue that, after all, if the disposable income of both the old and the young has substantially grown, albeit at different rates, the increasing *IGIR* might be not a sign of intergenerational distress or “unfairness”. We now introduce and discuss another statistic, i.e. the disposable income growth of different age groups. This statistic has two advantages. First, it allows us to investigate how income has changed individually for each age group; second, its differential between age groups, which we will label as the *growth rate differentials*, *GRD*, directly relates to the evolution of the *IGIR*.

Consider the average disposable income for a specific age-group j at a given period t ,

¹⁰For example, our measure would be affected by a higher employment rate among certain demographics or changes in the share of part-time employees. However, these sources of income dynamics are still a margin of interest when discussing overall intergenerational inequalities in a given country.

denoted by $y_{j,t}$. The country i 's age-group j 's income growth rate, annualized, between period T_i and $T_i + h_i$ is:

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

where $y_{j,T}$ denotes average income in period T for age group j . Let us drop the country index, i , for sake of notation. To unravel the relationship between age group income growth and the evolution of the income ratio $R_{j'}^j(t)$, let us define the change in *IGIR* between period T and $T + h$ as:

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

where $\Delta(x)$ denotes the change of a variable x from T to $T + h$. Using the notion of age group income growth, it becomes:

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

Rearranging, we have:

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

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

$$GRD \equiv g(y_j) - g(y_{j'}) \approx \frac{\Delta R_{j'}^j}{R_{j'}^j(T)}. \quad (3)$$

Equation (3) states that the growth rate differential (*GRD*) between two age-groups j and j' closely relates to the evolution of the *IGIR* for those age groups. Since the income ratios of the 50-64 and 25-34 groups are close to 1, the interpretation of this difference in growth rates does not suffer from small-number distortions. Furthermore, the *GRD* has the desirable property that it can be easily decomposed in the contribution of different sub-components of income, allowing us to dig deeper into the causes of the changes in intergenerational inequalities. We will discuss this point in Section 3.

As a first illustrative step, we compute the age-group specific growth rates and their differential. For each country i , we consider net income at two data points, T_i and $T_i + h_i$, between 1997 and 2019,¹¹ and study how it has grown across time for five different age groups. We define the age groups as follows: *young adults*, aged 16-24; *early career*, aged 25-34; *middle-career*, aged 35-49, *late career*, aged 50-64, and *retirement-age*, aged 65+. Table III summarises the average income growth, for each age group, by geographical region. The start and end dates that we use for this computation are provided in Table I. In Southern Europe, the income of the 25-34 category fell by an average of 2.3 percentage points per year; in the rest of Western Europe, it increased by a tiny 0.3 annualised percentage points. While the US-Canada-Australia group shows a much larger income growth, this is mostly due to Australia itself (+1.6 p.p.), while in the US, the 25-34 income grew by only 0.7 p.p. per year. The figures are even smaller for the 16-24 age group, which experienced negative average income growth everywhere in Western Europe, but for the UK (where it is only slightly positive).

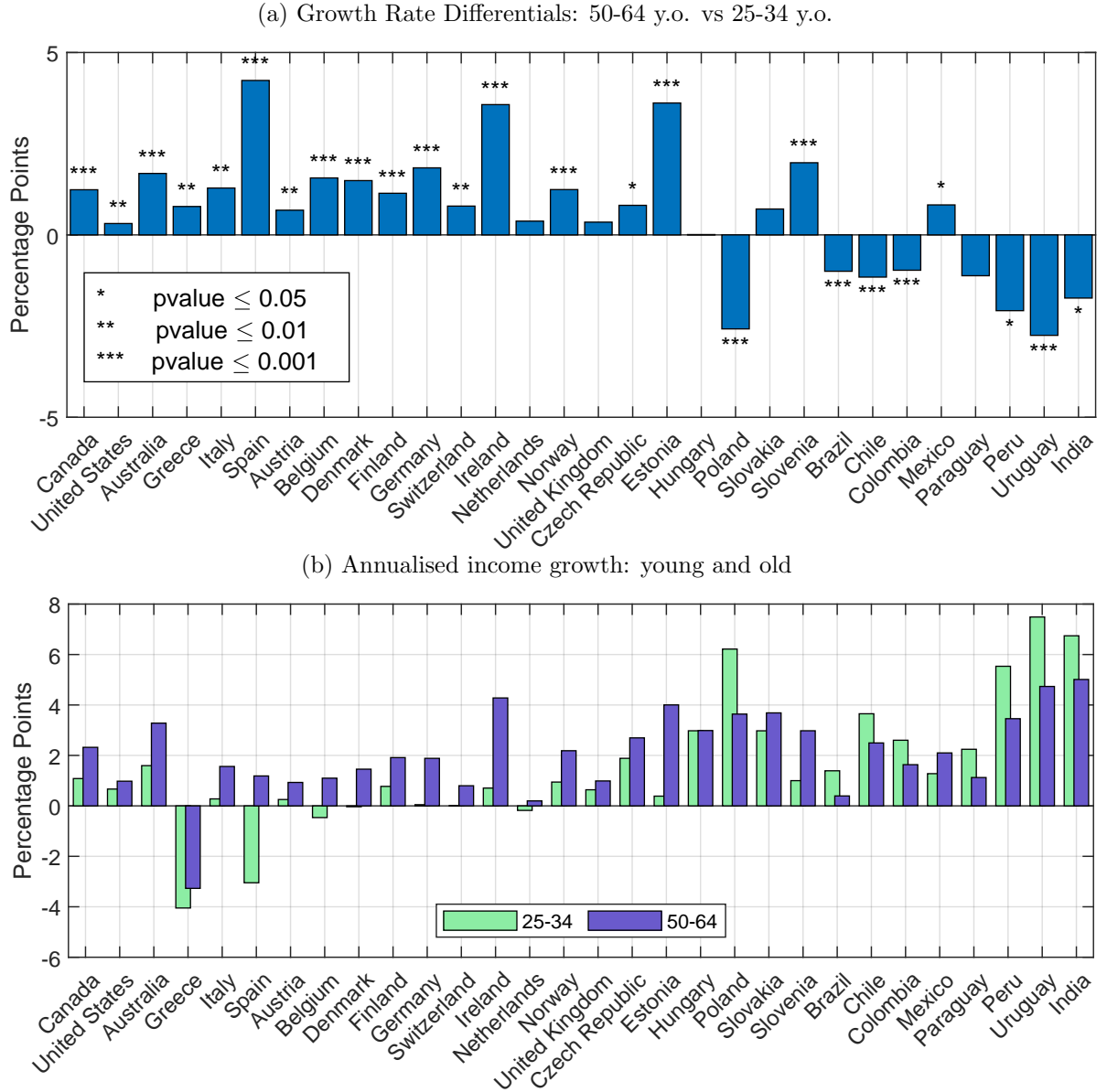
TABLE III. Mean Income Growth (annualised percentage points), by age and region

Region	Age Group				
	16-24	25-34	35-49	50-64	65+
<i>Rich Countries</i>					
Southern Europe	-4.7	-2.3	-1.1	-0.2	1.4
Central Europe and UK	-0.8	0.3	1.0	1.6	2.0
US, Canada, Australia	0.7	1.1	1.8	2.2	2.8
<i>Transition Economies</i>					
Eastern Europe	3.1	2.6	3.5	3.3	3.2
<i>Developing Economies</i>					
Rest of the World	4.1	3.9	2.4	2.6	2.8

Note: Geographical regions are as follows. Southern Europe: Greece, Italy, Spain; Central Europe and UK: Austria, Belgium, Denmark, Finland, Germany, Ireland, Switzerland, Netherlands, Norway, UK. Eastern Europe: Czech Republic, Estonia, Hungary, Poland, Slovakia, Slovenia. Rest of the World: Brazil, Chile, Colombia, Mexico, Paraguay, Peru, Uruguay, India. Means are across countries, with equal weight given to each country. The periods over which the growth rates are calculated are provided in Table I.

¹¹For each country, the first observation is set between 1997 and 2007. The second and last observation is set between 2010 and 2019. Since we do not have data available for each country at each year, the initial period T_i and the final period $T_i + h_i$ and, therefore, their gap h_i are country-specific. Moreover, since the methodology with which a country's data are collected may change over time, we select a single methodology for each individual country and discard all observations not adhering to it.

Figure 2. Growth Rate Differentials and young-old Income Growth Rates



Note: Panel (a) displays the annualised disposable income Growth Rate Differential (GRD), comparing 50-64 years old individuals with 25-34 years old ones. A positive value indicates that the income of the old has increased faster than the one of the young over the reference periods. We report statistical significance with respect to the null hypothesis $GRD_i = 0$. Panel (b) reports the underlying growth rates of net income used to calculate the GRD . The dates between which the GRD and the growth rates are calculated are provided in Table I.

We are now ready to display the growth rate differentials (GRD), and displayed in Figure 2a. As in the previous section, we focus on the 50-64 (old) and the 25-34 (young) age groups. In Appendix A.2 we show further results for the 65+ and 16-24 groups. Consistently with the finding in Figure 1, the GRD are positive for *all* rich countries, while they are negative for

most developing economies. Transition economies show mixed results. A few countries (Spain, Ireland, and Estonia) show particularly large yearly *GRD*, of about 4 percentage points per year, while most rich countries show a *GRD* of around 1.5 p.p. per year. In countries with negative *GRD*, the speed of the fall in inequalities seems to be more contained than the speed of the increase in rich countries.

To highlight what are the main drivers of the *GRD*, in Figure 2b we display the growth rates specific for the young and the old. This figure confirms that the positive *GRD* in rich countries are driven by a stagnant income growth for the young and a positive, larger income growth for the old. Lower-income countries are characterised by very large annualised income growth rates for the old, with the young's income growth rate being approximately similar (transition economies) or even larger (developing economies).¹²

This observation leads to the second stylized fact.

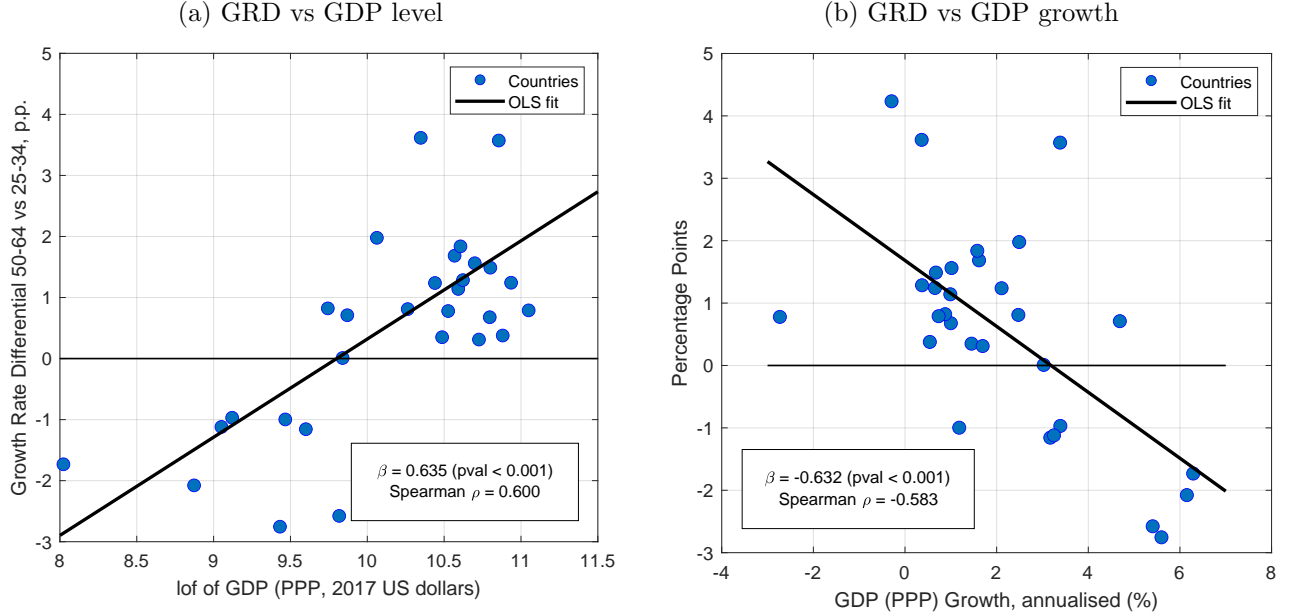
Stylized fact 2 Growth rate differentials are positive for all rich countries, where the income of the young did not grow, while the one of the old increased substantially; instead, growth rate differentials are negative for most lower-income countries, where the income of both young and old grew at fast rates.

This relationship between income groups and *GRD* can be better visualised in Figure 3. In panel (a) we plot the *GRD* against the GDP per capita, in log, of each country at the beginning of the sample, while in panel (b) we plot the *GRD* against its per capita PPP GDP growth, calculated in the whole sample available for each country. The *GRD* shows a strong positive correlation with the GDP level (Pearson = 0.69, Spearman = 0.60), and a significant negative one with average income growth (Pearson = -0.63, Spearman = -0.58). The fact that the evolution of the *IGIR* correlates with a country's income and its growth rate is a relevant result because it suggests how there may be structural relationships between the evolution of intergenerational inequalities and the level, or speed, of development of a country. We will

¹²Since the growth rates of age groups within a country are strongly connected to the *average* growth rate, we provide results regarding the “centered growth rates” in Appendix A.3.

discuss these phenomena further in Section 4 by providing possible explanations for these correlations.

Figure 3. *GRD* and country income level and growth



Note: Panel (a) plots the Growth Rate Differential *GRD* calculated between 50-64 years old individuals and 25-34 years old ones, against the log of PPP GDP (calculated at the beginning of the period of analysis). The time interval for which the *GRD* are computed, are reported for each country in Table I. The black line shows the linear fit. In the box, we report the Pearson (ρ) and the Spearman correlation between the two variables. Panel (b) plots the *GRD* against the annualised growth rate over the reference period of the PPP GDP presented in Panel (a).

The role of capital income. One might wonder whether the lack of individual data on capital income is potentially troublesome for our analysis. In principle, the relative magnitude of that income component or its variation across time among different age groups could significantly change our conclusions regarding the size and direction of the *GRD*. In Appendix A.4 we show, using household-level data, that the role of capital for household income appears to be marginal and, if anything, excluding it from the analysis leads to underestimating inter-generational inequalities and their trend. As a result, not observing capital income is not a crucial issue for our results.

Takeaway Using a dataset for 42 countries, we have found an increasing trend in the inter-generational income ratio in rich countries in the last two decades, and a stable or decreasing one in lower-income countries. These facts suggest a global regularity in the dynamics of inter-

generational income inequalities. Also, we find that the income *GRD* between old and young correlates positively with a country’s GDP level and negatively with its GDP growth, confirming that the increase in intergenerational income inequalities is a phenomenon associated to high income levels.

The increase of *IGIR* in rich countries is due to the young earning a lower or similar income than in the past and the old earning higher incomes. Instead, the stationarity or fall of *IGIR* in lower-income countries arises from the fact that the income of *all* age groups has been increasing¹³ either in a similar way across age groups, or faster for the young.

These results point at two facts that researchers and policymakers should consider in the future. First, the phenomenon of intergenerational inequalities needs to be understood also from an international perspective. Models attempting to explain intergenerational inequality and propose policies for alleviating it need to consider how that phenomenon also strongly correlates with the current level of development of a country. Understanding the causes of this correlation is essential to design welfare and tax schemes for current and future generations. Second, the fact that the increased intergenerational inequality in high-income countries has, at least partially, come from a fall in the income of the young confirms and generalises the recent findings regarding the fall in income of young Millennials with respect to previous cohorts (Guvenen et al., 2022; Cribb, 2019; Afman, 2020). This phenomenon is potentially worrisome for two reasons. From an economic efficiency point of view, assuming that the lifetime income path of each individual has simply become steeper, lower incomes for young individuals may exacerbate borrowing constraints, other market frictions, and non-linearities in consumption,¹⁴ thus leading to aggregate welfare losses. However, more considerable differences in income between young and old may foster other dimensions of inequalities, poverty and deprivation, including the transmission of inequalities across generations, as well as having detrimental effects on the concept of intergenerational “fairness”.

In the following sections, we provide a partial answer to some of these questions and concerns, analysing the channels through which intergenerational income inequalities have

¹³The only two exceptions are the 16-24 group in Czech Republic, and the 65+ group in Paraguay.

¹⁴Consider fixed costs such as rent or baseline food baskets.

increased in high-income countries, and decreased in developing economies. We will also provide empirical evidence for how some specific mechanisms may help explaining the documented intergenerational inequalities trends.

3 Decomposing of Intergenerational Inequality Growth

We now investigate the sources of the intergenerational inequalities discussed in the previous section. Specifically, we decompose the growth rate differentials defined above into the contribution of different income components. This exercise allows us to understand how the intergenerational inequalities have changed over time through different channels, some of which are more connected to policy, while other to market forces and economic growth.

3.1 Income Decomposition

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

$$y = ey^g + p\Theta^g - \tau, \quad (4)$$

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

For the countries that do not have data on gross labor income¹⁵ and for which we cannot separately isolate the role of taxes, their *average* country disposable income is:

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

where y^n denotes average net labor income conditional on being employed, and Θ^n denotes the average amount of net transfers conditional on receiving a non-zero value.

¹⁵Belgium, Chile, Germany, Greece, Hungary, India, Ireland, Italy, Mexico, Netherlands, Paraguay, Poland, Slovakia, Slovenia, Spain, Uruguay.

We are interested in computing the factors contributing to the growth/decline of disposable income for each age group. Using the approximation in equation (4), the *growth rate* of average disposable income of age group j between period T and $T + h$ is, for the countries for which gross labor income is available:

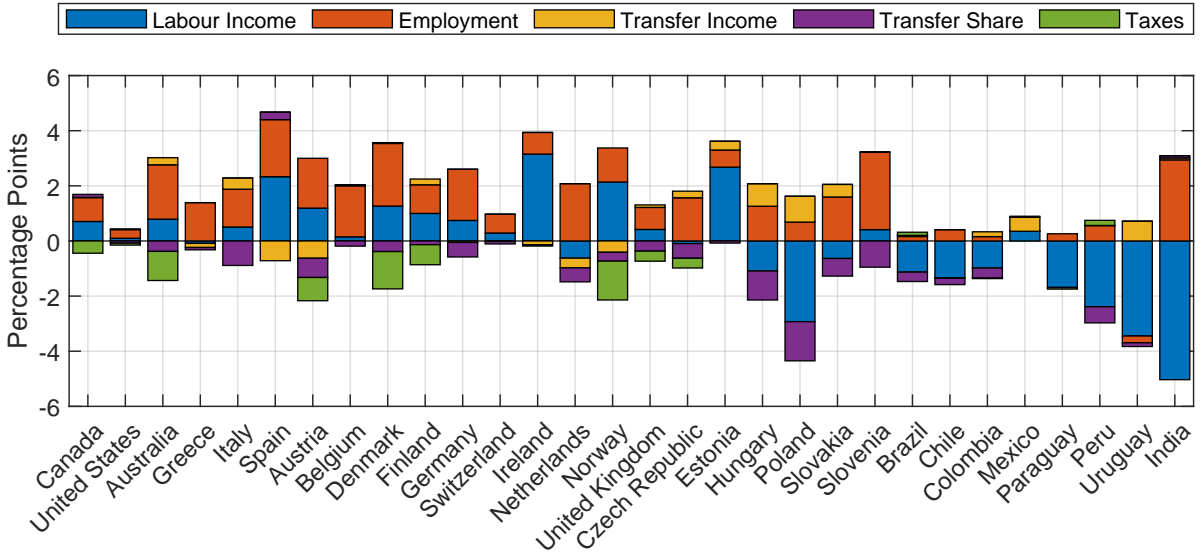
$$\frac{\Delta y_j}{y_{j,T}} = \underbrace{\frac{e_{j,T} \Delta y_j^g}{y_{j,T}}}_{\text{Gross labor Income}} + \underbrace{\frac{y_{j,T}^g \Delta e_j}{y_{j,T}}}_{\text{Employment}} + \underbrace{\frac{p_{j,T} \Delta \Theta_j^g}{y_{j,T}}}_{\text{Transfer Income}} + \underbrace{\frac{\Theta_{j,T}^g \Delta p_j}{y_{j,T}}}_{\text{Transfer Share}} - \underbrace{\frac{\Delta \tau_j}{y_{j,T}}}_{\text{Tax}}, \quad (5)$$

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

By subtracting each of the right-hand side terms computed for the young from the corresponding one computed for the old, we can decompose the overall *GRD* into the contribution of the old-young growth differentials on each component, as displayed in Figure 2.

3.2 Results

Figure 4. GRD Decomposition, by income components



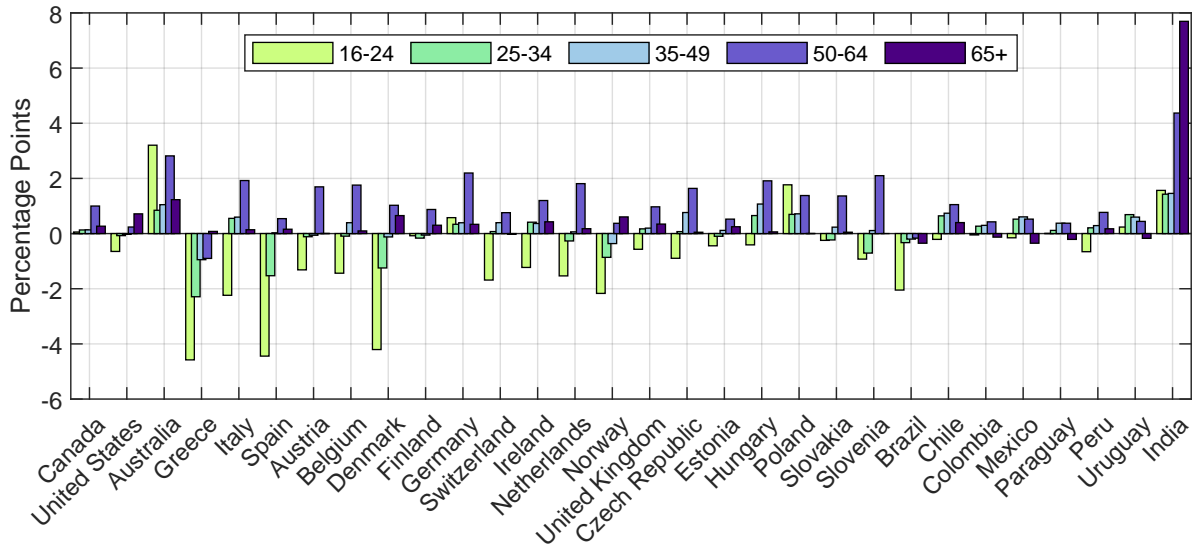
Note: The figure depicts the decomposition of the Growth Rate Differential (*GRD*) calculated for disposable income, comparing 50-64 years old individuals with 25-34 years old ones. “labor income” refers to the contribution to the *GRD* of differences in growth of the average labor income received conditional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

Figure 4 illustrates the contributions to the overall *GRD* between old and young of each sub-components on the right-hand side of equation (5). A positive value means that the specific sub-components grew faster for the 50-64 age group than for the 25-34 one. We now describe the main findings.

First, in rich countries, the main contributor to the increase in intergenerational inequalities between early and late-career individuals has been the increase in differences in employment rates: while the young had reduced their employment rate, the old have increased it. To expand further on this point, in Figure 5 we display the contribution of employment to income growth, $\frac{y_{j,T}^g \Delta e_j}{y_{j,T}}$, for each age group. Besides a few exceptions, such as Australia or Poland, employment changes have reduced income for the younger age groups, and they have increased it for older generations. One might wonder whether the negative effect of employment changes on income growth for the younger age groups is purely driven by higher education enrollment. In Figure 6 we compute the change in employment rate (green bar) and in education enrollment (red bar) for a subset of countries for which those data are available. For the available countries, we see that - apart from Greece, Spain and the Netherlands - the young have actually become more active (being either in education or employment), but more are staying in higher education for longer. In addition, the effect of later retirement for the old can be observed from the negative contribution of “*transfer share*”, which indicates that fewer individuals are receiving pension payments. Notice that this rise in employment differences is not necessarily a worrying outcome for young workers, as higher employment among the old implies fewer pensions being paid from the social security system and more taxes being collected from the old. Nevertheless, a few contributions (Bianchi et al., 2021; Bertoni and Brunello, 2021; Mohnen, 2019) have highlighted how higher employment rates among older workers due to delaying retirement may hinder the career progression and hiring of younger workers. Moving to lower-income countries, we observe similar trends in Eastern Europe, where employment explains almost all the positive contribution to age inequalities, but not in South America, where the young joined *both* employment and higher education, pushing up - or keeping approximately stable - the youth employment rate.

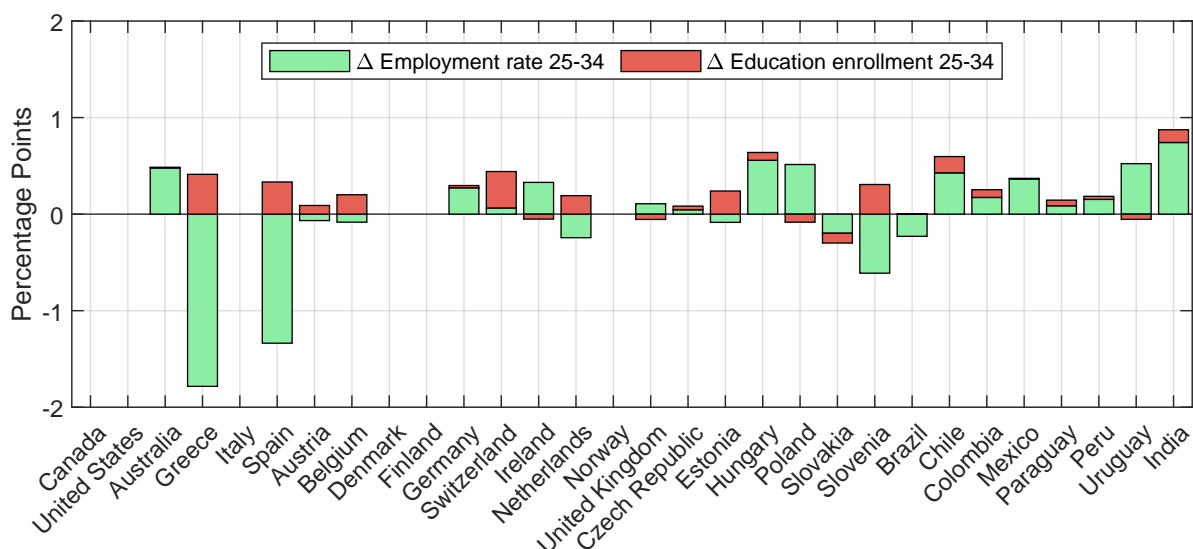
The second-largest contributor of the *GRD* is the differences in *labor income* growth, conditional on being employed. In most high-income countries, the faster income growth of 50-64 employed individuals determined a further increase in the income inequalities with respect to the 25-34 age group. In order to highlight this point, in Figure 7 we display the contribution of labor income, conditional on being employed, to income growth for each age group, i.e. $\frac{e_{j,T}\Delta y_j^g}{y_{j,T}}$. The main contributor to the growth rate differential in rich countries is a faster increase in the labor income of old workers, rather than a fall in the young's one. Instead, in lower-income countries, the labor income of young workers grew faster than the one of old workers, determining a net fall in intergenerational income inequalities, thus resulting in observed negative *GRD*.

Figure 5. Contribution of Employment component to income growth



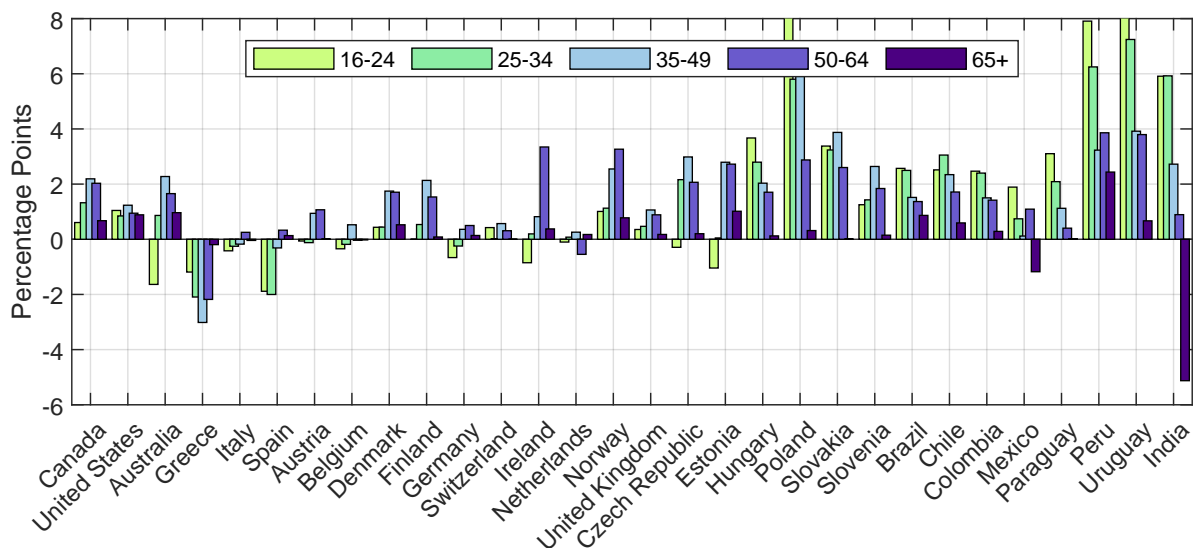
Note: The figure depicts the contribution of changes in the employment rate to the total growth rate of disposable income of five age groups: 16-24, 25-34, 35-49, 50-64, and 65+. The difference between these values for the fourth and second age group gives the “Employment” component of the *GRD* depicted in Figure 4. The dates between which the *GRD* and its components are calculated are provided in Table I.

Figure 6. Contributions to change in share of individuals engaged in either employment or education, 25-34 years old



Note: The figure depicts the annualised changes, between the initial and final year of the decomposition period, in the percentage of individuals between 25-34 who are either employed (green bar) or exclusively in education (red bar). A positive green bar means that the share of individuals in employment has increased. A positive red bar means that the share of individuals in education and with no employment has increased. The sum of the two bars represent the net change in individuals who are either in employment or education. Due to limited data availability for enrollment, we cannot display this statistic for certain countries (Canada, US, Italy, Denmark, Finland, Norway). The dates between which these figures are calculated are provided in Table I.

Figure 7. Contribution of labor Income (conditional on being employed) to income growth

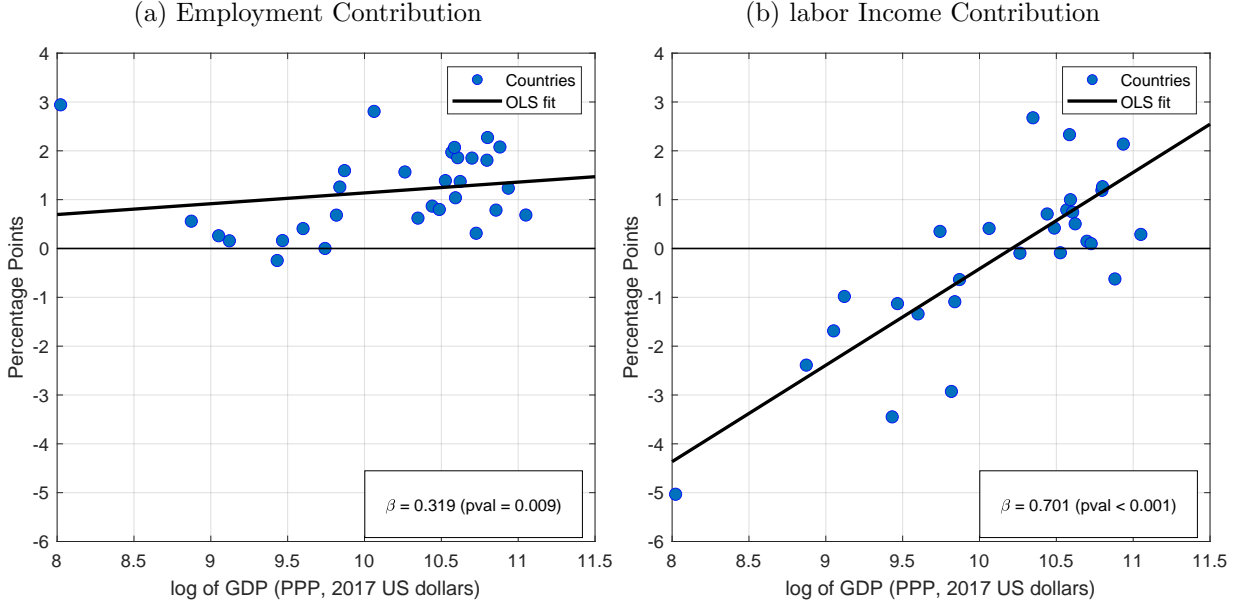


Note: The figure depicts the contribution of changes in the average labor income received, conditional on being employed, to the total growth rate of disposable income of five age groups: 16-24, 25-34, 35-49, 50-64, and 65+. The difference between these values for the fourth and second age group gives the “labor Income” component of the *GRD* depicted in Figure 4. The dates between which the *GRD* and its components are calculated are provided in Table I.

We provide direct evidence for the relationships between GDP levels and contributions to *GRD* by plotting, in Figure 8, the per capita PPP GDP (in 2017 US dollars, in log) of each country at the beginning of the sample against the contribution of employment (panel a), and labor income (panel b) to the growth rate differentials. Using the same scale, a reader can immediately evaluate the relative contributions of the two components to the *GRD*. We observe a significant and strong positive correlation between GDP level and labor income contribution. Instead, the correlation is smaller and non-significant for the employment contribution, possibly because this component is more likely to be directly affected by country-specific fiscal policies (such as retirement age and pension reforms) than market forces. Importantly, notice that while the two contributions go in the same direction in higher-income countries, the negative labor income contribution counteract the positive employment contribution in lower-income countries. This counteracting effect strongly contributes to the negative or close to zero *GRD* in poorer countries. These observations lead to our third stylized fact.

Stylized fact 3 In rich countries, the main contributor to the positive *GRD* is the divergence in employment rates between young and olds. In lower-income countries, the main contributor to negative *GRD* is the faster increase in labor income, conditional on being employed, of the young with respect to the old.

Figure 8. Employment and Labor Income Contribution to *GRD* vs GDP level



Note: Panel (a) plots the “employment” component of the *GRD* of disposable income against the log of PPP GDP (calculated at 2017 dollars, for the initial year of the reference period). The black line shows the linear fit. In the box, we present the linear correlation (ρ) between the two variables. Panel (b) plots the “labor income” component of the *GRD* against the log of PPP GDP (calculated at 2017 dollars, for the initial year of the reference period). Other specifics are as in panel (a). The countries and the dates between which the *GRD* and its components are calculated are provided in Table I.

Take away These results are relevant for two reasons. Firstly, we have highlighted how the channels that affect the *GRD* the most are different between high-income and lower-income countries, but similar within income group. Employment trends seem to be the main cause of the rise in *IGIR* in rich countries, while the fall in developing countries is almost completely led by faster rising wages for the employed young. The income components is also highly correlated with the income level of the countries. The existence of these patterns justifies our initial intention of providing a *global* analysis: by including countries at different stages of development, we have been able to separate global trends and channels from others that appear to be mostly connected to the level of development of a country. Secondly, they suggest that the causes of the rise, or fall, in *IGIR* should be explored by looking first at phenomena connected to the long-run development path of each economy. In light of this, in next section we will propose a number of possible explanations for the overall and income-group trends in *GRD*, focusing on the effect of long-run trends in fundamentals such as education and technology. Indeed, we will conclude that such long-run trends appear to have been at the

root of the rise in *IGIR* in rich countries, but there is still space for other factors.

4 Channels and Drivers of Intergenerational Inequality Trends

This section explores possible drivers and channels of the global trends in intergenerational inequalities. That is, we provide evidence for how specific theories can, or seem unlikely to, explain the overall intergenerational inequality trends, and the diverging trend between high- and lower-income countries. In particular, we ask whether those theories, and the associated channels, are consistent with the evidence documented in the previous sections. We explore four relevant phenomena for growth, human capital, and the labor markets of the last few decades: 1. the educational expansion; 2. technical and structural change; 3. the rise in female labor force participation; and 4. the role of the Great Recession.

4.1 Education Expansion

Education trends may be important to explain the evolution of intergenerational inequalities for two reasons. First, because more educated groups have higher average wages and employment rates, increases and falls in the gaps in educational achievements across age groups could potentially explain the observed intergenerational inequality. Second, more educated individuals have steeper lifetime income profiles, meaning that higher overall education achievement levels may be naturally connected to higher intergenerational inequalities. We will address both of these concerns.

In order to assess the importance of education trends for our findings, we propose three exercises. First, we conduct a naive counterfactual exercise: we fix the educational shares of each age group to the ones of the base year of our analysis, and then we compute counterfactual *GRDs*, which are, therefore, only driven by changes in the *remuneration* of education across different age groups. We show that the trends in the generations' educational achievements can explain a large share of the increase in the *IGIR* in rich countries. Second, we use

the Barro and Lee (2013) education achievement dataset to document that the educational achievements of young and old generations have been converging in rich countries but are diverging - in particular for higher education - in transition economies, and - in particular for high-school education - in developing economies. Then, we use these data to show that the relative education achievements between old and young indeed correlate with changes in intergenerational inequalities. Third, we compute the *GRD* within education groups to establish whether the trends observed for the aggregate *GRD* vary between different education levels. This third exercise answers to whether the rise in *IGIR* may be fully attributed to changes in education achievements, or if there are common trends across education groups that must be explained in some other way.

4.1.1 Fixed Education Share counterfactual

Let us describe the counterfactual exercise. We can represent the average disposable income growth rate between period T and $T + h$, annualized, for each age group j , and ignoring the country-specific notation, as:

$$g(y_j) = \frac{1}{h} \frac{\sum_z \gamma_{z,j,T+h} y_{z,j,T+h} - \sum_z \gamma_{z,j,T} y_{z,j,T}}{\sum_z \gamma_{z,j,T} y_{z,j,T}}. \quad (6)$$

Here, z denotes the index of four possible education attainment sub-groups: college graduates, high-school graduates, less than high school, and individuals still enrolled in education regardless of current achievement. $\gamma_{z,j,T}$ denotes the share of individuals with education level z in the age group j at time T , and sum to one across all z . By adding and subtracting $\gamma_{z,j,T+h} y_{z,j,T}$ in the numerator of equation (6), we obtain:

$$g(y_j) = \frac{1}{h} \frac{\sum_z \gamma_{z,j,T+h} \Delta y_{z,j}}{\sum_z \gamma_{z,j,T} y_{z,j,T}} + \frac{1}{h} \frac{\sum_z y_{z,j,T} \Delta \gamma_{z,j}}{\sum_z \gamma_{z,j,T} y_{z,j,T}},$$

where Δx denotes the difference of variable x between period $T + h$ and T .

Consequently, the *GRD* differential between two generations j and j' can be decomposed

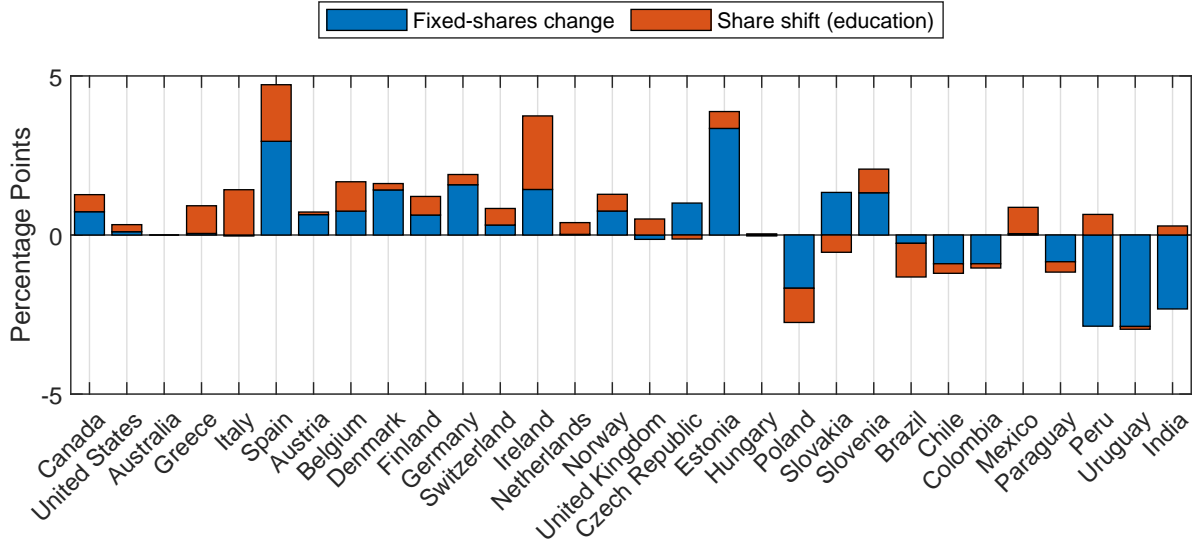
as:

$$\begin{aligned}
g(y_j) - g(y'_j) = & \underbrace{\left(\frac{1}{h} \frac{\sum_z \gamma_{z,j,T+h} \Delta y_{z,j}}{\sum_z \gamma_{z,j,T+h} y_{z,j,T}} - \frac{1}{h} \frac{\sum_z \gamma_{z,j',T+h} \Delta \bar{y}_{z,j'}}{\sum_z \gamma_{z,j',T+h} y_{z,j',T}} \right)}_{\text{Fixed-shares income differential}} + \\
& + \underbrace{\left(\frac{1}{h} \frac{\sum_z y_{z,j,T} \Delta \gamma_{z,j}}{\sum_z \gamma_{z,j,T} y_{z,j,T}} - \frac{1}{h} \frac{\sum_z y_{z,j',T} \Delta \gamma_{z,j'}}{\sum_z \gamma_{z,j',T} y_{z,j',T}} \right)}_{\text{Share shift differential}}.
\end{aligned} \tag{7}$$

Assuming that the income of each group z is exogenous from the characteristics (\bar{y}, γ) of each other group, we can then isolate two separate effects of the growth rate differentials. With this assumption our analysis neglects possible general equilibrium effects. These effects, however, can be captured only with a fully specified general equilibrium model, in which we would have to make assumptions on the possible channels and their transmission mechanisms. Instead, in this exercise we do not restrict the analysis to such mechanisms. The first term of equation (7), labelled *Fixed-shares income differential* represents the contribution of income growth specific to a given education level to the *GRD*; the second term, labelled *Share-shift differential* represents the contribution of shifts in education attainments to *GRD*.

Figure 9 represents the results of this decomposition. We find that - had education achievements, and enrollment remained the same as those of the base year - the growth of intergenerational inequality would have been sensibly lower in high-income countries, as the share-shift differential (red bars) component explains a relevant share of both the total *GRD* among rich countries. In this group, the mean share shift effect (0.75 percentage points per year) is equal to 49 percent of the mean *GRD*, and explains 24 percent of its variance among the 22 rich countries in our sample. In several countries such as the US, Greece, Italy, the Netherlands, and the UK it virtually explains the whole *GRD*, being negligible (approx. 10 percent of the total *GRD*) only in Austria, Denmark, and Germany. The evolution of educational composition does not seem to have played an important role for lower-income countries, apart from Mexico (where it explains most of the increase) and Brazil (where it explains most of the fall).

Figure 9. Growth Rate Differential, fixed-share education counterfactual



Note: The figure depicts the results of the counterfactual exercise for education presented in Section 4. The total *GRD* for disposable income, calculate for 50-64 and 25-34 years old individuals, is decomposed into two components: the counterfactual *GRD*, had education shares remained the same across age groups between T_i and $T_i + h_i$ (“Fixed-shares change”, blue bar), and the effect of the shift in education shares of the two age groups (“Share shift (education)”, red bar). Positive values for either components mean that they contributed positively to the *GRD*; that is, they favoured the old over the young. The dates between which the *GRD* and its components are calculated are provided in Table I.

4.1.2 The role of intergenerational education gap

Long-term education trends are a possible explanation for the findings reported above. To show that, we use the Barro and Lee (2013) database to compute the intergenerational gap in schooling years for each country by taking the difference, at any given period, in schooling years between the 55-64 and the 25-34 age groups. For robustness, we also consider the intergenerational gap in secondary and tertiary education only.¹⁶ In Figure 10 we plot how the two intergenerational education gaps have evolved between 2000 and 2015. Rich countries saw the most considerable positive change, meaning that the old became more educated faster than the young. The same finding holds when considering all the education levels (light bar), or only the secondary and tertiary education levels (dark bar). Instead, transition economies and developing countries experienced much smaller positive variations in the overall schooling years, or even negative variations (meaning that the young became more educated faster than the old) for the number of years in post-primary education. Additionally, notice that the

¹⁶For a further discussion on evidence regarding education trends, see Supplementary material B.1.

absolute value of the variations in developing economies is small, consistently with the small role of changes in relative education shares observed in Figure 9, as obtained from the LIS dataset.

Figure 10. Change in Old-Young difference in years of schooling, 2000-2015



Note: The figure depicts the change in the differential of education achievement (measured in years of schooling) of old (50-64 years old) and young (25-34 years old), between 2000 and 2015. The light green bar represents the change in the education achievement gap across all levels of schooling. The dark green bar represents the change in the education achievement gap across secondary and tertiary education only.

Given the findings reported above, one might wonder whether the evolution of education is a relevant factor in shaping the evolution of the *IGIR*. To investigate this question, we regress the time variation of the *IGIR* over the gap in schooling years between young and old, a proxy for the gap in the human capital accumulation of different generations.¹⁷

Specifically, in order to eliminate the effects of exogenous time trends, we adopt the following specification in first difference:

$$\Delta_t^{\text{ann}}(IGIR_{i,t}) = \alpha + \beta \Delta_t^{\text{ann}}(X^{\text{old}} - X^{\text{young}}) + \varepsilon_{it}, \quad (8)$$

¹⁷Since the Barro and Lee (2013) data refer to five-year periods (2000-2004, 2005-2009, etc...), we realign our observed income ratios to match the Barro-Lee dates, as long as they are no more than two years part. Suppose that for a country we observe the *IGIR* in 2002, 2003, 2004 and 2009. Then, we attribute the 2002 observation to the year 2000 observation in the Barro-Lee dataset, the 2004 *IGIR* to the 2005 Barro-Lee observation, and the 2009 *IGIR* to the 2010 Barro-Lee date. We drop the 2003 *IGIR* observation, as it is the furthest apart from the 2005 Barro-Lee date, already associated with a closer observation.

where, $h_i(t)$ represents the number of years between country i 's observation at time t and the previous non-empty observation; $\Delta_t^{\text{ann}}(x)$ represents the first difference of a variable x between t and $t + h_i(t)$, annualised; X^j represents the independent variable of interest, calculated for the age-group j . For each specification, we will detail the variable X used. Each datapoint is, therefore, a country-year observation.¹⁸

Table IV displays the estimates of the regression. Column (1) reports the baseline result, where we use as X variable the average years of schooling. That is, we regress the (annualised) change in *IGIR* on the (annualised) change in the old-young gap in schooling years. This regression reveals that an increase in the measure of the inter-generational schooling gap is associated with an increase in the *IGIR* growth rate. In particular, one additional year of schooling in favour of the old is associated with a 2.9 percentage points faster annualised *IGIR* growth. The result is significant at the 5 percent level. We obtain similar results, but somehow more significant, when we use as independent variable the difference in schooling years beyond primary school (column 2); this regression is particularly relevant because it is possible that only variations in the difference in schooling levels that guarantee higher returns to education may have a strong effect on the evolution of intergenerational inequality.

One might wonder whether the effect of the education gap on the *IGIR* is non-linear, as it may vary with the overall education level of the countries. To allow for this possibility, we control for the current average level of education of the young, including the interaction term of the two regressors. Hence, we test if the education-gap effect may be stronger in countries with an already higher level of schooling year, in a similar spirit to specification (2). Indeed, in column (3), we show that the interaction term is significant, meaning that relationship between the old-young schooling delta and *IGIR* may be non-linear. We also test for the joint significance of the linear and interaction term of the schooling gap and find it strongly significant. In column (4), we perform the same exercise with the post-primary schooling delta: also in this case, the linear and interaction terms are jointly significant, even though they are not so individually. Finally, columns (5) and (6) add geographical region fixed effects

¹⁸Recall that we have 42 countries for our analysis, each with a variable number (up to 7) of observations, thus amounting to a total of 146 observations.

to the estimation, with results qualitatively similar to the other specifications.

TABLE IV. Regression of IGIR annualised growth rate against old-young delta in education achievement

	(1)	(2)	(3)	(4)	(5)	(6)
old-young schooling Δ , fd [1]	2.902* (1.415)		2.637 (1.423)		2.392 (1.446)	
old-young post-primary schooling Δ , fd [2]		2.898* (1.085)		1.621 (1.300)		1.183 (1.247)
25-34 y.o. years of schooling (demeaned) [3]			0.201 (0.105)	0.221* (0.104)	0.111 (0.191)	0.112 (0.195)
Interaction [1] \times [3]			1.395* (0.617)		1.241 (0.653)	
Interaction [2] \times [3]				1.277 (0.794)		1.199 (0.868)
Constant	0.600** (0.181)	0.697*** (0.165)	0.486* (0.183)	0.597** (0.169)	0.784*** (0.216)	0.884*** (0.206)
Observations	146	146	146	146	146	146
R^2	0.027	0.025	0.059	0.050	0.089	0.079
Joint test p-value			0.0173	0.0358	0.0371	0.0896
Socio-Economic Region FE					X	X

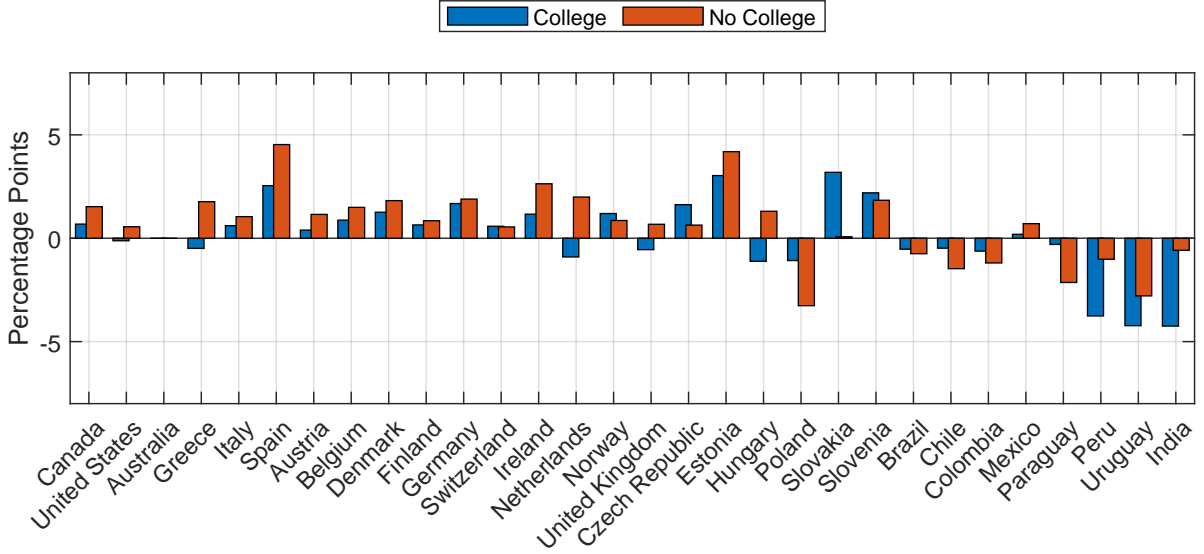
Note: Significance levels: * = 5%, ** = 1%, *** = 0.1%. Standard errors in parenthesis are clustered by country. “fd” means first difference, annualised by further diving for the years between the observations over which the first difference is calculated. Δ refers to the absolute deviation in years of schooling, as defined by the appropriate variable. “Joint test p-value” refers to the p-value of a joint test against a null hypothesis H_0 : schooling Δ + interaction term = 0; values below 0.05 imply that the association between the schooling Δ and the dependent variable is statistically significant. The dependent variable is always the growth rate of *IGIR*, annualised, and adjusted to match the timing of the Barro-Lee dataset by realigning our observed *IGIR* to match the Barro-Lee dates, as long as they are no more than 2 years part. In case two observations of *IGIR* are equally distant from a Barro-Lee dataset date for a country, we give precedence to the one in preceding years over the one in following years. The annualisation of the dependent variable and the regressors is performed to take into account the fact that the panel of country-year observations is unbalanced.

4.1.3 *GRD* by education level

Given the relevance of education gaps for intergenerational inequality, one might wonder whether the *GRD* between age groups are specific only to certain education groups. That is not the case and, on the contrary, the trends observed for the aggregate *GRD* are also observed within education group. To show this point, we divide the population into college-graduates and individuals without college degree, and compute the *GRD* of income for each of the two groups. The results are plotted in Figure 11. We find a pattern consistent with the aggregate one: for the vast majority of the countries in which the *GRD* is positive (negative) we

usually find a positive (negative) education-group *GRD*, for both college- and less-than-college educated individuals.

Figure 11. Growth Rate Differential, by education group



Note: The figure depicts the *GRD* for disposable income, calculate for 50-64 and 25-34 years old individuals, calculated separately for individuals who have completed college education (blue bar) and individuals who hold at most a high-school degree (red bar). The dates between which the *GRD* and its components are calculated are provided in Table I.

Take-away Overall, these results suggest that the catch-up in the overall education achievement of the old over the young is responsible for a relevant share of the observed increase in intergenerational inequalities in rich countries. While our counterfactual does not take into account the endogeneity of the returns to education to the relative supply and demand of skills, further statistical evidence suggests that changes in education shares are indeed correlated to changes in *IGIR*, and potentially more so in countries where the “old” demographic is currently transitioning toward a larger share of College graduates faster than the young. Nevertheless, *IGIR* are increasing (falling) in rich (developing) countries also for other reasons. In fact, we find that the sign of the *GRD* among college and non-college educated individuals is mostly the same within the same country, a sign that other economic or policy forces are acting in the same way on young or old individuals, regardless of education achievement. In the next sections, we explore other possible explanations to the sign and worldwide distribution of the *GRD*.

4.2 Technical and Structural Change

The role of the evolution education attainments for intergenerational inequality may be directly connected to the incentives to pursue further education which - in turn - might be strictly related to the differentials in returns to skills and technical or structural change. This section analyses how technical change (TC, henceforth) may have affected intergenerational inequalities. In general, TC increases the demand and returns of specific skills that benefit from the improved technology. We refer to Skill-Biased Technical Change (SBTC, henceforth) when technology improvement affects some skills more than others. Previous literature, as (Autor and Dorn, 2009, 2013), has found that SBTC seems to benefit the young more than the old, specifically when the bias is in favour of new skills that are under-supplied in the economy. In this case, the young shift into growing occupation titles, both high- and low-skilled, faster than the old, as they have a longer investment horizon in human capital terms. Consequently, in the presence of SBTC that favours *new* skills (i.e. different from the one currently held by current old workers) (as in Adão et al. (2021)), one could expect that SBTC is a relevant determinant of the evolution of intergenerational inequality. A similar argument can be made for structural change, even without technical change: if the demand for specific sectors/goods grows faster due to non-homothetic consumers' preferences or other mechanisms, such as economies of scale or agglomeration effects, one can observe a similar advantage for the young if the skills required in the sectors/occupations with growing demand are different from the current skillset of the old.

In order to investigate the role of technical/structural change on the evolution of intergenerational inequality we conduct two exercises, in the same spirit of the ones seen when investigating education. First, we create a counterfactual measure of *GRD*; then, we investigate how the evolution of intergenerational sectorial employment share across different age group correlates with *IGIR* growth.

4.2.1 Sectorial Employment Share counterfactual

In our first exercise, we construct counterfactual *GRDs* as if the occupational share change of old individuals had been the same as the one observed for the young. This approach is equivalent, in a partial-equilibrium setting, to assuming “unbiased” effects of technical change in their outcome across cohorts. This assumptions can be indifferently interpreted as the outcome three different working examples: i) as the long-run equilibrium of a model of skill-biased technical change, after the economy is shocked by a single, permanent technology shock; ii) in case technical change is not skill-biased, but just increases demand for certain tasks (which translate into “occupations”) that all individuals are able to carry out; iii) in case the old had the same incentives of the young to retrain into new skills/occupations after a skill-biased technical change.

As occupations, we choose (i) professionals, (ii) technical occupations, (iii) blue collars (production workers, low-skill service workers), and (iv) elementary and agricultural occupations.¹⁹ These are large occupational groups, yet strongly connected to tasks and wages and thus ideal to work with when some countries have as little as 5000 individual observations per year.

Our goal is then to isolate the role the *occupational shift gap* on the intergenerational inequality. Let us start with the standard definition of the average labor income growth, y^g , conditional on being employed, for age-group j , between period T and $T + h$. Here, we highlight the fact that labor income can come from being employed in one of the occupation $z \in Z$:

$$g(y_j^g) = \frac{1}{h} \frac{\sum_z \gamma_{z,j,T+h} y_{z,j,T+h}^g - \sum_z \gamma_{z,j,T} y_{z,j,T}^g}{\sum_z \gamma_{z,j,T} y_{z,j,T}^g}.$$

Here $\gamma_{z,j,T}$ denotes the share of individuals in occupation z and in the age group j at time T , and sum to one across all z . We can choose a reference age-group, j_0 , which will be the benchmark reference for the occupational shift gap. Adding and subtracting terms in the numerator, the previous expression becomes:

¹⁹We classify these accordingly to the ISCO major occupational groups: professionals = 1,2; technical = 3,4; blue collars = 5, 7, 8; elementary and agriculture = 6, 9. We drop all occupations related to armed forces, unclassified, and missing observations.

$$g(y_j^g) = \frac{1}{h} \frac{\sum_z (\Delta\gamma_{z,j_0} + \gamma_{z,j,T} + \gamma_{z,j,T+h} - \Delta\gamma_{z,j_0} - \gamma_{z,j,T}) y_{z,j,T+h}^g - \sum_z \gamma_{z,j,T} y_{z,j,T}^g}{\sum_z \gamma_{z,j,T} y_{z,j,T}^g}.$$

The term $\Delta\gamma_{z,j_0}$ denotes the variation, Δ , of the share of occupation z for a chosen reference age group j_0 , between period T and $T + h$.

Rearranging, the growth rate of income for age-group j is:

$$g(y_j^g) = \underbrace{\frac{1}{h} \frac{\sum_z (\Delta\gamma_{z,j_0} + \gamma_{z,j,T}) y_{z,j,T+h}^g - \sum_z \gamma_{z,j,T} y_{z,j,T}^g}{\sum_z \gamma_{z,j,T} y_{z,j,T}^g}}_{\text{Parallel shift growth component}} + \underbrace{\frac{1}{h} \frac{\sum_z (\Delta\gamma_{z,j} - \Delta\gamma_{z,j_0}) y_{z,j,T+h}^g}{\sum_z \gamma_{z,j,T} y_{z,j,T}^g}}_{\text{Occupational shift gap growth component}}.$$

The first term, which we label as *parallel shift* effect, represents the growth of income “as if” all the occupation shares for the age-group j evolved as the one for the reference age-group, j_0 . The second term, which we label as *occupational shift gap* effect, represents the growth of income due to age group j ’s occupational shares changing differently from the reference age group.

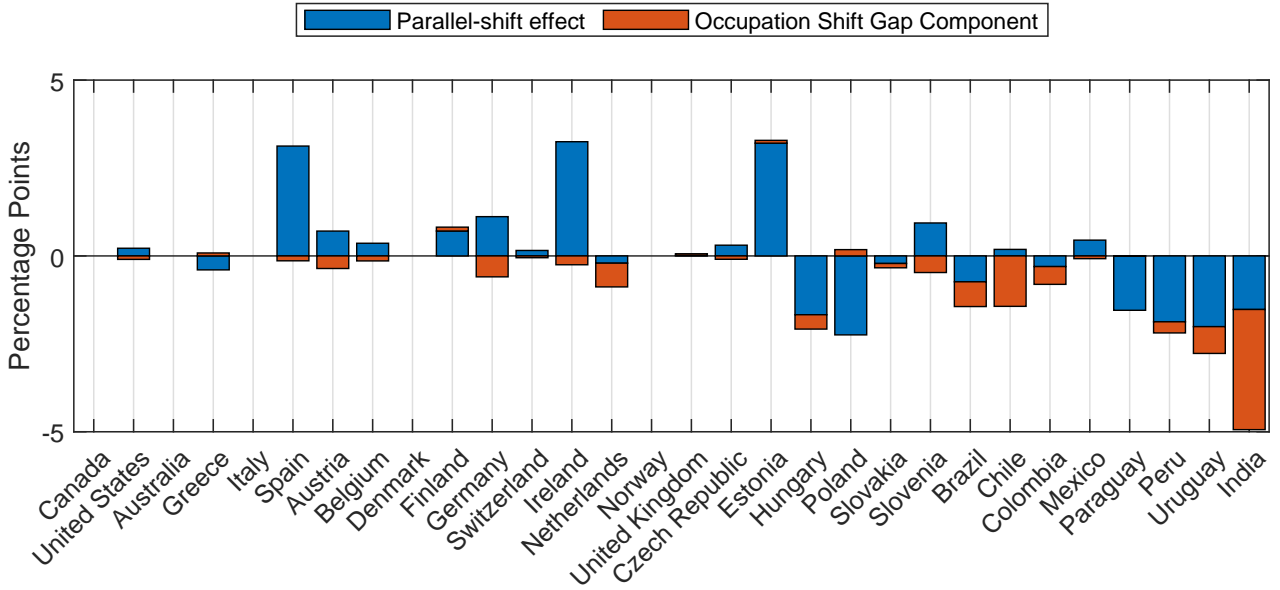
Finally, the *GRD* between old and young can be obtained by setting the two age-group accordingly and using the young age group as a reference. In this case the *occupational shift gap* is:

$$\text{Occupational Shift Gap} \equiv \frac{1}{h} \frac{\sum_z (\Delta\gamma_{z,\text{old}} - \Delta\gamma_{z,\text{young}}) y_{z,\text{old},T+h}^g}{\sum_z \gamma_{z,\text{old},T} y_{z,\text{old},T}^g}. \quad (9)$$

This component of the *GRD* is small whenever the term $(\Delta\gamma_{z,\text{old}} - \Delta\gamma_{z,\text{young}})$ is close to zero for all occupations $z \in Z$. This can happen for several reasons, for example because of lack of occupation shifts ($\Delta\gamma_{z,\text{old}} = \Delta\gamma_{z,\text{young}} = 0$), or in case of parallel occupation shifts ($\Delta\gamma_{z,\text{old}} = \Delta\gamma_{z,\text{young}} \neq 0$). While both the empirical and theoretical literature argues that the second case is improbable after a single permanent shock, it may not be unlikely considering also *past* shocks. In fact, they might set off a transition that can last decades, during which formerly young workers in new occupations/sectors grow older, leading to occupational shifts in the “old” demographic due to decades-old technical/structural change.

In Figure 12 we plot the results of this decomposition. The red bar represents the Occupational Shift Gap component as from equation (9), while the blue bar represents the residual GRD calculated among employed individuals only (equivalent to the “parallel shifts” term of the decomposition). We find an important negative Occupational Shift Gap in lower-income countries, where it explains a considerable part of the negative growth rate differential (40 percent on average). On the other hand the Occupational Shift Gap is negative but small in most high-income countries. This suggests that while there has been *some* technical/structural change that translated into the young picking up new occupations even in rich countries, the *new* technical/structural change has not been fast enough to outpace the *past* one, or that it was not particularly skill-biased in favour of the young.

Figure 12. Growth Rate Differential, employed individuals only. Decomposed by Technical Change Component and residual.

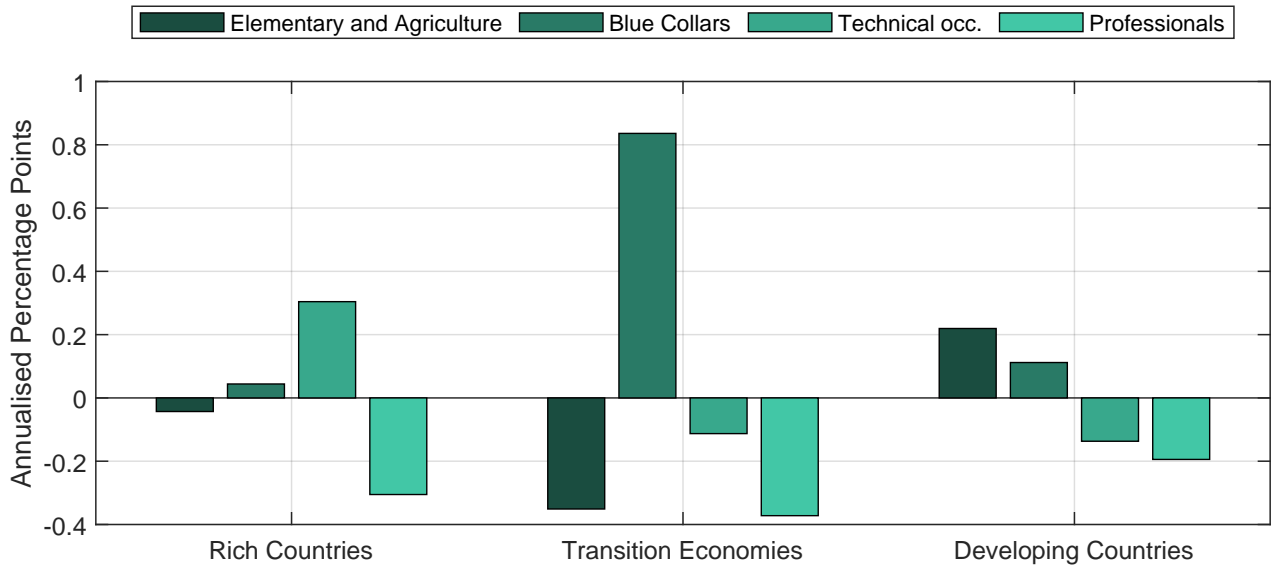


Note: The figure depicts the results of the counterfactual exercise for technical/structural change presented in Section 4. The “labor income” component of GRD for disposable income, calculate for 50-64 and 25-34 years old individuals, is decomposed into two components: the counterfactual “labor income” component of GRD , had occupation shares among employed individuals experienced the same change among young and old individuals between T_i and $T_i + h_i$ (“Parallel-shift effect”, blue bar), and the effect of deviations from the parallel trends between the two age groups (“Occupation Shift Gap Component”, red bar). Positive values for either components mean that they contributed positively to the “labor income” component of GRD ; that is, they favoured the old over the young. The dates between which the “labor income” component of GRD is calculated are provided in Table I.

To provide further evidence of the phenomena behind these estimates, in Figure 13 we plot the ageing of each of the four broad occupation groups by income group. Specifically, we

plot the change (in annualised percentage points) of the gap in the share of old and young employed in such occupation groups. A positive value reflects an occupation that grew faster among old workers relative to young ones, between the first and last year used in Section 3. There is a clearly ordered dynamic in lower-income countries: the least-skilled occupations saw the fastest ageing, while technical and professional occupations saw a shift toward young workers. In rich countries, the young shifted toward professional occupations faster than older workers. Instead, older employed workers moved faster toward technical occupations from lower-skilled ones than the young did, possibly because the cohort that became old at $T + h$ had already shifted away from lower-skilled occupations when they were young themselves.²⁰ For this reason, the young in rich countries did not benefit - in relative terms to the old - as much from this occupational shift as the young in other country groups did.

Figure 13. Occupation aging (change in the difference in employment share between old and young in each occupation), by country income group



Note: The figure depicts the annualised change in the differential of employment in four main occupation groups (Professionals, Technical occupations, Blue Collars, Elementary and Agriculture) between old (50-64 years old) and young (25-34 years old). A positive value means that the share of old individuals employed in that occupation has been growing faster than the one of the young. That is, that occupation has been “aging”. The dates between which the growth rates of employment shares across occupations have been calculated for each country are the same of the Growth Rate Differential, and can be found in Table I.

²⁰This trend may be dampened due to the increase in effective retirement ages, which may have regarded mostly workers in low and mid occupations, as professionals are more likely to have a high educational title and less physically demanding jobs.

4.2.2 The role of high-skilled occupation gap

Finally, following a similar approach as in section 4.1.2, we test whether changes in the differences in high-skilled occupation shares between old and young can explain the changes in the *IGIR*. We perform the same regression as detailed in equation (8), but choose as independent variables two measures of high-skilled occupations: one that includes technical and professional occupations, which we label as “high-skilled occupations”, and one that only includes professional occupations. We keep all countries available in our detailed analysis, but we exclude the following observations as we judge them to be too noisy: all Paraguay and Ireland, Austria 2007 and 2008, Hungary 2012.²¹

Table V reports the results. The change in the old-young gap in high-skilled employment is positively associated with the contemporaneous change in the *IGIR*. In particular, an additional percentage point of the gap in high-skilled employment favouring the old is associated with 0.60 percentage points increase in *IGIR*. When we limit the analysis to professional occupations (column 2), the relationship is around 0.62 additional percentage points. Columns (3) and (4) also add region (rich, transition, developing) fixed-effects to the regression and confirm that the results are robust.

TABLE V. Regression of *IGIR* annualised change against old-young employment gap in top occupation

	(1)	(2)	(3)	(4)
Old-young high-skill emp. share Δ , fd	0.600** (0.177)		0.575** (0.180)	
Old-young professional emp. share Δ , fd		0.616** (0.169)		0.629** (0.170)
Constant	0.549* (0.252)	0.604* (0.266)	0.993*** (0.242)	1.145*** (0.231)
Observations	226	226	226	226
R^2	0.066	0.081	0.092	0.116
Socio-Economic Region FE			X	X

Note: Significance levels: * = 5%, ** = 1%, *** = 0.1%. Standard errors clustered by country. “fd” means first difference, annualised by further dividing for the years between the observations over which the first difference is calculated. Δ refers to the absolute deviation in years of schooling, as defined by the appropriate variable. The annualisation of the dependent variable and the regressors is performed to take into account the fact that the panel of country-year observations is unbalanced.

²¹The significance of the results is not affected by this choices, but the fit is considerably affected by dropping the full time series of Paraguay and Ireland.

Take-away The evidence we have provided so far is consistent with many hypothesis of technical and structural change discussed in the literature. We find global evidence for the fact that the shift toward new occupations regards mainly the young, as previously argued by [Autor and Dorn \(2009, 2013\)](#) for the U.S. and by [Porzio et al. \(2020\)](#) for lower income countries. Our results highlight that shifts across occupations are a relevant determinant of changes in the evolution of intergenerational inequalities in lower-income, and somehow contributed to lower *GRD* also in some rich countries. We suggest that this may be due to a sharp shift of the young away from very low-skilled occupations in lower-income countries, a phenomenon not as evident in higher-income ones. In fact, in higher-income countries and Eastern Europe, the share of older workers employed in elementary occupations has been falling faster than the young's. [Adão et al. \(2021\)](#) provides a theoretical framework and empirical evidence for how and when SBTC leads to larger occupational (skill) readjustment among the young than among the old. In its spirit, a possible rationalisation of the results regarding the evolution of intergenerational inequality due to occupation shifts may be rationalized as follows: while lower-income countries may be experiencing stronger forces that pull young individuals out of elementary occupations (possibly due to better, or more targeted, education) for the first time, in higher-income countries the continuous skill-biased technical change that favours the young is partially (or even completely) counterbalanced by past trend that favoured young individuals in the 1980s and 1990s (ITC revolution, rise in college education), and is now reflected into older generations.

4.3 Female labor Force Participation

In this section, we explore whether recent trends in female employment have had a role in shaping intergenerational inequality. This link could arise, for example, if such trends are mainly driven by young or older women instead of being uniform across the age distribution. In fact, the age bias for the increase in female labor force participation during the 80s and 90s has been widely documented for several countries ([Thévenon, 2013](#)). Thus, as we did for the trends in education and occupations, it is natural to ask whether the dragging forward of such past trends can explain the observed *GRD*, as well as whether the stylized facts reported

for aggregate *GRD* are common for all genders.

To answer the first question, we perform a counterfactual exercise. Similarly to what we did for occupation shares, we create a counterfactual with parallel trends between old and young workers. In particular, we decompose how the growth rate differential in labor income between old and young would have been if these two age groups had experienced the same evolution of female employment share, on top of their specific male one. This approach allows us clearly separate the *overall* trends of employment rates across age groups from differences in trends of female employment rates.

To derive this decomposition, let us consider the definition of growth rate of labor income for age group j , and denoting “male” as “m” and “female” as “f”; it writes:

$$g(e_j y_j^g) = \frac{1}{h} \frac{(e_{m,j,T+h} y_{m,j,T+h}^g + e_{f,j,T+h} y_{f,j,T+h}^g) - (e_{m,j,T} y_{m,j,T}^g + e_{f,j,T} y_{f,j,T}^g)}{\sum_z e_{z,j,T} y_{z,j,T}^g}.$$

Recall that e_j denotes the average employment rate and y_j^g denotes the average labor income rate, conditional on employment, for age group j .

Let define as $\psi_j = \Delta(e_{f,j}) - \Delta(e_{m,j})$, where, as usual, $\Delta(x)$ denotes the change of variable x between period T and $T + h$. Therefore, ψ_j is the difference in employment rate change between females and males in those two periods. Then, fixing a reference age group j_0 , the growth of labor income for age group j can be defined as:

$$\begin{aligned} g(e_j y_j^g) = & \frac{1}{h} \frac{[(e_{m,j,T} + \Delta(e_{m,j})) y_{m,j,T+h}^g + (e_{f,j,T} + \Delta(e_{m,j}) + \psi_{j_0}) y_{f,j,T+h}^g] - (e_{m,j,T} y_{m,j,T}^g + e_{f,j,T} y_{f,j,T}^g)}{\sum_z e_{z,j,T} y_{z,j,T}^g} \\ & + \frac{1}{h} \frac{(\psi_j - \psi_{j_0}) y_{f,j,T+h}^g}{\sum_z e_{z,j,T} y_{z,j,T}^g}. \end{aligned} \tag{10}$$

Let us denote the first term on the right-hand side of equation (10) as Π_j . Finally, taking as reference group the young, the growth rate differential of interest can be simply computed by subtracting the labor income growth rate of the young to the one of the old, i.e.

$$g(e_{\text{old}}y_{\text{old}}^g) - g(e_{\text{young}}y_{\text{young}}^g) = \underbrace{\Pi_{\text{old}} - \Pi_{\text{young}}}_{\text{Parallel-shift effect}} + \underbrace{\frac{1}{h} \frac{(\psi_{\text{old}} - \psi_{\text{young}}) y_{f,\text{old},T+h}}{\sum_z e_{z,\text{old},T} y_{z,\text{old},T}}}_{\text{Gender Employment Gap}}$$

Therefore, we are able to decompose the labor income growth rate differential between the old and the young in two components. The first one, labelled as “*Parallel shift effect*” can be interpreted as the contribution due to the female employment rate growing at the same rate among old and young, while taking as given the growth rate of employment of male individuals. The second one, labelled “*Gender Employment Gap effect*”, represents the contribution arising from differences in the growth in the female employment rate of old and young.

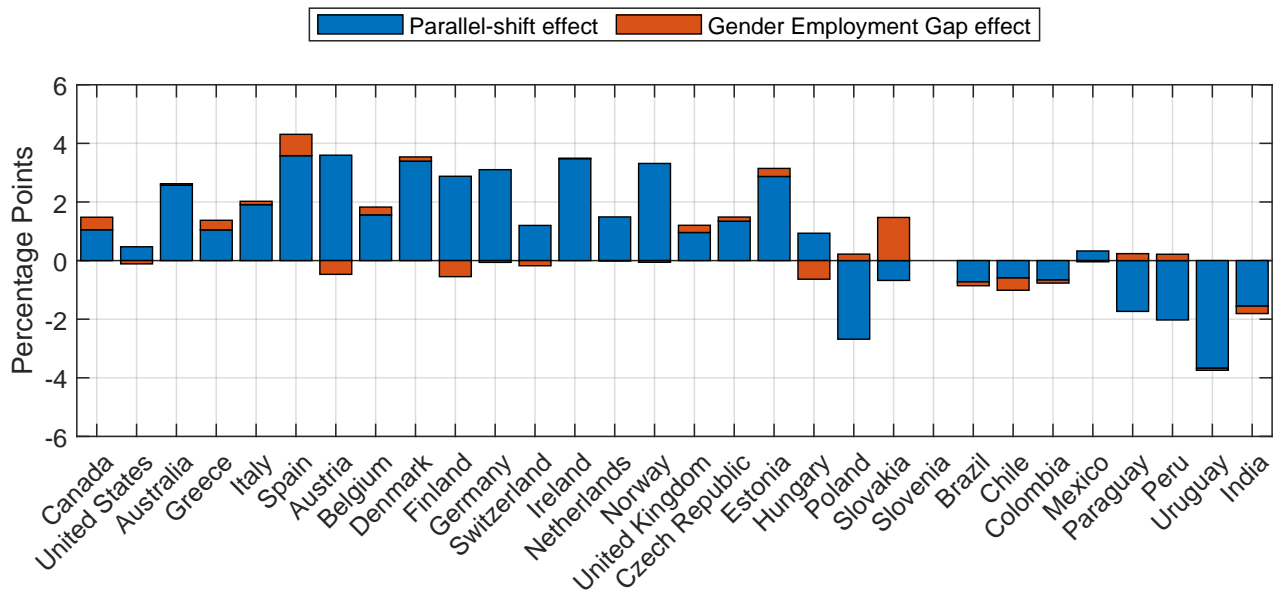
The results of this decomposition are illustrated in Figure 14, where we plot the “*Parallel shift effect*” (blue bar) and the “*Gender Employment Gap effect*” (red bar) together. We can see that the effect of differentials in trends in female employment appears to be negligible for most countries, suggesting that the main causes must be linked to other phenomena, including the ones discussed in the previous sections. The gender employment gap effect contributed in a slightly positive way in most rich countries, consistently with the evidence that the labor force participation rates are stabilising in these countries.

To answer to the second question, whether the *GRDs* are different across sexes, we plot the *GRD* for each sex in Figure 15. Again, we do not find relevant differences in the sign across sexes, meaning that there are common factors that affected the *IGIR* of both sexes, and that these forces prevail over sex-specific effects. On the other hand, we observe that the *GRD* are consistently larger for female than for male, meaning that there are indeed sex-specific forces that are affecting *IGIR* within each sex.

4.4 “Scarred Generation” Theory

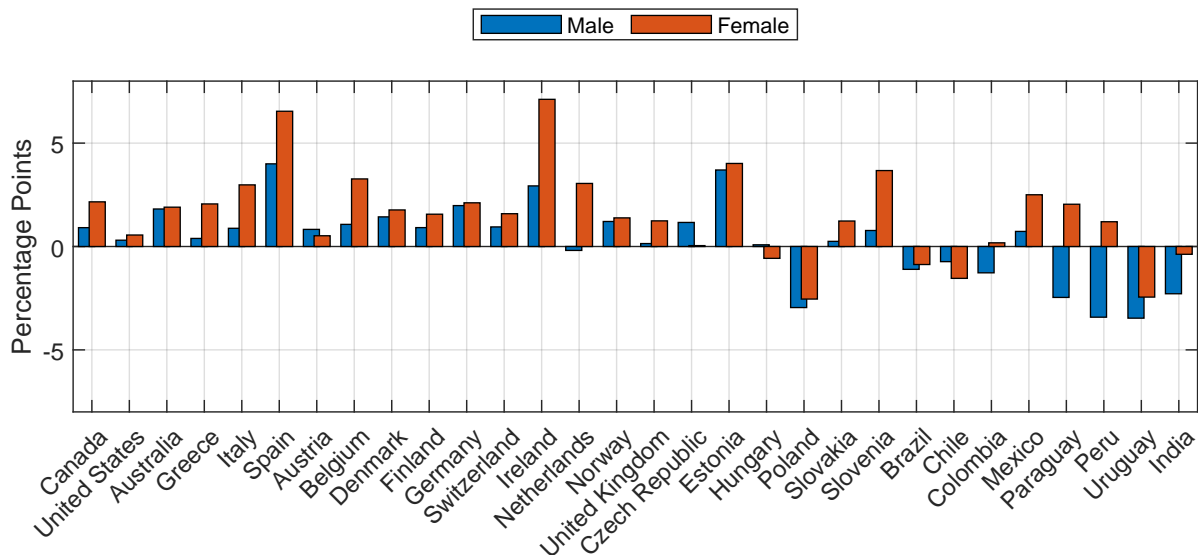
Finally, we test an alternative theory of the causes of the observed intergenerational inequality. The “scarred generation” theory refers to the possible role that the 2007-2009 recession has had on affecting the income of the young and the old differently since the young’s income

Figure 14. Growth Rate Differential: ey^g component only, and decomposed by trends in gender employment gap effect and residual.



Note: The figure depicts the results of the counterfactual exercise for female labor force participation presented in Section 4. The sum of the “labor income” and “employment” components of *GRD* for disposable income, calculate for 50-64 and 25-34 years old individuals, is decomposed into two components: the counterfactual component of *GRD* (“Parallel-shift effect”, blue bar), and the effect of deviations from the parallel trends between the two age groups and sexes (“Gender Employment Gap effect”, red bar). Positive values for either components mean that they contributed positively to the two components of the *GRD*; that is, they favoured the old over the young. The dates between which the components of *GRD* is calculated are provided in Table I.

Figure 15. Growth Rate Differential, by Sex



Note: The figure depicts the *GRD* for disposable income, calculate for 50-64 and 25-34 years old individuals, calculated separately for males (blue bar) and females (red bar). The dates between which the *GRD* and its components are calculated are provided in Table I.

might have been depressed as a consequence of the dire economic conditions that people born in the late 1980s and early 1990s had to face when entering the labor market. This hypothesis relates, from a more general point of view, to several contributions to the literature that had shown how the labor outcomes of individuals strongly depend on the economic conditions that they faced when they entered the labor market (Brunner and Kuhn, 2014; Altonji et al., 2016; Andrews et al., 2020). Periods of slow growth or recessions disproportionately affect young workers (more often employed in temporary or seasonal jobs, and with less experience overall); even after the recession is over, the unemployment spells and the inability to move from job to job as quickly as during periods of high growth may affect future earnings.

In this section, we explore whether this channel may explain the observed trends in intergenerational inequalities and their differences across countries. To do so, we build a set of indicators of “lifetime” labor market conditions for each cohort. That is, for each country i and time t , we calculate for each cohort of persons who have age $a \in [25, 59]$: i) the average real GDP per-capita growth rate, and ii) the share of years of negative real GDP per-capita growth, that they had to face between the year when they turned 18 years old and T . Then, for each country-year pair, we average these values for the “young” (25-34 years old) and the “old”.²² Finally, we take the difference between the indicator of the old X_{it}^{old} and the one of the young X_{it}^{young} . These indicators represent the difference in lifetime labor market conditions that the “old” and “young” at time t had to face during their lifetime. We drop all observations for which we cannot build a history of labor market conditions since 25 years old for individuals below 55 years old at the observation date and, among the surviving countries, all those left with less than three observations after this cleaning process. Then, we regress the *IGIR* annualised change onto the indicator’s (annualised) first difference, in line with how illustrated for equation (8). We report the results in Table VI. We do not find any significant result, and the explained variance is close to zero, despite the sign of the coefficients are as expected: when the current old cohort experienced higher (less) growth (recessions) than the young cohort, *IGIR* increases faster. While this does not mean that the mechanism is not at

²²Because of data availability, we are unable to reconstruct the histories of GDP growth experienced by 60-65 years old individuals during their youth. Thus, we define “old” as 50-59 years old.

work, as several contributions dedicated to the topic have found credible results, our results highlight how this specific phenomenon does not seem to explain the variations observed in our sample. This result is credible for two reasons. Firstly, *IGIR* has been increasing in advanced economies since way before the Great Recession, and even during the late-90s Great Moderation and tech boom. An indicator capturing recessions or slow-growth periods would not be able to explain this non-cyclical trend. Secondly, individuals who were 50-64 in the reference period (2000-2015) have also been exposed to intense recessions and economic slowdowns during their youth: the median person aged 50 in 2005 entered the labor market during or immediately after the 1973 oil crisis and experienced the 1979 oil crisis and the stagflation period before his 30s.

TABLE VI. Regression of change in IGIR against labor market condition differentials

	Lifetime		Youth (18-30) only	
	(1)	(2)	(3)	(4)
Mean Growth Differential, fd	-0.00161 (0.0195)			
Mean Recession Exposure Differential, fd		-0.0361 (0.134)		
Mean Growth Differential, youth only, fd			0.0000356 (0.0122)	
Mean Recession Exposure Differential, youth only, fd				-0.00476 (0.103)
Constant	0.0102*** (0.00223)	0.0100*** (0.00229)	0.0103*** (0.00250)	0.0102*** (0.00221)
Observations	212	212	194	212
R^2	0.016	0.016	0.018	0.016
Socio-Economic Region FE	X	X	X	X

Note: Significance levels: * = 5%, ** = 1%, *** = 0.1%. Standard errors clustered by country. All observations for which we were unable to build a life-long history of per-capita GDP growth of individual who are 55 years old or less were dropped. Then, we dropped all countries for which remained less than 3 observations after this first procedure. The table present a regression of the change in IGIR between two datapoints against several indicators of the economic/labor market conditions experienced by the young and the old. The annualisation of the dependent variable and the regressors is performed to take into account the fact that the panel of country-year observations is unbalanced.

5 Conclusions

The issue of income inequality is topical in the economic debate. Recently, one specific angle of this phenomenon has attracted the attention of policymakers and economists: how are resources distributed among different age groups? Are the young becoming poorer with respect to the old? In this paper, we study the intergenerational income (*IGI*) inequality across 42 countries at different stages of their economic development. The international dimension of our analysis is crucial to uncover regularities and dissimilarities of the evolution of *IGI* inequality and to relate them to long-run economic trends. To our knowledge, our paper is the first one to provide a similar analysis.

First, we establish some stylized facts about *IGI* inequality across the globe. In the last 20 years, intergenerational income inequality has increased in all advanced economies. Individuals aged 50-64 went from earning on average, in a given year, around the same income as young ones (aged 25-34) to earning almost 28 percent more than them. This sharp increase is mainly due to the income of the young falling or remaining stable, while the one of the old increased at sustained rates. Nevertheless, this trend is absent or even reverted in countries with lower GDP per capita. By decomposing how income has grown in the last decades for each age group, we show that in rich countries, the main contributor to the increased *IGI* is the divergence in employment rates between young and old. Instead, in lower-income countries, we observe a strong counteracting force driven by a faster increase in labor income, conditional on being employed, of the young with respect to the old. This force is strong enough to reduce *IGI* inequality in those poorer countries.

Second, we propose some possible explanations for the observed stylized facts, focusing on the effect of long-run trends in economic fundamentals. We find that changes in the differential in education achievement and high-skill occupation employment between young and old are strongly connected to the changes in income intergenerational inequalities but in non-obvious ways. In high-income countries, old individuals are catching up with younger ones in educational achievement: this share shift can explain half of the rise in *IGI* inequalities between 1997 and 2019 in rich countries. Instead, the faster shift of young workers into better-

paid occupations is at the centre of the fall in *IGI* inequalities in lower-income countries, where it explains 40 percent of the average fall.

We argue that the rise in *IGI* inequalities in high-income countries is, at least in part, a natural consequence of long-run trends in economic developments. Similarly, the fall (or stability) in lower-income countries appears to be a transitory phenomenon led by fast transformations of the economy, with current young generations strongly benefitting from higher education levels and structural/technical change. Nevertheless, local policies and economic factors are still likely to explain the residual part of these trends and influence both education and training.

Our results are relevant for policymakers. First, they suggest that the upward trends in *IGI* inequality in high-income countries have been the effect of decades-long transition dynamics. Nevertheless, they also suggest that tackling intergenerational inequalities may indeed *need* public policies aimed at ensuring intergenerational fairness, as it seems implausible that we will see, without policy intervention, a reduction in *IGI* inequalities in rich countries.

Our results are also relevant for academics, as they open further research questions. First, because part of *IGI* inequality is a consequence of long-run economic trends, its welfare cost is not clear. In addition to the clear political and long-term public budgeting implications (for example, for the balance of pension funds), are *IGI* inequalities economically inefficient, and what is their welfare costs? Second, is there a trade-off between the intensive (wage) and extensive (employment) margins of *IGI* inequalities? Moreover, if yes, what outcome is the most desirable? Also, what are the likely future trends in *IGI* inequality? Since education and technical change seem inevitable - and desirable - sources of long-term economic development, are *IGI* inequalities in lower-income countries set to experience the same trajectory as the ones observed already in higher-income ones? Furthermore, if so, what does it imply for long-term generational policies that policymakers should adopt in order to ensure intergenerational fairness? We believe that our work and findings are relevant to setting the stage to address those questions.

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A Appendix

A.1 Intergenerational Income inequalities vs age-wage gap

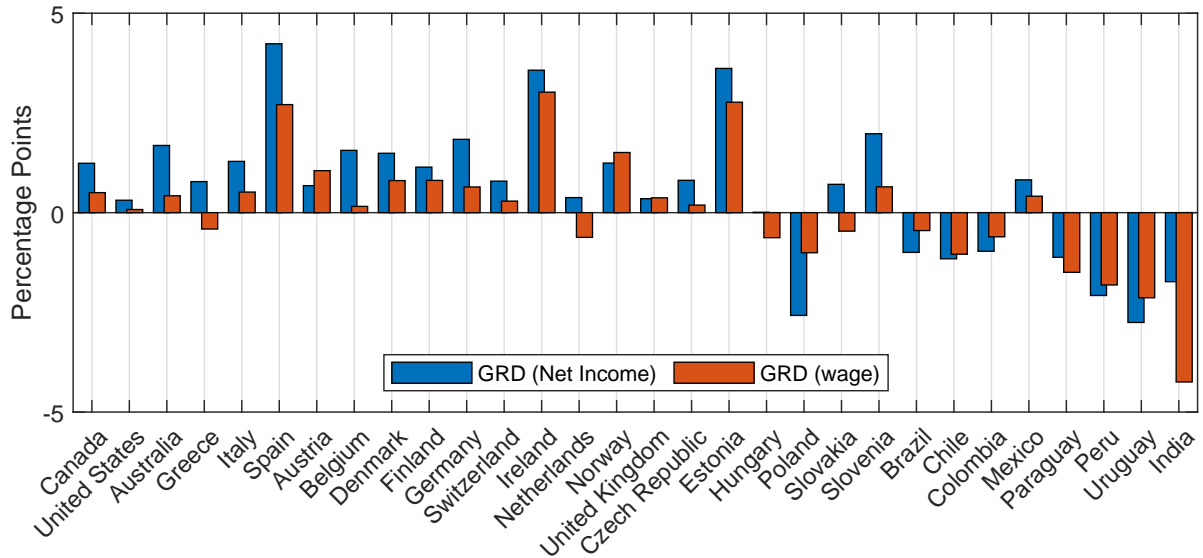
The statistics we derive are closely related to the concept of “age-wage gap”, as defined by [Bianchi and Paradisi \(2021\)](#). In similar ways, other studies have focused on the differences in wages of young and old individuals. Even more, several contributions focus mostly on male and full-time employees with no unemployment spells. While this choice of analysis all have precise reasons connected to data availability and consistency over time (for example, due to the change in female labour force participation over time), they all suffer from the drawback of not accounting for all dimensions of individual income. Nevertheless, if all components of income move in similar ways for the main sub-populations, changes in our *IGIR* or in the age-wage gap could be similar. In this section, we explore whether this is the case.

Figure [A.1](#) plots the growth rate differential (*GRD*) of net income (the same presented in the main text) against the *GRD* of wages. The latter figure can be interpreted as the growth rate of the age-wage gap, defined as the wage ratio between old and young workers. We find that the *wage GRD* seems to downplay the changes in *GRD*. In rich countries, it is almost always smaller than the net income *GRD*. In some countries, such as Greece and the Netherlands, it even assumes the opposite sign. In our transition economies it is always smaller, in absolute value, or of opposite sign. Finally, in developing countries - where most of the net income *GRD* comes from wages - the two figures are quite close to each other, although the wage *GRD* seems to downplay the fall in inequalities for most countries. The average difference between the absolute value of the income *GRD* and the wage *GRD* is of 0.4 percentage points. While these differences may appear small, the reader should consider how these represent *annualised* figures. For example, the small 0.25 p.p. yearly difference for the U.S. figure translates into a 5.5 percentage point underestimation of the increase in income inter-generational inequalities over the period of interest when using the wage-only definition. For Germany, this difference is of 25 percentage points.

In this sense, changes in relative wages between old and young seem to underestimate

(or even get the wrong sign, in most extreme cases) the changes in overall income. On the other hand, the qualitative evidence seem to point in the same direction of our results, showing common trends across countries at similar stages of economic development. In fact, the correlation between the GRD of wages and of net income is 0.88.

Figure A.1. Growth Rate differential, 50-64 vs 25-34: Disposable income vs Wage.



Note: The figure compares the Growth Rate differential (*GRD*) calculated for disposable income, as in the main text, and for wages only. The latter is similar to what other contributions to the literature have focused on. The disposable Income *GRD* is almost always larger in module than the Wage *GRD* (0.4 annualised percentage points, on average), but the two have a high degree of correlation (0.88). The dates between which the *GRD* is calculated are provided in Table I in the main text.

A.2 Different definition of young/old

Retirement-age and young adults. Panel (b) of Figure A.2 illustrates the net income *GRD* between individuals aged 65+ and those aged 16-24. Again, we observe similar patterns to the ones observed for the baseline definition in the main text. The *GRD* is positive in rich countries and some transition economies. It is, instead, negative in developing countries. Notice the difference in the scale of the graph with respect to figure 2, showing how the *GRD* are larger for the 65+/16-24 definition of old and young.

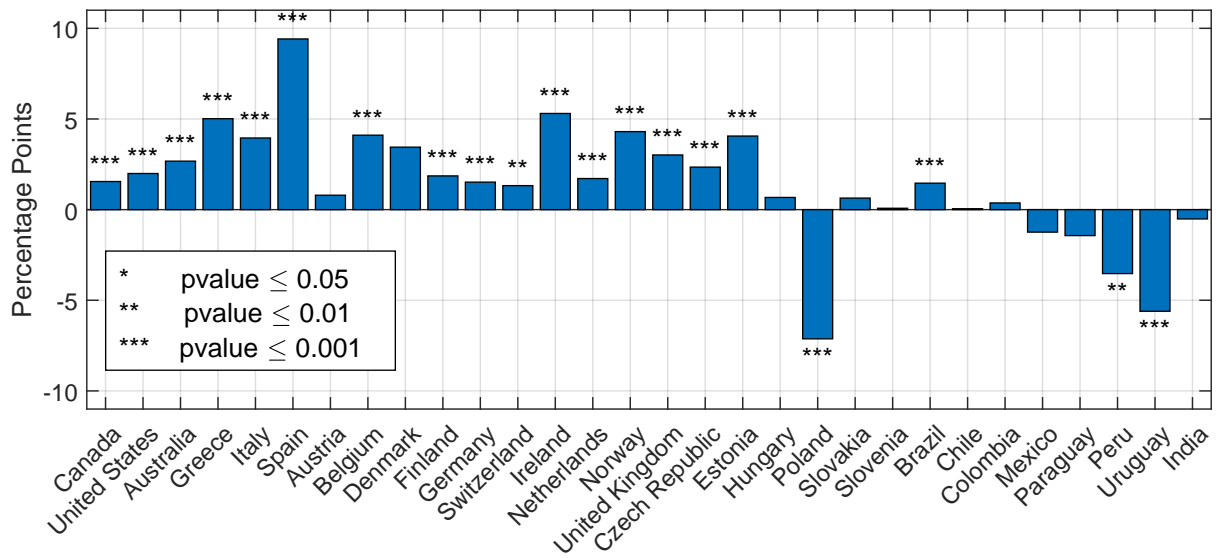
In Figure A.3 we test whether this observation of correlation between the *GRD* and the income of a country holds for the alternative old-young definition too. We find that this is the case: the *GRD* is significantly correlated with the log of PPP GDP per-capita at the beginning of the sample, with a correlation coefficient of 0.60 and a Spearman ρ of 0.70.

Finally, in Figure A.4 we explore the determinants of the increase in income inequalities between the 65+ and the 16-24 age groups. Again, in rich countries most of the increase was led by a difference in the contribution of employment growth, this time due to a sharp fall in employment rates among the youngest group, and a stationary figure for the older one in most countries (as the pension age only recently started passing 65 y.o. in some countries). The second largest contributor was the rise in transfer income, including pensions, conditional on receiving a transfer. This may be seen as a natural phenomenon that occurs when new retirees spent their working life in a labour market with higher average wages than the average retired individual that died between the beginning and the end of the sample.²³ However, it may be exacerbated (hindered) by policies aimed at increasing (reducing) pension benefits. In low-income countries, income inequalities between old and young fell due to the fast increase in labour income (conditional on employment) of the young, similarly to the main text's result for the different definition of old and young. At the same time, we observe how some low-income countries introduced relevant pension reforms, such as a reduction in the national retirement age or the expansion of the coverage and size of minimum/public payments to retirees. This is reflected in the positive contribution of the *transfer share*, meaning that more old individuals

²³This due to paying more contributions, and possibly for longer working lives.

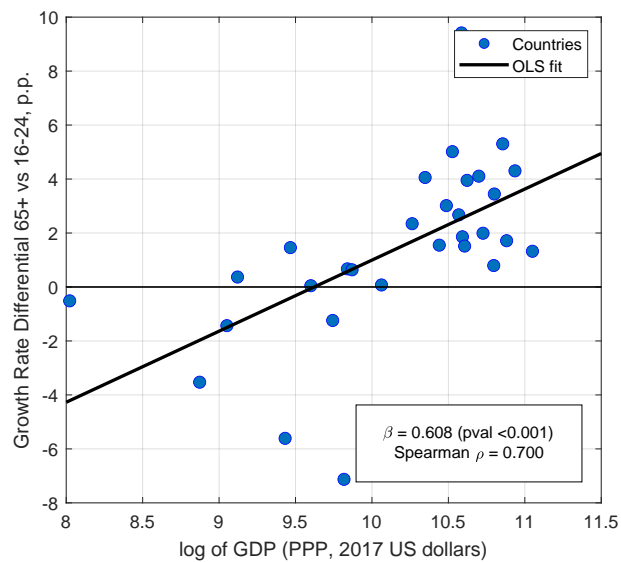
are receiving pension payment transfers.

Figure A.2. Growth Rate Differentials: 50: 65+ y.o. vs 16-24 y.o.



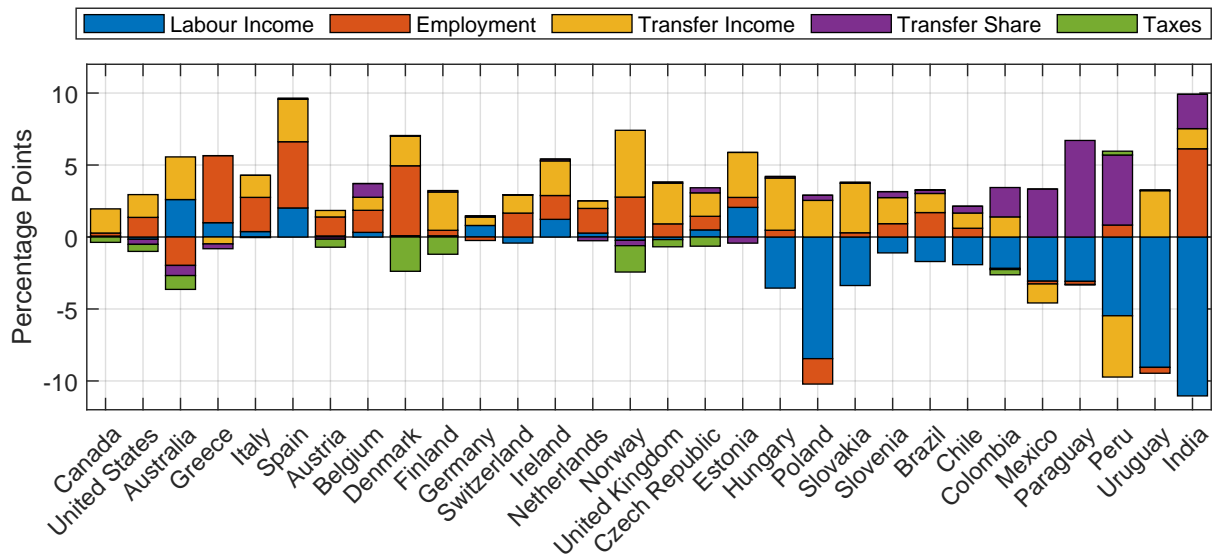
Note: The figure depicts the Growth Rate differential (*GRD*) calculated for net income, comparing 65+ years old individuals with 16-24 years old ones. The dates between which the *GRD* is calculated are provided in Table I in the main text.

Figure A.3. GRD (65+ y.o. vs 16-24 y.o.) and country income level



Note: The figure plots the *GRD* presented in figure A.2 for 65+ vs 16-24 years old (vertical axis) against the log of PPP GDP (in 2017 dollars) at the beginning of the sample period for each country. The black line represents the linear fit. The box reports the Pearson correlation (ρ) and the Spearman correlation (Spearman ρ) between the two variables. The initial years of the period, the final year and the 30 countries depicted in the figure are reported in Table I in the main text.

Figure A.4. *GRD* Decomposition, by income component, by income components; 65+ against 16-24



Note: The figure depicts the decomposition of the Growth Rate differential (*GRD*) calculated for net income, comparing 65+ years old individuals with 16-24 years old ones. “Labour income” refers to the contribution to the *GRD* of differences in growth of the average labour income received conditional on being employed. “Employment” refers to the contribution toward the total *GRD* of differences in growth of the employment rate. “Transfer Income” refers to the contribution of differences in growth of the average transfer received, conditional on receiving one. “Transfer Share” refers to the contribution of differences in growth of the share of individuals receiving a transfer. “Taxes” refers to the contribution of differences in growth of the average amount of taxes paid on labour income and transfers. The five components sum to the total *GRD*. The dates between which the *GRD* and its components are calculated are provided in Table I in the main text.

A.3 Centered Growth Rates

Because the level of the growth rates for each country depends on the growth rate of the economy as a whole, we can provide a better way to visualise the patterns of different age groups across different countries by removing this level effect. In other words, we would like to remove the country-specific average income-growth to highlight the within-country differences between age-group specific growth rates.

Notice that we can define the overall income of a country i at a time t , $y_{i,t}$ as the weighted average of age-group specific average income $y_{i,j,t}$, where the weights are the population share of those age groups. Specifically:

$$y_{i,t} = \sum_j \alpha_{i,j,t} y_{i,j,t},$$

where $\alpha_{i,j,t}$ denotes the share of each age group j in the population at time T for country i . We now remove from the notation the country-index i , for simplicity.

It follows that the country average income growth rate, $g(y)$ between period T and $T + h$ is:

$$g(y) = \frac{1}{h} \frac{\sum_j \alpha_{j,T+h} y_{j,T+h} - \sum_j \alpha_{j,T} y_{j,T}}{\sum_j \alpha_{j,T} y_{j,T}}$$

The average income growth rate depends on the evolution of the shares of each age group in the population, $\alpha_{j,T+h}$ and $\alpha_{j,T}$. In fact, an economy whose workforce age composition is changing over time may experience a “free” increase, or decrease, in average disposable income, as the distribution of people across working age, career stages, education, or retirement may shape the average dynamics of income. Assuming that the income of each group is exogenous from the income of every other group,²⁴ we can adjust the observed average growth rate of income to create a *demographics-corrected* average growth rate that captures the growth of average income between T and $T + h$, had the demographics remained fixed at those of time T . We can compute this as:

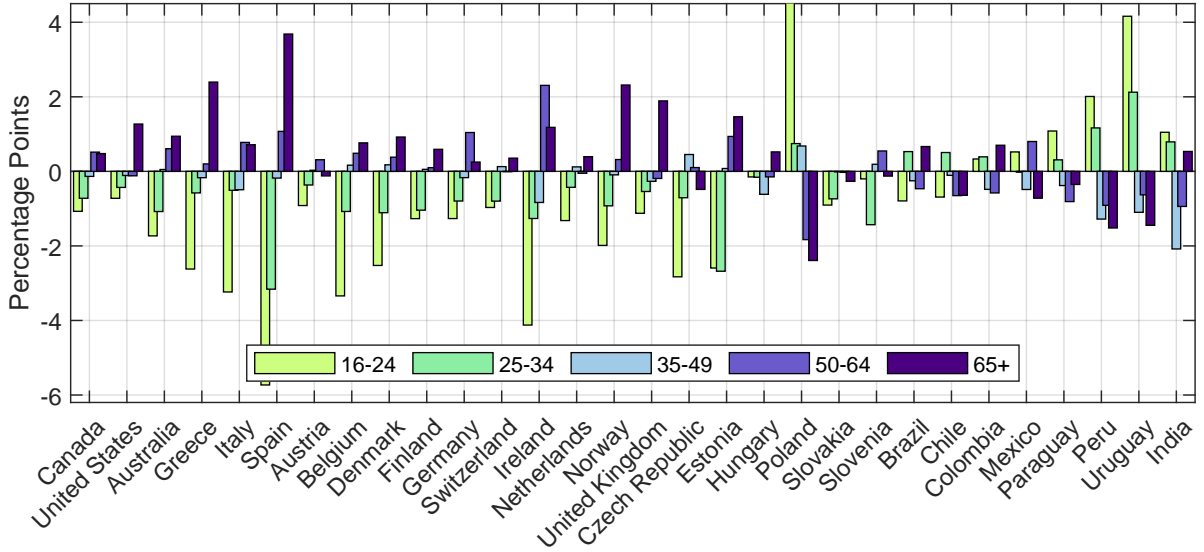
²⁴For a reason why this may not be the case, see Jeong et al. (2015) and Angelini (2021). Nevertheless, this would not affect our results regarding the growth rate differentials.

$$\tilde{g}(y) = \frac{1}{h_i} \frac{\sum_j \alpha_{j,T} [y_{j,T+h} - y_{j,T}]}{\sum_j \alpha_{j,T} y_{j,T}}.$$

Our statistics of interest, plotted in Figure A.5, is then the centered growth rate \tilde{Q} .²⁵

$$\tilde{Q}_{ij} = g_i(y_j) - \tilde{g}_i(y).$$

Figure A.5. Annualised Growth in excess of adjusted mean: Disposable Income



Note: The figure depicts the annualised growth rate of disposable income in excess of the country's adjusted mean growth rate (\tilde{Q}_{ij}), for each of the five age groups. The dates between which the calculation is performed are provided in Table I in the main text.

We derive another stylized fact, obviously linked to the ones presented in the main text.

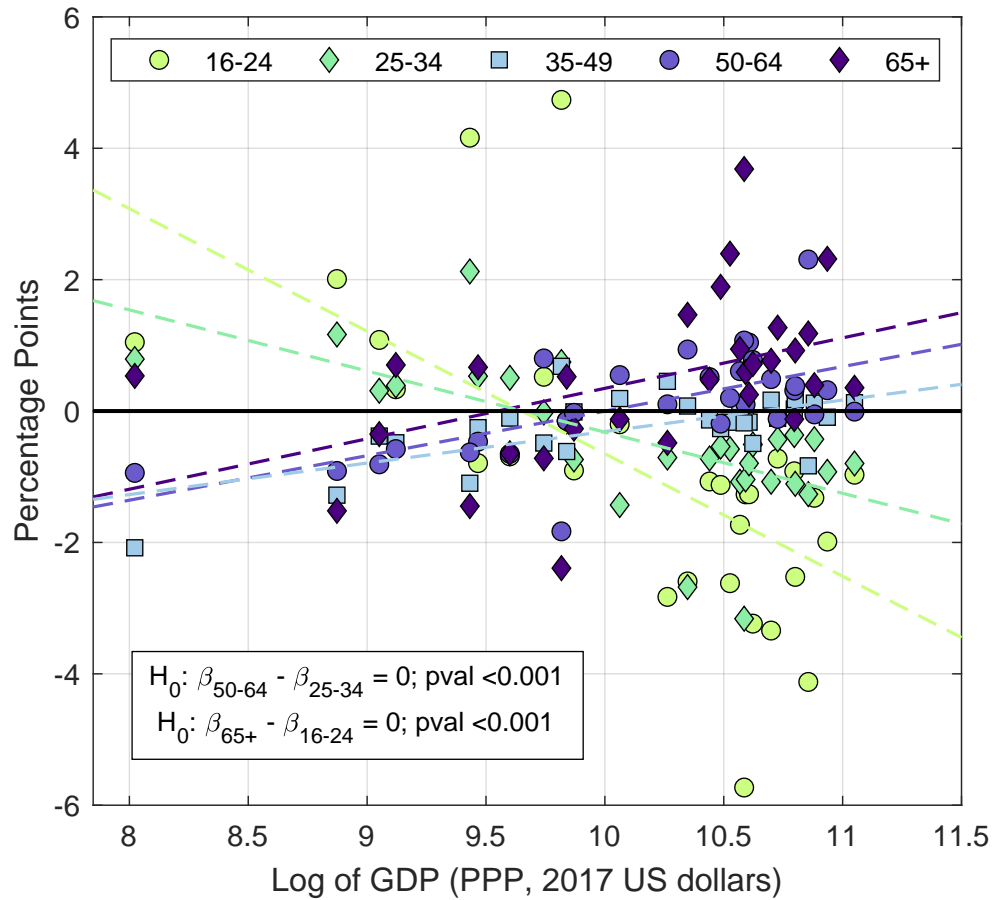
Stylized fact 4 In all high-income countries, the net income of under-35 individuals grew less than the demographics-corrected average, while the income of over-50 grew more. This phenomenon, pronounced in high-income countries, is milder or reverted in lower-income countries.

The relationship mentioned in the Stylized fact 4 can be better visualized in Figure A.6. Here, we plot the five age-group specific income growth rate (net of the demographics-adjusted

²⁵It can be noted how we could just subtract any constant for each country i , as we are just offsetting each age group by the same value within each country. However, this approach gives us an additional information, that is: what age groups are below, and which ones are above, the country's corrected average income growth.

average) against the against the PPP GDP (in constant 2017 dollars) of each country at the beginning of the sample. While the income growth rates for the younger groups (green circles and diamonds) have a significant negative correlation with overall income, the ones for the older groups (purple circles and diamonds) have a significant positive correlation. It is striking how the regression coefficients are monotonically increasing with age-groups (the lower for the youngest, the higher for the oldest).

Figure A.6. Annualised Growth in excess of adjusted mean: Disposable Income, and GDP



Note: The figure depicts the annualised growth rate of income in excess of the country's adjusted mean (\tilde{Q}_{ij}), for each of the five age groups, against the log of PPP GDP (in 2017 dollars, calculated at the beginning of the reference period). The dashed lines represent the linear fit of the two variable, for each age group. The text box in the figure shows the p-value of the tests with null hypothesis that the slope of the fit for the old is the same of the one of the young, with two different definitions of young and old. The dates between which the calculation is performed are provided in Table I in the main text.

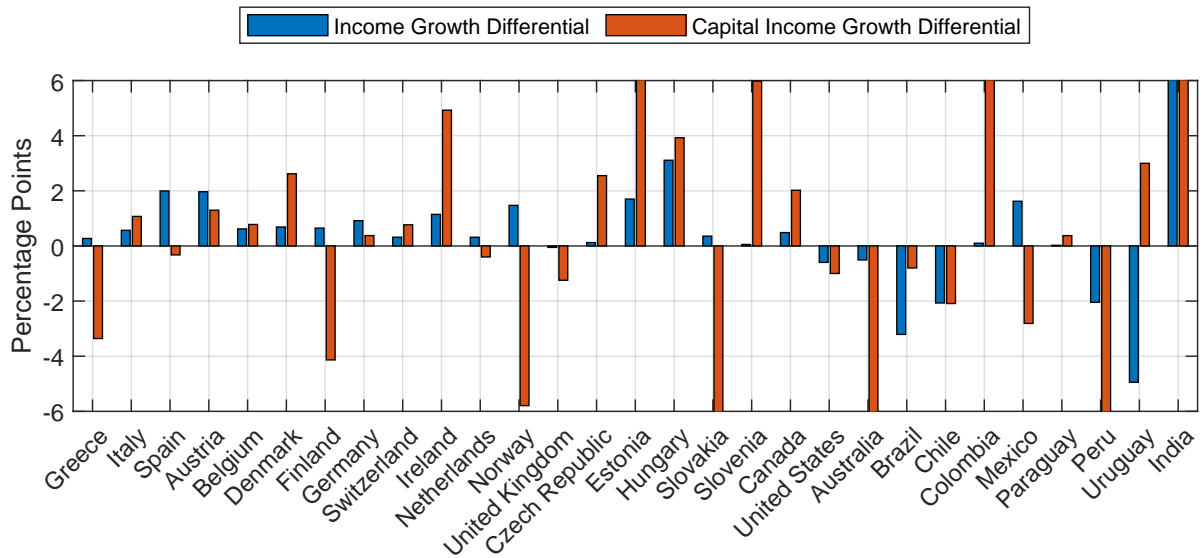
A.4 Capital Income

In Section 2 and 3 we omitted capital income among the income components, as individual data are not available for capital income, we study the role of capital income and how it may affect our analysis. Using the same age groups we use for individuals, we divide households into “young” and “old” according to the age of the head member. Then, we calculate the growth rate differential of capital and total income individually. Finally, we compute the share of capital income with respect to total household income, and compute the contribution of the differential in capital growth rates to the total observed differential in total income growth rates between old and young households. In Figure A.7 we plot the growth rate differentials of total and capital household income. We do not find a clear pattern for the growth rate differential of capital income, which is positive (capital income grew faster for the old) for some countries and negative (capital income grew faster for the young) for others.

However, the contribution of capital to the total growth rate differential in household income is small in *all* countries and positive almost everywhere, as capital income represents a tiny share of the young’s total income, ranging between 0.4 percent and 5.2 percent²⁶ (median 1.0 percent) for the young, but between 0.5 percent and 10 percent (median 3.2 percent) for households whose head was 50-64 years old. We show these results in Figure A.8. For this reason, even large growth rates in capital income among the young are unable to produce any relevant effect on our estimates.

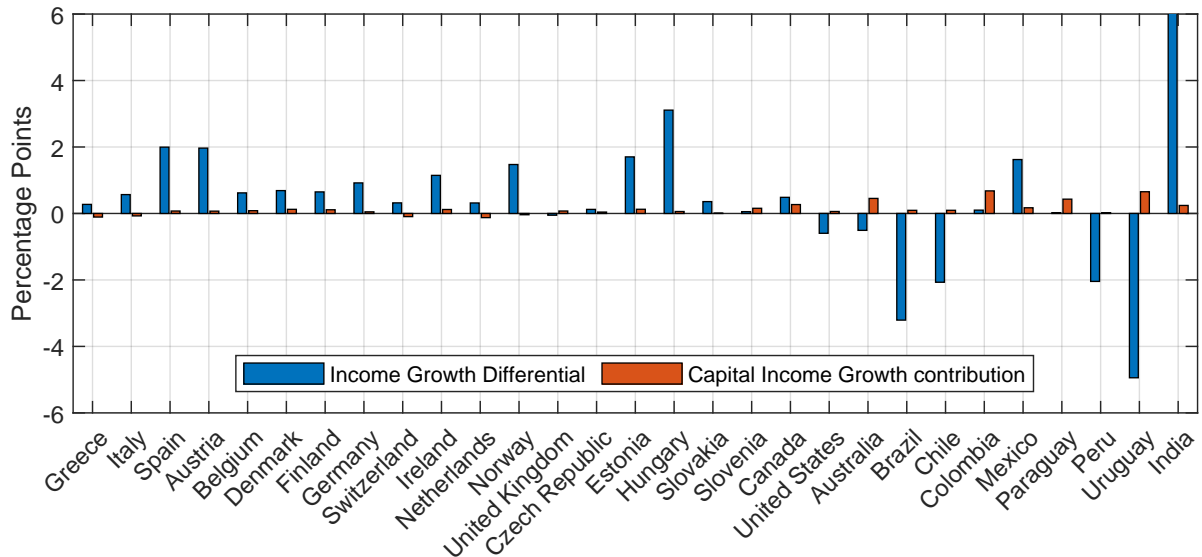
²⁶Apart from Italy, where capital income in our data is particularly high, possibly due to the joint effect of imputed income from owned houses and the extremely high home ownership share, the maximum among all other 28 countries is 2.1 percent.

Figure A.7. Growth Rate differential, 50-64 vs 25-34. Household level.



Note: The figure depicts the *GRD* for disposable income (blue bar), calculated for households whose household head is 50-64 (“old”) and 25-34 (“young”), and the *GRD* calculated for capital income (red bar) for the same age groups. The dates between which the *GRD* and its components are calculated are provided in Table I in the main text.

Figure A.8. Growth Rate differential, 50-64 vs 25-34. Household level.



Note: The figure depicts the *GRD* for disposable income (blue bar), calculated for households whose household head is 50-64 (“old”) and 25-34 (“young”), and the contribution to the total *GRD* given by the capital income component (red bar) for the same age groups. The dates between which the *GRD* and its components are calculated are provided in Table I in the main text.

B Supplementary material

B.1 Further evidence on education trends

In this section, we present further evidence of the long-term education trends in rich, transition, and developing countries. This analysis complements the one in the main text, showing the data underlying our results reported in Section 4.

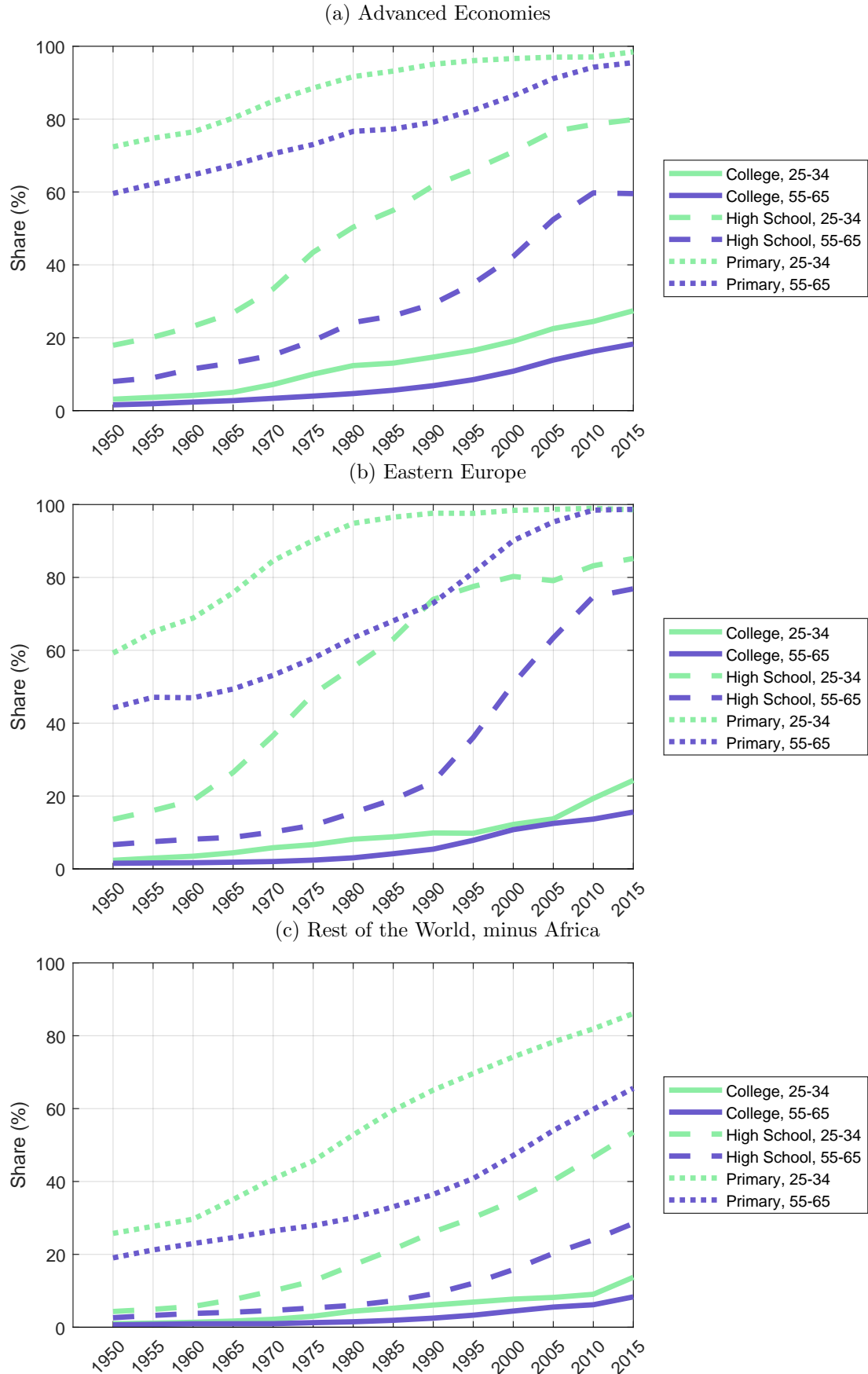
First, we present the absolute levels of education achievement around the globe in Figure B.1. Here we use all countries in the Barro and Lee (2013) dataset. We drop all countries and observations for which there are clear tabulation errors or unharmonised data. In rich countries, we see how almost all the population, young or old, as reached the end of primary school education by 2015. However, the catch-up in primary education of the 55-65 years old has started only in the late 1980s/early 1990s, when the gap with the young reached its maximum. Similarly, also high-school achievement reached a maximum gap in favour of the young in 1990s, and has halved since then. Finally, while the college achievement gap has remained mostly constant (peaking in 1980s), the relative gap has been closing down too.

Moving to Transition Economies, both young and old showed - by 2015 - very similar rates of primary and high-school education. Also here, the gaps reached a maximum in 1980s/1990s in favour of the young, and kept reducing since then. Viceversa, the college achievement gap had completely closed down by 1995, but started widening again in the XXI Century.

Finally, in the rest of the world (with exclusion of Africa), we observe a gap between young and old in primary education of about 20-30 percentage point that has been slowly narrowing down since the 1990s. On the other hand, the gap in high-school achievement has been widening at an increasing rate. Between 2010 and 2015, we also observe a widening of the gap in college achievement, which was close to zero before that.

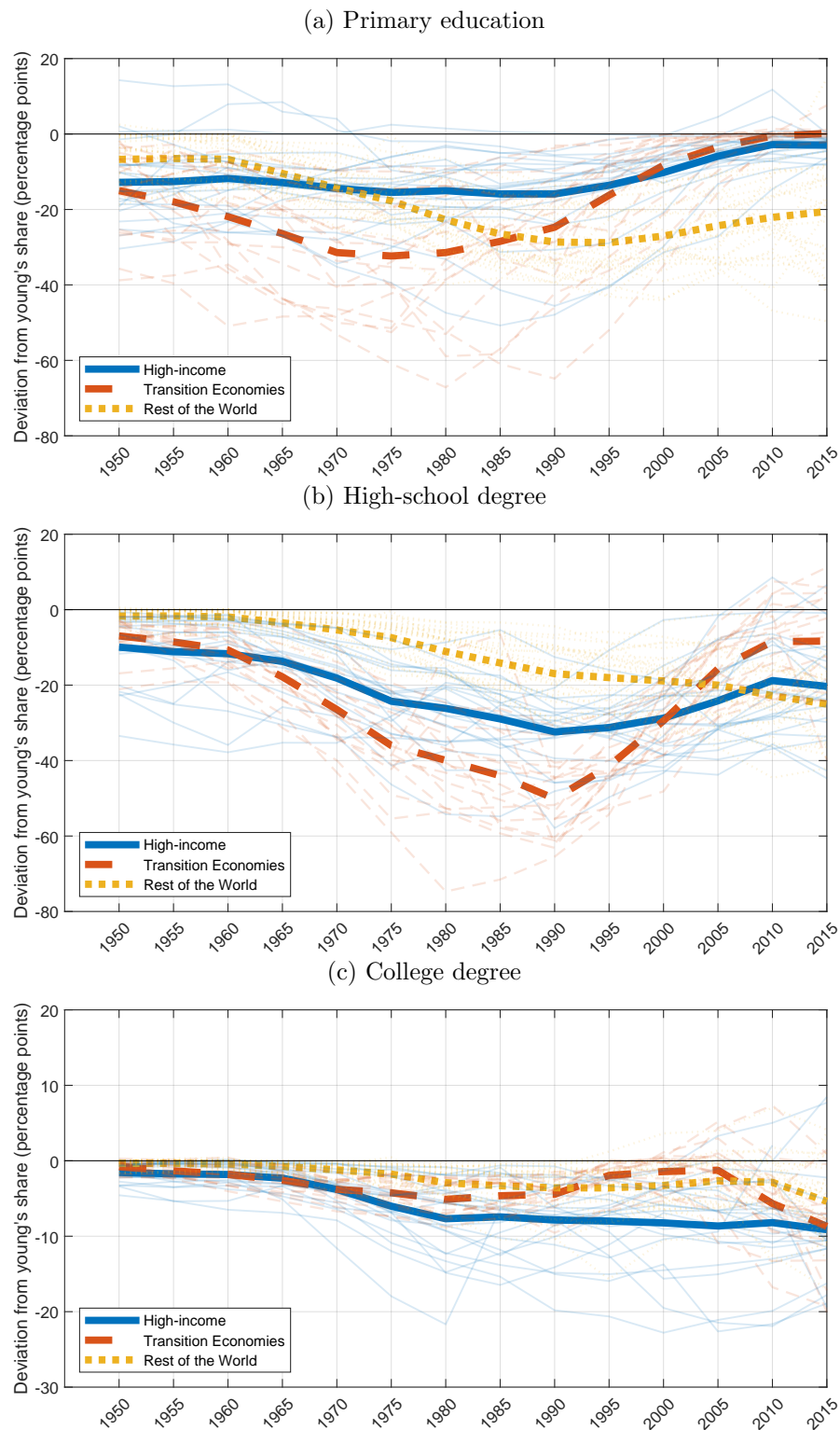
In Figure B.2 we plot the absolute gaps, in percentage points, of the education achievement of young and old for each group of country and education level. In Figure B.3 we report the percentage deviation in education achievement.

Figure B.1. Share of individual that holds at least the given education level, by age



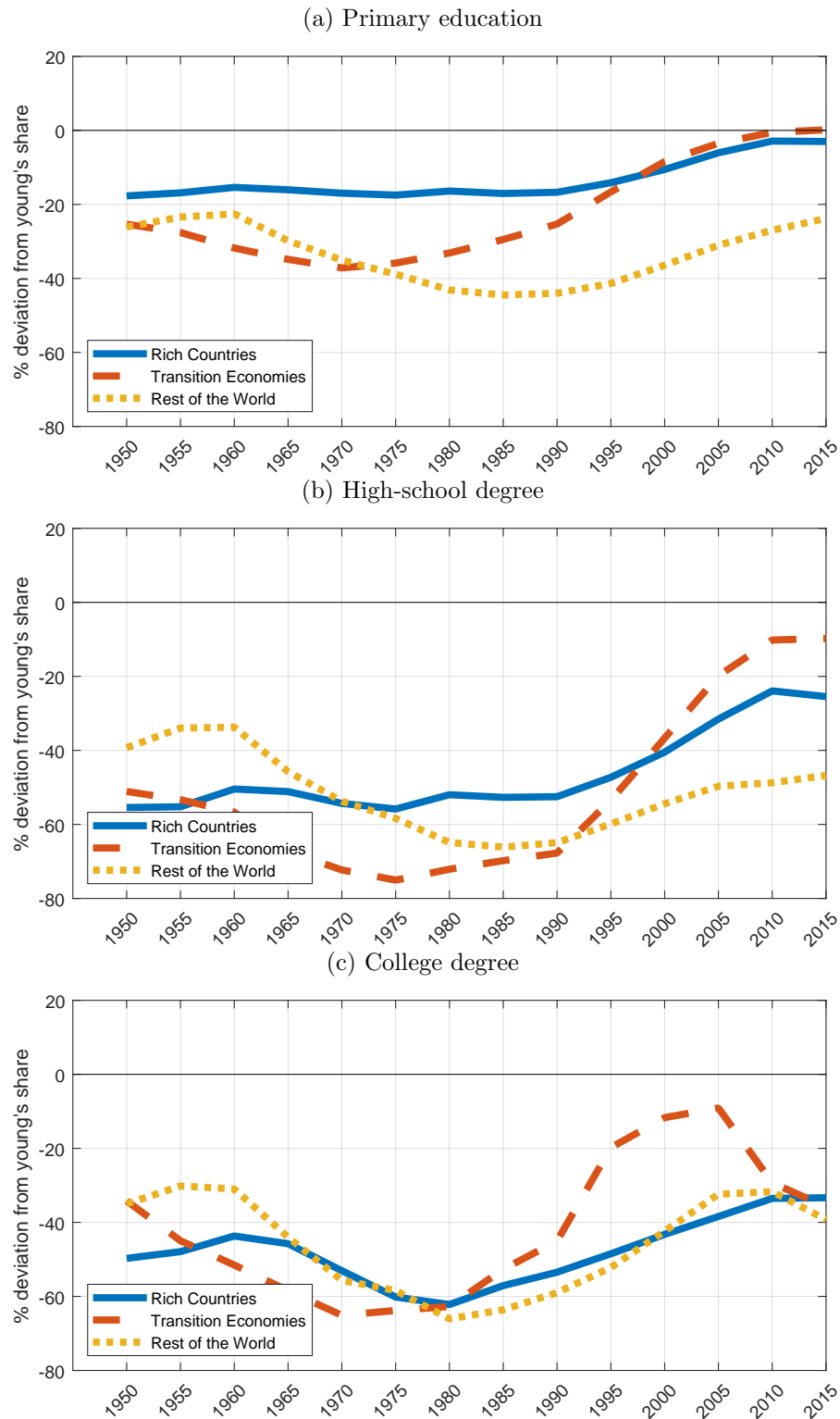
Note: The figure depicts the share of individuals aged 55-64 and 25-34 who have achieved at least a given level of education. Data are from the [Barro and Lee \(2013\)](#) database. Averages across countries are simple means. That is, we do not weight by population.

Figure B.2. Trends in Education: Delta between Old and Young share that achieved at least:



Note: The figure depicts the difference in the share of individuals aged 55-64 and 25-34 who have achieved at least a given level of education. Data are from the [Barro and Lee \(2013\)](#) database. Averages across countries (thick lines) are simple means. That is, we do not weight by population. Thin lines represent individual countries' plots.

Figure B.3. Trends in Education: Percentage difference between Old and Young share that achieved at least:



Note: The figure depicts the percentage difference in the share of individuals aged 55-64 and 25-34 who have achieved at least a given level of education. Data are from the [Barro and Lee \(2013\)](#) database. Averages across countries (thick lines) are simple means. That is, we do not weight by population.

B.2 Data availability

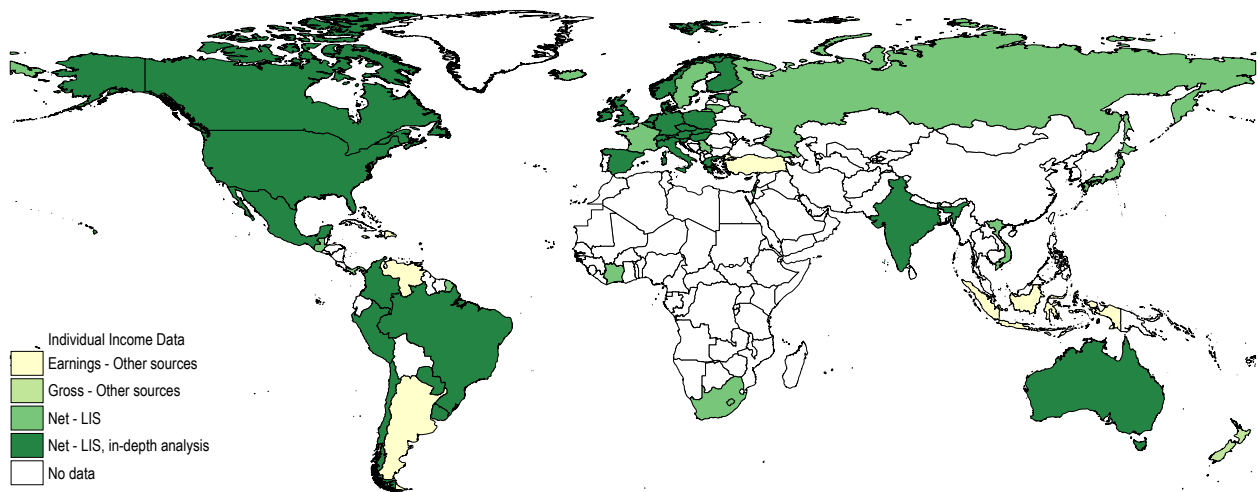
In the main text, we use the LIS database as only source for our statistics. This choice is driven by the fact that all income definitions are harmonised, and thus - up to particular situations - data are quite comparable across countries and across time. On the other hand, for the in-depth analysis, we have discarded a few countries with short time series or large breaks in their data. In Figure B.4 we report a visual representation of the geographical distribution of the LIS countries with individual income data (light green) and those selected for the in-depth analysis (dark green). We drop Egypt, China, Japan, Georgia, and Vietnam due to their poor data availability and consistency.

On top of these, we collect data from a few additional sources. Using publicly available income tabulations, we obtain time series for New Zealand (net income) and Turkey (gross income, with a slightly different definition of “old” due to the local population structure). From IPUMS International microdata, we obtain time series for Venezuela, Indonesia, and Jamaica. Moreover, from IPUMS International²⁷ we also obtain additional income data for Canada and Italy, which we had already available in the LIS database, but for different time periods. From IPUMS microdata,²⁸ we obtain USA Census income data dating back up to 1940. We obtain the series for Argentina (2004-2014) from the public use labour survey microdata.

²⁷Minnesota Population Center (2019).

²⁸Ruggles et al. (2020).

Figure B.4. Data availability, by country and type



Note: The map depicts the available countries for our analysis. Dark green countries represent those used for the computation of the *GRD*. Countries in green are those available in the LIS dataset. Countries in light green (New Zealand only) are those for which we have data on gross income from other sources (such as tabulations, or other microdata). Countries in yellow are those for which we have data on earnings (gross or net) from other sources (such as tabulations, or other microdata).

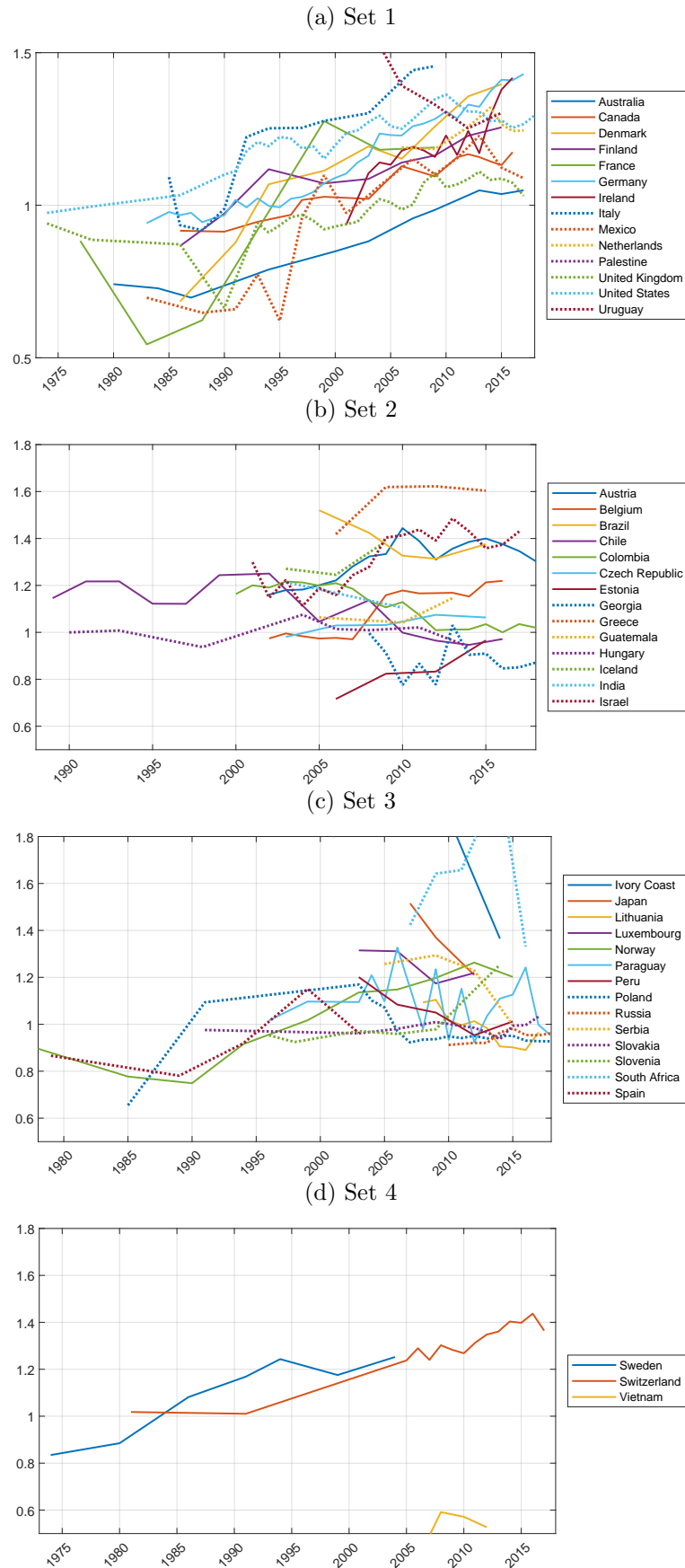
B.3 Individual countries' trends

LIS Data In Figure B.5 we plot individual country trends, as made available in the LIS database.

Additional countries In Figure B.6 we plot the *IGIR* of additional countries, using data obtained from IPUMS International (Dominican Republic, Indonesia, Jamaica, Venezuela), tabulations (New Zealand, Turkey), or public use microdata (Argentina). For the three countries with data availability after 2000, we observe that the two developing countries (Argentina, Turkey) experienced a fall in the *IGIR* over time. This was particularly sharp for Turkey. New Zealand, part of the rich countries group, we observe an upward trend since before 2000 which seems to have accelerated around 2009.

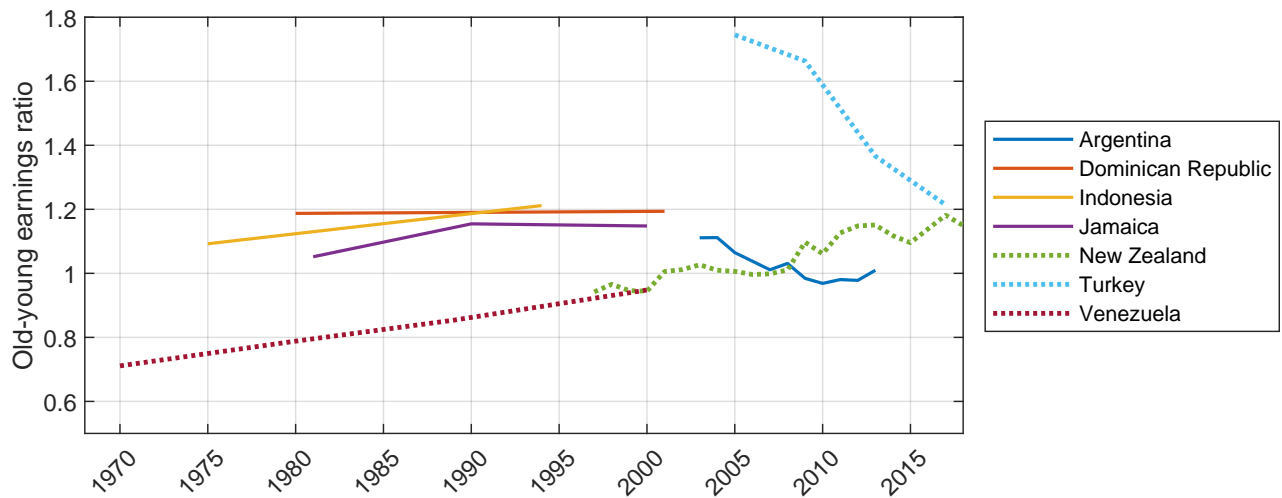
Historical US Data Using Census microdata from IPUMS, we are able to look at almost 80 years of data for the US. We observe that the *IGIR* has never been as high as the most recent datapoint (2019). This result is similar to the one derived in the LIS database, which after 2000 is based on the same data source, but is confirmed for even earlier periods. In fact, we are able to look at earnings until 1949, and wages in 1939. The *IGIR* reached a minimum in 1949, increasing by 1959 to then remain approximately stationary between until 1979. Since then, the *IGIR* has been increasing year by year, until the flattening of the curve between 2009 and 2019.

Figure B.5. *IGIR*: 50-64 year old vs 25-34 years old



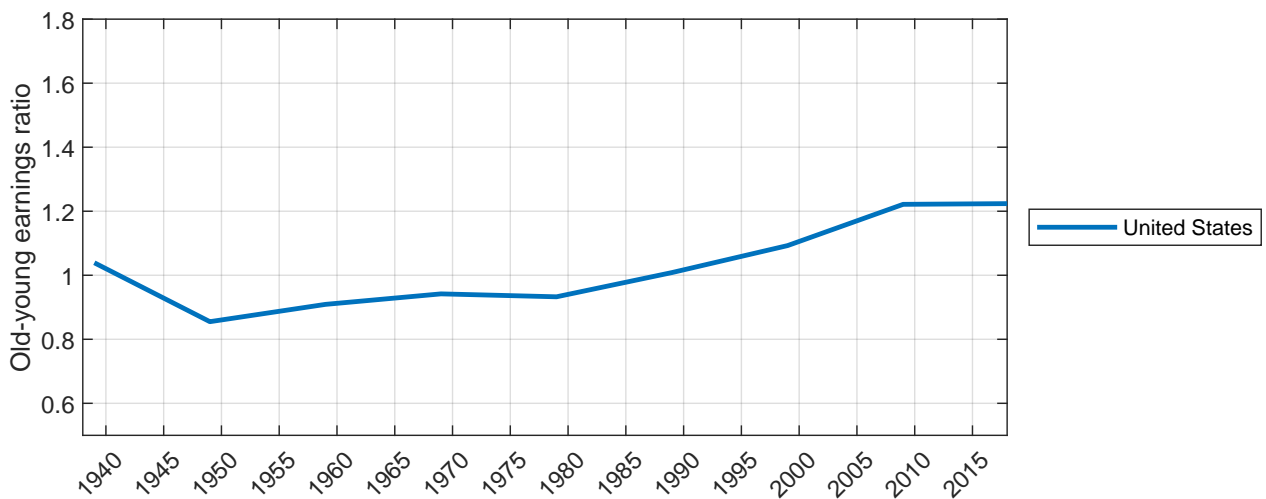
Note: The three panels depict the Intergenerational Income Ratio (*IGIR*) of the countries available in the LIS dataset.

Figure B.6. *IGIR*: 50-64 year old vs 25-34 years old. Non-LIS countries



Note: The figure depicts the Intergenerational Income Ratio (*IGIR*), for individuals aged 50-64 vs 25-34, of the countries available through IPUMS International microdata (Dominican Republic, Indonesia, Jamaica, Venezuela), aggregate tabulations (New Zealand, Turkey), or microdata from other sources (Argentina)

Figure B.7. *IGIR*: 50-64 year old vs 25-34 years old. US IMPUS data



Note: The figure depicts the Intergenerational Income Ratio (*IGIR*) for the U.S.A. between 1939 and 2019, for individuals aged 50-64 vs 25-34. The 1939 observation uses earnings instead of net income.