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Global income polarization

Relative and absolute perspectives

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Abstract: This paper presents the first global and regional estimates of polarization and bipolarization spanning the period 1960–2020. The study relies on group data to implement a flexible parametric model to obtain the global income distribution and polarization estimates. The study introduces a battery of sensitivity tests to assess the reliability of polarization estimates under various assumptions, with particular emphasis on the impact of survey under-coverage of top incomes on global polarization levels and trends. Overall, we find that relative bipolarization has consistently decreased since 1980, while in absolute terms it has increased since 1960. The more general measure of relative polarization has also exhibited a steady decline since 1980; however, the trend in its absolute counterpart depends on the size of a sensitivity parameter, which reflects whether individuals cluster with peers of similar income or are segregated from different income groups. Consequently, absolute polarization declined over time for lower values of this parameter but increased for higher values.

Key words: global income distribution, bipolarization, polarization

JEL classification: D63, C15, C46

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1 Introduction

In recent decades, income inequality has taken centre stage in political debates. The recognition that high income inequalities can potentially hinder economic growth, prosperity, and poverty reduction efforts has fuelled a rapid expansion of the literature on global inequality (see, for example, Anand and Segal 2017; Bourguignon and Morrisson 2002; Dowrick and Akmal 2005; Jorda and Niño-Zarazúa 2019; Lakner and Milanovic 2016; Niño-Zarazúa et al. 2017). Empirical evidence suggests that a well-established middle class (i.e a relatively large group of the population with income levels close to the median) contributes to economic growth and development (Chun et al. 2017; Easterly 2001a,b; Loayza et al. 2012). Moreover, countries with a prosperous middle class are less likely to face political unrest, as the poorest members of society are motivated to work hard and fulfil their aspirations to achieve a middle-class status (Pressman 2007). Individuals with similar economic status tend to share political views, which in turn contains the risk of social conflict (Acemoglu and Robinson 2006).

The size of the middle class can be assessed using bipolarization indices, which quantify the extent to which a population is divided into two distinct groups, one on each side of the median. A large middle class goes hand in hand with low levels of bipolarization, and may also contribute to reduced inequality (Formisano 2015; Winkelmann and Winkelmann 2010). However, these two distributional phenomena do not necessarily move in the same direction because, while closely related, inequality and bipolarization are grounded in distinct theoretical foundations.

While there is a growing body of studies exploring global inequality, research on the evolution of global polarization is surprisingly scarce (Bresson and Yalonetzky 2021; Roope et al. 2018). The scant literature primarily focuses on bipolarization but, despite its strong theoretical appeal, there are no studies that consider the potential existence of more than two poles, which might be located anywhere in the global income distribution.

This paper contributes to the literature on the global distribution of income by conducting the most extensive analysis of global and regional polarization trends from 1960 to 2020. Using polarization measures proposed by Duclos et al. (2004), we provide, to the best of our knowledge, the first estimates of global polarization that consider the possible existence of multiple poles. Our analysis incorporates both absolute and relative polarization measures. As with inequality, the different ways in which polarization is conceptualized reflect distinct normative judgements about how we should think of income gaps, and can lead to different conclusions regarding the extent of polarization and its trends over time (see Bosmans et al. 2014; Niño-Zarazúa et al. 2017; Roope et al. 2018).

As in much of the existing literature on income inequality, we encounter data limitations. Individual-level records are unavailable for many countries, especially in the early years of the analysed period. Consequently, we rely on grouped data to estimate the global income distribution. It should be remarked that the absence of individual-level data should not undermine the reliability of our estimates. This is because we use a flexible parametric model and conduct a comprehensive series of robustness checks to assess the sensitivity of our estimates to sample selection choices and the sources from which we obtain income data. Furthermore, we account for the higher non-response rate among the wealthiest individuals by implementing an estimation strategy designed to address the potential omission of top income earners (Jorda and Niño-Zarazúa 2019).

The remainder of the paper is organized as follows. In the following section, we introduce the theoretical framework for measuring polarization, and its relationship with inequality, using absolute and relative measures. Section 3 discusses the fully parametric model we use to approximate the global income distribution. In Section 4 we present the data used to estimate the global income distribution and the selection algorithm. In Section 5 we present the results of our analysis, before concluding with a discussion of the implications of our findings.

2 Measuring polarization

In this section we delve into the fundamental conceptual foundations for measuring three distinct distributional phenomena: polarization, bipolarization, and inequality. Despite their close relationships, these three concepts are rooted in different theoretical frameworks.

The concept of polarization relies on the alienation–identification framework formalized by Esteban and Ray (1994). This framework posits that society can be divided into various groups, with individuals identifying more closely with those within their own group while feeling alienated from individuals in other groups. These groups can be defined based on a range of characteristics, although, in the context of this paper and most applications, the focus is on income. Group identity strengthens as individuals become more similar in terms of income, which tends to increase polarization. Moreover, when different such groups are further apart in terms of economic distance, this increases alienation, and so polarization. Consequently, polarization measures developed within this framework focus on the distribution of income and the distance between an arbitrary number of groups.

Bipolarization measures, in contrast, consider the existence of only two groups in society, one on each side of the median income. This concept is conventionally associated with the size of the middle class, essentially representing the gap between the lower and upper tails of the income distribution. Bipolarization measures are characterized by two fundamental properties: 'increasing spread' and 'increased bipolarity'. Increasing spread refers to a shift of income from the middle to the tails of the distribution, which weakly increases bipolarization. Consequently, as the distribution becomes more dispersed from the median, bipolarization does not decrease. On the other hand, increasing bipolarity involves reducing income disparities either below or above the median, a movement that weakly increases bipolarization (Chakravarty and D'Ambrosio 2010).

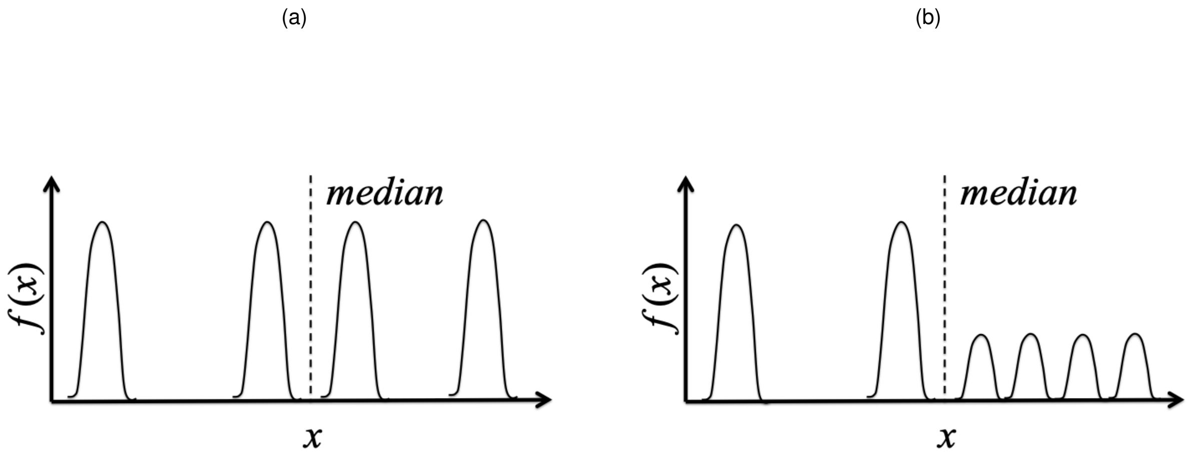
While polarization and bipolarization measures are conceptually distinct, they share three essential properties, as highlighted by Esteban and Ray (2012). First, polarization is inherently concerned with groups, making the contribution of isolated individuals negligible. Second, when there are at least two groups, polarization increases as income disparities within a group decrease. This underscores a crucial difference from inequality measures, which would register a fall after a progressive transfer since virtually all of them satisfy a weak version of the Pigou–Dalton.[1] Consequently, unless individuals are organized into a single economic group, the rankings of distributions by inequality and polarization measures can diverge. Third, both polarization and bipolarization rise when the gap between groups widens. Alternatively, when income differences within groups decrease, making the groups more homogeneous, polarization and bipolarization increase.

It is worth noting that bipolarization and polarization measures can move in opposite directions. To illustrate this point, Duclos and Taptué (2015) provide the example given in Figure 1. The four poles observed in the initial distribution, two at each side of the median, become six after an increased bipolarity movement. The two poles observed at the right of the median are divided into four poles of the same size, leaving between-group inequality unchanged. While this movement leads to greater bipolarization

[1] The majority of widely used relative inequality measures, such as the Gini coefficient and mean log deviation, as well as some absolute measures, such as the absolute Gini, satisfy a strong version of the Pigou–Dalton transfer principle, such that any progressive transfer must strictly decrease inequality.

levels in panel (b), the six poles are less clearly defined than the four poles in panel (a). Consequently, polarization decreases.

Figure 1: The impact of an increased bipolarity movement on the income distribution



Source: adapted from Duclos and Taptué (2015).

Similarly, inequality and bipolarization capture distinct aspects of the income distribution. A Pigou–Dalton transfer on either side of the median results in lower within-group inequality, leading to higher bipolarization due to the increased bipolarity property, as well as higher polarization because individuals become more homogeneous on the opposite sides of the median. In contrast, this progressive transfer would be deemed by most inequality measures to reduce inequality. While it is evident that trends in inequality and bipolarization can diverge, certain movements can lead to similar trends. For instance, any progressive transfer from one side of the median to the other would decrease both inequality and bipolarization.

A plethora of polarization and bipolarization indices have been proposed in the literature. Therefore, the selection of measures for analysing the evolution of (bi)polarization is a critical decision. Previous research on income inequality has underscored the importance of assessing changes in income distribution from both relative and absolute perspectives. This emphasis arises from the recognition that population preferences vary in their support for these contrasting normative values, and that these different measures can yield conflicting judgements regarding inequality rankings (Bosmans et al. 2014; Niño-Zarazúa et al. 2017; Roope et al. 2018). These two categories of measures provide different insights into how increases in total income resulting from economic growth should be distributed to keep polarization levels constant. Absolute measures would remain unaffected by an equal increase in all incomes. In contrast, relative polarization would remain unchanged if each income experienced the same proportional change.

Let $\mathbf{x}$ be an i.i.d. random sample of size N from a continuous income distribution $f(x)$ defined over the support $S = [0, \infty)$. Duclos et al. (2004) proposed the following polarization index:

$$DER(\alpha) = \int\int f(x)^{1+\alpha} f(y)|x-y|dxdy \tag{1}$$

where $\alpha \in [0.25, 1]$ is the so-called 'polarization aversion' parameter, which captures the influence of the identification effect and distinguishes this measure from traditional inequality indices. A higher value of α amplifies the differentiation between polarization and inequality. Notably, when $\alpha = 0$, Equation (1) becomes equivalent to the absolute Gini index.

While the DER index quantifies absolute polarization, it can be easily transformed into a relative index by multiplying Equation (1) by $\mu^{\alpha-1}$, where μ denotes the mean income.

To measure bipolarization, we employ the index developed by Foster and Wolfson (2010), which can be expressed as:

$$FW = (G^{(b)} - G^{(w)})\frac{\mu}{m} \tag{2}$$

where m is the median income, which sets the division of the distribution of income into two parts. $G^{(w)}$ is the population-weighted average of the Gini indices of these two groups; and $G^{(b)}$ is the Gini index, assuming that all individuals on each side of the median have the same income. The absolute version of this measure is given by multiplying Equation (2) by the median (m).

3 Methods

The estimation of polarization measures is relatively straightforward when individual-level income data are available. However, despite the substantial increase in household surveys generated over the past four decades, data with global coverage typically include only per capita income (or expenditure) and a limited number of income shares. Analysing inequality and polarization using this type of grouped data requires specific assumptions about the shape of the income distribution.

A common approach in empirical work has been to assume that all individuals within each income group possess the same income (see, for example, Bourguignon and Morrisson 2002; Dowrick and Akmal 2005; Lakner and Milanovic 2016; Milanovic 2011). The popularity of this method arises not only from its simplicity, but also because it does not require imposing a particular distributional model on the empirical data. However, estimates based on this approach tend to underestimate the actual level of inequality because they fail to account for inequalities within income shares. Thus, while inequality measures based on this framework are regarded as lower bounds (Kakwani 1980), this approach tends to overstate polarization because it assumes individuals within income shares are more homogeneous than they actually are.

Parametric models are a robust statistical method for estimating the distribution of income from grouped data, providing more accurate estimates than non-parametric approaches (Jorda et al. 2021).[2] However, only a limited number of analyses have employed these methods to estimate income inequality, possibly due to concerns about the risk of misspecification bias. Selecting an appropriate parametric model is challenging, especially when analysing the global income distribution, which includes a diverse group of countries. To mitigate the risk of misspecification bias, we adopt a well-suited functional form known as the generalized beta distribution of the second kind (GB2). This distribution nests the parametric assumptions found in the literature (see Jenkins 2009; McDonald 1984) and is found to offer an excellent fit to income data across various time periods and countries (Jorda et al. 2021).[3] The GB2 distribution can be expressed in terms of the probability density function (PDF) as follows:

$$f(x;a,\beta,p,q) = \frac{ax^{ap-1}}{\beta^{ap}B(p,q)[1+(x/\beta)^a]^{p+q}}, \quad x \geq 0 \tag{3}$$

where a, p, q are shape parameters, β is the scale parameter, and $B(x,y) = \int_0^1 t^{x-1}(1-t)^{y-1}dt$ is the beta function. Hajargasht and Griffiths (2020) developed minimum distance estimators for the parameters of the GB2 distribution using grouped data in the form of income shares. These estimators are conveniently accessible through the R package `GB2group` (Jorda et al. 2022).

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[2] An alternative methodology, which avoids the need to predefine the shape of the distribution, involves estimating a non-parametric kernel distribution (Sala-i Martin 2006). While this approach is flexible, its robustness has been questioned, particularly regarding its performance at the tails (Dhongde and Minoiu 2013; Jorda et al. 2021).

[3] These functional forms include the Beta 2 distribution (Chotikapanich et al. 2012), the lognormal distribution (Niño-Zarazúa et al. 2017; Roope et al. 2018), and the Weibull distribution (Chotikapanich et al. 1998; Pinkovskiy and Sala-i Martin 2014).

Despite the flexibility of the GB2 distribution, directly estimating Equation (3) would yield biased estimates of the income distribution because top income earners are under-represented in household surveys. Burkhauser et al. (2017) identify two main sources of under-coverage in household surveys. First, rich individuals tend to under-report their income levels; and second, survey sampling design often fails to cover representative subsamples of high-income earners, and these individuals also tend to refuse participation in household surveys, resulting in sample under-representation and thus truncation in the income distribution at the upper tail. As a result, household surveys may only accurately represent the income distribution for the poorest t per cent of the population, thus providing right-truncated samples of the income distribution.[4]

The estimation of income distributions from truncated samples requires adapting the estimation strategy to consider this data pattern. Following Jorda and Niño-Zarazúa (2019), we estimate the following model, which considers the right truncation of the income distribution based on survey data:

$$L(u|u<t) = \frac{L(u)}{L(t)} \tag{4}$$

where $L(u)$ is the Lorenz curve of the entire population, $t \in [0,1]$ is the proportion of the total population covered by the survey, and so $L(t)$ is the Lorenz curve at the truncation point—that is, the share of the total income held by the population covered in the survey.

As explained in Section 4, available data are provided in the form of income shares. Hence, even though we are interested in the distribution of income ($f(x)$), the estimation relies on the Lorenz curve. Substituting the formula of the Lorenz curve of the GB2 distribution (see Arnold and Sarabia 2018) in Equation (4), we obtain

$$L_t(u;a,p,q) = \frac{B\left(B^{-1}(u;p,q);p+\frac{1}{a},q-\frac{1}{a}\right)}{B\left(B^{-1}(t;p,q);p+\frac{1}{a},q-\frac{1}{a}\right)} \tag{5}$$

where $q > 1/a$ and $B^{-1}(x;p,q)$ is the inverse of the incomplete beta function ratio given by $B(v;p,q) = \int_0^v t^{p-1}(1-t)^{q-1}dt/B(p,q)$.

The parameters of the distribution are estimated by minimizing the squared deviations between the income shares and the theoretical points of the truncated Lorenz curve of the GB2 distribution given in Equation (5). Although the parameters are estimated from a truncated Lorenz curve, these estimates belong to the distribution of the whole population given in Equation (3).

The main challenge in the estimation of Equation (5) is the definition of the truncation point (t). Insights from country case studies suggest that survey non-response is generally not a concern for the bottom 99 per cent of the income distribution (Burkhauser et al. 2017; Jenkins 2017). However, it is important to note that this evidence is predominantly drawn from industrialized economies. In developing countries, the non-response rate $(1-t)$ is expected to be even lower than 1 per cent, as the richest individuals represent a smaller proportion of the population (Anand and Segal 2017). Given the lack of information about the actual proportion of the richest individuals not included in household surveys,[5] we provide estimates assuming different truncation levels up to 1 per cent.[6]

[4] Many previous studies have attempted to address this issue by correcting survey-based estimates using tax data (Anand and Segal 2015, 2017; Hong et al. 2020)). However, merging these data sources can introduce a source of measurement error due to the 'apples and oranges' comparability problem (Burkhauser et al. 2017; Jenkins 2017). Reconciling the income definitions between household surveys and tax records is often impossible when working with grouped data.

[5] Although there have been recent advancements in determining optimal truncation levels, these methods require the use of individual data (Diaz-Bazan 2015).

[6] This potential limitation has also been encountered by previous studies in global inequality, which often opt for setting an arbitrary threshold (Anand and Segal 2015, 2017; Lakner and Milanovic 2016).

The β parameter plays no role in the estimation of Equation (5) because the Lorenz curve is independent of scale. To estimate the scale parameter, we equate the theoretical expression of the mean of the GB2 distribution to an estimate of per capita income and solve it for the β parameter:

$$\hat{\beta} = \mu \frac{B(\hat{p}, \hat{q})}{B(\hat{p} + \frac{1}{\hat{a}}, \hat{q} - \frac{1}{\hat{a}})} \tag{6}$$

where μ denotes the per capita income, $B(.,.)$ stands for the beta function, and $\hat{a}, \hat{p}, \hat{q}$ are the parameters estimated using an equally weighted minimum distance estimator between Equation (5) and the observed income shares.

The population mean is unknown, so we substitute μ with an estimate of per capita income. Therefore, μ is not a parameter to be estimated. As mentioned in Section 4, for benchmark estimates we use per capita gross domestic product (GDP) as an approximation of average income. This indicator is also employed to estimate the scale parameter when we consider potential under-coverage issues in household surveys. Hence, changing the level of truncation (t) affects the parameter estimates but not the mean of the distribution (μ) because we consider per capita GDP to be a reliable estimate of mean income, independent from the potential bias of household surveys.

Equations (5) and (6) are estimated for each country–year dataset. Although the same functional form is fitted to all countries over the entire period, the parameters of the GB2 distribution vary across countries and over time. For each year, the global income distribution is then computed as a mixture of the national distributions weighted by population. Polarization measures are computed by simulation of a synthetic sample from the global distribution.

4 Data

To analyse the evolution of global polarization, we use data on income shares from the World Income Inequality Database (WIID) (UNU-WIDER 2022), released in June 2022. This version contains information on Gini coefficients and income (or expenditure) shares for over 200 countries from 1867 to 2020, and is one of the most comprehensive databases of income distribution currently available. Despite its wide coverage, the WIID is not a complete and balanced panel of observations. Our analysis focuses on the period 1960–2020 at five-year intervals. Whenever we had missing data for the exact year, we chose the closest observation within a window of the previous/next five years of each data point.

A potential drawback of the WIID is the lack of comparability of the underlying country–year datasets due to differences in terms of the unit of analysis, the equivalence scale, the quality of the data, and the welfare concept. To minimize the problems that may arise from mixing heterogeneous definitions, we developed an algorithm that gives preference to observations of the highest quality. The preferred unit of analysis is the individual rather than the household because our analysis focuses on interpersonal polarization. To transform household income into an equivalent individual income, we opt for income per capita, as this is the conventional method in distributional studies. We give preference to datasets from nationally representative surveys. Concerning the welfare concept, we prioritize datasets that refer to net income data over consumption. Finally, income is the preferred welfare concept over earnings even in cases where it is not clear whether income is gross or net.

Mixing welfare concepts could potentially bias the results, especially for expenditure-based and income-based estimates because these variables present fairly different distributional patterns. Consumption expenditure typically exhibits lower inequality levels, so it might be expected that polarization patterns may also differ. Hence, we propose a method to harmonize data based on both welfare concepts. We construct an average index for net income relative to consumption for each income share from country–year observations with both income and consumption expenditure data. We group countries into eight world regions to better capture the idiosyncrasy of the income–consumption relationship in different regional settings (see Appendix Tables A1 and A2).[7]

Besides income shares, we also need to gather data on mean incomes to estimate the global distribution of income. Previous studies on global inequality have generally used national accounts, specifically GDP per capita, to approximate the mean of income distributions (Atkinson and Brandolini 2010; Bhalla 2002; Bourguignon and Morrisson 2002; Chotikapanich et al. 2012; Dowrick and Akmal 2005; Jordá et al. 2014; Niño-Zarazúa et al. 2017; Sala-i Martin 2006). However, critics have raised concerns about the discrepancies between mean incomes from national accounts and income surveys. Per capita GDP includes retained earnings of corporations, depreciation, and components of government revenue that are not distributed back to households in the form of social assistance or social security transfers. As a result, this indicator tends to overestimate mean income levels (Deaton 2005).

Despite the potential limitations of national accounts, empirical analyses that use survey means are scarce due to the limited availability of data (Anand and Segal 2015; Lakner and Milanovic 2016; Milanovic 2011). There is also a substantive reason for using national accounts. Due to the poor representation of the upper tail of the distribution, mean incomes from household surveys are downward-biased (Anand and Segal 2008). Therefore, as one of the contributions of this study is to account for the effect of the under-coverage of top incomes on global polarization trends, data from national accounts may actually be a better proxy for the actual average income level. For our benchmark estimates, we retrieve data on per capita GDP adjusted by purchasing power parities (PPP) at constant 2017 prices from the World Bank's World Development Indicators.

With the selection criteria described above, we cover approximately 70 per cent of the global population in 1960 (see Appendix Table A3). The proportion of the population covered steadily increases, reaching above 90 per cent from 1990 to 2015. The representativeness of the sample was substantially lower for 2020, as many countries had not yet reported their data. Therefore, estimates before 1990 and in 2020 should be interpreted with caution.

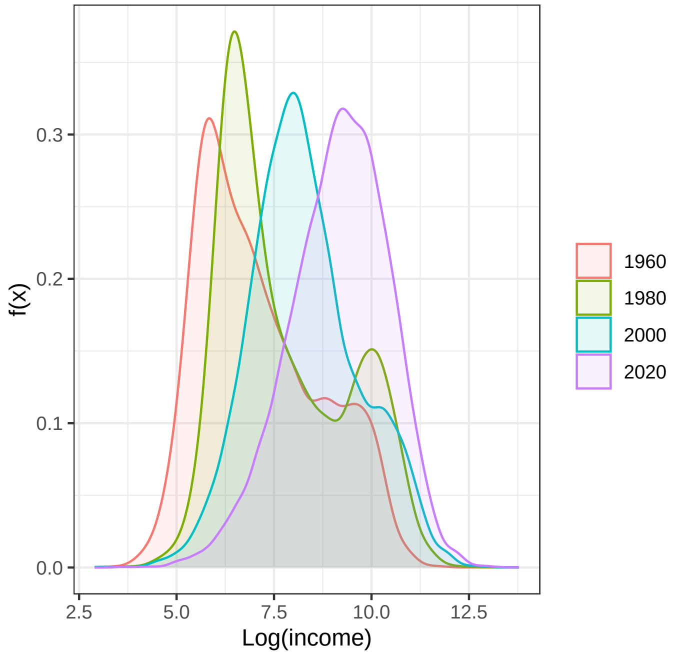
5 Results

This section presents the global bipolarization and polarization estimates for the period 1960–2020. Before delving into (bi)polarization trends, we first present the evolution of the global distribution of income in Figure 2, without considering the lower response rate of the richest individuals. In 1960, we observe three different poles in the global distribution of income, the main one around US$350 and two smaller peaks of individuals at US$7,000 and US$14,000. These two peaks merged during the 1970s, resulting in a bimodal distribution. The main mode moves up to US$450, and a second peak is observed around US$17,500. These two peaks move rightwards and become more pronounced over the next decade. In the 1980s the first mode is observed around US$650 and there is a second group of individuals clustering at US$23,500. As these poles stand further apart, (bi)polarization might have increased over this period.

[7] Previous studies attempted to harmonize WIID data with the absolute average difference between income and consumption shares (Deininger and Squire 1996; Niño-Zarazúa et al. 2017) or using a seemingly unrelated equations model to define the relationship between the welfare concepts (Pinkovskiy and Sala-i Martin 2014). There is no ideal methodology that ensures the comparability of income and consumption data. As imperfect as it might be, our proposal is an intuitive method that, in contrast to other approaches, does not lead to negative income shares.

During the 1990s, the two modes of the income distribution began to converge. This convergence was driven by the significant progress in average income levels in some countries that transitioned from the lower-income pole to the higher-income one. Notably, the remarkable economic growth in large countries, particularly China, contributed to a rightward shift in the global income distribution (Lakner and Milanovic 2016). Additionally, these two poles became less pronounced, suggesting a reduction in (bi)polarization at the global level. By 2010, the global income distribution had transformed into a bell-shaped curve, with the mode observed at US$7,000.

Figure 2: Evolution of the global distribution of income: 1960–2020



Note: the global distribution of income in each benchmark year is computed using a synthetic sample of $N = 10^5$ individuals from a mixture of GB2 distributions estimated using Equations (5) and (6).

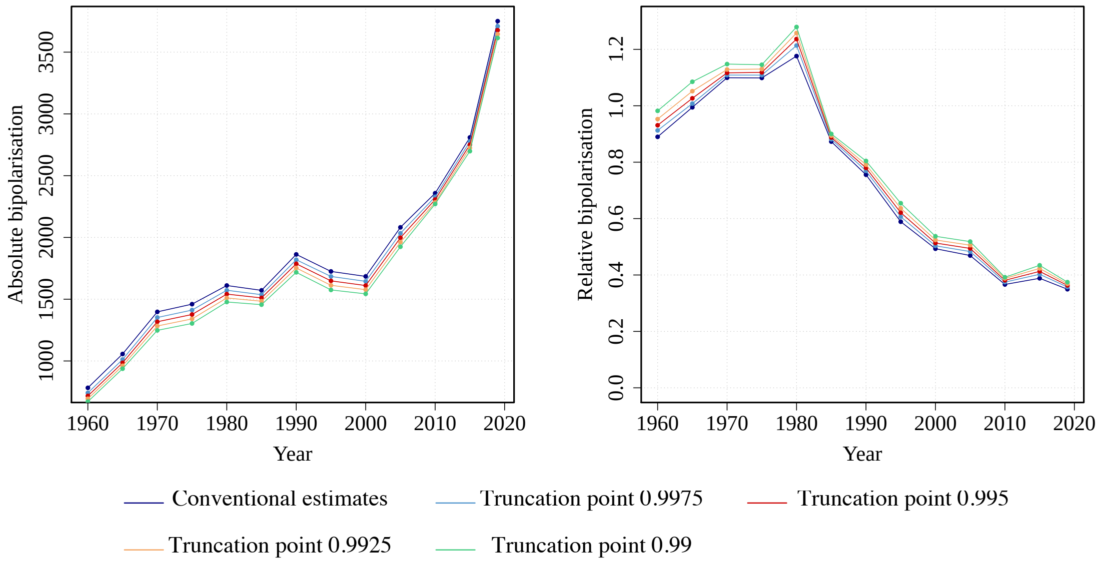
Source: authors' compilation using data from the WIID.

5.1 Global trends in bipolarization

We turn our attention to the evolution of absolute and relative bipolarization measures, from 1960 to 2020, as illustrated in Figure 3. The absolute Foster and Wolfson (FW) index is computed using the relative index formula (Equation 2), multiplied by the median. To estimate the impact of survey undercoverage at the upper tail on global polarization, we employ the method proposed in Section 3, with different assumptions regarding the proportion of the population covered by household surveys. Since there is no universal truncation point, and non-response rates are expected to vary over time, our method offers flexibility in defining country-specific truncation points. However, a major challenge arises from the lack of information about non-response rates in household surveys. Therefore, we assume that all countries are affected by the same level of truncation. We provide a collection of estimates for non-response rates of 0.25, 0.5, 0.75, and 1 per cent, resulting in truncation points of t equal to 0.9975, 0.995, 0.9925, and 0.99, respectively. To mitigate sampling error, we excluded income values lower than 1, which accounted for less than 1 per cent of the sample in all years. This exclusion had negligible impact, typically only affecting values in the third decimal place, as shown in Table A4.

Figure 3: Evolution of absolute and relative bipolarization from 1960 to 2020: FW index

(a) Absolute bipolarization (b) Relative bipolarization



Note: the global distribution of income in each benchmark year is computed from a mixture of GB2 distributions estimated using Equations (5) and (6). The FW index is estimated by Monte Carlo simulation using samples of size $N = 10^5$. Observations with values lower than US$1 were removed. The results with complete samples are presented in Table A4.

Source: authors' compilation using data from the WIID.

The blue line on the graph represents the trend of the FW index without accounting for potential non-response issues in household surveys. Our findings indicate that both relative and absolute bipolarization increased from 1960 to 1980. However, in line with Roope et al. (2018), we find that these two indices began to show divergent trends after 1980. According to the FW index, absolute bipolarization modestly increased from 1980 to 2000, and rapidly increased thereafter. In stark contrast, the relative index steadily decreased until 2020, though this decline was rather slow during the last decade of this period. As a result, relative bipolarization saw a dramatic decrease over the analysed period, dropping from 0.9 in 1960 to 0.35 in 2020, while absolute bipolarization increased substantially from 782.54 to 3,751.[8]

Relative and absolute bipolarization trends do not appear to be significantly affected by the consideration of non-response issues in household surveys. However, the actual values of the FW index are not entirely robust to changes in the truncation point (t). In the case of relative bipolarization, the FW index value increases somewhat with higher non-response rates. Conversely, the absolute FW index decreases as the level of truncation increases. The reason behind these diverging patterns appears to be related to the impact of survey under-coverage on the top incomes and its effect on the median of the income distribution. Household surveys tend to overestimate the median, so when we account for the omission of the richest individuals, the value of this statistic decreases. For all truncation levels, this decline in the median consistently more than offsets the increase in the relative FW measure.

5.2 Global trends in polarization

We now focus on the evolution of global polarization measures from 1960 to 2020. A summary of these estimates is provided in Table 1 and Figure 4. Following Duclos, Esteban, and Ray (DER) (Duclos

[8] While our findings are consistent in this regard with Roope et al. (2018), one of the few other studies on global bipolarization found that both relative and absolute measures increased from 2002 to 2012 (Bresson and Yalonetzky 2021).

et al. 2004), we divide the DER polarization index (Equation 1) by 2 to facilitate its comparison with the absolute Gini index (i.e. when $\alpha = 0$). The DER estimates are derived from synthetic samples with a size of 10^5. We excluded values lower than 1, which had a negligible impact when $\alpha = 0.25$ (as shown in Table A5). However, it is worth noting that as α approaches 1, these exclusions have a significant impact, as evidenced in Tables A7 and A8. For instance, when non-response rates are at 1%, the DER index estimates ($\alpha = 1$) in 2010 were 282.31 for the complete sample and 0.3534 for the restricted sample. In the previous year, these estimates were 0.4753 and 0.4741 for the complete and restricted samples, respectively. This highlights the extreme sensitivity of the DER index to the lower end of the distribution when α approaches its upper limit. Consequently, DER estimates may be susceptible to significant sample variability, potentially leading to questionable conclusions on trends in polarization.

Table 1 presents estimates of both the absolute and the relative versions of the DER index for various values of α, without considering the potential under-coverage of top incomes in household surveys. The results reveal that the decline in relative polarization becomes more pronounced as the polarization sensitivity parameter increases. The DER index decreased from 0.5506 in 1960 to 0.4017 in 2020 for $\alpha = 0.25$, from 0.5538 to 0.3268 for $\alpha = 0.5$, from 0.6526 to 0.2872 for $\alpha = 0.75$, and from 0.8324 to 0.2642 for $\alpha = 1$.

Table 1: Evolution of relative and absolute polarization from 1960 to 2020

	Relative polarization				
	DER ($\alpha = 0$)	DER ($\alpha = 0.25$)	DER ($\alpha = 0.5$)	DER ($\alpha = 0.75$)	DER ($\alpha = 1$)
1960	0.7326	0.5506	0.5538	0.6526	0.8324
1965	0.7361	0.5623	0.5809	0.7078	0.9378
1970	0.7286	0.5662	0.5931	0.7340	0.9884
1975	0.7279	0.5663	0.5948	0.7362	0.9893
1980	0.7285	0.5706	0.6025	0.7503	1.0129
1985	0.7219	0.5403	0.5323	0.6081	0.7474
1990	0.6937	0.5105	0.4817	0.5220	0.6087
1995	0.6886	0.4894	0.4426	0.4543	0.4979
2000	0.6852	0.4775	0.4223	0.4205	0.4442
2005	0.6637	0.4631	0.4016	0.3894	0.4003
2010	0.6179	0.4282	0.3569	0.3272	0.3161
2015	0.6093	0.4251	0.3535	0.3224	0.3101
2020	0.5720	0.4017	0.3268	0.2872	0.2642
	Absolute polarization				
	DER ($\alpha = 0$)	DER ($\alpha = 0.25$)	DER ($\alpha = 0.5$)	DER ($\alpha = 0.75$)	DER ($\alpha = 1$)
1960	3,189.0571	295.0759	36.5388	5.3007	0.8324
1965	4,049.6353	359.2028	43.0854	6.0962	0.9378
1970	5,045.6311	429.8327	49.3609	6.6959	0.9884
1975	5,366.5513	450.6013	51.0676	6.8219	0.9893
1980	5,986.3102	492.4676	54.6139	7.1433	1.0129
1985	6,231.2170	483.8150	49.4537	5.8613	0.7474
1990	6,788.6716	502.3029	47.6483	5.1916	0.6087
1995	6,833.2919	486.5550	44.0945	4.5346	0.4979
2000	7,223.6231	496.7878	43.3603	4.2610	0.4442
2005	8,223.3118	543.8325	44.7039	4.1087	0.4003
2010	8,485.2054	543.1644	41.8285	3.5424	0.3161
2015	9,301.5565	583.8115	43.6763	3.5838	0.3101
2020	10,761.5864	645.3144	44.8198	3.3634	0.2642

Note: the global distribution of income in each benchmark year is computed from a mixture of GB2 distributions estimated using Equations (5) and (6) and setting $t = 1$. The DER index is estimated by Monte Carlo simulation using samples of size $N = 10^5$. To reduce the sampling error, observations with values lower than US$1 were removed, which represented less than 1 per cent of the sample in all years. The estimates computed from complete samples are presented in Tables A5, A6, A7, and A8.

Source: authors' compilation using data from the WIID.

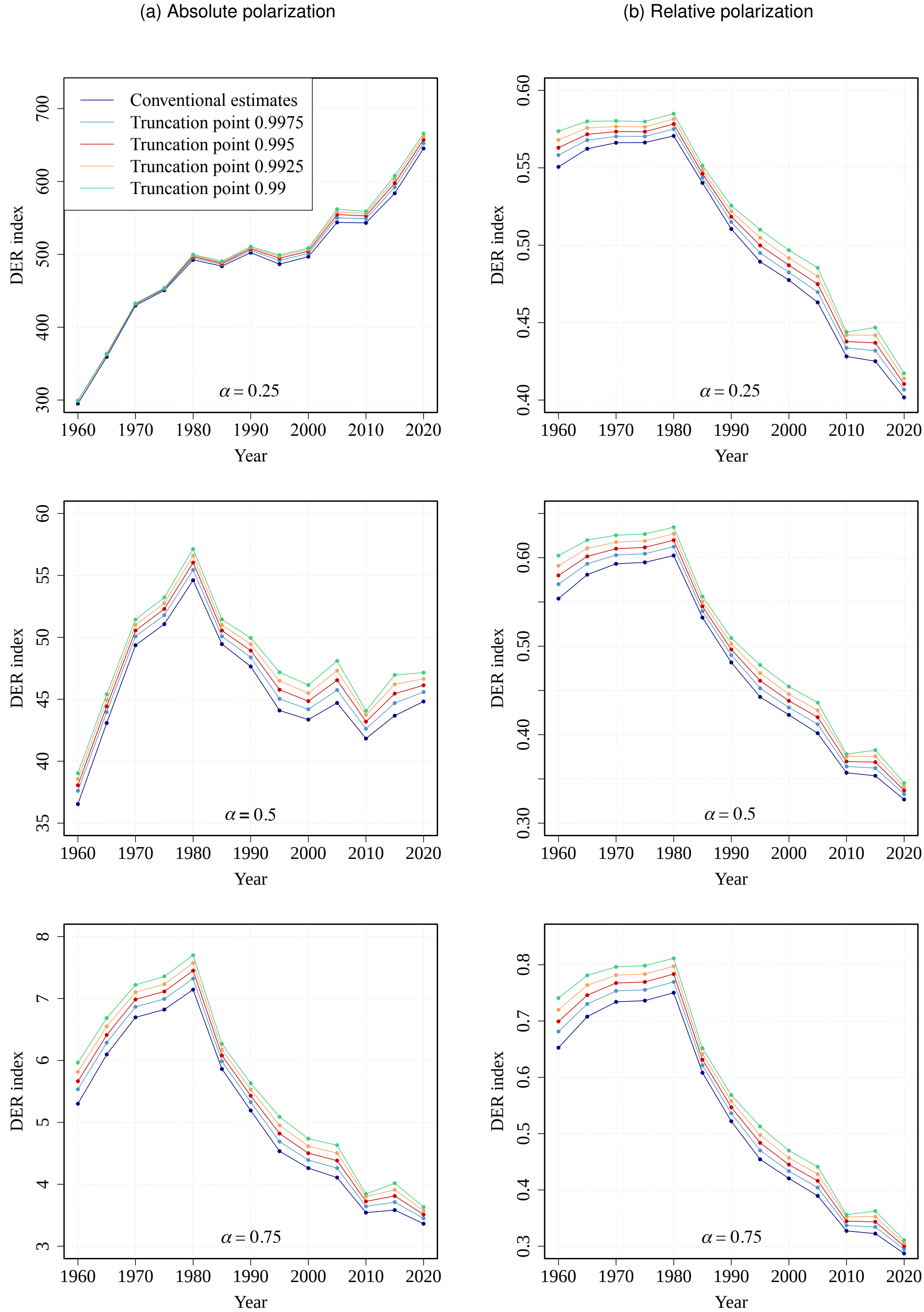
Table 1 also includes inequality estimates (DER with $\alpha = 0$) to illustrate how polarization differs from inequality. While both global inequality and polarization exhibit a downward trend from 1960 to 2020, noticeable discrepancies between these two distributional phenomena emerge in certain years, even for very low values of α. For example, the Gini index (DER$(\alpha = 0)$) declined from 1965 to 1970, whereas the DER$(\alpha = 0.25)$ index suggests a slight increase in polarization during the same period. Thus, while global inequality and polarization are correlated, our results highlight empirical differences between them that become more prominent as the sensitivity parameter increases.

The discrepancy between global polarization and inequality trends becomes particularly apparent when comparing absolute measures. Absolute global inequality exhibits an upward trend from 1960 to 2020, with the absolute Gini index (i.e. when $\alpha = 0$) increasing from 3,189.06 to 10,761.59. On the other hand, the absolute DER index shows an upward trend over the entire period only for small values of α, that is, when the polarization index is not very sensitive to the identification effect. As the α parameter increases, the evolution of absolute and relative polarization trends becomes more similar. In the limit, when $\alpha = 1$, there is no difference between relative and absolute polarization according to the DER index. This implies that polarization remains constant when all incomes grow in the same proportion or when the same absolute amount of income is added or subtracted from all individuals.

We now analyse the potential bias in polarization estimates arising from survey non-response in the upper tail of the income distribution. Figure 4 illustrates the evolution of the DER polarization measure for various values of α (0.25, 0.5, and 0.75) under different assumptions regarding household survey coverage; specifically, t = 100, 99.75, 99.5, 99.25, and 99 per cent of the population. Similarly to the pattern observed in bipolarization, relative DER polarization increases as the population covered by household surveys decreases. Unlike bipolarization measures, absolute DER polarization measures also increase as the population covered by household surveys decreases. It is important to note that these results are based on the assumption of constant non-response rates over time. However, prior empirical evidence from the US and the UK suggests that survey under-coverage of top incomes has become more severe in recent decades (Jenkins 2017).

Despite the absence of information about the proportion of the richest individuals that are not covered by household surveys, our analysis still provides valuable insights into the evolution of global polarization. In fact, we cannot conclude that polarization increased from 1960 to 1980, as its evolution depends on the non-response rates of household surveys in each year. However, the decline in global relative polarization from 1980 to 2020 is a robust finding that holds regardless of the proportion of the richest population not covered by household surveys. Similarly, the trends revealed by the DER measure of absolute polarization remain consistent and insensitive to different truncation points throughout the analysed period.

Figure 4: Evolution of absolute and relative polarization from 1960 to 2020: DER index



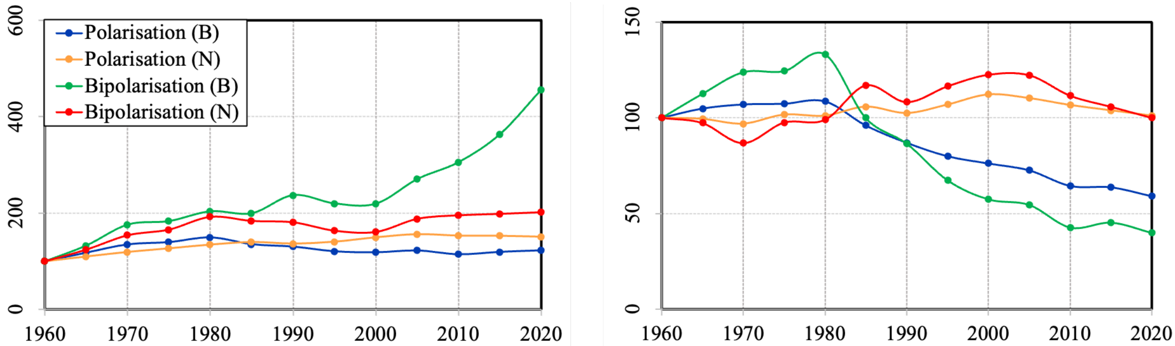
Note: the global distribution of income in each benchmark year is computed from a mixture of GB2 distributions estimated using Equations (5) and (6). The FW index is estimated by Monte Carlo simulation using samples of size $N = 10^5$. Observations with values lower than US$1 were removed. The results with complete samples are presented in Table A4.
Source: authors' compilation using data from the WIID.

5.3 The role of China and India in global polarization estimates

Previous literature on the evolution of the world income distribution suggests that China and India have played a pivotal role in the overall reduction of relative inequality over the past few decades. Now we aim to explore whether these countries are also key factors in the evolution of absolute and relative (bi)polarization at the global level. Figure 5 illustrates the evolution of the FW and DER indices using the entire sample of countries in our baseline specification (B) and a sample excluding China and India (N). In terms of absolute bipolarization, both cases show similar trends until 2005, when baseline estimates began to grow exponentially, increasing five-fold by 2020 compared to 1960. During this period, the FW index remains relatively stable when China and India are not included in the sample. Consequently, the surge in global absolute bipolarization during those 15 years appears to be driven primarily by changes in the levels and distribution of income within these two countries. The role of China and India in the evolution of absolute global polarization seems to be more moderate, particularly before 1980. Trends start to diverge after 1990, when polarization shows a decreasing trend for the entire sample, while it increases when these countries are excluded.

Figure 5: Impact of China and India in the evolution of absolute and relative polarization from 1960 to 2020

(a) Absolute (bi)polarization (b) Relative (bi)polarization



Note: polarization is normalized to be 100 in 1960. (B) stands for the baseline results, and (N) represents the global estimates without including China and India in the sample. The global distribution of income in each benchmark year is computed from a mixture of GB2 distributions estimated using Equations (5) and (6). The FW and DER indices are estimated by Monte Carlo simulation using samples of size $N = 10^5$.

Source: authors' compilation using data from the WIID.

The influence of China's and India's income distributions is particularly pronounced in the evolution of relative measures. From 1960 to 1980, global bipolarization appears to remain relatively stable when these countries are excluded, whereas, for the entire sample, it increases by 33 per cent. After 1980, the FW measure for the whole sample steadily decreases, but if we exclude China and India it exhibits an ascending trend until 2005. In terms of polarization, the DER index did not show substantial changes until 1980, when it started to exhibit a downward trend, resulting in a 40 per cent reduction by the end of the period. However, when China and India are not included in the sample, this statistic remains relatively stable throughout the entire period. Overall, the role of China and India in these (bi)polarization trends is similar to the role they have been found to have played in analyses of global inequality trends, in that the changes in these countries have been a major force in reducing global relative measures in recent decades.

5.4 Regional polarization

While the analysis so far has focused on the evolution of global relative and absolute polarization and bipolarization, there are good reasons to suspect the presence of considerable variation in the levels and trends of polarization across world regions. This may occur due to a myriad of reasons, including variation in the extent and nature of redistributive policies that might lead to reductions in income gaps between groups, or when there are significant changes in the structure of economies and labour markets that affect the size of the middle class.

We begin the discussion by presenting in Table 2 the results of the FW bipolarization indices by world regions, following the World Bank regional classification. Both relative and absolute FW indices observe a considerable variation in the levels of bipolarization across world regions. When looking at the absolute polarization measure, countries in North America (NA) and Europe and Central Asia (ECA) show the highest levels of bipolarization in the mid-1960s. While all regions show substantial increases in absolute bipolarization, EAP presents the most significant increase from 1960 to 2020.

Table 2: Evolution of regional bipolarization from 1960 to 2020: FW index

	Relative bipolarization						
	EAP	ECA	LAC	MENA	NA	SA	SSA
1960	0.395	0.204	0.269	0.263	0.124	0.215	0.269
1965	0.581	0.182	0.299	0.270	0.148	0.212	0.404
1970	0.565	0.170	0.305	0.380	0.148	0.203	0.443
1975	0.561	0.151	0.330	0.391	0.153	0.188	0.330
1980	0.501	0.138	0.280	0.182	0.152	0.224	0.336
1985	0.414	0.155	0.274	0.246	0.173	0.221	0.314
1990	0.408	0.172	0.284	0.193	0.179	0.213	0.342
1995	0.362	0.268	0.288	0.206	0.175	0.221	0.362
2000	0.211	0.264	0.298	0.207	0.170	0.246	0.356
2005	0.261	0.225	0.271	0.215	0.169	0.238	0.338
2010	0.190	0.190	0.251	0.199	0.174	0.225	0.315
2015	0.243	0.187	0.236	0.193	0.185	0.235	0.312
2019	0.228	0.179	0.216	0.207	0.178	0.215	0.276
	Absolute bipolarization						
	EAP	ECA	LAC	MENA	NA	SA	SSA
1960	145.911	2033.401	848.142	649.167	2,221.991	162.177	444.669
1965	214.082	2,249.107	1,002.345	845.704	3,075.297	179.139	747.769
1970	258.296	2,623.924	1,300.373	1,066.351	3,331.646	200.488	1,011.057
1975	330.552	2,755.370	1,760.155	1,624.626	3,637.950	181.305	643.382
1980	380.371	3,125.714	1,979.981	536.488	4,129.957	210.244	646.288
1985	475.675	3,547.778	1,748.551	1,314.906	5,187.000	242.450	376.342
1990	634.107	3,488.762	1,632.156	968.318	5,904.983	281.791	510.358
1995	842.380	4,118.101	1,743.921	1,125.042	5,901.169	329.951	403.001
2000	651.556	4,692.523	1,911.846	1,256.359	6,558.619	408.354	391.445
2005	1,218.046	4,910.359	2,010.782	1,389.930	7,084.625	478.320	475.978
2010	1,471.869	4,728.261	2,282.614	1,645.641	7,184.080	606.176	507.311
2015	2,390.733	5,023.046	2,352.091	1,636.114	7,989.698	754.486	590.913
2019	2,572.717	5,002.676	2,208.656	1,987.623	8,004.398	759.973	602.929

Note: EAP, East Asia and the Pacific; ECA, Europe and Central Asia; LAC, Latin America and the Caribbean; MENA, Middle East and North Africa; NA, North America; SA, South Asia; SSA, Sub-Saharan Africa. The global distribution of income in each benchmark year is computed from a mixture of GB2 distributions estimated using Equations (5) and (6) and setting $t = 1$. The FW index is estimated by Monte Carlo simulation using samples of size $N = 10^5$. To reduce the sampling error, observations with values lower than US$1 were removed, which represented less than 0.1 per cent of the sample in all years. The estimates computed from complete samples are presented in Tables A5, A6, A7, and A8.

Source: authors' compilation using data from the WIID.

Surprisingly, this region also experienced a substantial decrease in relative bipolarization, with a score of 0.395 in 1960 declining to 0.228 in 2019. Similarly, ECA saw a decline from 0.204 in 1960 to 0.179 in 2019, indicating a reduction in relative bipolarization. Latin America and the Caribbean (LAC) exhibited a consistent downward trend in the last two decades, with relative bipolarization decreasing from 0.298 in 2000 to 0.216 in 2020. The Middle East and North Africa (MENA) also experienced some fluctuations, with a slight decrease overall from 0.263 in 1960 to 0.207 in 2019. North America (NA) saw an upward trend in relative bipolarization, rising from 0.124 in 1960 to 0.178 in 2019. South Asia (SA) remained relatively stable, with a score of 0.215 in both 1960 and 2019. Bipolarization levels in Sub-Saharan Africa (SSA) fluctuated through the period, but with little change overall, relative bipolarization moving from 0.269 in 1960 to 0.276 in 2019.

Interestingly, when we estimate polarization based on the DER index, we find a relatively similar pattern for various regions. This is observed in Table 3, which presents both relative and absolute polarization estimates based on $\alpha = 0.5$, without correcting for non-response bias in survey data (i.e. with a truncation point $t = 1$). For instance, the relative polarization index shows that countries in EAP had the highest level of polarization in the world from the 1960s up to the mid-1990s, and the same pattern is observed with respect to bipolarization. However, there is generally less variation over time in the DER estimates than in the bipolarization estimates.

Table 3: Evolution of regional polarization from 1960 to 2020: DER index ($\alpha = 0.5$)

Relative polarization							
	EAP	ECA	LAC	MENA	NA	SA	SSA
1960	0.484	0.249	0.310	0.299	0.195	0.268	0.357
1965	0.603	0.246	0.318	0.307	0.217	0.264	0.388
1970	0.644	0.231	0.322	0.381	0.217	0.259	0.398
1975	0.578	0.220	0.332	0.369	0.218	0.257	0.336
1980	0.586	0.210	0.305	0.244	0.216	0.278	0.338
1985	0.484	0.220	0.302	0.290	0.232	0.275	0.312
1990	0.460	0.230	0.320	0.258	0.237	0.268	0.358
1995	0.406	0.281	0.323	0.276	0.236	0.273	0.379
2000	0.299	0.277	0.327	0.276	0.234	0.288	0.374
2005	0.327	0.261	0.309	0.286	0.234	0.287	0.359
2010	0.270	0.241	0.292	0.271	0.237	0.275	0.352
2015	0.276	0.239	0.284	0.272	0.242	0.288	0.335
2020	0.264	0.236	0.271	0.283	0.239	0.275	0.316
Absolute polarization							
	EAP	ECA	LAC	MENA	NA	SA	SSA
1960	17.408	28.432	23.721	19.242	27.419	8.912	21.512
1965	26.510	30.219	25.599	22.507	33.113	9.207	27.155
1970	32.686	31.987	28.806	30.896	34.907	9.568	31.242
1975	31.085	32.485	33.364	37.280	36.587	9.485	20.747
1980	34.670	34.410	33.574	15.311	38.591	10.584	20.875
1985	31.152	35.989	31.452	26.743	43.991	11.250	14.426
1990	32.958	36.069	33.015	21.797	47.540	11.887	20.739
1995	32.072	41.983	34.654	25.564	48.890	12.937	19.803
2000	21.700	44.210	36.265	26.954	51.861	14.878	19.437
2005	31.157	44.362	35.339	29.588	54.000	16.326	20.244
2010	29.226	42.836	35.383	30.498	54.684	17.653	21.012
2015	33.489	43.978	35.695	31.204	58.009	20.705	20.750
2020	33.451	43.968	33.318	35.404	57.937	20.108	20.004

Note: EAP, East Asia and the Pacific; ECA, Europe and Central Asia; LAC, Latin America and the Caribbean; MENA, Middle East and North Africa; NA, North America; SA, South Asia; SSA, Sub-Saharan Africa. The global distribution of income in each benchmark year is computed from a mixture of GB2 distributions estimated using Equations (5) and (6) and setting $t = 1$. The FW index is estimated by Monte Carlo simulation using samples of size $N = 10^5$. To reduce the sampling error, observations with values lower than US$1 were removed, which represented less than 0.1 per cent of the sample in all years.

Source: authors' compilation using data from the WIID.

The evolution of the absolute DER index is similar to the trends observed for the FW index in most regions. Countries in NA show the highest level of polarization, followed by countries in LAC, which saw an increase in polarization from 1960 to 2020. While countries in SA have had the lowest level of absolute polarization among world regions, they have also experienced the highest growth rate in the DER index between 1960 and 2020.

5.5 Robustness checks

As discussed in Section 4, we developed an algorithm that relied on a set of selection rules to construct the global income distribution from secondary datasets provided by the WIID. These rules are based on arbitrary choices, which may introduce a source of uncertainty in our estimates. In this section, we assess the sensitivity of polarization trends to these choices, as well as the use of per capita GDP to approximate the level of mean income in each country. Tables 4 and 5 present the estimates of global (bi)polarization using both the absolute and relative versions of the FW index and the DER measure, respectively.

Table 4: Global bipolarization estimates from 1960 to 2020: FW index

	Baseline	Non-corrected	GNI	Four-year	Three-year	Two-year
Relative bipolarization						
1960	0.853	0.783	0.437	0.893	0.660	0.690
1965	0.961	0.894	0.481	1.055	1.086	1.163
1970	1.058	0.984	0.785	1.104	1.093	1.190
1975	1.063	1.013	0.899	1.099	1.175	1.182
1980	1.138	1.057	0.934	1.247	1.255	1.265
1985	0.853	0.799	0.811	0.857	0.857	0.799
1990	0.739	0.716	0.685	0.740	0.740	0.709
1995	0.575	0.555	0.632	0.574	0.573	0.571
2000	0.490	0.462	0.538	0.489	0.492	0.493
2005	0.465	0.446	0.498	0.465	0.447	0.446
2010	0.364	0.355	0.360	0.363	0.361	0.357
2015	0.386	0.382	0.388	0.386	0.384	0.351
2020	0.340	0.337	0.337	0.336	0.316	0.307
Absolute polarization						
	Baseline	Non-corrected	GNI	Four-year	Three-year	Two-year
1960	766.236	744.987	431.523	745.413	1,317.393	1,453.429
1965	1,016.893	982.703	572.334	1,033.592	1,045.472	961.039
1970	1,348.520	1,307.655	2,083.841	1,366.529	1,299.888	1,312.317
1975	1,404.138	1,406.326	2,192.850	1,425.616	1,460.833	1,458.781
1980	1,559.040	1,520.373	2,380.858	1,607.333	1,611.157	1,539.043
1985	1,529.049	1,475.387	2,137.440	1,531.261	1,540.777	1,340.723
1990	1,816.379	1,755.221	1,947.831	1,842.297	1,848.440	1,648.082
1995	1,684.007	1,624.084	1,639.630	1,680.226	1,680.356	1,674.732
2000	1,680.781	1,593.741	1,712.181	1,701.060	1,713.403	1,756.211
2005	2,072.099	2,023.764	2,113.042	2,068.649	1,939.315	1,952.983
2010	2,340.699	2,247.573	2,266.494	2,342.814	2,355.495	2,392.073
2015	2,786.245	2,750.762	2,767.889	2,789.291	2,801.945	3,324.226
2020	3,494.582	3,452.192	3,566.259	3,513.588	3,588.857	3,655.528

Note: the global distribution of income in each benchmark year is computed from a mixture of GB2 distributions estimated using Equations (5) and (6) and setting $t = 1$. The FW index is estimated by Monte Carlo simulation using samples of size $N = 10^5$. To reduce the sampling error, observations with values lower than US$1 were removed, which represented less than 0.01 per cent of the sample in all years.

Source: authors' compilation using data from the WIID.

As mentioned above, we used both income and consumption data to maximize data coverage. Consumption data have been rescaled using the factors provided in Tables A1 and A2 to ensure comparability with income datasets. The first test examines how the harmonization of income and consumption data may have impacted the evolution of global bipolarization (see column *non-corrected* in Tables 4 and 5). When comparing the baseline estimates to those derived from the same dataset but without correcting consumption shares, we observe that while polarization tends to be lower in the non-corrected results, both sets of estimates yield similar trends. The difference between corrected and non-corrected estimates appears to be more pronounced during the first two decades of the study, affecting both absolute and relative polarization.

Table 5: Global polarization estimates from 1960 to 2020: DER index ($\alpha = 0.5$)

	Relative polarization					
	Baseline	Non-corrected	GNI	Four-year	Three-year	Two-year
1960	0.554	0.528	0.477	0.569	0.437	0.442
1965	0.581	0.552	0.486	0.602	0.608	0.635
1970	0.593	0.564	0.505	0.604	0.608	0.623
1975	0.595	0.585	0.520	0.603	0.618	0.620
1980	0.602	0.597	0.524	0.622	0.624	0.633
1985	0.532	0.526	0.519	0.534	0.534	0.535
1990	0.482	0.490	0.508	0.481	0.481	0.483
1995	0.443	0.445	0.506	0.442	0.442	0.442
2000	0.422	0.421	0.492	0.422	0.423	0.422
2005	0.402	0.397	0.473	0.401	0.399	0.398
2010	0.357	0.351	0.429	0.356	0.355	0.353
2015	0.353	0.352	0.426	0.353	0.352	0.334
2020	0.327	0.325	0.399	0.325	0.315	0.310
	Absolute polarization					
	Baseline	Non-corrected	GNI	Four-year	Three-year	Two-year
1960	36.539	34.834	24.191	37.338	34.938	36.247
1965	43.085	40.924	27.695	44.952	45.552	46.449
1970	49.361	46.919	46.466	50.450	50.164	51.486
1975	51.068	50.226	50.776	52.021	53.698	53.885
1980	54.614	54.089	52.604	56.936	57.137	57.388
1985	49.454	48.889	51.030	49.671	49.748	48.044
1990	47.648	48.497	48.749	47.828	47.885	46.652
1995	44.094	44.357	46.970	44.027	44.013	43.895
2000	43.360	43.248	46.230	43.624	43.816	44.176
2005	44.704	44.178	46.818	44.627	43.517	43.561
2010	41.829	41.182	41.866	41.751	41.784	41.912
2015	43.676	43.487	43.807	43.683	43.593	44.740
2020	44.820	44.648	45.151	44.761	44.334	44.242

Note: the global distribution of income in each benchmark year is computed from a mixture of GB2 distributions estimated using Equations (5) and (6) and setting $t = 1$. The FW index is estimated by Monte Carlo simulation using samples of size $N = 10^5$. To reduce the sampling error, observations with values lower than US$1 were removed, which represented less than 0.01 per cent of the sample in all years.

Source: authors' compilation using data from the WIID.

The baseline estimates rely on per capita GDP data for rescaling national income distributions. However, some might argue that per capita gross national income (GNI) provides a better approximation of mean income, as it includes total income from residents and businesses, regardless of where they are based. Column *GNI* in Tables 4 and 5 presents global polarization estimates using per capita GNI to approximate national mean income. When comparing these figures with our baseline estimates, we observe significant differences in the estimated levels of polarization. However, the trends appear to be quite similar, especially after 1995. Notable differences in the proportion of the population covered each year by both sets of estimates might partially explain the gap between the figures. Per capita GNI data availability is much more limited, resulting in estimates that cover less than 50 per cent of the global population before 1995, while estimates based on GDP cover around 70 per cent of the global population over the entire period analysed (see Table A9).

Now we consider the impact of adjusting the width of the timeframe for selecting national datasets. For each benchmark year, the data selection algorithm chose datasets within a five-year window, assuming that national income distributions remained unchanged over that period. The last three columns of Tables 4 and 5 contain polarization estimates that consider narrower timeframes of four, three, and two years. As the data requirements become more demanding, the population covered each year decreases (as shown in Table A9). However, this does not seem to have a significant impact on polarization estimates. In fact, the estimates of FW and the DER measures remain close even when using a two-year window. This is primarily because the vast majority of income and expenditure surveys are conducted within three years of the benchmark (as indicated in Table A3).

6 Conclusions

Inequality and polarization are two distributional phenomena that, though closely intertwined, may exhibit entirely different trends. Despite the extensive literature on global inequality, significant gaps persist in our understanding of global polarization trends. This paper contributes to addressing this issue by analysing the evolution of global and regional polarization measures from 1960 to 2020. In the case of the more general conception of polarization, allowing for multiple possible poles, to the best of our knowledge, this paper provides the first estimates of polarization levels and trends at the global level. Additionally, it updates and extends previous studies on global bipolarization levels.

Our findings indicate that while absolute and relative bipolarization levels increased from 1960 to 1980, these two indices exhibited contrasting trends thereafter. Consequently, global bipolarization decreased significantly in relative terms over the analysed period, while the absolute index displayed a notable increase. Similarly, relative polarization also declined during this period, but trends in absolute polarization depend on the magnitude of the sensitivity parameter. Specifically, we observed that absolute polarization increased for low values of this parameter but decreased for high values.

While polarization and bipolarization are conceptually distinct, relative measures for these two phenomena reflect similar trends at the global level. In contrast, absolute measures of polarization and bipolarization capture marked differences in their trends over time, depending on the size of the polarization parameter α. Importantly, these findings remain robust under various additional checks, including considerations such as the exclusion of the richest individuals in the income distribution, changes in the data selection procedure and homogenization processes, and variations in the sources of mean income data.

Although we have confidence in the reliability of our estimates, it is important to acknowledge several limitations in our estimates. First, due to the absence of individual-level data, we rely on aggregated data in the form of income shares. Previous research has highlighted that the use of aggregated data for estimating inequality, and consequently polarization, could introduce a source of measurement error when non-parametric techniques are employed to approximate income distribution. However, it is worth noting that parametric models have proven to provide accurate inequality estimates for nearly all countries, with exceptions being primarily limited to economies in transition characterized by a bimodal income distribution (Jorda et al. 2021). These bimodal distributions, where a well-established middle class coexists with a large proportion of impoverished citizens, are relatively rare. As such, it is reasonable to conclude that our results should not be significantly affected by this potential source of measurement error.

Our estimates may also be subject to the impact of under-coverage and under-reporting in household surveys. While we have addressed non-coverage issues at the upper end of the income distribution, the literature on income inequality underscores the fact that surveys often fail to accurately capture the lower tail of the income distribution. This occurs due to survey designs that do not effectively cover low-income populations (Skoufias et al. 2001).

Furthermore, the richest individuals tend to under-report income levels. Modelling under-reporting behaviours requires micro-data from both surveys and tax records, and we do not have access to this detailed information at the global scale. In the case of inequality analysis, we would be confident that these informational limitations would yield lower-bound estimates; however, in the case of (bi)polarization measures, where the impact of under-reporting at the upper tail on the distribution of poles is not necessarily straightforward, it is harder to predict the direction of the bias.

Our estimates could also be affected by data comparability issues. These issues stem from variations in the type of income measured in the survey (whether it is consumption, gross income, or net income), the unit of analysis (whether it is household or individual), and the equivalence scale used to adjust household income for the number of individuals. Following Jenkins' criteria (Jenkins 2015), we have outlined the data selection algorithm and assessed the robustness of our results when subjected to various data treatments, as detailed in Section 5.5.

Another source of uncertainty arises from the use of PPP to convert national currencies into an international numeraire, facilitating cross-country comparisons of living standards. In this paper, we have employed the 2017 PPP data released by the International Comparability Program (ICP) at the World Bank. These data series offer the most current assessment of relative purchasing power across countries. While it could have been possible to use previous versions of PPP data, it should be noted that the evolution of global polarization is unlikely to be significantly affected, given that poverty and inequality trends have proven to be robust across different PPP datasets (Atamanov et al. 2020; Warner et al. 2014). An alternative source of PPP data could have been the Penn World Tables. However, these series are constructed using the Geary–Khamis method, which tends to overestimate the incomes of poorer countries. In contrast, estimates from the ICP rely on the Elteto–Koves–Szulc method, which, among the available alternatives, appears to be the most suitable for estimating the global income distribution (Anand and Segal 2008).

Despite the potential limitations outlined above, our analysis improves our understanding of the income distribution dynamics at the global level. The study provides the first estimates of regional and global income polarization trends, and extends the evidence on bipolarization trends, complementing the existing evidence on global inequality. While there are still challenges to address in improving the measurement of income distribution, the methods employed in this study provide a robust approach to approximating the global income distribution from grouped data and mitigating measurement errors arising from under-coverage issues in household surveys.

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Appendix A

Table A1: Regional income/consumption indices used to correct consumption shares (ten data points)

Region	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
High-income countries	0.8155	0.9309	0.9606	0.9784	0.9921	1.0012	1.0097	1.0142	1.0157	1.0385
EAP	0.8027	0.9104	0.9164	0.9442	0.9649	0.9835	1.0007	1.0175	1.0341	1.0723
LAC	0.6062	0.7338	0.7993	0.8443	0.8805	0.9135	0.9467	0.9806	1.0221	1.1664
MENA	0.8329	0.8896	0.9204	0.9503	0.9738	0.9930	1.0053	1.0144	1.0152	1.0585
SA	0.3772	0.5855	0.6627	0.7238	0.7798	0.8381	0.9098	1.0022	1.1185	1.3179
SSA	0.5549	0.7481	0.8332	0.8861	0.9319	0.9691	0.9969	1.0145	1.0202	1.1106

Note: correction factors are obtained from 350 pairs of country–year comparable data on income and consumption retrieved from the latest version of WIID.

Source: authors' compilation based on the WIID.

Table A2: Regional income/consumption indices used to correct consumption shares (five data points)

Region	Q1	Q2	Q3	Q4	Q5
High-income countries	0.8855	0.9707	0.9962	1.0131	1.0284
EAP	0.8076	0.9399	0.9856	1.0170	1.0664
LAC	0.6856	0.8241	0.8984	0.9654	1.1191
MENA	0.8672	0.9367	0.9841	1.0101	1.0429
SA	0.5173	0.6840	0.7997	0.9579	1.2712
SSA	0.6730	0.8623	0.9525	1.0066	1.0798

Note: correction factors are obtained from 350 pairs of country–year comparable data on income and consumption retrieved from the latest version of WIID.

Source: authors' compilation based on the WIID.

Table A3: Panel summary statistics

	1960	1965	1970	1975	1980	1985	1990	1995	2000	2005	2010	2015	2020
Number of surveys	42	52	55	54	61	75	108	132	153	161	165	164	132
Years between the survey and the benchmark year (%)													
0	19	23	38	30	31	28	29	46	42	48	56	50	49
+/-1	29	12	24	28	34	29	30	27	24	22	19	23	16
+/-2	21	19	15	24	5	16	17	15	14	17	12	13	10
+/-3	17	23	9	4	15	12	14	5	9	4	7	7	11
+/-4	5	13	4	11	3	7	4	3	5	5	4	4	10
+/-5	10	10	11	4	11	8	7	4	7	4	2	4	5
Income/ consumption sources (%)													
Income (net)	2	15	24	37	36	32	26	32	28	30	36	37	39
Consumption	7	4	13	17	18	33	42	45	54	57	53	51	45
Income (gross)	55	50	40	31	31	13	14	10	2	1	2	2	2
Income (net/gross)	36	31	24	11	13	17	18	13	16	11	9	10	14
Earnings	0	0	0	4	2	4	1	1	0	1	0	0	0
Population covered (%)													
East Asia and the Pacific	82	83	83	92	89	89	95	96	90	97	99	99	93
Europe and Central Asia	25	35	49	51	47	53	92	99	100	99	96	95	94
Latin America and the Caribbean	75	86	87	79	77	90	91	91	93	93	92	92	88
Middle East and North Africa	46	50	60	45	38	47	69	72	79	69	79	80	51
North America	91	91	91	90	90	90	90	90	100	100	100	100	101
South Asia	95	97	98	99	99	99	100	100	100	101	101	101	25
Sub-Saharan Africa	42	23	18	29	31	48	66	79	93	97	98	100	83
World	68	70	74	77	76	80	91	94	94	96	97	98	73

Source: authors' compilation based on the WIID.

Table A4: Estimates of the FW index under different methodological assumptions

	FW index				Obs. removed	
	Conventional	Conventional (>US$1)	Non-coverage 1%	Non-coverage 1% (>US$1)	Conventional	Non-coverage 1%
1960	0.8533	0.8533	0.9421	0.9419	2	21
1965	0.9606	0.9606	1.0449	1.0446	2	18
1970	1.0581	1.0581	1.0999	1.1000	0	1
1975	1.0627	1.0627	1.1031	1.1031	0	2
1980	1.1380	1.1380	1.2231	1.2231	0	2
1985	0.8533	0.8533	0.8781	0.8781	5	5
1990	0.7389	0.7388	0.7854	0.7852	6	28
1995	0.5748	0.5748	0.6383	0.6360	5	457
2000	0.4895	0.4895	0.5346	0.5329	2	430
2005	0.4653	0.4653	0.5139	0.5138	0	26
2010	0.3644	0.3644	0.3932	0.3899	0	786
2015	0.3861	0.3861	0.4296	0.4296	0	2
2020	0.3397	0.3397	0.3632	0.3632	0	1

Note: the global distribution of income in each benchmark year is computed from a mixture of GB2 distributions estimated using Equations (5) and (6) and setting $t = 1$ for figures in columns labelled as *conventional* and $t = 0.99$ for figures in columns labelled as *non-coverage*. The FW index is estimated by Monte Carlo simulation using samples of size $N = 10^5$.

Source: authors' estimates based on data from the WIID.

Table A5: Estimates of the DER ($\alpha = 0.25$) index under different methodological assumptions

	DER index ($\alpha = 0.25$)				Obs. removed	
	Conventional	Conventional (>US$1)	Non-coverage 1%	Non-coverage 1% (>US$1)	Conventional	non-coverage 1%
1960	0.5506	0.5506	0.5740	0.5737	2	21
1965	0.5623	0.5623	0.5805	0.5800	2	18
1970	0.5662	0.5662	0.5803	0.5803	0	1
1975	0.5663	0.5663	0.5799	0.5799	0	2
1980	0.5706	0.5706	0.5850	0.5850	0	2
1985	0.5403	0.5403	0.5514	0.5514	5	5
1990	0.5105	0.5105	0.5257	0.5256	6	28
1995	0.4894	0.4894	0.5281	0.5101	5	457
2000	0.4775	0.4775	0.5144	0.4968	2	430
2005	0.4631	0.4631	0.4860	0.4854	0	26
2010	0.4282	0.4282	0.4962	0.4440	0	786
2015	0.4251	0.4251	0.4469	0.4469	0	2
2020	0.4017	0.4017	0.4172	0.4172	0	1

Note: the global distribution of income in each benchmark year is computed from a mixture of GB2 distributions estimated using Equations (5) and (6) and setting $t = 1$ for figures in columns labelled as *conventional* and $t = 0.99$ for figures in columns labelled as *non-coverage*. The DER index is estimated by Monte Carlo simulation using samples of size $N = 10^5$.

Source: authors' estimates based on data from the WIID.

Table A6: Estimates of the DER ($\alpha = 0.5$) index under different methodological assumptions

	DER index ($\alpha = 0.5$)				Obs. removed	
	Conventional	Conventional (>US$1)	Non-coverage 1%	Non-coverage 1% (>US$1)	Conventional	Non-coverage 1%
1960	0.5538	0.5538	0.6057	0.6025	2	21
1965	0.5809	0.5809	0.6237	0.6199	2	18
1970	0.5931	0.5931	0.6255	0.6255	0	1
1975	0.5948	0.5948	0.6268	0.6268	0	2
1980	0.6025	0.6025	0.6345	0.6345	0	2
1985	0.5323	0.5323	0.5562	0.5562	5	5
1990	0.4817	0.4817	0.5099	0.5092	6	28
1995	0.4427	0.4426	0.7610	0.4788	5	457
2000	0.4223	0.4223	0.7378	0.4543	2	430
2005	0.4016	0.4016	0.4423	0.4362	0	26
2010	0.3569	0.3569	1.2597	0.3780	0	786
2015	0.3535	0.3535	0.3826	0.3826	0	2
2020	0.3268	0.3268	0.3453	0.3453	0	1

Note: the global distribution of income in each benchmark year is computed from a mixture of GB2 distributions estimated using Equations (5) and (6) and setting $t = 1$ for figures in columns labelled as *conventional* and $t = 0.99$ for figures in columns labelled as *non-coverage*. The DER index is estimated by Monte Carlo simulation using samples of size $N = 10^5$.

Source: authors' estimates based on data from the WIID.

Table A7: Estimates of the DER ($\alpha = 0.75$) index under different methodological assumptions

	DER index ($\alpha = 0.75$)				Obs. removed	
	Conventional	Conventional (>US$1)	Non-coverage 1%	Nn-coverage 1% (>US$1)	Conventional	Non-coverage 1%
1960	0.6652	0.6652	0.7821	0.7551	2	18
1965	0.7135	0.7135	0.8176	0.7882	2	18
1970	0.7377	0.7377	0.8012	0.8012	0	1
1975	0.7433	0.7433	0.8059	0.8059	0	2
1980	0.7533	0.7533	0.8191	0.8192	0	2
1985	0.6096	0.6095	0.6541	0.6541	5	6
1990	0.5227	0.5226	0.6041	0.5690	8	30
1995	0.4557	0.4556	6.9947	0.5153	5	487
2000	0.4204	0.4204	5.7104	0.4699	2	437
2005	0.3898	0.3898	0.4426	0.4421	2	27
2010	0.3269	0.3269	16.0349	0.3559	1	781
2015	0.3219	0.3219	0.3633	0.3634	1	2
2020	0.2903	0.2903	0.3166	0.3166	2	2

Note: the global distribution of income in each benchmark year is computed from a mixture of GB2 distributions estimated using Equations (5) and (6) and setting $t = 1$ for figures in columns labelled as *conventional* and $t = 0.99$ for figures in columns labelled as *non-coverage*. The DER index is estimated by Monte Carlo simulation using samples of size $N = 10^5$.

Source: authors' estimates based on data from the WIID.

Table A8: Estimates of the DER ($\alpha = 1$) index under different methodological assumptions

	DER index ($\alpha = 1$)				Obs. removed	
	Conventional	Conventional (>US$1)	Non-coverage 1%	Non-coverage 1% (>US$1)	Conventional	Non-coverage 1%
1960	0.8550	0.8551	1.2194	1.0056	2	18
1965	0.9486	0.9487	1.3141	1.0779	2	18
1970	0.9955	0.9955	1.1077	1.1077	0	1
1975	1.0037	1.0037	1.1154	1.1154	0	2
1980	1.0190	1.0190	1.1356	1.1356	0	2
1985	0.7501	0.7500	0.8244	0.8243	5	6
1990	0.6098	0.6095	0.9806	0.6823	8	30
1995	0.4996	0.4995	111.8270	0.5892	5	487
2000	0.4437	0.4437	87.5507	0.5147	2	437
2005	0.4005	0.4005	0.4753	0.4741	2	27
2010	0.3152	0.3152	282.3089	0.3534	1	781
2015	0.3090	0.3090	0.3641	0.3641	1	2
2020	0.2678	0.2678	0.3009	0.3009	2	2

Note: the global distribution of income in each benchmark year is computed from a mixture of GB2 distributions estimated using Equations (5) and (6) and setting $t = 1$ for figures in columns labelled as *conventional* and $t = 0.99$ for figures in columns labelled as *non-coverage*. The DER index is estimated by Monte Carlo simulation using samples of size $N = 10^5$.

Source: authors' estimates based on data from the WIID.

Table A9: Data coverage: robustness checks

	Baseline	GNI	Four-year	Three-year	Two-year
1960	42 (68%)	10 (22%)	38 (64%)	36 (42%)	29 (37%)
1965	52 (70%)	19 (25%)	47 (68%)	40 (66%)	28 (61%)
1970	55 (74%)	29 (38%)	49 (72%)	47 (70%)	42 (68%)
1975	54 (77%)	26 (38%)	52 (76%)	46 (73%)	44 (72%)
1980	61 (76%)	29 (37%)	54 (73%)	52 (72%)	43 (70%)
1985	75 (80%)	37 (41%)	69 (79%)	64 (78%)	55 (73%)
1990	108 (91%)	56 (48%)	100 (90%)	96 (90%)	81 (83%)
1995	132 (94%)	86 (79%)	127 (94%)	123 (93%)	117 (93%)
2000	153 (94%)	109 (80%)	143 (92%)	136 (91%)	122 (88%)
2005	161 (96%)	117 (83%)	155 (96%)	148 (93%)	141 (93%)
2010	165 (97%)	136 (89%)	161 (96%)	155 (96%)	144 (93%)
2015	164 (98%)	164 (98%)	158 (97%)	152 (96%)	141 (76%)
2020	132 (73%)	114 (67%)	126 (72%)	113 (66%)	99 (63%)

Note: these figures indicate the number of countries included and the proportion of the global population covered in parentheses.

Source: authors' compilation based on the WIID.