Global Income Distribution: From the Fall of the Berlin Wall to the Great Recession

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We present an improved panel database of national household surveys between 1988 and 2008. In 2008, the global Gini index is around 70.5%, having declined by approximately 2 Gini points. China graduated from the bottom ranks, changing a twin-peaked global income distribution to a single-peaked one and creating an important global "median" class. 90% of the fastest growing country-deciles are from Asia, while almost 90% of the worst performers are from mature economies. Another "winner" was the global top 1%. Hence the global growth incidence curve has a distinct supine S shape, with gains highest around the median and top. JEL codes: D31

This paper provides new evidence on the evolution of global interpersonal income inequality between 1988 and 2008. We measure inequality among all individuals in the world irrespective of their country of residency thus implicitly assuming a "cosmopolitan" social welfare function (Atkinson and Brandolini 2010) and translating the concern for within-country inequality to the global level (Pogge 2002; Singer 2002). Over this period, the face of globalization changed dramatically with the end of the Soviet Union and the integration of many developing countries into the world economy. Our analysis of global

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interpersonal inequality captures the effects of these tectonic shifts on both within- and between-country inequality.

We find that the inequality in the global income distribution, as measured for example by a Gini index, is high (compared with within-country inequality) and does not change substantially over this period. However, this hides reranking of country-deciles as some have grown much faster than others over this period. Because our data set is a panel of country-deciles, we can directly compare the growth of say, the top 10% in urban China with that of the bottom 10% in the United States. We can thus go beyond country-level analyses and take changes in within-country inequality into account. For example, for the global interpersonal income distribution it matters both that the growth in China has been exceptionally high but also that this growth has been faster at the top of the Chinese distribution.

This paper offers three main contributions to the study of global income inequality (see the reviews by Anand and Segal [2008, 2014] for a very comprehensive summary of the literature on this topic). First, we compile a new and improved database of national household surveys in response to criticism of earlier data sets. An important part of the literature on global inequality anchors income distribution data to national accounts, typically to GDP per capita. However, we argue, following Anand and Segal (2008), that household surveys are the appropriate source of information if one is interested in comparing the (disposable) income of the world's citizens. Second, this allows us to present more credible results on the level of global interpersonal income inequality between 1988 and 2008. Third, we create balanced and unbalanced panels of country-deciles for five benchmark years (in five-year intervals). Hence we can go further than the statements about which countries affected global inequality, by looking into a more disaggregated distribution of country-deciles. We can identify those country-deciles that have gained and lost most over this 20-year period, and most importantly, we derive global growth incidence curves (GICs) showing which parts of the global distribution benefited the most (and the least) during globalization. This allows us to put empirical content to the often discussed questions of the emergence of the "global middle class" or income gains of the global top 1%.

Our interest in global interpersonal inequality is founded upon a concern for individual well-being, which treats persons the same irrespective of their country of residence.[1] This cosmopolitan view is not shared by everyone and

1. Milanovic (2005) distinguishes between three concepts of global inequality. First, unweighted international inequality is the inequality in per capita incomes amongst the countries in the world. Second, population-weighted international inequality or between-country inequality (Anand and Segal 2008) measures inequality among persons by assigning everybody the per capita income of his place of residence. It thus ignores any within-country inequality. Third, global interpersonal inequality captures the inequality of individual incomes. Anand and Segal (2008) add concept zero, which is the inequality in total (rather than per capita) income among countries. In this paper we focus on global interpersonal inequality throughout.

there exists a large philosophical literature on this issue (e.g., Nagel 2005). However, it is important to recognize the increasing role played by international organizations, and that the cosmopolitan view is the only one consistent with their constitutions. One might also have an instrumental concern for global interpersonal inequality if extreme global inequality leads to increased international tension, conflict or large scale migration. Furthermore, changes in global inequality capture some of the effects of globalization (Anand and Segal 2008). Globalization supported fast economic growth in many populous developing countries (mainly in Asia), thus reducing between-country inequality. At the same time, it is blamed for increasing inequalities within both rich (Autor et al. 2013) and poor (Goldberg and Pavcnik 2007) countries. Global interpersonal inequality captures both these effects in a unified framework.

Measuring global inequality empirically is substantially more difficult compared with within-country inequality. In the absence of a global household survey, we need to resort to combining national surveys. Our database includes 565 household surveys across five benchmark years and each country-year observation is represented by the average income of 10 income decile groups.[2] National surveys collect information in terms of local currencies, which we convert into a common currency using within-country inflation to correct for changes in the price level over time, expressing first everything in constant 2005 local currency units, and then using the 2005 purchasing power parity (PPP) exchange rates to adjust for cost of living differences across countries.[3,4] In constructing our global distribution we mix income and consumption surveys. We refer to them interchangeably, as is customary in this literature, although we are obviously fully aware of the important differences between the two concepts. However, we improve on earlier approaches by keeping the type of survey (income or consumption) constant over time for a particular country.

The remainder of this paper is structured in four parts. Section II summarizes our data construction and methodology. Section III provides summary statistics on our database and presents the main results regarding global inequality. We report a number of different inequality measures and derive global and regional GICs. Section IV moves from a cross-sectional focus to a panel analysis. Therefore, it lets us track the movement of individual country-deciles in the

2. Each decile is weighted by its population, so we measure interpersonal global income inequality where each individual is assigned the income of his or her income decile. Population data are taken from the World Development Indicators (WDI).

3. Analyses of national income inequality are often done on nominal incomes, thus assuming a common national price level. We follow these national studies by ignoring differences in the price level within countries (except for the case of China, India, and Indonesia where we allow for rural-urban price differentials).

4. As we discuss in more detail below, our main results use the 2005 PPP exchange rates. We present robustness checks for the recently published 2011 PPP exchange rates in the appendix.

global distribution, and highlights what parts of the initial (1988) distribution gained most and least during the next 20 years. Section V presents conclusions. We report a number of robustness checks in the appendix.

I. Data Construction and Methodology

Data Sources

The data used in this paper consist of country-year average decile income/consumption covering the period 1988 to 2008: this means average per capita income (the term is used interchangeably for income and consumption) for a given decile in country i and year t. The data come from a number of sources. PovcalNet is the starting point of our database, contributing more than two-thirds of the surveys.[5] PovcalNet is the compilation of a large number of household surveys stored by the World Bank research department. It has been mostly used to compute estimates of world poverty, as in Chen and Ravallion (2010), and thus lacks data on rich countries. Recently, Ravallion (2014a) has used these data to estimate the overall inequality in the *developing* world. From PovcalNet we obtain average per capita incomes, already converted in 2005 $PPPs, and decile shares, which we combine to compute decile average incomes.[6] Next, we merge it with the updated World Income Distribution (WYD) data (Milanovic 2012). PovcalNet and WYD provide almost 98% of all data. We convert these data into country-year deciles in order to obtain a consistent database.[7] Where possible we fill remaining gaps with data from the Luxembourg Income Study (LIS), the British Household Panel Survey (BHPS), the European Union Survey of Income and Living Conditions (SILC), and data from country statistical offices.[8] Overall we end up with 565 surveys across the five benchmark years 1988, 1993, 1998, 2003, and 2008 (table 1).

A recent literature using data from tax records has argued that the incomes of the very rich are understated in household surveys (Atkinson, Piketty, and Saez 2011). This could arise because the rich are less likely to participate in surveys (Groves and Couper 1998) and more likely to underestimate their own income,

5. PovcalNet is the on-line tool for poverty measurement developed by the Development Research Group of the World Bank, http://iresearch.worldbank.org/PovcalNet. Data downloaded on July 29, 2012, which refers to the last PovcalNet update on February 28, 2012.

6. PovcalNet uses grouped data derived from household surveys to calculate these decile shares.

7. The vast majority of country-year observations are already in deciles or in equally spaced quantiles (e.g., ventiles), so they can be easily converted. In total 13 country-years were imputed by fitting a log-normal Lorenz curve using the "ungroup" command included in the DASP Package (Abdelkrim and Duclos 2007). This procedure implements the Shorrocks and Wan (2008) adjustment thus ensuring that the fitted Lorenz curve matches the original points.

8. The sources for the final database (country-years in parentheses) are: PovcalNet (379), WYD (173), LIS (8), SILC (2), and one survey each from BHPS (Bardasi et al. 2012), Statistics Finland, and Statistics Portugal.

TABLE 1. Summary Statistics

	Benchmark year					
	1988	1993	1998	2003	2008	Mean
Number of surveys	75	115	121	133	121	565[a]
A. Years between survey year and benchmark year (%, by benchmark year)						
−2	12.0	9.6	9.1	7.5	7.4	9.1
−1	26.7	18.3	14.9	18.8	11.6	18.0
0	29.3	34.8	41.3	30.1	65.3	40.2
1	18.7	20.9	18.2	21.1	11.6	18.1
2	13.3	16.5	16.5	22.6	4.1	14.6
Total	100.0	100.0	100.0	100.0	100.0	100.0
Within +/−1 of benchmark	74.7	73.9	74.4	69.9	88.4	76.3
B. Income vs. Consumption surveys (%, by benchmark year)						
Consumption	33.3	46.1	48.8	57.1	55.4	48.1
Income	66.7	53.9	51.2	42.9	44.6	51.9
C. GDP (% of regional GDP represented in the database)						
World	90.6	97.0	96.5	95.9	93.0	94.6
Mature economies	95.7	99.9	99.8	98.4	96.9	98.1
China	100.0	100.0	100.0	100.0	100.0	100.0
India	100.0	100.0	100.0	100.0	100.0	100.0
Other Asia	90.5	96.1	98.0	97.3	97.1	95.8
Middle East and North Africa	52.1	55.4	45.4	48.5	22.3	44.7
Sub-Saharan Africa	21.9	82.9	78.3	81.8	77.4	68.5
Latin America and Caribbean	94.8	98.3	99.0	98.9	98.4	97.9
Russia, Central Asia, South-East Europe	50.7	94.2	94.3	100.0	90.8	86.0
D. Population (% of regional population represented in the database)						
World	81.1	92.3	91.9	93.6	90.6	89.9
Mature economies	95.0	99.9	99.6	96.7	97.0	97.6
China	100.0	100.0	100.0	100.0	100.0	100.0
India	100.0	100.0	100.0	100.0	100.0	100.0
Other Asia	74.6	85.4	88.7	88.7	88.7	85.2
Middle East and North Africa	60.4	69.5	63.6	68.4	47.8	61.9
Sub-Saharan Africa	28.5	72.9	68.0	80.2	74.1	64.7
Latin America and Caribbean	88.2	92.9	94.9	96.4	94.4	93.4
Russia, Central Asia, South-East Europe	28.4	87.4	87.4	99.4	84.4	77.4

[a] Showing the total number of surveys.

Note: The last column is the (unweighted) average over the five benchmark years.

Source: Authors' analysis based on data described in the text.

because the sample size of a standard household survey is too small to pick up these incomes, or because extreme incomes in the survey data are top-coded or eliminated as outliers. This evidence suggests that our estimates of global inequality are likely to be downward-biased. The tax record data, particularly among the developing countries, are too rare to be useful for a comprehensive adjustment for missing top incomes at a global level. In a longer version of this paper (Lakner and Milanovic 2013), we have used the gap between national accounts consumption and household survey income as a (very rough) proxy for the extent of top income underreporting.[9] We discuss these results in more detail below and report a summary in the appendix.

Each country's distribution is represented by the average incomes of the 10 deciles. This is not dissimilar from other studies in the literature such as Bourguignon and Morrisson (2002) who use 11 quantiles. This ignores any within-decile inequality, thus, as argued by Anand and Segal (2008), understating within-country inequality and perhaps global inequality. Our choice of deciles was dictated by PovcalNet, where more detailed information is unavailable. Because of consistency and ease of discussion, we decided to use deciles also in those surveys where more detailed information was available.

The surveys included in the database need to meet two conditions: First, they need to be within two years of a benchmark year. Second, they need to be at least three and no more than seven years from the previous and next survey. The rationale of the second condition is not to allow surveys that are either too close or too far apart from the "ideal" interval of five years since a lot of the analysis is based on the assumption that five-year intervals hold throughout the sample. Table 1 shows the years between the survey year and the benchmark year. Our first benchmark year is 1988 because survey coverage is very poor prior to that.

We use a mix of income and consumption surveys. Although there are obviously important differences between the distributions of income and consumption, we do not adjust for them because any such adjustment, applied to deciles, would be arbitrary.[10]

One of the innovations of our database is that we restrict the welfare concept to be the same over time for a given country. This avoids any spurious changes arising from a change in the welfare concept being used. For each country, income or consumption was chosen so as to maximize the number of benchmark years covered (subject to the two conditions mentioned before). As table 1 shows, in the overall sample the number of consumption and income surveys is

9. Anand and Segal (2014) follow a different approach to adjust for missing top incomes in the global distribution. They use the top 1% income share from the World Top Incomes Database (Alvaredo et al. 2013) where available (around 18–23 countries per year). For the remaining countries, they impute the top income share from a cross-country regression. Pinkovskiy (2013) estimates nonparametric bounds on the global Atkinson index allowing for any country-level income distribution given fractile shares and a Gini index. With a sufficiently high nonresponse at the top, the direction of change of global welfare between 1970 and 2006 becomes ambiguous.

10. Inequality tends to be lower when measured by consumption than by income (Deininger and Squire 1996), and (at least in the US) has increased by less in consumption-terms (Fisher, Johnson, and Smeeding 2013). In the full PovcalNet data (not the sample used in this paper), the average Gini index of consumption surveys (38%) is approximately 10 Gini points lower than the average Gini over the income surveys (48.4%). This is more than the Gini adjustment proposed by Li, Squire, and Zou (1998) of 6.6 Gini points.

TABLE 2. Panel Summary Statistics: Number of Countries by Panel Duration

Regions	Total	Number of benchmark years 1	2	3	4	5	Number of countries with data in . . . 1988 and 2008	1993 and 2008
World	162	22	24	27	31	58	63	90
Mature economies	39	0	2	2	10	25	29	34
China	2	0	0	0	0	2	2	2
India	2	0	0	0	0	2	2	2
Other Asia	19	2	5	1	3	8	8	11
Middle East and North Africa	11	4	1	1	3	2	2	3
Sub-Saharan Africa	43	11	9	14	5	4	4	16
Latin America and Caribbean	26	4	3	0	5	14	15	17
Russia, Central Asia, South-East Europe	20	1	4	9	5	1	1	5

Note: The last two columns allow for gaps in the panel.
Source: Authors' analysis based on data described in the text.

almost equal. In earlier years, the majority of surveys collected information on income, whereas in recent years the reverse is true. This can be explained by the improved survey coverage of poor countries where consumption surveys are more common.[11]

We are also interested in changes of a given country-decile over time. Hence, the panel dimension of our data is crucial. Table 2 shows how many countries' surveys are available for all five benchmark years, 4, 3, and so forth. For example, for 58 countries (out of a total of 162), mostly mature economies and Latin American countries, we have the complete panel; for 31 countries, we have data for four benchmark years and so forth. We can look at the changes between 1988 and 2008 for 63 countries, although, as a robustness check, we also consider the period 1993 to 2008, for which the regional coverage of Sub-Saharan Africa and Russia/Central Asia/South-East Europe improves considerably.

Welfare Concept

We are interested in analysing the global distribution of (annual) per capita income (in constant 2005 $PPP). Per capita incomes ignore any economies of scale in household consumption and within-household inequality. However, they have the advantage that they are simple to compute and have natural counterparts

11. In China, India, and Middle East/North Africa, our database only uses consumption surveys (with the exception of All-China where income surveys are used). In Sub-Saharan Africa 98% of surveys are consumption surveys. In other Asia, 91% are consumption surveys. On the other hand, in the mature economies and Latin America, 97% and 96%, respectively, are income surveys.

in the national accounts (which do not compute equivalized incomes). The effect of using a different equivalence scale on world inequality is not clear a priori.[12]

We use PPP exchange rates to account for price differences across countries. Market exchange rates would understate the real standard of living in poor countries, thus overstating global inequality (Anand and Segal 2008). Because we are dealing with household income or consumption, we use the PPP exchange rates for private consumption rather than the GDP conversion factors. In our baseline results, we use the 2005 PPP exchange rates, which are more robust than earlier rounds (Anand and Segal 2008; Deaton and Heston 2010; Ravallion 2010; Ackland, Dowrick, and Freyens 2013).[13] Recently, a new set of PPP exchange rates have been released, which allow international price comparisons in 2011. There is an ongoing debate over the reliability of these new exchange rates (Deaton and Aten 2014; Ravallion 2014b).[14] Furthermore, it makes sense to express the welfare aggregate in 2005 prices because this lies inside our period of investigation.

Incomes obtained from PovcalNet are already converted to 2005 PPP dollars. For the additional surveys we replicate the approach in PovcalNet: after accounting for currency conversions,[15] we convert incomes into local currency units in 2005 prices using domestic consumer price indices (CPIs). Then, we apply the 2005 PPP consumption exchange rates to convert into international dollars. Therefore, we compare prices across countries only once and rely on domestic consumer price inflation for the within-country and across-time comparisons.

PPP exchange rates only exist at the country-level, so we ignore any price differences that exist within countries. As a result we probably overstate within-country inequality. We treat the rural and urban areas of the three most populous developing countries, China, India, and Indonesia as separate "countries" and allow for different PPP exchange rates.

12. In their study of the LIS data, Atkinson, Rainwater, and Smeeding (1995) find that the inequality of per capita household income is greater than the inequality of household income adjusted by a square root equivalence scale. The precise effect on cross-country comparisons of inequality depends on the joint distribution of family size and income as well as on the precise equivalence scales being used.

13. First, the 2005 round had the largest global coverage to date, including China for the first time and India for the first time since 1985. Second, the 2005 PPP exchange rates are computed according to the Elteto and Köves (1964) and Szulc (1964) (EKS) index, whereas the Penn World Tables and earlier estimates by the World Bank use the Geary-Khamis (GK) method (Khamis 1972). The GK index is subject to the Gerschenkron (1947) effect (or substitution bias) which says that a country's consumption is overvalued when evaluated at the prices of another country. The EKS index does not suffer from this bias because it averages the consumption weights from both countries, making "a compromise that is arguably the best that can be done in the circumstances" (Deaton and Heston 2010, 11). Nevertheless, the 2005 PPP exchange rates are not without criticism. Urban bias in price collection has received particular attention in the case of China, where the 2005 ICP round led to a substantial upward revision of the previous price level (which had been mostly based on guesswork). We follow the approach by Chen and Ravallion (2010) of treating the official PPP rate as representative of urban China and using a downwardly adjusted PPP rate for rural China.

14. For example, the urban bias in the price collection is unclear, which is especially important in developing countries.

15. Currency conversions include changes in the currency being used, such as the formation of the Eurozone, and currency redenominations as often observed in high-inflation environments.

We have grouped countries into eight regions. The first group consists of "mature economies," which are the EU-27 countries (members in 2008) plus the high-income countries in the world.[16] We treat India and China as regions in their own right. The remaining groups are defined as residuals according to the geographic regions used in the World Development Indicators (WDI).

II. The Cross-Sectional Distribution over Time

Summary Statistics and Inequality Measures

Since we are interested in analyzing the world distribution of income, a first question to ask is how much of the world is represented by the surveys included in our database (table 1). Because high-income countries are more likely to have a survey that can be included in our data set, the coverage is higher when measured in terms of GDP than in terms of population. Our data represent 95% of world GDP on average and more than 90% in all benchmark years. On average (and in all years since 1993), our data also cover 90% of the world's population.

There are, however, substantial differences across regions. The coverage of Sub-Saharan Africa and Russia/Central Asia/SE Europe has improved markedly, in particular after 1988. Our coverage of the Middle East and Northern Africa regions declined, particularly in the most recent benchmark year and more so in terms of GDP than population.[17] In the latter part of the analysis we present a robustness check for the period from 1993 to 2008 because 1988 has such a poor coverage of Sub-Saharan Africa and Russia/Central Asia/SE Europe.

Table 3 presents our main results on the inequality in the global distribution of income calculated across the unbalanced panel of country-deciles. Compared with within-country distributions, global inequality, as measured by the Gini index, is very high: it ranges between 70.5% and 72.2%.[18,19] Changes between benchmark years have been around 0.5%, with the exception of the period 2003 to 2008, when the Gini decreased by 1.9% or 1.36 Gini points. Between 1988 and 2008, the global Gini fell by some 2.3% or 1.7 Gini points. This finding is

16. To be precise, the mature economies include EU-27, Australia, Bermuda, Canada, Hong Kong, Iceland, Israel, Japan, Korea, New Zealand, Norway, Singapore, Switzerland, Taiwan, and United States.

17. This appears to be driven by the dropping out of Iran and Tunisia in 2008, which together represent 26% of the region's GDP and 23% or the region's population in 2008. Coverage in this region remains low because we miss big countries such as Saudi Arabia or the United Arab Emirates, which account for 17% and 10% of regional GDP, respectively.

18. For example, the Gini indices at the country-level reported in PovcalNet (the full sample, not the sample used in this paper) range from 19.4% to 74.3%, with an average of 42.2%. Only Jamaica (70.81%) and Namibia (74.33%) have Gini coefficients exceeding 70%. This data set excludes rich countries, which tend to have lower inequality, so the average within-country Gini from PovcalNet is probably upward-biased.

19. The global Gini index is approximately 3 Gini points lower when using the 2011 PPP exchange rates, but the time trend remains very similar (table A.3).

TABLE 3. Global and Regional Inequality

	Benchmark year					1988–2008 change (%, pp)	1993–2008 change (%, pp)
	1988	1993	1998	2003	2008		
A. Global inequality (%)							
Gini index	72.2	71.9	71.5	71.9	70.5	−2.3	−2.0
GE(0) (Theil-L)	114.2	110.7	107.1	107.6	102.7	−10.1	−7.2
GE(1) (Theil-T)	102.2	102.4	102.8	104.9	100.3	−1.9	−2.1
GE(2)	173.7	179.2	193.0	204.3	201.4	15.9	12.4
Atkinson index A(2)	83.5	82.8	81.8	82.0	82.0	−1.9	−1.1
Atkinson index A(1)	68.1	67.0	65.7	65.9	64.2	−5.7	−4.1
Atkinson index A(0.5)	43.5	43.0	42.4	42.8	41.0	−5.7	−4.6
B. Regional Gini indices (%)							
Mature economies	38.2	38.9	39.1	38.8	41.9	9.7	7.9
China	32.0	35.5	38.5	41.8	42.7	33.5	20.6
India	31.1	30.1	31.4	32.4	33.1	6.3	9.9
Other Asia	44.5	44.3	46.6	41.8	45.0	1.1	1.6
M. East and N. Africa	41.8	42.0	43.5	39.4			
Sub-Saharan Africa		53.5	52.1	56.5	58.3		9.0
L. America and Caribbean	52.7	54.6	56.5	55.7	52.8	0.3	−3.3
Russia, C. Asia, SE Europe		48.3	40.1	41.8	41.9		−13.3
C. Decomposition by country: between-country contribution (%) (change is in percentage points)							
GE(0) between contribution	83.2	80.1	78.2	77.9	76.7	−6.5	−3.4
D. Average annual incomes per capita (in 2005 PPP-adjusted USD), by percentiles							
Bottom 10%	201	203	217	228	251	24.9	23.3
P40-P50	552	620	715	766	941	70.6	51.8
P50-P60	791	877	975	1045	1359	71.7	54.8
P60-P70	1323	1353	1538	1616	2089	57.9	54.5
P80-P90	7414	7158	7177	7097	7754	4.6	8.3
P90-P95	12960	13150	13472	14221	15113	16.6	14.9
P95-P99	21161	21452	22660	24474	26844	26.9	25.1
Top 1%	38964	39601	46583	51641	64213	64.8	62.1
E. Average annual incomes per capita (in 2005 PPP-adjusted USD), by region							
World	3295	3287	3471	3631	4097	24.3	24.6
Mature economies	11457	12272	13366	15019	15832	38.2	29.0
China	484	572	789	1018	1592	228.9	178.3
India	538	560	638	642	723	34.4	29.1
Other Asia	671	804	882	943	1129	68.3	40.4
M. East and N. Africa	1773	1875	1974	1762			
Sub-Saharan Africa		742	719	779	762		2.7
L. America and Caribbean	3153	2982	3188	3024	3901	23.7	30.8
Russia, C. Asia, SE Europe		2757	2298	2544	4464		61.9

Notes: For the decomposition by country, changes are in percentage points. For all other rows, changes are measured in percent. Observations are weighted by their population. Some cells are missing because of poor GDP or population coverage in particular benchmark years.

Source: Authors' analysis based on data described in the text.

robust to using a balanced sample of countries over this period (table A.1). For comparison, between 1988 and 2008 the Gini index increased by 3 Gini points in Germany and 6 points in the United States. As another yardstick, generating such a decline in the Gini would require everyone to give up 2.3% of income to a common pool which is shared equally.[20]

We could easily derive bootstrapped standard errors for the Gini index in order to account for sampling uncertainty (i.e., the fact that we have used a sample rather than the population). However, as Anand and Segal (2008) argue, these standard errors would not be appropriate because they assume that there exists a single global household survey with a clearly defined sampling uncertainty. In contrast, we have combined a large number of national household surveys, each of which has its own sampling uncertainty. As a result, plausible standard errors should probably be substantially bigger than the bootstrapped standard errors, making the observed changes insignificant.

Our estimates of the global Gini index are greater than many of the previous estimates in the literature (Anand and Segal 2008). The studies listed there differ fundamentally in their methodology, such as the use of national accounts aggregates as opposed to household surveys only, the type of PPP exchange rates, and the interpolation for missing years. Most of the difference, however, is due to these studies using the "old" 1993-based PPP exchange rates, which give substantially lower price levels for China, India, Indonesia, Bangladesh, and several other Asian countries, and hence imply higher incomes in those relatively poor countries. For example, Warner et al. (2012) find a Gini of 70% in 1993 using 2005 PPPs, compared with 66% in Bourguignon and Morrisson (2002) who use 1990 PPPs. In Bourguignon (2012), who also uses 2005 PPPs, the global Gini index declines approximately twice as fast as our results (from 71% in 1989 to 66% in 2006).[21] All these studies anchor average income levels to GDP per capita. The closest study to ours is Milanovic (2012), who uses surveys only and applies the 2005 PPP exchange rates. Our estimate of the global Gini coefficient is greater than Milanovic's (2012), although the gap is falling over time, from 4.4 Gini points in 1988 to 1.8 points in 2003. The direction of change between benchmark years is the same with the exception of the period between 1988 and 1993.

Given that the Lorenz curves for 1988 and 2008 (not shown here) intersect, we present results for alternative measures of inequality, such as the Generalized Entropy and Atkinson indices. The Gini index attaches a particular weight to inequality at different points along the income distribution. The Theil-L (or GE(0), or mean log deviation) index is particularly sensitive to differences in shares among low incomes, whereas the GE(2) index is sensitive to differentials at the top of the distribution (Cowell 2009) and also sensitive to extreme values (Cowell and Flachaire 2007). The Theil-T (or GE(1)) index is an intermediate case.

According to the top-sensitive GE(2) index, inequality increased between all benchmark years. On the other hand, the bottom-sensitive Theil-L index shows

20. Atkinson (2003) provides a useful metric in terms of the required tax increase to bring about an observed change in the Gini index. This assumes an approximately linear tax and transfer system. Like Deaton (2010), we also assumed no government absorption. Assuming a positive government absorption (e.g., part of the transfer is wasted), would raise the required tax rate.

21. These figures are only approximate as they are read from figure 1 in Bourguignon (2012).

falling inequality between 1988 and 1998 and a marginal, but probably insignificant, increase from 1998 to 2003. This appears to suggest that between 1988 and 2003, inequality among lower incomes was falling, whereas it increased among higher incomes. Between 2003 and 2008, there has been a fall across the board but a stronger change for the bottom-sensitive GE(0) measure.

We have computed the Atkinson (1970) index for three levels of inequality aversion ε. The higher ε, the stronger is the aversion to inequality in the distribution of incomes and the higher the weight attached to lower incomes. For $\varepsilon = 0$, society is indifferent to the degree of income inequality. With $\varepsilon = \infty$, only the position of the poorest group matters.

According to all three levels of ε considered here, inequality is highest in 1988. A(1) and A(0.5) agree on the relative rankings of the benchmark years (from lowest to highest inequality: 2008, 1998, 2003, 1993, 1988). For A(2), which is the highest level of inequality aversion considered here, 2008 has a higher level of inequality than 1998, and the level is not different between 2003 and 2008 (at least to one decimal point). Furthermore, $\varepsilon > 2$ would show increasing inequality between 2003 and 2008 (in contrast to all the other measures reported here).

As discussed above, the literature on top incomes suggests that household surveys underestimate inequality. As a result, our estimate of the global Gini index is likely to be downward biased. In the appendix, we report estimates of the global Gini where we have attempted to adjust for this. As explained in Lakner and Milanovic (2013), our method allocates the excess of national accounts private consumption over the household survey mean to the top 10% within every country and "elongates" the distribution using a Pareto imputation. This adjustment increases the global Gini index by between 4 and 6 Gini points, and the decrease in global inequality over these 20 years dissipates almost entirely.

In summary, there remains some uncertainty on the trends in global inequality over time for a number of reasons. First, there exists no unambiguous ranking as the Lorenz curves in 1988 and 2008 intersect. Second, even if one were to choose a particular inequality measure, such as the Gini index, the changes have been small relative to the likely (sampling and nonsampling) error. Third, the adjustment for missing top incomes further supports a cautious view about the time trend.

Regional Inequalities and Between-Country Decomposition of Global Inequality

The Gini index calculated across all individuals living in a region is highest in Latin America and Sub-Saharan Africa (table 3). The mature economies have seen a strong increase in the last benchmark year. Inequality in China has risen strongly between 1988 and 2008, by more than 10 Gini points. The increase in India has been much more moderate. The Gini index for Sub-Saharan Africa increased by approximately 5 Gini points between 1993 and 2008. Within Middle East and Russia/Central Asia/SE Europe, inequality appears to have fallen.

Inequalities within Latin America and Other Asia have remained virtually unchanged with some ups and downs in the intervening period.

For the world as a whole, we present a decomposition of the Generalised Entropy class measures, which are, in contrast to the Atkinson and Gini indices, additively decomposable.[22] We concentrate on the GE(0) index because interpreting the within-group component as the residual inequality after equalising average incomes across countries is only correct for this index out of the GE-class (Anand and Segal 2008).[23] The between-country contribution has declined over our 20-year period, suggesting that countries' incomes, weighted by their populations, have become more similar (converged).[24] In 2008, equalizing mean incomes between countries while keeping the within-country distributions unchanged would reduce global inequality by approximately 77%. Alternatively, equalizing all incomes within each country would reduce global inequality by 23% only. In other words, despite its relative decline, the between-county component still remains by far the more important source of global inequality.[25]

Global Growth Incidence Curves

The bottom part of table 3 displays growth in average incomes by income fractile. The group that has grown the fastest is the one between the 50th and 60th percentiles (growth rate of 71.7% over 20 years), followed by the P40-P50 group (70.6%) and the global Top 1% (64.8%). Perhaps a more useful way to illustrate this pattern is through a variant of the global GIC (Ravallion and Chen 2003).[26] It compares the mean income of a given fractile group (e.g., the bottom 10%, the top 1%) in (say) 2008 with the mean income of the same fractile group in 1988. This is shown in figures 1(a), 1(b), and 1(c) where the y-coordinate is simply the total growth rate between these two dates. A downward- (upward-) sloping GIC implies that economic growth has an equalizing (disequalizing) effect on the income distribution, that is, it is pro-poor (pro-rich). These are anonymous GICs because they wholly ignore the composition of people that find themselves in the same fractile group of the income distribution in two different years.

22. The Atkinson index is decomposable by population subgroups, whereas for example the Gini index is not. However, the Atkinson index is not additively decomposable in the sense that it can be broken up into a weighted average of the within- and between-group inequalities (Bourguignon 1979).

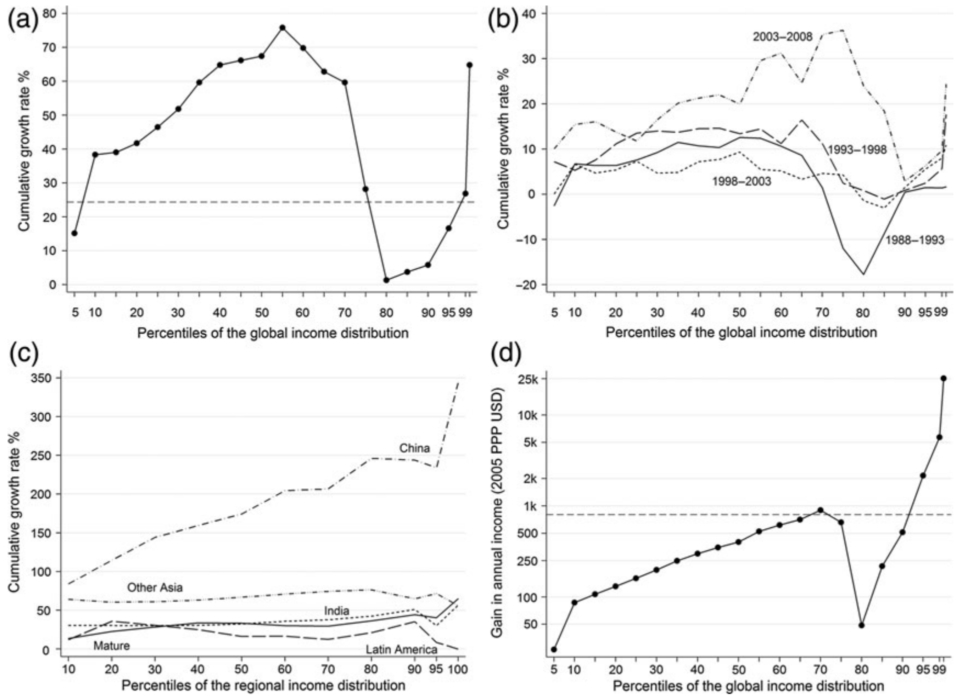
23. The GE(0) index is defined in terms of population shares, whereas GE(1) uses income shares. Redistributing income among countries in order to equalise average incomes, would change income (but not population) shares. In that sense, only the interpretation of GE(0) is consistent because full elimination of one source of inequality (between- or within-inequality) will not affect the level of another.

24. In an earlier draft, we also decomposed inequality by regions. The between-region contribution declined faster than the between-country contribution. This suggests that regions have become even more similar to each other than countries.

25. Using the 2011 PPPs, the between-country contribution is around 3 percentage points lower (table A.3).

26. The original GIC, as defined by Ravallion and Chen (2003), shows the growth rate in incomes for the same percentile (e.g., the 10th percentile of the global distribution) between the initial and final period. In contrast, we compare the mean incomes of the same fractile group (e.g., the bottom 10%) over time.

FIGURE 1. Growth Incidence Curves. 1a: Global growth incidence curve 1988–2008. 1b: Global growth incidence curve, over time. 1c: Growth incidence curve 1988–2008, by region. 1d: Absolute income gains, 1988–2008 (on logarithmic y-axis)



Notes: Population-weighted. In panels A, B and C, y-axis displays growth rate in average income of fractile group (in 2005 PPP USD). In panel D, y-axis displays absolute gain in average income of fractile group (in 2005 PPP USD) on logarithmic axis. In panels A, B and D, figure evaluated at ventile groups (e.g. bottom 5%); top ventile is split into top 1% and 4% between P95 and P99. In panel C, figure evaluated at decile groups (e.g. bottom 10%); top decile is split into two ventile groups. (A) Horizontal line shows growth rate in global mean of 24.34% (1.1% p.a.). (C) Figure shows mature economies, Asia, and Latin America/Caribbean. (D) Horizontal line shows absolute gain in the global mean of USD802 (in 2005 PPP USD).

Source: Authors' analysis based on data described in the text.

Figure 1(a) shows the global GIC for the period 1988 to 2008. As we already saw from table 3, growth was highest in the P50-P60 range. From around the 75th percentile, growth is lower than the growth in the global average. Then, for the top 1% of the global distribution, growth reverts to being higher than the average. This gives the GIC curve a distinct supine *S* shape, with two peaks, around the median and at the very top, and a trough around the 80th–85th percentile.[27]

Figure 1(b) repeats the global GIC for the separate five-year periods between benchmark years. The GIC for 2003–2008 lies almost uniformly above the other

27. This is very similar when using the 2011 PPPs (figure A.1).

periods suggesting that growth has been highest over this period. During 1988–1993 incomes declined particularly for the percentiles between the 70th and up to around the 88th. The quinquennial curves suggest that the supine *S* shape was present throughout the 20-year period. The gains for the median and the top have been particularly strong in the last 2003–8 period, whereas the losses for the groups around the 80th percentile have been exceptionally high in the first (1988–93) period.

Figure 1(c) shows the 20-year GICs for five regions.[28] With the exception of the top 5% in Latin America, the GICs are everywhere above zero. Growth appears strongly pro-rich in China and less so in the mature economies and India, whereas the GIC is flat for Other Asia and displays no clear direction for Latin America. The growth in average incomes (i.e., the vertical position of the regional GICs) is also summarized in the last part of table 3. This clearly illustrates the success of China and the rest of Asia, a good performance of mature economies and India, and a very disappointing outcome for Sub-Saharan Africa, as well as the Middle East and North Africa.

While the global GIC showed relatively large gains for the portion of the distribution around the median, we need to recall that these gains were measured in relative (percentage) terms. But precisely because global incomes are distributed extremely unequally, incomes at the top are several orders of magnitude greater than incomes at the median (in 1988, the average per capita income of the top 1% was close to $PPP 39,000, while the median income was approximately $PPP 600), the absolute gains are much greater for higher percentiles. Figure 1(d) shows that the average per capita income for the top 1% increased by $PPP 25,000 between 1988 and 2008, while the absolute gain at the global median was only $PPP 400. The absolute gains among the poorer percentiles were even less. The overall outcome was thus that 44% of the increase of global income between 1988 and 2008 went to the top 5% of world population.[29]

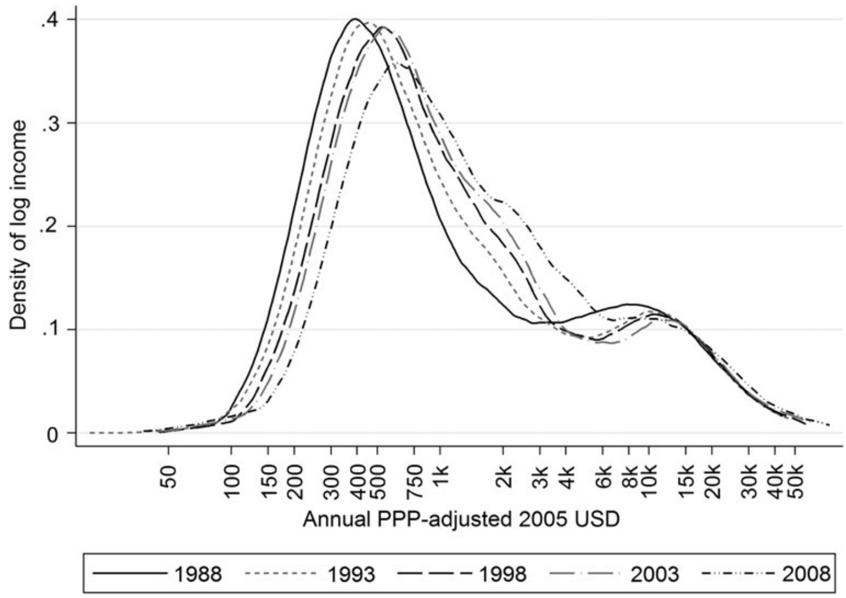
The changing shape and regional composition of the global distribution

Figure 2 shows how the global distribution of income has changed over time. Income growth is shown by the rightward movement of the income distribution. The 1988 distribution had two peaks, one around $PPP 400 and another around $PPP 8,000. In 2008, the second peak has disappeared, and there is much more mass around the $PPP 3,000 mark. As implied by the almost universally positive five-year period GICs (figure 1(b)), the global distribution charts a rightward movement in every individual five-year period with the most striking development being the expansion of the proportion of the global population with incomes between $PPP 750 and $PPP 6,000 (i.e., between approximately $PPP 2

28. The GICs by region are evaluated at decile groups (mean-on-mean) with the top decile being split into two ventiles. This is because for China and India, which are regions by themselves, we have at most 20 observations.

29. These are, of course, not necessarily the same country-deciles (nor people) who were in the top 5% in 1988. We return to this issue in the next section where we discuss (quasi) nonanonymous GICs.

FIGURE 2. The Global Distribution of Income over Time



Notes: Population-weighted; on logarithmic x-axis.
Source: Authors' analysis based on data described in the text.

and $PPP 16 per day). That population has expanded from 1.16 billion people or 23% of world population in 1988 to almost 2.7 billion people or 40% of world population 20 years later.[30] Thus, the twin-peak global distribution (Quah 1996) has all but disappeared.

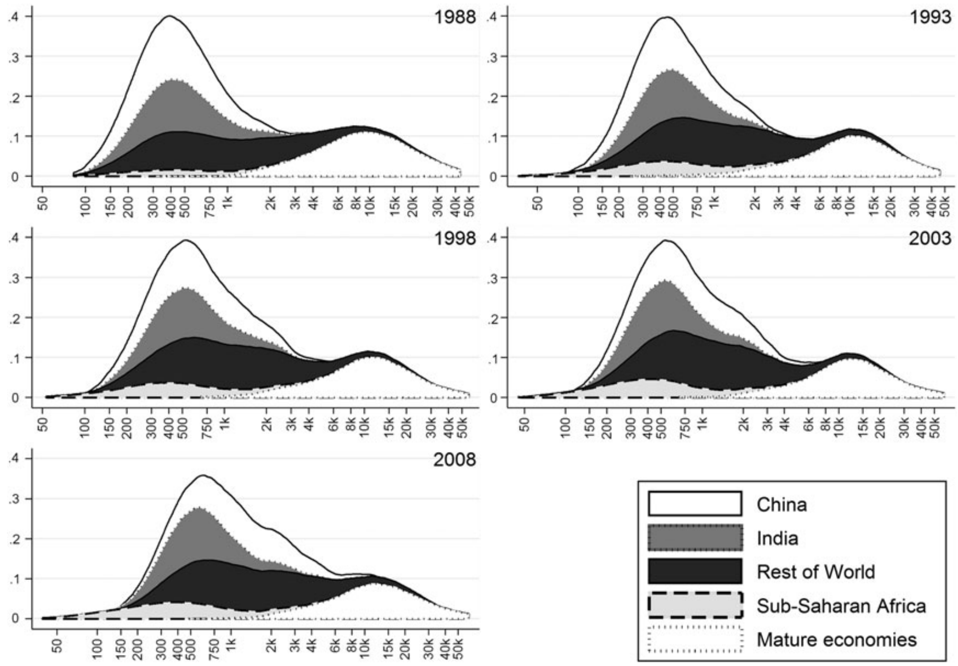
In order to disentangle these changes further, figure 3 shows stacked kernel densities by region.[31] Not surprisingly, the growth in China has had a profound effect on the global distribution. The change in the overall shape of the distribution appears to be driven by the upward income movement of the upper deciles in China. Both China and India have moved up along the income distribution, while Sub-Saharan Africa seems caught at the bottom.[32]

30. The total numbers are for the entire world population, not only the population covered by the surveys here.

31. These charts have been created as overlaid (cumulative) kernel densities. Because the last density is shown on top we proceed in reverse order: The first density to be plotted is the global density including all regions (which is the same as figure 2). Second, we plot the density for all regions, except China. We proceed by removing one region at a time. The area under the global density is 1. The other incomplete densities are scaled down according to the regional population share in a particular year. For instance, in 2008 the second density we plot is scaled down to $0.7828 = 1 - x$, where x is China's population share in 2008. We are using an Epanechnikov kernel and the default bandwidth, selected optimally by Stata. The bandwidth is allowed to vary for different years, but for every benchmark year it is the same across the different cumulative kernel densities.

32. With the 2011 PPPs India appears richer but the main conclusions are robust (figure A.2).

FIGURE 3. The Global Distribution of Income, Logarithmic Scale



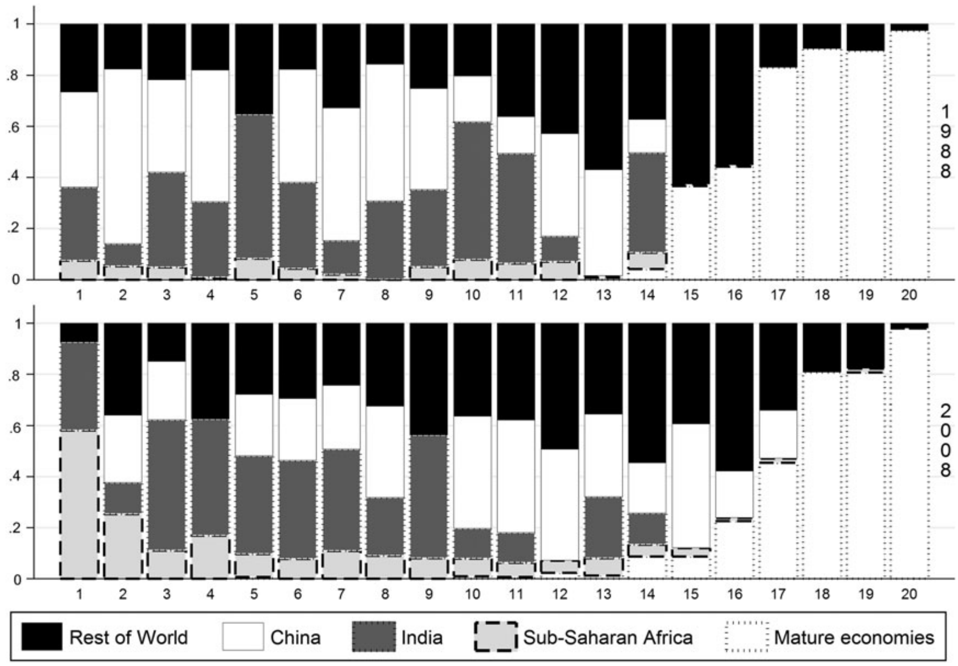
Notes: Population-weighted; x-axis: PPP-adjusted 2005 USD (annual); y-axis: Density of log income.

Source: Authors' analysis based on data described in the text.

The upward movement of China because of its magnitude in terms of population and amount of growth is particularly well illustrated in the stacked kernel densities. In 1988, the Chinese population was symmetrically distributed atop of the mode of the global distribution exclusive of China. In other words, China and the rest of the world had about the same modal income. With each successive five-year period, the Chinese distribution shifted more to the right (toward higher income levels) so much that by 2008 about four-fifths of the Chinese population had an income greater than the modal non-China global income. The income mode in China is now clearly greater than in the rest of the world. It is this rightward movement of the Chinese distribution that has most contributed to the change from a two-peaked global distribution in 1988 to a single peak distribution 20 years later. This has largely happened because China has "filled up" the relatively hollow part of the global income distribution between $PPP 2,000 and $PPP 6,000.

Figure 4 focuses on the change in the regional composition of the global income distribution between 1988 and 2008. The chart shows the regional composition of the population in each ventile of the global distribution. As before, we can see a clear upward movement of China. The top decile in China reaches as far as the 17th ventile (i.e., between 80th and 85th percentiles) of the global

FIGURE 4. The Regional Composition of the Global Distribution of Income



Notes: Population-weighted; x-axis: ventile of PPP-adjusted 2005 USD (annual); y-axis: share of ventile population from a particular region.

Source: Authors' analysis based on data described in the text.

distribution in 2008, whereas in 1988, the richest Chinese were only between the 65th and 70th percentiles. Conversely, in 2008 China has entirely graduated from the bottom 5% of the world, while in 1988 it made up almost 40% of the population in that group.

As the bottom incomes in China have moved up the global distribution, Sub-Saharan Africa and to a smaller extent India have expanded their population shares in the bottom ventile. The distribution of Sub-Saharan Africa is very spread out with some decile groups (from South Africa and Seychelles) reaching the top 10% of the global distribution. India has not moved dramatically, which is explained by the fact that its growth rate has been similar to the global average.

The global 20-year GIC showed that fractile groups between the 75th and approximately 95th percentiles grew slower than the global average (figure 1(a)). In 1988, the percentiles between the 70th and the 85th (ventile groups 15, 16, and 17) originated primarily from the mature economies and Latin America, and to a smaller extent from the Middle East and North Africa. By 2008, China and to a lesser extent Russia[33] had moved into these percentiles, reducing the shares of the mature economies and Latin America and the Middle East almost dropping out

33. The first observation that we have for Russia is for benchmark year 1993.

completely (not all regions shown separately). It is these compositional changes that explain the shape of the global GIC. The GIC does not track a particular fractile group but rather compares the incomes of a given fractile in the *different* initial and final distributions. When comparing the top Chinese incomes in 2008 with the Latin American incomes in 1988, we obtain a below-average growth rate. This is despite the fact that the top Chinese incomes have grown substantially faster than the global average. However, the (quasi) nonanonymous GICs, which keep the composition of fractiles the same as in the original year, are discussed next.

III. Changes over Time: Who Are the Winners and Losers?

Quasi-nonanonymous Growth Incidence Curves

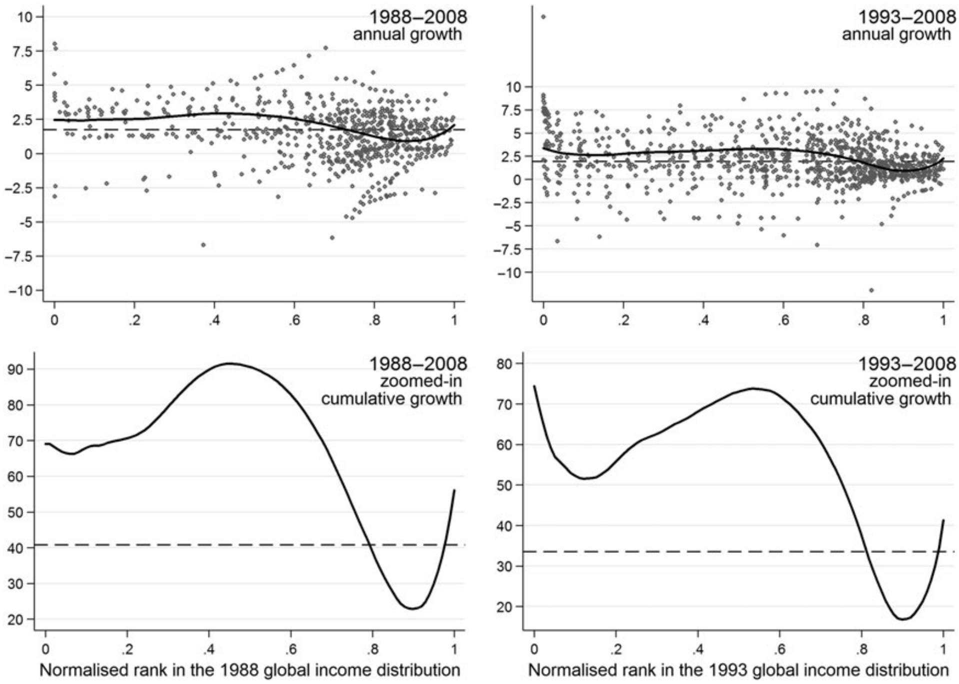
In order to identify the winners and losers, we first consider "income mobility profiles" (van Kerm 2009), or "nonanonymous growth incidence curves" (Grimm 2007; Bourguignon 2011). When applied to individual-record data, the distinction into anonymous and nonanonymous GICs is straightforward: the (standard) anonymous GIC compares the incomes of, say, the 20th percentile in the initial and final period distributions. As long as there is some mobility in the distribution, the individuals at this percentile might be different. By contrast, the nonanonymous GIC is the (nonparametric) regression of income growth against the rank (percentiles) in the initial distribution. Because this growth rate is obtained for each individual, it is nonanonymous, taking into account the joint distribution of initial and final incomes. However, in our case the unit of analysis are income-deciles of a particular country, so while we preserve the identity of a particular country-decile, these deciles are defined over different people. Hence we refer to our figures as "quasi-nonanonymous" GICs.

Figure 5 shows the quasi-nonanonymous GICs for 1988–2008 and 1993–2008. It plots the growth over the next 20 (15) years against the normalized fractional rank in the 1988 (1993) global income distribution. In order to exploit both the cross-sectional and the panel dimensions of our data, each observation included in the quasi-nonanonymous GIC is ranked in the complete cross-sectional 1988 distribution (population-weighted) (not only among the 63 countries observed in 1988 and 2008).[34] For the two time periods, we present charts with and without the scatter plot.[35] The scatter plots show the wide dispersion of growth rates around the fitted line. Judging from the scale of the y-axis, the

34. Fractional ranks are derived from a smooth cumulative distribution estimator which ensures that the mean rank is 0.5, estimated using the fracrank Stata routine by Philippe van Kerm.

35. There are two reasons why observations in the scatter plot are not equally distributed along the horizontal axis and appear concentrated among the upper ranks. First, the ranks are computed in the cross-sectional distribution, whereas the scatter plot includes only those country-deciles that are observed in 1988 and 2008, many of which are from rich countries. Second, country-deciles are weighted by population size in calculating the ranks, whereas this information does not show up in the scatter points so countries with smaller population (which are also generally richer) are "overrepresented" by the scatter plot.

FIGURE 5. Quasi-nonanonymous Growth Incidence Curve



Notes: Y-axis: Growth rate (%). Population-weighted. Solid line shows predicted value from kernel-weighted local polynomial regression (default bw, epanechnikov, cube polynomial). The horizontal lines show growth rate in mean of 40.77% (1.72% p.a.) during 1988–2008, and 33.53% (1.95% p.a.) during 1993–2008. Including countries observed in 1988 and 2008 (N = 63), and in 1993 and 2008 (N = 90), respectively.

Source: Authors' analysis based on data described in the text.

dispersion is greater for the 1993–2008 period, but this is driven by one outlier close to the bottom ranks in 1993. The fitted line (a kernel-weighted local polynomial regression) is shown more clearly in the bottom panels.

It is immediately apparent that the shape of the quasi-nonanonymous curves is very similar to the shape of the anonymous GIC (figure 1(a)): they all display a supine *S* shape driven essentially by very slow growth around the 80th and 90th percentiles of the global income distribution and local maxima around the median of the income distribution and for the very top. However, if we compare the 1988–2008 results, it is clear that the gains among the country-deciles that were in the top 1% in 1988 were less than the gains we obtain by simply comparing income levels of the top 1% in 2008 and 1988. This is expected: not every country-decile that was in the top 1% in 1988 managed to remain in the top 1%. Similarly, some country-deciles that were not among the top 1% in 1988 and have exhibited high growth are now (in 2008) in the top 1%. We find the equivalent result for the 1988 poorest country-decile whose growth rate was higher than what we found from the anonymous GIC. Furthermore, some of these differences might arise from restricting the sample to those countries that are present both in 1988 and 2008. Over the 1993–2008 period, growth was highest around the 60th percentile. The shape of the fitted line also seems to have changed with some high growth rates among the very bottom 1993 ranks.

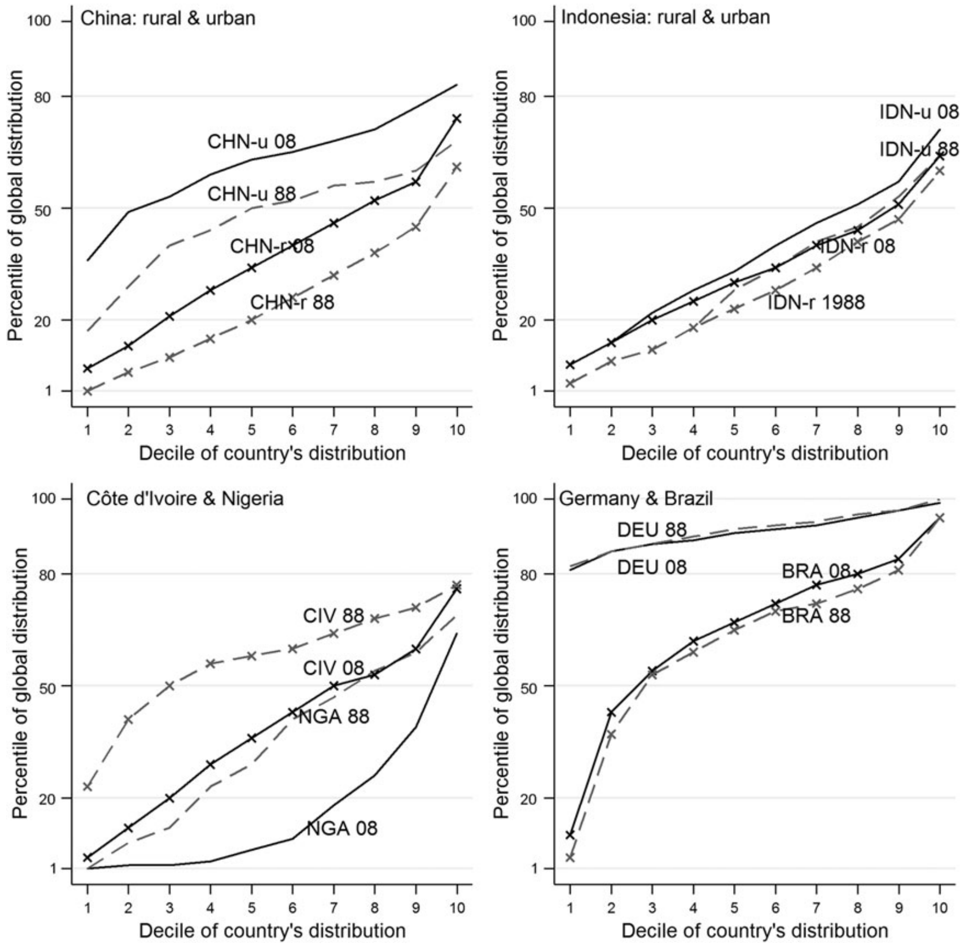
Over the 1988–2008 period, growth was highest for those country-deciles around the 40th percentile of the 1988 global distribution, and lowest for those around the 85th percentile. Groups that were most successful come overwhelmingly from China and India; groups that were least successful are predominantly from the mature economies. Thus, three-fourths of the population that was between the 36th and 45th global percentiles (inclusive of the 45th) in 1988 belonged to the country-deciles, generally around the middle of their national income distributions, from China and India. If we include other Asia too, 90% of people who were in those most successful percentiles are from Asia. Chinese deciles, for example, multiplied their incomes by a factor of around 2.7.

In contrast, the country-deciles between the 81st and 90th (inclusive of the 90th) percentile in 1988 are overwhelmingly from mature economies and come from the lower halves of their national income distributions. Out of total 420 million people belonging to this group, about 365 million are from the mature economies (or differently, 135 out of 165 country-deciles). Even when we exclude from the mature economies those that in 1988 were Communist, the share of the "traditional" rich economies among this group is still very large: 78% of people. Some examples with particularly low real growth rates among rich economies include almost the entire lower halves of the income distributions in Austria, Germany, Denmark, Greece, and the United States. They all had overall 20-year growth rates of less than 20%, which translates, in the best case, as 0.9% per capita annually.

Most Successful and Least Successful Country-Deciles

A simple way to evaluate the success of various country-deciles is to compare their positions in the global income distribution. This can obviously be done for every country-decile and every year. In figure 6, we do it for several selected countries (2008 values are always drawn as a solid line, 1988 values as a dashed line). The top left panel illustrates the already discussed remarkable upward mobility (in the global income distribution) of Chinese rural and urban deciles. In 2008, the Chinese top urban decile is at the 83rd global percentile, while 20 years earlier it was at the 68th. In other words, if somebody stayed in that same decile in China over 20 years and his income followed the average growth path of the decile, he would have leap-frogged, in terms of income, more than 900 million people worldwide. It is interesting that in 2008, the Chinese top *rural* decile is at a higher global position than the Chinese top *urban* decile was in 1988. The same development, although less dramatic, is illustrated by the improvements in the position of Indonesian rural and urban deciles shown in the upper right panel of figure 6.

FIGURE 6. Position of National Deciles in Global Distribution (1988 and 2008)



Notes: In this figure, China-rural, China-urban, Indonesia-rural and Indonesia-rural are treated as "national" income distributions. 2008 values are always drawn as a solid line, 1988 values as a dashed line.

Source: Authors' analysis based on data described in the text.

But when we turn to the bottom left panel the situation is exactly the reverse. There we see that Nigeria's and Côte d'Ivoire's deciles have almost uniformly slid down the global income distribution. It is only the top Ivoirian decile that has managed to preserve its 1988 position. Finally, in the bottom right panel, we show the evolutions in Germany and Brazil. The position of German deciles has remained very high and displays very little change. Brazil is an example of a reasonably fast growth across its income spectrum and improvements in the distribution so much so that all its deciles, except the highest, are now placed globally higher than they were in 1988.

IV. Conclusions

The paper has provided evidence on the evolution of the global income distribution during a crucial period of accelerated globalization spanning the period from the end of Communist regimes in Eastern Europe and the Soviet Union to the beginning of the global financial crisis. In many respects, this might have been the most globalized period ever in history. It is very important to study what were its effects on the level and distribution of income among the world population. Our results confirm earlier findings that the level of global inequality remains high, with a Gini of around 70%, and while inequality appears to have declined in the most recent years, these changes are probably not robust to plausible standard errors (if one could formulate and calculate them). Furthermore, once we adjust for underestimation of top incomes, the decrease in the Gini index dissipates.

The shape of the global income distribution has also changed during the 20 years considered here. In 1988, the global income distribution displayed a twin-peak shape, which has since disappeared mostly thanks to the high growth of China whose deciles have “filled up” the area between $PPP 2,000 and $PPP 6,000 that was relatively “hollow” in 1988. The period has also witnessed a remarkable increase in what may be called a “global median class,” with incomes ranging from $PPP 2 per capita per day to $PPP 16 per capita per day: the share of the global population belonging to that group has increased from some 23% to 40%.

Particularly important is the shape of the anonymous and quasi-nonanonymous GICs for the period 1988–2008. They both show large relative gains around the median of the global income distribution that accrued mostly to the middle or upper-middle income deciles from Asia, and especially from China. By contrast, the lowest real income gains were registered in the area around the 80th–90th global percentiles where low-income deciles from the mature economies were overrepresented. A striking fact is that among the percentiles in 1988 that turned out 20 years later to have been the most successful part of the global income distribution, 90% of people came from Asia. Among the 1988 percentiles that 20 years later turned out to have been the least successful part of the global income distribution, 86% came from mature economies.

We would like to close with a methodological and practical point. As our paper and similar papers on global poverty and inequality show, the work on global issues from the data provided by individual countries’ statistical offices is possible but unnecessarily complex and subject to much larger margins of errors than if there were a single worldwide income or consumption household survey. Technically such an advance is fully feasible. The European SILC survey, which includes 33 countries, shows that it can be done. We hope that a single-template worldwide household survey, executed by national statistical agencies, will begin to be seriously considered by the United Nations and the World Bank.

V. Appendix

We report three robustness checks of the results in the main text. First, we show that the results on the global Gini index are robust to using the balanced sample of countries. Second, we present estimates of the global Gini after adjusting for missing top incomes in household surveys. Third, we report our main cross-sectional results using the 2011 PPP exchange rates.

Balanced Sample

Table A.1 shows the global Gini for the balanced sample of countries. Depending on the start date, there are four balanced samples. In all benchmark years and across the four balanced samples, the Gini index is always within 1 Gini point of the results for the unbalanced sample (reproduced from table 3). If we focus on the balanced samples starting in 1993 or later, the difference lies within 0.5 Gini points.

Missing Top Incomes

Table A.2 reports the results from the adjustment for missing top incomes (for more information, see Lakner and Milanovic 2013). The number of observations drops to 520 because we miss national accounts information for some country-years, and because now we treat China, India and Indonesia as single countries. Row 1 replicates the baseline Gini index using only the information from household surveys for this new sample. It lies within 0.5 Gini points of the estimates in table 3, except for 2008 when the new baseline Gini is 0.9 points lower than the one obtained from the full sample.

Table A.1. Global Gini Index (%) for Balanced Sample

	Benchmark year					1988–2008 change (%)	1993–2008 change (%)
	1988	1993	1998	2003	2008		
Unbalanced (Table 3)	72.2	71.9	71.5	71.9	70.5	−2.3	−2.0
N	(75)	(115)	(121)	(133)	(121)		
Balanced (1988–2008)	72.8	72.8	72.3	72.5	70.9	−2.6	−2.7
N	(58)	(58)	(58)	(58)	(58)		
Balanced (1993–2008)		72.0	71.7	71.7	70.0		−2.8
N		(78)	(78)	(78)	(78)		
Balanced (1998–2008)			71.8	71.8	70.1		
N			(92)	(92)	(92)		
Balanced (2003–2008)				72.1	70.4		
N				(107)	(107)		

Notes: Table shows global Gini index (%) for unbalanced baseline and four balanced samples (depending on start year). Number of countries in parentheses. Observations are weighted by their population.

Source: Authors' analysis based on data described in the text.

TABLE A.2. Robustness Check on the Global Gini Index: Accounting for Missing Top Incomes

	Benchmark year					1988–2008 change (%)	1993–2008 change (%)
	1988	1993	1998	2003	2008		
1 Survey data only	72.5	71.8	71.9	71.9	69.6	−4.0	−3.1
2 Private consumption and top-heavy Pareto	76.3	76.1	77.2	78.1	75.9	−0.6	−0.3
3 (2) and top 10% share < = 50%	75.8	75.3	76.2	76.6	74.5	−1.7	−1.0
4 (2) and top 10% share < = 40%	75.1	74.4	74.7	74.4	72.5	−3.5	−2.5
Number of surveys	63	105	112	126	114		

Notes: Observations are weighted by their population. All calculations are done across the sample of 520 country-years for which private consumption from national accounts is available.

Source: Authors' analysis based on data described in the text.

In row 2, we allocate the entire gap between national accounts private consumption and the survey mean to the top decile, and fit a Pareto distribution to obtain more detailed top fractile groups. In some cases such an adjustment may seem excessive, so we consider these results to be an extreme upper bound. For example, if the survey mean is equal to only 50% of private consumption (which is similar to the value observed in India) then simply "ascribing" these 50% to the top decile is probably excessive. The Gini increases by between 4 and 6 points compared to the baseline. The effect of the adjustment increases over time, so the decline between 1988 or 1993 and 2008 disappears.

Rows 3 and 4 try to remove some of these excessive adjustments. In the World Top Incomes Database (Alvaredo et al. 2013), the top 10% share ranges from 14% (Mauritius in 2005) to 46% (United States in 2010), with an average of 32% (approximately France in 1990s). Rows 3 and 4 censor the top 10% share at 50% and 40% respectively. In other words, we replace any excessive top 10% shares by the cut-off and recompute the national accounts adjustment. Censoring the top 10% share at 40% gives the midpoint between the baseline and the extreme adjustment, while censoring at 50% gives values closer to the latter. Furthermore, when using the more restrictive bounds of 40%, the decline between 1988 and 2008 is quite similar to the baseline with only survey data.

TABLE A.3. Global and regional inequality with 2011 PPP exchange rates

	Benchmark year					1988–2008 change (%, pp)	1993–2008 change (%, pp)
	1988	1993	1998	2003	2008		
Number of surveys	75	115	121	133	120		
A. Global inequality (%)							
Gini index	69.4	69.1	68.4	68.7	67.0	−3.4	−2.9
GE(0) (Theil-L)	100.1	97.3	93.4	93.9	88.6	−11.5	−9.0
GE(1) (Theil-T)	93.0	92.7	92.3	94.1	89.0	−4.3	−4.0
GE(2)	155.8	158.8	168.9	177.9	172.4	10.6	8.5
Atkinson index A(2)	80.0	79.5	78.0	78.5	78.2	−2.3	−1.6
Atkinson index A(1)	63.2	62.2	60.7	60.9	58.8	−7.1	−5.5
Atkinson index A(0.5)	39.7	39.2	38.4	38.7	36.8	−7.4	−6.2
B. Regional Gini indices (%)							
Mature economies	37.8	38.5	38.7	38.3	41.1	8.8	6.8
China	32.0	35.5	38.5	41.8	42.7	33.5	20.6
India	31.1	30.1	31.4	32.4	33.1	6.3	9.9
Other Asia	44.6	44.5	46.8	41.9	44.9	0.6	0.8
M. East and N. Africa	39.1	38.7	39.8	36.8			
Sub-Saharan Africa		56.8	54.4	55.4	56.9		0.3
L. America and Caribbean	52.0	53.9	56.4	55.6	52.2	0.3	−3.3
Russia, C. Asia, SE Europe		49.2	41.1	42.6	42.7		−13.2
C. Decomposition by country: between-country contribution (%) (change is in percentage points)							
GE(0) between contribution	80.8	77.3	75.1	74.7	72.9	−7.9	−4.3

Note: See notes to table 3. We lose one country in 2008 (West Bank and Gaza) due to missing CPI.

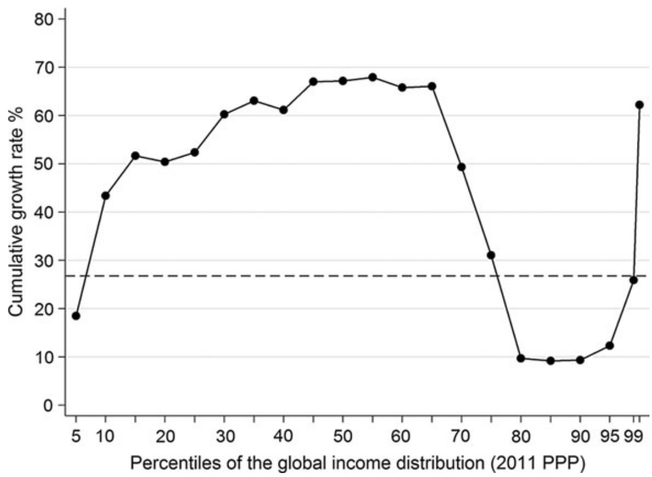
Source: Authors' analysis based on data described in the text.

Alternative PPP Exchange Rates

In the main text, we use the 2005 PPP exchange rates throughout. This part of the appendix presents some of our main results for the 2011 PPPs. To convert incomes from 2005 PPPs to 2011 PPPs, we require two ingredients: the PPP exchange rates in 2005 and 2011 and the country's CPI between 2005 and 2011.[36] For those countries where we account for rural/urban price differences (China, India, and Indonesia), we have assumed that the urban bias in the PPP exchange rates has remained unchanged between ICP 2005 and ICP 2011. At the time of writing, no further evidence on the urban bias in the ICP 2011 was available, so this is arguably the simplest assumption.

36. The 2011 PPP conversion factors for individual consumption expenditure by households are taken from http://icp.worldbank.org/, accessed May 1, 2014. Additional conversion factors are obtained from the WDI, which imputes 2011 PPP exchange rates for countries which did not participate in ICP 2011. We use the CPI from WDI, and supplement this with information from the World Economic Outlook (October 2014). We were unable to obtain a CPI for West Bank and Gaza in 2011.

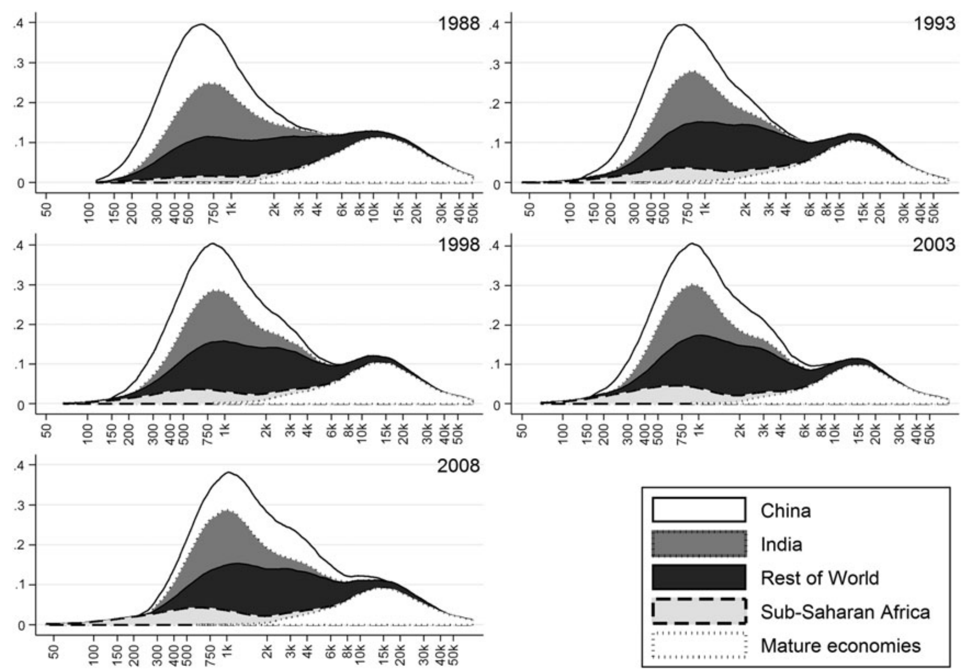
FIGURE A.1. Global Growth Incidence Curve 1988–2008 (2011 PPP)



Notes: Y-axis displays the growth rate in average income of the fractile group (in 2011 PPP USD). Population-weighted. Growth incidence evaluated at ventile groups (e.g., bottom 5%); top ventile is split into top 1% and 4% between P95 and P99. The horizontal line shows the growth rate in the mean of 26.74% (1.19% p.a.).

Source: Authors' analysis based on data described in the text.

FIGURE A.2. The Global Distribution of Income (2011 PPP), Logarithmic Scale



Notes: Population-weighted; x-axis: PPP-adjusted 2011 USD (annual); y-axis: Density of log income.

Source: Authors' analysis based on data described in the text.

Table A.3 replicates the main results from table 3 using 2011 PPP exchange rates. Using the 2011 PPPs reduces the global Gini by approximately 3 points to around 67% in 2008. Of course, applying a different set of PPP exchange rates leaves within-country inequality unchanged. According to the GE(0) index, the share of overall inequality explained by differences between countries falls by some 3 percentage points, to around 73% in 2008. Using national accounts consumption per capita, Inklaar (2014) also finds that the 2011 PPPs reduce differences between countries. However, it is important to bear in mind that the 2011 PPPs lead to a levels-effect, i.e., the direction and size of the changes over time in table 3 are largely robust.

Figure A.1 shows the global GIC between 1988 and 2008 using the 2011 PPPs. The peak and trough appear somewhat less extreme in this chart, although the shape remains very similar. Figure A.2 shows the global distribution in the five benchmark years decomposed for China, India, Sub-Saharan Africa, the mature economies, and the rest of the world. Compared with figure 3, India appears richer. However, the main conclusion about the shift from a twin- to a single-peak still holds.

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