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Building a global income distribution brick by brick

Lucas Chancel

Amory Gethin

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Abstract

This technical note provides detailed information on the methods used to estimate global income inequality dynamics in the World Inequality Report 2018 and in the article "The Elephant Curve of Global Inequality and Growth," by F. Alvaredo, L. Chancel, T. Piketty, E. Saez, and G. zucman, 2017. WID.world Working Paper Series (No. 2017/20), forthcoming in American Economic Review.

We show that income inequality at the world level can be relatively well estimated from 1980 to 2016, by combining data on national incomes and available Distributional National Accounts.

Our contribution is threefold. First, we attempt to go beyond country-level inequality data by comparing inequality dynamics between and within large geographic aggregates such as Europe, North America or Asia. Second, we combine data on income inequality within these aggregates to estimate a global distribution of income since 1980. We discuss the impact of several alternative methodologies to measure global inequality and show they have limited impacts on our overall results on the evolution of global inequality. Finally, we estimate the future evolution of global inequality between 2016 and 2050 by testing several assumptions about national income and population growth rates and inequality dynamics.

This note also includes in its appendix a number of figures and tables, which summarize the key results of our analysis. We also provide a "Global Inequality User Guide" for readers seeking to reproduce our results.

As data for more countries becomes available, we hope to be able to gradually improve our estimates of global inequality by testing more scenarios on the evolution of past and future global inequality.

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Introduction

This note provides technical information on the method and steps used to estimate global inequality between 1980 and 2016, as presented in the 2018 World Inequality Report (WIR 2018) and in the article "The Elephant Curve of Global Inequality and Growth," by F. Alvaredo, L. Chancel, T. Piketty, E. Saez, and G. zucman, 2017. WID.world Working Paper Series (No. 2017/20). It comes with a set of computer codes available on WID.world allowing the production of the inequality series and the graphs presented in the analysis.

Users willing to replicate the results presented below should use the frozen version of the WID.world database (from September 2017), rather than the online version, which is regularly updated may generate slightly different estimates.

Section 1 presents the main concepts used to estimate global inequality. Section 2 describes the list of countries included in the analysis and the adjustments made to cover the whole 1980-2016 period. Section 3 details the steps used to aggregate country-level data into a merged distribution of income inequality. Section 4 provides information on the method and scenarios used to predict global inequality trajectories between 2016 and 2050.

1 Concepts

1.1 Pre-tax national income

The income distribution concept used to estimate global inequality is pre-tax national income. Pre-tax national income is the sum of all pre-tax personal income flows accruing to the owners of the production factors, labor and capital, before taking into account the operation of the tax/transfer system, but after taking into account the operation of the pension, unemployment and other social insurance systems. A more detailed description of the concepts and methods used in the WID.world project and the Distributional National Accounts (DINA) methodology is available in Alvaredo et al. (2016). [1]

[1] See also Box 2.4.1 of the World Inequality Report 2018 for a discussion on pre-tax and post-tax national income estimates.

1.2 Adult population

Our benchmark population is the adult individual. For nearly all countries, this corresponds to individuals aged 20 or more (see WID.world for country-specific details). Similarly, when aggregating country-level or regional-level distributions to produce global inequality estimates, we use the adult population of the corresponding aggregates.

1.3 National income

National income aims to measure the total income available to the residents of a given country. It is equal to the gross domestic product (the total value of goods and services produced on the territory of a given country during a given year), minus fixed capital used in production processes (e.g. replacement of obsolete machines or maintenance of roads) plus the net foreign income earned by residents in the rest of the world.

For any given pre-tax income distribution, we systematically rescale the averages of different income groups to match the national income of the corresponding aggregate. This means that we distribute the total national income produced in the economy to different income groups based on the relative share of total income they owned.

Example: in 2015, the Top 10% earners in terms of pre-tax income among the adult population in China earned 41.4% of total income. Given that the average national income per adult in China was € 13 144 at the time (in Purchasing Power Parity), the average income of the Top 10% was therefore:

$$\frac{€\ 13\ 144 \times 41.4}{10} = €\ 54\ 416$$

1.4 Market Exchange Rate and Purchasing Power Parity

We provide two versions of global inequality estimates depending on whether country-level and regional-level national incomes are converted to market exchange rate 2016 euros, or purchasing power parity 2016 euros.

The Market Exchange Rate (MER) is the rate at which one currency can be exchanged for another. Purchasing Power Parity (PPP) is the exchange rate that equates the price of a basket of identical traded goods and services in two countries. Converting values to PPP therefore accounts for differences in costs of living between countries, enabling comparisons between income levels in different countries. Given that market exchange rates do not take into account these differences (1€ converted in Indian rupees at market exchange rates enables a consumer to buy more goods and services in India than if it was spent in France, for instance), global inequality is likely to be higher when estimated at market exchange rates. In both MER and PPP estimates, all country-level distributions are first converted to constant local currency values using the corresponding national income deflator. Therefore, figures account for inflation.

2 Countries and regions included

2.1 Countries with full DINA available from WID.world

At the time of writing, all countries for which distributional national accounts (full income distribution from the poorest to the richest individuals) are available are used to estimate global inequality:

- Brazil
- China
- France
- India
- The Middle-East
- Russia
- The United States[2]

For all these countries or regions, distributions are based on estimations combining fiscal, survey and national accounts data. Specific details on estimation of income inequality for these aggregates can be found in original articles available from the WID.world library.

[2] For the US, many percentile groups at the bottom of the distribution have negative thresholds While this is fully relevant when analysing income inequality (see Piketty, Saez and Zucman 2016), it may be misleading when aggregating several countries, since other countries could also have negative thresholds but these would be normalized to 0 due to data quality or estimation procedures in these countries. Therefore, we choose to systematically normalize negative thresholds and averages to 0.

2.2 UK and Germany

At the time of writing, DINA estimates are not complete for the UK and Germany, but detailed estimates on top income shares, levels and thresholds are available for these countries on WID.world. This provides a rich source of information on the overall distribution of national income in these countries. We thus infer preliminary DINA estimates for the UK and Germany, based on known top income shares in these two countries and the distribution of national income in the remaining part of the distribution. For these two countries, we have data on the Top 10% of the distribution, but no data on the distribution of income within the Bottom 90%. We infer the whole distribution by using the following method:

- We keep Top 10% income shares (and thus Bottom 90% income shares) as they are provided in the WID.world database.
- We know the average income of the bottom 90%, which differs in Germany, the UK and France.
- We infer the distribution of income within the Bottom 90% in Germany and the UK by assuming that its composition (*relative* to the Top 10%) is the same as in France.

This method is indeed not fully satisfactory and will be refined when DINA estimates are available for Germany, the UK and other European countries. However, alternative specifications used to infer the distribution of incomes within the bottom 90% in Germany and the UK had only very little impacts on the distribution of Western Europe as a whole. This suggests that our general conclusions on Western Europe, and hence on broader global regions, will be robust to future country-level improvements. Indeed, such improvements will be important to better assess the evolution of inequality at the country level rather than at the global or regional level (which is our focus here).

2.3 Sub-Saharan Africa

For Africa, full distributional national accounts are only available for Côte d'Ivoire at the time of writing and fiscal income shares are available for a handful of countries. WID.world fellows are currently working on DINA estimates for several African countries. In order to approximate the whole distribution of income in Sub-Saharan Africa, we use available survey data and correct these estimates at the top with available tax data estimates in these countries or in other African countries, with Ivory Coast as a useful benchmark (Czajka 2017). For more information on the procedure followed, see the dedicated Technical Note (Chancel and Czajka, WID.world Technical Note 2017/6).

2.4 Adjustments

Our aim is to track the evolution of global inequality over the whole 1980-2016 period. Yet, inequality estimates for certain countries display temporal gaps. We fill these gaps by using the following method:

- We interpolate linearly all gaps between two years. If the Top 1% income share in unavailable for 1991, but was 20% in 1990 and 22% in 1992, for instance, we fill in the gap by assuming that it was the mean between 1990 and 1992 levels, i.e. 21%.

- In the case of gaps between 2016 and the most recent year available, we extrapolate all missing years by holding income shares constant and letting the average income of different income groups follow the growth of the average national income per adult. If data is available for 2015 but not for 2016 in a given country, for instance, and that the average national income per adult in this country grew by 2% in 2015, then we let the average income of all income groups grow by 2% between 2015 and 2016. The same procedure is applied backwards when inequality data is missing between 1980 and the earliest year available. In the context of a general rise in inequality since the 1980s, this assumption is conservative.

3 Estimating global inequality

Given the available distributions listed above, we use a two-step procedure to estimate global inequality. First, we combine country-level distributions in order to estimate income inequality dynamics in subregions of the world for which we have no data. We then merge all subregions and calibrate the resulting distribution to the average national income per adult of the world.

3.1 From countries to subregions

While all the countries or regions listed above cover an important share of the world adult population, important geographical areas are still missing in our analysis. In particular, this might result in seriously underestimating global inequality, since we would omit world regions who differ greatly in their average income. Given that we have data on national incomes for nearly all countries in the world (see Blanchet and Chancel, 2016), it seems plausible to add missing regions to our estimation by using a gross approximation of income inequality within these areas. Put it differently, the between-country component of inequality is properly estimated (thanks to available aggregate national income data for close to 100% of global income), while the within-country component of global inequality relies on a more assumptions, somehow acceptable given that we already cover close to 75% of world income with relatively precise within-country inequality estimates. For a complete list of subregional aggregates, see Table A2.

This approximation is done by merging data from neighbouring countries, rescaling the predicted aggregate to its national income, and then predicting new income inequality dynamics within this aggregate from its growth path between 1980 and 2016. All distributions are merged using a mixture model (see the Generalized Pareto Interpolation tool, "gpinter", available online). Gpinter uses the average national incomes per adult, the adult populations and the thresholds and averages of different income groups in two (or more) countries and returns the income distribution and average income of the aggregate composed of these countries.

More precisely, we use the following method to infer the distribution of income within subregions for which we have no data:

1) We create two merged distributions using Gpinter: one composed of France, Germany and the UK, and the other composed of China and India.

2) We duplicate specific distributions to obtain new world subregions:

- “Other Western Europe” is the France-Germany-UK merged distribution.
- “Eastern Europe” is the France-Germany-UK merged distribution.
- “Other Asia” is the China-India merged distribution.
- “Other North America” is the distribution of the US.
- “Other Latin America” is the distribution of Brazil.
- For Russia, we simply rescale the distribution to the average national income of Russia and Ukraine combined.

3) We calibrate the income distributions of “Other Asia”, “Eastern Europe”, “Other North America”, “Other Latin America” and “Other Western Europe” by rescaling averages to the national income per adult of the corresponding subregion. Therefore, we assume inequality and inequality dynamics to be the same in the projected region, but projected regions differ in the level and evolution of average income per adult. The final “Other Asia” aggregate, for instance, has the same income shares as the merged distribution of China and India, but has the average national income per adult of the rest of Asia (excluding Russia) across the whole 1980-2016 period. From this aggregate, we finally build “Asia” (excluding Russia), which is the merged distribution of China, India and Other Asia.

Similarly, “Other Western Europe” is the merged distribution of France, Germany and the UK, rescaled to the average national income of the rest of Western Europe (25 countries). From this aggregate, we finally build “Western Europe”, which is the merged distribution of France, Germany, the UK, and “Other Western Europe”.

3.2 From subregions to regions

After having predicted income inequality in subregions of the world for which we have no data, we are left with 15 countries or subregions. In the same way as above, we merge again different subregions together to get inequality estimates at the level of world regions:

- Europe is the merged distribution of France, Germany, the UK, the rest of Western Europe and Eastern Europe.
- Asia is the merged distribution of China, India and the rest of Asia.
- US-Canada is the merged distribution of the US and of Canada.
- Latin America is the merged distribution of Brazil and the rest of Latin America.

If we add Subsaharan Africa and the Middle East, we now have six world regions, which together covering close to 100% of world population and national income. These aggregates are useful to capture broad evolutions of inequality within and between the main geographical areas of the world, bearing in mind the limits of our method associated current lack of inequality data.

3.3 From regions to global inequality

As highlighted in this introduction, we merge five different combinations of subregions in order to apprehend how one can gradually build a global distribution of inequality from our procedure, and to compare the results obtained from our scenarios.

Scenario 1: the US and Western Europe are merged. Western Europe is the merged distribution of France, Germany and the UK, rescaled to the national income and adult population of Western Europe as a whole[3].

Scenario 2: China, India, the US and Western Europe are merged.

Scenario 3: Brazil, China, India, the Middle East, Russia, the US and Western Europe are merged.

Scenario 4: all 15 subregions or countries are merged. These are Africa, Other Asia, Brazil, China, Germany, Eastern Europe, France, the UK, India, the Middle East, Other North America, Russia, Other Latin America, the US and Western Europe.

Scenario 5: all subregions are included, except Other Asia and Other Latin America.

Appendix F provides results for the different scenarios. Our baseline scenario is Scenario 4 in 2016 PPP Euros. It combines all countries and subregions available to estimate a global distribution of income that has the largest geographical coverage. Note that in estimating global inequality, we combined all subregions and countries rather than directly merging the 6 world regions defined above. This is because using all the information available (at the country level, subregional level and regional level) rather than merging distributions which are already aggregated gives us a slightly more precise estimate.

In theory, given that we have data on the national income per adult in most countries around the world, inferring inequality in each country with the same method as above and then merging all countries would have produced even more precise estimates. Yet, this would be computationally very intensive and would not add much to the analysis, since we are already covering an important share of global income and global population with available distributional national accounts (respectively about 75% and 65%), and differences in income levels between our subregions are already sufficiently large to capture the main differences in average incomes between most

[3] Western Europe here is therefore not exactly the same as "Western Europe" detailed in 3.1. More precisely:

- For scenarios 1, 2, 3, Western Europe = France + Germany + UK.
- For scenarios 4 and 5, Western Europe = France + Germany + UK + Other Western Europe.

Both versions of Western Europe are rescaled to the national income of Western Europe as a whole (28 countries, including France, Germany and the UK).

countries in the world. We performed tests where we combined a larger number of countries, and as expected, results were very similar.

3.4 Distinguishing inequality between and within countries

Increasing inequality at the world level comes from differences in average national incomes per adult *between countries*, as well as from differences in average income between individuals *within countries*. We attempt to separate these two dimensions by using a very simple procedure.

Inequality within countries: to estimate the degree of inequality within countries, we attribute to each subregion the average national income of the world and re-compute the average income of each percentile group by using income shares (see formula in 1.3). We then merge all subregions to get a counterfactual global distribution of income. For each year, this corresponds to the level of income inequality that would exist if all countries in the world had the same average national income per adult.

Inequality between countries: to estimate the degree of inequality between countries, we use country-level data on average national incomes per adult. We consider each country to be an observation, and we perform a simple percentile analysis based on the country-level distribution of average income, weighed by adult population. For each year, this corresponds to the level of income inequality that would exist if for any given country around the world, all individuals living in this country would earn exactly the average national income per adult.

3.5 Robustness check: alternative calibration method

Assuming that inequality levels and trends are approximately the same within world regions seems to be a reasonable procedure. Yet, differences in growth rates between projecting and projected regions may lead to inconsistencies. In "Other Asia", for instance, national income growth was lower than in China or India, so assuming that income shares grew at the same rate could lead to underestimating the growth rate of the average income of the Bottom 50% across the period in this region. The publication of new DINA estimates for "Other Asia" countries, on which WID.world fellows are currently working, will allow us to better assess this question.

For the 2018 World Inequality Report, we use the calibration procedure described in 3.1. Below, we present an alternative method for inferring inequality in subregions. By contrast with the method in 3.1 which uses *levels* (income shares) to compute inequality in projected subregions, the following two-step method is based on inequality *dynamics*. Rather than assuming that the share of *income* captured by income group is the same in the projected region ("Other Asia") as in the projecting region (the merged distribution of China and India) over 1980-2016, this procedure assumes that inequality levels are the same in 1980, but after 1980 only the share of *growth* captured by income group is the same:

1) For each distribution, we compute the share of growth captured by income group between 1980 and 2016. Consider that the average income of the Top 1% grew from $a_{top1}^{1980} = €1000$ to $a_{top1}^{2016} = €5000$ between 1980 and 2016, while the average national income per adult grew only from $avg^{1980} = €500$ to $avg^{2016} = €600$. Then the share of growth captured by the Top 1% is equal to:

$$Share\ of\ growth\ captured = 0.01 \times \frac{a_{top1}^{2016} - a_{top1}^{1980}}{avg^{2016} - avg^{1980}} = 0.01 \times \frac{4000}{100} = 0.04 = 4\%$$

2) We then start from the distribution of income in 1980 (obtained from the method described in 3.1), and predict income inequality dynamics by combining the share of growth captured by income group with the evolution of the average national income per adult in these subregions. Formally, the average income $ainc_p^{t+1}$ of percentile p at time $t+1$ is equal to:

$$ainc_p^{t+1} = ainc_p^t + \frac{sharegrowth_p}{size_p} \times (avg^{t+1} - avg^t)$$

Where $sharegrowth_p$, $size_p$ and avg^{t+1} are respectively the share of growth captured by percentile p, the population size of percentile p (1% for the Top 1%, for instance), and the average national income per adult at date $t+1$.

Some key results obtained with this calibration method are available in **Appendix C.** Results are qualitatively similar to those obtained with static calibration. When calibrating income shares based on the share of growth captured by income group, income is higher at the bottom of the distribution and is slightly lower at the very top. The elephant curve is in fact even more pronounced in this alternative method. This variation is largely due to "Other Asia", which accounts for the largest share of world national income for which we do not have DINA estimates. In the "dynamic calibration" methodology, bottom groups in Other Asia grow relatively more than middle and top income groups of Other Asia, as compared hence moderately increasing growth rates at the bottom of the global growth curve and slightly reducing them at the middle of the global distribution. Overall impacts on the results are however limited given that this region represents a relatively low share of world national income (about 16.5%, see Figure A2).

4 Projections

After having estimated the dynamics of global income inequality between 1980 and 2016, we project the evolution of global inequality between 2016 and 2050, so as to answer a simple yet fundamental question: which of the two great forces governing global income inequality dynamics (between-country and witin-country inequality) is likely to dominate in the future?

Projections are carried in two steps. First, we predict income inequality at the subregional level based on assumptions about the growth rate of national income based, the growth rate of adult population and the share of growth captured by income group. We then merge all subregional distributions (as in scenario 4) for each year between 2016 and 2050 to get global inequality estimates for this period.

4.1 National incomes

The evolution of national incomes in countries around the world are based on OECD forecasts[4]. The OECD provides predictions about Gross Domestic Product annual growth rates up to 2050 for most countries around the world. We use these growth rates to carry forward the total national income of each country, and we then aggregate the resulting projections into the subregions defined above.

For countries included in our analysis but not included in OECD forecasts, we apply the same national income growth rate, calculated so that the total growth rate of the world's national income between 2016 and 2050 matches OECD's forecasts about global GDP growth. After aggregating countries into subregions, we noted that some subregions in the emerging world had surprisingly low growth rates implied by OECD world forecasts. We chose to be more optimistic about growth rates in the emerging world than the OECD:

- Africa is assumed to growth at an average annual growth rate of 3%.
- Other South America is assumed to growth at an average annual growth rate of 2.5%.
- Other Asia is assumed to growth at an average annual growth rate of 2.5%.

[4] OECD (2017), GDP long-term forecast (indicator). doi: 10.1787/d927bc18-en.

We view this relative optimism as a conservative assumption: the higher the growth rates in the emerging world, the faster the reduction of global inequality, via the between-country equality channel. We stress that results of global inequality projections are remarkably robust to these alternative growth rates scenarios, as long as growth rates are held at "reasonable" levels (between 2% and 7%). This result reinforces our main conclusion: it is within-country inequality, more than between-country convergence, that is likely to govern global income inequality dynamics in the coming decades.

4.2 Adult populations

Projections about adult population growth are from the United Nations' World Population Prospects. The UN provides annual growth rates forecasts up to 2050 for nearly all countries around the world. We therefore apply the same procedure as for national incomes, carrying forward adult populations based on their predicted annual growth rates.

4.3 Scenarios about inequality dynamics

Now that we have predicted the evolution of average national income per adult in all subregions between 2016 and 2050, we have to make assumptions about how growth is distributed among the adult population of each aggregate. As explained in 3.1, the evolution of the average income per adult of each income group (percentile) between two dates is given by:

$$ainc_p^{t+1} - ainc_p^t = \frac{sharegrowth_p}{size_p} \times (avg^{t+1} - avg^t)$$

Where $sharegrowth_p$, $size_p$ and avg^{t+1} are respectively the share of growth captured by percentile p, the population size of percentile p (1% for the Top 1%, for instance), and the average national income per adult at date $t+1$. In order to predict global inequality, we thus have to predict the evolution of inequality within countries by making assumptions about the share of growth captured by income group. In the World Inequality Report 2018, we assess three scenarios:

Business-as-usual scenario: assumes that inequality will grow at the same speed as it did between 1980 and 2016 in the corresponding subregion. In China, for instance, the Top 1% captured 15% of income growth between 1980 and 2016. Based on the above formula, equipped with average growth projections from the OECD, and assuming that the Top 1% continues to capture 15% of national income growth for every year between 2016 and 2050, we can therefore predict the average income of the Top 1% in China every year up to 2050.

US 1980-2016 scenario: assumes that in all subregions, inequality will grow at the same speed as it did in the US between 1980 and 2016. The Top 1%, for instance, captured about 35% of growth over the period in the US, so we can predict the evolution of inequality in other subregions by assuming that the Top 1% will capture 35% of growth every year between 2016 and 2050 and by computing the corresponding average income based on the above formula.

Europe 1980-2016 scenario: assumes that in all subregions, inequality will grow at the same speed as it did in Europe as a whole between 1980 and 2016. The Top 1%, for instance, captured about 18% of growth over the period in Europe, so we can predict the evolution of inequality in other subregions by assuming that the Top 1% will capture 18% of growth every year between 2016 and 2050 and by computing the corresponding average income based on the above formula.

After having predicted national incomes, adult populations and inequality trajectories within subregions between 2016 and 2050, we finally estimate the evolution of global inequality by merging all subregions for each scenario and for each year in the period. This gives us an estimation of the different possible trajectories of global income inequality in the next three decades.

5 Conclusion

Despite the limited available data on global inequality, we have attempted to estimate the main features of global inequality dynamics in the last 40 years by making assumptions about inequality trajectories within broad geographical areas, and on the basis of Distributional National Accounts already covering a large share of global income. Interestingly, and partly because existing inequality data from WID.world already covers about three quarters of world income and two thirds of world population, our results are relatively robust to alternative specifications for missing countries.

We have proceeded in a transparent manner, providing detailed codes and sources on WID.world, so as to contribute to increase the level of transparency of existing global inequality statistics.

As more reliable estimates will become available for a growing number of "missing" countries, especially in South-East Asia, Africa, Eastern Europe and Latin America, we will be able to get a more precise picture of global inequality. In the future, we also hope to gradually improve our projections of global inequality by testing more scenarios and formulating plausible assumptions about growth dynamics in the long run.

Appendix A – Descriptive statistics

Table A1 – Share of world population and total national income (€ PPP 2016) covered by global inequality scenarios

Scenario	Countries / Regions covered	Population covered (% of world)	National income covered (% of world)
1	Western Europe, USA	14%	33%
2	China, Western Europe, India, USA	53%	60%
3	Brazil, China, Western Europe, India, Middle-East, USA, Russia	65%	73%
4	Africa, Asia, Europe, Middle-East, USA-Canada, Russia, Latin America	100%	100%
5	Africa, Asia, Brazil, Europe, Middle-East, USA-Canada, Russia	94%	95%

Table A2 – Composition of world subregions

Subregion	Number of countries	List of countries
Brazil	1	Brazil
China	1	China
Eastern Europe	23	Albania, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Czechoslovakia, Estonia, Hungary, Kosovo, Latvia, Lithuania, Macedonia, Moldova, Montenegro, Poland, Romania, Serbia, Slovakia, Slovenia, USSR, Yugoslavia
France	1	France
Germany	2	German Democratic Republic, Germany
India	1	India

Middle-East and Northern Africa	22	Algeria, Armenia, Azerbaijan, Bahrain, Egypt, Georgia, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Palestine, Qatar, Saudi Arabia, Syrian Arab Republic, Tunisia, Turkey, United Arab Emirates, Yemen
Oceania	23	American Samoa, Australia, Cook Islands, Fiji, French Polynesia, Guam, Kiribati, Marshall Islands, Micronesia, Nauru, New Caledonia, New Zealand, Niue, Northern Mariana Islands, Palau, Papua New Guinea, Samoa, Solomon Islands, Tokelau, Tonga, Tuvalu, Vanuatu, Wallis and Futuna
Other Asia	31	Afghanistan, Bangladesh, Bhutan, Brunei Darussalam, Cambodia, Hong Kong, Indonesia, Iran, Japan, Kazakhstan, Korea, Kyrgyzstan, Lao PDR, Macao, Malaysia, Maldives, Mongolia, Myanmar, Nepal, North Korea, Pakistan, Philippines, Singapore, Sri Lanka, Taiwan, Tajikistan, Thailand, Timor-Leste, Turkmenistan, Uzbekistan, Viet Nam
Other Latin America	44	Anguilla, Antigua and Barbuda, Argentina, Aruba, Bahamas, Barbados, Belize, Bolivia, Cayman Islands, Chile, Colombia, Costa Rica, Cuba, Curacao, Dominica, Dominican Republic, Ecuador, El Salvador, Falkland Islands, Grenada, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Montserrat, Netherlands Antilles, Nicaragua, Panama, Paraguay, Peru, Puerto Rico, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Sint Maarten (Dutch part), Suriname, Trinidad and Tobago, Turks and Caicos Islands, Uruguay, Venezuela, Virgin Islands, British, Virgin Islands, US
Other North America	4	Bermuda, Canada, Greenland, Saint Pierre and Miquelon

Russia	2	Russian Federation, Ukraine
Sub-Saharian Africa	52	Angola, Benin, Botswana, Burkina Faso, Burundi, Cabo Verde, Cameroon, Central African Republic, Chad, Comoros, Congo, Cote d'Ivoire, DR Congo, Djibouti, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Saint Helena, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, South Sudan, Sudan, Swaziland, Tanzania, Togo, Uganda, Western Sahara, Zambia, Zanzibar, Zimbabwe
USA	1	USA
United Kingdom	1	United Kingdom
Western Europe	25	Andorra, Austria, Belgium, Channel Islands, Denmark, Faroe Islands, Finland, Gibraltar, Greece, Holy See, Iceland, Ireland, Isle of Man, Italy, Liechtenstein, Luxembourg, Malta, Monaco, Netherlands, Norway, Portugal, San Marino, Spain, Sweden, Switzerland

Figure A1 – Share of world population by region in 2016

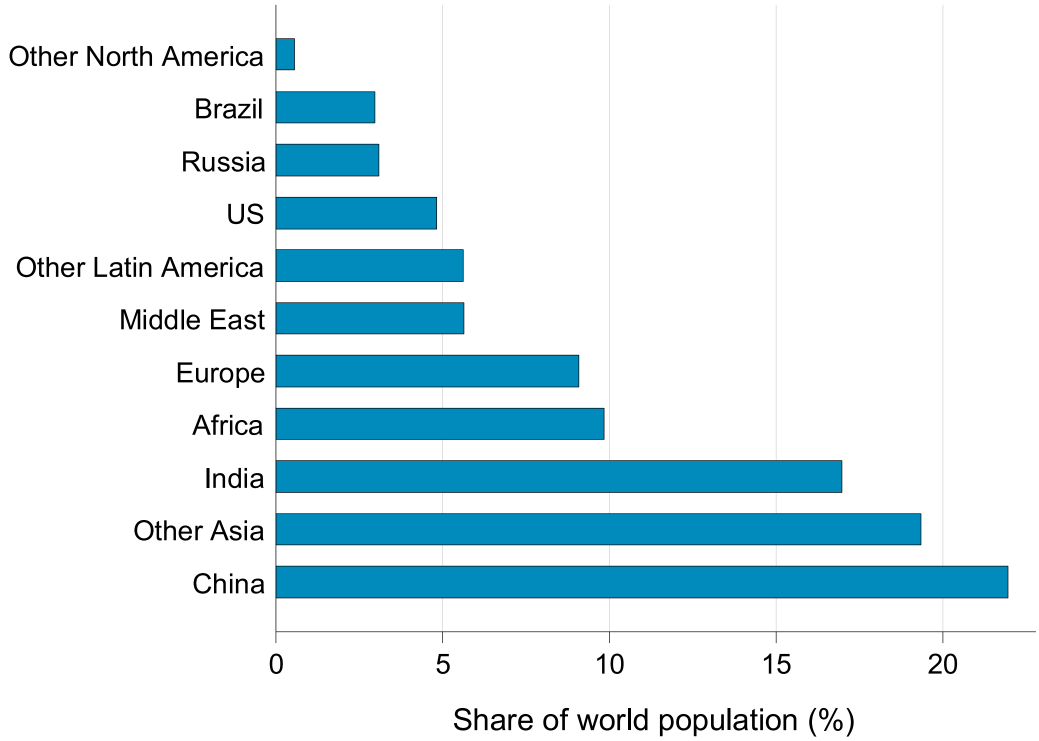
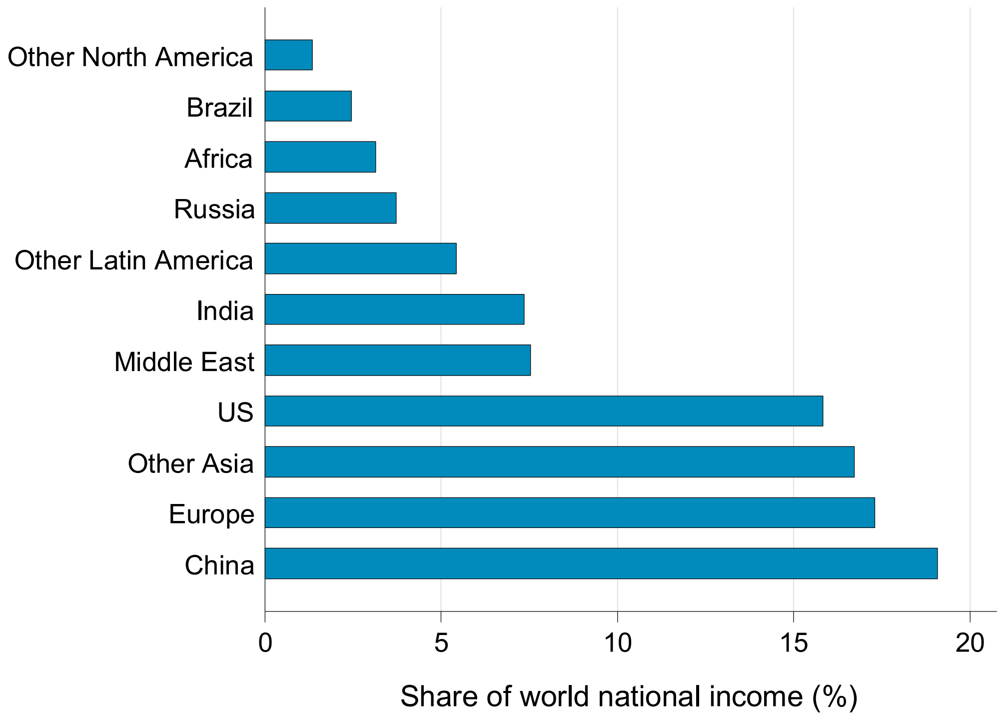


Figure A2 – Share of world national income by region in 2016



Appendix B – Results of global inequality estimates

Figure B1 – Global inequality dynamics, 1980-2016

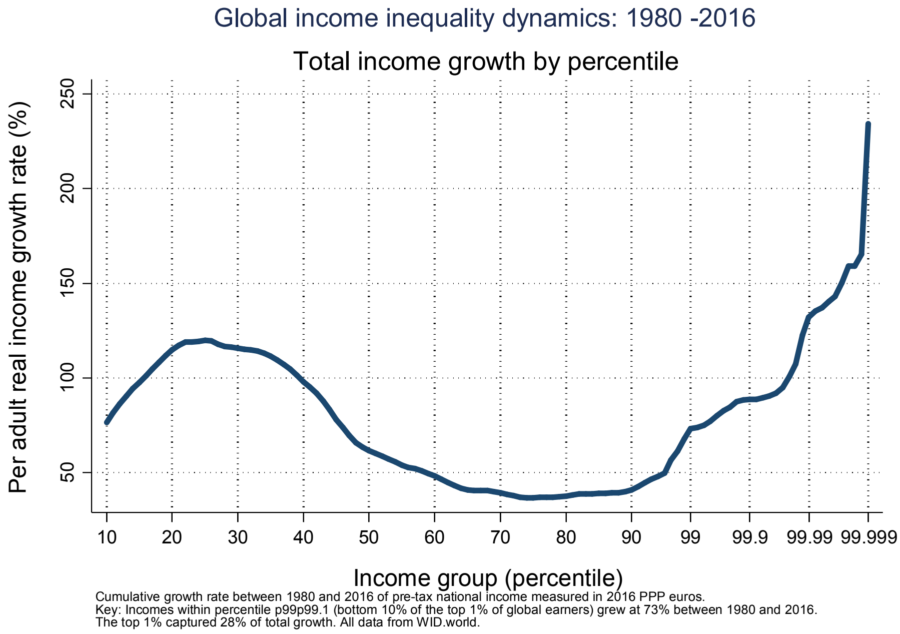


Figure B2 – Share of growth captured by income group, 1980-2016

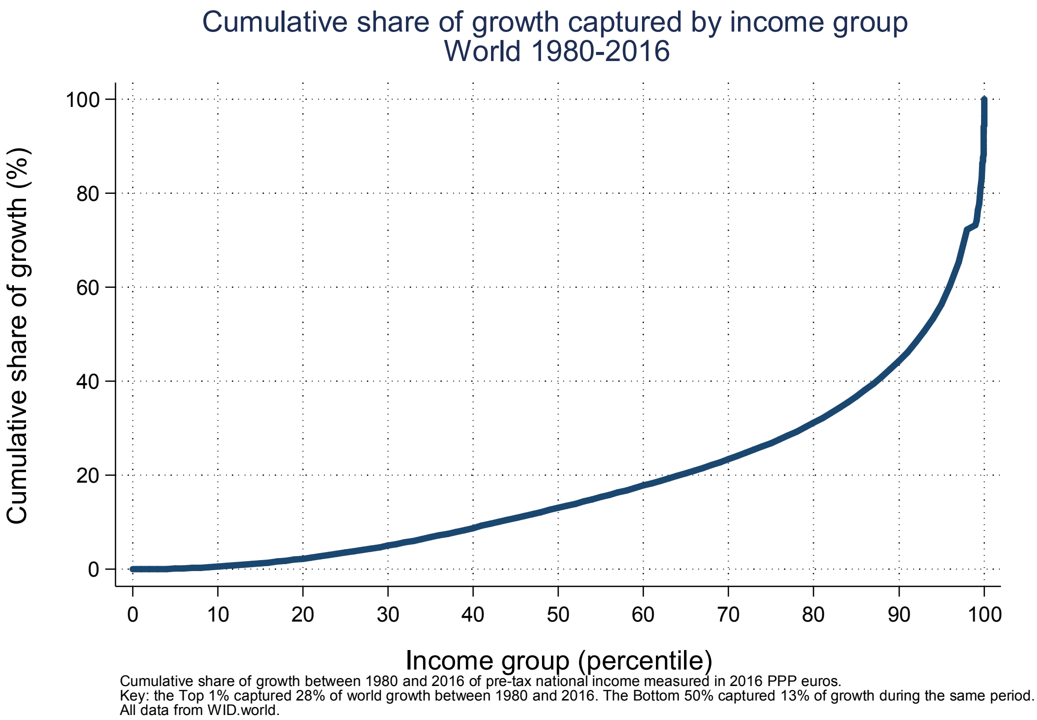


Figure B3 – Top 10% income shares in world regions, 1980-2016

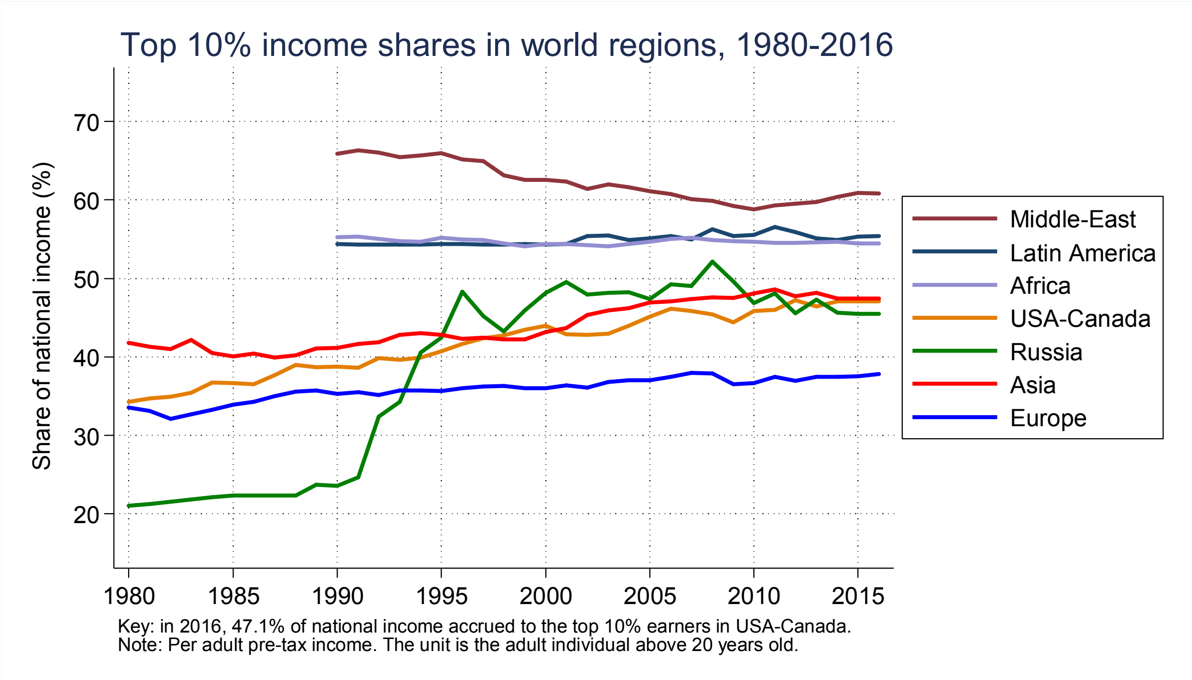


Figure B4 – Top 10% share of global income, 1980-2016

(standard calibration)

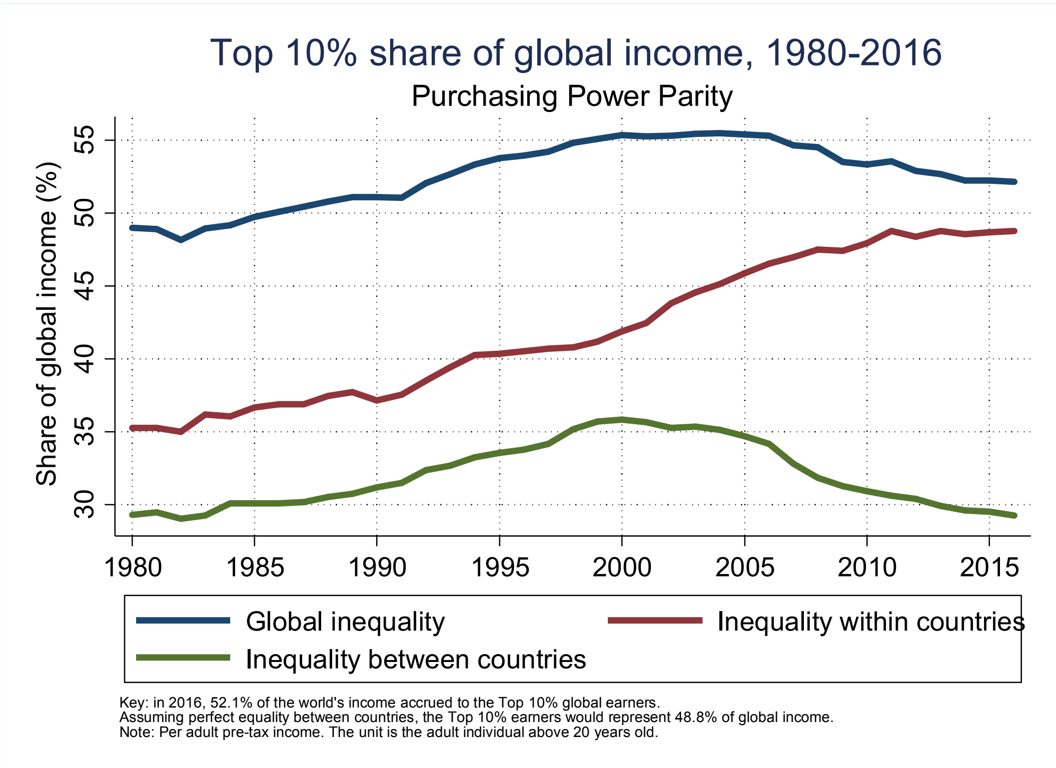


Table B1 – Income growth and inequality in world regions								
	Total cumulated per adult real growth							
Income group (distribution of per-adult pre-tax national income)	**Africa**	**Asia**	**Western Europe**	**Ex USSR**	**Middle-East**	**North America**	**Latin America**	**World**
Full population	20 %	199 %	40 %	16 %	89 %	71 %	2 %	59 %
Bottom 50%	44 %	169 %	26 %	-36 %	127 %	8 %	10 %	94 %
Middle 40%	20 %	171 %	34 %	-9 %	107 %	50 %	-4 %	41 %
Top 10%	16 %	240 %	58 %	151 %	77 %	135 %	4 %	69 %
incl. Top 1%	*30 %*	*363 %*	*72 %*	*579 %*	*62 %*	*224 %*	*13 %*	*101 %*
incl. Top 0.1%	*58 %*	*643 %*	*76 %*	*2200 %*	*56 %*	*347 %*	*33 %*	*133 %*
incl. Top 0.01%	*117 %*	*977 %*	*87 %*	*7105 %*	*60 %*	*488 %*	*59 %*	*184 %*
incl. Top 0.001%	*226 %*	*1326 %*	*120 %*	*21820 %*	*70 %*	*684 %*	*91 %*	*234 %*
Distribution of pre-tax income among adults. Estimates combine survey, fiscal and national accounts data. All data from WID.world								

Table B2 – Share of growth captured by income group in world regions								
Income group (distribution of per-adult pre-tax national income)	**Africa**	**Asia**	**Western Europe**	**Ex USSR**	**Middle-East**	**North America**	**Latin America**	**World**
Full population	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
Bottom 50%	22 %	12 %	14 %	-71 %	11 %	2 %	64 %	13 %
Middle 40%	34 %	38 %	38 %	-28 %	33 %	33 %	-76 %	30 %
Top 10%	44 %	50 %	48 %	200 %	56 %	65 %	112 %	57 %
incl. Top 1%	*27.65 %*	*19.19 %*	*18.26 %*	*125.81 %*	*21.55 %*	*33.69 %*	*181.87 %*	*27.71 %*
incl. Top 0.1%	*9.94 %*	*9.06 %*	*6.98 %*	*75.03 %*	*7.31 %*	*17.45 %*	*202.62 %*	*13.65 %*
incl. Top 0.01%	*2.36 %*	*4.68 %*	*2.98 %*	*37.62 %*	*3.33 %*	*8.71 %*	*156.64 %*	*7.23 %*
incl. Top 0.001%	*0.49 %*	*2.17 %*	*1.39 %*	*18.34 %*	*1.73 %*	*4 %*	*104.06 %*	*3.64 %*
Distribution of pre-tax income among adults. Estimates combine survey, fiscal and national accounts data. All data from WID.world								

Appendix C – Results from an alternative calibration method

Figure C1 – Global inequality dynamics, 1980-2016

(dynamic calibration)

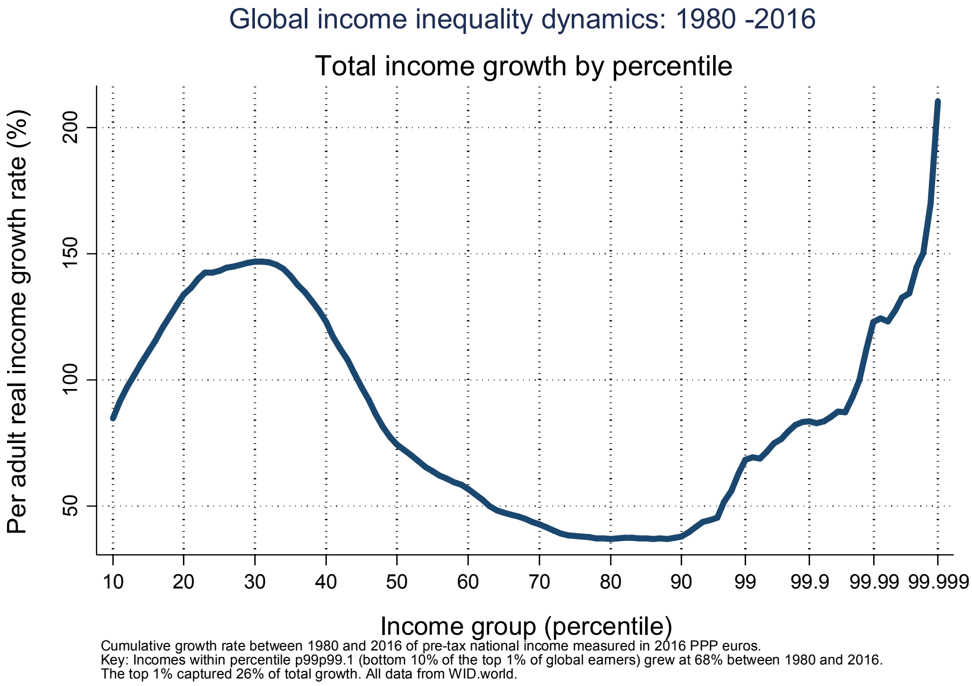


Figure C2 – Share of growth captured by income group, 1980-2016

(dynamic calibration)

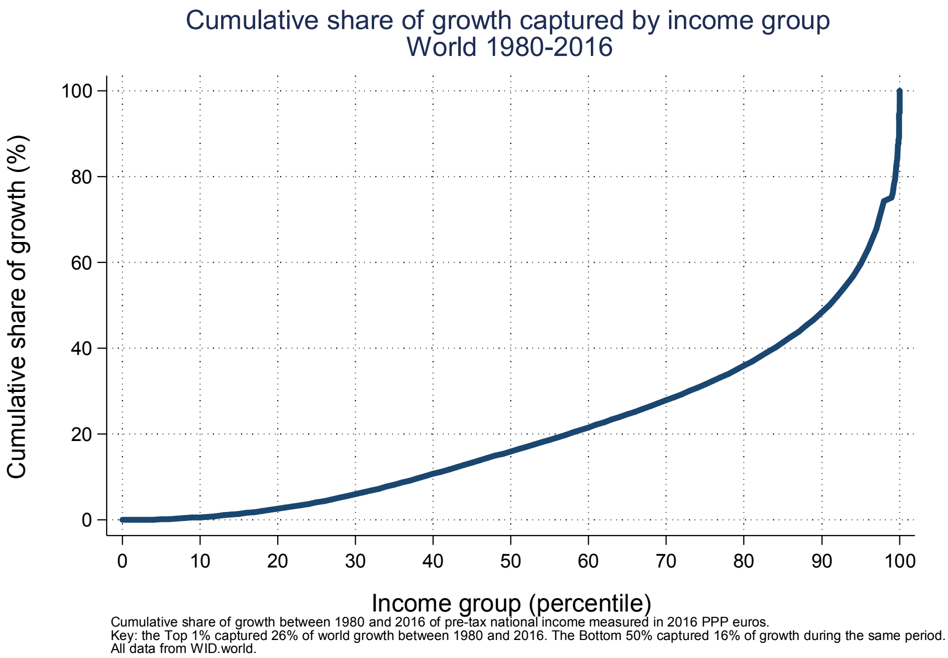


Figure C3 – Top 10% income shares in world regions, 1980-2016

(dynamic calibration)

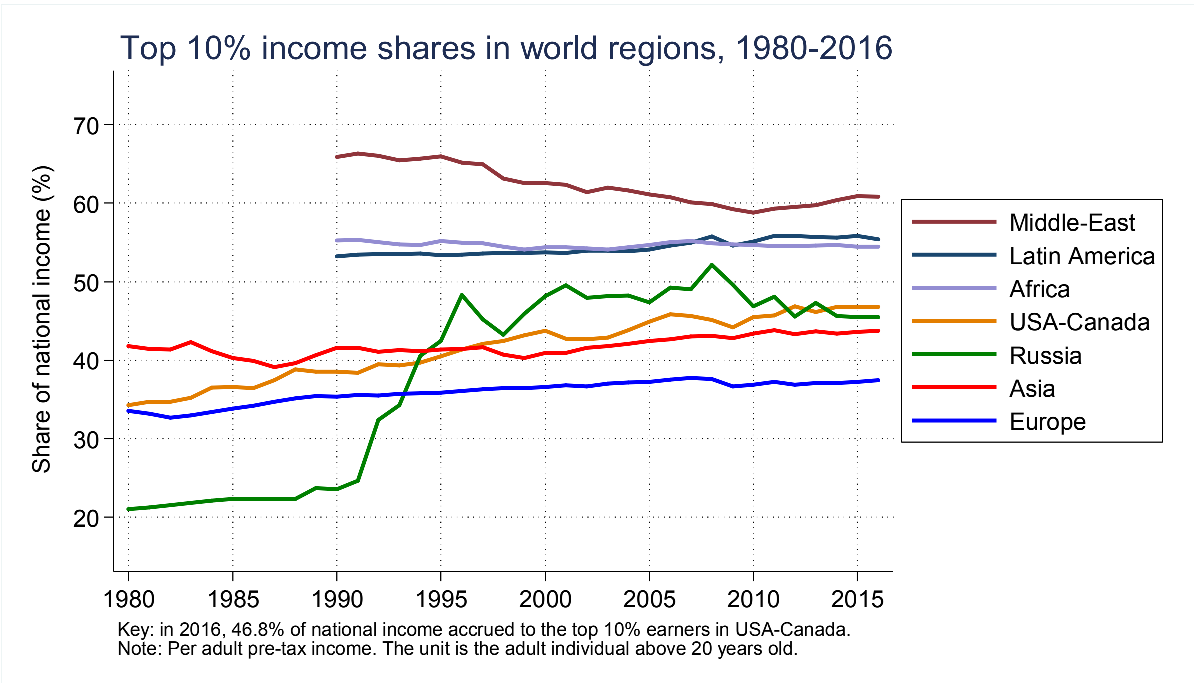


Figure C4 – Top 10% share of global income, 1980-2016

(dynamic calibration)

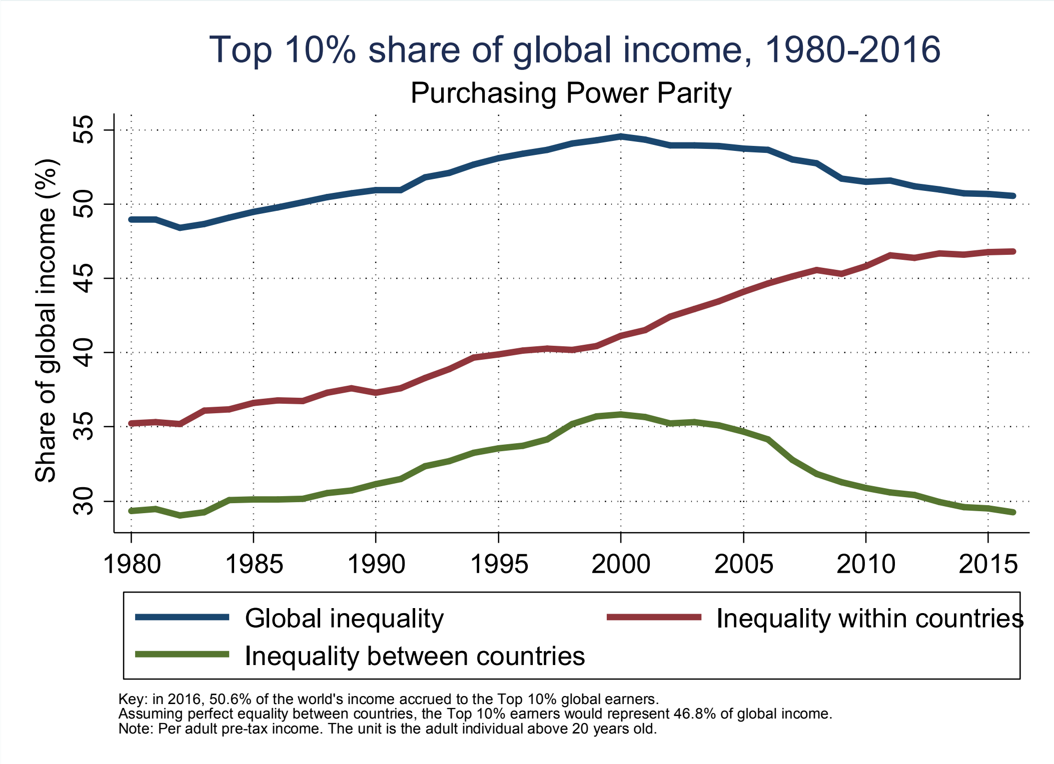


Table C1 – Income growth and inequality in world regions (dynamic calibration)								
	Total cumulated real growth per adult							
Income group (distribution of per-adult pre-tax national income)	**Africa**	**Asia**	**Western Europe**	**Ex USSR**	**Middle-East**	**North America**	**Latin America**	**World**
Full population	20 %	199 %	40 %	16 %	89 %	71 %	2 %	59 %
Bottom 50%	44 %	213 %	27 %	-36 %	127 %	10 %	10 %	115 %
Middle 40%	20 %	182 %	34 %	-9 %	107 %	51 %	-4 %	43 %
Top 10%	16 %	213 %	56 %	151 %	77 %	134 %	4 %	64 %
incl. Top 1%	*30 %*	*308 %*	*70 %*	*579 %*	*62 %*	*221 %*	*14 %*	*94 %*
incl. Top 0.1%	*58 %*	*534 %*	*73 %*	*2200 %*	*56 %*	*341 %*	*35 %*	*123 %*
incl. Top 0.01%	*117 %*	*798 %*	*84 %*	*7105 %*	*60 %*	*479 %*	*62 %*	*169 %*
incl. Top 0.001%	*226 %*	*1072 %*	*109 %*	*21820 %*	*70 %*	*666 %*	*96 %*	*210 %*

Distribution of pre-tax income among adults. Estimates combine survey, fiscal and national accounts data. All data from WID.world

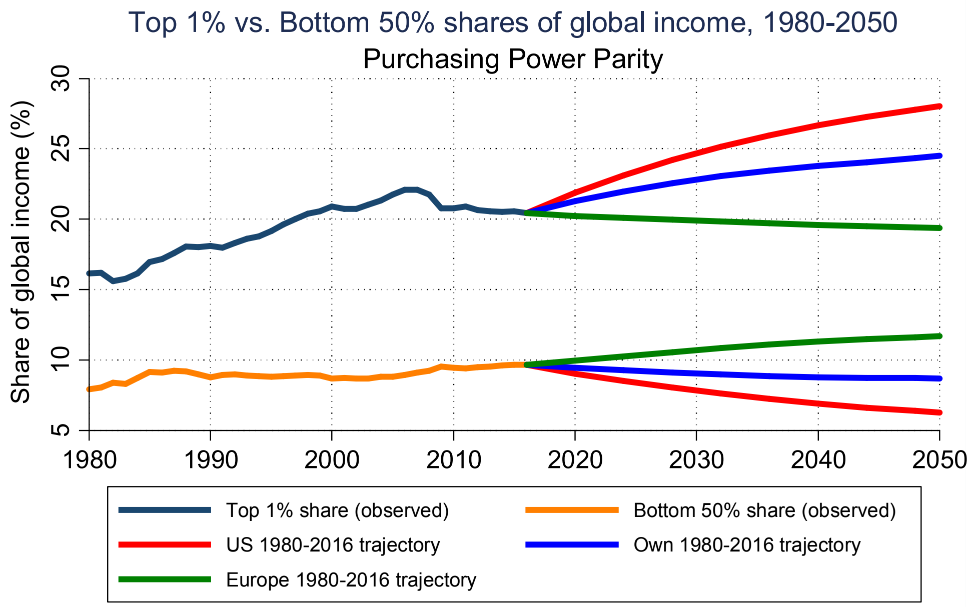
Table C2 – Share of growth captured by income group in world regions (dynamic calibration)								
Income group (distribution of per-adult pre-tax national income)	**Africa**	**Asia**	**Western Europe**	**Ex USSR**	**Middle-East**	**North America**	**Latin America**	**World**
Full population	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
Bottom 50%	22 %	14 %	15 %	-71 %	11 %	3 %	64 %	15 %
Middle 40%	34 %	41 %	38 %	-28 %	33 %	33 %	-79 %	31 %
Top 10%	44 %	45 %	47 %	200 %	56 %	64 %	115 %	53 %
incl. Top 1%	*27.65 %*	*16.26 %*	*17.66 %*	*125.81 %*	*21.55 %*	*33.17 %*	*188.27 %*	*25.77 %*
incl. Top 0.1%	*9.94 %*	*7.53 %*	*6.72 %*	*75.03 %*	*7.31 %*	*17.14 %*	*210.4 %*	*12.63 %*
incl. Top 0.01%	*2.36 %*	*3.82 %*	*2.85 %*	*37.62 %*	*3.33 %*	*8.55 %*	*162.83 %*	*6.66 %*
incl. Top 0.001%	*0.49 %*	*1.75 %*	*1.27 %*	*18.34 %*	*1.73 %*	*3.9 %*	*109.64 %*	*3.27 %*

Distribution of pre-tax income among adults. Estimates combine survey, fiscal and national accounts data. All data from WID.world

Appendix D – Global inequality projections

Figure D1 – Global income inequality projections

Top 1% vs. Bottom 50% shares



Notes: Distribution of real per adult income at Purchasing Power Parity. Average national income growth projections based on OECD forecasts. Population growth projections based on UN forecasts.
The distribution of growth within countries (actual or projected) is from WID.world.

Figure D2 – Global income inequality projections

Bottom 50% vs. Average incomes, 1980-2050

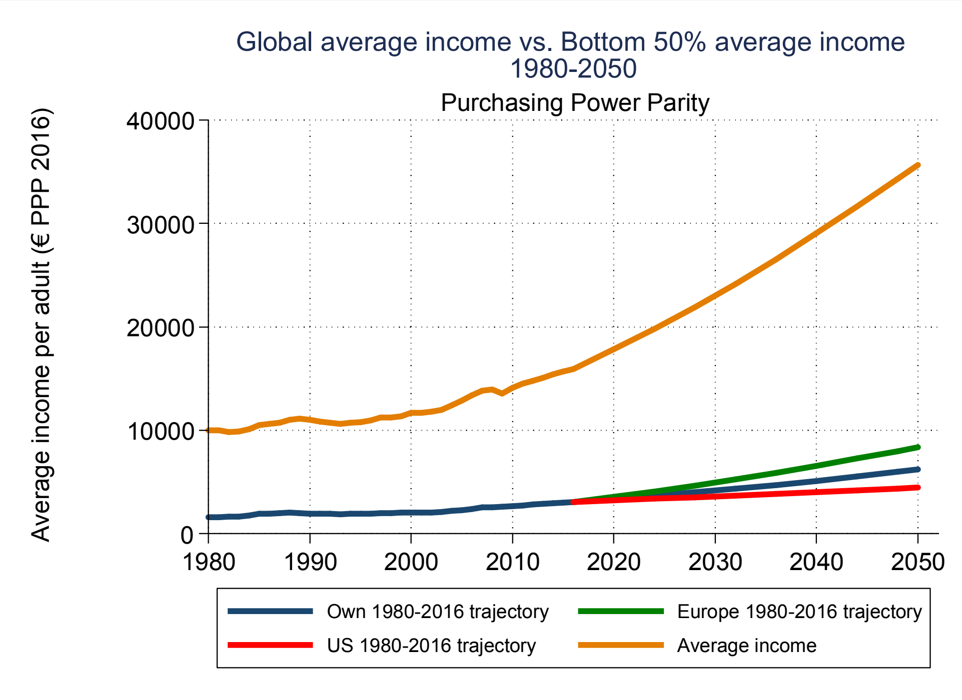
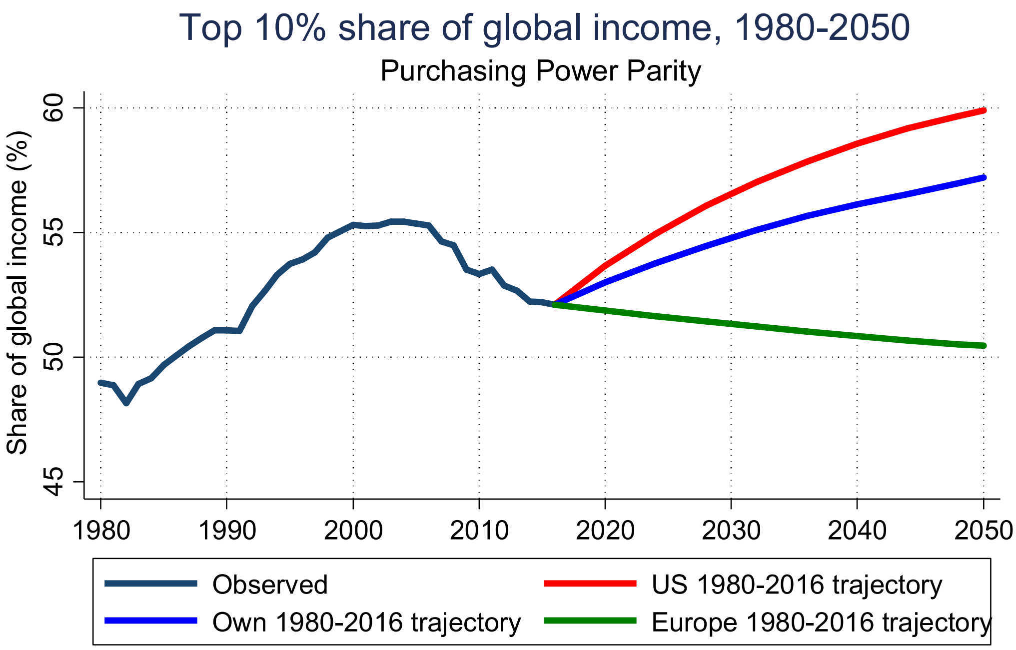


Figure D3 – Global income inequality projections

Top 10% share, 1980-2050



Notes: Distribution of real per adult income at Purchasing Power Parity. Average national income growth projections based on OECD forecasts. Population growth projections based on UN forecasts. The distribution of growth within countries (actual or projected) is from WID.world.

Appendix E – Geographic repartitions of global income

Figure E1 - Geographic breakdown of global income, 2016

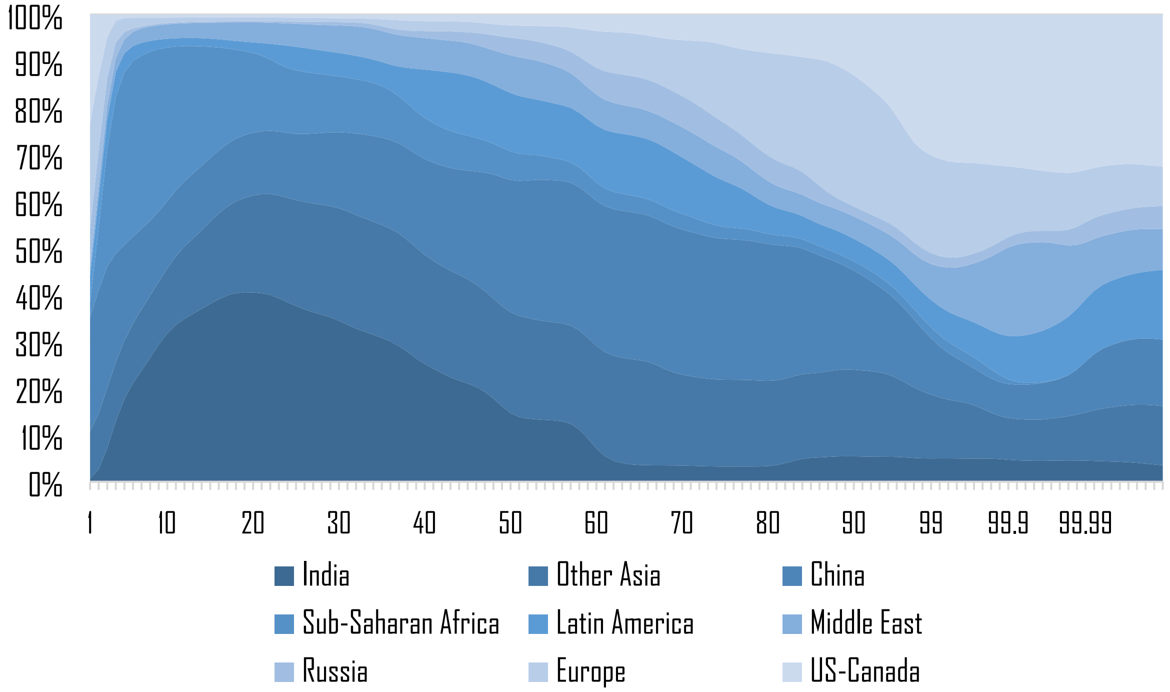


Figure E2 - Geographic repartition of the Top 10%, 1980-2016

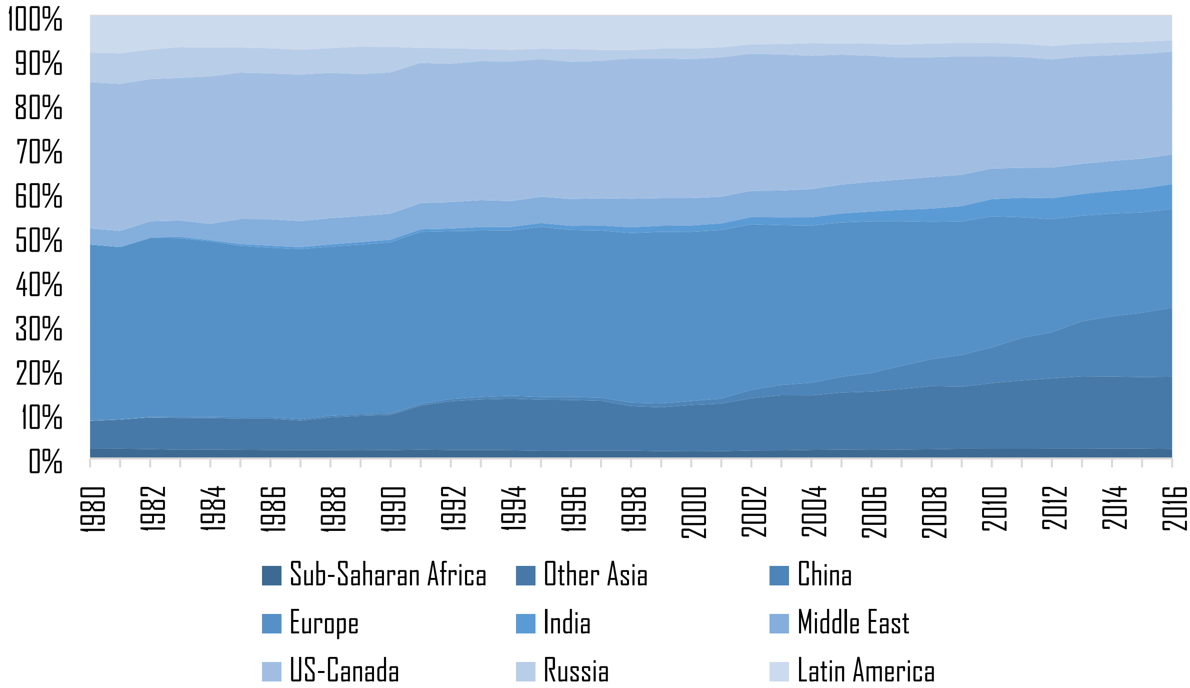
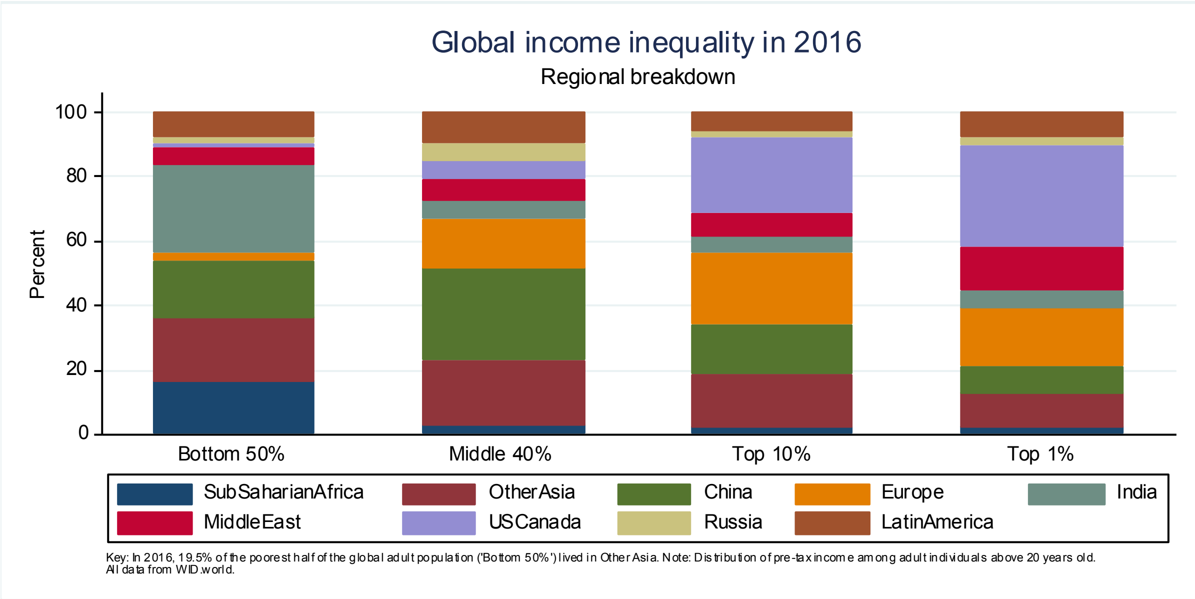


Figure E3 – Geographic breakdown of main global income groups, 2016



Appendix F – Comparing different world aggregates

Figure F1 – Global inequality dynamics in four world aggregates, 1980-2016

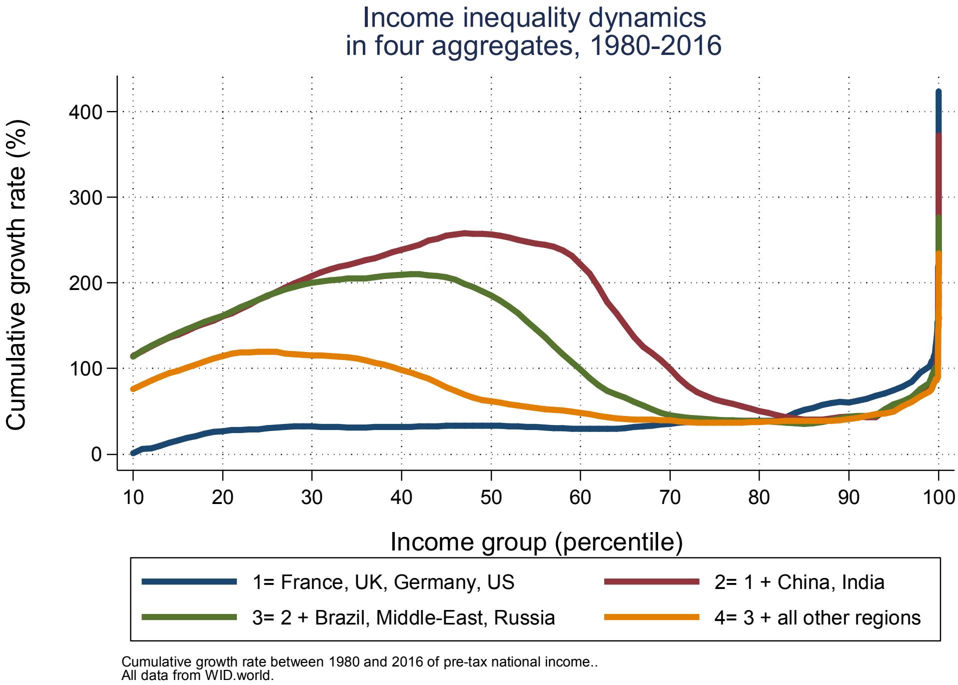


Figure F2 – Cumulative share of growth captured by income group in four world aggregates, 1980-2016

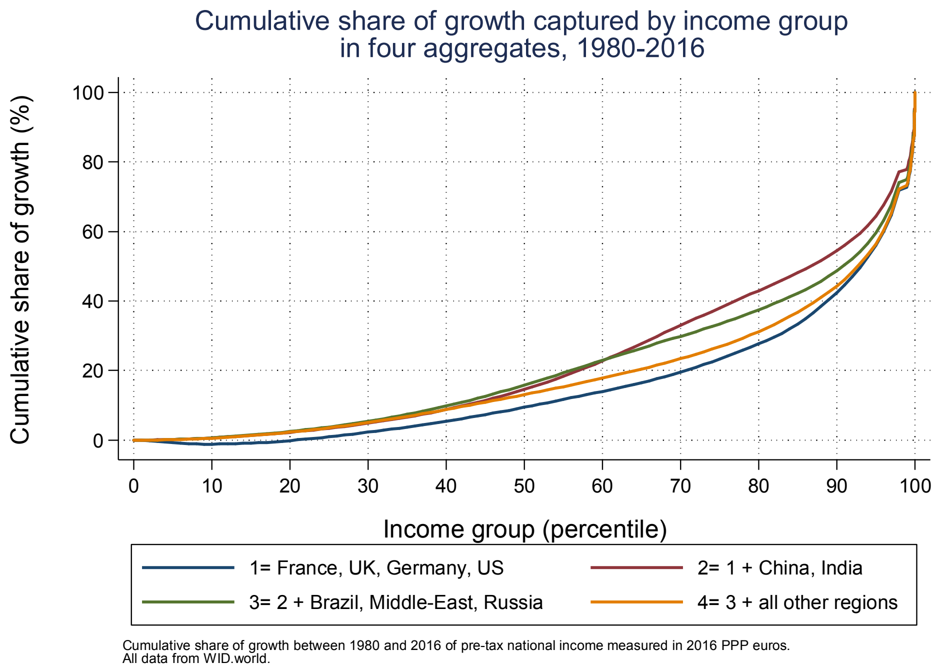


Figure F3 – Top 10% share of global income in four world aggregates, 1980-2016

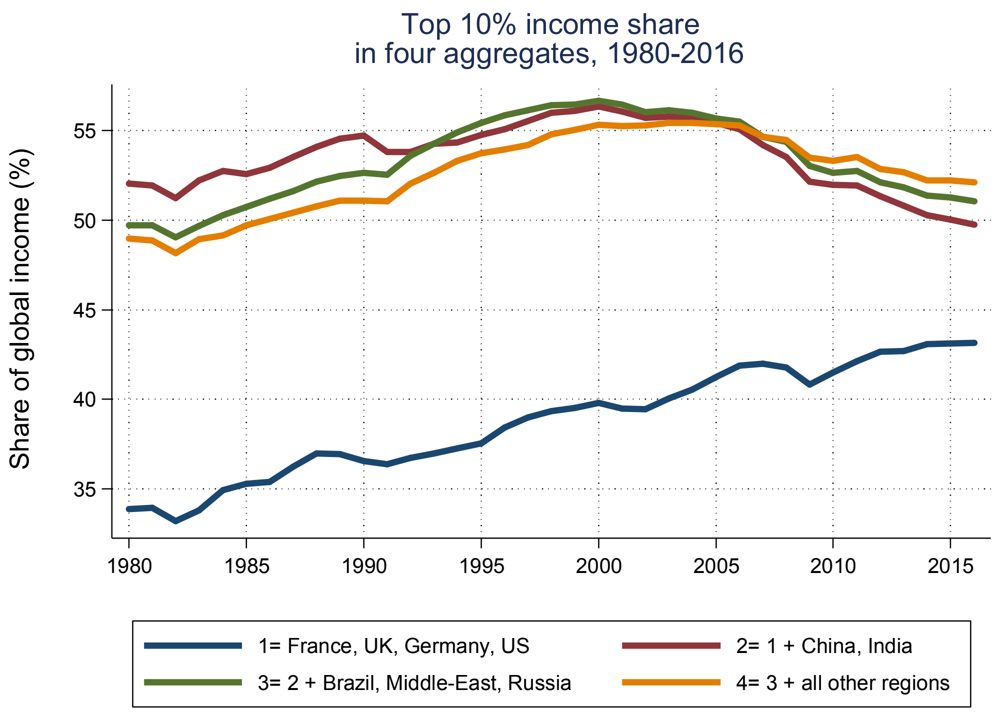


Figure F4 – Top 1% share of global income in four world aggregates, 1980-2016

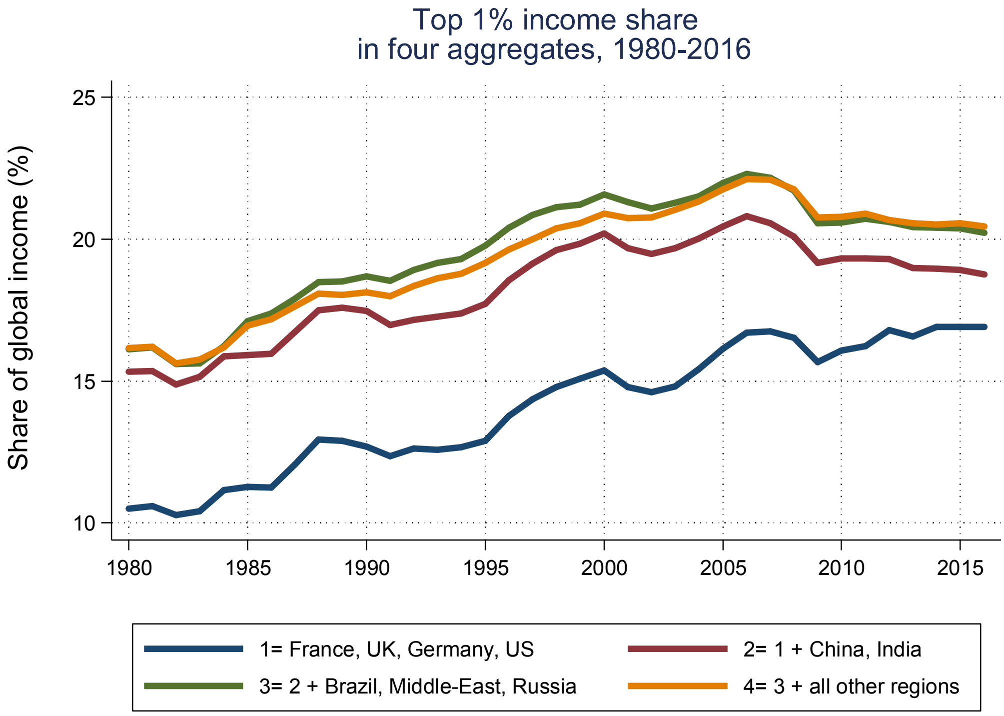


Figure F5 – Bottom 50% share of global income in four world aggregates, 1980-2016

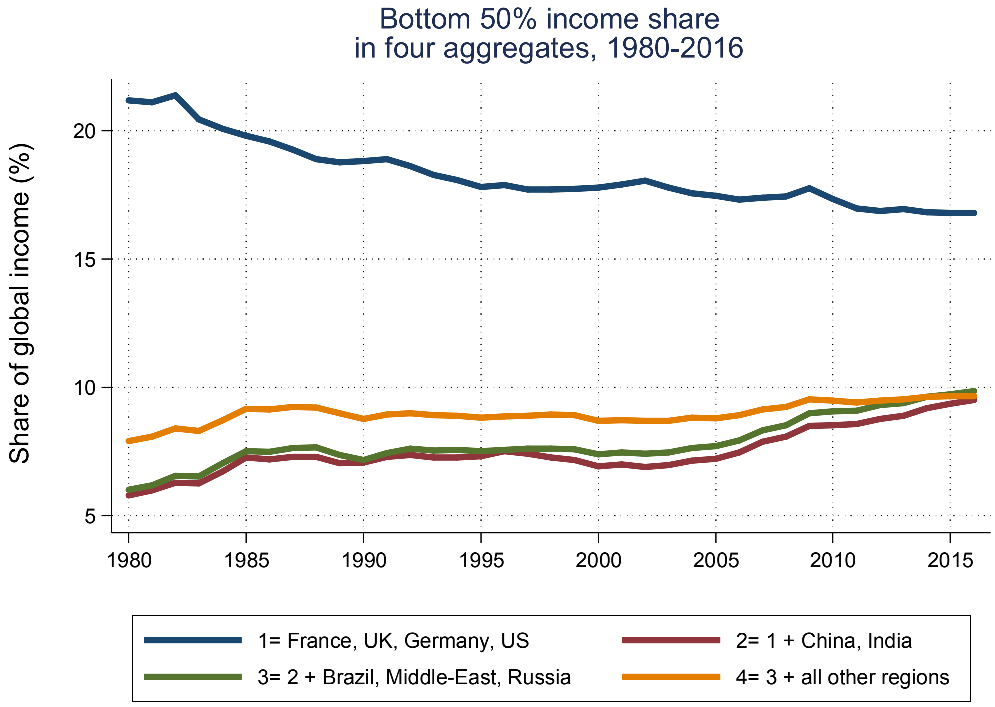


Figure F6 – Middle 40% share of global income in four world aggregates, 1980-2016