International migration, population growth and global income inequality

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1. Introduction

During the last decades, there have been increasing concerns as to whether the benefits of economic growth might have been unequally distributed across world citizens. This is why global interpersonal income inequality (i.e., income inequality across individuals all over the world – from now onwards referred to as "global income inequality"[1]) is a matter of enormous interest both for scholars and policy makers alike. In this paper, we propose a novel approach to assess the role of population dynamics in determining the trends in global income inequality. More specifically, we aim at estimating the extent to which global income inequality dynamics are influenced by international migration and countries' natural population growth.

Since the pioneering works by Berry, Bourguignon and Morrisson (1983) and Grosh and Nafziger (1986), numerous studies have attempted to measure the levels and trends of global income inequality (e.g., Milanovic 2002, Bourguignon and Morrisson 2002, Anand and Segal 2014, Laekner and Milanovic 2016, Niño-Zarazúa, Roope and Tarp 2017, Gradín 2024, Milanovic 2024). In a nutshell, these studies suggest that, during the last two centuries, global income inequality has followed an inverted U shape, increasing as a consequence of the Industrial Revolution and peaking sometime before the year 2000.[2] In addition, they show that the composition of global income inequality has been shifting over time. Before reaching its peak, global income inequality was mostly attributable to differences across countries' mean income levels (i.e., between-country inequality). Sometime near the end of the 20th century, between-country inequality began to fall (partly because of China's unprecedented economic growth) and inequality within countries began to increase. Consequently, both components now roughly account for 50% of global income inequality (Gradín 2024).

While the decomposition of global income inequality in its within- and between-country components has been scrutinized exhaustively, there is a third fundamental ingredient in the global distribution of income that has gone largely unnoticed: the population distribution across countries and its changes over time. Indeed, income inequality has to do with the extent to which certain shares of income are owned by certain shares of individuals, and this

[1] To be clear, this means that the basic unit of analysis is the individual (rather than, say, the country), and that we treat the whole world as a single society. This corresponds to 'concept three' inequality according to the different inequality concepts put forward in the pioneering work of Milanovic (2005).

[2] Such trends are based on relative inequality measures, like the Theil index, or the Gini coefficient. Absolute inequality measures suggest that global income inequality has increased sharply during the same period, though (Niño-Zarazúa, Roope and Tarp 2017, Gradín 2024).

is where population size plays a key role. Individuals worldwide live separated in countries' (a partition that determines the size of the between- and within-country inequality components), and the population size of those countries change at very different rates.[3] These often-dramatic changes in countries' population size have an impact on global income inequality that, so far, has been unaccounted for.

In turn, changes in countries' population size are driven by two fundamental forces: "population natural increase" (i.e., the difference between births and deaths) and "international migration" (i.e., the movement of individuals from one country to another). Traditionally, ideas on population change are rooted in the so-called "slow demography" paradigm, "*which emphasizes an inertial, predictable, self-contained view of population dynamics, mostly dependent on fertility and mortality*" (Billari 2022, p.9). Yet, the speed of demographic change can also be very high when international migration is taken into consideration – specially in wealthy countries with relatively small populations (as is the case for many European countries that are the destination of international migration flows). The main aim of this paper is to assess the influence that populations' natural growth *and* international migration have had on global income inequality, separately.

While there is a long and venerable strand of research (dating back to the pioneering work of Malthus) analyzing whether population growth can hinder or boost countries' economic growth,[4] virtually nothing is known about the effects that the former can have on global income inequality.[5] Likewise, the effect of international migration on income differences among individuals around the globe is largely unknown, and has been a fertile ground for speculative ideas going in opposite directions. On the one hand, international migration has been posited as a potentially important mechanism through which income differences across individuals around the globe can be *reduced*. Indeed, given (i) the large differences in mean income levels between countries, and (ii) the existence of easy means of transportation to quickly move from one place to another, several scholars have suggested that international migration can be a fundamental mechanism of adjustment to reduce income inequalities across world citizens (Pritchett 2006, Milanovic 2012, 2015). Along these lines, Milanovic (2012, p.125) heralds the movement of individuals across international borders as "*probably, the most powerful tool for reducing global poverty and inequality*". On the other hand, the strong selectivity involved in the process of migration have led other scholars to suggest that migration might further *increase* income differences across world citizens. In the global competition for talent, only those who have the skills and the ability to overcome the many

[3] While many countries have increased their populations at a fast pace during the last decades (that is the case of several low-income countries like, Niger, or South Sudan), some high-income countries have seen stalls and even declines in their population numbers (e.g., Japan, Italy).
[4] Indeed, countless studies have attempted at understanding whether countries' economic prospects might be jeopardized by unchecked population growth. A good summary of this enormous body of research can be found in Birdsall et al (2001).
[5] Gradín (2024) is the only study we are aware of that deals with a somewhat related but different topic. In that paper, the author quantifies the contribution that certain countries or regions (e.g., China or India) have had on global income inequality. Instead, here we focus on the effect that natural population growth and international migration across all countries around the world have had on the trends in global income inequality (further details shown below).

obstacles that international migrants have to face to cross borders can finally reap the opportunities offered abroad (De Haas 2023). On top of that, there is a raging debate over whether international migrants increase or decrease income inequality both within origin and destination countries (e.g., Borjas 2003, Card 2005, 2009, Blau and Kahn 2015). All in all, there is much uncertainty regarding what the impact of international migration on global income inequality might be.

Previous attempts at testing competing hypotheses regarding the impact of international migration and/or countries' population growth on global income inequality are very scarce – an issue that can be largely attributable to the lack of necessary data. Clemens and Pritchett (2008) and Kapur and McHale (2009) investigate the relationship between international migration and global income inequality *between countries*. Their estimates suggest that international migration contributed to slightly decrease the between-country component of global income inequality around the year 2000. Unfortunately, those analyses (i) do not take into consideration the within-country component of global inequality (which is nowadays almost as important as its between-country counterpart), (ii) they rely on data collected 25 years ago, and (iii) are based on migrant stocks rather than actual migration flows (an issue that could be potentially problematic because it ignores the amount of time that migrants might have spent in destination countries).

The main aim of this paper is to partially fill this gap by estimating the *direct* (i.e., first-order) effects that countries' natural population growth and international migration flows have had on recent trends in global income inequality. To do so, we go beyond well-known statistical and counterfactual decomposition techniques (like the *influence functions* (Hampel 1974)) and develop new tools to assess the sensitivity of global income inequality to changes in the population distribution across countries. Inter alia, we introduce the so-called *bilateral influence functions* to estimate how an infinitesimally small movement of population from one country to another can affect the global distribution of income. Our empirical estimates are based on a variegated set of data sources (e.g., the United Nations' World Population Prospects (WPP) database for population data, estimates from Guy and Abel (2019) for bilateral international migration flows around the globe, household surveys from multiple sources and the UNU-WIDER "World Income Inequality Database" (WIID) for economic data). Our findings suggest that international migration and countries' natural population growth have typically contributed to *increase* global income inequality between 1990 and 2020 for our preferred income inequality measure (the Mean Log Deviation). Decomposition techniques further indicate that (i) fast population growth in low and lower-middle income countries and (ii) large international migration flows from upper middle-income countries towards high-income countries have been mostly responsible for the inequality enhancing effects of population dynamics over the global distribution of income. Together, the two "population-related" effects are non-negligible and become an increasingly strong determinant of the changes in global income inequality.

The rest of the paper is organized as follows. In section 2 we describe the sources of empirical data used in the paper. In section 3 we introduce the methods employed in the paper to arrive to our empirical findings, which are reported in section 4. A discussion of those and other related findings is introduced in section 5 and section 6 concludes.

2. Data

To calculate our models and present our findings, we need information about world countries' mean income levels, interpersonal income inequality, population size and population change. In turn, population change needs to be separated into its natural growth and international migration components. In this section we describe the different data sources that have been used in our analyses.

2.1. Economic data

The measurement of global income inequality is fraught with difficulties arising from the lack of sufficiently detailed data collected in a consistent manner both across countries and over time. This forces researchers to make difficult decisions when deciding the geographical and temporal coverage of their analyses, as each of those decisions have their advantages and disadvantages. To make our findings as robust as possible, we have decided to apply our techniques to two different data sets; the so-called "Core" and "Extended" data sets.

2.1.1. The Core data set

One approach to estimate global income inequality is to simply pick the country-year observations for which household-level (micro) data obtained from household surveys (1) exist, (2) are accessible, and (3) they are sufficiently detailed to construct high-quality percentile distributions. The most comprehensive collection of data points along these lines is the one recently compiled by Milanovic (2024), which is publicly available[6] and will be used in this paper under the label of "Core" dataset (Appendix 1 shows the countries included in the analysis). The years covered in this database are 2008, 2013 and 2018. The sources of data used to construct the Core dataset are the World Bank's POVCAL, the Luxembourg Income Study (LIS), the SEDLAC database for Latin America and the EU-SILC for some European countries. Some of those surveys are consumption-based while others are income-based. While it would be desirable to use the same concept of well-being everywhere, a study by Jayadev et al (2015) suggests that the combination of income- and consumption-based surveys should not bias estimates of global income inequality (further details shown in Milanovic (2022)).

The inclusion of data points based on observed country-years with the highest available quality is the main strength of the Core database. This ensures reliability of the ensuing findings. Unfortunately, household surveys are not collected everywhere, and they are often collected on an irregular basis. This implies that the set of countries used to estimate global

[6] The data can be accessed from https://stonecenter.gc.cuny.edu/research/the-three-eras-of-global-inequality-1820-2020-with-the-focus-on-the-past-thirty-years-published/

income inequality vary over time, an issue that might compromise the reliability of time trend assessments.[7] In addition, this is further aggravated by the constraints imposed by our methods, which require the *same* set of countries to be included in two consecutive observation years to work (further details shown below). This extra requirement further reduces the set of country-years that can be incorporated into the analysis, thus limiting the scope and representativity of our empirical findings. To overcome this limitation ensuing from the constraints in the geographical and temporal coverage of the Core dataset, we also apply our methods to the so-called "Extended" dataset.

2.1.2. The Extended dataset

To enlarge the set of country-year observations included in our analyses we rely on the latest version of the UNU-WIDER "World Income Inequality Database" (WIID), which document the levels of income inequality within most world countries (UNU WIDER 2022). More specifically, we rely on the so-called "country dataset", which collects information on per capita net income inequality for 209 countries or territories over the longest possible period for which reliable data are available. Like its Core counterpart, the Extended dataset also uses information from well-known international sources (e.g., LIS, SEDLAC, EU-SILC) and mixes consumption- and income-based household surveys. In addition, while most household surveys measure net income, some of them are in gross (before tax) terms. To correct for these potential distortions and make the results as comparable and standardized as possible, some adjustments have been applied (see UNU WIDER 2022 for further technical details).

The UNU-WIDER dataset is presented in different versions – one which resembles the Core dataset (i.e., only presenting the "true" observed data points) and another extended version that fills all data gaps by estimating income inequality levels for all possible country-year combinations using interpolation and regression-based techniques. The latter is the version we have used in this paper, and is freely accessible from https://www.wider.unu.edu/database/world-income-inequality-database-wiid. We will refer to it as the "Extended" dataset. Its main strength is the comprehensive geographical and temporal coverage, with a uniform country representation for all possible years (i.e., for every year, the set of countries from which one computes global income inequality is almost exhaustive and does not change over time). Its main weakness is that most country-year data points are based on interpolation and regression-based imputations rather than "real" observations derived from household surveys, an issue that could be potentially problematic for some specific countries with scarce data. Yet, the studies that have used the UNU-WIDER database to estimate global income inequality trends report findings that are highly coherent with other analyses based on "true" data points only (see Niño-Zarazúa, Roope and Tarp 2017, Gradín 2024).

[7] Implicitly, this assumes that the set of countries S_1 used to estimate global income inequality in time t_1 is as representative as S_2, another set of countries used to estimate global income inequality in time t_2 (with $S_1 \not\subset S_2$ and $S_2 \not\subset S_1$) – an issue that could be potentially problematic depending on the size of the sets $S_1 \setminus S_2$ and $S_2 \setminus S_1$.

Lastly, another ingredient that is needed in both the Core and Extended databases to estimate global income inequality is the income per capita (GDP per capita) in PPP[8] for the different countries included in each dataset. These values are mainly taken from the integrated series using the World Bank's World Development Indicators, with complementary information from the Maddison project and the Penn World Tables.

To facilitate the interpretation of our empirical findings, some results will be shown for the World Bank's four-tier income group country classification (i.e., "Low income", "Lower middle-income", "Upper middle-income" and "High income" countries) rather than for each country separately. For the sake of simplicity, we stick to the income group classification made in year 2015 (i.e., we do not allow countries to move across income categories over time).

2.2. Population data

To measure population size, we take advantage of the United Nations' "World Population Prospects" (WPP) database. In the WPP database, users can download information about all world countries' population size from 1950 onwards. Since the migration data used in this paper is only available from 1990 onwards (see below), we restrict our analysis to the 30-year period between 1990 and 2020. Results will be presented in 5-year intervals starting in 1990 (that is: 1990-1995, 1995-2000, 2000-2005, 2005-2010, 2010-2015 and 2015-2020). Population size indicators are freely accessible from: https://population.un.org/wpp/

2.3. Migration flow data

The measurement of international migration flows is plagued with difficulties, among other things because some countries do not publish the corresponding data due to the high costs of data collection systems. Currently existing approaches to estimate migration flows are based on the comparison of migrant stocks over time (Abel and Cohen 2019). In turn, these approaches are separated in three broad categories. The first group of methods is based on the comparison of successive bilateral stocks for a given pair of countries to estimate the size of the flow in each direction. The second group uses migrant stock data to estimate migration flow rates, which are later multiplied by the corresponding populations at risk. The third group of methods treats changes in migrant stocks as a residual in a demographic accounting equation, whereby total population change is defined as the sum of migration flows and the natural growth of that population (i.e., births minus deaths; see more details below).

Abel and Cohen (2019) present and compare six different methods to estimate bilateral migration flows between all origin-destination country pairs based on United Nations and World Bank migrant stock data. The first two methods (known as "Stock difference, drop

[8] Here we use the adjustment to constant 2017 USD from the International Comparison Program (see UNU WIDER 2022).

negative" and "Stock difference, reverse negative") belong to the first of the three categories mentioned above, the third method (referred to as "Migration rates") corresponds to the second one, and the last three (known as "Demographic Account Minimisation Open", "Demographic Account Minimisation Closed" and "Demographic Pseudo Bayesian Closed") belong to the third category. All the bilateral migration flow estimates between more than 200 countries from these six methods are freely accessible from Abel and Cohen (2019) for 5-year intervals starting in 1990 and finishing in 2020. We have replicated all our empirical findings for each of the six estimation methods.

3. Methods

3.1. Inequality measures

There are many indicators that can be used to measure income inequality. In this paper, we rely on different members of the class of generalized entropy measures owing to their useful decomposability properties (see below). We privilege the mean logarithmic deviation (MLD) as our preferred inequality measure for being the only member in that class that is both path independent[9] (Foster and Shneyerov 2000) and that satisfies the intuitive principle of "monotonicity in distance"[10] (Cowell and Flachaire 2024). However, to test the robustness of our findings, we also explore what happens to other well-known members of the generalized entropy measures, like the Theil index and the coefficient of variation squared.

Let $\boldsymbol{y} = (y_1, \cdots, y_n)$ be the per capita income distribution across all households around the world. The inequality indices used in this paper belong to the class of generalized entropy measures, which is defined as

$$\mathrm{GE}_t(\theta) = \begin{cases} \dfrac{1}{\theta(\theta-1)} \displaystyle\sum_i f_{i,t} \left[\left(\frac{y_{i,t}}{\mu_t} \right)^{\theta} - 1 \right] & if \;\; \theta \neq 0,1 \\ \displaystyle\sum_i f_{i,t} \ln \left(\frac{\mu_t}{y_{i,t}} \right) & if \;\; \theta = 0 \\ \displaystyle\sum_i f_{i,t} \left(\frac{y_{i,t}}{\mu_t} \right) \ln \left(\frac{y_{i,t}}{\mu_t} \right) & if \;\; \theta = 1 \end{cases} \qquad [1]$$

[9] Path independent inequality measures are a class of income inequality metrics that can be decomposed into two additive components—between-group and within-group inequality—in a way that is not dependent on the "representative income functions" used to define these groups (i.e., via the so-called *smoothed* and *standardized* distributions). The between-group and within-group components of inequality measures that do not satisfy this axiom can influence each other in intuitively unappealing ways (see further technical details in Foster and Shneyerov 2000).

[10] This axiom basically states that when the income of just one person is changed in a direction "away from equality" (e.g., a rich individual becoming richer or a poor individual becoming poorer), then inequality should increase (Cowell and Flachaire 2024). Surprisingly, popular measures like the Gini and the Theil indices do not abide by this principle.

where $f_{i,t}$ is the population share of household i, $y_{i,t}$ is the per capita income of household i, μ_t is the average per capita income, all measured in time t, and θ is a parameter chosen by the user. Lower values of θ are associated with greater sensitivity to inequality at the lower end of the distribution, and higher values of θ place more weight to inequality at the upper end. When $\theta = 0$, $GE_t(0)$ corresponds to the MLD (which will be denoted as L_t), and $GE_t(1)$ yields the well-known Theil entropy measure (henceforth T_t). Lastly, $GE_t(2)$ is ordinally equivalent to the coefficient of variation squared (which will be referred to as CV_t^2).

3.2. Decomposing global income inequality levels

Importantly, the four inequality measures discussed so far are *additively decomposable* (Shorrocks 1980). This means that, when the set of all households around the world are partitioned across a set of J countries $\{C_1, \cdots, C_J\}$, the inequality measures can be rewritten as follows

$$\mathrm{GE}_t(\theta) = \begin{cases} \frac{1}{\theta(\theta-1)} \sum_i p_{i,t} \left[\left(\frac{\mu_{j,t}}{\mu_t}\right)^\theta - 1 \right] + \sum_{j=1}^{J} p_{j,t} \mathrm{GE}_{j,t}(\theta) \left(\frac{\mu_{j,t}}{\mu_t}\right)^\theta = GE(\theta)_B + GE(\theta)_W \quad if \;\; \theta \neq 0,1 \\ \sum_{j=1}^{J} p_{j,t} \ln\left(\frac{\mu_t}{\mu_{j,t}}\right) + \sum_{j=1}^{J} p_{j,t} L_{j,t} = L_B + L_W \quad if \;\; \theta = 0 \\ \sum_{j=1}^{J} p_{j,t} \left(\frac{\mu_{j,t}}{\mu_t}\right) \ln\left(\frac{\mu_{j,t}}{\mu_t}\right) + \sum_{j=1}^{J} p_{j,t} \left(\frac{\mu_{j,t}}{\mu_t}\right) T_{j,t} = T_B + T_W \quad if \;\; \theta = 1 \end{cases} \qquad [2]$$

where $\mu_{j,t}$, $L_{j,t}$, $T_{j,t}$ and $p_{j,t}$ are the mean income level, the level of inequality as measured by the MLD and the Theil index, and the population share of country j for time t, respectively. J is the total number of countries included in the analysis. Lastly, μ_t is the world's mean income in time t, and is simply defined as the population weighted sum of world countries' mean income levels (i.e., $\sum_j p_{j,t}\, \mu_{j,t}$).

From now onwards, we will generically write I_t and $I_{j,t}$ to refer to global income inequality and inequality within country j in time t in those cases where the choice of the specific inequality measure does not matter (that is: in those properties or statements that are valid for the three inequality measures considered in this paper). In addition, the time subindices (t) will be dropped from the equations whenever they are not needed.

The first terms in the equations shown in [2] are the so-called "between-country inequality" component (usually denoted as I_B), which measures the amount of inequality that would be observed in case there was no variation in incomes across individuals belonging to the same country. The second terms in equations [2] are the "within-group inequality" component (typically denoted as I_W), which is a weighted average of the country-specific income inequality levels. The additive decomposability property mentioned above requires overall inequality to correspond exactly to the sum of the two components (that is: $I = I_W + I_B$).

3.3. Decomposing changes in global income inequality

The changes over time in global income inequality I_t (as measured by the three inequality measures shown in equation [2]) can be attributable to the combination of three proximal factors: (i) changes in countries' average income levels (i.e., the $\mu_{j,t}$), (ii) changes in countries' income inequality levels (i.e., the $I_{j,t}$), and (iii) changes in countries' population size (i.e., the $p_{j,t}$) – see equations shown in [2]. Using standard counterfactual decomposition techniques, we break down changes in global income inequality as

$$I_2 - I_1 = \Delta I = \Delta_B I + \Delta_W I + \Delta_P I \qquad [3]$$

where $\Delta_B I$, $\Delta_W I$ and $\Delta_P I$ capture the effect that changes in countries' average income levels, within country inequality and population size have had on ΔI, respectively (full details shown in the Appendix 2). Essentially, these counterfactual techniques assess by how much would global income inequality change in case only one of the three ingredients in equations [2] (i.e., countries' average income levels, within country inequality and population size) changed over time. In such assessment, we follow the Shapley approach to avoid path-dependency issues (see Appendix 2 for details).

Changes in countries' population size between times t_1 and t_2 can be written as the following demographic accounting/balancing equation

$$P_2 - P_1 = B - D + In - Out = N + M \qquad [4]$$

where B and D are the births and deaths occurring in that country during that period and In and Out are the corresponding number of in-migrants and out-migrants (Preston et al 2001). Finally, $N := B - D$ is the so-called "population natural growth" and $M := In - Out$ the "international migration" flow.

Applying the same counterfactual techniques used to derive equation [3] and making use of the accounting equation in [4], changes in global income inequality (ΔI) can be further decomposed as

$$\Delta I = \Delta_B I + \Delta_W I + \Delta_N I + \Delta_M I \qquad [5]$$

where the additional terms $\Delta_N I$ and $\Delta_M I$ (which, together, add up to the $\Delta_P I$ term in equation [3]) capture the effects that countries' natural population growth and international migration flows have had on ΔI, respectively (full details shown in Appendix 2). To calculate them, we will take advantage of the different migration estimation methods proposed by Abel and

Cohen (2019). Importantly, the $\Delta_B I, \Delta_W I$ terms are *not* affected by the choice of migration estimation method, and the sum of the two population-related components (i.e., $\Delta_N I + \Delta_M I = \Delta_P I$) is the same no matter what migration estimation method we choose (a property ensuing from the closed form of equation [4] – see Appendix 2 for technical details).

While counterfactual methods like the ones applied here do not establish causation, they provide a "heuristically useful and methodologically transparent approach in which researchers can easily identify the main sources (if not causes) of change" (Eloundou-Enyegue et al. 2017, p. 60).

3.4. Decomposing the natural population growth effect

The four-component decomposition proposed in equation [5] is very useful to assess the macro level drivers of global income inequality change. Yet, the natural population growth component (i.e., the $\Delta_N I$ term) is an aggregate quantity affected by the demographic experience of all world countries *simultaneously*. As a consequence, it might not be representative of the numerous individual country effects, which might be pushing in opposite directions. To better understand the forces underlying the behaviour of this aggregate term, we propose a decomposition method to assess the contribution of each country (or group of countries) to the $\Delta_N I$ component. For that purpose, in this subsection we introduce the notion of 'influence functions', show some of their basic properties and indicate how they can be used to estimate countries' contribution to the $\Delta_N I$ component.

Influence functions

We start by introducing the following notation. Let s_i be the population size of country $i \in \{1, \cdots, J\}$ and let $S = \sum_{i=1}^{J} s_i$ be the world population size. Likewise, let $\mathbf{\Pi} = (s_1/S, \cdots, s_J/S) = (p_1, \cdots, p_J)$ denote the vector of countries' population shares at a given point in time (in contrast to equations [1] and [2], we drop the time (t) subindex in the following equations for simplicity). Now, for any $i \in \{1, \cdots, J\}$ and for any $\varepsilon > 0$, let's define

$$\mathbf{\Pi}_i(\varepsilon) := \left(p_1^*(\varepsilon), \cdots, p_J^*(\varepsilon)\right) \qquad [6]$$

where

$$p_i^*(\varepsilon) = \frac{s_i + \varepsilon}{S + \varepsilon} \qquad [7]$$

and

$$p_j^*(\varepsilon) = \frac{s_j}{S + \varepsilon} \qquad [8]$$

for all $j \in \{1, \cdots, J\} \setminus \{i\}$. The J-dimensional vector $\mathbf{\Pi}_i(\varepsilon)$ contains the world countries' population shares that obtains when an "small" quantity of individuals (ε) is added to country 'i'.[11] Now, let $I(\mathbf{\Pi})$ denote the amount of global income inequality that obtains from I when $\mathbf{\Pi}$ is the vector of countries' population shares, and analogously for $I\big(\mathbf{\Pi}_i(\varepsilon)\big)$. With this notation, we can now define

$$\varphi_i^I := \lim_{\varepsilon \to 0} \frac{I\big(\mathbf{\Pi}_i(\varepsilon)\big) - I(\mathbf{\Pi})}{\varepsilon} \qquad [9]$$

This quantity measures the impact on global income inequality (as measured by I) of a (ceteris paribus) marginally increasing population size in country i (that is: under the assumption that such small increase in population size does not alter any other of the parameters involved in the calculation of I, like countries' average income or income inequality). Using the terminology of mathematical statistics, these are the so-called 'Influence Functions' (IF), which have been used extensively to explore several robustness properties of any estimator (for instance, inequality measures) – including their sensitivity to small changes in the underlying distributions (Hampel 1974, Cowell and Victoria-Feser 1996, Cowell and Flachaire 2002, 2007).

When the size of a specific country i increases infinitesimally, it has an impact on both the within- and the between-group components of global income inequality (i.e., I_W and I_B). In the following proposition, we show the functional forms of the influence functions defined in equation [9] for the within-group and between-group components of the three inequality measures used in this paper.

Proposition 1. When I is measured with the MLD, the influence functions for L_W, L_B and L equal

$$\begin{cases} \varphi_i^{L_W} = \dfrac{1}{S}(L_i - L_W) \\ \varphi_i^{L_B} = \dfrac{1}{S}\left(\dfrac{\mu_i - \mu}{\mu} + \ln\left(\dfrac{\mu}{\mu_i}\right) - L_B\right) \\ \varphi_i^{L} = \dfrac{1}{S}\left(-L + \dfrac{\mu_i - \mu}{\mu} + \ln\left(\dfrac{\mu}{\mu_i}\right) + L_i\right) \end{cases} \qquad [10]$$

When I is measured with the Theil index, the influence functions for T_W, T_B and T equal

[11] Using the terminology that is common in mathematical statistics, one says that $\mathbf{\Pi}_i(\varepsilon)$ is a small 'contamination' of $\mathbf{\Pi}$.

$$\begin{cases} \varphi_i^{T_W} = \frac{1}{S}\left(\frac{\mu_i}{\mu}(T_i - T_W)\right) \\ \varphi_i^{T_B} = \frac{1}{S}\left(\frac{\mu-\mu_i}{\mu} + \frac{\mu_i}{\mu}\ln\left(\frac{\mu_i}{\mu}\right) - \frac{\mu_i}{\mu}T_B\right) \\ \varphi_i^{T} = \frac{1}{S}\left(\frac{\mu-\mu_i}{\mu} - \frac{\mu_i}{\mu}T + \frac{\mu_i}{\mu}\ln\left(\frac{\mu_i}{\mu}\right) + \frac{\mu_i}{\mu}T_i\right) \end{cases} \qquad [11]$$

When I is measured with the Coefficient of Variation squared, the influence functions for CV_W^2, CV_B^2 and CV^2 equal

$$\begin{cases} \varphi_i^{CV_W^2} = \frac{1}{S}\left(\left(\frac{\mu-2\mu_i}{\mu}\right)CV_W^2 + \left(\frac{\mu_i}{\mu}\right)^2 CV_i^2\right) \\ \varphi_i^{CV_B^2} = \frac{1}{S}\left(\left(\frac{\mu-2\mu_i}{\mu}\right)(CV_B^2+1) + \left(\frac{\mu_i}{\mu}\right)^2\right) \\ \varphi_i^{CV^2} = \frac{1}{S}\left((1+CV^2)\left(\frac{\mu-2\mu_i}{\mu}\right) + (1+CV_i^2)\left(\frac{\mu_i}{\mu}\right)^2\right) \end{cases} \qquad [12]$$

Proof. See Appendix 3.

As shown in Appendix 3, the effect of an infinitesimal increase in the population of country i on I_B is contingent on the position of that country's mean income level (μ_i) within the distribution of world countries' mean income levels. Whenever μ_i is placed at the tails of such distribution, the effect tends to be positive (i.e., contributing to increase inequality) and large. Whenever μ_i is located near 'the center' of such distribution (i.e., within the bounds of a certain interval denoted as $(\mathcal{L}_I, \mathcal{U}_I)$), the effect is negative (i.e., contributing to decrease between-country inequality – see Appendix 3). That is: increasing the populations of countries near the world's mean income levels will contribute to decrease the between-country component of global income inequality (and vice versa).

The effect of an infinitesimal population increase on I_W depends on the level of income inequality of that country (I_i) with respect to the level of global income inequality within countries (I_W) – see technical details in Appendix 3. In countries with higher (resp. lower) income inequality than the world average I_W, the effect will contribute to increase (resp. decrease) I_W. That is: increasing the population size of highly unequal countries will contribute to increase the within-country component of global income inequality (and vice versa).

Approximating countries' contribution

Finally, we show how influence functions can be used to estimate countries' contribution to the $\Delta_N I$ component. As indicated by Hampel (1974), influence functions are essentially the first derivative of an estimator. As such, they can be used to generate linear approximations of the changes in that estimator over time using Taylor polynomials of degree 1.[12] Following this logic, we can now introduce the next definition.

Definition 1. Let N_j be country j's natural growth between times t_1 and t_2 (i.e., the difference between births and deaths during that period) for all $j \in \{1, \cdots, J\}$. Then we can define the following estimator

$$\widehat{\Delta_N} I := \sum_{j=1}^{J} \varphi_j^I \cdot N_j \qquad [13]$$

Because of the way in which it is defined, $\widehat{\Delta_N} I$ is a linear approximation of the effect of countries' natural population growth on global income inequality. While not being an exact decomposition, in the empirical section we show that such approximation can indeed be very accurate (further details shown below, in particular see footnote #16). When this happens, the $\Delta_N I$ term can be approximated very closely by a sum of the contributions of each country separately (the contribution of country j being $\varphi_j^I \cdot N_j$ for all $j \in \{1, \cdots, J\}$[13]).

Since the number of countries we are dealing with in the empirical section is quite high (above 100 and 200 in the Core and Extended datasets, respectively), to simplify the presentation we summarize our findings for broad groups of countries (i.e., the four income group categories of the World Bank). Formally, this means that if the set of countries $\{1, \cdots, J\}$ is partitioned in G exhaustive and mutually exclusive groups labeled by g (i.e., $\{1, \cdots, J\} = \sqcup_{g=1}^{G} K_g$), then

$$\Delta_N I \cong \sum_{g=1}^{G} \mathcal{C}_g \qquad [14]$$

where

$$\mathcal{C}_g := \sum_{j \in K_g} \varphi_j^I \cdot N_j \qquad [15]$$

[12] According to Taylor's theorem, any real-valued function $f(x)$ that is differentiable at the point $x = a$ can be linearly approximated around that point through $f(a) + f'(a)(x - a)$, a polynomial of degree 1. Thus, a change in $f(x)$ near $x = 0$ can be approximated as $\Delta f = f(x) - f(0) \approx f'(0)(x - 0) = f'(0)x$. This is the formula upon which equation [13] is based.

[13] Observe that countries' natural growth can be negative (i.e., deaths can be more numerous than births). When this happens, the N_j terms are, thus, negative. In those situations, one would like that influence functions measure how infinitesimally small *decreases* in countries' population sizes affect global income inequality. Since the inequality functions we are working with are differentiable (implying that the right-hand and left-hand limit versions of equation [9] coincide), the corresponding influence functions assess their sensitivity to *changes* in either direction. This means that the linear approximation in equation [13] can be used both to capture the effects of increasing and decreasing populations on global income inequality.

In other words, the $\Delta_N I$ term can be approximated by the sum of the contributions of each of the groups in which world countries are partitioned. Since G is typically much smaller than J, the G terms decomposition shown in equation [14] is much easier to interpret empirically than the J terms decomposition shown in equation [13].

3.5. Decomposing the migration effect

While informative, the migration effect component identified in equation [5] (i.e., the $\Delta_M I$ term) is a macro level aggregate quantity that accounts for the *combined* effect of all bilateral migration flows between all possible origin-destination dyads on global income inequality. Akin to the ideas presented in the previous subsection, here we present a novel methodological approach to estimate the effect that the migration flow between each country pair has on global income inequality. This is particularly important to identify what migration flows are the main contributors to the changes in global income inequality (an information that is hidden when inspecting the $\Delta_M I$ term). For that purpose, we introduce some further notation. Given any pair of countries $i, j \in \{1, \cdots, J\}$ (with $i \neq j$) and any $\epsilon > 0$, let's define

$$\mathbf{\Pi}_{ij}(\epsilon) \coloneqq \left(\widetilde{p_1}(\varepsilon), \cdots, \widetilde{p_J}(\varepsilon)\right) \qquad [16]$$

where

$$\widetilde{p_i}(\varepsilon) = \frac{s_i - \epsilon}{S} \qquad [17]$$

$$\widetilde{p_j}(\varepsilon) = \frac{s_j + \epsilon}{S} \qquad [18]$$

and

$$\widetilde{p_l}(\varepsilon) = p_l \qquad [19]$$

for all $l \in \{1, \cdots, J\} \setminus \{i, j\}$. The components of the J-dimensional vector $\mathbf{\Pi}_{ij}(\varepsilon)$ represent the world countries' population shares that obtains when an "small" number of individuals (ϵ) migrate from country 'i' towards country 'j'. We can now define

$$\psi_{ij}^I \coloneqq \lim_{\epsilon \to 0} \frac{I\left(\mathbf{\Pi}_{ij}(\epsilon)\right) - I(\mathbf{\Pi})}{\epsilon} \qquad [20]$$

This quantity measures the impact of an infinitesimally small shift of population moving from country 'i' to country 'j' on global income inequality (as measured by I) under the assumption that such small population shift does not alter any other of the parameters involved in the calculation of I. Importantly, this means that the small share of individuals moving from one country to another do neither affect the receiving nor the sending countries' average income and income inequality levels – a simplifying assumption that is useful to assess the first-order effects of migration flows, and whose validity will be further discussed after the empirical findings section.

Since equation [20] captures the effect of moving small population shares between country pairs on income inequality, ψ_{ij}^{I} will be referred to as a *bilateral influence function* (henceforth 'BIF'). While the influence functions defined above (φ_j^I) assess how much would inequality change when the population mass in country j increased infinitesimally, their bilateral counterparts measure how much would that inequality be affected if such population increase were attributable to a migratory flow that decreased the sending country population size by the same amount. Such migratory flows can affect both the within-country and the between-country components of global income inequality. Like before, the functional form of the bilateral influence functions depends on the underlying inequality measure. The following proposition shows the equations of ψ_{ij}^{I} for the within-group and between-group components of the three global income inequality measures used in this paper.

Proposition 2. When I is measured with the MLD, the bilateral influence functions for L_W, L_B and L equal

$$\begin{cases} \psi_{ij}^{L_W} = \dfrac{1}{S}\left(L_j - L_i\right) \\ \psi_{ij}^{L_B} = \dfrac{1}{S}\left(\dfrac{\mu_j - \mu_i}{\mu} + \ln\left(\dfrac{\mu_i}{\mu_j}\right)\right) \\ \psi_{ij}^{L} = \dfrac{1}{S}\left(\dfrac{\mu_j - \mu_i}{\mu} + \ln\left(\dfrac{\mu_i}{\mu_j}\right) + L_j - L_i\right) \end{cases} \qquad [21]$$

When I is measured with the Theil index, the bilateral influence functions for T_W, T_B and T equal

$$\begin{cases} \psi_{ij}^{T_W} = \dfrac{1}{S}\left(\dfrac{\mu_j}{\mu}T_j - \dfrac{\mu_i}{\mu}T_i + \dfrac{\mu_i - \mu_j}{\mu}T_W\right) \\ \psi_{ij}^{T_B} = \dfrac{1}{S}\left(\dfrac{\mu_j}{\mu}\ln\left(\dfrac{\mu_j}{\mu}\right) - \dfrac{\mu_i}{\mu}\ln\left(\dfrac{\mu_i}{\mu}\right) + \dfrac{\mu_i - \mu_j}{\mu}(1 + T_B)\right) \\ \psi_{ij}^{T} = \dfrac{1}{S}\left(\dfrac{\mu_i - \mu_j}{\mu}(1 + T) + \dfrac{\mu_j}{\mu}\left(\ln\left(\dfrac{\mu_j}{\mu}\right) + T_j\right) - \dfrac{\mu_i}{\mu}\left(\ln\left(\dfrac{\mu_i}{\mu}\right) + T_i\right)\right) \end{cases} \qquad [22]$$

When I is measured with the Coefficient of Variation squared, the bilateral influence functions for CV_W^2, CV_B^2 and CV^2 equal

$$\begin{cases} \psi_{ij}^{CV_W^2} = \frac{1}{S}\left(CV_j^2\left(\frac{\mu_j}{\mu}\right)^2 - CV_i^2\left(\frac{\mu_i}{\mu}\right)^2 - 2\frac{\mu_j - \mu_i}{\mu}CV_W^2\right) \\ \psi_{ij}^{CV_B^2} = \frac{1}{S}\left(\frac{\mu_j^2 - \mu_i^2}{\mu^2} - 2\frac{\mu_j - \mu_i}{\mu}(1 + CV_B^2)\right) \\ \psi_{ij}^{CV^2} = \frac{1}{S}\left(\frac{\mu_j^2(1 + CV_j^2) - \mu_i^2(1 + CV_i^2)}{\mu^2} - 2\frac{\mu_j - \mu_i}{\mu}(1 + CV^2)\right) \end{cases} \quad [23]$$

Proof. See Appendix 4.

We now describe how the bilateral influence functions defined above react to certain migration flows. For that purpose, we introduce the following definition and proposition.

Definition 2. When an individual from country i moves to a country j with higher average income (i.e., $\mu_j > \mu_i$), we say that that is an 'income increasing move'. When the average income of the destination country is lower than in the origin (i.e., $\mu_j < \mu_i$), we talk about an 'income decreasing move'.

Proposition 3. For the three inequality measures used in this paper, an income increasing (resp. decreasing) move between two countries with average incomes below the world mean (i.e., $\mu_i, \mu_j \leq \mu$) contributes to reduce (resp. increase) $\psi_{ij}^{I_B}$. Likewise, an income increasing (resp. decreasing) move between two countries with average incomes above the world mean (i.e., $\mu \leq \mu_i, \mu_j$) contributes to increase (resp. decrease) $\psi_{ij}^{I_B}$.

Proof. See Appendix 4.

According to proposition 3, infinitesimally small migratory movements towards higher income countries with both origin and destination countries' mean incomes below the world mean contribute to compress the global income distribution, thus reducing inequality.[14] Analogously, when such movements involve two countries with mean income levels above the world mean, the global income distribution widens, thus increasing inequality. However, the proposition remains silent about the income increasing moves involving countries with average incomes below and above the world mean (i.e., $\mu_i < \mu < \mu_j$). In that case, the effects could be positive or negative, depending on the mean income levels at origin and destination.

The effect of an infinitesimal migration flow from country i towards country j on I_W depends on the income inequality levels in both the sending and receiving countries (i.e., I_i, I_j). In general, movements from higher inequality countries towards lower inequality countries will contribute to reduce I_W, while movements from low inequality towards high inequality

[14] Again, this happens under the simplifying assumption that such migration movements do neither affect the receiving nor the sending countries' average income and income inequality levels.

countries will have the opposite effect. However, while such interpretation is straightforward for the case of the L, it is less clear in the cases of T and CV^2 (see the corresponding $\psi_{ij}^{I_W}$ equations in [21]-[23]) – another reason why L is our preferred inequality measure in this paper.

To understand the behavior of the bilateral influence functions, in the empirical section of the paper we will plot the values of $\psi_{ij}^{I_W}$ and $\psi_{ij}^{I_B}$ for all possible combinations of origin and destination countries.

Approximating country pairs contributions

Akin to the standard influence functions, the bilateral influence functions defined above can be thought as the first derivative of an inequality measure when the population distribution across countries shift towards the direction of an infinitesimally small migration flow between country pairs. Following the same logic as in the previous subsection, we can now introduce the following definition.

Definition 3. Let M_{ij} be migration flow from country i towards country j between times t_1 and t_2 for all $i, j \in \{1, \cdots, J\}$ with $i \neq j$. Then we can define the following estimator

$$\widehat{\Delta_M} I := \sum_{i=1}^{J} \sum_{j=1}^{J} \psi_{ij}^{I} \cdot M_{ij} \qquad [24]$$

$\widehat{\Delta_M} I$ is a linear approximation of the effect of bilateral migration flows on global income inequality. Even if $\widehat{\Delta_M} I$ is *not* an exact decomposition of $\Delta_M I$, in the empirical section we show that the approximation can be quite accurate (see footnote #18 below). When that is the case, the $\Delta_M I$ component can be very closely approximated by a sum of the contributions of all country pairs (the contribution of country pair (i, j) being $\psi_{ij}^{I} \cdot M_{ij}$ for all $i, j \in \{1, \cdots, J\}$ with $i \neq j$). Importantly, while ψ_{ij}^{I} measures how sensitive global income inequality is to an infinitesimally small migration movement from country i towards country j, M_{ij} captures the actual migration flow between those two countries during the study period. Following this approach, we can pinpoint the sender-receiver country dyads that contribute the most to changes in global income inequality attributable to international migration.

With above 100 or 200 countries in our Core and Extended datasets, respectively, one could potentially report the contributions of more than 100·100 or 200·200 country pairs combinations – a potentially complicated landscape that can be difficult to communicate. To simplify the presentation of results in the empirical section, countries will be grouped in broad categories of countries (i.e., the four income group categories of the World Bank), and the results shown for those categories. Like in the previous subsection, if the set of countries

$\{1,\cdots,J\}$ is partitioned in G exhaustive and mutually exclusive groups labeled by g (i.e., $\{1,\cdots,J\} = \bigsqcup_{g=1}^{G} K_g$), then

$$\Delta_M I \cong \sum_{g=1}^{G} \sum_{h \neq g} \mathcal{C}_{gh} \qquad [25]$$

where

$$\mathcal{C}_{gh} \coloneqq \sum_{i \in K_g} \sum_{j \in K_h} \psi_{ij}^{I} \cdot M_{ij} \qquad [26]$$

Since G is typically much smaller than J, the $G(G-1)$ terms decomposition shown in equations [25] and [26] is much easier to interpret empirically than the decomposition shown in equation [24], with $J(J-1)$ terms.

4. Results

4.1. Descriptive findings

Global income inequality trends

Figure 1 shows the trends in global income inequality as measured with the Mean Log Deviation, the Theil index and the coefficient of variation squared. When using the Core dataset, we can see what happens between the years 2008 and 2013 and between the years 2013 and 2018. Since the set of countries used to determine global income inequality in that dataset varies between 2008-2013 and 2013-2018, (i) the two set of estimates are shown separately and (ii) they do not coincide exactly in the common year of 2013 (Appendix 1 shows the sets of countries used in each case). When using the Extended dataset, we can observe the trends from 1990 until 2020 in five-year intervals. No matter what dataset we use, our findings suggest that the values of the Mean Log Deviation systematically declined over time. Regarding the Theil index, we observe very similar patterns except for a small inequality plateau between 1990 and 1995. When using the coefficient of variation squared, we observe increases in global income inequality between 1990 and 2000 followed by monotonic declines (no matter what dataset we use). These trends cohere with the ones identified in other recent studies (e.g., Niño-Zarazúa, Roope and Tarp (2017), Milanovic (2022, 2024), Gradin (2024)).

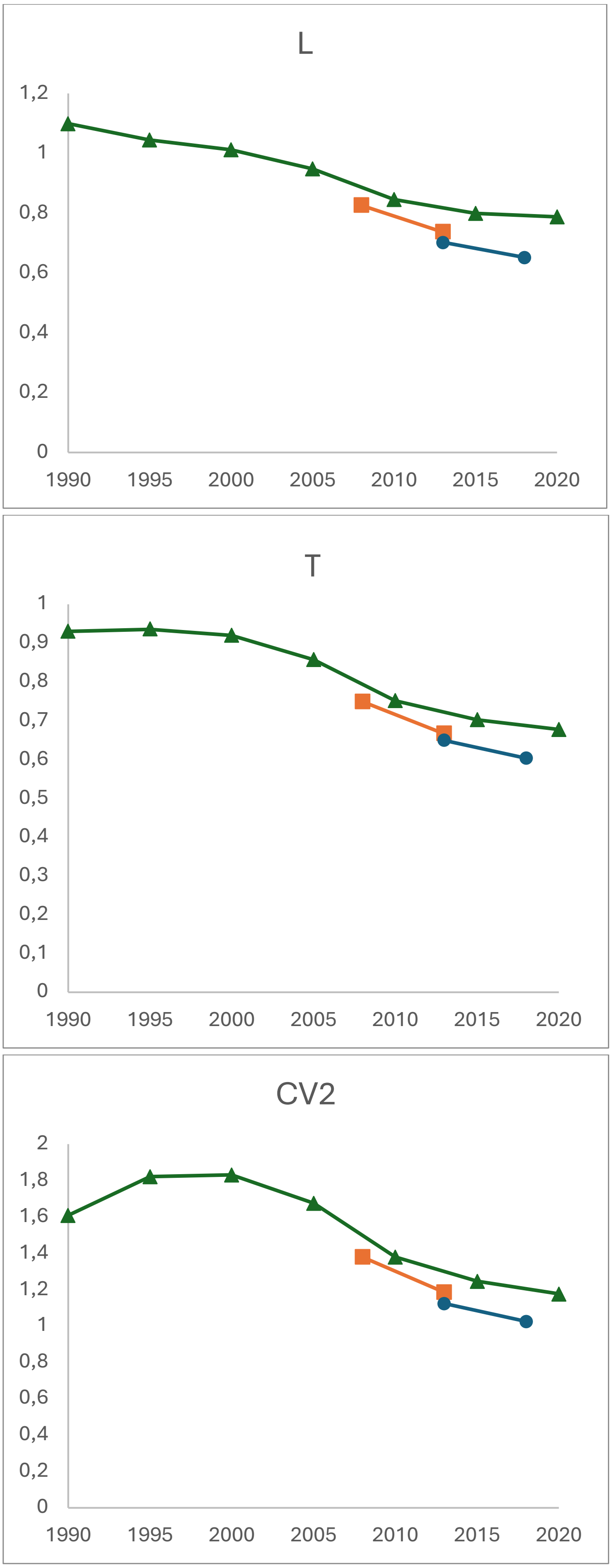

Figure 1. Trends in global Mean Log Deviation, the Theil index and the Coefficient of Variation squared between 1990 and 2020. Source: Author's elaboration based on data from Milanovic (2021) and the "World Income Inequality Database" (WIID).

Population growth

Between 1990 and 2020, the world population size increased almost linearly, from 5313 million inhabitants in 1990 up to 7836 million in 2020 (see Figure 2). By income regions, we observe that all of them have experienced sustained population growth. Yet, some have increased faster than others. The region of 'High income countries' is the one growing at the slowest pace (from 1184 million individuals to 1397 between 1990 and 2020). In contrast, the group of the Lower middle-income countries is the one growing the fastest in population size (moving from 1711 million individuals to 2967 in 30 years). Upper middle-income and low-income countries are somewhere in between (see Figure 2).

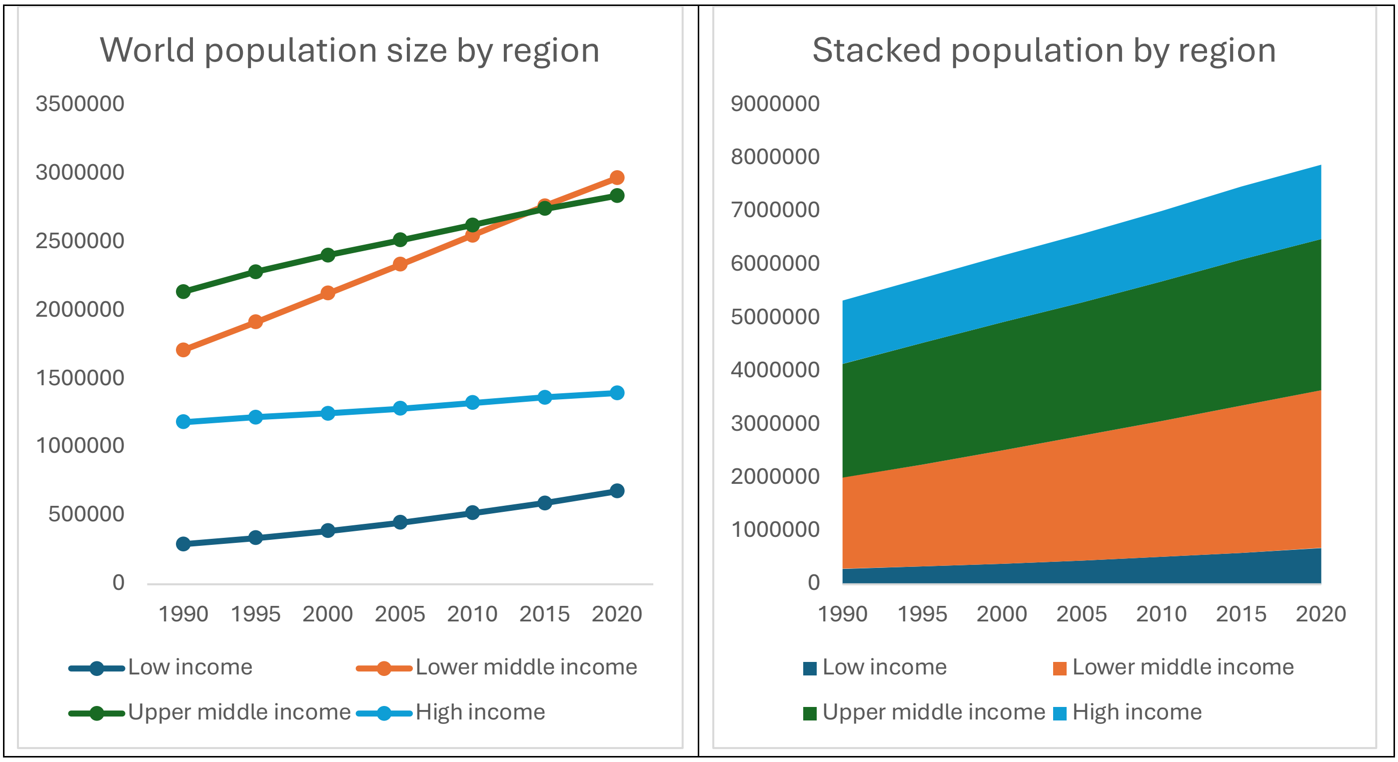

Figure 2. Evolution in population size for the world and its four income regions. Source: Author's elaboration based on data from the United Nations' World Population Prospects (WPP) and the World Bank.

International migration

No matter what statistical method we use to estimate international migration flows, the corresponding geographical and temporal patterns one observes are typically very complicated (see Abel and Cohen (2019) and the chord diagrams shown therein). This is due to the large number of countries around the world and the long time-length of our analyses (30 years). To simplify the presentation and facilitate the identification of broad patterns, in the different panels of Table 1 we show the size of the international migration flows between the four World Bank's income regions from 1990-1995 until 2015-2020 estimated with the

"Demographic Pseudo Bayesian Closed" method suggested by Abel and Cohen (2019). In Appendix 5 we show the results corresponding to the other five estimation methods (while the absolute numbers change across methods, the overall patterns are broadly the same).

		Destination				
	1990-1995	Low	Lower Middle	Upper Middle	High	**Total**
Origin	Low	2,92	2,74	0,36	0,67	**6,70**
	Lower Middle	2,34	5,13	2,02	7,51	**16,99**
	Upper Middle	1,87	1,11	2,35	15,61	**20,94**
	High	0,37	3,68	5,80	11,74	**21,58**
	Total	**7,50**	**12,66**	**10,53**	**35,52**	**66,21**

		Destination				
	1995-2000	Low	Lower Middle	Upper Middle	High	**Total**
Origin	Low	1,39	2,58	0,60	1,17	**5,74**
	Lower Middle	2,12	4,73	2,59	7,62	**17,06**
	Upper Middle	0,30	0,99	2,19	16,19	**19,67**
	High	0,25	4,27	6,85	12,29	**23,67**
	Total	**4,07**	**12,57**	**12,23**	**37,28**	**66,14**

		Destination				
	2000-2005	Low	Lower Middle	Upper Middle	High	**Total**
Origin	Low	0,79	1,87	0,77	1,57	**5,01**
	Lower Middle	2,03	5,67	4,44	14,52	**26,67**
	Upper Middle	0,32	0,92	2,28	17,23	**20,75**
	High	0,41	3,17	7,39	14,57	**25,54**
	Total	**3,56**	**11,63**	**14,89**	**47,88**	**77,97**

		Destination				
	2005-2010	Low	Lower Middle	Upper Middle	High	**Total**
Origin	Low	0,76	2,10	1,32	1,43	**5,62**
	Lower Middle	1,88	5,57	3,74	19,52	**30,71**
	Upper Middle	1,23	1,79	2,47	17,17	**22,65**
	High	0,42	5,19	7,97	15,10	**28,67**
	Total	**4,29**	**14,65**	**15,50**	**53,21**	**87,65**

		Destination				
	2010-2015	Low	Lower Middle	Upper Middle	High	**Total**
Origin	Low	3,12	4,07	4,16	2,25	**13,60**
	Lower Middle	2,04	5,08	4,86	21,85	**33,83**
	Upper Middle	0,41	1,49	2,50	16,54	**20,94**
	High	0,56	5,56	8,94	15,92	**30,98**
	Total	**6,12**	**16,21**	**20,46**	**56,57**	**99,35**

Destination

	2015-2020	Low	Lower Middle	Upper Middle	High	**Total**
Origin	Low	3,17	2,10	1,13	1,49	**7,89**
	Lower Middle	1,72	4,76	8,03	24,15	**38,66**
	Upper Middle	0,70	1,53	2,45	16,25	**20,93**
	High	1,29	6,67	10,33	20,31	**38,61**
	Total	**6,88**	**15,06**	**21,94**	**62,21**	**106,09**

Table 1. Estimated bilateral migration flows (in millions of individuals) between the four World Bank income regions ("Low income", "Lower Middle income", "Upper Middle income", "High income") according to the "Demographic Pseudo Bayesian Closed" method in 5-year periods between 1990 and 2020. Source: Author elaboration based on data from Abel and Cohen (2019).

As shown in the different panels of Table 1, the total number of individuals migrating between countries all over the world has increased over time. While about 66 million individuals were estimated to migrate internationally between 1990 and 1995, that number rose above 106 million between 2015 and 2020. In addition, high-income countries are, by far, the most popular destination (e.g., often three times higher than upper middle income countries, which usually are the second most popular destination). For instance: between 2015 and 2020, more than 62 million individuals migrated to a high-income country, while the number of migrants that went to an upper middle income country was almost 22 million. In contrast, many less migrants moved towards a low-income country (e.g., less than 7 million people between 2015 and 2020). Inspecting the region of origin, one can conclude that migration flows coming from low income countries have been relatively small. For instance, between 1990 and 1995, 6.7 million individuals migrated from a low-income country, which roughly represented 10% of the total number of international migrants during that period (66 million). That share even declined to slightly above 7% between 2015 and 2020 (see the last panel in Table 1). Another common pattern across the 6 time periods analyzed in Table 1 is that a large fraction of international migrants come from either upper middle or high income countries. In particular, more than half of the international flows originate from these two groups of countries. Lastly, among the 16 combinations of regional migration flows between the four income regions considered in Table 1, the most numerous flows tend to be those observed between lower middle towards high income countries or between upper middle towards high income countries.

4.2. Inequality decompositions

Decomposing changes in global income inequality: The Core dataset

According to the information collected in the Core dataset, global income inequality declined both between 2008 and 2013 and between 2013 and 2018, no matter if the former was measured via the Mean Log deviation, the Theil index or the coefficient of variation squared (see Figure 1). In the Figures below, we show the results of the 4-term inequality change decomposition method presented in equation [5] (see Figures 3 and 4). In all cases (i.e., in both time periods and for the three inequality measures), the most important factor driving inequality declines is the increasing similarity between countries' mean income levels (i.e., shrinking between-country income inequality, which is captured through the $\Delta_B I$ term). For instance, in the case of L, the $\Delta_B L$ term between 2008-2013 equals -0.08, thus almost matching the global inequality change during that period ($\Delta L = -0.09$). The effect of within-countries' income inequality is smaller, and its direction is contingent on the choice of the inequality measure. For L, the $\Delta_W L$ term is positive (i.e., changes in within-countries' inequality levels contribute to increase L) between 2008-2013, but negative between 2013-2018. For T, the $\Delta_W T$ are quite small and for CV^2, $\Delta_W CV^2$ are positive (and considerably large between 2013-2018). These differences can be partially attributable to the different sensitivity of the three inequality measures to alternative parts of the distribution.

Inspecting the size and direction of the two population-related components of the decomposition (i.e., $\Delta_N I$ and $\Delta_M I$) in Figures 3 and 4, we see that they are relatively small, but typically non-negative. This means that countries' natural population growth *and* international migration patterns contribute to increase global income inequality, no matter if the latter is measured using L or T. The different bars in those Figures represent the $\Delta_N I$ and $\Delta_M I$ effects corresponding to the six methods we have used to estimate international migration flows proposed by Abel and Cohen (2019) (see methods section). The size of the bars is roughly similar across methods – except for the "Migration rates" one, which tends to give more emphasis to the $\Delta_M I$ component than the rest. For CV^2, the $\Delta_M CV^2$ term is virtually zero no matter how international migration is estimated. Interestingly, the size of the two population-related components put together (i.e., $\Delta_N I + \Delta_M I$) is roughly comparable to the size of the $\Delta_W I$ term, both for L and T. This suggests that the effect of countries' changing population size on changes in global income inequality can be as large as the effect of changing income inequality within those countries – that is: population change can be a non-negligible and increasingly important driver of global inequality change.

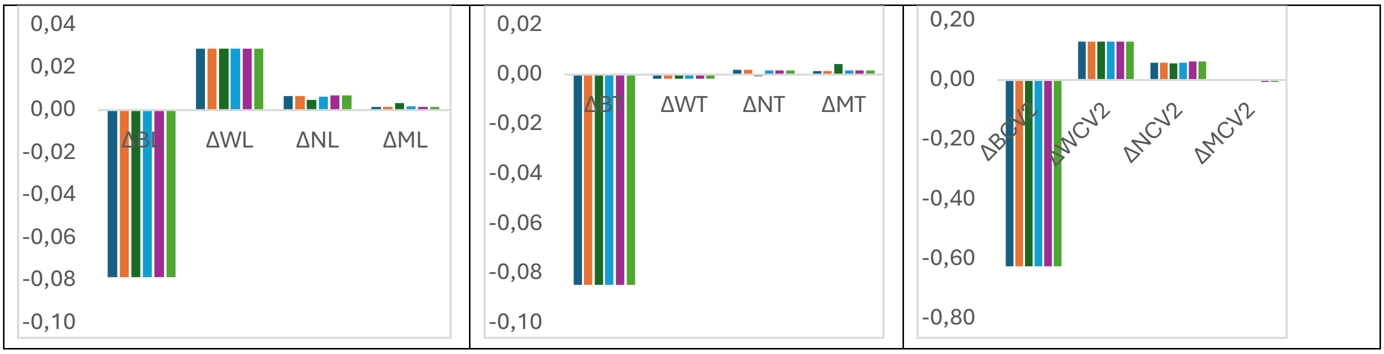

Figure 3. Global income inequality decompositions between 2008 and 2013 using the Core database. The three panels correspond the changes in the mean log deviation, Theil index and coefficient of variation squared, respectively. Source: Author's own elaboration based on the Core database.

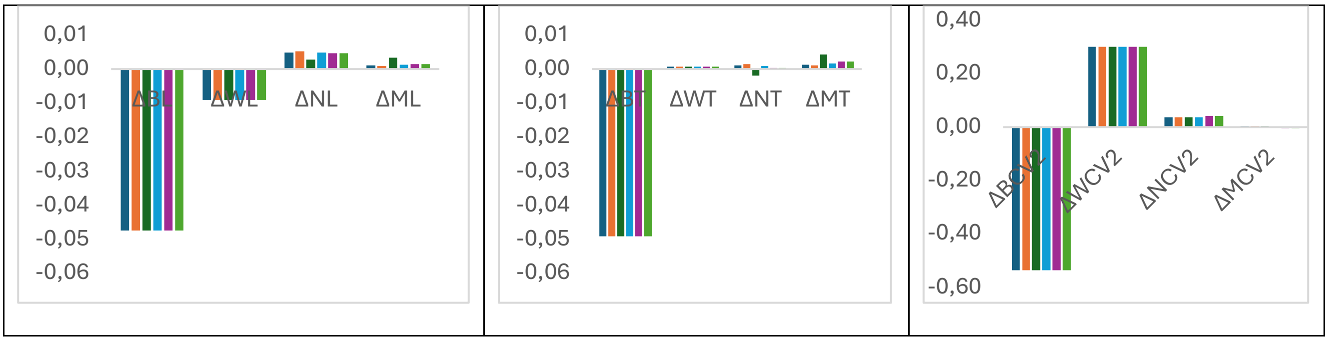

Figure 4. Global income inequality decompositions between 2013 and 2018 using the Core database. The three panels correspond the changes in the mean log deviation, Theil index and coefficient of variation squared, respectively. Source: Author's own elaboration based on the Core database.

Decomposing changes in global income inequality: The Extended dataset

In Figures 5, 6 and 7 we show the four-term inequality change decompositions corresponding to equation [5] applied to the six 5-year periods between 1990-1995 until 2015-2020 of the Extended dataset for the three inequality measures considered here. In those Figures, we show the results arising from the "Demographic Pseudo Bayesian Closed" method to estimate international migration flows (the results corresponding to the other migration estimation methods are very similar, so they will not be shown here – they can be found in Appendix 6). Once again, most of the decline in global income inequality between 1990 until 2020 shown in Figure 1 is attributable to the shrinking inequality between countries' mean income levels (i.e., the $\Delta_B I$ term). Indeed, for all five-year periods analyzed here, the $\Delta_B I$ term is always negative (i.e., pushing global income inequality downwards) and the largest in size among the four components. The within-country inequality effect (i.e., the $\Delta_W I$ term) is typically much smaller, but its size and direction depends on the chosen inequality indicator and the analyzed period. For $\Delta_W L$, the sign changes over time, contributing positively in some periods and negatively in others. Regarding $\Delta_W T$ and $\Delta_W CV^2$, they are always positive, thus contributing to increase global income inequality.

Importantly, the two population-related effects, $\Delta_N I$ and $\Delta_M I$, are mostly positive (i.e., enhancing global income inequality), with the former typically being larger than the latter (especially in more recent time periods). For the cases of L and T, the addition of the $\Delta_N I$ and $\Delta_M I$ terms is often higher than the within-country inequality effect (i.e., the $\Delta_W I$ term) in most of the periods analyzed here. This means that shifts in countries' population sizes have often been a stronger determinant of the changes in global income inequality than within-country inequality. For the case of CV^2, the natural population growth effect ($\Delta_N I$) is systematically positive (i.e., inequality enhancing) and the migration effect ($\Delta_M I$) is almost negligible.

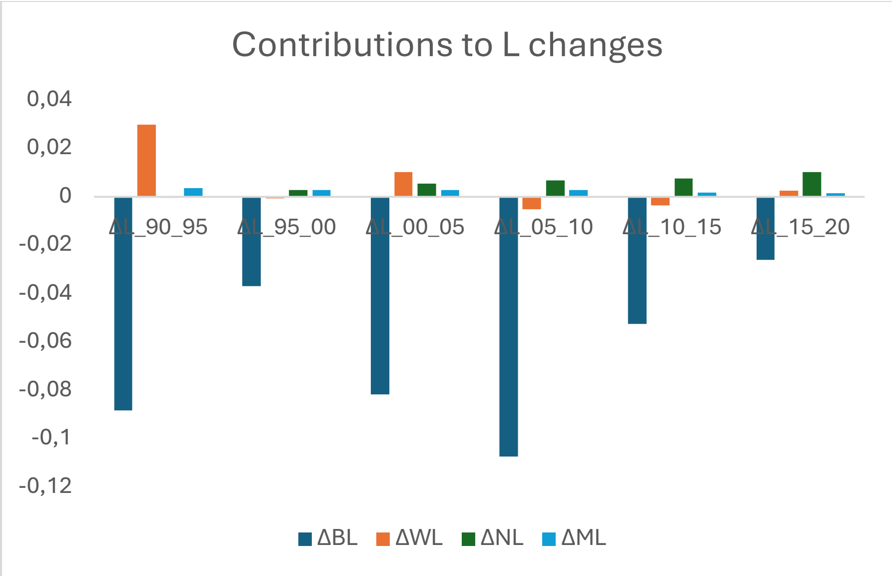

Figure 5. 4-way decomposition of global income inequality 5-year changes (as measured by L) between 1990 and 2020. Results based on the "Demographic Pseudo Bayesian Closed" method to estimate bilateral migration flows. Source: Author's own elaboration based on the Extended database.

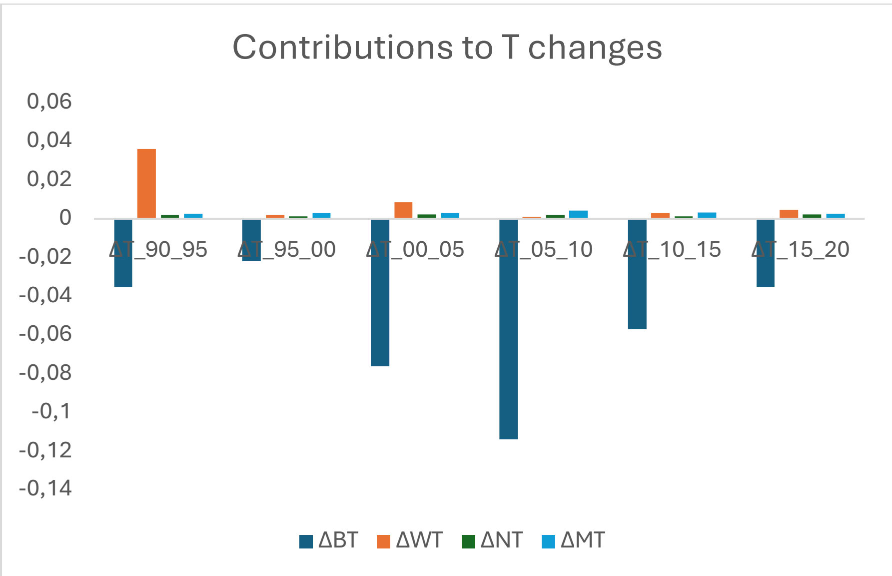

Figure 6. 4-way decomposition of global income inequality 5-year changes (as measured by T) between 1990 and 2020. Results based on the "Demographic Pseudo Bayesian Closed" method to estimate bilateral migration flows. Source: Author's own elaboration based on the Extended database.

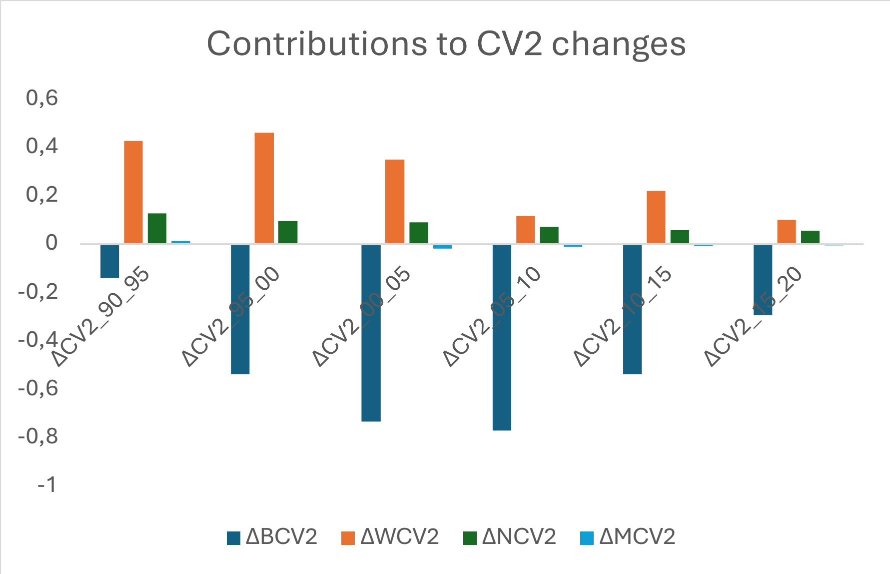

Figure 7. 4-way decomposition of global income inequality 5-year changes (as measured by CV^2) between 1990 and 2020. Results based on the "Demographic Pseudo Bayesian Closed" method to estimate bilateral migration flows. Source: Author's own elaboration based on the Extended database.

So far, the results we have reported from the Core and Extended datasets are highly coherent. While the values of the inequality indicators (i.e., those shown in Figure 1) and their decompositions (shown in Figures 3-7) are not the same in both cases, the relative sizes of the different components and the direction of change (i.e., declining inequality and relative contribution of the 4-term components) are highly consistent. For this reason, in the remainder of the results section we will only present the results corresponding to the Extended dataset, which covers a longer time span and consistently uses the same set of countries throughout.[15]

Decomposing natural population growth effects ($\Delta_N I$)*: The Extended dataset*

The explore what groups of countries contribute to the natural population growth effects (and in what direction), we apply the decompositions presented in equations [13]-[15] for the three inequality measures used in this paper.[16] To simplify the presentation, we use the linear approximation $\widehat{\Delta_N I}$ to assess the contribution of the World Bank's four income group categories to $\Delta_N I$ (rather than showing the contribution of each country separately). The decomposition results for $\Delta_N L$, $\Delta_N T$ and $\Delta_N CV^2$ are shown in Figures 8-10, respectively

[15] Those ensuing from the Core dataset are not presented here but are available upon request.

[16] The mean log deviation turns out to be the inequality measure for which the linear approximation suggested in equation [13] has the better fit. Indeed, the relationship between $\Delta_N L$ and its first-order approximation ($\widehat{\Delta_N L}$) is very strong: the association between both measures in our (6 time periods * 6 migration estimation methods =) 36 data points is highly linear, with a correlation coefficient $r = 0.98$. For the case of $\Delta_N CV^2$ and $\widehat{\Delta_N CV^2}$ the association is also very high ($r = 0.95$), but it is considerably lower for $\Delta_N T$ and $\widehat{\Delta_N T}$ ($r = 0.35$).

(they are based on the "Demographic Pseudo Bayesian Closed" method to estimate bilateral migration flows[17]).

Depending on the chosen inequality measure, the natural population growth effect can increase over time (as is the case of $\Delta_N L$), remain stable ($\Delta_N T$) or decrease over time ($\Delta_N CV^2$) – but in any case, it is always positive (i.e., countries' natural population growth contributes to push global income inequality upwards). Importantly, the composition of the aggregate $\Delta_N I$ effect varies considerably across indicators, but there are some commonalities as well (see Figs. 8-10). Overall, natural population growth in the group of upper-middle income countries contributes to decrease global income inequality, while the opposite happens with low and lower-middle income countries. The faster-than-average natural population growth in countries at the lower part of the global income distribution is contributing to increase global income inequality (though with varying intensities across indicators). Interestingly, natural population growth in high-income countries is deemed to be inequality enhancing for the mean log deviation, inequality depressing for the coefficient of variation squared, and somewhere in between for the Theil index – a pattern that can be attributable to the different sensitivity of these measures to changes occurring in different parts of the distribution.

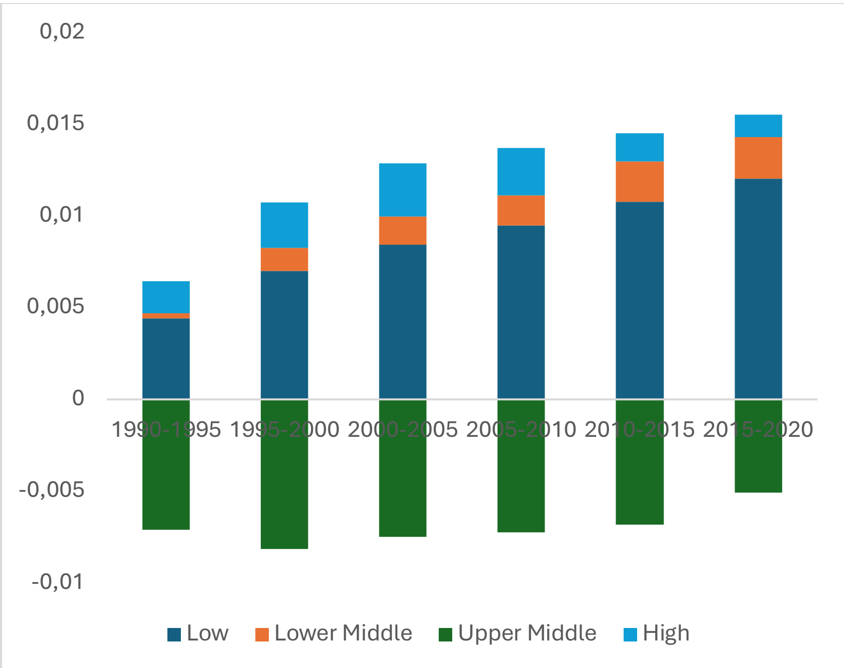

Figure 8. Decomposition of the $\Delta_N L$ term between 1990-1995 and 2015-2020 according to the World Bank classification of "Low-income", "Lower-middle", "Upper-middle" and "High" income countries using the "Demographic Pseudo Bayesian Closed" method to estimate bilateral migration flows. Source: Author's own elaboration based on the Extended database.

[17] The results arising from choosing the other five migration estimation methods are highly similar, so they are not shown here. They are available upon reasonable request to the author.

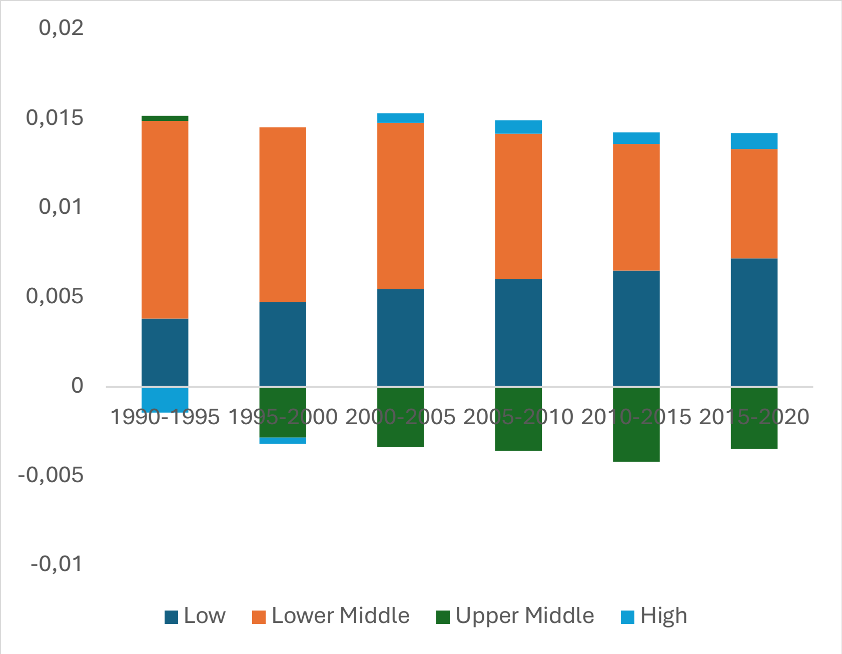

Figure 9. Decomposition of the $\Delta_N T$ term between 1990-1995 and 2015-2020 according to the World Bank classification of "Low-income", "Lower-middle", "Upper-middle" and "High" income countries using the "Demographic Pseudo Bayesian Closed" method to estimate bilateral migration flows. Source: Author's own elaboration based on the Extended database.

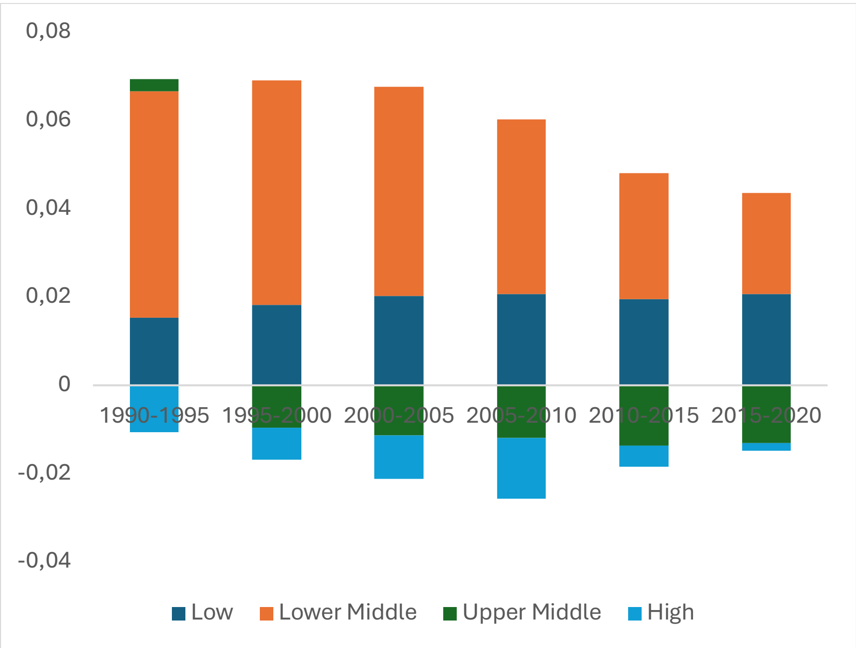

Figure 10. Decomposition of the $\Delta_N CV^2$ term between 1990-1995 and 2015-2020 according to the World Bank classification of "Low-income", "Lower-middle", "Upper-middle" and "High" income countries using the "Demographic Pseudo Bayesian Closed" method to estimate bilateral migration flows. Source: Author's own elaboration based on the Extended database.

Decomposing migration effects ($\Delta_M I$)*: The Extended dataset*

We now document the main drivers of the migration effects component (i.e., the $\Delta_M I$ term) applying the decompositions presented in equations [21]-[26].[18] For that purpose, we report the values of the bilateral influence functions $\psi_{ij}^{I_B}$ and ψ_{ij}^{I} for all country pairs (i, j) (see Figures 11-13) and the contribution of the different country pairs to the $\Delta_M I$ component (Tables 2-4). For the sake of brevity, throughout this subsection we will mostly present the results corresponding the year 2015 (or the time period 2015-2020) and the ones based on the "Demographic Pseudo Bayesian Closed" method to estimate bilateral migration flows. The results for other time periods and those based on other migration estimation methods are shown in appendix 7.

To have an intuition of how global income inequality reacts under "small" bilateral migration movements, Figures 11-13 plot the between-country and overall bilateral influence functions (i.e., $\psi_{ij}^{I_B}$ and ψ_{ij}^{I}) for the three inequality measures considered in this paper (i.e., L, T and CV^2) for all origin-destination country pairs $i, j \in \{1, \cdots, J\}$, using data from 2015. To facilitate interpretability, countries are sorted in ascending order in terms of 2015 GDP per capita – both in the vertical and horizontal axes. In the three Figures, blue tones indicate country pairs for which the corresponding migration flow would be inequality reducing, while red tones indicate the ones that would be inequality enhancing. By construction, the bilateral influence functions are anti-symmetric (i.e., $\psi_{ij}^{I_B} = -\psi_{ji}^{I_B}$ and $\psi_{ij}^{I} = -\psi_{ji}^{I}$ for all $i, j \in \{1, \cdots, J\}$ – see equations [21]-[23]), so the number of blue cells is always the same as the number of red cells.

The between-country influence function shown in panel A of figure 11 ($\psi_{ij}^{L_B}$) suggests that, roughly speaking, between country income inequality as measured by the mean log deviation would decline when either individuals from low-income or high-income countries migrated towards lower-middle or upper-middle income countries. Similarly, between country income inequality would increase when individuals from either lower-middle or upper-middle income countries migrated towards low-income or high-income countries. Interestingly, the distribution of blue and red cells shifts considerably when considering the Theil index and, specially, the coefficient of variation squared (see panel A in figures 12 and 13, showing $\psi_{ij}^{T_B}$ and $\psi_{ij}^{CV_B^2}$). In the latter case, most income increasing moves (i.e., migration towards a country with higher average income than the country of origin; recall Definition 2) would decrease between country income inequality, while most income decreasing moves would increase it.

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[18] Once again, the mean log deviation turns out to be the inequality measure for which the term $\widehat{\Delta_M I}$ defined in equation [24] better approximates the original $\Delta_M I$ term. In that case, the relationship between $\Delta_M L$ and its linear approximation ($\widehat{\Delta_M L}$) is quite strong: the association between both measures in our (6 time periods * 6 migration estimation methods =) 36 data points is highly linear, with $r = 0.93$. For T and CV^2, the corresponding correlation coefficients are $r = 0.72$ and $r = 0.63$, respectively.

Inspecting panel B in figures 11-13, one observes that the overall influence functions ψ_{ij}^{I} exhibit less well-defined patterns. The reason why they look somewhat blurred is that they reflect the joint combination of the between-country *and* within-country effects (that is, the $\psi_{ij}^{I_B}$, $\psi_{ij}^{I_W}$ terms in equations [21]-[23]), which might not necessarily go in the same direction. Despite the blurriness, international migration tends to affect between country inequality more strongly than within country inequality[19], so the overall patterns and the conclusions drawn from the A panels of figures 11-13 roughly apply to those shown in the corresponding B panel.

[19] This is because in 76%, 73% and 55% of all possible cases, the values of $\psi_{ij}^{I_B}$ are higher than those of $\psi_{ij}^{I_W}$ (for $I = L, T$ and CV^2, respectively), so the values of the former dominate those of the later when calculating $\psi_{ij}^{I} = \psi_{ij}^{I_B} + \psi_{ij}^{I_W}$.

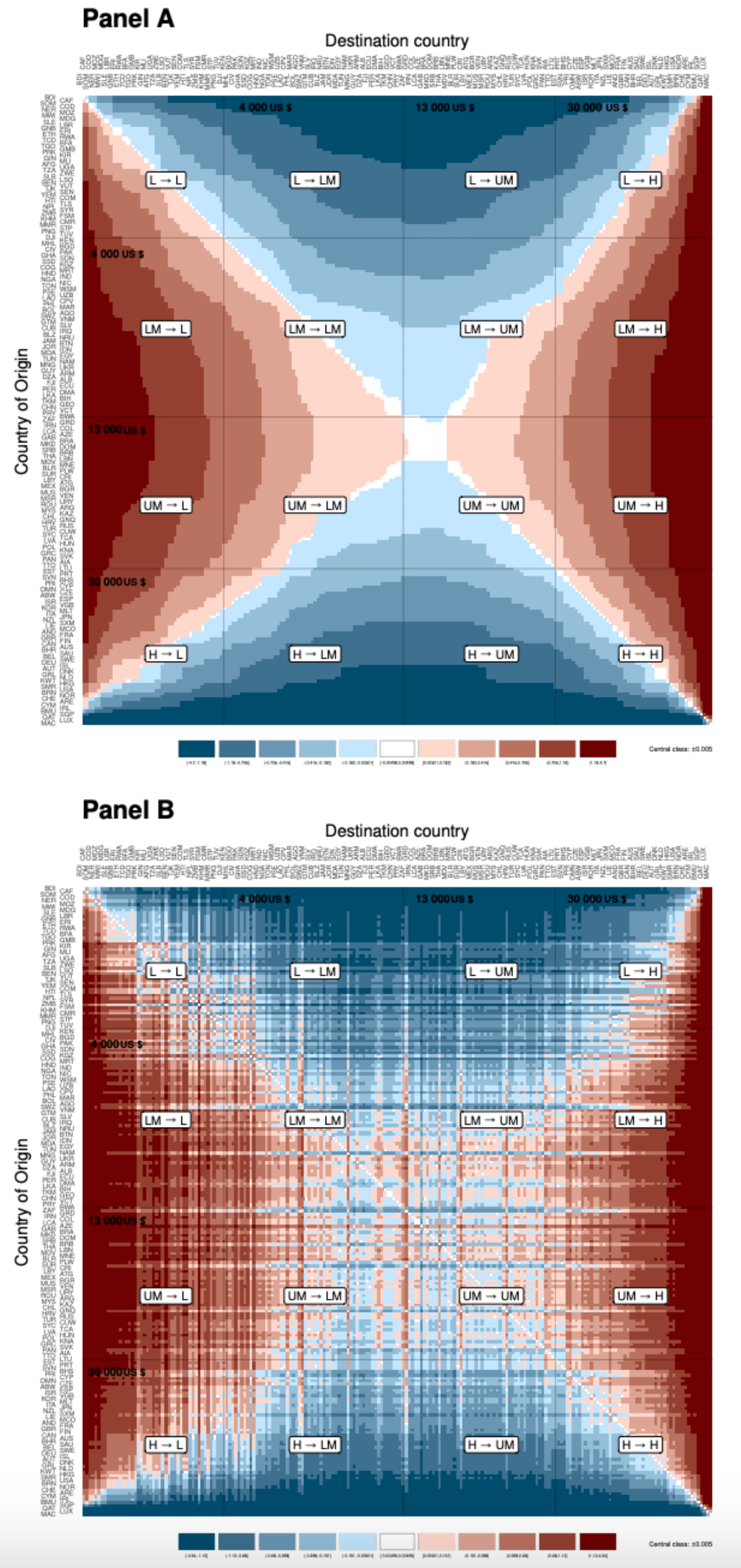

Figure 11. Heatmap of the between-country bilateral influence function ($\psi_{ij}^{L_B}$, panel A) and the overall bilateral influence function (ψ_{ij}^{L}, Panel B) for the mean log deviation using data from 2015. Vertical and horizontal reference lines separate “Low (L)”, “Lower-middle (LM)”, “Upper-middle (UM)” and “High (H)” income countries according to the World Bank classification. Source: Author elaboration based on data from the Extended dataset.

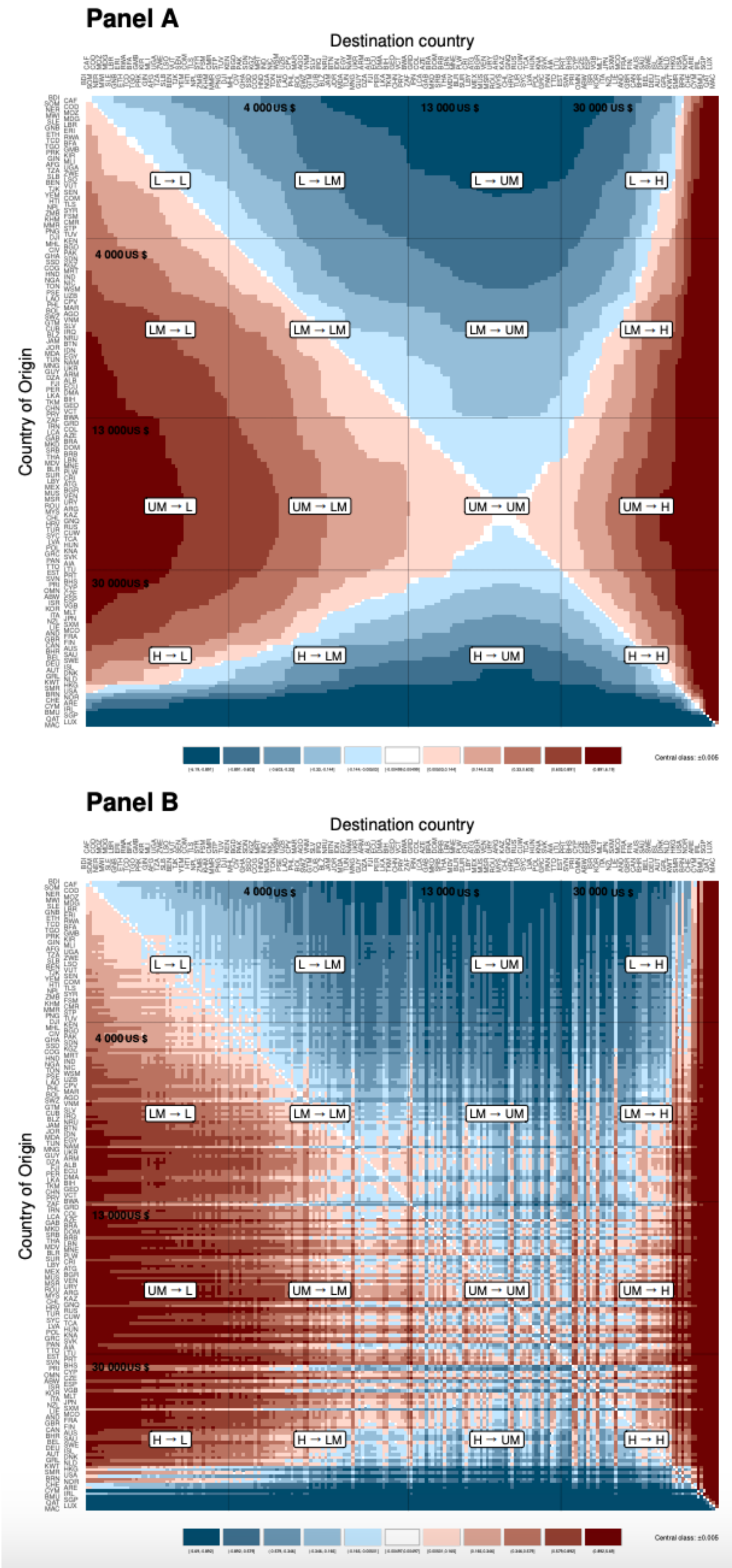

Figure 12. Heatmap of the between-country bilateral influence function ($\psi_{ij}^{T_B}$, panel A) and the overall bilateral influence function (ψ_{ij}^{T}, Panel B) for the Theil index using data from 2015. Vertical and horizontal reference lines separate "Low (L)", "Lower-middle (LM)", "Upper-middle (UM)" and "High (H)" income countries according to the World Bank classification. Source: Author elaboration based on data from the Extended dataset.

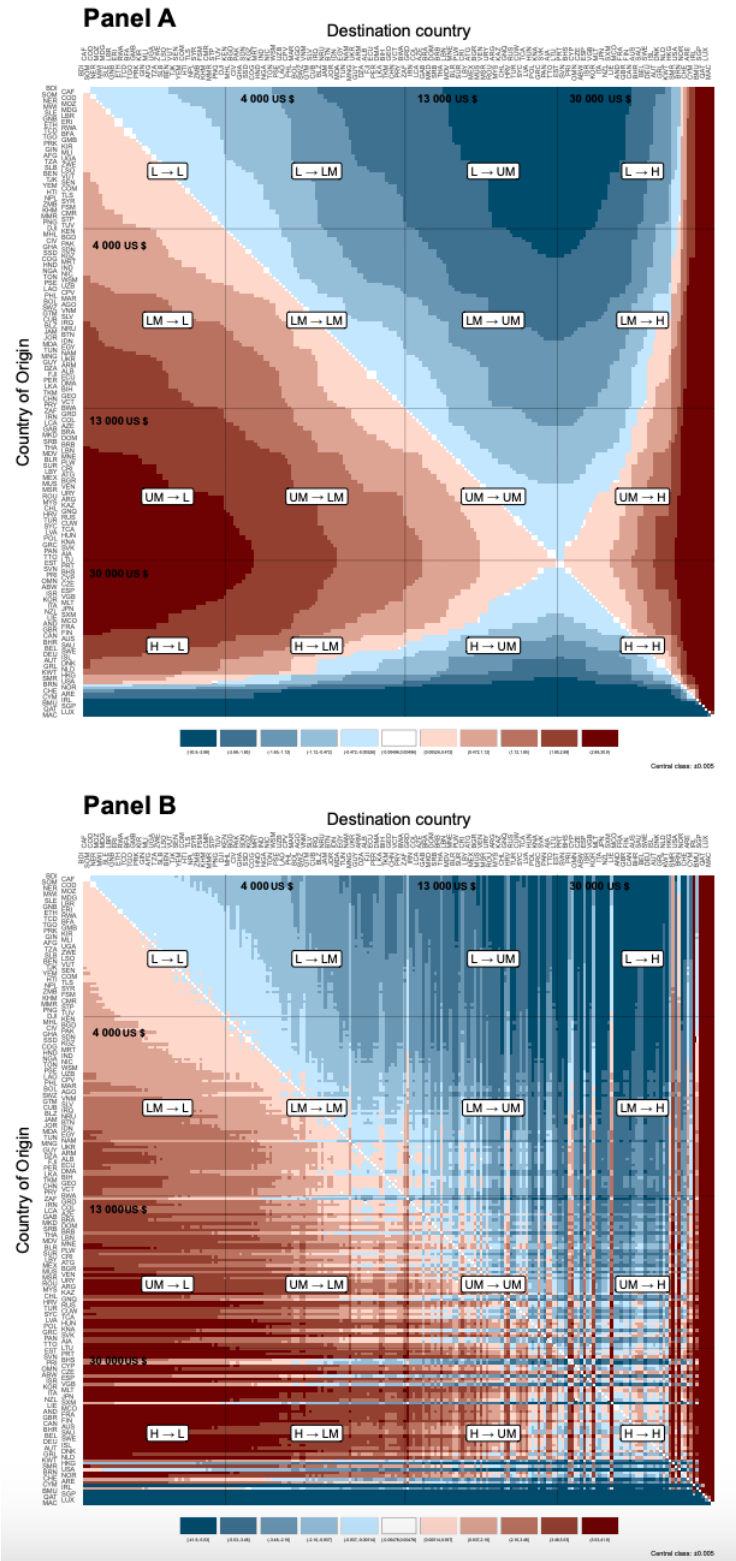

Figure 13. Heatmap of the between-country bilateral influence function ($\psi_{ij}^{CV_B^2}$, panel A) and the overall bilateral influence function ($\psi_{ij}^{CV^2}$, Panel B) for the coefficient of variation squared using data from 2015. Vertical and horizontal reference lines separate "Low (L)", "Lower-middle (LM)", "Upper-middle (UM)" and "High (H)" income countries according to the World Bank classification. Source: Author elaboration based on data from the Extended dataset.

So far, we have shown the sensitivity of global income inequality measures to "potential" (i.e., not necessarily observed) migration flows between country pairs via the corresponding bilateral influence functions. We now report the actual effects of such migratory movements on global income inequality based on the estimated international flows of migrants. To do so, we calculate the values of $\psi_{ij}^{I} \cdot M_{ij}$ (see equation [24]) among all country dyads for the three inequality measures considered here and aggregate the results according to the World Bank's classification of countries in four income regions (see equations [25] and [26]).[20] Tables 2, 3 and 4 show the results corresponding to the mean log deviation, the Theil index and the coefficient of variation squared, respectively. Since the original numbers in those tables are quite small, they have been multiplied by 100 to facilitate readability. For the sake of brevity, we only report the results for the earliest and more recent time periods in the Extended dataset: 1990-1995 and 2015-2020 (the results for other periods are roughly similar).

Irrespective of the inequality measure, it is clear that some pairs of income regions exhibit much higher migration effects than others (i.e., the effects are not evenly distributed across region pairs). In addition, many of those effects are positive (i.e., inequality enhancing) and many others are negative (inequality depressing), so there are many forces pushing in opposite directions (that is: cancelling each other) – see Tables 2-4.

For the mean log deviation, international migration originating from low- and high-income countries has contributed to decrease global income inequality, and migration flows emanating from lower middle- and upper middle-income countries have been inequality enhancing, both in 1990-1995 and 2015-2020, (see the last column with the totals in Table 2). Likewise, international migration flows heading towards low- and high-income countries have been inequality enhancing, and those moving towards lower middle- and upper middle-income countries have contributed to decrease inequality, both in 1990-1995 and 2015-2020, (see the last row with the totals in Table 2). The migration flows from lower middle- and upper middle-income countries towards high income countries are the ones that have contributed the most (by far) to increase global income inequality. At the other extreme, the migration flows that have contributed the most to reduce global income inequality are the ones from high-income towards upper middle-income countries.

Regarding the Theil index, the overall patterns for 2015-2020 resemble very much those of the mean log deviation described above, but less clearly so between 1990 and 1995 (see Table 3). Finally, the coefficient of variation squared behaves in a very different way. Roughly speaking, migration flows originating from high-income countries are inequality enhancing, while those originating in any other region tend to be inequality depressing (see the last column in Table 4). In addition, migration flows heading towards low- or lower middle-income countries are inequality enhancing, while those targeting upper middle- and high-income countries contribute to decrease inequality (last row in Table 4). Overall,

[20] The Figures in appendix 8 show the same results at the country level (i.e., before aggregating across income regions) – they are not shown here for the sake of brevity and simplicity.

migration flows where the destination region is richer (resp. poorer) than the region of origin are inequality reducing (resp. enhancing) for the coefficient of variation squared.

	1990-1995	Destination L	Destination LM	Destination UM	Destination H	Total
Origin	L	-0.005	-0.027	-0.008	0.004	**-0.036**
Origin	LM	0.026	-0.005	-0.028	0.152	**0.145**
Origin	UM	0.035	0.006	-0.003	0.252	**0.290**
Origin	H	-0.002	-0.067	-0.081	0.069	**-0.081**
	Total	**0.054**	**-0.092**	**-0.120**	**0.476**	**0.318**

	2015-2020	Destination L	Destination LM	Destination UM	Destination H	Total
Origin	L	0.006	-0.020	-0.016	-0.005	**-0.035**
Origin	LM	0.018	-0.003	-0.030	0.198	**0.183**
Origin	UM	0.009	0.009	0.008	0.190	**0.216**
Origin	H	0.000	-0.066	-0.122	-0.014	**-0.202**
	Total	**0.033**	**-0.080**	**-0.160**	**0.368**	**0.163**

Table 2. Contribution to the migration effect component of the mean log deviation ($\Delta_M L$) across the four income region combinations between 1990-1995 (upper panel) and 2015-2020 (lower panel). Results multiplied by 100 to facilitate readability. Source: Author elaboration based on data from the Extended dataset.

	1990-1995	Destination L	Destination LM	Destination UM	Destination H	Total
Origin	L	0.001	-0.016	-0.011	-0.006	**-0.032**
Origin	LM	0.010	-0.002	-0.033	0.042	**0.016**
Origin	UM	0.006	0.009	-0.002	0.016	**0.028**
Origin	H	0.002	0.010	0.000	0.029	**0.040**
	Total	**0.018**	**0.001**	**-0.047**	**0.080**	**0.053**

	2015-2020	Destination L	Destination LM	Destination UM	Destination H	Total
Origin	L	0.003	-0.009	-0.012	-0.010	**-0.029**
Origin	LM	0.010	-0.003	-0.034	0.031	**0.005**
Origin	UM	0.008	0.011	0.013	0.095	**0.126**
Origin	H	0.006	-0.015	-0.067	-0.019	**-0.095**
	Total	**0.027**	**-0.017**	**-0.099**	**0.096**	**0.007**

Table 3. Contribution to the migration effect component of the Theil index ($\Delta_M T$) across the four income region combinations between 1990-1995 (upper panel) and 2015-2020 (lower panel). Results multiplied by 100 to facilitate readability. Source: Author elaboration based on data from the Extended dataset.

	1990-1995	Destination L	Destination LM	Destination UM	Destination H	Total

Origin	L	-0.010	-0.035	-0.028	-0.028	**-0.101**
	LM	0.036	-0.013	-0.099	0.146	**0.070**
	UM	0.117	0.034	-0.016	-0.422	**-0.286**
	H	0.015	0.018	0.115	-0.002	**0.146**
	Total	**0.157**	**0.004**	**-0.027**	**-0.305**	**-0.172**

		Destination				
	2015-2020	L	LM	UM	H	Total
Origin	L	0.006	-0.078	-0.132	-0.113	**-0.316**
	LM	0.019	-0.013	-0.180	-0.565	**-0.738**
	UM	0.020	0.050	-0.003	-0.075	**-0.008**
	H	0.025	0.134	0.038	0.031	**0.229**
	Total	**0.071**	**0.094**	**-0.276**	**-0.722**	**-0.834**

Table 4. Contribution to the migration effect component of the coefficient of variation squared ($\Delta_M CV^2$) across the four income region combinations between 1990-1995 (upper panel) and 2015-2020 (lower panel). Results multiplied by 100 to facilitate readability. Source: Author elaboration based on data from the Extended dataset.

5. Discussion

Summary

Global income inequality indicates the extent to which monetary resources are more or less concentrated across individuals among and within countries around the globe. The demographic composition of world's countries and their dynamics are thus intimately related to such inequality and its trends over time. Yet, surprisingly little is known about that relationship. In this paper we investigate how population dynamics affect the trends in global income inequality. More specifically, we assess how the latter is affected by the two main drivers of population change: countries' natural growth and international migration. The highly political and sensitive nature of these phenomena, together with the scarcity of reliable statistical data, has promoted the elaboration of untested hypotheses running in opposite directions. While some scholars suggest that international migration is a powerful mechanism that can dramatically reduce the income differences between countries (e.g., Pritchett 2006, Milanovic 2012, 2015), others contend that migration is a complex phenomenon not exclusively involving movements from the "Global South" towards the "Global North" and which is often accessible to a selected minority of individuals (De Haas 2023) – thus with unclear implications for global income inequality.

Applying decomposition and counterfactual techniques to a variety of economic and demographic data sources, our findings suggest that population dynamics are a non-negligible and increasingly important factor (often more important than the changes in income inequality within countries) that, so far, has been largely overlooked in the study of global income inequality. The unequal rates of natural population growth between 1990 and 2020 (with higher rates typically occurring in low- and lower-middle income countries) have contributed to concentrate increasingly higher shares of the world population at the bottom of the income distribution, thus pushing global income inequality upwards – a result that coheres with some of the findings reported in Gradín (2024). The effect of international migration flows on global income inequality is contingent on the chosen inequality measure, ranging between small but “positive” (i.e., inequality enhancing) effects for some measures and negligible effects for others. The inequality enhancing effects of international migration flows are largely attributable to the relatively large migration flows between lower-middle and, specially, upper-middle income countries towards high income countries.

Strengths

To our knowledge, this is the first study investigating how populations’ natural growth and international migration flows affect the trends in global income inequality – an important issue that figures prominently in the economic, social and political debates of societies worldwide. The lack of previous analyses on this topic is largely attributable to the scarcity of sufficiently detailed data – an issue we have tried to overcome taking advantage of recently available sources of economic and demographic data. To assess the reliability and robustness of our findings, we have tested our approach using different sources of income data, state-of-the-art estimates of international migration flows and several popular inequality measures. Overall, our results consistently point towards the same direction.

To attain our research objectives, we propose novel counterfactual and decomposition methods. The so-called “bilateral influence functions” – which are an extension of the well-known “influence functions” (Hampel 1974) – allow determining how sensitive global income inequality measures are to migration flows between country pairs. In addition, the proposed decomposition methods quantify the contribution that each country pair has made to change global income inequality – thus permitting to identify the source of change. Beyond the study of global income inequality analyzed here, the proposed methods open potentially fertile research lines to investigate the sensitivity of inequality measures to income changes in different parts of the distribution (an issue that could be useful in the study of income mobility, the effectiveness of redistribution/taxation schemes, and so on).

Last but not least, the ideas and results presented in the paper can be potentially useful for policy makers interested in understanding the relationship between demographic dynamics and inequality. While countries’ natural population growth is a strongly inertial process upon which it is very difficult to intervene (e.g., attempts at promoting or limiting fertility must tackle many factors simultaneously (Sobotka et al 2020)), the possibility of encouraging or deterring international migration is often within the reach of national policy makers worldwide – an issue that is being increasingly debated in countries around the globe.

Limitations

This study has several limitations. On the one hand, our methods rely on strong and oversimplifying assumptions that might not accord with reality in some instances. The most important one is that international migrants are assumed to change origin and destination countries' population shares, but not the corresponding income distributions. During the last decades, the impact of migrants on receiving countries' wage distributions has been the subject of an intense debate. At one extreme, some studies suggest that the arrival of international migrants reduces wages, especially for low-skilled native workers who are most directly competing with those immigrants (e.g., Borjas 2003). At the other extreme, several other studies reach the opposite conclusion (e.g., Card (2005, 2009), Blau and Kahn (2015)). For instance, Card (2005) finds a "*surprisingly weak relationship between immigration and less-skilled native wages*" (page F309), and Blau and Kahn (2015) conclude that "[…] *overall it seems to us that most research does not find quantitatively important effects of immigration on native wage levels or the wage distribution*" (page 839). Likewise, studies have failed to identify a noticeable effect of emigration on sending countries' economic growth via remittances (e.g., Barajas et al 2009, Clemens and McKenzie 2018, De Haas 2023). Overall, those analyses would lend some support to the parsimonious assumption adopted in the present study. In any case, attempts at introducing more sophisticated hypotheses regarding the impact of immigration on sending and destination countries' inequality levels are fraught with conceptual and practical difficulties (with the lack of empirically reliable data for all possible origin-destination country pairs being a major obstacle).

On the other hand, several limitations exist with the data that try to estimate migration flows across countries. The movements of individuals across national borders are particularly difficult to capture and might be underestimated. Some individuals might cross such borders very often in five years of time (the basic time "unit of analysis" in this paper), but those movements might never be recorded by national registers, especially for undocumented migrants. Likewise, some migrants might return to their country of origin, but such movements are not necessarily registered by official statistics. These imperfections might potentially bias the estimation of true migration flows. To mitigate the limitations that such data unavoidably has, we have relied on the six most popular and reliable methods to estimate international migration flows that are currently available (see Abel and Cohen (2019)). Importantly, our findings are not particularly sensitive to the choice of those alternative methods; the different results are strongly consistent.

Lastly, our analyses do not take into consideration other important economic effects related to international migration, like the so-called "brain drain", "brain gain" or "brain circulation" (Kone and Özden 2017), the effect of migrants' remittances on sending countries (Yang 2011), and so on. While extremely important, these phenomena are beyond the scope of the current study, which is focused on the direct (i.e., first-order) effects of demographic change on global income inequality. Despite their simplicity, the counterfactual methods used in this paper are extremely useful to derive first-order approximations of complex phenomena that, otherwise, could only be approximated more realistically with sophisticated models whose implementation (i) requires huge amounts of data that are not yet currently available (e.g., the skills of migrants in all possible country pair combinations), and (ii) depends on somewhat arbitrary decisions that are prone to a wide range of misspecifications and measurement errors.

Could had it been otherwise?

In recent years, international migration has been posited as a potentially important mechanism of adjustment to reduce income inequalities across world citizens (Milanovic 2012). However, our findings suggest that, between 1990 and 2020, international migration has not contributed to decrease global income inequality. Depending on the chosen inequality measure, migration is either found to slightly increase global income inequality (that is the case of the mean log deviation and the Theil index) or have a negligible effect because of equalizing and dis-equalizing forces cancelling each other (as is the case with the coefficient of variation squared). The decomposition techniques proposed here suggest that, to have an inequality depressing effect, migration flows would need to occur among country dyads other than the ones where they have actually occurred. The relatively large migration flows from upper middle towards high-income countries have largely contributed to push inequality upwards (see the red cells in Figures 11-13). Instead, if the flows had been more intense in the country pairs indicated by the blue cells in Figures 11-13 (e.g., from low-income countries towards lower-middle or upper-middle income countries), migration would have had an equalizing effect. Relatedly, one might wonder what would happen to global income inequality if all individuals worldwide were to realize their desires to migrate. It is well-known that international migration is very costly (indeed, this is why it is more common among citizens from upper-middle rather than those from lower income countries) and many individuals who would be willing to migrate are unable to do so (De Haas 2023). We leave this highly speculative exercise for future research.

6. Conclusion

Populations' natural growth (i.e., the difference between births and deaths) and international migration are the two basic forces shaping countries' demographic change. In this paper we have shown that they have played a non-negligible and increasingly prominent role in determining the trends in global income inequality between 1990 and 2020 – the former through the faster-than-average population growth in low and lower-middle income countries, and the latter through the relatively large migration flows from upper middle-income countries towards high-income ones. These two population-related effects are not contributing to decrease global income inequality, just the opposite. While international migration has generally contributed to increase inequality, its effect is quantitatively small – the intensity and direction of the flows would need to be much higher and involve other corridors to have a sizeable impact. To become forces of global equalization, low- and lower middle-income countries would need to slow down their populations' natural growth (e.g., via fertility reductions) and the share of international migration flows originating from low-income countries would need to increase considerably.

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