

AFTER THE FINANCIAL CRISIS: THE EVOLUTION OF THE GLOBAL INCOME DISTRIBUTION BETWEEN 2008 AND 2013

BY **BRANKO MILANOVIC***

*Graduate Center, City University of New York
International Inequalities Institute, London School of Economics*

Using the newly created, and in terms of coverage and detail, the most complete household income data from more than 130 countries, the paper analyzes the changes in the global income distribution between 2008 and 2013. This was the period of the global financial crisis and recovery. It is shown that global inequality continued to decline, largely due to China's and India's high growth rates that explain about two-thirds of the global Gini decrease between 2008 and 2013. Income growth of the global top 1 percent slowed significantly. The slowdown is present even after survey data are corrected for the likely underestimation of highest incomes.

JEL Codes: D30, D31

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1. INTRODUCTION

The Global Financial Crisis of 2007–08 and its aftermath have had significant effects on income distribution in many countries (OECD, 2011, 2015; Cord *et al.* 2014; Raitano, 2016; World Bank, 2016; Kaplanoglou and Rapanos, 2018). It had no less significant effects on the global income distribution. It affected distributions within countries and the rates of growth of countries, which together determine changes in the global income distribution. Yet so far the changes in the global income distribution after the financial crisis have not been studied. The objective of this paper is to fill that gap. It covers the period 2008–13. The beginning year is the year of the financial crisis. It is also the year when an earlier paper using a similar methodology (Lakner and Milanovic, 2016) ends. The end-year of this paper is 2013, by which time all major Western countries that were most affected by the financial crisis had returned to positive growth. The two papers together extend over quarter a century and enable researchers, given that the underlying data are available online, to study the period more thoroughly by focusing either on different periods or different regions.

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*Correspondence to: Branko Milanovic, Stone Center on Socio-Economic Inequality, City University of New York, 365 Fifth Avenue, New York, NY 10013, USA (bmilanovic@gc.cuny.edu).

It may be useful to mention that global income distribution treats every individual in the world the same, regardless of what country they live in. Every individual's income can be formally decomposed into the mean income of person's country, and their relative income position within the country. Changes in global income distribution may thus be seen as a product of changes that are often studied in two distinct parts of economics: between-country inequality, or income convergence or divergence that must (in this case) be population-weighted, and changes in within-country inequalities. Both, as will be shown in the paper, have played a role in the period studied here, although the importance of income convergence, especially that of China and India, was greater than the importance of changes in national inequalities.

The structure of the paper is as follows. Section 1 describes the data used in the calculation of the global income distribution in 2008 and 2013. Section 2 presents a descriptive analysis of global and regional changes in inequality, and mean and median incomes between the 2 years. Section 3 focuses on the global growth incidence curves in several versions: anonymous and quasi non-anonymous (the term is explained below), balanced and unbalanced panel, and international (PPP) dollars and current US dollars. The essential features of the change in the global income distribution remain unaffected whatever version is chosen. Section 4 looks at how the global income distribution and global growth incidence curve change when national top incomes are "corrected" for their likely underestimation by household surveys. Section 5 discusses developments in the relative positions of countries and "classes" (income percentiles) in the global income distribution. By looking at the positions of individual countries' percentiles in the global income distribution, we are able to move away from a simplistic comparison of mean country incomes or GDPs per capita. The paper ends with conclusions.

2. SECTION 1. DATA DESCRIPTION

2.1. *Global Coverage*

In both 2008 and 2013, for all countries we use household-level (micro) data obtained from household surveys. Each country's data are "compressed" by creating one hundred percentiles where individuals are ranked in (national) percentiles according to their household per capita consumption or household per capita disposable income. Disposable income is equal to market income (the sum of gross wages, self-employment income, imputed value of home consumption and housing services, interest, dividends, and rents) plus government cash and near-cash transfers minus direct taxes. We adjust for household size using per capita measurement which is consistent with the existing work on global poverty and inequality; using equivalent units is not practicable in conditions where relative prices of private and public goods differ widely, as they do globally. Percentiles are used to minimize the effect of outliers (both at the top and the bottom) and also because some of the databases we use (POVCAL) do not allow direct access to individual-level data. Income or consumption are reported in national currencies which are converted

TABLE 1
COVERAGE OF COUNTRIES, WORLD POPULATION AND GDP

	Number of Countries Included		Population Covered by Surveys (in Million)		Percent of Total Population Covered		Percent of Total Dollar GDP Covered	
	2008	2013	2008	2013	2008	2013	2008	2013
Africa	38	36	891	963	91	85	79	75
Asia	29	26	3697	3944	95	96	89	89
Latin America and the Caribbean	18	19	540	599	94	98	95	98
Eastern Europe and Central Asia	27	26	371	362	92	88	99	91
WENAO	24	24	849	876	100	100	100	99
<i>World</i>	<i>136</i>	<i>131</i>	<i>6347</i>	<i>6745</i>	<i>94</i>	<i>95</i>	<i>96</i>	<i>95</i>

Abbreviation: WENAO, Western Europe, North America and Oceania.

into international or PPP consumption-based dollars¹ derived from the 2011 International Comparison Project. In the text, “percentile” always refers to a given group of recipients. Thus, income of a given percentile always means the average income of recipients who belong to that percentile, not the threshold income for that percentile.

It is important to underline that these are the most detailed extant global data, both in terms of country coverage, and thus population and GDP inclusion, as well as in terms of how finely grained the data are (one hundred fractiles for each country). The data are much better than what we had until now both in terms of country coverage and distributional detail. This also obviates the need for approximations or interpolations using externally obtained data (i.e., outside household surveys) except in the case of the very top of national income distributions (discussed in Section 4).

Table 1 presents the most salient characteristics of the data. At the global level, we include between 94 and 96 percent of GDP and population. There are however important regional differences. While for rich countries (Western Europe, North America and Oceania, WENAO) both their populations and income are almost fully included, African coverage, especially in terms of the continent’s GDP, is relatively low, at 79 percent in 2008 and 75 percent in 2013. In both years, the population coverage of Africa is also the lowest of all regions. The reasons for that are obvious: Africa still lags in the number and regularity of household surveys as well as researchers’ ability to access them. For example, some countries (e.g., Algeria) do not release micro data from household surveys. The lack of regularity is a problem in countries like Sudan and DR Congo which might have a survey

¹PPP dollars are consumption-based, that is they give the number of domestic currency units that are equal in purchasing power of consumption to the numeraire (1 US dollar in the United States). The new preliminary 2017 PPPs were published in May 2020 (see World Bank, 2020). Because they fall outside the time frame of the study, I use the 2011 PPPs, which will continue to be used by the World Bank in its estimates of world poverty.

in 1 year but then no information for a decade. Since in accordance with the previous work (Lakner and Milanovic, 2016), the surveys to be included in the database should not be more than 2 years off in either direction from the benchmark years of 2008 or 2013, the number of available African surveys is reduced. African countries tend to be poorer than the rest of the world (and those that lack regular surveys even more so), and it is thus likely that the less than complete coverage of Africa imparts a downward bias to the calculated global inequality. For other regions, as Table 1 makes clear, both the population and income (GDP) coverages are in excess of 90 percent in almost all cases, and above 95 percent in most.

To improve the precision and reliability of the data, in 2013 we also use Chinese, Indian and Indonesian data split into rural and urban areas with different PPPs. The official International Comparison Project PPPs are assumed to apply only to urban areas, and a different (lower) price level is used for rural areas.² The rationale for that is absence of full market integration within these large countries and the existence of *hukou* registration system in China which, at least formally, limits mobility of labor. The total number of countries is 136 in 2008 and 131 in 2013. This means that the database is composed of 13,600 country/percentiles in 2008, and 13,100 country/percentiles in 2013 (or 13,400 if we use rural/urban decompositions for China, India and Indonesia). These building blocks (country/percentiles) are used to create global percentiles where normally each global percentile is composed of percentiles from various countries. For example, the global top 1 percent is dominated by country/percentiles from rich countries, and very low (poor) global percentiles are populated by poor countries' country/percentiles.

The two most important sources of data are World Bank's POVCAL and Luxembourg Income Study (LIS). However, individual county surveys, the SEDLAC database (for Latin America) and the SILC data for some European countries are also used. The breakdown of sources is shown in Annex 1.

There are two additional important types of information regarding the surveys that need to be mentioned: (i) the breakdown between surveys that are consumption-based and those that use income, and (ii) the years when the surveys are conducted. Table 2 provides that information. Income and consumption surveys are split overall into about half-and-half (with a slight preponderance of consumption-based surveys in both years), but their regional distributions are very different. African surveys are almost all consumption-based. The only significant exception is South Africa which uses income surveys. About 2/3 of Asian surveys are consumption-based while in Eastern Europe and Central Asia, the shares of the two are about equal. However, in Asia, for the two most populous countries (China and India) we use income-based surveys. This is of particular relevance for India whose consumption-based surveys (National Sample Survey) have generated an intense debate because their results have been increasingly at odds with those obtained from the national accounts. The most recent 2017–18 “thick” round of NSS was withdrawn from the public use in 2019 because of “questionable quality of data”. This generated intense discussion as some of its preliminary results had

²The difference between urban and rural price levels reflects the difference in the cost of the subsistence basket. This was also the approach used by Lakner and Milanovic (2016) in global inequality study as well as in numerous global poverty studies (see e.g., Chen and Ravallion, 2010).

TABLE 2
DESCRIPTION OF HOUSEHOLD SURVEYS USED

	Number of Consumption-Based Surveys		Number of Income-Based Surveys		Number of Surveys Conducted in the Benchmark Year or +/- 1 Year	
	2008	2013	2008	2013	2008	2013
Africa	35	33	3	2	23	18
Asia	20	21	9	10	20	24
Latin America and the Caribbean	0	1	18	18	17	19
Eastern Europe and Central Asia	16	12	11	12	27	22
WENAO	0	1	24	23	23	23
World	71	68	65	65	109	106

previously been leaked (Subramanian, 2019). This is why for both years we use more reliable Indian income surveys. Finally, almost all Latin American and the Caribbean, and WENAO surveys are income-based.

In an important work which “converted” consumption surveys into income surveys (and the reverse) based on the estimated relationship between fractiles from the surveys that had both consumption and income data, Jayadev *et al.* (2015) do not find that combining income- and consumption-based surveys imparts a bias to the world-wide estimates of inequality. While it would be desirable to have surveys from all countries use the same “measuring rod” (income or consumption) and use the same statistical framework and income definitions (as for example LIS does *ex post*, and SILC *ex ante*), we are currently far from that objective. Table 2 also shows that $\frac{3}{4}$ of the surveys are conducted in the benchmark year or within 1 year before or after the benchmark year. For the surveys not conducted in the benchmark year, we adjust the data by the consumer price index between the survey year and the benchmark year.

2.2. How Good are the Surveys?

The issue of how well household survey data cover the entirety of national income or of consumption has recently gained in importance due to the growing realization that in surveys’ top incomes are often underestimated (see Yonzan *et al.* 2020). This has led to the discussion of various ways in which the top of the income distribution may be adjusted by combining survey and fiscal data (Eckerstropher *et al.*, 2016; Blanchet *et al.*, 2017; Goda and Sanchez, 2017; Blanchet *et al.* 2018; Atkinson and Jenkins, 2020; Lustig, 2020). Obviously, such approaches are easier to implement in the case of single countries, and especially so if reliable tax data exist, than at the global level. In Section 4, we present one such possible global adjustment.

However, it is important also to establish how closely the results from household surveys correlate with information that we have from national accounts.

TABLE 3
COMPARISON OF HOUSEHOLD SURVEYS AND NATIONAL ACCOUNTS

	Total income (Consumption) from Surveys to Household Final Consumption from National Accounts (in Percent)		Mean Per Capita Income Growth 2008-2013 (Cumulative, in Percent)	
	2008	2013	Surveys	National Accounts (GDP Per Capita)
Africa	79	59	9	31
Asia	90	87	41	40
Latin America and the Caribbean	63	61	32	28
Eastern Europe and Central Asia	66	65	19	12
WENAO	82	75	-4	2
<i>World</i>	75	75	11	13

Note: Income (consumption) from household surveys and consumption from NA are both measured in nominal dollar amounts; the same for the growth rates. The calculations are always done for all countries included in the surveys (full non-balanced sample). The ratios are regional population or income weighted averages.

Table 3 shows, at regional levels, the ratio between income or consumption from surveys and household final consumption from national accounts, as well as a comparison of average 2008–13 per capita growth rates from surveys with comparable growth rates from national accounts. In both cases, the underlying variables are expressed in nominal US dollars in order to avoid potential problems of different PPPs used in household surveys and national accounts. The data are population or income weighted (whatever weighting is appropriate), that is, they represent weighted averages for each region.

In both years (Table 3), household surveys (HS) account for about $\frac{3}{4}$ of household final consumption reported in national accounts (NA). We do not expect that they would account for one hundred percent because household final consumption in national accounts is by definition different: it includes consumption of NGOs, FISIM (Financial and Insurance Services Indirectly Measured), imputed consumption from housing (which is omitted in many surveys), and consumption of institutionalized population (homes for the elderly, prisons, student boarding homes) that is not covered by surveys. In the United States, for example, the ratio between income from Current Population Surveys and NA consumption is around 75 percent in both years. The percentages vary between the regions. In Asia and WENAO, they are the highest (between 75 percent and 90 percent), and in Latin America and the Caribbean (as well as in Africa in 2013) they are the lowest (around 60 percent). The low ratio in Latin America can be related to high inequality and likely non-participation or underestimation of income among the richest part of the population (for an early meta-study see Székely and Hilgert, 1999). Moreover, India, for which we are using income surveys available in LIS, and whose consumption-based surveys first highlighted the rising discrepancy

between surveys and national accounts is doing relatively well with coverage of 47 percent in 2008 and 61 percent in 2013. China's surveys' coverage is slightly above 100 percent in both years (115 percent in 2008 and 114 percent in 2013).

When it comes to the rate of (cumulative) income growth between 2008 and 2013, surveys and national accounts produce very similar results except in Africa, where GDP per capita (over the sample of countries included in surveys) shows a growth of 31 percent vs. only 9 percent according to the surveys. In all other cases, the differences are quite small, and the ranking of regions by the rate of growth is the same whether measured by GDP per capita or survey-based per capita income. It is worth noting that the slowest growing region (that of rich countries) shows 2 percent growth between 2008 and 2013 according to GDP per capita but negative 4 percent growth according to surveys.

It is important to focus for a moment on survey coverage of populous Asian countries because they, together with the WENAO region, largely determine what happens with global income distribution. They have however in the past faced issues of inadequate or unreliable coverage leading to volatile or not fully plausible results. Additionally, Asian PPPs were doubtful as in 2005 when the then round of International Comparison Project came up with unexpectedly high price levels for Asia, and thus low real incomes. In 2011 ICP, these problems were corrected (see Deaton and Aten, 2017). To avoid unnecessary conversions, it is best to compare surveys with private household consumption from National Accounts using nominal US dollars.

Figure 1 shows the growth rates of surveys' mean income/consumption and NA household consumption in nominal dollars between 2008 and 2013 for seven large Asian countries (and the US, for comparative purposes). For China, Japan and Indonesia, the differences between the two measures are non-existent or very small. For India, Vietnam and Thailand, surveys show significantly faster growth (the opposite holds for Bangladesh). Higher survey growth in the three countries means that the survey coverage of NA consumption has increased. In India, it went up from 47 percent to 61 percent, still a relatively low number but certainly an improvement compared to past NSS consumption surveys. In Vietnam, the coverage increased from 72 percent to be almost equal to the value in National Accounts. In Thailand, it went up from 62 percent to 78 percent. For all of Asia, the growth rates of survey mean income/consumption, and of private consumption from National Accounts were the same: 9 percent per annum. All of this seems to indicate that surveys have become better and more reliable. It also means however that the better coverage itself will bias upward the measured rates of growth over the period.

It is worth pointing out that such measured average rates of growth, and especially, the growth rate of the median should not be incautiously compared with rates of growth of real per capita GDP. What has happened in several countries in Asia is the following: (1) NA consumption has outstripped growth of GDP raising the share of private consumption in GDP, by more than a point in both India and China, and two points in Japan, then (2) increased survey coverage of consumption (as in India, Thailand, and Vietnam) has pushed the survey growth rates above those of NA consumption, and finally (3) as in China, Vietnam, and Thailand, the growth at the median –as we shall see below—has been greater than at the mean.

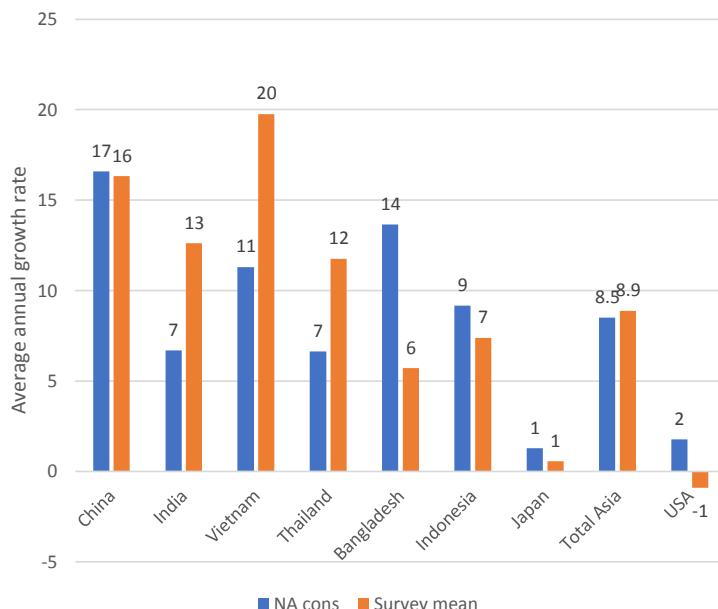


Figure 1. Average Annual Growth Rate (in percent) of Survey Mean Income and Household Private Consumption from National Accounts (Nominal Dollars)

Source: Household survey data from the current database; national account private final consumption from World Bank Word Development Indicators database (version October 2019). All data in nominal US dollars. [Colour figure can be viewed at wileyonlinelibrary.com]

Thus, in the end, when we compare the median HS-based growth to GDP per capita growth there are three “adjustments” that have to be taken into account.

3. MAIN RESULTS

3.1. Tectonic Shifts

Table 4 shows that regional inequalities (inequality across all individuals of a given region), measured by both Gini and Theil indexes, have barely changed. In four regions (WENAO, Eastern Europe and Central Asia, Latin America and the Caribbean, and Africa) Gini's are the same (or one Gini point off) in 2013 as in 2008; only in Asia, is Gini 4 points lower in 2013. The same result obtains if we use Theil index. The ranking by regional inequalities has only slightly changed. Historically, Asia has been the most heterogeneous continent (see Milanovic, 2002). This is no longer exactly the case because its regional Gini of 55 is the same as Africa's. Latin American inequality is slightly less, at 52, while Eastern Europe and Central Asia, and WENAO have substantially lower regional inequalities of around 40 Gini points.

However, global inequality decreased by 4.8 Gini points or 15 Theil points. The lack of changes in inter-personal regional inequalities (except in Asia) already suggests that the main source of change in global inequality is not to be found in within-national inequality changes, nor even in significant

TABLE 4
REGIONAL AND GLOBAL INEQUALITY, REGIONAL AND GLOBAL MEDIAN AND MEAN INCOME

	Gini (in %)		Theil0 (in %)		Median Income (in PPP dollars)		Mean Income (in PPP dollars)			
	2008	2013	2008	2013	2008	2013	Change in %	2008	2013	Change in %
Africa	55	55	56	54	803	937	17	1403	1702	21
Asia	59	55	66	56	1252	2202	76	2675	3974	49
Latin America and the Caribbean	53	52	53	50	2514	3274	30	4198	5232	25
Eastern Europe and Central Asia	41	41	29	29	4010	5652	41	5345	7662	43
WENAO	41	40	31	30	14058	14935	6	18807	18992	1
<i>World</i>	<i>66.4</i>	<i>61.6</i>	<i>91</i>	<i>76</i>	<i>1674</i>	<i>2708</i>	<i>62</i>	<i>4817</i>	<i>5919</i>	<i>23</i>

Note PPP dollars based on 2011 International Comparison Project results. Calculations of Gini and Theil are made for household per capita disposable income (or consumption) expressed in PPP dollars. Theil index used is Theil(0) or mean log deviation.

within-regional convergence, but in the changes in the relative positions of regions, that is in between regional convergence. It is noticeable (Table 4) that the richest region, WENAO, has practically not grown between 2008 and 2013, whereas the second poorest, and the most populous, region, Asia, has seen its mean income increase by almost 50 percent (in PPP dollars). It is this type of convergence (the “rising Asia”) which is, as we shall see in the next section, the main reason behind the rather dramatic decline in global inequality after the financial crisis. The same is confirmed by looking at median regional incomes: in Asia, the median income has risen by 76 percent while in the “rich world” it has gone up by only 6 percent.

While the ranking of regions by mean income has not changed, Asia has moved much closer to the three richer regions and pulled further away from Africa. In effect, if we use the richest region (WENAO) as the numeraire all other four regions have become closer (in relative terms) to the rich world. It is these “tectonic” shifts (driven by differential growth rates of individual countries) that are determining the changes in the global income distribution.

3.2. *Within-National Inequalities*

The other component which determines the evolution of the global income inequality is within-national inequalities. As Table 5 shows, in almost 3/5 of the countries for which we have inequality data in both 2008 and 2013, there was no salient change in inequality. (A “salient” change, or at least the change that we believe is real because small changes can be due to the variability of sampling, is, following Aaberge *et al.* (2017), considered to be at least 3 Gini points in either direction). Among the rest, in 33 countries there was a decline in inequality and in 20 countries an increase. In calculations of global inequality, inequality changes in populous countries (like China which registered a decrease in within-national inequality) will play a bigger role. Still given that almost 3/5 of the countries did not have a significant change in inequality and that the others are split relatively evenly between those with an inequality increase and those with a decrease, there is no a priori expectation that changing national inequalities might have played an important role in driving global inequality. This is not unexpected because national inequalities move slowly and for them to have a perceptible effect on global inequality we normally need to use a time-horizon in excess of 5 years.

When it comes to the regional distribution of inequality changes, it is remarkable that in more unequal regions (especially so in Latin America) inequality declines outstripped inequality increases. In Latin America and the Caribbean, significant declines were registered by 8 countries and none showed an increase. (Note however that the countries that experienced a decrease in inequality are relatively small while the “giants” like Brazil and Mexico display stable inequalities). Moreover, in the most equal regions (Eastern Europe and Central Asia, and WENAO), inequality increases outnumber inequality declines. This is very obvious in WENAO where the ratio is 5 to 1, and two big countries (Spain and Italy) are among those with substantial inequality increases.

TABLE 5
WITHIN-NATIONAL INCOME CHANGES, 2008 TO 2013

Countries with Gini...			
	Increases (>3 Gini Points)	Decreases (Greater, in Absolute Terms, than 3 Gini Points)	No Change
Africa	Burundi Cameroon Egypt Ethiopia Kenya Mozambique Nigeria (7 countries)	Burkina Faso Botswana Cote d'Ivoire Guinea Gambia Liberia Mauritania Niger Rwanda Tunisia South Africa (11 countries)	13 countries
Asia	Seychelles Taiwan (2 countries)	China Fiji Iran Iraq Mongolia Malaysia Thailand Timor Leste Vietnam (9 countries)	13 countries
Latin America and the Caribbean	0	Bolivia Dominical Republic Ecuador Guatemala Honduras Peru El Salvador Uruguay (8 countries)	10 countries
Eastern Europe and Central Asia	Armenia Estonia Montenegro Slovakia Slovenia Tajikistan (6 countries)	Kyrgyz Republic Kosovo Macedonia Romania (4 countries)	16 countries
WENAO	Austria Cyprus Spain Italy Luxembourg (5 countries)	Iceland (1 country)	18 countries
<i>World</i>	20	33	70

3.3. Decomposing the Change in Global Inequality

As already implied by regional convergence (namely, of all regions with respect to the richest, WENAO), the decline in global inequality was driven by the between-country component, that is by the decrease in inequality between mean country incomes. Using Gini decomposition, we find that the between component

TABLE 6
DECOMPOSITION OF THE CHANGE IN GLOBAL INEQUALITY BETWEEN 2008 AND 2013

	2008	2013	Change
Gini			
Between country component	55.7	50.5	-5.2
Within country component	2.3	1.6	-0.7
Overlap term	8.4	9.5	+1.1
<i>Total Gini</i>	66.4	61.6	-4.8
Theil(0)			
Between country component	56.3	45.3	-11.0
Within country component	34.7	30.6	-4.1
<i>Total Theil(0) or mean log deviation</i>	91.0	75.9	-15.1

was reduced by 5.2 points; using Theil(0), we find a reduction of 11 Theil points (Table 6).

Using Theil index, the within-component (the part of global inequality due to the sum of inequalities within nations) was 4.1 points less in 2013 than in 2008. This was principally caused by the decreasing inequality in China. The within-component proper of the Gini coefficient is often very small because it is the sum of the double-weighted individual Gini coefficients (each country Gini is weighted by the product of county's population and country's income shares). As we can see in Table 6, it was practically unchanged between 2008 and 2013. But what was interesting is the increase in the overlap component of the Gini which is sensitive to the mass of population with "overlapping" incomes, that is of the populations of mean-poorer countries whose individual incomes are higher than individual incomes of people from mean-richer countries. That this component has gone up clearly implies that the correlation between one's county and one's individual income has become less strong. This is an important effect brought about by the global convergence of mean country incomes.³

One expects that China had played an important role in the global decrease of inequality between 2008 and 2013. The question is how to best estimate that impact. A reasonable counterfactual is to assume that China has had the average global per capita growth (23 percent between 2008 and 2013). In that case, the global Gini would have been 63.3 against the actually recorded Gini of 61.6. This means that China's above-average growth performance is responsible for the reduction of more than 1.7 Gini points of global inequality. If we do the same type of calculation for both China and India, we obtain that their (combined) above-average growth rates are responsible for 2/3 of global inequality reduction.⁴ It is interesting to focus on the contribution of Indian growth: although it was less than

³The third variable that could theoretically explain the change is variation in population. But obviously such population changes between countries over a 5-year interval are very modest. If we calculate 2013 Gini with the population shares of 2008, the results are practically the same as with 2013 population shares.

⁴Note that had Chinese and Indian growth been lower it would have also reduced global mean growth. So the counterfactual slightly overestimates the effects of higher Chinese and Indian growth.

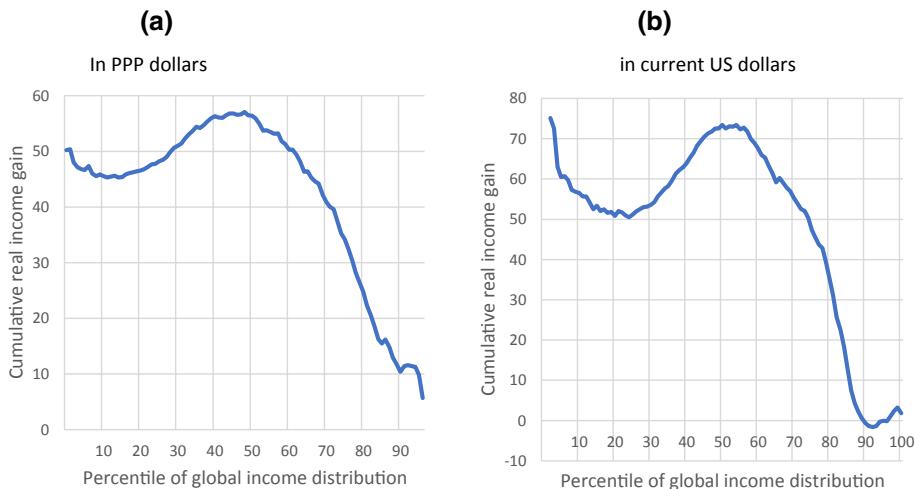


Figure 2. Cumulative Percentage Growth of Per Capita Income at Different Points of the Global Income Distribution 2008–13, Full Sample; Unbalanced Panel

Note: a,b show cumulative growth between 2008 and 2013. Composition of global percentiles in the two figures is not the same; people who are in a given global percentile according to PPP dollars are not necessarily the same as people who are in that percentile according to US dollars. [Colour figure can be viewed at wileyonlinelibrary.com]

China's, the fact that India is poorer, makes its growth rate, *ceteris paribus*, a stronger "engine" of global inequality reduction. In other words, in the near future China's growth (on account of its relatively high income level) will cease to be globally inequality-reducing.

4. GROWTH INCIDENCE CURVES AND INEQUALITY CHANGES BETWEEN 2008 AND 2013

The uneven regional growth rates, the continued catch-up of Asia, and generally quiescent within-national inequalities suggest both that the growth rates of different parts (percentiles) of the global income distribution were not the same and that the global growth incidence curve (GGIC) is likely to display pro-poor features (i.e., with growth rates higher among the poor percentiles than among the rich) principally on the account of slow growth in rich countries.

Figure 2 with panels *a* and *b* which display GGICs calculated, respectively, using household per capita income in PPP dollars and in nominal dollars show that the globally poor and those who are around the global median had experienced especially strong growth. Using real PPP dollars, those around the median registered cumulative growth of about 60 percent, or almost 10 percent per annum over the 5-year period. For those from the 82nd global income percentile all the way to the top, the cumulative growth between 2008 and 2013 was below 20 percent. The lowest growth of all percentiles was registered by the very top of the global income distribution (6 percent in real terms). It is interestingly also the only global percentile that has registered merely a single-digit growth. Since the average growth rate has been 23 percent (see Table 4), the share of the global top 1 percent

has diminished from 13.2 percent to 11.4 percent. Likewise, the share of the top 5 percent has gone down from 35.5 percent to 31.6 percent. As we have already seen, the overall distribution has become more equal; but it has become so in a specific way where the largest gains have been realized around the middle of the income distribution, or more exactly between the 35th and 70th percentiles.

The shape of GGIC, when the calculation is done using nominal US dollars, is very similar. (Note that the composition of the percentiles, that is, of people included there, when percentiles are calculated using nominal US dollars will be different from the composition of the percentiles calculated by ranking people according to PPP dollars.) The dip in the growth rate between the 10th and 40th percentile is now more pronounced, the growth is again the highest around the median of the global income distribution (reaching at the peak of slightly over 70 percent, cumulatively), and again it goes down rather precipitously, moving into the negative territory around the 90th percentile. Percentiles 90–96 have all either zero or slightly negative growth: minus 1 to 2 percents. At the very top of the global income distribution, percentiles 99 and 100, had very modest cumulative growth rates of 2 and 3 percent. The shares of the top groups are, as expected, higher when we measure incomes in nominal dollars than in PPP dollars. They have nevertheless declined in dollar terms too. The top 5 percent received almost 45 percent of total global income in 2008; that share declined to 41 percent. The richest 1 percent share went down from 16 percent of global income to 15 percent.

The growth incidence curves shown in Figure 2 are called “anonymous” because they compare income levels at a given percentile in 2 years regardless of who is at that position. This means that generally not the same country/percentiles would be there in both years. For example, if Chinese percentiles grow at an above-average rate they will move to the right (toward higher global percentiles) in 2013 than they were in 2008. We cannot of course have a full “non-anonymous” GGIC which would require that we keep all individuals at their 2008 positions and display their growth rates over the next 5 years. This is impossible because household surveys used here are not longitudinal and each survey, being a snapshot of that country’s distribution at a given point in time, will include different people.

However (as in Lakner and Milanovic, 2016) we can define the “quasi non-anonymous” GGIC where we keep country/percentiles at their 2008 positions and calculate growth rates across such unchanged composition of each global percentile. The “quasi-non-anonymous” GGIC is a balanced panel. This approach allows us to find out what groups of people have experienced particularly fast growth. The results are shown in Figure 3 (the data are in PPP dollars).⁵ The shape of the curve is similar to what we find in the case of anonymous growth: rather uniform increases of about 70 percent exist throughout the bottom half of the global population. There is for example no indication of a U-shaped pattern among the lower global percentiles that we discerned in Figure 2a,b. Around the median point of the 2008 global income distribution, the growth rate begins to decelerate, and it falls

⁵The GGIC is ventile-based in order to provide a smoother curve. The composition of each 2008 global percentile is very heterogeneous (it normally includes percentiles from very diverse countries), and the growth rates over the 2008–13 period were also very different. Using ventiles gives a more “stylized” picture of the change.

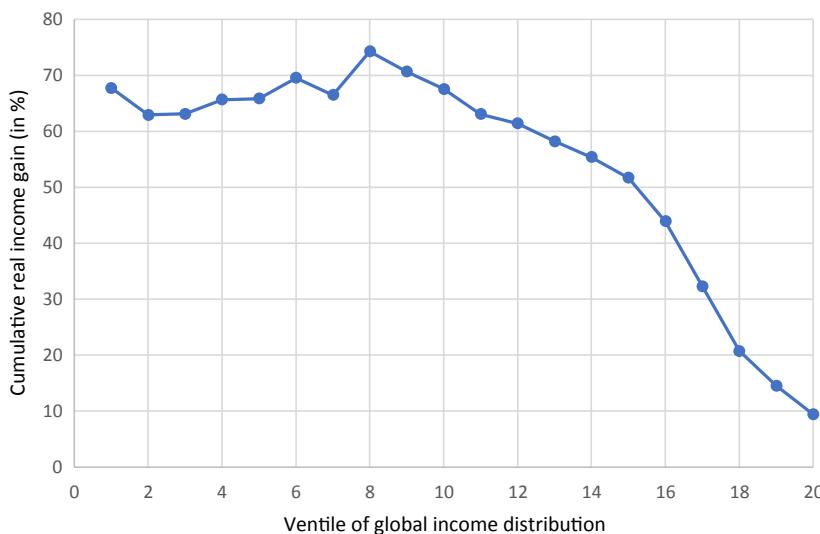


Figure 3. Cumulative Percentage Growth of Per Capita Income (in PPP Dollars) at Different Points of the Global Income Distribution, 2008–13; Quasi-Non-Anonymous Balanced Panel

Note: The graph shows cumulative income growth between 2008 and 2013 for 20 ventiles of global income distributions with each ventile's composition (country/percentiles within it) “fixed” as it was in 2008. It thus shows the average growth of country/percentiles that were at a given position in 2008 over the next 5 years. [Colour figure can be viewed at wileyonlinelibrary.com]

regularly after that point, reaching its lowest level, of only about 10 percent, for the richest ventile (5 percent of population) of the 2008 population. By definition, we know, that the growth rate of the top will always be the same or less with non-anonymous than anonymous GIC. This is because non-anonymous top 1 percent can grow at the same rate as anonymous top 1 percent only if everybody who was originally in the top 1 percent remained there. If one or more persons dropped out, non-anonymous top growth must be less than anonymous. Thus, a part of the deceleration observed at the top is due to reshuffling. However, we have already seen in anonymous GICs and it is confirmed here that country/percentiles that were among the richest in 2008 had grown very slowly in the next 5 years.

What were the country/percentiles that belonged to the top 1 percent of the global income distribution in 2008 and what was their real growth experience? The overall growth of the 2008 top 1 percent was 7.2 percent. More than $\frac{1}{2}$ of the people in the global top 1 percent were Americans. They belonged to the top 11 American country/percentiles in 2008 and their cumulative growth rate in the following 5 years was between 5.5 percent and 7 percent with the exception of the top US percentile that registered a negative growth of 6 percent. It is remarkable that 15 million people out of 63 million that were in the global top 1 percent in 2008 experienced negative growth. They included the top decile (i.e., all ten percentiles) of the Canadian and Icelandic income distributions, the two top percentiles of the French, seven top percentiles of the British, the very top of the Greek, Dutch and Italian income distributions, and the top 4 percentiles in Taiwan. Overall, 87 percent of those who were (a) in the global top 1 percent in 2008, and (b) experienced

negative growth subsequently were part of the WENAO rich world. For the global 2008 top ventile, that proportion is almost the same (86 percent). It thus clearly emerges that the significant slowdown in growth of the richest parts of the global distribution in 2008 was due to the negative income shock among the very tops of national income distributions in rich countries.

Moreover, who were the country/percentiles around the 40th to 50th global percentiles (“the global middle class”) that experienced the fastest growth between 2008 and 2013 (Figure 3)? The country/percentiles that were at that point of the global distribution were extremely varied: there are no fewer than 110 countries with “representatives” among these almost 600 million people. And clearly not all of them had the average experience of that group, namely a cumulative growth of around 70 percent. As expected, the most important in terms of the population, are the Chinese country/percentiles (132 million people belonging to the Chinese country/percentiles 38 to 47), Indian (103 million people, belonging to Indian percentiles 75 to 83), Indonesian (47 million belonging to the Indonesian percentiles 48 to 58), Nigerian (18 million people, Nigerian percentiles 67 to 78), and the Philippines (country/percentiles 47 to 60), Mexico (country/percentiles 25 to 35) and Vietnam (country/percentiles 57 to 72), each of the latter three with 11 to 13 million people. Many of them indeed had high growth rates. For the Chinese country/percentiles the average cumulative growth was 133 percent, for the Indian 102 percent, Vietnam 123 percent. One should not forget however how heterogeneous were experiences of that group—despite the fact that on average its incomes rose very rapidly. Thus, for example, the cumulative growth of the Nigerians who belonged there was -14 percent, and of Mexicans only +12 percent. In other words, the middle of the global income distribution that on average grew very rapidly between 2008 and 2013, was extremely diverse. As already mentioned, it included people from more than 100 countries and it would be wrong to generalize that there was something unique to that group that made it prosper. It included dissimilar people from various countries (only their incomes were similar) and it can be hypothesized that their fortunes were to a large degree determined by the economic experience of the countries where they lived.

5. CORRECTING FOR THE UNDERESTIMATION OF TOP INCOMES

There are two ways to adjust the global income distribution for underreporting of top incomes in individual countries’ surveys. The first was introduced by Lakner and Milanovic (2013, 2016) who, using national decile data, did two adjustments: the first was to “extend” the individual country distributions, using an estimated Pareto relationship, to the top 5 percent and top 1 percent. This was the method first suggested by Atkinson (2007). In addition, Lakner and Milanovic used the gap between consumption from national accounts and income or consumption from household surveys and allocated it to the top decile, the top ventile, and the top 1 percent using the same Pareto relationship. The latter procedure was termed by them “top-heavy adjustment [because the entire gap was allocated to the top decile] with Pareto tail”.

Another method was used by Anand and Segal (2015, 2017). For the countries (group A) for which the authors had information on the top 1 percent of fiscal incomes they replaced the top 1 percent shares from household surveys by the corresponding (top 1 percent) shares from fiscal data. For the bulk of countries which indeed lack fiscal data (group B), they imputed the estimated top 1 percent shares based on the relationship between surveys' top 10 percent share and fiscal top 1 percent share obtained from group A countries. This, not fully intuitive, approach is based on the observed relationship that "the income share of the top 10 percent in the household survey data is strongly correlated with the income share of the top 1 percent in the independently estimated top incomes [fiscal] dataset" (Anand and Segal, 2017, p. 13). Additionally, the top 10 percent share was smoothed using a Pareto adjustment. Anand and Segal's goal was to look at the global top 1 percent rather than at the whole distribution and thus their correction was concerned with the national top 1 percents only. The method implies that the entire underestimation comes from the underestimation of national top 1 percents. This may be, at times, considered too restrictive. There is possibly also a third approach used by Alvaredo *et al.* (2018) which also combines household survey and fiscal data. However, their sample size (the number of actual countries included) is small, there are many extrapolations, and the method is not clearly explained.

The reason why global income distribution cannot be corrected the way it is done at times for individual countries (e.g., for the UK, see Office of National Statistics, 2020; Jenkins, 2017; Burkhauser *et al.*, 2018; for the United States, see Burkhauser *et al.*, 2008) is because national corrections take advantage of the existence of very detailed fiscal data that are then combined with equally detailed, and often "corrected" or reweighted, household survey data. But majority of countries do not assess direct taxes in addition to payroll or wage taxes withdrawn at source and thus fiscal data are seldom compiled. Moreover, even when they are compiled they fail to account for the bulk of the working population in countries with large informal sectors. For other countries (e.g., India, China, Russia), fiscal data refer to a very small part of the population: around 0.2 percent in China (Piketty *et al.*, 2017; Additional Table T11), between 0.5 percent and 3 percent, and only since 2010, about 6 percent in India (Chancel and Piketty, 2019, Figure 4); less than 1 percent in Russia (Novokmet *et al.*, 2017; Online Appendix Table P2-12). In Russia, for example, individuals subject to direct taxes that are reported in the government's tabulations of tax-payers, are only those with very high incomes above an annually established threshold. All others are subject only to the 13 percent direct tax withdrawn at source and are not included in fiscal tabulations. This means that when studies for these countries are made, most of the time around 99 percent of the data points are derived from household surveys. Even in Brazil where direct taxation is more widespread, only 20 percent of the population is covered by tax data (Blanchet *et al.*, 2018, Figure 8, p. 20). Moreover, the definitions of income and recipients (tax units, households, or individuals) from fiscal and household data are as a rule different and they cannot be compared unless much more information and micro data are available. For individual countries that have sufficiently detailed data, this can be done, but as the recent paper by Yonzan *et al.* (2020) shows, even for countries that have some of the best survey and fiscal data (US, Germany and France), aligning survey-based income and recipient

definitions with those from the fiscal data is a very complex exercise. It is clear that a detailed attempt to adjust HS data using fiscal information can only be applied to a small subset of rich countries.

To adjust *global* income distribution, by correcting for *national* income underestimations, one therefore needs to apply a method that can be used for all countries and that would be, by necessity, much “rougher”. We have decided to correct the top ten percentiles of each country’s distribution by augmenting their incomes by the ratio between mean household private consumption from NA and mean income/consumption from surveys. If the survey mean is 80 percent of per capita private consumption, the ratio NS/HS is 1.25 (1/0.8) and all top ten percentiles of that country’s distribution are multiplied by 1.25. Other than being straightforward to apply to all countries the method has two advantages. First, it uses the gap between national accounts and HS as a measure (indicator) of underreporting. Second, while it never fully “exhausts” that gap it exhausts more of it in the case of countries with recorded greater inequality.⁶ More unequal countries will tend to have a higher top decile share; therefore, more of the overall gap will be allocated to it. For example, if the top decile receives one-half of total HS reported income, then the adjustment will involve one-half of the overall gap. This can be seen as follows. The adjusted income of i -th percentile (y_i^*) can be written $y_i^* = y_i \left(\frac{c}{m} \right)$ if $i > 90$ and $\frac{c}{m} > 1$ where y_i is unadjusted income of one of the top ten percentiles, c =mean per capita household private consumption from national accounts, and m =mean per capita income (consumption) from household surveys. If we write the unadjusted income as a product of that percentile’s share in total income and HS mean, so that $y_i^* = m * s_i \left(\frac{c}{m} \right)$ we easily notice that the adjustment will be greater as the share of a given top percentile is greater.

The method, therefore, uses two important pieces of information: the NA-HS gap, and recorded inequality. Both of them can be reasonably expected to be correlated with (the unobserved) underreporting of top incomes. To be clear, this approach implicitly argues that (a) the higher the NA-HS gap, the greater is top income underreporting, and (b) the higher the measured top income shares, the greater part of the gap is explained by the top income underreporting.⁷

It may be interesting to show how much the adjustment increases Ginis and top 1 percent and top 10 percent shares of selected countries in 2013, with the

⁶Lakner and Milanovic (2016) method mentioned above was exhausting the entire gap by definition. The “non-exhaustion” of the entire NA-HS gap may be considered as an advantage of the current method because there are items in National Accounts that should *not* be included in survey income. (I owe this observation to Angus Deaton.)

⁷We are basically looking at the correlates of an unobserved variable (top underreporting) and assume that it is positively associated with the overall NA-HS gap and with recorded inequality. This is different from, even if related to, the approach used by Deaton’s (2005). According to Deaton the log ratio between the observed (“uncorrected”) mean from household surveys and “true” mean (which we assume to be from NA) is

$$\ln \left(\frac{\text{uncorrected mean}}{\text{true mean}} \right) = \ln \frac{e^\mu - \alpha\sigma^2}{e^\mu} = \ln \left(e^{-\alpha\sigma^2} \right) = -\alpha\sigma^2$$

where μ = the “true” mean, σ = the “true” standard deviation of log incomes, and incomes are assumed to be distributed lognormally. The equation implies that in “truly” more unequal countries we should expect greater underestimation of the mean and hence higher NA/HS values.

TABLE 7
GINI, TOP 1 PERCENT AND TOP 10 PERCENT SHARES WITH UNADJUSTED AND ADJUSTED DATA (SELECTED COUNTRIES, YEAR 2013)

	Gini			Top 1 Percent share			Top 10 Percent Share		
	Unadjusted		Adjusted	Unadjusted		Adjusted	Unadjusted		Adjusted
	Here	Other	Here	Other	Here	Other	Here	Here	Here
Germany	31	34	5.4	6.2	7.3	7.5 ^a	24.9	28.5	
UK	35	38	35 ^a	6.3	8.9	10 ^d	27.3	31.7	
USA	41	47	44 ^d	6.8	8.7	20.2 ^e	30.0	39.3	
Russia	41	47	7.0	8.7			32.5	40.1	
Indonesia-urban	43	55	8.2	12.2			33.4	49.9	
China	43	43	6.4	6.4	6.4	13.9 ^c	30.5	30.5	
Mexico	50	66	12.6	19.2			40.5	62.2	
India	51	59	11.3	14.6			40.0	52.0	
Brazil	52	57	61 ^b	11.4	13.4		40.9	47.9	
South Africa	66	72	15.7	19.2			52.9	64.5	

Note Countries ranked by unadjusted Gini (from the least unequal to the most unequal). Top 10 percent and top 1 percent share as in percent of global income.

^aUK, Office for National Statistics (2020, Figures 6 and 7, pp. 12–13; year 2013–14).

^bBrazil, Blanchet *et al.* (2018, Figure A-6, p. 50; year 2013).

^cChina, Piketty *et al.* (2017, Table 2, year 2015), per adult; includes imputed income from undistributed corporate profits.

^dUS, Congressional Budget Office (2014), Figure 6, p. 16 and Figure 14, p. 26; year 2011).

^eRussia, Novokmet *et al.* (2017, Table 1, p. 186), per adult; includes imputed income from undistributed corporate profits.

similar adjustment of course conducted for 2008 too (see Table 7). For the United States, for example, the adjusted Gini is 47 vs. the unadjusted (household-survey based) Gini of 41. For Mexico that has historically displayed a very large gap between national accounts and household survey data, the Gini goes up from 50 to 66. The shares of the top 1 percent and top 10 percent likewise increase significantly: the top 1 percent share for Mexico goes up from less than 13 percent to more than 19 percent, while the top decile share increases from 40 percent to 62 percent. As Table 7 illustrates, there are sizeable adjustments for all high inequality countries like India, Brazil and South Africa. The adjustments are substantial, but less, for urban Indonesia and Russia. For Germany and China where the gap between NA and HS is almost non-existent, the unadjusted and adjusted Ginis, as well as the top shares, are the same.

When we compare the adjusted Ginis and top shares obtained here with independent detailed country estimates that combine survey and tax data, and use similar definitions of income (disposable income) and recipients (persons) as here, the differences in the estimates are small. For the United States, our adjusted Gini almost exactly matches the similar estimate for the US inequality obtained by Korinek *et al.* (2005) when they account for non-compliance (refusal to participate in surveys) and income underreporting: Korinek *et al.* (2005) find that the US Gini goes up by almost 5 points; we find here the increase of 6 Gini points. Our US adjusted Gini is slightly higher (and the adjusted top 1 percent slightly lower) than the corresponding survey-cum-fiscal estimates made by the US Congressional Budget Office (2014). Similar estimates that combine survey and fiscal data for the UK also give results very close to our adjusted values. It is only for China and Russia where the closest comparable estimates cover only the adult population and include the (very roughly) imputed value of undistributed corporate profits that the top 1 percent shares exceed significantly the ones we obtain here. The reason for this seems to be the following: information on company ownership and thus on the part of corporate profit that belongs to various individuals is either unavailable or cannot be linked to individual fiscal data. The authors of studies on Russia and China then assume that unobserved ownership of undistributed profits mimics ownership of observed capital income which may, at times, be an unwarranted assumption.

When we perform the adjustment, although it relates only to the top ten percentiles of each country, the changes affect many parts of the global income distribution. Consider, for example, the adjustment for Mexico. Its top ten percentiles, using unadjusted data, span the range from the 79th to the 100th global percentile (the Mexican top 1 percent is part of the global top 1 percent). As their incomes are increased, they will tend to move to higher or lower global percentiles (depending also on what happens to other countries' top ten percentiles) and that movement, and the implicit reranking, will affect mean incomes of global percentiles. Because the upward income adjustment in the case of Mexico is very significant, its top ten percentiles now span the range from the 93rd to the 100th global percentile. In other words, people who are around the top decile threshold in Mexico (national percentile 91) are no longer estimated to be at the level of the global 79th percentile but at the global 93rd percentile. Conversely, for Sweden, where the adjustment was zero, some of its top percentiles will slide in global ranking (from 99th to 98th

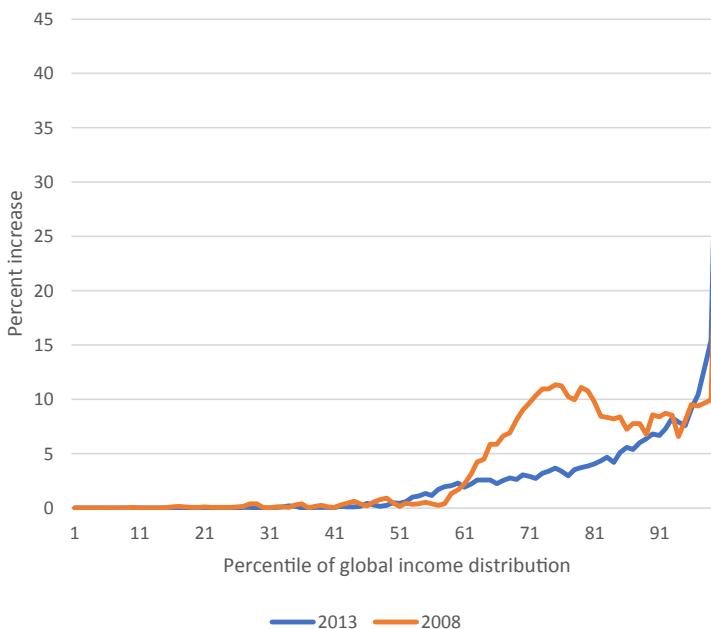


Figure 4. Income Change (in Percent), at Different Percentiles of the Global Income Distribution, Due to the Adjustment for Underestimation of the Tops of National Income Distributions

Note: The graph shows how much income of a given percentile of global income distribution is changed when an adjustment (described in the text) for the underestimation of the top 10 percent of national income distribution is conducted. People who are in a given global percentile before and after the adjustment are not necessarily the same because the adjustment affects rankings. [Colour figure can be viewed at wileyonlinelibrary.com]

global percentile). What is important to emphasize is that *national* top adjustments will have implications not only for the top of the global income distribution but for different parts of the *global* distribution, including even low or middle global percentiles. In other words, global reranking due to national top income adjustments may be significant.

Figure 4 shows the changes at the global level caused by the adjustment. The overall global income increases, on account of adjustment, by 11 percent in 2008 and 6 percent in 2013. As can be seen, the effects span the entire distribution but unevenly: for low global percentiles, as expected, the adjustments are practically non-existent, often less than 1 percent. When they are positive it is due to some top percentiles of poor African countries “escaping” from these low global percentiles upwards, and the new country/percentiles “falling” into those low global percentiles being richer than the “escapees” were originally. The effects around the 70th–80th global percentile are more important: an increase of around 5 percent and even 10 percent. In 2008, a large increase in that portion of the global income distribution is almost entirely due to the upward readjustment of the Indian top ten percentiles. For the very top of the global income distribution, the adjustment gains are, as expected, quite significant: income of the percentile 99 increases by 10 percent in 2008 and 15 percent in 2013, while the global top 1 percent gains 33 percent in 2008 and even 42 percent in 2013.

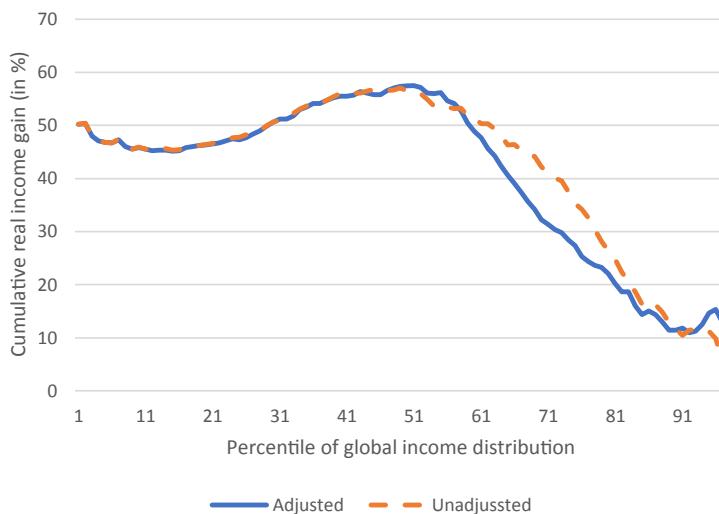


Figure 5. Global Growth Incidence Curve with National Top Income Adjustments and Without Adjustments (Cumulative Growth 2008–13, in Percent, in International Dollars; Full Anonymous Sample)

Note: This is a comparison of global income-adjusted and non-adjusted (reported) global GICs, both based on the full sample of countries. The unadjusted GGIC is the same as shown in Figure 2a. [Colour figure can be viewed at wileyonlinelibrary.com]

What happens to the new GGIC will, therefore, depend on how global distributions are affected by the adjustments in both 2008 and 2013. Figure 5 shows the new adjusted global growth incidence curve against the unadjusted GGIC. Income gains up to the 60th percentile are the same. The global median growth, for example, is 57 percent whether we use adjusted or unadjusted data. After approximately the 60th global percentile, the adjusted GGIC shows smaller gains which however reverse for the global top 5 percent that, according to the adjusted data, appear to have gained more than without the adjustment. Note that this means that our adjustment of top national incomes has been more “pro-rich” in 2013 than in 2008.

The “adjusted” curve continues to display its distinct “inverted U” shape that was found for the period 1988–2008 by Milanovic (2012) and Lakner and Milanovic (2016). However, the gains of the top compared to the highest gains which are still registered around the median of the global income distribution are much less than in the 1988–2008 period. In that period, the average annual per capita real growth of the global top 1 percent was very close to the growth of the median (2.5 percent vs. 2.8 percent; Lakner and Milanovic, 2016, Table 3, p. 216). This is what gave to the curve its upward trunk-like tick for highest incomes. Here, even after the top adjustment, the average annual growth of the global top 1 percent (2.5 percent) remains significantly below the growth of the median (9.4 percent), and even below the growth rate of the mean (3.3 percent). This implies a diminished share of the global top 1 percent even with the adjusted data.

The adjustment brings two important messages: first, the “correction” of national tops affects not only the top of the global income distribution but the entire distribution; second, it more than doubles the estimate of the *global* top 1

TABLE 8
INCOME GROWTH AT DIFFERENT PARTS OF THE GLOBAL INCOME DISTRIBUTION AND MEASURES OF
INEQUALITY

Unadjusted National Household Survey Data								Top-Adjusted National Surveys	
Full Sample; Anonymous, PPP Dollars				Balanced Sample, Anonymous, Nominal US Dollars		Quasi Non- Anonymous; PPP Dollars		Full Sample; Anonymous, PPP Dollars	
	2008	2013		2008	2013		2008	2013	
Income shares (in %)									
Bottom 20 percent	1.6	2.0	0.6	0.9	1.6	2.1	1.5	1.8	
Bottom half	8.4	10.4	3.7	5.3	8.4	11.1	7.6	9.7	
Top 5 percent	35.5	31.6	44.7	41.0	35.5	30.3	37.8	36.3	
Top 1 percent	13.2	11.4	16.4	15.0	13.2	11.1	15.7	15.0	
Inequality									
Gini	66.4	61.6	77.5	72.7	66.4	60.3	68.2	64.2	
Theil (0)	91.0	75.9	149.0	120.8	90.8	71.0	97.8	83.0	

percent's income growth from 6 percent to 13 percent over the 5-year period, but still fails to bring it close to the growth rate of the median.

How do various ways of looking at the global distribution of income affect our results? Table 8 gives shares of the top 1 and top 10 percent, and two synthetic measures of inequality (Gini and Theil (0)) for each of the four different ways of assessing global income distribution. Here are some conclusions:

1. The bottom quintile and the bottom half of the income distribution have gained income shares under all scenarios.
2. The top 5 percent and the top 1 percent have lost income shares under all scenarios. The loss of the top 1 percent share is the least (only 0.7 percentage points) when we adjust for top income underestimation. In other cases, the loss ranges between 1.4 and 1.9 percentage points. However, even in the most favorable case for the very rich, top 1 growth at best parallels mean income growth (a condition needed to keep the share constant) but falls way behind the growth around the global median. This however was not the case in the 1988–2008 period. There is, therefore, a perceptible slowdown in the growth of highest incomes. The global financial crisis that hit the rich countries much more than the rest of the world is the main reason behind the slowdown.
3. The Gini and the Theil indices decreased in all cases, and the differences between the scenarios are not very substantial. The global Gini in PPP dollar terms is in 2013 between 61 and 64 points, higher than in any individual country, save South Africa, but below its 2008 level by between 4 or 5 points.

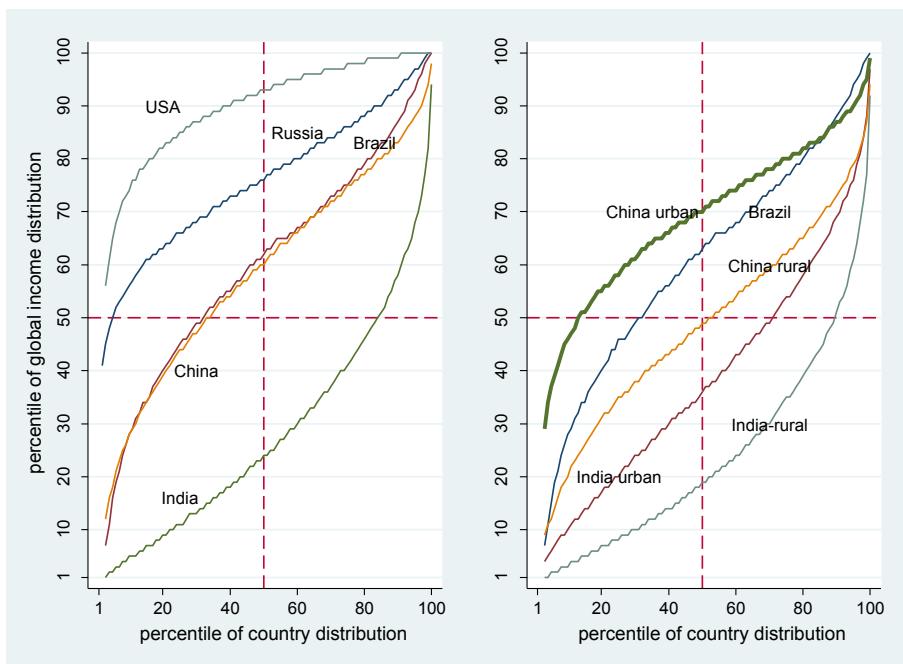


Figure 6. Position of National Income Percentiles in the Global Distribution, 2013

Note: the graph contrasts the percentile positions of a given group in national and global income distributions. For example, the fiftieth US percentile (US median; on the horizontal axis, left panel) is relatively rich in global terms and is located at the 93rd global percentile (vertical axis). The opposite is true for India. All amounts used to rank the percentiles are in PPP dollars. The data are for benchmark year 2013. [Colour figure can be viewed at wileyonlinelibrary.com]

6. SELECTED NATIONAL PERCENTILES: THEIR GLOBAL POSITION AND GROWTH BETWEEN 2008 AND 2013

6.1. Global Position of Some Country/Percentiles

Global income distribution data allows us to do a number of important calculations. One of their advantages is that they let us place individual countries' distributions in their global context. Figure 6 shows one such comparison where national income percentiles are displayed along the horizontal axis, and their position in the global income distribution is shown on the vertical axis. This is almost equivalent to testing for the first-order stochastic dominance except that it is done not by comparing incomes directly but indirectly through the global percentile position to which a given income level corresponds. (Note however that the ordinal comparison is a blunter instrument than the strict first-order stochastic dominance because two somewhat different incomes can be placed in the same global percentile; one may reject first-order dominance by looking at ordinal comparisons while accepting it cardinally.)

A person at the median income level in the United States ($x = 50$) has an income level that places him/her at the 93rd global income percentile (Figure 6, left panel). Even the poorest Americans (from the third poorest US percentile) have, as the figure shows, an income that puts them above the global median (i.e., above $y = 50$). We also note that Russia dominates, at any income percentile except

the very top, Brazil and China, and also that latter two countries are practically undistinguishable all the way to the national 80th percentile, after which Brazilians are richer than the Chinese. In other words, the top quintile of the Brazilians are richer than the equivalent top quintile of the Chinese. Indians are poorer, at any point of national distributions, than the equivalently placed people in other countries shown here; however at the very top of the income distribution, the richest 1 percent of Indians are at the (very high) 94th global percentile. Similar graphs can be constructed using any group among more than 130 countries included in 2013.

Another way to look at the world is to compare median incomes. This is a comparison which is arguably more meaningful than the comparison of average incomes. The comparison of medians however can only be done if we have access to full national distributions. For example, disposable per capita income at the US median is \$PPP 18,200 per year; a person at the equivalent Chinese urban median has \$PPP 5,400, and a person at the Indian urban median has only \$PPP 1,600. Therefore, the ratio between US (de facto urban since most of the US population lives in urban areas) and Chinese urban incomes is, at the median point, more than 3 to 1, and is almost 12 to 1 with respect to urban India.

Similarly, we can look at the average income of the Chinese urban top 1 percent: it is equal to the average income of the Americans situated at the 85th national percentile. Thus the richest urban Chinese have, on average, the standard of living of the American upper middle class.

Obviously, similar calculations can be made for the lower ends of national income distributions. Thus, more than 70 percent of the Malagasy population lives on an income lower than the World Bank global poverty line of \$PPP 1.9 per day (not shown here). But even the poorest people in Denmark have an income that is three times higher than that; moreover their income would place the poorest people in Denmark at the 98th (sic) percentile of Madagascar's income distribution. We thus get a much greater insight into the enormity of income gaps that exist between nations and between income groups worldwide. Very often, as in the previous example, the poorest West Europeans or Americans would, if placed in an African income distribution, be among the top percentiles.

Decomposing populations of very large countries like India, China and Indonesia into their urban and rural parts is important for two reasons: first, these populations often enjoy substantially different standards of living even when the PPP exchange rates used for rural population are lower than those used for the urban population (and thus adjust for the differential in the price level), and second, we are dealing there with large numbers of people representing an important share of the world population (the three countries together include almost 2.9 billion people or 43 percent of the total population included in 2013). It is thus helpful to present a more finely grained picture than that of national percentiles.

Figure 6 (right panel) shows the position of urban and rural parts of India and China together with Brazil (as a whole country) displayed for comparative purposes. We note that incomes in urban China are higher than in Brazil throughout most of income distribution and that only after the 89th percentile Brazilian incomes become higher. China urban and China rural are almost two different countries: not only is a person at a given urban percentile always better off than a person at an equivalent rural percentile, but that difference (as we can see from

TABLE 9
GLOBAL POSITIONS OF VARIOUS NATIONAL (RURAL AND URBAN) INCOME PERCENTILES

	Brazil	China Urban	China Rural	India Urban	India Rural	Indonesia Urban	Indonesia Rural	USA
10th percentile	28	46	20	10	3	22	16	76
Median	63	70	52	36	19	44	32	93
75th percentile	77	80	62	54	35	61	44	98
90th percentile	88	87	73	69	51	74	55	100
Top 1 percent	100	99	94	97	92	97	85	100
Heterogeneity of the bottom (the median to bottom 10%)	35	24	32	16	16	22	16	17
Heterogeneity of the rich (90th percentile to the median)	25	17	21	33	32	30	23	7

Notes “Heterogeneity of the bottom” shows the gap between the global ordinal position of the median and 10th percentile. “Heterogeneity of the rich” shows the gap between the global ordinal position of the 90th percentile and the median.

Table 9) is particularly large among the poor. A person at the 10th urban percentile is 26 global percentage points better off than a person at the 10th rural percentile and is more similar, in her income level, to the person who is at the rural median. Nevertheless China's rural distribution does dominate the Indian *urban* distribution until the very high parts of the distribution, and not surprisingly, is first-order dominant over the Indian rural population. Chinese rural incomes exceed Indian rural incomes by a ratio of between 2 and 4 at all income percentiles except the top 5 percent where the ratio is less than 2. The gap is the least at the top 1 percent level where Chinese incomes are only 24 percent higher than Indian.

Table 9 allows us to look at what may be termed heterogeneities within the lower and upper parts of national income distributions (measured, respectively, by the distance in global percentile points between the national median and the national bottom tenth percentile, and the national median and the national 90th percentile). Brazil stands out by the heterogeneity in the bottom of its distribution such that the median of its income distribution is much higher than the tenth percentile; rural China comes close second. What this statistic reveals in effect is extreme poverty of the lowest parts of the income distributions in rural China and Brazil.

When it comes to the heterogeneity among the rich, India (both urban and rural) and urban Indonesia stand apart from the others: the high ends of their distributions (90th percentile) is significantly richer than the median. In effect, the gap of over 30 global percentile points represents a gap of almost 2 billion people. In other words, if everybody in the world were ranked according to their per capita real income there would be some 2 billion people between a relatively rich person at the 90th percentile in urban India (or urban Indonesia) and a person at their respective areas' medians.

Differently, the US, on account of its high income throughout, stands at the other extreme: the gap among the people in the upper part of the US income distribution is, in global ordinal terms, small because even those at the US median income are at a high worldwide position. The ordinal difference between the US 90th and 100th percentiles is non-existent reflecting the fact that the 11 highest US percentiles are all in the global top 1 percent. Now, incomes of the people who are in the top American decile obviously differ. Yet the fact that they all "inhabit" the same global percentile probably has implications for their consumption patterns, interests, and how they perceive themselves and the rest of the world. Global positioning, while not researched (not least because of lack of adequate data) is unlikely to be irrelevant, especially in an era of globalization.

6.2. Slowdown of Western Growth

We have already mentioned the difference of national growth experiences during the period under study here. Figure 7 shows national GICs for China, India, US and Germany with cumulative growth rates over the period 2008–13. The bottom Chinese income percentiles have seen their real income more than double while the richest percentiles gained about 80 percent. The growth has thus been broadly pro-poor. Indian growth has on the contrary been pro-rich, with low incomes growing at 50 percent–55 percent and top incomes at more than 70 percent. American growth was much slower throughout with most of

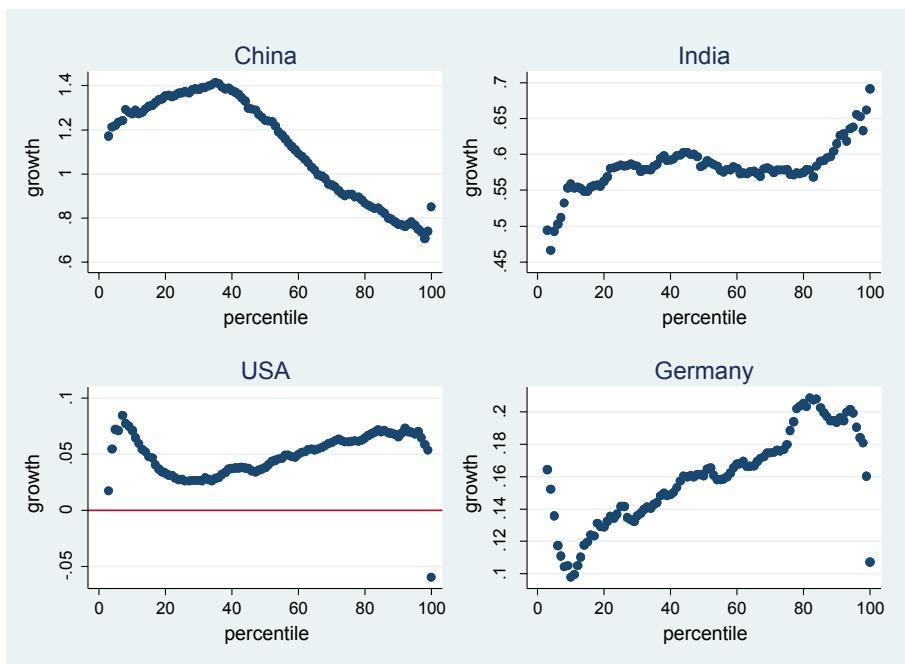


Figure 7. National Growth Incidence Curves, 2008–13

Note: The vertical axis show cumulative income growth between 2008 and 2013. Value of 0.05 is 5% growth. The scales of the four graphs are different to better highlight growth rates of the countries. [Colour figure can be viewed at wileyonlinelibrary.com]

the population gaining about 5 percent, and the top 1 percent losing 5 percent. Finally, German growth was pro-rich up to the 80th percentile, with gains ranging between 10 percent and 20 percent; at the very top though, like in the United States, growth was much less (although still positive). Even the most successful percentiles in the US and Germany have grown at slower rates than the least successful percentiles in India and China. It is these broad-based large differences in real growth that are the main engine behind the reduction of global inequality discussed in Sections 2 and 3.

7. CONCLUSIONS

The global financial crisis and the recession that followed were a huge shock to the system that existed roughly from the mid-1980s to 2008. But the effects of the crisis were uneven, both across countries and income groups. The Global Recession was much stronger in the rich countries than in the “emerging” Asia and this fact was sufficient to make global income inequality continue on its downward trajectory on which it was since the turn of the century. Moreover, it even accelerated it as both India and China continued to grow strongly and within-national inequalities in most countries were quiescent. However, unlike during the previous two decades, the slowdown in the rich world (and no perceptible increase of inequality in these countries) affected income growth of the global top 1 percent

which still continues to be populated mostly by the richest people from the rich countries. Unlike in the case of the “elephant chart” (Lakner and Milanovic, 2016) that very vividly caught the evolution of the global distribution between 1988 and 2008, and where both the plutocratic top of the distribution and the “new Asian middle class” grew at approximately the same rates, in the period 2008–2013, the top of the global income distribution grew cumulatively by only about 10 percent in real terms versus more than 50 percent for the middle of the global income distribution. Even when we adjust highest national incomes for the likely underestimation, the growth of the top of the global pyramid increases to about 12–13 percent which is still far below the growth of the middle. The crisis thus did represent a break in the trend for the growth of the top of global income distribution, and this pertains not only to the top 1 percent but more broadly to the top 5 percent or even to the top decile. This was one of the major effects of the global financial crisis: it arrested the exceptionally fast income growth of the richest people in the world. But it did not perceptibly affect convergence of mean country incomes, nor did it improve the relative position of Western middle classes whose income growth continued to be sluggish and to lag behind the world median.

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Supplementary Material

Annex 1. Data sources (number of surveys) used to create global income distributions in 2008 and 2013

Annex 2. The distribution of absolute income gains between 2008 and 2013

Figure A1. Absolute increase of per capita income between 2008 and 2013 (in PPP dollars) at different points of the global income distribution; full sample; unbalanced panel