An Empirical Analysis of the World Income Distribution: Drastic Improvement in World Income Inequality during the 2000s

Soondong Hong* Heejoon Han† Chang Sik Kim‡

April 2018

Abstract

This paper nonparametrically estimates distribution of world citizens' income and investigates world income inequality for the period from 1970 to 2010. We consider 188 countries that account for 98.68% of the world population and almost 100% of the world GDP in the year 2010. Various income inequality indices such as the Gini coefficient reveal that the world income inequality drastically decreased during the 2000s while it slightly declined from 1970 to 2000. This is because inequality across countries substantially decreased during the 2000s even if inequality within each country kept increasing during the 1990s and the 2000s. These findings still hold when we include top income tax data in the analysis. We also propose more sophisticated methods to impute missing top income share data and to combine them with income survey data.

JEL classification: H00, I30

Keywords: World distribution of income, income inequality, top income tax data, inequality decomposition

*Dep. of Economics, Sungkyunkwan University. E-mail: sunnyest10@skku.edu.

†Corresponding author. Dep. of Economics, Sungkyunkwan University. E-mail: heejoonhan@skku.edu.

‡Dep. of Economics, Sungkyunkwan University. E-mail: skimcs@skku.edu.

1 Introduction

Global distribution of income and world income inequality has been a major subject of numerous research. Various approaches and assumptions have been made to more accurately estimate world distribution of income (WDI) and world income inequality in literature. Recently, related research has gained much attention, partly because more data has become available. Household income surveys and standardized databases of national accounts statistics have been updated and constantly expanded to the global level. Researchers use new data such as top income data from tax records as in Atkinson et al. (2011) and Pikettty (2014) to study income inequality.

Recent studies on world income inequality have focused on the concept of income differences of all individuals in the world.[1] These studies estimate distribution of world citizens' income and analyze inequality of world citizens' income. See Anand and Segal (2014), Bourguignon and Morrisson (2002), Chotikapanich et al. (2012), Liberati (2015), Pinkovskiy and Sala-i-Martin (2009), Sala-i-Martin (2006), van Zanden et al. (2014) and Warner et al. (2014) among others. We also consider such a concept of world income inequality in this paper.

To estimate WDI, several researchers adopted parametric methods, in which one chooses an appropriate form of income distribution. For example, Chotikapanich et al. (2012) and Warner et al. (2014) specified income distribution of each country as beta distribution and Liberati (2015), van Zanden et al. (2014) and Pinkovskiy and Sala-i-Martin (2009) used log normal distribution. While the parametric method has its merits, it inevitably involves a misspecification problem. Monte Carlo simulation results in Krause (2014) show that a parametric specification of Lorenz Curve may lead to incorrectly-shaped income density function.[2] To overcome such a misspecification problem, nonparametric estimation methods

[1]This corresponds to the concept referred to as "global inequality" in Milanovic (2005). See Anand and Segal (2008) and Milanovic (2005) for explanations on other concepts of world income inequality.

[2]Krause (2014) shows that various parametric distributions can be derived from the shape of the same Lorenz curve, and Lorenz curve estimation based on minimizing the MSE can lead to an Lorenz curve whose density has an incorrect modality.

were instead adopted to estimate WDI as in Sala-i-Martin (2002, 2006)

In this paper, we use a nonparametric method to estimate WDI for recent four decades from 1970 to 2010[3] and examine how it changed over time. In addition, we analyze world income inequality using various income inequality measures. In estimating WDI and analyzing world income inequality, there are several distinct features in our approaches compared to those in existing literature. First, we consider more countries and populations than previous studies, which would reduce sample selection bias and, therefore, induce less biased results on world income inequality. Our analysis includes a total of 188 countries for the period from 1970 to 2010. These 188 countries accounted for 98.68% of the world population and almost 100% of the world GDP in the year 2010. To the best of our knowledge, this is the largest number of countries considered in related literature. Second, we adopt improved methods to impute missing income survey data. It is inevitable that many income survey data are missing particularly for low-income countries. We extend and modify imputation methods by Sala-i-Martin (2006) and, specifically, use alternative interpolation methods.

Third, more importantly, we also analyze the case in which top income tax data are combined with income survey data and adopt more sophisticated methods to impute missing top income shares and to combine them with income survey data. Household income surveys typically exclude richest individuals or under-report their incomes, which may cause substantial bias in estimating income inequality. To overcome such a problem, we additionally use top income shares based on income tax data providing more precise information on top income shares (see Anand and Segal (2014), Atkinson et al. (2011) and Pikettty (2014) among others). To impute missing top income shares, we adopt a panel model allowing for time and individual heterogeneity. It is shown that the model fits data much better than the existing method by Anand and Segal (2014).

The main findings of this paper are as follow. First, evolution of estimated WDI shows

[3]Readers are referred to Bourguignon and Morrisson (2002) and Van Zanden et al. (2014) for global income inequality before 1970. Both papers analyzed long-term changes of world income inequality beginning in 1820.

that the mode of distribution shifts right and deviation from the center has been less in the last four decades. WDI was bimodal in 1990 and changed to unimodal in 2010. Second, most importantly, the Gini coefficient and other income inequality indices indicate that world income inequality drastically improved during the 2000s. The Gini coefficient decreased by 7.87% during the 2000s, a drastically rapid decrease considering the Gini coefficient declined only by 0.91% from 1970 to 2000.

Third, when we decompose world income inequality into two components, across-country inequality and within-country inequality, each component provides more detailed explanation on change in world income inequality. Inequality within each country substantially increased during the 1990s and the 2000s, which is in accordance with the common perception that income inequality recently deteriorated. Conversely, inequality across countries decreased more substantially during the 2000s. Since across-country inequality accounts for approximately 70% of world income inequality, this is the main reason why world income inequality drastically improved during the 2000s.

Fourth, results also reveal that China and India played key roles in improving world income inequality from 1980 to 2010. However, the Sub-Saharan Africa region played a role in deteriorating world income inequality for the last four decades. Fifth, when we include top income tax data in our analysis, the main findings in this paper prevail; world income inequality drastically improved during the 2000s and it was mainly due to rapid improvement in across-country inequality during the period.

The rest of the paper is organized as follows. Section 2 explains data and methodology to estimate world distribution of income. Section 3 provides results on estimated world distribution of income and various income inequality indices. Section 4 presents results for the case when top income shares are combined and Section 5 concludes the paper.

2 Method to Estimate World Distribution of Income

2.1 Data

While Sala-i-Martin (2006) used 138 countries to estimate WDI from 1970 to 2000, we use 188 countries for the period from 1970 to 2010. The additional fifty countries[4] account for substantial portions of world population and GDP: 5.63% of world population and 4.29% of world GDP in 2010. Inclusion of these fifty countries would reduce sample selection bias and, therefore, induce less biased results on world income inequality. In the year 2010, total population of these 188 countries was 98.68% of the world population and total GDP of these 188 countries was close to 100% of world GDP. To estimate WDI, we use GDP, population and quintile income shares of each country.

We obtain real GDP and population of each country from the Penn World Table (version 7.1). Specifically, GDP is based on 2005 USD and PPP-adjusted.[5] For countries with missing GDP data, we impute them using GDP growth rate[6]. However, there are countries with missing GDP data for a long period. For the former Soviet Union Republics, we used GDP growth rate of the Soviet Union until 1989 as in Sala-i-Martin (2006, Section II.D).

Considering data availability for more countries and a lengthier sample period, we use quintile income shares as in Sala-i-Martin (2006). We obtain quintile income shares of each country from the UNU-WIDER (United Nations University's World Institute for Development Research, version 3.0B). It provides information on distribution of income based on microeconomic income surveys for each country.[7]

[4]Afghanistan, Albania, Bahamas, Bahrain, Bermuda, Bhutan, Bosnia and Herzegovina, Brunei, Bulgaria, Cambodia, Croatia, Cuba, Czech Republic, Djibouti, Eritrea, Iraq, Kiribati, Kuwait, Lao PDR, Lebanon, Liberia, Libya, Macao, Macedonia, Maldives, Malta, Marshall Islands, Micronesia Fed. Sts., Moldova, Mongolia, Montenegro, Oman, Palau, Puerto Rico, Qatar, Samoa, Saudi Arabia, Serbia, Slovak Republic, Slovenia, Solomon Islands, Somalia, Sudan, Suriname, Swaziland, Tonga, United Arab Emirates, Vanuatu, Vietnam, Yemen.

[5]While we do not address the detailed issue of purchasing power parity (PPP) exchange rates in the paper, it is one of the key issues in estimating WDI and measuring world income inequality. As noted in Milanovic (2012), information about the level of prices in various countries plays a crucial role since price information can provide us with a criterion for comparison of individual or average welfare in different countries.

[6]Available from the National Accounts Main Aggregate Database.

[7]Deininger and Squire (1996) reported microeconomic income surveys, and extended and updated surveys

2.2 Methodology

To estimate WDI, we basically follow the imputation method by Sala-i-Martin (2006). However, wider availability of survey data globally enables us to improve estimation of WDI and, therefore, we adopted a few modified approaches as explain below. We estimate annual income distribution for each of the 188 countries and integrate country distributions for all levels of income to construct WDI. We use population-weighted income per capita as mean of each country's income distribution (see Sala-i-Martin (2006) for more details). Next, we complement mean of distribution with within-country information on income distribution contained in income surveys. Specifically, we use quintile income shares in the UNU-WIDER.

To estimate annual income distribution, we must have quintile income shares for each country and each year. However, since surveys are unavailable annually for every country, we must impute missing data. For example, Table 1 reports quintile income shares in China. It shows that surveys are not conducted annually and so we must impute missing data to estimate China's annual income distribution.

< place Table 1 here >

Sala-i-Martin (2006) divided the sample of countries into three groups based on data availability and applied different approaches for each group to impute missing income share data.[8] Sala-i-Martin (2006) defined Group A as countries of which income surveys are reported for more than one year from 1970 to 2000, and used a simple linear time-trend forecast to estimate missing values of quintile income shares. As explained in footnote 9 in Sala-i-Martin (2006), regressions were estimated independently for each of the five quintiles.

However, when we apply his method on countries of which income surveys are available for more than one year, there are 26 countries whose linear time-trend extrapolations of

are available in the UNU-WIDER.

[8] Bourguignon and Morrisson (2002), Pinkovskiy (2013), Pinkovskiy and Sala-i-Martin (2009) and Rougoor and van Marrewijk (2015) imputed missing income share data according to economic and geographical characteristics without grouping countries.

quintile income shares severely violate basic conditions for income shares; quintile shares are all positive and the last quintile income share is the largest. Linear time-trend extrapolations provide several negative quintile income shares for eighteen countries[9] and the fourth quintile income share is higher than the last quintile shares for a few years for eight country[10]. Compared to Sala-i-Martin (2006), we consider a lengthier sample period and larger number of countries, and use updated quintile income shares of individual countries. If basic conditions for income shares are violated, it is more desirable to adopt another method to replace the linear time-trend interpolation method to estimate missing values.

Consequently, we classify Group A and Group B differently from those in Sala-i-Martin (2006). Compared to Sala-i-Martin (2006), we impose an additional condition for Group A such that linear time-trend forecasts of missing quintile income shares satisfy basic conditions of income shares. If basic conditions for income shares are violated, we classify those countries as Group B while Sala-i-Martin (2006) defined Group B as countries of which only one income survey is reported from 1970 to 2000. We divide the sample of countries into the following three groups:

Group A – Countries of which linear time-trend forecasts of missing quintile income shares satisfy basic conditions for income shares (quintile shares are all positive and the last quintile share is the largest) and GDP per capita is available.

Group B – Countries of which linear time-trend forecasts of missing quintile income shares violate basic conditions for income shares and GDP per capita is available.

Group C – Countries of which income surveys are not reported and GDP per capita is available.

The list of countries in each group is provided in Appendix.

Income Shares for Countries in Group A

[9] Afghanistan, Angola, Bhutan, Cameroon, Central African Republic, Guinea, Guinea-Bissau, Iraq, Maldives, Micronesia, Namibia, Nicaragua, Singapore, Syria, Tanzania, Turkmenistan, Yemen and Zimbabwe.

[10] Albania, Belize, Bosnia and Herzegovina, Cuba, Gambia, Guyana, Iceland, Macedonia

There are 114 countries in Group A, which accounted for 91.32% of world population and 95.85% of world GDP in 2010. For Group A, Sala-i-Martin (2006) used the linear time-trend forecast method to estimate missing data. When we must extrapolate missing data, we adopt the linear time-trend forecast method as in Sala-i-Martin (2006). However, when we need to interpolate missing data, we use the linear interpolation method instead of the linear time-trend forecast method. We adopt such a modified approach because it can provide improved estimates of missing data. Figures 1 and 2 present illustrations for China and India and show that linear interpolation provides better estimates, particularly for the fourth and the last quintiles in China and for the first, second and last quintiles in India.

< place Figures 1 and 2 here >

Since Group A covers most of the world population, one may want to consider only Group A to construct WDI. However, as Sala-i-Martin (2006) pointed out, it would lead to sample selection bias because countries that do not belong to Group A tend to be poor and their exclusion would induce biased results on world income inequality.

Income Shares for Countries in Group B

There are 49 countries in Group B, which accounted for 6.50% of world population and 2.13% of world GDP in 2010. Sala-i-Martin (2006), for each country in Group B, imputed shares for missing years by averaging trends for "neighboring countries" in Group A. "Neighboring countries" are those in "region" as defined by the World Bank[11] (see Sala-i-Martin (2006) for more details). In Sala-i-Martin (2006), quintile income shares for countries in Group B were available only for one year, and even if available quintile income shares are quite different from imputed estimates from neighboring countries, such differences were ignored by Sala-i-Martin (2006). Conversely, many countries in Group B have surveys reported for more than one year in our data set and it would be more desirable to account

[11]The regions are East Asia and Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa (MENA), South Asia, Sub-Saharan Africa, High-Income Non-OECD and High-Income OECD.

for the differences between available quintile income shares and imputed estimates from the neighboring countries. We use the following modified approaches to obtain more reasonable imputed values for quintile income shares.

Suppose that surveys are available for 2001 and 2003 in an arbitrary country. We can obtain imputed estimates of quintile income shares from neighboring countries as in Sala-i-Martin (2006). For example, available last quintile shares and corresponding neighboring averages are presented as follow:

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Actual data	40	(42)	45	(43)	(41)	(39)	(37)	(35)	(33)	(31)
Average	30	28	31	31	31	31	31	31	31	31
Deviation	10	(12)	14	(12)	(10)	(8)	(6)	(4)	(2)	(0)

Note: Average means the average of neighboring countries. Deviation implies the difference between an actual value and an average. Imputed values are in parentheses.

First, we consider the year 2002 for which we need to interpolate missing data. If we simply use neighboring average as imputed value for the year 2002, it will be 28, which is too different from actual income shares in the year 2001 and 2003. Instead, we adopt the following two-step procedure. First, we obtain estimated deviation for the year 2002 by using linear interpolation of deviations, which will be twelve. Second, we add it to the neighboring average and obtain the imputed value for the year 2002, which is 42. Obviously, it is a better estimate compared to the simple replacement of the neighboring average.

Next, we consider the period from 2004 to 2010 for which we need to extrapolate missing data. We first set deviation for the last year 2010 to be zero and obtain estimated deviation by linear interpolation. Here, we assume that the country's income shares will converge to neighboring averages. Then, we combine neighboring average and estimated deviation for each missing year.

Income Shares for Countries in Group C

There are 25 countries in Group C, which accounted for 0.85% of world population and 2.03% of world GDP in 2010. Compared to Group B, Group C has much smaller population share but higher GDP share. This is because there are many high income and non-OECD countries in Group C (for example, Bahrain, Kuwait, Macao, Qatar, Saudi Arabia and United Arab Emirates). For these countries, income surveys are unavailable. Following Sala-i-Martin (2006), we impute neighboring countries' average quintile shares and average time trend of each of the shares in Groups A and B to construct quintile income shares for each country in Group C.

Estimation of Country Distributions and Constructing World Distribution of Income

In the previous step, an income share is assigned to each quintile of each country for each year. Remaining steps are as follows; we approximate each country's annual income distribution and integrate annual country distributions to estimate the annual WDI. For these remaining steps, we follow the method in Sala-i-Martin (2006). We use a nonparametric kernel method to approximate each country's annual income distribution and adopt the same bandwidth for all countries and periods (see Section II.F in Sala-i-Martin (2006) for details). We adopt the Gaussian kernel and select bandwidth by following Silverman's (1986) rule of thumb: the bandwidth h is set to be $h = 1.06 \times \hat{\sigma} \times n^{-1/5}$, where $\hat{\sigma}$ is the standard deviation of the entire sample and n is the number of observations for each year. Once the kernel density function for a particular year and country is estimated, we anchor it so that its mean corresponds to PPP-adjusted GDP per capita. Finally, we construct an annual WDI by integrating all country distributions.

3 Results Without Top Income Shares

3.1 Estimated World Distribution of Income

Figure 3(a) presents estimates of annual WDI from 1970 to 2010 in a 3-D plot and Figure 3(b) provides those for 1970, 1980, 1990, 2000 and 2010. When we examine evolution of WDI over time, mode of distribution shifts right and deviation from its center is less. This indicates that mean of WDI increases and variance of WDI decreases over time. When we examine data, mean increased by 12.00% and variance decreased by 7.66% from 1970 to 2010. Estimated WDI reveals that incomes of the world's citizens increased over time.

< place Figures 3(a) and 3(b) here >

Another feature is that WDI was bimodal in 1990 and changed to unimodal in 2010. In Figures 3(a) and 3(b), the vertical line represents probability. Figure 4 provides WDI but the vertical line in Figure 4 represents population.[12] This figure corresponds to Figure IV in Sala-i-Martin (2006), in which WDI in 1990 was also slightly bimodal. Our results show that WDI was bimodal from the late 1980s to mid-1990s and "twin peaks" disappeared in 2010. The evolution of WDI over time may indicate that, recently, global income inequality substantially improved. In the next subsection, we adopt precise measurements of income inequality to understand the evolution of world income inequality in the last four decades.

< place Figure 4 here >

3.2 World Income Inequality

We first examine the Gini coefficient, the most typical measure of income inequality. We calculate the Gini coefficient using income share data.[13] Figure 5 provides the plot of the

[12] In estimating WDI in Figure 4, the only different step is the following. After the kernel density function for a particular year and country is estimated, we decompose it into 100 centiles and normalize it so that the area is equal to that year's total population of the country.

[13] We applied other methods to calculate the Gini coefficient and the results were similar. For example, we also calculated the Gini coefficient using the cumulative distribution function of the estimated WDI as in Cowell (2000) and the result was similar.

world Gini coefficient from 1970 to 2010 and Table 2 reports the Gini coefficient with other measurements of income inequality. The Gini coefficient exhibits a downward trend after it reaches its peak (0.692) in 1973. From 1970 to 2010, the Gini coefficient decreased by 8.71%, implying that worldwide income inequality substantially improved. One of the most significant features is that global income inequality was markedly improved during the 2000s. From 1970 to 2000, it fluctuated between 0.677 and 0.692 and slightly decreased; it decreased by 0.12%, 0.34% and 0.46% during the 1970s, 1980s and 1990s, respectively. However, the Gini coefficient rapidly decreased by 7.87% during the 2000s. This is a drastically rapid decrease considering it decreased only by 0.91% from 1970 to 2000.

< place Table 2 and Figure 5 here >

Sala-i-Martin (2006, Table III) reported that the Gini coefficient decreased by 2.4% from 1970 to 2000. The difference between his result and our result is due to differences in data and methods to impute missing data. It should be noted that difference between his result and our result is relatively minor. However, there can be substantial differences if one adopts a different estimation method for WDI. For example, Pinkovskiy and Sala-i-Martin (2009) adopted parametric estimations of WDI and results showed that the Gini coefficient decreased by 6.36% from 1970 to 2000, which is significantly different from the result in Sala-i-Martin (2006) or this paper.

It is worthwhile to mention recent studies that cover the 2000s. Liberati (2015, Table 1) reported that the Gini coefficient decreased by 2.98% from 1970 to 2000 and dropped by 4.97% from 2000 to 2009. Pinkovskiy and Sala-i-Martin (2009, Table 3) reported that the Gini coefficient decreased by 6.36% from 1970 to 2000 and decreased by 3.32% from 2000 to 2006. Rougoor and van Marrewijk (2015, Figure 5) showed the Gini coefficient slightly decreased during the 1990s and decreased substantially from 2000 to 2009. Warner et al. (2014, Table 5) presented that the Gini coefficient decreased by 3.65% from 2000 to 2005 while it decreased by 2.24% from 1993 to 2000.

< place Figure 6 here >

We report seven other indices of income inequality in Table 2 and Figure 6: two Atkinson indices with coefficients 0.5 and 1, respectively, the variance of the logarithm of income, the ratio of the income of top 20 percent of the distribution to the bottom 20 percent and the ratio of the top 10 percent to the bottom 10 percent of the distribution, the Mean Logarithmic Deviation (MLD, corresponding to the generalized entropy index with coefficient 0) and the Theil index (corresponding to the generalized entropy index with coefficient 1). Figure 6 presents plots of these seven indices. Except for top-20-percent-to-bottom-20-percent ratio and top-10-percent-to-bottom-10-percent ratio[14], most indices show similar results as the Gini coefficient; most importantly, global income inequality declined rapidly during the 2000s. Two Atkinson indices with coefficients 0.5 and 1, respectively, and MLD slightly decreased from 1970 to 2000 and rapidly decreased during the 2000s as the Gini coefficient decreased. The variance of log income and the Theil index slightly increased by 0.08% and 0.75%, respectively, from 1970 to 2000 but rapidly decreased by 8.46% and 18.97% during the 2000s.

Various income inequality indices indicate that world income inequality drastically improved during the 2000s compared to the period from 1970 to 2000. One may think that this finding contradicts to common perception that income inequality recently deteriorated. We address this issue in the next subsection by decomposing world income inequality into across-country inequality and within-country inequality.

3.3 Inequality Decomposition

We decompose global income inequality into two components: across-country inequality and within-country inequality. The "across-country" component is the amount of inequality that

[14] While the top-20-percent-to-bottom-20-percent ratio and the top-10-percent-to-bottom-10-percent ratio declined substantially by 18.61% and 20.37%, respectively, from 1970 to 2010, they exhibited different trends compared to the rest indices. For example, the top-20-percent-to-bottom-20-percent ratio rapidly decreased during the 1980s and 1990s but increased during the 2000s.

would exist in the world if all citizens within each country had the same level of income, but there were differences in per capita incomes across countries. For across-country inequality, every citizen's income is assumed to be his or her country's per capita income. The "within-country" is the difference between overall global inequality and across-country inequality. The within-country inequality is the amount of inequality that would exist in the world if all countries had the same income per capita but the actual within-country differences across individuals.

Among eight inequality indices we consider, the MLD and Theil index belong to the class of generalized entropy index and are decomposable (see Cowell (1995) and Sala-i-Martin (2002) for details on generalized entropy index and decomposition). Table 3 provides decomposition of global income inequality using the MLD and Theil index.

< place Table 3 here >

In 1970, 79.5% of global MLD was accounted for by across-country inequality and only 20.5% of global MLD was accounted for by within-country inequality. This implies that world income inequality was mainly due to across-country inequality in 1970. While the global MLD declined by 19.0% in the last four decades, each component exhibited opposite trends; across-country inequality decreased substantially by 30.6% but within-country inequality increased by 26.1% from 1970 to 2010. Within-country inequality substantially increased during the 1990s and 2000s: 11.4% (during the 1990s) and 6.6% (during the 2000s). This is in accordance with common perception that income inequality recently deteriorated. However, across-country inequality decreased more substantially and rapidly declined by 23.9% during the 2000s. This is the main reason why global income inequality drastically improved during the 2000s considering that across-country inequality comprises approximately 70% of global MLD. From 1970 to 2010, decrease of across-country inequality was larger than increase of within-country inequality, consequently reducing overall global income inequality. In 2010, only 68.1% of global MLD came from across-country component (down from 79.5% in 1970) and 31.9% originated from within-country component (up from 20.5% in 1970).

When we examine decomposition of the Theil index, results are generally similar to those for the MLD. In 1970, 76.1% of the global Theil index was accounted for by across-country inequality and 23.9% was accounted for by within-country inequality. For the last four decades, across-country inequality declined by 27.5% while within-country inequality increased by 10.6%. In particular, across-country inequality rapidly declined by 27.2% during the 2000s. Conversely, within-country inequality increased during the 1990s and 2000s: 12.5% (during the 1990s) and 6.0% (during the 2000s). It is interesting to note that within-country inequality increased the most during the 1990s for the MLD and the Theil index. In 2010, only 67.6% of global Theil index came from across-country component (down from 76.1% in 1970) and 32.4% originated from within-country component (up from 23.9% in 1970).

For the MLD and the Theil index, across-country inequality has been decreasing but within-country inequality has been increasing in the last four decades. In particular, across-country inequality rapidly declined during the 2000s while within-country inequality substantially increased during the 1990s and 2000s. We confirm common perception that income inequality recently deteriorated is true if we consider within-country income inequality. Within-country inequality shows that when we consider one country, income inequality recently deteriorated. Meanwhile, we also confirm that this does not contradict our finding that global income inequality substantially improved during the 2000s. This is because across-country inequality accounting for approximately 70% of global inequality improved significantly during the 2000s. When we consider whole population of the world, income inequality substantially improved during the 2000s.

3.4 Main Convergers

Sala-i-Martin (2006) argued that 1970-2000 was a convergence period and that China played the most significant role among "main convergers". World income inequality declined for the period and one of the main reasons was rapid development in countries like China. As shown in the previous subsections, world income inequality decreased drastically during the 2000s mainly due to improvement in across-country inequality. In this subsection, we investigate which country or region played the role of main converger for the period.

< place Table 4 here >

Table 4 provides population ratios of eight regions of the world in 2010. China belongs to the East Asia and Pacific region and accounts for 19.4% of world population. India belongs to the South Asia region and comprises 17.1% of world population. The Sub-Saharan Africa region and the Latin America and Caribbean region account for 12.4% and 8.2%, respectively, of world population. Figure 4 provides plots of various Gini coefficients: 1) Gini coefficient including all countries, 2) Gini coefficient excluding China, 3) Gini coefficient excluding India, 4) Gini coefficient excluding Sub-Saharan Africa, 5) Gini coefficient excluding Latin America and Caribbean and 6) Gini coefficient excluding both China and India. Table 5 reports change rates of these Gini coefficients for each decade.

< place Table 5 and Figure 7 here >

When China was excluded, the Gini coefficient increased from 1978 to 2000 and increased by 5.06% from 1970 to 2000. Considering that the Gini coefficient including China slightly decreased by 0.91% until 2000 as shown in Figure 7, this implies that China was one of the main convergers until 2000. Even during the 2000s, China was one of the main convergers; the Gini coefficient would decrease by 5.11% instead of 7.87% when China was excluded. While China played the most significant role as a main converger during the 2000s, India also played a role as a main converger for the period; the Gini coefficient would decrease by 7.08% instead of 7.87% during the 2000s when India was excluded. When China and India were excluded, the Gini coefficient would increase by 4.06% and 4.84%, respectively, for the 1980s and 1990s and would decrease only by 2.71% instead of 7.87% during the 2000s. Our result is in accordance with previous studies. Chotikapanich et al. (2012), Jones (1997), Liberati (2015) and Milanovic (2012) also emphasized the effect of China and India in the change of world income inequality.

However, when the Sub-Saharan Africa region was excluded, the Gini coefficient would decrease more substantially for the entire period including the 2000s. The Gini coefficient would decrease by 9.58% instead of 7.87% during the 2000s when the Sub-Saharan Africa region was excluded. This indicates that the region was one of "main divergers" during the 2000s. Meanwhile, influence of the Latin America and Caribbean region was marginal; the Gini coefficient would decrease by 7.82% instead of 7.87% during the 2000s when the region was excluded.

4 Inclusion of Top Income Tax Data

The results in the previous section are based on income survey data. However, it is well known that income survey data are biased particularly for top income shares due to under-reporting of the very rich. Therefore, one probably argues that the main findings in the previous section could be misleading due to under-reporting in top income shares and it would be more desirable to include top income shares of each country in analysis of world income inequality. We address this issue in this section and examine if the main findings in the previous section prevail even when we include top income data in our analysis.

Recently, there have been efforts to combine top income shares with income survey data. Anand and Segal (2014) combined top 1% share of income tax data with income survey data. Their detailed method is explained in the next subsection. Meanwhile, Lakner and Milanovic (2013) imputed top 1% and 5% income shares by using the difference between survey incomes and household final consumption expenditure from the national account and assumed a specific distribution (Pareto distribution) for WDI.

When we combine data on top income shares with income survey data, we use the income tax based top income shares provided by the World Top Income Database[15] that comprises

[15] It is constructed by Facundo Alvaredo, Tony Atkinson, Thomas Piketty and Emmanuel Saez. Available

precise information on top income shares. Recently, studies based on top income tax data gained much attention (see Atkinson et al. (2011) and Pikettty (2014) among others) and Anand and Segal (2014) used the same data set. It should be noted that top income tax data considers taxable income while income survey data considers disposable income.[16] Due to such a difference in definitions of income, we should be cautious when we interpret results in this section. It would be better if we use only one kind of income for analysis. However, data based on tax data are available only for small number of countries and are limited to estimate distribution of world citizens' income. Hence, it is desirable to develop more rigorous methods to combine top income tax data with income survey data in estimating distribution of world citizens' income. In the next subsection, we propose and investigate an alternative way to combine top income tax data with income survey data.

4.1 Data and Methodology

Top income shares are available only for 29 countries from the World Top Income Database. Table 6 reports countries of which top income shares are available. Among these 29 countries, 27 countries belong to Group A and two countries (Mauritius and Singapore) belong to Group B. Table 6 shows that top 10%, 5%, 1%, 0.05%, 0.1%, 0.05% and 0.01% income shares are available and that there are missing data for several countries. Considering data availability, we use top 1% and 5% income shares from the World Top Income Database.

< place Table 6 here >

We explain the method by Anand and Segal (2014) before we describe our approach to combine top income tax data with income survey data. Anand and Segal (2014) combined top 1% share of income tax data from the World Top Income Database with Milanovic's

at http://wid.world/.

[16] Lakner and Milanovic (2013) provide detailed explanations on the difference between tax data and survey data in defining income.

(2012) dataset[17] of household surveys for five years (1988, 1993, 1998, 2002 and 2005). Assuming that survey data represent only the bottom 99% of the population in each country, they multiply population in each income group in the surveys by 0.99 and append the top percentile with income share from tax data. In their study, the top 1% income share data were available for about twenty countries (ranging from 18 to 23 countries in each year). For those countries that do not have top income data, they impute top 1% shares using the following simple linear regression;

$$top1\%share_{it} = \beta_0 + \beta_1 top10\%share_{it} + \beta_2 mean\_income_{it} + \epsilon_{it} \tag{1}$$

where $top1\%share_{it}$ is top 1% income share from tax data, $top10\%share_{it}$ is top 10% income share from survey data, and $mean\_income_{it}$ is mean income from surveys. They used 104 country-years observations and estimated eq. (1) using pooled OLS method. However, they did not consider either time or individual heterogeneity in eq. (1). Not controlling this heterogeneity invites risk of yielding biased results, see e.g. Baltagi (2013), and using a panel model provides more degrees of freedom, efficiency, and less collinearity among variables.

While Anand and Segal (2014) did not consider either time heterogeneity or individual heterogeneity, we adopt a model allowing for both time and individual heterogeneity;

$$y_{it} = \alpha + \mu_i + \lambda_t + x'_{it}\beta + \varepsilon_{it}, \tag{2}$$

where y_{it} is top 1% or 5% income share for country i and year t and x_{it} =(top 20% income share$_{it}$, logged GDP per capita$_{it}$)$'$. In eq. (2), μ_i represents individual heterogeneity across countries and λ_t accounts for time heterogeneity. To reduce number of parameters to estimate, we let λ_t to have the same value for each decade. For 29 countries from the World Top Income Database, top 1% or 5% income share is missing for several years. Therefore, we

[17] The survey data in Milanovic (2012) consider between 92 and 119 countries and cover between 87% and 92% for the five years: 92 countries (87% of the world population) in 1998 and 119 countries (92% of the world population) in 2005.

have an unbalanced panel and we adopt the fixed effect estimation method. For comparison, we also estimate the pooled model

$$y_{it} = \alpha + x_{it}'\beta + \varepsilon_{it}, \tag{3}$$

which corresponds to the model adopted by Anand and Segal (2014).

Table 7 reports estimation results of these two models. The model allowing for time and individual heterogeneity exhibits much higher adjusted R^2 than the pooled model; it is 0.83 in both top 1% and 5% income shares while it is 0.47 (top 1%) and 0.43 (top 5%) for the pooled model. This shows that the model allowing for time and individual heterogeneity fits data much better than the pooled model. Hence, we use this model instead of the pooled model to impute missing top income shares. Both explanatory variables, top 20% income share and logged GDP per capita, are estimated significant in all cases and their coefficients are smaller for the model with time and individual heterogeneity than the pooled model.

< place Table 7 here >

Using estimates of the model with time and individual effects, we impute missing top income shares. For countries without top income share data, we use the average of estimated individual effect μ_i in neighboring countries for each year. As explained in Section 2.2, neighboring countries are those belonging to the same region defined by the World Bank. However, there is no country for which top income share data are available in the regions of 'Europe and Central Asia' and 'Middle East and North Africa'. For countries in these two regions, we use estimates of neighboring regions. For countries in 'Europe and Central Asia', we use estimates from 'South Asia'. For countries in 'Middle East and North Africa', we use estimates from 'Sub-Saharan Africa'.

Once missing top income shares are imputed for every country and every year, we merge top income shares with quintile income shares obtained in Section 2. Particularly, we merge the fifth quintile income share with the top income shares for each country. Since top income shares nest other top income shares, i.e. top 5% income share includes top 1% income share, we can accordingly obtain income share and population share for each section such as income share between top 1% and top 5%.

Given any country and any year, if we calculate GDP per capita of each top income share, magnitude should be in an order of top 1%, top 5%, top 10% and top 20% by construction; i.e., GDP per capita of top 1% income share is the largest and that of top 20% income share is the smallest. However, there are some countries of which such a natural condition does not prevail for several years after we impute top 1% and 5% income shares. For example, for China and Rwanda, imputed GDP per capita of top 1% income share is less than that of top 5% income share for a few years. In case of Mauritius, imputed GDP per capita of top 5% income share is less than that of top 10% income share for a few years.[18] Numbers of countries of which such a natural condition is violated are provided as follow:

Model	Top 1%	Top 5%	Top 10%
Model with time and individual effects	2	1	59
Pooled model	4	45	92

This table shows that when we use the pooled model to impute missing top income shares, there are more countries of which the condition is violated. For example, there is only one country where imputed GDP per capita of top 5% is less than that of top 10% if we adopt the model allowing for time and individual heterogeneity. Conversely, there are 45 countries where such a condition is violated if we adopt the pooled model. Therefore, this result also supports our choice of the model allowing for time and individual heterogeneity to impute missing top income shares. Meanwhile, there are 59 or 92 countries of which imputed GDP per capita of top 10% is less than that of top 20%. This is why we decide to exclude top 10% income share data in estimating WDI.

Once we merge top 1% and 5% income shares with quintile income shares, we estimate

[18]For these years in three countries, we use change rate of top 20% income share to impute top 1% or 5% income shares.

WDI by following the method described in Section 2. Using this estimated WDI, we adopt precise measures of income inequality to understand evolution of world income inequality in the last four decades.[19]

4.2 Results with Top Income Shares

When top income shares are combined, results are generally similar to those in Section 3 in which top income shares are not considered. While there are differences, the main finding in Section 3 prevail even when we combine top income tax data. We can observe that world income inequality rapidly improved during the 2000s mainly due to rapid improvement in across-country inequality during the period.

< place Figures 8 and 9 here >

Figure 8 provides estimates of annual WDI in 1970 and 2010 for cases with/without top income shares. When top income shares are included, the shape of WDI is similar but the right tail of WDI is lengthier due to inclusion of top income shares. Figure 9 provides world Gini coefficients with/without top income shares and Table 8 reports various measures of income inequality for cases with top income shares. Not surprisingly, value of the Gini coefficient is higher for all years when top income shares are included. Nevertheless, the trend of the Gini coefficient is similar in both cases. From 1970 to 2000, it slightly decreased by 0.44% while it decreased by 0.91% when top income shares are excluded. During the 2000s, it rapidly decreased by 7.17% while it decreased by 7.87% when top income shares are excluded. From 1970 to 2010, it decreased by 7.58% while it decreased by 8.71% when top income shares are excluded. When top income shares were included, improvement of world income inequality slightly slowed. This implies that top income shares increased more than other shares in the last four decades. However, it should be noted that even if there is such a difference, the trend of the Gini coefficient is similar regardless of top income shares.

[19] We also estimated a model allowing for only individual heterogeneity and imputed missing top income shares by using its estimates. The estimated WDI and income inequality indices were similar in this case.

< place Table 8 and Figure 10 here >

We report seven other indices of income inequality in Figure 10 and Table 8. In general, these other indices of income inequality exhibit similar trends as those in Figure 6 and Table 2 in which top income shares are excluded. Two Atkinson indices with coefficients 0.5 and 1, respectively, the variance of log income, the top-10-percent-to-bottom-10-percent ratio, MLD and Theil index also rapidly declined during the 2000s as the Gini coefficient did. Meanwhile, the top-20-percent-to-bottom-20-percent ratio still shows a different trend; it rapidly decreased during the 1980s and 1990s but increased during the 2000s.

Finally, we decompose global income inequality into two components: across-country inequality and within-country inequality. Table 9 provides decomposition of global income inequality using the MLD and Theil index. Compared to the case in which top income shares are excluded, within-country component accounts for a larger portion of overall global inequality for both the MLD and the Theil index. In 1970, within-country component comprises 22.3% of the MLD and 30.3% of the Theil index while it accounts for 20.5% of the MLD and 23.9% of the Theil index when top income shares are excluded. This difference is not surprising because within-country inequality deteriorates as top income shares are included.

< place Table 9 here >

We can observe the same features for the MLD and the Theil index as those in the case in which top income shares are excluded. First, across-country inequality decreased in the last four decades; -30.3% for the MLD and -27.5% for the Theil index. Second, within-country inequality increased in the last four decades; 28.3% for the MLD and 32.6% for the Theil index. Third, across-country component rapidly declined during the 2000s (-23.9% for the MLD and -27.2% for the Theil index). Fourth, within-country component rapidly increased during the 1990s (14.3% for the MLD and 22.0% for the Theil index).

In case of the MLD, inclusion of top income shares does not make any significant difference; aggregate MLD and each component exhibit similar trends as those in the case in which top income shares are excluded. It should be also noted that change of the MLD is rather similar to that of the Gini coefficient because it exhibits a slight decrease for 1970-2000 and a rapid decrease for the 2000s. However, the Theil index is substantially affected. Within-country component increased by 32.6% in the last four decades while it decreased by only 10.6% when top income shares were excluded. Consequently, within-country component accounts for 44.3% of global Theil index in 2010, which is larger that 32.4% in the case in which top income shares were excluded.

5 Conclusion

In the paper, we used GDP, population and quintile income shares of each country to estimate world distribution of income. Quintile income share data are from the UNU-WIDER income survey data. We nonparametrically estimated world distribution of income and calculated the world income inequality indices from 1970 to 2010. We adopted improved methods to impute missing income share data of individual countries. Specifically, we applied alternative interpolation methods in group specific imputation procedures. Moreover, we also investigated the case when top income tax data are included. It is well known that income survey data have the problem of non-response and under-reporting of top income groups. To take this into account, we used the most recent available income share data based on the World Top Income Database. We proposed an alternative way to impute missing top income shares by using a panel model allowing for time and individual heterogeneity.

Regardless that top income tax data are included or not, our results clearly show that world income inequality drastically improved during the 2000s compared to the period from 1970 to 2000. One may think that this finding contradicts to common perception that income inequality recently deteriorated. However, analysis of inequality decomposition provides proper explanation on such a seemingly contradictory result. Inequality within each country increased during the 1990s and 2000s, supporting the common perception. However, income inequality across countries, accounting for approximately 70% of the whole inequality, substantially decreased during the 2000s, leading to drastic improvement of world income inequality during the 2000s. It is shown that China and India played the most significant role in improving world income inequality from 1980 to 2010. Conversely, the Sub-Saharan Africa region played a role in deteriorating world income inequality from 1970 to 2010.

Our analysis included total 188 countries, which accounted for 98.68% of world population and almost 100% of world GDP in 2010. To analyze distribution and inequality of world citizens' income, it is preferable to include as many countries as possible to reduce sample selection bias. Meanwhile, it is inevitable that much income survey data or top income tax data are missing particularly for low-income countries. Therefore, it is critical to apply appropriate methods to impute missing income data to precisely estimate world distribution of income and world income inequality. In the study, we adopted several improved methods to impute missing data and proposed an alternative method to combine top income tax data with income survey data. There is future potential to improve imputation methods as more data becomes available. Household income survey data, top income tax data and national accounts statistics are constantly updated and expanded to the global level. It would be of interest if one extends/improves the method to combine top income tax data with income survey data.

A Tables and Figures

Table 1. Available quintile income shares in China

Year	1st quintile	2nd quintile	3rd quintile	4th quintile	5th quintile
1970	8.40	13.30	17.10	22.50	38.70
1972	8.60	13.20	17.10	22.50	38.60
1975	8.90	13.70	17.20	22.30	37.90
1980	7.93	12.27	18.42	24.72	36.66
1982	8.47	13.73	17.94	22.26	37.60
1983	8.65	14.57	17.01	24.26	35.51
1984	10.08	13.61	19.08	23.18	34.05
1985	8.71	12.91	16.25	23.38	38.75
1986	7.56	11.94	15.96	25.94	38.60
1987	6.92	11.12	15.95	28.44	37.57
1988	6.60	10.92	16.12	28.84	37.52
1989	6.46	11.58	15.87	24.06	42.03
1990	7.01	11.89	16.14	23.98	40.98
1991	6.44	11.40	14.85	31.25	36.06
1992	6.02	10.70	15.81	25.82	41.65
1993	7.35	11.32	15.80	22.30	43.23
1995	5.00	8.80	13.60	22.10	50.60
1998	5.86	10.20	15.10	22.20	46.64
2001	4.66	9.00	14.22	22.13	49.99
2002	4.55	8.45	13.65	23.41	49.96
2004	4.25	8.48	13.68	21.73	51.86
2005	4.99	9.85	14.99	22.24	47.93

Note: Available from the UNU-WIDER (United Nations University's World Institute for Development Research, version 3.0B).

Table 2. Various measures of world income inequality

Year	Gini	A(0.5)	A(1)	Variance	20/20	10/10	MLD	Theil
1970	0.687	0.389	0.630	1.826	12.43	34.55	0.993	0.898
1971	0.687	0.390	0.630	1.828	13.23	34.19	0.995	0.899
1972	0.691	0.395	0.638	1.877	13.95	37.51	1.016	0.908
1973	0.692	0.397	0.642	1.904	13.19	38.15	1.025	0.912
1974	0.689	0.393	0.638	1.898	13.26	39.72	1.016	0.898
1975	0.686	0.389	0.633	1.871	13.57	38.40	1.001	0.887
1976	0.689	0.394	0.641	1.923	13.71	42.93	1.024	0.897
1977	0.688	0.393	0.639	1.922	13.57	42.74	1.019	0.893
1978	0.685	0.389	0.634	1.896	13.92	39.85	1.004	0.884
1979	0.688	0.392	0.638	1.916	14.28	40.09	1.016	0.894
1980	0.686	0.390	0.637	1.933	14.79	42.17	1.014	0.884
1981	0.684	0.387	0.632	1.895	13.79	39.35	0.998	0.878
1982	0.680	0.381	0.623	1.848	13.24	36.18	0.976	0.867
1983	0.679	0.380	0.621	1.822	13.30	34.66	0.969	0.869
1984	0.679	0.380	0.621	1.824	13.14	33.76	0.969	0.872
1985	0.679	0.379	0.617	1.789	12.41	32.45	0.959	0.874
1986	0.679	0.379	0.616	1.783	12.19	34.66	0.958	0.876
1987	0.678	0.378	0.614	1.766	11.06	36.31	0.951	0.877
1988	0.678	0.378	0.615	1.777	11.62	34.89	0.954	0.875
1989	0.683	0.384	0.622	1.810	11.19	34.25	0.973	0.892
1990	0.684	0.385	0.623	1.824	10.10	35.24	0.976	0.895
1991	0.685	0.386	0.626	1.848	10.71	36.18	0.983	0.898
1992	0.685	0.386	0.624	1.832	9.70	33.67	0.979	0.902
1993	0.685	0.386	0.621	1.796	10.15	32.72	0.970	0.908
1994	0.683	0.384	0.620	1.804	10.13	32.05	0.967	0.905
1995	0.677	0.377	0.612	1.784	9.21	30.92	0.947	0.888
1996	0.679	0.379	0.614	1.794	9.00	31.24	0.952	0.893
1997	0.678	0.379	0.615	1.808	8.58	31.74	0.953	0.894
1998	0.682	0.383	0.619	1.826	8.70	30.60	0.965	0.906
1999	0.679	0.380	0.615	1.813	8.56	28.77	0.955	0.901
2000	0.680	0.382	0.617	1.828	8.43	30.07	0.961	0.905
2001	0.677	0.377	0.611	1.790	8.04	28.77	0.943	0.894
2002	0.676	0.376	0.613	1.816	9.20	27.32	0.948	0.887
2003	0.671	0.369	0.604	1.786	8.95	27.40	0.926	0.869
2004	0.664	0.362	0.595	1.756	7.96	28.16	0.903	0.850
2005	0.662	0.360	0.596	1.779	10.73	27.19	0.905	0.842
2006	0.655	0.352	0.586	1.747	9.32	27.13	0.881	0.820
2007	0.648	0.344	0.577	1.731	9.72	29.10	0.861	0.795
2008	0.642	0.338	0.571	1.717	10.13	30.60	0.845	0.776
2009	0.628	0.324	0.553	1.662	10.27	27.74	0.806	0.739
2010	0.627	0.323	0.553	1.673	10.12	27.51	0.805	0.733

Table 2. Continued

Year	Gini	A(0.5)	A(1)	Variance	20/20	10/10	MLD	Theil
% Change 1970-1980	-0.12%	0.12%	1.20%	5.83%	18.99%	22.07%	2.08%	-1.58%
% Change 1980-1990	-0.34%	-1.33%	-2.19%	-5.63%	-31.71%	-16.43%	-3.72%	1.21%
% Change 1990-2000	-0.46%	-0.85%	-0.94%	0.20%	-16.60%	-14.67%	-1.58%	1.14%
% Change 2000-2010	-7.87%	-15.41%	-10.46%	-8.46%	20.08%	-8.52%	-16.24%	-18.97%
% Change 1970-2000	-0.91%	-2.06%	-1.95%	0.08%	-32.22%	-12.95%	-3.27%	0.75%
% Change 1970-2010	-8.71%	-17.16%	-12.20%	-8.39%	-18.61%	-20.37%	-18.98%	-18.37%

Note: Gini is the Gini coefficient. A(0.5) is the Atkinson index with coefficient 0.5. A(1) is the Atkinson index with coefficient 1. Variance is the variance of log income. 20/20 is the ratio of the income of top 20 centile to bottom 20 centile. 10/10 is the ratio of the income of top 10 centile to bottom 10 centile. MLD is the Mean Logarithmic Deviation. Theil is the Theil index of income inequality.

Table 3. Decomposition of world income inequality

	Mean log deviation					Theil index				
Year	Global	Across	% Across	Within	%Within	Global	Across	% Across	Within	%Within
1970	0.993	0.789	79.5%	0.204	20.5%	0.898	0.684	76.1%	0.215	23.9%
1971	0.995	0.790	79.4%	0.205	20.6%	0.899	0.682	75.8%	0.217	24.2%
1972	1.016	0.811	79.9%	0.205	20.1%	0.908	0.694	76.4%	0.214	23.6%
1973	1.025	0.821	80.1%	0.204	19.9%	0.912	0.698	76.6%	0.214	23.4%
1974	1.016	0.820	80.7%	0.197	19.3%	0.898	0.693	77.1%	0.205	22.9%
1975	1.001	0.800	79.9%	0.201	20.1%	0.887	0.679	76.5%	0.208	23.5%
1976	1.024	0.821	80.2%	0.202	19.8%	0.897	0.690	76.9%	0.207	23.1%
1977	1.019	0.816	80.1%	0.203	19.9%	0.893	0.688	77.0%	0.205	23.0%
1978	1.004	0.802	79.8%	0.202	20.2%	0.884	0.683	77.2%	0.201	22.8%
1979	1.016	0.811	79.8%	0.205	20.2%	0.894	0.689	77.1%	0.205	22.9%
1980	1.014	0.800	78.9%	0.214	21.1%	0.884	0.681	77.0%	0.203	23.0%
1981	0.998	0.788	78.9%	0.210	21.1%	0.878	0.678	77.2%	0.200	22.8%
1982	0.976	0.769	78.8%	0.207	21.2%	0.867	0.667	77.0%	0.200	23.0%
1983	0.969	0.766	79.0%	0.203	21.0%	0.869	0.670	77.1%	0.199	22.9%
1984	0.969	0.762	78.7%	0.207	21.3%	0.872	0.673	77.2%	0.199	22.8%
1985	0.959	0.757	78.9%	0.202	21.1%	0.874	0.676	77.3%	0.198	22.7%
1986	0.958	0.756	79.0%	0.201	21.0%	0.876	0.677	77.3%	0.199	22.7%
1987	0.951	0.753	79.2%	0.198	20.8%	0.877	0.677	77.2%	0.200	22.8%
1988	0.954	0.752	78.8%	0.202	21.2%	0.875	0.682	77.9%	0.194	22.1%
1989	0.973	0.760	78.2%	0.212	21.8%	0.892	0.693	77.7%	0.199	22.3%
1990	0.976	0.760	77.8%	0.216	22.2%	0.895	0.696	77.7%	0.199	22.3%
1991	0.983	0.757	77.0%	0.226	23.0%	0.898	0.695	77.4%	0.203	22.6%
1992	0.979	0.748	76.4%	0.231	23.6%	0.902	0.693	76.8%	0.210	23.2%
1993	0.970	0.741	76.4%	0.229	23.6%	0.908	0.690	76.0%	0.218	24.0%
1994	0.967	0.735	76.0%	0.232	24.0%	0.905	0.686	75.8%	0.219	24.2%
1995	0.947	0.713	75.2%	0.234	24.8%	0.888	0.671	75.5%	0.217	24.5%
1996	0.952	0.712	74.9%	0.239	25.1%	0.893	0.672	75.2%	0.221	24.8%
1997	0.953	0.708	74.3%	0.245	25.7%	0.894	0.668	74.8%	0.225	25.2%
1998	0.965	0.716	74.2%	0.249	25.8%	0.906	0.680	75.0%	0.226	25.0%

Table 3. Continued

	Mean log deviation					Theil index				
Year	Global	Across	% Across	Within	%Within	Global	Across	% Across	Within	%Within
1999	0.955	0.713	74.6%	0.243	25.4%	0.901	0.679	75.4%	0.222	24.6%
2000	0.961	0.720	74.9%	0.241	25.1%	0.905	0.681	75.2%	0.224	24.8%
2001	0.943	0.706	74.8%	0.238	25.2%	0.894	0.669	74.9%	0.225	25.1%
2002	0.948	0.688	72.5%	0.261	27.5%	0.887	0.652	73.5%	0.235	26.5%
2003	0.926	0.676	72.9%	0.251	27.1%	0.869	0.639	73.5%	0.231	26.5%
2004	0.903	0.659	73.0%	0.244	27.0%	0.850	0.621	73.1%	0.229	26.9%
2005	0.905	0.646	71.3%	0.260	28.7%	0.842	0.606	72.0%	0.235	28.0%
2006	0.881	0.630	71.6%	0.251	28.4%	0.820	0.588	71.7%	0.232	28.3%
2007	0.861	0.611	70.9%	0.250	29.1%	0.795	0.566	71.1%	0.230	28.9%
2008	0.845	0.595	70.4%	0.250	29.6%	0.776	0.545	70.2%	0.231	29.8%
2009	0.806	0.557	69.1%	0.249	30.9%	0.739	0.507	68.7%	0.231	31.3%
2010	0.802	0.548	68.1%	0.257	31.9%	0.733	0.496	67.6%	0.238	32.4%
% Change 1970-1980	2.1%	1.3%		4.9%		-1.6%	-0.4%		-5.4%	
% Change 1980-1990	-3.7%	-5.0%		1.2%		1.2%	2.2%		-2.0%	
% Change 1990-2000	-1.6%	-5.3%		11.4%		1.1%	-2.1%		12.5%	
% Change 2000-2010	-16.2%	-23.9%		6.6%		-19.0%	-27.2%		6.0%	
% Change 1970-2000	-3.3%	-8.9%		18.3%		0.7%	-0.4%		4.3%	
% Change 1970-2010	-19.0%	-30.6%		26.1%		-18.4%	-27.5%		10.6%	

Note: Global measures indicate the overall index of inequality for the Mean log deviation and the Theil index, respectively. Across represents the across-country inequality. The column %Across provides the percentage of the global index that can be attributed to across-country inequality. Within refers to the within-country inequality. The column %Within shows the percentage of the global index that can be attributed to the within-country inequality.

Table 4. Population shares of each region

Region	Population Shares
East Asia and Pacific	27.6%
South Asia	23.2%
High income: OECD	15.1%
Sub-Saharan Africa	12.4%
Latin America and Caribbean	8.2%
Middle East and North Africa	4.8%
Europe and Central Asia	4.0%
High income: non-OECD	3.1%

Note: The table reports the population share of each region in 2010. The region is defined by the World Bank.

Table 5. Change rate of Gini coefficient for each decade

	All countries	No China	No India	No Africa	No Latin	No China and India
% Change 1970-1980	-0.12%	-0.15%	-0.65%	-0.65%	0.32%	-0.97%
% Change 1980-1990	-0.34%	2.10%	0.61%	-0.99%	-0.51%	4.06%
% Change 1990-2000	-0.46%	3.06%	-0.01%	-1.17%	-0.49%	4.84%
% Change 2000-2010	-7.87%	-5.11%	-7.08%	-9.58%	-7.82%	-2.71%
% Change 1970-2000	-0.91%	5.06%	-0.06%	-2.78%	-0.68%	8.04%
% Change 1970-2010	-8.71%	-0.30%	-7.14%	-12.09%	-8.44%	5.11%

Note: Table reports change rate of Gini coefficient for each decade and each case. For example, 'No China' means the case in which the population in China is excluded.

Table 6. Countries of which top income shares are available

	10%	5%	1%	0.50%	0.10%	0.05%	0.01%
Argentina		o	o	o	o		o
Australia	o	o	o	o	o	o	o
Canada	o	o	o	o	o		o
China	o	o	o	o	o		
Colombia			o	o	o	o	o
Denmark	o	o	o	o	o	o	o
Finland	o	o	o				
France	o	o	o	o	o		o
Germany	o	o	o	o	o		o
India			o	o	o		o
Indonesia			o		o	o	o
Ireland	o		o	o	o		
Italy	o	o	o	o	o		o
Japan	o	o	o	o	o	o	o
Korea, Rep.	o	o	o	o	o	o	o
Malaysia	o	o	o	o	o	o	o
Mauritius	o	o	o	o	o	o	
Netherlands	o	o	o	o	o	o	o
New Zealand	o	o	o	o	o		
Norway	o	o	o	o	o	o	
Portugal	o	o	o	o	o		o
Singapore	o	o	o	o	o	o	o
South Africa	o	o	o	o	o	o	o
Spain	o	o	o	o	o		o
Sweden	o	o	o	o	o	o	o
Switzerland	o	o	o	o	o		o
Taiwan	o	o	o		o		o
United Kingdom	o	o	o	o	o	o	o
United States	o	o	o	o	o		o

Note: The table reports countries and percentages for which top income shares are available. For example, top 5%, 1%, 0.5%, 0.1% and 0.01% income shares are available for Argentina. Source: The World Top Incomes Database.

Table 7. Estimation results of top income shares

	β_1	β_2	adjusted R^2
y_{it} =top 1% income share			
Model with time and individual heterogeneity	0.25***	0.21***	0.83
	(0.02)	(0.08)	
Pooled model	0.36***	1.20***	0.47
	(0.01)	(0.10)	
y_{it} =top 5% income share			
Model with time and individual heterogeneity	0.35***	1.16***	0.83
	(0.03)	(0.12)	
Pooled model	0.55***	3.88***	0.43
	(0.02)	(0.23)	

Note: The table reports the estimation results of the following two models. The model with time and individual heterogeneity is given as

$$y_{it} = \alpha + \mu_i + \lambda_t + x_{it}'\beta + \varepsilon_{it},$$

where $y_{it}$is top 1% or 5% income share for country $i$and year $t$and x_{it}=(top 20% income share$_{it}$, logged GDP per capita$_{it}$)$'$and $\beta = (\beta_1, \beta_2)'$ .We let $\lambda_t$to have the same value for each decade. The pooled model is given as

$$y_{it} = \alpha + x_{it}'\beta + \varepsilon_{it}.$$

Standard errors are given in parentheses. ***denotes significance at the 1% level.

Table 8. Various measures of world income inequality when top income shares are combined

Year	Gini	A(0.5)	A(1)	Variance	20/20	10/10	MLD	Theil
1970	0.696	0.404	0.638	1.809	12.58	32.69	1.016	0.981
1971	0.696	0.403	0.638	1.802	13.17	32.50	1.014	0.979
1972	0.699	0.408	0.644	1.845	13.84	34.61	1.033	0.989
1973	0.701	0.410	0.648	1.872	12.87	35.22	1.043	0.993
1974	0.697	0.406	0.645	1.867	12.79	36.89	1.034	0.978
1975	0.694	0.402	0.639	1.842	13.07	34.50	1.019	0.967
1976	0.698	0.407	0.647	1.893	13.38	39.31	1.041	0.976
1977	0.696	0.405	0.645	1.891	13.51	37.47	1.035	0.969
1978	0.693	0.401	0.640	1.864	13.54	35.88	1.020	0.961
1979	0.696	0.404	0.644	1.884	14.16	36.36	1.032	0.970
1980	0.694	0.402	0.643	1.900	14.73	39.53	1.029	0.960
1981	0.691	0.398	0.637	1.864	13.21	36.71	1.012	0.951
1982	0.687	0.392	0.629	1.817	13.24	33.91	0.990	0.939
1983	0.687	0.392	0.627	1.795	13.25	33.37	0.985	0.942
1984	0.687	0.392	0.627	1.796	12.94	32.21	0.984	0.947
1985	0.687	0.392	0.624	1.766	12.64	32.06	0.977	0.951
1986	0.687	0.392	0.624	1.760	12.25	33.47	0.977	0.955
1987	0.686	0.392	0.621	1.738	11.17	33.66	0.969	0.964
1988	0.687	0.393	0.623	1.747	11.62	31.87	0.975	0.976
1989	0.692	0.399	0.630	1.779	10.90	30.71	0.994	0.993
1990	0.693	0.401	0.631	1.784	10.14	31.69	0.997	1.005
1991	0.694	0.402	0.634	1.808	10.71	33.03	1.004	1.004
1992	0.694	0.402	0.632	1.790	9.86	32.08	0.999	1.013
1993	0.694	0.402	0.630	1.759	10.15	32.48	0.992	1.016
1994	0.693	0.401	0.628	1.767	10.20	31.67	0.989	1.014
1995	0.688	0.395	0.621	1.748	9.41	30.08	0.970	0.999
1996	0.689	0.397	0.623	1.755	9.72	30.53	0.975	1.011
1997	0.689	0.398	0.625	1.771	9.53	30.67	0.980	1.016
1998	0.692	0.402	0.629	1.783	9.18	31.22	0.990	1.034
1999	0.690	0.399	0.625	1.772	9.32	29.11	0.981	1.034
2000	0.693	0.404	0.629	1.777	8.47	28.73	0.991	1.058
2001	0.689	0.399	0.623	1.745	8.47	27.27	0.974	1.038
2002	0.689	0.397	0.624	1.768	10.30	26.72	0.976	1.025
2003	0.683	0.391	0.616	1.739	9.96	27.12	0.955	1.009
2004	0.677	0.385	0.607	1.706	8.70	26.82	0.934	1.000
2005	0.677	0.386	0.609	1.723	10.07	26.02	0.938	1.007
2006	0.670	0.379	0.600	1.689	8.67	26.70	0.915	0.989
2007	0.664	0.371	0.592	1.673	8.47	28.33	0.896	0.968
2008	0.658	0.365	0.585	1.661	8.22	27.10	0.879	0.942
2009	0.645	0.350	0.568	1.611	8.86	25.64	0.840	0.894
2010	0.644	0.349	0.568	1.620	9.49	24.23	0.839	0.890

Table 8. Continued

Year	Gini	A(0.5)	A(1)	Variance	20/20	10/10	MLD	THEIL
% Change 1970-1980	-0.35%	-0.48%	0.69%	5.05%	17.09%	20.93%	1.22%	-2.15%
% Change 1980-1990	-0.08%	-0.17%	-1.78%	-6.12%	-31.16%	-19.82%	-3.05%	4.65%
% Change 1990-2000	-0.01%	0.70%	-0.37%	-0.39%	-16.50%	-9.35%	-0.61%	5.28%
% Change 2000-2010	-7.17%	-13.65%	-9.71%	-8.82%	12.09%	-15.67%	-15.38%	-15.84%
% Change 1970-2000	-0.44%	0.06%	-1.47%	-1.76%	-32.69%	-12.11%	-2.48%	7.80%
% Change 1970-2010	-7.58%	-13.60%	-11.03%	-10.43%	-24.56%	-25.88%	-17.47%	-9.28%

Note: Same as Table 2.

Table 9. Decomposition of world income inequality with top income share

	Mean log deviation					Theil index				
Year	Global	Across	% Across	Within	%Within	Global	Across	% Across	Within	%Within
1970	1.016	0.790	77.7%	0.226	22.3%	0.981	0.684	69.7%	0.297	30.3%
1971	1.014	0.790	77.9%	0.224	22.1%	0.979	0.682	69.7%	0.297	30.3%
1972	1.033	0.811	78.6%	0.221	21.4%	0.989	0.694	70.2%	0.295	29.8%
1973	1.043	0.822	78.8%	0.221	21.2%	0.993	0.699	70.3%	0.295	29.7%
1974	1.034	0.820	79.3%	0.214	20.7%	0.978	0.693	70.8%	0.285	29.2%
1975	1.019	0.800	78.5%	0.219	21.5%	0.967	0.679	70.2%	0.288	29.8%
1976	1.041	0.821	78.9%	0.220	21.1%	0.976	0.690	70.7%	0.286	29.3%
1977	1.035	0.816	78.8%	0.219	21.2%	0.969	0.688	71.0%	0.280	29.0%
1978	1.020	0.802	78.6%	0.219	21.4%	0.961	0.683	71.1%	0.278	28.9%
1979	1.032	0.811	78.6%	0.221	21.4%	0.970	0.689	71.0%	0.281	29.0%
1980	1.029	0.800	77.8%	0.228	22.2%	0.960	0.681	70.9%	0.279	29.1%
1981	1.012	0.788	77.8%	0.224	22.2%	0.951	0.678	71.3%	0.273	28.7%
1982	0.990	0.769	77.7%	0.221	22.3%	0.939	0.667	71.0%	0.272	29.0%
1983	0.985	0.766	77.8%	0.219	22.2%	0.942	0.670	71.2%	0.272	28.8%
1984	0.984	0.762	77.4%	0.222	22.6%	0.947	0.673	71.1%	0.274	28.9%
1985	0.977	0.757	77.5%	0.220	22.5%	0.951	0.676	71.1%	0.275	28.9%
1986	0.977	0.757	77.5%	0.220	22.5%	0.955	0.677	70.9%	0.278	29.1%
1987	0.969	0.753	77.7%	0.216	22.3%	0.964	0.677	70.2%	0.287	29.8%
1988	0.975	0.752	77.1%	0.223	22.9%	0.976	0.682	69.9%	0.294	30.1%
1989	0.994	0.761	76.5%	0.233	23.5%	0.993	0.693	69.8%	0.300	30.2%
1990	0.997	0.760	76.2%	0.237	23.8%	1.005	0.696	69.3%	0.309	30.7%
1991	1.004	0.757	75.5%	0.246	24.5%	1.004	0.695	69.2%	0.309	30.8%
1992	0.999	0.748	74.9%	0.251	25.1%	1.013	0.693	68.4%	0.320	31.6%
1993	0.992	0.741	74.7%	0.251	25.3%	1.016	0.690	67.9%	0.326	32.1%
1994	0.989	0.735	74.3%	0.254	25.7%	1.014	0.687	67.7%	0.328	32.3%
1995	0.970	0.713	73.4%	0.258	26.6%	0.999	0.671	67.2%	0.328	32.8%
1996	0.975	0.713	73.1%	0.263	26.9%	1.011	0.672	66.5%	0.339	33.5%
1997	0.980	0.709	72.3%	0.271	27.7%	1.016	0.668	65.7%	0.348	34.3%
1998	0.990	0.716	72.4%	0.274	27.6%	1.034	0.680	65.7%	0.354	34.3%

Table 9. Continued

	Mean log deviation					Theil index				
Year	Global	Across	% Across	Within	%Within	Global	Across	% Across	Within	%Within
1999	0.981	0.713	72.7%	0.268	27.3%	1.034	0.679	65.7%	0.355	34.3%
2000	0.991	0.720	72.6%	0.271	27.4%	1.058	0.681	64.4%	0.377	35.6%
2001	0.974	0.706	72.5%	0.268	27.5%	1.038	0.669	64.5%	0.368	35.5%
2002	0.976	0.688	70.5%	0.288	29.5%	1.025	0.652	63.6%	0.373	36.4%
2003	0.955	0.676	70.8%	0.279	29.2%	1.009	0.639	63.3%	0.371	36.7%
2004	0.934	0.659	70.6%	0.275	29.4%	1.000	0.621	62.1%	0.379	37.9%
2005	0.938	0.646	68.8%	0.293	31.2%	1.007	0.606	60.2%	0.400	39.8%
2006	0.915	0.631	68.9%	0.285	31.1%	0.989	0.588	59.5%	0.401	40.5%
2007	0.896	0.611	68.2%	0.285	31.8%	0.968	0.566	58.4%	0.403	41.6%
2008	0.879	0.595	67.6%	0.285	32.4%	0.942	0.545	57.8%	0.397	42.2%
2009	0.840	0.557	66.3%	0.283	33.7%	0.894	0.507	56.8%	0.386	43.2%
2010	0.839	0.548	65.3%	0.291	34.7%	0.890	0.496	55.7%	0.394	44.3%
% Change 1970-1980	1.2%	1.3%		0.8%		-2.2%	-0.4%		-6.2%	
% Change 1980-1990	-3.1%	-5.0%		3.9%		4.6%	2.2%		10.7%	
% Change 1990-2000	-0.6%	-5.3%		14.3%		5.3%	-2.1%		22.0%	
% Change 2000-2010	-15.4%	-23.9%		7.2%		-15.8%	-27.2%		4.7%	
% Change 1970-2000	-2.5%	-8.8%		19.7%		7.8%	-0.4%		26.7%	
% Change 1970-2010	-17.5%	-30.6%		28.3%		-9.3%	-27.5%		32.6%	

Note: Same as Table 5.

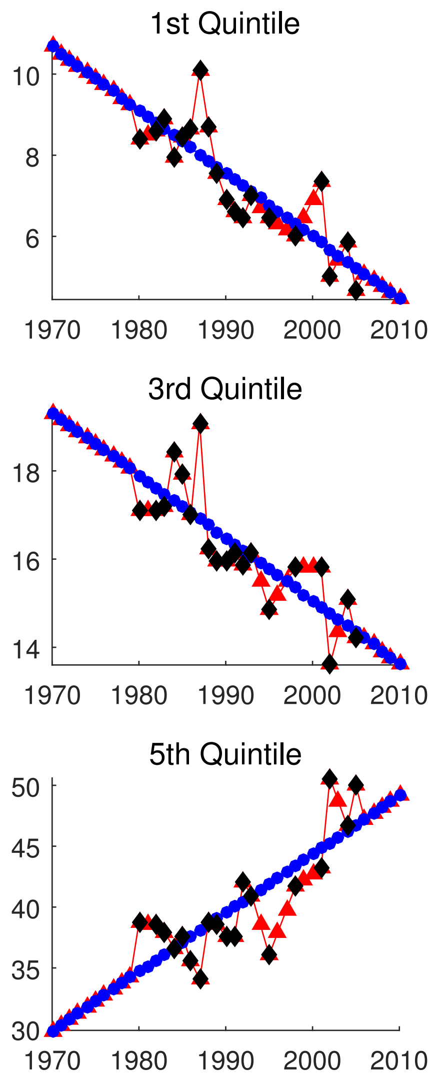

Figure 1. Imputation of income shares for China. Diamonds indicate actual available data. Circles refer to the imputed values by the linear time-trend forecast method. Triangles represent the imputed values by linear interpolation and extrapolation using linear time-trend forecast.

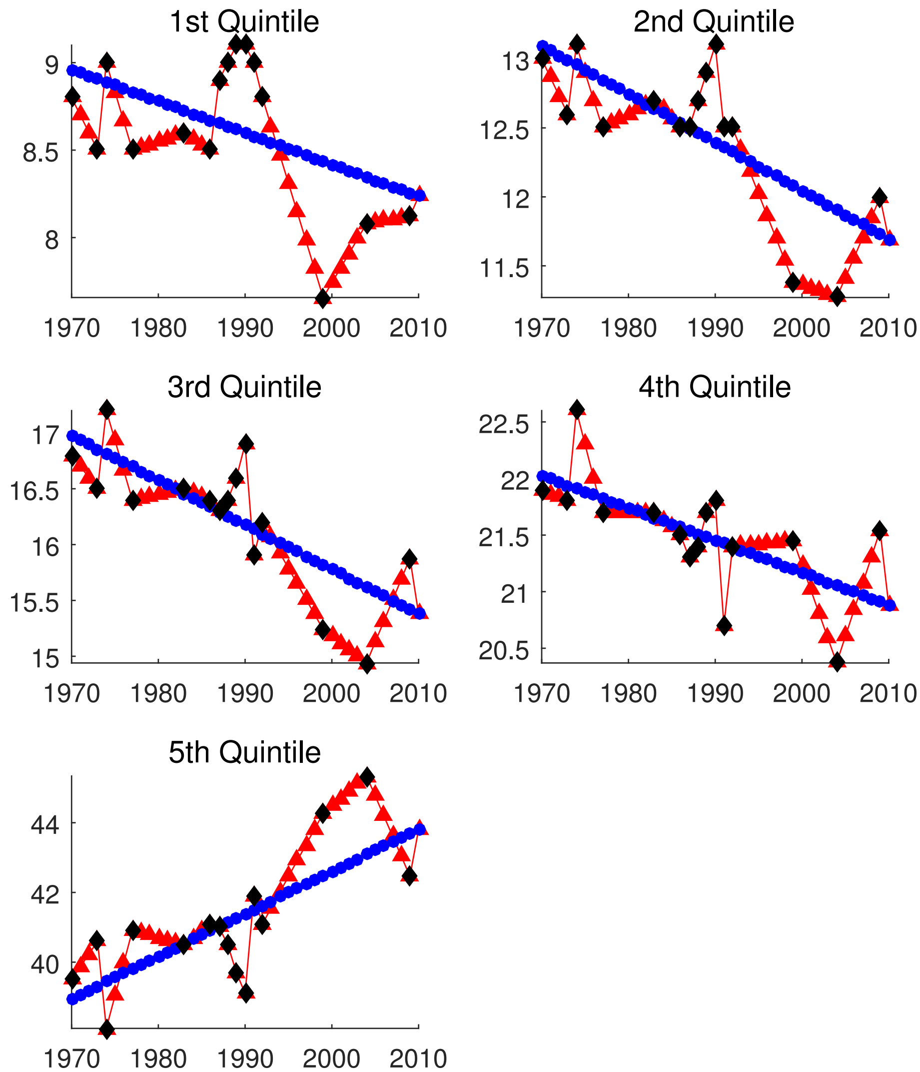

Figure 2. Imputation of income shares for India. Same as Figure 1.

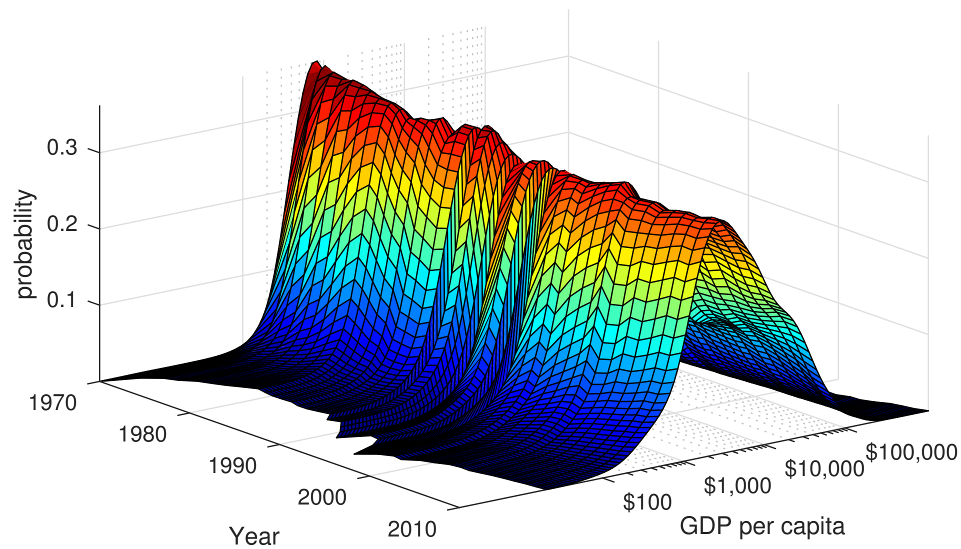

Figure 3(a). 3-D plot of the estimated world distribution of income

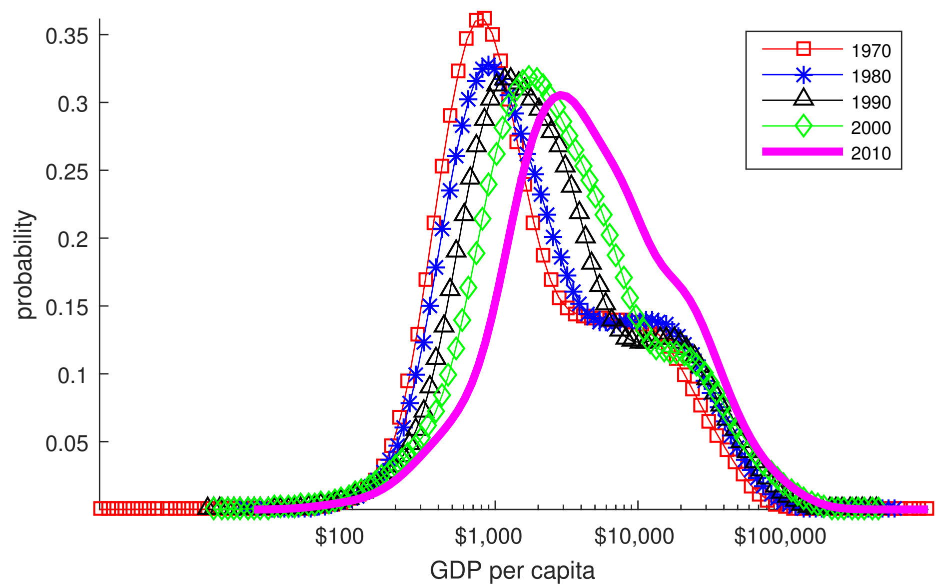

Figure 3(b). Estimated world distribution of income in various years

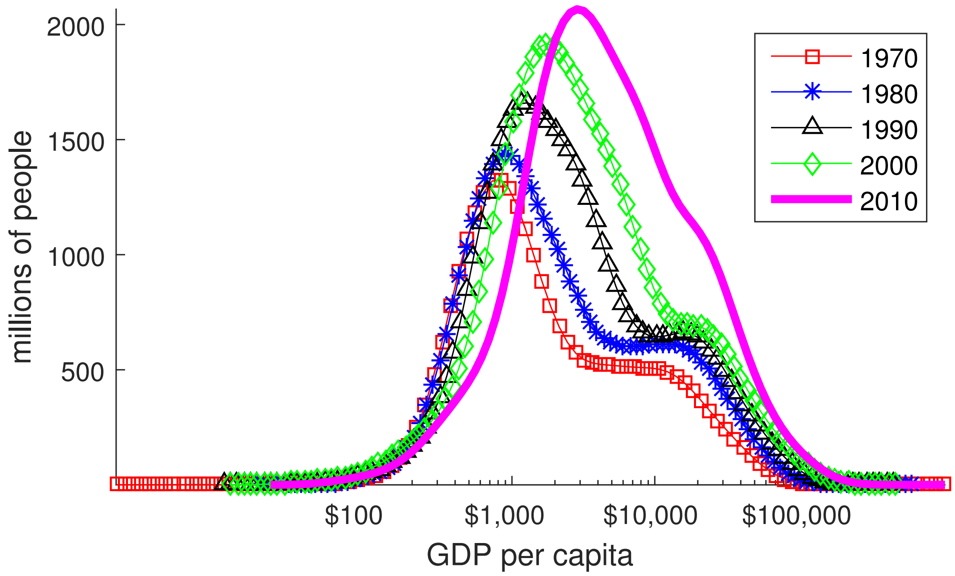

Figure 4. Estimated world distribution of income in various years (population-normalized version)

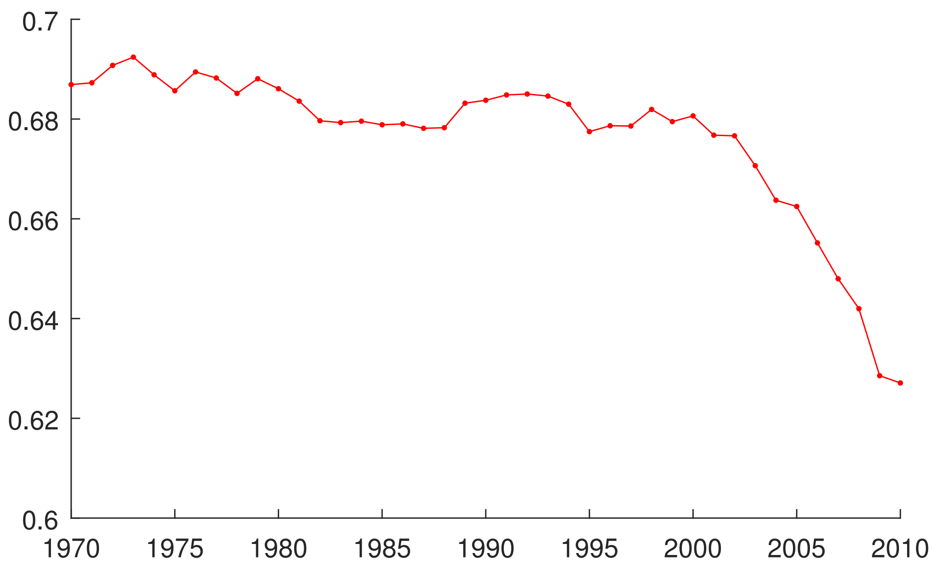

Figure 5. Global Gini coefficient

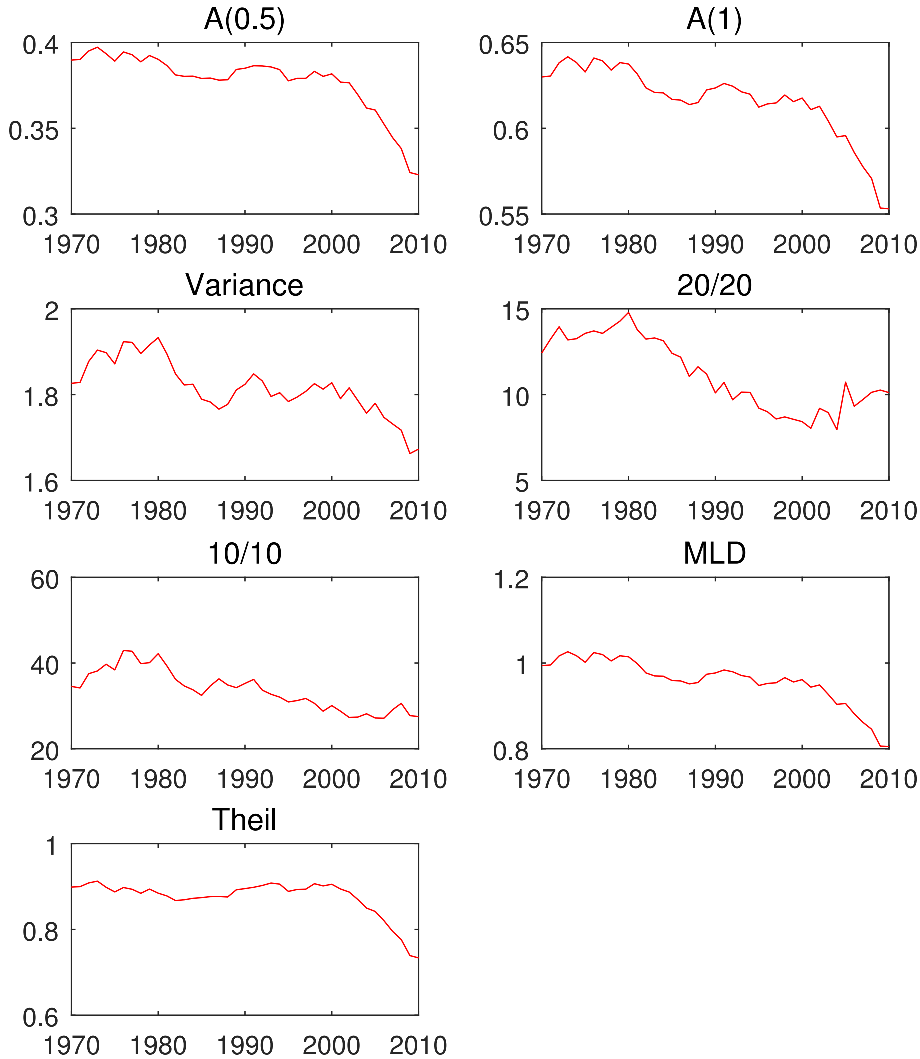

Figure 6. Seven other global inequality indices. Same as the note of Table 2.

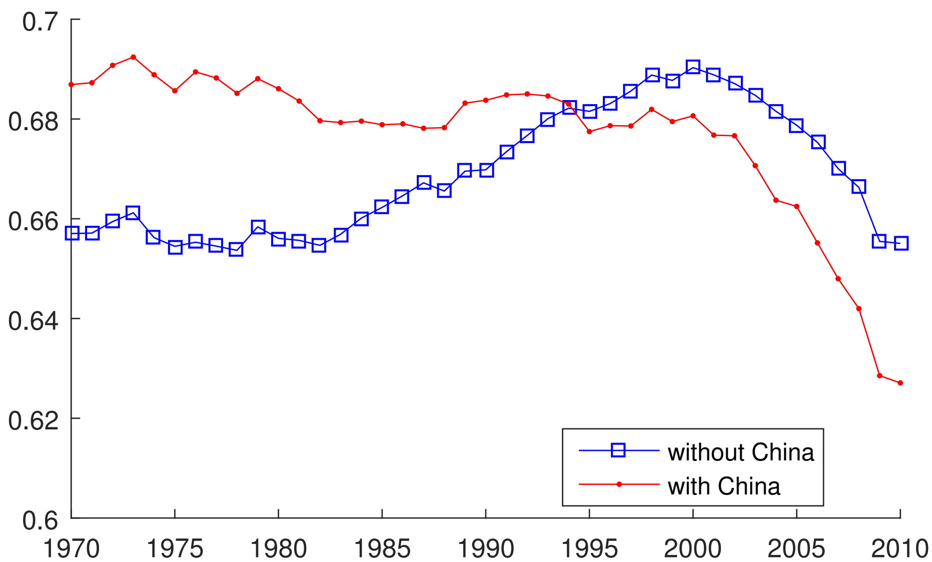

Figure 7. Global Gini coefficients for the cases with and without China

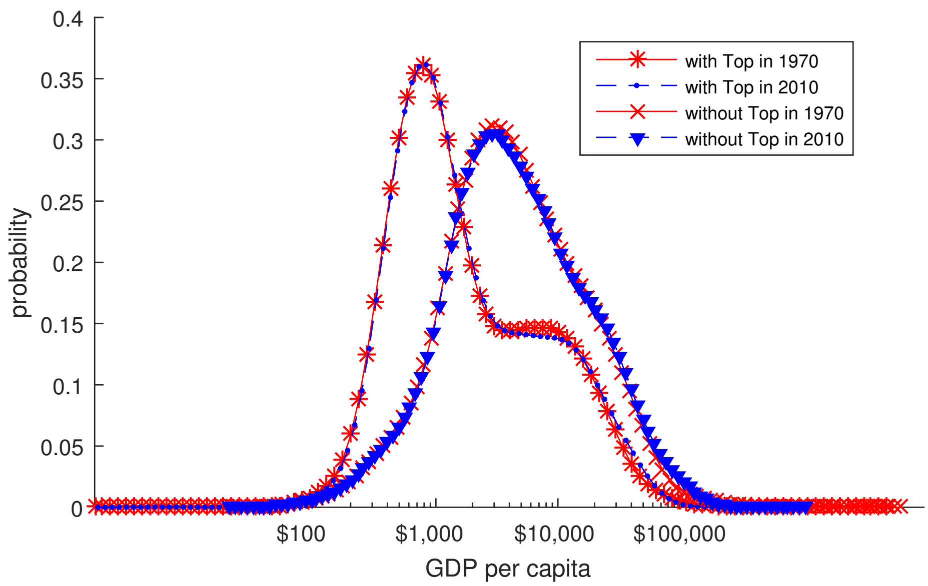

Figure 8. Estimated world distribution of income with and without top income shares

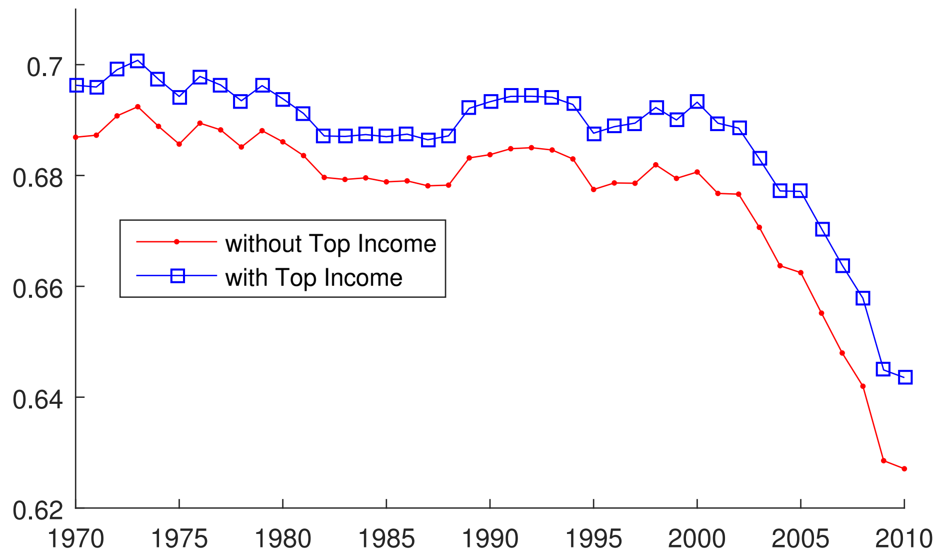

Figure 9. Global Gini coefficients for the cases with and without top income shares

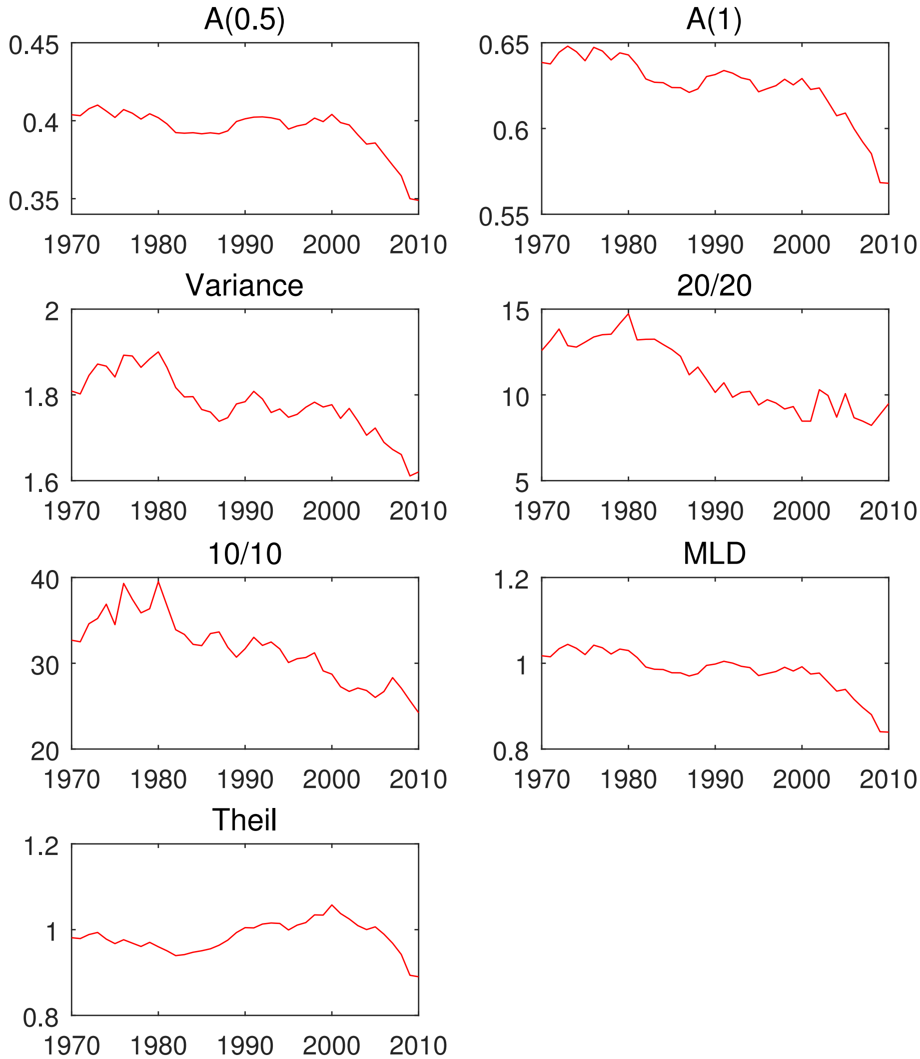

Figure 10. Seven other global inequality indices when top income shares are combined

B Countries in Each Group

Countries in Group A: Algeria, Argentina, Armenia, Australia, Austria, Azerbaijan, Bangladesh, Barbados, Belarus, Belgium, Bolivia, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Canada, Chile, China, Colombia, Costa Rica, Côte d'Ivoire, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Ethiopia, Fiji, Finland, France, Georgia, Germany, Ghana, Greece, Guatemala, Honduras, Hong Kong, Hungary, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea, Rep. , Kyrgyz Republic, Lao PDR, Latvia, Lesotho, Lithuania, Luxembourg, Madagascar, Malawi, Malaysia, Mali, Malta, Mauritania, Mexico, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Nepal, Netherlands, New Zealand, Niger, Nigeria, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russia, Rwanda, Senegal, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, Swaziland, Sweden, Switzerland, Taiwan, Tajikistan, Thailand, Trinidad and Tobago, Tunisia, Turkey, Uganda, Ukraine, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela, Vietnam, Zambia

Countries in Group B: Afghanistan, Albania, Angola, Bahamas, Belize, Benin, Bhutan, Bosnia and Herzegovina, Cabo Verde, Cameroon, Central African Republic, Chad, Comoros, Congo, Dem. Rep., Congo, Rep. ,Cuba, Djibouti, Gabon, Gambia, Guinea, Guinea-Bissau, Guyana, Haiti, Iceland, Iraq, Liberia, Macedonia, Maldives, Mauritius, Micronesia, Fed. Sts., Namibia, Nicaragua, Papua New Guinea, Puerto Rico, Sao Tome and Principe, Serbia, Seychelles, Sierra Leone, Singapore, Somalia, St. Lucia, Sudan, Suriname, Syria, Tanzania, Togo, Turkmenistan, Yemen, Zimbabwe

Countries in Group C: Antigua and Barbuda, Bahrain, Bermuda, Brunei, Dominica, Equatorial Guinea, Eritrea, Grenada, Kiribati, Kuwait, Lebanon, Libya, Macao, Marshall Islands, Oman, Palau, Qatar, Samoa, Saudi Arabia, Solomon Islands, St. Kitts & Nevis, St.Vincent & Grenadines, Tonga, United Arab Emirates, Vanuatu

<Number of countries in each region>

Region	Group A	Group B	Group C
East Asia and Pacific	10	2	7
South Asia	5	3	0
High income: OECD	30	1	0
Sub-Saharan Africa	21	24	1
Latin America and Caribbean	16	7	3
Middle East and North Africa	6	4	2
Europe and Central Asia	15	5	0
High income: non-OECD	11	3	12
Total	114	49	25

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