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Preliminary Estimates of Global Posttax Income Distributions

Matthew FISHER-POST
Amory GETHIN

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Abstract

This technical note combines data from household surveys, government budgets, tax simulators, national accounts, and detailed fiscal incidence studies to construct a new database on the distributional incidence of taxes and transfers in 174 countries in 2018. Our estimates are consistent with net national income and allocate the entirety of tax revenue and government expenditure to individuals. Taxes and transfers reduce inequality in nearly all countries in the world, but with large variations, ranging from less than 20% in Sub-Saharan Africa to over 45% in Western Europe and the United States. Although the resulting series provide a good first-order approximation of differences in redistribution across countries, they should be considered as preliminary and will be updated in future work.

*Matthew Fisher-Post: Paris School of Economics; matthew.fisher-post@psemail.eu. Amory Gethin: Paris School of Economics; amory.gethin@psemail.eu (Grant ANR-17-EURE-001). We thank Thomas Blanchet, Umberto Cattaneo, Ignacio Flores, Ugo Gentilini, Nicolas Hérault, Wouter Leenders, Sarah Lowder, Valeria Nesterenko, Ian Orton, Thomas Piketty, Emmanuel Saez, Jenny Smart, and Gabriel Zucman for useful comments and suggestions.

1. Introduction

Despite a momentous renewal of public and scholarly attention to inequality, most existing estimates of income distributions fail to systematically account for the role of government taxes and transfers—above all for the developing world. Existing inequality statistics generally provide data on the distribution of household income or consumption, with little information on the extent to which government intervention affects poverty and inequality. While significant efforts have been made in recent years to improve our understanding of the incidence of taxes and transfers in specific countries (e.g., Blanchet, Chancel, and Gethin, 2022; Lustig, 2018; Piketty, Saez, and Zucman, 2018), there is a critical lack of cross-country, long-run data on how redistribution in its different forms has evolved in the past decades. As a result, it remains difficult to answer questions as fundamental as: which countries are most successful at reducing income disparities through taxes and transfers? Are differences in inequality between countries primarily driven by differences in the distribution of pretax incomes ("predistribution"), or by differences in tax-and-transfer systems ("redistribution")? Which countries have been most successful at enforcing progressive tax-and-transfer systems in the past decades and why? With what consequences?

This project makes a first step towards answering these questions. To do so, we deploy new data and methods to construct a comprehensive database on the distribution of taxes and transfers in 174 countries. Our estimates of redistribution account for all forms of taxes and transfers, including personal income taxes, corporate taxes, consumption taxes, local taxes, cash transfers, and public health expenditure. We distribute all taxes and transfers using a common methodological framework, Distributional National Accounts (DINA; Blanchet et al., 2021), which ensures that our estimates are comparable across countries and consistent with national accounts aggregates. Our dataset also accounts for the inherent uncertainty associated with estimating redistribution, which allows us to separate true differences in tax-and-transfer progressivity from potential measurement error.

Our key methodological innovation is to develop techniques for estimating the incidence of taxes and transfers in the absence of detailed microdata. Our starting point is the existence of two separate types of datasets. On the one hand, there is now plenty of historical data on the distribution of pretax incomes, aggregate tax revenue, and the level and composition of government expenditure for most countries in the world, thanks to considerable harmonization efforts made in recent years (e.g., Bachas et al., 2022; Blanchet et al., 2021). The recent literature has also uncovered a number of strong empirical regularities, such as the greater progressivity of indirect taxes in poor countries (Bachas, Gadenne, and Jensen, 2022) and the relationship between income tax progressivity and development (Jensen, 2022). On the other hand, there are only a handful of studies providing high-quality estimates of the incidence of all taxes and transfers on inequality, mostly restricted to the rich world and Latin America (Blanchet, Chancel, and Gethin, 2022; Bozio et al., 2022; Bruil et al., 2022; Fisher-Post, Herault, and Wilkins, 2022; Flores, De Rosa, and Morgan, 2022; Piketty, Saez, and Zucman, 2018). Thanks to these few detailed studies, however, we can learn about the typical distribution of different taxes and transfers and by how much it is likely to vary across time and space. Drawing on this simple insight, we can construct bounds on tax-and-transfer progressivity in each country, which can be more or less narrow depending on the quality of available data. We can also use existing studies as a "training sample," to gauge the ability of our model to reproduce key results from existing work despite much scarcer information.

Exploiting our new database, we document a number of preliminary descriptive findings on differences in government redistribution around the world. In most regions of the world, we find that taxes tend to be mildly progressive overall, with the top 10% paying slightly more taxes than the bottom 50% as a fraction of their pretax income. However, there are large differences between world regions, with the tax systems of Eastern European and Latin American countries being particularly regressive. Overall, the progressivity of tax systems tends to be primarily driven by the relative weights of (regressive) indirect taxes and (progressive) corporate and income taxes.

Turning to transfers, we also document very large differences across countries, which correlate strongly with economic development. In the average Sub-Saharan African country, the poorest 50% benefit from less than 1% of national income in the form of social assistance and healthcare, compared to more than 6% in Northern Europe. Europe and the United States stand out as the most redistributive in terms of transfers, with public healthcare expenditure playing a key role in the U.S.

Combining taxes and transfers, we find that redistribution only marginally affects the ranking of countries in terms of inequality: countries that are the most equal in terms of pretax income also end up being the most equal in terms of posttax income. This is consistent with the view that "predistribution," not "redistribution," remains the dominant driver of differences in income inequality (Blanchet, Chancel, and Gethin, 2022; Bozio et al., 2022). We do observe large differences in redistribution across world regions, however. More equal countries in terms of pretax income tends to have more progressive tax-and-transfer systems, which implies that redistribution exacerbates differences in inequality between countries. Overall, we find that taxes and transfers reduce income inequality by about 15-20% in Sub-Saharan African and Asia, compared to 40-50% in Latin America, Europe, and the United States.

Our new dataset maps uncharted territory at the intersection of several literatures. Among these, we can broadly distinguish two strands of scholarship: one that has studied the incidence and impact of taxes and transfers; and another has aimed to measure inequality with precision, in a way consistent with measures of growth and total national income.

In the former, tax incidence analysis has a long and storied tradition, from Musgrave (1953) to TaxFoundation (1967) to Kakwani (1977) to Lambert (1992) to Fullerton and Metcalf (2002) to Saez, Slemrod, and Giertz (2012). The central question of this literature is to ask *on whom* the burden of taxation falls, and to decipher the economic consequences of fiscal policy. Some studies in this line of work have emphasized the time- and context-dependent behavioral responses to specific taxes, while others have emphasized the role of taxes and transfers to equalize income distributions. Few studies have taken comprehensive account of all taxes, all transfers, and all incomes, measuring the movement from pretax to posttax income distributions in a way that is consistent with macroeconomic estimates of national income.

In the latter tradition of inequality measurement, a set of recent studies has produced worldwide estimates of pretax income inequality in distributional national accounts (DINA): that is, the income that accrues to all earners directly on the marketplace, before taxes and transfers (but after social insurance), with the distribution of income adding to 100% of annual national income in the national accounts.[1] Gathered together in the World Inequality Database, these estimates represent a scholarly benchmark as the only existing long-run, worldwide, harmonized estimates of total national income distribution.[2] However, notwithstanding the few exceptions outlined above, the bulk of these income distributions are estimated before the operation of government tax and transfer policies—leaving an open question on the absolute and relative importance of government fiscal policy to impact inequality. The central contribution of this paper is to build those posttax income distributions for 174 countries since 1980.

Finally, our work also directly relates to renewed efforts at providing detailed estimates of the incidence of taxes and transfers in the developing world, in particular those of the Commitment to Equity institute (Lustig, 2018; World Bank, 2022). Our main contribution here is to cover all taxes and transfers (including corporate income taxes, which are usually excluded from this framework), as well as the evolution of redistribution over time (in contrast to CEQ studies, which generally do not go back before the 2010s).

The article is organized as follows. Section 2 presents the methodology used to construct our new database on government redistribution in 174 countries. Section 3 presents preliminary findings. Section 4 concludes.

[1]For background and details on the concept of pretax income and its estimation, refer to Blanchet et al. (2021).
[2]See `wid.world`.

2. Methodology

This section covers the methodology used to build our new database on government redistribution worldwide. Section 2.1 covers general methodological principles. Sections 2.2 and 2.3 outline the data sources used for the distribution of pretax income and government revenue and expenditure aggregates. Section 2.4 presents a new database on government redistribution in 45 countries, compiled from seven studies following the DINA framework, which we use to both inform and validate our distributional incidence assumptions. Sections 2.5, 2.6, 2.7, 2.8, 2.9, and 2.10 describes the methodology used to allocate personal income taxes, corporate taxes, consumption taxes, property and wealth taxes, other taxes, and social contributions, respectively. Section 2.11 is dedicated to the distribution of social assistance transfers and other government expenditure. Finally, section 2.12 provides a comprehensive analysis of the reliability of our methodology by investigating its ability to reproduce estimates from more detailed DINA studies.

2.1. Methodological Principles

Income Concepts Our methodology directly follows the Distributional National Accounts (DINA) framework outlined in Piketty, Saez, and Zucman (2018) and Blanchet et al. (2021), which provides a set of guidelines for estimating the distribution of income, taxes, and transfers in a way that is consistent with the national accounts. Unlike standard approaches to the measurement of inequality, the DINA methodology involves distributing all forms of income to individuals, as well as all types of taxes paid and transfers received directly or indirectly by individuals. The DINA method generally acknowledges three income concepts: factor national income, pretax national income, and posttax national income. By construction, all three incomes concepts add up to net national income (gross domestic product, minus consumption of fixed capital, plus net foreign income).

Factor national income is the sum of income flows derived from labor and capital before any form of government intervention. It involves allocating incomes usually observed in surveys and tax data, such as compensation of employees and dividends, but also income flows only received indirectly by households, such as imputed rents or the retained earnings of corporations, which are also part of net national income.

Pretax national income corresponds to income after the operation of the pension and unemployment systems, but before the operation of the tax-and-transfer system. It is equal to factor income, minus social contributions paid, plus social benefits received.

Posttax national income corresponds to income after the operation of the tax-and-transfer system. All taxes are allocated and removed from individual incomes, including personal income taxes, corporate taxes, property and wealth taxes, and consumption taxes. Similarly, moving from pretax to posttax national income implies distributing the entirety of general government expenditure, including cash transfers, in-kind benefits (e.g., healthcare), and collective government expenditure (e.g., public order and safety).

Objective In this paper, given data limitations on the distribution of factor income, we focus on measures of government redistribution that compare the distribution of pretax national income to that of posttax national income. This is the measure of redistribution most widely used in existing studies, since it has the advantage of not making estimates of redistribution too sensitive to demographic factors such as the size of the elderly population (e.g., Blanchet, Chancel, and Gethin, 2022; Flores, De Rosa, and Morgan, 2022; Piketty, Saez, and Zucman, 2018). Starting with data on the distribution of pretax income z, we thus aim to measure the distribution of taxes $T(z)$ and government transfers $G(z)$, so as to reach posttax income y:

$$y = z - T(z) + G(z)$$

Our analysis therefore relies on three key ingredients: data on the distribution of pretax income, data on total taxes collected and total transfers disbursed in each country, and data on the distributional incidence of each type of tax and transfer. We turn to each of these three ingredients in the following sections.

2.2. Distribution of Pretax Income

Our starting point is a database on the distribution of pretax national income compiled in the World Inequality Database, which covers 174 countries over the 1980-2019 period.[3] The dataset was constructed by compiling estimates from existing DINA studies, which were systematically harmonized and combined to yield comparable distributional statistics (see Chancel and Piketty, 2021). For each country-year, the data covers pretax income thresholds and averages for 127 generalized percentiles (g-percentiles), corresponding to each percentile within the bottom 99%, followed by a more detailed decomposition of incomes at the top up to the top 0.001% (p99.999p100). By construction, following the DINA framework, average income is consistent with net national income, as recorded in the World Inequality Database (see Blanchet and Chancel, 2016; United Nations, 2009). The database also provides information on the share

[3]See wid.world.

of pretax income coming from capital income and labor income, for each g-percentile. This decomposition is consistent with aggregate factor income shares estimated in Bachas et al. (2022).

2.3. Tax Revenue and Government Expenditure Aggregates

Tax Revenue To allocate taxes to individuals, we rely on aggregate tax revenue series recently constructed by Bachas et al. (2022), who combine national accounts data with government revenue statistics to estimate the evolution of macroeconomic tax rates in more than 150 countries since 1965. Their database provides information on total tax revenue as a share of net domestic product, disaggregated into six categories: personal income taxes (code 1100 in the OECD classification of taxes), corporate taxes (1200), social contributions (2000, 3000), property and wealth taxes (4000), indirect taxes (5000), and other taxes (6000).

Government Expenditure To distribute transfers, we use preliminary series from Gethin (2023), who estimates harmonized series on the level and composition of general government expenditure by function of government (COFOG). The database provides information on government expenditure on general public services, economic affairs, public order and safety, housing and community services, recreation and culture, defense, environmental protection, and social protection in all countries in the world since 1980. Social protection is itself disaggregated into social insurance (which we do not distribute in posttax income series, given that it is already accounted for in pretax income, as discussed below) and social assistance.

2.4. Distribution of Taxes and Transfers: Compilation of Estimates from Existing DINA Studies

Having compiled data on pretax income inequality and government revenue and expenditure, the bulk of our work consists in developing methods for estimating the distributional incidence of taxes and transfers in each country. To do so, we start by collecting data on the incidence of taxes and transfers in countries for which detailed, high-quality estimates are available from existing DINA studies. At the time of writing, we were able to identify seven studies for which the quality of data was sufficiently good for inclusion in the sample, covering the United States (Piketty, Saez, and Zucman, 2018), France (Bozio et al., 2018), the Netherlands (Bruil et al., 2022), Australia (Fisher-Post, Herault, and Wilkins, 2022), other European countries (Blanchet, Chancel, and Gethin, 2022), Latin America (Flores, De Rosa, and Morgan, 2022), and South

Africa (Chatterjee, Czajka, and Gethin, 2022). In each case, we collect information on incidence profiles, that is, the share of taxes paid as a percentage of pretax income at different points of the income distribution. Crucially, all these studies closely follow the principles outlined in the Distributional National Accounts guidelines, using the same methodology to allocate all taxes and transfers to individuals in a national accounts framework. Together, they provide unique insights into variations in tax-and-transfer progressivity over time and space.

Table 1 provides information on the data collected from these studies. Our database covers 45 countries in total, with significant time variation for the United States (1962-2019), France (1990-2018), Australia (1990-2018), and South Africa (1993-2019). We cover the 2007-2017 period for other European countries, while series span from 2000 to 2020 for Latin American countries. Put together, our database of tax-and-transfer progressivity covers 657 country-years.

We use these different estimates for two purposes. First, we exploit these series to derive *bounds* on variations in the progressivity of specific taxes, such as the corporate income tax, for which country-specific information in unavailable. Second, we use these estimates as a "validation sample", to gauge the extent to which our simplified methodology is able to reproduce results from these more detailed studies.

2.5. Distribution of Personal Income Taxes

We now turn to the methodology used to allocate personal income taxes.

To introduce our method, consider the following equation:

$$T_i = \int_{p \geq K}^{p100} \tau_i(z)\, dz \tag{1}$$

For each type of tax and overall, the aggregate revenue received by the government is equivalent to the sum of taxes paid by all tax units, or the definite integral of effective tax rates applied to incomes over the distribution. The function $\tau_i(z)$ gives the taxes of type i paid by pretax income z, for each g-percentile p.

In the case of the personal income tax (PIT), the only tax units that pay any PIT are those whose income places them above the personal income tax exemption threshold K. We retrieve these exemption thresholds for more than 90 countries from Jensen (2022), and retrieve the missing country-years from Bachas et al. (2022).[4]

Starting from the PIT exemption threshold, we simulate the structure of personal income tax incidence using statutory rate schedules from the World Tax Indicators (WTI) database (see Peter, Buttrick, and Duncan, 2010). This database parameterizes the progressivity of the income tax structure. It observes the statutory income tax rate at several levels of the pretax income distribution: at average income, then at two and three and four times that level, and finally the top marginal tax rate.[5]

From this basis, we can approximate a (continuous) schedule of statutory income tax incidence. We assign the statutory tax rate as zero at the exemption threshold K, rising to the top marginal tax rate at p99.999p100 (the highest g-percentile), with kink points at the rates observed in WTI. Rates are interpolated linearly between each observed value.

Finally, we account for the empirical regularity that capital income is taxed less than labor income in PIT systems worldwide. Globally, we find that only 36% of corporate operating surplus (profits) is distributed in the form of dividends. We use this parameter to include only 36% of capital income in the personal income tax schedule. Taxable income (in this concept), then, is less than total pretax income (in the DINA sense), and particularly so for the top g-percentiles where capital income is concentrated.

After building this statutory rate schedule, we fit its 'predicted' revenues to the revenues received by the government observed in Bachas et al. (2022), corresponding to T in the equation above. In this way, we simulate statutory rates in order to estimate effective tax rates throughout the distribution. It is important to note that the WTI statutory rates do not match–but are proportional to–the effective rates we estimate. This mismatch between statutory and effective rates is to be expected, and can be true for a number of reasons that we do not observe in aggregate data (e.g., mismeasurement of the rate schedule, tax evasion or avoidance, differences within the rate schedule according to different types of [non-]taxable income, etc.).

Since we do not observe many of the nuances by which an effective tax rate will differ from the statutory rate, we are almost forced to assume that the progressivity schedule from the statutory schedule is the correct one (i.e., proportional to the effective rate schedule)—and holds as valid for the distribution of income tax rates along the income distribution.

[4]Bachas et al. (2022) impute the exemption threshold for country-years missing from Jensen (2022) in a way that is consistent with the findings of the latter study, which discovered that the PIT exemption threshold (expressed as a percentile of the income distribution) falls with rising per capita income, across countries and over time.

[5]While the WTI covers 189 countries, it does not observe years beyond 2005, so we extend the database with inputs from Strecker (2021) and Vegh and Vuletin (2015, updated 2019), the latter of which can also be used to corroborate top marginal tax rates from WTI. For a few remaing country-years we retrieve statutory rates schedule from PwC (2023).

However, we do not have to leave this as an assumption, and can instead test the goodness-of-fit against the existing DINA studies mentioned above. For reference, see Figure 1 to compare the time series of US personal income tax rates between the benchmark estimates of Piketty, Saez, and Zucman (2018) and those of the present simulation—comparing the benchmark to our simulation at each of three representative points on the income distribution: p50, p90, and p99. As can be readily seen in the graph, the fit is excellent, and our simulated effective PIT rates rarely differ by more than half of a percentage point, matching on both levels and trends.

Given the goodness-of-fit of our simulation against the training sample of microdata-founded estimates of PIT incidence, we are confident to extend our estimates to the worldwide sample of countries for whom we have collected precise data on the minimum set of parameters listed above (the minimum from which we can estimate PIT incidence, as discussed here).

From there, we can move to a discussion of corporate income tax incidence, and that of other direct and indirect taxes.

2.6. Distribution of Corporate Income Taxes

Following the DINA guidelines, we allocate the corporate income tax proportionally to corporate equity. Figure 2 plots the distribution of the corporate income tax burden as estimated in available DINA studies. The x-axis represents generalized percentiles, while the y-axis represents the share of pretax income coming from corporate equity holdings. All series are normalized to 1 for the top 0.001% of the pretax income distribution, to highlight differences in the concentration of the corporate tax burden across country-years. As shown by the light grey dots, the corporate income tax is always progressive and highly concentrated at the very top of the income distribution in every single DINA studies with available data. That being said, there are variations across countries: for instance, corporate equity is much less concentrated in the Netherlands, where private pension wealth is more broadly distributed, than in Latin America, where capital income accrues to a greater extent to the top of the distribution.

The three lines represent the three scenarios used to allocate the corporate income tax accordingly, which draw on these empirical variations to derive bounds on the concentration of the corporate income tax. In the benchmark scenario, we take the average of profiles observed, which implies that the bottom percentiles pay about 5% of the tax rate faced by the top 0.001%, the 90^{th} percentile about 25% of that rate, and the 99^{th} percentile about 40% of that rate. Our upper bound implies a much greater concentration of the CIT, with an effective tax rate close to 0 for all percentiles within the bottom 80%. Finally, the lower bound corresponds to a much less concentrated CIT burden, with the bottom percentile facing an ETR of about 20% of that of the top g-percentile.

2.7. Distribution of Indirect Taxes

We assume that indirect taxes are paid by consumers, accounting for the fact that some goods are untaxed because they are bought on the informal market. Our methodology thus involves two steps: estimating consumption from pretax income, and estimating the share of informal consumption throughout the income distribution.

Income-to-Consumption Ratios The first step consists in estimating the ratio of income to consumption by generalized percentile. Following Chancel et al. (2023), who provide empirical evidence on variations in savings rates throughout the income distribution, we model the ratio of pretax income to consumption as logit-shaped, and generate three typical profiles corresponding to more or less steep savings rates (and thus more or less regressive indirect taxes). Figure 3 plots the three profiles. In the benchmark scenario, we assume that the income-to-consumption ratio is about two times higher for the 99^{th} g-percentile than for the median. For the upper bound, we assume that the profile is steeper (and thus indirect taxes more regressive), with a value reaching 4.5 at the very top. For the lower bound, we assume a flatter profile, reaching about 2 at the very top. These three profiles map well onto the empirical variations in consumption-to-income ratios documented in Chancel et al. (2023).

Informal Consumption Ratios Following Bachas, Gadenne, and Jensen (2022), we account for the fact that low-income households tend to purchase goods in informal markets to a greater extent than high-income households. This implies that a greater fraction of their consumption goes untaxed, especially in low-income countries where informality is high. First, we collect data on the share of consumption made in informal markets by percentile in a sample of low- and middle-income countries from Bachas, Gadenne, and Jensen (2022). Second, we smooth their estimates by modeling the informality share as a linear function of an individual's rank in the consumption distribution. Third, we assume that the slope of informal consumption is itself linear in GDP, which allows us to let the effect of informality on the progressivity of consumption taxes vary with the level of economic development.

Figure 4 shows that informality is relatively greater among low-income earners in poor countries than in rich countries, consistently with the findings of Bachas, Gadenne, and Jensen (2022). In Mozambique, for instance, the share of consumption made in the formal sector is about 3.5 higher among top 1% earners than among the bottom 1%. Meanwhile, the ratio is below 1.4 in

Chile, which means that accounting for informal consumption makes consumption taxes only mildly more progressive.

Hence, we estimate the share of consumption $s_{ct}(p)$ made in the formal market for percentile p in country c at time t as a linear function, whose slope depends on the level of economic development:

$$s_{ct}(p) = p \times \theta_{ct} \quad (2)$$

$$\theta_{ct} = \alpha + \beta GDP_{ct} \quad (3)$$

With GDP_{ct} denoting GDP per capita, expressed in real 2021 PPP US dollars. α and β are computed using the data shown in figure 3 (the linear fit is represented by the red line), which allows us to impute informality curves for each country-year in the sample.

Figure 5 illustrates how accounting for informality changes the progressivity of indirect taxes in Niger, one of the poorest countries in our sample. The two lines plot consumption taxes paid as a fraction of pretax income, before (blue line) and after (red line) accounting for the fact that low-income households tend to rely more heavily on informal markets to purchase goods and services. Accounting for informality appears to make indirect taxes substantially less regressive, although this effect is not sufficiently strong to make them progressive as a share of income. Consumption taxes thus tend to disproportionately fall on low-income households in nearly all countries in our sample, except for the poorest countries, for which they turn out to be approximately flat.

2.8. Distribution of Property and Wealth Taxes

Property and wealth taxes include taxes on immovable property, wealth taxes, inheritance and gift taxes, and taxes on financial and capital transactions. Following Piketty, Saez, and Zucman (2018), we assume that residential property taxes are paid by households proportionally to housing wealth, while business property taxes and inheritance and gift taxes are distributed proportionally to total wealth excluding housing (that is, in the same way as corporate taxes).[6]

The Bachas et al. (2022) dataset does not provide a decomposition of property and wealth taxes into different categories, so we rely on the OECD tax database. First, we distribute recurrent taxes on net wealth (series 4200) and estate, inheritance and gift taxes (4300). Data on these broad categories is available for 108 countries. Second, we separate business property

[6]For residential property taxes, we use the average tax incidence profile observed in the United States (1962-2019) and South Africa (1993-2019), the only two countries for which data is available in our training sample.

taxes (4110) from residential property taxes (4120), a decomposition that is available for 49 countries. Third, we assume that all other property and wealth taxes are distributed as residential property taxes, that is, proportionally to housing wealth.[7] We assume three different scenarios in countries with missing data: a benchmark scenario in which 50% of property and wealth taxes fall on total wealth and 50% on residential property, an upper bound in which they exclusively fall on total wealth, and a lower bound in which they exclusively fall on residential property.

2.9. Distribution of Other Taxes

Other taxes include a number of miscellaneous items, such as user fees, penalties, fines, and poll taxes, which represent on average less than 3% of tax revenue. These taxes are generally not conditioned on income or consumption, which implies that their burden is much higher among low-income groups than high-income groups when expressed in proportion of their income. Accordingly, we make the simplifying (and probably conservative) assumption that they are distributed similarly to indirect taxes, that is, in a regressive way.

2.10. Distribution of Social Contributions

Although our pretax income concept already deducts social contributions from factor income, it is useful to estimate the incidence of social contributions to get a more comprehensive view of the progressivity of the tax system in each country. To do so, we assume that social contributions are paid proportionally to labor income (as measured in the World Inequality Database), excluding labor income that is not taxed due to exemptions or evasion.

To estimate the share of labor income that is taxable, we rely on a unique database provided by the International Labor Organization (ILO), which compiles labor force surveys fielded in over 150 countries since the 1990s. For about 110 countries, we have microdata on wages or mixed income received by individuals, together with information on whether they paid social contributions in the last month or year. We use these surveys to estimate the share of individuals that pay social contributions by income percentile. We then incorporate these estimates into our database, assuming that the ranking of an individual in the wage distribution is the same as its ranking in the pretax income distribution. Finally, we allocate social contributions to "taxable labor income," increasing the tax burden of each percentile proportionally to the share

[7] This can be justified by the fact that in nearly all countries, these taxes mostly consist in stamp duties and real estate transfer duties, whose incidence is generally similar to that of residential property taxes.

of individuals liable to social contributions relative to other percentiles.[8]

Figure 6 shows how accounting for informality and exemptions changes our estimates of the incidence of social contributions in the context of Argentina in 2019. The blue line shows that allocating contributions proportionally to labor income implies a strictly decreasing tax burden, from 10-11% at the bottom of the distribution to less than 6% within the top 1%. This is consistent with the fact that the share of pretax income coming from capital is higher at the top than at the bottom of the pretax income distribution. A large share of low-wage earners work in the informal sector in Argentina, however. As a result, corrected estimates show a distinctive U-shaped pattern, with the effective tax rate rising from about 2% at the bottom of the distribution to 10% for middle income groups, before declining back to close to 0% at the very top.

2.11. Distribution of Government Transfers

Social Assistance Social assistance expenditure corresponds to cash and in-kind transfers received by individuals and households, as defined in the system of national accounts (e.g., Eurostat, 2019). Notice that social assistance excludes social insurance transfers (mainly unemployment and pension benefits), which are already included in our definition of pretax income. We collect data on aggregate expenditure and the incidence of transfers from various sources, and distribute social assistance accordingly.

Data on aggregate expenditure comes from Gethin (2023), who draws on various sources to derive harmonized series on the evolution of spending on social assistance programs around the world. These series should be considered as highly preliminary and will be revised in future work.

Data on the incidence of social transfers comes from four sources: Piketty, Saez, and Zucman (2018) for the United States, Blanchet, Chancel, and Gethin (2022) for 30 European countries, the World Bank's ASPIRE database for 101 countries, and the database of the Commitment to Equity Institute for 3 countries (Iran, Togo, and Venezuela). For the 45 countries not covered by any of these sources, we derive lower and upper bounds on the incidence of social assistance. In our benchmark scenario, we allocate transfers using the average profile observed in all countries; for the lower bound, we allocate them using the average profile observed in the 10

[8] Assume for instance that 1% of individuals pay social contributions among the bottom decile of wage earners, compared to 10% among the top decile. Then, the effective tax rate on the labor income of the top pretax income decile is assumed to be ten times higher than that of the bottom pretax income decile. Notice that social contributions paid by the top decile as a share of pretax income may still be lower than that of the bottom decile, however, if capital income is sufficiently large at the top.

countries with the most regressive profiles; and for the upper bound, we allocate them using the average profile observed in the 10 countries with the most progressive profiles.

Health Following Blanchet, Chancel, and Gethin (2022), we make the simplifying assumption that health is distributed equally throughout the income distribution, that is, on a lump sum basis. However, we make an exception for the United States, for which we use estimates from Piketty, Saez, and Zucman (2018) on the distributional incidence of public healthcare expenditure. Given these highly simplistic assumptions, our estimates of the distribution of health spending should be viewed as highly preliminary.

Other Government Expenditure Other government expenditure includes spending on education, transport, public order and safety, administration, defense, and all other types of public services. In line with other existing studies, we allocate it proportionally to posttax disposable income (pretax income, minus direct taxes, plus cash transfers), that is, in a distributionally neutral way.

2.12. Validation

Our DINA database does not only allow us to calibrate our estimates. It can also be used as a validation sample, to test the ability of our simplified methodology to reproduce broad patterns of tax progressivity across countries and time periods.

We compare our estimates of the total effective tax rate by pretax income group in the United States to that of Piketty, Saez, and Zucman (2018). Piketty, Saez, and Zucman (2018) distribute all types of taxes in an extremely granular way, combining exhaustive tax microdata with detailed revenue series and various surveys. In contrast, we allocate taxes in a much coarser manner, combining stylized profiles for corporate and indirect taxes with a highly simplified version of the personal income tax schedule. Despite our lack of detailed data, we are able to reproduce remarkably well the overall shape of tax progressivity in the United States, with rates rising from about 15% at the bottom of the distribution (outside of social security contributions) to 20-30% within the top 10%. While our estimates are not perfect, somewhat overestimating the effective tax rate of percentile 99 and underestimating taxes paid at the very top, our confidence interval is able to capture Piketty, Saez, and Zucman (2018) estimates for nearly all generalized percentiles.

Figure 7 generalizes this idea by comparing our estimates of tax progressivity to that of existing DINA studies for all country-years available. Tax progressivity is measured as the coefficient of a regression of the effective tax rate on generalized percentile, which can simply be interpreted as the slope of the profile of taxes paid by income group in a given country-year.[9] There is a strong correlation between our estimates and that of existing DINA studies ($\hat{\rho} = 0.65$). On average, tax progressivity ends up being slightly higher with our methodology, because we tend to be more conservative on the regressivity of indirect taxes. Our simplified personal income tax schedule also fails to account for sharing of taxes within the household, which mechanically increases the exemption threshold in comparison to equal-split estimates from DINA studies, thus marginally overestimating tax progressivity. Overall, however, our simplified methodology does remarkably well at reproducing results from existing work.

Appendix figure A.4 compares our estimates of posttax inequality to that of existing DINA studies by world region, focusing on the top 10% to bottom 50% average income ratio. While we do obtain lower posttax inequality estimates in Western Europe, the US, and Latin America, we reproduce relatively well differences in posttax income concentration and redistribution across regions. Latin America is the region for which are estimates differ the most from Flores, De Rosa, and Morgan (2022), probably for three main reasons. First, we account for informality in consumption and are more conservative in our estimates of the regressivity of indirect taxes, which significantly lowers effective tax rates at the bottom. Second, we distribute business property taxes proportionally to corporate equity, following Piketty, Saez, and Zucman (2018), while Flores, De Rosa, and Morgan (2022) allocate them proportionally to imputed rents, making them substantially more regressive. Third, our simulation of the personal income tax does not account for re-ranking effects and income splitting within the household, which tends to make it more progressive at the top. We hope to improve upon this latter point in future work.

3. Preliminary Findings

Our new database can be used to document many novel facts on differences in government redistribution around the world and their evolution in the past decades. In the following section, we provide preliminary evidence in this direction, focusing on the size and progressivity of taxes (section 3.1), the size and progresssivity of social assistance and health transfers (section 3.2), and the overall impact of taxes and transfers on inequality (section 3.3).

[9] More specifically, tax progressivity is measured as β in the following regression: $\tau_{ctp} = \alpha_{ct} + \beta_{ct} p + \varepsilon_{ctp}$, where c denotes countries, t denotes years, and p denotes each generalized percentile. We estimate the model for all percentiles above p50 due to greater noise at the bottom of the distribution, driven by particularly low incomes within the bottom 50%. We also exclude series from Blanchet, Chancel, and Gethin (2022), which are more noisy and of slightly lower quality than estimates from other countries.

3.1. The Incidence of Taxes

We start by documenting worldwide differences in the size and structure of taxes. Figure 8 plots the average effective tax rate (ETR) faced by the bottom 50% (p0p50), the middle 40% (p50p90), and the top 10% (p90p100) of the pretax income distribution in different regions of the world. These figures (as well as the other figures mentioned in this technical note) correspond to population-weighted averages of the indicator in each country. That is, we first compute effective tax rates by group in each country, and then compute cross-country averages by region, weighting them by population size. Two main results stand out. First, there are large differences in aggregate tax rates between regions, with effective tax rates being lowest in Sub-Saharan Africa (10-20% of national income) and highest in Europe (25-30%). Second, top 10% earners face a greater tax rate than the bottom 50% in most world regions, but differences between income groups tend to be small: in nearly no world region does the ETR of the top 10% exceed that of the bottom 50% by more than 10 percentage points.

Figure 9 provides a more precise picture of differences in progressivity by showing the ratio of the top 10% effective tax rate to that of the bottom 50% in each world region. While there is significant uncertainty due to the lack of precise data on the distributional incidence of each type of tax, Latin America and Eastern Europe stand out as the only regions where the tax system is regressive as a whole. Meanwhile, the top 10% ETR is more than 50% higher than that of the bottom 50% in the United States (outside of social contributions), which would represent the greatest tax progressivity of all regions (in line with the findings of Blanchet, Chancel, and Gethin, 2022).

3.2. The Incidence of Transfers

We now turn to the analysis of transfers, focusing on social assistance and healthcare, the two components of government expenditure that we do not allocate in a distributionally neutral way. Figure 10 plots the share of national income redistributed to the bottom 50% in the form of social assistance and public healthcare by world region in 2019. There are very large differences across regions, ranging from only 0.7% of national income in Sub-Saharan Africa to over 6% in Northern Europe. Social assistance and healthcare each represent about half of the total on average, but there is significant heterogeneity between regions, with public healthcare spending being exceptionally large in the United States and particularly low in Southern Asia.

3.3. The Net Impact of Taxes and Transfers on Inequality: A Global Map of Redistribution

Combining taxes and transfers, our database allows us to provide the first global map of government redistribution. Figure 11 compares the bottom 50% share in terms of pretax national income and posttax national income in all 174 countries in 2019. There are two main results. First, there is a very strong correlation between pretax and posttax inequality: notwithstanding a few exceptions, the ranking of countries in terms of pretax and posttax income inequality is almost exactly the same. This is consistent with the fact that "predistribution," rather than redistribution, stands out as the primary determinant of differences in inequality across countries (Blanchet, Chancel, and Gethin, 2022). Second, redistribution tends to be greater in more equal countries, as visible in the fact that countries further right of the figure tend to be more distance from the 45-degree line. For instance, the bottom 50% income share is less than 20% in terms of pretax income in Norway, but increases to almost 35% in terms of posttax income. Meanwhile, pretax and posttax inequality are almost the same in China and India, with the bottom 50% share reaching about 15%.

Figure 12 compares the average top 10% to bottom 50% income ratio by world region in terms of pretax and posttax income.[10] In both concepts, Western Europe is the least unequal region, while Latin America is the most unequal region. Accounting for redistribution does not lead to significant re-ranking of regions in terms of income inequality, with the exception of the United States, which appears relatively less unequal after accounting for the incidence of taxes and transfers. Extending this perspective, figure 13 compares the overall effect of redistribution on inequality in different world regions in 2019. The "extent of redistribution" is measured as the percent difference in the top 10% to bottom 50% average income ratio, following Bozio et al. (2022). The US, Western European, and Northern European tax-and-transfer system appear to reduce inequality the greatest, by about 40-45%, closely followed by Eastern Europe. Meanwhile, redistribution is particularly low in Sub-Saharan Africa and Asia, with the indicator reaching only 15-20%.

Finally, Figure 14 provides a global map of the extent to which government redistribution reduces inequality in each of the 174 countries in our data. In nearly all countries in the world, the indicator is greater than 0: tax-and-transfer systems almost never increase inequality. There are significant differences across countries, however, with the percent reduction in inequality enabled by taxes and transfers ranging from less than 10% to more than 50%. Overall, there

[10] Appendix figure A.3 shows the same indicator, but focusing on region-wide inequality instead of population-weighted averages of the indicator. The results are broadly similar.

are clear regional patterns, with government redistribution being significantly more efficient at reducing inequality in Western European countries, Northern America, and Latin America in comparison to African and Asian countries.

4. Conclusion

In this paper, we have constructed new estimates of the distributional incidence of taxes and transfers in 174 countries. Combining data from different sources with bounds on tax-and-transfer progressivity from existing studies, we derived estimates of redistribution that are comparable across countries while accounting for the measurement uncertainty associated with the absence of detailed microdata. We showed that our model is able to replicate results from existing work remarkably well, and that bounds on measures of redistribution can be easily tightened as better data becomes available. Drawing on our new database, we then uncovered a number of preliminary results on redistribution around the world.

We see at least three avenues for future work. First, there is a need to improve the precision of our estimates, which remain too uncertain to draw precise conclusions on redistribution and its evolution in specific countries. We hope to do so by collecting more information on the specificities or different taxes and transfers in each country, as well as using microdata in countries where it is possible.

Second, our estimates of the distribution of government spending remain highly stylized. In particular, we allocate health expenditure on a lump sum basis, ignoring potential inequalities in access to healthcare, and do not account for potential differences in the distributional incidence of other public goods either. Future work should pay more attention to the incidence of public goods, given the potentially large effects on poverty and inequality that collective public expenditure items may have, including education, transport infrastructure, and police services. For a preliminary attempt, see Gethin (2023).

Third, there is a need to better understand what drives differences in redistribution across countries and over time. Is there a mechanical relationship between the size of the welfare state and economic development? Or are other variables, such as state capacity or the type of political regime, more determinant in explaining the incidence of taxes and transfers on inequality? Drawing on our new database opens new avenues for studying these questions, which we hope to take on in future work.

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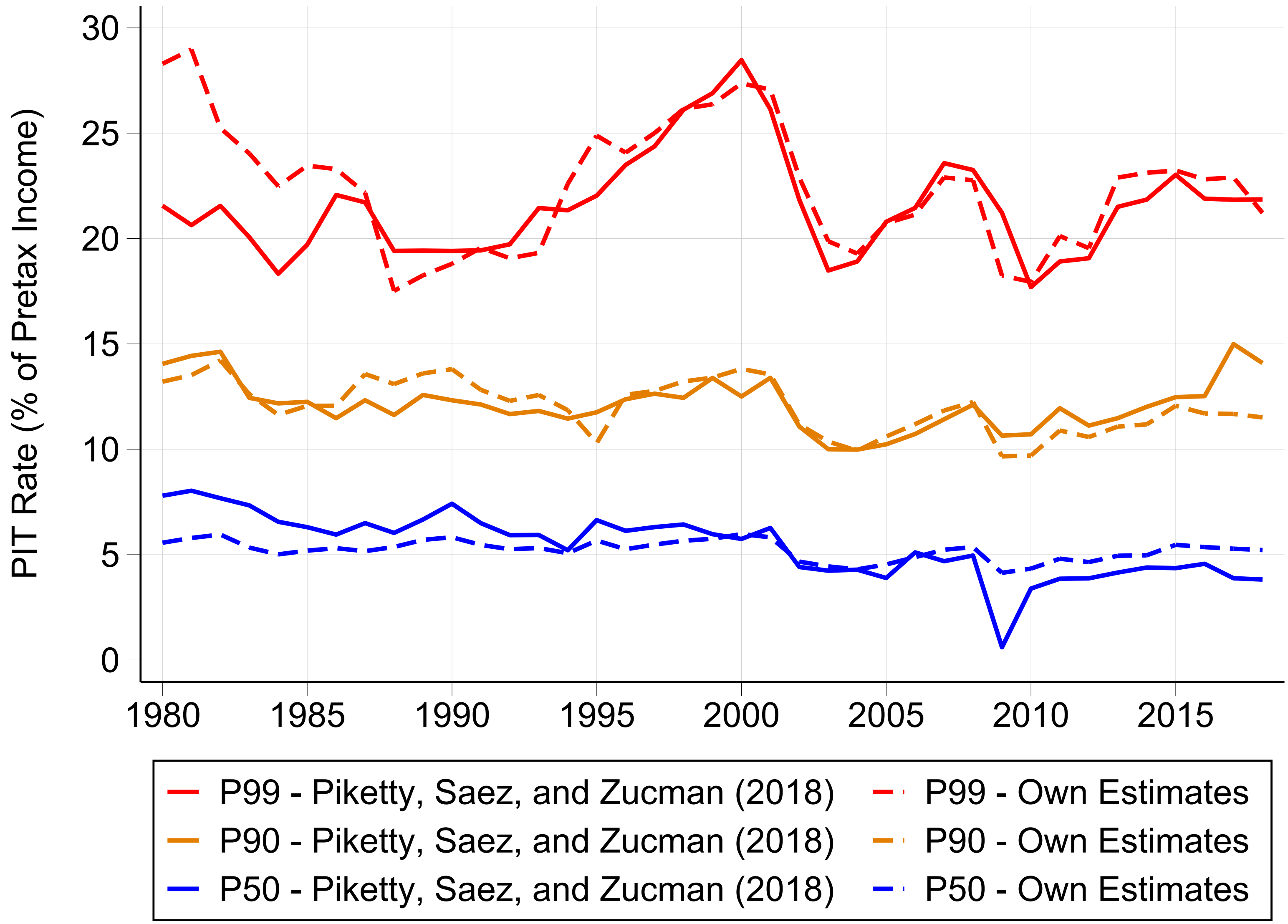
Table 1 – Country and Time Coverage of Distributional Incidence Estimates in Existing DINA Studies

Country	Years	Paper
USA	1962-2019	Piketty, Saez, and Zucman (2018)
France	1990-2018	Bozio et al. (2018)
Netherlands	2016	Bruil et al. (2022)
Australia	1991-2018	Fisher-Post, Herault, and Wilkins (2022)
Austria	2007-2017	Blanchet, Chancel, and Gethin (2022)
Belgium	2007-2017	Blanchet, Chancel, and Gethin (2022)
Bulgaria	2007-2017	Blanchet, Chancel, and Gethin (2022)
Croatia	2009-2017	Blanchet, Chancel, and Gethin (2022)
Cyprus	2007-2017	Blanchet, Chancel, and Gethin (2022)
Czech Republic	2007-2017	Blanchet, Chancel, and Gethin (2022)
Denmark	2007-2017	Blanchet, Chancel, and Gethin (2022)
Estonia	2007-2017	Blanchet, Chancel, and Gethin (2022)
Finland	2007-2017	Blanchet, Chancel, and Gethin (2022)
France	2007-2017	Blanchet, Chancel, and Gethin (2022)
Germany	2007-2017	Blanchet, Chancel, and Gethin (2022)
Greece	2007-2017	Blanchet, Chancel, and Gethin (2022)
Hungary	2007-2017	Blanchet, Chancel, and Gethin (2022)
Iceland	2007-2015	Blanchet, Chancel, and Gethin (2022)
Ireland	2007-2017	Blanchet, Chancel, and Gethin (2022)
Italy	2007-2017	Blanchet, Chancel, and Gethin (2022)
Latvia	2007-2017	Blanchet, Chancel, and Gethin (2022)
Lithuania	2007-2017	Blanchet, Chancel, and Gethin (2022)
Luxembourg	2007-2017	Blanchet, Chancel, and Gethin (2022)

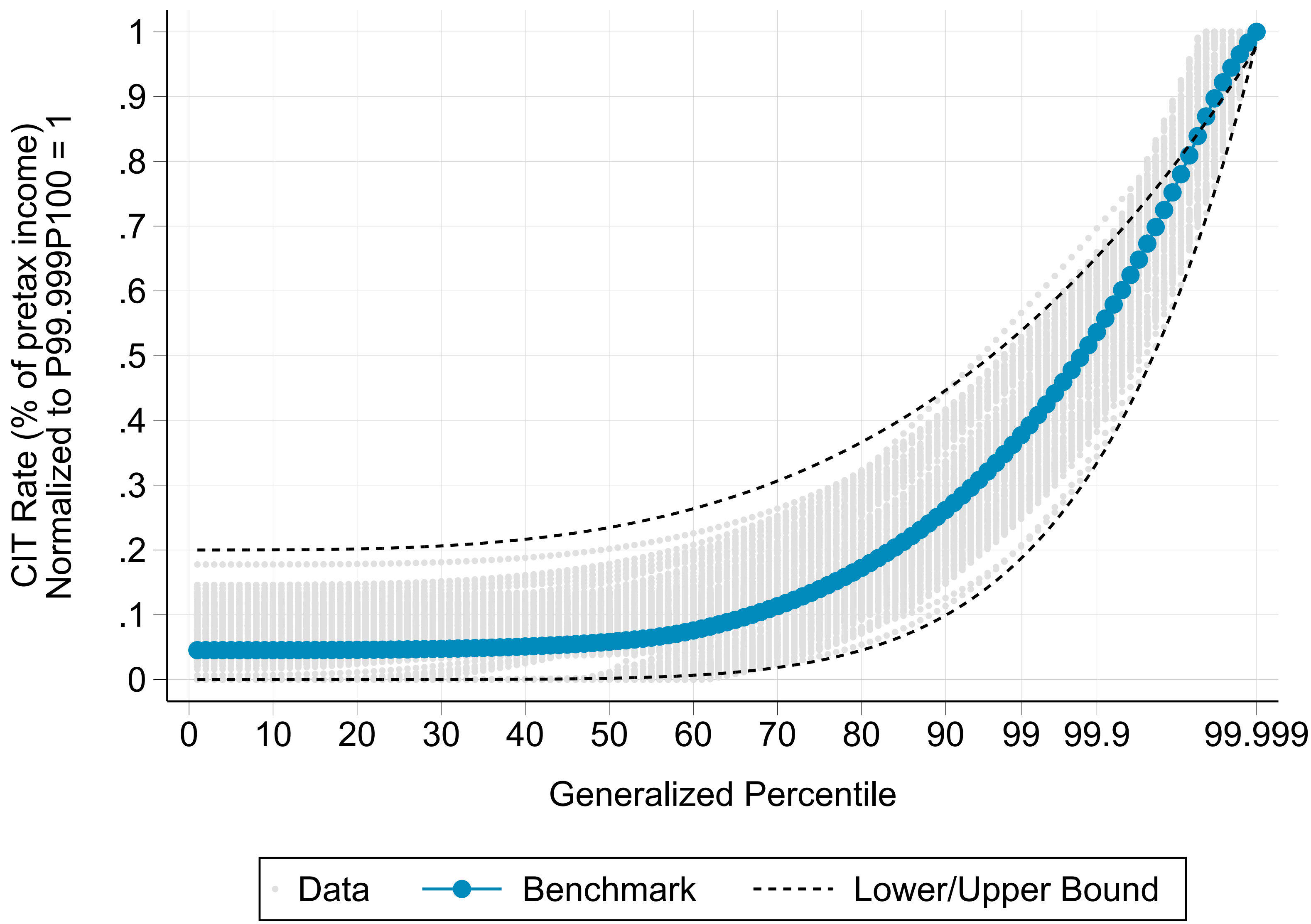
Malta	2007-2013	Blanchet, Chancel, and Gethin (2022)
Netherlands	2007-2017	Blanchet, Chancel, and Gethin (2022)
Norway	2007-2017	Blanchet, Chancel, and Gethin (2022)
Poland	2007-2017	Blanchet, Chancel, and Gethin (2022)
Portugal	2007-2017	Blanchet, Chancel, and Gethin (2022)
Romania	2007-2017	Blanchet, Chancel, and Gethin (2022)
Serbia	2012-2017	Blanchet, Chancel, and Gethin (2022)
Slovakia	2007-2017	Blanchet, Chancel, and Gethin (2022)
Slovenia	2007-2017	Blanchet, Chancel, and Gethin (2022)
Spain	2007-2017	Blanchet, Chancel, and Gethin (2022)
Sweden	2007-2017	Blanchet, Chancel, and Gethin (2022)
Switzerland	2007-2017	Blanchet, Chancel, and Gethin (2022)
United Kingdom	2007-2017	Blanchet, Chancel, and Gethin (2022)
Argentina	2000-2019	Flores, De Rosa, and Morgan (2022)
Brazil	2001-2020	Flores, De Rosa, and Morgan (2022)
Chile	2000-2020	Flores, De Rosa, and Morgan (2022)
Colombia	2002-2020	Flores, De Rosa, and Morgan (2022)
Costa Rica	2010-2020	Flores, De Rosa, and Morgan (2022)
Ecuador	2001-2020	Flores, De Rosa, and Morgan (2022)
El Salvador	2001-2019	Flores, De Rosa, and Morgan (2022)
Mexico	2000-2020	Flores, De Rosa, and Morgan (2022)
Peru	2000-2020	Flores, De Rosa, and Morgan (2022)
Uruguay	2000-2020	Flores, De Rosa, and Morgan (2022)
South Africa	1993-2019	Chatterjee, Czajka, and Gethin (2021)

Figure 1 – Distributional Incidence Profiles: Personal Income Tax (USA, 1980-2018)



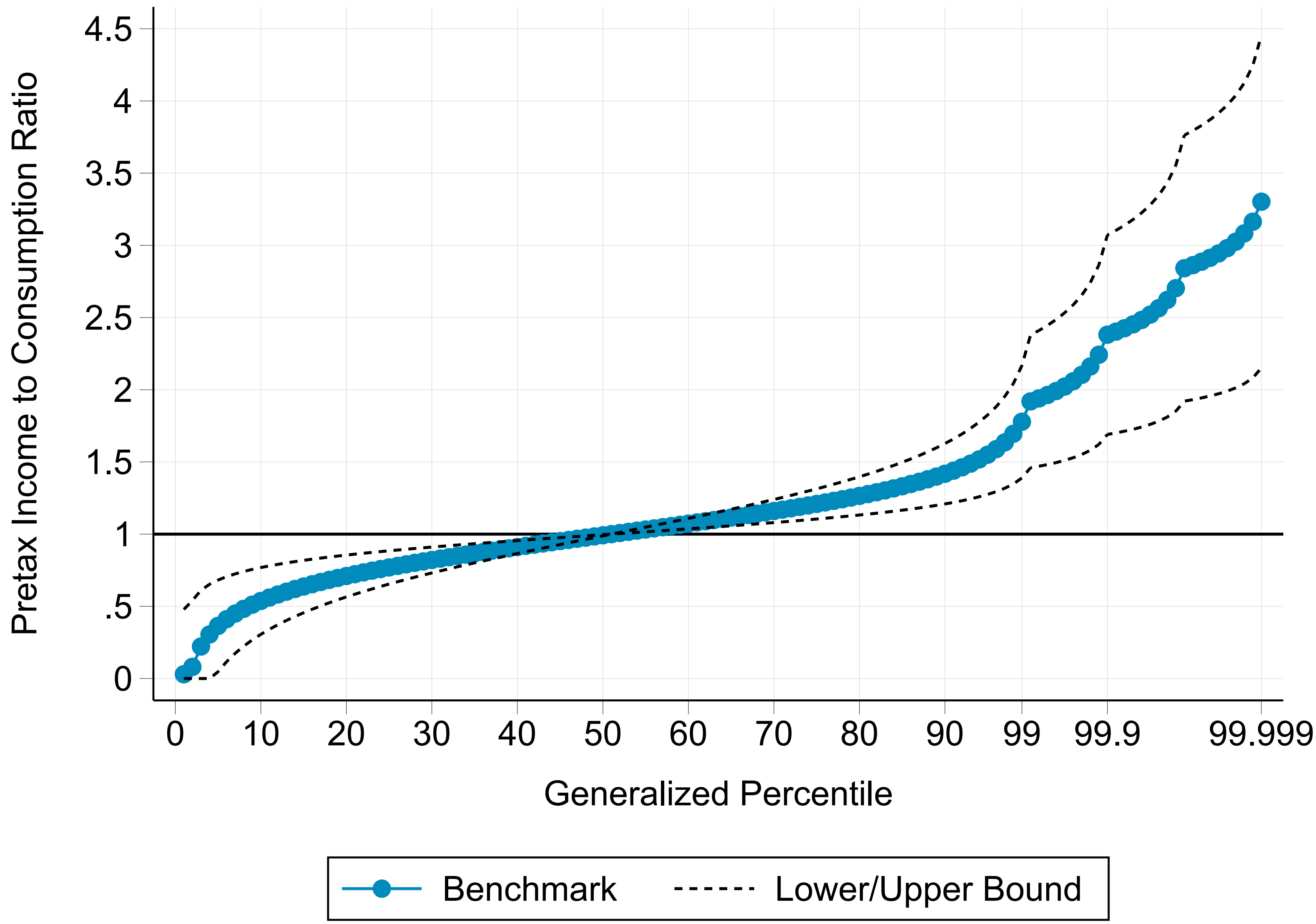
Notes. Authors' elaboration combining own estimates and data from Piketty, Saez, and Zucman (2018).

Figure 2 – Distributional Incidence Profiles: Corporate Income Tax



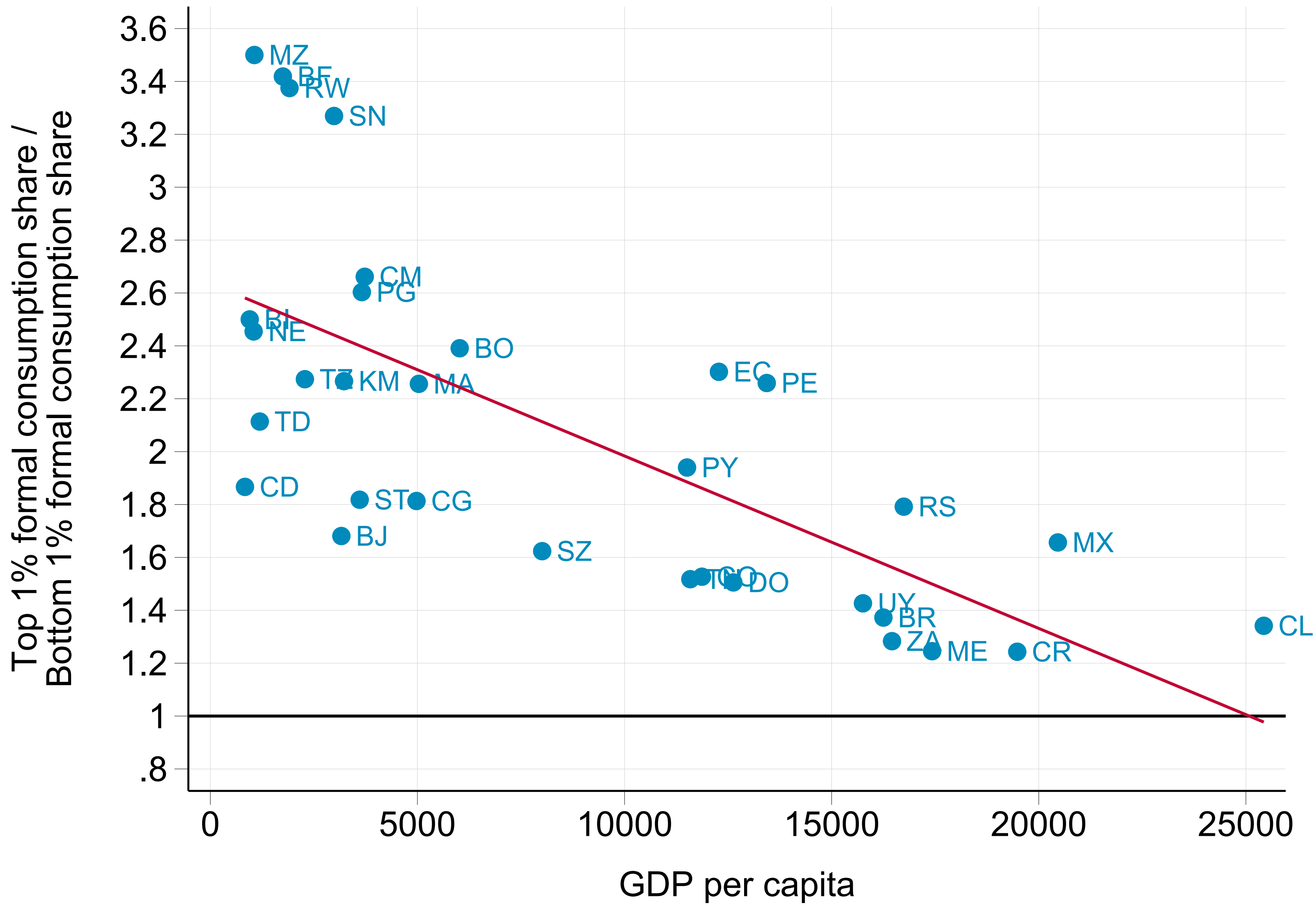
Notes. Authors' elaboration. The figure plots the three stylized profiles used to distribute corporate taxes in each country. The blue line represents the benchmark profile; dashed lines represent upper and lower bounds. Grey points correspond to actual distributional profiles estimated in existing DINA studies. All series are normalized to 1 for the p99.999p100 group.

Figure 3 – Distributional Incidence Profiles: Income to Consumption Ratio



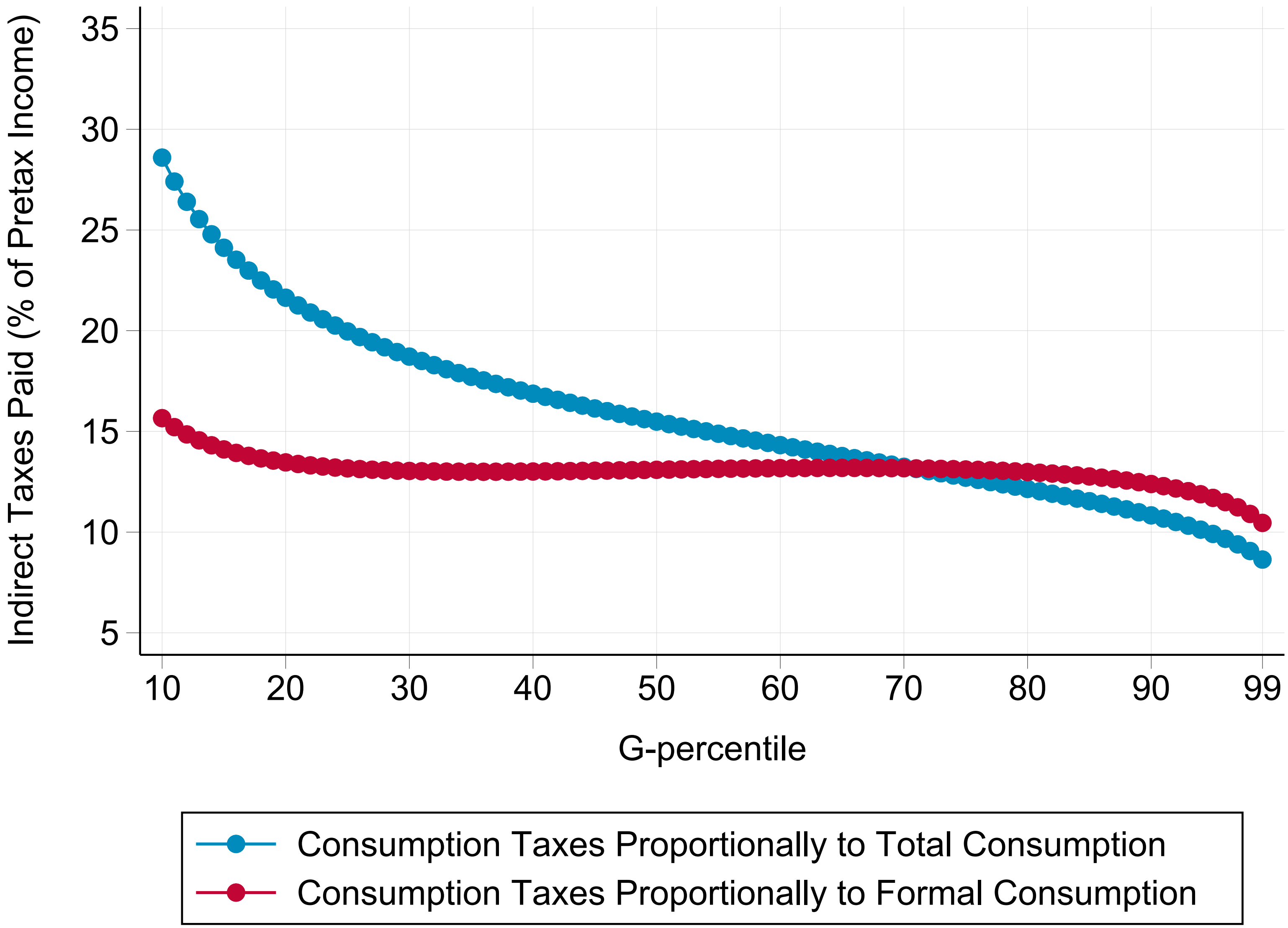
Notes. Authors' elaboration. The figure plots the three stylized profiles used to estimate consumption from pretax income in each country. The blue line represents the benchmark profile; dashed lines represent upper and lower bounds. See Chancel et al. (2023) for more detail.

Figure 4 – Informal Consumption Elasticity and Economic Development



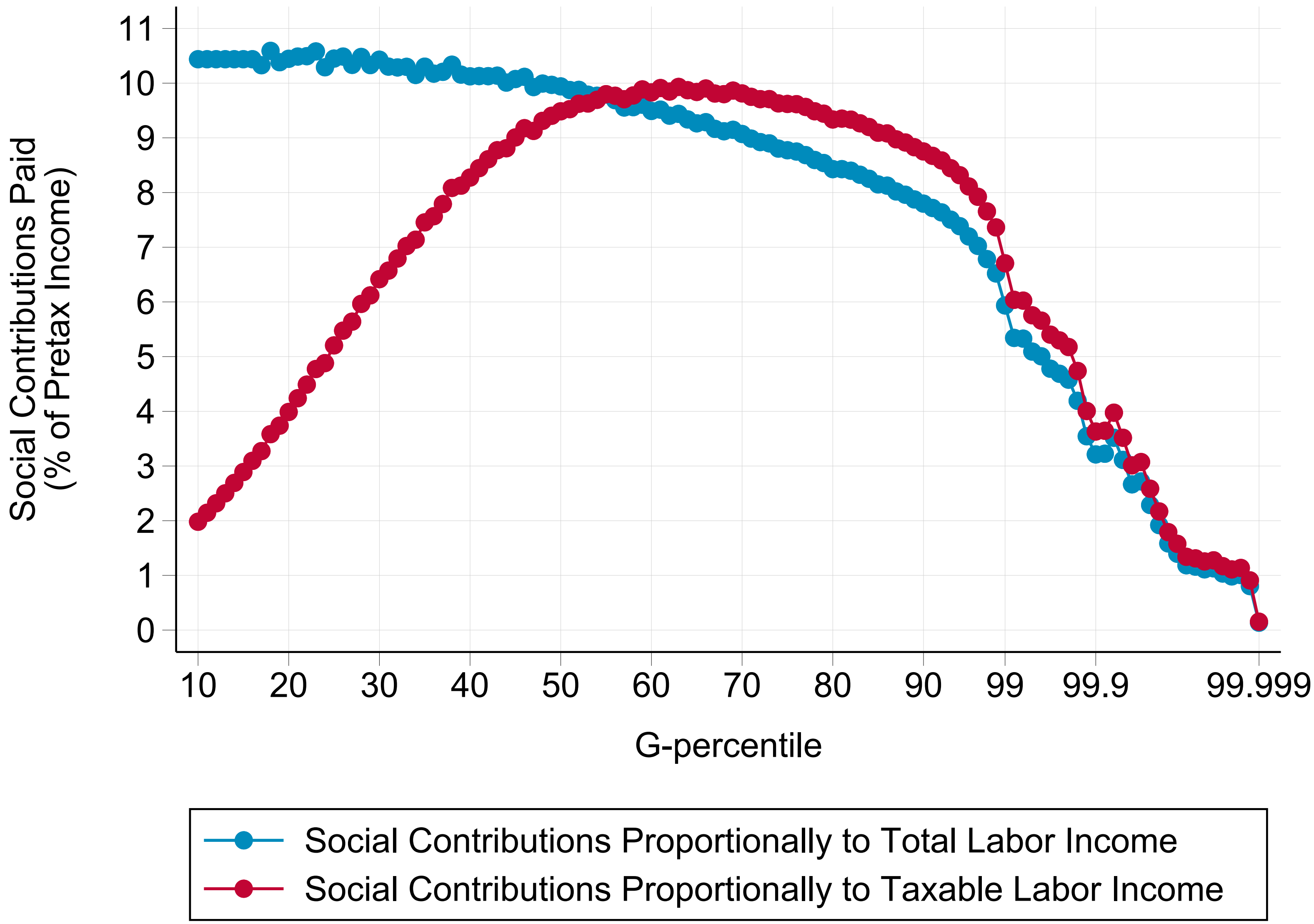
Notes. Authors' elaboration combining data from the World Inequality Database (GDP per capita) and Bachas, Gadenne, and Jensen, 2022 (informality). The figure plots the relationship between GDP per capita expressed in 2021 PPP USD and the gap in informal consumption between top and bottom income groups. In poorer countries, low-income households purchase more goods and services in informal markets than high-income households to a greater extent than in high-income countries.

Figure 5 – Incidence of Indirect Taxes and Informality: Niger, 2019



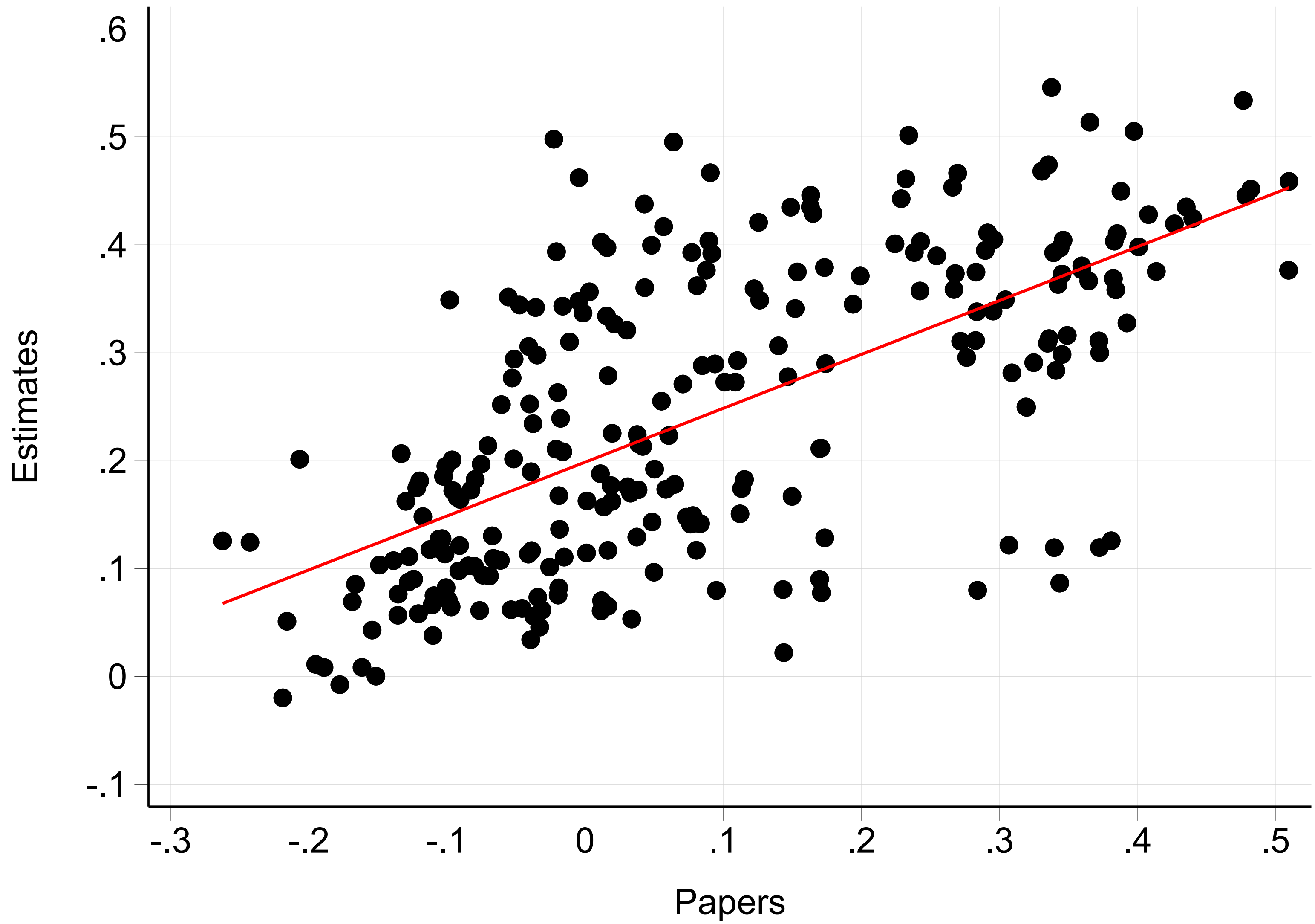
Notes. Authors' elaboration. The figure plots estimates of the distributional incidence of indirect taxes in Niger in 2019, before and after accounting for informal consumption. Before accounting for informal consumption, consumption taxes are very regressive, because low-income households tend to dissave, while high-income households display large positive savings. After accounting for the fact that low-income households tend to more intensively consume in informal markets, however, consumption taxes appear to only be mildly regressive.

Figure 6 – Incidence of Social Contributions and Informality: Argentina, 2019



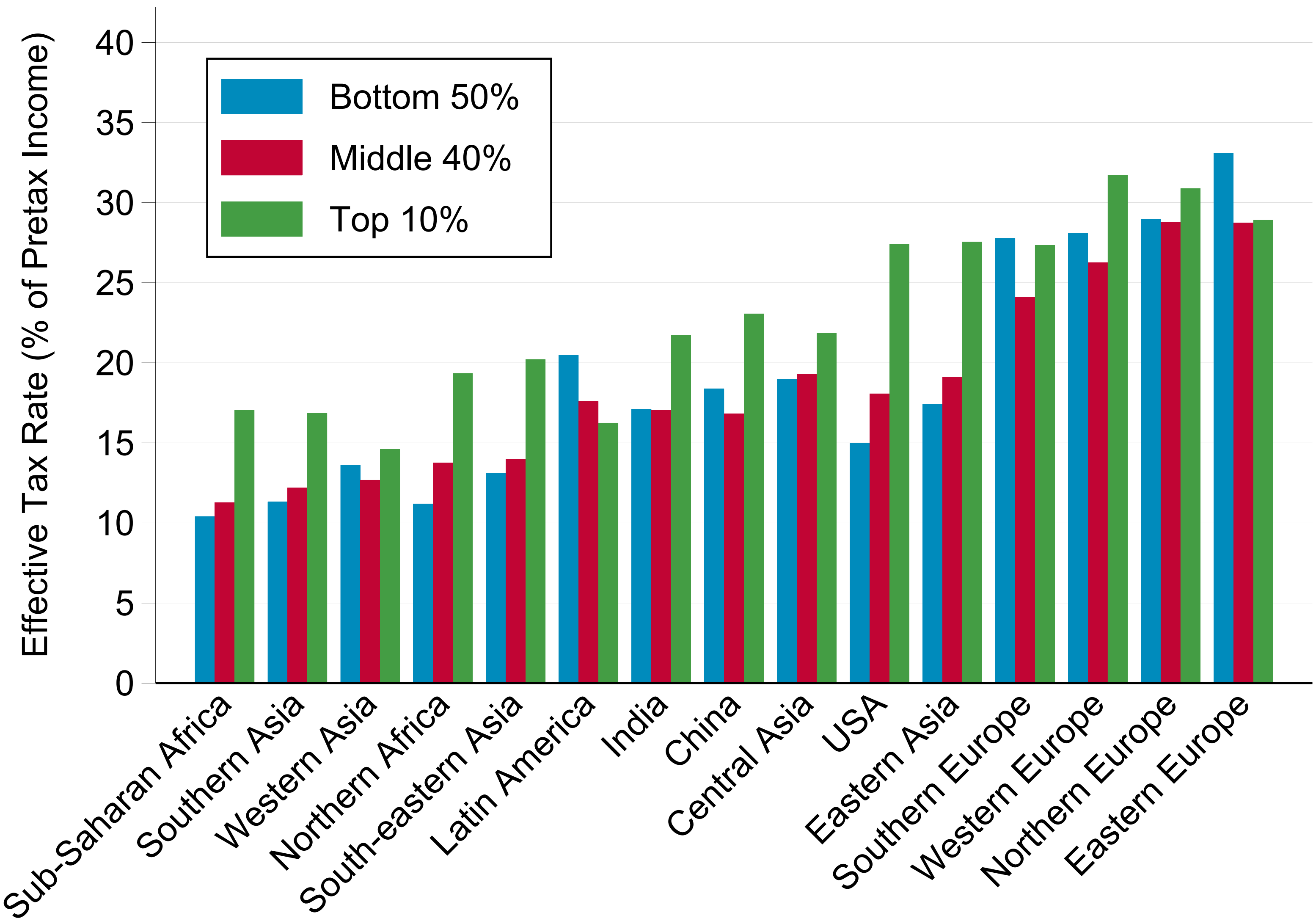
Notes. Authors' elaboration. The figure compares the distributional incidence of social contributions in Argentina before and after accounting for the fact that contribution payments different alongside the wage distribution. Distributing contributions proportionally to total labor income (blue line) implies a much more regressive profile than when distributing them proportionally to taxable labor income (red line), that is, accounting for the fact that a large share of low-wage earners do not pay social contributions.

Figure 7 – Validation: Cross-Country Differences in Tax Progressivity



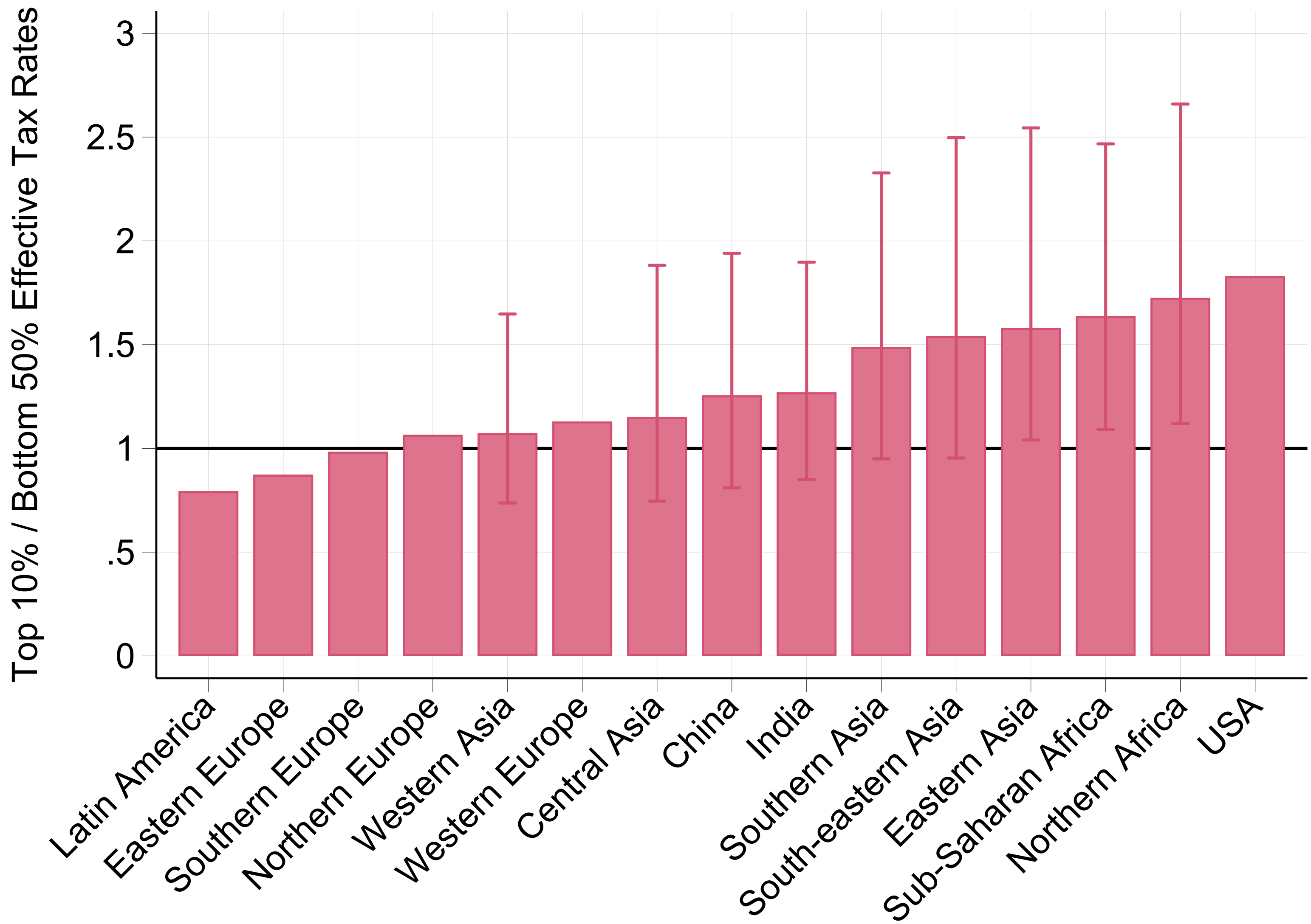
Notes. Authors' elaboration. The figure compares our estimates of tax progressivity to that of DINA papers across all country-years available. Excludes estimates from Blanchet, Chancel, and Gethin (2022). Tax progressivity is measured as the coefficient of a regression of the effective tax rate on generalized percentile for each country-year, focusing on the top 50% of the pretax income distribution. Excludes social contributions.

Figure 8 – Taxes Paid By Income Group and World Region, 2019



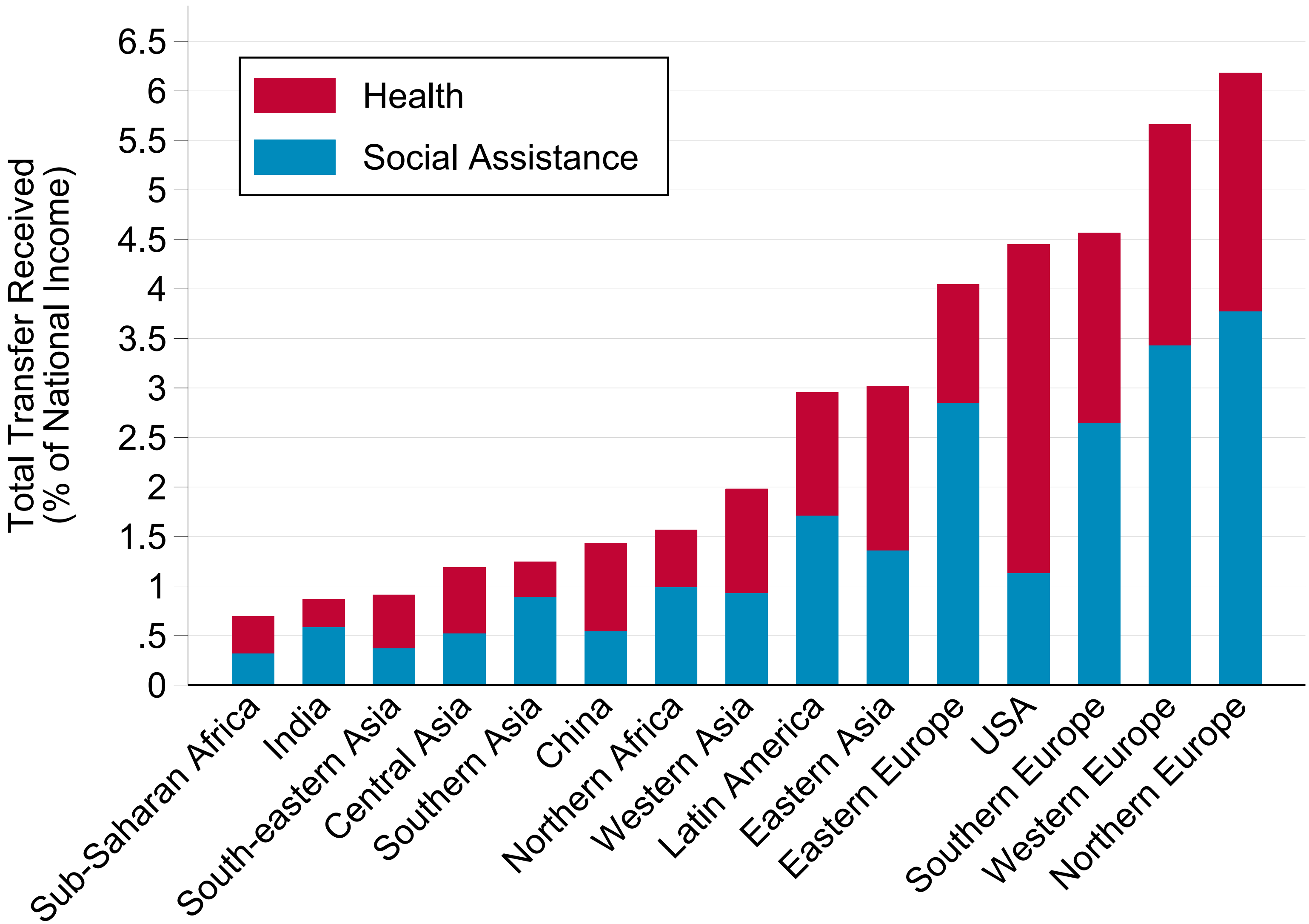
Notes. Authors' elaboration combining own estimates and estimates from DINA studies (Latin America, Western Europe, Southern Europe, Northern Europe, Eastern Europe, USA: see table 1). Population-weighted average of effective tax rates by income group in each country. Excludes social contributions.

Figure 9 – Tax Progressivity by World Region, 2019: Ratio of Top 10% to Bottom 50% Effective Tax Rates



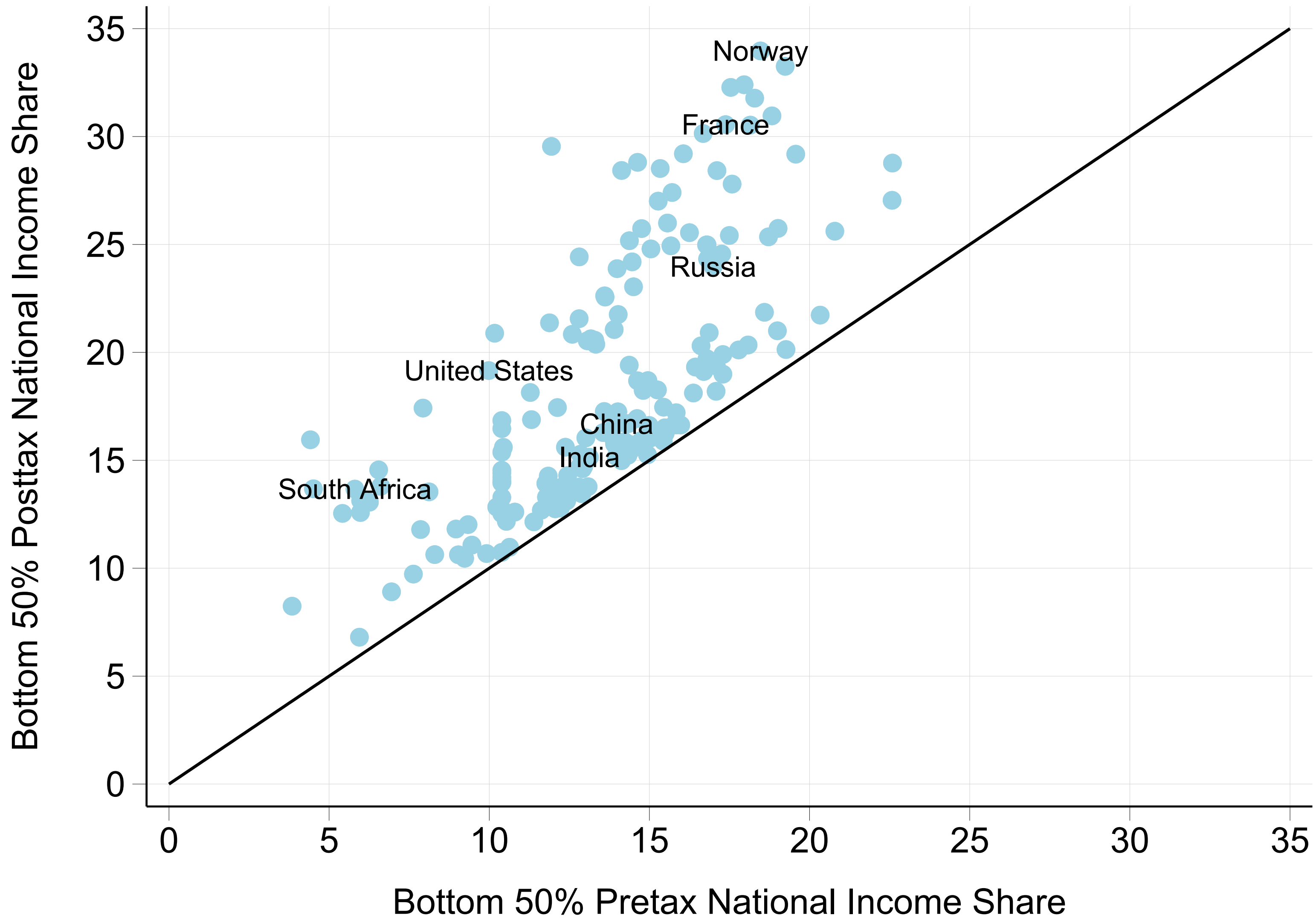
Notes. Authors' elaboration combining own estimates and estimates from DINA studies (Latin America, Western Europe, Southern Europe, Northern Europe, Eastern Europe, USA: see table 1). Population-weighted average of effective tax rates by income group in each country. Excludes social contributions.

Figure 10 – Social Assistance and Health Transfers Received by the Bottom 50% by World Region, 2019



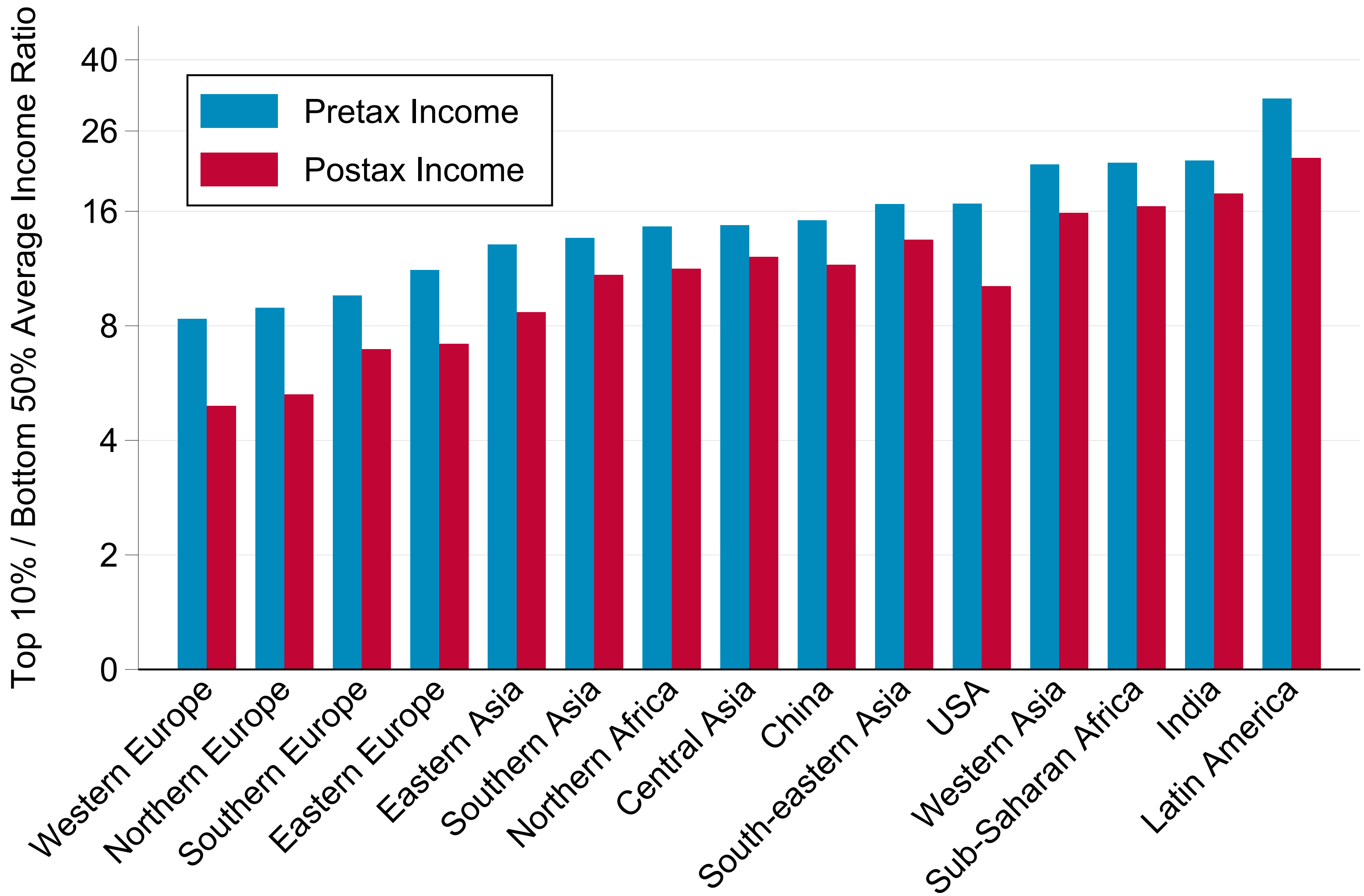
Notes. Authors' elaboration combining own estimates and estimates from DINA studies (Latin America, Western Europe, Southern Europe, Northern Europe, Eastern Europe, USA: see table 1). Population-weighted average of transfers received by income group in each country.

Figure 11 – Bottom 50% Pretax versus Posttax National Income Shares by Country



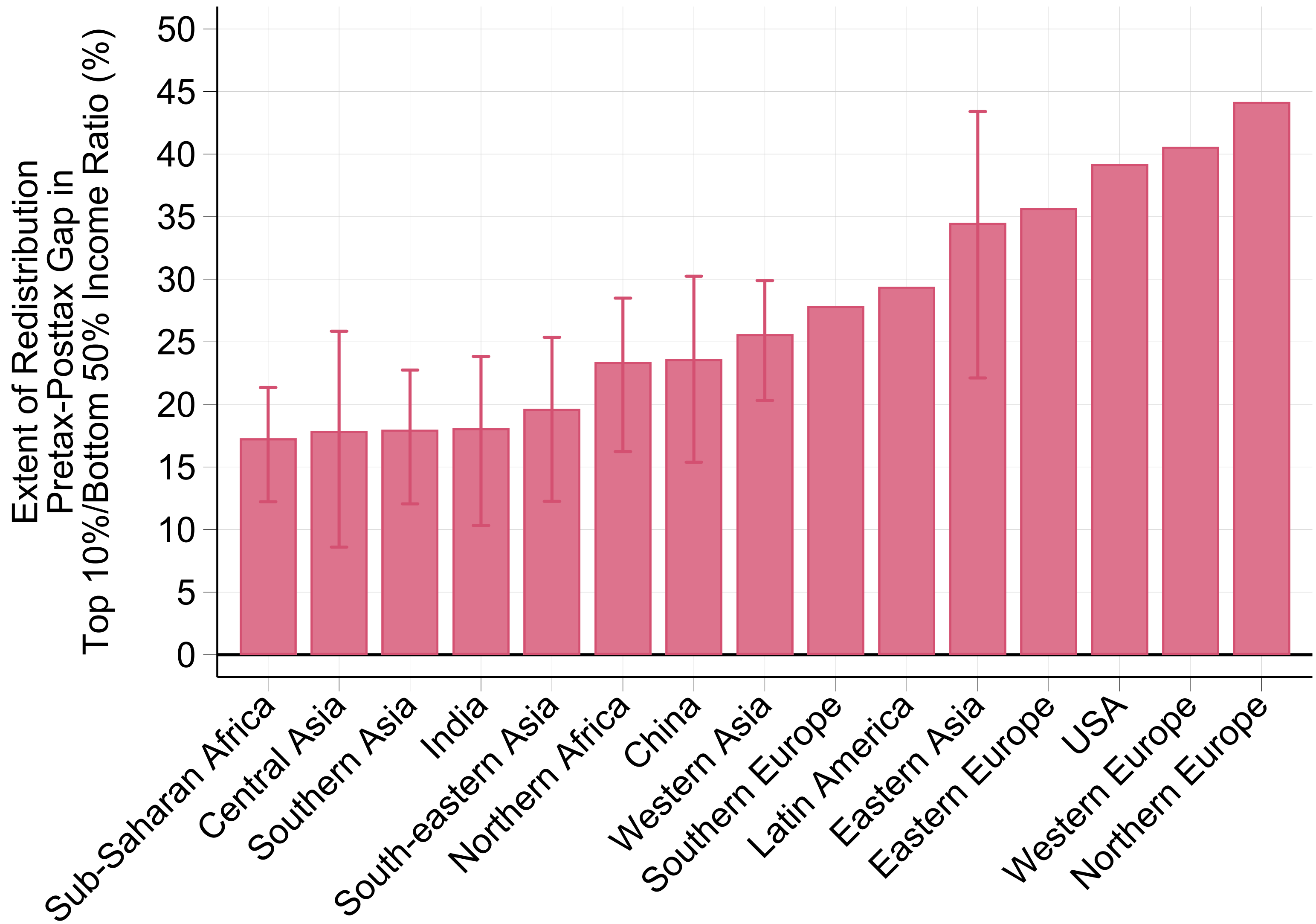
Notes. Authors' elaboration combining own estimates and estimates from DINA studies (Latin America, Western Europe, Southern Europe, Northern Europe, Eastern Europe, USA: see table 1).

Figure 12 – Top 10% to Bottom 50% Average Income Ratio by World Region



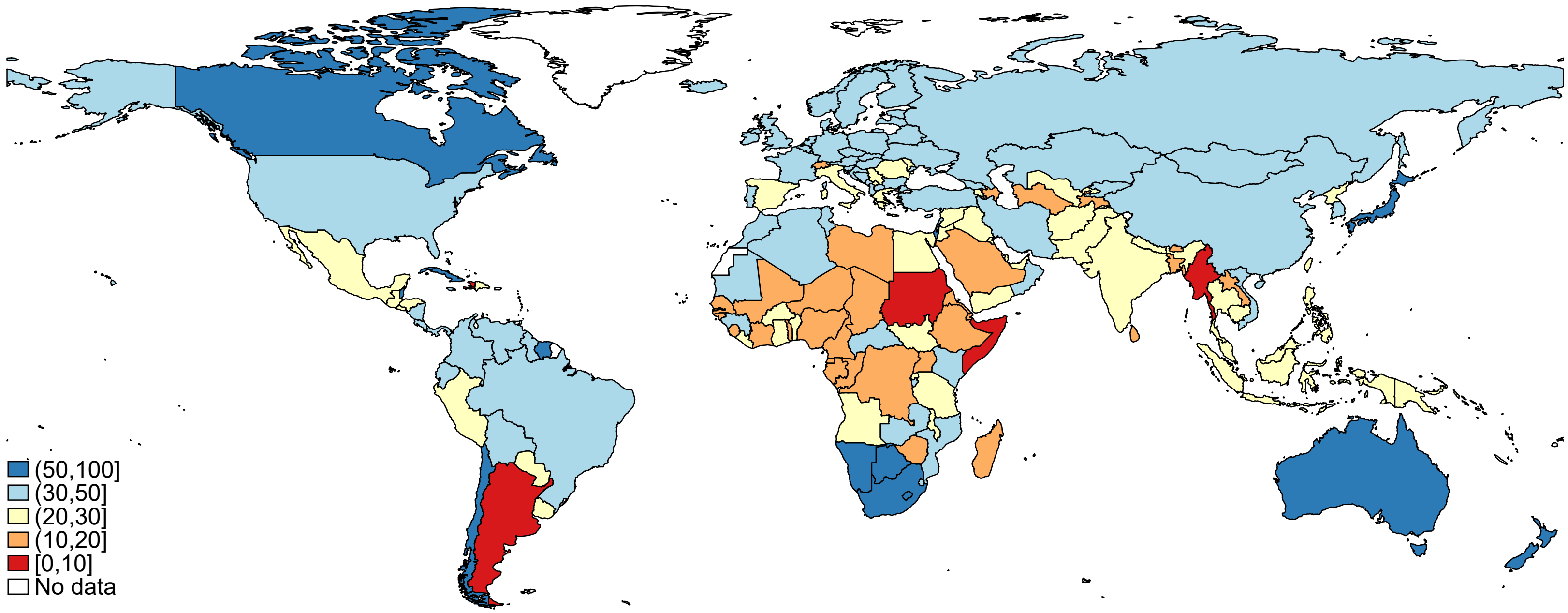
Notes. Authors' elaboration combining own estimates and estimates from DINA studies (Latin America, Western Europe, Southern Europe, Northern Europe, Eastern Europe, USA: see table 1). Figures correspond to population-weighted averages of the indicator in each country.

Figure 13 – Extent of Redistribution by World Region
Percent Reduction in Top 10% to Bottom 50% Income Ratio, Pretax - Posttax



Notes. Authors' elaboration combining own estimates and estimates from DINA studies (Latin America, Western Europe, Southern Europe, Northern Europe, Eastern Europe, USA: see table 1). Figures correspond to population-weighted averages of the indicator in each country.

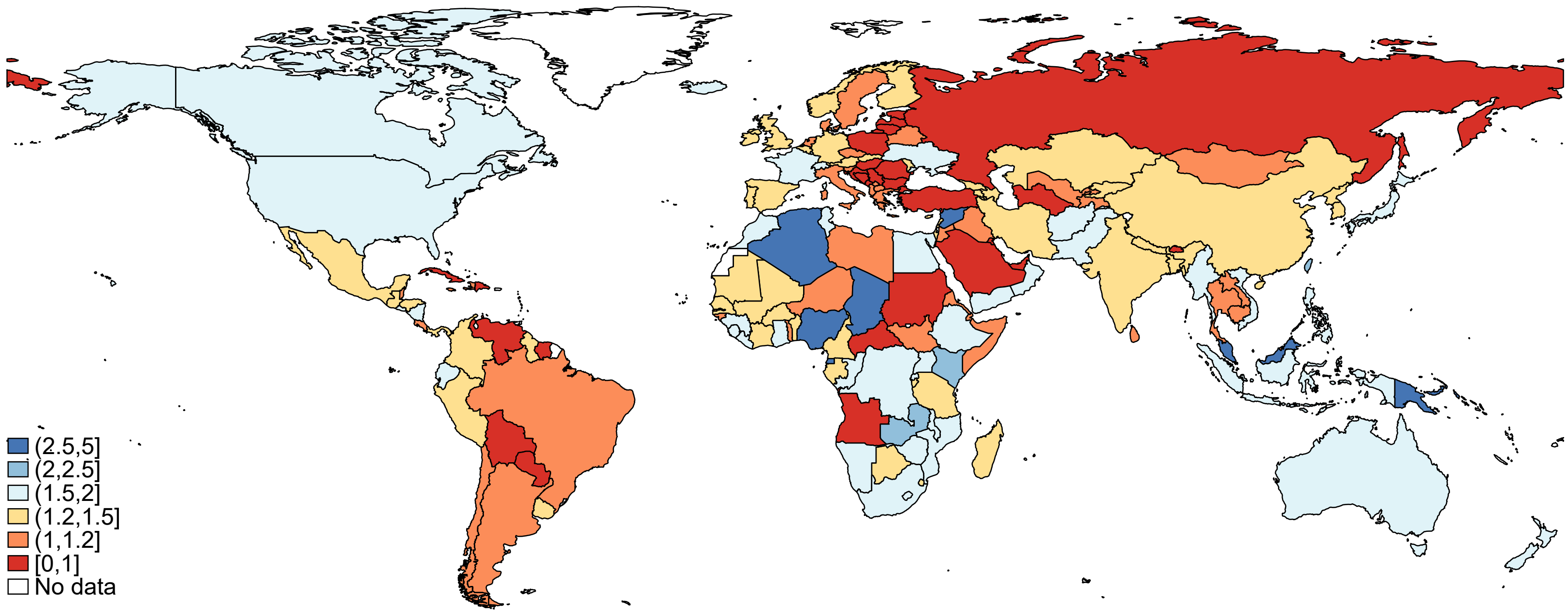
Figure 14 – A Global Map of Redistribution
Percent Reduction in Top 10% to Bottom 50% Income Ratio, Pretax - Posttax



Notes. Authors' elaboration combining own estimates and estimates from DINA studies (Latin America, Western Europe, Southern Europe, Northern Europe, Eastern Europe, USA: see table 1).

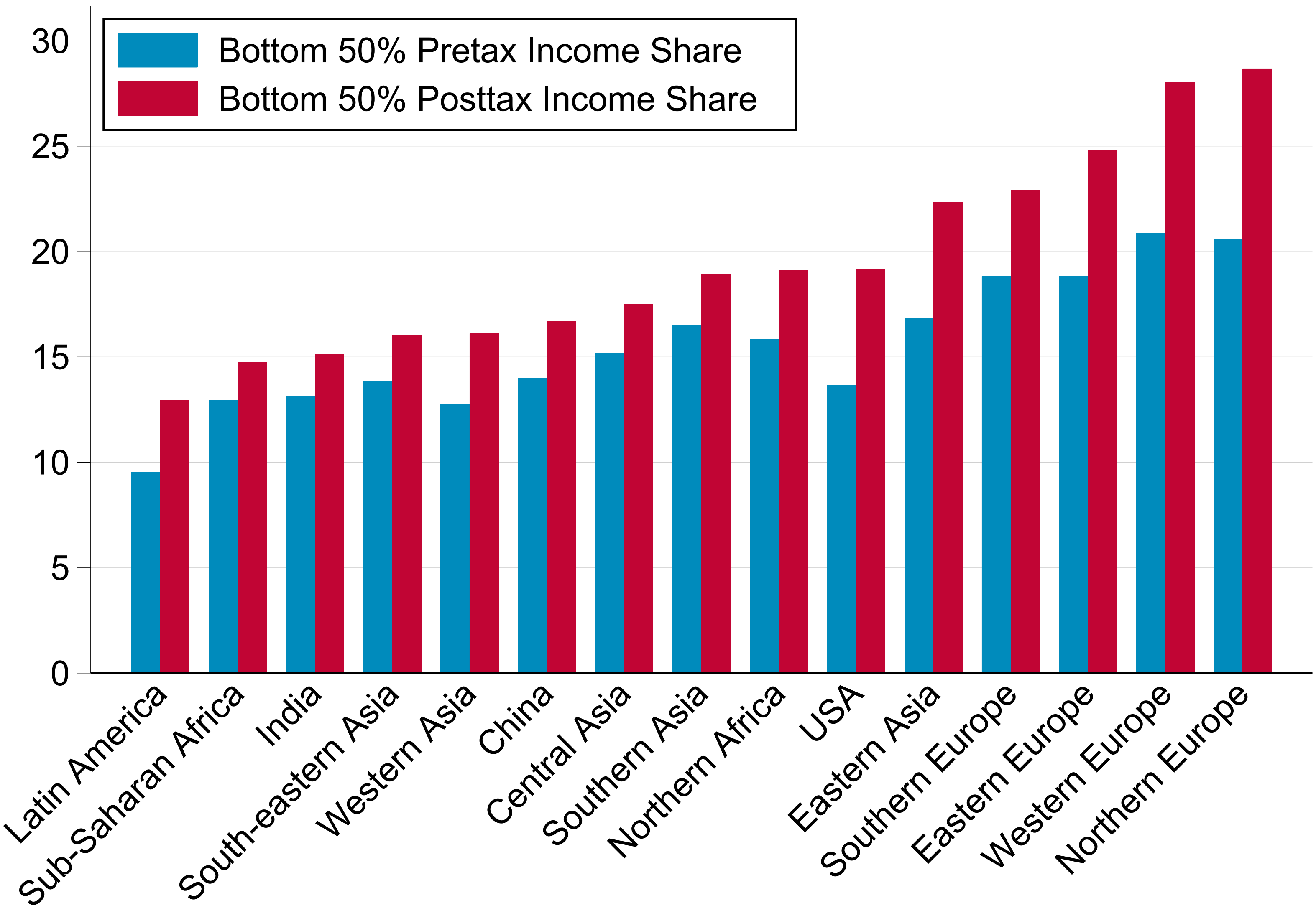
Appendix

Figure A.1 – Tax Progressivity Around the World: Ratio of Top 10% to Bottom 50% Effective Tax Rates



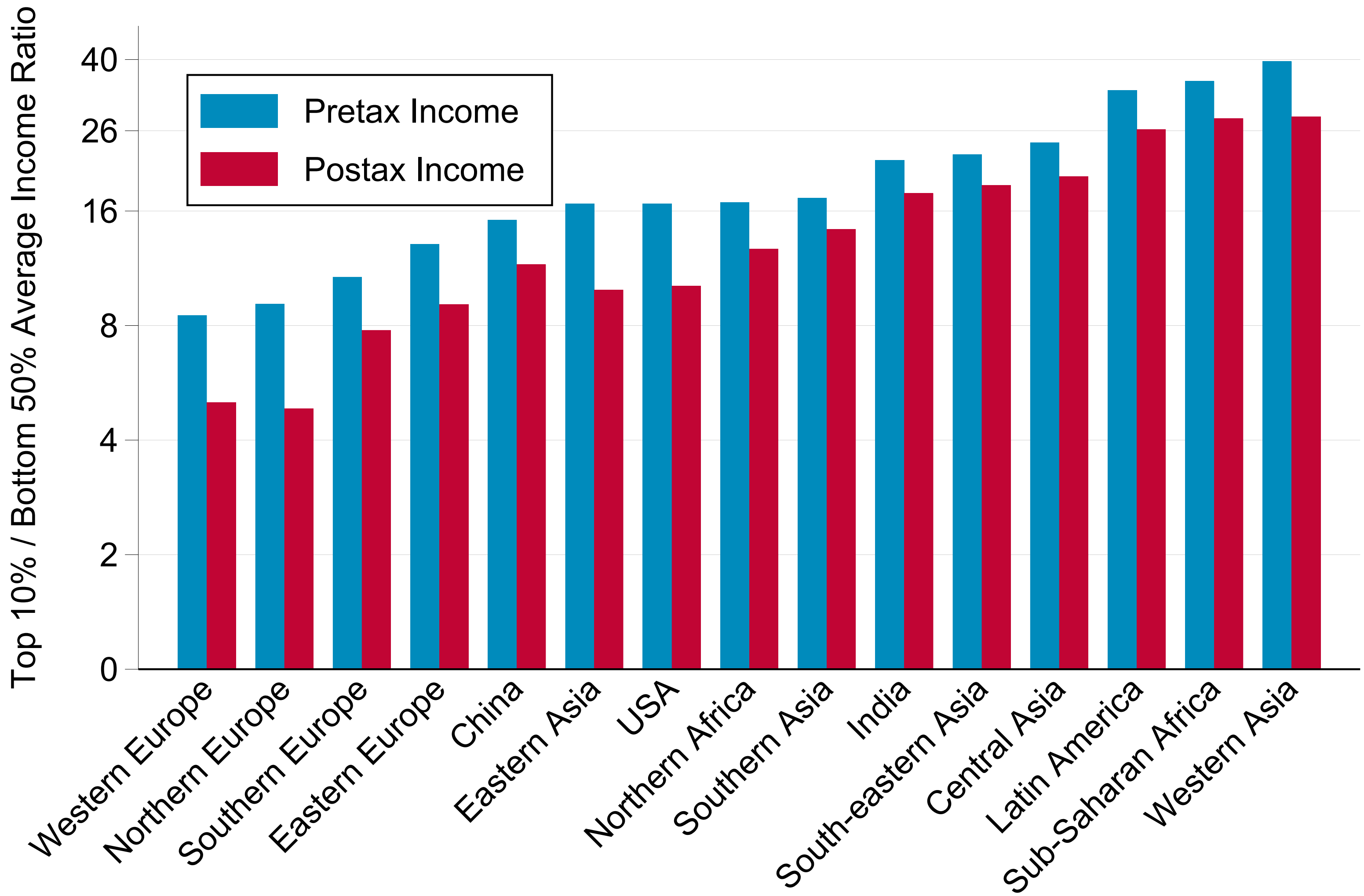
Notes. Authors' elaboration combining own estimates and estimates from DINA studies (Latin America, Western Europe, Southern Europe, Northern Europe, Eastern Europe, USA: see table 1).

Figure A.2 – Bottom 50% Pretax versus Posttax National Income Shares by World Region



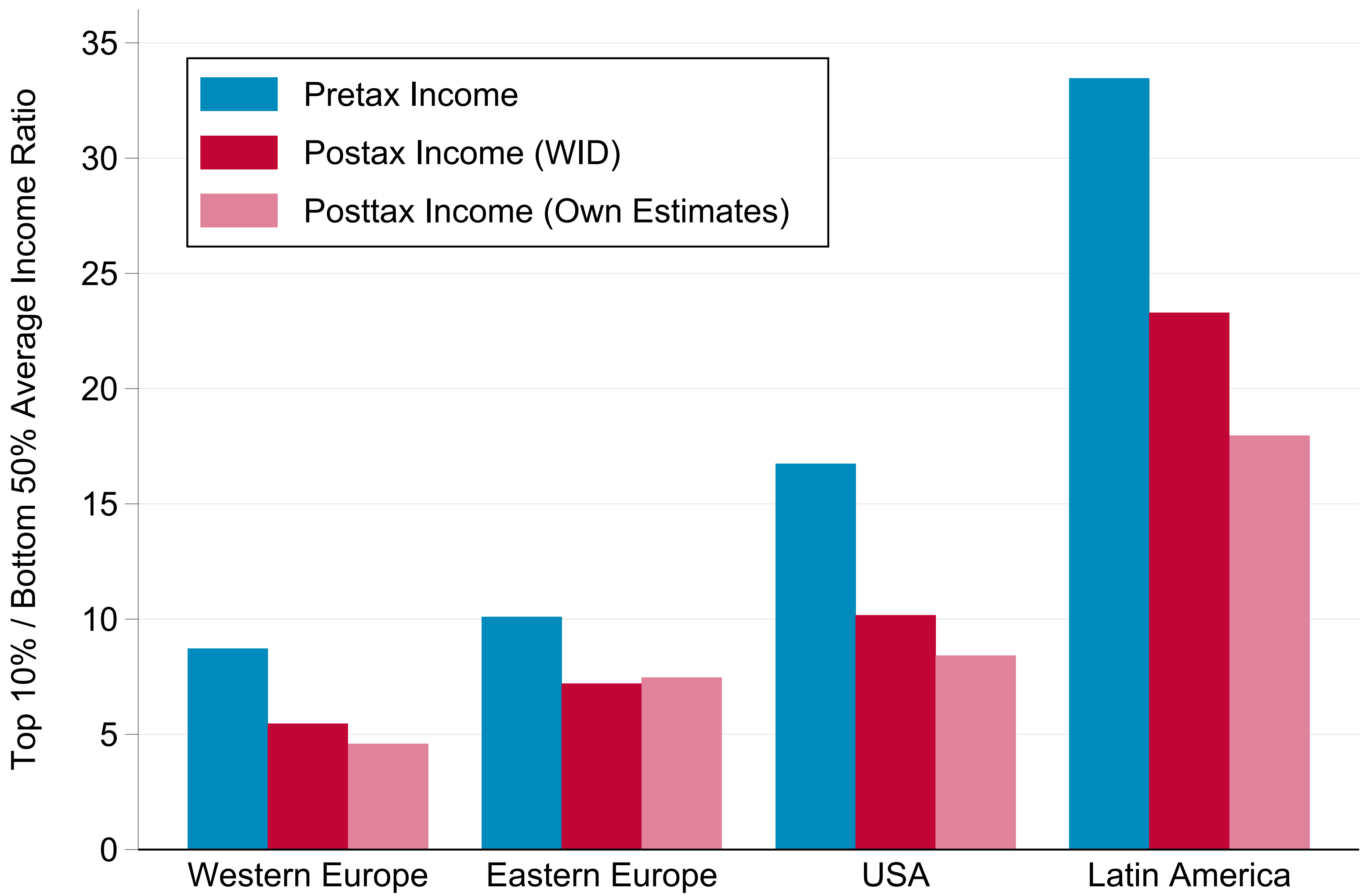
Notes. Authors' elaboration combining own estimates and estimates from DINA studies (Latin America, Western Europe, Southern Europe, Northern Europe, Eastern Europe, USA: see table 1). Figures correspond to population-weighted averages of the indicator in each country.

Figure A.3 – Top 10% to Bottom 50% Average Income Ratio by World Region (Region-Wide Inequality)



Notes. Authors' elaboration combining own estimates and estimates from DINA studies (Latin America, Western Europe, Southern Europe, Northern Europe, Eastern Europe, USA: see table 1). Estimates correspond to the ratio of top 10% to bottom 50% average incomes in each region as a whole (that is, accounting for differences in average incomes between countries, adjusted for differences in purchasing power using 2021 PPP conversion factors).

Figure A.4 – Validation: Top 10% to Bottom 50% Average Income Ratio, DINA Studies versus Own Estimates



Notes. Authors' elaboration combining own estimates and estimates from DINA studies (Latin America, Western Europe, Southern Europe, Northern Europe, Eastern Europe, USA: see table 1). The figure compares the top 10% to bottom 50% average income ratio in terms of pretax income, in terms of posttax income as estimated in existing DINA studies, and in terms of posttax income as estimated using our methodology. Figures correspond to population-weighted averages of the indicator in each country.