

Empirical Challenges Comparing Inequality across Countries

The Case of Middle-Income Countries from the LIS Database

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1 Introduction

In the past few decades, the focus in research on income inequality has been predominantly on the high-income OECD countries (see, e.g., Atkinson and Brandolini 2001). More recently, research has turned to an analysis of top-income share and its historical development (e.g. Atkinson et al. 2011), again covering mostly high-income Anglo-Saxon and Nordic countries. The research analysing income inequality in middle-income and developing countries from the Middle East and North Africa (MENA) region, Asia, sub-Saharan Africa, and Latin America is still evolving.

Some of the recent examples, and perhaps the closest studies to ours in terms of the focus on middle-income countries, are studies by Alvaredo and Gasparini (2015) and Lakner and Milanovic (2016). Lakner and Milanovic (2016) analyse global income inequality with international data (combining different household surveys) covering the period 1988–2008. The authors show that the global Gini index reached 70.5 per cent in 2008 and report that the income inequality levels were quite stable over the analysed time period, though inequality levels varied between sub-regions. The lowest income inequality was observed for India, with the Gini spanning from 31.1 per cent in 1988 to 33.1 per cent in 2008. Mature economies experienced growth in the Gini from 38.2 per cent to 41.9 per cent during the same time period. The highest inequality levels were observed in sub-Saharan Africa, increasing from 53.5 per cent in 1993 to 58.3 per cent in 2008. According to the authors, the fastest increase in inequality was observed in China, where the Gini index rose from 32.0 per cent in 1988 to 42.7 per cent in 2008, overall representing an increase of 33.5 per cent.

Alvaredo and Gasparini (2015) show that national income inequality for developing countries first increased during the 1980s and 1990s, and then dropped during the 2000s. They also explore possible determinants of changing inequality over time and across countries, finding an inverse U-shaped relationship between the Gini coefficient and log gross national income (GNI) per capita, consistent with the Kuznets hypothesis. Despite caveats related to consistency and comparability of microdata from low-income countries, the authors highlight that significant progress has been made in measuring and monitoring income inequality and poverty.

Other examples studying income inequality and poverty in developing and middle-income countries are those by Assaad et al. (2016, 2017) for the MENA countries, Piketty and Qian (2009) for China and India, Gasparini et al. (2011) for Latin America, and Novokmet et al. (2017) for Russia. Regarding the empirical evidence based on the LIS data, Gornick et al. (2009) were among the first to report inequality trends for the Latin American countries. More recently, the LIS data source has been utilized to demonstrate income inequality and (child) poverty in middle-income countries; see, for example, Rasch (2017) and Evans et al. (2018).

The main goal of our study is to update the existing evidence on income and expenditure/consumption inequality, focusing on a set of middle- and high-income countries from Asia (East and South), the MENA region, and Latin America. To present the results in a comparative perspective, we also add high-income countries from neighbouring areas. Before going into data analysis, we take advantage of LIS Datacentre experience in harmonizing income and consumption microdata from middle-income countries to illustrate some caveats to be considered when executing cross-country comparative research involving both affluent and less developed countries.

From the empirical point of view, the main contribution of this study is two-fold. First, we extract household- and individual-level income and consumption aggregates for which we compute various inequality measures. Then we merge the computed indicators (country-level averages) with macroeconomic characteristics obtained from the World Bank Indicators database. Our final database covers almost forty years (from 1976 to 2016), with an unbalanced panel of twenty countries, summing to 150 observations.

By using descriptive and regression analyses, we aim to uncover possible correlations between recent trends in income and expenditure/consumption inequality measures and compositional population statistics related to educational attainment and gender participation in the labour market. We also explore the different magnitudes of correlation between our inequality measures and some institutional indicators capturing countries' economic stage development.

As such, our empirical analysis updates the findings of Alvaredo and Gasparini (2015) and Lakner and Milanovic (2016) on inequality trends in middle-income countries by including more recent years. In the second part, we contribute to the macro-level analysis of Roine et al. (2009), who analyse macroeconomic determinants of economic inequality in a panel of sixteen high-income countries.

The chapter unfolds as follows. Section 2 discusses the main challenges when harmonizing microdata from developing and middle-income countries. In Section 3 data and variables are presented, while Section 4 describes the applied methodology. Empirical results are presented and discussed in Section 5. Finally, Section 6 concludes and offers policy implications.

2 The Challenges of Harmonizing Data from Middle-Income Countries

From its inception in the 1980s, LIS has been historically focused on high-income countries. A pilot project was carried out in 2007 with the collaboration of a team at the World Bank in order to study the feasibility of including middle-income countries in the LIS database. Following the decision to go ahead with this expansion, LIS has made some conceptual adjustments and changes to its list of harmonized variables in order to accommodate more diverse labour market characteristics, social benefit structures, consumption patterns, transnational income flows, and within-country variability.

Among the main changes achieved with the major template revision, which took effect in 2011, the following were mostly aimed at, at the same time, maximizing its applicability to datasets from both high- and middle-income countries:

- Adjustment of the disposable household income (DHI) concept, such that it also includes non-monetary income from labour and from public and private third parties. The main reason for this enlargement of the DHI concept stemmed from the fact that in many middle-income countries the proportion of non-monetary incomes from own-consumption and social and/or private assistance-based transfers was too important to be left out, and in fact these amounts are much more often available in middle-income countries than in high-income countries, where many data providers do not even collect them, given their irrelevance.
- Adjustment of the concept of household member to ensure that persons who are physically present in the household but whose incomes do not contribute to the household income (namely live-in domestic servants, boarders,

and lodgers) are not accounted for in the creation of total household income or the calculation of the equivalence scale.

- Inclusion of a number of living arrangement variables allowing for a better analysis of multi-unit/multi-generation households, so that, if available, information on partnership and parenthood of adults outside the nuclear family is retained.
- Inclusion of variables containing information on an array of new topics, including rural/urban indicator, farming activity indicator, type of dwelling, involvement in marginal/informal work, and characteristics of a second job.

Additional challenges are typically found when dealing with income microdata from these sources, as discussed presently. Because of the diversity of *rural versus urban areas*, in many middle-income countries income surveys either only cover urban areas, where it is easier to capture incomes, or use very different instruments (including different sampling and questionnaires) for the urban and rural areas.¹

The definition of *household membership* (and ensuing treatment of individual incomes when creating household-level incomes) is of particular relevance in middle-income countries. Family members temporarily absent are sometimes treated as household members, sometimes not, and it is often difficult to distinguish the two situations—this is particularly challenging when adults are temporarily absent to work elsewhere (e.g. the case of absent household heads or spouses) as it considerably changes the way their incomes should be accounted for (include their total income as labour incomes or only the part that they send back to the family as remittances).

Multi-generational households, and more generally large or *complex households*, are much more common; depending on who is defined as the household head (the older or middle generation in the case of three-generational households), the characteristics of the household—often based on the head and its nuclear family—will differ. In the case of polygamy, many of the usual indicators that are typically based on the head and a single spouse become much more difficult to create.

When turning to the labour market information, and especially to the *employment definition*, it should be noted that in many surveys of middle-income countries, the labour market module follows the method of the ‘catch-all’ question on

¹ This issue proved particularly challenging with the Chinese survey, where the integration of the three different samples (urban, rural, and rural-to-urban migrants) into a unique national sample required some adjustments to the weights and to the variables themselves that risked the quality of the resulting file (to the point that for the year 2007, where the issue was particularly severe, LIS decided not to make the Chinese data public).

employment: after responding that he or she does not have a job or does not work, an interviewee is asked a series of questions to determine whether he or she has done any activity in order to help the family (such as cultivating fruits and vegetables, selling products in the street, carrying out services for other persons, helping out in a household business, etc). Given the large extent to which these activities are performed by women and children in many middle-income countries, considering these activities as ILO employment (under the argument that they fall under either the category of paid work for at least one hour, or of unpaid family work) increases the employment rates considerably, creating large gaps between population with positive earnings and population employed, as well as potentially creating a bias versus those countries that do not include such questions.²

A related point concerns child labour. In most middle-income countries, information about the labour market is collected for children as well, in order to analyse its diffusion. Some surveys have a special section for children only; in other cases (some of) the same questions asked for adults are also asked for children. In both cases, the creation of a fully comparable labour market participation rate (or employment rate) between those different countries becomes very tricky. In addition, there are typically many questions on unofficial work, non-regular activities, household production, and illegal labour (not registered, not covered by social insurance, not taxed) in order to capture some measure of *informal labour*. These questions are typically very different from survey to survey (often referring to the institutional set up of the country), and are almost impossible to harmonize.

Finally, the wide extent of persons having *multiple jobs* makes the harmonization (and hence ensuing comparison) of job characteristics challenging, especially when the questionnaires ask about different types of work in different sections of the questionnaire (e.g. work in a family business separately from work on the farm separately from other jobs). This is troublesome because (a) it is often not clear if the persons report the same jobs in several sections of the questionnaire, hence incurring the risk of double-counting the jobs; (b) it becomes difficult to determine which is the main job.

When looking at the income variables, several issues are at stake when considering middle-income countries. First and foremost, indicators of inequality, poverty, and well-being are still prevalently based on *consumption rather than income*

² A very clear example of this arises in Peru (with data from the National Household Survey—ENAHU), which, together with Switzerland, is the country that exhibits the highest employment rate of all LIS countries. Like in the surveys of most other Latin American countries, individuals are first asked if they have a job; if they respond that they do not, then they are asked if they have carried out any activity to help out the family, and the question includes a long list of possible marginal activities. The very high number of persons who answer negatively to the first question and positively to the second implies that the employment mostly consists of marginal employment. It is, however, very likely that the way the question is formulated invites many people who would not have answered positively with a different question, to answer positively.

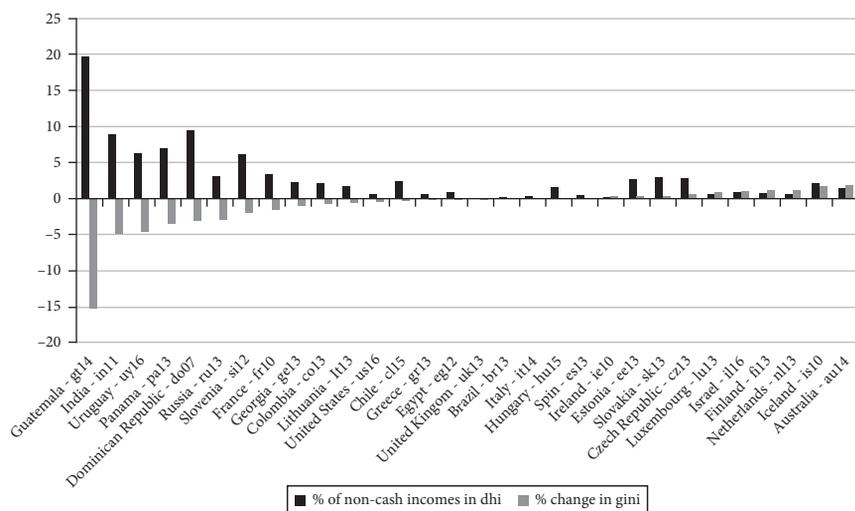


Figure 4.1 Impact of non-monetary incomes

Source: Authors, based on data from the LIS database.

data, which often implies that income microdata are either non-existent or insufficient for the purpose of calculating robust income indicators (not collected, collected but not provided, collected but not exhaustive to capture the totality of household income). As already mentioned, the enlargement to the middle-income countries group has been followed by a necessary adjustment of the concept of total disposable income to include also *non-monetary incomes* from labour (notably own-consumption of products stemming from farming activities) and public and private transfers (notably public and private assistance as benefits in-kind): see Figure 4.1.

Whereas the adjustment was necessary to get a more unbiased picture of the households' standards of living in those countries, the inclusion of those incomes in the data has often proven to be particularly tricky. The first problem is due to the fact that the coverage of the non-monetary incomes collected by the different surveys differs widely across countries, hence implying a situation in which comparability is at stake. For example, in surveys that are mostly focused on consumption, the value of most goods and services consumed but not paid for (either because they are own-produced or because they are received from the employer, the government, charitable institutions, or other private households) is collected with great detail and precision, whereas in other types of surveys the data on the availability of those goods becomes much more scarce.

Another problem arises with the non-monetization of quantities of goods and services; at this stage, LIS has taken the approach of only including those incomes that have been monetized by the data provider, thus increasing the potential bias due to the fact that in some countries, for purely practical rather than conceptual

reasons, the final income concept includes more non-monetary incomes than is the case in others.

Somewhat arbitrary assumptions are to be made in the case that non-monetary incomes are collected in different sections of the questionnaire (among the consumption variables, among the household-level incomes from household activities, and among individual-level labour incomes); it becomes clear that those amounts will certainly overlap to some extent, and the creation of a final amount that does not include any under- or over-counting of some income sources proves extremely hard to obtain.

Independently from (but related to) the issue of the non-monetary incomes, another problematic area is that of the *self-employment incomes* in general—especially those from farming activities and informal activities. As those incomes are more irregular and difficult to measure by nature, the reliability of a total household income variable which is composed in large part of those types of incomes naturally becomes much more difficult. In addition, when it is collected at the household level only (as is often the case in middle-income countries where surveys have specific sections about the household activities), the creation of a comprehensive measure of total individual labour income becomes impossible, hence restricting the possibility of using such an important variable in many analyses: see Figure 4.2.

Other than the measurement of the income itself, its classification into the different income subcomponents can also become more problematic in middle-income countries. One particular issue refers to the classification of *employer-provided pensions and benefits into labour income versus social security*: while benefits provided by the employer (such as allowances and subsidies paid together with the

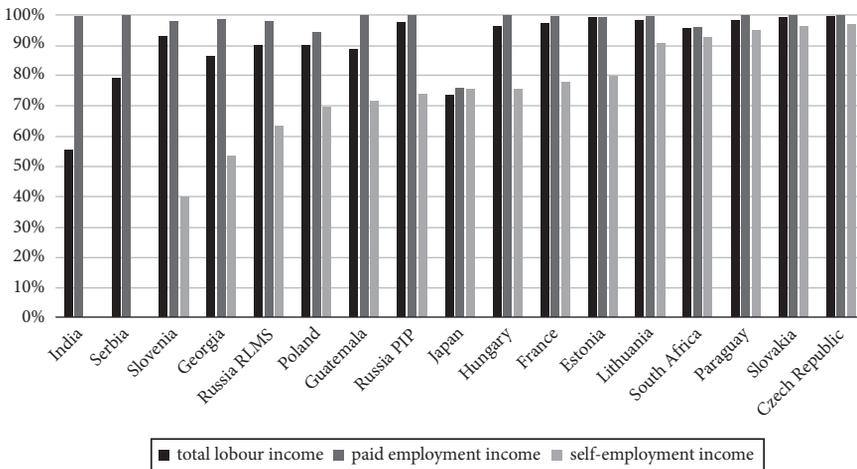


Figure 4.2 Labour income availability at the individual level

Source: Authors, based on data from the LIS database.

basic wage income) have typically been considered as labour income in high-income countries, when moving to middle-income countries it becomes clear that some of those benefits were actually replacing an almost non-existent social security and were thus much closer to social security benefits than labour income. Similarly, the usual distinction between *social insurance, assistance, and universal benefits* has often proved irrelevant in middle-income countries, where the employment-related benefits stem purely from the willingness of the employer and not from the benevolence of the government, and most of the—strictly speaking, public—benefits are targeted to the very poor.

The *treatment of taxes and social security contributions* also differentiates middle- from high-income countries (Figure 4.3). The issue in high-income countries is centred on the difference between the countries/surveys that provide income data gross of taxes and contributions and those that provide the data after such deductions. More specifically, in the first case all the incomes provided are gross, and the totality of taxes and contributions are deducted from total gross income to obtain the concept of disposable income; on the other hand, for countries that provide each income source already net of taxes and contributions, the sum of all income subcomponents is already net of taxes and contributions, and hence corresponds to the concept of disposable income. As a result, while at the level of total disposable income the variables are perfectly comparable, the comparability is reduced by the fact that at the subcomponent level some datasets provide gross incomes and others net incomes. For middle-income countries the challenge concerning the treatment of taxes is rather different. The very low reliance on direct taxes in most middle-income countries makes the above-mentioned issue almost irrelevant, as the difference between ‘gross’ and ‘net’ datasets is very tiny. It actually becomes problematic to even simply distinguish the surveys

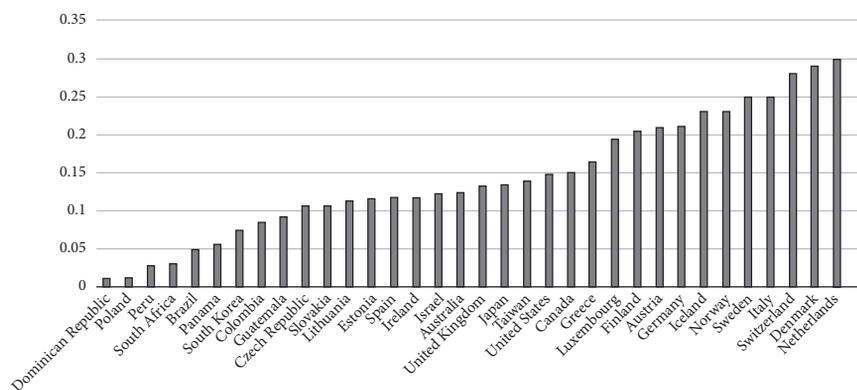


Figure 4.3 Taxes and social security contributions as a percentage of total gross income

Source: Authors, based on data from the LIS database.

between gross and net, as the situation is either a mixture of the two (in some cases with only wage income being gross of taxes and contributions and all others net), or simply is not defined at all by the data provider itself.³ Several middle-income countries even provide the income data only in gross terms, without indication of the amount of taxes and contributions paid on them, which results in having to simulate taxes and contributions in order to obtain a measure of disposable income comparable to other countries.⁴ In any case, even in the presence of full information on taxes and contributions, the low reliance on direct taxes relative to indirect ones in middle-income countries adds a bias to the comparability of well-being indicators based on DHI. If indirect taxes were also taken into account, the true difference in high- and middle-income countries' inequality might even be greater than is shown by the figures.

From a more technical point of view, an issue that can often become serious, especially in data from middle-income countries (but not necessarily confined to those), is the presence of a large number of observations with *missing (or inconsistent) data*. When the percentage of households with missing (or zero) total disposable income goes beyond a certain threshold,⁵ and especially when the data provider does not account for this in the calculation of the weights, the potential bias due to the non-random distribution of those households is large enough to put at risk any country-level analysis of the income distribution. See Figure 4.4 for an overview of the percentage of households with missing DHI in a selection of LIS countries.

All in all, in spite of the efforts made at the various levels of the data production chain (survey conception, implementation, data editing, and data harmonization), there remain some important gaps in order to ensure perfect consistency of the income micro-datasets coming from high- and middle-income countries, and the question of whether those two sets of data can be analysed within the same framework or whether they should be kept separate remains an important one. LIS has adopted the view that a common framework is possible, but cannot stress enough the importance of highlighting all the caveats that go with such an approach.

³ This is the case, for example, in India, where, given the almost irrelevance of taxes, the data provider does not specify whether the incomes should be reported before or after such deductions. The end result is therefore a mix of the two depending on the observations, without any indication as to what the situation is for each observation.

⁴ This is the case in the National Household Sample Survey (PNAD) of Brazil, the Colombian Great Integrated Household Survey (GEIH), and the Continuous Household Survey (ECH) of Panama.

⁵ LIS typically uses 10 per cent as the threshold requiring some careful treatment, and 20 per cent as the maximum acceptable threshold for reliable income estimates. For Tunisia, for example, LIS obtained data from the only existing income microdata (the Tunisian Labor Market Panel Survey—TLMPS), but after data inspection decided not to include it in the LIS database due to an excessively large portion of the sample having missing household income (about half of the households).

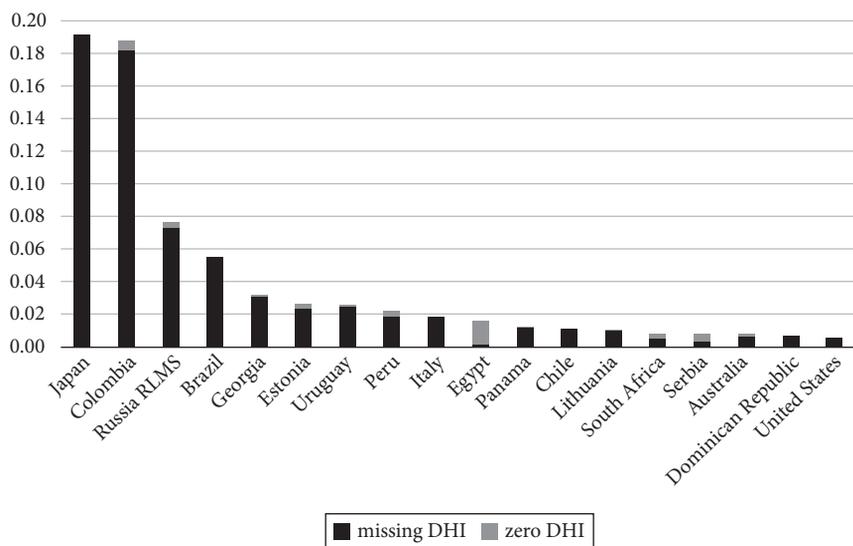


Figure 4.4 Extent of missing or zero income

Source: Authors, based on data from the LIS database.

3 Data and Variables

3.1 Dataset

The present sample of countries is drawn from the LIS database, the largest available income database of harmonized microdata collected from about fifty countries, spanning five decades. In addition to broad coverage of countries across the world, its advantage is a large set of standardized variables, making the results directly comparable. LIS datasets contain household- and individual-level data, such as labour income, capital income, social security and private transfers, taxes and contributions, expenditures, employment conditions, and usual demographics.

In our empirical analysis we primarily focus on middle-income countries, including Brazil, China, India, Mexico, Russia, and South Africa. To present the results in a comparative perspective, we consider other middle-income countries (Colombia, Paraguay, Uruguay) and some high-income countries (Chile, Hungary, Israel, Mexico, Poland, Slovenia, South Korea, Taiwan, and the USA) as potential benchmarks. In the regression analysis, we expand the country sample to include other high-income countries (Australia, Austria, Italy, and Peru).⁶

⁶ The choice of the benchmark countries is mostly influenced by the country's sample length, reliability of the survey data, regional diversity, and finally the country's economic environment with

3.2 Variables

Our main outcome (household-level) variables are household pre-tax market income (consisting of labour and capital income), household disposable income, and household monetary consumption, as well as the total individual-level labour income. Note that values in all outcome variables were bottom- and top-coded⁷ and equivalized, applying the square root scale. The covariates, which are further used in the empirical part, include basic information on gender, education, and employment status of individuals.

In addition to variables used in the microeconomic inequality analysis, we consider a set of macroeconomic country-level characteristics that have been shown to be significant determinants of economic inequality (e.g., Alvaredo and Gasparini 2015; Davies et al. 2017; Roine et al. 2009). Similarly to previous studies, the macroeconomic characteristics considered include GDP per capita, share of agriculture in GDP, share of urban households, life expectancy, age dependency ratio and share of government spending in GDP.⁸ A natural question here is what the associations between inequality and such macroeconomic indicators should look like. Following Roine et al. (2009), we summarize the impact of the main contextual variables. First, standard Kuznets theory predicts different inequality levels across a country's development path, suggesting an inverse U-shape relationship between GDP per capita and inequality. Standard theory also suggests that the growth of financial markets goes hand in hand with lower inequality. In terms of trade liberalization, the standard Heckscher–Ohlin theory predicts that trade openness should favour the rich, hence increasing inequality levels. Finally, central government spending (as a proxy for the welfare state) is believed to equalize incomes of households.

4 Methodology

In our empirical analysis, we first compute a set of inequality indicators for income and consumption aggregates, as well as for major population subgroups. Then we correlate the estimated inequality measures with some country-level macroeconomic indicators. We obviously anticipate that in all cases causality may

respect to the core countries (i.e. matching gross domestic product (GDP) per capita, trade openness, financial development, etc). A comprehensive overview of the sample countries and years available is presented in Table A1 of Checchi et al. (2018). In Table A2 of the same paper we report descriptive statistics for the covariates.

⁷ The values in main outcome variables were bottom-coded at 0 and top-coded at ten times the median of the corresponding non-equivalized variable.

⁸ A full list of country characteristics along with their definitions is presented in Table A3 of Checchi et al. (2018).

go in both directions, and therefore these are to be considered as mere descriptive statistics. In the next two subsections we briefly summarize our methodological framework.

4.1 Inequality Measures

In this section we describe the inequality measures that we apply to the main outcome variables: household-level disposable income and total consumption, and individual-level labour income. For the reader's convenience, we briefly recall the definition of the main inequality indicators we are going to use in the analysis. Following Cowell (2011), let us consider a population of households (individuals), indexed by $i = 1, \dots, n$ with income (consumption) y_i , the arithmetic mean of the income (consumption) for the population is given by $\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$. The main inequality indicator that we present through the paper is the *Gini index*, which can be written as follows:

$$Gini = \frac{1}{2n^2 \bar{y}} \sum_{i=1}^n \sum_{j=1}^n |y_i - y_j|.$$

A second inequality measure that we apply is the *Atkinson index*, which is given by:

$$A_\epsilon = 1 - \left[\frac{1}{n} \sum_{i=1}^n \left[\frac{y_i}{\bar{y}} \right]^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}},$$

where ϵ represents the weighting parameter measuring aversion to inequality. In our case, we compute the Atkinson index for ϵ taking values of 0.5, 1, and 2. The higher the parameter, the stronger the expression of inequality aversion captured by the index.

The third and final inequality measure we consider is the *mean log deviation index*, which can be written as:

$$MLD = \frac{1}{n} \sum_{i=1}^n \log \left(\frac{\bar{y}}{y_i} \right)$$

and has the advantage of being exactly decomposable in a between-group and within-group component. In our case, we consider groups created out of gender and three educational categories.

In addition to the three inequality metrics discussed previously, we compute some percentile ratios and income shares. The *percentile ratio* exhibits the proportion of one income group over the other. Instead of analysing the distribution as a whole, it compares two points of the distribution. In our case we compare the average income of the richest 90 per cent of the households (individuals) to the poorest 10 per cent. The *income shares* measure gives an overview of what share of the total income is held by a certain subpopulation group. In our analysis, we focus on the bottom 50 per cent, top 90 per cent, and 95 per cent of households (earners).

4.2 Regression Analysis

In the second stage of our empirical framework, we run a set of country-level regressions in which we correlate the computed (average) inequality measures to macroeconomic indicators capturing the country's economic development. We estimate the relationships by the following linear regression:

$$\text{Inequality}_{it} = \beta_0 + \beta X_{it} + \delta_i + u_{it},$$

where the left-hand side variable is a specific inequality indicator estimated for country i in period t , X_{it} and presents a vector of country-level characteristics including indicators such as GDP per capita, employment rate, educational attainment in the population, life expectancy, etc, along with the corresponding coefficients β to be estimated. We also control for country fixed effects δ_i in the regressions. Note that controlling for time fixed effects is more problematic, since the survey years are not coincident among countries.

5 Results

5.1 Descriptive Analysis

We start our analysis of inequality trends by showing the inequality levels for the BRICS middle-income countries (Brazil, China, India, Russia, and South Africa). We also add figures for the USA as a benchmark country. To cross-check the picture emerging from the LIS database, we also include inequality measures and income shares from external sources: for inequality measures we collected additional data from the UNU-WIDER WIID database,⁹ whereas for income shares, we considered data from the World Inequality Database.¹⁰

⁹ www.wider.unu.edu/project/wiid-world-income-inequality-database.

¹⁰ <https://wid.world>.

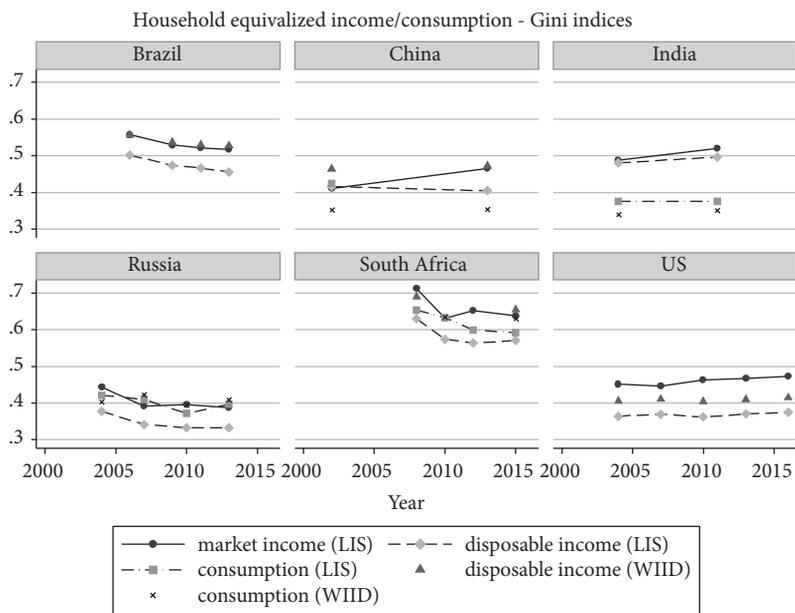


Figure 4.5 Trends in income inequality (Gini index) in selected middle-income countries (USA as benchmark)

Note: Gini indices obtained from the WIID database are per capita, therefore they exhibit higher levels compared to the equivalized LIS numbers (except India for consumption).

Source: Authors, based on data from the LIS database and WIID database.

In Figure 4.5, the first aspect to be considered is that inequality in market incomes is always higher than inequality in disposable incomes, the average difference being around 5 percentage points, with consumption inequality (when available) taking an intermediate value (this is true in Russia and South Africa).¹¹ One might notice that household consumption is covered only for a subset of countries in the LIS database. Pearson correlation between the Gini index of household disposable income and the Gini index of household (monetary) consumption is 0.87. This might imply that where information on consumption is not available, we could infer a trend for consumption inequality based on the income inequality data, and vice versa.

Moving on now to consider inequality trends, from Figure 4.5 we observe that inequality is on a declining trend in the case of Brazil: for example, the Gini index of household disposable income declined from 50 per cent in 2006 to 46 per cent in 2013. The decline in inequality in Latin America is a known phenomenon

¹¹ The average Gini indices for BRICS countries in LIS are 0.51, 0.46, and 0.47 for gross market incomes, disposable incomes, and consumption respectively. The corresponding averages obtained from WIID are 0.49 and 0.44 for disposable incomes and consumption.

(see Cornia 2014) that extends to most Latin American countries available in our dataset. Among the suggested explanations, one may consider a drop in the skill premium following an expansion of secondary education and the adoption of a new development model by a growing number of progressive governments which adopted prudent but more equitable macroeconomic, tax, social assistance, and labour policies. For example, Lustig et al. (2013) argue that overall decrease in income inequality in Latin American countries was dominated by a decline in labour income inequality that occurred due to expansion of employment and hours worked. These changes raised the incomes of, especially, the poor (roughly defined as the bottom half of the distribution), at the expense of the élites (again roughly identified as the top 5 per cent or 10 per cent in the distribution; see Figure 4.6).

Going back to Figure 4.5, for China and India we can hardly talk of any trend, as there are only two data points available for each country in the LIS database. With this caveat in mind, we observe that in the case of China inequality in market income is on the rise, while the (admittedly limited) redistributive activities of the public sector contained this trend, leading to a constant inequality in terms of disposable incomes: in fact, the Gini index of pre-tax market incomes rose from 41 per cent to 46 per cent between 2002 and 2013, while the Gini index of

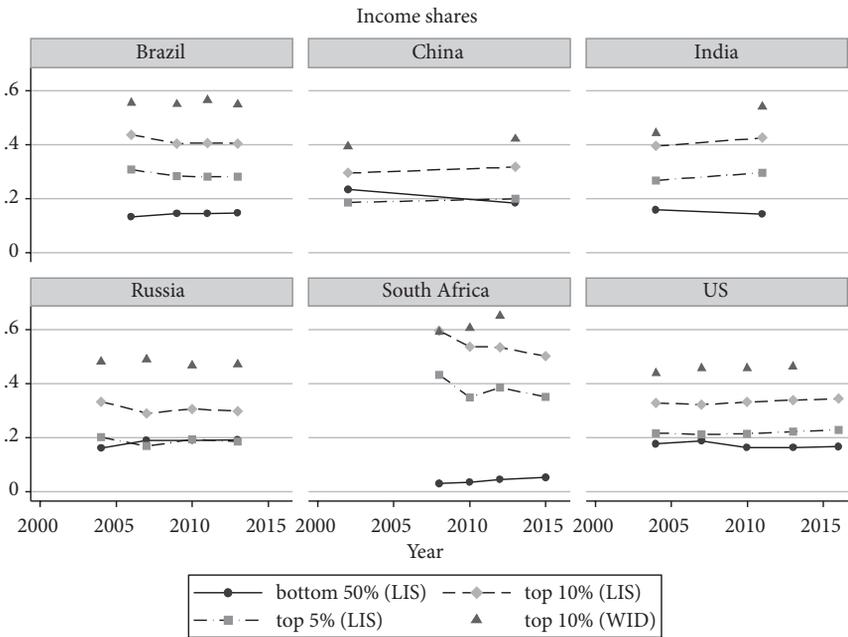


Figure 4.6 Evolution of income shares held by households with incomes below the 50th, and above the 90th and 95th percentiles

Source: Authors, based on data from the LIS database and the WIID database.

household disposable income spans around 40 per cent.¹² The rising trend in pre-tax income inequality is confirmed in other studies, though it may hide an even higher peak reached around the year 2008 (Jain-Chandra et al. 2018; Ghosh 2012). Income shares observed in Figure 4.6 suggest that most of the gains from growth accrued to the richest 10 per cent (though LIS data underestimate this share due to inability to capture the top incomes, as detectable when comparing with WID top incomes data). Contrary to the Latin American experience, differences in educational attainment at tertiary level and the skill premium are identified as drivers of the increase in income inequality (Jain-Chandra et al. 2018).

According to LIS data, India experienced a similar increase in market income inequality between 2004 and 2011, with the Gini index of pre-tax household income rising from 0.49 to 0.52, while the corresponding figures for disposable incomes rose from 0.48 to 0.49 (confirming that in middle- and low-income countries the distinction between the two income concepts is conceptually weak—see Section 2). In the case of India, we can only compare the consistency of our results against the WIID database for household consumption, showing that the trends for consumption inequality are very similar between LIS and WIID (see again Figure 4.5). Income shares indicate a robust expansion of the élites, though it is weaker than what is recorded by corresponding WID data for the top 10 per cent: see Figure 4.6. The rising trend would reverse a declining trend detected in the beginning of the previous decade, as a consequence of trade liberalization undertaken by local governments at the end of the previous century (Krishna and Sethupathy 2012). Chancel and Piketty (2017), in a recent paper, conclude that economic transformation from a socialist planning to a capitalist economy was the main driver of unequal distribution of income and wealth in India. Over a comparable time interval, we do not find an equivalent trend in income inequality for countries available in the LIS database, since both Taiwan and South Korea exhibit rather stable inequality trends: see Checchi et al. (2018: Figure A2).

Inequality trends for Russia presented in Figure 4.5 indicate a declining trend in income inequality, with the Gini index of household disposable income dropping from 41 per cent in 2000 to 33 per cent in 2013.¹³ A possible reduction in inequality found in LIS data stands in sharp contrast to results from top incomes analysis: Novokmet et al. (2017) claim that official inequality estimates vastly underestimate the concentration of income in Russia. While income shares of the top 10 per cent exhibit a declining trend in LIS survey data, tax records indicate

¹² In the case of China, the LIS figures for household disposable income inequality are somewhat lower compared to numbers from the external WIID database (due to different equivalency scale applied). Note that trends in both cases are very similar, with the two lines being almost parallel.

¹³ As in the case of India, we can only compare the validity of our computed inequality measures for household consumption: Figure 4.5 shows that consumption inequality computed on LIS data is somewhat lower than corresponding figures from the WIID database.

an opposite trend.¹⁴ The Russian declining trend in inequality is partly in contrast with other Central and Eastern European countries (Hungary, Poland, and Slovenia), as detectable in Checchi et al. (2018: Figure A3).

Finally, we consider income inequality trends for South Africa (see again Figure 4.5). Among all the countries considered here, income inequality in South Africa, measured by all three indices, is by far the highest. Based on the Gini index of DHI, this inequality was as high as 63 per cent in 2008. It had gradually dropped to 57 per cent by 2015. As regards consistency with external data sources, we can only compare consumption inequality against the WIID figures. As there are only two points available, we cannot confirm whether the trends are well captured. Nevertheless, one might notice that consumption inequality has opposite trends between 2008 and 2010 based on LIS and WIID figures. When cross-checking with national sources, the problem of data quality (coverage, weights, imputations) emerges immediately, since various data imputations of missing income values may produce alternative trends, though all of them are on the rise.¹⁵ This is also confirmed by the trend in income shares of the top 10 per cent from WID, while in the LIS data the corresponding top-income share would have lost approximately 10 percentage points. In the case of South Africa, there is no other sub-Saharan country available in the LIS database. The closest country to compare the trends against is Israel, where the ethnic divide is also rather pronounced. Apart from the lower level of aggregate inequality, in the latter country inequality seems also to be declining (see Checchi et al. 2018: Figure A4).

Overall, we may conclude that the inequality trend in BRICS countries exhibits different patterns, with Latin America and Eastern Europe on a declining trend while Eastern Asia and South Africa are on the rise. Despite the enormous differences in economic structure among these countries, we make an attempt to investigate whether common causes may underlie these changes. We resort to the common within/between decomposition analysis based on the mean log deviation index, and we focus on personal labour earnings, where the identification of common sources of inequality (like gender and education) is easier. In Figure 4.7 we report the result of such a decomposition, where two covariates are considered—gender and education—and consequently the employed population is divided into

¹⁴ 'The Gini coefficient jumped from about 0.3–0.4 in self-reported survey data to over 0.6 using the leaked tax data, and the top 10% income share moved from about 30% to over 50% of total income' (Novokmet et al. 2017: 13).

¹⁵ 'Using Sequential Regression Multiple Imputation (SRMI) to impute values for reported zero or missing incomes, Yu (2009) found a strong increase (seven or eight points) in the Gini coefficient between 1996 and 2001 (Table 4.3). Supporting evidence comes from other studies employing alternative measures: Leibbrandt et al. (2006) found an increase in the Gini from 0.68 to 0.73 using one method, and from 0.74 to 0.79 using another; Simkins (2004) found that the Gini coefficient for households grew from 0.66 to 0.69; and Ardington et al. (2005) concluded that the Gini coefficient rose from 0.74 to 0.82. There is thus agreement about the trends, though the levels vary widely' (Van Der Berg 2010: 12).

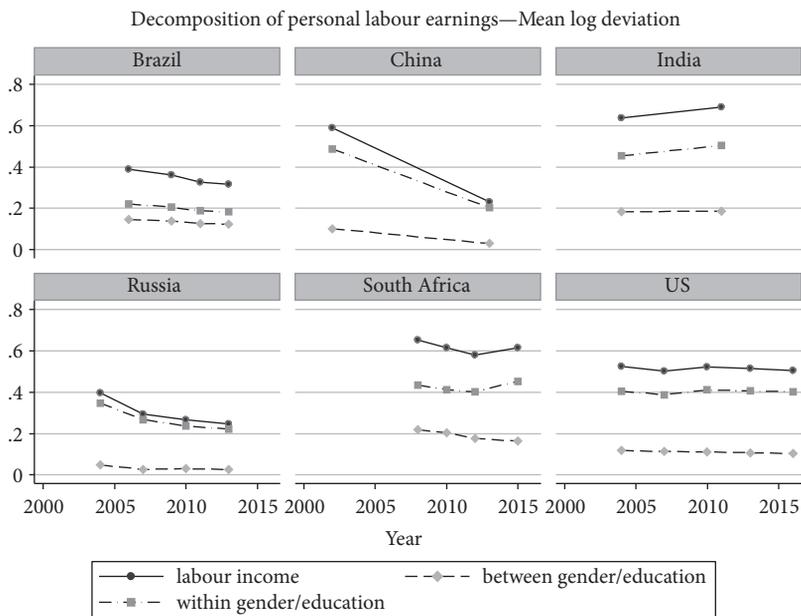


Figure 4.7 Inequality decomposition in labour incomes

Source: Authors, based on data from the LIS database.

six groups (two genders by three educational attainments). The between-group component (the inequality that would have been observed had each group member an income equivalent to the group mean) is intended to capture the return to education and/or the gender gap contributions to inequality: in all countries this dimension declines, though from different starting points. In previously centrally planned economies, this dimension of inequality was almost non-existent, while for the other countries it reached between one-third and one-half of observed earnings inequality. Within-group inequality (namely the inequality that can be attributed to unobserved components) is on the rise in India and South Africa, while a strong reduction can be observed in China. The limitation of this approach is the exclusion of people without labour earnings from the analysis, which makes these countries not strictly comparable. Nevertheless, the decomposition indicates that traditional inequality drivers—gender and education—see a reduction of their explanatory power with reference to income inequality.

5.2 Regression Results

We now turn to a multivariate analysis in an expanded sample that includes other countries in the same area and/or at a similar level of development. Detailed summary statistics of the variables considered are reported in Table 4.1. We can

Table 4.1 Descriptive statistics of variables used in the empirical analysis

Variable	Obs.	Countries	Mean	Std. dev.	Min.	Max.
Gini index equivalized household factor income	148	21	0.43	0.08	0.27	0.71
Gini index equivalized disposable household income	150	21	0.37	0.10	0.21	0.63
Atkinson index equivalized household factor income $e = 0.5$	148	21	0.17	0.06	0.06	0.43
Atkinson index equivalized household factor income $e = 1$	148	21	0.35	0.09	0.12	0.74
Atkinson index equivalized household factor income $e = 2$	148	21	0.82	0.13	0.31	1.00
Income share bottom 50 per cent (based on household factor income)	144	21	0.19	0.05	0.03	0.30
Income share top 10 per cent (based on household factor income)	147	21	0.33	0.07	0.22	0.60
Income share top 5 per cent (based on household factor income)	147	21	0.21	0.06	0.12	0.43
Income share top 1 per cent (based on household factor income)	147	21	0.07	0.03	0.03	0.17
Gini index personal labour earnings	143	20	0.40	0.08	0.21	0.57
Atkinson index personal labour earnings $e = 0.5$	143	20	0.14	0.05	0.04	0.27
Atkinson index personal labour earnings $e = 1$	143	20	0.28	0.10	0.08	0.50
Atkinson index personal labour earnings $e = 2$	143	20	0.60	0.19	0.18	0.97
MLD personal labour earnings	143	20	0.34	0.15	0.08	0.69
MLD personal labour earnings—between six groups (sex and education)	143	20	0.08	0.04	0.02	0.22
MLD personal labour earnings—within six groups (sex and education)	143	20	0.26	0.11	0.07	0.53
Decile ratio p90/p10 of personal labour earnings	143	20	9.92	7.18	2.50	32.00
Employment rate among men (16–65)	150	21	0.72	0.09	0.40	1.00
Employment rate among women (16–65)	150	21	0.51	0.12	0.20	1.00
Share female low education 15–65	150	21	0.25	0.11	0.07	0.47
Share female high education 15–65	150	21	0.08	0.06	0.01	0.28

Share male low education 15–65	150	21	0.23	0.10	0.08	0.46
Share male high education 15–65	150	21	0.07	0.05	0.01	0.19
Age dependency ratio (% of working-age population)	138	20	0.52	0.09	0.36	0.90
Life expectancy at birth (years)	138	20	75.13	4.85	53.72	83.09
Log GDP per capita	135	20	9.30	0.95	6.43	10.96
Urban population (% of total)	139	20	0.73	0.13	0.29	0.95
Government expenditure (% of GDP)	129	20	0.29	0.11	0.11	0.51
Government spending on education (% of GDP)	103	19	4.63	0.99	2.25	6.70
Agriculture, forestry, and fishing, value added (% of GDP)	122	20	0.05	0.04	0.01	0.20
Market capitalization of listed domestic companies (% of GDP)	107	19	61.96	49.29	2.08	246.47

Source: Authors, based on data from the LIS database and the World Bank Indicators database.

see that our countries differ in terms of the computed inequality indicators (e.g. Gini index of the household disposable income ranges from 0.20 to 0.63), but also in terms of underlying social conditions (e.g. life expectancy ranges from 53 to 83 years).

We also explore existing correlations between income inequality measures and a set of institutional variables.¹⁶ We present four scatterplots in Figure 4.8. The results of these unconditional correlations suggest that income inequality (captured by the Gini index of household disposable income) is negatively correlated with the log of GDP per capita (measured in current US dollars), share of public expenditure (percentage of GDP), and life expectancy (years). On the other hand, the age dependency ratio is positively linked with income inequality. This might suggest that in countries with an ageing population and limited replacement pension systems, income inequality becomes an issue. We are fully aware that such graphs do not imply any causal relationships and do not consider potential covariance among these variables. To cope with these problems in a more consistent approach, we move to multivariate regressions.

¹⁶ Note that from now onward we extend the sample of country/year in order to get a more precise estimation of the variable correlations. We are thus working with 21 countries and 150 observations, with an average of 7.4 surveys per country. The countries are (number of surveys in brackets): Australia (8), Austria (9), Brazil (4), Chile (12), China (2), Colombia (4), Hungary (8), India (2), Israel (11), Italy (12), South Korea (4), Mexico (12), Paraguay (6), Peru (4), Poland (9), Russia (5), Slovenia (6), South Africa (4), Taiwan (11), the USA (12), and Uruguay (5). Note that for South Korea personal labour earnings are not collected.

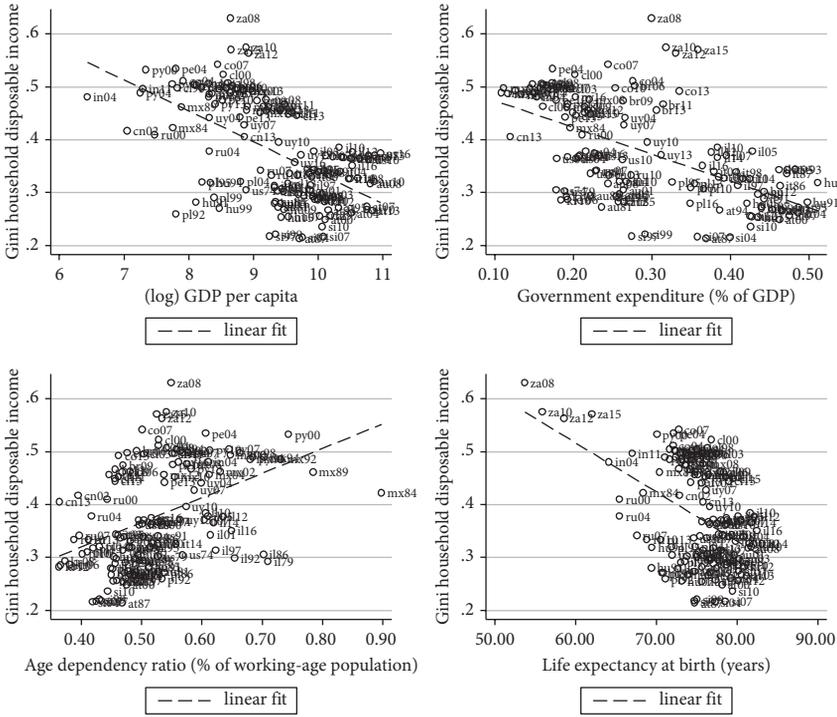


Figure 4.8 Income inequality (Gini index) versus selected macroeconomic country characteristics

Note: Gini index of DHI (top-coded and equalized according to the OECD equivalence scale) presented on the vertical axis.

Source: Authors, based on data from the LIS database and the World Bank Indicators database.

The results of our multivariate analysis are presented in Tables 4.2–4.4. In Table 4.2 we consider three outcome variables (factor household income, DHI, and personal labour earnings), three inequality indicators (Gini index, Atkinson index with alternative risk aversion coefficients— $\epsilon = 0.5$ and $\epsilon = 2$ —and alternative income shares). Since we do not control for country fixed effects (though residuals are clustered at country level), these are to be intended as simple conditional correlations, meant to explore the data. Among the most persistent results we notice that compositional variables (employment rates and educational attainment by gender) exhibit significant correlations, though with inconsistent patterns. On the contrary, GDP per capita turns out always to be insignificantly correlated with any inequality measure, similarly to proxies for production composition (agriculture share, trade openness) and public expenditure. Two variables exhibit positive correlation with inequality: one is a proxy for financial development (the market capitalization of listed domestic companies) and the other is a measure of urbanization (though it is positively associated with total income inequality, but negatively associated with labour earnings). However, the

Table 4.2 Regression analysis: OLS including all contextual variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12
	Household factor income (labour + capital)						Household disposable income			Personal labour earnings		
	Gini index	Atkinson e = 0.5	Atkinson e = 2	share bottom50	share top90	share top95	Gini index	Atkinson e = 0.5	Atkinson e = 2	Gini index	Atkinson e = 2	p90p10
Employment rate among men (16–65)	0.13	0.07	-0.40*	0.19**	0.09	0.09	0.26	0.19	-0.24	0.63***	1.28***	47.16***
Employment rate among women (16–65)	[0.120]	[0.106]	[0.214]	[0.070]	[0.086]	[0.073]	[0.180]	[0.117]	[0.504]	[0.138]	[0.298]	[10.954]
	0.06	0.06	0.34**	-0.15**	-0.01	-0.02	-0.07	-0.04	0.3	-0.09	0.06	2.49
Share female low education 15–65	[0.114]	[0.101]	[0.133]	[0.061]	[0.078]	[0.062]	[0.120]	[0.080]	[0.386]	[0.093]	[0.227]	[13.946]
	-1.22***	-0.68***	0.76	0.41	-0.88***	-0.79***	-0.96	-0.55	-2.51***	-0.67**	0.35	-19.8
Share female high education 15–65	[0.302]	[0.230]	[0.677]	[0.264]	[0.277]	[0.199]	[0.572]	[0.351]	[0.835]	[0.254]	[0.588]	[45.905]
	-0.60**	-0.43**	-0.52	0.2	-0.39*	-0.34*	-0.29	-0.18	-1.52*	-1.05***	-1.82	-85.09**
Share male low education 15–65	[0.236]	[0.199]	[0.707]	[0.225]	[0.213]	[0.174]	[0.311]	[0.199]	[0.855]	[0.282]	[1.198]	[37.238]
	1.25***	0.80***	-0.32	-0.34	0.82***	0.75***	0.97*	0.60*	2.40***	0.67***	0.29	28.92
Share male high education 15–65	[0.290]	[0.234]	[0.742]	[0.309]	[0.275]	[0.210]	[0.545]	[0.336]	[0.658]	[0.191]	[0.773]	[43.557]
	0.01	0.06	0.64	0.29	-0.13	-0.12	-0.01	0	0.99	1.71**	4.42*	145.17*
	[0.330]	[0.243]	[0.662]	[0.291]	[0.332]	[0.286]	[0.390]	[0.252]	[0.700]	[0.623]	[2.226]	[70.498]

Continued

Table 4.2 Continued

Variables	1	2	3	4	5	6	7	8	9	10	11	12
	Household factor income (labour + capital)						Household disposable income			Personal labour earnings		
	Gini index	Atkinson e = 0.5	Atkinson e = 2	share bottom50	share top90	share top95	Gini index	Atkinson e = 0.5	Atkinson e = 2	Gini index	Atkinson e = 2	p90p10
Age dependency ratio (% of working-age population)	0.27** [0.098]	0.14* [0.079]	-0.31* [0.151]	-0.19*** [0.063]	0.16* [0.076]	0.1 [0.059]	0.26* [0.137]	0.13 [0.093]	0.43 [0.363]	0.30* [0.155]	0.3 [0.465]	29.95 [20.890]
Life expectancy at birth (years)	-0.01*** [0.003]	-0.01** [0.003]	0 [0.004]	0.00** [0.002]	-0.01*** [0.003]	-0.01*** [0.002]	-0.01* [0.005]	-0.01* [0.003]	0 [0.010]	-0.01*** [0.003]	-0.01 [0.006]	-0.53* [0.278]
Log GDP per capita	0.01 [0.018]	0.01 [0.016]	0.09** [0.033]	0 [0.012]	0 [0.014]	0 [0.013]	-0.02 [0.023]	-0.02 [0.016]	0.02 [0.065]	0.01 [0.026]	0.04 [0.067]	3.24 [3.560]
Urban population (% of total)	0.15** [0.064]	0.07 [0.054]	-0.17 [0.116]	-0.12*** [0.037]	0.17** [0.062]	0.15** [0.060]	0.17* [0.082]	0.09 [0.062]	-0.32* [0.184]	-0.09 [0.096]	-0.71*** [0.192]	-32.75*** [8.638]
Government expenditure (% of GDP)	-0.08 [0.067]	0.03 [0.049]	0.06 [0.207]	0.08 [0.050]	-0.07 [0.053]	-0.06 [0.044]	-0.11 [0.133]	-0.03 [0.086]	-0.14 [0.255]	-0.21** [0.093]	-0.40* [0.218]	-8.21 [13.887]
Government spending on education (% of GDP)	0 [0.010]	0 [0.008]	-0.04** [0.013]	-0.01 [0.008]	0.01 [0.008]	0 [0.006]	0 [0.015]	0 [0.009]	-0.09* [0.047]	0.03*** [0.006]	0.06** [0.023]	2.73*** [0.752]

Agriculture, forestry, and fishing, value added (% of GDP)	0.2 [0.314]	-0.07 [0.268]	-0.02 [0.644]	-0.37* [0.181]	0.22 [0.293]	0.23 [0.284]	-0.06 [0.522]	-0.2 [0.362]	-0.6 [1.155]	0.07 [0.617]	-1.23 [1.573]	19.6 [75.907]
Trade openness (% of GDP)	0.02	0.01	-0.05	0	0.01	0.01	0	0	-0.27***	0.05	0.16	6.82
Market capitalization of listed domestic companies (% of GDP)	[0.028]	[0.026]	[0.047]	[0.019]	[0.024]	[0.024]	[0.039]	[0.027]	[0.084]	[0.047]	[0.094]	[5.833]
	0.06***	0.05***	0.01	-0.02***	0.05***	0.04***	0.08***	0.05***	0.16**	0.09***	0.14**	7.28**
	[0.014]	[0.013]	[0.030]	[0.007]	[0.012]	[0.012]	[0.019]	[0.014]	[0.057]	[0.025]	[0.056]	[2.604]
Observations	75	75	75	74	75	74	77	77	77	71	71	71
R-squared	0.85	0.793	0.515	0.795	0.88	0.872	0.857	0.848	0.556	0.831	0.669	0.632

Note: Robust standard errors in brackets. Standard errors clustered at country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors, based on the LIS database and World Bank Indicators database.

Table 4.3 Regression analysis: country fixed effects selecting some contextual variables

Variables	1	2	3	4	5	6	7	8	9	10
	Household factor income (labour + capital)						Household disposable income		Personal labour earnings	
	Gini index	Atkinson e = 2	share bottom50	share top90	share top95	Gini index	Atkinson e = 2	Gini index	Atkinson e = 2	p90p10
Employment rate among men (16–65)	-0.26**	0.12	0.18**	-0.19*	-0.11	-0.13	-0.71**	-0.34**	-0.66	3.72
Employment rate among women (16–65)	[0.113]	[0.138]	[0.076]	[0.101]	[0.080]	[0.095]	[0.325]	[0.122]	[0.410]	[15.151]
Share female low education 15–65	0.12	-0.40***	-0.04	0.06	0.02	0	0.26	0.28**	0.44	-1.84
Share female high education 15–65	[0.087]	[0.129]	[0.069]	[0.082]	[0.072]	[0.079]	[0.220]	[0.120]	[0.400]	[16.612]
	0.14	-0.48	-0.12	0.14	0.19**	0.02	-0.86	0.13	-0.13	-15
Share female low education 15–65	[0.144]	[0.426]	[0.101]	[0.091]	[0.085]	[0.114]	[0.552]	[0.094]	[0.267]	[17.744]
Share male low education 15–65	-0.08	-0.44	0.32	-0.11	-0.1	0.03	-0.04	-0.23	-0.42	-92.87**
Share male high education 15–65	[0.212]	[0.639]	[0.238]	[0.213]	[0.150]	[0.209]	[0.777]	[0.160]	[0.778]	[31.871]
	0.23**	-0.13	-0.03	0.18	0.16*	0.04	0.59**	0.08	-0.42	-22.99
Age dependency ratio (% of working-age population)	[0.102]	[0.161]	[0.108]	[0.108]	[0.087]	[0.133]	[0.265]	[0.094]	[0.332]	[19.263]
Life expectancy at birth (years)	0.97***	0.99	-0.63***	0.84***	0.70***	0.4	3.25**	1.09***	3.33***	136.31***
	[0.177]	[1.045]	[0.185]	[0.175]	[0.160]	[0.234]	[1.278]	[0.340]	[0.980]	[40.248]
	0.05	-0.31**	-0.09	0.02	0.06	0.03	0.34	-0.18**	-0.63**	-33.59**
	[0.112]	[0.150]	[0.122]	[0.112]	[0.084]	[0.116]	[0.417]	[0.077]	[0.158]	[12.440]
	0.01	0.02**	0	0	0	0	0.01	0.01**	0.02**	1.62**
	[0.005]	[0.006]	[0.004]	[0.005]	[0.004]	[0.004]	[0.009]	[0.004]	[0.008]	[0.720]

Log GDP per capita	-0.02 [0.016]	-0.01 [0.025]	0.01 [0.012]	-0.02 [0.015]	-0.01 [0.014]	-0.02 [0.014]	-0.09** [0.033]	-0.05** [0.017]	-0.13*** [0.039]	-4.57** [1.987]
Urban population (% of total)	0.08 [0.328]	-0.4 [0.659]	-0.4 [0.311]	0.37 [0.305]	0.44** [0.209]	0.06 [0.305]	-0.12 [1.072]	-0.98** [0.374]	-3.15*** [0.809]	-188.85*** [61.310]
Government expenditure (% of GDP)	-0.19* [0.098]	-0.2 [0.220]	-0.03 [0.076]	-0.15 [0.093]	-0.11 [0.075]	-0.12 [0.104]	-0.51 [0.313]	-0.12 [0.125]	-0.07 [0.335]	3.18 [15.923]
Observations	127	127	123	126	126	129	129	122	122	122
R-squared	0.289	0.271	0.326	0.234	0.216	0.179	0.331	0.373	0.332	0.311
Number of countries	21	21	21	21	21	21	21	20	20	20

Note: Robust standard errors in brackets. Standard errors clustered at country level. Country fixed effects included. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors, based on the LIS database and World Bank Indicators database.

Table 4.4 Regression analysis: country fixed effects selecting some contextual variables—most recent observations (year > 2000)

Variables	1	2	3	4	5	6	7	8	9	10
	Household factor income (labour + capital)									
	Household disposable income									
	Gini index	Atkinson e = 2	share bottom50	share top90	share top95	Gini index	Atkinson e = 2	Gini index	Atkinson e = 2	p90p10
Employment rate among men (16–65)	0.11	0.54	0.07	0.1	0.13	0.16	0.37	-0.06	-0.42	2.05
Employment rate among women (16–65)	[0.170]	[0.348]	[0.114]	[0.143]	[0.145]	[0.108]	[0.389]	[0.146]	[0.508]	[26.774]
	-0.25	-0.79*	0.12	-0.21	-0.22	-0.24**	-0.78**	0.05	0.07	9.72
Share female low education 15–65	[0.146]	[0.388]	[0.115]	[0.133]	[0.127]	[0.092]	[0.365]	[0.166]	[0.629]	[32.745]
	-0.29	-2.05	-0.04	-0.11	-0.2	-0.62	-5.16***	-0.08	-0.68	-29.26
Share female high education 15–65	[0.565]	[1.984]	[0.421]	[0.502]	[0.474]	[0.413]	[1.798]	[0.488]	[2.336]	[83.711]
	0.07	0.47	-0.07	0.19	0.14	0.11	-0.8	-0.22	-1.59	-101
Share male low education 15–65	[0.400]	[1.279]	[0.286]	[0.292]	[0.227]	[0.261]	[1.124]	[0.731]	[1.956]	[130.952]
	0.11	0.11	0.14	0.18	0.31	0.43	1.66	-0.33	-1.65	-96.12
Share male high education 15–65	[0.527]	[1.345]	[0.357]	[0.513]	[0.500]	[0.434]	[1.175]	[0.450]	[1.987]	[66.203]
	-0.31	-1.45	0.33	0.08	0.22	0.02	1.9	-0.47	0.33	-99.34
	[0.433]	[1.039]	[0.201]	[0.332]	[0.289]	[0.347]	[1.269]	[0.695]	[2.645]	[100.619]
Age dependency ratio (% of working-age population)	0.13	-0.86*	-0.07	-0.04	-0.12	0.02	0	0.4	1.31*	66.45
Life expectancy at birth (years)	[0.189]	[0.428]	[0.140]	[0.147]	[0.116]	[0.151]	[1.007]	[0.267]	[0.689]	[50.825]
	0	0.01	0	-0.01	0	0	0	0	0.01	1.04
Log GDP per capita	[0.005]	[0.008]	[0.004]	[0.005]	[0.004]	[0.003]	[0.008]	[0.005]	[0.014]	[0.936]
	-0.01	-0.07***	0.01	-0.01	-0.01	-0.02*	-0.17***	-0.01	-0.02	1.35
	[0.014]	[0.024]	[0.008]	[0.013]	[0.011]	[0.010]	[0.049]	[0.020]	[0.050]	[2.713]

Urban population (% of total)	-0.08	-0.62	-0.03	0.11	-0.07	-0.39	-0.72	-0.08	-0.32	-137.18
	[0.641]	[1.211]	[0.393]	[0.499]	[0.429]	[0.481]	[1.005]	[0.662]	[1.734]	[105.797]
Government expenditure (% of GDP)	-0.09	-0.52	-0.04	-0.05	-0.06	-0.17**	-0.89**	-0.1	-0.72*	-2.74
	[0.095]	[0.405]	[0.092]	[0.080]	[0.065]	[0.074]	[0.335]	[0.157]	[0.391]	[21.288]
Observations	83	83	81	83	82	83	83	79	79	79
R-squared	0.306	0.243	0.354	0.359	0.287	0.428	0.346	0.196	0.15	0.198
Number of countries	21	21	21	21	21	21	21	20	20	20

Note: Robust standard errors in brackets. Standard errors clustered at country level. Country fixed effects included. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors, based on data from the LIS database and the World Bank Indicators database.

main limit of this approach is the missing values on some variables (as can easily be detected in Table 4.1, where market capitalization and public expenditure are absent in one-third of the sample).

For this reason, in Table 4.3 we adopt a more parsimonious model, in order to raise the number of observations. We also abandon the Atkinson index (with $\epsilon=0.5$), given its high correlation with the Gini index ($\rho=0.98$ for household factor income), and we introduce country fixed effects.¹⁷ We currently find that educational attainment in the male population tends to polarize the income distribution, thus raising inequality, while employment rates reduce it. The GDP per capita and the population urban share are now negatively associated with labour market inequality, though still uncorrelated with total income inequality. However, the timespan covered by these regressions is rather wide, spanning from 1974 to 2016. Therefore, we have chosen to restrict the sample period to most recent observations, in order to obtain a model more compatible with the BRICS sample (which is only observed after the year 2000).

In Table 4.4 we present our preferred model, which contains a limited number of statistically significant coefficients, especially when looking at inequality in factor incomes or in personal labour earnings. However, more consistent results emerge when considering household disposable incomes (columns 6 and 7 of Table 4.4), irrespective of whether we use the Gini index or the Atkinson index with $\epsilon=2$, which focuses more on lower values: inequality declines when more women enter the formal labour market (female employment rate), when public expenditure increases, and when GDP per capita rises.¹⁸

6 Concluding Remarks

In this chapter we have presented recent developments in income and consumption inequality, focusing on a set of middle-income countries (Brazil, China, India, Russia, and South Africa) that have been recently added to the LIS database and for which there is limited coverage and comparability in the empirical literature.

We started by discussing the main challenges when harmonizing income and consumption survey microdata from the middle-income countries, and what implications this has for the analysis of economic inequality.

In our empirical exercise, we first estimated a variety of income (consumption) inequality indicators separately for each country and year for the whole

¹⁷ Year fixed effects cannot be included since LIS surveys are available in neighbouring years, but not necessarily coincident ones.

¹⁸ We have also considered a random-effect model, as well as relaxing the error clustering assumption, without finding more statistical significance in the results. Only life expectancy obtains a significant negative sign, but we acknowledge that causality may go in both directions.

population, as well as for subpopulation groups. We described the trends of these five countries against of the trends of neighbouring countries, finding declining trends in inequality in Brazil, Russia, and South Africa, against rising trends in East Asia (India and China). By then merging inequality indicators with World Bank Indicators data, we created an unbalanced panel database covering around twenty-one countries over the time period from 1976 to 2016. Our panel data analysis updates the findings of Roine et al. (2009), who estimated macroeconomic determinants of economic inequality for fifteen high-income countries.

Results from the country-level panel regressions revealed the following patterns. For our analysed sample of countries, the relationship between income inequality and GDP per capita exhibits a negative correlation, jointly with the (female) employment rate. It is also negatively correlated with public expenditure in GDP, while other controls (such as trade openness, share of agriculture, financial openness) come out as not significant when country fixed effects are taken into account. None of the country-level correlation results implies a causal relationship. However, the robustness of the results would be reinforced were more countries to be available in the sample—especially the low-income ones, which differ in many economic circumstances from the high-income countries. Therefore, the LIS Datacenter aims in future to acquire more microdata from other low- and middle-income countries, in addition to those already covered in the database.

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