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Essays on Inequality and Fiscal Policy

Matthew Fisher-Post

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Doctorat en Sciences Économiques

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Essays on Inequality and Fiscal Policy

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To my family, friends, and teachers

Abstract

This dissertation comprises five chapters on inequality and fiscal policy.

Chapter 1 builds and analyzes a new global database of effective tax rates on capital and labor, and establishes a new stylized fact: while effective capital tax rates have fallen since 1965 in developed countries, in developing countries they have recently risen. In many countries, globalization appears to have supported governments' ability to tax capital.

In Chapter 2, data on public expenditures complement the Chapter 1 data on tax revenues, and we estimate the incidence of both along comprehensive pretax national income distributions, worldwide since 1980. We find that redistribution rises with development, but this is entirely due to transfers; tax progressivity is uncorrelated with per capita income. Redistribution has increased in most world regions, except in Africa and Eastern Europe, where it has stagnated.

Shifting gears from worldwide estimates to single-country studies, Chapter 3 examines the midcentury decline in inequality in the United States of America. New attention to archival data reveals that the decline in inequality favored the middle class more than the working poor—with one exception: Midcentury *wage* compression lasted for the entire postwar era. I explain one generation-defining trend with another, and demonstrate the causal impact of World War II service on postwar wages, particularly for those at the bottom of the wage distribution.

The fourth chapter estimates of the full distribution of all national income in Australia for the period 1991 to 2018, and find that in fact inequality of post-tax national income is lower and increased less than inequality of survey-based (post-transfer, disposable) income between 1991 and 2018. Australian inequality is much lower than that of the United States, and similar to that of France, with those at the bottom of the income distribution faring noticeably better in France and Australia than in the US.

Finally, in Chapter 5, we estimate pre- and post-tax income distributions for Canada and its provinces from 1982 to 2021. Since the mid-2000s, income inequality has decreased slightly although it remains far above the levels observed in the early 1980s. Across Canadian provinces, Ontario has consistently had higher inequality than Quebec although the gap has closed in recent years. Quebec has the most progressive tax and transfer system. During the pandemic, post-tax income inequality initially fell with large temporary transfer programs, but pre-tax income inequality has increased since then.

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Chapter 1

Globalization and Factor Income Taxation

with Pierre Bachas, Anders Jensen and Gabriel Zucman

Abstract

This chapter builds and analyzes a new global macro-historical database of effective tax rates on capital and labor in 154 countries. We establish a new stylized fact: while effective capital tax rates fell in developed countries between 1965 and 2018, they rose in developing countries since 1990. Multiple research designs at the country, sector and firm-level suggest that trade openness contributed to this rise, by increasing the share of output produced in corporations and larger firms, where effective capital taxation is higher. In contrast to a common view, globalization appears in many countries to have supported governments' ability to tax capital.

1.1 Introduction

How has globalization affected the relative taxation of capital and labor? Has it uniformly eroded the amount of taxes paid by capital owners, shifting the burden to workers? Or have some countries managed to increase effective capital tax rates, and if so how?

Answering these questions is critical to better understand the macroeconomic effects and social sustainability of globalization in uncertain times (Goldberg and Reed, 2023).

Based on a new long-run global database of effective tax rates on capital and labor, we document that in developing countries, effective capital tax rates have increased in the post-1990 era of hyper-globalization. Consistently across several research designs, we find that a significant share of this rise can be explained by trade openness. By expanding the share of economic activity occurring in the corporate sector, and within the corporate sector in larger firms, our results show that trade improves the effective collection of taxes, particularly corporate income taxes. Globalization has also had widely noted negative effects on capital taxation, due to international tax competition that applies downward pressure on corporate statutory tax rates. We find that the positive tax capacity effect of trade we uncover prevailed in developing economies, causing openness to increase overall government tax revenues (as a % of GDP). The revenue consequences of globalization have not been systematically investigated in developing countries due to limited data, and concerns over potential revenue losses have persisted as a key obstacle to further integration across borders (World Bank, 2020). In contrast to a common view, our findings show that globalization has not uniformly eroded governments' ability to raise revenue, and instead appears to have supported capital taxation in many countries.

To establish these results, this paper makes two contributions. The first is to build and analyze a macro-historical database of effective tax rates on capital (ETR_K) and labor (ETR_L) covering 154 countries, with over half starting in 1965, until 2018. Each ETR divides all taxes collected on the factor by the national income that accrues to it; by relying on actual taxes collected, $ETRs$ capture the net past effect of all tax rules and, importantly for developing countries, tax evasion and avoidance. Complementary to existing ETR series that focus on developed countries, our data provides a global coverage by digitizing and harmonizing thousands of historical and recent public finance records in developing countries. The global database allows us to systematically characterize the evolution of effective tax rates in developing countries and compare trends across development levels.

A novel fact emerges from this database: the evolution of capital taxation has been asymmetric across development levels. In high-income countries, effective capital tax rates declined, from a high of 38-39% in the late 1960s to 32-33% in the late 2010s. By contrast, in developing countries, effective capital tax rates have been on a rising trend since the beginning of the 1990s, albeit starting from a low level. Effective capital tax rates rose from 10% in 1989 to 18% in 2018, with more pronounced increases in larger economies. For example, ETR_K rose from 6% to 24% in China, 5% to 12% in India, and 7% to 27% in Brazil. The positive trend in capital taxation is driven by the corporate sector: the average effective corporate tax rate rose from 12% in 1989 to 20% in 2018.

This rise of capital taxation in low- and middle-income countries had not been noted in the literature before, due to a lack of data on the evolution of taxation globally. The finding appears robust. It holds: when we exclude China and oil-rich countries; with other approaches to computing capital and labor income in unincorporated businesses (where factor shares are not directly observable); and with alternative ways of splitting personal income tax revenue between capital versus labor.

Our second contribution is to formulate and test a hypothesis that sheds light on the rise of capital taxation in developing countries. We hypothesize that openness exerts a positive effect on developing countries' capacity to tax, consistent with trade leading to the expansion of larger firms relative to smaller ones (Mrázová and Neary, 2018) and firm-level effective taxation rising with size, due to better enforcement and higher statutory tax burdens (Almunia and Lopez-Rodriguez, 2018; Best, Shah, and Waseem, 2021).¹ Our hypothesis is motivated by the observation that the rise in ETR_K coincides with trade liberalization. Since the beginning of the 1990s, many developing countries opened their markets and reduced tariffs, leading to a boom in international trade that reshaped the economies of Mexico, India, and China among others (Goldberg, 2023). By disproportionately benefiting larger firms, trade can increase the share of economic activity in corporations and more formal businesses, where effective taxation of capital (and labor) is higher.

To motivate the tax capacity hypothesis, Figure 1.1 shows that the share of domestic output from the corporate sector (profits and employee compensation) has grown over time in developing countries, at the expense of mixed-income (income of self-employed and unincorporated businesses). While the corporate sector accounted for 53% of domestic output in 1989, prior to the hyper-globalization era, it grew to 62% by 2018; mixed income fell from 32% to 20% over the same period. Thus, developing countries have experienced a relocation of activity from a hard-to-tax sector to a sector with stronger effective taxation.

We establish the second contribution in two steps. First, we study the impact of trade on taxation in developing countries, with a focus on ETR_K and corporate taxes. Second, we study mechanisms that link trade to taxation, with a focus on the tax capacity channel.

We implement three research designs to study how trade impacts taxation. First, we estimate the non-parametric association within a country over time between ETR and trade openness. Second, we analyze major trade liberalization events that occurred in seven large developing countries, including China's WTO accession in 2001, and caused sharp reductions in trade barriers (Brandt et al., 2017; Goldberg and Pavcnik, 2016). We use synthetic control methods and present event-study results. Third, we extend the trade instruments from Egger, Nigai, and Strecker (2019) to our sample.

All three designs show that, in developing countries, trade leads to a large increase in ETR_K , and a smaller increase in ETR_L . The effect is sizable: trade openness can account for 33% of the documented rise in ETR_K since 1989. Although studying macroeconomic outcomes presents identification challenges, the results are consistent

¹Higher effective taxation in the corporate sector stems both from stronger enforcement and higher statutory taxes than in the non-corporate sector. Our notion of tax capacity is that these co-determined forces jointly lead to higher ETR_K with firm size (where size is measured as firm output, in our case revenue).

across research designs, which differ in their identifying assumptions, and are robust to numerous sensitivity checks. Across the research designs, we also find that trade leads to an increase in total tax revenues (as a % of GDP). Reflecting trade's positive impact on ETR_K , over half of this increase comes from higher corporate income taxes (CIT), and a smaller share from personal income taxes and payroll. Indirect taxes (combining tariff revenues and domestic consumption taxes) slightly rise, but the coefficient is not significant.

We then turn to investigate mechanisms. In the IV and liberalization event-studies, we find that trade increases the share of domestic output produced in the corporate sector, relative to the unincorporated business sector (mixed-income).² Thus, output is expanded in the corporate sector where enforcement is stronger and effective taxation is higher (Slemrod and Velayudhan, 2018). Moreover, within the corporate sector we find that trade increases the average effective tax rate on capital, suggesting the expanded corporate output accrues to firms whose ETR_K increases with their output (our proxy for firm size). These two effects of trade are consistent with the tax capacity channel. Simultaneously, we find that trade reduces the statutory corporate tax rate, consistent with a tax competition channel where globalization pushes governments to reduce the statutory tax burden on capital. On net, the positive tax capacity impact outweighs the tax rate reduction in developing countries, causing trade to increase ETR_K at the country-level.

In contrast, we find no tax capacity effect of trade in developed countries, but a stronger decrease in statutory corporate tax rates. These results help reconcile the asymmetric evolution of capital taxation in developing and developed countries.

We sharpen our mechanism analysis by conducting a firm-level investigation of the tax capacity channel. We merge multiple administrative datasets in Rwanda, which allows us to observe each firm's integration into international trade and corporate tax payments. The integration measure accounts for the firm's indirect exposure to trade through its production network (Almunia et al., 2023b). Rwanda provides an interesting setting: starting from a relatively low share of domestic output, the corporate sector has grown significantly since the 1990s, in tandem with a rise in trade openness and tax collection. Using the shift-share design of Hummels et al. (2014) for identifying variation, we find that trade integration increases both a firm's ETR_K and its size. Though limited to a single country, these firm-level results provide micro-evidence for trade's positive impact on ETR_K , and support the tax capacity mechanism whereby trade's impact is mediated by a positive firm size- ETR_K gradient.

Finally, we study sources of heterogeneity in the pro-tax impact of trade. During our sample period, developing countries have invested in domestic tax enforcement, such as large taxpayer units (Basri et al., 2019). We find that trade's impacts on the tax capacity mechanism and on ETR_K hold in the absence of these enforcement policies and, more generally, outside of periods of significant fiscal pressure (Cagé and Gadenne, 2018). Thus, trade's pro-tax impact appears to be a broad feature of the globalization process which does not hinge on governments' initial enforcement and revenue needs. At the same time, we find that openness' pro-tax impact depends on the nature of the trade shock, in ways that are consistent with recent theoretical work on trade and formalization (Dix-Carneiro et al., 2021).

²Trade leads to a sharp rise in corporate profits and an insignificant change in employee compensation.

Combining multiple empirical strategies, our results at the country, corporate sector, and firm-level consistently suggest that trade openness increases ETR_K and contributed to the newly documented rise of ETR_K in developing countries since the early 1990s. Based on a new global database, our findings show that globalization has supported effective capital taxation and overall revenue collection in many countries around the world.

Section 1.2 discusses related literature. Section 1.3 describes the methodology and data. Section 1.4 presents findings on the long-run evolution of ETR . Section 1.5 analyzes trade’s impact on ETR and Section 1.6 investigates the mechanisms. Section 1.7 concludes.

1.2 Related Literature

Globalization and tax structure Our paper contributes to the macro literature on globalization and tax structure (Alesina and Wacziarg, 1998), reviewed in Adam, Kammas, and Rodriguez (2013). The “race to the bottom” hypothesis posits that governments reduce taxes on factors that become more mobile (e.g., capital) following trade liberalization (Slemrod, 2004). To achieve revenue neutrality, governments raise taxes on less mobile factors (e.g., labor).³ The “social insurance” hypothesis postulates that governments raise revenue to insure workers displaced by international competition, often via social security and payroll taxes (Rodrik, 1998). These studies mainly focused on high-income countries. By expanding the scope to developing countries, we formulate and test a new mechanism, where trade increases ETR by expanding activity in firms with higher effective tax collection. Our results suggest that globalization has supported the ability of governments to tax capital in many countries.

Our results are based on a new global database of effective tax rates, which complements existing datasets (including Carey and Rabesona, 2004; Kostarakos and Varthalitis, 2020; McDaniel, 2007) by expanding coverage to developing countries (details in Section 1.3).⁴ Our backward-looking ETR measure is complementary to the literature on forward-looking capital tax rates (including Devereux and Griffith, 1999), which models in detail the statutory tax burden a firm would face under different conditions. This literature finds that the statutory tax burden on capital has fallen in developed and developing countries, consistent with the “race to the bottom” mechanism (including Devereux, Griffith, and Klemm, 2002; R. Kumar and James, 2022; Steinmüller, Thuncke, and Wamser, 2019).

Effective taxation and trade in developing countries Our paper contributes to the micro-oriented literature on trade and public finance in developing countries. Many studies focus on *border taxes* and evasion (e.g., Fisman and Wei, 2004; Javorcik and Narciso, 2017; Sequeira, 2016) or cross-border income-shifting (e.g., Bilicka, 2019; Londoño-Vélez and Tortarolo, 2022; Wier, 2020). We focus instead on trade’s impacts on the *domestic tax bases* of capital and labor and domestic economic

³Within labor in OECD countries, Egger, Nigai, and Strecker (2019) find that globalization in the post-1994 era led to a reduction in income taxes for the top 1% of workers and increased income taxes for middle-class workers.

⁴We complement other work in economic history on taxation (including Cogneau et al., 2021), by providing long-run measures of factor effective tax rates.

structure.⁵ Our results are intuitive when considering that the trade literature finds positive effects of openness on domestic outcomes including market shares (McCaig and Pavcnik, 2018), firm size (Alfaro-Ureña, Manelici, and Vásquez, 2022), and local development (Méndez and Van Patten, 2022), which the public finance literature has separately identified as determinants of effective taxation (Besley and Persson, 2014; Best, Shah, and Waseem, 2021).⁶ We contribute by linking these two bodies of work and directly studying trade's impacts on domestic tax bases at the country, sector and firm level.

By incorporating domestic tax bases, we can comprehensively study the total tax revenue impacts of globalization. Previous studies on trade's revenue impact in developing countries have produced mixed findings, possibly due to differences in sample, methods and tax base focus (including Baunsgaard and Keen, 2009; Buettner and Madzharova, 2018; Cagé and Gadenne, 2018). We contribute by implementing multiple identification strategies in the largest sample to date and find that trade's impacts on domestic tax bases are sufficiently large that openness increases total tax revenue (as a % of GDP). These impacts of trade are mediated by the tax capacity mechanism, which is rooted in two distinct insights from the trade and the public finance literatures. First, a large class of models predicts that trade leads to the expansion of large firms relative to small firms (Mrázová and Neary, 2018); for empirical evidence, see Bernard et al. (2007). Second, in developing countries small firms are mainly informal, and effective taxation increases with firm size (measured as firm revenue)⁷; this positive gradient arises because effective tax collection is higher in larger firms and corporations due to their visibility, complex production structures, and employment of many workers (Almunia et al., 2023b; Waseem, 2020). The resulting information trails improve enforcement (Naritomi, 2019; Pomeranz, 2015), though with limits (Carillo, Pomeranz, and Singhal, 2017).⁸

The positive size-gradient also arises because the tax code in developing countries often leads to higher statutory tax burdens for larger firms and corporations (R. Kumar and James, 2022): Bachas et al. (2023) find a positive size-statutory tax gradient among corporations in 15 countries. Our mechanism is motivated by Abbas and Klemm (2013), who hypothesize that the corporate sector expansion could explain why the reduction in statutory corporate tax burdens in developing countries has not led to a reduction in CIT revenue (% of GDP).⁹ The mechanism also relates to studies in high-income countries that link CIT collection to the corporate sector's statutory burden, output-share and profitability (Clausing, 2007; Griffith and Miller, 2014; Sørensen, 2007).

⁵The theoretical literature has focused on trade's impact on the optimal indirect tax mix between border and consumption taxes in developing countries (e.g. Emran and Stiglitz, 2005) and mainly abstracted from direct taxes. Benzarti and Tazhitdinova (2021) study the impact of indirect taxes on trade flows.

⁶Our results, which focus on the corporate output-share, are compatible with findings from trade-formalization studies, which instead focus on the share of formal workers or firms (Section 1.6).

⁷See also Kopczuk and Slemrod (2006), Bachas, Fattal, and Jensen (2019), Best, Shah, and Waseem (2021), Kleven et al. (2011), and La Porta and Shleifer (2014).

⁸In developed countries including the US, the large corporate sector is considered an important determinant of effective tax collection (Kleven, Kreiner, and Saez, 2016; Slemrod and Velayudhan, 2018).

⁹See also Quinn (1997), M. Kumar and Quinn (2012) and Abramovsky, Klemm, and Phillips (2014).

We focus on a mechanism based on firm size, but many links between trade, firm structure, and taxation remain to be explored (Atkin and Khandelwal, 2020; Parenti, 2018).

1.3 Construction of Effective Tax Rates

This section presents a new database of effective tax rates (ETR) on labor and capital, which covers 154 countries, starting in 1965 when possible, until 2018. We first outline the conceptual framework to build ETR , then present the data sources, and finally discuss the sample coverage. Further details are in Appendix A1.1.

1.3.1 Methodology

Effective tax rates We compute macroeconomic effective tax rates following the methodology of Mendoza, Razin, and Tesar (1994). The effective tax rate on labor, denoted ETR_L , is the total amount of taxes effectively collected on labor divided by total labor income in the economy; similarly for capital, denoted ETR_K :

$$ETR_L = \frac{T_L}{Y_L} \quad \text{and} \quad ETR_K = \frac{T_K}{Y_K} \quad (1.1)$$

To construct the numerators, each type of tax revenue is assigned to labor or capital:

$$T_L = \sum_j \lambda_j \cdot \tau_j \quad \text{and} \quad T_K = \sum_j (1 - \lambda_j) \cdot \tau_j \quad (1.2)$$

where λ_j is the allocation to labor of each type j of tax τ_j . Types of taxes j follow the OECD Revenue classification. We allocate taxes as follows: (1) corporate income taxes, wealth taxes, and property taxes are allocated to capital; (2) payroll taxes and social security payments are allocated to labor; (3) personal income taxes (PIT) are allocated partly to labor and partly to capital, in a country-time specific manner (details below). Indirect taxes are neither assigned to labor nor to capital (but analyzed directly in Section 1.5.3). Table A1.1 provides a detailed allocation summary.

To construct the denominators, we decompose net domestic product as follows:

$$Y = Y_L + Y_K = \underbrace{CE + \phi \cdot OS_{PUE}}_{Y_L} + \underbrace{(1 - \phi) \cdot OS_{PUE} + OS_{CORP} + OS_{HH}}_{Y_K} \quad (1.3)$$

Labor income Y_L equals compensation of employees (CE) plus a share ϕ of mixed income (operating surplus of private unincorporated enterprises, OS_{PUE}). Capital income Y_K equals the remaining share $(1 - \phi)$ of mixed income, plus corporate firms' profits net of depreciation (operating surplus of corporations, OS_{CORP}), plus actual and imputed rental income (operating surplus of households, OS_{HH}).¹⁰

We also measure the effective tax rate on corporate profits, \overline{ETR}_C^K , as the ratio of corporate income taxes to corporate profits. This is an average effective tax rate at the corporate sector level; in Section 1.6, we analyze the firm-level corporate effective tax rate.

¹⁰We decompose net domestic product (NDP), which subtracts consumption of fixed capital from gross domestic product (GDP). NDP is lower than GDP, by 10% on average. We exclude capital depreciation since it does not accrue to any factor of production and is usually tax-exempt. Factor incomes also exclude indirect taxes (which are also excluded in the numerator of ETR).

These macroeconomic *ETRs* rely on several conventions and assumptions (see Carey and Rabesona, 2004). First, as is done in the literature, they do not factor in economic incidence in that the economic cost of taxes is not “shifted” from one factor of production to another: all labor taxes are allocated to labor and all capital taxes are allocated to capital. Second, the tax revenue streams need to be comparable to their macroeconomic tax bases measured in national accounts. This generates two key challenges for our *ETRs*: (i) in the numerator, what share of personal income tax revenues to allocate to capital versus labor; and (ii) in the denominator, what share of mixed income to allocate to capital versus labor. We outline below our benchmark assumptions (detailed discussion is in Appendix A1.1.2).

Allocation of personal income taxes (PIT) The main empirical difficulty in assigning taxes to labor and capital concerns the allocation of PIT. A naive procedure allocates 70% of the PIT to labor and 30% to capital, roughly matching the labor and capital shares of domestic product. In practice, however, recent work highlights that not all labor and capital income is subject to PIT, since not all individuals are required to file PIT, and exemptions apply to some income types (Jensen, 2022). Exemptions for capital (e.g., imputed housing rents, undistributed profits) are typically larger than for labor (e.g., pension contributions). Further, labor and capital income might not face the same tax rate: dual-income tax systems tax labor income with progressive rates but capital income with flat rates. In the US, Piketty, Saez, and Zucman (2018) use detailed tax and national accounts data to measure that 75% of labor income is subject to PIT, versus 33% of capital income. This suggests allocating 15% of PIT to capital and 85% to labor.¹¹

Starting from this baseline where 15% of PIT revenues derive from capital, we perform two country-year adjustments: (i) we raise capital revenues for country-years with a high PIT exemption threshold in the income distribution (Jensen, 2022); (ii) we lower it in country-years where dividends face lower taxes than wages. The resulting capital share of PIT revenue varies between 7% and 32% across country-years. Over time, this share falls from a global average of 19% in 1965 to 14% in 2018, due to a reduction in PIT exemption thresholds and increased prevalence of dual tax systems.

In the absence of detailed tax records in every country and year, these adjustments provide an imperfect approximation of the true capital share of PIT. We therefore implement two simple robustness checks where the share allocated to capital is fixed over time at either 0% or 30%, representing low and high-end scenarios.

The labor share of mixed income The labor share of mixed income (unincorporated enterprises) is hard to measure.¹² For our benchmark series we assume $\phi = 75\%$, i.e., 25% of mixed income is considered capital income.¹³ In the absence

¹¹If 75% of labor income is taxable and labor income is 70% of national income (resp. 33% and 30% for capital income), then $75\% \times 70\% / (75\% \times 70\% + 33\% \times 30\%) = 84\%$ of the PIT is labor income.

¹²The UN’s national accounts framework outlines the combination of multiple methods to overcome challenges of measuring the *level* of mixed income in economies with widespread informality. While information on the methods used is not available on a country-year basis, an inspection of the published frameworks suggests no change in methodologies for mixed income over time.

¹³This is below the 30% used in Distributional National Accounts (DINA) guidelines (Blanchet et al., 2021), but since the global average of the corporate sector’s capital share is 27%, assuming a lower capital share for unincorporated enterprises seems reasonable (see Guerriero, 2019).

of a consensus over alternatives this assumption has the advantage of being transparent, though factor shares are unlikely in practice to everywhere be time and country-invariant. We therefore implement two robustness checks, which create time and year variation in ϕ . The first method, based on ILO (2019), uses micro-data to estimate the country-specific labor income of self-employed based on the observable characteristics of these workers and their comparison with employees.¹⁴ Second, we assign to ϕ the observed country-year labor share of the corporate sector (as in Gollin, 2002).

The exact *ETR* formulas which include the above adjustments are in Appendix A1.1.2.

Usefulness and limitations of ETR Since national account statistics are compiled following harmonized guidelines, *ETRs* are conceptually comparable over time and across countries, though the data limitations described above should be kept in mind. By relying on taxes actually collected, the *ETRs* incorporate tax avoidance and evasion behavior as well as the net past effects of all tax policies, including rates, exemptions and credits. This is particularly relevant in a development context, where due to widespread evasion, knowledge of statutory tax rules only provides a partial picture of effective tax burdens.

The *ETRs* are backward-looking measures that comprehensively capture how much capital and labor have effectively paid in taxes. They are helpful for three reasons. First, knowing how much revenues are effectively collected from each factor is important when governments face fiscal pressure (Besley and Persson, 2014): this is characteristic of most developing countries, where potential revenue losses or gains is a key policy determinant. Second, the level of the *ETR* and its deviation from a statutory rate is frequently an input into policy-making to understand the size of tax gaps (e.g. the recent focus on the firm-level *ETR* in the global minimum tax agreements). Finally, the tax burden levied on each factor is an important starting point to determine the economic incidence of a tax system.

A limitation of macroeconomic *ETRs* is that they are impacted by both the tax code and economic changes. Thus, studying *ETRs* is most helpfully done in combination with analyzing its mechanisms, which we focus on in Section 1.6. Related, we emphasize that the *ETR* should not be interpreted as a proxy for the statutory tax burden. An important complementary body of work carefully measures legal tax burdens (Devereux and Griffith, 1999), by constructing forward-looking average tax rates on capital based on the simulated present value of returns and costs of a new investment. Driven by differing objectives, the backward-looking and forward-looking measures are related, yet distinct.¹⁵

¹⁴Details in Appendix A1.1.2. A challenge with this method is that it can create implausibly large estimates of the level of mixed income compared to their values in national accounts. We implement an adjustment to help with this limitation, but for this reason we choose to use ILO (2019) only for robustness.

¹⁵This is particularly the case for \overline{ETR}_C^K : see [supplementary appendix](#) for a detailed discussion. Our measure of \overline{ETR}_C^K also relates to the CIT-efficiency measure by IMF (2014). In the [supplementary appendix](#) we find that CIT-efficiency measured with our data in the relevant sample matches well the IMF (*ibid.*) series.

1.3.2 Data sources

National accounts

To measure factor incomes for 154 countries since 1965 when possible, we create a panel of national accounts using data from the System of National Accounts (SNA) produced by the United Nations. We first use the 2008 SNA online repository that has global coverage for recent decades. In turn, the UN Statistics Division provided us with access to the 1968 SNA offline data which covers historical data from the 1960s and 1970s. To the best of our knowledge, our paper is the first to harmonize and integrate the 2008-SNA and 1968-SNA datasets.¹⁶ Estimating factor incomes requires information on all the components of national income (equation 1.3). Whenever we have national income for a country-year but information on a component is missing, we attempt to recover it with information from the second SNA dataset, as well as using national accounting identities with non-missing values for the other income components. In the remaining cases, we impute component values following DINA guidelines (Blanchet et al., 2021), with further details available in Appendix A1.1.1.

Tax revenue

We construct a new tax revenue dataset that disaggregates taxes by type following the OECD Revenue Statistics classification of taxes. Our database includes all taxes—on personal and corporate income, social security and payroll, property, wealth and inheritance, consumption and international trade—at all levels of government. We ensure a systematic separation of income taxes into personal and corporate income. We collect new archival data and integrate it with existing data sources.

When available, OECD Revenue Statistics data ([link](#)) is the preferred source, as it covers all types of tax revenues and goes back to 1965 for OECD countries. It accounts for 2,875 country-year observations (42.3% of the sample). Its drawback is its limited coverage of non-OECD countries, as it covers 93 countries in total and only covers developing countries more recently. We add data from ICTD ([link](#)). ICTD includes most developing countries, with coverage that starts in the 1980s. ICTD sometimes combines personal and corporate income taxes, and sometimes lacks social security. ICTD adds 1,246 country-year observations (18.3% of the sample).

To complement these existing sources, we conducted archival data collection to digitize records from government budgets and national statistical yearbooks. This adds 2,011 new country-year observations.¹⁷ We supplemented these archival records with countries' online publications, and offline data from the IMF Government Finance Statistics (1972-1989). In total, this data collection adds 2,678 observations (39.4% of the sample).

Building a dataset based on newly digitized historical sources necessarily requires making a number of decisions. To increase the credibility of our data, we follow four guiding principles. First, we seek to build long historical time-series that overlap in years with existing sources. We aim to only use two data sources per country, but use the overlapping years between multiple sources to corroborate that they are comparable in levels of tax revenue and types of taxes in place.¹⁸ For this reason,

¹⁶Relative to recent work (including Guerriero, 2019; Karabarbounis and Neiman, 2014), our data expands coverage in space and time, mainly to developing countries, and systematically attempts to measure factor incomes for total domestic output (vs. only for the corporate sector).

¹⁷The archives were accessed in the Government Section of the Lamont Library ([website link](#)).

¹⁸OECD is the preferred starting point and archival data is initially second in priority since it often dis-aggregates tax types and goes back far in time, but we revise this based on the source

a switch in data source rarely leads to a significant change in trend. Second, for the historical periods without overlap with existing data, we corroborate the levels of tax to GDP with academic and policy studies. Third, we draw on historical studies to verify that large changes in revenues collected reflect policy, economic or political changes rather than data artifacts. Fourth, we aim to be conservative and exclude countries in time periods where concerns exist about data quality, due to the economic and political context.

To help assess our approach, the [supplementary appendix](#) provides additional material. We provide a table which outlines, in each of the 154 countries, the main considerations and our choices relating to the four guiding principles. The table emphasizes the uncertainty surrounding specific countries and time periods, and flags instances where the data appears worthy of inclusion but should be interpreted with caution (all our main results are unchanged if we exclude these instances). Moreover, we provide in-depth country case-studies with direct links to the initial archival sources; the case-studies currently cover all countries with more than 15 million inhabitants but will ultimately expand to cover all 154 countries. We invite comments from researchers to help improve the accuracy of the series as we continuously update the data.

1.3.3 Data coverage of effective tax rates

The final *ETR* sample contains 6,799 country-year observations in 154 countries (Figure [A1.1](#)). The number of countries starts at 78 in 1965 and grows to 110 by 1975 (due to independence or country creation). The key jump in coverage—from 117 to 148—corresponds to the entry of ex-communist countries in 1994, including China when it arguably built a modern tax system (Appendix [A1.1.1](#)). The data is effectively composed of two quasi-balanced panels. The first covers 1965-1993 and excludes communist regimes, accounting for 85-90% of world GDP. The second covers 1994-2018 and includes former communist countries, accounting for 97-98% of world GDP. Figure [A1.1](#) shows coverage by development level. We use the World Bank income classification in 2018, classifying low and middle-income countries (LMICs) as developing countries and high-income countries (HICs) as developed countries. We refer interchangeably to LMICs as developing countries and HICs as developed countries. Our sample contains 5,144 observations in LMICs and 1,655 observations in HICs.

Comparison with existing datasets Our database complements previous *ETR* series by expanding coverage to LMICs. Table [A1.2](#) summarizes the coverage of existing *ETR* series, which focus on HICs (Carey and Rabesona, 2004; Kostarakos and Varthalitis, 2020; McDaniel, 2007; Mendoza, Razin, and Tesar, 1994). Our benchmark *ETRs* rely on specific choices: Table [A1.2](#) summarizes the methodological differences with existing *ETR* series, which relate mainly to allocating capital to both mixed income and PIT.¹⁹ The alternative choices are covered by the robustness checks of Section [1.3.1](#), which are implemented in Section [1.4.2](#).

that best matches the OECD data. The [supplementary appendix](#) summarizes the data sources used for each country.

¹⁹A comprehensive discussion of the methodological differences is provided in the [supplementary appendix](#).

1.4 Stylized Facts on Global Taxation Trends

1.4.1 Evolution of effective tax rates on capital and labor

Figure 1.2 documents the evolution of effective tax rates on capital and labor from 1965 to 2018. Aggregates are dollar-weighted, i.e., the global effective tax rate on capital equals worldwide capital tax revenues divided by worldwide capital income. These series can thus be interpreted as the average tax rate on a dollar of capital income derived from owning an asset representative of the world's capital stock. The top panel shows global trends and the bottom panels separate HICs and LMICs.

Globally, effective tax rates on labor and capital converged between 1965 and 2018, due to a rise in labor taxation and a drop in capital taxation. The global ETR_L rose from 16% in the mid-1960s to 25% in the late 2010s, while ETR_K fell from 32% to 26%.

The global trends mask heterogeneity by development levels. While labor taxation rose everywhere, the decline in capital taxation only occurred in HICs: the effective capital tax rate fell from 38-39% to 32-33% between the late 1960s and late 2010s, fueled by a large reduction in effective corporate tax rates, which fell from 27% to 19%. In contrast, starting from a low level, ETR_K increased in LMICs, with the rise happening entirely since the beginning of the 1990s. ETR_K started at 10% in the mid-1960s and was at the same level in 1989; in between, there was a rise and decline in the late 1970s, but this temporary change was fully driven by resource-rich countries (Figure 1.3). From 10% in 1989, ETR_K saw a sustained increase over the next two decades which reached 18% in 2018. The rise in capital taxation is partly driven by higher effective taxation in the corporate sector: the effective corporate tax rate rose from 12% to 20% between 1989 and 2018 in LMICs.²⁰

1.4.2 The rise of capital taxation in developing countries

The secular decline in ETR_K in HICs has been documented before (Dyreng et al., 2017; Garcia-Bernardo, Janský, and Tørsløv, 2022), but the rise in ETR_K in LMICs starting at the beginning of the 1990s is novel. We therefore need to establish that this result is robust to the assumptions we used to construct the ETR series.

The ETR series depends on four main methodological decisions: (1) how to assign PIT revenue to capital vs labor; (2) how to allocate mixed income to capital vs labor; (3) balanced vs. unbalanced panel; (4) weights to aggregate countries. Our benchmark series: (1) assigns PIT to capital vs. labor for each country-year using data on PIT exemption thresholds and the tax treatment of dividends relative to wages; (2) allocates a fixed 25% of mixed income to capital; (3) consists of two quasi-balanced panels before and after 1994 (when China, Russia and other former command economies enter the sample); and (4) weighs countries by their share of worldwide factor income in each year. We assess how results change when varying one, several, or all of these choices at the same time.

²⁰Figure A1.2 shows that both corporate tax revenues and corporate profits increased since 1989 but the former outpaced the latter, causing \overline{ETR}_C^K to rise. Corporate profits and tax revenue are the largest components that determine changes in ETR_K . Smaller contributions to ETR_K 's rise come from the decline in mixed-income, and the steady increase in property and wealth taxes, which outpaced income from rents, albeit starting from a very low level (0.3% of NDP in 1989).

Figure 1.4 investigates the robustness of the ETR_K trend in LMICs.²¹ Panel (a) varies the allocation of personal income tax (PIT) revenue. Our benchmark follows a data-driven country-year assignment; instead we consider two simpler scenarios where the share allocated to capital is fixed, at either 0% or 30% (low and high-end scenarios). Due to high PIT exemption thresholds in LMICs, the benchmark country-specific assignment is closer in levels to the 30% than to the 0% scenario. Though the capital share allocated to PIT slightly changes over time (Section 1.3.1), the time-invariant robustness series track the trends in the benchmark series closely. This is because the PIT remains limited in LMICs, such that its split into labor versus capital is of minor consequence.

Panel (b) varies the assignment of factor shares in mixed income. We implement two robustness checks, creating mixed income labor shares that vary at the country-level based on the ILO (2019) method, and at the country-year level based on the observed corporate labor share. Both alternative series are very similar to the benchmark.

Panel (c) quantifies the effect of country entry into the panel. In our benchmark, China, Russia, and other former command economies enter in 1994. In this robustness, we balance the panel by imputing missing observations between 1965 and 1993; we use the observed ETR_K value for that country in 1994 and the trends in ETR_K observed for other LMICs in 1965-1993. The imputation raises ETR_K between 1965 and 1993, because Russia had both a high ETR_K and a high weight when entering the sample in 1994.

Panel (d) aggregates countries using net domestic product (NDP), instead of capital income weights. The NDP weights are either time-varying or fixed in 2010. These alternative weighting procedures suggest a slightly higher increase in ETR_K over time.

Finally, panel (e) plots all 54 combinations of the four methodological choices. The rise in ETR_K in LMICs between 1989 and 2018 is clearly apparent in each of the 54 series. How wide is the range of increases and how does our benchmark series compare? Computing the 1989-2018 change in the 54 series, we obtain a fairly tight range of ETR_K increases, between 6.4ppt and 10.3ppt. Our benchmark is at 8.7ppt, which is close to the mean increase of 9.2ppt; there are larger increases than our benchmark in 43 series and smaller increases in 10.²² Our benchmark series corresponds to an 87% increase in the effective tax rate on capital in LMICs since 1989, reflecting both the strong growth and low baseline.

Comparison with previous studies Pre-existing ETR series mainly cover HICs, which limits the comparison to our sample. In HICs, our benchmark ETR trends are comparable to previous studies, but the levels differ by 16.5% on average (Figure A1.3). This difference is primarily due to methodological assumptions about the allocation of capital to mixed income and PIT (Table A1.2). However, the alternative methodologies from the pre-existing series are contained within the range of ETR trends produced by our robustness checks. In HICs, that range of ETR_K

²¹The robustness for ETR_L in LMICs, and ETR_L and ETR_K in HICs are shown in the [supplementary appendix](#).

²²Setting 1989 as the base year is partly arbitrary, but it allows us to fix a starting level for $ETRs$ immediately before the period of strong trade liberalization in LMICs. If we instead compute the change in ETR_K between 2018 and the lowest point in a given series, the range of changes is 6.8-11.3ppt across the 54 series, with a mean at 9.6ppt and our benchmark at 9.4ppt.

trends is indeed wide (due to the quantitative importance of the PIT; ETR series in [supplementary appendix](#)). However, the range of ETR_K trends in LMICs is comparatively tighter (Figure 1.4); this is because the rise in ETR_K in LMICs is primarily driven by the corporate sector (Figure A1.2), which is not strongly affected by the methodological differences between our study and pre-existing studies.

1.4.3 Where has capital taxation risen?

Figure 1.3 shows the ETR_K series for subsamples of countries. Panel (a) plots ETR_K series for the most populous LMICs: Brazil, China, India and Indonesia. All display a marked ETR_K rise over time. Starting in 1989 (1994 for China) until 2018, ETR_K rose from 7% to 27% in Brazil, 6% to 24% in China, 5% to 12% in India, and 9% to 15% in Indonesia.

China’s weight and fast-rising capital taxation imply that it plays a key role in the aggregate ETR_K trend in LMICs. Panel (b) shows that, when excluding China, the rise in ETR_K is half as large (from 10% to 15%) and a more significant part of the rise occurred earlier in the 1990s. Panel (c) shows that oil-rich countries, measured as deriving more than 7% of GDP in oil in 2018, have been on a completely distinct path. Reflecting the oil commodity shocks, their ETR_K rose in the 1970s but fell in the 1980s, and have stayed flat since. Excluding oil-rich countries yields a more pronounced ETR_K rise, from 9% in 1989 to 21% in 2018, and a flat ETR_K series from 1965 to 1989. If we exclude both China and oil-rich countries, we observe a rise in ETR_K from 9% in 1989 to 17% in 2018, which is similar in magnitude to the benchmark series.

Panel (d) reveals that, among non-oil-rich countries, the ETR_K rise is stronger in large LMICs, defined as the 19 countries with a population above 40 million in 2018. Even when excluding China, the ETR_K of the other 18 most populated countries rose from 9% to 18% between 1989 and 2018; in smaller countries, ETR_K rose from 10 to 14% over the same period. The ETR_K has risen by more than 5 percentage points in 13 of the 19 largest LMICs since 1989, and has only fallen in one country (Russia).²³

In short, the rise in effective capital taxes is more pronounced in larger countries, including China, but is a general pattern in developing countries, except for oil-rich ones.

1.4.4 Suggestive evidence for the role of globalization

We saw that ETR_K fell in HICs but rose in LMICs. Importantly, the rise in LMICs starts in the early 1990s, which coincides with the onset of the “hyper-globalization” period that could a priori have made capital more mobile and harder to tax.²⁴ Instead, could trade globalization have caused ETR_K to rise in LMICs? Here we take a first pass at investigating this question. We create 5-year growth rates within countries in trade and $ETRs$. We plot binned scatters of ETR against trade openness (measured as the share of imports and exports in NDP), after residualizing all variables against year fixed effects. Figure 1.5 depicts these within-country associations, which condition on global time trends. Mirroring the heterogeneity in long-run trends, we

²³The [supplementary appendix](#) shows the individual countries’ ETR_K and ETR_L time series.

²⁴Individual trends in the four largest LMICs (Figure 1.3) also suggest an association between liberalization episodes and an uptick in ETR_K (Brazil in 1988; China in 2001; India in 1991; Indonesia in the mid-1980s).

observe differences by development level in the association between trade and ETR_K : openness is associated with increases in ETR_K in LMICs, but with decreases in ETR_K in HICs.²⁵ In sum, from a global and historical perspective, the correlational evidence suggests that trade may have contributed to the newly documented rise in ETR_K in developing countries.

Naturally, LMICs have undergone significant development since the 1960s and this growth is likely to also have contributed to the long-run rise in ETR_K . In the [supplementary appendix](#), we find that the associations in Figure 1.5 hold in LMICs when controlling for GDP per capita growth. This correlational evidence, combined with the observation that while globalization is a major process in LMICs, its revenue impacts are still not established (Section 1.1), motivate us to investigate trade as a determinant of ETR and study its mechanisms.

1.5 Trade Globalization and Capital Taxation

In this section, we implement two distinct research designs to investigate the impact of trade openness on capital and labor taxation in developing countries.

1.5.1 Event-studies for trade liberalization

Empirical design

In the first design, we implement event studies of trade liberalization policy events in key developing countries. To discern sharp breaks from trends in our outcomes, our selection criteria was to select events that caused large trade barrier reductions and which have been studied in the literature. This led us to select the six events from the review papers by Goldberg and Pavcnik (2007, 2016) (Colombia in 1985, Mexico in 1985, Brazil in 1988, Argentina in 1989, India in 1991, Vietnam in 2001), and add the well-known event of China’s accession to WTO in 2001 (Brandt et al., 2017). These liberalization events led to large reductions in tariffs: from 59% to 15% in Brazil; 80% to 39% in India; and, 48% to 20% in China. We can rely on pre-existing narrative analyses to discuss threats to identification and interpretation of results.²⁶ Appendix A1.2.1 provides more details on our selection criteria and the liberalization events.

For each of the seven treated countries and outcomes, we construct a synthetic control country, as a weighted average over the donor pool of never-treated countries (Abadie, Diamond, and Hainmueller, 2010).²⁷ We match on the level of each outcome in the 10 years prior to the event, while minimizing the mean squared prediction error between the event-country and the synthetic control.²⁸ We plot the average levels of the outcome for treated and synthetic control countries by relative time to the event. Moreover, we estimate the event-study model in 10 years both before and after the events:

²⁵The [supplementary appendix](#) further shows that early globalized LMICs saw trade and ETR_K rise in tandem prior to the 1990s and stagnate thereafter. By contrast, LMICs which participated in the second wave of globalization post-1990 saw a rise in trade and ETR_K in the 1990-2018 period.

²⁶The reductions in trade barriers are sometimes implemented over several years. To be conservative, we focus on the earliest start year for each event as defined in published studies.

²⁷For each country-event, we can include eventually-treated countries in the donor-pool (excluding those with treatment within 5 years of the event); the results, available upon request, are similar.

²⁸The [supplementary appendix](#) lists the countries included in the synthetic control for each event and each outcome.

$$y_{ct} = \sum_{e=-10, e \neq -1}^{10} \beta_e \cdot \mathbf{1}(e=t)_t \cdot D_c + \theta_t + \kappa_c + \pi_{Year(t)} + \epsilon_{ct} \quad (1.4)$$

where we include fixed effects for event-time, θ_t , country κ_c , and calendar year, $\pi_{Year(t)}$ (the latter control for shocks that correlate with events clustered in calendar time). D_c is a dummy equal to one if country c is treated. The coefficient β_e captures the difference between treated and synthetic control countries in event time e , relative to the pre-reform year $e = -1$ (omitted period). Since inference based on small samples is challenging, we plot 95% confidence bounds using the wild bootstrap, clustered at the country event level. In Table A1.3 we estimate the simple difference-in-differences, which captures the average treatment effect in the 10 years post-liberalization, and the imputed treatment effect based on Borusyak, Jaravel, and Spiess (2021), which addresses challenges from two-way fixed effects and heterogeneous event-times.

Event-study results

Figure 1.6 displays the event studies in levels (left-hand panels) and the dynamic regression coefficients (right-hand panels). The top panels show that, as expected, trade openness rises in the years post-event by 10 percentage points, and its trend changes in post-reform years compared to pre-liberalization years.²⁹ The middle panels show that ETR_K followed stable pre-trends and sharply rises post-liberalization, by 4 to 5 percentage points. The bottom panels show ETR_L also rose, but only by 2 percentage points. Despite the small sample size, the dynamic post-treatment coefficients for each period are often significant at the 5% level. The p-values for the joint significance of all post-reform dummies are well below 5%. Table A1.3, Panel A, reports the DiD results, which are marginally more significant when estimated from imputed treatment effects. Panel B shows that results are comparable when we jointly match on all outcomes for each country-event.

The identifying assumption is that there are no changes in confounding determinants of ETR that coincide with the liberalization events. The breaks from stable pre-trends imply that confounding changes would have to sharply coincide with the event onset. Narrative analyses of the timing for each event (Appendix A1.2.1) do not suggest obvious concurrent changes. Moreover, using data from Wacziarg and Wallack (2004), we verify that other cross-border reforms (e.g. capital liberalization) or domestic reforms (e.g. privatization) do not occur in the same year as the trade events.³⁰ However, reforms sometimes occur a few years after: for example, Mexico joined NAFTA and removed capital inflow restrictions, Argentina and Brazil joined MERCOSUR, and India liberalized its FDI rules (Appendix A1.2.1). These reforms occurred several years post-trade liberalization, but $ETRs$ sharply rise in the immediate post-event years. This discussion highlights that the causal interpretation of trade-centered macroeconomic reforms requires caution. A plausible interpretation is that the short-run rise in $ETRs$ with sharp breaks from stable pre-trends reflects the impact of trade reforms, but that the medium-run coefficients also reflect the impacts of additional, mainly cross-border, reforms.

²⁹The absence of a pre-reform dip limits concerns about inter-temporal substitution, although some of the liberalization events may have been predictable, including China's WTO accession.

³⁰Only Mexico had a concurrent domestic reform, and results hold without it: see [supplementary appendix](#).

Our results are based on a (small) sample of liberalization events that satisfied specific criteria. In Appendix A1.2.3, we study the robustness to using very different selection criteria for trade liberalization. Specifically, we re-estimate the event-study using the 68 liberalization events in LMICs from Wacziarg and Welch (2008). We find very similar impacts of trade on *ETR* using this alternative and expanded set of liberalization events.

We further probe the identification and robustness of our results. First, given the limited number of liberalization events, we investigate if the average effects are influenced by one particular event. Removing one treated country at a time, we find the dynamic treatment effects for all subsets of events are similar to the full sample (supplementary appendix). Second, Table A1.3 addresses concerns related to the control group. We find similar results when we remove from the donor pool each liberalizing country's 5 major export and import trading partners (measured in the immediate pre-event years), alleviating concerns of spillovers to countries in the control group.³¹ Results are also comparable when the donor pool excludes countries that have already liberalized (based on *ibid.*), to guard against the concern that the trends in the synthetic control group reflect the longer-run effects of the treatment (liberalization). Finally, to lessen the concern that treated and control countries experience different unobservable shocks, we find similar results when the donor pool for each treated country is restricted to the same region (or to LMICs only).

1.5.2 Regressions with instrumental variables for trade

Empirical design

Our second design employs instrumental variables for trade. One attractive feature is that the IV provides causal estimates under different identifying assumptions than the event-study. We estimate the following model in developing countries:

$$y_{ct} = \mu \cdot trade_{ct} + \Theta \cdot X_{ct} + \pi_c + \pi_t + \epsilon_{ct} \quad (1.5)$$

where y_{ct} is the *ETR* (or another outcome) in country c in year t , $trade_{ct}$ is the share of imports and exports in NDP, and π_c and π_t are country and year fixed effects.³² We cluster ϵ_{ct} at the country level. X_{ct} contains confounding determinants of *ETR*: the exchange rate, gross capital formation, log of population, and capital openness (Chinn and Ito, 2008; Rodrik, 1998). *ETR* time series are sometimes volatile (Figure 1.3), so we winsorize *ETR* at the 5%-95% level by year separately for LMICs and HICs.

OLS estimation of equation (1.5) may be biased due to reverse causality and unobservable confounding factors that correlate with trade. To try to address these issues, we use the two instruments for trade from Egger, Nigai, and Strecker (2019). The first instrument, denoted $Z^{gravity}$, relies on the structure of general equilibrium models of trade. Under the standard gravity model assumptions, it

³¹We also verify that none of the main countries in the synthetic control (supplementary appendix) had external or domestic reforms in the event-year or in the post-event periods (using the data in Wacziarg and Wallack, 2004). Consistent with this, the levels of the outcomes in the synthetic control are relatively stable throughout the event periods. Finally, note that if the spillovers correspond to coordination of policies, this would likely bias our estimation towards finding null effects.

³²We include fixed effects for imputed and interpolated values, as well as for each tax and national account data source (Section 1.3.2), to ensure results are not driven by changes to data quality. Results also hold without imputed values and within each data source (Table A1.4).

uses the average bilateral trade frictions between exporting and importing countries as variation (aggregated to the country-year level). This instrument is valid if the distribution (not the level) of trade costs among individual country-trading pairs is not influenced by $ETRs$ in the import or export country. The second instrument, denoted $Z^{oil-distance}$, interacts time-series variation in global oil prices with a country-specific measure of access to international markets. Access is captured by the variance of distance to the closest maritime port for the three most populated cities. This time-invariant measure captures the internal geography of a country and impacts transportation costs: following a global shock to oil prices, transportation costs will be higher in countries with less concentrated access to ports, leading to a larger drop in imports and exports. This instrument is valid if the interaction between global oil prices and country-specific measures of spatial concentration is uncorrelated with changes in $ETRs$. Conceptually, both instruments capture variation in trade costs driven by economic forces that are plausibly exogenous to $ETRs$ and their determinants (details in [supplementary appendix](#)).

In LMICs, the 1st-stage is stronger in the 2000s and at higher income levels for Z^{oil} , and in earlier periods and at lower income levels for $Z^{gravity}$ ([supplementary appendix](#)). Restricting the analysis to sub-samples where one of the instruments has a strong first-stage introduces bias (Mogstad, Torgovitsky, and Walters, 2021). Instead, we combine the two instruments to estimate a local average treatment effect that is representative of LMICs across income levels and time periods. Table [A1.5](#) shows the 1st-stage.³³

Instrumental variable results

Table [1.1](#) presents the results in LMICs for ETR_K in Panel A, and ETR_L in Panel B.³⁴ In column (1), the OLS uncovers positive, significant associations between trade and both $ETRs$. In column (2), we employ the two instruments. The 1st-stage Kleibergen-Paap F-statistic is 24.59. The IV shows that trade causes an increase in both effective tax rates, and the coefficient for ETR_K (0.151) is three times larger than for ETR_L (0.047). These magnitudes are economically meaningful: moving from the 25th to the 75th percentile of trade openness in LMICs would cause a 8.9 percentage points increase in ETR_K .

The remaining columns of Table [1.1](#) present three sets of robustness checks. In the first set (Columns 3 to 7), we modify the specification. The most notable difference is that the coefficient on ETR_K increases (to 0.211) when we weigh the regression using NDP (Column 4), putting thus more weight on the variation in larger developing countries. The results hardly change when we: use non-winsorized $ETRs$ (Column 3); include controls (Column 5);³⁵ allow oil-rich countries to be on a separate non-parametric time path (Column 6), which addresses the concern that the identifying variation for $Z^{oil-dist}$ is correlated with trends in $ETRs$ specific to oil-rich countries (Figure [1.3](#)); winsorize trade openness (Column 7).

³³Table [A1.6](#) shows the instruments impact imports and exports, and trade in intermediate goods-services (G-S) and final G-S. Thus, our IV-estimates comprehensively reflect the impacts of trade through rises and falls in final and intermediate goods and services that flow both in and out of the country.

³⁴Relative to ETR coverage, the sample size drops by 4.5% due to data-availability of instruments.

³⁵Results also hold when controlling for GDP per capita (not shown).

In the second set of robustness checks, we implement the alternative capital and labor assignments to PIT and mixed-income, described in Section 1.4.2. In our benchmark, the capital share of mixed income is time-invariant, yet trade may cause factor shares to change. In columns (8)-(9), we allow factor shares to respond to trade by implementing the two methods which create country-year varying capital-shares of mixed income: the results are comparable. They also remain similar when we fix the capital share of PIT at 0% (column 10) or at 30% (column 11) in all countries over time. In the third robustness set (columns 12-13), we estimate IVs using each instrument separately. The 1st-stage F-statistic is 45.13 for $Z^{gravity}$ and 10.75 for Z^{oil} . The IV estimates are comparable, though larger when based on Z^{oil} . Leveraging the opposite sign effects of the two instruments on trade, the reduced form results (Table A1.5) suggest that openness effects are symmetric: increased trade increases both ETR_L and ETR_K , while reduced trade decreases both $ETRs$.

Finally, our results are based on an unbalanced panel combining several data sources (Section 1.3.2- 1.3.3). Table A1.4 shows that the results are qualitatively similar within each data-source for taxes (newly digitized government records; OECD; ICTD) and national accounts (UN SNA, 1968, 2008), as well as in both quasi-balanced panels (pre and post-1994) and in a strongly balanced panel (1965-2018).³⁶

Quantifying the role of trade How much of the ETR_K rise in LMICs since 1989 can be accounted for by rising trade? Between 1989 and 2018, the weighted ETR_K in LMICs rose by 8.7ppt (Section 1.4.2) and trade openness by 13.6ppt. The NDP-weighted IV for trade’s impact (col.4 of Table 1.1) is arguably the most comparable, since the ETR_K trends in Section 1.4 are also weighted. Using this estimate would imply that trade openness accounts for 33% of the rise in ETR_K ($0.211 * 0.136 / 0.087 = 0.329$). Considering all estimates in Table 1.1 generates a range of 21-42%.³⁷

1.5.3 Impacts of trade openness on total tax revenues

We find positive effects of trade on capital and labor taxation, but how does trade impact *overall* tax revenues, including indirect taxes? This is a relevant question, as trade-induced tax losses from liberalization remain an important concern for policymakers (Hallaert, 2010). Table 1.2 presents the OLS and the IV estimation of the effect of trade on total taxes (% of NDP), in LMICs, as well as on individual tax revenue streams. Total taxes include direct taxes on capital and labor, as well as indirect taxes (sum of taxes on trade and domestic consumption).³⁸

The trade coefficient for total tax collection is positive and significant in both the OLS and the IV. The IV coefficient (0.101) is economically large: moving from the 25th to the 75th percentile of openness in LMICs would cause a 5.9ppt increase in total taxes (the unweighted average tax/NDP ratio in LMICs is 17.6%). This result is mainly driven by higher corporate income taxes, which account for just over half of the increase in total taxes, and to a lesser extent by social security and personal income taxes.³⁹ Trade has a positive, but statistically insignificant, effect on indirect taxes.

³⁶Variation between coefficients may reflect data quality or 1st-stage and treatment heterogeneity.

³⁷For reasons discussed in 1.5.1, we do not use the event-study estimates for this exercise.

³⁸Long-run trends in taxation by type and development level are in the [supplementary appendix](#).

³⁹CIT grew significantly, as a share of NDP, between 1989 and 2018: see Figure A1.2.

Trade’s impact on total taxes is robust to using NDP-weights; including controls; winsorizing trade; and using each instrument separately (Table A1.7).

We can also study the impact of the trade liberalization events from Section 1.5.1 on total tax revenue. Using the event-study methodology, Figure A1.4 shows that the trade events led to an increase in overall tax collection, with a break from the stable pre-trend.

One limitation is that we do not separately study trade’s impact on tariff revenues versus domestic consumption taxes, as our data does not contain a systematic breakdown between these two indirect taxes. This reflects our initial focus on direct capital and labor taxes, but additional data work would permit a separation of these indirect taxes.⁴⁰

Both the event study and the IV indicate that trade leads to higher overall taxation in LMICs. This finding relates to the literature on the net impact of openness on tax revenues, which finds mixed results due to differences in sample, empirical strategy and definition of openness (Section 1.2);⁴¹ moreover, some of these studies focus on the net impact of trade on indirect taxes and abstract from direct domestic taxes. We contribute by comprehensively studying the total tax impact of openness, based on implementing several identification strategies in the largest sample of developing countries to date.

1.6 Mechanisms

This section investigates mechanisms for trade’s impact on taxes, especially ETR_K .

1.6.1 Outlining the tax capacity mechanism

The *tax capacity* mechanism combines two distinct insights from the trade and public finance literature (Section 1.2): first, trade expands activity in corporate structures and larger firms relative to smaller businesses and self-employment; second, effective taxation increases with firm size. To fix ideas, consider the following decomposition of ETR^K :

$$ETR^K = \int_{i \in C} ETR_i^K f(i) di + \int_{i \in NC} ETR_i^K f(i) di \quad (1.6)$$

$$= \mu_C^K \cdot \overline{ETR}_C^K + (1 - \mu_C^K) \cdot \overline{ETR}_{NC}^K \quad (1.7)$$

This decomposition shows that the effective tax rate on capital ETR^K is composed of two parts.⁴² The first part captures capital taxation within the corporate sector. It is the product of the corporate sector’s share of NDP, μ_C^K , and the average effective tax rate on capital in the corporate sector, \overline{ETR}_C^K . The former is directly measured in national accounts (employee compensation plus corporate profits net of depreciation),

⁴⁰While the sign of openness’ impact on tariff revenue could in principle differ depending on whether the reduction in trade costs is initially due to economic forces (as in the IV) or policy changes (as in the event study), we find positive impacts in both cases on domestic capital and labor taxes, and on total taxes.

⁴¹An important study in this literature, Baunsgaard and Keen (2009) writes in the conclusion: ”it is possible that indirect effects operating through higher levels of openness and income consequent upon trade reform have more than offset the direct loss of revenue identified here.”

⁴²In this section, capital taxation is denoted with a K -superscript to accommodate additional notation.

while the latter is computed as the ratio of corporate income tax revenue to corporate profits. In the second part, \overline{ETR}_{NC}^K measures the effective tax rate on capital in the non-corporate sector; it is multiplied by the non-corporate sector's income share, $1 - \mu_C^K$, which includes mixed income of unincorporated enterprises and household surplus (rents and imputed rents).⁴³

In LMICs, \overline{ETR}_C^K is 50% larger than the overall ETR^K (19.9% versus 13.3%). This stems from both stronger enforcement and higher statutory tax burdens in the corporate sector.⁴⁴ Hence, the expansion of the corporate sector relative to the non-corporate sector (i.e. an increase in μ_C) could increase ETR^K .

The conjecture that trade exerts a tax capacity effect is rooted in the literature on trade and firm size (described in Dix-Carneiro et al., 2021). First, trade can lead to increased market opportunities that disproportionately benefit large exporters (Melitz, 2003). Second, trade can expand the availability of intermediate goods and lower their prices, which could disproportionately benefit initially larger firms (for example due to fixed costs as in Kugler and Verhoogen, 2009). Through these two channels, trade could expand the corporate sector's share of national income (μ_C), as larger firms are more likely to be incorporated. Moreover, by benefiting initially larger firms or leading to firm size growth within the corporate sector, trade could also increase the average effective corporate tax rate, \overline{ETR}_C^K . This effect would be driven by a positive firm size- ETR_i^K gradient, where size is measured as firm revenue. The positive gradient arises because compliance and enforcement increase with size.⁴⁵ It also arises because the tax code in LMICs often leads to higher statutory tax burdens for larger firms (R. Kumar and James, 2022): using administrative tax data, Bachas et al. (2023) find a positive association between firm size and the statutory effective tax rate for corporate firms in 15 LMICs.⁴⁶

1.6.2 Results on mechanisms: Tax capacity and race to the bottom

We investigate mechanisms relating trade to ETR , focusing on the tax capacity and 'race to the bottom' channels. In the race to bottom, international tax competition leads governments to reduce statutory corporate tax rates, which would reduce

⁴³ \overline{ETR}_{NC}^K is measured as the ratio of tax revenue from property and wealth, self-employment, and the PIT assigned to capital, over capital mixed-income and the surplus of the household sector. It is thus composed of a mix of variables, which are arguably not as well measured as those from the corporate sector.

⁴⁴The ability to levy higher tax rates is endogenous to enforcement (Bergeron, Tourek, and Weigel, 2024). Our notion of tax capacity is that these co-determined forces jointly contribute to effective taxation.

⁴⁵See studies cited in Section 1.2. For example, Best, Shah, and Waseem (2021) uncover a negative size-evasion gradient using randomized audit data on firms in Pakistan, finding also that firm-size is the most significant predictor of evasion. Models of tax compliance provide micro-foundations for the negative size-evasion gradient (including Kleven, Kreiner, and Saez, 2016; Kopczuk and Slemrod, 2006).

⁴⁶The gradient is positive everywhere except at the very top of the size-distribution, where it becomes negative. The gradient is driven by preferential tax treatments that increase with firm size and with characteristics that correlate with size such as total profits. The gradient can also reflect avoidance behavior, if larger firms are on average less able to take actions that reduce their legal tax liability.

\overline{ETR}_C^K (Section 1.2). We study both mechanisms in LMICs with the empirical strategies of Section 1.5.

Table 1.3 shows the OLS (Panel A) and the IV (Panel B) from equation 1.5. Consistent with race-to-bottom, column (1) shows that trade causes a decrease in the statutory CIT rate (significant at 10%).⁴⁷ The CIT rate is an imperfect proxy of firms' tax incentives as it ignores the tax base (Abbas and Klemm, 2013), but it can be measured in our full sample.

In line with the tax capacity mechanism, trade raises the corporate share of domestic output (μ_C), and reduces mixed income by an equivalent magnitude.⁴⁸ This is consistent with the conjecture that trade disproportionately benefits larger firms, which are more likely to be incorporated. Trade also raises \overline{ETR}_C^K (column 6), consistent with the trade-induced corporate output accruing to firms whose ETR_C^K -size gradient is positive.

How is the additional income of the corporate sector allocated between capital and labor? Columns (4)-(5) show that the corporate sector rise is entirely driven by higher corporate profits, while the change in employee compensation growth is small and statistically insignificant.⁴⁹ This, in turn, causes trade to expand the capital share, both of national income and of the corporate sector (columns 7-8).⁵⁰

The mechanism IV-results are robust to several checks (Table A1.7): using NDP weights; including controls; winsorizing the trade variable; and, estimating IVs separately based on each instrument. The CIT rate result remains less robust than the tax capacity results.

Figure A1.4 studies the same mechanism-outcomes but using the event-study design (Section 1.5.1). The trade liberalization events led to a decrease in the CIT rate and raised both corporate income (μ_C) and the effective corporate tax rate (\overline{ETR}_C^K). Some individual event-time coefficients are less precisely estimated, but the post-event dummies are jointly statistically significant for all outcomes. Although they are based on different identifying variation in trade, the event-study and IV results are therefore both consistent with the existence of the tax-capacity and race-to-bottom mechanisms in developing countries.

⁴⁷The outcome is the first-differenced tax rate (Romer & Romer, 2010). Table A1.7 shows results with the level of the CIT rate. We combine data from Végh and Vuletin (2015), Egger, Nigai, and Strecker (2019), Tax Foundation ([link](#)) and country-specific sources. A next step could be to study trade's impact on the more detailed statutory measures (Section 1.2). The downward trend in CIT rates in LMICs ([supplementary appendix](#)) is related to, but does not fully capture, changes over time in the detailed statutory measures.

⁴⁸The quality of data-sources used by national statistics offices can affect the measurement of mixed income in LMICs, but we find no impact of trade on countries' statistical capacity ([World Bank link](#)).

⁴⁹There is also a null effect of trade on households' operating surplus OS_{HH} (result not shown).

⁵⁰This could occur due to an increase in markups. De Loecker and Eeckhout (2021) find that markups have risen in most regions over the past 40 years. De Loecker et al. (2016) and Goldberg (2023) study the impact of trade on markups. Gupta (2023) and Atkin et al. (2015) find that markups increase with firm size, respectively in India and Pakistan. The rise in corporate profits and limited change in employee compensation may also arise if trade raises firms' labor market power (Felix, 2022). Finally, it may arise if trade benefits more capital-intensive production in developing countries, including through a reduction in CIT rates (Kaymak and Schott, 2023).

1.6.3 Firm-level investigation of tax capacity mechanism

The tax capacity mechanism is based on a firm level channel, combining a positive impact of trade on firm size with a positive firm size- ETR^K gradient. While the macro-results on μ_C and \overline{ETR}_C^K in the previous subsection are consistent with it, in this subsection we directly investigate the tax capacity mechanism at the firm level.

We conduct the analysis in Rwanda between 2015 and 2017, where we leverage multiple administrative datasets to observe each formal Rwandan firm's exposure to trade and domestic tax payments. To our knowledge, there is limited firm level evidence in LMICs on how trade impacts a firm's domestic effective tax rate. Rwanda is an interesting setting as the corporate sector, starting from a comparatively low output share, has grown significantly since the 1990s, in tandem with a rise in trade openness and tax revenues.

We use corporate income tax returns to measure each firm's effective tax rate ETR_i^K as the ratio of corporate taxes paid divided by reported net profit. Net profit is revenue minus material, labor, operational, depreciation and financial costs. In Rwanda, this firm-level ETR_i^K varies due to firm characteristics (including revenue, our proxy for size), reduced rates and exemptions (Mascagni, Monkam, and Nell, 2016). This ETR_i^K can also vary due to tax avoidance but, since the denominator is based on tax returns, it will not capture outright evasion.⁵¹ The corporate ETR_i^K in Rwanda is everywhere positively associated with size (proxied by firm revenue), apart from in the top percentile (Bachas et al., 2023). Outside of the very top, an increase in firm i 's size may cause ETR_i^K to rise.

We merge the CIT returns with customs data to record firms' direct exposure to trade. Following recent work (reviewed in Atkin and Khandelwal, 2020; Bernard and Moxnes, 2018), we measure a firm's total exposure to trade by also accounting for the firm's indirect exposure via its linkages to domestic suppliers that use traded goods in their production.⁵² We merge administrative data that record transaction linkages between formal firms (details on data and sample in Appendix A1.3.1). To measure a firm's total trade exposure in a network setting, we follow the methodology in Dhyne et al. (2021) that uses similar datasets to measure Belgian firms' exposure to trade. Specifically, we define firm i 's total foreign input share as the share of inputs that it directly imports (s_{Fi}), plus the share of inputs that it buys from its domestic suppliers l (s_{li}), multiplied by the total import shares of those firms:

$$s_i^{Total} = s_{Fi} + \sum_{l \in V_i} s_{li} \cdot [s_{Fl} + \sum_{r \in V_l} s_{rl} \cdot (s_{Fr} + \dots)] \quad (1.8)$$

where V_i is the set of domestic suppliers of firm i , and V_l is the set of domestic suppliers of firm l . The denominator of the input shares is the sum of imports and purchases from other firms. We limit the recursive calculation in (1.8) to inputs from a firm's immediate suppliers l and the suppliers to their suppliers r (adding more

⁵¹For this reason, \overline{ETR}_C^K measured in national accounts differs from the (appropriately weighted) corporate ETR_i^K measured in tax returns. They also differ because of conceptual differences in the measurement of profits: see the [supplementary appendix](#) for a detailed discussion.

⁵²Recent papers study domestic linkages in LMICs and their role in propagating trade shocks (including Almunia et al., 2023b; Fieler, Eslava, and Xu, 2018; Javorcik, 2004).

levels only marginally raises s_i^{Total}).⁵³ Inspecting s_i^{Total} and s_{Fi} reveals that while just under 30% of Rwandan formal firms import directly, 93% rely on trade directly or indirectly through suppliers which use foreign inputs in their production. Most firms are therefore dependent on foreign trade, but only a limited number show that dependence through the direct foreign inputs observed in customs data. The median total foreign input share is 48%.

We estimate regressions in the sample of corporate firms of the form:

$$ETR_{it}^K = \mu \cdot s_{it}^{Total} + \Theta \cdot X_{it} + \pi_t + \pi_i + \epsilon_{it} \quad (1.9)$$

where ETR_{it}^K and s_{it}^{Total} are the corporate effective tax rate and total trade exposure of firm i in year t , and π_t and π_i are year and firm fixed effects. X_{it} includes number of employees and number of clients and suppliers, and ϵ_{it} is clustered at the firm level.

In Table 1.4, the OLS estimation of (1.9) shows that a within-firm increase in trade exposure is associated with a higher corporate effective tax rate. This result holds with only year fixed effects π_t (column 1); with industry-geography fixed effects (column 2); with firm controls X_{it} (column 3); with firm fixed effects π_i (column 4).

In Table 1.4, column (5), we implement an IV that generates firm-level variation in trade exposure using the shift-share design from Hummels et al. (2014). The identifying variation is trade shocks from changes in the world export supply of specific country-product combinations in which a Rwandan firm had a previous import relationship. Specifically, the direct import trade shock for firm i in year t is:

$$\log M_{it}^D = \log \sum_{a,c} s_{ic,t-1}^{a,M} \cdot WES_{a,c,t} \quad (1.10)$$

where $s_{ic,t-1}^{a,M}$ is the share of imports of firm i in year $t-1$ that falls on product a from country c , and $WES_{a,c,t}$ is the world export supply (excluding sales to Rwanda) of country c for product a . Product a is measured at the detailed six-digit HS level. Rwandan firms import over 3,510 distinct products from 174 different countries of origin.

The shocks to Rwandan firms' trading environment are time-varying and specific to each partner-country \times product being traded. They capture transportation costs and worldwide shocks to export supply for the relevant country \times product, and contain granular variation across products and countries. The identification strategy rests on the joint hypotheses that these shocks are plausibly exogenous to Rwandan firms' trading environment and that they create varied impacts across firms because Rwandan importers have few imported inputs in common. Indeed, the customs data shows that the median number of unique importing firms in a given HS6 product \times country and time period is 1; the 95th percentile is 3. Hence, if only one Rwandan firm imports metal cored wires from Turkey, an idiosyncratic shock to Turkey's global export supply of those wires will affect just one firm in Rwanda. Note also that, to construct the trade shocks, we rely on prior information about importers' sourcing patterns, which removes concerns over contemporaneous shocks affecting both the choice of imported goods and firm outcomes.

⁵³We focus on firms' exposure to imports through their supplier network; we find qualitatively similar results when we study firms' exposure to exports through their client network (results available).

We build the trade shocks for all firms. In turn, the 1st-stage instruments are the firm’s own trade shocks, as well as the trade shocks to its suppliers and to the suppliers of its suppliers. Specifically, the 1st-stage regression is:

$$s_{it}^{Total} = \beta_1 \cdot \log M_{it}^D + \beta_2 \cdot \log M_{it}^S + \beta_3 \cdot \log M_{it}^{SS} + \kappa_t + \kappa_i + \epsilon_{it} \quad (1.11)$$

where $\log M_{it}^D$, $\log M_{it}^S$, and $\log M_{it}^{SS}$ are the trade shocks to firm i , to firm i ’s suppliers, and to the suppliers of firm i ’s suppliers. We construct weighted averages of trade shocks in the supplier network using the recursive formulation in (1.8) (details in Appendix A1.3.1).

We find that both direct trade shocks to a firm’s own imports and indirect shocks to a firm’s network of suppliers cause significant changes to the firm’s total exposure s_{it}^{Total} , generating a strong 1st-stage (Kleibergen-Paap F-statistic of 18.17).

The IV specification shows that trade causes an increase in the individual firm’s effective tax rate on capital (column 5). In Panel B, the IV reveals that trade causes an increase in firm size (proxied by revenue). Panel C shows a positive OLS association between firm size and ETR_i^K (we cannot use the IV in this panel due to the exclusion restriction).

In Appendix A1.3.1, we find that the main results are robust to controlling for trade shocks to firm i ’s potential suppliers (firms that operate in the same industry and geographical area as i ’s current suppliers but are not currently supplying to i) and horizontal suppliers (firms that are suppliers to firm i ’s current clients). These results provide additional support for the exogeneity assumption.⁵⁴

Though the analysis in Rwanda is based within a single country over a limited time range, it supplements the macro-level results in two ways. First, it provides firm-level identified evidence that trade exerts a positive impact on effective corporate taxation in a developing country, which complements the country-level results in LMICs. Second, by showing that trade increases firm size and that size is positively associated with ETR^K , it supports the tax capacity mechanism interpretation that trade’s impact on ETR^K is mediated by a positive size- ETR^K gradient.

Discussion: Links to trade-formality literature At the firm, sector and country level, we find positive effects of trade on outcomes related to formalization. Recent studies focused on the number of formal versus informal firms or formal versus informal workers, and found mixed evidence that trade increases formality by these measures (reviews in Engel and Kokas, 2021; Ulyssea, 2020).⁵⁵ One way to reconcile our results with these studies is to note that our focus is on the share of output produced in larger and formal firms: output expansion in these firms may occur without changes to the number of formal or informal firms, and does not imply an increase in the number of formal workers, since informal workers may work in formal firms and contribute to their output (Ulyssea, 2018). In 1.6.4, we also show that openness’ impact on our formal-outcomes depends on the nature of the trade shock, consistent with recent theoretical work in trade (Dix-Carneiro et al., 2021).

⁵⁴In an extension, we find that increased *output* exposure to imports through the client network has positive effects on ETR^K , though this average effect could mask heterogeneity across firms.

⁵⁵Bosch, Goñi-Pacchioni, and Maloney (2012), Cruces, Porto, and Viollaz (2018), Dix-Carneiro and Kovak (2019), and Goldberg and Pavcnik (2003)

1.6.4 Sources of heterogeneity in trade’s pro-tax impacts

We return to the country-level IV (equation 1.5) to study sources of heterogeneity in trade’s pro-tax impacts on the tax capacity mechanism and ETR .

Heterogeneity: Domestic enforcement reforms Over our sample period, LMICs have implemented tax enforcement policies. A challenge for the mechanism interpretation is that trade, potentially due to revenue concerns, may have prompted governments to implement these policies that increase ETR^K . To investigate this, we measure the year of adoption (if any) in LMICs of four policies that increase domestic tax enforcement: (i) large taxpayer unit; (ii) organizational integration of customs and domestic tax authorities; (iii) VAT; (iv) international accounting standards (IAS).⁵⁶ We estimate heterogeneous IV effects by including an interaction term between trade and the policy adoption variable in (1.5).⁵⁷ Table A1.8 shows a positive effect of trade on ETR^K without these policies, though the effect is larger following their adoption. Trade has a similar impact on the corporate income-share (μ_C) with and without the enforcement policies, but trade’s positive impact on \overline{ETR}_C^K is significantly amplified when enforcement policies are in place.⁵⁸ That is, the trade-induced expansion of the corporate sector seems to occur regardless of enforcement policies, but the extent to which the additional corporate output translates into higher effective corporate taxation is reinforced when such policies have been enacted.⁵⁹

Governments in LMICs may have sought to raise domestic revenue, possibly in response to openness, through other channels apart from these specific enforcement policies. We investigate this in Table A1.9, finding that trade’s positive impact on the tax capacity mechanism and ETR^K hold outside of periods of significant revenue loss, when defined in various ways including the episodes of trade revenue loss in Cagé and Gadenne (2018). Thus, trade’s pro-tax impacts appear to be broadly present in the globalization process in LMICs, and do not hinge on government’s revenue need or enforcement investments.

Heterogeneity: Nature of trade shock Trade theories highlight that the impacts of trade on formality-related outcomes depend on the nature of the trade shock. In Appendix A1.3.2, we use both instruments and equation (1.5) in LMICs to investigate if the ETR and mechanism impacts differ along two dimensions (Dix-Carneiro et al., 2021): imports versus exports; and, trade in intermediate versus final goods and services (G-S). We find that *exports* increase ETR^K and the corporate income-share (μ_C), while *imports* decrease both outcomes. These results are consistent with ‘Melitz-type’ demand effects, whereby increased exports represent a ‘pure’ positive demand shock for export-oriented firms, while increased imports may constitute a

⁵⁶The enforcement focus on large firms increases collection (Almunia and Lopez-Rodriguez, 2018; Basri et al., 2021). The customs-tax unification improves domestic audit capacity (IMF, 2022). The VAT creates information trails (Almunia et al., 2023a; Waseem, 2020). IAS deepen accounting requirements for tax reporting (Barth, Landsman, and Lang, 2008).

⁵⁷The timing of adoption for each reform is endogenous; however, our focus is on the trade coefficients with and without these reforms in place, which are identified (Bun and Harrison, 2019).

⁵⁸Only the VAT was adopted in all liberalizing countries by the time of the events studied in Section 1.5.1.

⁵⁹Intuitively, the enforcement policies all disproportionately raise enforcement on larger firms, thereby further increasing the slope of the ETR^K -size gradient inside the corporate sector. Whether these enforcement policies are themselves driven by globalization is a topic for future research.

negative demand shock for domestic firms, disproportionately affecting larger ones. In additional IV regressions, trade in *intermediate G-S* increases ETR^K and μ_C , while trade in *final G-S* decreases both outcomes.⁶⁰ Results are similar for \overline{ETR}_C^K . These results are consistent with the increased availability of intermediate goods benefiting larger firms; by contrast, the increased availability of final goods may constitute a negative domestic demand shock, particularly for larger firms. These results suggest trade's pro-tax impacts depend on the nature of the trade shock.

Heterogeneity: Developing vs developed countries We investigate if trade's impacts on mechanisms and ETR differ across development levels, by expanding our sample to include HICs. We expect that the tax capacity mechanism is less likely to operate in HICs, where enforcement constraints on effective taxation are less binding and the corporate sector's size has been stable since the 1970s (Figure 1.1). On the other hand, the race-to-bottom is likely to be active in HICs, given previous research (Section 1.2). Table A1.10 reports heterogeneous IV effects by augmenting (1.5) with an interaction between trade and a dummy for high-income countries.⁶¹ Trade only raises ETR^K in LMICs, but raises ETR^L everywhere. The negative race-to-bottom effect on the CIT rate is much stronger in HICs than in LMICs. The positive impact of trade on tax capacity outcomes (μ_C , \overline{ETR}_C^K) is limited to LMICs, with null effects in HICs.⁶² These results suggest countervailing mechanisms that differ by development level, through which trade may have contributed to the diverging trends in ETR^K between HICs and LMICs documented in Figure 1.2.

We study additional country characteristics in the [supplementary appendix](#). We find that trade's negative impact on the CIT rate is larger in countries that are smaller and with fewer capital restrictions – two settings where capital flight concerns are more pronounced (Hines, 2006). Mirroring this result, trade's positive impact on ETR^K occurs in larger countries and with more capital restrictions. The tax capacity and race-to-bottom mechanisms therefore appear to occur simultaneously: countries with larger markets and lower capital mobility reap more of the tax-capacity benefits of trade.

Extension: Capital openness We focused on trade openness but another relevant dimension of globalization is capital openness (Ilzetzi, Reinhart, and Rogoff, 2019; Van Patten, 2022). Due to differences in reporting requirements, data on capital openness is not as available and comparable as trade data, and finding credible exogenous variation for capital openness is challenging. Notwithstanding, we try to investigate the impacts of capital openness in Appendix A1.4. We rely on capital inflow liberalization events for 25 developing countries from Chari, Henry, and Sasson (2012), which capture the first time that foreign investment in the domestic stock market is allowed. Employing the event-study design of Section 1.5.1, we find that capital liberalization events raise capital openness and positively impact ETR^K and the tax capacity mechanism (μ_C , \overline{ETR}_C^K). The pro-tax impacts of globalization in LMICs may be robust to using capital instead of trade openness.

⁶⁰Which suggests that imports of intermediate (final) G-S increases (decreases) ETR_K and μ_C .

⁶¹We note these results should be interpreted with caution, given the econometric challenges of estimating IV effects with multiple endogenous regressors (Andrews, Stock, and Sun, 2019).

⁶²The IV-coefficients for developing countries differ qualitatively between Table A1.10 and Tables 1.1-1.3. This is because the two instruments' strength changes in the 1st-stage regression (Table A1.5).

1.7 Conclusion

This paper provides evidence on long-run trends in capital taxation and causal effects of globalization. Based on a new macro-historical database, we document that effective capital tax rates have increased in developing countries in the post-1990 era of hyper-globalization. By expanding the share of economic activity in incorporated and larger firms, we find that trade improves the effective collection of taxes, particularly corporate income taxes. We provide evidence on this tax capacity effect across multiple research designs and at the country, corporate sector and firm-level. Despite a simultaneous negative effect on corporate statutory tax rates induced by international tax competition, the positive tax capacity effect is sufficiently large that trade increases the effective tax rate on capital and overall government revenues (% of GDP) in developing countries.

Due to limited data, the revenue consequences of globalization in developing countries had not been systematically investigated and policy concerns over revenue losses have persisted in a context of uncertainty surrounding the future of globalization (Goldberg and Reed, 2023). We find that globalization has pro-tax impacts that have supported the effective taxation of capital and overall revenue collection in many countries.

Our results show that openness increased the share of market income going to corporations, profits, and capital. Simultaneously, trade's pro-tax impacts mean that developing countries raised more taxes from capital. As a result, openness is likely to have widened pre-tax income inequality, but its effect on post-tax income inequality is more nuanced. We adopted a macro focus, but a next step could be to combine the *ETRs* with individual-level estimates of the progressivity of capital (and labor) taxes. This would allow a comparison of the distributional effects of globalization on pre versus post-tax income, raising empirical questions for future research (Goldberg, 2023; Pavcnik, 2017).

Tables

Table 1.1 – Trade Impacts on Effective Taxation of Capital and Labor in Developing Countries

| | Benchmark | | Robustness: Specification and covariates | | | | | Robustness: $K - L$ assignment to taxes and factor shares | | | | Robustness: Individual instruments | |
|---|---------------------|---------------------|--|-------------------|-------------------------------|--|---------------------|---|----------------------------------|-----------------------------|------------------------------|------------------------------------|------------------------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
| Panel A: ETR_K | | | | | | | | | | | | | |
| Trade | 0.048*** (0.013) | 0.151*** (0.047) | 0.135*** (0.037) | 0.211* (0.121) | 0.141** (0.055) | 0.136*** (0.044) | 0.159*** (0.046) | 0.161*** (0.052) | 0.140*** (0.045) | 0.147*** (0.045) | 0.158*** (0.047) | 0.148*** (0.047) | 0.277*** (0.095) |
| Panel B: ETR_L | | | | | | | | | | | | | |
| Trade | 0.009* (0.005) | 0.047*** (0.016) | 0.052*** (0.016) | 0.059 (0.043) | 0.037* (0.019) | 0.048*** (0.016) | 0.049*** (0.016) | 0.048*** (0.016) | 0.051*** (0.017) | 0.049*** (0.016) | 0.042*** (0.015) | 0.044*** (0.016) | 0.214*** (0.067) |
| Specification | OLS | IV | IV | IV | IV | IV | IV | IV | IV | IV | IV | IV | IV |
| 1 st stage Kleibergen-Paap F-statistic | | 24.59 | 24.59 | 34.51 | 14.14 | 23.24 | 34.84 | 24.59 | 24.59 | 24.59 | 24.59 | 45.13 | 10.75 |
| Modifications to IV in col. (2) | | | ETR winsorize | NDP weights | Include country-year controls | Include 1(oil-rich)*year fixed effects | Winsorize trade | Assign based on ILO (2019) | Assign based on corp. K -share | Assign 0% of PIT to capital | Assign 30% of PIT to capital | Only use $Z_{gravity}$ instrument | Only use $Z_{Oil-Dist}$ instrument |
| N | 4916 | 4916 | 4916 | 4916 | 3938 | 4916 | 4916 | 4916 | 4916 | 4916 | 4916 | 4916 | 4916 |

Notes: This table presents results from estimating the effect of trade on effective tax rates in developing countries. Developing countries are low and middle-income countries according to the World Bank income classification in 2018. The outcome is the effective tax rate on capital, ETR_K , in Panel A and the effective tax rate on labor, ETR_L , in Panel B. Trade is measured as the sum of exports and imports divided by net domestic product (NDP). Column (1) presents the OLS results from estimating equation (1.5). All other columns use IV; at the bottom of each column, we report the 1st-stage Kleibergen-Paap F-statistic. The benchmark IV specification is in column (2), with the corresponding 1st-stage regression reported in Table A1.5. The remaining columns modify the benchmark specification of column (2). In column (3), the outcome is non-winsorized, while in column (4) we include country-year NDP weights. In column (5), we include the country-year controls described in Section 1.5.2. In column (6), we include interactive fixed effects between a dummy for oil-rich countries and year dummies. Oil-rich countries derive more than 7% of GDP from oil in 2018. In column (7), we use the trade variable which is winsorized at the 5%-95% percentile on a yearly basis. In columns (8)-(9), we modify the assignment rule for mixed income's capital factor share, respectively by using the ILO (*ibid.*) method and by assigning the capital share in the corporate sector. In columns (10)-(11), we assign respectively 0% and 30% of personal income taxes (PIT) to capital taxes. In columns (12)-(13), we estimate the IV using the individual instruments $Z_{gravity}$ and $Z_{oil-distance}$, respectively. For more details, see Section 1.5.2. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. Standard errors in parentheses are clustered at the country level.

Table 1.2 – Trade Impacts on Types of Taxes (% of NDP) in Developing Countries

| | Total taxes (1) | CIT (2) | Property and Wealth (3) | PIT (4) | Social Security (5) | Indirect (6) |
|--|-----------------------|---------------------|-------------------------------|--------------------|---------------------------|------------------|
| Panel A: OLS | | | | | | |
| Trade | 0.036*** (0.011) | 0.021*** (0.003) | -0.001 (0.001) | 0.003* (0.002) | 0.001 (0.001) | 0.010 (0.006) |
| Panel B: IV | | | | | | |
| Trade | 0.101*** (0.033) | 0.053*** (0.014) | 0.004 (0.003) | 0.011** (0.005) | 0.013** (0.006) | 0.018 (0.023) |
| 1 st -stage Kleibergen- Paap F-statistic | 24.59 | 24.59 | 24.59 | 24.59 | 24.59 | 24.59 |
| N | 4916 | 4916 | 4916 | 4916 | 4916 | 4916 |

Notes: This table shows the impacts of trade on collection of types of taxes, expressed as a percent of net domestic product (NDP), in developing countries. OLS results are in Panel A and IV results are in Panel B. Developing countries are low and middle-income countries according to the World Bank income classification in 2018. Trade is measured as the sum of exports and imports divided by NDP. All regressions in Panel B are based on the IV model described in Section 1.5.2. At the bottom of each column, we report the 1st-stage Kleibergen-Paap F-statistic. The corresponding 1st-stage regression is reported in Table A1.5. The outcome differs across columns: Column (1) is total taxes, which is the sum of direct taxes on capital and labor and indirect taxes on trade and domestic consumption; column (2) is corporate income taxes (CIT); column (3) is taxes on property, wealth and inheritance; column (4) is personal income taxes (PIT); column (5) is social security and payroll; column (6) is indirect taxes, which combines trade taxes and domestic consumption taxes. For more details on these types of taxes, see Table A1.1 and Appendix A1.1.1. For more details on the IV, see Section 1.5.2. * p<0.10 ** p<0.05 *** p<0.01. Standard errors in parentheses are clustered at the country level.

Table 1.3 – Trade Impacts on Mechanism Outcomes in Developing Countries

| | First-diff. CIT rate (1) | National income components | | | | Factor shares | | |
|---|--------------------------------|----------------------------------|----------------------------------|-----------------------------|---------------------------------|-----------------------------|--------------------------------------|--------------------------------------|
| | | Corporate totl. income (2) | Household mixed income (3) | Corporate profits (4) | Employee compensation (5) | Corporate ETR_K (6) | Capital share natl. income (7) | Capital share corp. sector (8) |
| Panel A: OLS | | | | | | | | |
| Trade | -0.003*** (0.001) | 0.038*** (0.013) | -0.016 (0.011) | 0.026*** (0.009) | 0.006 (0.011) | 0.074*** (0.019) | 0.020** (0.008) | 0.029** (0.012) |
| Panel B: IV | | | | | | | | |
| Trade | -0.012* (0.007) | 0.179*** (0.044) | -0.184*** (0.041) | 0.176*** (0.035) | -0.014 (0.036) | 0.163** (0.075) | 0.150*** (0.034) | 0.192*** (0.050) |
| 1 st stage Kleibergen- Paap F-Statistic | 24.59 | 24.59 | 24.59 | 24.59 | 24.59 | 24.59 | 24.59 | 24.59 |
| N | 4916 | 4916 | 4916 | 4916 | 4916 | 4916 | 4916 | 4916 |

Notes: This table presents results from estimating the effects of trade on mechanism outcomes in developing countries. Developing countries are low and middle-income countries according to the World Bank income classification in 2018. Trade is measured as the sum of exports and imports divided by net domestic product (NDP). Panel A presents OLS results and Panel B presents the IV results, based on the instruments described in Section 1.5.2. At the bottom of each column in Panel B, we report the 1st-stage Kleibergen-Paap F-statistic. Across the columns, the outcome differs: column (1) is the first-differenced statutory corporate income tax (CIT) rate; column (2) is the corporate income share of net domestic product, where corporate income is the sum of corporate profits and corporate employee compensation; column (3) is the mixed income share of net domestic product; column (4) is the corporate profit share of net domestic product; column (5) is the employee compensation share of net domestic product; column (6) is the average effective tax rate on corporate profits; column (7) is the capital share of net domestic product; column (8) is the capital share of corporate income. For sake of space, we omit showing the insignificant impact of trade on OS_{HH} , the remaining component of national income. For more details on the outcomes, see Section 1.3.1 and Section 1.6.2. For more details on the instrumental variables, see Section 1.5.2. * p<0.10 ** p<0.05 *** p<0.01. Standard errors in parentheses are clustered at the country level.

Table 1.4 – Firm-Level Regressions in Rwanda: ETR_K , Trade and Size

| | (1) | (2) | (3) | (4) | (5) |
|--|---------------------|---------------------|---------------------|---------------------|---------------------|
| Panel A outcome: ETR_K | | | | | |
| S^{Total} | 0.100*** (0.021) | 0.087*** (0.017) | 0.075*** (0.017) | 0.025* (0.014) | 0.133** (0.060) |
| Panel B outcome: Log revenue | | | | | |
| S^{Total} | 1.362*** (0.466) | 1.351** (0.542) | 1.078** (0.475) | 0.202* (0.107) | 1.444*** (0.233) |
| Panel C outcome: ETR_K | | | | | |
| Log revenue | 0.040* (0.023) | 0.092*** (0.029) | 0.077** (0.027) | 0.029*** (0.003) | - - |
| Estimation | OLS | OLS | OLS | OLS | IV |
| 1 st -stage Kleibergen-Paap F-statistic | | | | | 18.17 |
| Year FEs | Y | Y | Y | Y | Y |
| Industry-Geography FEs | | Y | Y | | |
| Firm controls | | | Y | Y | Y |
| Firm FEs | | | | Y | Y |
| N | 18478 | 18478 | 18478 | 18478 | 18478 |

Notes: This table presents firm-level regression results from corporate firms in Rwanda between 2015 and 2017. The outcome differs across panels: Panels A) and C) is the effective tax rate on corporate profits, ETR_i^K ; Panel B) is log of annual revenue. In Panels A) and B), the reported regression coefficient is for total foreign input share, S^{Total} ; in Panel C), it is for log annual revenue. Columns (1)-(4) present OLS results from estimating variations of equation (1.9): Column (1) includes year fixed effects; column (2) adds industry-geography fixed effects; column (3) adds firm-year controls (number of employees and total number of clients and suppliers); column (4) adds firm fixed effects. Column (5) is the IV estimation where the total foreign input share (S^{Total}) is instrumented with trade-shocks to firms and their supplier network based on the shift-share design of Hummels et al. (2014). The instruments are described in detail in Section 1.6.3 and Appendix A1.3.1. In column (5), we also report the 1st-stage Kleibergen-Paap F-statistic from estimating the 1st-stage in equation (1.11). Details on the sample are provided in Appendix A1.3.1. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. Standard errors in parentheses are clustered at the industry-geography level in columns (1)-(3), and at the firm-level in columns (4)-(5) (results are robust to clustering at firm-level in all columns).

Figures

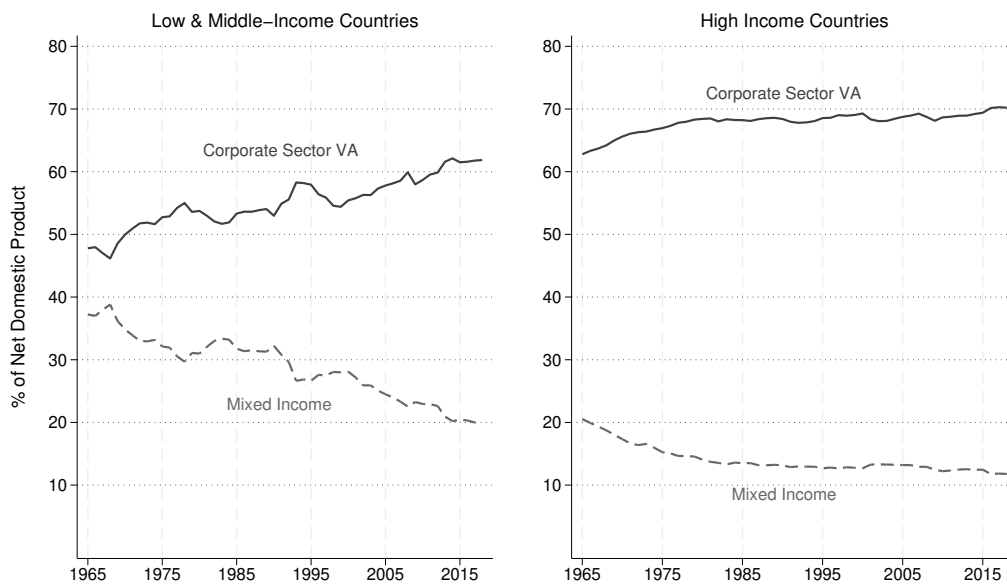


Figure 1.1 – Corporate Sector Income and Mixed Income (1965-2018)

Notes: These panels plot the time series of corporate sector income and of mixed income between 1965 and 2018 by level of development, from national accounts statistics. Both outcomes are expressed as a percent of net domestic product and weighted by countries' net domestic product in constant 2010 USD. Corporate income is the sum of corporate profits and corporate employee compensation. Mixed income accounts for income from self-employed and unincorporated businesses. The left panel show the results for low and middle-income countries (N=117), and the right panel show the results for high income countries (N=37), based on the World Bank income classification in 2018.

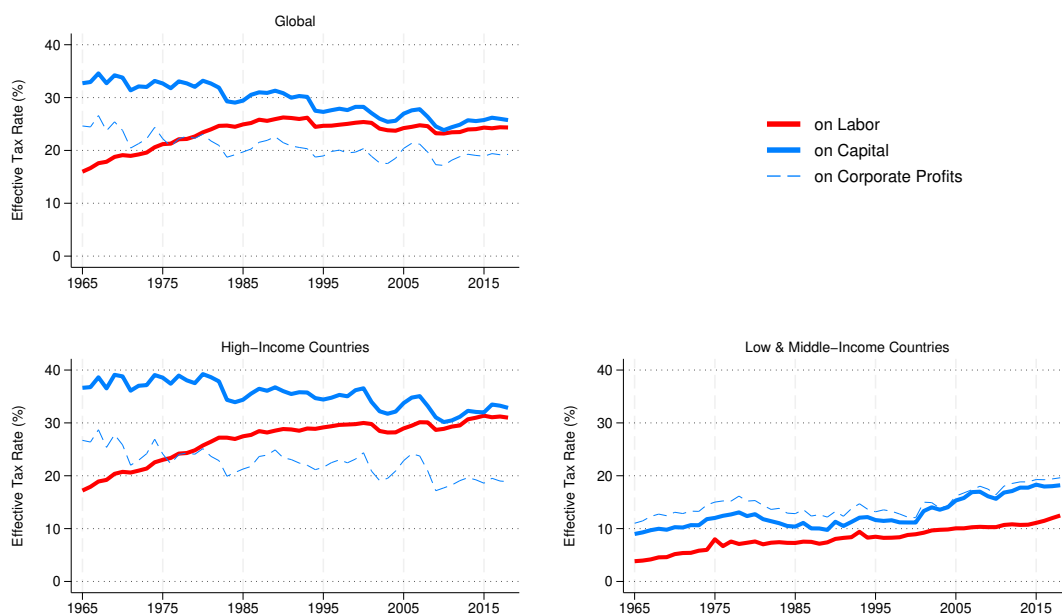


Figure 1.2 – Effective Taxation of Capital and Labor (1965-2018)

Notes: This figure plots the time series of average effective tax rates on labor (red) and capital (blue), as well as the average effective tax rate on corporate profits (blue dashed line). The top-left panel corresponds to the global average, weighting country-year observations by their share in that year's total factor income, in constant 2019 USD ($N=154$). The bottom-left panel shows the results for high-income countries ($N=37$), and the bottom-right panel for low- and middle-income countries ($N=117$). Income classification is based on the World Bank income groups in 2018. The dataset is composed of two quasi-balanced panels. The first covers the years 1965-1993 and excludes communist regimes. It accounts for 85-90% of world GDP during those years. The second covers 1994-2018 and integrates former communist countries, in particular China and Russia, and accounts for 97-98% of world GDP. This figure is discussed in Section 1.4.1.

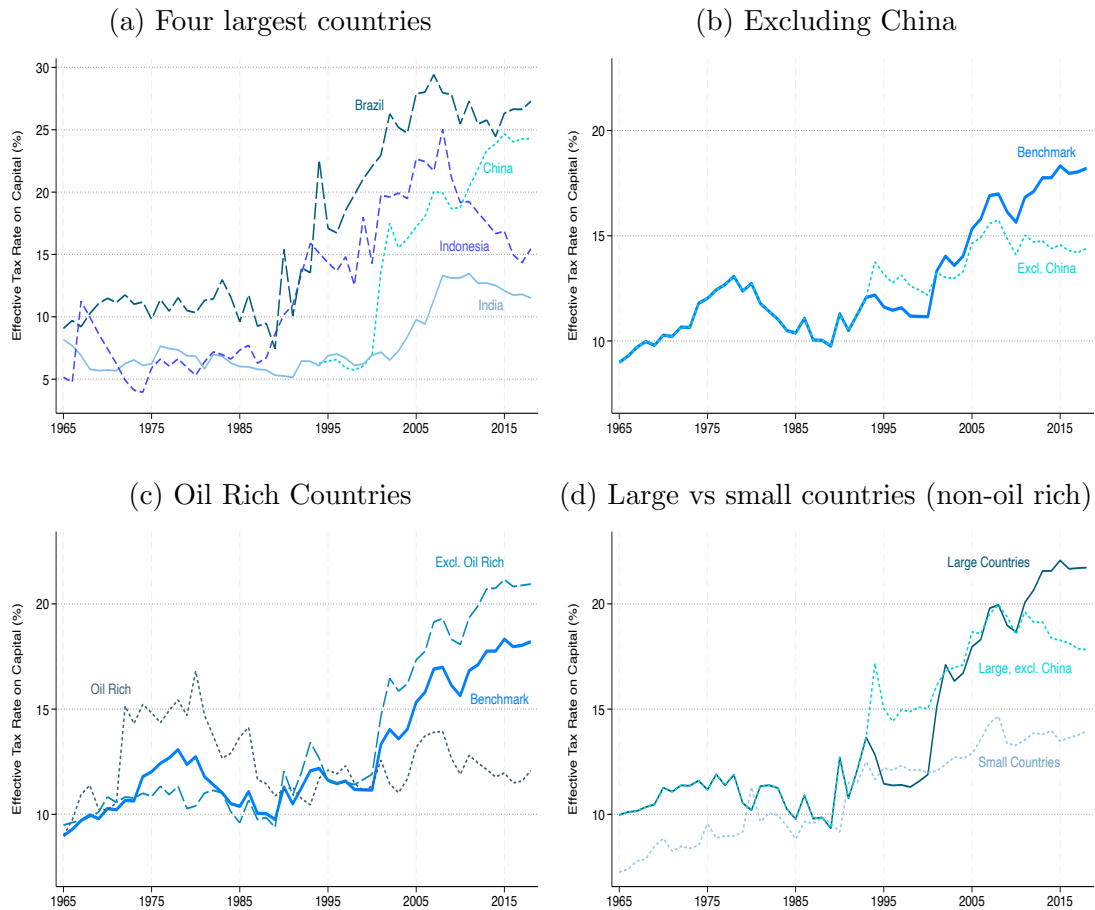


Figure 1.3 – Heterogeneity of Effective Capital Taxation in Developing Countries

Notes: These panels show the evolution of the effective tax rate on capital, ETR_K , for major developing countries and sub-samples of developing countries. Developing countries are low and middle-income countries according to the World Bank income classification in 2018. Panel (a) plots the ETR_K series for the four largest (most populous) developing countries: Brazil, China, India, Indonesia. Panel (b) compares our benchmark series to the series that excludes China. Panel (c) plots the ETR_K series for a sample of oil-rich countries (countries with more than 7% of GDP from oil in 2018), and the benchmark ETR_K series without these countries. Within the sample of non-oil rich developing countries, panel (d) compares large countries to small countries. Large countries are defined as having a population above 40 million in 2018. This figure is discussed in Section 1.4.3.

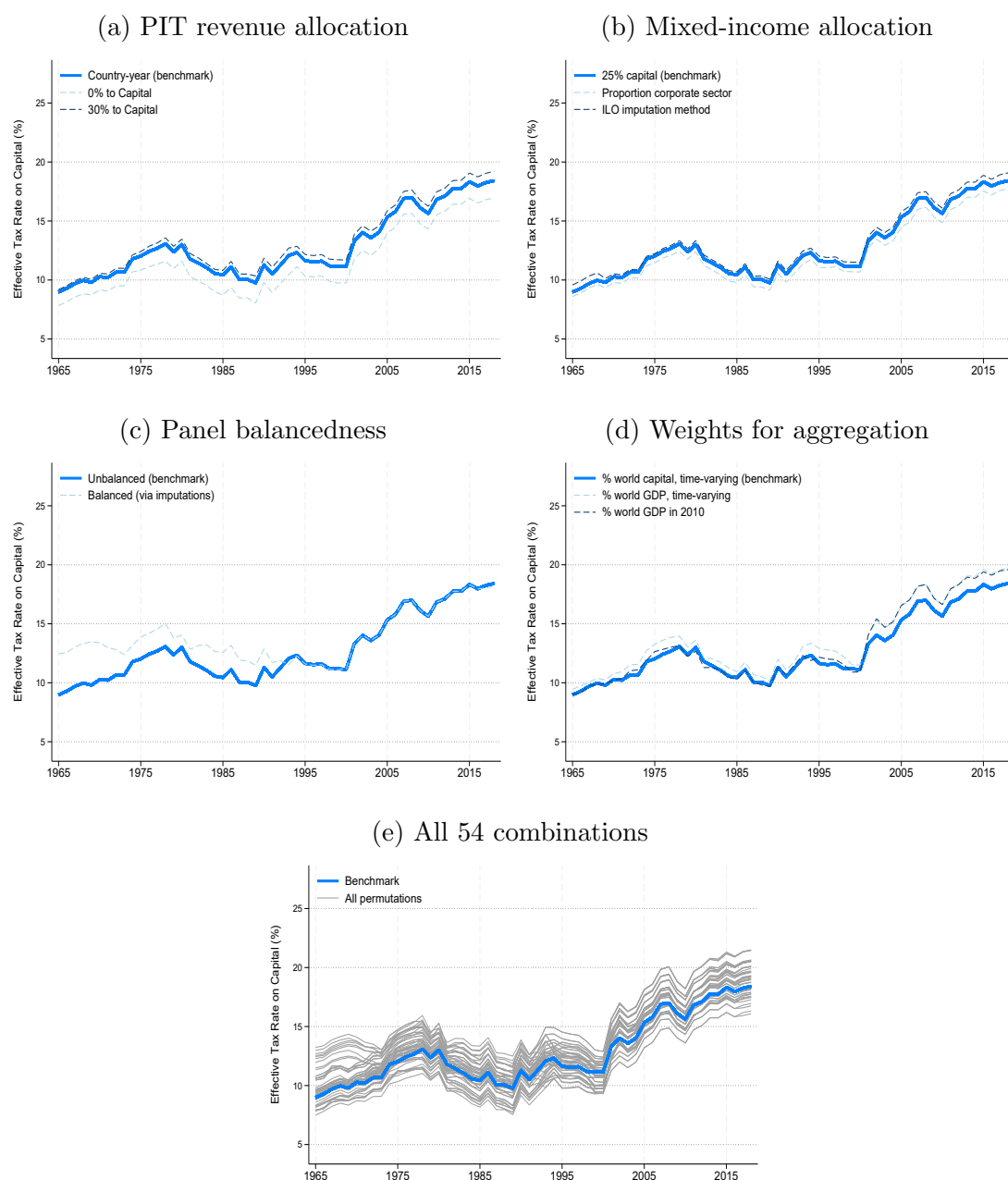


Figure 1.4 – Robustness of Effective Capital Taxation in Developing Countries

Notes: These panels show trends in the effective tax rate on capital in the 117 developing countries in our sample. The panels vary our four key methodological choices: the allocation of personal income tax revenue to capital vs labor (panel a); the allocation of mixed income to capital vs labor (panel b); presenting results for an unbalanced panel of countries vs a balanced panel via imputations (panel c); and, the use of weights to aggregate individual countries' time-series (panel d). Panel (e) shows all 54 possible combinations that can be constructed by combining these choices. In all panels, the blue line corresponds to our benchmark series. Developing countries are low and middle-income countries according to the World Bank income classification in 2018. This figure is discussed in Section 1.4.2.

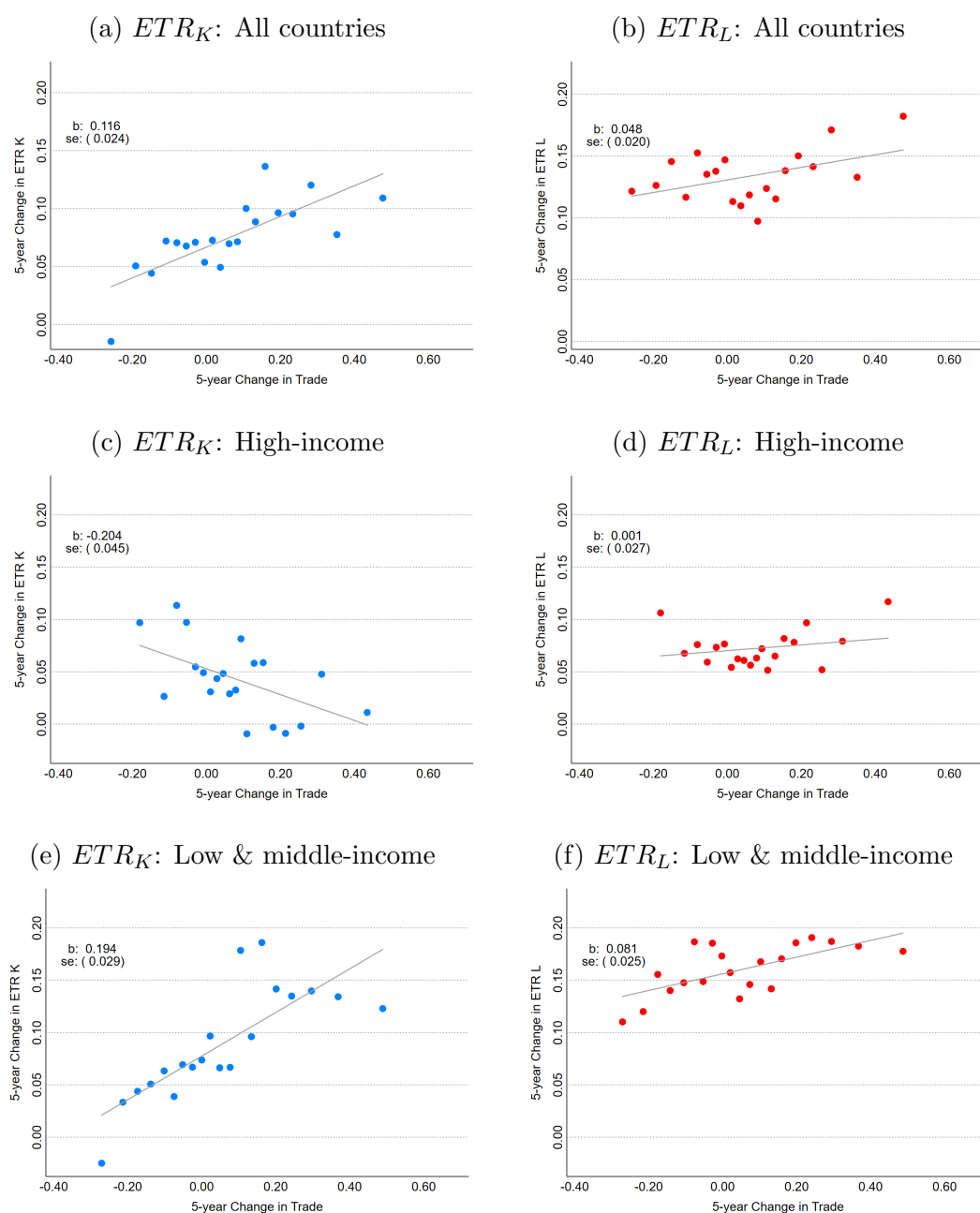


Figure 1.5 – Within-Country Associations between Effective Tax Rates and Trade

Notes: These panels show the association between trade and effective tax rates. The outcome is the effective tax rate on capital, ETR_K , and on labor, ETR_L , in the left-side and right-side panels, respectively. The top panels show the associations in all countries; the middle panels show the associations in high-income countries (based on World Bank income classification in 2018); the bottom panels show the associations in low and middle-income countries. Trade is measured as the sum of import and exports as a share of net domestic product. Both the x-axis and y-axis are measured as within-country percent changes over 5 years. Each graph shows binned scatter plots of each outcome against trade, after residualizing all variables against year-fixed effects. Each dot corresponds to a ventile (20 equal-sized bins) of the residualized trade variable, with average values of trade and ETR calculated by ventile. In each graph, the line represents the best linear fit based on the underlying country-year data, with the corresponding slope coefficient and standard error reported in the top-left corner. For more details, see Section 1.4.4.

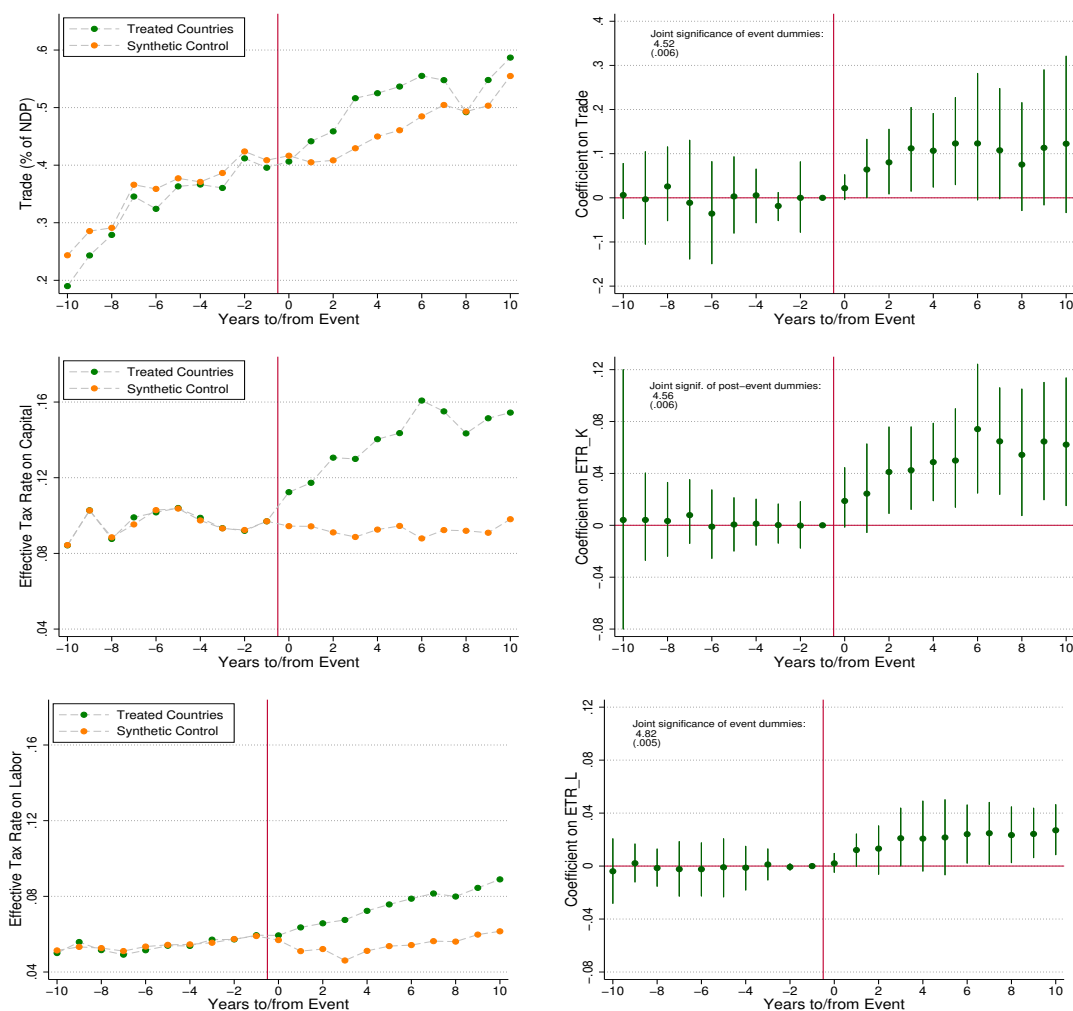


Figure 1.6 – Event Study of Trade Liberalization Reforms

Notes: These figures show event-studies for trade liberalization in seven large developing countries: Argentina, Brazil, China, Colombia, India, Mexico and Vietnam. The panels correspond to different outcomes: trade (top panels); effective tax rate on capital (middle panels); effective tax rate on labor (bottom panels). The left-side graphs show the average level of the outcome in every year to/since the event for the treated group and for the group of synthetic control countries. The right-hand graphs show the β_e coefficients on the to/since dummies, based on estimating the dynamic event-study regression in equation (1.4). The bars represent the 95% confidence intervals. Standard errors are clustered at the country-event level and estimated with the wild bootstrap method. The top-left corners report the F-statistic on the joint significance of the post-event dummies, with the p-value in parentheses. Details on methodology in Section 1.5.1.

Chapter 2

Government Redistribution and Development

with Amory Gethin

Abstract

This chapter builds and analyzes a new database on the distributional incidence of taxes and transfers in 151 countries from 1980 to 2019. Our estimates allocate the entirety of tax revenue and public expenditure to individuals, combining household surveys, national accounts, government budgets, tax simulators, and existing fiscal incidence studies. We establish five main findings. (1) Tax-and-transfer systems always reduce inequality, but with large variations. (2) About 90% of these variations are driven by transfers, while only 10% come from taxes. (3) Redistribution rises with development, but this is entirely due to transfers; tax progressivity is uncorrelated with per capita income. (4) Redistribution has increased in most world regions, except in Africa and Eastern Europe, where it has stagnated. (5) About 80% of variations in posttax inequality are driven by differences in pretax inequality (“predistribution”), while 20% are driven by the direct effect of taxes and transfers (“redistribution”). Countries with higher redistribution display lower levels of pretax inequality, however, pointing to a potentially large role of redistributive policies in indirectly shaping the distribution of market incomes.

2.1 Introduction

Despite a momentous renewal of attention to inequality, even the most recent studies often fail to account for the distributional effects of government taxes and transfers—above all in the developing world. Publicly available inequality statistics generally provide data on the distribution of household disposable income or consumption, with little information on the extent to which government intervention affects poverty and inequality. While significant recent efforts have been made in specific countries, 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 simple as: which countries do the most to reduce income disparities through taxes and transfers? Is redistribution higher than it was forty years ago? Are differences in inequality primarily driven by differences in the distribution of market incomes (“predistribution”), or by differences in tax-and-transfer systems (“redistribution”)?

This article makes a first step towards answering these questions. Combining new data sources and methods, we assemble a comprehensive database on the distribution of taxes and transfers in 151 countries since 1980. 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 education and 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 over time, and consistent with national income and government budget aggregates.

In the absence of survey or tax microdata, which largely do not exist for our sample, several methodological innovations allow us to estimate the distributional incidence of taxes and transfers. Tax revenue aggregates, by type of tax, are drawn from Bachas et al. (2022), while pretax income distributions are available from the World Inequality Database (Blanchet et al., 2021). We model the distributional incidence of taxes from a number of parameters on *inter alia* statutory tax schedules, functional income concentrations, and the relative weights of disaggregated tax components, for which we put together data from several sources. Similarly, we complement our new series on total government expenditure, by function, with information on the distributional incidence of social assistance, education, and healthcare, drawing on related work by Gethin (2023). We validate our estimates against those of existing studies where those exist, ensuring that our simplified methodology accurately reproduces results from preexisting work.

Our database reveals five new stylized facts on worldwide fiscal progressivity, in levels and trends. First, tax-and-transfer systems always reduce inequality. One way to measure this is to compare the top 10% to bottom 50% average income ratio in terms of pretax and posttax income. Taxes and transfers reduce this ratio in all 151 countries in our sample. This effect varies considerably, however, from 15% in the average African country to over 30% in Europe and the United States.

Second, transfers are the dominant driver of this redistributive effect. Taxes appear to have almost no effect on inequality in most regions of the world: low-income households face about the same effective tax rate as high-income households. As a result, removing taxes from individual incomes reduces inequality by about 2% in the average country. In contrast, transfers always strongly reduce inequality, typically

by about 20%. Putting these two facts together, we estimate that over 90% of the effect of tax-and-transfer systems on inequality comes from transfers, while less than 10% comes from taxes.

Third, redistribution rises with development, but this is entirely due to transfers. Tax progressivity is uncorrelated with per capita income, despite noticeable regional patterns. For instance, Western European and Anglosphere countries have slightly progressive tax systems, while the distribution of taxes is strongly regressive in Eastern Europe and Latin America, mainly due to the prevalence of high indirect taxes and less progressive personal income taxes. In contrast, the impact of transfers on inequality rises sharply with development: the raw correlation between the total transfer received by the bottom 50% as a share of national income and GDP per capita exceeds 0.6. This finding mainly arises from the fact that high-income countries spend more on cash and in-kind transfers, but can also be explained by their greater reliance on more progressive forms of public spending—in particular social assistance and healthcare. In the average African country, less than 2% of national income is transferred to the poorest 50% of the population in the form of government transfers, compared to over 6% in Europe and the United States.

Fourth, there has been no cross-country convergence in redistribution. The net effect of taxes and transfers on inequality has increased significantly in the average country, from a reduction of approximately 10% in 1980, to 20% in 2019. However, this average figure masks considerable heterogeneity. Redistribution has risen significantly in Western Europe, the Anglosphere, and Latin America, while it has stagnated in Eastern Europe and Africa. The gap in redistribution between low- and high-income countries has remained about the same. Upper-middle-income countries have caught up with high-income countries, but this is mainly due to the rise of fiscal progressivity in China.

Fifth, despite large cross-country differences in tax-and-transfer systems, variations in inequality are primarily driven by differences in pretax inequality (“pre-distribution”) rather than by variations in taxes and transfers (“redistribution”). In line with existing work focusing on Europe and the United States (Blanchet, Chancel, and Gethin, 2022; Bozio et al., 2022), we find that countries displaying the highest levels of pretax inequality also end up displaying the highest levels of posttax inequality. A simple cross-country regression of the bottom 50% posttax income share on the bottom 50% pretax income share yields an R-Squared of over 0.8. By this measure, predistribution accounts for over 80% of cross-country variations in inequality, while redistribution accounts for less than 20%. We do find a strong correlation between predistribution and redistribution, however: countries with more progressive tax-and-transfer systems display lower levels of pretax inequality. This suggests that while the *direct* effect of taxes and transfers explains little of variations in posttax inequality, redistributive policies might still play a much more important role in *indirectly* shaping the distribution of market incomes.

Our work stands at the confluence of two main strands of the literature on inequality and fiscal policy: one that has studied the incidence and impact of taxes and transfers, and another that has aimed to measure inequality in a way consistent with measures of growth and total national income.

In the former, tax incidence analysis maintains an illustrious tradition, from Musgrave (1953), Tax Foundation (1967) and Kakwani (1977) through Lambert (1992), Fullerton and Metcalf (2002) and Saez, Slemrod, and Giertz (2012). The

central question of this literature has been to ask on whom the burden of taxation falls. Studies in this line have emphasized context-specific behavioral responses to taxation, and 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 slew of recent DINA studies have generated worldwide evidence on pretax income inequality levels and trends (see Chancel et al., 2022).¹ Gathered together in the World Inequality Database, these data series represent a scholarly benchmark as the preeminent long-run, worldwide, harmonized estimates of total national income distributions. However, the majority of these income distributions are estimated only pretax²—before the operation of government tax and transfer policies—leaving open an important empirical question, on the ability of fiscal policy to impact inequality.

The central contribution of this paper is to close that gap and estimate comprehensive posttax income distributions, worldwide since 1980. As such, our work relates perhaps most directly to the Commitment to Equity initiative (CEQ Institute; see Lustig, 2022), whose pioneering efforts have made important strides to estimate the incidence of taxes and transfers in the developing world.^{3,4} Our main contribution beyond their work is to cover all countries, all incomes, and all taxes and transfers, as well as the evolution of redistribution over time.

The remainder of this article is organized as follows. Section 2.2 establishes our methods to estimate worldwide fiscal progressivity since 1980, and demonstrates the robustness of the approach. Section 2.3 presents our analysis and the main findings that emerge. Section 2.4 concludes.

2.2 Data and Methodology

This section covers the methodology used to build our new database on government redistribution worldwide. Section 2.2.1 covers general methodological principles. Section 2.2.2 outlines the data sources used for the distribution of pretax income and government revenue and expenditure aggregates. It also presents our core “calibration” and “validation” database on government redistribution in 45 countries, compiled from seven studies following the DINA framework—which we use to inform and to test several distributional incidence assumptions. Section 2.2.3 describes the methodology used to allocate taxes and transfers. Finally, section 2.2.4 investigates the ability of our methodology to reproduce estimates from seven existing DINA studies.

¹Pretax income 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. For background and further details on the concept of pretax income and its estimation, refer to Blanchet et al. (2021) and the [World Inequality Database](#).

²Several important exceptions are discussed in sections 2.2.4 and 2.2.5 below.

³CEQ studies generally do not precede the year 2010, and usually cover but one year per country. Equity income from ownership of corporations, as well as corporate income taxes, are usually excluded from this framework.

⁴See also World Bank (2022), which followed in the direction of Lustig (2022).

2.2.1 Conceptual Framework

Concepts Our methodology follows the distributional national accounts (DINA) framework (Blanchet et al., 2021; Piketty, Saez, and Zucman, 2018), which offers a foundation to estimate the distribution of income, taxes, and transfers in a way that is consistent with national accounting principles (UN SNA, 2008). Unlike previous approaches to the measurement of inequality, the DINA methodology distributes all income flows to all individuals, as well as all types of taxes paid and transfers received, to arrive at both pretax and posttax income distributions that match 100% of national income.

The DINA approach generally establishes three income concepts: factor national income, pretax national income, and posttax national income, all of which add up to net national income. Factor national income refers to market income flows deriving from labor and capital, before any form of government intervention.⁵ 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 insurance benefits received. Finally, posttax national income corresponds to income after the operation of the tax-and-transfer system. All taxes are allocated and removed from individual pretax incomes, including personal income taxes, corporate taxes, property and wealth taxes, and indirect 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).

Table 2.1 summarizes the income concepts and fiscal instruments treated in this paper.

Objective We focus on measures of government redistribution that compare the distribution of pretax national income to that of posttax national income.⁶ Starting with data on the distribution of pretax income z , we aim to measure the distribution of taxes $T(z)$ and government transfers $G(z)$, so as to reach posttax income y :

$$y = z - T(z) + G(z) \tag{2.1}$$

Our analysis therefore relies on three key ingredients: data on the distribution of pretax income, data on total taxes collected and 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 turn.

⁵It can be expressed net or gross of indirect taxes on production. 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.

⁶As in the existing studies that apply the DINA framework, we prefer to measure the distance between pretax income and posttax income, rather than between factor income and posttax income. This comparison has the advantage of not making estimates of redistribution too sensitive to demographic factors, such as the size of the elderly population (where retired persons earn zero factor income but do receive significant social security benefits). Furthermore, even if social insurance contributions do resemble a tax—as a *compulsory* levy, *unrequited* at the time of payment—social insurance benefits resemble less of a redistributive transfer, and rather may be considered as deferred compensation, similar to any private-sector pension or annuity.

2.2.2 Data Sources

Data on Pretax Income Distributions Our starting point on the distribution of pretax national income is the World Inequality Database, which covers 174 countries over the 1980-2019 period. The database was constructed by compiling estimates from existing DINA studies, which have been systematically harmonized and combined to yield comparable distributional statistics (see Chancel and Piketty, 2021). For each country-year, the data cover pretax income thresholds and averages for 127 generalized percentiles (g-percentiles), corresponding to each percentile within the bottom 99% (*p0p1* through *p98p99*), followed by a more detailed decomposition of incomes within the top 1%. 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; UN SNA, 2008). The database also provides information on the share of pretax income coming from capital income and labor income, for each g-percentile (Blanchet, 2022). This decomposition is consistent with aggregate factor income shares estimated in Bachas et al. (2022).

Data on Tax Revenue Aggregates To study the distribution of taxes paid by individuals, we first need to know the magnitude and composition of government revenue. We rely on aggregate tax revenue series recently constructed by Bachas et al. (*ibid.*), 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 national income, disaggregated into six categories: personal income taxes (code 1100 in the OECD classification of taxes; OECD, 2022), corporate income taxes (1200), social insurance contributions (2000, 3000), property and wealth taxes (4000), indirect taxes (5000), and other taxes (6000).

Data on Public Expenditure Aggregates To study the distribution of transfers, we similarly need to know the magnitude and composition of government expenditures. We use data 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 social protection, education, healthcare, and other public spending in about 170 countries since 1980. Social protection is itself disaggregated into social insurance (pension and unemployment benefits) and social assistance.

Data for Validation Having compiled data on pretax income inequality and disaggregated government revenue and expenditure, we need to estimate the distributional incidence of taxes and transfers in each country-year for which the above aggregates are observed. 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. Table 2.2 provides information on the data collected from these studies: in total, the database covers 657 country-years over 45 countries, with significant time and geographical variation. From each study, we collect information on tax and transfer incidence profiles, that is, the share of taxes paid and transfers received by pretax income generalized percentile.

Taken together, the fiscal incidence data from these studies provides unique insights into variations in tax-and-transfer progressivity over time and space. We use these different estimates for validation of our estimates, as discussed further in section 2.2.4 below.

2.2.3 Distribution of Taxes and Transfers

Each tax and transfer, for each country-year, has a unique distributional profile. We now discuss the distributional estimates for each type of tax and transfer in turn. To introduce our method, consider the following equation:

$$T_i = \int_{p \geq K}^{p100} \tau_i(z) dz \quad (2.2)$$

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 . The equivalent is true for transfers (negative taxes). By construction, our estimates always match revenue and expenditure totals T_i on aggregate. Our goal is to estimate the shape of $\tau_i(z)$ over the income distribution, for each type of tax and transfer i .

Personal Income Taxes For personal income taxes (PIT), only taxpayers with income above the PIT exemption threshold K pay any taxes. We estimate K for all country-years from Bachas et al. (2022) and Jensen (2022). Above the PIT exemption threshold, we simulate the structure of personal income tax incidence using statutory rate schedules from the World Tax Indicators (WTI) database (Peter, Buttrick, and Duncan, 2010). This database provides information on the average and marginal statutory income tax rates at average income (where taxable income equals per capita national income), then at two and three and four times that level, and finally the top marginal tax rate. We complement the WTI with inputs from Strecker (2021) and Vegh and Vuletin (2015) and online sources. From this basis, we can approximate a continuous schedule of statutory personal income tax rates.

Drawing on additional data sources (see Appendix A2.1), we also make three critical distinctions: (1) between countries whose PIT systems tax married couples' joint income vs. those that only tax individual incomes; (2) between countries whose PIT systems tax capital income differently from labor income, noting differential rates on dividends and on capital gains; and (3) between the pretax and *taxable* income distributions (since (1) and (2) may occasion some re-ranking).

In this simplified simulation, the elements of the PIT system can be summarized as follows, to estimate the tax rate τ for any g -percentile p and its corresponding income level z :

$$\tau(z)_{PIT} = \sum_{j=1}^3 \frac{\tau_j z_j}{z} \quad (2.3)$$

Where j refers to PIT on labor income (employee compensation and mixed income), dividend income, and capital gains (with taxable incomes z_j taxed at rate τ_j).

After modeling this statutory PIT schedule, we fit its “predicted” revenues proportionally to actual revenues observed in Bachas et al. (2022) and corresponding to T_{PIT} in equation (2.2) above.

Corporate Income Taxes Following Blanchet et al. (2021), we allocate the corporate income tax (CIT) proportionally to income from corporate equity. High-quality estimates of corporate equity ownership (and, therefore, corporate income tax burdens) by generalized percentile are available for the Netherlands (Bruil et al., 2022), the United States (Piketty, Saez, and Zucman, 2018), and South Africa (Chatterjee, Czajka, and Gethin, 2021).⁷ In our benchmark estimates, in the absence of better information, we thus take the average of the three corresponding tax incidence profiles. We then proportionally scale up the CIT incidence profile in each country-year so as to match total CIT revenue.

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. They are by far the least significant revenue item, averaging 2% of national income and rarely exceeding 4%. Like 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, wealth, and financial transaction taxes are distributed proportionally to capital income excluding mixed income and imputed rents (that is, in the same way as corporate taxes).

Unfortunately, we do not observe the concentration of housing wealth, so we assume that residential property taxes are paid proportionally to pretax income. This is consistent with evidence from South Africa and the United States suggesting that the distribution of housing property taxes is relatively flat (Chatterjee, Czajka, and Gethin, 2021; Piketty, Saez, and Zucman, 2018). For other wealth taxes, we use the same corporate tax stylized profile as above.

The data source for total property and wealth tax revenue is Bachas et al. (2022), while we use the OECD tax database (OECD, 2022) to decompose these taxes into housing property, business property, and other taxes on wealth. For countries and years missing in the OECD database, we assume that 50% of property and wealth taxes fall on residential property, while 50% fall on business property and net wealth.

Indirect and Other Taxes As in Blanchet et al. (2021), we assume that indirect taxes are paid by consumers, but we also account for the fact that part of consumption goes untaxed because it is made in the informal sector. First, we estimate income-to-consumption ratios along the income distribution. Second, we estimate the share of informal consumption in total consumption by generalized percentile.

For the first step, our benchmark scenario assumes that the income-to-consumption ratio is logit-shaped and about two times higher for the 99th percentile than for the median (see Appendix Figure A2.2). This is in line with evidence from Chancel et al. (2023), who combine data on income-consumption ratios by pretax income percentile from a number of studies and show that this profile provides a good approximation of the typical empirical profile observed.

⁷See Appendix Figure A2.1, which plots these three profiles by generalized percentile.

For the second step, 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. Here, we draw on recent empirical evidence by Bachas, Gadenne, and Jensen (2022), who estimate the share of consumption made in informal markets, by income percentile, in a sample of developing countries. Informality is relatively greater among low-income earners in poor countries than in rich countries.⁸ Drawing on this empirical regularity documented in Bachas, Gadenne, and Jensen (*ibid.*), 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:

$$s_{ct}(p) = p \times \theta_{ct} \quad (2.4)$$

$$\theta_{ct} = \alpha + \beta GDP_{ct} \quad (2.5)$$

Where GDP_{ct} denotes GDP per capita, expressed in constant 2021 PPP USD. Accounting for informality makes indirect taxes significantly less regressive, in particular in low-income countries, although this effect is generally not sufficiently strong to make them progressive as a share of income.⁹

Finally, other residual taxes include a number of miscellaneous items, such as user fees, penalties, fines, and poll taxes, which usually represent less than 0.5% of national income. 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.

Social Contributions We also construct estimates of the distribution of social contributions. Social insurance systems are already accounted for in pretax income, so we do not need to deduct social contributions to reach posttax income. However, we still estimate their incidence to arrive at a more comprehensive view of the magnitude and progressivity of the tax system in each country.

We assume that social contributions are paid proportionally to labor income, excluding income that is not taxed due to exemptions or evasion. To do so, we rely on a unique database provided by the International Labor Organization (ILO), which compiles labor force surveys fielded in about 150 countries since the 1990s. For approximately 110 countries, we observe whether individuals paid social contributions, and estimate the propensity to do so along the labor income distribution. Informal work and exemptions are generally more prevalent at the bottom of the distribution, while capital income is more prevalent at the top. As a result, middle-income groups often display the highest effective tax rates.¹⁰

Social Assistance Benefits Social assistance expenditure consists in both cash and in-kind transfers received by households, such as conditional cash transfers and

⁸See Appendix Figure A2.3.

⁹Appendix Figure A2.4 illustrates how accounting for informality changes the progressivity of indirect taxes in Niger, one of the poorest countries in our sample.

¹⁰Appendix Figure A2.5 illustrates how accounting for informality and exemptions changes our estimates of the incidence of social contributions, in the context of Argentina in 2019.

food stamps, as defined in the system of national accounts (see Eurostat, 2019). Note that social assistance excludes social insurance transfers (mainly unemployment and pension benefits), which are already included in our definition of pretax income, as discussed above. Data on aggregate expenditure come from Gethin (2023), who draws on various sources to derive harmonized series on the evolution of spending on social assistance programs around the world.

Data on the incidence of social transfers come 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 (World Bank, 2018), and the database of the Commitment to Equity Institute for 3 countries (Iran, Togo, and Venezuela; Lustig, 2022). For the 45 countries not covered by any of these sources, our benchmark scenario allocates transfers using the average profile observed in all countries.

Education We consider two alternative scenarios for the distribution of education spending. One option is to allocate education proportionally to posttax disposable income (pretax income, minus direct taxes, plus cash transfers), in line with what was done for DINA studies covering the United States (Piketty, Saez, and Zucman, 2018) and Europe (Blanchet, Chancel, and Gethin, 2022). Another option is to allocate education spending to children attending school in the household. This approach has been adopted by DINA studies covering Latin America (De Rosa, Flores, and Morgan, 2022) and South Africa (Gethin, 2022), among others, as well as by the CEQ institute in a number of studies (Lustig, 2022). Gethin (2023) extends this approach to all countries in the world since 1980, combining data on education spending with a unique set of surveys covering school attendance and household income worldwide.

The school attendance approach has the advantage of allocating education expenditure to individuals actually benefiting from the education system at a given point in time. The main disadvantage is that it can be sensitive to various demographic and compositional factors overestimating the progressivity of education spending. For instance, education spending may appear progressive mainly because low-income households tend to have more children, or because households with children tend to have young parents with lower incomes. Students attending university and living alone may also appear in survey data as a particularly poor household, making tertiary education spending implausibly progressive. There may also be large inequalities in school spending and school quality across geographical areas, which are generally not observed. For all these reasons, while education spending is probably more equally distributed than posttax disposable income, it should also probably be allocated in a more unequal way than the school attendance approach suggests.

In the main results, we thus present series with education spending allocated proportionally to posttax disposable income. We reproduce all findings with the school attendance approach in the appendix, drawing on estimates from Gethin (*ibid.*). We view the construction of more precise measures of the distribution of education spending, such as indicators relying on public education transfers that children can expect to receive as a function of their socioeconomic background, as an important target for future research.¹¹

¹¹See for instance Piketty (2022), Figure 32, documenting large inequalities in public education spending received by French cohorts.

Health and Other Transfers Data on the distributional incidence of health-care come from Gethin (*ibid.*), who mostly relies on series from the CEQ database (Lustig, 2022). In line with other DINA studies, all other government expenditure is distributed proportionally to posttax disposable income, that is, in a distributionally neutral way. This includes spending on transport, public order and safety, administration, defense, and all other types of public goods.

See Table 2.1 for a brief summary of the income concepts and fiscal instruments discussed above.

2.2.4 Comparison With Existing DINA Studies

Our compilation of data from earlier DINA studies covering 45 countries allows us to verify to what extent our simplified methodology provides a good approximation of patterns of fiscal progressivity across countries and over time. If the validation exercise shows that our new estimates match the sample of existing estimates, we can more confidently trust these new estimates outside of that sample.

One major difficulty is that the DINA studies collected for this validation exercise are not always perfectly comparable with one another. Two main issues should be stressed in particular. First, existing DINA studies do not always use the exact same methodology to allocate each type of tax. For instance, Piketty, Saez, and Zucman (2018) distribute business property taxes proportionally to corporate equity, while other DINA studies most often distribute them either proportionally to pretax income or in ways undocumented by the authors. Similarly, the quality of data available to measure the concentration of corporate equity varies tremendously across countries, from exceptionally detailed administrative data in the Netherlands (Bruil et al., 2022) to dividends and employer income reported in surveys in the case of Latin America (De Rosa, Flores, and Morgan, 2022).

Second, and partly because of limitations in data sources available, effective tax rates paid by percentile can be very noisy in a number of existing DINA studies. For instance, Blanchet, Chancel, and Gethin (2022) rely on surveys to measure the distribution of direct taxes, which makes estimates of their progressivity quite noisy from one year to another, especially at the top of the distribution. More importantly, all DINA studies rely on surveys reporting the joint distribution of pretax income and consumption to allocate indirect taxes. Because of the existence of many zero or very low pretax incomes in such surveys, consumption-to-income ratios can easily diverge, making estimates of the distributional incidence of consumption taxes particularly volatile. In South Africa, for instance, the bottom 50% pretax income share is less than 3%, leading effective tax rates as a share of pretax income to diverge towards infinity for most households within this group (Chatterjee, Czajka, and Gethin, 2021).

With these limitations in mind, Figure 2.1 compares our estimates of the effective tax rates faced by percentiles $p50$, $p75$, $p90$ and $p99$ to those of existing DINA studies. With few exceptions, our estimates are clustered along the 45-degree line, suggesting that our simplified approach does a good job at reproducing broad cross-country and time variations in taxes paid by different pretax income groups.

We provide three additional validation exercises in the appendix. First, we compare our measures of absolute progressivity by type of tax to those reported in existing DINA studies (see Appendix Figure A2.6). The two estimates fall very close

to each other in the case of personal income taxes and corporate taxes. However, because of the issue of low pretax incomes highlighted above, the fit of indirect taxes is much more variable. Given well-known challenges at measuring the relationship between income and consumption in surveys (Chancel et al., 2023), whether our smoothed estimates or those of existing DINA studies are more reliable is difficult to say. On average, however, it is reassuring that our measures of the progressivity of indirect taxes falls quite close to average progressivity found in existing work.

Second, we zoom in on effective tax rates paid by income group in specific countries, focusing on DINA studies with the least volatile estimates. Appendix Figures A2.7, A2.8, and A2.9 present this comparison for the United States, the Netherlands, and South Africa, respectively. Although our estimates are not perfect, our simplified methodology reproduces the strong regressivity of taxes in the Netherlands and the relatively more progressive tax systems of the United States and South Africa remarkably well.

In a third validation of our method, we compare our estimates of overall tax progressivity against those of existing studies in each country (see Appendix Figure A2.10). Progressivity is measured as the percent change in the top 10% to bottom 50% average income ratio obtained when removing taxes from pretax incomes (see section 2.3.1 for more details on this indicator). Because of issues highlighted above, our estimates of this indicator unsurprisingly do not correlate perfectly with those of existing papers, yet there does appear to be a strong and positive relationship. We view this as additional reassuring evidence that our methodology captures broad cross-country variations in tax systems relatively well.

2.2.5 Integration of Existing DINA Studies in our Database

Finally, while our estimates accurately capture broad variations in tax and transfer progressivity, existing DINA studies should be considered as of better quality, given that they rely on actual country-specific surveys and tax data to allocate taxes and transfers. We thus replace our series with those of Piketty, Saez, and Zucman (2018) for the United States, Blanchet, Chancel, and Gethin (2022) for Europe, and De Rosa, Flores, and Morgan (2022) for Latin America. Given the lack of detailed tax and transfer incidence profiles comparable to ours, we only replace series covering total taxes paid by percentile and posttax income distributions (with the exception of the United States, for which we also replace transfers).

European and Latin American series only cover a subset of our period of interest, generally corresponding to the post-2000 period. To ensure time consistency, we thus adjust our 1980-2000 series based on the difference observed between our series and theirs in the first year available. For taxes paid, we rescale effective tax rates paid by generalized percentile based on the ratio of ETRs between the two sources. For posttax inequality series, we rescale the average income of each generalized percentile based on the ratio of average incomes between the two sources.

A last adjustment comes from the fact that Piketty, Saez, and Zucman (2018) and Blanchet, Chancel, and Gethin (2022) allocate education spending proportionally to posttax disposable income, while we allocate it based on school attendance of children in the household, as in De Rosa, Flores, and Morgan (2022). To ensure that the final series are conceptually consistent, we thus remove education distributed proportionally from the European and U.S. series and add back education distributed

based on the school attendance approach (taken from Gethin, 2023). For Latin America, we leave the series unchanged, given that education is allocated using a method conceptually similar to ours. Appendix Figures 2.9 to 2.18, as well as Appendix Table 2.3, show that our main findings remain robust to distributing education spending proportionally to posttax disposable income.

2.3 A Global Perspective on Government Redistribution

This section presents the main results on levels and trends in government redistribution around the world. Section 2.3.1 presents facts on tax progressivity, while section 2.3.2 turns to the analysis of transfers and the overall effect of government redistribution on inequality. Finally, section 2.3.3 investigates the role played by differences in the distribution of pretax incomes (“predistribution”) versus taxes and transfers (“redistribution”) in explaining cross-country differences in inequality.

2.3.1 Levels and Trends in Tax Progressivity

A Global Map of Tax Progressivity

Taxes Are Weakly Progressive or Regressive in Most World Regions We start by documenting worldwide differences in the size and structure of taxes. Figure 2.2 shows the evolution of aggregate tax revenue by world region between 1980 and 2019. For simplicity and tractability, we divide the world in six groups of countries throughout the paper: the Anglosphere (United States, United Kingdom, Canada, Australia, and New Zealand), Western Europe, Eastern Europe (including Russia), Latin America, Asia, and Africa. We then calculate total tax revenue as a share of national income in each country and plot the resulting population-weighted average by world region.

Total taxation has increased in Asia, Latin America, and Western Europe, while it has remained stable in Africa, the Anglosphere, and Eastern Europe. Western Europe and Anglosphere countries stand out as having much larger tax revenue from personal income taxes, while indirect taxes are more widespread in other world regions. Overall, there have not been major changes in the composition of taxes within each region, although there are some exceptions. In Eastern Europe, in particular, corporate tax revenue has declined significantly at the same time as indirect taxation has expanded as a share of national income.

Figure 2.3 plots the 2019 average effective tax rate (ETR) faced by each percentile of the pretax income distribution in different regions of the world. Throughout this section, we include social contributions in our analysis of tax progressivity (results excluding social contributions are qualitatively similar). Two main results stand out. First, consistently with Figure 2.2, there are large differences in aggregate tax rates between regions, with macroeconomic tax rates being lowest in Sub-Saharan Africa (10-20%) and highest in Western Europe (over 40%). Second, differences between income groups are small in most regions: nowhere in the world does the average ETR of the top 10% earners exceed that of the bottom 50% by more than 10 percentage points. In Africa, Asia, and Western Europe, taxes paid are essentially flat throughout the income distribution, while they are slightly more progressive

at the top in the Anglosphere. Latin America and especially Eastern Europe are the only regions where tax systems are unambiguously regressive. Indeed, Eastern European (and ex-Soviet) countries tend to rely heavily on indirect taxes as a source of revenue (approximately 15% of national income, while closer to 9% in the rest of the world), and have moved toward flat taxation of household income in recent decades.

Taxes Have Little Effect on Inequality in Most Countries Given limited variations in effective tax rates along the income distribution in most regions of the world, one should not expect taxes to play a substantial role in reducing inequality. Figure 2.4 presents a global map of tax progressivity in 2019, providing a more granular picture on cross-country differences in the distribution of taxes worldwide. We summarize the progressivity of taxes with a simple indicator: the percent difference in inequality, measured as the top 10% to bottom 50% average income ratio, before and after removing taxes from individual incomes:

$$\gamma_{\tau} = \frac{r_{pre} - r_{net}}{r_{pre}} \quad (2.6)$$

Where *pre* refers to pretax income, *net* refers to net-of-tax income (pretax income minus taxes), and $r = \frac{\bar{y}_{p90p100}}{\bar{y}_{p0p50}}$ is the ratio of the average income (pretax or net of taxes) of the top 10% richest to that of the bottom 50% poorest individuals in each country-year.

Positive values thus indicate progressive tax systems, while negative values indicate regressive tax systems. As shown in Figure 2.4, taxes have little effect on inequality: in many countries, they reduce the inequality ratio r by less than 5%. The geographical patterns documented in Figure 2.3 clearly stand out. Latin American and Eastern Europe countries have strongly regressive tax systems. Western European and Southern African countries display the most progressive tax systems, although the magnitude of the effect is generally small, on the order of 5-15%.

Robustness to Other Indicators A concern with this analysis is that this indicator of tax progressivity may not be perfectly comparable across countries. In countries with higher pretax inequality, in particular, taxes may appear mechanically more progressive. The overall impact of taxes may also end up being mechanically higher in countries with greater aggregate tax revenue (see discussion in Appendix A2.2). As an alternative to this measure of “absolute” progressivity, we thus consider two other indicators, “relative” and “normalized” progressivity. Relative progressivity corresponds to the percent difference in the effective tax rates of the top 10% and bottom 50% in each country. Normalized progressivity corresponds to absolute progressivity computed over a single, “normalized” distribution, which ensures that it is insensitive to differences in pretax inequality across countries. Maps comparable to Figure 2.4 are presented for these indicators in Appendix Figures A2.25 and A2.24. The results are similar.

Trends in Tax Progressivity Since 1980

Tax Progressivity Has Stagnated in Most World Regions We now turn to documenting trends in tax progressivity worldwide. To start, consider Figures 2.5 and

2.6, which plot the level and composition of taxes paid by percentile in the average country in 1980 and 2019. This figure is constructed by dividing taxes by pretax income for each percentile in each country, and then taking the population-weighted average of this indicator over all countries in the world.

Two results stand out. First, there has been an increase in worldwide taxation, which ranged from 18-22% of income in 1980, and increased to 22-26% by 2019. Second, there has been no clear change in average worldwide tax progressivity since 1980; if anything, tax progressivity has declined. Overall, top-income groups face slightly higher effective tax rates than earners at the middle of the income distribution, because of the particularly progressive nature of personal income and corporate income taxes. Yet taxes are also slightly higher at the very bottom of the distribution, where consumption is high relative to pretax income and the burden of indirect taxes is thus particularly large. While direct taxes have grown (and PIT systems have become slightly more progressive), so have indirect taxes, leading to little change in average tax progressivity.

Figure 2.7 decomposes this general result geographically by showing the evolution of tax progressivity by world region. Eastern Europe has seen a particularly pronounced and steady decline in progressivity: taxes had more or less no effect on the income distribution in 1990, while they increased inequality by over 25% in 2019. In all other regions, tax progressivity has remained remarkably stable since 1980, mirroring the overall pattern documented in Figures 2.5 and 2.6.

There Has Been No Cross-Country Convergence in Effective Tax Rates

Increases in average tax rates coupled with differences in progressivity imply that taxation has changed differentially for different income groups. We bring these dynamics into focus at the regional level, charting top 1%, top 10%, and bottom 50% effective tax rates since 1980, by region and on average, in Appendix Figures A2.11, A2.12, and A2.13. Top 1% effective tax rates have declined substantially in the Anglosphere and Eastern Europe. Western Europe has overtaken the Anglosphere as the region that taxes the richest the most, but the gap is even greater among low incomes, which explains why tax progressivity is still higher in the latter. Eastern Europe began the post-Soviet era on a par with Western neighbors for top-income taxation, but since then have reverted toward the global mean. No countries tax their poorest citizens as much as do the countries of Eastern Europe. Africa stands out as the only region with no significant change in taxation at all: on average, effective tax rates have remained low and stable for all income groups. All in all, there is no clear convergence between countries in effective tax rates paid.

2.3.2 Levels and Trends in Total Government Redistribution

The Distribution of Government Transfers

We now turn to the analysis of transfers, including social assistance, education, healthcare, and other public goods. Figure 2.8 plots the average share of national income received by the bottom 50%, the middle 40%, and the top 10% in the form of cash and in-kind transfers by world region in 2019.¹²

¹²Appendix Figure C1 ([online](#)) reproduces this figure with education distributed using the school attendance approach.

The Size of Transfers Varies Substantially Across Regions There are large differences across regions in the amount of transfers received by low-income groups, with total expenditure received by the bottom 50% ranging from about 6% of national income in Africa to 18% in Western Europe. On average, cash transfers, healthcare, education, and other public goods each represent about a quarter of transfers received, but with substantial variations across regions. Redistribution in the form of social assistance is particularly developed in Europe, while public healthcare spending is exceptionally large in the United States (and targeted to the poor lacking private insurance). In Africa and Asia, in-kind transfers represent the bulk of redistribution.

The Progressivity of Transfers Varies Substantially Across Regions The countries of Western Europe and the Anglosphere particularly stand out for both *relative* and *absolute* progressivity. In Latin America, Asia, and Africa, on the other hand, top earners receive a greater share of government transfers than do the bottom 50% of the income distribution. This is mainly the result of our assumption that transfers other than social assistance and healthcare are received proportionally to disposable income, that is, in a very unequal way. Because Latin America, African, and Asian countries spend little on these functions of government, public expenditures appear to be the least progressive in these regions. Even under this conservative assumption on the low progressivity of public goods other than healthcare, however, government transfers are unambiguously progressive.

The Net Impact of Taxes and Transfers on Inequality

Tax-and-Transfer Systems Always Reduce Inequality, But With Large Variations Combining taxes and transfers, our database allows us to provide a global map of government redistribution, in Figure 2.9.¹³ The “extent of redistribution” is measured as the percent difference in the top 10% to bottom 50% average income ratio, as in equation (2.6) above (and in, e.g., Bozio et al., 2022).

Two results stand out. First, tax-and-transfer systems always reduce inequality: the indicator is strictly positive in all countries in the world. Second, there are large variations in the extent of redistribution, ranging in 2019 from less than 10% in several Sub-Saharan countries to over 30% in countries such as the United States, Norway, and South Africa. Overall redistribution follows clear regional patterns, being highest in Northern America and Europe, and lowest in Latin America, Sub-Saharan African (excluding Southern Africa), and Asia.

Figure 2.10 shows that, in all regions of the world, tax-and-transfer systems mostly redistribute income from the top 10% to the bottom 50%.¹⁴ On net, the middle 40% generally neither benefit nor lose much from the tax-and-transfer system. The net transfer received by the bottom 50% is highest in the Anglosphere and Western Europe, and lowest in Asia and Africa.

Transfers Account for 90% of Redistribution Combining our previous results on the lack of strong tax progressivity and large differences in the size and distri-

¹³Appendix Figure C2 ([online](#)) reproduces this figure with education distributed using the school attendance approach.

¹⁴Appendix Figure C3 ([online](#)) reproduces this result with education distributed using the school attendance approach.

butional incidence of transfers, we can expect transfers to be the dominant drivers of redistribution. We formalize this in Table 2.3, which compares how inequality changes before and after removing taxes and adding transfers to individual incomes.¹⁵ In 2019, the top 10% to bottom 50% income ratio was approximately $r = 18$ in the average country (calculated as the population-weighted average of the indicator across all countries). Removing taxes barely affects inequality, while adding government transfers reduces inequality by over 3 percentage points. By this measure, taxes account for less than 10% of the effect of government redistribution on inequality, while transfers account for over 90%. There are significant variations across regions: the contribution of taxes reaches about 30% in the Anglosphere and Africa, while it is negative in Eastern Europe and Latin America, where taxes increase inequality. Overall, transfers largely dominate taxes in reducing inequality in most countries in the world.

Table 2.4 provides more detailed results on the redistributive impact of different categories of taxes and transfers.^{16,17} Estimates from existing DINA studies do not allow us to derive such a detailed decomposition, so this table uses our own estimates for Europe and Latin America, which explains why the results differ slightly from those in Table 2.3. We calculate the progressivity of each type of tax or transfer as the percent reduction in inequality it occasions (as in equation 2.6 above). For instance, the statistic for personal income taxes γ_{PIT} corresponds to the percent reduction in the top 10% to bottom 50% ratio before and after removing personal income taxes from pretax income. Positive values indicate that the tax or transfer reduces inequality, while negative values indicate that it increases inequality.

The first column displays the results in the average country, taking the population-weighted average of the corresponding indicators across all countries in the world. Personal income taxes and corporate taxes each reduce inequality by about 4%, while indirect taxes increase inequality by about 8%. The effect of property and wealth taxes is negligible.

The effect of transfers on inequality is significantly higher: social assistance and healthcare expenditure each reduce inequality by about 10%. All in all, the progressivity of personal income taxes and corporate taxes thus appears to be more or less cancelled by the regressivity of indirect taxes, leading to a tax system that reduces inequality by only 3% in the average country. Meanwhile, all transfers are strongly progressive, which explains why they play a dominant role in reducing inequality.

Interesting regional variation stands out. Personal income taxes play a key role in reducing inequality in the Anglosphere and Western Europe, while indirect taxes increase inequality most in Europe and Latin America. Social assistance is the most significant driver of redistribution in Europe, while healthcare plays a more important role in Africa.

¹⁵Appendix Table C1 ([online](#)) reproduces these findings with education distributed using the school attendance approach.

¹⁶See Appendix Table A2.1 for similar results in 1980.

¹⁷Appendix Table C2 [[online](#)] reproduces these findings with education distributed using the school attendance approach.

Trends in Government Redistribution Since 1980

We now present results on the evolution of overall redistribution using two complementary indicators. Figure 2.11 plots the evolution of the extent of redistribution by world region, measured as the percent reduction in the top 10% to bottom 50% income ratio operated by the tax-and-transfer system.¹⁸ This figure tells us whether government redistribution reduces inequality more today than in the past. Meanwhile, Figure 2.12 plots the evolution of the share of national income redistributed to the bottom 50%, which tells us to what extent redistribution increases the incomes of the poorest individuals in each region (see Appendix Figure C5 [online] for similar results with education distributed using the school attendance approach).

Redistribution has increased in most regions. In the average country, the extent of redistribution increased from about 10% to 20% from 1980 to 2019. This average figure hides considerable heterogeneity, with significant increases in redistribution in Western Europe, the Anglosphere, and Asia compared to complete stagnation in Eastern Europe and Africa. The same result extends to the net transfer received by the bottom 50%, which increased from about 2% to 2.5% of national income in the average country but barely changed in Eastern Europe and Africa. Overall, there is no evidence of cross-country convergence in the redistributive power of tax-and-transfer systems.

Government Redistribution Over the Course of Development

We conclude this section with a correlational analysis of the relationship between government redistribution and economic development.

Tax Progressivity Is Uncorrelated With GDP per capita There is little correlation between tax progressivity and per capita income (Figure 2.13). The raw correlation between tax progressivity and GDP per capita is approximately $\rho = -0.09$. In other words, total taxation increases as countries develop, but there is little progressivity in the increase, and little tax progressivity overall: effective taxation on the poorest rises in parallel to effective taxation on the richest, and started at a similar rate. Overall, the tax system appears to increase or reduce inequality by less than 10%, throughout the vast majority of countries in the world.

Transfer Progressivity Is Positively Correlated With GDP By contrast, low-income households benefit from much greater government transfers in rich countries than in poor countries. Figure 2.14 plots the share of national income received by the bottom 50% in the form of cash and in-kind transfers (expressed as a share of national income), against GDP per capita.^{19,20} The raw correlation between the two variables is $\rho = 0.64$. In Anglosphere and Western European countries, the bottom 50% receive 15-20% of national income, versus 2-8% in most African countries.

¹⁸Appendix Figure C4 (online) reproduces this figure with education distributed using the school attendance approach.

¹⁹This figure slightly differs conceptually from the previous one in that it shows the absolute level of spending rather than transfers expressed as a percentage of income. The result would be similar if we were to express transfers received as a share of pretax income.

²⁰Appendix Figure C6 (online) reproduces this figure with education allocated using the school attendance approach.

Transfers thus appear to reduce inequality much more in high-income countries than in low-income countries. There are interesting exceptions, however. For instance, the bottom 50% benefit from about the same transfer in South Africa as in China, despite the latter being slightly richer.

This positive relationship between transfers and development is not only driven by the fact that high-income countries have larger governments: high-income countries also provide more progressive transfers. Appendix Figure A2.14 reproduces Figure 2.14, but focusing on transfers received by the bottom 50% as a fraction of total public spending. There is a large positive relationship between the two variables. In many African countries, less than 25% of government expenditure accrues to the bottom 50%, while this share exceeds 40% in nearly all Anglosphere and Western European countries. This result is driven by the fact that high-income countries spend much more on social assistance and healthcare than low-income countries. The bulk of transfers in low-income countries correspond to other forms of public goods, such as administration or public order and safety, which we distribute proportionally to disposable income, that is, in a highly unequal way.

Net Redistribution Is Positively Correlated with GDP Putting these two results together yields Figure 2.15, which plots GDP per capita versus the percent reduction in the top 10% to bottom 50% income ratio through taxes and transfers (see Appendix Figure C7 [online] for the same figure with education distributed using the school attendance approach). The raw correlation between total tax-and-transfer progressivity and development is $\rho = 0.53$. Outliers exist—where income is low but progressivity high, or vice versa—but the general trend looks more like that of Figure 2.14 than that of Figure 2.13. The progressivity of transfers dominates that of taxes, and high-income countries generally redistribute through transfers.

High-income countries thus appear to redistribute significantly more than low-income countries, both today and in 1980. This can be seen more clearly in Appendix Figures A2.15 and A2.16, which plot the evolution of total fiscal progressivity and net transfers received by the bottom 50%, respectively, by country income group. High-income countries redistribute more than lower-income countries, and this gap has not changed much over time—if anything, it has widened. Upper middle-income countries have been catching up since the turn of the century, but the effect is almost entirely explained by China’s fiscal transformation.²¹

2.3.3 Predistribution versus Redistribution: A Global Perspective

We conclude this paper with a brief analysis of the relationship between pretax and posttax income inequality. We start by showing that pretax inequality is the dominant driver of cross-country differences in posttax inequality. While tax-and-transfer systems do vary substantially across countries, they do not significantly alter the

²¹While China’s macroeconomic tax rate (i.e., total public revenue from taxes) hovered near 15% of national income in the 1980s and 1990s, it has since risen to more than 25% of national income. See Bachas et al. (2022) for further discussion on the case of China. Taxes have not become more progressive in China, nor are transfers much more targeted towards the poor than they were pre-2000, but the aggregate revenue of China’s government allows it to more effectively transfer a larger share of national income to the poorest.

ranking of which countries are the most or least unequal in the world. Moving beyond this direct effect of taxes and transfers, we then provide suggestive evidence that redistribution may have significant indirect effects on pretax inequality. Accounting for this indirect effect would potentially lead to putting a much greater weight on redistributive policies in accounting for cross-country differences in inequality.

Pretax Versus Posttax Inequality

We start by comparing the bottom 50% share in terms of pretax national income and posttax national income in all 151 countries in 2019 (see Figure 2.16, and Appendix Figure C8 [\[online\]](#)) for comparable results with education distributed based on school attendance).²² This comparison provides direct suggestive evidence on the role of pretax inequality (“predistribution”) versus taxes and transfers (“redistribution”) in shaping the final distribution of income. If posttax inequality is entirely driven by taxes and transfers and pretax inequality played no role, then pretax and posttax inequality should be uncorrelated. On the contrary, if posttax inequality is entirely driven by the distribution of income before taxes and transfers, then we should expect the ranking of countries to remain exactly the same before and after accounting for taxes and transfers.

The main takeaway is that 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 finding goes in line with previous evidence focusing on Europe and the United States (Blanchet, Chancel, and Gethin, 2022). A useful way of quantifying this relationship is to run a cross-country regression of the posttax bottom 50% income share on the bottom 50% pretax income share in 2019. This regression delivers an R-Squared of over 0.8. By this measure, “predistribution” accounts for over 80% of cross-country variations in income inequality, while “redistribution” accounts for less than 20%.

We extend this analysis to the bottom 50%, top 10%, and top 1% income shares by region in the appendix (see Appendix Figures A2.18, A2.19, and A2.20). The results are similar: regions with the most equal pretax income distributions generally also have the most equal posttax income distributions.

Redistribution Versus Pretax Inequality

A natural limitation of the previous analysis is that redistribution might indirectly affect pretax inequality. For instance, greater investments in social assistance, education, and healthcare may play a key role in generating higher pretax income growth for low-income households. Answering this question rigorously would require data sources and identification strategies that go beyond those mobilized in this paper. However, it is still interesting to investigate whether countries redistributing more are also those that display the lowest levels of pretax inequality.

Figure 2.17 plots the extent of redistribution versus the bottom 50% pretax income share across countries in 2019 (see Appendix Figure C9 [\[online\]](#)) for the specification with education distributed based on school attendance).²³ The correlation

²²See also Appendix Figure A2.17 for comparable results on the top 10% to bottom 50% average income ratio.

²³See also Appendix Figure A2.21 for comparable results on the top 10% to bottom 50% average income ratio.

between the two variables is positive and significant ($\rho = 0.33$): countries with more progressive tax-and-transfer systems display lower levels of pretax inequality on average. There are important exceptions, however, including highly unequal countries with substantial government redistribution (such as the United States and South Africa), but also equal countries with weakly progressive tax-and-transfer systems (such as many Eastern European countries). This modest but positive correlation is again consistent with previous evidence focusing on Europe and the United States (*ibid.*).

One concern is that it may be easier to reduce inequality through taxes and transfers in more unequal countries, given that relative incomes at the bottom of the distribution are particularly low in these countries. We thus complement this analysis with a focus on the net transfer received by the bottom 50%, expressed as a share of national income, in Figure 2.18 (see Appendix Figure C10 [online] for the specification with education distributed based on school attendance). The correlation between this measure of redistribution and the bottom 50% pretax income share is now much higher, reaching $\rho = 0.54$.²⁴

The takeaway is that taxes and transfers could well contribute to strongly reducing pretax inequality indirectly. This would potentially lead to putting a much greater weight on redistributive policies in explaining cross-country differences in inequality. There are still important exceptions, however: for instance, South Africa redistributes more than India, yet displays dramatically higher levels of pretax inequality. Similarly, Latin American countries are characterized by high levels of pretax inequality at the same time as quite progressive tax-and-transfer systems. Our analysis suggests that higher redistribution can lead to lower pretax inequality, but this is far from an iron law. Understanding the conditions under which redistributive policies successfully curb income disparities and their exact contribution to cross-country differences in predistribution represents a fruitful avenue for future research.

2.4 Conclusion

In this paper, we have constructed new estimates of the distributional incidence of taxes and transfers in 151 countries from 1980 to 2019. Combining data from several sources on tax-and-transfer progressivity, we derived estimates of redistribution that are consistent, comprehensive, and comparable across countries and over time. We showed that our simplified methodology is able to replicate results from existing work remarkably well.

Drawing on this database, we have uncovered a number of new stylized facts on the evolution of fiscal progressivity around the world since 1980. Most strikingly, we have documented that the global profile of taxation was and has remained essentially flat. Anglosphere countries, despite recent well-documented decreases in tax progressivity, remain the countries whose taxes do the most to reduce inequality. Other regions' tax profiles are less progressive—and, in the case of many Latin American and Eastern European countries, even regressive overall.

²⁴See Appendix Figure A2.22 for comparable results on the top 10% to bottom 50% average income ratio.

Because transfers strongly benefit low-income households, however, tax-and-transfer systems always reduce inequality. They do so much more in high-income than in low-income countries, mainly because the former display larger welfare states, but also because they better target government transfers towards low-income households. There has been little cross-country convergence in redistribution. If anything, the gap has only widened: from 1980 to 2019, the share of national income transferred to low-income households increased in Western Europe and the Anglosphere while it stagnated in Africa.

As a result, taxes and transfers have done little to change the global picture of inequality. In a static sense, predistribution matters demonstrably more than redistribution, explaining about 80% of cross-country variations in posttax income inequality. And the consequences of inequality in redistribution across countries are stark: the poorest people, in the poorest countries, benefit less from redistribution and public services than do the poorest in richer countries.

There remains a need to better understand what drives differences in distribution and redistribution, across countries and over time. For any society the optimal levels, composition, and distributional incidence of taxes and transfers must surely depend on a range of factors whose investigation lies beyond the scope of this article. We hope that the new database constructed in this paper—which estimates the levels, composition, and distributional incidence of all taxes and transfers, worldwide since 1980—will contribute to further evidence-based examination of efficiency and equity in fiscal policy.

Tables

Table 2.1 – Income Concepts and Fiscal Instruments

| <i>income concepts</i> | |
|--------------------------------------|---|
| pretax national income | adds to 100% of national income (GDP plus net foreign income, minus depreciation, i.e., consumption of fixed capital) and is equal to market income after the operation of the social security system (subtracting social insurance contributions paid, adding social insurance benefits received). Pretax distributions are drawn from WID . |
| posttax national income | adds to 100% of national income and is equal to pretax income subtracting all taxes (see below) and adding all transfers (see below)—implies distributing the entirety of government expenditure, including both individual (cash and in-kind benefits) and collective (e.g., defense, infrastructure) expenditures. |
| <i>tax revenues</i> | |
| personal income tax | “taxes levied on the net income (gross income minus allowable tax reliefs) and capital gains of individuals” (OECD, 2022). Distributions are estimated with data from Bachas et al. (2022) , Jensen (2022) , Peter, Buttrick, and Duncan (2010) , Strecker (2021) , and Vegh and Vuletin (2015) , for both labor and capital incomes within PIT. |
| corporate income tax | “taxes levied on the net profits (gross income minus allowable tax reliefs) of enterprises” (OECD, 2022). Distributions are estimated with data from Bachas et al. (2022) , Bruil et al. (2022) , Chatterjee, Czajka, and Gethin (2021) , and Piketty, Saez, and Zucman (2018) . |
| social contributions | “compulsory payments paid to general government that confer entitlement to receive a (contingent) future social benefit” (OECD, 2022). Distributions are estimated with data from Bachas et al. (2022) and from more than 1000 country-years (across > 100 countries) of survey microdata from ILO . |
| wealth and property taxes | “recurrent and non-recurrent taxes on the use, ownership or transfer of property. These include taxes on immovable property or net wealth, taxes on the change of ownership of property through inheritance or gift and taxes on financial and capital transactions” (OECD, 2022). Distributions are estimated with data from Bachas et al. (2022) , Chatterjee, Czajka, and Gethin (2021) , and Piketty, Saez, and Zucman (2018) . |
| indirect and other taxes | “taxes and duties levied on the production, extraction, sale, transfer, leasing or delivery of goods, and the rendering of services, or in respect of the use of goods or permission to use goods or to perform activities. . . [or] presumptive taxes not included elsewhere in the classification,” including notably consumption taxes, trade taxes, and duties and fees (OECD, 2022). Distributions are estimated with data from Bachas et al. (2022) and Bachas, Gadenne, and Jensen (2022) . |
| <i>public expenditures</i> | |
| social assistance expenditure | cash and in-kind transfers received by households (Eurostat, 2019). Distributions are estimated with data from Blanchet, Chancel, and Gethin (2022) , Lustig (2022) , Piketty, Saez, and Zucman (2018) , and World Bank (2018) . |
| education expenditure | “direct expenditure by public entities on educational institutions as well as educational-related public subsidies given to households and administered by educational institutions” (Eurostat, 2019). Distributions are estimated with data from Blanchet, Chancel, and Gethin (2022) , De Rosa, Flores, and Morgan (2022) , Gethin (2022, 2023) , Lustig (2022) , Piketty (2022) , and Piketty, Saez, and Zucman (2018) . |
| health expenditure | “outlays on health include expenditure on services provided to individual persons and services provided on a collective basis” (Eurostat, 2019). Distributions are estimated with data from Gethin (2023) and Lustig (2022) . |
| other expenditures | The remainder of government expenditure (classified as in Eurostat, 2019) is estimated with data from Bachas et al. (2022) and Gethin (2023) . |

Table 2.2 – Country and Time Coverage of Fiscal Incidence Estimates in Existing DINA Studies

| Study | Countries | Years |
|--|---|------------|
| Piketty, Saez, and Zucman (2018) | United States of America | 1962-2019 |
| Chatterjee, Czajka, and Gethin (2021) | South Africa | 1993-2019 |
| Bozio et al. (2018) | France | 1990-2018 |
| Fisher-Post, Herault, and Wilkins (2022) | Australia | 1991-2018 |
| Bruil et al. (2022) | Netherlands | 2016 |
| De Rosa, Flores, and Morgan (2022) | Argentina, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Mexico, Peru, Uruguay | 2000-2020* |
| Blanchet, Chancel, and Gethin (2022) | Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom | 2007-2017* |

Notes: * signifies unbalanced panel.

Table 2.3 – Extent of Redistribution by World Region: the Dominant Role of Transfers

| | Top 10% / Bottom 50% Average Income Ratio | | | Extent of Redistribution: Percent Reduction in Inequality | | |
|----------------|--|----------------|----------------------------|--|------------------------------|--------------------------------|
| | Pretax Income | After Taxes | After Taxes & Transfers | Through Taxes | Through Taxes & Transfers | Tax Share of Redistribution |
| Africa | 20.0 | 18.9 | 16.3 | 4.2% | 13.5% | 30.9% |
| Anglosphere | 14.8 | 13.0 | 8.6 | 11.6% | 42.2% | 27.4% |
| Asia | 17.4 | 17.0 | 14.5 | 2.9% | 17.3% | 16.6% |
| Eastern Europe | 11.2 | 13.0 | 7.6 | -13.7% | 32.2% | -42.6% |
| Latin America | 31.6 | 35.0 | 28.1 | -10.6% | 12.5% | -84.4% |
| Western Europe | 8.7 | 8.4 | 5.6 | 3.8% | 36.0% | 10.7% |
| World Average | 18.2 | 18.0 | 14.9 | 1.8% | 19.3% | 9.3% |

Notes: Population-weighted averages of indicators in each country. After taxes: top 10% to bottom 50% average income ratio in terms of net-of-tax income (pretax income minus all taxes). After taxes and transfers: top 10% to bottom 50% average income ratio in terms of posttax income (pretax income minus all taxes plus all transfers). Tax share of redistribution: ratio of extent of redistribution through taxes over extent of redistribution through taxes and transfers. Estimates for Eastern Europe, Western Europe, Latin America, the United Kingdom, and the United States come from existing DINA studies. All other series from this paper. Taxes exclude social contributions.

Table 2.4 – Extent of Redistribution by World Region: Decomposition by Tax and Transfer, 2019

| | World Average | Anglosphere | Western Europe | Eastern Europe | Latin America | Asia | Africa |
|-------------------------|------------------|-------------|-------------------|-------------------|------------------|-------|--------|
| Personal Income Taxes | 4.4% | 12.4% | 14.0% | 3.7% | 4.6% | 3.1% | 3.2% |
| Corporate Taxes | 4.2% | 3.7% | 3.7% | 4.4% | 4.0% | 4.6% | 3.3% |
| Property & Wealth Taxes | 0.6% | 0.8% | 1.3% | 0.6% | 0.4% | 0.6% | 0.0% |
| Indirect Taxes | -7.7% | -7.3% | -14.7% | -23.4% | -10.2% | -6.9% | -3.3% |
| Social Contributions | -1.3% | -5.7% | -2.5% | -6.6% | -0.7% | -0.9% | 0.2% |
| All Taxes | 3.1% | 12.1% | 9.5% | -12.3% | 0.9% | 2.9% | 4.2% |
| Social Assistance | 10.4% | 16.6% | 22.9% | 20.7% | 23.5% | 7.5% | 5.5% |
| Healthcare | 10.3% | 28.4% | 15.8% | 11.2% | 20.3% | 7.5% | 6.5% |
| All Transfers | 18.3% | 36.7% | 33.4% | 28.2% | 34.7% | 14.2% | 10.9% |

Notes: Population-weighted averages of indicators in each country. The table reports the negative of the percent change in the top 10% to bottom 50% income ratio before and after removing the corresponding tax or adding to corresponding transfer to pretax income. For instance, the top row reports the percent reduction in inequality resulting from removing personal income taxes from individual incomes. Positive values indicate that the corresponding tax or transfer reduces inequality. All series from this paper (existing DINA studies do not provide comparable, detailed decompositions by type of tax).

Figures

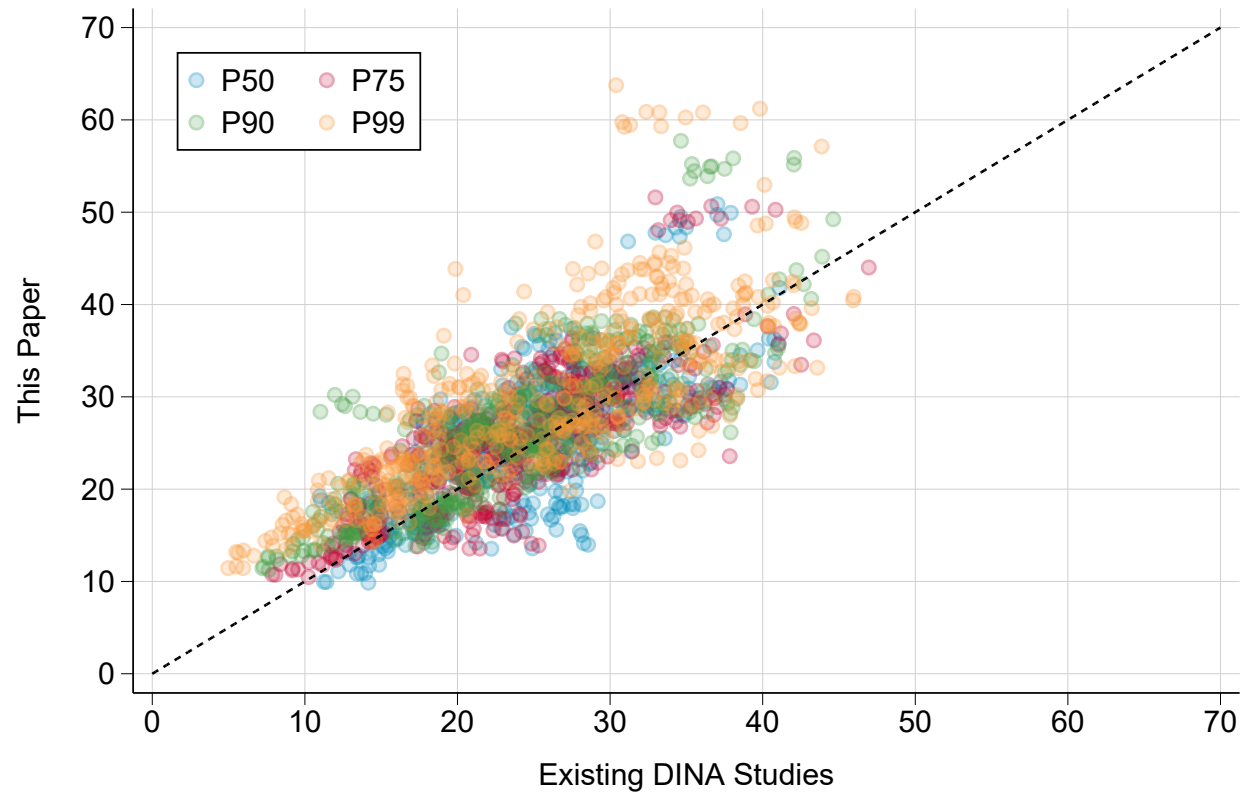


Figure 2.1 – Validation: Comparison of Effective Tax Rates to Existing DINA Studies at p50, p75, p90 and p99

Notes: Axes represent effective tax rate at indicated points along the income distribution.



Figure 2.2 – Tax Revenue by World Region, 1980-2019

Notes: Population-weighted averages of tax revenue aggregates in each country. Data from Bachas et al. (2022).

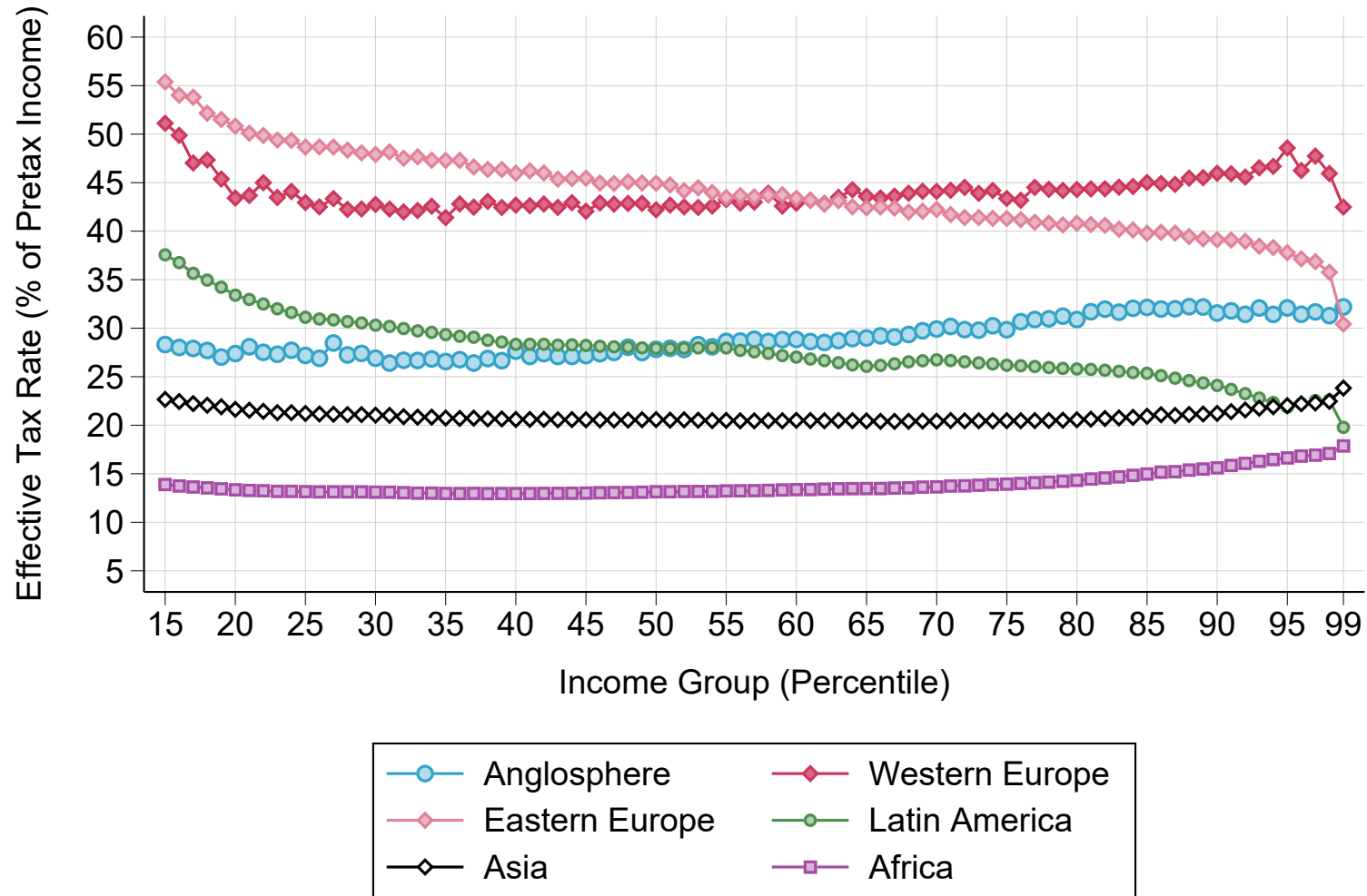


Figure 2.3 – Effective Tax Rate by Income Group and World Region, 2019

Notes: Population-weighted averages of effective tax rates by percentile in each country. Taxes include social contributions.

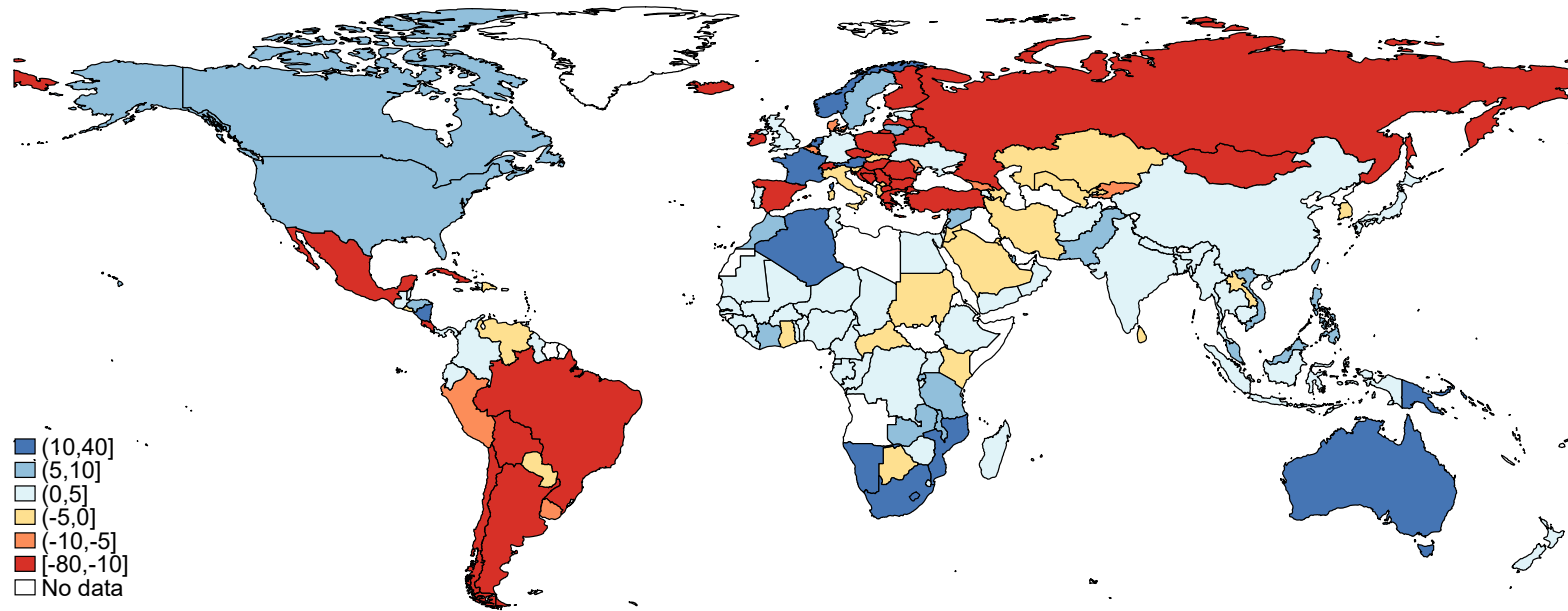


Figure 2.4 – Tax Progressivity Around the World: Percent Reduction in Top 10% to Bottom 50% Average Income Ratio

Notes: The figure compares pretax versus net-of-tax income. (Net-of-tax income is pretax income minus taxes.) Taxes include social contributions.

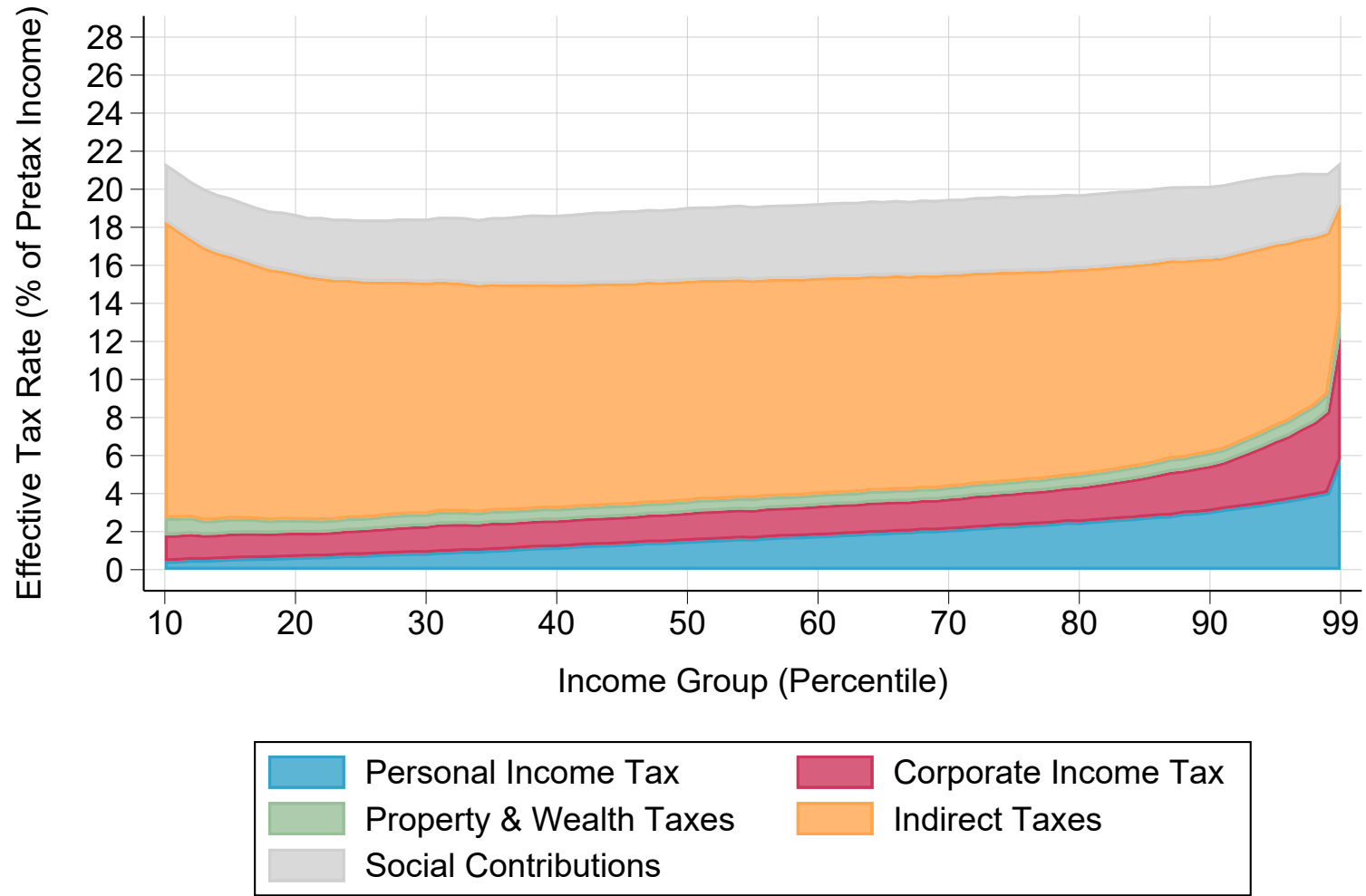


Figure 2.5 – Composition of Taxes Paid by Percentile: Global Average, 1980

Notes: Population-weighted averages of effective tax rates by percentile in each country.

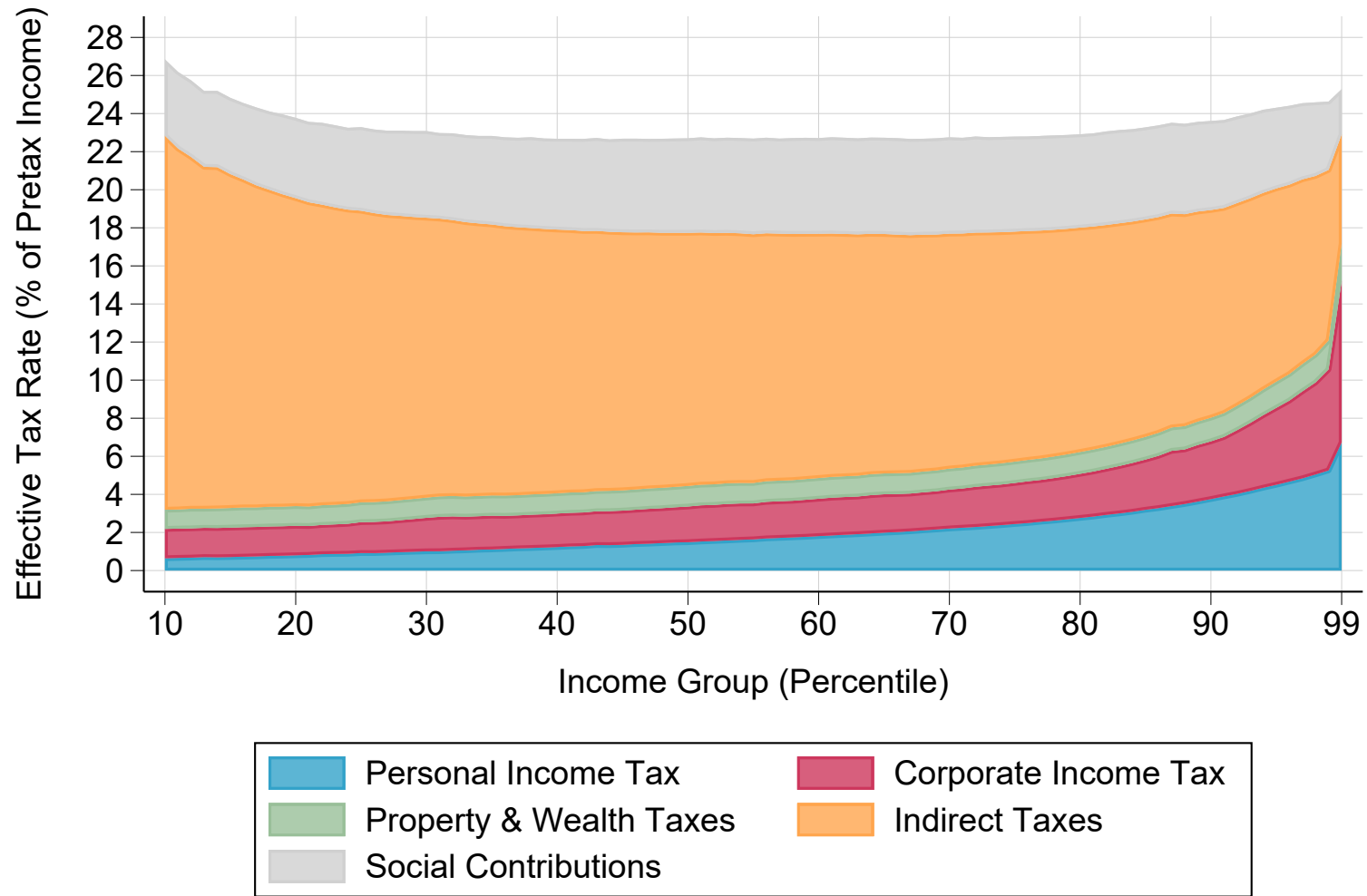


Figure 2.6 – Composition of Taxes Paid by Percentile: Global Average, 2019

Notes: Population-weighted averages of effective tax rates by percentile in each country.

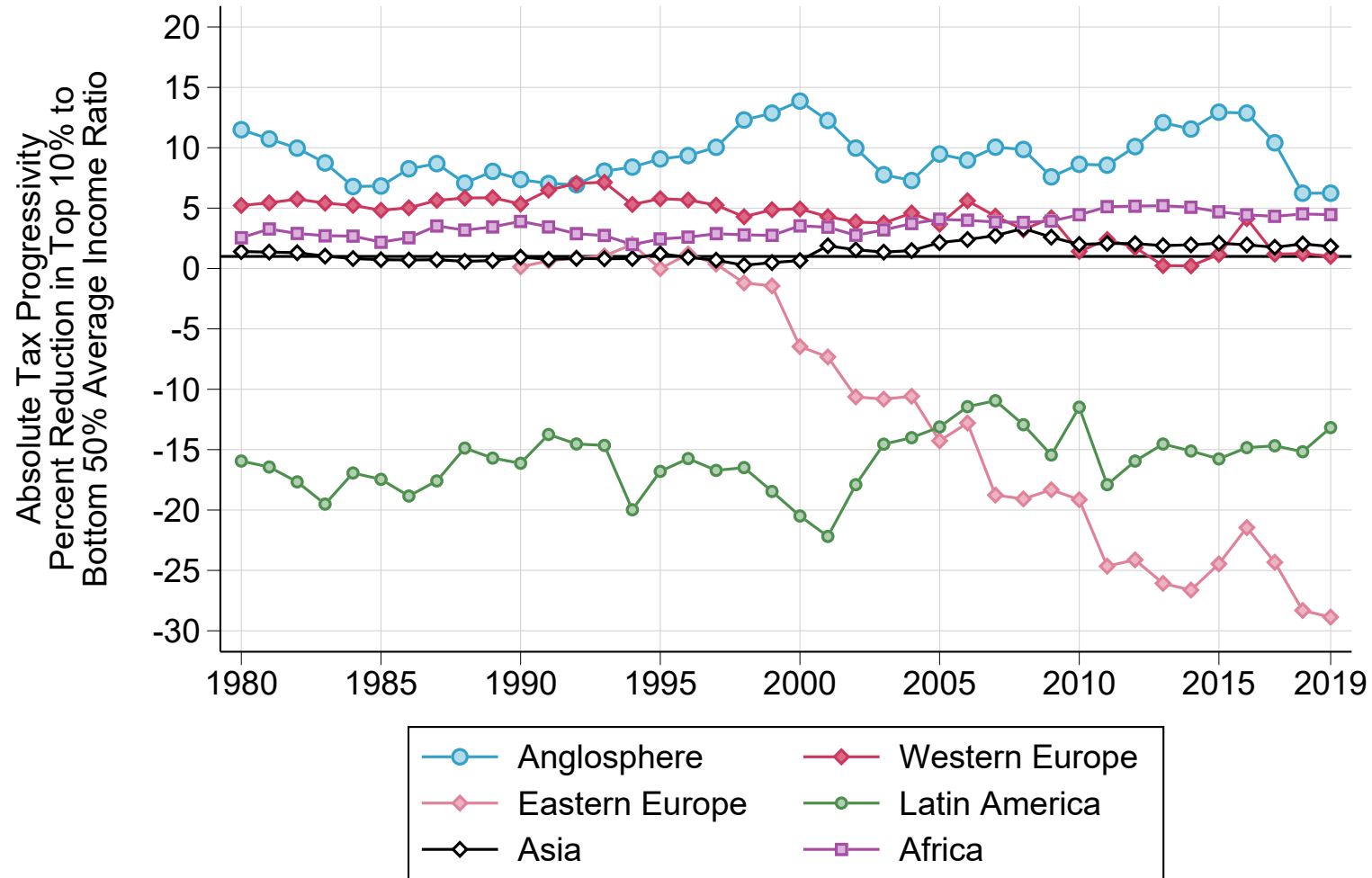


Figure 2.7 – Tax Progressivity by World Region, 1980-2019: Percent Reduction in Top 10% to Bottom 50% Average Income Ratio.

Notes: The figure compares pretax versus net-of-tax income. (Net-of-tax income is pretax income minus taxes.) Taxes include social contributions here. Population-weighted averages of tax progressivity in each country.

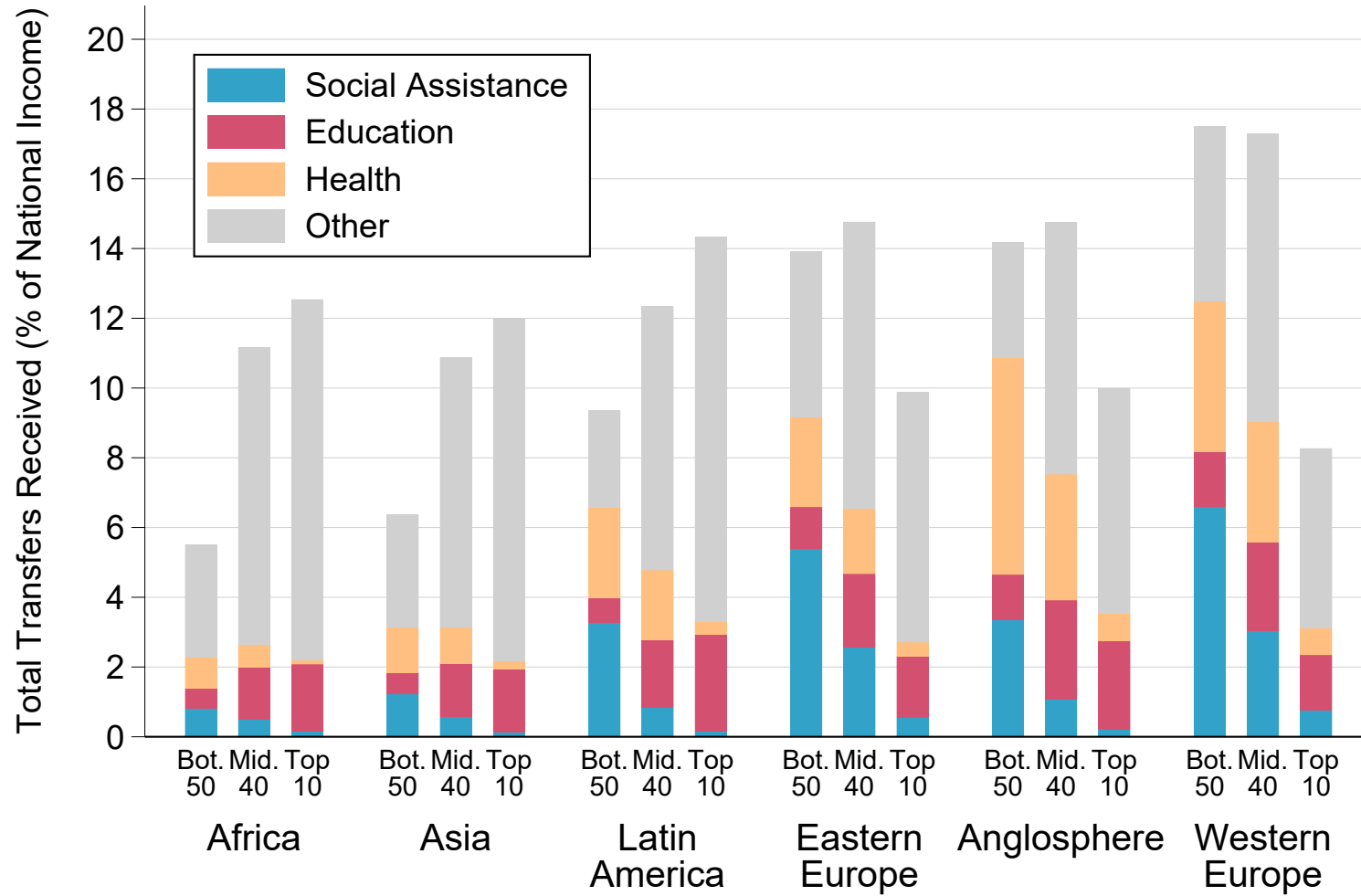


Figure 2.8 – Government Transfers Received by Income Group and World Region, 2019

Notes: Population-weighted average of transfers received by income group in each country. Bot. 50: bottom 50% (p0p50); Mid. 40: middle 40% (p50p90); top 10: top 10% (p90p100).

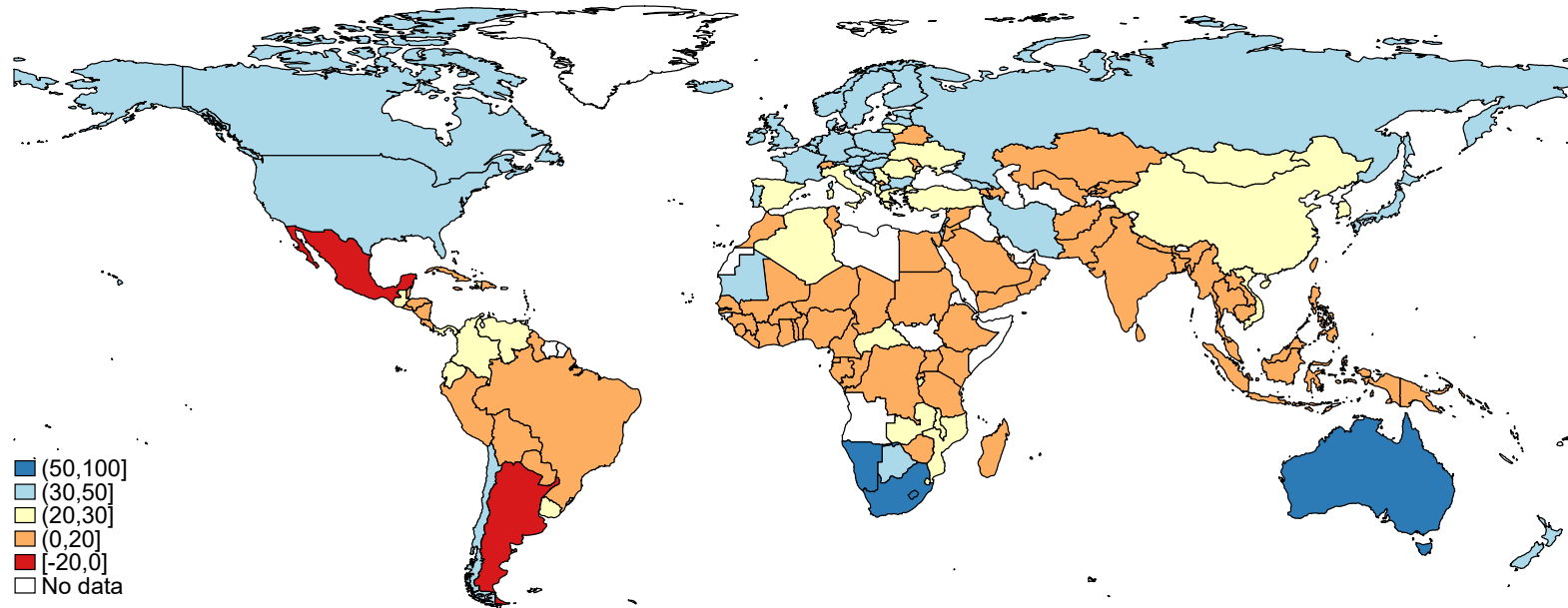


Figure 2.9 – A Global Map of Redistribution
 Percent Reduction in Top 10% to Bottom 50% Income Ratio, Pretax - Posttax

Notes: Posttax income: pretax income, minus all taxes, plus all transfers. Taxes exclude social contributions.

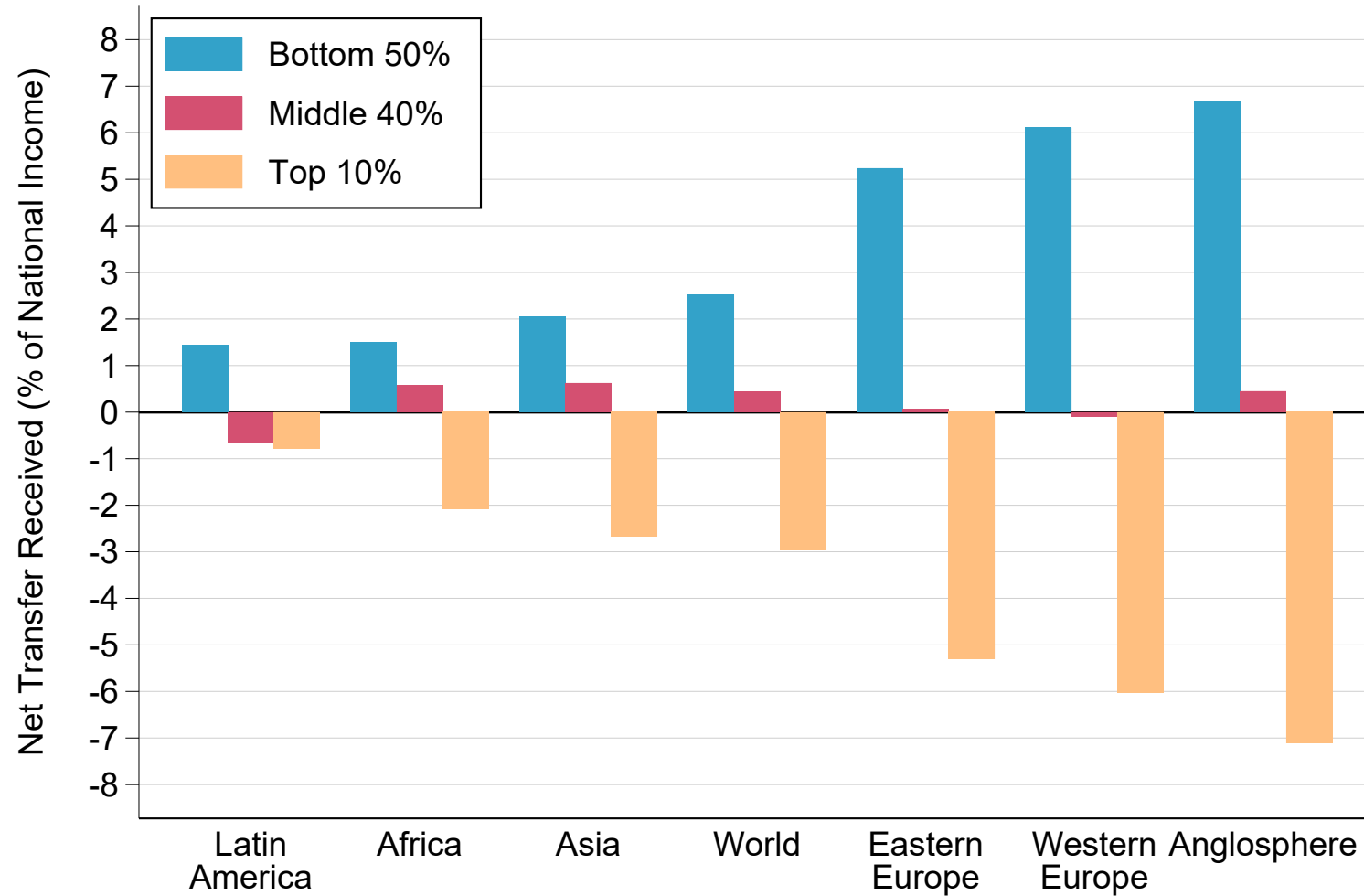


Figure 2.10 – A Global Map of Redistribution: Net Transfers Operated Between Pretax Income Groups, 2019

Notes: Net transfer: all transfers received minus all taxes paid, expressed as a share of national income. Taxes exclude social contributions. Population-weighted averages of net transfers received by income group in each country.

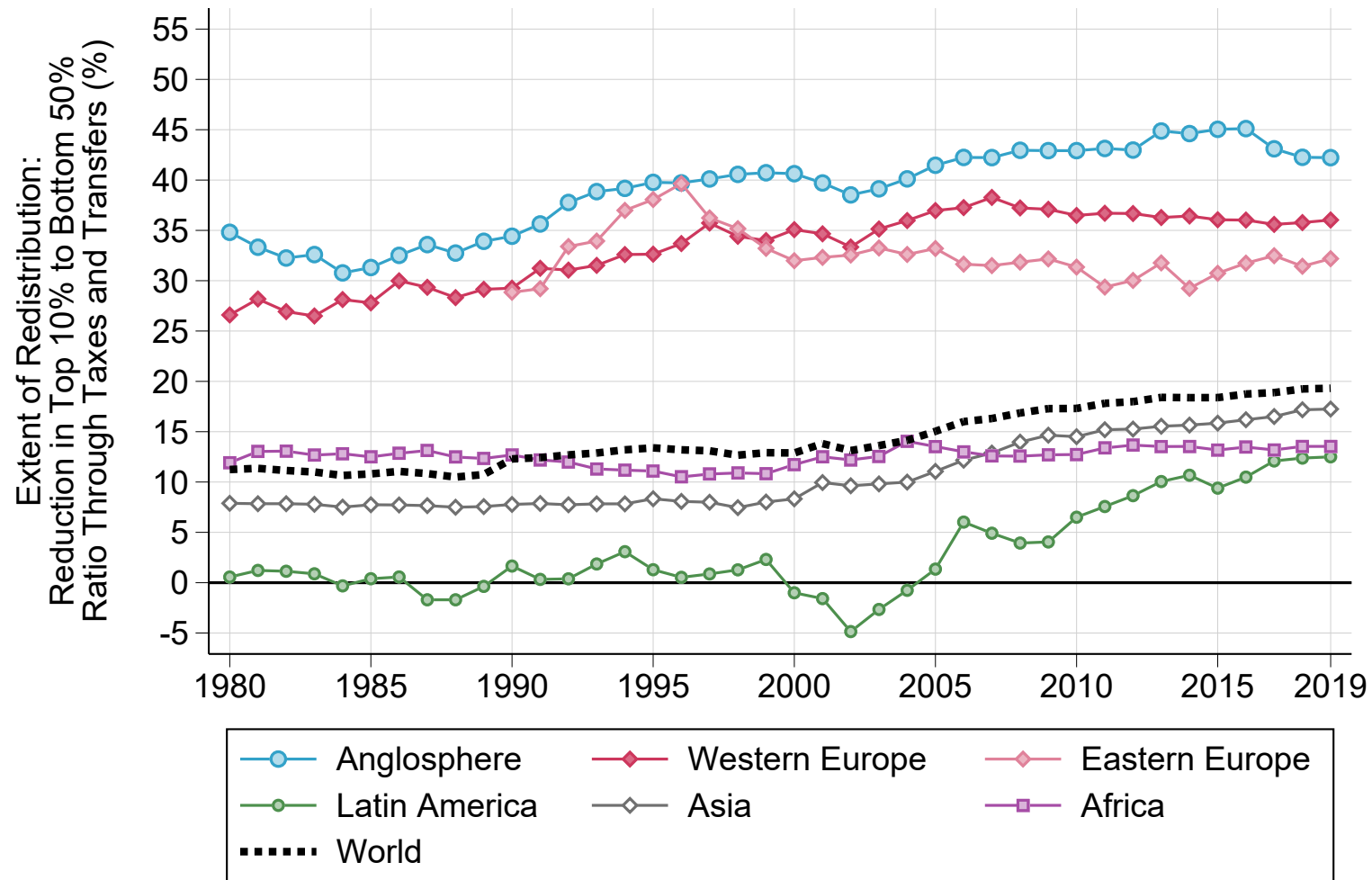


Figure 2.11 – Extent of Redistribution by World Region, 1980-2019

Notes: The figure shows the percent reduction in the top 10% to bottom 50% income ratio, from pretax to posttax. Population-weighted averages of the extent of redistribution in each country.

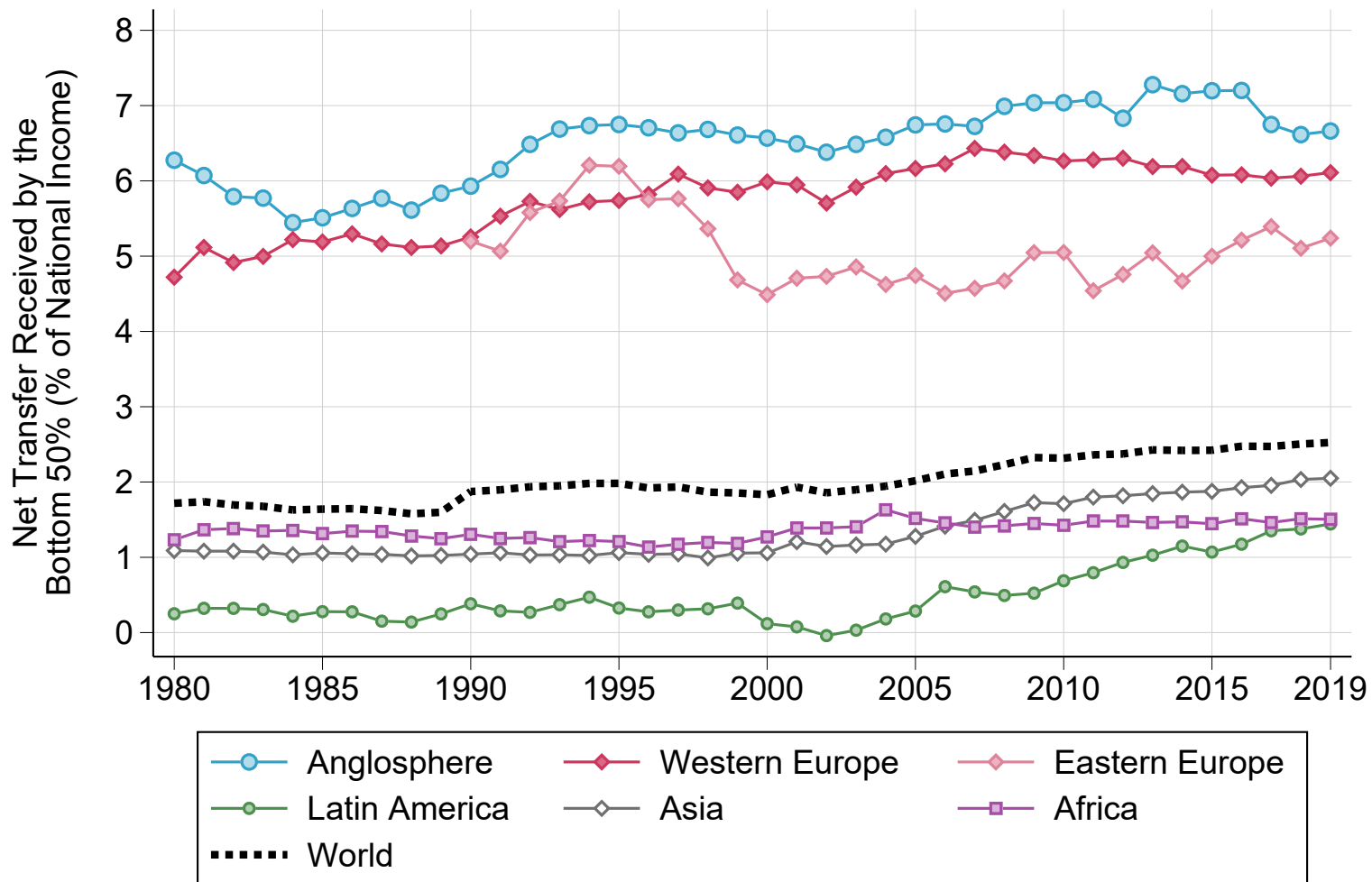


Figure 2.12 – Extent of Redistribution by World Region, 1980-2019:
Net Transfer Received by the Bottom 50% (% of National Income)

Notes: Net transfer: all transfers received minus all taxes paid, expressed as a share of national income. Population-weighted averages of net transfers received in each country.

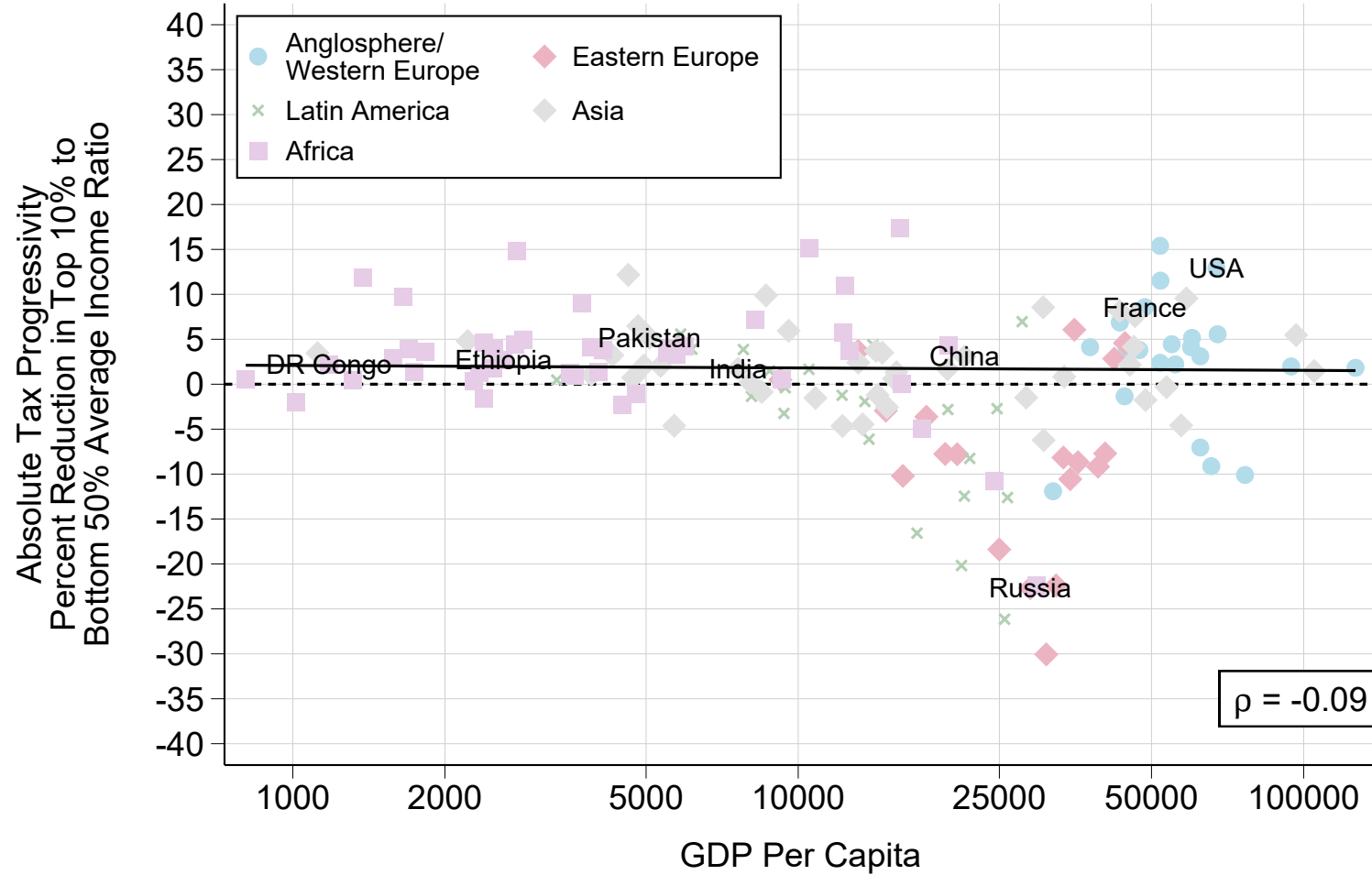


Figure 2.13 – Tax Progressivity Over the Course of Development

Notes: The figure shows the percent reduction in the top 10% to bottom 50% income ratio, from pretax income to net-of-tax income. (Net-of-tax income is pretax income minus taxes.) Taxes exclude social contributions.

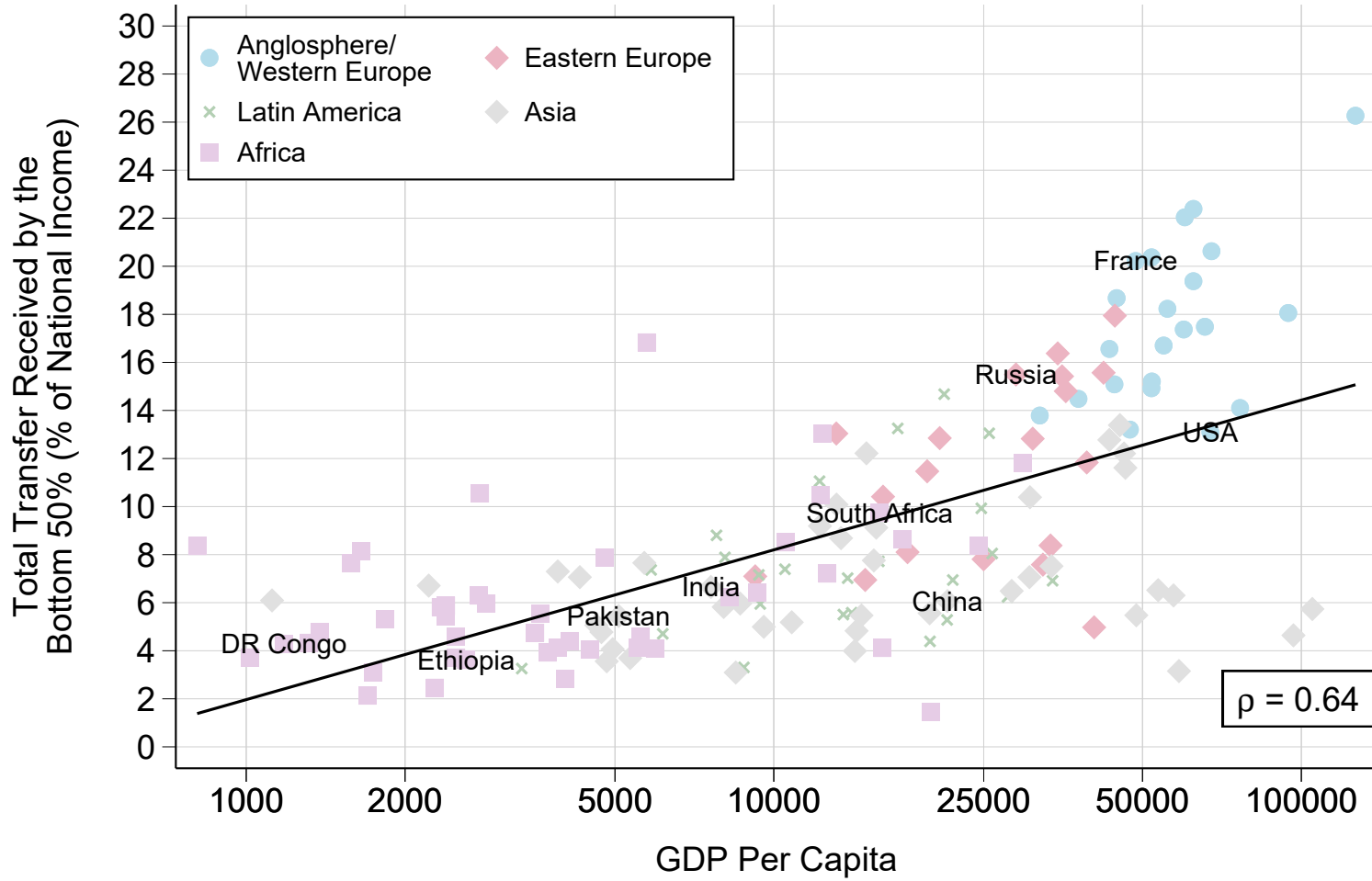


Figure 2.14 – Transfer Progressivity Over the Course of Development

Notes: The figure shows the total transfer received by the bottom 50%, as a percentage of national income. (Total transfer received is the sum of all transfers received, before paying any taxes on these, expressed as a share of national income.)

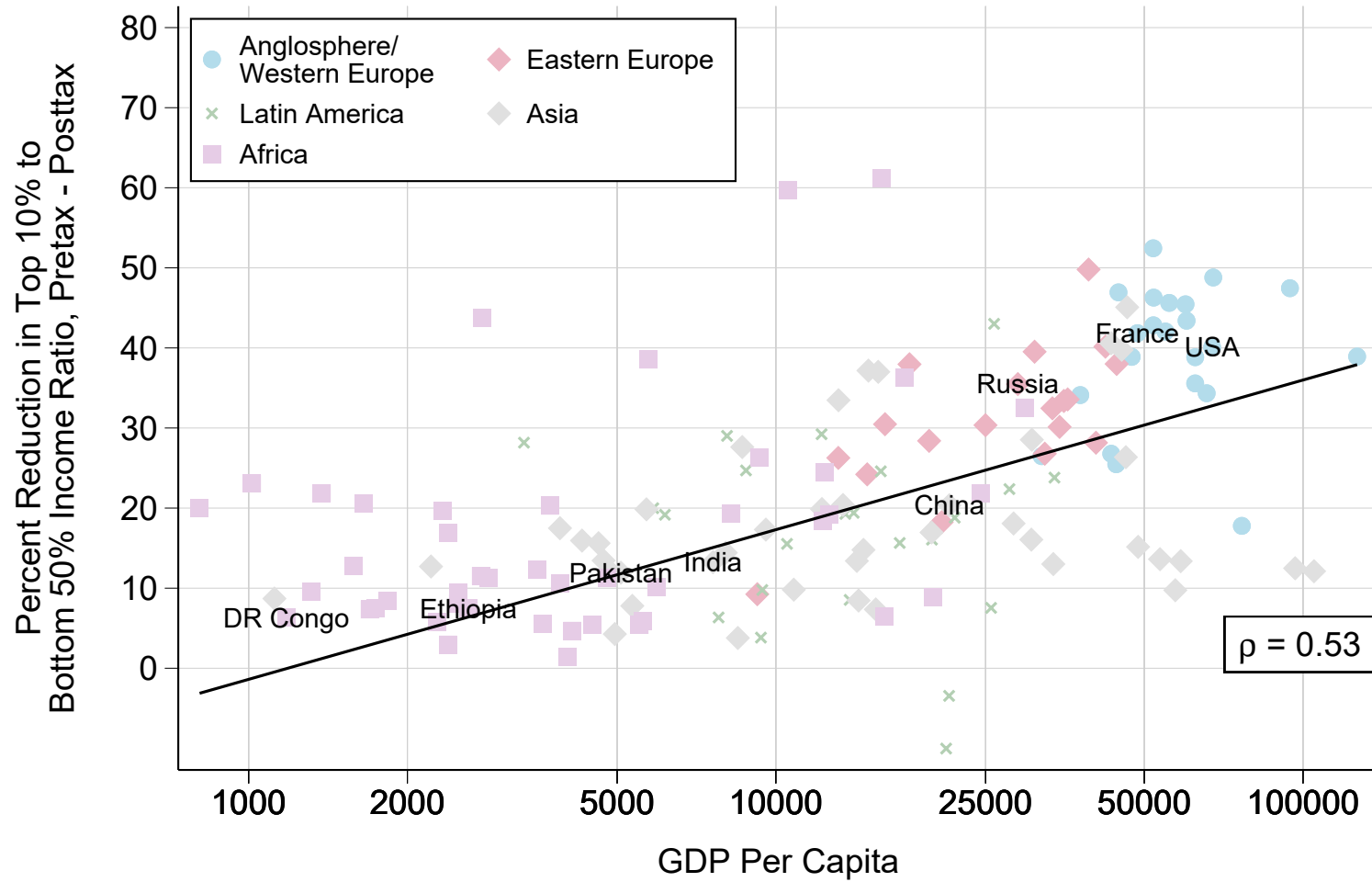


Figure 2.15 – Net Redistribution Over the Course of Development

Notes: The figure shows the percent reduction in the top 10% to bottom 50% income ratio, from pretax income to posttax income.

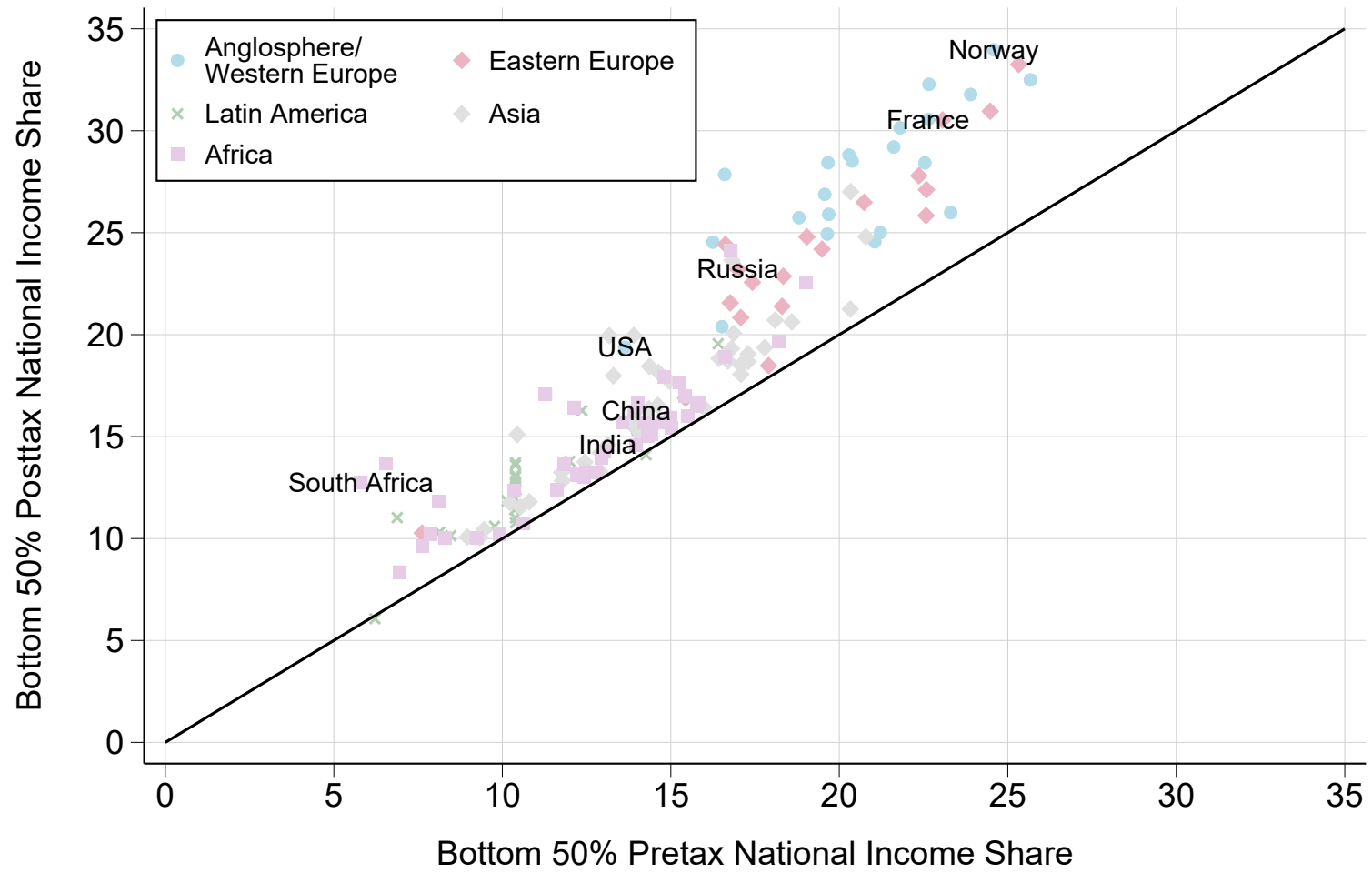


Figure 2.16 – Predistribution versus Redistribution:
Bottom 50% Pretax versus Posttax National Income Shares by Country, 2019

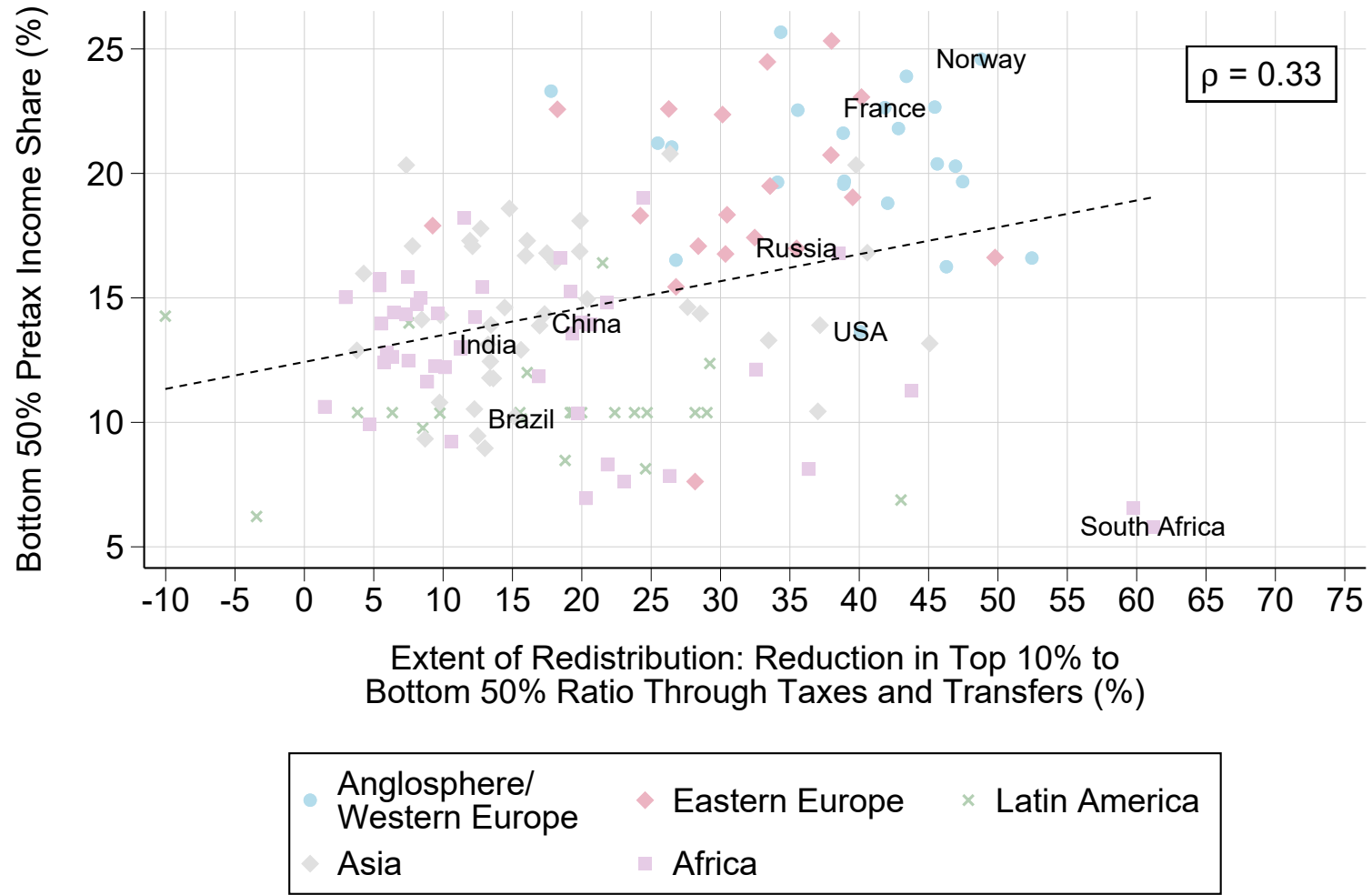


Figure 2.17 – Predistribution versus Redistribution:
Bottom 50% Pretax Income Share versus Extent of Redistribution, 2019

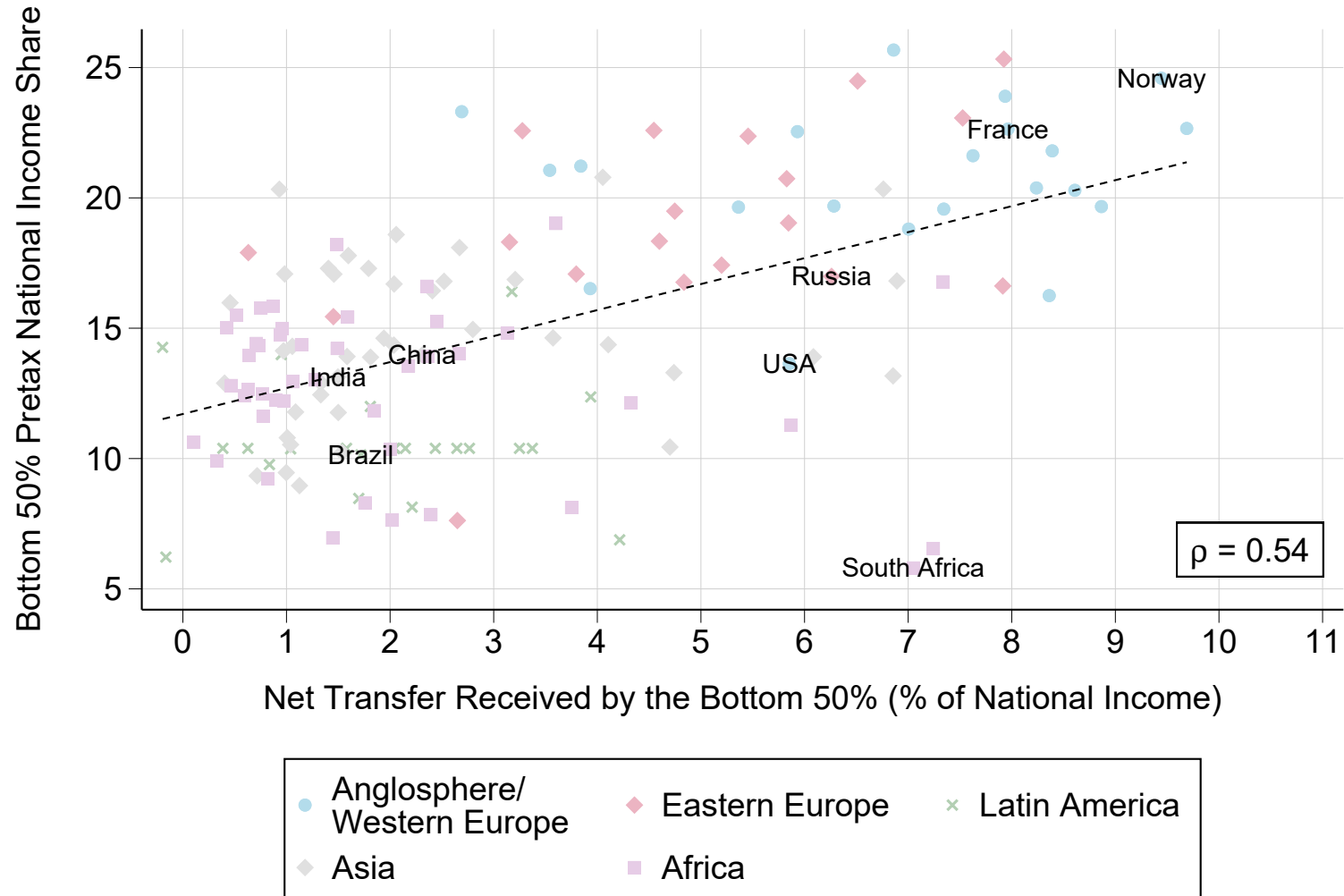


Figure 2.18 – Predistribution versus Redistribution: Bottom 50% Pretax Income Share versus Net Transfer Received, 2019

Chapter 3

National Service and the Great Leveling: New Evidence on Midcentury American Inequality

Abstract

The mid-20th century American decline in income inequality has been called “the greatest leveling of all time,” despite a similarly unmatched rate of economic growth (Lindert and Williamson, 2016). This paper returns to archival tax records and survey data to study early and midcentury trends in income and wage inequality within the middle class. I find that: (i) pre-war economic growth reached the upper middle class sooner than the poorest households; and (ii) wartime relative income gains for the poorest were short-lived, while they proved more durable for the upper middle class; but (iii) postwar *wage* compression lasted 30 years, to the particular benefit of the working poor. To explain this, I propose a novel mechanism—that World War II service (and accompanying human capital) spurred postwar income gains and economic mobility. After linking the full-count US Census of 1950 to that of 1940, and both of these to a unique dataset on WWII enlistees, I exploit an exogenous discontinuity in the probability of being drafted to show the causal impact of service on wages. This impact was strongest for the poorest.

3.1 Introduction

This investigation will re-examine long-run trends in income distribution in the 20th century United States by returning to previously unused archival data with a new method for statistical inference, and I will attempt to explain these new trends with a natural experiment that captures the World War II veteran wage premium.

The foundation for this work, Piketty and Saez (2003) tracked US wealth and income inequality over the 20th century, a series that has since been expanded to include the early 21st century (Saez, 2016). More recently, Piketty, Saez, and Zucman (2018) harmonized long-run macroeconomic data with the same tax data and more recent survey estimates, in order to provide an estimate of the full national income distribution, one that includes all sources of income in the national accounts. Taken together, these analyses show that income inequality¹ in the US has risen to a level not seen since the early 20th century.

This study will attempt to extend the detail found in those later estimates, to the earlier era—and to explain these results. Where the existing distributional national accounts study for the United States only begins in 1962 (for the *full* income distribution and not only the top 10 percent), I provide estimates back to 1913 (the beginning of the federal income tax). Where several complementary hypotheses have attempted to explain the midcentury decline in income inequality, I contribute one further explanation: that World War II service itself contributed to productivity gains for lower- and middle-class wage earners.

To place this study in the context of the literature from Piketty and Saez (2003) to present, first I show the existing long-run series on American fiscal income inequality at the tax unit level, Figure 3.1. Overlaid in blue is a preview of the new results.

Continuing in the tradition of this literature, after the Piketty, Saez, and Zucman (2018) study, I also now observe the top 10% and top 1% shares not only on a tax unit basis, but also since 1962 on the basis of equal-split adults.² Also since 1962, we now know the evolution of middle-class and lowest income shares, including the share of total fiscal income that accrued to the bottom 50% of earners, and that to the 50th to 90th percentiles (what we can call the middle 40%). Bottom 50% and middle 40% shares are shown in Figure 3.2 in dark green, while top 10% and top 1% shares are shown in red. The dash line overlay is a preview of the new results.

I extend this innovative historical record from 1962 back to 1913. While Piketty, Saez, and Zucman (*ibid.*) have estimated the full percentile distribution of US income shares since 1962, this had not yet been done for the years prior to 1962. Nor had this been done for the income from wages and salaries, which is the most significant source of total fiscal income, and especially for middle-class households. From there, I scale up the inference from fiscal income to pre-tax distributional national accounts.³

Finally, I propose that—among complementary hypotheses on education, technology and trade—World War II service helps explain wage growth, and particularly

¹Wealth inequality has followed suit (Saez and Zucman, 2016).

²The concept of equal-split adults (splitting tax-unit income equally among the adults within a tax unit) eliminates any bias in the series that might owe to demographic characteristics, by which high-income earning households (and tax units) might file as a married couple more frequently than low-income households (which would bias the measure of inequality upward, if we compare rich couples with poor individuals).

³For a more thorough discussion of the income concepts used in this paper, please refer to Blanchet et al. (2021).

the upward economic mobility of the working class. For those who served, there was a significant wage premium, one which can be interpreted causally by way of a natural experiment on the probability of being drafted.

The purpose of this study, then, is: (1) to contribute new estimates of the distribution of American income prior to 1962; and (2) to make sense of these patterns, with a new (but complementary) explanation, in the context of what is already known about the evolution of American income inequality in the 20th century.

One of the principal results can be summarized in Figure 3.3. As in Piketty, Saez, and Zucman (*ibid.*), we can observe here that the bottom 90 percent share of national income has indeed changed over time, but that the split within the bottom 90 has been relatively stable since the middle of the 20th century. What the new results now show, however, is that the gains of the poorest 50 percent earlier in the century were not proportional to the gains of the middle 40 percent. The relative gains from the New Deal, World War II and postwar eras were both more pronounced and have been more durable for the upper middle class than for the poorest. However, postwar *wage* compression lasted longer, to the particular benefit of the working poor.

Finally, I propose a new explanation for this significant wage compression. Several explanations for postwar wage compression have been explored in previous studies, including perhaps most notably a “race between education and technology” (in the eponymous monograph of Goldin and Katz, 2008), in which skills matched technology and jobs during much of the postwar era before lagging since; and a progressive tax code during the postwar era which has flattened since the 1980s (Piketty, 2014). Lindert and Williamson (2016) pointed to:

- demographic factors (a slowdown in labor supply growth);
- trade policy (a relatively closed domestic economy and lack of international competition);
- financial sector retrenchment (due to tight regulation);
- technological change (favoring unskilled workers); and
- returns to education and skill (with unparalleled increases in human capital attainment).

Most recently, Artola Blanco and Gómez-Blanco (2024) confirmed the compression in the postwar wage distribution, but also found a composition effect as salaried workers turned to self-employed.

I contribute and test one further hypothesis: Service in World War II particularly benefited the working poor. Exploiting a discontinuity in the probability of being drafted⁴—fathers before December 7, 1941 were disproportionately exempted from

⁴Angrist and Krueger (1994) follow a similar intuition for an IV estimate to argue that the veteran wage premium was illusory and largely a question of selection into service. However, their instrumental variable (to predict the probability of being drafted without otherwise predicting wages) is the soldier’s quarter of birth. As such, its identifying variation occurs only among those who turned 18 years old between 1944 and 1946, as the war (and the probability of being drafted at one’s 18th birthday) declined. As I will try to demonstrate in sections 3.2 and 3.3, the LATE on teenagers and on those who enlisted very late in the war (or after it ended) misses the treatment effect on those for whom service mattered more. Older soldiers served for longer, and their service may have occurred at a more propitious age.

the draft, or drafted later—I show that the birthdate of a man’s eldest child predicts his service in WWII, and consequently predicts his wages in 1950. World War II veterans experienced a significant wage premium in the postwar economy, and we can interpret this as a causal effect of their service. The effect was greatest for those who served in their early twenties; for those who served longer; and for those who came from poor and working-class backgrounds.

3.2 Data and Method

3.2.1 Income distribution estimates

Prior to this study, the full picture of early and mid-20th century patterns of income distribution had been missing. Data had been the largest constraint. For the early 20th century American economy, Piketty, Saez, and Zucman (2018) summarize the missing data issue as follows:

For the pre-1962 period, no micro-files are available so we rely instead on the Piketty and Saez (2003, updated to 2015) series of top income shares, which were constructed from annual tabulations of income and its composition by size of income.

Piketty and Saez (2003), in turn, had written:

Before 1944, because of large exemptions levels, only a small fraction of individuals had to file tax returns and therefore, by necessity, we must restrict our analysis to the top decile of the income distribution.

Until now, the paucity of pre-1962 data has inhibited analysis of early 20th century changes across the whole of the income distribution. However, as total income (national accounts) data was not missing for these years, and since top decile income data was not missing, it was possible to estimate the “top 10” vs. “bottom 90” percent split in the income distribution.

A recent methodological advance allows to estimate a generalized Pareto curve and “nonparametrically recover the entire distribution based on tabulated income or wealth data as is generally available from tax authorities” (Blanchet, Fournier, and Piketty, 2022).⁵ This type of tabulation remains the extent of the tax data for the period 1913-1961. So, in the absence of tax microdata, such precision to smooth the income density distribution is a welcome source of new estimation.

However, several imputations are necessary for the generalized Pareto interpolation technique to treat the data without bias. First, it is necessary to treat tax units as equal-split adults. Even if the relative distribution of two-income households had not changed over time (it did), tax incentives also could have changed in a way that was heterogeneous across the income distribution. The increasing level of households filing tax returns jointly or separately (whether due to changing incentives, or an increasing number of women in the labor force, or both) could give a misleading impression of middle-class growth if one does not account for the trend by calculating these propensities with greater precision.

⁵Applied to United States data 1962-2014, the method is shown to closely follow the true distribution using only threshold tabulations.

A particular challenge in the construction of this dataset was the treatment of missing tax units who did not file tax returns. There are several approaches one can take to deal with missing data, and I explore two of them. One approach is to assign missing income and missing people to the leftmost side of income distribution, under the realistic inference that poorer households more frequently do not file tax returns, often because they are below the income threshold for filing (Saez, 2016). Another approach would be to assume that these non-filers were randomly or equally distributed throughout the lower deciles, an approach that is applied with success to French historical income data in Garbinti, Goupille-Lebret, and Piketty (2018). I show results from both methods, and ultimately select the former as more appropriate in the context of this data.

An even greater challenge for imputation of missing tax data is in the pre-World War II period, when the majority of American households did not file tax returns—namely, those below the top 10% of the income distribution. (The filing threshold was higher.) To deal with this missing middle-class tax data, I integrate a historical survey on American family income from 1929-44, harmonized with the tax data (Goldsmith, 1951). To the extent that they are representative and include reliable information on missing tax units, data from this Goldsmith-OBE series helps to assign the non-missing tax units to their appropriate and realistic rankings in the imputed income distribution—prior to generalized Pareto interpolation the fills in the rest of the cumulative distribution function.

These methods can be validated using post-1962 data: If the survey data distributions match the IRS Statement of Income (SOI) tabulations in the years immediately after 1962, according to micro-data tax records, we can infer that a similar match exists in the years immediately prior to 1962. That inference may be less robust as we move farther into history from this time period, but I pay special attention to changes in filing requirements and in federal income tax legislation,⁶ and to pre-World War II survey statistics. As a final step for this data series, I move from fiscal income to pre-tax national income concepts, harmonizing tax data with national accounts to match and distribute 100% of the annual macroeconomic totals from the National Income and Product Accounts. See Appendix A3.1 for further details on data construction.

Using this method to harmonize survey data with administrative tax tabulations, I was able to extend estimates of the lower 90% income distribution to the World War II period and before. That is, I complement the Piketty and Saez (2003) and Piketty, Saez, and Zucman (2018) benchmark series on top shares with data even for the bottom 50% and middle 40% of earners.

This harmonized series, with Goldsmith-OBE series integrating to SOI tax data, creates a unified long-run series on income distribution that includes pre-1962 fiscal income shares. Compared to the Piketty and Saez (2003), this new series is robust and comparable in most years. (See Figure 3.4.) These estimates also match closely at the level of top 1% shares (Figure 3.5). In their time periods of overlap, these new estimates are similar to those in Piketty and Saez (*ibid.*) and Piketty, Saez, and Zucman (2018), and match closely.

Of course, the advantage of using this new dataset for the pre-war years goes beyond just the appeal of a replication study with more detailed data. As discussed among the results in section 3.3 below, the new income distribution estimates show

⁶See also Witte (1985).

the postwar wage compression—which I try to help explain with a novel investigation of the WWII veteran wage premium.

3.2.2 Causal estimates for WWII service and wage growth

To understand the egalitarianism of the postwar era, and in particular the wage compression that was among its defining characteristics, I investigate an old hypothesis with new evidence.

Studies as early as De Tray (1982) have observed a WWII veteran wage premium. However, Angrist and Krueger (1994) explored further and concluded that the wage premium was the illusory effect of selection bias, where those who served had a latent earnings potential higher than those who did not. They instrumented for the probability of service via the quarter of one’s birth, as the overall probability of being drafted declined with age—for those who turned 18 between 1944 and 1946 (as the draft itself declined). With this instrument, the authors found no impact of service on wages, and concluded that the OLS effect was merely from selection into service. While Mettler (2005) argued that veterans also benefited from preferential hiring, and from education opportunities in the GI Bill (similar to Goldin and Katz, 2008; Lindert and Williamson, 2016), the question has remained largely settled since (Gabriel, 2017).

I re-open this inquiry and test the hypothesis of a causal effect of WWII service, with new data and a new instrument.

The new data is the newly available 1950 complete-count decennial United States Census, which I link to the 1940 version of the same (by way of the Integrated Public Use Microdata Series, IPUMS; Ruggles et al., 2024).⁷ In fact, the IPUMS 1940 data is also linkable to the WWII Army Enlistment Dataset from the innovative CenSoc project (Goldstein et al., 2023), so I link this dataset of army veterans and the circumstances of their enlistment, to the linked 1940 and 1950 full-count Census wage distributions from IPUMS.⁸

The new instrument exploits a discontinuity in draft probability around a fatherhood deadline of December 7, 1941. This setup relies on a similar intuition to that of Angrist and Krueger (1994), as a natural experiment with an exogenous predictor for the probability of service, where the instrument for service would only affect later earnings by way of this channel. Whereas their instrument examined teenagers whose 18th birthday occurred as the probability of being drafted decreased from 1944 through 1946, this instrument is valid for all men eligible to be drafted, although I prefer to restrict the sample to a narrower event window of fatherhood before or after Pearl Harbor. Arguably, men who become fathers may have different earnings potential from men who do not. And men who become fathers later in life (or closer to 1950) may differ in unobserved ways from men who became fathers earlier in life (or closer to 1940). However, men whose eldest child was born immediately after

⁷The 1950 full-count Census is newly available as of January 2024 (see [link](#)).

⁸Unfortunately, these wage distributions are top-coded at \$5,000 and \$10,000 in 1940 and 1950 current USD, respectively. (And they only cover wages, with limited coverage of any other income or wealth concepts, with many missing values that we assume are missing at random.) As such, even the full-count Census data provides limited information about the top of the wage distribution (and less or no information about other incomes). However, I assume that the relative rankings along the wage distribution are unbiased, and that the orders of magnitude on wage amounts are reliable, as well.

Pearl Harbor are unlikely to differ significantly from men whose eldest child was born just before Pearl Harbor. Their most salient difference would be in the probability of being drafted.

The original Selective Training and Service Act of September 1940, authorizing the draft via the Selective Service System, provided for the ‘dependency deferment’ (Class III-A) of all registrants with dependent children. However, as the army expanded, later amendments tightened the criteria for deferment (Selective Service System, 1947). After the attack on Pearl Harbor (December 7, 1941) and declaration of war the next day, the February 1942 edition of the Selective Service System regulations stated that “no registrant shall be deferred by placing him in Class III-A... if he acquired such status on or after December 8, 1941” (*ibid.*).

An April 1943 memorandum to local draft boards clarified “the order in which men 18 through 37 years of age would be called for induction [draft] as (1) single men with no dependents, (2) single men with collateral dependents [e.g., dependent family members other than children], (3) married men with wives only, and (4) men with children” (Selective Service System, 1946). The memorandum also quoted the regulation in question:

622.31. Class III-A: Man with child or children deferred by reason of maintaining bona fide family relationship. ... In Class III-A shall be retained or placed any registrant who with his child or children maintains a bona fide family relationship in their home, provided such status was acquired prior to December 8, 1941. (*ibid.*)

Subsequently, Public Law 197 of December 1943 “prohibited the induction of fathers until all nonfathers in the country had been processed for induction,” where:

The term “father” shall include only a person who was married prior to December 8, 1941, who has maintained a bona fide family relationship with his family since that date, and who has a child as defined in this section. ...

The term “child” as used in these regulations means a legitimate child born prior to September 15, 1942, a stepchild, adopted child, foster child, or a person who is in the relationship of child to the registrant, who became such prior to December 8, 1941, who is less than 18 years of age, or who by reason of mental or physical defects is incapable of self-support, who is unmarried, and with whom the registrant has maintained a bona fide family relationship in their home since December 7, 1941. (Selective Service System, 1947)

Note that these 1943 criteria for deferment eligibility actually required fathers to be married prior to December 8, 1941, and allow for ‘pre-Pearl Harbor’ children to be born up to September 15, 1942 (i.e., with conception prior to Pearl Harbor). In practice, we do not observe in the 1950 Census whether men were married before Pearl Harbor, only their marital status in 1950.⁹ That there is some ambiguity on whether the child for dependency deferment eligibility was born prior to December 7, 1941 or prior to September 15, 1942, is mitigated by the fact that our data was measured on April 1, 1950 (Census Day) and only asked for ‘age’ but not the precise birthday. Therefore, we can study several event windows with respect to April 1, 1942: If a man’s eldest child was at least 8 years old on April 1, 1950, we count him a ‘pre-Pearl Harbor’ father; if younger than 8 on April 1, 1950, then a ‘post-Pearl Harbor’ father.

⁹And occasionally the duration of marriage, but with a preponderance of missing values. Of course, we also only observe surviving children who remained in the household through 1950. In any case, I take the eldest child’s age as a sufficient instrument, and control for marital status in 1950.

As will become clear in the results section 3.3.2 below, among fathers the probability of service increased dramatically around the 8-year-old eldest-child age cutoff.

There are non-compliers on both sides of the running variable (age of eldest child)—i.e., some pre-Pearl Harbor fathers were drafted; and some post-Pearl Harbor fathers were not drafted—so this instrument represents a fuzzy discontinuity. However, it is possible to observe directly whether Census respondents served in World War II,¹⁰ so it becomes possible to estimate the local average treatment effect (LATE) and not merely the intent-to-treat (ITT) effect. The linked CenSoc data, although it is a reduced sample of the linked 1940-50 full-count Censuses data, also allows us to observe: (i) whether the veteran was drafted or volunteered; (ii) whether they were drafted from civilian status (rather than a military-adjacent occupation, e.g., National Guard service); and (iii) their date of enlistment (a proxy for their length of service until the end of the war).

In sum, the model I would like to estimate is a standard Mincer (1958) earnings function:

$$y_{1950} = \beta_1 educ + \beta_2 exper + \beta_3 exper^2 + \alpha WWIIservice + \xi X + \epsilon \quad (3.1)$$

where (log) wages in 1950, y_{1950} , is regressed on years of *education* and *experience* (and its square term). The parameter α represents the impact of service in World War II on wages, and is the parameter of interest. X is a vector of controls including dummies for age cohort, race, urban location in 1950, and marital status in 1950.

However, one might worry about selection into service, whether because individuals with higher latent earnings potential may have disproportionately volunteered, or because the military would reject (not draft) individuals who were “physically, mentally, or morally unfit for service” (Class IV-F; Selective Service System, 1950) whom we may imagine had a lower latent earnings potential. Among married fathers, less than 2% were placed in this category Class IV-F (compared to approximately 20% of the larger population of registrants), which suggests that fathers represent a particularly valid subsample from among whom to instrument for the probability of being drafted.

The probability to serve in World War II, then, can be instrumented in the following first-stage equation:

$$WWIIservice = \gamma_1 educ + \gamma_2 exper + \gamma_3 exper^2 + \theta Z + \zeta X + u \quad (3.2)$$

where Z is the April 1, 1942 eldest-child age cutoff for pre- vs. post-Pearl Harbor fatherhood, and covariates are the same as in equation 3.1.

Beyond these cross-section regressions with only 1950 Census data, the linked 1940 Census (and CenSoc) datasets allow for a panel fixed-effects design, albeit with the sample size slightly reduced to those who were observed in 1940 (and in army enlistment records)—and, in particular, whose wages or parent’s wages were observed in 1940.

¹⁰So-called ‘sample-line individuals,’ randomly one per household, were asked a battery of extra questions in the 1950 US Census, and among these (when the respondent was male and of age) whether they had served in World War II.

The panel fixed-effects model can be written as follows:

$$y_{it} = \lambda WWIIservice_{it} + \delta_i + \pi_t + \phi X_{it} + e_{it} \quad (3.3)$$

where y_{it} is the difference between 1940 and 1950 values; *World War II service* can be instrumented as in equations 3.1 and 3.2 above; δ_i and π_t are individual and time fixed effects, respectively; and most of the controls above are unnecessary because constant within the individual over time.¹¹

The dependent variable y_{it} can be interpreted as a change in log wages,¹² or instead, the model can be specified as a rank-rank regression (Chetty et al., 2014), where the outcome of interest is a change in rank of within-cohort wage distributions. For 1950 Census respondents linked to the the 1940 Census but whose 1940 wages are not reported (e.g., because they were not yet in the labor force), it is occasionally possible to link their father’s within-cohort wage distribution ranking in 1940.

The results from estimating these models are presented in section 3.3.2 below, after discussing the results for the new inequality series overall.

3.3 Results

3.3.1 Income inequality, 1913-75

From the harmonized Goldsmith-OBE data series discussed in section 3.2.1 and Appendix A3.1, it is possible to estimate the shape of the income distribution below the 90th percentile, both for tax units and for equal-split adults, as well. I present the new data series first for tax units (Figures 3.6 and 3.7) and then for equal-split adults (Figures 3.8 and 3.9).

If the results can be summarized in a single graph, it is the Figure 3.10 portrait of 100 years of pre-tax income.

Immediately apparent is the dramatic rise of top incomes in the pre-World War II era, and its fall in the wartime and post-war era. These tectonic shifts predominantly affected the middle class households (tax units) in the 50th to 90th percentile distributions. Of course, incomes of the lower 50% of households fell sharply during the Great Depression and rose even more notably during and after the war, but the magnitude of these changes was not as large as that of the “middle” 40% households.¹³

We will discuss the implications of these results further below, but it is also worthwhile to show the long-run trends for equal-split adults (which accounts for changes in the size of a tax unit and household over the span of the income distribution).

First I show top 10% and top 1% fiscal income shares, to add detail to the Piketty and Saez (2003) series and extend this feature from Piketty, Saez, and Zucman (2018) to the pre-1962 data. The distribution among tax units (same as above) is highlighted here in gray.

¹¹I can control for the move from rural to urban location, or vice versa, between 1940 and 1950.

¹²Or, more specifically, as the log of the 1950 to 1940 wage ratio: $\log(y_{1950}) - \log(y_{1940}) = \log\left(\frac{y_{1950}}{y_{1940}}\right)$.

¹³The spike from 1941-45 likely indicates the effect of armed forces mobilization among lower 50% earners, particularly soldiers’ wages.

In the case of topmost income shares, the breakdown of data by equal-split adults does not make a great difference, although the level is slightly higher for top 10% shares before the war, and slightly lower after. If higher-earning households are less likely than lower-earning households to file tax returns jointly, this was more true before the war than after. In fact, the turning point was tax legislation in 1947. Before 1947 married couples with two incomes had incentive to file separately—the tax scale was the same for additive or separate incomes, which under progressive taxation particularly favored two-high-income households.

Next we can turn to the middle 40% and bottom 50% of equal-split adults, again showing the previous distribution (tax units) in gray for comparison, in Figures 3.11 and 3.12.

What seems immediately clear from the Goldsmith-OBE data is the rapid rise in both bottom-50% and middle-40% shares of fiscal income during the Great Depression and into the post-World War II era. While this follows logically from the previously observed (and well documented) fall in top 10% shares, before now we could not be sure that this was not merely an effect of the composition of tax units. It is not. We will return to this finding in the discussion section below.

Meanwhile, we can examine these trends further by showing the progression of wage income over the same time period. First of all, in Figure 3.13 we can compare the new results to Piketty and Saez (2003) top 10% shares of wage income inequality. On a tax-unit basis, we observe a close match between the newly interpolated wage income distribution, and the previous Piketty and Saez (*ibid.*, updated to 2015) and Piketty, Saez, and Zucman (2018) series.¹⁴ We can show an even closer match at the top 1% of the distribution (Figure 3.14).

We also see a close match in the overall average wage income (see Appendix Figure A3.1),¹⁵ and the same is true for wage income thresholds (e.g., median, 90th and 99th percentiles).

Since we observe a close fidelity of the new series to the earlier picture of top 10% shares offered by the benchmark series, we can have confidence in the further inferences on the inner working of the wage distribution, below the 90th percentile: the share of wage income going to the bottom 50% and the share going to the middle 40%. As with fiscal income, neither of these have been previously observed for the pre-1962 wage income distribution, neither for equal-split adults nor for tax units.

These results are displayed in Figures 3.15 and 3.16, with equal-split adults in dark red and tax units in dark green.

These results follow those above (indeed for tax units they are the same as presented in the comparison above), forming the early part of the U-curve that we see in both income and wage inequality over the 20th century into the 21st. As above for fiscal income, here for wages we can see the significance of tracking equal-split adults and not just tax units—and indeed the effect switches at 1947 here, too. Before 1947, higher-earning households would file separately more frequently than lower-earning

¹⁴If the new series is slightly lower in its interpretation of income going to the top 10% share, this may be a function of imputing all missing wage income and missing tax units at the far left of the income distribution, below the filing requirement threshold. However, the error is small, within less than 1% of total wage income, and does not affect the direction and pattern of the overall trend.

¹⁵The match of existing to new estimates on overall income is not quite perfect, as the smoothing function needs to make some adjustments to accommodate the observed distribution and impute non-filers into the lefthand side of the distribution, but it comes very close.

households (when weighted by the size of the income concerned), and after 1947 less frequently.

Beyond the ability to examine these top shares according to equal-split adults, we can now look inside the bottom 90% of the overall wage income distributions to show the evolution of wage income accruing to the poorest 50% of earners, over the entire period 1927-75. (See Figure 3.17.)

The results are similar between tax units and equal-split adults—a sharp and durable increase in wage income to the bottom 50% during and after World War II. Perhaps it is worth noting that the post-war spike in income shares to the bottom 50% is not quite as strong among equal-split adults as among tax units. This could be an artifact of the number of working spouses that joined the workforce during and after the war and could be found in tax units disproportionately toward the base of the income distribution. Among poorer families the rise in two-earner households filing taxes jointly would have been sharper than among wealthier families. (In Figure 3.18, we actually see the reverse effect among the middle 40% of wage earners.¹⁶) To split equally the income of tax units filing jointly dampens the wage increase, but that increase was powerful nonetheless.

3.3.2 Veterans' wage premium and economic mobility

What explains the bottom 50% increase in relative (and absolute) wages during the war and throughout postwar era? Beyond the factors discussed elsewhere in the literature and above, it is possible to demonstrate a causal impact of World War II service on 1950 wages.

Table 3.1 shows the OLS regression of wages on education and experience, with or without controls, in cross-section for the 1950 full-count Census (among sample-line individuals who were asked about their WWII-veteran status, and for whom both wages and control variables were nonmissing). Model (2) adds WWII-veteran status to the canonical Mincer (1958) model of columns (1), while Model (3) interacts veteran status with education in order to test the impact of the GI Bill education subsidies available only to veterans. However, 1950 is likely too early a timeframe to observe the wage impact of GI Bill-subsidized education investment, as the returning veterans who took advantage of the program would have still been in school, or too early within the education-experience tradeoff to experience the benefit of the former.

¹⁶The war marked a decline in the share of total wage income accruing to the middle 40% of earners. Again, however, this depends on the perspective. Whereas the tax units' approach shows a more precipitous drop in wage income share after the war, the approach among equal-split adults suggests instead a steady share of wage income accruing to middle-class workers. After 1945, the trends for bottom 50% wage income seem to move in tandem, and we do not see much, if any, difference driven by a distinction on joint vs. single filers (comparing tax units vs. equal-split adults series), as may have been expected if households continued to file differently over this part of the income distribution in a proportion other than the one by which they earned wages jointly or doubly. However, the middle 40% series shows a persistent 3- to 5-percentage-point gap in the post-war period, between tax units (lower share) and equal-split adults (higher). If middle-class tax units appear to earn less of a share of wage income than middle-class adults equally-split, the trend is inverse among top 10% earners. Among the top 10% wage earners, there is a similarly persistent post-war gap, but a gap where tax units claim the higher share of total wage incomes, and equal-split adults the lower. Such effect may be the consequence of post-1947 filing changes in which high-earning couples started filing jointly more frequently; or it may signal a rise in upper middle-class earners who assortatively match and file jointly; or both.

Nonetheless, the 1950 wage premium for veterans is unmistakable in Model (2)—if anything amplified in Model (3) controlling for those veterans who had returned to school by 1950.

The question, of course, is whether the OLS impact of WWII service on wages is *causal*, or merely a correlation of earnings potential with selection into service.

Table 3.2 introduces the instrumental variable of eldest-child's birthdate with respect to Pearl Harbor, according to several event windows from one year to seven years. (In the 1-year version, fathers whose eldest child was born between April 2, 1941 and April 1, 1942 are compared to fathers whose eldest child was born between April 2, 1942 and April 1, 1943. In the 7-year version, the extreme dates are widened to April 2, 1935 and April 1, 1949, respectively.) World II service is predicted according to logistic regression and linear probability models, with and without controls, although the variation across specifications hardly matters. Even controlling for age, the 7-year window around April 1, 1942 has the highest predictive power, and the greatest difference between the probability of service for post- vs. pre-Pearl Harbor fathers. Overall, nearly 48% of men in our sample (men aged 18-42 in 1946, who responded to the 1950 full-count US Census as 'sample-line individuals,' with information on their veteran status as well as wages and control variables) served in World War II. Only 21% of pre-Pearl Harbor fathers served, although the statistic increases to 25.6% among those whose eldest child was born within 7 years before Pearl Harbor. In the one-year window around April 1, 1942 (eldest child aged 8 years on April 1, 1950), 36% of pre-Pearl Harbor fathers served, while nearly 50% served among 1-year post-Pearl Harbor fathers (eldest child aged 7 years on April 1, 1950), or 43.3% on average. For sample size, intuition, and clarity (see section 3.2.2), the 3-year window will be the preferred specification, but results do not change much according to the choice of event window for the instrument.

The three-year window is examined more closely in Table 3.3. Nearly 55% of post-Pearl Harbor fathers (within three years) served in World War II, against only 32% of pre-Pearl Harbor fathers (within three years). The latter were nearly 2.5 years older, although their wages (and within-cohort wage percentile) were very similar.¹⁷ Likely reflecting this age difference, pre-Pearl Harbor fathers were more likely to have their own wage observed in (and linked from) the 1940 Census, whereas post-Pearl Harbor fathers were more likely to have their father's wage observed in (linked from) the 1940 Census, implying that they were more likely to have been members of their parents' household at the time of the 1940 Census.

With the same logic as Table 3.2 on the first-stage estimates, Table 3.4 presents the second-stage IV estimates for each of the event windows discussed. If we look at the 3-year window, with controls, and take the effect sizes literally, service in World War II is associated with a 6% increase in 1950 wages. The tighter 1-year event window (still with controls) actually predicts a larger effect size, on the order of a 10% increase in 1950 wages.

Of course, it is unlikely that the impact of service on earnings would be equal for all individuals. Table 3.5 presents the results by age cohort, presented according to men's ages in 1946. In Model (1) of this table, the headline OLS results for all men 18-42 in 1946 correspond to the OLS results in Table 3.1. In Model (2), the headline IV results for the three-year window correspond to the results in Table 3.4. Heterogeneous impacts by cohort are then examined with separate regressions for

¹⁷Note that I control for age cohorts in these regressions, as well.

each age group. The age group 18-20 in 1946 corresponds to the sample studied by Angrist and Krueger (1994), so it no surprise that the effect size is minimal (and, with controls, actually reverses sign)—although the positive sign for the instrument on fatherhood [if particularly weak among teenagers, for whom fatherhood was rare] hints at a different story than the result of instrumenting on quarter-of-birth.¹⁸

The most dramatic impact of service is observed among men aged 21-25 in 1946, both in OLS and IV estimates. While the OLS impact for this group is marginally more important for this cohort than for subsequent cohorts, the IV result is staggering. Taken at face value, service in the war led to a more than 100% increase in postwar wages, for post-Pearl Harbor fathers compared to pre-Pearl Harbor fathers. This was also the cohort most likely to serve in the war, in general. However, we might believe that there is some unobserved heterogeneity among those within the 21- to 25-year-old age group at 1946, who became fathers between 1939 and 1942 (between their ages 14 and 21 at the extremes) rather than between 1942 and 1945 (their ages 17 and 24 at the extremes), even controlling for age.

The next cohort, ages 26-30 at 1946—while perhaps less impressionable to a ‘formative’ life experience building human capital than their 21- to 25-year-old comrades, and more vulnerable to a mid-career interruption or tradeoff from service—may represent a group for whom pre-Pearl Harbor fatherhood in the 3-year birthdate window (between ages 19 to 26) is less different from post-Pearl Harbor fatherhood in the 3-year birthdate window (between ages 22 and 29); or, more specifically, that the individuals themselves (‘early’ vs. ‘late’ fathers) would be more similar, such that the change in their probability of getting drafted is a cleaner experiment. For this group, World War II service is estimated to generate at least an 18% increase in 1950 wages.

For individuals age 31 and over, the OLS effect decreases and the IV effect disappears. We might conclude that the impact of World War II service was less for this group, whether due to a larger tradeoff in the interruption of veterans’ existing career trajectories or a mismatch between the type of ‘training’ that service represents and the stage of life of these soldiers, or another factor.

Nonetheless, for a sizeable subsample of veterans who served in the war during their early and mid-twenties, the experience proved an unmistakable stimulus for subsequent earnings capacity.

In fact, the effect was greatest for those in the lower half of the wage distribution of 1940. Table 3.6 shows the same cross-section OLS and IV results, but restricted to those whose 1940 position in the wage distribution (or their father’s) could be linked to 1950 wages.

In the IV estimates here, in Panel A, for those who found themselves in the bottom 50% of the 1940 wage distribution (for their age), WWII service is associated with a 10% increase in 1950 wages. There is no discernable effect for individuals who were in the top half of the 1940 wage distribution, although the OLS suggests even a negative impact. In Panel B, an even greater effect is observed among those whose father’s position was bottom 50% in 1940 (age-specific wage distributions), although in Panel B some relevant effects exist (in IV, if not OLS) even for those whose father was higher in the 1940 wage distribution.

¹⁸In Angrist and Krueger (1994), the sign for the IV estimate actually turned negative (while the sign of the OLS estimate was positive), suggesting that young draftees at the end of the war experienced an earnings tradeoff relative to a counterfactual education or work experience.

Finally, Table 3.7, Panel A, shows the results of panel regressions among the linked subsample from 1940 and 1950 full-count US Censuses. With individual fixed effects that difference out any time-invariant individual characteristics, the quasi-experiment on date of fatherhood around Pearl Harbor is, in principle, even more appealing—even if it does restrict the sample to those whose wages were observed in 1940 and linked to the 1950 full-count US Census. The effect size in the results of Table 3.7 is even larger than those of the previous tables (e.g., Table 3.4) above, which would seem to confirm the experimental result of the impact of WWII service on wages.

Panel B restricts the sample even further, by excluding any veterans who were not drafted from civilian occupations. (In this case, the treatment is tightened to focus only those who did not volunteer for service, and were not affiliated in any military-adjacent occupation prior to their induction.) The link to the CenSoc database on WWII army enlistees allows to pinpoint those veterans who were drafted (“selectees”) from a “civilian” source, and all other veterans (whether observed as volunteer enlistees, or unobserved in CenSoc data) can be excluded from the estimate.¹⁹ After restricting treatment to civilian draftees, the estimate of WWII’s impact rises to a more than 100% increase in 1950 over 1940 wages.

For these civilian draftees, further evidence from CenSoc in Panel C indicates that length of service—the intensity of the ‘treatment’—mattered. Within the CenSoc sample of WWII veterans drafted from civilian occupations, longer service predicted higher 1950 wages. The 3-year window of fatherhood around Pearl Harbor is an effective IV even in this case, because it predicts a deferment of service and therefore less service time overall, even when we are restricting the sample to men who were drafted and did serve. If we take the effect sizes at face value, every three months of wartime service was associated with a more than 1% increase in 1950 wages.

With these results in mind, we can conclude with a brief discussion on the importance of these results in the larger context of the economic history of the era.

3.4 Discussion

What was the position of middle- and working class income earners in the early 20th century, in both relative and absolute terms?

It is indisputable that, at the top of the distribution, income shares decreased over the middle of 20th century before increasing again.

More than merely echoing earlier findings, however, the new results presented here show that the postwar fall of inequality was disproportionately to the benefit of the ‘middle’ 40% of income earners, more than to the poorest half of the population. The greatest drama in the story was the changing proportion of income shares to upper-middle-class vs. top income earners, while poor people earned a relatively constant share of the distribution.²⁰ Changes in economywide shares of national

¹⁹Unfortunately, draft classifications are not observed, nor does CenSoc provide any data on the men who did not enlist, so we cannot exclude men who were classified as ‘unfit’ by their local draft boards. However, as discussed in section 3.2.2 above, this represents less than 2% of fathers (Selective Service System, 1947).

²⁰In fact, the fiscal income share accruing to the bottom 50% of the population remained stable during the entire postwar era, to such an extent that it began to resemble an immutable macroeconomic parameter (Feldstein, 1980). Recent history has taught otherwise.

income represented a conflict between the upper and middle classes, more than any opportunity for gains among the poorest.

However, one exception has been the story of midcentury wage inequality. A lasting wage compression defined the postwar era. The bottom 50% wage share increased by more than 50% during the war years, and remained level for a generation. While the slide of the working-class wage share after 1975 is beyond the scope of this paper, the postwar ‘Great Leveling’ still offers lessons.

In fact, the results of this paper suggest that the midcentury decrease in inequality was perhaps not (only) a ‘leveling’ of top incomes. Rather, the results remind us that this was an era defined by new possibilities for the working class. Part of this is a human capital story. And national service, in World War II, constituted a type of training whose impact mattered more for postwar wages than either education or experience—and particularly for those who started at the bottom of the wage distribution.

What type of training this service constituted—whether ‘soft’ skills (communication, leadership, discipline) or ‘hard’ skills (engineering, technology, manufacturing)—cannot be established with certainty by the analysis in this paper. However, we can probably rule out the ‘signaling’ hypotheses that wartime service was only valuable for its reputation effects, or a network, or a later hiring preference. It is unlikely that these would have been in place so soon after the war as to show themselves in 1950 wage data. If anything, those who did not serve would have had access to stronger production networks, uninterrupted by service. Similarly, the effect of the GI Bill on wages would not have been felt yet, and in fact veterans’ (subsidized) education investment may have been negatively correlated with wages in 1950.

We can also rule out that pure selection bias explains veterans’ productivity.

Under these conditions, the demonstrated wage premium for World War II veterans—an effect size estimated higher among civilian draftees than among all enlistees; and with increasing returns on the intensive margin (duration of wartime service)—suggests a formative experience that, for many, translated directly into postwar earnings.

Whatever else the costs and benefits of World War II, its impact on human capital is notable. More than an unrepeatable set of circumstances in history, the economic mobility of the greatest generation offers an example for our time. National service can serve the country and the citizen at once.

Tables

Table 3.1 – OLS results: Impact of WWII service on (log) wages, 1950

| | (1) | | (2) | | (3) | |
|-------------------------------------|-----------------------------|----------------------------|-----------------------------|----------------------------|-----------------------------|----------------------------|
| education | 0.0287*** (0.000115) | 0.0163*** (0.000166) | 0.0284*** (0.000115) | 0.0161*** (0.000166) | 0.0331*** (0.000161) | 0.0189*** (0.000199) |
| experience | 0.0671*** (0.000293) | 0.0569*** (0.000710) | 0.0657*** (0.000294) | 0.0574*** (0.000710) | 0.0640*** (0.000296) | 0.0525*** (0.000734) |
| experience ² | -0.00153*** (0.00000827) | -0.00184*** (0.0000196) | -0.00145*** (0.00000840) | -0.00184*** (0.0000196) | -0.00140*** (0.00000847) | -0.00171*** (0.0000203) |
| WWII veteran | | | 0.0660*** (0.000983) | 0.0302*** (0.00101) | 0.155*** (0.00229) | 0.0836*** (0.00230) |
| education · $\mathbb{1}$ (WWII vet) | | | | | -0.00976*** (0.000225) | -0.00593*** (0.000229) |
| controls | | ✓ | | ✓ | | ✓ |
| R-squared | 0.033 | 0.063 | 0.034 | 0.063 | 0.035 | 0.064 |
| N | 3,892,814 | 3,892,814 | 3,892,814 | 3,892,814 | 3,892,814 | 3,892,814 |

Notes: Model (1) is the Mincer (1958) model regressing log wages on years of education, years of experience, and years of experience squared. Model (2) includes World War II service as a covariate. Model (3) tests the effect of World War II service interacted with education, as in the postwar G.I. Bill (or prewar human capital). Each model is estimated with and without control variables. Controls include dummies for age; race (nonwhite); urban vs. rural location in 1950; and marital status in 1950. Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

Table 3.2 – First-stage results: Impact of eldest child’s birthdate on probability of WWII service

| | (1) | | (2) | | % WWII vets | N |
|---|---------------------|-----------------|--------------------|------------------|--------------------------|------------------|
| | Logistic regression | | Linear probability | | | |
| all men age 18-42 in 1946 | | | | | 47.7% | 3,892,814 |
| pre-Pearl Harbor fathers | | | | | 21.2% | 1,156,184 |
| <i>eldest child’s birthdate, wrt Pearl Harbor</i> | | | | | | |
| 7-year window | 1.142*** | 1.064*** | 0.249*** | 0.221*** | 49.6% | 1,835,592 |
| | (0.00382) | (0.00388) | (0.000812) | (0.000814) | <i>o/w 1941 fathers:</i> | |
| R-squared | | | 0.230 | 0.266 | 25.6% | 732,606 |
| F-statistic | | | 94053.5 | 74026.5 | | |
| 5-year window | 0.940*** | 0.892*** | 0.205*** | 0.186*** | 46.8% | 1,291,680 |
| | (0.00421) | (0.00429) | (0.000906) | (0.000901) | <i>o/w 1941 fathers:</i> | |
| R-squared | | | 0.194 | 0.226 | 28.2% | 555,557 |
| F-statistic | | | 51053.6 | 42792.9 | | |
| 3-year window | 0.668*** | 0.650*** | 0.144*** | 0.135*** | 44.1% | 763,650 |
| | (0.00515) | (0.00525) | (0.00111) | (0.00110) | <i>o/w 1941 fathers:</i> | |
| R-squared | | | 0.161 | 0.188 | 31.7% | 353,911 |
| F-statistic | | | 16924.8 | 15260.4 | | |
| 1-year window | 0.452*** | 0.451*** | 0.0970*** | 0.0937*** | 43.3% | 287,777 |
| | (0.00813) | (0.00826) | (0.00174) | (0.00171) | <i>o/w 1941 fathers:</i> | |
| R-squared | | | 0.139 | 0.164 | 36.2% | 134,554 |
| F-statistic | | | 3124.0 | 2999.5 | | |
| controls | | ✓ | | ✓ | | |

Notes: Model (1) presents the logistic regression of WWII service on eldest-child birthdate windows with respect to Pearl Harbor (December 7, 1941). Model (2) presents the linear probability model of the same. For example, the ‘3-year window’ compares the probability of WWII service of [1 = fathers whose eldest child was born between April 2, 1942 and April 1, 1945 (post-Pearl Harbor fathers)] vs. [0 = fathers whose eldest child was born between April 2, 1939 and April 1, 1942 (pre-Pearl Harbor fathers, approximately)]. All specifications include covariates for education and experience (and its square term), à la Mincer (*ibid.*). Both models are estimated with and without control variables. Controls include dummies for age; race (nonwhite); urban vs. rural location in 1950; and marital status in 1950. Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

Table 3.3 – Balance table for 3-year window of eldest child birthdate

| | eldest child birthdate | | <i>N</i> |
|---|------------------------|-------------------|----------|
| | pre-Pearl Harbor | post-Pearl Harbor | |
| <i>Panel A: WWII service, wages and covariates in 1950 full-count US Census</i> | | | |
| new fathers age 18-42 in 1946 | 353,911 | 409,739 | 763,650 |
| served in WWII | 31.7% | 54.8% | |
| age in 1946 | 31.3 | 28.8 | |
| years of education (1950) | 9.0 | 9.3 | |
| married (1950) | 99.0% | 99.2% | |
| urban (1950) | 60.5% | 62.5% | |
| nonwhite | 7.1% | 6.7% | |
| wage in 1950 (current USD) | 2,786 | 2,759 | |
| within-cohort wage percentile | 57.8 | 58.6 | |
| <i>Panel B: Wages (and parent wages) in 1940 full-count US Census</i> | | | |
| linked wage in 1940 | 42.8% | 25.7% | 256,946 |
| wage in 1940 (current USD) | 1,055 | 902 | |
| within-cohort wage percentile | 61.2 | 58.1 | |
| linked father's wage in 1940 | 6.2% | 12.2% | 71,635 |
| father's wage in 1940 (current USD) | 1,143 | 1,304 | |
| father's within-cohort wage percentile | 51.5 | 54.2 | |

Notes: The ‘3-year window’ subsample compares fathers’ eldest child’s birthdate: [1 = fathers whose eldest child was born between April 2, 1942 and April 1, 1945 (post-Pearl Harbor fathers)] vs. [0 = fathers whose eldest child was born between April 2, 1939 and April 1, 1942 (pre-Pearl Harbor fathers, approximately)]. For the variables presented in this table, all p-values testing between-group difference in means are significant at $p < 0.0005$.

Table 3.4 – IV results: Impact of WWII service on (log) wages, 1950

| <i>birthdate window, wrt Pearl Harbor</i> | | | <i>N</i> |
|---|-----------|-----------|-----------|
| 7-year window | 0.131*** | 0.0584*** | 1,835,592 |
| | (0.00614) | (0.00689) | |
| F-statistic | 94053.5 | 74026.5 | |
| 5-year window | 0.128*** | 0.0564*** | 1,291,680 |
| | (0.00834) | (0.00910) | |
| F-statistic | 51053.6 | 42792.9 | |
| 3-year window | 0.137*** | 0.0605*** | 763,650 |
| | (0.0145) | (0.0153) | |
| F-statistic | 16924.8 | 15260.4 | |
| 1-year window | 0.166*** | 0.102*** | 287,777 |
| | (0.0339) | (0.0347) | |
| F-statistic | 3124.0 | 2999.5 | |
| controls | | ✓ | |

Notes: The model presented here corresponds to model (2) in Tables 3.1 and 3.2 above—and instruments for the probability of WWII service via the eldest child’s birthdate, with results for several birthdate windows around Pearl Harbor (December 7, 1941). For example, the ‘3-year window’ compares the probability of WWII service of [1 = fathers whose eldest child was born between April 2, 1942 and April 1, 1945 (post-Pearl Harbor fathers)] vs. [0 = fathers whose eldest child was born between April 2, 1939 and April 1, 1942 (pre-Pearl Harbor fathers, approximately)]. Both specifications include covariates for education and experience (and its square term), à la Mincer (1958). The second is estimated with control variables. Controls include dummies for age; race (nonwhite); urban vs. rural location in 1950; and marital status in 1950. Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

Table 3.5 – Life cycle timing of national service: OLS and IV results by age cohort

| | (1) | | | | (2) | | |
|------------------------------|-------------------------|-------------------------|-----------|-------------|----------------------|-----------------------|----------|
| | OLS | | <i>N</i> | % WWII vets | IV | | <i>N</i> |
| men age 18-42 in 1946 | 0.0660*** (0.000983) | 0.0302*** (0.00101) | 3,892,814 | 47.7% | 0.137*** (0.0145) | 0.0605*** (0.0153) | 763,650 |
| F-statistic | | | | | 16924.8 | 15260.4 | |
| age 18-20 | 0.0441*** (0.00284) | -0.0131*** (0.00286) | 419,765 | 48.6% | 1.461 (1.469) | 1.068 (2.566) | 9,245 |
| F-statistic | | | | | 2.189 | 0.604 | |
| age 21-25 | 0.125*** (0.00226) | 0.0687*** (0.00225) | 819,221 | 74.7% | 1.408*** (0.259) | 1.066** (0.455) | 105,837 |
| F-statistic | | | | | 74.04 | 21.00 | |
| age 26-30 | 0.0846*** (0.00210) | 0.0481*** (0.00207) | 808,965 | 65.8% | 0.359*** (0.0326) | 0.184*** (0.0348) | 263,450 |
| F-statistic | | | | | 3020.9 | 2575.9 | |
| age 31-35 | 0.0250*** (0.00207) | 0.0158*** (0.00205) | 776,405 | 38.5% | 0.0289 (0.0181) | -0.0116 (0.0181) | 230,330 |
| F-statistic | | | | | 11060.5 | 10915.1 | |
| age 36-42 | -0.00191 (0.00223) | 0.00273 (0.00222) | 1,068,458 | 19.5% | -0.0137 (0.0324) | -0.00613 (0.0321) | 154,788 |
| F-statistic | | | | | 4866.1 | 4869.9 | |
| controls | ✓ | | | | ✓ | | |

Notes: Model (1) presents the second set of OLS results from Table 3.1, regressing (log) wages on WWII service, with separate regressions estimated for each age cohort. Model (2) does the same but disaggregates the results of Table 3.4, where the eldest-child birthdate ‘3-year window’ (with respect to December 7, 1941) instruments for the probability of WWII service. All specifications include covariates for education and experience (and its square term), à la Mincer (1958). Both models are estimated with and without control variables. Controls include dummies for age; race (nonwhite); urban vs. rural location in 1950; and marital status in 1950. Robust standard errors in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 3.6 – Service and mobility: Results by 1940 wage bracket

| | OLS | | <i>N</i> | IV | | <i>N</i> |
|--|-------------------------|--------------------------|-----------|-----------------------|----------------------|----------|
| | (1) | | | (2) | | |
| <i>1940 wage distribution ranking</i> | | | | | | |
| linked sample, all | -0.00244 (0.00200) | 0.00204 (0.00200) | 1,074,241 | 0.0664*** (0.0226) | 0.0180 (0.0228) | 256,946 |
| F-statistic | | | | 7074.8 | 6976.2 | |
| p0p50 | 0.0293*** (0.00309) | 0.0203*** (0.00308) | 428,831 | 0.234*** (0.0382) | 0.107*** (0.0387) | 89,709 |
| F-statistic | | | | 2347.4 | 2250.1 | |
| p50p90 | -0.0202*** (0.00286) | -0.00791*** (0.00289) | 495,806 | 0.0602* (0.0311) | 0.0371 (0.0309) | 122,595 |
| F-statistic | | | | 3574.5 | 3638.0 | |
| p90p100 | -0.0230*** (0.00578) | -0.00994* (0.00586) | 149,604 | 0.0357 (0.0641) | 0.0517 (0.0659) | 44,639 |
| F-statistic | | | | 1021.9 | 982.4 | |
| <i>father's 1940 wage distribution ranking</i> | | | | | | |
| linked sample, all | 0.0511*** (0.00269) | 0.0202*** (0.00279) | 494,622 | 0.506*** (0.0720) | 0.344*** (0.0769) | 71,635 |
| F-statistic | | | | 648.2 | 560.1 | |
| p0p50 | 0.0805*** (0.00406) | 0.0424*** (0.00417) | 207,673 | 0.528*** (0.132) | 0.349** (0.147) | 30,903 |
| F-statistic | | | | 188.1 | 148.8 | |
| p50p90 | 0.00713* (0.00387) | -0.0123*** (0.00403) | 237,024 | 0.341*** (0.0897) | 0.237** (0.0942) | 33,876 |
| F-statistic | | | | 390.6 | 356.4 | |
| p90p100 | 0.0285*** (0.00933) | -0.0151 (0.00987) | 49,925 | 0.485** (0.234) | 0.418* (0.238) | 6,856 |
| F-statistic | | | | 73.94 | 71.99 | |
| controls | | ✓ | | | ✓ | |

Notes: Model (1) regresses log 1950 wages on WWII service, with separate regressions estimated within each 1940 wage bracket: p0p50 (bottom 50% of wage earners); p50p90 (middle 40%); and p90p100 (top 10%). The 1940 wage corresponds either to the 1950 Census individual (whose 1950 wages are the dependent variable) in Panel A, or to his father in Panel B—but in both cases taking the within-cohort income distribution rank, from age-specific 1940 wage distributions. Model (2) does the same as the OLS model but uses the eldest-child birthdate ‘3-year window’ (with respect to December 7, 1941) to instrument for the probability of WWII service. All specifications include covariates for education and experience (and its square term), à la Mincer (*ibid.*). Both models are estimated with and without control variables. Controls include dummies for age; race (nonwhite); urban vs. rural location in 1950; and marital status in 1950. Robust standard errors in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 3.7 – Panel fixed effects: Effect of WWII service on (log) wages, 1940-50

| | OLS | | | IV | | |
|---|--------------------------|--------------------------|-----------|-------------------------|-------------------------|----------|
| | (1) | (2) | <i>N</i> | (3) | (4) | <i>N</i> |
| <i>Panel A: Panel fixed-effects</i> | | | | | | |
| WWII service | 0.111*** (0.00261) | 0.108*** (0.00260) | 1,055,967 | 0.858*** (0.0282) | 0.853*** (0.0281) | 251,987 |
| <i>Panel B: Restrict to civilian draftees</i> | | | | | | |
| WWII civilian draftees | 0.210*** (0.00445) | 0.205*** (0.00443) | 784,727 | 1.128*** (0.0493) | 1.120*** (0.0492) | 181,237 |
| <i>Panel C: Wartime service (in months)</i> | | | | | | |
| WWII service time [civilian draftees] | 0.00214*** (0.000292) | 0.00200*** (0.000291) | 85,259 | 0.00337*** (0.00124) | 0.00354*** (0.00123) | 20,529 |
| controls | | ✓ | | | ✓ | |

Notes: This table shows the results of panel regressions of the difference in 1950 vs. 1940 (log) wages, for men aged 18-42 in 1946 whose records are linked between 1940 and 1950 full-count US Censuses. Panel A presents OLS and IV results (where WWII service is instrumented as above, using the ‘3-year window’ of eldest-child birthdate around Pearl Harbor). Panel B restricts the treated sample (veterans) to those who were observed as ‘selectees’ from ‘civilian’ occupations in the CenSoc database (Goldstein et al., 2023), linked to the 1940 full-count US Census in that study and also to the 1950 in this study. Panel C estimates, for these draftees, the marginal effect of one additional month of service from the date of enlistment to the end of the war on September 2, 1945. All specifications include covariates for education and experience (and its square term), à la Mincer (1958). Models are estimated with and without controlling for a rural-urban move between 1940 and 1950. Previous controls (and other time-invariant individual characteristics) are differenced out via individual fixed effects. Standard errors in parentheses are clustered at the level of the individual. * p<0.10 ** p<0.05 *** p<0.01.

Figures

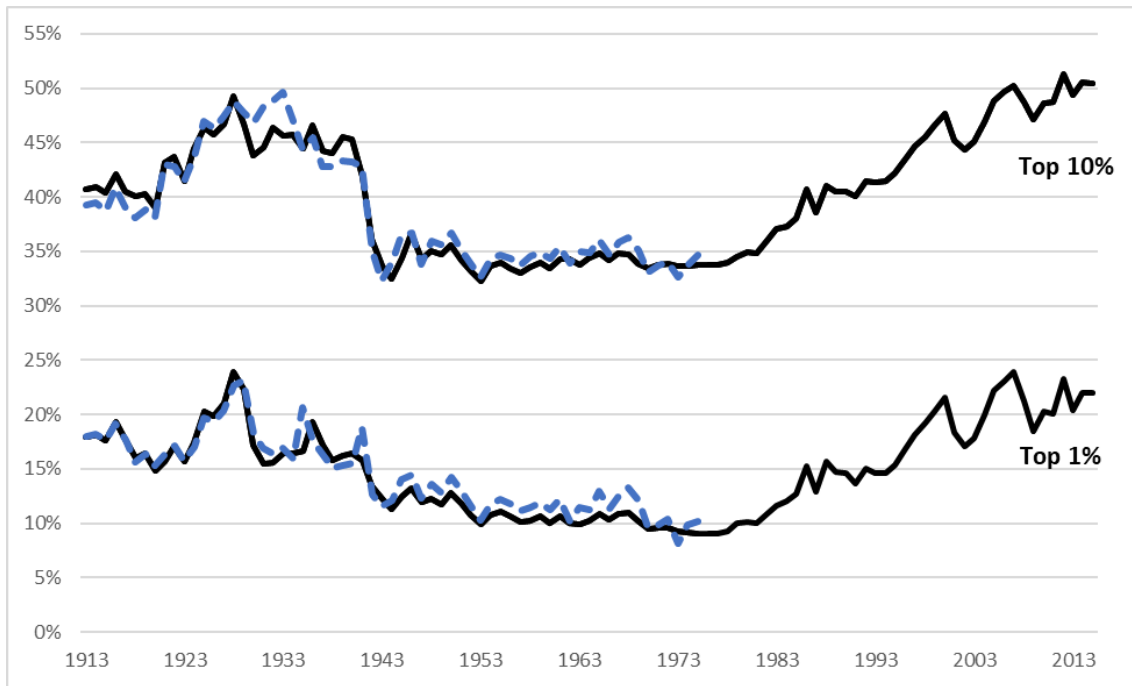


Figure 3.1 – Top 10% and top 1% fiscal income share, tax units, 1913-2014

Notes: Adapted from Piketty and Saez ([ibid.](#)) benchmark series. Blue dash line overlay is a preview of the results.

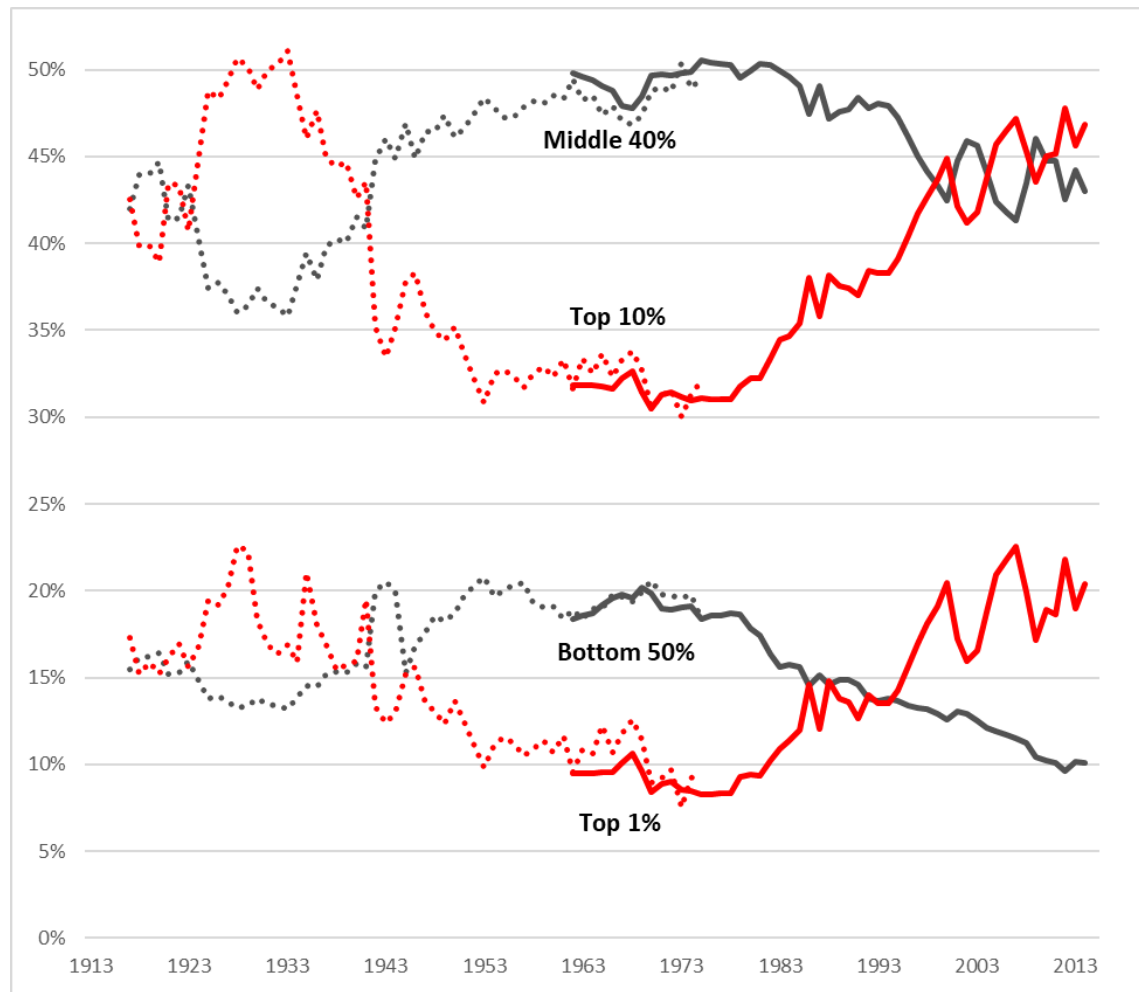


Figure 3.2 – Fiscal income share, equal-split adults, 1913-2014

Notes: Adapted from Piketty, Saez, and Zucman (2018) benchmark series. Dashed lines preview results, for Top 10%, top 1%, middle 40%, and bottom 50%.

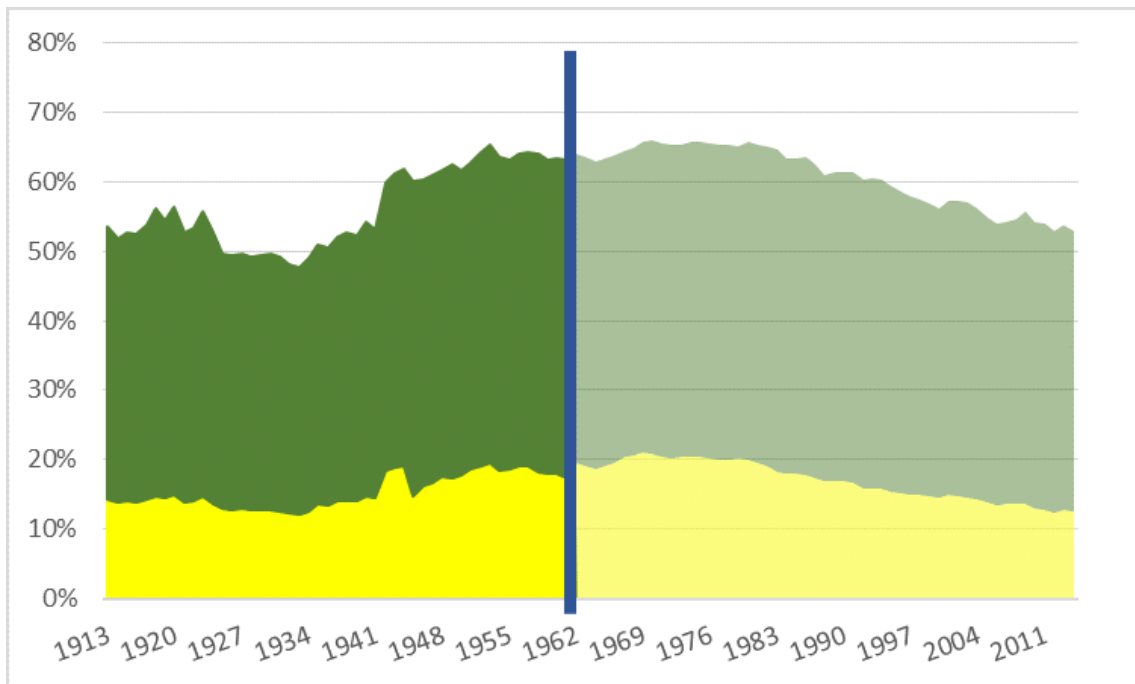


Figure 3.3 – Pre-tax national income share, equal-split adults, 1913-2014

Notes: Dark shaded areas pre-1962 are new results. Light shaded areas after 1962 are from Piketty, Saez, and Zucman (*ibid.*). Middle 40% is in green, above; bottom 50% is in yellow, below. By construction, the unshaded area (to 100%) represents the top 10% share.

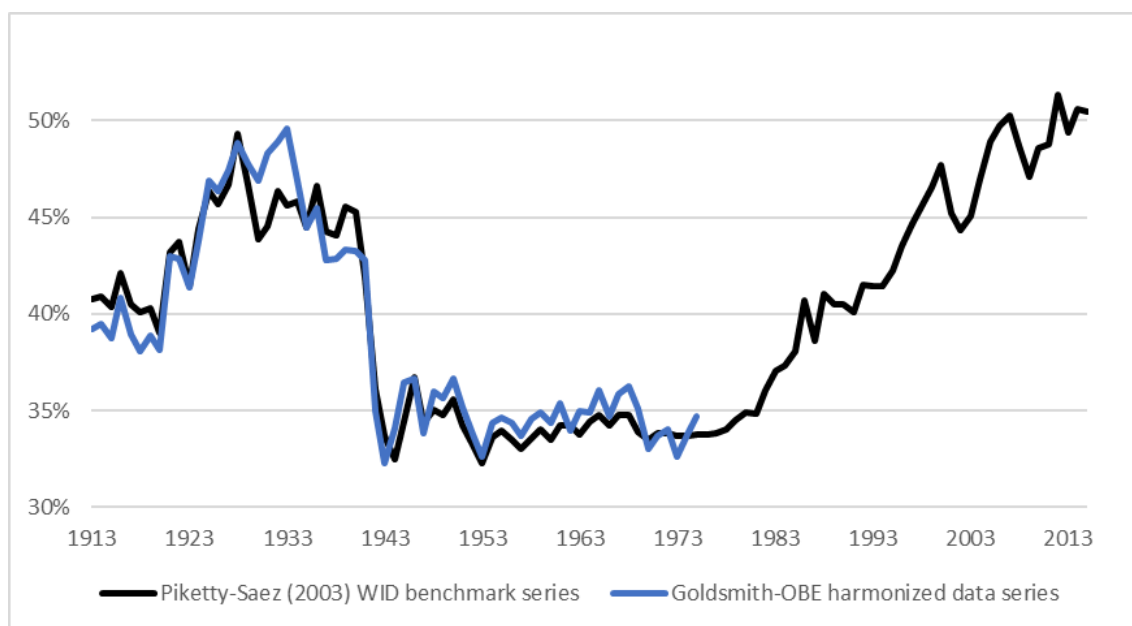


Figure 3.4 – Top 10% share of total fiscal income, tax units, 1913-75

Notes: Harmonized Goldsmith-OBE pre-war interpolations and raw SOI data post-war, compared to Piketty and Saez (2003) benchmark estimates.

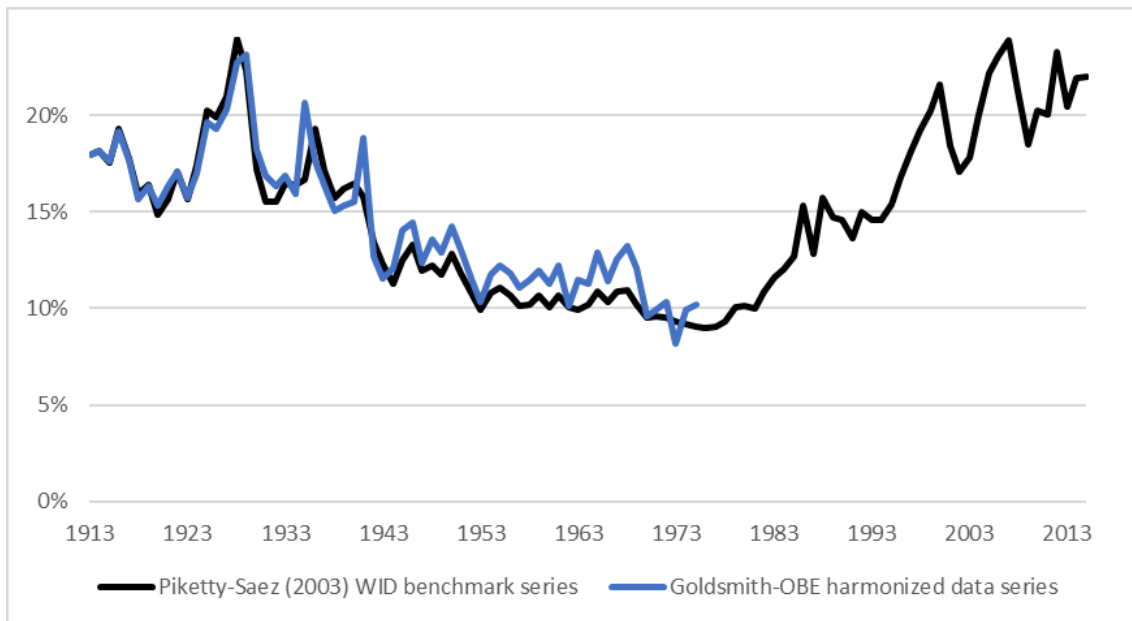


Figure 3.5 – Top 1% share of total fiscal income, tax units, 1913-75

Notes: Harmonized Goldsmith-OBE (see Goldsmith, 1951) pre-war interpolations and raw SOI data post-war, compared to Piketty and Saez (2003) benchmark estimates.

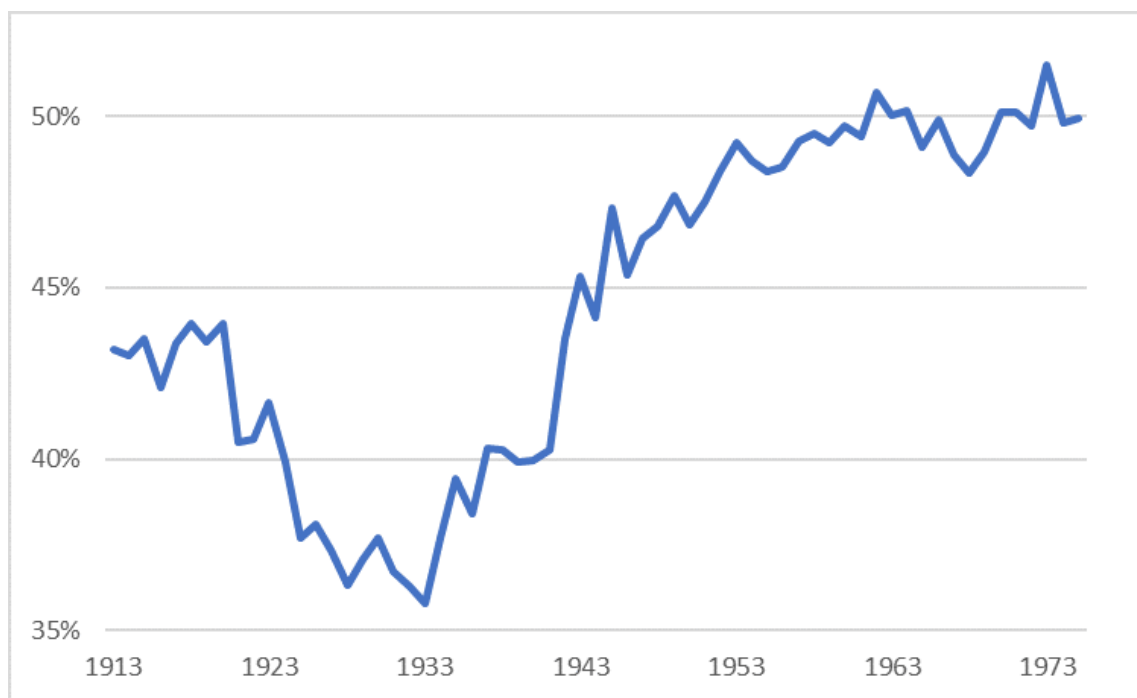


Figure 3.6 – Middle 40% share of total fiscal income, tax units, 1913-75

Notes: Goldsmith-OBE (see Goldsmith, [1951](#)) pre-World War II interpolations harmonized with SOI tax data.

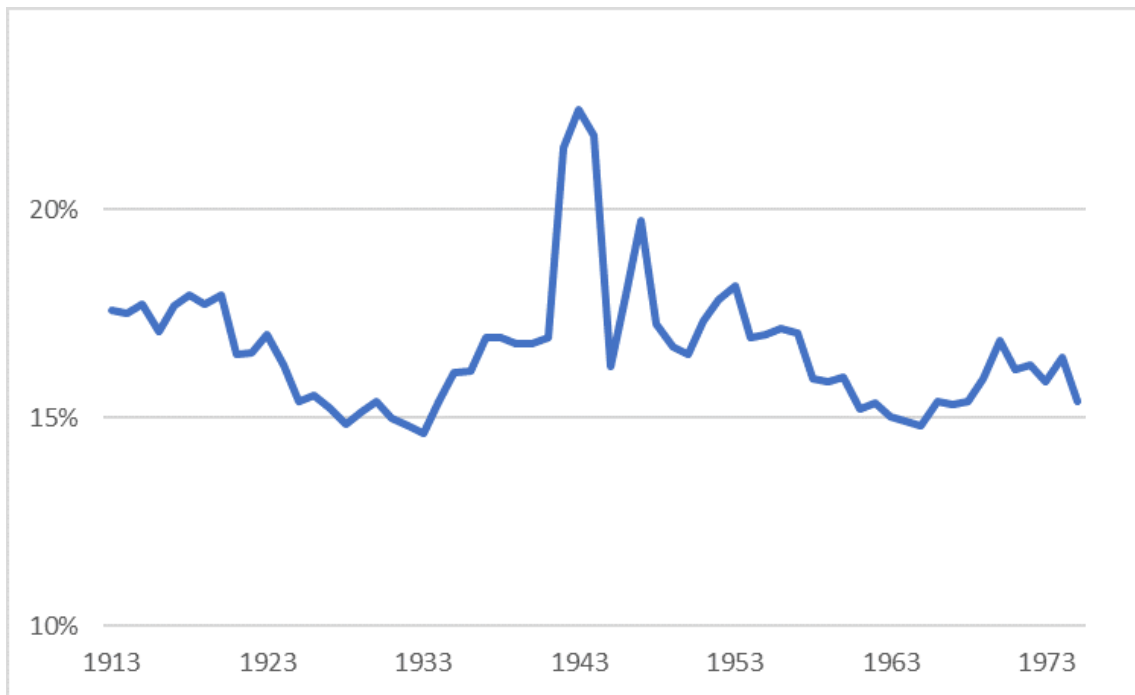


Figure 3.7 – Bottom 50% share of total fiscal income, tax units, 1913-75

Notes: Goldsmith-OBE (see [ibid.](#)) pre-World War II interpolations harmonized with SOI tax data.

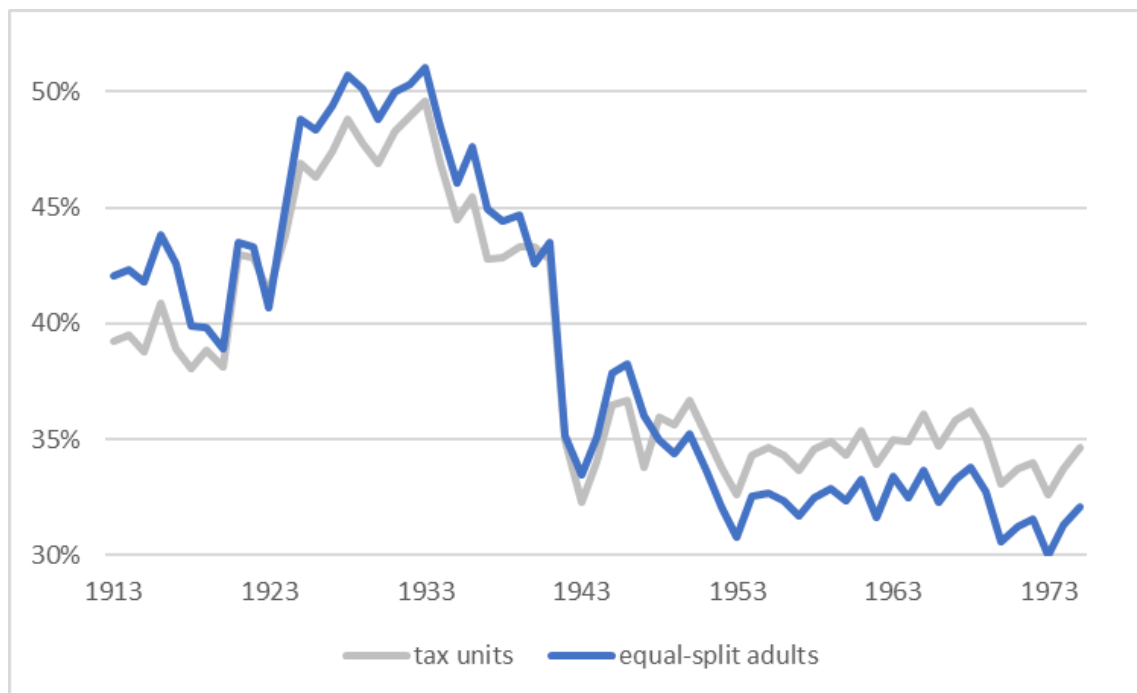


Figure 3.8 – Top 10% share of total fiscal income, equal-split adults, 1913-75

Notes: Goldsmith-OBE (see Goldsmith, 1951) pre-World War II interpolations harmonized with SOI tax data.

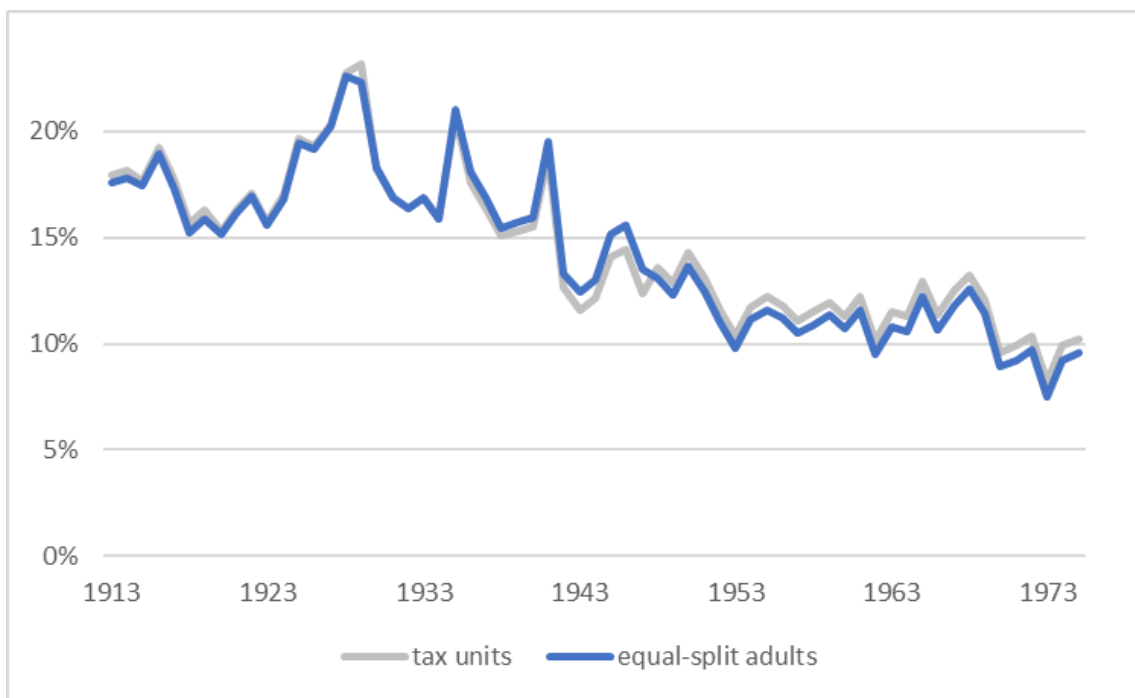


Figure 3.9 – Top 1% share of total fiscal income, equal-split adults, 1913-75

Notes: Goldsmith-OBE (see [ibid.](#)) pre-World War II interpolations harmonized with SOI tax data.

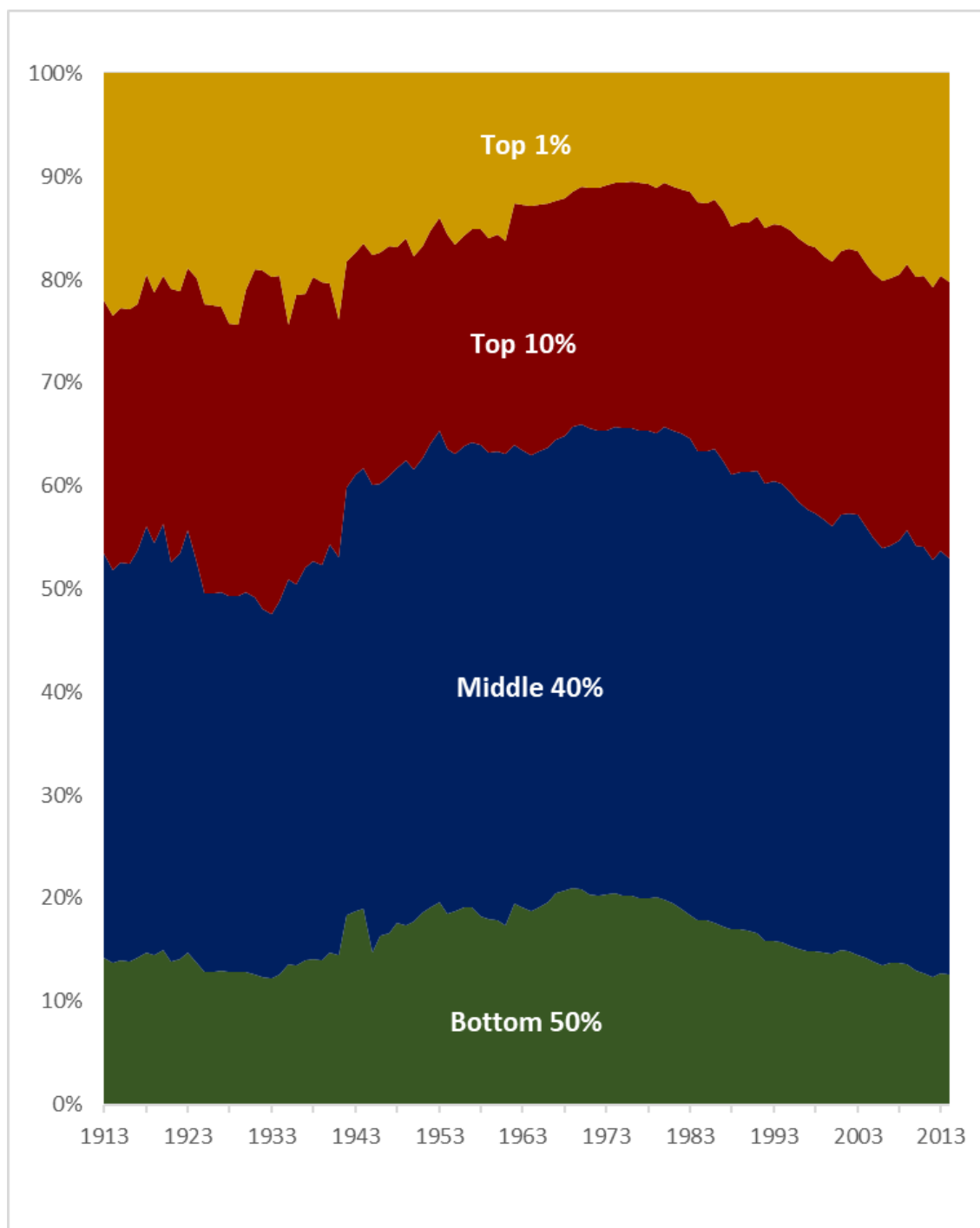


Figure 3.10 – Shares of total pre-tax income, equal-split adults, 1913-2014

Notes: Estimates for 1913-61 are new.

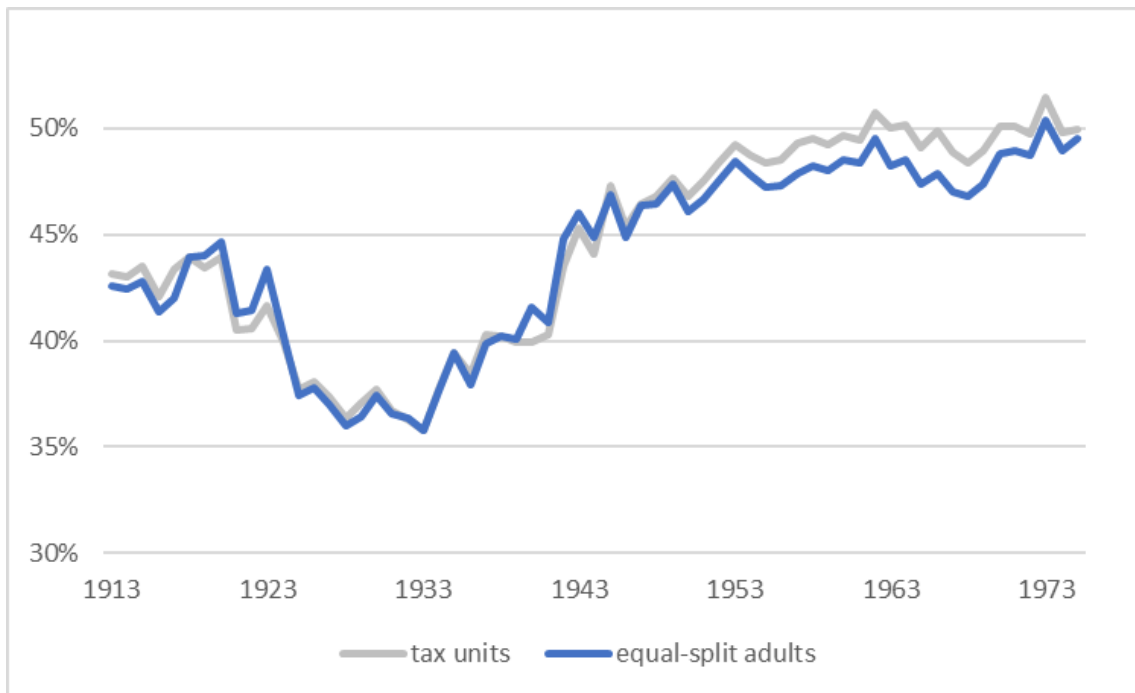


Figure 3.11 – Middle 40% share of total fiscal income, equal-split adults, 1913-75

Notes: Goldsmith-OBE (see Goldsmith, [1951](#)) pre-World War II interpolations harmonized with SOI tax data.

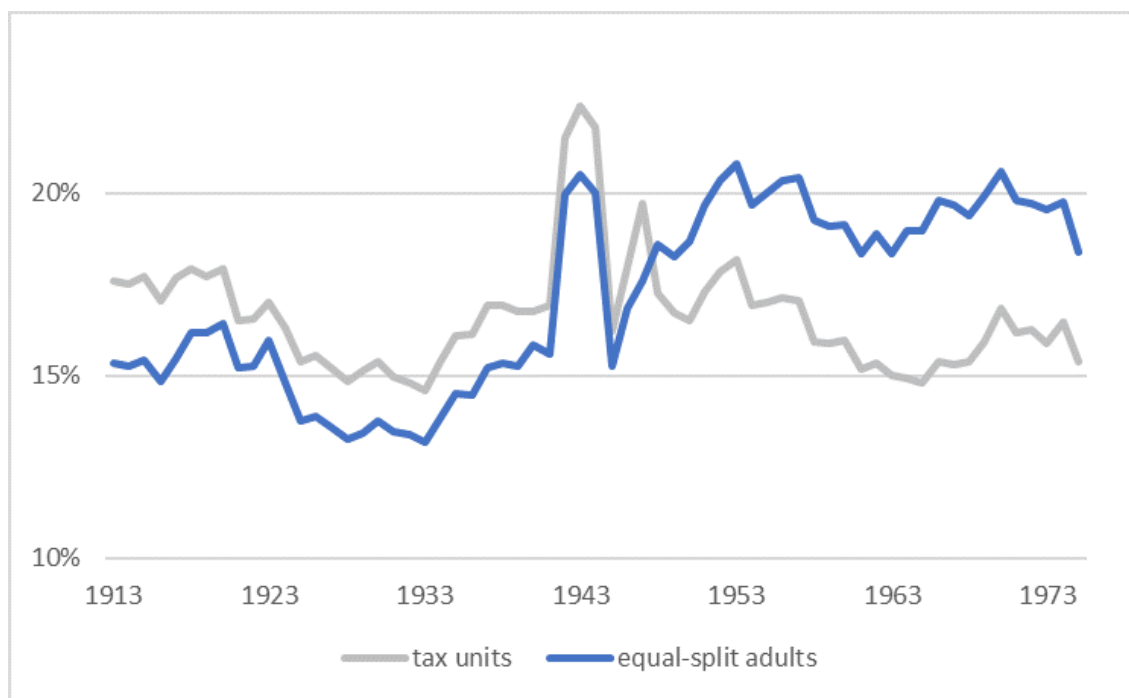


Figure 3.12 – Bottom 50% share of total fiscal income, equal-split adults, 1913-75

Notes: Goldsmith-OBE (see Goldsmith, 1951) pre-World War II interpolations harmonized with SOI tax data.

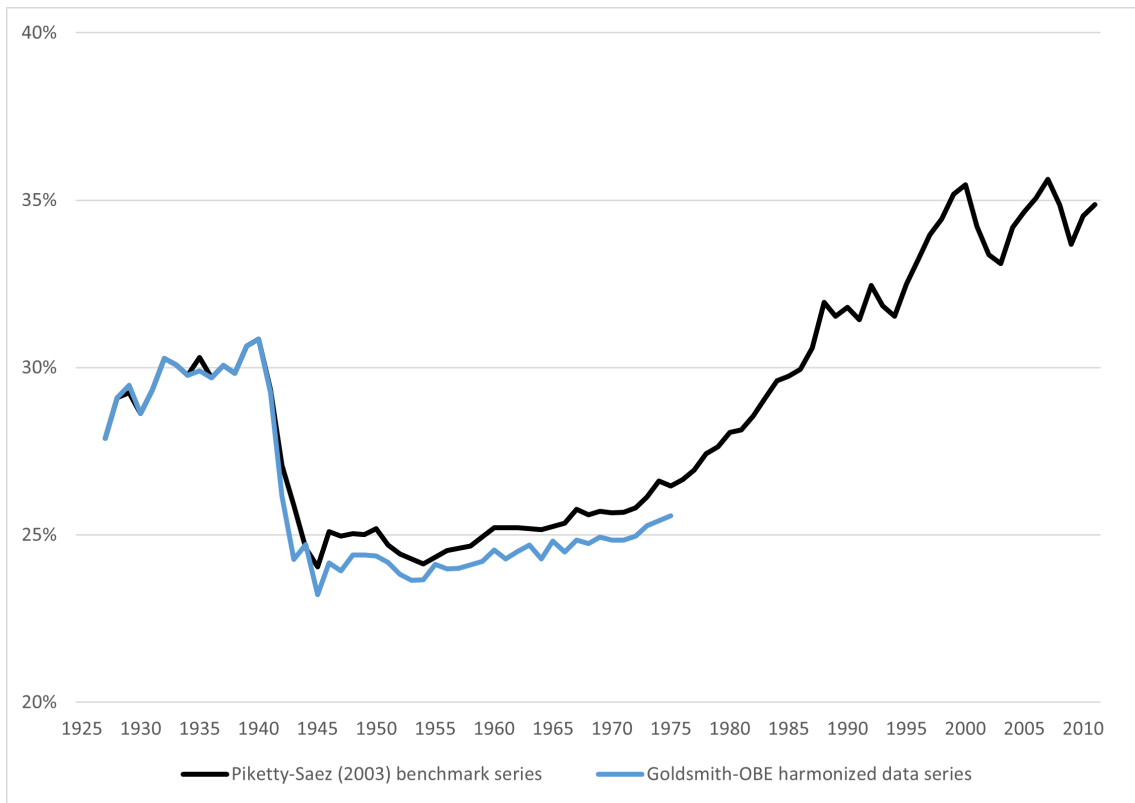


Figure 3.13 – Top 10% share of total wage income, tax units, 1927-2011

Notes: Goldsmith-OBE (see Goldsmith, 1951) harmonized data series, compared to Piketty and Saez (2003) benchmark series.

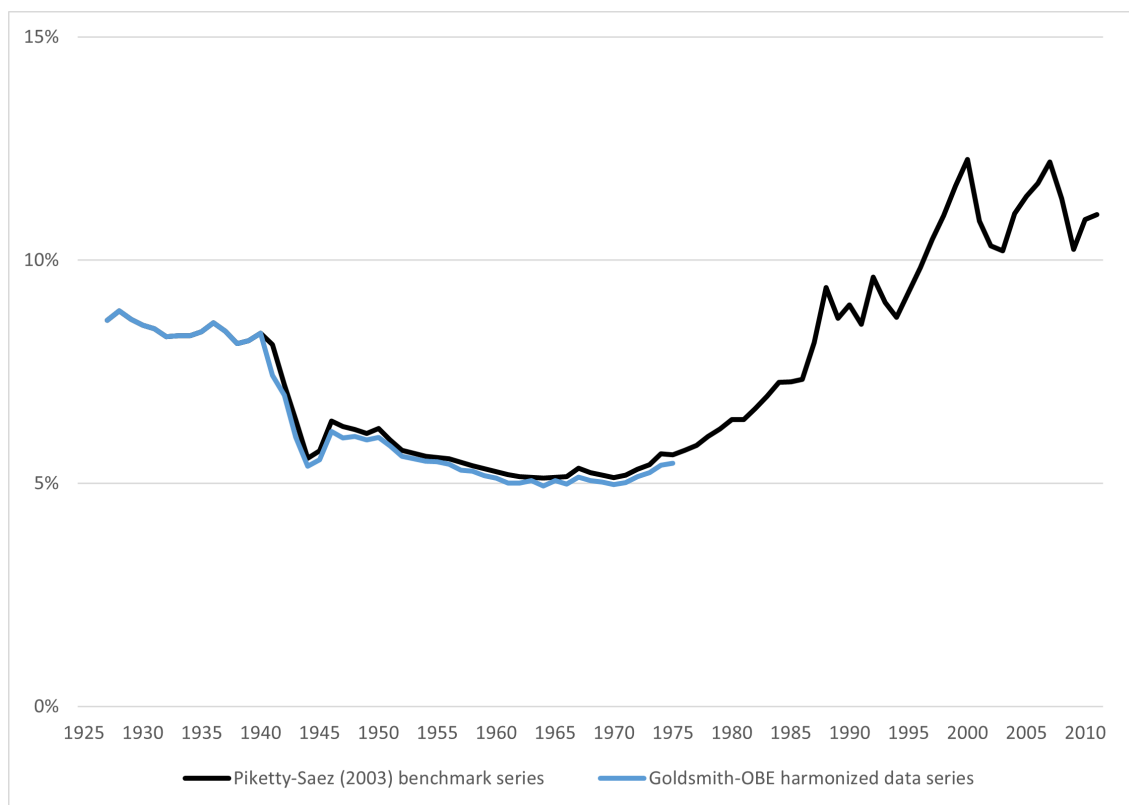


Figure 3.14 – Top 1% share of total wage income, tax units, 1927-2011

Notes: Goldsmith-OBE (see Goldsmith, 1951) harmonized data series, compared to Piketty and Saez (2003) benchmark series.

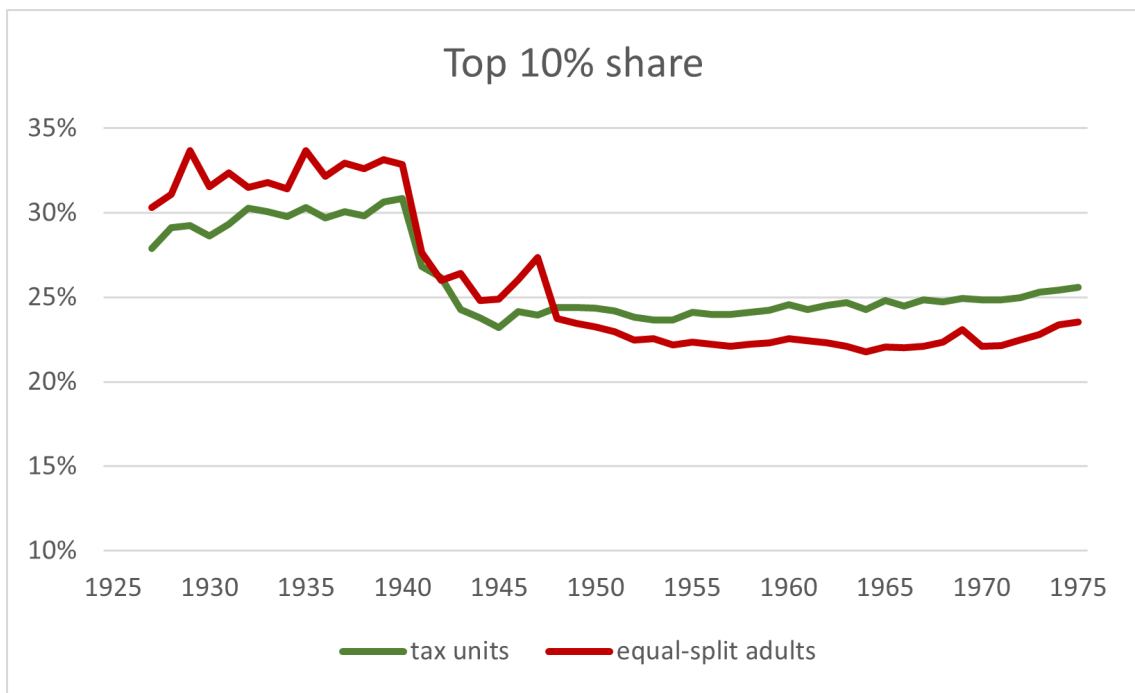


Figure 3.15 – Top 10% share of total wage income, 1927-75

Notes: Goldsmith-OBE (see [ibid.](#)) harmonized data series.

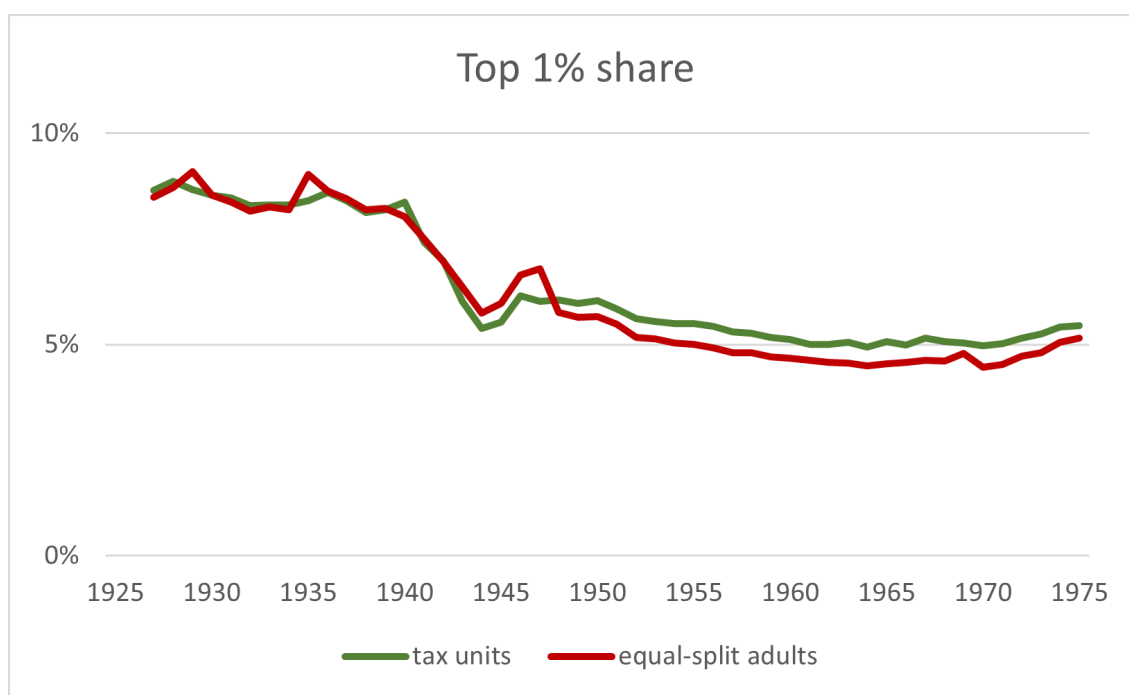


Figure 3.16 – Top 1% share of total wage income, 1927-75

Notes: Goldsmith-OBE (see Goldsmith, 1951) harmonized data series.

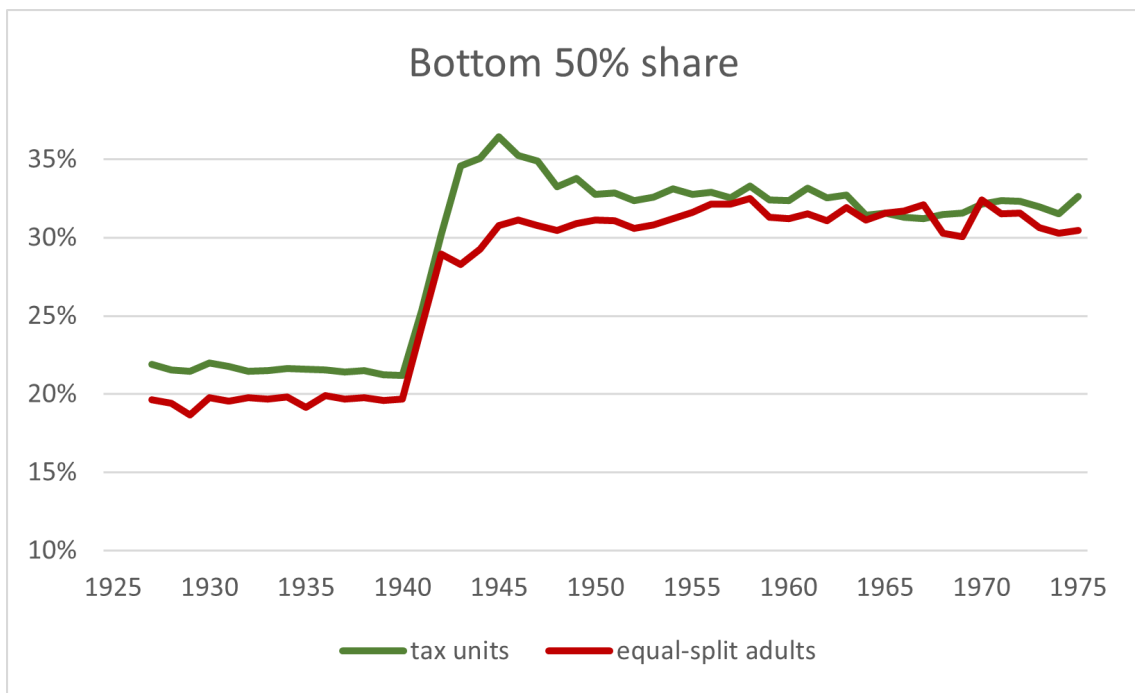


Figure 3.17 – Bottom 50% share of total wage income, 1927-75

Notes: Goldsmith-OBE (see [ibid.](#)) harmonized data series.

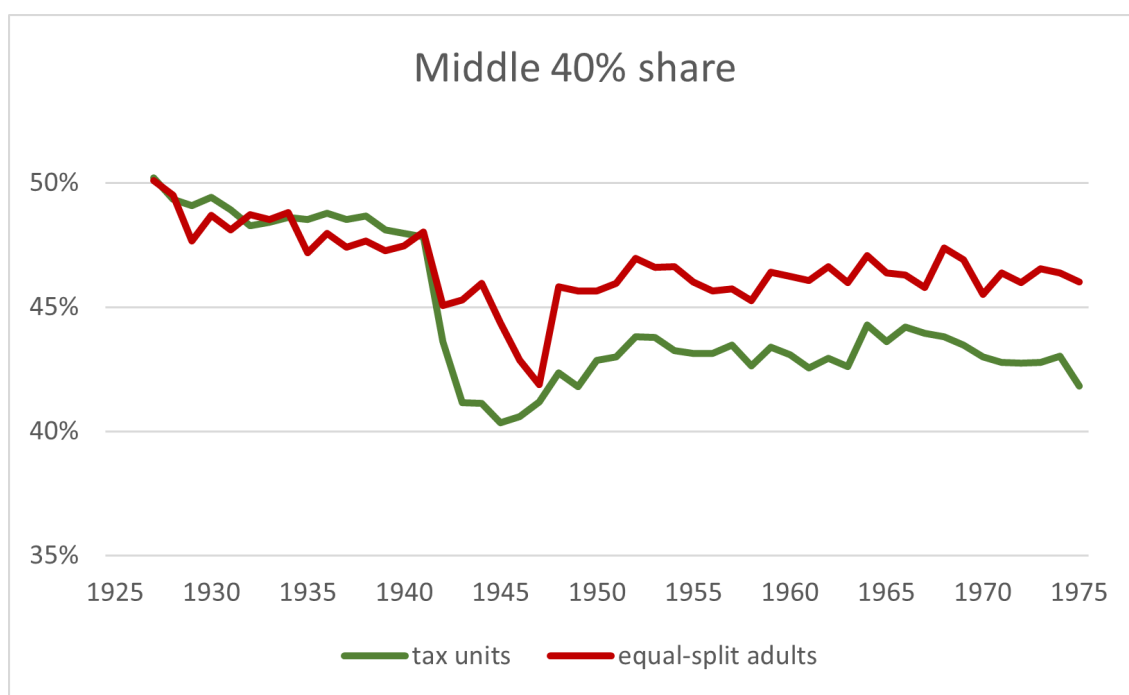


Figure 3.18 – Middle 40% share of total wage income, 1927-75

Notes: Goldsmith-OBE (see Goldsmith, 1951) harmonized data series.

Chapter 4

Distributional National Accounts for Australia, 1991-2018

with Nicolas Hérault and Roger Wilkins

Abstract

We produce estimates of the full distribution of all national income in Australia for the period 1991 to 2018, by combining household survey with administrative tax microdata and making adjustments to match National Accounts aggregates. We find that inequality of post-tax national income is lower and increased less than inequality of survey-based (post-transfer, disposable) income between 1991 and 2018. International comparisons reveal that Australian inequality is much lower than that of the United States, while it is similar to that of France, with those at the bottom of the income distribution faring noticeably better in France and Australia than in the US.

4.1 Introduction

A recent literature led by researchers affiliated with the World Inequality Database (Blanchet, Chancel, and Gethin, 2022; Bozio et al., 2018; Garbinti, Goupille-Lebret, and Piketty, 2018; Piketty, Saez, and Zucman, 2018; Piketty, Yang, and Zucman, 2019) has attempted to provide a more complete picture of the distribution of income through allocating all of the income as measured in National Accounts to individual members of society. The guiding principle for these ‘Distributional National Accounts’ (DINA) is to allocate the entirety of national income to individuals in line with their ‘beneficial receipt’ of the income—that is, according to how much of the income effectively accrues to them.

By doing so, a new picture of the income distribution is obtained, which is an alternative to—and arguably more comprehensive than—those of traditional inequality studies using household survey or administrative tax data on their own. Traditional studies typically only capture cash incomes, thereby missing important income components such as in-kind benefits from government-provided goods and services, imputed rents on owner-occupied housing, and retained earnings of companies.¹ By accounting for these additional income components, the Distributional National Accounts approach therefore generates estimates of individuals’ incomes that are on average larger than obtained from household surveys or income tax data and which should more accurately reflect the distribution of all (cash and in-kind) income.

In this paper we attempt to produce statistics on the distribution of income in Australia as measured by the National Accounts.² Our approach is guided by Blanchet et al. (2021), which details the income concepts and methods of implementation adopted by the World Inequality Database (WID). The guidelines are, however, not completely prescriptive because of the substantial variation across countries in institutional features and data availability. Our approach is therefore considerably influenced by the particular institutional features of Australia and the relative strengths and weaknesses of the available data sources.

Four main national income concepts are identified in Blanchet et al. (*ibid.*) as being of interest: pre-tax factor income; pre-tax post-replacement income; post-tax disposable income; and post-tax national income. Pre-tax factor income approximately corresponds to total income accruing to capital and labour, where all of national income is attributed to capital and labour. Pre-tax post-replacement income is the same as pre-tax factor income, but with an adjustment made to account for the public pension system by allocating pension payments to recipients and deducting the contributions used to fund them (such that it still sums to national income). Post-tax disposable income deducts all taxes attributable to individuals and adds cash transfers. Consistent with the principle of distributed income aggregating to National Accounts totals, the total value of taxes deducted equals the total value of taxes collected by government (not just income taxes). However, government expenditure is not allocated to individuals and thus the sum of post-tax disposable income is less than national income. Post-tax national income addresses this deficiency by

¹Some earlier studies that have examined the effect of in-kind benefits on inequality include Garfinkel, Rainwater, and Smeeding (2006), as well as Paulus, Sutherland, and Tsakoglou (2010).

²This paper builds on earlier work by Fisher-Post (2020).

distributing all of government expenditure, inclusive of items not readily attributable to individuals, such as national defence.

We construct measures of all four income concepts, but the results we present are primarily for pre-tax post-replacement income and post-tax national income on the basis that these are the main pre-tax and post-tax income concepts of interest, respectively corresponding to measures of the distributions of market income and ‘post-government’ income (the latter corresponding to ‘beneficial receipt’ of income).

We are not the first to attempt to describe the distribution of income in Australia adopting a National Accounts income concept. In line with broader efforts by national statistical agencies that produce National Accounts, the Australian Bureau of Statistics (ABS) has, on four occasions since 2014, released distributional information by combining information from its biannual household income survey with the household income account of the National Accounts data (most recently in 2021; see ABS, 2021a).³ The methods have been refined over time. In the most recent release, for each of nine years between 2003-04 and 2019-20, statistics are presented on the distribution of various components of the national household income account across households.

While complementary to the analysis we undertake, the ABS approach is somewhat different to that advocated by Blanchet et al. (2021). Most important is that the income concept differs. Under the ABS approach, only income captured in the household income account is distributed to households, and thus components of national income not captured in the household income account, including retained earnings of corporations and government expenditure, are excluded. Additionally, the distributional information produced by the ABS is limited, presenting only the total, mean and share of each income component of the household income account for broad groupings of households: by main source of income (five groups), by equivalised income quintile, by household type (seven groups), by age group of the household ‘reference’ person (six groups) and by wealth quintile.

Compared with the ABS outputs, we therefore present distributional information that is based on income concepts more in line with the DINA guidelines, which are concerned with the total of national income, and not the total of income as measured in the household income account. Furthermore, we present more detailed distributional information, most notably at the top of the distribution, and information for a larger array of demographic groups than is produced by the ABS.⁴

4.2 Distributing national income to individuals

In building DINA estimates for Australia, we follow approaches taken for, *inter alia*, France, the US and China (Garbinti, Goupille-Lebret, and Piketty, 2018; Piketty, Saez, and Zucman, 2018; Piketty, Yang, and Zucman, 2019), as well as the DINA Guidelines (Blanchet et al., 2021).

The goal is to distribute to individuals all of the National Accounts measure of income, defined as GDP plus net foreign income minus consumption of fixed capital. We construct four measures of income that are distributed to individuals, although

³See also Zwijnenburg (2022) and OECD (2024) for further methodological discussions.

⁴We do not attempt to make direct comparisons with the ABS results because of the many differences in approach, including the unit of analysis, income concept, distributional measures of interest and time-period examined.

only three of these sum to a National Accounts aggregate. In the following we briefly describe the data and methods used to produce each income distribution.

4.2.1 The use of tax and survey data

Our approach draws on both unit record tax data and income survey data. The tax data set, known as ALife, comprises a 10% random sample of tax returns covering the period 1991 to 2018. The income survey data come from the Australian Bureau of Statistics' Survey of Income and Housing (SIH), covering the period 1994 to 2018, but with some gaps.

After examining both ALife and the SIH, we determined that the best approach was to primarily base cash income estimates on the SIH, but with ALife tax data used to adjust incomes for the top 1%. This is because the tax data appear inferior in income capture for most of the distribution (Figure 4.1). Although non-labour income is higher in ALife than in the SIH for people with above-median incomes, it is not enough to compensate for the undercoverage of labour income (see Appendix Figures A4.1 and A4.2 for a breakdown of Figure 4.1 by income source).

Our approach is something of a departure from existing studies, which have given greater weight to tax records data. However, DINA need to be flexible to national circumstances. Australia is by no means unique in the finding that income survey data is at least as good as tax data for incomes below the top 1% (see Burkhauser et al., 2012 for the US and Burkhauser et al., 2018 for the UK). Perhaps requiring some explanation is why the survey data actually captures more income below the 99th percentile than the tax data. Two main explanations exist: some forms of income are nontaxable and are even received by high income earners; and there are incentives to minimise income reported to tax authorities that do not apply to statistical agencies.

Aside from better capture of the incomes of the bottom 99%, additional reasons to use the SIH include better flexibility to look at different income concepts and income units (including the household unit) as well as information on wealth. We distribute incomes of households on an 'equal-split adults' basis, meaning each adult household member is assigned an equal share of the total household income, as per the 'broad equal-split series' in the DINA Guidelines (Blanchet et al., 2021, p.23). Although our baseline estimates are based on these broad equal-split series, we also build and use the 'narrow-split series' to ensure consistency in the comparison with the US and France. The 'narrow-split series' distributes income to all adult individuals by splitting income equally within a couple, but not within the extended household.

While the SIH is our preferred 'core' data source, it nonetheless has important limitations which need to be addressed. It is only available from 1994-95, and it has only been conducted every second year from 1997-98 to 2002-03 and from 2003-04 onwards. It also only has wealth data (and hence information on superannuation (private retirement account) balances and home equity required to distribute capital income in 2003-04, 2005-06 and 2009-10 onwards).

To produce estimates in non-SIH years, we interpolate distributions and adjust according to changes in the components of the National Accounts in those years. We use the GDP deflator to either inflate the distribution from the closest earlier year or to deflate it from the closest later year. If both an earlier and a later year are

available, we apply both methods separately and compute the final DINA estimates by taking the average of the two series thus obtained.

We follow the cell-mean imputation method we developed for the UK in Burkhauser et al. (2018), using tax data (ALife) to impute incomes of the top 1% in the survey data.⁵ In addition to imputing gross income from tax data for the top 1%, we also use the labour/capital income-source composition as is obtained from the tax data. However, the tax data offer less detail and thus less flexibility in then adjusting incomes to match National Accounts totals (e.g., mixed-income is not directly observable in ALife). We address this issue by maintaining the assumption that the income-source compositions within capital and labour incomes are as obtained from the survey data.

Our procedure ensures that total ‘tax gross income’ for the top 1%—and for each of the 1,000 groups within the top 1%—is the same in the (adjusted) SIH and ALife data.

4.2.2 The use of National Accounts

We align each income component in the adjusted SIH microdata to the National Accounts. We mostly proceed by adjusting the microdata proportionally and uniformly to the relevant National Accounts aggregates (see Appendix A4.2 for a detailed discussion of the approach undertaken for each income component). We start with factor income, distinguishing labour income, mixed income, and capital income and, within the latter, superannuation, imputed rent and other capital income. We thus obtain pre-tax factor income, to which we add the Age Pension to obtain pre-tax national income. From pre-tax national income to post-tax disposable income we deduct all taxes and add all government cash transfers to individuals’ pre-tax incomes. Finally, we obtain post-tax national income by distributing government expenditure to individuals.

4.3 Income inequality in Australia 1991-2018

4.3.1 Comparisons of DINA with household survey estimates

Of considerable interest is how inferences on levels and trends in inequality are affected by moving from traditional household-survey based estimates for household equivalised disposable income to DINA estimates of inequality. Figure 4.2 compares the Gini coefficient for three of the DINA income concepts with the Gini coefficient for equivalised disposable income captured in the SIH (where the modified OECD scale is used to equalise income; see Hagenaars, De Vos, Asghar Zaidi, et al., 1994).

Comparing across the DINA income concepts, moving from pre-tax national income to post-tax disposable income and then to post-tax national income is associated with decreases in the Gini coefficient. Notably, the Gini coefficient for post-tax national income is consistently below the Gini coefficient for equivalised disposable (cash) income obtained from survey data. This is important because it shows that incorporating in-kind benefits such as health and education substantially reduces inequality in Australia. In fact, this reduction in inequality, as measured

⁵We use a cell size equal to 1/100,000th of the total adult population. A few preliminary adjustments to ALife data are required: see Appendix A4.1.

by the Gini coefficient, is similar in magnitude to that achieved by taxes and cash transfers.

We also note differences in trends between the DINA and survey series. Between 1994 and 2018, the Gini coefficient for (survey-based) equivalised disposable income increased from 0.30 to 0.33, whereas it remained stable for DINA post-tax national income (0.27 to 0.28). This appears mostly due to the redistributive effect of in-kind transfers, as the Gini coefficient for DINA disposable income (i.e., before in-kind transfers) also increased over the period, from 0.34 to 0.38.

Comparing SIH equivalised disposable income for the full population with SIH equal-split disposable income for adults only reveals very small differences in inequality as measured by the Gini coefficient. This suggests that going from equal-split income among adults, as per the DINA series, to equivalised adult among the full population, as per the standard SIH series, cannot explain much of the difference between the two series.

The significant remaining difference between DINA and SIH series (when both are measured as disposable income, among equal-split adults) can likely be attributed most of all, to the presence in DINA series of capital incomes (accruing to the highest-earning households) which are observed in national accounts data, but unobserved in the survey data. To fully account for capital income substantially increases the measure of inequality.

4.3.2 DINA estimates of pre- and post-tax income shares

Figure 4.3 presents estimated shares of pre-tax and post-tax national income over the 1991 to 2018 period of the bottom 50%, top 50% excluding the top 10%, top 10% excluding the top 1%, and the top 1%. Pre-tax income provides information on how a ‘market income’ concept of income is distributed across individuals. The share of the bottom 50% remained relatively steady, at approximately 20%, but the top 50 to 10% group experienced a decline from over 50% to 47.5%, with the decline occurring between 1991 and 2008, since when there has been no net change. The income share of the top 10% to 1% rose from 22% to 23.4%, while the top 1% income share rose from 7% to 9.4%, with all the increase occurring between 1995 and 2008 (and indeed there is a small decline evident after 2008).^{6,7}

Post-tax national income series provide information on the distribution across individuals of ‘beneficial receipt’ of total income in the National Accounts. Government redistribution in a broad sense, as captured by the comparison of pre-tax and post-tax national incomes, contributed to mitigate the changes in pre-tax income shares between 1991 and 2018. The relative rise in top income shares and the relative fall in the top 50 to 10% incomes shares are less pronounced for post-tax income. Notable, however, is that the income share of the bottom 50%, after rising slightly between 1991 and 2007, subsequently fell to 2010, and has only recovered its 1991 level.

We can also go beyond top income shares and estimate changes in mean real individual incomes by income group. Since 1991, the mean pre-tax income of the

⁶Note that individuals and households do not necessarily belong to the same pre-tax and post-tax income group.

⁷Series (in Stata files) that describe thresholds, averages and shares for each of the 127 ‘generalised percentiles’ (or g-percentiles) for each income concept are available through the [World Inequality Database](#).

top 1% has increased by a factor of more than four. This compares with nearly 3.5 for the top 10% to 1% and approximately 2.9 to 3 for the two groups comprising the bottom 90% (Appendix Table A4.6). Consistent with the findings of Figure 4.3, differences in income growth across the four income groups are more subdued for post-tax national income than for pre-tax national income. The increase in mean pre-tax income increase ranged from a factor of 3 for the top 50 to 10% to 3.7 for the top 1% (Appendix Table A4.7).

In Figure 4.4, we examine real income growth for the whole period but at a finer level by providing estimates by percentile income group.⁸ For pre-tax income, both the bottom 20% and the top 5% have done better than the average adult, who saw income grow at an average of 1.7% per annum. However, differences between the bottom, middle and top of the distribution mostly disappear when moving from pre-tax to post-tax national income, with the notable exception that growth was still higher for the top 5%. Moreover, among the top 5%, the top 1%, and top 0.1% in particular, have clearly experienced growth rates that are larger than the average.

Attributing these changes in the Australian income distribution to specific events or policies is a difficult exercise and remains outside the scope of this paper. However, a few remarks can be made. While the top 10% has seen an increase in its income share at the expense of the rest of the population, the changes over nearly 30 years remain limited in scale. Nonetheless, the bottom 50% income group fared relatively well between 1991 and 2007, a period in which Australia experienced strong economic growth and a trend decline in unemployment. The Global Financial Crisis (GFC) of 2008 coincided with a sharp fall in the bottom 50% income share. The sluggish economic recovery experienced by Australia since then coincides with only a small increase in the bottom 50% share, which remains lower in 2018 than its average level before 2008. Finally, the main step-increase in the income share of the top 10% occurred in 2008 and 2009. As noted, this is the period of the GFC, which top income groups may have weathered relatively well compared with low-income groups. Also perhaps important is that 2008 was the last year that saw an increase in the income threshold above which the top marginal tax rate applies. This threshold was increased from \$60,000 in 2003 to \$180,000 in 2008 as part of an agenda of tax-transfer reforms implemented in the 10 years leading up to the GFC. These reforms increased inequality through the reduction of the redistributive effect of the tax and transfer system (Herault and Azpitarte, 2015, 2016).

4.4 International comparisons: Australia, US and France

In this section we compare our DINA estimates for Australia to those reported by Piketty, Saez, and Zucman (2018) for the US and by Garbinti, Goupille-Lebret, and Piketty (2018) for France for four income groups: top 1%, top 10%, top 50 to 10% and bottom 50%.⁹

⁸In addition, Appendix Figures A4.3 and A4.4 provide pre- and post-tax income shares by year and by quintile.

⁹Results for Australia differ slightly from those presented in the previous section because we use the ‘narrow equal-split’ series (see Section 4.2.1) and we report top 10% income shares rather than top 10 to 1% income shares to ensure comparability with estimates for the US and France reported by these two papers.

Figure 4.5 reveals that differences in the distribution of post-tax national income across the three countries are stark.¹⁰ The top 10% in the US received nearly 34% of income in 1991, and this had risen to 39% in 2018. In France, the top 10% received nearly 28% of income in 1991 and this share fell slightly to 26% in 2017, the latest year available. In Australia, the top 10% income share was 23 to 24% between 1991 and 2001, but then increased to 27% in 2011 and subsequently declined only to 25% by 2018. For the top 1%, the US again has a much higher income share and greater growth in the income share than France and Australia.¹¹ The top 1% share is higher in France than in Australia, though the gap which was 2 to 3 percentage-points in the 1990s has been declining since the early 2000s to 1 percentage-point in the most recent as the top 1% share increased in Australia while it remained stable in France.

The income share of the bottom 50% is highest in Australia and lowest in the US. There is little net change evident over the full period for Australia, but there is a slight increase for France and a considerable decline for the US. At the end of the period, the income share of the bottom 50% was 30% in Australia, 29% in France and 19% in the US. Here the contrast with pre-tax income shares is striking because the bottom 50% income shares are 4 to 5 percentage-points lower in Australia than in France (Appendix Figure A4.5). The fact that post-income shares are similar in both countries reveals the more targeted nature of government expenditures in Australia than in France. Indeed, Australia is known for being one of the OECD countries with the most targeted welfare system (Whiteford, 2013).

For the top 50 to 10%, income shares are more similar across the three countries, although across the entire period, Australia has the highest income share and the US the lowest, and the gap widened slightly between 1991 and 2018.

Recent work shows that if Europe is less unequal than the US, it has more to do with lower levels of pre-tax income inequality than with more equalizing tax-and-transfer systems (Blanchet, Chancel, and Gethin, 2022). We can draw the same conclusion for Australia as the differences with the US are already clearly apparent in the pre-tax income distribution (Appendix Figure A4.5).

In Figure 4.6, we abstract from yearly changes and examine differences in income levels by percentile income group across the three countries. We use purchasing power parity (PPP) exchange rates to convert French and Australian income levels to US dollars. For each percentile of the income distribution, we plot the ratios of French and Australian incomes to US incomes. Thus, when the curve lies above one (i.e., the red line), incomes at those percentiles are higher than in the US. This exercise, with all its limitations, reveals that only those below the 15th percentile did better in Australia than in the US in 1991. By 2017, however, Australians below the 30th percentile have higher PPP-adjusted incomes than their US counterparts. There is a remarkable convergence of French and Australian distributions of post-tax national income, which by 2017 look very similar. Driving this convergence is the fact the Australian middle class has moved closer to the living standard of the US middle class, while the French middle class has moved farther away. The downward slopes indicate that as we go from the bottom to the top of the distribution, the

¹⁰Results for pre-tax national income presented in Appendix Figure A4.5 also reveal stark differences.

¹¹Our new series here provides additional compelling evidence to a growing consensus that the US remains (and is increasingly becoming) the outlier among its Anglosphere and OECD peers. To explain that trend, however, is beyond the scope of this paper.

differential initially in favour of Australia (and France) over the US reverses around the 30th percentile and keeps growing such that incomes at the top are markedly higher in the US. Thus, the majority of people in the US—the top 70%—are better off than their French and Australian counterparts.

4.5 Inequality disaggregated by demographics

A valuable feature of the DINA series for Australia is that it is primarily based on survey data, which contains demographic information not typically available in administrative data sources such as tax records. Here, we exploit this extra richness of the survey data to shed further light on the distribution of national income across and within various population groups.

In what follows we consider immigrant status as illustrations of the value of this feature. We focus on the post-tax national income series based on the equal-splitting of household income between all adult members (i.e., the ‘broad equal-split series’).¹²

We first present and discuss differences in mean incomes before turning to the income shares of national income within each subgroup. Mean incomes are useful to show differences in levels across groups, regardless of the size of each group. Mean income is preferred over income shares because the latter are a reflection of both mean incomes and population shares. The income shares within each subgroup (e.g., among immigrants) are then presented to shed light on the levels and trends of inequality within each subgroup.

Approximately one-quarter of the Australian population is foreign-born. The ABS SIH data allow us to distinguish foreign-born and native-born individuals.¹³ Figure 4.7 shows that mean post-tax national income is greater for native-born Australians than for immigrants throughout the 1991–2018 period. The gap increased after the 1990s to reach almost 8% (or about \$6,000) in 2018, compared to 6% (\$3,000) in 1991. This trend may in part reflect changes over time in the source-country composition of immigration, which has increasingly comprised people of diverse cultural and linguistic origins. Labour market conditions may also be part of the explanation. Strong labour market conditions in the 1990s may have contributed to immigrants closing the gap to natives, while the weak labour market of the late 2000s and 2010s may have had the opposite effect. However, labour market conditions cannot explain why immigrants fared relatively badly in the early 2000s, when conditions were very favourable.

Figure 4.8 shows that income shares are, perhaps surprisingly given the mean income differences, similarly distributed among immigrants and among the native-born.

¹²See Fisher-Post, Herault, and Wilkins (2022) for a discussion of results by age, sex, education and area of residence (i.e., cities versus regional areas) and for results based on individualistic series.

¹³More detailed information on country of birth is available in some survey years, but not consistently across our period of analysis. Over this period, the source-country composition of immigrants shifted from predominately European countries to predominately Asian countries. As a result, while in 1991 approximately 64% of immigrants living in Australia were born in European countries and 20% were born in Asian countries, by 2021, the corresponding proportions were 30% and 43%, respectively (ABS, 1993, 2021b).

4.6 Conclusion

We have produced the first DINA estimates for Australia, spanning the period 1991 to 2018. Our estimates suggest Australia has a somewhat similar distribution to France, with both countries having considerably more equitable distributions but also lower PPP-adjusted incomes than the US. Australia has, however, had greater growth in inequality than France.

Significantly, our DINA estimates for Australia indicate that income inequality is lower and has increased less between 1991 and 2018 when all income as measured in the National Accounts is distributed to individuals compared with a focus on cash incomes as is conventional in household survey-based studies of income inequality.

In contrast to other DINA studies internationally, our reliance on household survey data to anchor our distributional analysis has allowed us to consider income differences between and within demographic groups. The analysis presented in this paper has only investigated these differences in a cursory fashion, but clearly there is considerable potential to exploit this feature of our series in future research.

While in the long run it would be ideal to publish synthetic microfiles for public research consumption, the confidentiality requirements of ABS and ALife data access currently preclude this. However, detailed distributional information has been made available through the [World Inequality Database](#).

A further important future research direction is to attempt to extend the DINA estimates back to earlier years. Unit record income survey data is sparser prior to the 1990s, and indeed non-existent prior to 1975. Similarly, unit record tax data only extends back to 1991. Methods for producing DINA estimates will therefore need to rely on more aggregated forms of data, such as the tax tables used to produce the original (cash income) top income shares for WID.

Further refinement of Australian DINA estimates is also possible and should be a priority for further research. For instance, our assumption that in-kind income from government expenditure is equally distributed across the population is consequential but almost certainly not accurate. On balance, government expenditure is likely to be progressive in its effects, as evidenced by the ABS in its periodic ‘fiscal incidence’ studies (ABS, 2018). However, while it is easy to come up with alternative choices and assumptions, implementation is often impeded by the lack of data. In addition, further refinements should ideally occur through refinements and extensions to the DINA guidelines in order to facilitate comparability of DINA estimates across countries.

Figures

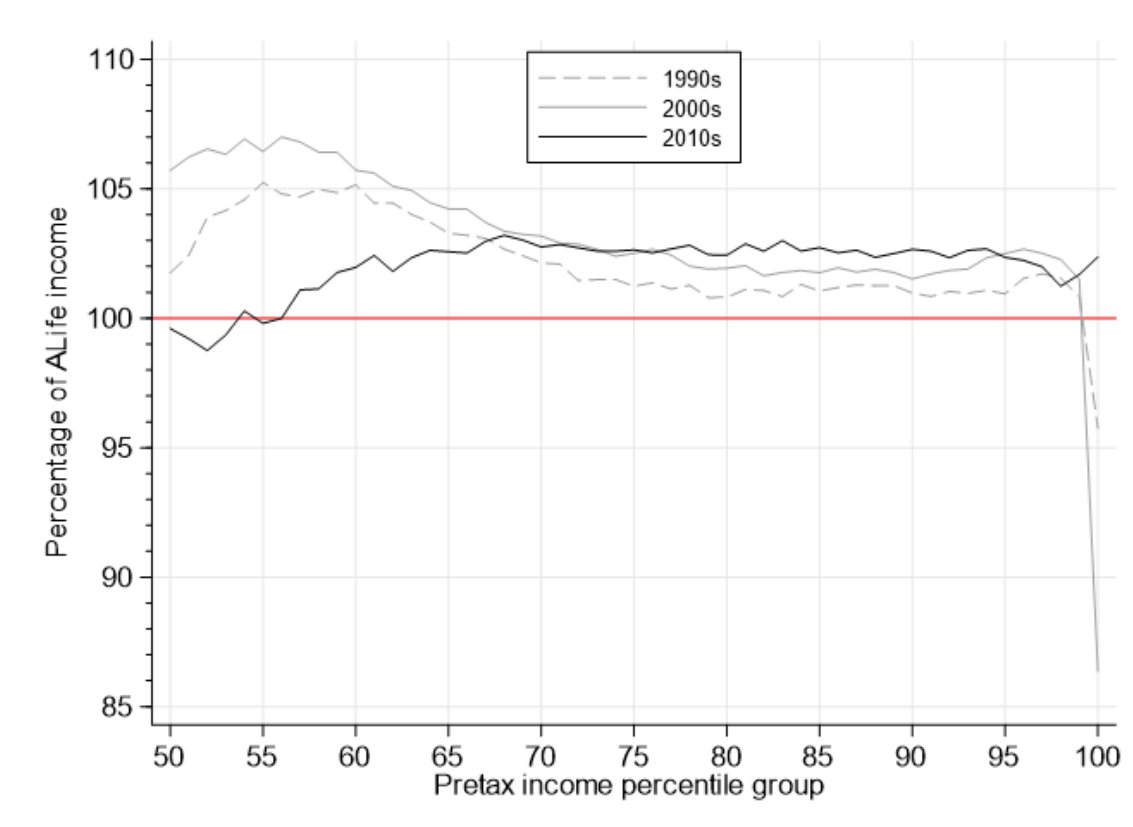


Figure 4.1 – SIH survey relative to ALife tax data, by percentile – Pre-tax income

Notes: This figure reports the ratio of total income in the survey data (SIH) to the total income in the tax data (ALife) for each income percentile group. A ratio of one (100%) means that the two sources are perfectly aligned. A ratio of 90% means that total income is 10% lower in the survey than in the tax data for that percentile group.

Source: Authors' calculations based on ALife and SIH data.

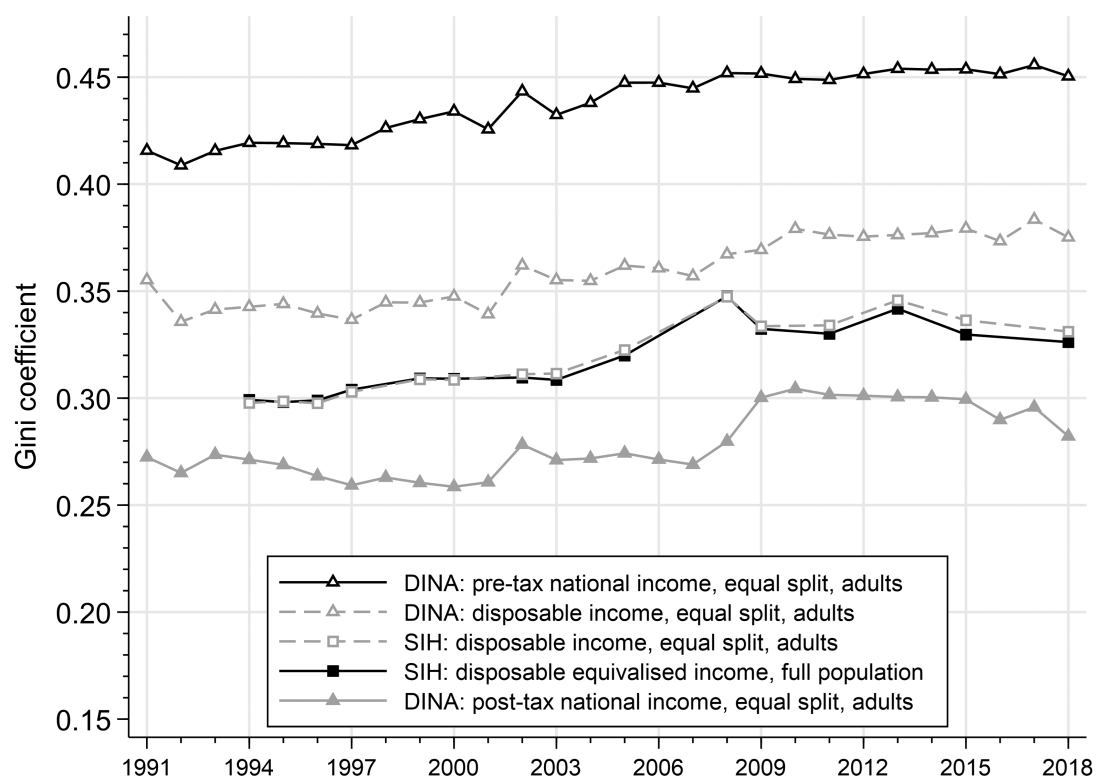


Figure 4.2 – Gini coefficients for DINA vs. household equivalised income, 1991-2018

Notes: The figure compares the Gini coefficient estimates based on the DINA series (household income equally split among adults) to those obtained from the survey data alone (SIH)—using either equivalised income (for the full population) or broad equal-split income (for the adult population). See Section 4.2.1 for further discussion of these concepts.

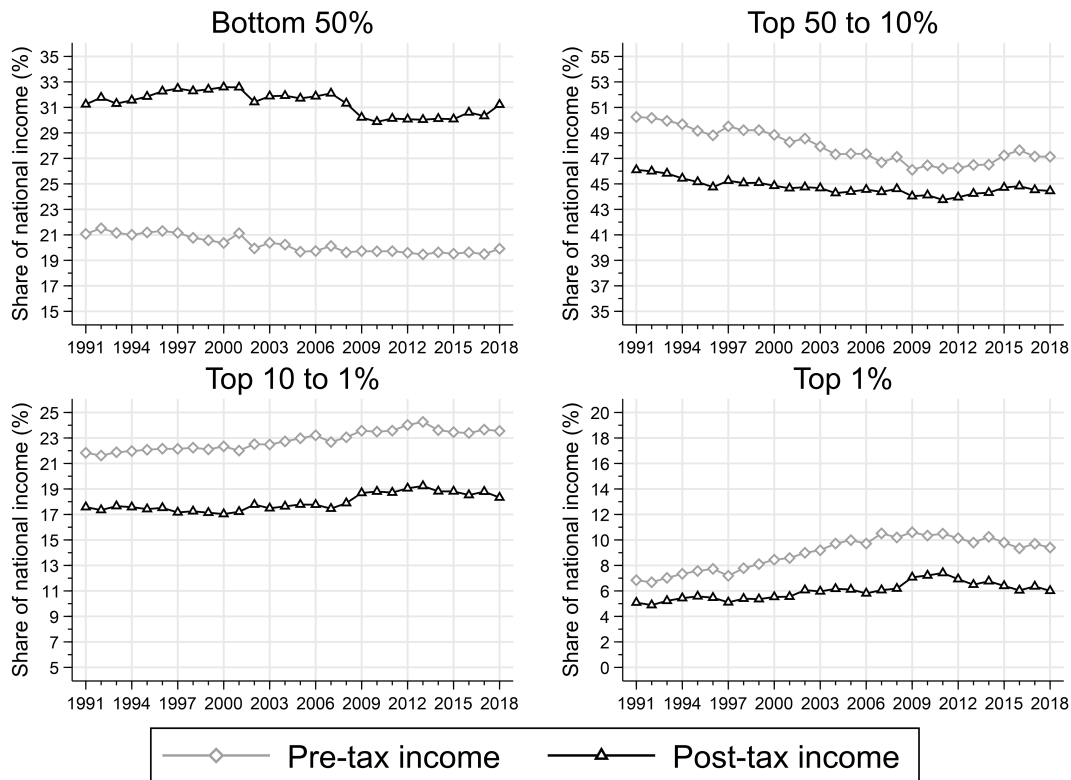


Figure 4.3 – Pre-tax and post-tax national income shares, 1991-2018

Notes: Distribution of pre-tax national income (before all taxes and transfers, except age pensions) and post-tax national income (after all taxes and transfers) among adults. Broad equal-split adults series (household income equally split among adults). Note that people do not necessarily belong to the same pre-tax and post-tax income group.

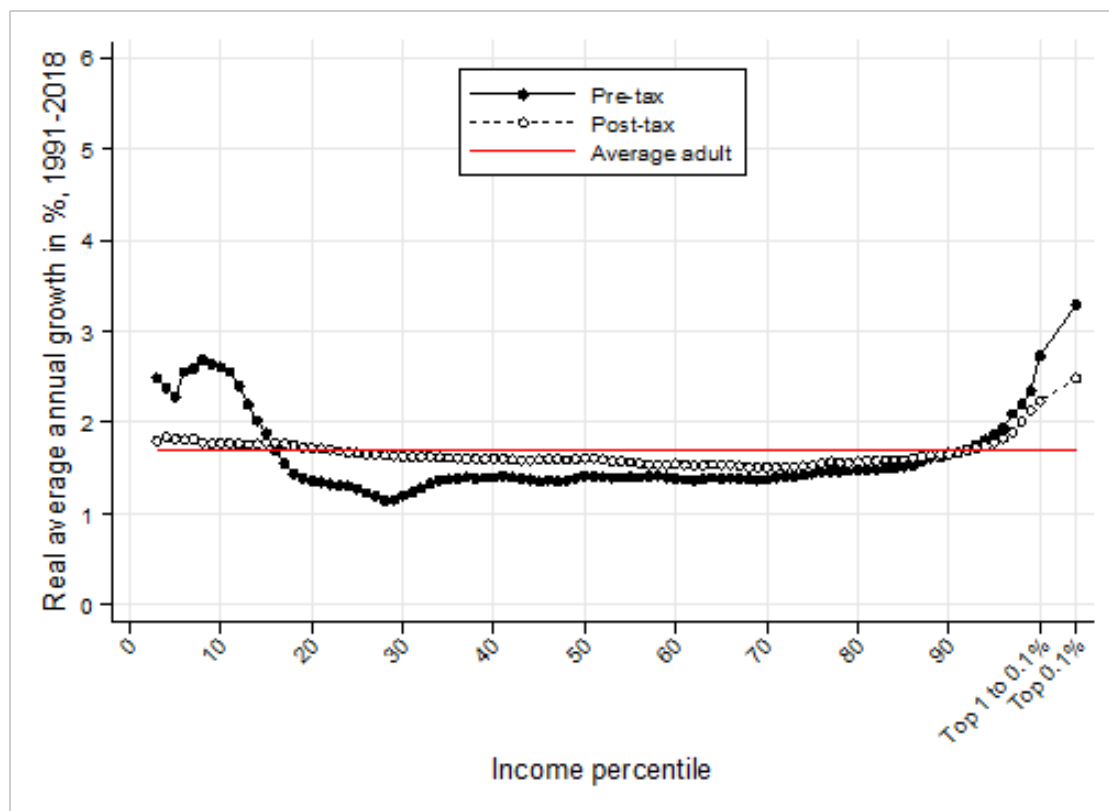


Figure 4.4 – Real average annual growth per adult, 1991-2018

Notes: Distribution of pre-tax national income (before all taxes and transfers, except age pensions) and post-tax national income (after all taxes and transfers) among adults. Broad equal-split adults series (household income equally split among adults). Index based on mean incomes in constant dollars. The red line shows the overall average per-adult real annual national income growth rate over the period, which is (by construction) the same for pre- and post-tax income series.

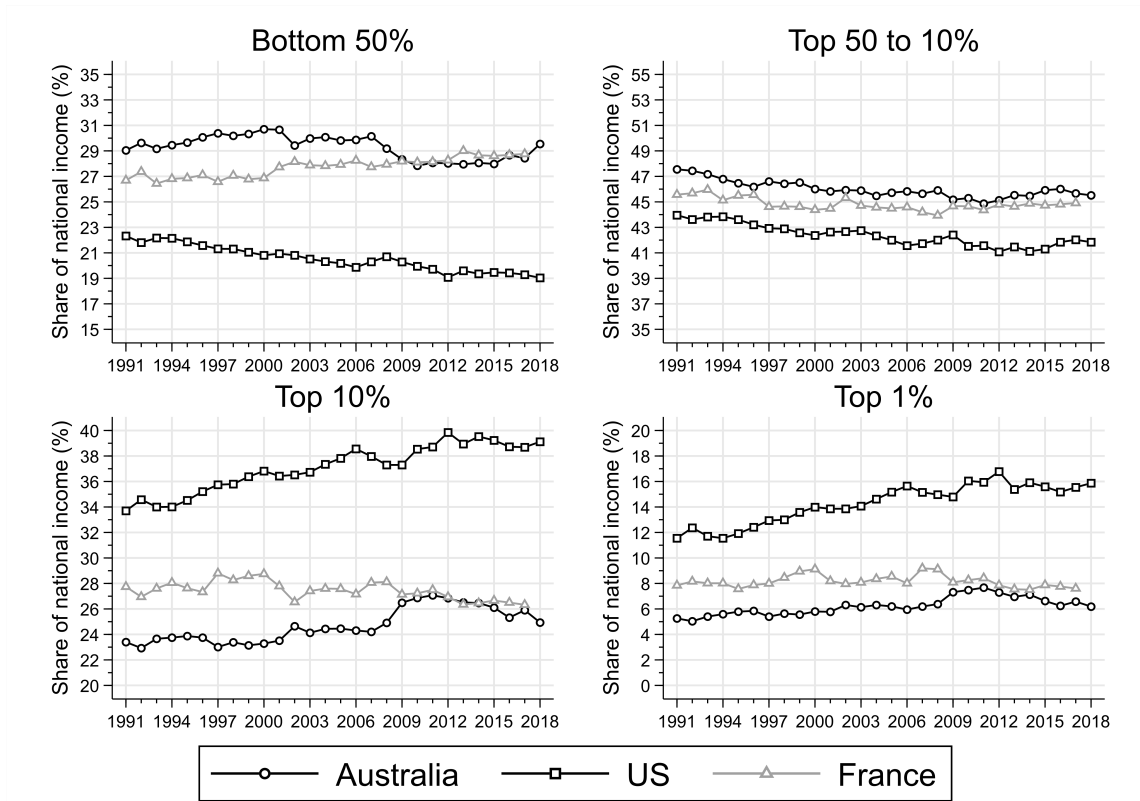


Figure 4.5 – Post-tax income shares: Australia, US and France, 1991-2018

Notes: Distribution of post-tax national income (after all taxes and transfers) among adults. Narrow equal-split adults series (income of married couples divided by two).

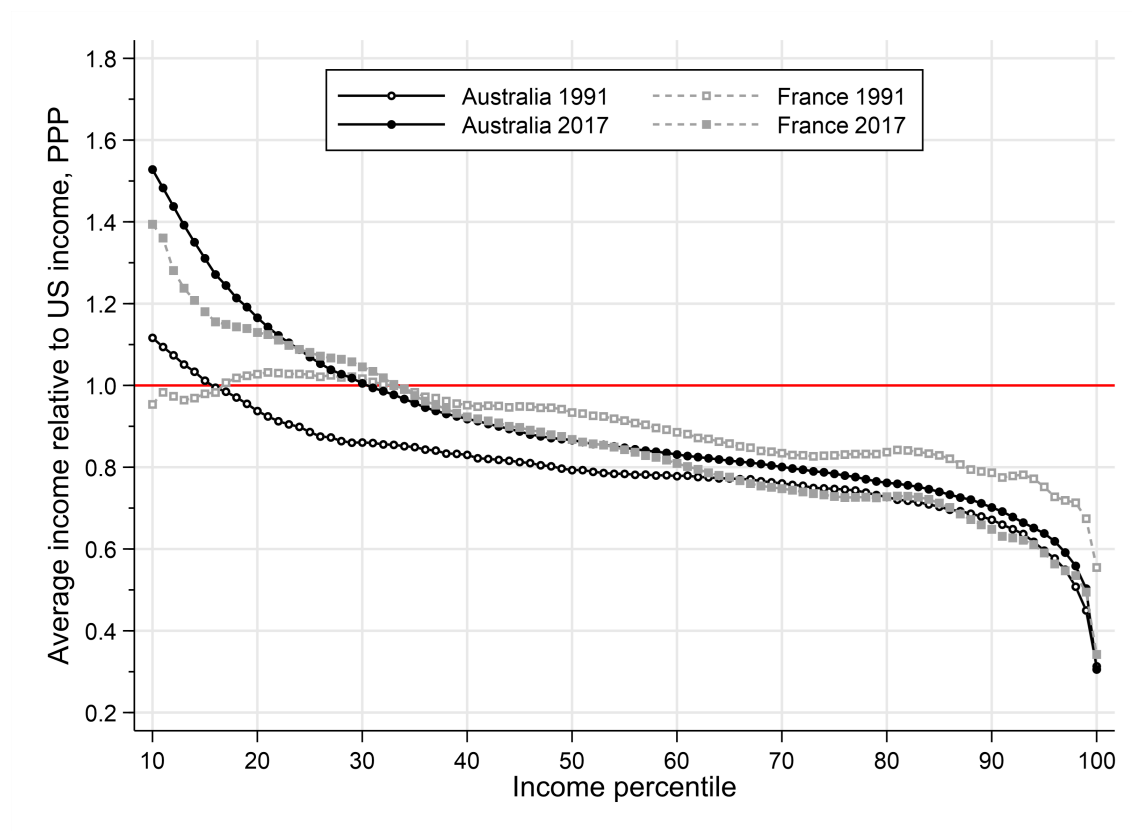


Figure 4.6 – Post-tax income by percentile: Australia, US and France 1991 & 2017

Notes: Distribution of post-tax national income (after all taxes and transfers) among adults. Narrow equal-split adults series (income of married couples divided by two). Comparisons are based on purchasing power parity (PPP) exchange rates (source: World Inequality Database). 2017 is the latest year for which estimates are available for all three countries.

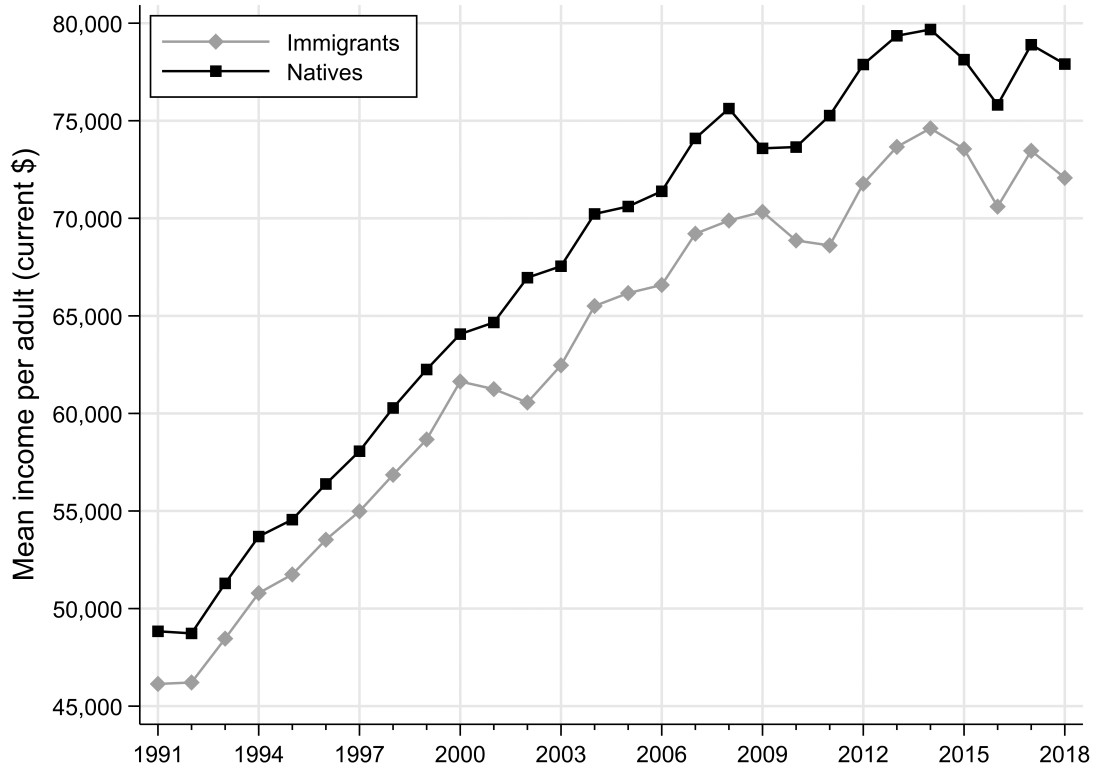


Figure 4.7 – Post-tax national income for immigrants and natives, 1991-2018

Notes: Broad equal-split adults series (household income equally split among adults).



Figure 4.8 – Post-tax income shares among immigrants and natives, 1991-2018

Notes: Broad equal-split adults series (household income equally split among adults).

Chapter 5

Distributional National Accounts for Canada and Provinces, 1982-2021

with Silas Xuereb, François Delorme and Camille Lajoie

Abstract

In this chapter we estimate the distribution of all national income in Canada, and five sub-regions, from 1982 to 2021. We apply distributional national accounts (DINA) methodology to tax tabulations, combined with national accounts data and survey data. Pre-tax and post-tax income data are analysed.

We find that top income shares published by Statistics Canada tend to underestimate income inequality relative to top income shares calculated using DINA, as DINA account for people who do not file taxes and for undistributed capital income that is retained in corporations.

In line with previous research, income inequality in Canada increased significantly from 1982 until the mid-2000s. From 1982 until 2000, the real income of the bottom 50% of Canadians stagnated while that of the top 0.01% quadrupled. Since the mid-2000s, income inequality has decreased slightly although it remains far above the levels observed in the early 1980s.

Across Canadian provinces, Ontario has consistently had higher inequality than Quebec although the gap has closed in recent years. Quebec has the most progressive tax and transfer system of the six sub-regions. In Alberta, record levels of inequality were reached in the mid-2000s and these appear to have been a significant driver of the national peak in inequality during this period.

Post-tax income inequality initially fell during the pandemic because large temporary transfer programs were introduced. However, pre-tax income inequality increased, especially in 2021 when record levels of corporate profits were reached.

5.1 Introduction

Long left to the wayside by academic economists and policymakers in North America, the study of inequality has lately returned to public attention (Piketty, 2014). In order to have an informed public debate on this topic, one of the first prerequisites is to have reliable data to understand the extent of inequality. This need led researchers to develop Distributional National Accounts (DINA) as a framework for producing reliable internationally comparable statistics about income distribution (Blanchet et al., 2021; Piketty, Saez, and Zucman, 2018).

Conventional measures of income inequality, such as those publicly produced by Statistics Canada, rely on income concepts available in tax data. These have two major pitfalls that DINA addresses (e.g., Garbinti, Goupille-Lebret, and Piketty, 2018; Piketty, Saez, and Zucman, 2018). First, because the types of income reported in tax data are not aligned across countries, these statistics are difficult to compare internationally. Second, not all of national income is reported in tax data. Most significantly, profits retained in corporations are not observed in personal income tax data, although they are included in national income. This income accrues disproportionately to high income earners, meaning traditional estimates of income inequality underestimate incomes at the top of the distribution. Furthermore, 10-12% of adults do not file tax returns at all in Canada (Robson and Schwartz, 2020), and so their income is missing from traditional estimates.¹

DINA rectify these problems by distributing all of net national income to individuals. This method requires making certain assumptions about unobserved income but ensures that the definition of income is comparable across countries and that untaxed forms of income and in-kind benefits are accounted for.

In this paper, we develop DINA estimates for Canada, each of the four largest provinces (Alberta, British Columbia, Ontario, and Quebec), the Prairies (Manitoba, Saskatchewan, and the Territories), and the Maritimes (New Brunswick, Newfoundland, Nova Scotia, and Prince Edward Island) from 1982 to 2021. The smaller provinces are grouped together because of the difficulty of applying national accounts methodology to small economies.

Producing subnational DINA estimates is a novel contribution to the literature as there has been little application of DINA below the national level. After providing an overview of previous research on income inequality in Canada, we describe the methods used to develop DINA in Canada. Then, we present our results, and describe the insights DINA can provide to help us understand observed trends in inequality in Canada from 1982 to 2021.

Similar to the trends observed in the United States, a significant body of evidence shows that Canada's income inequality, whether measured by top income shares or the Gini coefficient, increased greatly during the 1980s and 1990s (Delorme and Lajoie, 2023; Fortin et al., 2012; Lemieux and Riddell, 2015; Saez and Veall, 2005). However, although inequality continued increasing during the mid-2000s and fell during the financial crisis in both countries, traditional estimates show that inequality has remained relatively stable, or even decreased slightly, in Canada since 2009 (Delorme and Lajoie, 2023) while it has continued increasing in the United States.

¹Relative to other countries, Canada has high rates of tax filing and a high proportion of net national income observable in tax returns. Nonetheless, we show that one third of net national income is not observed in traditional inequality statistics.

There are many competing explanations for the rise inequality observed in the 1980s and 1990s although less attention has been paid to the more recent observed decline in inequality since the financial crisis. Explanations for the increase in inequality in Canada have largely fallen into three groups: 1) educational and technological change, 2) policies and institutions, and 3) competition with the US.

Skill-biased technological change was a popular explanation for rising inequality in Global North countries during the 1990s (e.g., Berman, Bound, and Machin, 1998) but has since fallen out of favour because of its inability to explain differences in inequality trends across Global North countries and the extreme concentration of wage increases within the top 1%. Recent research suggests that while technological change has contributed to increasing the earnings of those with advanced degrees relative to those without a degree in Canada, this explains only a small proportion of the rise in inequality (Lemieux and Riddell, 2015).

Instead, Fortin et al. (2012) emphasized the role of changes in institutions such as declining real minimum wages and unionization rates in contributing to rising inequality. Real minimum wages increased in most provinces during the 1980s and early 1990s but stagnated or declined between the mid-1990s and mid-2000s, when peak levels of inequality were reached. Real minimum wages have since increased again as inequality has declined (Galarneau and Fecteau, 2014). Card, Lemieux, and Riddell (2004) found that declining unionization was correlated with increasing wage inequality in Canada, the US, and the UK during the 1980s and 1990s.

Saez and Veall (2005) attributed a significant portion of the rise in inequality to the effects of the American labour market on the Canadian labour market. They showed that the rise in top incomes in Canada mirrored the rise in top incomes in the United States and that top earners were largely those with high labour incomes rather than those with high capital incomes. While a complete assessment of the forces contributing to changes in inequality is beyond the scope of this paper, our updated results shed new light on the contributions of labour and capital incomes to the growth in income inequality in Canada, and its subsequent fall since the mid-2000s.

At the provincial level, traditional estimates of inequality have shown that pre-tax and post-tax income inequality is higher in the rest of Canada than in Quebec. While differences in post-tax income inequality can be attributed to a larger social safety net in Quebec, differences in pre-tax inequality may stem from other factors.

Saez and Veall (*ibid.*) attribute this phenomenon to increased competition for high earning English speaking Canadians from the US labour market. They found that income inequality began at a higher level in 1982 and accelerated faster for the rest of Canada than for Quebec francophones during the 1990s. Importantly, Quebec anglophones experienced a similar acceleration in income inequality during this period.

We explore whether the lower and slower growing levels of income inequality in traditional estimates of inequality in Quebec hold true when incorporating the full distribution of national income.

As expected, estimates of top income shares are slightly higher using DINA than using traditional measures of income. Both pre-tax and post-tax income inequality increased significantly in Canada from 1982 through the mid-2000s. Since 2006, pre-tax top income shares have fallen and post-tax top income shares have fallen even further, reflecting increasing government redistribution. Despite this slight reversal,

income inequality remains significantly higher than it was in the early 80s. Average pre-tax income has increased by 20% for the bottom 50% since 1982 while it has more than doubled for the top 1% and quadrupled for the top 0.01%.

At the provincial level, we find that pre-tax inequality was lowest in Quebec and the rest of Canada throughout most of the past four decades although, since the mid-2000s, pre-tax inequality has fallen more in all other regions than in Quebec. Alberta's pre-tax income inequality contributed significantly to the peak in national inequality in the mid-2000s but has since declined more than any other province.

5.2 Data and Methodology

In this section, we describe the methods used to estimate distributional national accounts (DINA) for Canada. We develop estimates of the distribution of three different income concepts: pre-tax national income, post-tax national income, and post-tax disposable income. All incomes are in real 2022 dollars.

The main data source for all our estimates is the Longitudinal Administrative Databank (LAD), which contains a 20% sample of tax microdata for every year from 1982 to 2021. We obtained custom tabulations of the LAD from Statistics Canada which provide average incomes for several types of income for each percentile (plus the top 0.1% and top 0.01%) of the national equal-split income distribution.² The sorting variable is the LAD-defined market income plus employment insurance (EI) and Quebec/Canada Pension Plan (Q/CPP) income minus EI and Q/CPP contributions, designed to closely align with the DINA concept of pre-tax post-replacement fiscal income. Within each percentile, we observe several types of income, including employment income, several government transfers, capital gains, dividends, and self-employment income, as well as payroll and income taxes paid.

Summary statistics of income inequality based on the LAD (using individuals as the unit instead of equal-split adults) are directly available from Statistics Canada.³ The first step in converting this data into DINA is to convert the population included in the data to the population of all Canadian residents 20 years of age and older.⁴ The LAD includes people of all ages who filed their taxes plus a small number of nonfilers who have a social insurance number and some link to the tax system. Thus, we first remove taxfilers under the age of 20 from the database. We observe the location in the income distribution of taxfilers under the age of 25. Since 33.1% of taxfilers under the age of 25 are under the age of 20 (Robson and Schwartz, 2020), we remove 33.1% of the taxfilers under the age of 25 from the database.

Next, we need to add all nonfilers above the age of 20 so that all residents above the age of 20 are represented in the data. We compare the number of taxfilers in the data to population estimates in the World Inequality Database. The proportion of people aged 20 and over observed in the LAD rose during the 1980s and early

²Equal-split means that incomes of spouses are summed and then divided equally between the two spouses. This is the benchmark population unit used for DINA based on tax microdata which accounts for the fact that low-earning individuals with high-earning spouses have greater access to resources than unmarried low-earners. However, this may be an overly optimistic view of income sharing within couples.

³See, e.g., Statistics Canada Table 11-10-0055-01.

⁴DINA is primarily concerned with the distribution of earnings, not the distribution of consumption. Since adults are the primary earners of income, DINA distributes all of national income to adults rather than to the full population, including children.

1990s as tax credits based on taxfiling were introduced. In 1982, 87.5% of the 20 plus population are observed, increasing to 96.1% in 1994. This proportion has remained relatively stable ever since, ranging from 95-97.3% each year, until a small dip during the COVID-19 pandemic. In 2021, 94.8% of residents 20 plus are observed.

We impute nonfilers to the distribution based on the income distribution of nonfilers obtained by Robson and Schwartz (*ibid.*) through comparing 2015 tax and survey data. This distribution implies that about 13.5% of nonfilers are in the bottom decile of the distribution, with a relatively uniform distribution throughout the middle deciles, and only about 5% in the top decile. We assume that there are no nonfilers in the top centile of the distribution. Before 1994, when the proportion of unobserved adults is higher, we increase the share imputed at the bottom of the distribution, assuming that low-income individuals were less likely to file taxes when they had less of an incentive to do so.⁵

5.2.1 Pre-tax national income

Next, we distribute all the national income not observed in the tax data among all 20 plus adults. The income concepts of the LAD correspond closely to the concept of fiscal income in DINA (essentially, the income that is observable in tax data; Blanchet et al., 2021). We calculate measures of fiscal labour and capital income. Following convention, we treat self-employment income as 70% labour income and 30% capital income. To move from the fiscal income distribution to the pre-tax national income distribution, we adjust total labour and capital income to match total labour and capital income from national accounts. For labour income, there is very little adjustment because almost all labour income is observable in tax data. On the other hand, on average only 29% of capital income is observed annually. Most remaining capital income is distributed according to the distribution of fiscal capital income. Pension accrual is the exception, which is distributed according to the fiscal labour income distribution. This creates the distribution of pre-tax national income, the benchmark DINA concept for earned income, that is, income before the operation of the tax and transfer system.

5.2.2 Post-tax disposable income

Starting from our estimates of the pre-tax national income distribution, we distribute all taxes and government transfers to individuals to obtain the post-tax disposable income distribution. Taxes fall into four main categories: personal income taxes, corporate income taxes, sales and other direct taxes, and property taxes. Personal income taxes are observed in the LAD and thus we deduct observed personal income taxes paid from pre-tax national income, scaling total PIT to match total PIT collected according to national accounts (about 95% of PIT is observed). Corporate income taxes are distributed according to the distribution of corporate operating surplus (dividends plus undistributed corporate profits).

⁵The introduction of several refundable tax credits, which require a tax return to be filed before those eligible for them can receive them, has increased the total number of tax filers over time, essentially adding taxpayers with low, non-taxable incomes. By way of illustration, the percentage of the Quebec population aged sixteen and over who file a tax return has risen from 75% in the mid-1980s to over 95% today.

Property taxes should be distributed according to the distribution of real estate wealth. The 2019 Survey of Financial Security (SFS) public use microdata file (PUMF) was used to obtain the distribution of real estate wealth along the pre-tax income distribution. Since survey data often underestimates income and wealth at the top of the distribution, and the SFS PUMF is only available for 2019, we distribute 65% of property taxes according to the distribution of real estate wealth in 2019 and 35% according to the observed distribution of rental income. Sales and other direct taxes are distributed according to the distribution of disposable income (pre-tax income plus transfers less taxes and saving).⁶

Government transfers to individuals are observed in the LAD. Specifically, we add the following observed transfers to pre-tax national income less taxes paid to obtain the post-tax disposable income distribution: old age security, guaranteed income supplement, family benefits, GST/HST credit, child tax benefits, working income tax benefit, social assistance, workers' compensation, other federal tax credits, and provincial transfers. The addition of these transfers and the subtraction of the four types of taxes listed above provides the post-tax disposable income distribution.

5.2.3 Post-tax national income

Since taxes raised are larger than spending on transfers to individuals, total post-tax disposable income is less than national income. To obtain the post-tax national income distribution, which allows income levels to be compared across countries, we distribute the rest of government spending to individuals as “in-kind” transfers. It is very difficult to know who benefits from government consumption expenditure and so this distribution requires making significant assumptions. We follow the Blanchet et al. (2021) and Piketty, Saez, and Zucman (2018) in making these assumptions.

Government consumption expenditure can be broken down into collective and individual government consumption expenditure. Individual government consumption expenditure includes health and education spending while collective consumption expenditure includes all other government spending, including spending on administration and defense. Given that Canada has relatively equal access to public healthcare services and primary and secondary education, we allocate government spending on these categories equally to all individuals. Since access to tertiary education in Canada is related to family income levels, an equal lump sum allocation does not make sense for this form of individual consumption expenditure. We allocate spending on tertiary education and collective consumption expenditure according to the post-tax disposable income distribution, following Piketty, Saez, and Zucman (*ibid.*) so that including these expenditures is neutral to the income distribution.

5.2.4 Re-ranking

Because we are working from tabulated data rather than raw microdata files, there is the possibility for re-ranking to occur as we move from the pre-tax national income distribution to the post-tax income distributions. Specifically, an individual who is in the top 0.01% of the pre-tax national income distribution who has a particularly high

⁶Saving rates by income quintile are obtained from Statistics Canada Table [36-10-0587-01](#). Savings rates for the top g-percentiles are adjusted based on savings rates reported in the US in Saez and Zucman (2016).

tax bill in a certain year may not be in the top 0.01% of the post-tax national income distribution. To estimate whether this re-ranking is a problem, we compute the ratio of the average after-tax income to the average market income for each income group in Table 11-10-0055-01, where the after-tax income distribution is sorted by after-tax income and compare that to the ratio we observe in our tabulations where after-tax incomes are sorted by pre-tax fiscal income. We find that there is a small but consistent underestimation of average after-tax incomes in the top decile, and so applied an adjustment to the post-tax income distribution proportionate to this observed underestimation.

5.2.5 Distributional Provincial Accounts

One novel contribution of this work is that we present estimates of distributional national accounts at a subnational level. In particular, we estimate distributional national accounts at the provincial level for Ontario, Quebec, Alberta, and British Columbia, as well as at the regional level for the Prairies and Maritimes. These regions are combined to ensure a sufficient population size for distributional national accounts to be meaningful. We follow a very similar procedure as at the national level to construct distributional provincial accounts. This section describes the procedures and data sources used to construct the distributional provincial accounts where they differ from those used to construct the national estimates.

The custom tabulations from the LAD are also broken down by province so we begin our provincial estimates from this same tax data. We obtain estimates of all provincial aggregates from 2007 onwards, and most provincial aggregates prior to 2007, from Canada's provincial and territorial economic accounts. We scale all provincial totals to the national aggregate so that the sum of the 11 provincial and territorial aggregates always sum to the national aggregate. For provincial aggregates not available in provincial and territorial economic accounts before 2007 (including property taxes and government saving), we use fiscal data from the Department of Finance to estimate trends in these aggregates in each province. Before creating the provincial pre-tax income distribution, the Prairie provinces and territories are aggregated, and the Maritime provinces are aggregated.

5.3 Results

5.3.1 Empirical Results at the National Level

First, we present our estimates of income inequality in Canada using DINA. Figure 5.1 displays the long-term evolution of the top 10% pre-tax national income share in Canada from 1920-2021. Our updated estimates from 1982-2021 have been connected to the previous estimates by Saez and Veall (2005) from 1920-1982. Income inequality in Canada during this period peaked in the early 1920s and again in the late 1930s. The top 10% share fell greatly after WW2 and remained low until the 1980s when it began rising again.

In Figure 5.2, we present more detailed results for the 1982-2020 period. We divide pre-tax national income and post-tax disposable income divided into three broad groups: the top 10% of income earners, the middle 40% of income earners, and the bottom 50% of income earners. Consistent with previous research, we observe an

increase in inequality from the early 1980s until the mid 2000s followed by a slight decline in inequality. The top 10% share of pre-tax national income increased from 28.8% in 1982 to 38.7% in 2006 and fell to 35.0% in 2019 before rebounding to 36.3% in 2021. From 1982 to 1995, most of this increase stemmed from a decline in the bottom 50% share, from 21.9% to 17.0%. After 1995, the increase in pre-tax top 10% share mostly stemmed from a decline in the middle 40% share, from 49.4% in 1995 to 44.8% in 2006. Since 1995, the bottom 50% pre-tax income share has remained relatively stable, sitting at 17.3% in 2021. The middle 40% pre-tax income share has rebounded slightly from a low of 44.8% in 2006 to 46.4% in 2021.

Trends in post-tax disposable income shares are similar to those in pre-tax national income except in 2020. In 2020, while the pre-tax income share of the bottom 50% fell, the post-tax disposable income share increased due to the unprecedented federal pandemic transfers. Typically, the top 10% and middle 40% pre-tax income shares are about 3-5, and 1-2 percentage points higher, respectively, than the top 10% and middle 40% post-tax disposable income shares. The bottom 50% income share is increased by 3-6 percentage points due to the operation of the tax and transfer system. Since reaching a low of 21.6% in 2006, the bottom 50% post-tax disposable income share increased by 2.3 percentage points by 2021, while the bottom 50% pre-tax national income share has only increased by 0.7 percentage points, suggesting that the tax and transfer system has become increasingly progressive.

Over the whole period, then, the pre-tax income share of the top 10% has increased significantly, largely at the expense of the bottom 50% of income earners. Increasing progressivity of the tax and transfer system has partially, but not entirely, offset this effect on the post-tax distribution.

Next, we focus on estimates of the income share of the top 1%. Figure 5.3 displays the income share for three groups within the top 1%: the top 0.01%, the next 0.09% (the 99.9th percentile to the 99.99th percentile), and the next 0.9% (the 99th to 99.9th percentile). The income shares of all three groups increased from 1982 to 2006. The pre-tax national income share of the top 0.01% increased from 0.4% in 1982 to 1.5% in 2006 before falling to 1.1% in 2020. Over the same period, the post-tax disposable income share increased from 0.2% to 1.3% and then fell to 0.7%. In 2021, the pre-tax share rebounded to 1.3% and the post-tax share increased to 1.0%. All three income groups within the top 1% experienced increases in their pre-tax and post-tax income shares in 2021, a topic we will revisit in the section on COVID-19.

The significant fall in income shares of each group of the top 1% in 2016 has been attributed to high income Canadians bringing forward income to 2015 in order to avoid anticipated tax increases by the new Liberal government (Osberg, 2020).

Increasing inequality in Canada has stemmed from vastly unequal growth – in other words, as Canada’s economy grew during the 1980s and 1990s, this new wealth did not trickle down. Instead, this new income was entirely captured by the top half of the income distribution.

Figure 5.4 shows growth incidence curves for five income groups. From 1982 to 2000, the incomes of those in the bottom half of the income distribution were stagnant, growing by less than 2% over the whole period. On the other hand, the incomes of the top 1% grew by 144.5% and the incomes of the top 0.01% grew by 334.9%. The higher one’s income, the more it grew during this period.

Since 2000, this trend has reversed with the incomes of the bottom 50% growing more than any other group through 2021 (12.3%). However, the bottom 50% and

middle 40%'s gains have been seriously eroded since 2019. From 2019 to 2021, average pre-tax incomes of the bottom 50% fell by 4.8% and those of the middle 40% fell by 5.7%. At the same time, incomes of the top 1% have increased by 4.3% and incomes of the top 1% have increased 5.0. Furthermore, the gains of the bottom earners since 2000 have been incredibly small compared to the immense gains made by top earners in the preceding decades.

As a result, from 1982 to 2021, the average income of the bottom 50% has increased by 14.3%, compared to 36.2% for the middle 40%, 64.4% for the next 9%, 135.0% for the top 1% and 344.2% for the top 0.01%.

Comparison with traditional estimates of inequality What do these distributional national accounts results add to the previous literature and statistics on income inequality in Canada? To illustrate the contribution of DINA, the black line in Figure 5.5 presents the proportion of net national income which is observed in the LAD each year. On average, only 66.6% of net national income is observed in tax data each year – in other words, one third of national income is not allocated to anyone in traditional inequality statistics.

The distribution of this one third of national income can have a significant effect on inequality statistics, as shown below in Figure 5.6. Including this missing income in inequality statistics tends to increase estimates of inequality because while most of labour income is observed in the LAD (76% on average), only 29% of capital income is observed annually in the LAD, and capital income is more unequally distributed than labour income.

Figure 5.5 presents the top 1% pre-tax national income share compared to market income shares, using both equal-split (ES) and individuals (IND) as units. Individual market income shares are drawn directly from public Statistics Canada data while the equal-split market income series is calculated from the custom tabulation provided by Statistics Canada.⁷

This comparison allows us to estimate the effect of shifting from the traditional concept of inequality in market income to inequality in pre-tax national income, which distributes all of national income to individuals, as well as the effect of shifting from the individual unit of analysis to the equal-split unit of analysis, which is the typical unit used in DINA estimates.

First, we note that all four measures largely follow the same trends. The top 1% income share increased significantly from the early 1980s until the mid 2000s before falling steeply after the financial crisis using all four measures.

Second, pre-tax national income top 1% shares are consistently 1-3 percentage points higher than market income shares, regardless of the unit. The top 1% market income share for individuals has ranged from 7.6% in 1982 to 13.6% in 2006. Using pre-tax national income with individuals as the unit results in a higher top 1% income share (from 8.7% in 1982 to 16.3% in 2006) because much of the income not accounted for in tax data is undistributed corporate profits, which is mostly owned by high-income Canadians.

Shifting the unit of analysis from the individual to equal-split adults, however, reduces top income shares by 1-2 percentage points. Top 1% pre-tax national income shares using equal-split adults range from 7.2% in 1982 to 14.4% in 2006. The drop in inequality due to shifting from individuals to equal-split adults is reflective of

⁷Statistics Canada. (2022). Table 11-10-0055-01, High-income tax filers in Canada.

gender inequality – most people in the top 1% of individual earners are men (in 2020, 74.4% were men), and so when their income is split equally with their spouse, their incomes are greatly reduced.

Overall, it is clear that throughout the 1982-2021 period, top income shares published by Statistics Canada underestimate income inequality relative to top income shares calculated using DINA. This is because DINA account for people who do not file taxes and for undistributed capital income that is retained in corporations. It should be kept in mind that estimates of inequality presented in this paper using equal-split adults would be higher were they based on individuals as the unit of analysis.

5.3.2 Empirical Results at the Provincial Level

Now we examine how the income distribution differs across Canada. Figure 5.7 presents top 1% pre-tax national income shares in five regions and Canada as a whole. First, we note that trends in inequality have been similar across Canada. This suggests that, although provincial factors and policies have some effect on levels of inequality, factors and policies that affect all of Canada have played a greater role in the evolution of inequality over the past 40 years.

Throughout the period, the Prairies have consistently had one of the lowest top 1% pre-tax income shares of any region. Until the early 2010s, Quebec typically had the lowest top 1% pre-tax income share of the four major provinces. Since the early 2010s, however, the top 1% share has remained stable in Quebec while declining in BC and Alberta, leading Quebec to overtake them.

Ontario or Alberta has always had the highest top 1% share, with Alberta's reaching record highs during the early and mid-2000s. Alberta's top 1% shares have been more volatile than any other region, likely reflecting the reliance of the top 1% in Alberta on the oil and gas industry. Pre-tax profits in the oil and gas industry, which also peaked in the mid-2000s and plummeted in 2015 and 2016, show a strong correlation to top 1% shares in Alberta.⁸ Overall, workers in finance and insurance and mining, oil, and gas, were overrepresented among the top 1% in the mid-2000s and experienced significant increases in their incomes during these years (Lemieux and Riddell, 2015; Xuereb, 2022). The extremely profitable conditions in these industries likely contributed significantly to the peak in the top 1% share in Alberta, and nationally, in the mid-2000s.

To better understand the differences in income distribution and the effects of the tax and transfer system in Canada's two largest provinces, Ontario and Quebec, Figures 5.8 and 5.9 present pre-tax and post-tax income shares for the top 10%, middle 40%, and bottom 50% from 1982-2021. As with top 1% pre-tax income shares, trends in income shares are very similar in both jurisdictions. However, Ontario has consistently had a higher top 10% pre-tax income share and a lower bottom 50% pre-tax income share. The gap between the two provinces is even larger for post-tax income shares, especially for the bottom 50%. In 2021, the bottom 50% post-tax income share was 22.6% in Ontario and 26.5% in Quebec.

To assess the impacts of the tax and transfer system on income inequality in each region, Figure 5.10 displays the difference between the top 10% pre-tax and

⁸From 1988-2019, the correlation is 0.68. For oil and gas industry profits, see <https://www150.statcan.gc.ca/t1/tbl1/en/cv.action?pid=3310000701>.

post-tax income shares in each jurisdiction. Overall, Canada's tax and transfer system has become slightly more progressive over time, reducing the top 10% share by about 3% in 1982 and about 5% in 2021 (2020, at over 6%, is an outlier caused by pandemic-related government transfers). Quebec's tax and transfer system has been more progressive than other regions since the late 1990s although the gap narrowed in 2019. Since the late 1990s, Alberta, the Prairies, and the Maritimes have had the lowest levels of redistribution.

We can examine why Quebec's tax and transfer system is more progressive than Ontario's and the rest of Canada's empirically by examining taxes paid and transfers received across the income distribution in 2021. Effective tax rates, calculated as the sum of personal and corporate income taxes, taxes on wealth and property, and payroll taxes, divided by pre-tax national income are displayed in Figure 5.11.

Quebec has the highest effective tax rates across most of the distribution, with especially higher rates in the upper deciles. This contributes to Quebec's lower levels of post-tax inequality. Across Canada, the effective tax rate is 42% in the second decile, higher than the middle deciles due to the regressivity of sales taxes. From the third decile onwards, the tax system is slightly progressive, with average effective tax rates increasing from 33% in the third decile to 39% for the highest decile excluding the top 1%, and 45% for the top 0.1%.

Another measure of the progressivity of the tax and transfer system in each region is the average effective transfer rates for deciles in the bottom half of the income distribution, displayed in Figure 5.12. Quebec has the highest rates in each decile, with over 90% of pre-tax disposable income coming from government transfers in the second income decile. Higher government transfers to the bottom 50% and higher taxes in the top 50% both contribute to the greater progressivity of the tax and transfer system in Quebec. British Columbia and Alberta have the lowest effective transfer rates.

Comparison with traditional estimates of inequality At the provincial level, the use of DINA also affects estimated levels of income inequality. Reflecting the national statistics, typically only 60-70% of regional income is observed at the regional level each year (see Figure 5.13). The proportion of regional income observed in the LAD is relatively similar across regions.

Alberta was a slight outlier, with the lowest proportion of observed income until the mid-2010s because of its higher capital share. The Prairies' proportion of observed income fell from the 1980s through 2010, at the same as its' capital share increased from about 17% to over 30%. The share of observed income in the LAD often mirrors the capital income share – the higher the capital income share, the lower the share of observed income and the greater effect DINA can have on inequality statistics.

Figure 5.14 compares estimates of the top 1% share by region using pretax national income and using market income from LAD tabulations. In almost every year and region, estimates using pretax national income exceed those using market income. The difference was largest in all regions in the early to mid-2000s when capital shares peaked.

5.3.3 Labour and capital income

Next, we explore trends in labour and capital incomes for different income groups. These can help shed light on why pre-tax income inequality increased so significantly from the 1980s through the mid-2000s and since declined.

Figure 5.15 displays the composition of the top 1% and top 0.01% pre-tax income shares from 1982 to 2021. During the 1980s and early 1990s, it was increases in labour income that drove growth in top incomes. From 1982 to 1998, the top 1% share of pre-tax income that was labour income increased from under 5% to 8.4%. This only increased to 8.7% in 2006, while the top 1% share of pre-tax income that was capital income increased from 3.1% to 5.7% from 1998 to 2006, driving the peak in the top 1% share.

This is in line with the Saez and Veall (2005) argument regarding labour market competition for top executives driving increases in top income shares through 1998. However, this explanation can say little about the increasing top shares from 1998 to 2006. Instead, the explanation for rising inequality during this period is related to changes in the distribution of income between labour and capital, and increasing capital income concentration. The capital share of income increased from a low of 16.6% in 1998 to 24.7% in 2006 (the second-highest capital share throughout the whole period, behind 25.1% in 2005).

During the period of increasing inequality, and especially 1998-2006, capital income became increasingly concentrated. The top 1% earned only 12-13% of capital income during the early 1980s. By 1998, this had increased to 18.6%, and this increased further to 23.3% by 2006. This increase in concentration of capital income has come almost entirely at the expense of the bottom 50% of earners – their capital income share has declined from 21-23% during the 1980s to only 16.5% by 2006. These trends are relatively consistent across provinces, indicating that they've been driven by federal policies and factors.

These changes in capital income were likely driven by a combination of changing bargaining power between workers and owners, as well as the unique global market forces that led to large profits in finance and insurance, and the oil and gas industries during the early to mid-2000s. In particular, the increasing capital income share in the early 2000s was driven by Alberta, where the capital share reached 36% in 2006.

Since 2006, declines in both capital and labour incomes have contributed to falling top income shares. The top 1% share of pre-tax income that was labour income has declined by 1.4 percentage points and the share that was capital income declined by 1.4 percentage points between 2006 and 2021. This has coincided with the capital income share falling back to 19-22%, in line with levels observed in the 1980s.

In the bottom half of the distribution, where capital income is much less important, the decline in pre-tax income shares through the mid-2000s was driven by stagnant, or, during the early 1990s declining (in real terms), labour incomes (see Figure 5.16). Average capital income increased for the bottom 50% from 1982 to 2006 while average labour income was unchanged. From 2006 until the pandemic, labour incomes grew for the bottom 50%, resulting in a slight increase in the pre-tax income share.

5.3.4 COVID-19 and Canada's Response

To this point, we have mainly examined trends in inequality throughout the past 40 years, distinguishing between the increase up until the mid-2000s and the subsequent

smaller decline. In this section, we focus on 2020 and 2021 in particular to assess the impact of the COVID-19 pandemic and the government programs implemented in response, on income inequality in Canada.

2020 was a particularly unique year in that it is the only year on record with a significant divergence in trends in pre-tax and post-tax inequality. Average pre-tax incomes declined across the income distribution in 2020 as workers were laid off or had reduced hours in response to the COVID-19 pandemic. Low-income workers were most strongly affected: the average pre-tax income of the bottom 50% fell by 13% in 2020. This contributed to an increase in pre-tax inequality in 2020, with a decline in the bottom 50% share and an increase in the top 1% share.

In response to the pandemic and associated lockdowns, the federal government implemented large temporary social programs, including the Canada Emergency Response Benefit (CERB), to support workers (and businesses) who were impacted by the pandemic. These programs provided up to \$2,000 per month to workers whose employment was impacted by the pandemic, which was in some cases more than workers were earning prior to the pandemic. As a result, post-tax disposable incomes increased for all income groups in 2020, with the largest increase accruing to the bottom 50%. Thus, although pre-tax inequality increased in 2020, post-tax inequality decreased because of the significant increase in government transfers.

Both of these trends were reversed in 2021. During 2021, many government support programs were rolled back, contributing to a decline in the bottom 50% post-tax income share of 0.8 percentage points even though the pre-tax share rebounded as employment recovered. Canada's Official Poverty Rate, which fell from 10.3% to 6.4% in 2020, rebounded to 7.4% in 2021,⁹ and will likely rebound further in 2022 as some pandemic supports were still available in 2021.

At the other end of the income distribution, pre-tax and post-tax incomes of the top 1% recovered entirely in 2021. The overall pre-tax income share of the top 1% increased from 10.8% in 2019 to 11.6% in 2021, and the post-tax income share increased from 7.0% to 7.3%. The increasing top 1% share was largely due to increases in capital income for the top 1% in 2021, which increased by 13% relative to 2019, reaching its highest level since 2014. This is directly related to record levels of corporate profits in 2021 (which have since been surpassed by 2022).¹⁰ Research has also demonstrated that these record profits contributed to the high level of inflation in 2021, which disproportionately impacted low-income Canadians.^{11,12}

The experience of the COVID-19 pandemic demonstrates the power that federal policy has to affect the income distribution – post-tax income inequality fell in 2020 because of transfer programs implemented by the federal government. However, because these measures were temporary, the drop in inequality Canada experienced in 2020 was also temporary.

5.3.5 Canadian Inequality in International Context

One significant benefit of the DINA approach to estimating income inequality is that, by using a common definition of income, it produces statistics that are more

⁹<https://www.statcan.gc.ca/en/topics-start/poverty>

¹⁰<https://www150.statcan.gc.ca/t1/tbl1/en/cv.action?pid=3610011701>

¹¹https://centreforfuturework.ca/wp-content/uploads/2022/10/CLC_Inflation_Report_EN.pdf

¹²https://scholarworks.umass.edu/econ_workingpaper/343/

comparable across countries than those based on fiscal income. In Figures 5.17 and 5.18, we display the top 1% and top 10% shares, respectively, of Canada, the United States, France, Great Britain and Australia.

These are all countries for which the WID contains relatively high-quality estimates based on tax data and national accounts. Our updated estimates of inequality place Canada in the middle of these comparable countries. The United States has much higher top shares than Canada, which has similar top shares as Great Britain. France and Australia both have lower levels of inequality than Canada.

5.4 Conclusion

DINA methodology provides new insights into the evolution of income inequality in Canada, and its provinces, since 1982. In particular, top income shares are higher than those calculated based on tax data because tax data exclude non-filers and do not account for undistributed corporate profits. Traditional inequality estimates especially underestimated inequality during the mid-2000s when the capital income share peaked, meaning less of net national income was observable in tax data.

Overall, results confirm previous research showing that income inequality increased drastically from 1982 until the mid-2000s and has fallen since the financial crisis. The increase in the pre-tax income share of the top 10% since 1982 has largely come at the expense of the bottom 50%, although this effect is smaller for the post-tax distribution because the tax and transfer system has become more progressive. We showed that these effects have been strongest in Alberta, where inequality has been the most volatile and appears to be related to profits in the oil and gas industry.

Inequality in Canada has followed similar trends across regions, suggesting a common driving force. During the 1980s and 1990s, increasing inequality was driven by increasing inequality in labour incomes, which could be explained by increased labour market competition for top executives from the US, outsourcing of middle-class jobs, and falling unionization rates. However, the increase in national top shares between 1998 and 2006 was driven by an increasing capital income share and increasing concentration of capital income. This was led by residents of Alberta as oil and gas profits soared. This period of increasing inequality cannot be explained by the same reasons as the 1980s and early 1990s.

Quebec is no longer one of the regions with the lowest pre-tax income inequality because inequality has declined further in other regions since the 2008 financial crisis. However, Quebec continues to have the most progressive tax and transfer system among the five regions.

2020 was an outlier year for income inequality in Canada with increased pre-tax income inequality coinciding with decreased post-tax income inequality. In 2021, these trends were reversed as record corporate profits increased top incomes. The experience of 2020 demonstrates the power of fiscal policy to reduce post-tax income inequality. However, achieving a just distribution of income will require measures to that are permanent and address pre-tax inequality as well.

Figures

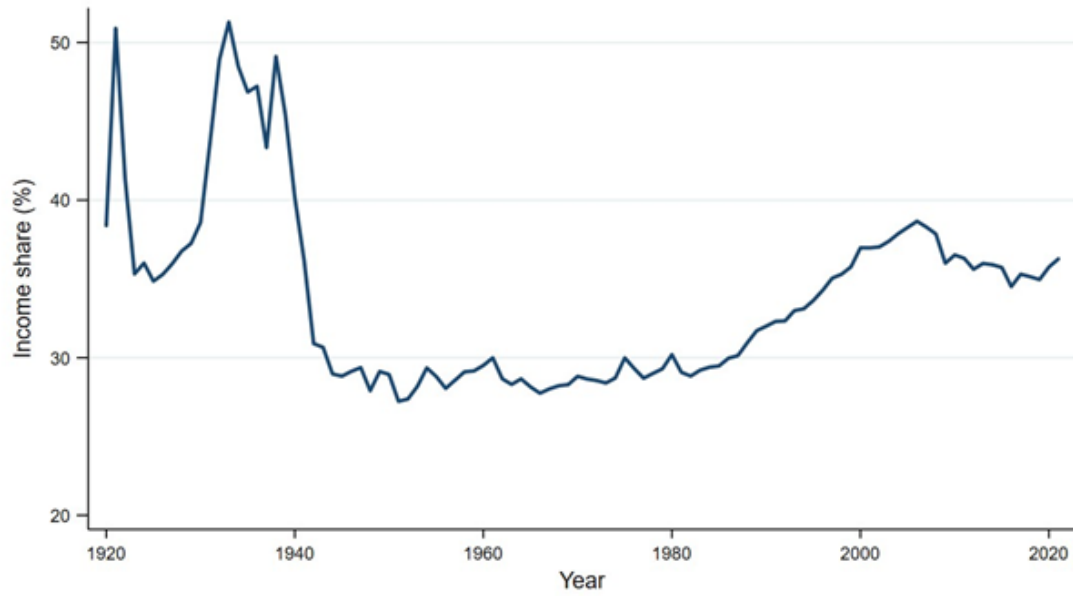


Figure 5.1 – Top 10% pre-tax national income share in Canada, 1920-2021

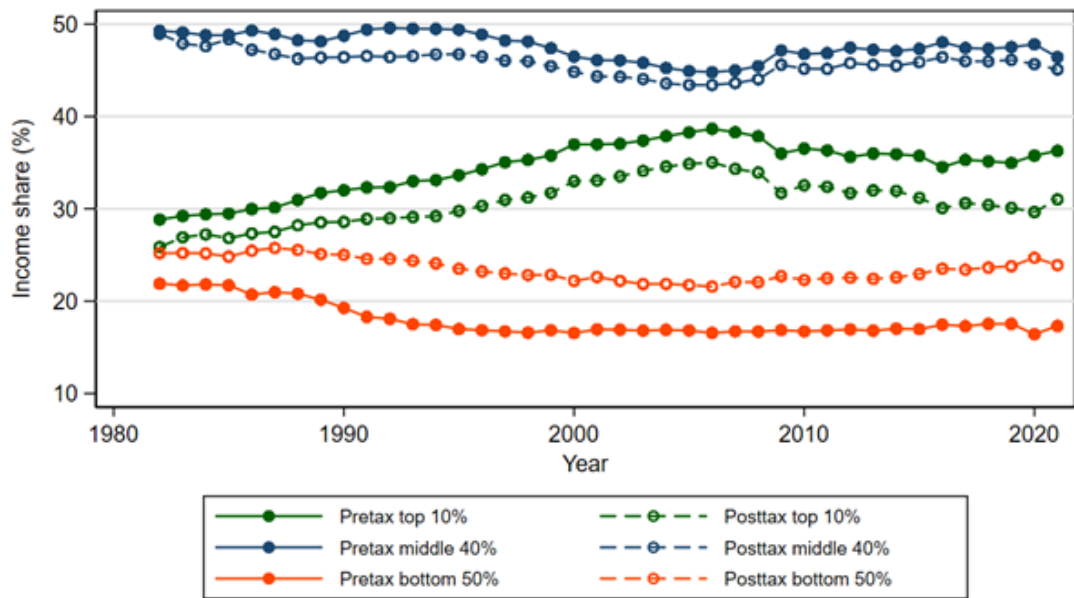


Figure 5.2 – Top 10%, middle 40%, and bottom 50% pre-tax national income and post-tax disposable income shares, 1982-2021

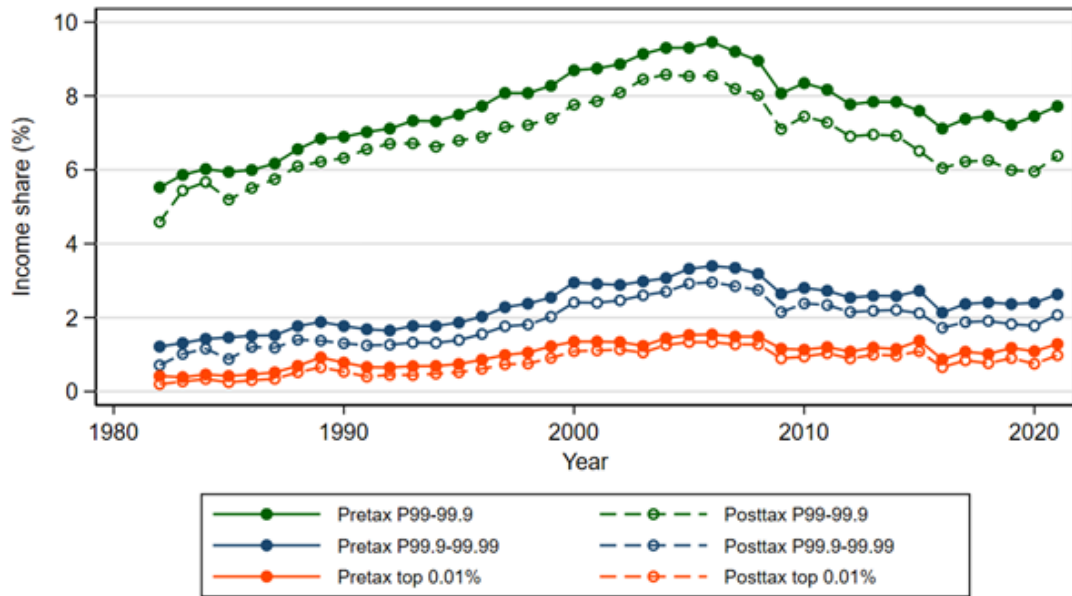


Figure 5.3 – Pre-tax and post-tax income shares for groups within the top 1% of income earners, 1982-2021

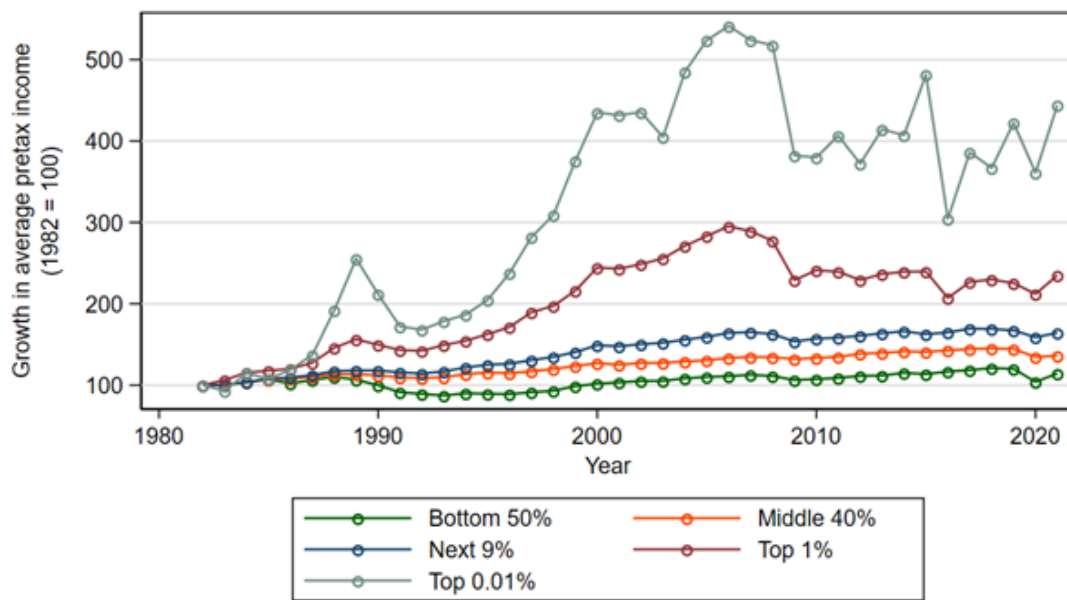


Figure 5.4 – Growth incidence curve by income group, 1982-2021

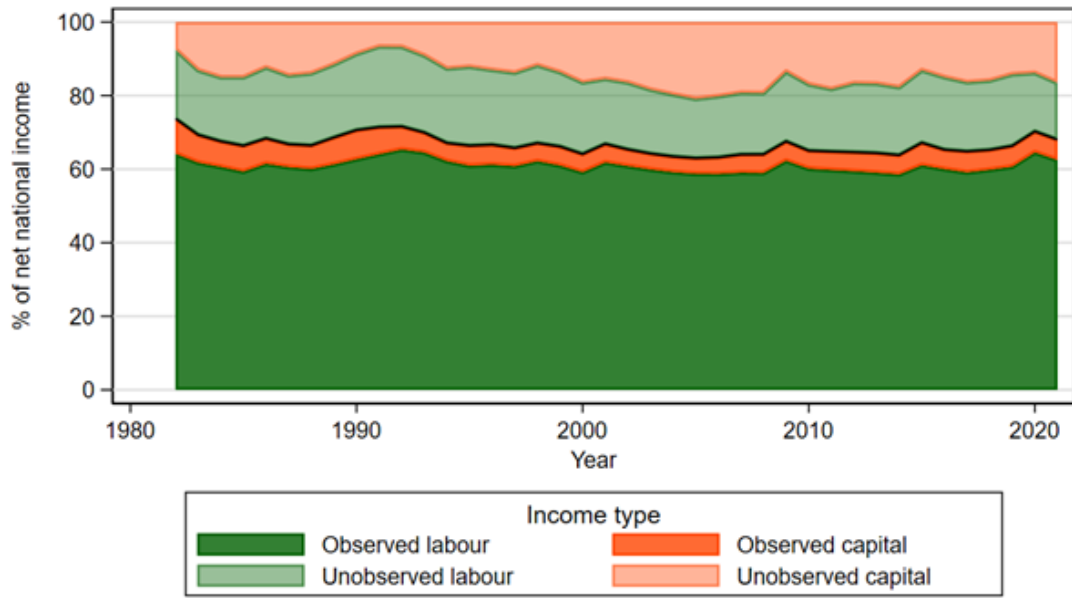


Figure 5.5 – Proportion of net national income observed in LAD by factor, 1982-2021

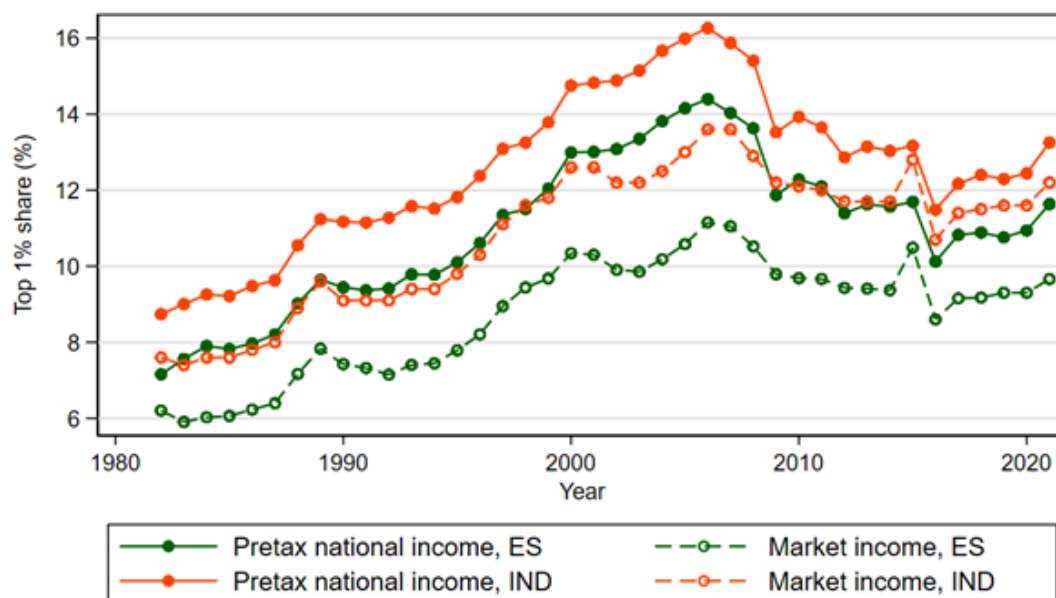


Figure 5.6 – Top 1% income shares using four different income definitions, 1982-2021

Notes: IND – individuals. ES – equal-split. Market income individuals series from Statistics Canada Table 11-10-0055-01, market income, equal-split series from Statistics Canada custom tabulation.

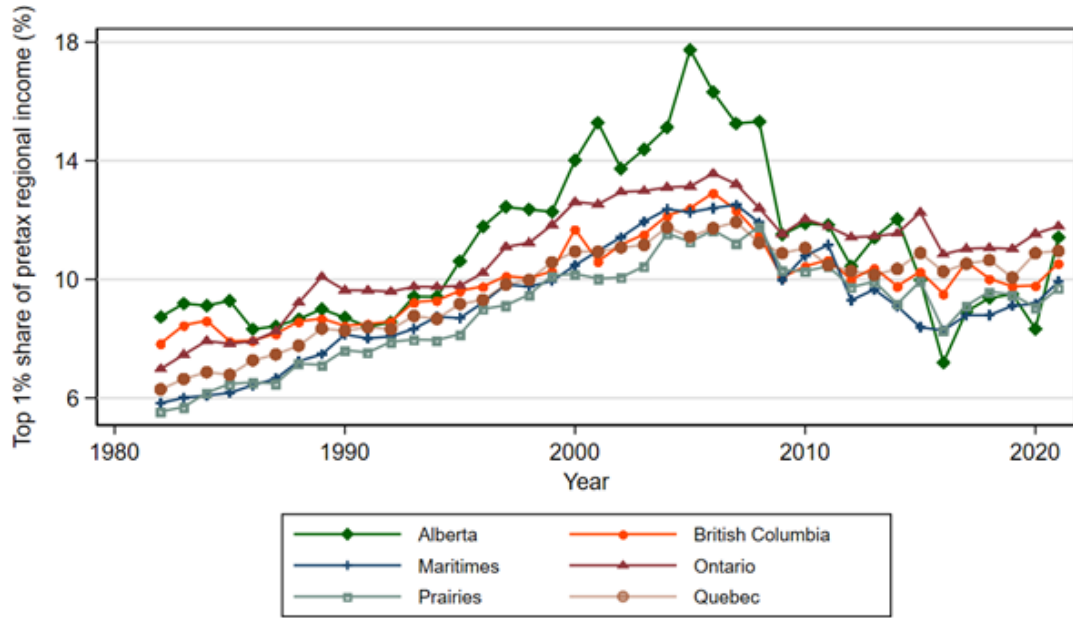


Figure 5.7 – Top 1% pre-tax regional income shares in five regions of Canada, 1982-2021

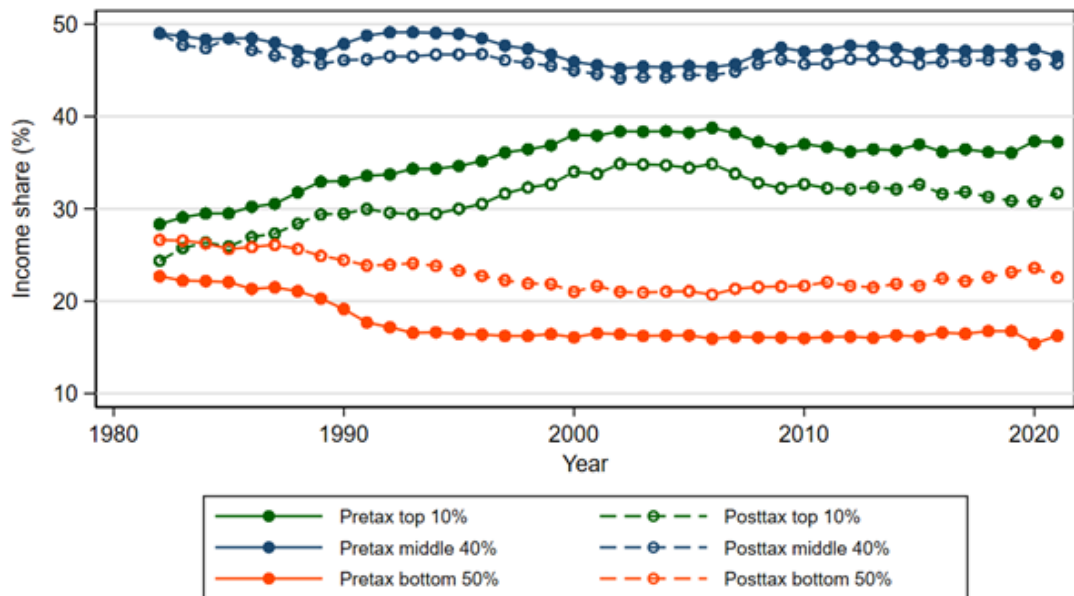


Figure 5.8 – Top 10%, middle 40%, and bottom 50% pre-tax national income and post-tax disposable income shares in Ontario, 1982-2021

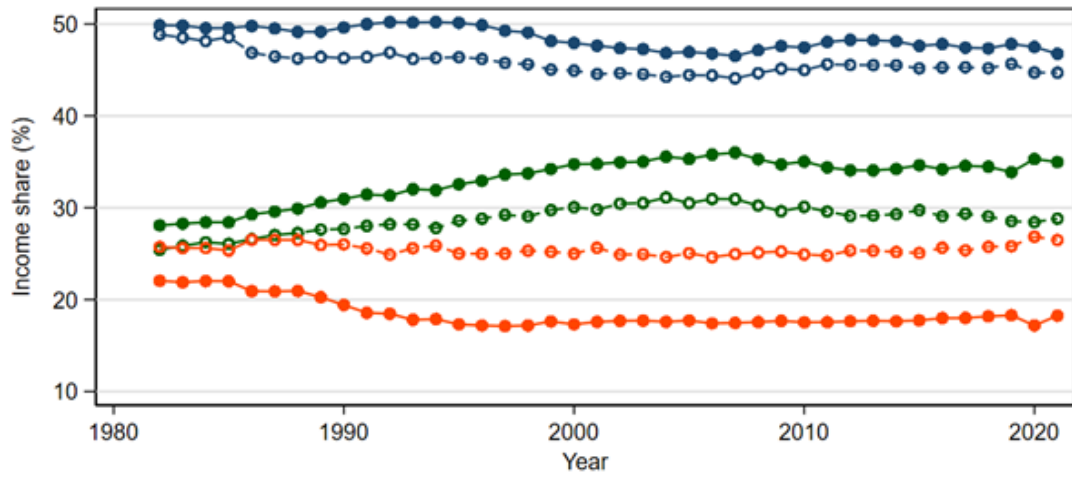


Figure 5.9 – Top 10%, middle 40%, and bottom 50% pre-tax national income and post-tax disposable income shares in Quebec, 1982-2021

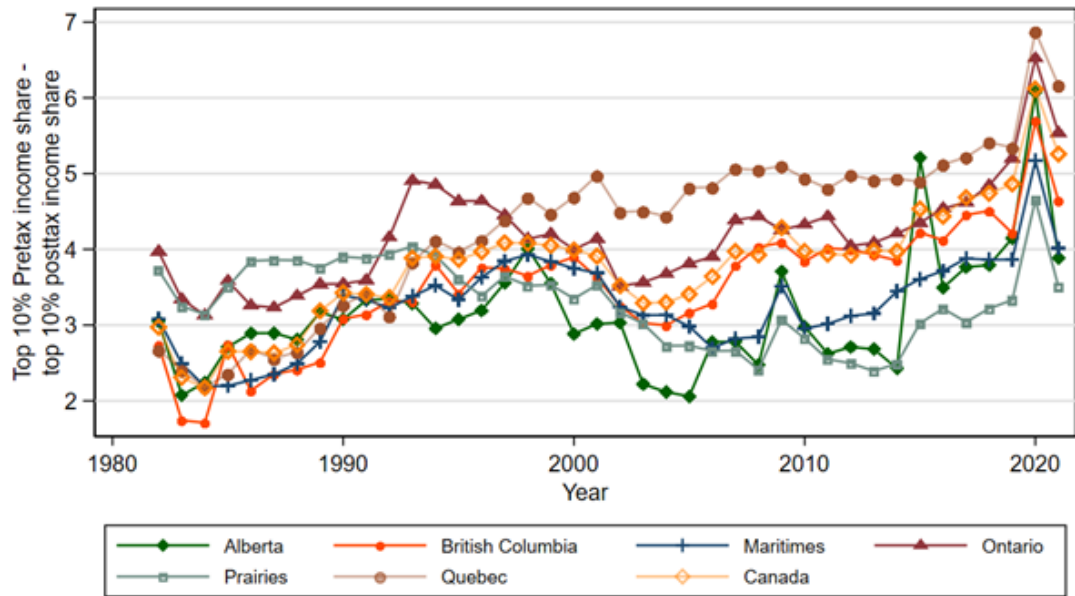


Figure 5.10 – Difference between top 10% pre-tax national income shares and top 10% post-tax disposable income shares by region, 1982-2021

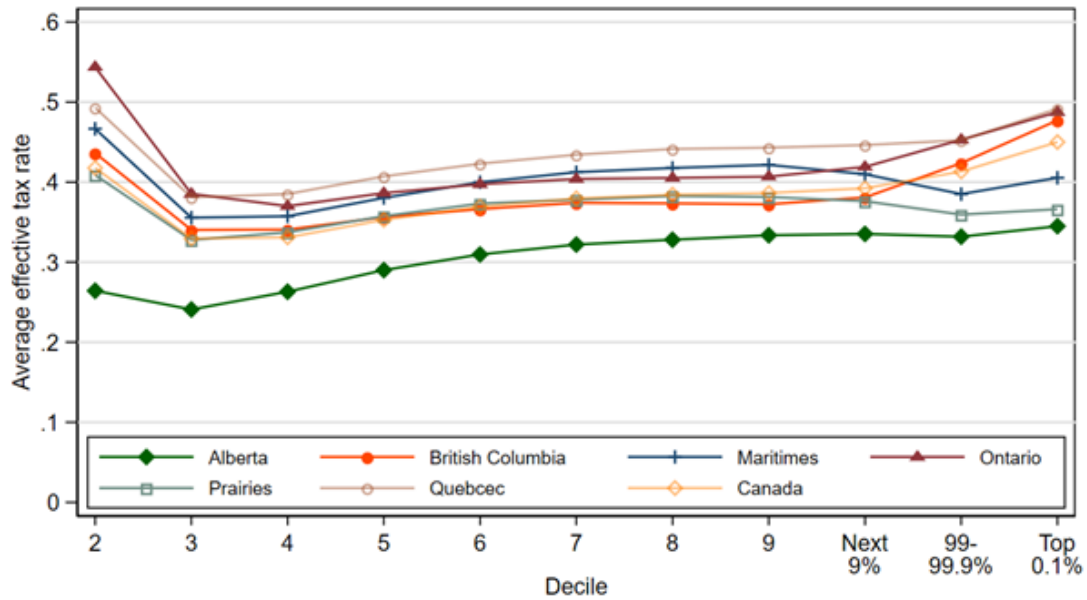


Figure 5.11 – Average effective tax rate by decile and region, 2021

Notes: The effective tax rate is the sum of all taxes paid, including personal and corporate income, property, sales, and payroll divided by total pre-tax income. The first decile is excluded because of the significant number of people with negative pre-tax incomes in this group.

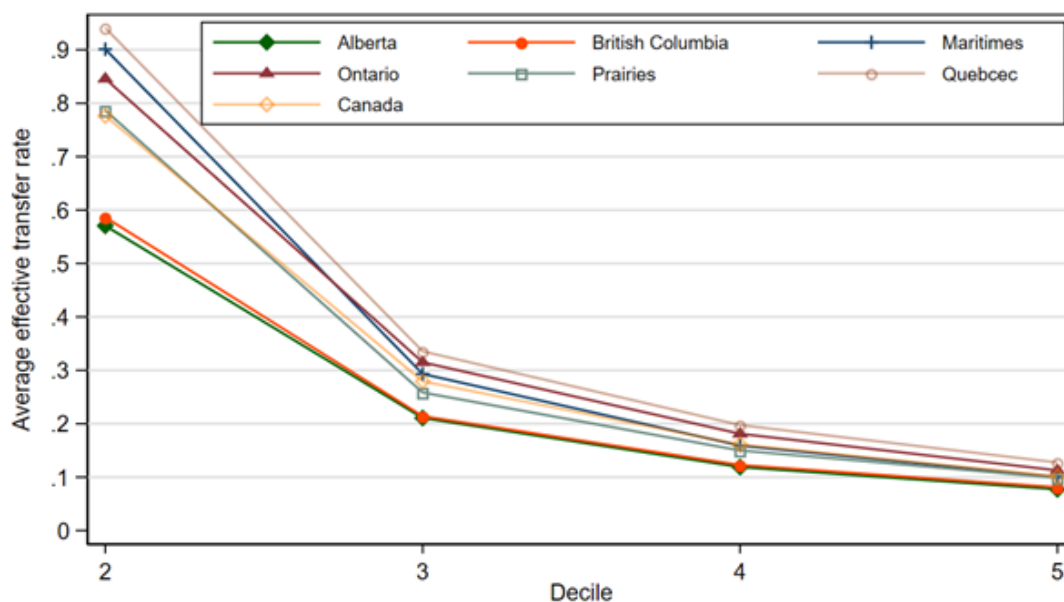


Figure 5.12 – Average effective transfer rate in bottom deciles by region, 2021

Notes: The effective transfer rate is the sum of government transfers received, including OAS, GIS, social assistance, Canada Child Benefit, GST/HST credit, Working Income Tax Benefit, family benefits, and other federal and provincial refundable tax credits divided by total pre-tax income. The first decile is excluded because of the significant number of people with negative pre-tax incomes in this group.

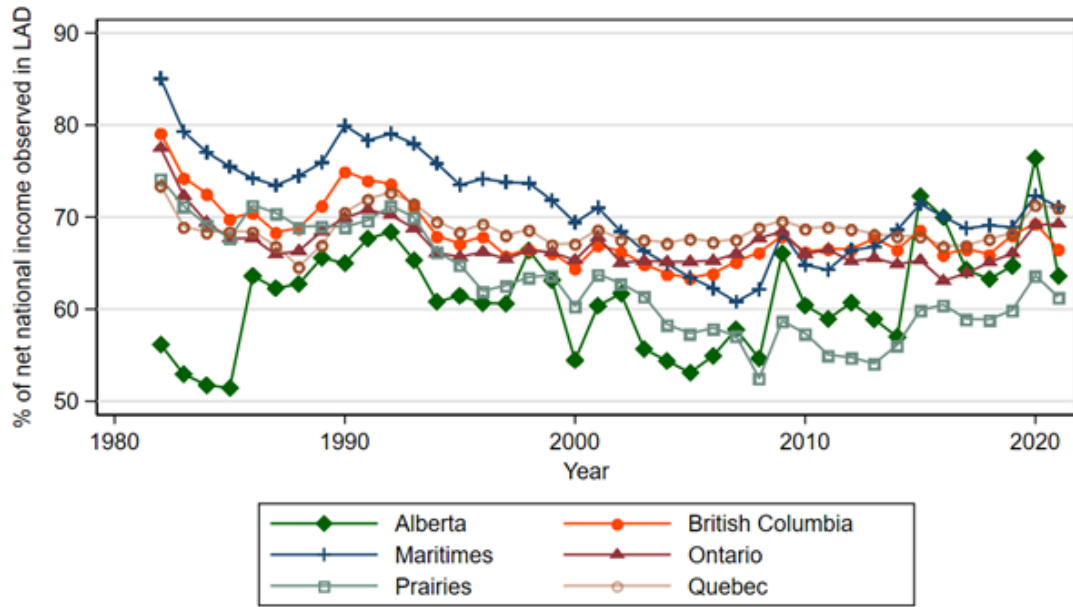


Figure 5.13 – Proportion of net national income observed in the LAD by region, 1982-2021

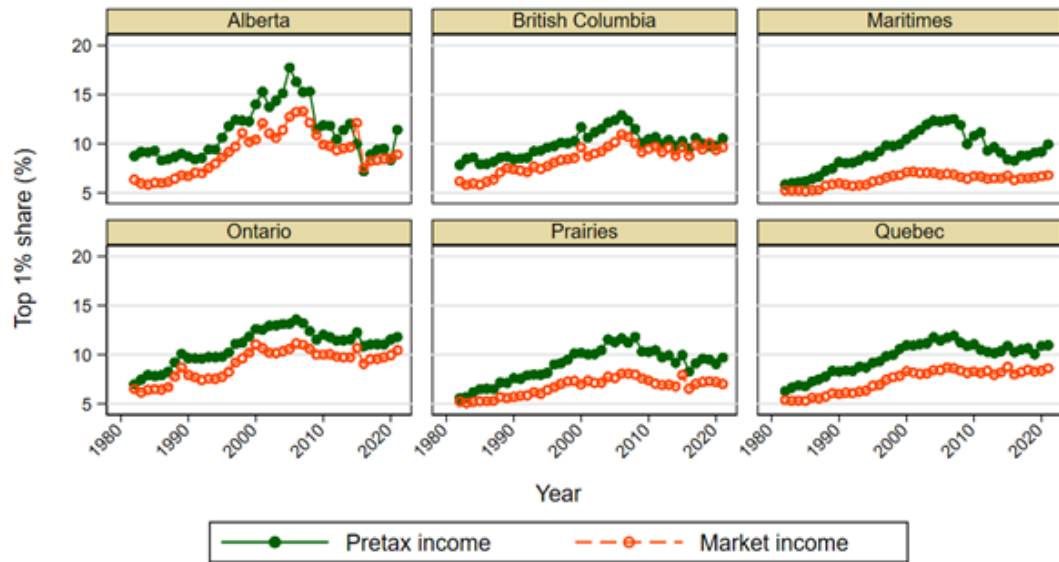


Figure 5.14 – Top 1% shares using pretax versus market income by region, 1982 to 2021

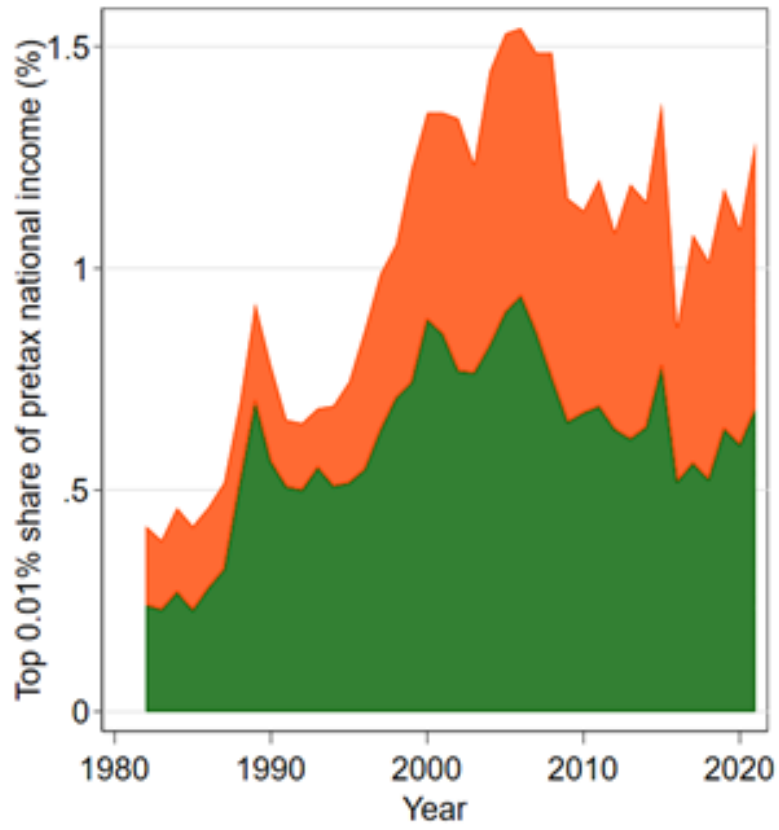


Figure 5.15 – Labour and capital income composition of the top 1% and top 0.01% pre-tax income share, 1982-2021

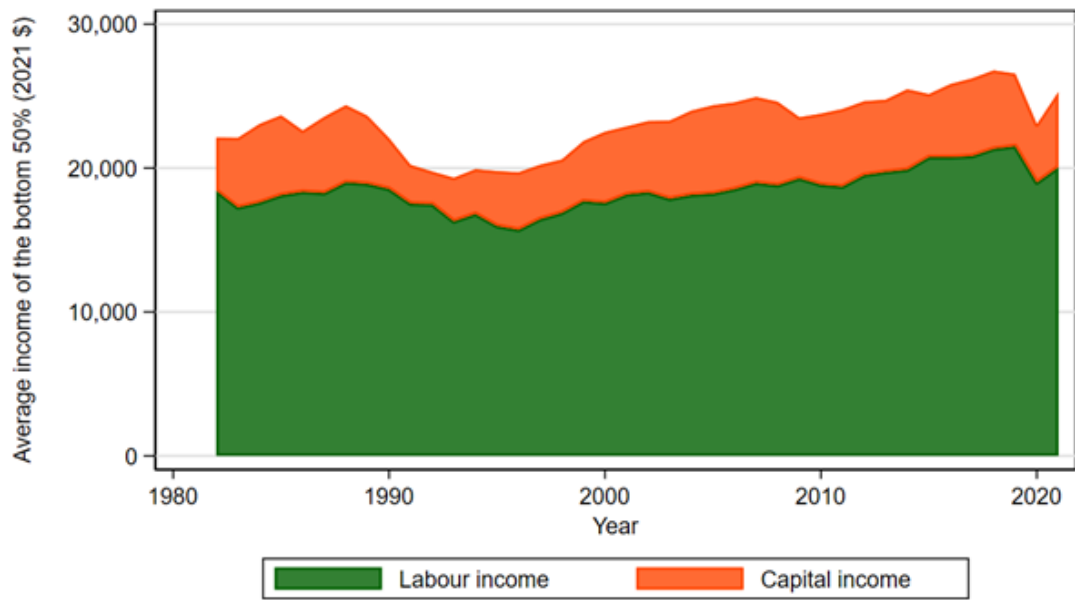


Figure 5.16 – Average labour and capital income of the bottom 50%, 1982-2021

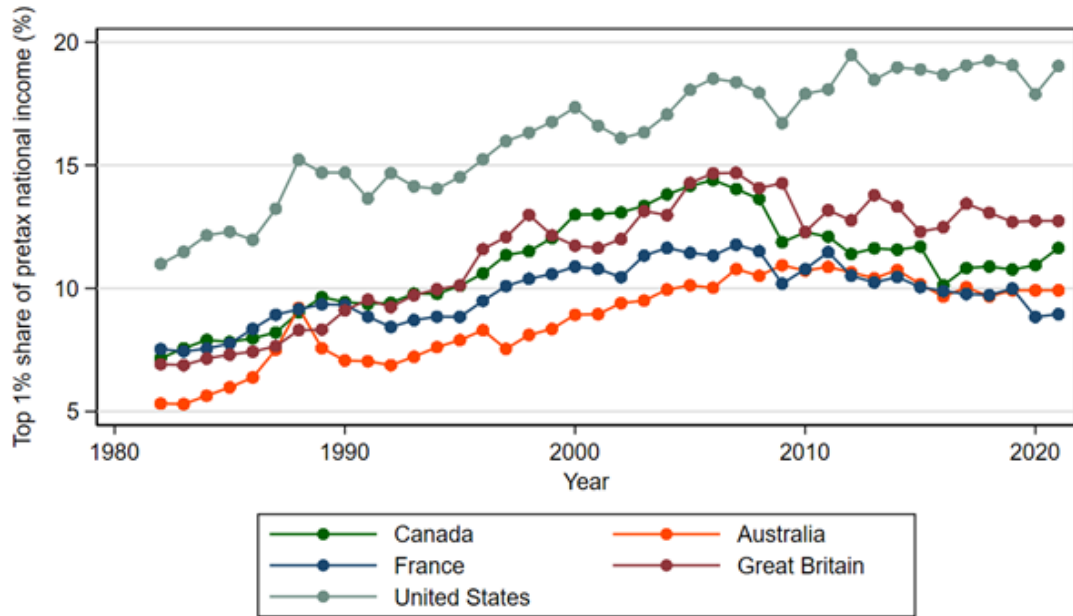


Figure 5.17 – Top 1% national pre-tax income shares in Canada and comparable countries

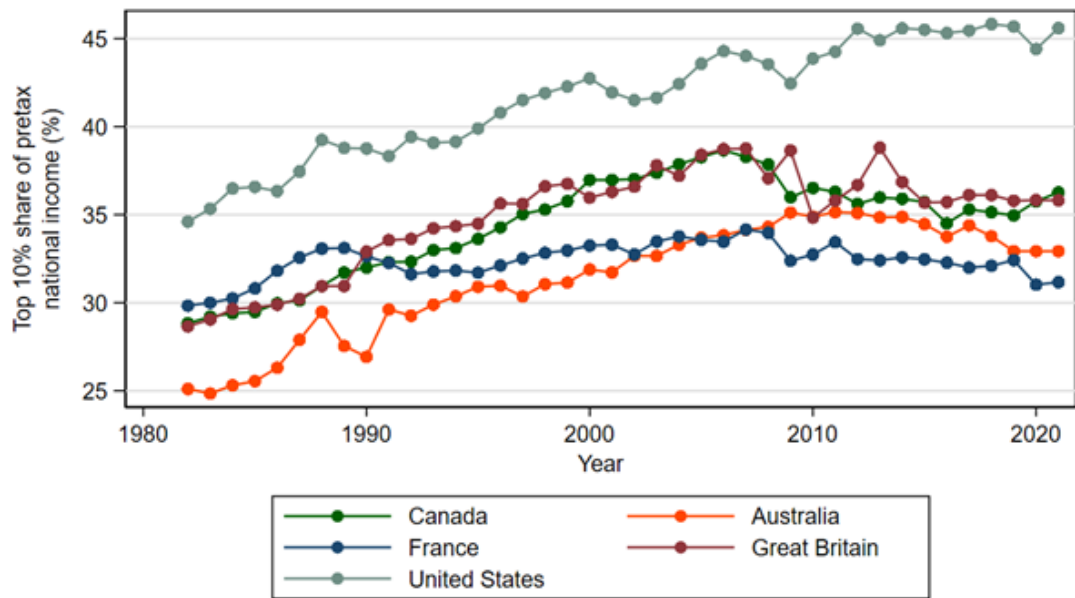


Figure 5.18 – Top 10% national pre-tax income shares in Canada and comparable countries

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Appendix A1

Appendix to Chapter 1

Globalization and Factor Income Taxation

A1.1 Data & Construction of Effective Tax Rates

This appendix section provides an overview of the data sources used to create our tax revenue and national income series (Section [A1.1.1](#)). Additionally, we discuss the methodology to measure effective tax rates (Section [A1.1.2](#)).

A1.1.1 Data sources

Tax revenue data Our tax revenue data draws from three key sources:

- (i) **OECD Government Revenue Statistics** ([website link](#)): OECD revenue statistics take precedence in our data hierarchy as it contains all types of tax revenues already arranged in the OECD taxonomy of taxes. While it covers all OECD countries, it only covers a subset of developing countries which typically start in the early 2000s.
- (ii) **ICTD Government Revenue Dataset** ([website link](#)): ICTD data covers many developing countries, but only begins in the 1980s. ICTD at times does not separate income taxes into personal vs. corporate taxes and often does not contain social security contributions.
- (iii) **Archival data**: The main archival data collection corresponds to the digitization of the Government Documents section in the Lamont Library at Harvard University ([website link](#)). For each country, we scanned, tabulated and harmonized official data from the public budget and national statistical yearbooks, to retrieve official tax revenue statistics. The [supplementary appendix](#) lists the main historical documents used in each country's time-series. In the case where the document is a statistical yearbook, the initial listed source is always a report produced by the finance ministry or the national tax authority. To complement hard-copy archival data, we retrieved countries' online reports, usually published by their national statistical office or finance ministry. We also used complementary sources, including offline archival Government Finance Statistics data from the IMF which covers the period 1972-1989. For social security contributions, we relied on two additional sources: the 'D61' statistic on social contributions in the household sector in SNA-1968 and SNA-2008, and data from Fisunoglu et al. ([2011](#)).

To increase the credibility of the tax revenue series based on newly digitized historical documents, we base our approach on the following four guiding rules:

1. We seek to build long time-series from the archival records in order to overlap with pre-existing sources (OECD, ICTD, IMF). We use the overlapping years to inspect that the different sources provide similar estimates of the overall levels of taxes collected and to verify that they report the same set of taxes in place. If discrepancies exist when data sources overlap, we inspect the accuracy of each source with additional information. For this reason, switches in data-source rarely lead to a significant change in trend.
2. In historical time-periods where no overlap exists with pre-existing sources, we find academic publications and policy reports to compare the estimated overall levels of tax/GDP. When discrepancies exist, we investigate its causes (e.g. inclusion of non-tax revenues, differences in estimated GDP numbers).

3. We take note of instances where the overall tax take, or individual tax types, see sudden and large changes. We use additional sources to try to determine the proximate causes as they relate to policy changes, political transitions or economic shocks. We flag cases where we cannot find the proximate cause or where the political or economic events induce very significant volatility in the time-series.
4. We aim to be conservative in our inclusion of countries and time-periods. Specifically, we exclude countries in time-periods where data exists but where significant concerns remain about its reliability (and where it proves difficult to find corroborating sources). These instances are often in periods of significant political or economic change. For example, we exclude Afghanistan in the late 1970s and early 1980s; Cambodia in the late 1980s and early 1990s; Dominican Republic in the early 1960s; and, Namibia in 1990.

The [supplementary appendix](#) contains a table which summarizes our decisions as they relate to these four guiding rules in each country in our sample. The table emphasizes the uncertainty that exists for specific countries in specific time periods and we flag instances where we assess the data to be worthy of inclusion but where it should still be interpreted with caution and additional investigations would be helpful. We confirm that none of our main results change if we exclude these flagged instances. Moreover, the [supplementary appendix](#) provides case-studies with additional details on our decisions and direct links to the initial historical documents for each country. The case studies are currently limited to 67 countries but will ultimately cover the entire sample.¹

Equipped with the historical time series, we have to construct long-run panels across sources. Below, we outline the instructions used to harmonize across sources and to improve data quality for the measurement of each type of tax. We flag instances where we consider the series to be legitimate, but where harmonization proved more challenging due to coinciding economic or political changes. For each country, the main decisions related to harmonization and data-quality are provided in the [supplementary appendix](#).

1. We first rely on OECD data whenever it exists. Archival data is initially second in priority, but we revise this based on whether ICTD data provides a long time series and separates personal from corporate income taxes. We also study if ICTD has the better match in overlapping time-periods with OECD data. When possible, we aim to use no more than two data sources per country.
2. We exclude country-years for communist/command economies. This implies that our panel size jumps in 1994, including when China and Russia first appear. The year 1994 is a few years removed from the dissolution of the Soviet Union but, as discussed below, arguably corresponds to China's establishment of a modern tax system (World Bank, 2008).
3. When none of the data sources separate PIT from CIT, we use academic sources and tax legislation to assign values.

¹We invite comments from researchers to improve the accuracy of the series as we build the case studies and expand the data to recent years.

4. To guard against omitting significant values of decentralized tax revenues, we use the OECD database on subnational government finance ([link](#)) to find the countries with significant state and local taxes, and we attempt to collect further data for these countries if necessary.
5. We linearly interpolate data when a given tax type is missing, but for no more than 4 years in a time-series and without extrapolation. We check for significant socio-economic changes that could cast doubt on the continuity of the tax revenue series and do not interpolate in such years.
6. We only use actual amounts of taxes collected, and do not rely on estimated values.

China's establishment of a modern tax system in 1994

In our benchmark setting, we only include formerly communist economies into our data starting in 1994. Given China's weight in the global economy, it is worth reviewing the reason for that choice. The tax revenue data for China covers most of our sample period although its quality improves markedly in the 1980s. Official statistics are available online: [link here](#).

Prior to the 1980s, China had a command economy model of 'profit delivery,' in which the state directly received the revenues of profitable SOEs, and subsidized unprofitable ones. A corporate income tax first appears in China in 1983-84, but the majority of the base continues to be state-owned enterprises. In 1985, the tax system was further reformed into a 'fiscal contracting' system whereby firms negotiated a fixed lump-sum payment (regardless of economic outcomes), which cannot be split into labor versus capital taxes (nor into consumption taxes). We therefore exclude the 'pseudo'-CIT revenue dating from 1985 through 1993.

Rather, we consider that China's modern tax system began in 1994. The World Bank (2008) shows that, in 1994, China established for the first time a central tax administration; reformed the 'fiscal contracting' system; unified the PIT; created a VAT; and reduced 'extra budgetary' (non-tax) revenues. Thus from 1994 onward we can categorize tax revenue precisely by type, assign them to capital or labor, and estimate our *ETRs*.

National accounts data To compute factor incomes of net domestic product, we combine two main datasets from the United Nations Statistics Division. The first is the 2008 System of National Accounts (SNA) online data repository. The second is the 1968 SNA archival material. The 2008 and 1968 SNAs initially have different reporting classifications; to the best of our knowledge, our project is the first to harmonize national accounts across these two sources.

To estimate capital and labor factor incomes requires information on the 4 main sub-components that make up net domestic product (see equation 1.3). However, in some country-years where we have information on domestic product from an SNA dataset, there may not be data on all four sub-components at the same time. This is more frequently the case for the 1968 SNA than for the 2008 SNA and it is most frequent for mixed income (OS_{PUE}). In these cases, we first attempt to recover the

value of the missing component using data from the other SNA dataset and national accounting identities with non-missing values for other components within the same country-year. For the remaining cases after applying this process, we impute values for the component. All of the regressions in Sections 1.5-1.6 include dummy variables for these composite cases; our main results also hold without the imputed values (Table A1.4). For the imputation, we follow the procedure from Blanchet et al. (2021). The World Inequality Database uses this procedure to impute consumption of fixed capital (depreciation) when it is missing in countries' series. For example, applying this procedure in our setting means that we model OS_{PUE} as a function of log national income per capita, a fixed country characteristic, and an AR(1) persistence term.

Table A1.11 summarizes the national accounts coverage in our dataset. The 'Complete SNA2008' row refers to country-years where all components of net domestic product are extracted from the 2008 SNA; similarly for the 'Complete SNA1968' row. The 'Composite' row counts instances where one component (or more) of net domestic product is initially missing from an SNA dataset and is retrieved from the other SNA dataset, is calculated via accounting identities, or is imputed.

A1.1.2 Construction of ETR

By combining data on disaggregated tax revenues and national income components, we construct effective tax rates on capital and labor (equations 1.1 and 1.2 in Section 1.3.1). Here we provide further details on the definitions of ETR . Computing ETR_L and ETR_K requires the following information for country c in year t :

$$ETR_{L,ct} = \frac{T_{L,ct}}{Y_{L,ct}} = \frac{\lambda_{PIT,ct} \cdot T_{1100,ct} + \lambda_{socsec,ct} \cdot T_{2000,ct}}{CE_{ct} + \phi_{ct} \cdot OS_{PUE,ct}}$$

$$ETR_{K,ct} = \frac{T_{K,ct}}{Y_{K,ct}} = \frac{(1 - \lambda_{PIT,ct}) \cdot T_{1100,ct} + (1 - \lambda_{CIT,ct}) \cdot T_{1200,ct} + (1 - \lambda_{assets,ct}) \cdot T_{4000,ct}}{(1 - \phi_{ct}) \cdot OS_{PUE,ct} + OS_{CORP,ct} + OS_{HH,ct}}$$

For each type of tax j , there is a $\lambda_{j,ct}$ allocation of the tax to labor which may vary by country-year (and $1 - \lambda_{j,ct}$ is the allocation to capital). The allocation for each type of tax is described in Table A1.1, where the types of taxes follow the OECD classification. In our benchmark assignment, these allocations are time- and country-invariant for all types of taxes, except for personal income taxes ($\lambda_{PIT,ct}$) which we discuss in detail below. Further, in our benchmark assumption, we assume that the labor share of mixed income, ϕ_{ct} , is fixed at 75% in all country-years ($\phi_{ct} = 0.75$). In robustness checks, we let ϕ_{ct} vary at the country-level, based on ILO (2019), or at the country-year level by using the labor share in the corporate sector. In our benchmark assignment, replacing the invariant parameters with their fixed numerical values, we therefore have:

$$ETR_{L,ct} = \frac{T_{L,ct}}{Y_{L,ct}} = \frac{\lambda_{PIT,ct} \cdot T_{1100,ct} + T_{2000,ct}}{CE_{ct} + 0.75 \cdot OS_{PUE,ct}}$$

$$ETR_{K,ct} = \frac{T_{K,ct}}{Y_{K,ct}} = \frac{(1 - \lambda_{PIT,ct}) \cdot T_{1100,ct} + T_{1200,ct} + T_{4000,ct}}{0.25 \cdot OS_{PUE,ct} + OS_{CORP,ct} + OS_{HH,ct}}$$

The parameter values are described in Table A1.1, both for the tax revenue numerator and the national income denominator. We now provide more details on λ_{PIT} and ϕ .

Labor share of personal income taxes: λ_{PIT} As discussed in Section 1.3.1, the level of personal income tax (PIT) that derives from capital versus labor income is rarely directly observed.² Thus, within PIT, an important parameter is the share of revenue assigned to labor, denoted λ_{PIT} . In the United States, Piketty, Saez, and Zucman (2018) find that approximately 85% of PIT revenue is from labor and 15% from capital. To construct country-year specific $\lambda_{PIT,ct}$, we start from the US benchmark ($\lambda_{PIT} = 85\%$) and make two adjustments:

- (a) First, the location of the PIT exemption threshold in the income distribution impacts λ_{PIT} , since the capital income share is higher for richer individuals. We retrieve PIT exemption thresholds from Jensen (2022). We assume countries with a higher PIT exemption threshold have a higher λ_{PIT} . Since the US has a low exemption threshold with $\lambda_{PIT} = 85\%$, we assign 85% of PIT to labor in countries where the PIT at least half of the workforce (mainly high-income countries). For countries where the PIT covers 1% or less of the workforce (lowest-income countries), we assign a maximum PIT capital share of 30%. For PIT thresholds with a coverage between 1% to 50% of the workforce, we linearly assign λ_{PIT} between 70% and 85%.
- (b) Second, we assume that countries where a dual PIT system is in place have a larger λ_{PIT} . Dual PIT systems set capital income taxation to a lower—often flat—rate, while labor income is taxed with progressive marginal tax rates. We compute the measure of the percent difference between the tax rate on dividends and the top marginal tax rate on labor income. Data on dividend vs wage income tax rates are taken from OECD Revenue Statistics and country-specific tax code documents. Since we only have dividend rates, we assume that 50% of capital income in PIT benefits from the lower rate (e.g., capital gains might not benefit). For this 50%, we multiply λ_{PIT} by the percent difference in dividend versus top marginal tax rates.

Labor share of mixed income: ϕ Section 1.3.1 noted the difficulty of estimating the labor share of mixed income (unincorporated enterprises). We assume a benchmark measure of $\phi = 75\%$. The implied capital share is lower than the 30% used in Distributional National Accounts guidelines (Blanchet et al., 2021). However, since the global average corporate capital share is 27%, assuming that the capital share of unincorporated enterprises is slightly lower appears reasonable (see Guerriero, 2019).

We implement two robustness checks. First, we set the labor share of mixed income equal to that of the corporate sector at the country-year level; specifically, $\phi_{ct} = \frac{CE_{ct}}{CE_{ct} + OSCORP_{ct}}$. This procedure follows Gollin (2002).

Second, we implement the ILO (2019) method which relies on harmonized household surveys and labor force surveys in developing countries between 2004 and 2017. Estimation of the relative labor income of self-employed is based on the observable

²PIT revenue from capital income includes taxes on dividends and capital gains and on the capital share of self-employment income. OECD revenue data occasionally reports tax revenue from capital gains, which was on average 4% of PIT in the period 2010-2018 (7.5% in the US).

characteristics of those workers and their comparison with employees. Relevant variables, including industry, occupation, education level and age, are used in a regression to uncover the determinants of labor income of employees. Given the estimated relationship between employee labor income and the explanatory variables, labor income is extrapolated to self-employed, generating a coefficient of relative earnings to employees, denoted γ_q . The method estimates a separate γ_q for different groups q of self-employed: self-employed workers; own-account workers; and, contributing family members. A correction procedure is implemented to reduce the bias from selection into self-employment. Total labor income in a given country-year is then determined as $Y_L^{ILO} = CE + \sum_q w_{emp} \cdot \gamma_q \cdot b_q$, where CE is the total compensation of employees in SNA, w_{emp} is the average employee wage (which relates CE to the total employee workforce), b_q is self-employed group q 's count in the workforce, and γ_q is the q -specific earnings coefficient relative to the average employee wage. Equipped with the Y_L^{ILO} estimate, we calculate the 'implicit' labor mixed income ($OSPUE_L$) as the difference between Y_L^{ILO} and the value of compensation for employees CE observed in the national accounts. Then, we compute the mixed income share allocated to labor. Specifically, ϕ^{ILO} is computed as follows: $\phi^{ILO} = \frac{(Y_L^{ILO} - CE)}{OSPUE} = \frac{OSPUE_L^{ILO}}{OSPUE}$

Finally, we compute the average ϕ^{ILO} for each country during 2004-2017 and assign this value to all years. We assign a country-specific but time-invariant value for two reasons. First, prior to 2004, the ILO lacks the required data to compute Y_L^{ILO} on a country-year basis. Second, when measured at the country-year level during the 2004-2017 period, ϕ^{ILO} varies little within country across years. Assigning a country-specific but time-invariant mixed income factor share may therefore be reasonable.

The main challenge is that the estimation framework for γ_q is not disciplined by the country's actual values in SNA. In particular, nothing prevents $\sum_q w_{emp} \cdot \gamma_q \cdot b_q > OSPUE$ - such that estimated labor mixed income is larger than the SNA actually observed entire mixed income. This would, implausibly, imply that $\phi^{ILO} > 100\%$. To remedy this concern, we winsorize ϕ^{ILO} at 100%. In cases where γ_q and b_q are not from ILO (*ibid.*), we also winsorize ϕ^{ILO} from below with the lowest observed country value in ILO (*ibid.*), which is 36%. While the ILO (*ibid.*) method generates important country-level variation, the global average value for ϕ^{ILO} , at 80%, does not differ much from our benchmark value $\phi = 75\%$.

Mixed income in China and the US We make mixed-income adjustment to the benchmark series for China and the United States. For China, Piketty, Yang, and Zucman (2019, hereafter PYZ) show that Chinese national accounts systematically underestimate mixed income and overestimate other factor incomes: for example, the income of self-employed agricultural workers is attributed to employee compensation in the SNA 2008 data and not to mixed income (as in other countries). We base our mixed income series on PYZ.

Following PYZ, we define mixed income as the sum of the income attributed to self-employed workers from agriculture and individual businesses. PYZ covers the period 1992-2014. For years before and after, we extend the series as follows:

- (a) For agriculture, relevant data is available dating back to 1952. We extend the series back to 1965 relying on the price deflator available at World Inequality Database. For more recent years (2014-2018), we predict the trend based on sources used in PYZ (National Bureau of Statistics, [link](#)).

- (b) For individual businesses, PYZ computes the income of this sector by combining several data sources. Unfortunately, a crucial part of it is not available prior to 1992, namely the 'flow of funds' data. Instead, our assumption is that, prior to 1980, Chinese individual businesses accounted for a negligible share of the economy. This observation is consistent with facts on self-employment structure in China at the micro and macro levels, and the trends presented in PYZ for the 1990s.³ For recent years (2014-2018), we predict the trend based on sources used in PYZ (National Bureau of Statistics, [link](#)).

The estimated series of mixed income in China follows the same trend as for the rest of LMICs, although it starts from a slightly higher initial level.

For the US, we use the factor shares from Piketty, Saez, and Zucman (2018), which (i) assumes a higher capital share of income for partnerships vs. other non-corporate businesses; and (ii) accounts for the rising capital intensity of partnerships since the 1980s.

A1.2 Trade Liberalization Event Studies

A1.2.1 Description of liberalization events

Our selection of trade events is determined by three criteria. First, the event is related to measurable policy reforms; this improves the transparency of the event-study design which is based on a well-defined policy event. Second, the policy reforms induced large changes in trade barriers; this increases the likelihood of observing sharp breaks in macroeconomic outcomes around the event-time. Third, the event has been studied in academic publications; this allows us to rely on events for which the positive effects on openness have previously been established.

These criteria led us to focus on the six trade liberalization events referenced in review articles by Goldberg and Pavcnik (2007, 2016) to which we add China's WTO accession event (studied in Brandt et al., 2017). Most of these selected events feature reductions in tariff rates: many of the countries did not participate in the early GATT/WTO negotiation rounds, making reductions in tariffs an available policy lever. The tariff reductions were large: Brazil cut tariff rates from 59% to 15%, India from 80% to 39% percent, and China from 48% to 20%. Mexico reduced tariff rates from 24% to 12% and import license requirements went from covering 93% of national production to 25%; Colombia's tariffs were reduced from 27% to 10% and import requirements dropped from 72% of national production coverage to 1%. In the selected countries, "tariff reductions constitute a big part of the globalization process" (Goldberg and Pavcnik, 2016). The timing of the events and academic references are provided in the [supplementary appendix](#).

Below are narrative analyses for some of the events:

- **Brazil** The liberalization event of 1988 is detailed in Dix-Carneiro and Kovak (2017). The authors note: "In an effort to increase transparency in trade policy, the government reduced tariff redundancy by cutting nominal tariffs... Liberalization effectively began when the newly elected administration suddenly

³At the micro level, self-employed workers represent less than 2% of workforce in the 1980s, but had similar income per capita as wage earners (Gustafsson and Zhang, 2022). At the macro level, very small-scale industries represented 0.4% of industry output in the 1970s, reaching 7% only in 1989 (Yusuf, 1994).

and unexpectedly abolished the list of suspended import licenses and removed nearly all special customs regimes.”

- **Colombia** Similarly to Brazil, tariff reductions in Colombia in 1985 were driven by the country’s decision to impose uniform rates across products and industries under the negotiation commitments to the WTO. Goldberg and Pavcnik (2007) note that this reform objective makes “the endogeneity of trade policy changes less pronounced here [in Colombia] than in other studies.”
- **China** Brandt et al. (2017) note that trade openness reforms had gradually been implemented in China prior to the country’s WTO accession in 2001, but that the tariff reductions implemented upon accession were large, “less voluntary” and largely complied with the pre-specified WTO accession agreements. Importantly, the potential accession to WTO contributed to the timing of privatization initiatives, in which the Chinese government restructured and reduced its ownership in state-owned enterprises. While the privatization efforts began in 1995 and were incremental, it is possible that additional sell-offs in the post-WTO years contribute to the observed medium-run trends in our outcomes.
- **India** The 1991 event in India occurred as a result of an IMF intervention that dictated the pace and scope of the liberalization reforms. Under the IMF program, tariff rates had to be harmonized across industries, which, like in Brazil and Colombia, led to a large average reduction in tariffs. Topalova and Khandelwal (2011) argue the Indian reform “came as a surprise” and “was unanticipated by firms in India.” The reforms were implemented quickly “as a sort of shock therapy with little debate or analysis.” The IMF program was in response to a set of events including “the drop in remittances from Indian workers in the Middle East, the increase in oil prices due to the Gulf War, and political uncertainty following the assassination of Rajiv Gandhi”.
- **Vietnam** The 2001 reform was implemented as a broad trade agreement that did not involve negotiations over specific tariffs (McCaig and Pavcnik, 2018). The reform was driven by the American government’s decision to reclassify Vietnam from ‘Column 2’ of the US tariff schedule to ‘Normal Trade Relations’. Column 2 was designed in the early 1950s for the 21 communist countries, including Vietnam, with whom the US did not have normal trading relations.

These descriptions of reform timing do not suggest that the liberalization events were directly triggered by changes in domestic taxation or factor incomes.

Goldberg and Pavcnik (2007) note other cross-border reforms that occurred during post-years of the liberalization events. Argentina’s 1989 event and Brazil’s 1988 event were followed by accession to Mercosur in 1991; India’s 1991 event was followed by foreign direct investment liberalization in 1993; and Mexico’s 1985 WTO accession was followed by a removal of capital inflow restrictions in 1989. These reforms occurred with some lag to the trade liberalization events.

A1.2.2 Event study methodology

Our sample is constructed by applying a synthetic matching procedure to every treated country for each outcome of interest. The donor pool has to be fully balanced

in all pre-event periods. To estimate the event study in equation (1.4) for a given outcome, the sample pools the seven treated countries and their synthetic control countries for 10 years before and after the events (yielding 294 observations). We estimate the event-study in equation 1.4 and the DiD model: $y_{ct} = \beta^{DiD} \cdot \mathbb{1}(e \geq 0)_t \cdot D_c + \theta_t + \kappa_c + \pi_{Year(t)} + \epsilon_{ct}$. The DiD model uses the same notation as equation (1.4). Moreover, we use the imputation method by Borusyak, Jaravel, and Spiess (2021) to report average treatment effects comparable to β^{DiD} with a technique that deals with issues with two-way fixed effects and heterogeneous event timing. Details are provided in the [supplementary appendix](#). All the DiD average treatment effects are reported in Table A1.3. We test if our results hold with a more restrictive synthetic control, by using our three main outcomes—trade, ETR_K and ETR_L —to construct one synthetic control group per treated country. The results are reported in Panel B of Table A1.3.

A1.2.3 Alternative trade liberalization event study

We present results based on an alternative measure of trade liberalization events. We use the events from Wacziarg and Welch (2008), which cover 141 countries at all levels of development between the 1950s and 1998. When merged with our data, the sample covers 68 liberalization events that occurred between 1965 and 1998 in developing countries. A trade liberalization event is defined to occur when all five of the following conditions no longer hold: (i) average tariff rates are above 40%; (ii) non-tariff barriers cover at least 40% of trade; (iii) the black market exchange rate is at least 20% lower than the official exchange rate; (iv) there is a state monopoly on major exports; (v) there is a socialistic system in place. These conditions are broader than our main liberalization event criteria (Section 1.5.1 and A1.2.1). At the same time, our main events are covered in this expanded event sample (with the exception of China and Vietnam, whose events are after the end of the sample period); this occurs because the reduction in tariff rates, one of our main event criteria, was the remaining event-condition to be satisfied in Wacziarg and Welch (*ibid.*). We estimate the effects of the liberalization events using the DiD model: $y_{ct} = \beta^{DiD} \cdot E_{ct} + \theta_t + \theta_c + \epsilon_{ct}$. y_{ct} is the outcome of interest in country c in year t , E_{ct} is the event indicator which takes on a value of 1 in all periods after a country has a liberalization event (and 0 otherwise), and θ_t and θ_c are year and country fixed effects, respectively. ϵ_{ct} is clustered at the country level. Estimation issues arising from heterogeneous treatment-timing may be important; for this reason, we focus on the imputed treatment effects based on Borusyak, Jaravel, and Spiess (2021). We restrict the sample to developing countries between 1965 and 2008.

Panel A of Table A1.12 reports the β^{DiD} impacts on trade, ETR_K and ETR_L . Despite being based on broader criteria, the trade liberalization events produce qualitatively similar results to the main event-study (Section 1.5.1), with positive impacts on openness and both $ETRs$, and a larger magnitude-impact on ETR_K than ETR_L . Figure A1.5 estimates the dynamic event-study. Liberalized and control countries are on parallel trends until the event onset; both $ETRs$ start to increase in the immediate post-event years. Panel B shows that the results are robust to estimating the effects in a fully balanced panel 10-years post-reform. In Panel C, the results hold when the control group is formed within-region. Panel D shows the results are robust to excluding countries which have cross-border capital liberalization events at any point during the sample-period (Bekaert, Harvey and Lundblad, 2000).

Finally, Panel E shows the results hold when we exclude countries with concurrent domestic reforms (Wacziarg and Wallack, 2004).

A1.3 Results on Tax Capacity Mechanism

A1.3.1 Firm-level analysis in Rwanda

Data-sources and sample Our analysis draws on three administrative datasets from the Rwanda Revenue Authority (RRA), for the years 2015-2017. These data sources can be linked through unique tax identifiers for each firm, assigned by the RRA for the purpose of collecting customs, corporate income and value-added taxes. The first data source is the customs records, which contain information on international trade transactions made in each year by each firm. We use this data to measure each firm's direct imports. The second data is the firms' corporate income tax (CIT) declarations merged with the firm registry. These data contain detailed annual information on firms' profits, revenue and costs. We use these data to measure each firm's effective tax rate. The third data source is the business-to-business transactions database. These data are retrieved through the electronic billing machines (EBM) that all firms registered for VAT are legally required to use (Eissa et al., 2014). For a given seller, EBMs record the transactions to each buyer identified by the tax firm-ID. We use this data to measure buyer-seller relationships.

When combined, these data allow us to construct the buyer-supplier relationships of the Rwandan formal economy and document firms' total trade exposure. Importantly, since the network data is based on tax-IDs, we cannot observe transaction linkages with informal, non-registered firms. This sample selection on formal firms also features in most recent network studies, by virtue of relying on administrative data, including in Chile (Huneus, Kroft, and Lim, 2021); Costa Rica (Alfaro-Ureña et al., 2018); Ecuador (Adão et al., 2022); India (Gadenne, Nandi, Santamaria, et al., 2022); Turkey (Demir et al., 2024); and Uganda (Almunia et al., 2023a).

Our sample is the set of firms that are registered for CIT and that report positive income during the years 2015-2017. Note that only a small number of firms are registered for CIT or VAT but not both, meaning that the overlap with the EBM transactions data is strong. However, restricting the sample to positive income is consequential, as a significant number of registered CIT firms are 'nil filers' that report zero income ('nil filers' are common in developing countries: Keen, 2012). We measure each firm i 's yearly effective tax rate on corporate profits, corresponding to corporate ETR_i^K in equation (1.6), as the ratio of corporate taxes paid divided by net profit. Net profit is revenue minus material, labor, operational, depreciation and financial costs.

The EBM data is meant to improve the enforcement of corporate taxes and VAT, and the reporting of linkages is more comprehensive for the relatively larger firms that are registered for these tax bases. For smaller incorporated firms that are instead registered to simplified tax bases (flat-amount or turnover), only a few of them are registered for VAT. Consequently, these firms are most likely to be recorded in the EBM data as clients in a particular transaction, making the coverage of their linkages less comprehensive. It is in principle also possible to measure ETR_i^K amongst these smaller, incorporated firms. However, the information on their tax returns regarding cost items is less detailed and additional assumptions on the relationship between

turnover and profit are required, which makes the profit measure in the denominator of ETR_i^K less precise. With these data-challenges in mind, we can include these additional tax-registered firms in the analysis; we find qualitatively similar results (available upon request).

Exposure to trade To measure a firm’s total exposure to trade, we follow Dhyne et al. (2021) who use similar administrative datasets as ours to measure trade exposure of Belgian firms. We define firm i ’s total foreign input share as the share of inputs that it directly imports (s_{Fi}), plus the share of inputs that it buys from its domestic suppliers l (s_{li}), multiplied by the total import shares of those firms:

$$s_i^{Total} = s_{Fi} + \sum_{l \in V_i} s_{li} \cdot [s_{Fl} + \sum_{r \in V_l} s_{rl} \cdot (s_{Fr} + \dots)]$$

where V_i is the set of domestic suppliers of firm i , and V_l is the set of domestic suppliers of firm l . The denominator of the input shares is the sum of purchases from other firms and imports. Note that s_i^{Total} is recursive: a firm’s total foreign input share is the sum of its direct foreign input share and the share of its inputs from other firms, multiplied by those firms’ total foreign input shares. We limit the calculation to the inputs from a firm’s immediate suppliers l as well as the suppliers to their suppliers r (adding more network-levels only marginally increases s_i^{Total}). s_i^{Total} reflects the direct import share of firm i ’s suppliers and the suppliers’ suppliers, each weighted by the share of inputs that each firm buys from other domestic firms. We focus on firms’ exposure to imports through their supplier network; in an extension, we find qualitatively similar results when studying firms’ exposure to exports through their client network (results available).

Figure A1.6 displays a histogram of s_i^{Total} and s_{Fi} for all formal Rwandan firms. While just under 30% of firms import directly, 93% rely on trade either directly or indirectly through their suppliers. In the median firm, the total foreign input share is 48% (it is 39% for the median Belgian firm in *ibid.*).

Impacts of trade exposure on ETR_i^K and size To visualize the association between trade exposure (s_i^{Total}) and ETR_i^K , we plot binned scatters of the variables against each other, after residualizing both against year fixed effects. In Figure A1.7, the dots correspond to equal-sized bins of the residualized trade variable. The line corresponds to the best linear fit regression on the underlying firm-level data ($N = 18478$). Figure A1.7 reveals a positive and strongly significant association: firms that are more exposed to international trade, both through direct imports and through links to importers in the supply network, have higher effective tax rates on corporate profits.

We investigate this association in a regression form in Table 1.4, deploying both OLS and IV. The IV applies the design in Dhyne et al. (*ibid.*) that extends the shift-share approach of Hummels et al. (2014) to a setting with shock pass-through via network linkages. The empirical strategies and the main results are described in Section 1.6.3. In additional regressions (not shown but available), we find that the results are robust to controlling for trade shocks to firm i ’s potential suppliers (firms that operate in the same industry and geographical area as i ’s current suppliers but are not currently supplying to i) and firm i ’s horizontal suppliers (firms that are suppliers to firm i ’s current clients).

We focus on firms' exposure to imports through their supply network, but firms may also be impacted by imports through their clients. In an extension, we find that increased output exposure to imports through the client network has positive effects on ETR^K (results available), though this average effect could mask heterogeneity across firms depending on the complementarity between imports and domestic inputs.

Because the estimation is within the corporate sector, this exercise cannot speak to the magnitude of trade's net impact on sector-level \overline{ETR}_C^K . These firm-level results on corporate ETR_i^K are therefore complementary to the country-level results on \overline{ETR}_C^K . An additional limitation is that the network linkage measures are derived from administrative data which, by construction, only exist for tax registered firms (Atkin and Khandelwal, 2020). This sample restriction implies that this firm-level regression is not suited to study the impacts of trade on the size of informal firms.

A1.3.2 Type of trade analysis

We investigate whether trade has differential impacts on ETR and mechanism outcomes depending on the nature of the trade variation (Section 1.6.4). We use our two instruments to investigate the impacts of: (i) imports versus exports (of trade in both intermediate G-S and final G-S); (ii) trade in intermediate G-S versus final G-S (summed across imports and exports). We use UN's Broad Economic Categories (Rev. 5) to classify final versus intermediate goods-services (G-S), combining capital goods with the latter. For the imports versus exports IV, the two 1st-stage regressions are

$$\begin{aligned} \log(\text{imp}_{ct}) &= \beta_1 \cdot Z_{ct}^{\text{gravity}} + \beta_2 \cdot Z_{ct}^{\text{oil-dist}} + \mu_c + \mu_t + \epsilon_{ct} \\ \log(\text{exp}_{ct}) &= \pi_1 \cdot Z_{ct}^{\text{gravity}} + \pi_2 \cdot Z_{ct}^{\text{oil-dist}} + \eta_c + \eta_t + \iota_{ct} \end{aligned}$$

where $\log(\text{imp}_{ct})$ and $\log(\text{exp}_{ct})$ are the logs of total imports to NDP and total exports to NDP, respectively, in country c in year t . The log-transformation improves the 1st-stage (results without logs are qualitatively similar). The 2nd-stage is

$$y_{ct} = \theta_1 \cdot \log(\text{imp}_{ct}) + \theta_2 \cdot \log(\text{exp}_{ct}) + \kappa_c + \kappa_t + \phi_{ct}$$

The set-up is similar for the second IV (intermediate G-S vs final G-S) where we replace $\log(\text{imp}_{ct})$ and $\log(\text{exp}_{ct})$ with the log of total trade in intermediate G-S to NDP and the log of total trade in final G-S to NDP. IV results for developing countries are in Panel A of Table A1.6, with 1st-stage regressions in Panel B. Note that it is ex ante unclear if the two instruments generate a strong overall first-stage. We gauge this by inspecting the Kleibergen-Paap F-statistics, which are not well above conventional threshold levels (13.56 and 8.21). Given this challenge, we limit our scope to studying whether the coefficient signs for the different types of trade are consistent with our simplified predictions (and whether they statistically differ from each other). The exclusion restriction requires that the regressors add up to total trade openness. For this reason, we cannot implement an IV which focuses on the impacts of final versus intermediate G-S for, say, imports only. This also implies that, for a given outcome, the hypotheses in our two IVs (final versus intermediate G-S; imports versus exports) will be correlated. We accordingly adjust the p-values for multiple hypotheses testing using the Romano-Wolf method.

The results are described in Section 1.6.4. Since we only have 2 instruments, we cannot decisively conclude on the impacts for the 4 types of trade (imports of

intermediate G-S, exports of intermediate G-S, imports of final G-S, exports of final G-S). Notwithstanding, the estimated IV coefficients are consistent with imports of final G-S decreasing ETR_K and mechanism outcomes $(\mu_C, \overline{ETR}_C^K)$, and imports of intermediate G-S increasing them.

A1.4 Capital Liberalization Events

To attempt to investigate the impact of capital liberalization on effective tax rates, we draw on Chari, Henry, and Sasson (2012). The authors measure capital liberalization events in 25 developing countries as the date when foreign investment in the domestic stock market was first allowed. They show that these events significantly increase foreign capital inflows, including foreign direct investment (FDI) and import of capital goods.⁴ Compared to other policies aimed at lifting FDI restrictions, liberalizing the domestic stock market occurs at a precise point in time, is not marked by policy-reversal or net capital outflow, and is unambiguously related to capital liberalization (Eichengreen, 2001). We employ the empirical design of Section 1.5.1 and create a synthetic control country for each of the 25 treated countries and for each outcome. We measure capital openness as the total sum of the stocks of foreign assets and liabilities (as in Gygli et al., 2019). We find similar results when using alternative measures of capital openness, including portfolio equity assets and liabilities and the Gygli et al. (ibid.) KOF financial globalization index.

Figure A1.8 reports the event-study results. Relative to a stable pre-trend, we observe a sustained rise in capital openness precisely at the time of the event. ETR_K also increases, with a small lag to the timing of the capital liberalization event; in the medium-run, the positive effect on ETR_K is significant at the 5% level. There is no discernible effect on ETR_L . Similar to the reasoning for the trade tax-capacity mechanism, the inflow of foreign capital, as well as any subsequent increase in capital goods imports and aggregate investment, may positively impact ETR_K by contributing to general growth of firms or by causing an expansion of initially larger firms. Consistent with this interpretation, we find that the capital liberalization events led to increases in the corporate output share and the average corporate effective tax rate (results not shown but available).

One important limitation is that the events considered here remove restrictions on capital *inflows* and are not informative of the impacts of increased capital *outflows*. In general, more work is needed to understand the determinants of policies that impact cross-border capital flows in developing countries and their effects on $ETRs$.

⁴FDI includes green field investments (building plants from scratch) and cross-border mergers and acquisitions (M&A). Chari, Henry, and Sasson (2012) note that M&A is impacted by stock market liberalization, makes up to 40-60% of FDI in developing countries, and can trigger subsequent green field investments.

Appendix 1 Tables

Table A1.1 – Main Tax Revenue and National Accounts Concepts

| <i>Panel A: Tax Revenue</i> | | | |
|-----------------------------|----------------------------|-------------------------------------|--|
| OECD revenue classification | type of tax j | incidence λ_j on labor | notes |
| 1100 | personal income tax (PIT) | $68\% \leq \lambda_{PIT} \leq 93\%$ | Taxes on individuals (wages, capital income, capital gains). $\lambda_{PIT,ct}$ varies by country and year: see Section A1.1.2 for details |
| 1200 | corporate income tax (CIT) | $\lambda_{CIT} = 0\%$ | Taxes on corporate profits. Unallocable income taxes (OECD category 1300) are split between PIT and CIT based on information from additional sources (see supplementary appendix) |
| 2000 / 3000 | social security & payroll | $\lambda_{soc.sec.} = 100\%$ | Includes all social security contributions as well as payroll taxes |
| 4000 | property & wealth taxes | $\lambda_{assets} = 0\%$ | Includes property, wealth and financial transaction taxes |
| 5000 | indirect taxes | excluded | Includes trade taxes, value-added taxes and other sales taxes and excise taxes. We consider these taxes as prior to factor income returns, such that they can be excluded from factor income taxation (Browning, 1978; Saez and Zucman, 2019). |
| 6000 | other taxes | excluded | Rare in occurrence and often quantitatively small |
| 7000 | non-tax revenue | excluded | Does not meet definition of taxation, can be quantitatively significant |

| <i>Panel B: National Accounts</i> | | | |
|-----------------------------------|------------------------------|----------------------|--|
| Natl. accounts acronym | national income component | benchmark allocation | notes |
| CE | compensation of employees | labor | Includes wages and salaries, employer and employee social contributions, and all payments from employers to their employees |
| OS _{PUE} | mixed income | $\phi = 75\%$ labor | ‘Operating surplus of private unincorporated enterprises’ includes income from self-employment, household business owners, and informal or unincorporated enterprises |
| OS _{HH} | imputed rent | capital | ‘Operating surplus of households’ is imputed rental income accruing to homeowners who live in their own home |
| OS _{CORP} | corporate profits | capital | ‘Operating surplus of corporations’ includes all corporate income after paying employees and expenses, and can be thought of as corporate-sector capital income |
| OS _{GOV} | government operating surplus | — | OS _{GOV} = 0, by construction in national accounts |
| NIT | net indirect taxes | excluded | ‘indirect taxes, net of subsidies’ usually comprise 8-15% of national income. |
| NFI | net foreign income | — | We treat domestic income without balancing the accounts to foreign earned income: many countries tax income earned domestically, regardless of citizenship, whereas net foreign income is taxed only with difficulty |
| CFC | depreciation | excluded | Factor income and our <i>ETR</i> are expressed net of ‘consumption of fixed capital’ |

Table A1.2 – Effective Tax Rates: Existing Databases

| Paper | Time | Countries | Source | Notes on methodological differences with our approach |
|-----------------------------------|-----------|-------------------|----------|--|
| Mendoza, Razin, and Tesar (1994) | 1965-1988 | G7 members | OECD | Difference: All mixed income is allocated to capital income. Difference: Labor and capital in the PIT are taxed at the same rate |
| Carey and Rabesona (2004) | 1975-2000 | 25 OECD countries | OECD | Difference: Mixed income allocation where self-employed pay themselves the annual salary earned by the average employee. Similarity: Labor and capital in PIT are not taxed at same rate, measure preferential tax treatment of pension funds and dividends. Difference: Social security contributions deducted from household income. |
| McDaniel (2007) | 1950-2003 | 30 OECD countries | OECD | Difference: Mixed income imputed to capital based on rest-of-economy share. Difference: Labor and capital in PIT are taxed at the same rate |
| Kostarakos and Varthalitis (2020) | 1995-2019 | EU-27 members | Eurostat | Follows Carey and Rabesona (2004) |

Table A1.3 – Synthetic Difference-in-Difference of Trade Liberalization

| | Trade (1) | ETR_K (2) | ETR_L (3) |
|---|---------------------|---------------------|---------------------|
| <i>Panel A: Synthetic control for each outcome separately</i> | | | |
| Post*Treat | 0.064 (0.047) | 0.045*** (0.015) | 0.020** (0.009) |
| Imputed treatment effect | 0.070* (0.039) | 0.047*** (0.009) | 0.020*** (0.005) |
| <i>Panel B: Synthetic control for all outcomes jointly</i> | | | |
| Post*Treat | 0.092* (0.044) | 0.033* (0.016) | 0.012 (0.008) |
| Imputed treatment effect | 0.101*** (0.028) | 0.033*** (0.006) | 0.012*** (0.004) |
| <i>Panel C: Donor pool excluding major trading partners</i> | | | |
| Post*Treat | 0.073 (0.055) | 0.047*** (0.015) | 0.018** (0.008) |
| Imputed treatment effect | 0.082** (0.035) | 0.048*** (0.009) | 0.018*** (0.004) |
| <i>Panel D: Donor pool restricted to not-yet liberalized</i> | | | |
| Post*Treat | 0.054 (0.058) | 0.054*** (0.014) | 0.013 (0.008) |
| Imputed treatment effect | 0.062* (0.034) | 0.054*** (0.009) | 0.013*** (0.005) |
| <i>Panel E: Donor pool restricted to same region</i> | | | |
| Post*Treat | 0.049 (0.060) | 0.034* (0.019) | 0.007 (0.008) |
| Imputed treatment effect | 0.058* (0.031) | 0.035*** (0.012) | 0.017*** (0.005) |
| <i>Panel F: Donor pool restricted to LMICs</i> | | | |
| Post*Treat | 0.076 (0.052) | 0.040** (0.016) | 0.016* (0.009) |
| Imputed treatment effect | 0.085** (0.034) | 0.041*** (0.008) | 0.016*** (0.005) |
| <i>N</i> | 294 | 294 | 294 |

Notes: This table shows the results from estimating the difference-in-difference effect and the imputed treatment effect - see Appendix A1.2.2 for details. In Panel A, the synthetic control is created separately for each outcome (trade, ETR_K , ETR_L) and each liberalization country-event. In Panel B, the synthetic control is created for all three outcomes jointly for each country-event. In Panel C, the donor pool for each country-event excludes the 5 major import and export trading partners of the country, measured in terms of total volume of trade in the year immediately preceding liberalization. In Panel D, the donor pool excludes all countries that have already liberalized by the time of the event (based on Wacziarg and Welch, 2008). In Panel E, the donor pool is restricted to countries in the same region. In Panel F, the donor pool is all low and middle-income countries (LMICs), based on the World Bank income classification in 2018. * p<0.10 ** p<0.05 *** p<0.01.

Table A1.4 – Trade Impacts on Effective Tax Rates in Different Samples

| | Sample changes related to tax revenue data | | | | Sample changes related to System National Accounts data | | | Sample changes related to time-periods and balancedness | | |
|---|---|-------------------------|---------------------------|---------------------------|--|--------------------------|--------------------------|--|-----------------------------|-----------------------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Panel A: ETR_K | | | | | | | | | | |
| Trade | 0.157*** (0.054) | 0.133*** (0.049) | 0.215** (0.098) | 0.206*** (0.068) | 0.162** (0.064) | 0.138** (0.062) | 0.183*** (0.052) | 0.110* (0.060) | 0.205** (0.098) | 0.150*** (0.052) |
| Panel B: ETR_L | | | | | | | | | | |
| Trade | 0.051*** (0.017) | 0.029*** (0.011) | 0.093* (0.049) | 0.028 (0.022) | 0.039** (0.018) | 0.037* (0.018) | 0.041** (0.020) | 0.041** (0.015) | 0.056** (0.021) | 0.067*** (0.020) |
| Modifications to bench- mark sample in Table 1.1 | Remove interpolated tax revenue | Only use HA tax data | Only use ICTD tax data | Only use OECD tax data | Remove composite SNA data | Only use SNA1968 data | Only use SNA2008 data | Only use pre-1994 years | Only use post-1994 years | Fully balanced panel 1965-2018 |
| N | 4563 | 2268 | 1004 | 1644 | 2752 | 983 | 1769 | 2122 | 2794 | 2879 |

Notes: This table presents results from estimating the effect of trade on effective tax rates in different samples across developing countries. The estimation is identical to the benchmark IV model in column (2) of Table 1.1; across columns, the sample differs from that benchmark sample. Developing countries are low and middle-income countries according to the World Bank income classification in 2018. The outcome is the effective tax rate on capital, ETR_K , in Panel A and the effective tax rate on labor, ETR_L , in Panel B. Trade is measured as the sum of exports and imports divided by net domestic product (NDP). In the first four columns, sample-changes are made to the tax revenue data: interpolated values are dropped in column 1; the only data-source is historical archives (HA) in column 2; the only data-source is ICTD in column 3; the only data-source is OECD in column 4. In the next three columns, sample-changes are made to the system of national accounts (SNA) data: in column (5), the composite SNA values are removed; in column (6), only data from SNA1968 are used; in column (7), only data from SNA2008 are used. In the final three columns, sample-changes are made regarding balancedness: in column (8), the quasi-panel between 1965 and 1993 is used; in column (9), the quasi-panel between 1994 and 2018 is used; in column (10), the fully balanced panel of countries between 1965 and 2018 is used. For more details on the interpolations, imputations and data-sources, see Section 1.3 and Appendix A1.1.

Table A1.5 – First-Stage and Reduced Form Regressions

| | 1 st -stage | | | Reduced form | | | | 1 st -stage | | | Reduced form | |
|---|------------------------|------------------------------|---------------------|----------------------|---------------------------------------|----------------------|----------------------|------------------------|--------------|----------------------------|----------------|----------------|
| | Trade (1) | ETR_K (2) | ETR_L (3) | Trade (4) | Trade*1 (High-inc.) (5) | ETR_K (6) | | ETR_L (7) | Trade (4) | Trade*1 (High-inc.) (5) | ETR_K (6) | ETR_L (7) |
| $Z_{gravity}$ | 0.069*** (0.010) | 0.010*** (0.002) | 0.003*** (0.001) | 0.014 (0.019) | 0.040*** (0.014) | 0.014* (0.008) | 0.002 (0.004) | | | | | |
| $Z_{oil-distance}$ | -0.116*** (0.036) | -0.033*** (0.009) | -0.020** (0.005) | -0.088*** (0.015) | -0.021 (0.014) | -0.022*** (0.007) | -0.015*** (0.003) | | | | | |
| 1 st -stage F-statistic | 24.59 | | | 22.82 | 11.75 | | | | | | | |
| 1 st -stage Sanderson-Windmeijer Weak Instruments F-statistic | 24.59 | | | 41.93 | 26.60 | | | | | | | |
| 1 st -stage Kleibergen-Paap F-statistic | 24.59 | | | | 15.34 | | | | | | | |
| Sample | | Developing countries only | | | Developing and developed countries | | | | | | | |
| N | 4916 | 4916 | 4916 | 6489 | 6489 | 6489 | 6489 | | | | | |

Notes: This regression table shows the first stage and the reduced form results. The sample is developing countries ($N = 49160$) in cols. (1)-(3), and developing and developed countries ($N = 6489$) in columns (4)-(7). Trade is exports and imports divided by net domestic product. Column (1) corresponds to the first-stage in developing countries, used in Tables 1.1-1.2-1.3. Columns (4)-(5) correspond to the first-stage in the full sample, which estimates heterogeneous effects by development level, and which is used in Table A1.10. We report several 1st-stage statistics: the F-statistic of excluded instruments; the Sanderson-Windmeijer multivariate F-test of excluded instruments; and, the Kleibergen-Paap F-statistic. When there is only one endogenous regressor (column 1), these three F-statistics are equivalent. Note in columns (4)-(5) that there is only one Kleibergen-Paap F-statistic, which evaluates the overall strength of the first-stage, even though there are two first-stage regressions. Columns (2)-(3) and (6)-(7) report the reduced form regressions of the instruments on the effective tax rates for capital, ETR_K , and labor, ETR_L . Developing (developed) countries are low and middle-income countries (high-income countries) according to the World Bank income classification in 2018. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. Standard errors in parentheses are clustered at the country level.

Table A1.6 – Type of Trade Analysis in Developing Countries

| Panel A: IV | ETR_K | | ETR_L | | Corporate Income | | Mixed Income | | Corporate ETR_K | |
|--|---------------------------------|---------------------------------|---------------------------------|---------------------------------|-------------------------------|--------------------------------|-------------------------------|---------------------------------|---------------------------------|---------------------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Export of G-S | 0.487* (0.263) [0.066] | | 0.225** (0.096) [0.019] | | 0.214* (0.123) [0.039] | | -0.159* (0.091) [0.119] | | 0.611* (0.339) [0.076] | |
| Import of G-S | -0.358*** (0.126) [0.059] | | -0.184*** (0.044) [0.013] | | -0.126* (0.074) [0.045] | | 0.069 (0.049) [0.145] | | -0.442*** (0.158) [0.033] | |
| Intermediate G-S | | 0.303*** (0.095) [0.053] | | 0.133*** (0.038) [0.012] | | 0.147** (0.070) [0.033] | | -0.119*** (0.045) [0.048] | | 0.385*** (0.122) [0.031] |
| Final G-S | | -0.245*** (0.051) [0.013] | | -0.125*** (0.023) [0.006] | | -0.089** (0.044) [0.019] | | 0.050** (0.024) [0.119] | | -0.302*** (0.056) [0.006] |
| F-test: Equality of coefficients [p-value] | 4.82 [0.030] | 14.78 [0.004] | 8.55 [0.004] | 19.06 [0.001] | 2.73 [0.096] | 4.33 [0.039] | 2.55 [0.113] | 5.98 [0.016] | 4.60 [0.034] | 15.35 [0.000] |
| N | 4572 | 4572 | 4572 | 4572 | 4572 | 4572 | 4572 | 4572 | 4572 | 4572 |

| Panel B: 1 st -stage | Import of G-S (1) | Export of G-S (2) | Intermediate G-S (3) | Final G-S (4) |
|---|----------------------|----------------------|-------------------------|----------------------|
| $Z_{gravity}$ | 0.287*** (0.034) | 0.252*** (0.060) | 0.282*** (0.034) | 0.268*** (0.052) |
| $Z_{oil-distance}$ | -0.077*** (0.011) | 0.003 (0.018) | 0.008 (0.013) | -0.116*** (0.019) |
| 1 st -stage F-statistic | 134.47 | 15.75 | 54.76 | 75.85 |
| 1 st -stage Sanderson-Windmeijer Weak Instrument F-statistic | 36.49 | 34.02 | 65.33 | 70.59 |
| 1 st -stage Kleibergen-Papp F statistic | 8.21 | | 13.56 | |
| N | 4572 | 4572 | 4572 | 4572 |

Notes: The sample is developing countries, which are low and middle-income countries according to the World Bank income classification in 2018. Panel A presents IV results, while Panel B presents 1st-stage results. In Panel A's odd-numbered columns, imports and exports are the regressors while in even-numbered columns it is trade in intermediate goods and services (G-S) and trade in final G-S. Outcomes differ across columns in Panel A: in cols. (1)-(2), effective tax rate on capital, ETR_K ; in cols. (3)-(4), effective tax rate on labor, ETR_L ; in cols. (5)-(6), corporate income share of net domestic product; in cols. (7)-(8), mixed income share of net domestic product; in cols. (9)-(10), average effective tax rate on corporate profits. For details on the outcomes and the instruments, see Table 1.1 and 1.3. Relative to those tables, the drop in sample size in this table is due to availability of the type of trade classification. For each coefficient, we report in brackets the p-values which correct for multiple hypotheses testing, using the Romano-Wolf method. Multiple hypothesis testing is accounted for within each outcome between the two IV estimations (exports and imports; final G-S and intermediate G-S). At the bottom of each column in Panel A, we report the F-test for the equality of coefficients. In Panel B, cols. (1)-(2) correspond to the first-stage regression that instruments simultaneously for imports and exports; cols. (3)-(4) is the first-stage regression which instruments simultaneously for intermediate G-S and final G-S. In Panel B, we report the F-statistic of excluded instruments; the Sanderson-Windmeijer multivariate F-test of excluded instruments; and, the Kleibergen-Papp F-statistic. * p<0.10 ** p<0.05 *** p<0.01. Standard errors in parentheses are clustered at the country level. For more details, see Section A1.3.2.

Table A1.7 – Robustness of Results for Total Taxes and Mechanisms

| | (1) | (2) | (3) | (4) | (5) | (6) |
|--|----------------------|-------------------------------------|--|---------------------------------|---|--|
| Panel A: Total taxes (% of NDP) | | | | | | |
| Trade | 0.105* (0.060) | 0.092** (0.039) | 0.097*** (0.031) | 0.106*** (0.032) | 0.099*** (0.032) | 0.170** (0.073) |
| 1 st stage K-P F-stat | 34.51 | 14.14 | 23.09 | 34.84 | 45.17 | 10.75 |
| N | 4916 | 3938 | 4916 | 4916 | 4916 | 4916 |
| Panel B: CIT rate (first-diff.) | | | | | | |
| Trade | 0.004 (0.011) | -0.007 (0.009) | -0.011* (0.006) | -0.013* (0.007) | -0.012* (0.007) | -0.030* (0.016) |
| 1 st stage K-P F-stat | 34.51 | 14.14 | 23.24 | 34.84 | 45.13 | 10.75 |
| N | 4916 | 3938 | 4916 | 4916 | 4916 | 4916 |
| Panel C: $\log(1+\text{CIT rate})$ | | | | | | |
| Trade | -0.009* (0.005) | -0.006 (0.007) | -0.009* (0.005) | -0.010* (0.005) | -0.009* (0.005) | -0.026* (0.014) |
| 1 st stage K-P F-stat | 34.51 | 14.14 | 23.24 | 34.84 | 45.13 | 10.75 |
| N | 4916 | 3938 | 4916 | 4916 | 4916 | 4916 |
| Panel D: Corp. income (% of NDP) | | | | | | |
| Trade | 0.188*** (0.051) | 0.197*** (0.047) | 0.173*** (0.044) | 0.189*** (0.046) | 0.179*** (0.045) | 0.211** (0.104) |
| 1 st stage K-P F-stat | 34.51 | 14.14 | 23.24 | 34.84 | 45.13 | 10.75 |
| N | 4916 | 3938 | 4916 | 4916 | 4916 | 4916 |
| Panel E: Mixed income (% of NDP) | | | | | | |
| Trade | -0.203*** (0.053) | -0.162*** (0.040) | -0.184*** (0.040) | -0.194*** (0.038) | -0.185*** (0.041) | -0.137 (0.112) |
| 1 st stage K-P F-stat | 34.51 | 14.14 | 23.24 | 34.84 | 45.13 | 10.75 |
| N | 4916 | 3938 | 4916 | 4916 | 4916 | 4916 |
| Panel F: Capital share of NDP | | | | | | |
| Trade | 0.102* (0.052) | 0.112** (0.044) | 0.145*** (0.032) | 0.158*** (0.033) | 0.152*** (0.035) | 0.107** (0.052) |
| 1 st stage K-P F-stat | 34.51 | 14.14 | 23.24 | 34.84 | 45.13 | 10.75 |
| N | 4916 | 3938 | 4916 | 4916 | 4916 | 4916 |
| Panel G: Corp. ETR_K | | | | | | |
| Trade | 0.238* (0.156) | 0.189* (0.096) | 0.148** (0.074) | 0.172** (0.077) | 0.160** (0.076) | 0.385** (0.183) |
| 1 st stage K-P F-stat | 34.51 | 14.14 | 23.24 | 34.84 | 45.13 | 10.75 |
| N | 4916 | 3938 | 4916 | 4916 | 4916 | 4916 |
| Modifications to IV in Panel B of Table 1.3 | NDP weights | Include country-year controls | Include 1(oil-rich)*year fixed effects | Winsorize trade at 5%-95% | Only use $Z_{gravity}$ instrument | Only use $Z_{Oil-Dist}$ instrument |

Notes: This table presents robustness checks for trade's impacts on several outcomes in developing countries. Developing countries are low and middle-income countries according to the World Bank income classification in 2018. Trade is the sum of exports and imports divided by net domestic product (NDP). The outcome differs across panels, and the specification differs across columns: each cell is the coefficient from a separate IV regression. We report the 1st-stage Kleibergen-Paap F-statistic separately for each IV regression. Panel A is total taxes as a % of NDP. Panel B is the first-differenced corporate income tax (CIT) rate. Panel C is the percent change from log of (1 + CIT rate). Panel D is the corporate income share of NDP. Panel E is the mixed income share of NDP. Panel F is the capital share of NDP. Panel G is the average effective tax rate on corporate profits. The different specifications across columns are the same as in Table 1.1 - please refer to that table for more details. * p<0.10 ** p<0.05 *** p<0.01. Standard errors in parentheses are clustered at the country level.

Table A1.8 – Impacts of Trade in LMICs, Heterogeneity by Enforcement Policy

| | ETR_K | ETR_L | Corp. income | Corp. ETR_K |
|---|----------|----------|--------------|---------------|
| | (1) | (2) | (3) | (4) |
| Panel A: Large Taxpayer Unit | | | | |
| Trade | 0.116* | 0.013 | 0.171*** | 0.117* |
| | (0.066) | (0.029) | (0.057) | (0.068) |
| Trade* $\mathbf{1}$ (LTU) | 0.089 | 0.084** | 0.019 | 0.113 |
| | (0.077) | (0.040) | (0.051) | (0.131) |
| Implied coef. for Trade with LTU | 0.205*** | 0.098*** | 0.190*** | 0.230** |
| | (0.062) | (0.029) | (0.042) | (0.097) |
| Panel B: Customs-Tax Integration | | | | |
| Trade | 0.121* | 0.018 | 0.172*** | 0.160* |
| | (0.064) | (0.038) | (0.052) | (0.094) |
| Trade* $\mathbf{1}$ (Customs-Tax) | 0.208 | 0.198* | 0.046 | 0.183 |
| | (0.185) | (0.109) | (0.112) | (0.249) |
| Implied coef. for Trade with Customs-Tax | 0.330** | 0.217** | 0.219** | 0.344* |
| | (0.153) | (0.090) | (0.089) | (0.202) |
| Panel C: Value-Added Tax | | | | |
| Trade | 0.116** | 0.015 | 0.171*** | 0.156* |
| | (0.058) | (0.025) | (0.054) | (0.089) |
| Trade* $\mathbf{1}$ (VAT) | 0.101 | 0.096** | 0.022 | 0.085 |
| | (0.081) | (0.043) | (0.054) | (0.115) |
| Implied coef. for Trade with VAT | 0.218*** | 0.111*** | 0.194*** | 0.241*** |
| | (0.064) | (0.032) | (0.045) | (0.087) |
| Panel D: International Accounting Standards | | | | |
| Trade | 0.132** | 0.023 | 0.160*** | 0.183** |
| | (0.054) | (0.022) | (0.051) | (0.088) |
| Trade* $\mathbf{1}$ (IAS) | 0.122 | 0.111** | 0.017 | 0.124 |
| | (0.087) | (0.042) | (0.055) | (0.135) |
| Implied coef. for Trade with IAS | 0.255** | 0.134*** | 0.177*** | 0.307*** |
| | (0.077) | (0.036) | (0.050) | (0.110) |
| N | 4916 | 4916 | 4916 | 4916 |

Notes: This table estimates heterogeneous IV effects of trade in developing countries (low and middle-income countries according to the World Bank income classification in 2018). Trade is the sum of exports and imports divided by net domestic product (NDP). Outcomes differ across columns: column (1) is the effective tax rate on capital, ETR_K ; column (2) is the effective tax rate on labor, ETR_L ; column (3) is the corporate income share of NDP; column (4) is the average effective tax rate on corporate profits. We estimate

$$y_{ct} = \mu \cdot trade_{ct} + \kappa \cdot trade_{ct} \cdot \mathbf{1}(A)_{ct} + \theta \cdot \mathbf{1}(A)_{ct} + \pi_c + \pi_t + \epsilon_{ct}$$

where $\mathbf{1}(A)_{ct}$ is an indicator variable which takes a value of 1 in all years after the administrative reform has been implemented. We instrument for $trade_{ct}$ and $trade_{ct} \cdot \mathbf{1}(A)_{ct}$ using the two instruments (Section 1.5.2). The coefficient on $\mathbf{1}(A)_{ct}$ is also estimated, but is not reported in the table. In Panel A, the administrative reform is the existence of a large taxpayer unit (LTU); this variable is coded based on the USAID's 'Collecting Taxes Database' ([website link](#)) and country-sources. In Panel B, the administrative reform is the integration of the customs authority and the domestic tax authority in a single revenue agency; this variable is coded based on USAID's 'Collecting Taxes Database' ([website link](#)), the OECD Tax Administration Comparative Series ([website link](#)), and country-sources. In Panel C, the administrative reform is the implementation of a value-added tax (VAT); this variable is coded based on Keen and Lockwood (2010) and country-sources. In Panel D, the administrative reform is the adoption of international accounting standards (IAS); this variable is coded based on the IAS country-profiles ([website link](#)). At the bottom of each column and panel, we report the implied coefficient and estimated standard error based on the linear combination of the $trade_{ct}$ and $trade_{ct} \cdot \mathbf{1}(A)_{ct}$ coefficients. * p<0.10 ** p<0.05 *** p<0.01. Standard errors in parentheses are clustered at the country level.

Table A1.9 – Impacts of Trade Outside of Periods of Tax Revenue Loss

| | ETR_K (1) | ETR_L (2) | Corp. income (3) | Corp. ETR_K (4) |
|---|---------------------|---------------------|---------------------|----------------------|
| Panel A: Excluding Trade-Induced Tariff Revenue Loss Periods (based on Cage and Gadenne, 2018) | | | | |
| Trade | 0.151*** (0.056) | 0.047** (0.020) | 0.183*** (0.045) | 0.203** (0.089) |
| N | 3954 | 3954 | 3954 | 3954 |
| Panel B: Excluding Periods of Indirect Tax Revenue Loss | | | | |
| Trade | 0.189*** (0.051) | 0.053*** (0.016) | 0.197*** (0.044) | 0.225*** (0.083) |
| N | 3011 | 3011 | 3011 | 3011 |
| Panel C: Excluding Periods of Total Tax Revenue Loss | | | | |
| Trade | 0.174*** (0.050) | 0.048*** (0.015) | 0.174*** (0.042) | 0.203** (0.081) |
| N | 3016 | 3016 | 3016 | 3016 |

Notes: This IV specification is the same as column (2) in Table 1.1, but modifications are made to the sample of developing countries. In Panel A, we exclude all country-year observations which belong to an episode of trade revenue loss, based on Cagé and Gadenne (2018). In a dataset of 130 countries between 1792 and 2006, the authors define such an episode by a fall in trade tax revenues as a percentage of GDP of at least 1 percentage point from a local yearly maximum to the next local yearly minimum that is accompanied by a non-decrease in the volume of imports as a share of GDP. In Panels B and C, we consider alternative definitions of revenue loss periods. In Panel B, we calculate the within-country yearly change in indirect taxes collected as a share of net domestic product (NDP), and take the three-year moving average. We then create terciles of this variable, separately for each country. We define periods of indirect tax revenue loss to be the observations which lie in the bottom tercile of this distribution, and exclude these country-year observations from the sample. In Panel C, we calculate the same revenue-loss variable, but based on changes in total taxes collected rather than indirect taxes collected. Trade is the sum of exports and imports divided by NDP. The outcome differs across columns: column (1) is the effective tax rate on capital, ETR_K ; column (2) is the effective tax rate on labor, ETR_L ; column (3) is the corporate income share of NDP; column (4) is the average effective tax rate on corporate profits. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. Standard errors in parentheses are clustered at the country level.

Table A1.10 – Heterogeneous Impacts of Trade by Development Level

| | ETR_K | ETR_L | First-diff. CIT Rate | Corp. Totl. Income | Mixed Income | Corp. Profits | Employee Comp. | Corp. ETR_K | Natl. K - Share | Corp. K - Share |
|--|--------------------|--------------------|----------------------------|--------------------------|--------------------|----------------------|---------------------|--------------------|-------------------------|-------------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Trade | 0.253** (0.127) | 0.116** (0.051) | -0.020 (0.021) | 0.279** (0.119) | -0.183* (0.106) | 0.176*** (0.049) | 0.056 (0.104) | 0.445** (0.193) | 0.131** (0.054) | 0.158** (0.064) |
| Trade* $\mathbf{1}$ (High-inc.) | -0.293 (0.215) | 0.014 (0.110) | -0.064* (0.033) | -0.502** (0.218) | 0.340** (0.138) | -0.312*** (0.099) | -0.214** (0.114) | -0.289 (0.320) | -0.197** (0.086) | -0.239** (0.110) |
| Implied coef. for Trade in High-inc. | -0.040 (0.127) | 0.130 (0.095) | -0.084*** (0.020) | -0.223 (0.154) | 0.160 (0.135) | -0.135* (0.072) | -0.158 (0.117) | 0.156 (0.173) | -0.066 (0.056) | -0.081 (0.081) |
| 1 st -stage Kleibergen- Papp F-statistic | 15.34 | 15.34 | 15.34 | 15.34 | 15.34 | 15.34 | 15.34 | 15.34 | 15.34 | 15.34 |
| N | 6489 | 6489 | 6489 | 6489 | 6489 | 6489 | 6489 | 6489 | 6489 | 6489 |

Notes: This table presents IV results from estimating the effects of trade on ETR and mechanism outcomes in the full sample of developing and developed countries. Trade is measured as the sum of exports and imports divided by net domestic product (NDP). We run the following IV regression: $y_{ct} = \mu \cdot trade_{ct} + \kappa \cdot trade_{ct} \cdot \mathbf{1}(HighIncome)_c + \Theta \cdot X_{ct} + \pi_c + \pi_t + \epsilon_{ct}$. The first-stage regression is reported in Table A1.5. At the bottom of each column, we report the implied coefficient and estimated standard error based on the linear combination of the $Trade$ and the $Trade * \mathbf{1}(High-inc.)$ coefficients. High-income is based on the World Bank income classification in 2018. We also report the 1st-stage Kleibergen-Paap F-statistic. Each column is a different outcome: column (1) is the effective tax rate on capital; column (2) is the effective tax rate on labor; column (3) is the first-differenced statutory corporate income tax rate; column (4) is the corporate income share of net domestic product, where corporate income is the sum of corporate profits and corporate employee compensation; column (5) is the mixed income share of net domestic product; column (6) is the corporate profit share of net domestic product; column (7) is the employee compensation share of net domestic product; column (8) is the average effective tax rate on corporate profits; column (9) is the capital share of net domestic product; column (10) is the capital share of corporate income. For more details on outcomes, see Section 1.3.1 and Section 1.6.2. For more details on the instrumental variables, see Section 1.5.2. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. Standard errors in parentheses are clustered at the country level.

Table A1.11 – Main Data Sources

| | Country-year obs. | % |
|-----------------------------|-------------------|-------------|
| Panel A: Tax revenue data | | |
| OECD | 2875 | 42.3% |
| Archives | 2678 | 39.4% |
| ICTD | 1246 | 18.3% |
| <i>N</i> | <i>6799</i> | <i>100%</i> |
| Panel B: Factor income data | | |
| Complete SNA2008 | 2455 | 36.1% |
| Complete SNA1968 | 1360 | 20.0% |
| Composite | 2984 | 43.9% |
| <i>N</i> | <i>6799</i> | <i>100%</i> |

Notes: See Section [A1.1.1](#) for more details on the data-sources for tax revenue and factor income.

Table A1.12 – Trade Liberalization Event-Study Based on Wacziarg and Welch (2008)

| | Trade | ETR_K | ETR_L |
|---|--------------------|--------------------|---------------------|
| | (1) | (2) | (3) |
| Panel A: <i>Benchmark</i> | | | |
| Post*Treat | 0.030 (0.048) | 0.021 (0.017) | 0.006 (0.006) |
| Imputed treatment effect | 0.090* (0.049) | 0.043** (0.016) | 0.021*** (0.005) |
| N | 4032 | 4032 | 4032 |
| Panel B: <i>Fully balanced panel, 10-year post-reform</i> | | | |
| Imputed treatment effect | 0.110** (0.054) | 0.031** (0.014) | 0.018*** (0.005) |
| N | 3082 | 3082 | 3082 |
| Panel C: <i>With region-year fixed effects</i> | | | |
| Imputed treatment effect | 0.084** (0.041) | 0.042** (0.016) | 0.021*** (0.005) |
| N | 4032 | 4032 | 4032 |
| Panel D: <i>Excluding countries with capital liberalization</i> | | | |
| Imputed treatment effect | 0.101* (0.057) | 0.028* (0.017) | 0.014** (0.006) |
| N | 2651 | 2651 | 2651 |
| Panel E: <i>Excluding countries with domestic reforms</i> | | | |
| Imputed treatment effect | 0.056 (0.051) | 0.040** (0.016) | 0.015*** (0.005) |
| N | 3551 | 3551 | 3551 |

Notes: This table shows the results from estimating the difference-in-difference regression and the imputed treatment effect of the 68 trade liberalization events from Wacziarg and Welch (*ibid.*), between 1965 and 2008. The sample is low and middle-income countries, based on the World Bank income classification in 2018. In Panel A, the post*treat coefficient corresponds to the β^{DiD} based on estimating the equation in Section A1.2.3. The imputed treatment effect is based on the method in Borusyak, Jaravel, and Spiess (2021). In Panel B, the sample is restricted to the fully balanced set of countries in the 10 years after the liberalization event. In Panel C, the estimation is augmented with region-by-year interactive fixed effects. In Panel D, the sample excludes all countries that have a capital liberalization reform at any point during the sample-period, based on Bekaert, Harvey and Lundblad (2000). In Panel E, the sample excludes all countries with domestic reforms which coincide in timing with their trade liberalization event, based on Wacziarg and Wallack (2004). Standard errors are clustered at the country level. For more details on the liberalization events, see Appendix A1.2.3. * p<0.10 ** p<0.05 *** p<0.01.

Appendix 1 Figures

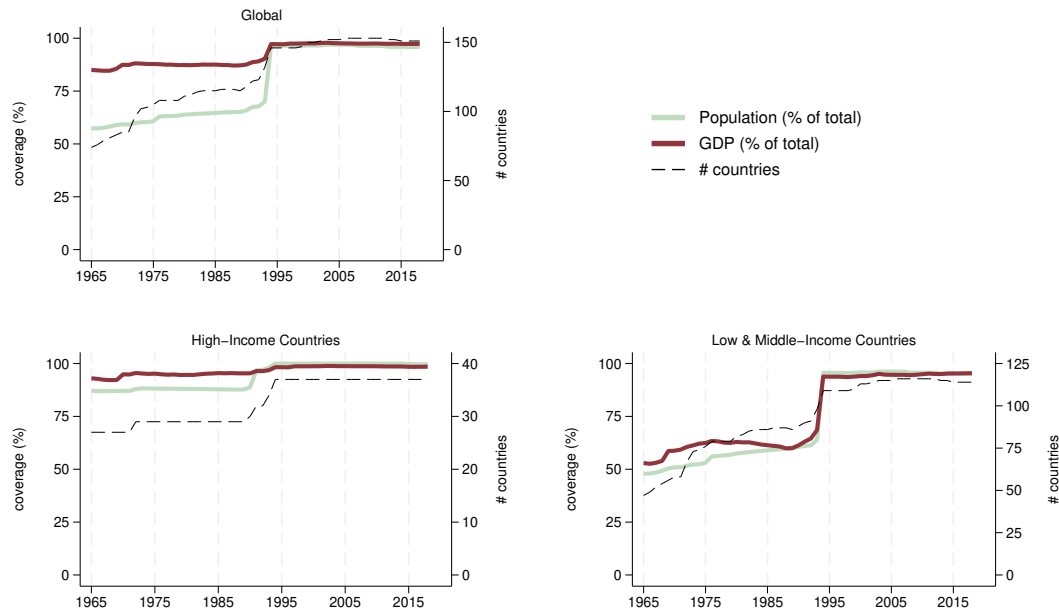
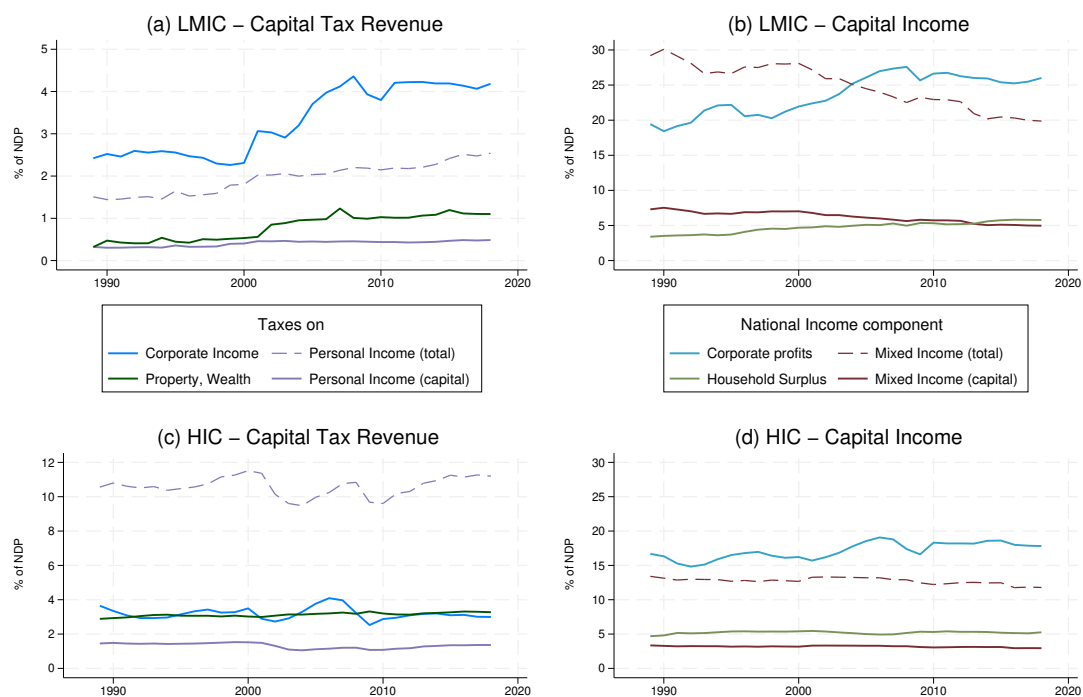


Figure A1.1 – Data Coverage of Effective Tax Rates

Notes: These panels show the coverage of our effective tax rate data between 1965 and 2018 at the global level (top left panel), in high income countries (bottom left panel), and in low- and middle-income countries (bottom right panel). Low, middle and high-income countries are based on the World Bank income classification in 2018. The solid lines plot the percent of total population and GDP that are covered in our data (left axis). The dashed lines show the number of countries in the data (right axis). The dataset is composed of two quasi-balanced panels. The first covers the years 1965-1993 and excludes communist regimes. The second covers 1994-2018 and integrates former communist countries, in particular China and Russia. See Section 1.3.3 for more details.


 Figure A1.2 – Evolution of ETR_K Components since 1989

Notes: These panels show the evolution of the components of ETR_K between 1989 and 2018. This period is selected to match the period of rising ETR_K in low and middle-income countries (LMICs). The left-hand side panels correspond to the taxes on capital (numerator of ETR_K): corporate income taxes; taxes on property, wealth and inheritance; and the share of personal income taxes allocated to capital (including capital gains and dividends). The right-hand side panels correspond to the national income components attributed to capital (denominator of ETR_K): corporate profits; operating surplus of households (rents); and the share of mixed-income attributed to capital. The top panels are for LMICs, while the bottom panels are shown, as comparison, for high-income countries (HICs). Series are weighted by countries' national domestic product in 2010. The tax revenue data between 1989-1993 for former command economies (e.g. China, Russia) is missing, and is imputed by assigning the 1994 values 5 years backward. LMICs and HICs are defined according to the World Bank income classification in 2018. This figure is discussed in Section 1.4.1.

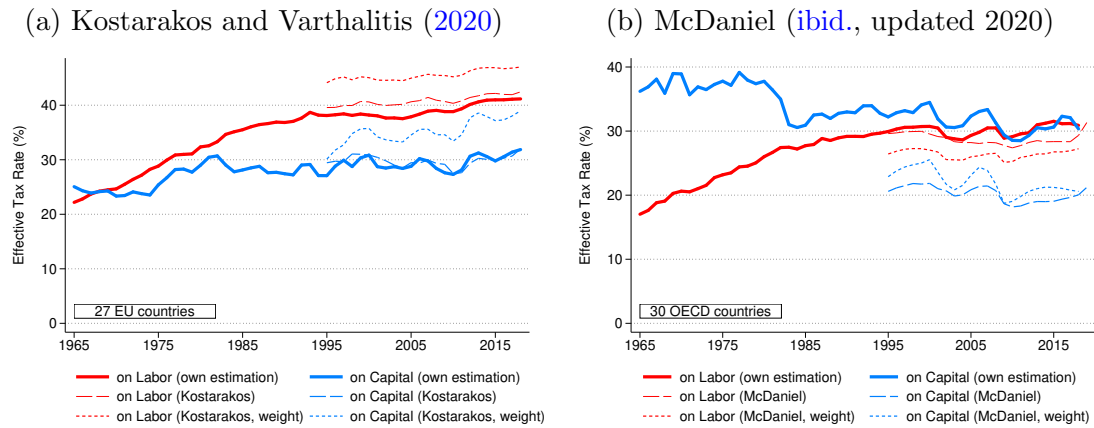


Figure A1.3 – Comparing *ETR* Evolution in Our Data and Existing Studies

Notes: These graphs provide a comparison of our *ETR* estimations with the recent literature. The left-hand graph compares our estimations with Kostarakos and Varthalitis (2020), based on EU-27 members from 1995 to 2019. The right-hand graph compares our estimations with the data in McDaniel (2007, updated 2020) that includes 30 OECD countries from 1995 to 2018. This extension covers the largest OECD countries, including the US, as well as Mexico and Turkey. (See also Table A1.2.) The solid line represents the results using our *ETR* measures and weights, but based on the exact country samples in the respective studies. The long-dash line replicates the *ETR* measures from the two studies. The short-dash line extends their *ETR* series but using our country-year weights. For a discussion of the differences between series, see Section 1.4.2, Table A1.2 and the supplementary appendix.

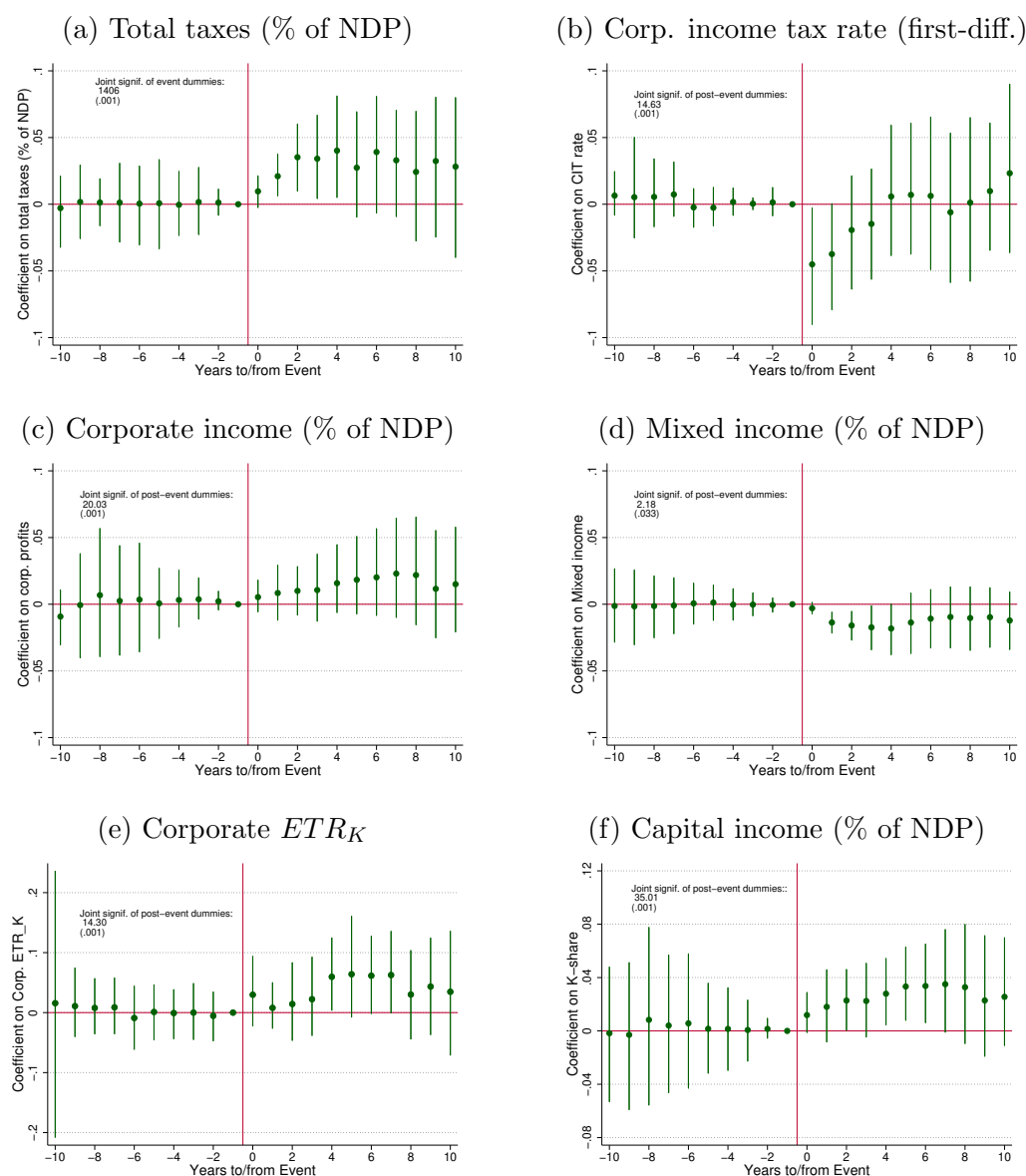


Figure A1.4 – Mechanism Impacts in Trade Liberalization Event Studies

Notes: These panels show the impacts of the trade liberalization events on total taxes collected and mechanism outcomes. The panels are constructed using the method in Section 1.5.1, and similarly to Figure 1.6. Across panels, the outcome differs: panel (a) is total tax revenue, as a percent of net domestic product (NDP); panel (b) is the first-differenced statutory corporate income tax rate; panel (c) is the corporate income share of net domestic product, where corporate income is the sum of corporate profits and employee compensation; panel (d) is the mixed income share of net domestic product; panel (e) is the average effective tax rate on corporate profits; panel (f) is the capital share of net domestic product. In each panel, the top-left corner reports the F-statistic for the joint significance of post-event dummies, with the p-value reported in parentheses.

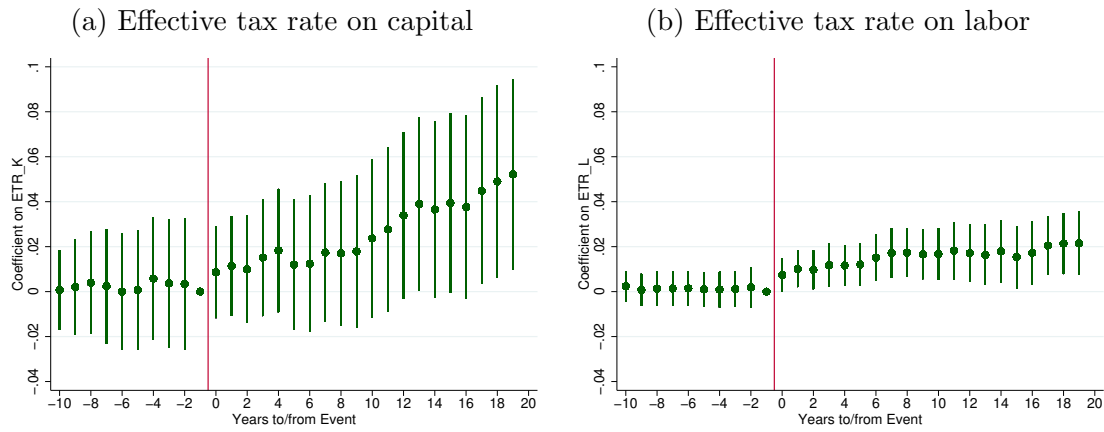


Figure A1.5 – Event-Study of Trade Liberalization Based on Wacziarg and Welch (2008)

Notes: These graphs show event-study impacts of the trade liberalization events from Wacziarg and Welch (*ibid.*) on ETR_K (left panel) and ETR_L (right panel).

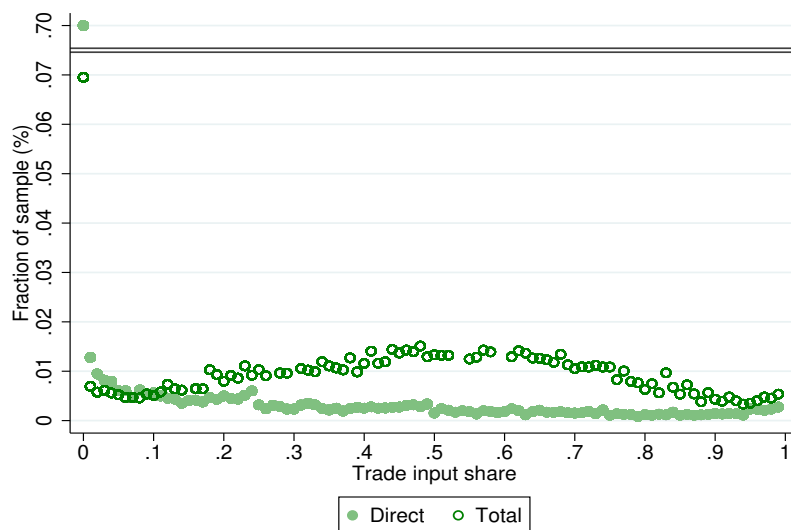


Figure A1.6 – Rwandan Firms’ Direct and Total Exposure to Trade in Imports

Notes: This figure shows the distribution of direct foreign input share, s_{Fi} , and total foreign input share, s_i^{Total} , for all corporate firms in Rwanda between 2015 and 2017. The measures are calculated annually, and the figure pools all firm-year observations. The horizontal line represents a scale break in the vertical axis. More details are in Section [A1.3.1](#).

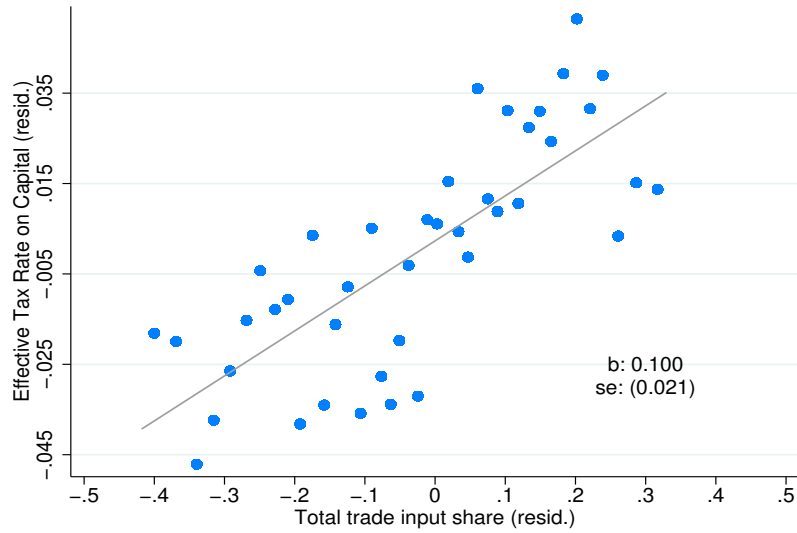


Figure A1.7 – Rwandan Firms’ Trade Exposure and Corporate Effective Tax Rate

Notes: This figure shows the firm-level association between total foreign input share, s_i^{Total} , and the corporate effective tax rate for all corporate firms in Rwanda between 2015 and 2017. The graph plots binned scatters of the variables against each other, after residualizing both variables against year-fixed effects. The dots correspond to equal-sized bins of the residualized trade exposure variable. The line corresponds to the best linear fit regression on the underlying firm-level data ($N = 18478$), which is also reported in column (1) of Table 1.4.

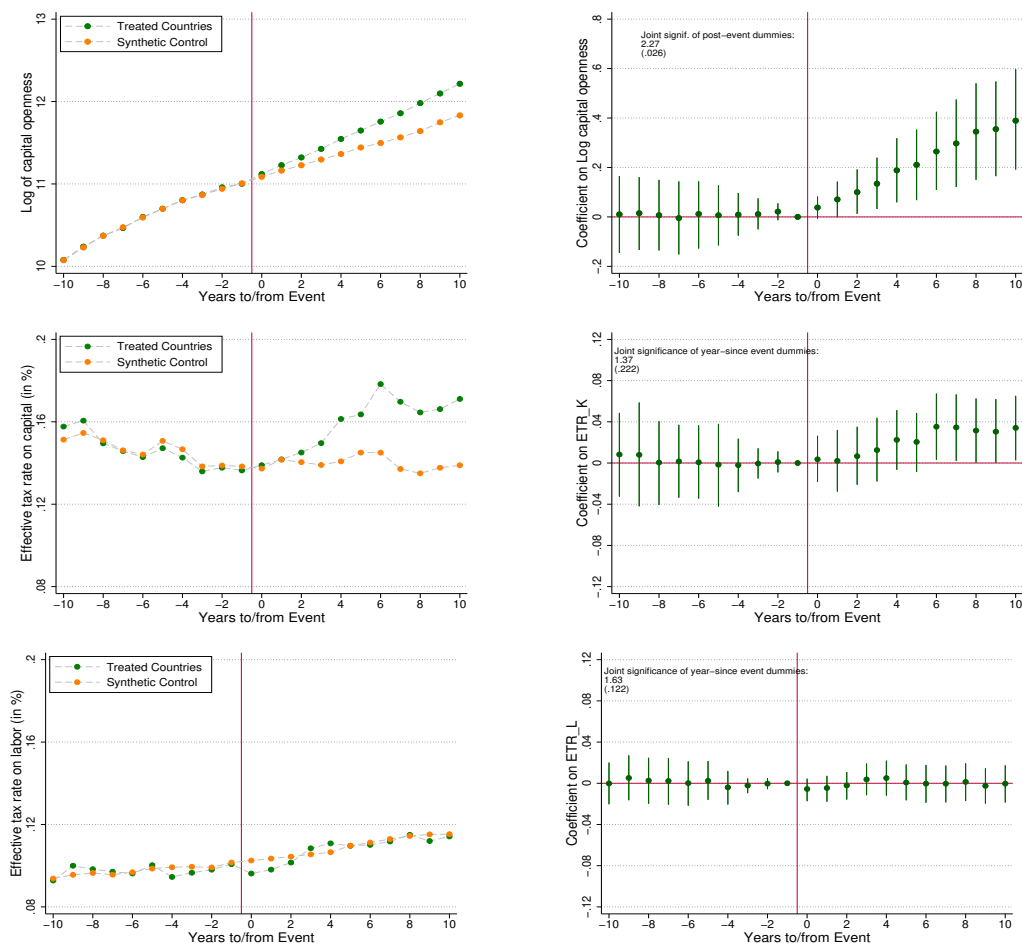


Figure A1.8 – Event Study of Capital Liberalization Reforms

Notes: These panels show event-studies for capital liberalization reforms in the 25 developing countries of Chari, Henry, and Sasson (2012). The panels correspond to different outcomes: capital openness (top panels); effective tax rate on capital (middle panels); effective tax rate on labor (bottom panels). Capital openness is the total sum of the stocks of foreign assets and liabilities, in constant USD. We use the log transformation for this outcome; results where the total sum is expressed as a percent of GDP are similar. The left-hand graphs show the average level of the outcome in every year to/since the event, for treated countries and for synthetic control countries. The right-hand graphs show the estimated β_e coefficients on the to/since dummies, based on equation (1.4) but where the trade liberalization events are replaced with capital liberalization events. The bars represent the 95% confidence intervals. Standard errors are clustered at the country level and estimated with the wild bootstrap method. The top-left corners report the F-statistic on joint significance of the post-event dummies, with the p-value in parentheses. Details are in Appendix A1.4.

Appendix A2

Appendix to Chapter 2

Government Redistribution and Development

A2.1 Distribution of Personal Income Taxes

In this appendix section, expanding on section 2.2.3 above, we provide more detail on methods and data used to estimate the distribution of personal income taxes. 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. We retrieve these exemption thresholds for more than 90 countries from Jensen (2022), and retrieve the missing country-years from Bachas et al. (2022). Bachas et al. (*ibid.*) 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.

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 average and marginal statutory income tax rates 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. 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 the remaining country-years (and to check robustness) we retrieve statutory (marginal) rates schedules from Ernst & Young (2006-23) and PwC (2023) and similar sources online, including national tax authorities' legislative documents and independent scholarly accounts. 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.

Note that we also distinguish between individualized and joint personal income taxation systems: Some countries tax married couples together (or allow tax units this option), and some countries tax individual incomes separately. The former, joint taxation, conforms naturally to the benchmark WID pretax DINA income concept, as these distributions are estimated for “equal-split adults” (where households' total income is split equally among all adult members). However, where PIT systems tax individual incomes, we must transform the WID pretax income distribution from that of “equal-split” adults to that of “individualized” adults.¹ We do this by way of microdata from the International Labour Organization (2020), whose universe of labor force survey microdata represents more than 100 countries since the 1990s. For countries whose PIT systems are individual but for which no (household-identified, individual) income survey microdata exists, we use “nearest-neighbor matching” to simulate the effect, matching the microdata from a handpicked neighboring country. For tractability and reliability of the estimate, we

¹Note that individualized income distributions are more unequal than equal-split income distributions. This is so by construction among top earners (only if all top earners were married to each other would their equal-split incomes equal their individualized incomes), and generally true throughout the distribution. The left tail of the individualized distribution contains many more observations with zero incomes (non-working spouses).

implicitly assume a generalized country fixed-effect [rather than by country and year, i.e., we do not allow each country's distribution-wide correlations between individualized and equal-split incomes to vary over time] and only use the latest-year survey.² In this way, we are able to estimate the ratio of individualized income to equal-split income, across the g-percentile distribution, and to easily move back-and-forth between equal-split and individualized income distributions.

After we assign taxes to individuals, we can transform the taxes paid by each household—from an effective rate on individualized income, to an effective rate on equal-split income. For example, for a married couple in an individualized tax system, earning two different levels of income and being taxed at two different rates, this transformation adds up both the incomes earned and the taxes paid by the couple, then divides these by two for the uniform effective rate on their (identical, by construction) equal-split incomes. For countries whose PIT system is on individuals' incomes rather than taxing married couples jointly, this ILO-microdata transformation effectively moves an individualized income tax schedule onto the equal-split income distribution, with effective tax rates transformed accordingly.

Finally, we account for the empirical regularity that capital income is taxed less than labor income in PIT systems worldwide.³ For each country for which we observe tax revenue aggregates (and statutory PIT rates on taxable income), we also tabulate the country's tax rates toward dividends and capital gains. While there are nuances within many tax administrations' policies on the taxability of dividends and capital gains [and other types of capital incomes], we simplify concepts for tractability on tax rates and tax bases in a DINA framework: Our benchmark concept for the rate of dividend taxation is the rate at which a resident is taxed on dividends from domestic companies. Similarly, our benchmark concept for the rate of capital gains taxation is the rate at which a resident is taxed on gains from selling shares in domestic companies. In the latter case, we also acknowledge reduced rates, or exemptions on short- vs. long-term capital gains, or other nuances in the treatment of this type of income.

These are not the only types of capital income that are taxed by PIT systems, but in our view they are the most significant and telling. Among other types of capital income that may be subject to tax in a PIT system: Mixed income comprises a capital share and a labor share; however, in most countries *all* self-employment income is taxed similarly to labor income from salaries and wages. Beyond that, many PIT systems cover (capital) income from rentals, from interest, from royalties, etc. It is perhaps worth noting that, from a DINA perspective, these are not in the “primary generation of income” account and would actually be double-counting part of national income if they were counted as individual's income without subtracting the corresponding part from, e.g., corporate profits (which indeed they would be in any fiscal system). In this sense, it seems reasonable to leave our simplified PIT simulation as taxing distributed (dividend) and

²It is true that labor force participation—including among spouses—and assortative matching of high-income earners may change over time, but it is also true that this survey data is not the most reliable source to capture the entire effect, as it has little to say about capital income nor about household enterprise. In detailed DINA studies of the United States and France, the disparity between individualized and equal-split distributions has remained relatively stable over the past 40 years.

³Globally, we find that only 36% of corporate operating surplus (profits) is distributed in the form of dividends.

undistributed (capital gain) corporate profits, with these two elements (summing to total corporate profits in the national accounts) also serving as a proxy for the tax treatment of other capital incomes. In any case, the tax treatment of interest, rents and royalties is usually very similar to that of dividends and capital gains. In our view, dividends and capital gains taxation represent emblematic proxies which together serve to cover what is *taxable* in pretax DINA capital incomes.

To assign dividend and capital gains rates that vary by country allows us a treatment of capital incomes under PIT systems that matches the rigor of the above-mentioned statutory rates on labor (salary, wage, and self-employment) income. The upshot is that much of capital income is untaxed, or taxed at a lower rate. Taxable income (in this concept) is less than total pretax income (in the DINA sense), and particularly so for the top g-percentiles where capital income is concentrated. Among DINA income concepts, we also exclude from the PIT tax base: imputed rent, government operating surplus, and indirect taxes. Social insurance benefits received are taxed as (deferred) labor income.

The elements of the PIT system, in this simplified simulation, can be summarized as follows, to estimate the tax rate τ for any g-percentile p and its corresponding income level z :

$$\tau(z)_{PIT} = \sum_{j=1}^3 \frac{\tau_j z_j}{z}$$

where j refers to three types of PIT taxes (with taxable incomes z_j taxed at rate τ_j):

- labor income (employee compensation and mixed income⁴);
- dividend income (distributed corporate profits); and
- capital gains income (undistributed corporate profits).

After building this statutory rate schedule, we fit its “predicted” revenues to actual PIT revenues received, observed in Bachas et al. (2022) and corresponding to T_{PIT} in equation (2.2) 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 “predicted” statutory rates above do not match—but rather 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., tax evasion or avoidance; unobserved deductions, allowances, exemptions and tax breaks that vary with income; differences within the rate schedule according to different types of [non-]taxable income, etc.).

Since we do not necessarily observe all the nuances by which an effective tax rate may differ from the statutory rate (even if we think that we have captured the main drivers above), we are *almost* forced to assume that the effective rate schedule retrieved from our statutory rate schedule is the correct one (i.e., that the “true” effective rate schedule is proportional to our estimated statutory rate

⁴All of self-employment (*viz.* mixed) income is treated as labor income, for the purposes of this PIT simulation—as is the case in most PIT systems.

schedule)—and holds as valid for the distribution of personal income tax rates along the pretax income distribution.

However, we do not have to leave this as an assumption, and can instead test its robustness (as a goodness-of-fit) against the existing DINA studies mentioned above. For reference, see Appendix Figure [A2.23](#) 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 (DINA) 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 set of parameters listed above (the minimum from which we can estimate PIT incidence, as discussed here).

A2.2 Measures of Fiscal Progressivity

In our main analysis, we summarize the progressivity of taxes (and/or transfers) with the percent difference in inequality, measured as the top 10% to bottom 50% average income ratio, before and after removing taxes from (and/or adding transfers to) individual incomes. This is equation (2.6):

$$\gamma_\tau = \frac{r_{pre} - r_{net}}{r_{pre}}$$

After some algebra, this absolute progressivity statistic γ_τ —the redistribution ratio representing the percent reduction in inequality from fiscal policy—reduces to:⁵

$$\gamma_\tau = \frac{\overline{ETR}_{p90p100} - \overline{ETR}_{p0p50}}{1 - \overline{ETR}_{p0p50}} \quad (\text{A2.1})$$

Since γ_τ is a function only of the ETR profile (i.e., of the bracket average ETRs at the top and bottom of the income distribution), it is independent of the pretax inequality ratio r_{pre} . For the same ETR profile, γ_τ highlights the same percentage of redistribution, regardless of the overall level of inequality.

We note, however, that the “naive” γ_τ of equations (2.6) and (A2.1) is sensitive to variations in the pretax income distribution *within* the top 10% or bottom 50% shares, i.e., different distributions of $p90p100$ or $p0p50$ incomes that would still deliver the same *average* income for the top 10% or bottom 50% shares, respectively.

To see why, imagine a monotonically increasing ETR profile within the bottom 50% of earners, e.g., from $ETR = 0\%$ at $p0$ to $ETR = 10\%$ at $p50$, and a steeply increasing income profile within the same bottom 50% of earners, such that most of the income of the bottom 50% is near $p50$. In this case, the average ETR of the bottom 50% of earners would be close to 10% (the ETR at $p50$). By contrast, if the income distribution were closer to flat within the bottom 50%, the same ETR profile would deliver an average ETR closer to 5%. The redistribution ratio would be higher in latter case (where the average ETR of the bottom 50% is lower). The same idea holds for the top of the distribution $p90p100$. Intuitively, we would prefer a progressivity statistic that delivers the same results when applying a given ETR profile to any pretax income distribution—and even robust to distributional variance within $p0p50$ or $p90p100$ (at the same \bar{y}_{p0p50} and $\bar{y}_{p90p100}$).

To test sensitivity and resolve this potential source of bias, we normalize pretax income distributions across all countries and years. Following the literature from Kakwani (1977) through Gerber et al. (2020), we assign as constant the arbitrary income distribution $y_p = p^2$, a distribution whose inequality ratio r_{pre} happens to be

⁵To arrive at equation (A2.1), we put r_{net} in terms of r_{pre} and plug into equation (2.6):

$$r_{net} = \frac{\bar{y}_{p90p100}^{net}}{\bar{y}_{p0p50}^{net}} = \frac{\bar{y}_{p90p100}^{pre} - \bar{y}_{p90p100}^{pre} \cdot \overline{ETR}_{p90p100}}{\bar{y}_{p0p50}^{pre} - \bar{y}_{p0p50}^{pre} \cdot \overline{ETR}_{p0p50}} = \frac{\bar{y}_{p90p100}^{pre}(1 - \overline{ETR}_{p90p100})}{\bar{y}_{p0p50}^{pre}(1 - \overline{ETR}_{p0p50})} = r_{pre} \cdot \frac{1 - \overline{ETR}_{p90p100}}{1 - \overline{ETR}_{p0p50}}$$

$$\gamma_\tau = \frac{r_{pre} - r_{pre} \cdot \frac{1 - \overline{ETR}_{p90p100}}{1 - \overline{ETR}_{p0p50}}}{r_{pre}} = 1 - \frac{1 - \overline{ETR}_{p90p100}}{1 - \overline{ETR}_{p0p50}} = \frac{(1 - \overline{ETR}_{p0p50}) - (1 - \overline{ETR}_{p90p100})}{1 - \overline{ETR}_{p0p50}}$$

close to the median value observed in our data. From this normalized pretax distribution, we calculate the net-of-tax distribution, as always, by subtracting taxes according to each country-year's observed ETR profile. Results of this exercise, in Figure A2.24, are visibly similar to those of the earlier Figure 2.4 (above).

In this way, we generate a statistic that is independent of all variation in pretax income distributions, while still capturing qualities of both relative and absolute progressivity.

By *relative* progressivity, we refer to the comparison of the ETR on top 10 percent earners vs. on bottom 50 percent earners (expressed as the percent difference $\frac{ETR_{p90p100} - ETR_{p0p50}}{ETR_{p0p50}}$, visible in, e.g., Figure A2.25). A higher ratio between the two would be more progressive, by construction. Other, similar measures of relative progressivity could include the regression coefficient (slope) of the tax rate profile (see Peter, Buttrick, and Duncan, 2010, and section 2.2.4 above)—but of course one would also want to know the y-axis intercept and not only the slope of the profile. These measures, then, while relatively informative, do not necessarily account for the total level of taxation.

With an *absolute* progressivity statistic, we do account for the total level of taxation. If the slope of the ETR profile is greater than (less than) zero, an increase in total taxation is an increase (decrease) in absolute progressivity, even with no change in the slope of the ETR profile (see Kakwani, 1977). For this reason, our benchmark measure of fiscal progressivity is the one in equations (2.6) and (A2.1) above.

Appendix 2 Tables

Table A2.1 – Extent of Redistribution by World Region: Decomposition by Tax and Transfer, 1980

| | World Average | Anglosphere | Western Europe | Eastern Europe | Latin America | Asia | Africa |
|-------------------------|------------------|-------------|-------------------|-------------------|------------------|-------|--------|
| Personal Income Taxes | 4.4% | 12.4% | 14.0% | 3.7% | 4.6% | 3.1% | 3.2% |
| Corporate Taxes | 4.2% | 3.7% | 3.7% | 4.4% | 4.0% | 4.6% | 3.3% |
| Property & Wealth Taxes | 0.6% | 0.8% | 1.3% | 0.6% | 0.4% | 0.6% | 0.0% |
| Indirect Taxes | -7.7% | -7.3% | -14.7% | -23.4% | -10.2% | -6.9% | -3.3% |
| Social Contributions | -1.3% | -5.7% | -2.5% | -6.6% | -0.7% | -0.9% | 0.2% |
| All Taxes | 3.1% | 12.1% | 9.5% | -12.3% | 0.9% | 2.9% | 4.2% |
| Social Assistance | 10.4% | 16.6% | 22.9% | 20.7% | 23.5% | 7.5% | 5.5% |
| Healthcare | 10.3% | 28.4% | 15.8% | 11.2% | 20.3% | 7.5% | 6.5% |
| All Transfers | 18.3% | 36.7% | 33.4% | 28.2% | 34.7% | 14.2% | 10.9% |

Notes: Population-weighted averages of indicators in each country. The table reports the negative of the percent change in the top 10% to bottom 50% income ratio before and after removing the corresponding tax or adding to corresponding transfer to pretax income. For instance, the top row reports the percent reduction in inequality resulting from removing personal income taxes from individual incomes. Positive values indicate that the corresponding tax or transfer reduces inequality.

Appendix 2 Figures

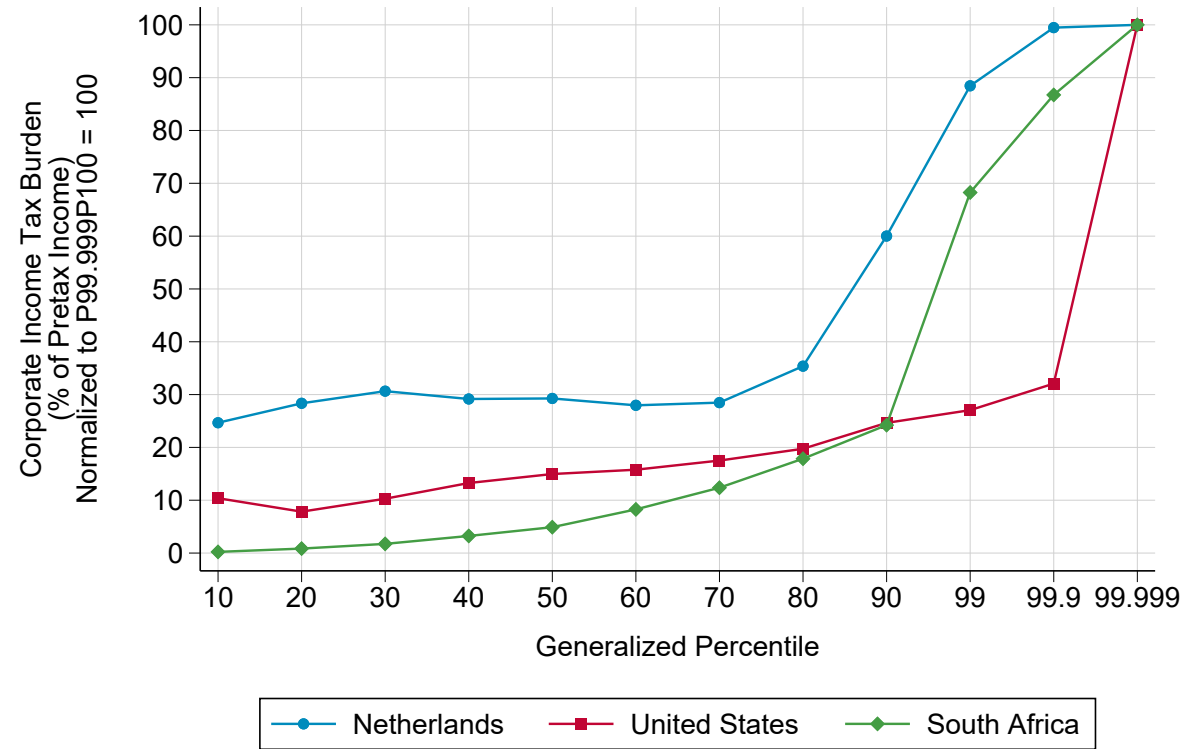


Figure A2.1 – Corporate Income Tax: Selected Estimates of Corporate Income Tax Progressivity

Notes: Netherlands data from Bruil et al. (2022), 2016. United States data from Piketty, Saez, and Zucman (2018), 2019. South Africa data from Chatterjee, Czajka, and Gethin (2021), 2010-2019 average.

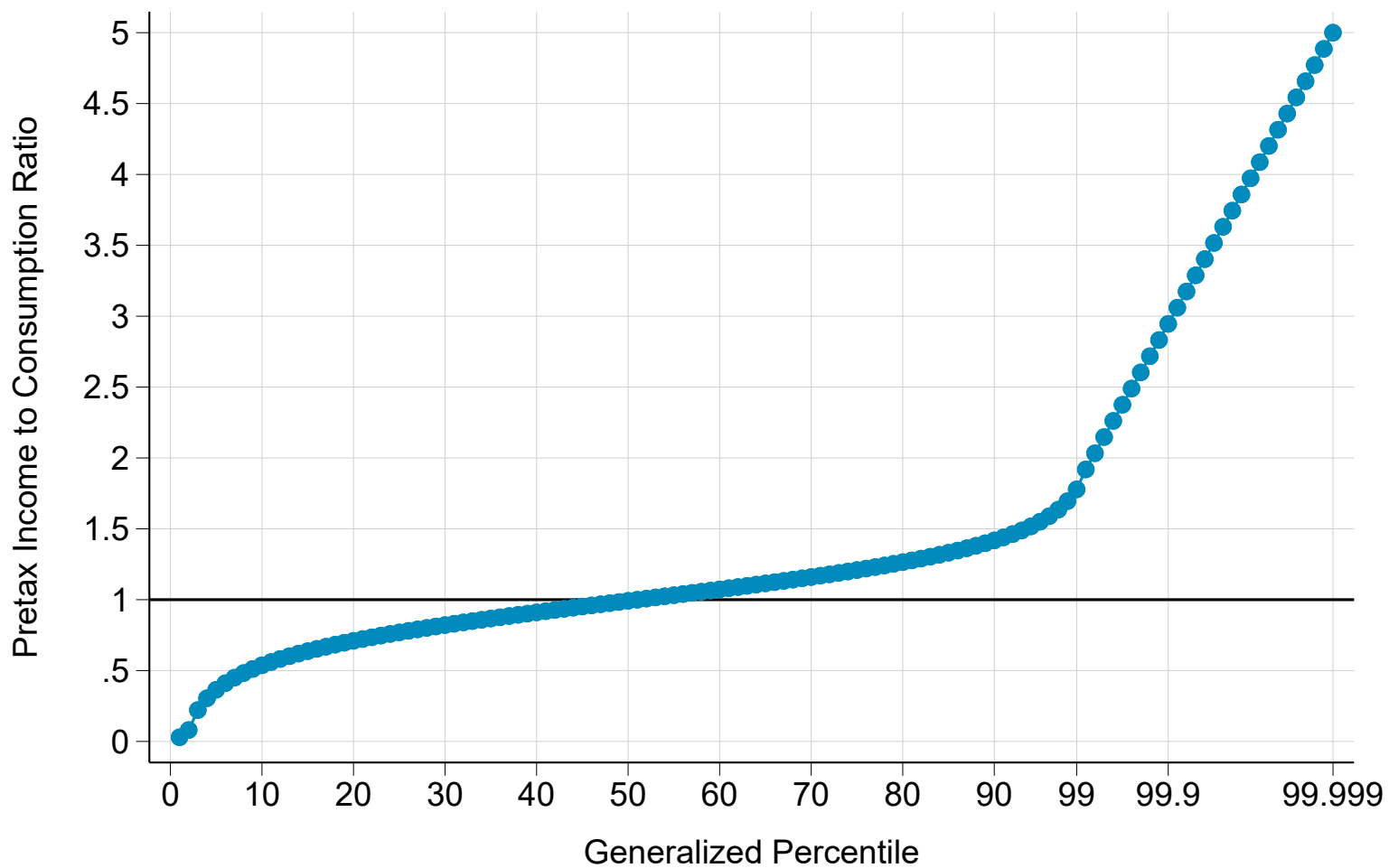


Figure A2.2 – Distributional Incidence Profiles: Income to Consumption Ratio

Notes: Authors' elaboration. The figure plots the stylized profile used to estimate consumption from pretax income in each country. See Chancel et al. (2023) for more details.

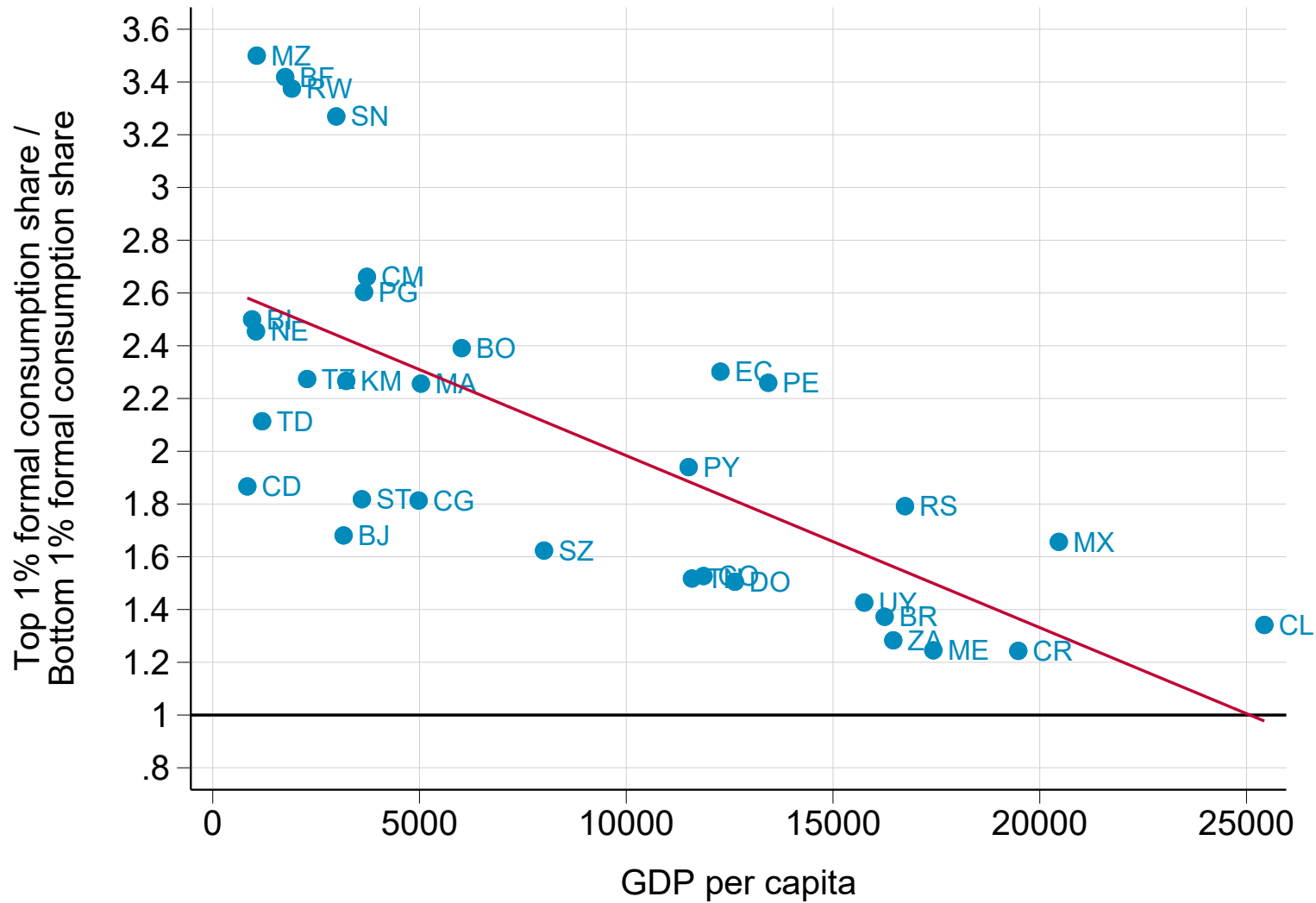


Figure A2.3 – Informal Consumption Elasticity and Economic Development

Notes: Authors' elaboration combining data from the World Inequality Database (GDP per capita) and *ibid.* (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.

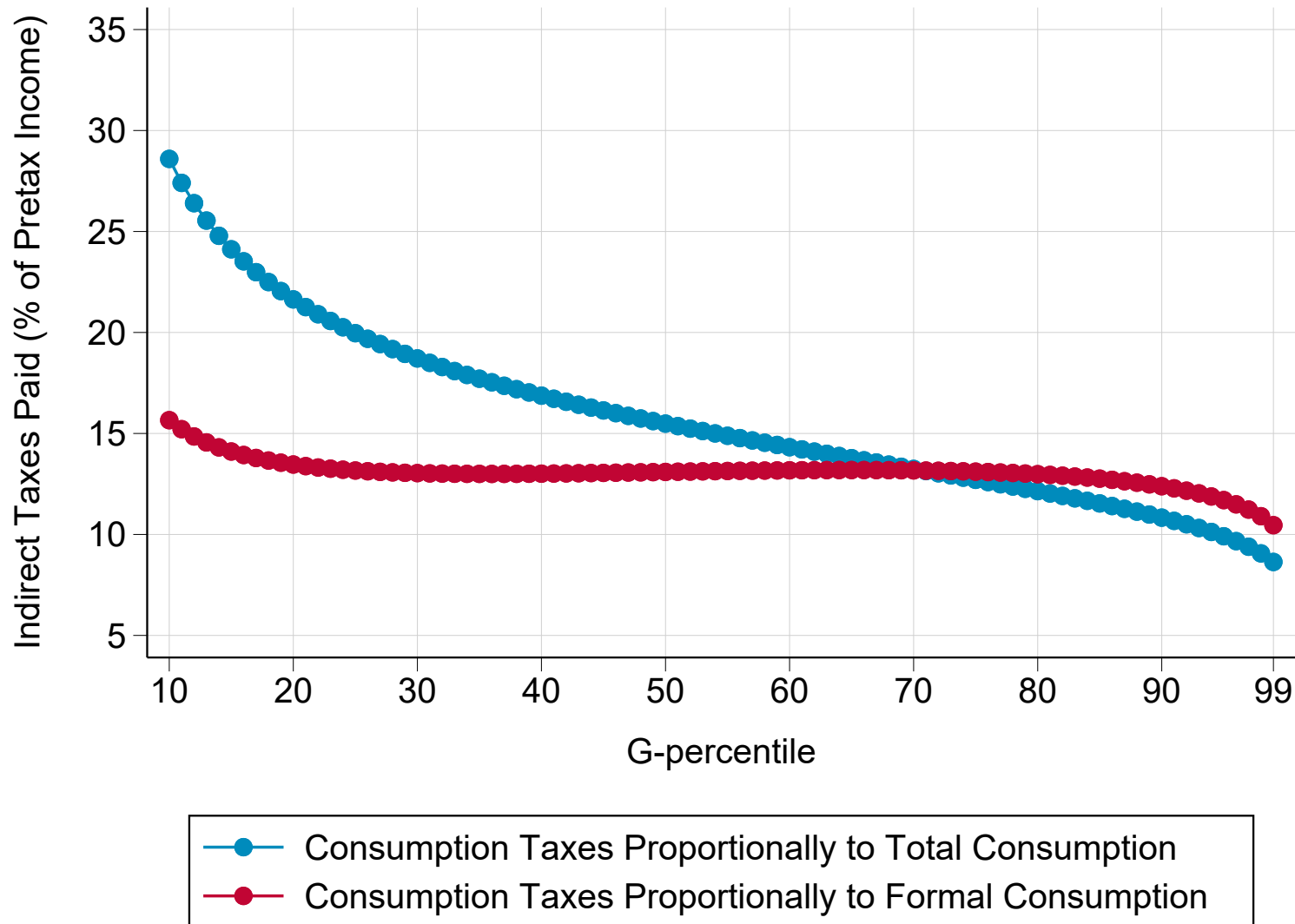


Figure A2.4 – Incidence of Indirect Taxes and Informality: Niger, 2019

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.

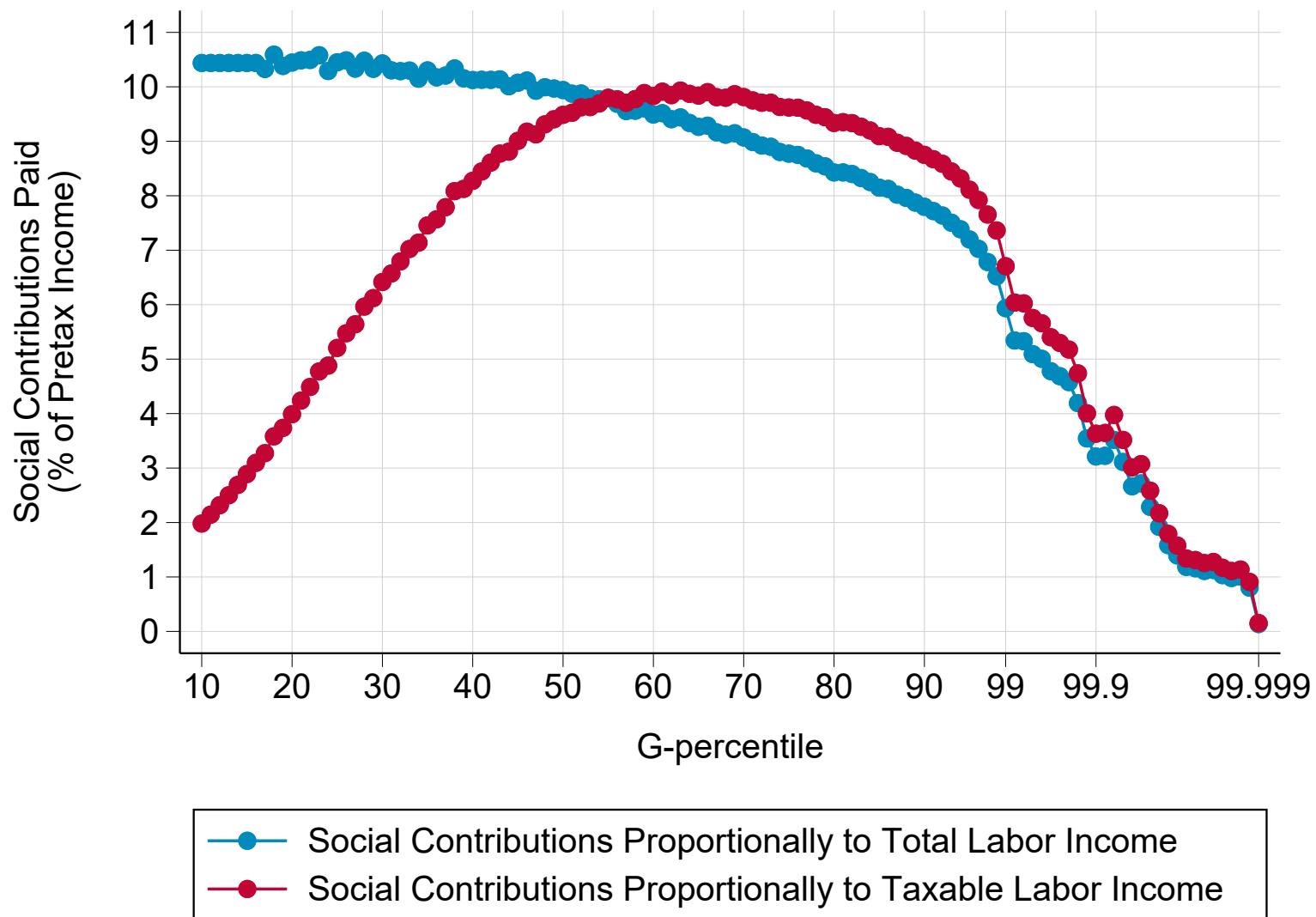


Figure A2.5 – Incidence of Social Contributions and Informality: Argentina, 2019

Notes: Authors' elaboration. The figure compares the distributional incidence of social contributions in Argentina before and after accounting for the fact that contribution payments differ 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.

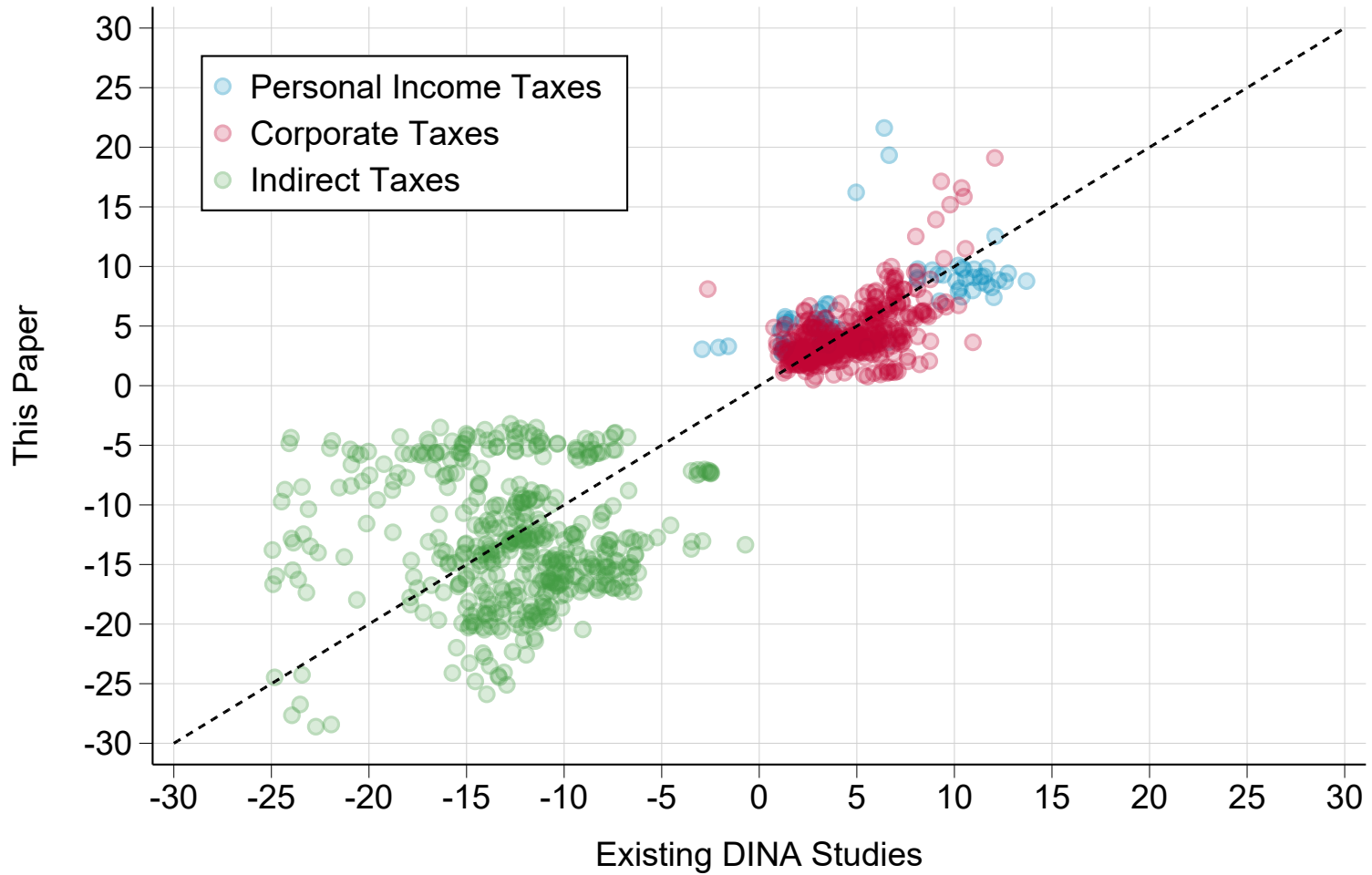


Figure A2.6 – Validation: Comparison of Distributional Tax Incidence, by Type of Tax

Notes: Axes represent tax progressivity summary statistic γ_τ .

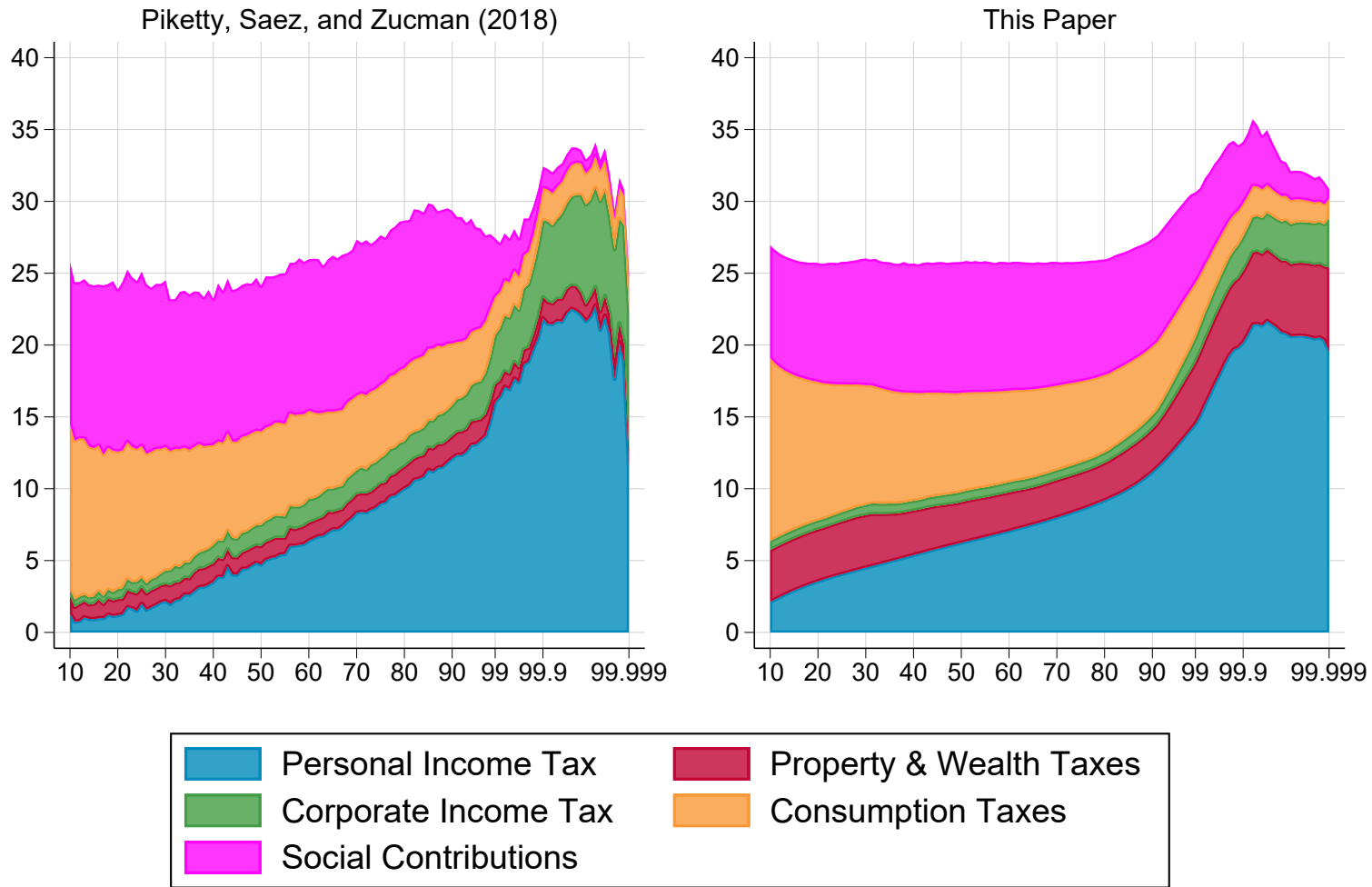


Figure A2.7 – Validation: United States
Level and Composition of Taxes Paid by Generalized Percentile

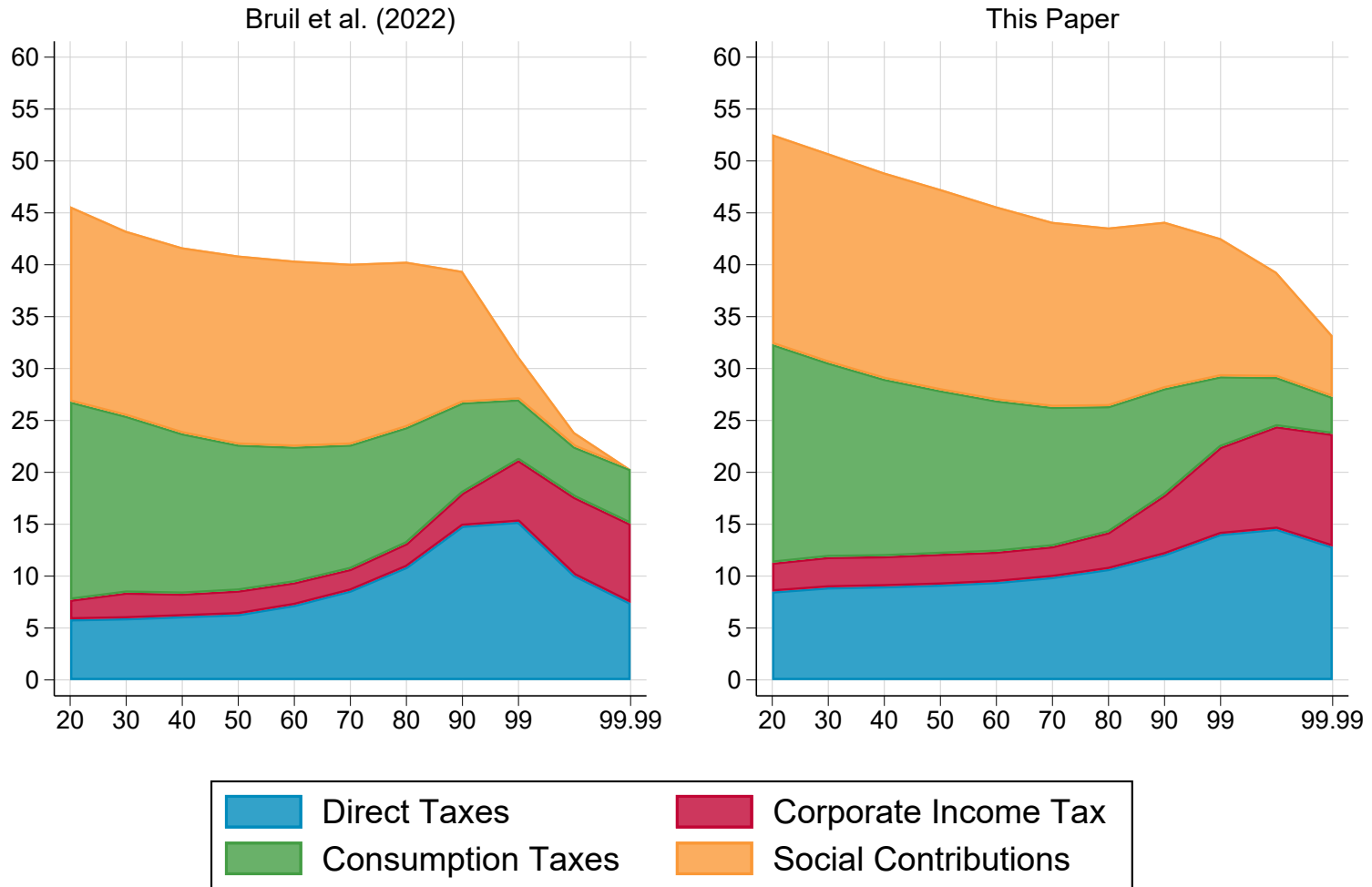


Figure A2.8 – Validation: Netherlands
Level and Composition of Taxes Paid by Generalized Percentile

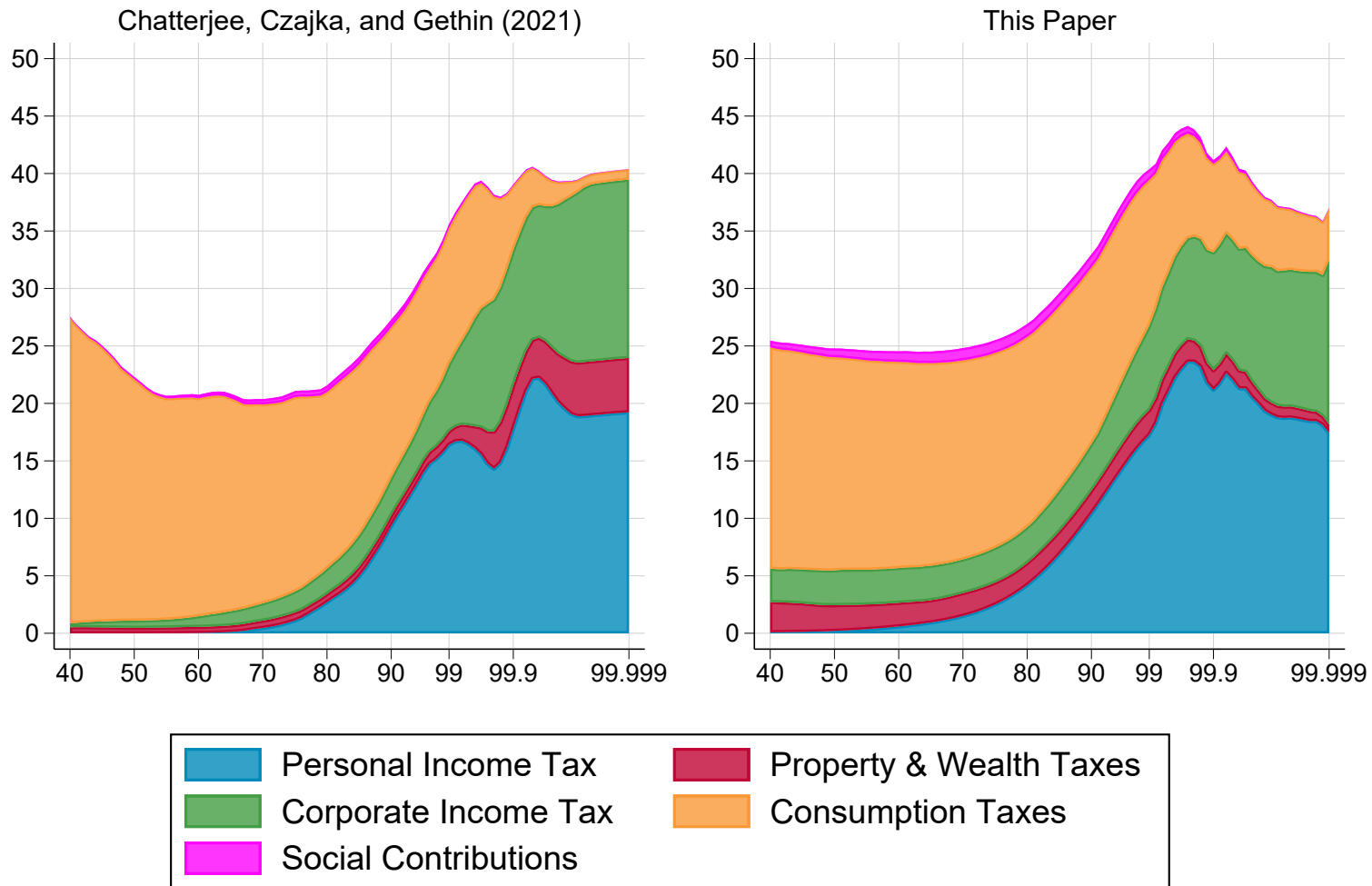


Figure A2.9 – Validation: South Africa, 2019
 Level and Composition of Taxes Paid by Generalized Percentile

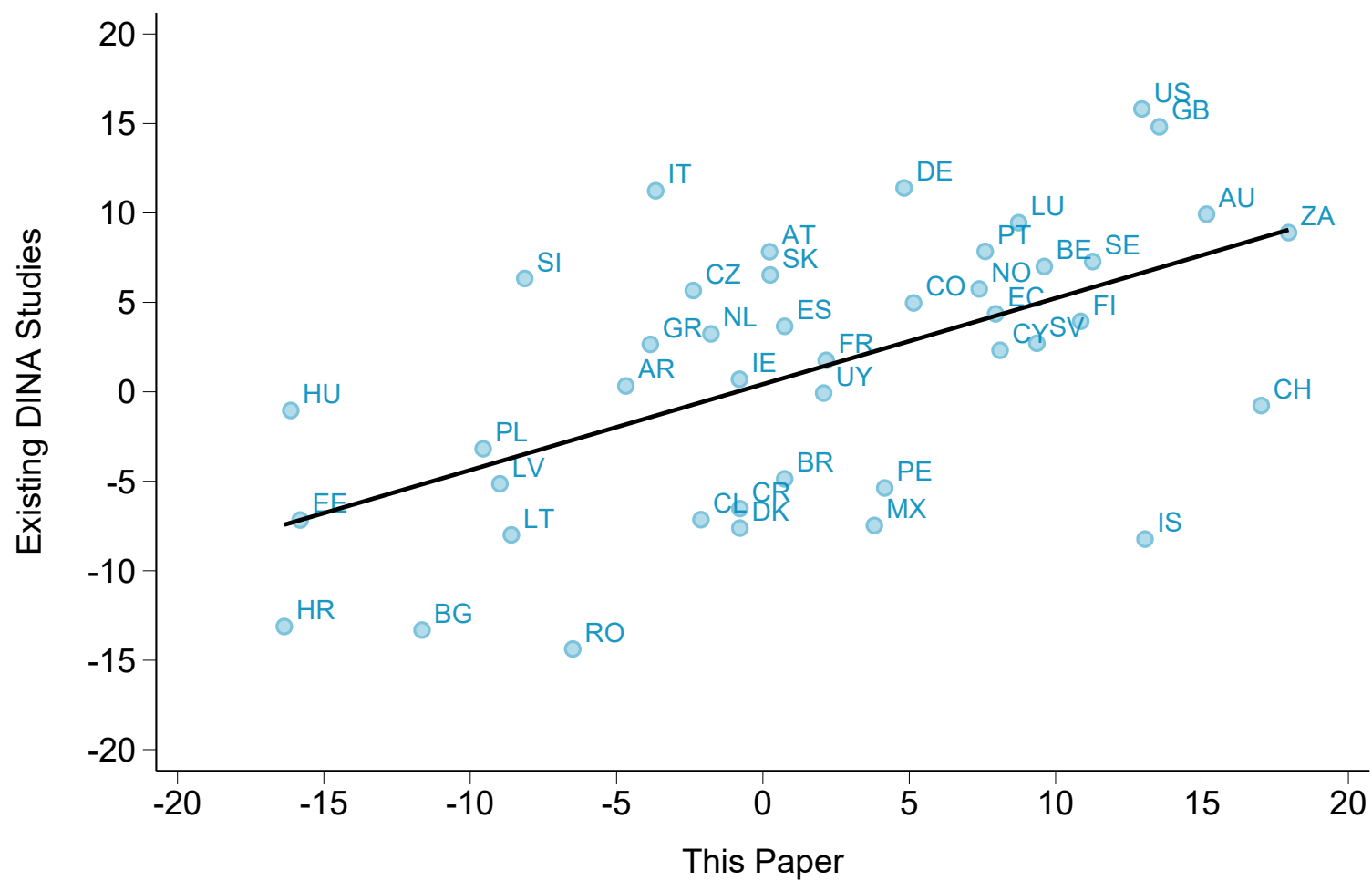


Figure A2.10 – Validation: Cross-Country Differences in Tax Progressivity

Notes: Authors' elaboration. The figure compares our estimates of tax progressivity to that of DINA papers across all country-years available. Tax progressivity is measured as the percent difference in the top 10% to bottom 50% average income ratio before and after removing taxes from pretax income.

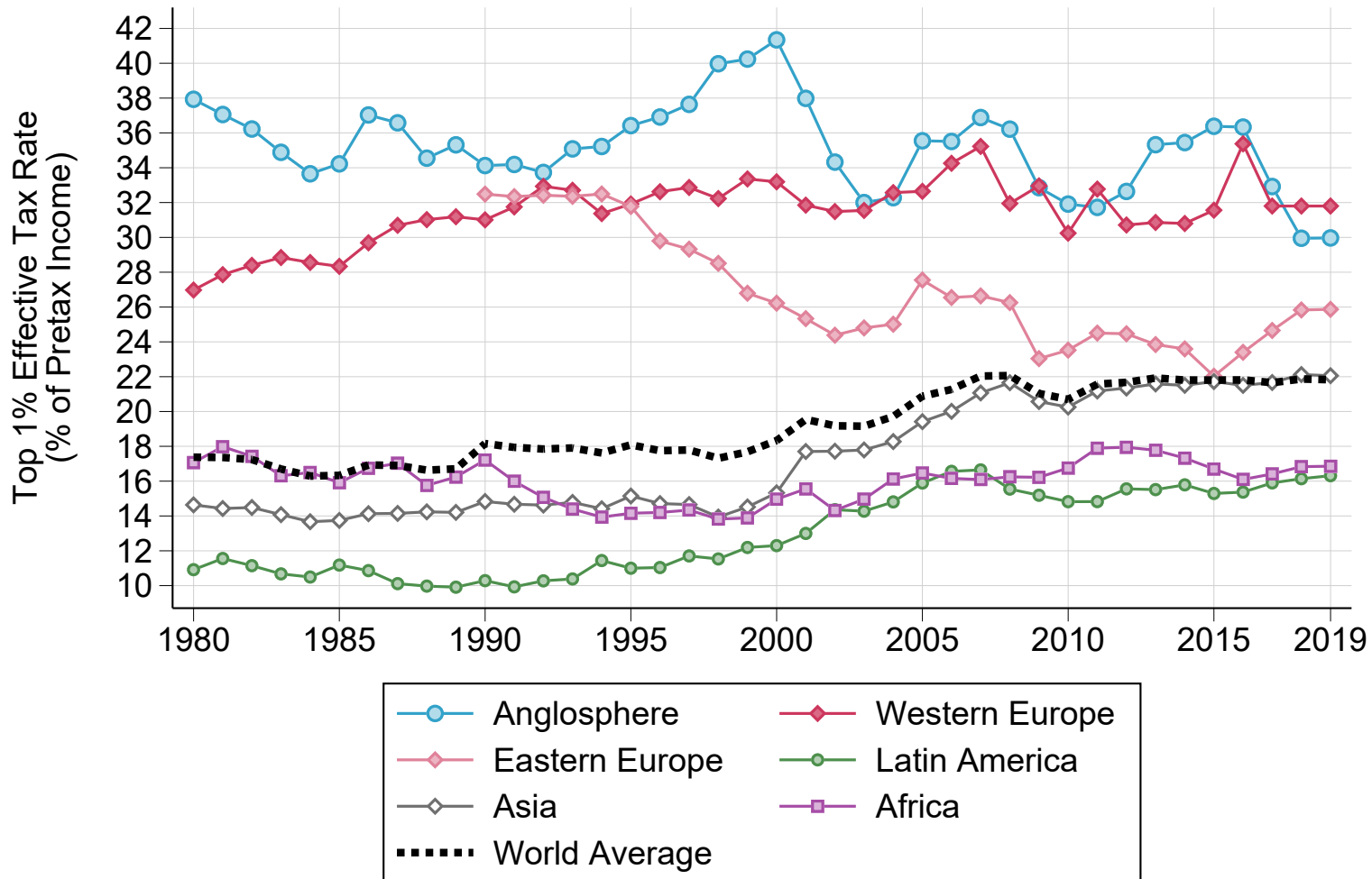


Figure A2.11 – Top 1% Effective Tax Rate

Notes: Authors' elaboration. Excludes social contributions.

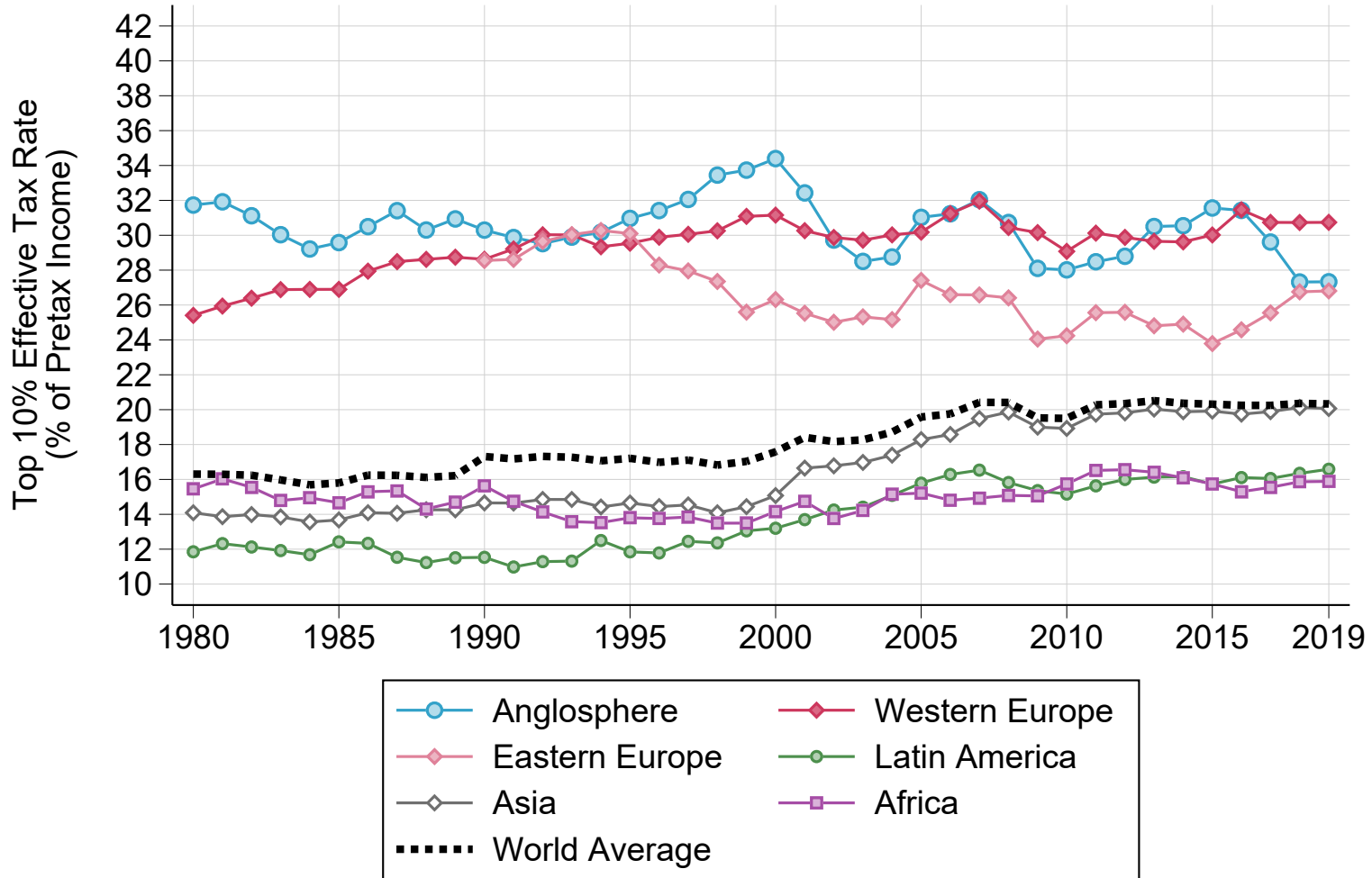


Figure A2.12 – Top 10% Effective Tax Rate

Notes: Authors' elaboration. Excludes social contributions.

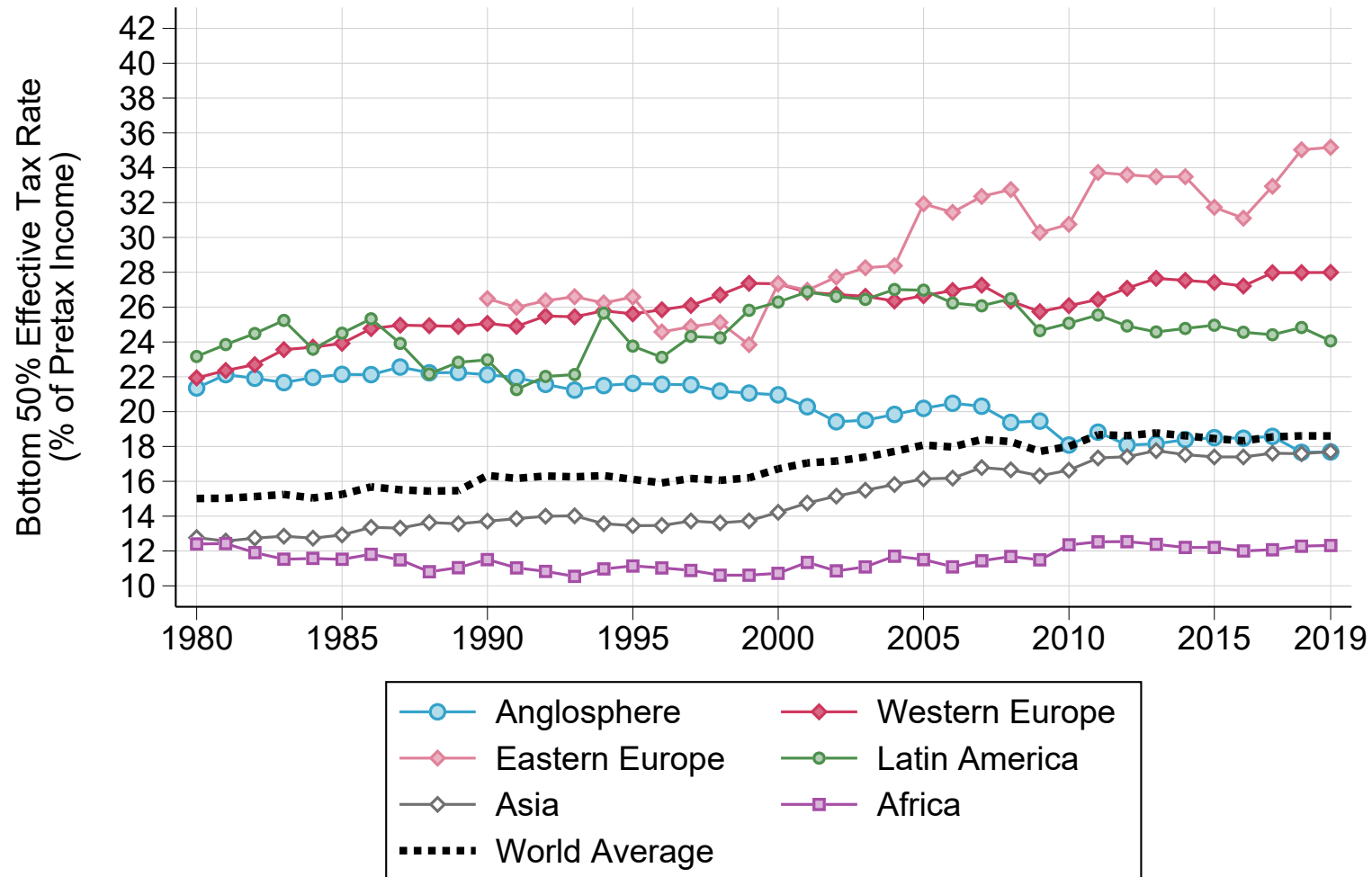


Figure A2.13 – Bottom 50% Effective Tax Rate

Notes: Authors' elaboration. Excludes social contributions.

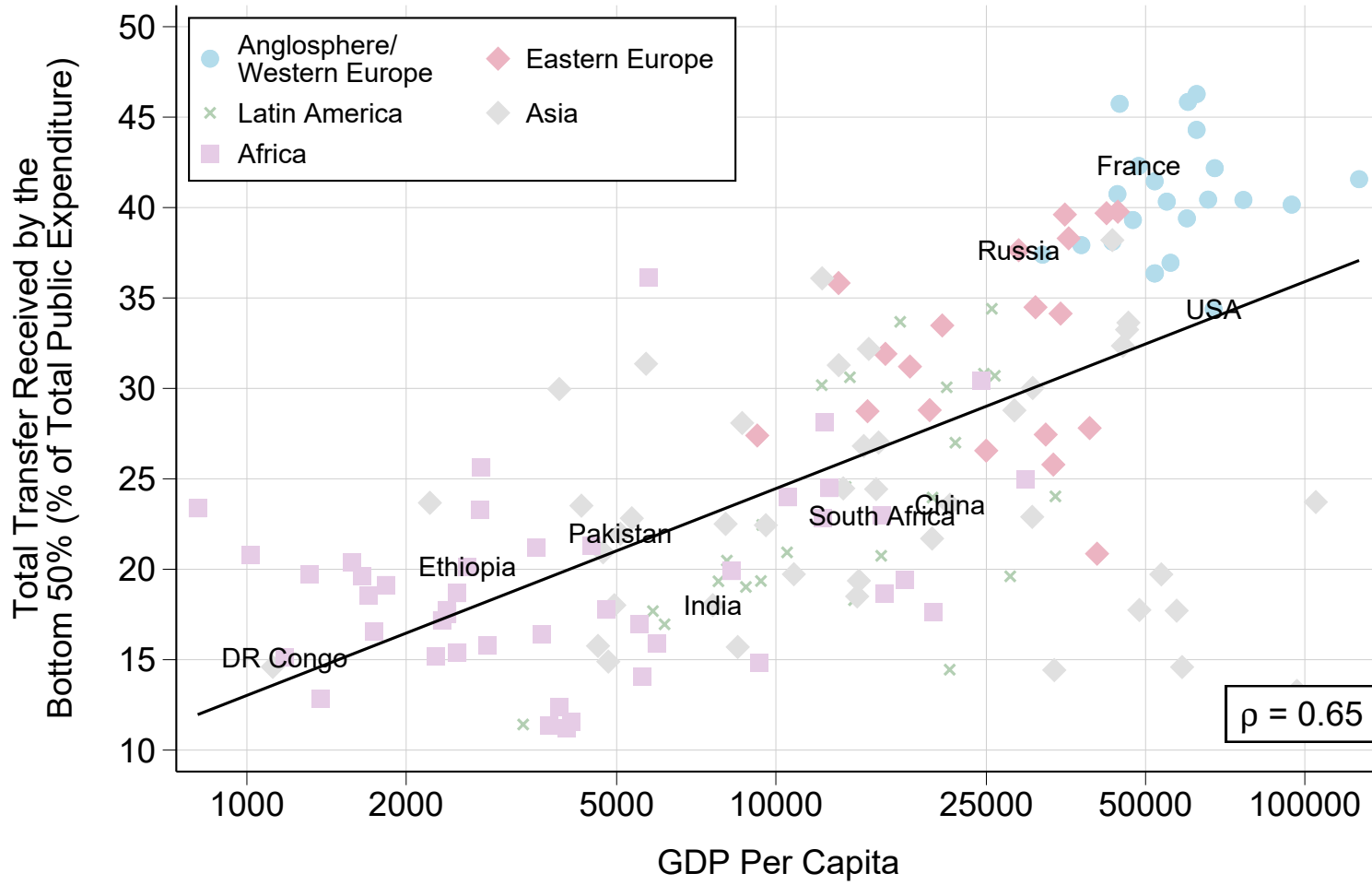


Figure A2.14 – Transfer Progressivity Over the Course of Development: Total Transfer Received by the Bottom 50% (% of Total Public Spending)

Notes: Total transfer received: sum of all transfers received (before paying taxes), expressed as a share of total government expenditure.

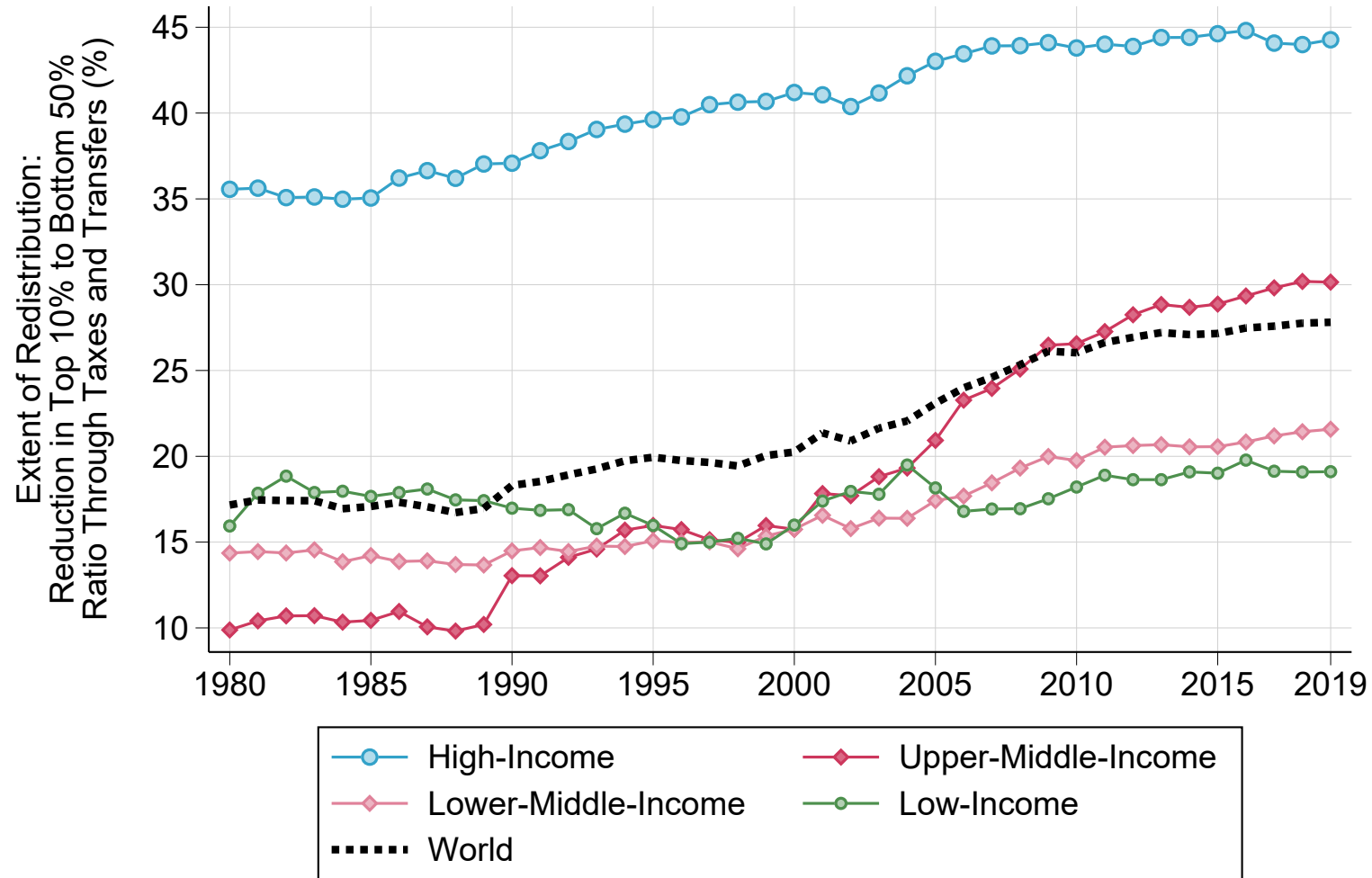


Figure A2.15 – Extent of Redistribution by Country Income Group, 1980-2019: Percent Reduction in Top 10% to Bottom 50% Income Ratio, Pretax - Posttax

Notes: Country income groups from the World Bank.

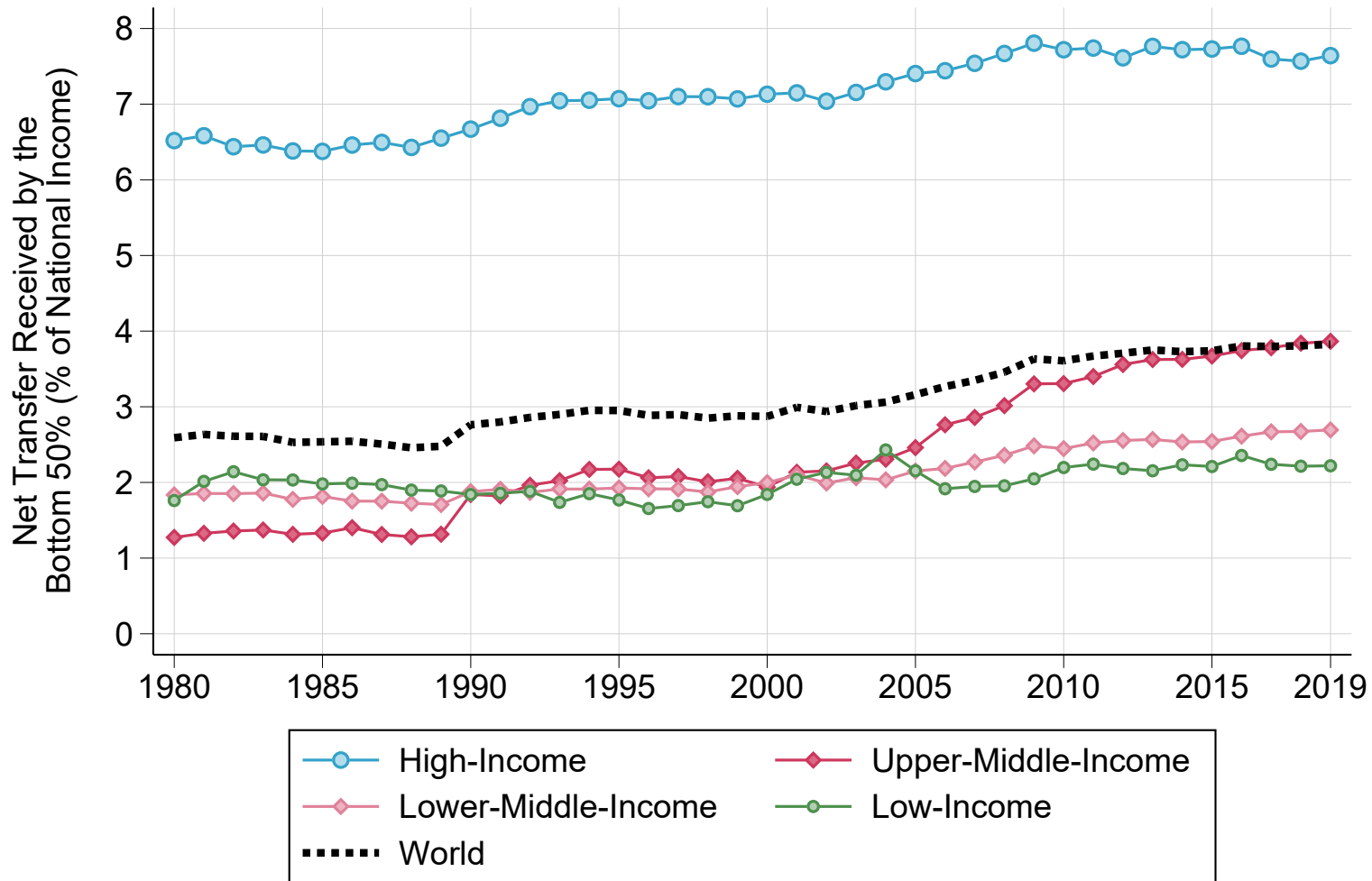


Figure A2.16 – Extent of Redistribution by Country Income Group, 1980-2019: Net Transfer Received by the Bottom 50% (% of National Income)

Notes: Country income groups from the World Bank.

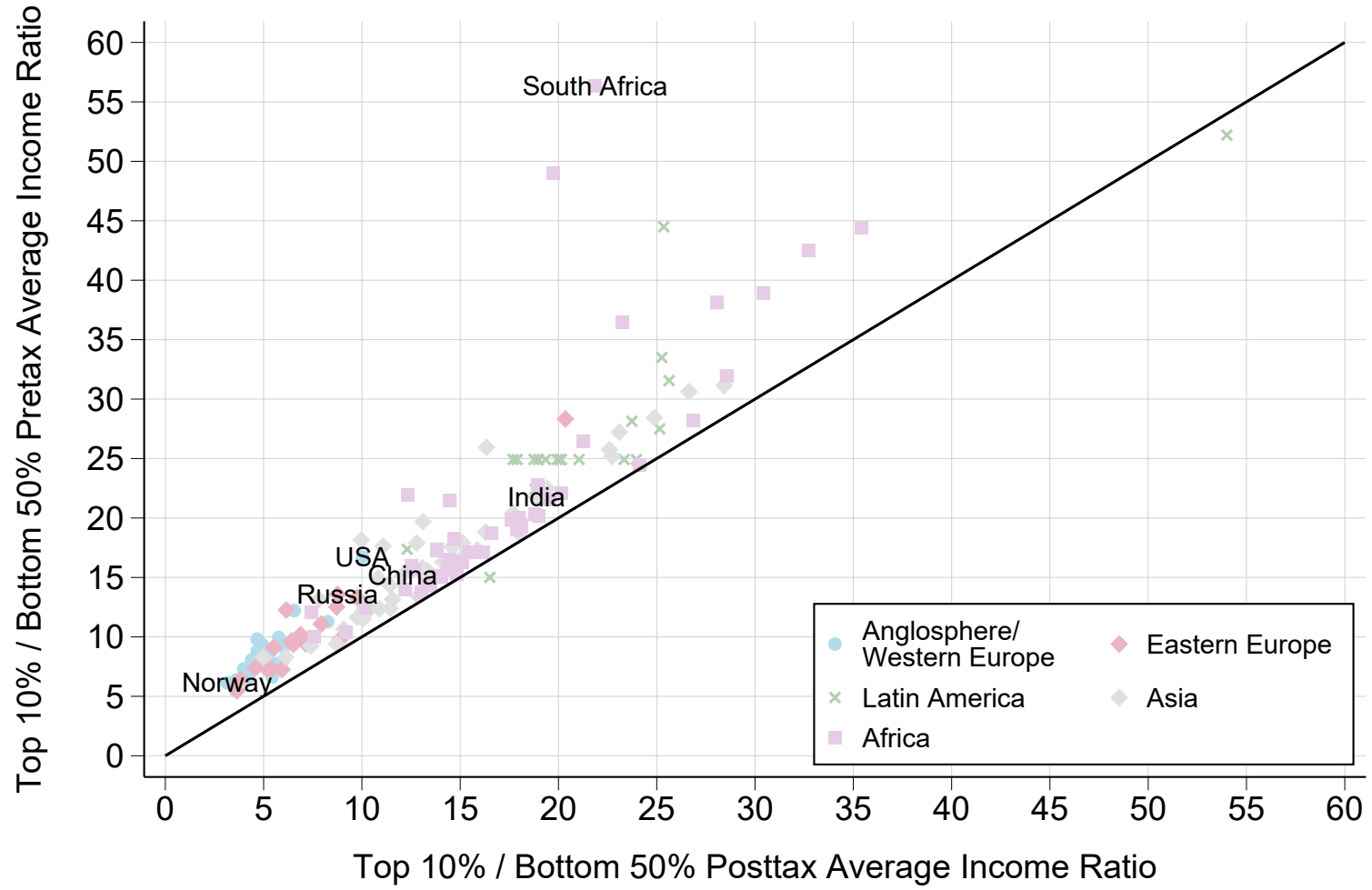


Figure A2.17 – Top 10% to Bottom 50% Income Ratio: Pretax Versus Posttax

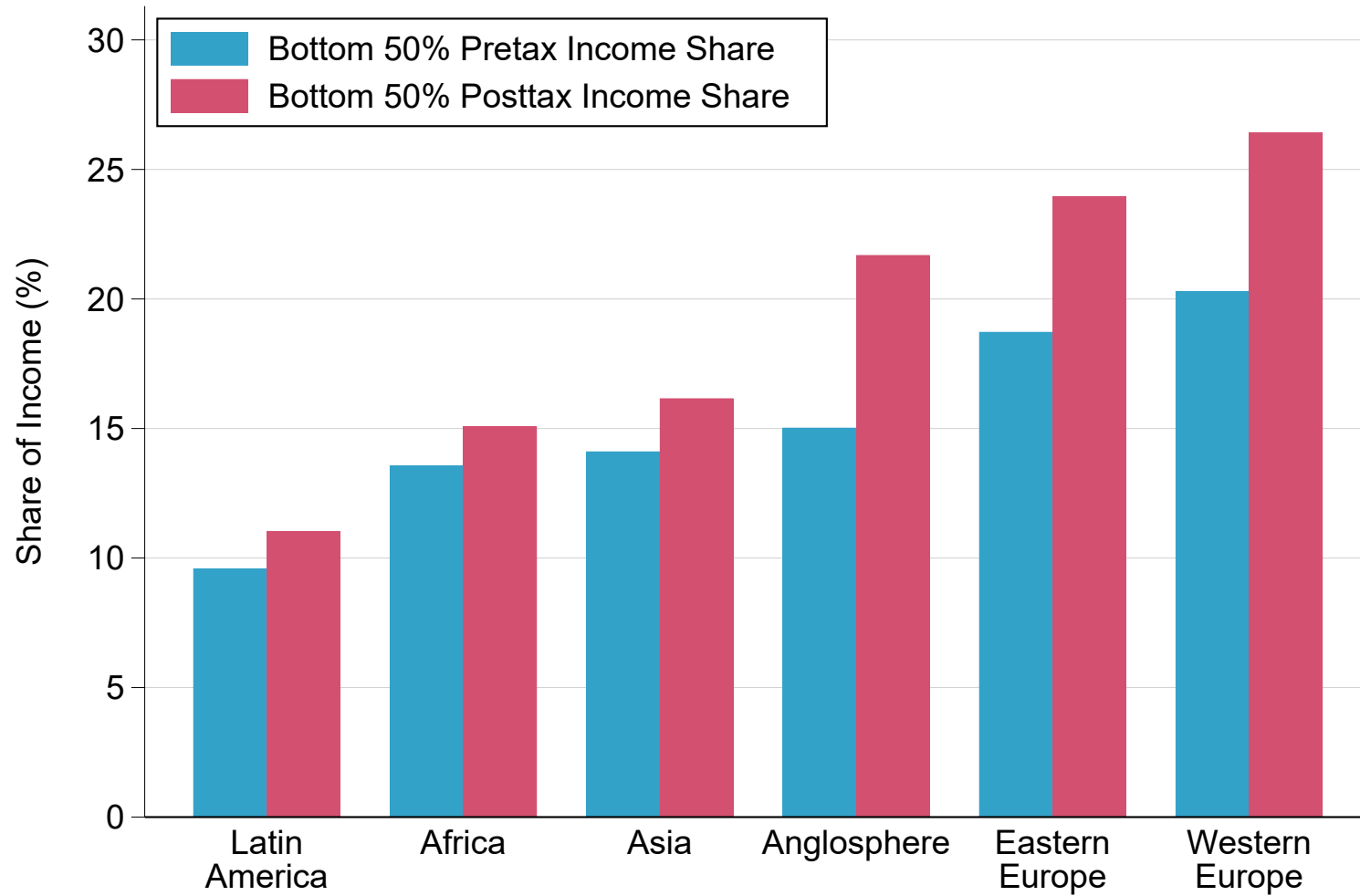


Figure A2.18 – Predistribution versus Redistribution: Bottom 50% Pretax versus Posttax National Income Shares by World Region, 2019

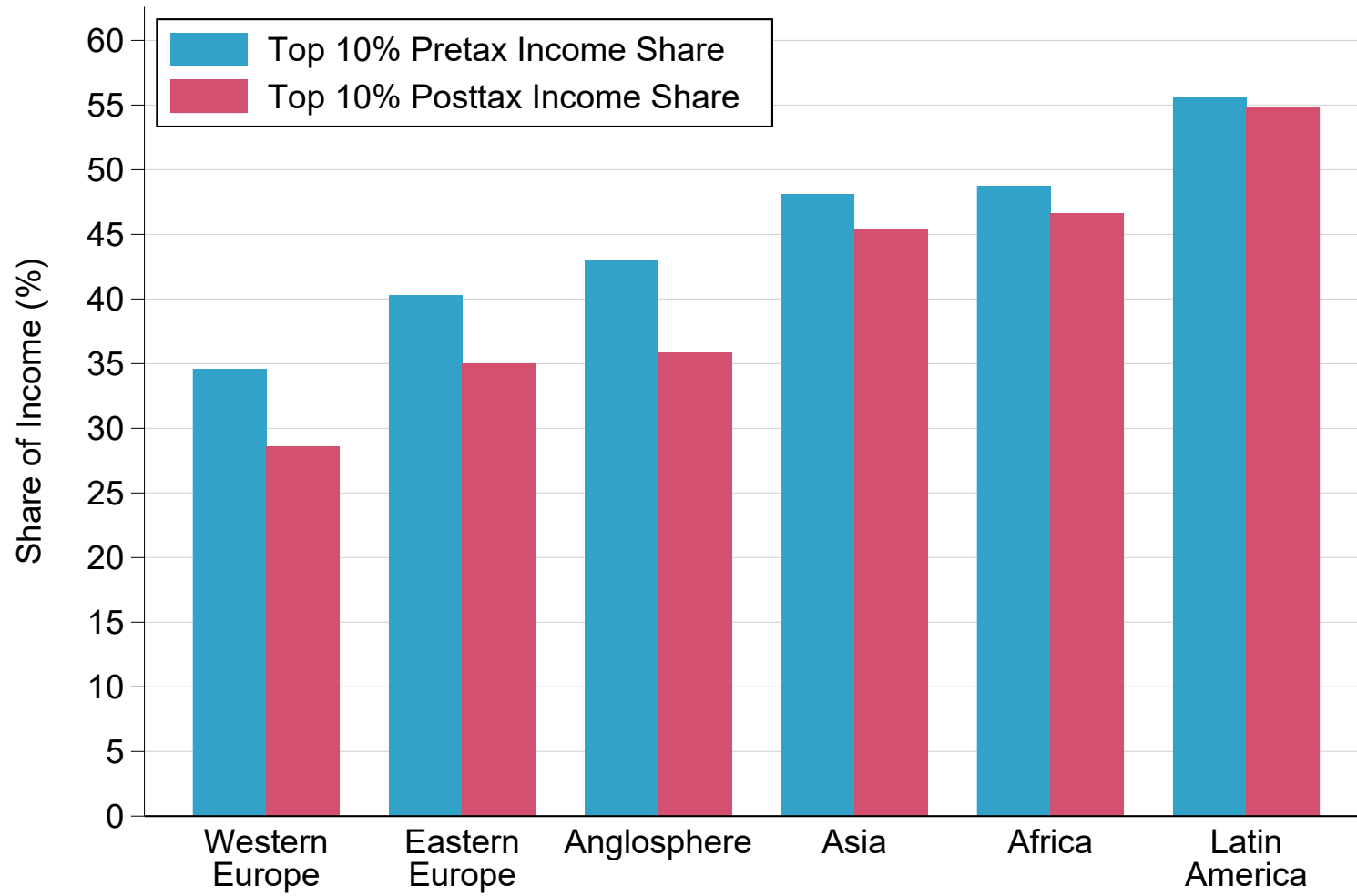


Figure A2.19 – Top 10% Pretax versus Posttax National Income Shares by World Region

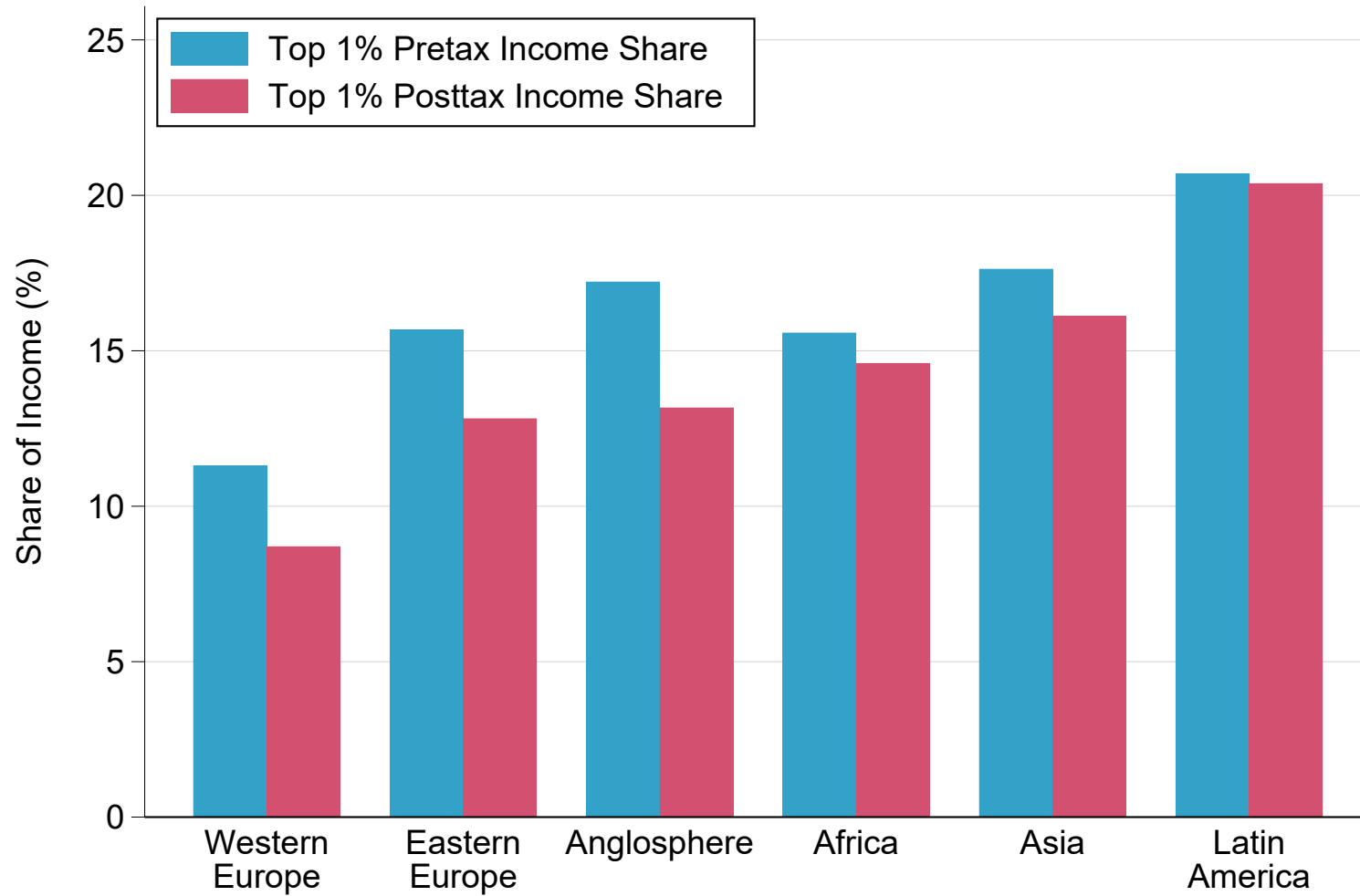


Figure A2.20 – Top 1% Pretax versus Posttax National Income Shares by World Region

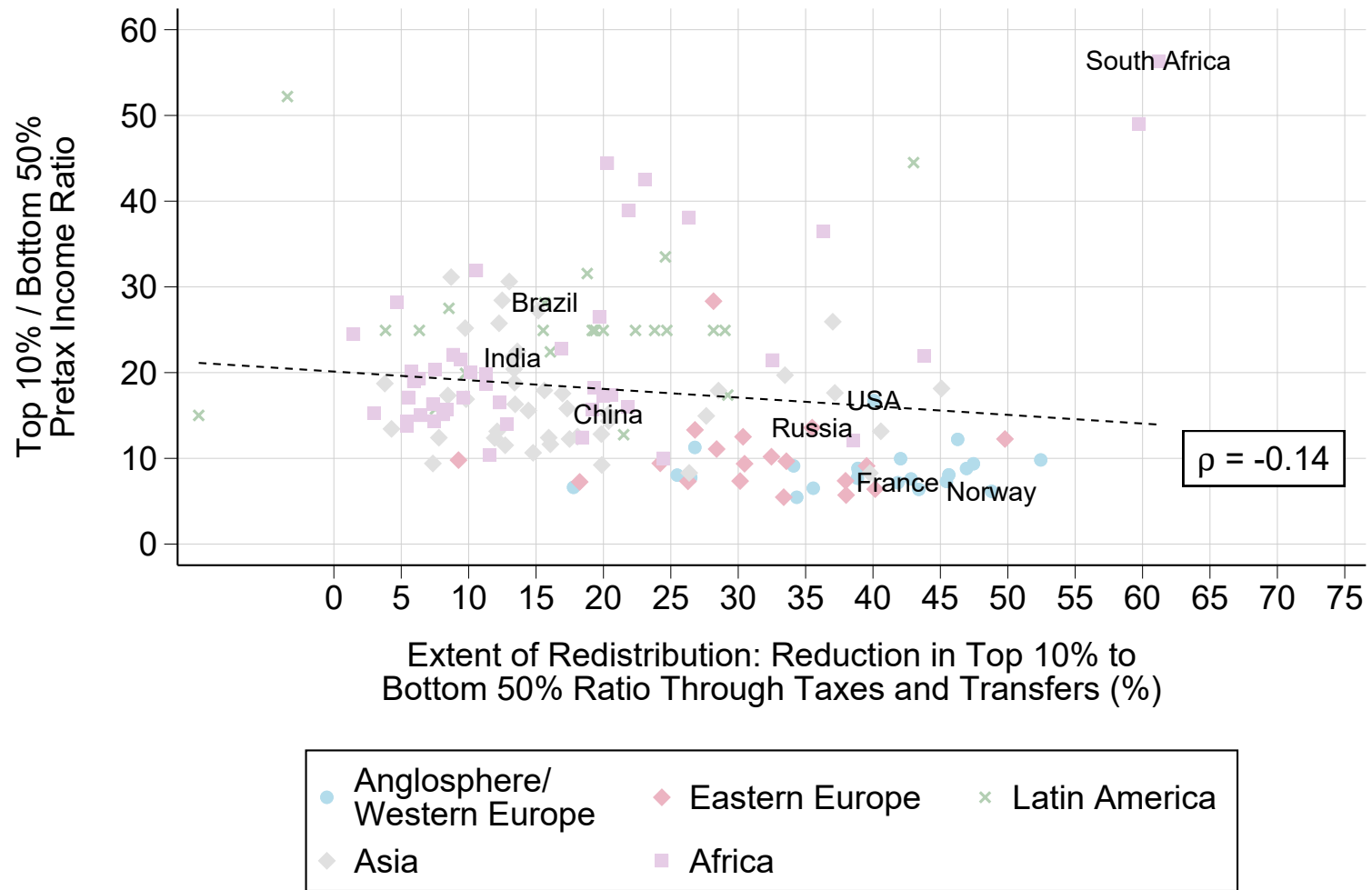


Figure A2.21 – Top 10% to Bottom 50% Pretax Income Ratio Versus Extent of Redistribution

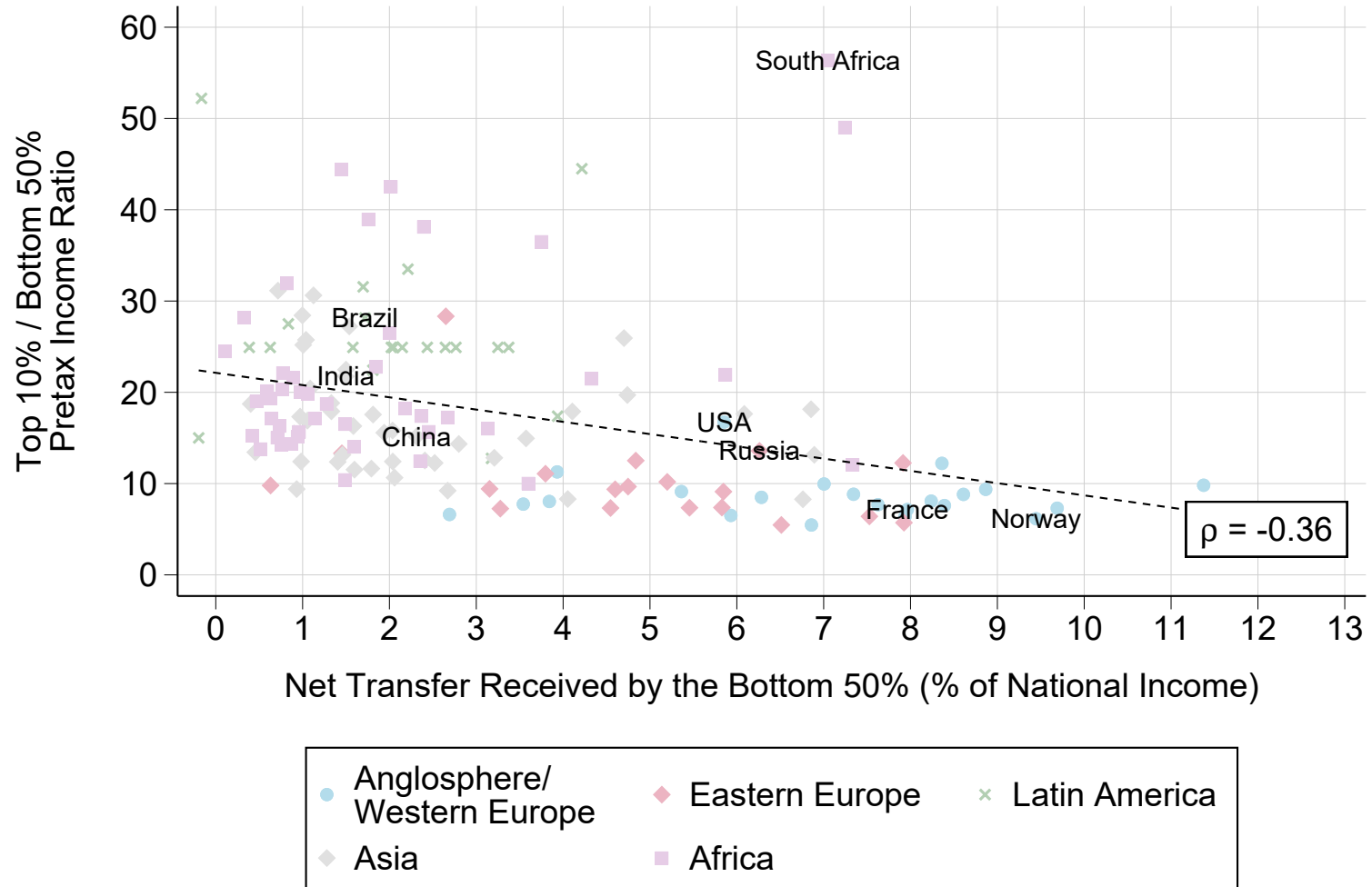


Figure A2.22 – Top 10% to Bottom 50% Pretax Income Ratio Versus Net Transfer Received by the Bottom 50%

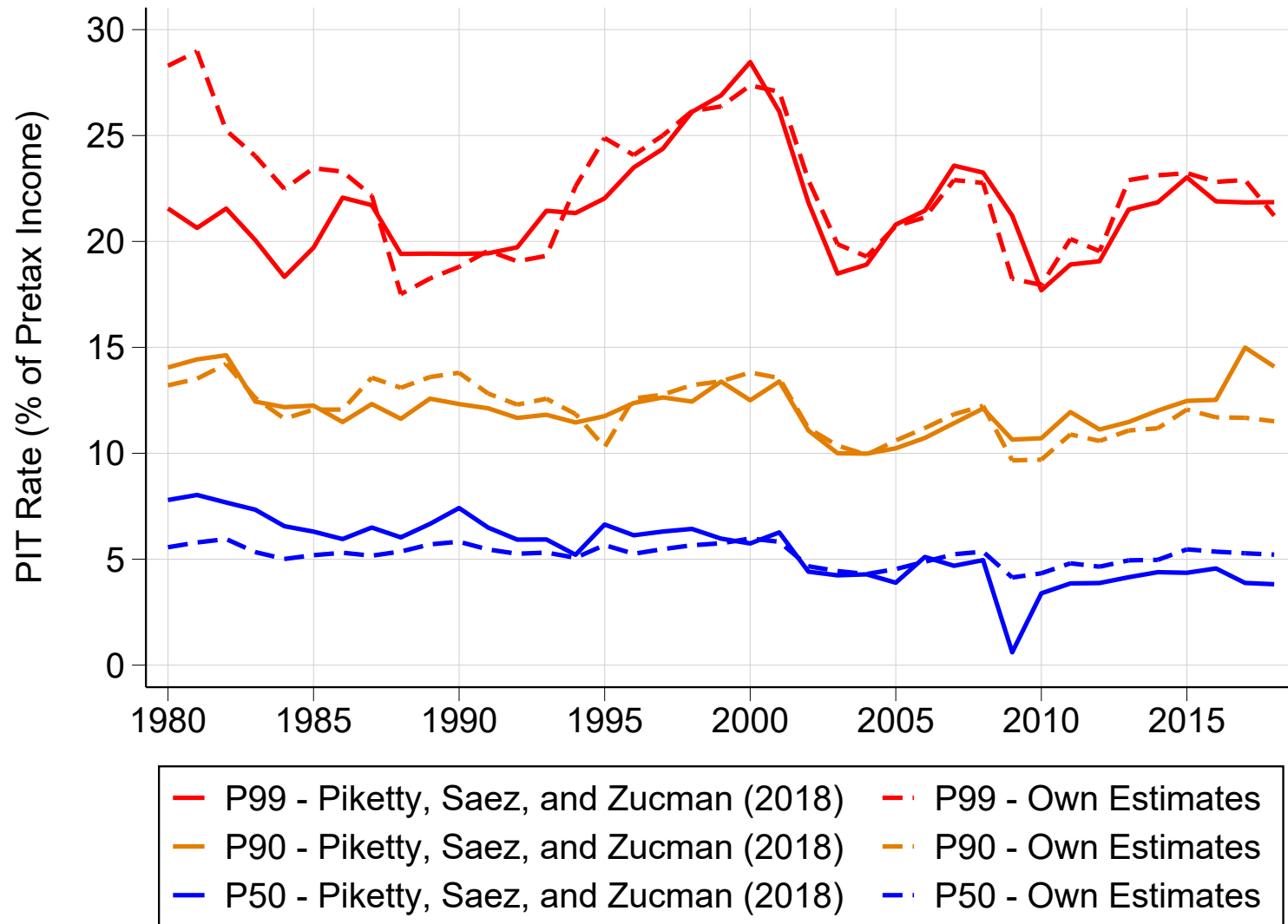


Figure A2.23 – Validation: Distributional Incidence of Personal Income Tax, United States, 1980-2018)

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

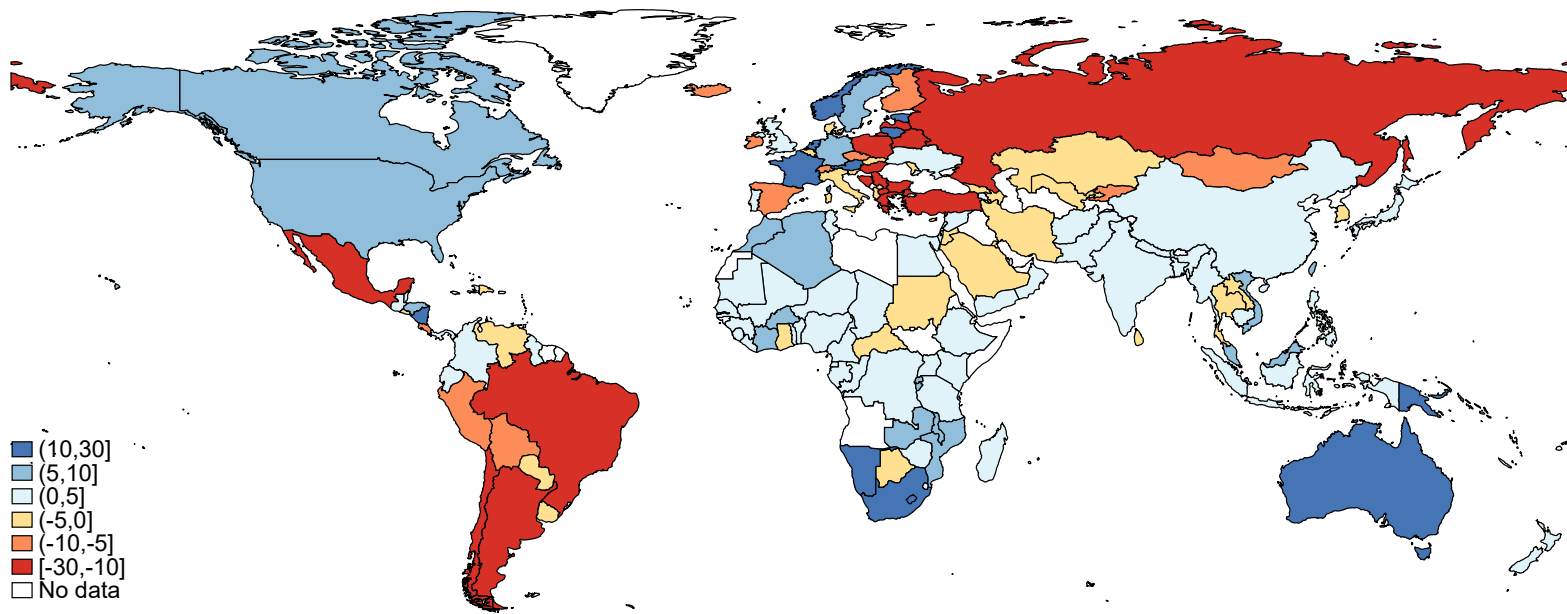


Figure A2.24 – Normalized Tax Progressivity Around the World, 2019

Notes: The figure shows the percent reduction in top 10% to bottom 50% average income ratio (pretax versus net-of-tax income). Includes social contributions.

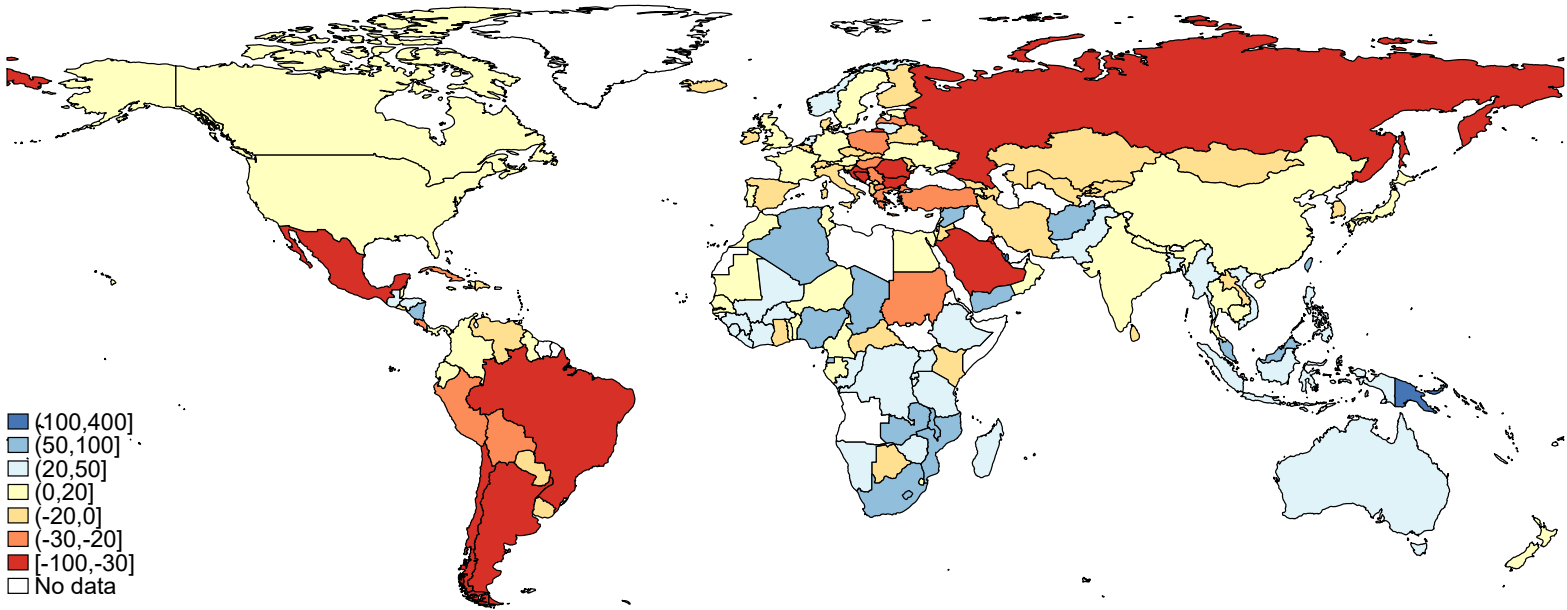


Figure A2.25 – Relative Tax Progressivity Around the World, 2019

Notes: The figure shows the ratio of top 10% to bottom 50% effective tax rates. Includes social contributions.

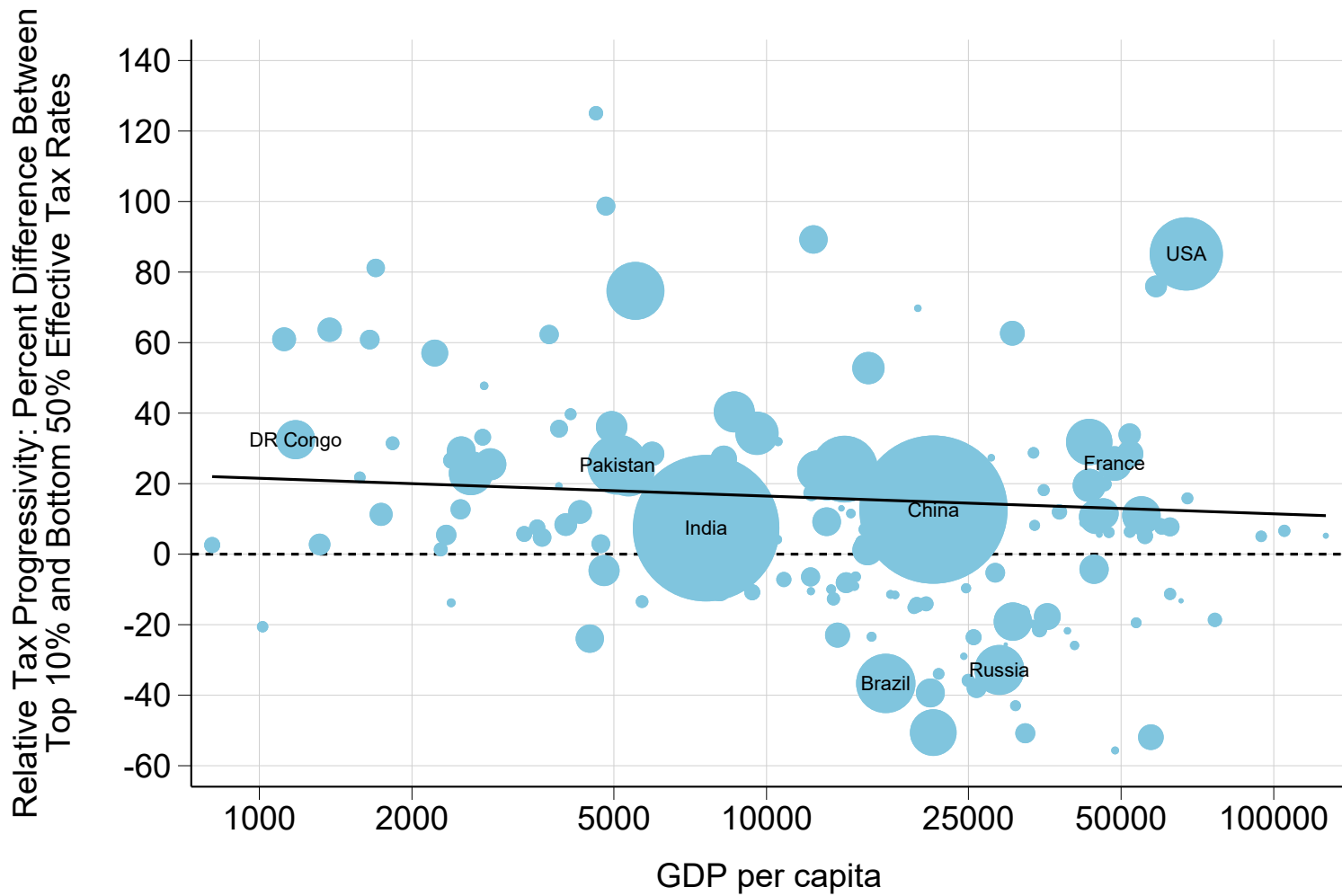


Figure A2.26 – Relative Tax Progressivity Over the Course of Development, 2019

Notes: The figure shows the percent difference between top 10% and bottom 50% effective tax rates. Excludes social contributions.

Relative Tax Progressivity: Percent Difference Between Top 10% and Bottom 50% Effective Tax Rates

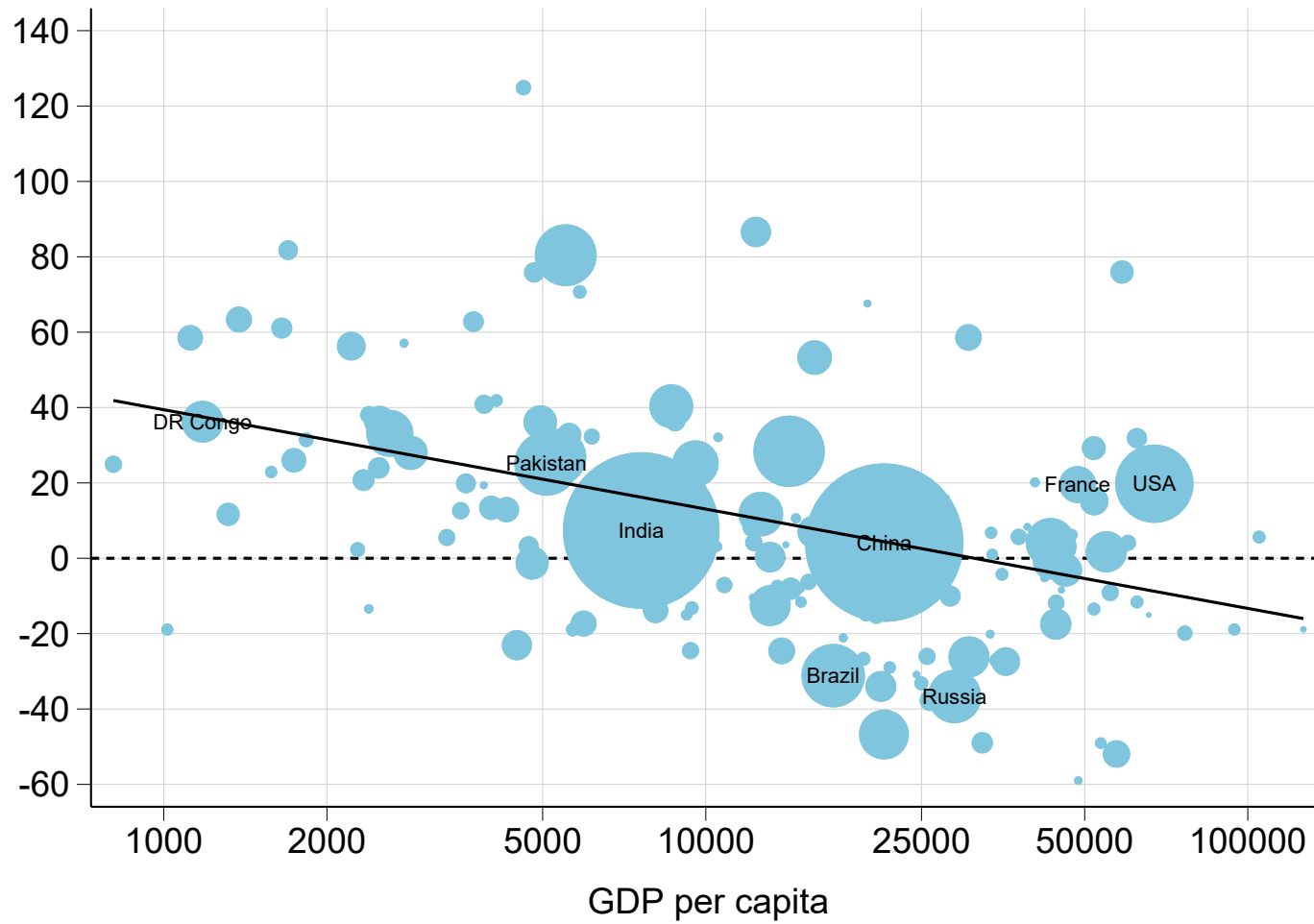


Figure A2.27 – Relative Tax Progressivity (Including Social Contributions) Over the Course of Development, 2019

Notes: The figure shows the percent difference between top 10% and bottom 50% effective tax rates. Includes social contributions.

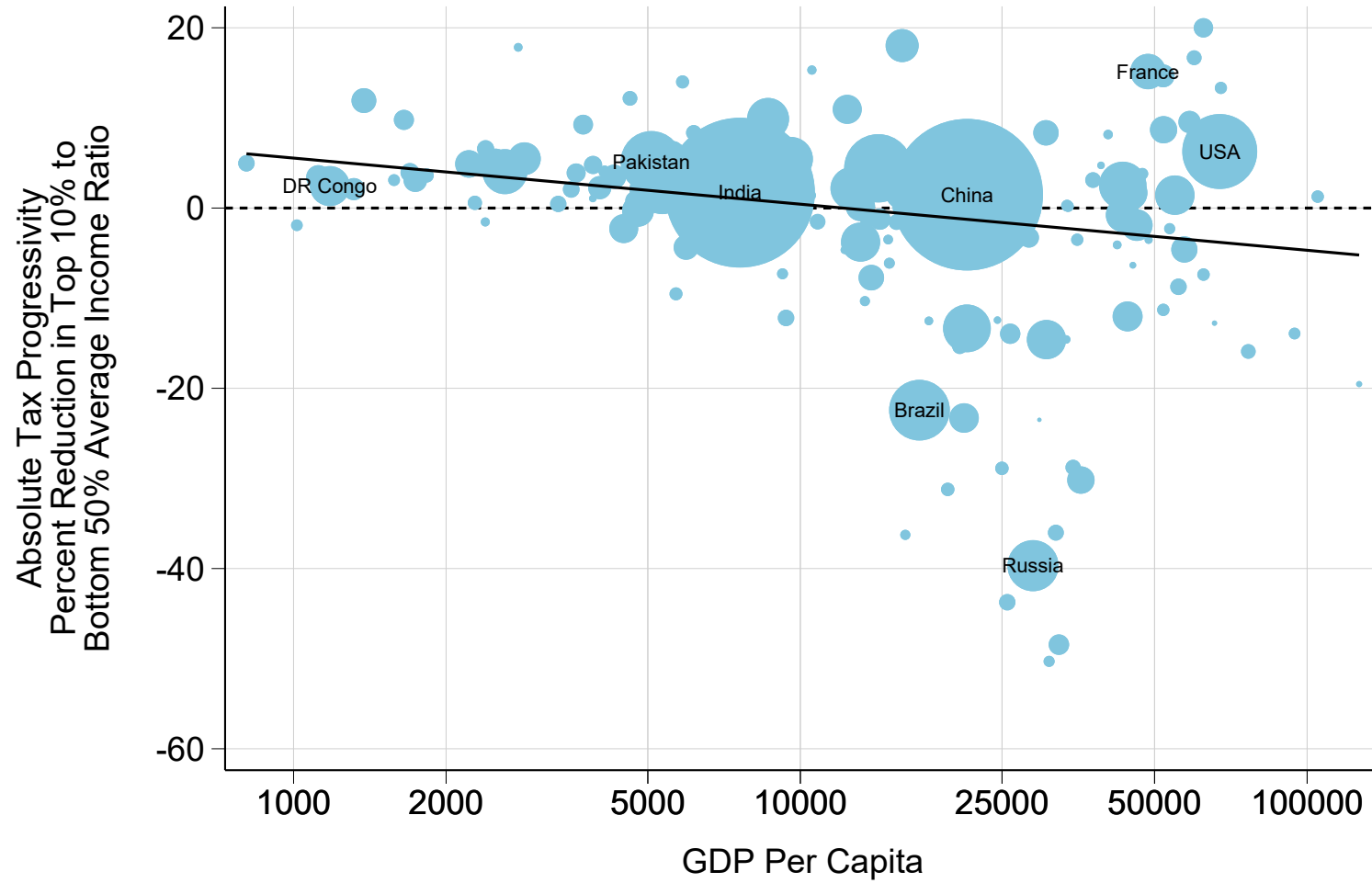


Figure A2.28 – Absolute Tax Progressivity (Including Social Contributions) Over the Course of Development

Notes: The figure shows the percent reduction in top 10% to bottom 50% average income ratio (pretax versus net-of-tax income). Includes social contributions.

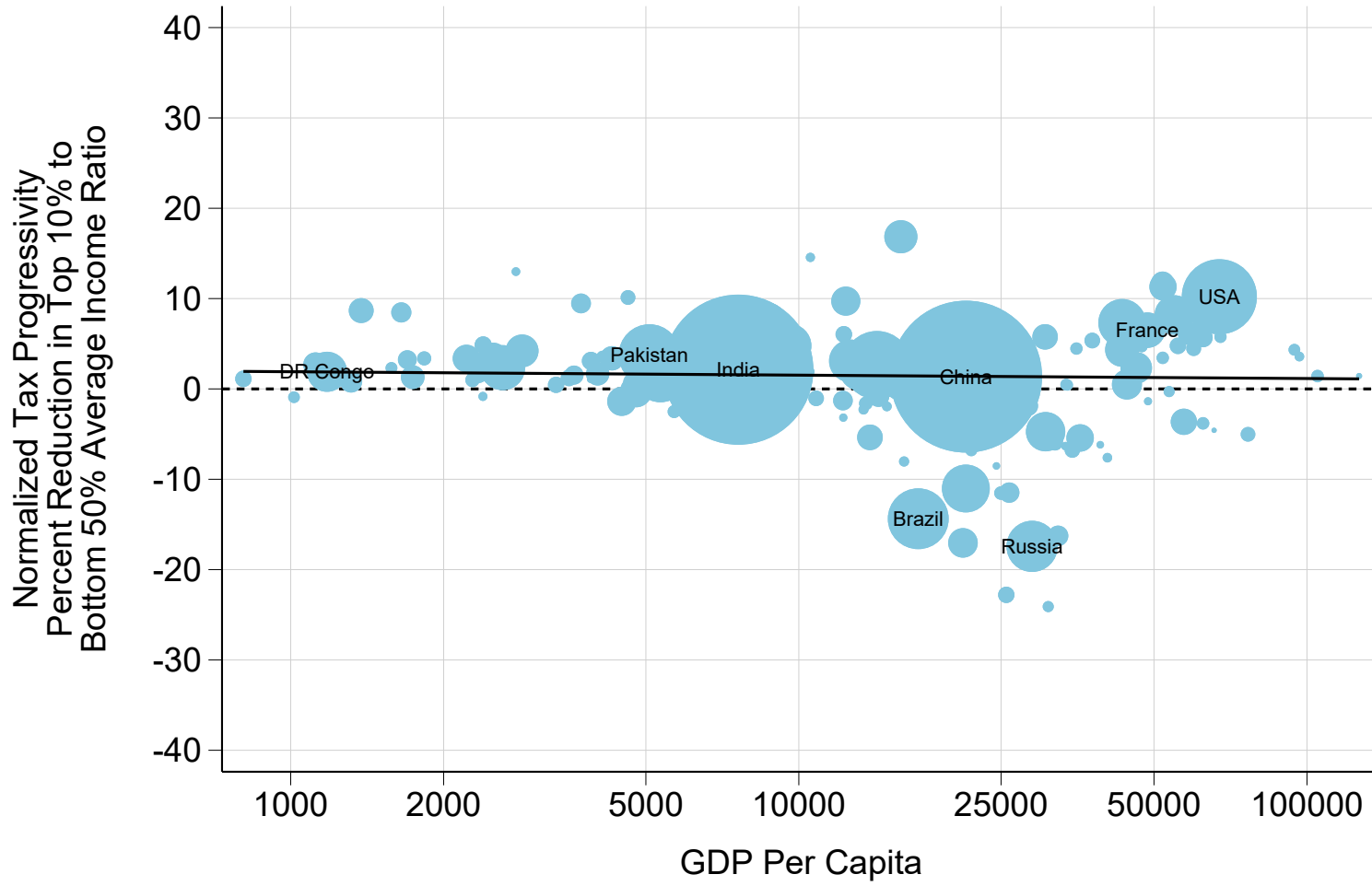


Figure A2.29 – Normalized Tax Progressivity Over the Course of Development

Notes: The figure shows the percent reduction in top 10% to bottom 50% average income ratio (pretax versus net-of-tax income). Excludes social contributions.

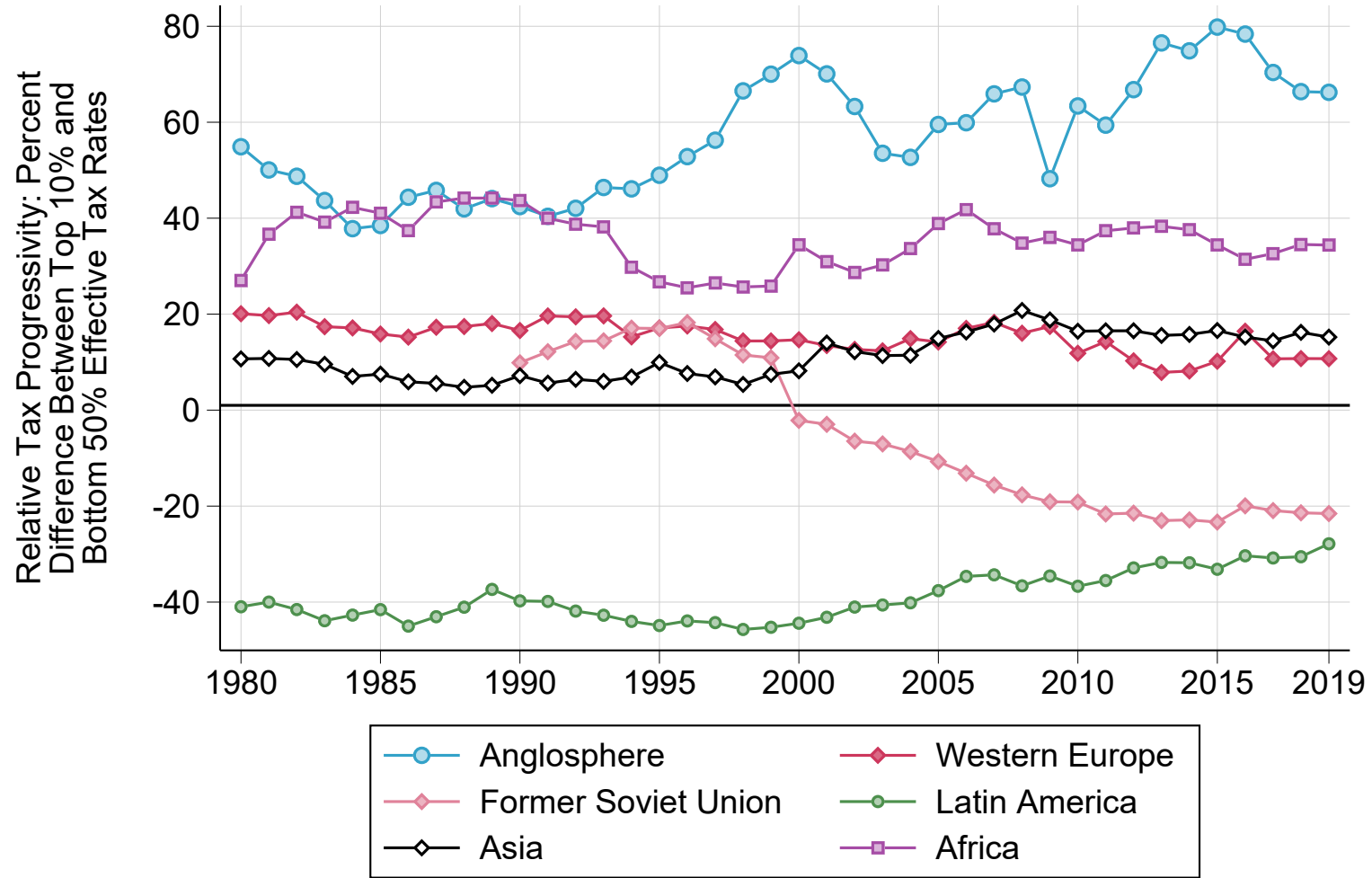


Figure A2.30 – Relative Tax Progressivity by World Region, 1980-2019

Notes: Excludes social contributions.

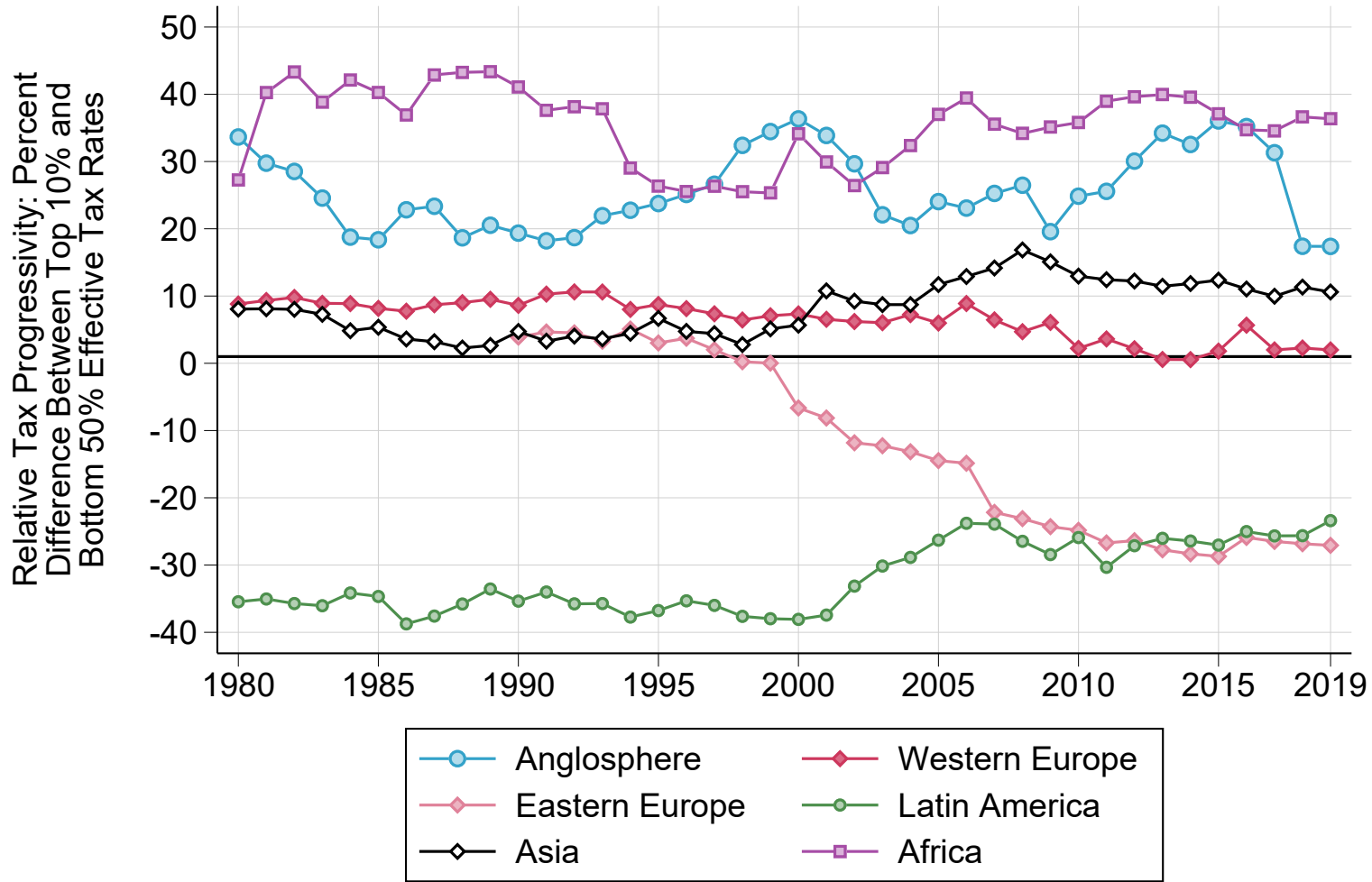


Figure A2.31 – Relative Tax Progressivity (Including Social Contributions) by World Region, 1980-2019

Notes: Includes social contributions.

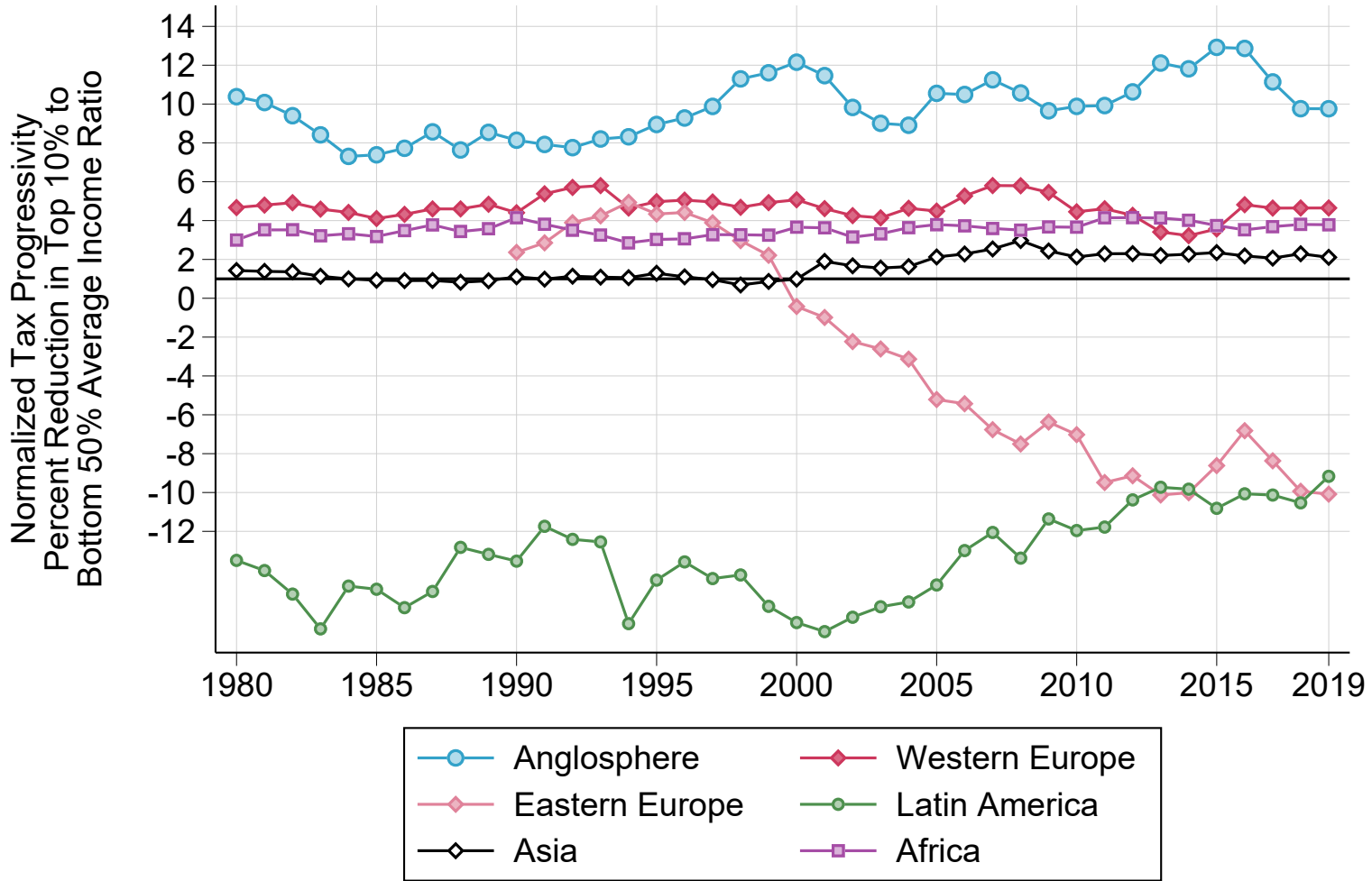


Figure A2.32 – Normalized Tax Progressivity by World Region, 1980-2019

Notes: Excludes social contributions.

Appendix A3

Appendix to Chapter 3

National Service and the Great Leveling

A3.1 Data and Methodology

A3.1.1 Sources

I begin with the same sources as Piketty and Saez (2003) and Piketty, Saez, and Zucman (2018). The annual Statement of Income reports of the United States Internal Revenue Service have documented brackets of earned income for the entire taxpaying population since 1916 (and in an earlier version from the Commissioner of Internal Revenue, 1913-15). While micro files (public use sample datasets) are available for the period after 1962, they are not available before, so I revert to meso-level data in tabular form, in which the SOI calculated the number of tax returns and gross income according to stepwise income brackets. These tables were presented each year in similar but not identical formats, with various levels of disaggregation and reformatting, e.g., by specific source of income, by type of tax return, or even by state. Threshold levels of tabulated income, categories for inclusion and exemption, and definitions of concepts all fluctuated over time, as did the legislation for tax filing and taxable status. Nonetheless, I build on the former studies to harmonize a more complete record of fiscal and wage income in the 20th century.

I take advantage of what few sources of information are available on the historical income distribution (see Figure A3.2).

It is clear that there is little information available before World War II (the Census at the time did not ask questions about income).¹ Autor and Goldin, among others (see Acemoglu and Autor, 2012; Autor, Dorn, and Hanson, 2013; Goldin and Katz, 2008) have contributed to the literature with studies of US wage trends, but the datasets are either strictly post-1962 (Autor, Dorn, and Hanson, 2013) or, at best, have limited explanatory power pre-1940 (Goldin and Katz, 2008). Goldin and Katz (*ibid.*) made use of occupational wage ratios to draw inferences about the evolution of the “skill premium” of white-collar vs. blue-collar jobs, but even if this data is informative, unfortunately it is neither comprehensive nor does it extend much before World War II. (Wage distributions can help explain total income distributions, but do not necessarily tell us much about the magnitude and concentration of capital incomes.) In the present study, I rely primarily on IRS data before complementing it with Goldsmith-OBE survey data for the years before 1945. We will return to discuss that method at the end of this appendix section.

Returning to the IRS archive first of all, then, I produce a dataset with income and wage and filing statistics for the entire register of tax brackets in every year for which the records are available. Beyond the top ten percent of highest-income tax returns, I include every recorded bracket of tax returns, including zero net income, so that we can later analyze the proportion of total income accruing to the bottom 50% of households, and to the “middle” 40% (51st to 90th percentiles of the distribution).

¹Note that the 1940 Census asked respondents for their *wage* income but this information was top-coded and frequently missing. We link it to the 1950 Census nonetheless.

A3.1.2 Generalized Pareto curves

The method I use to infer the entire distribution, including below the 90th percentile, is a generalized Pareto curve interpolation (Blanchet, Fournier, and Piketty, 2022). While the well-known original Pareto distribution function has been taken as roughly appropriate to interpolate the top percentiles of an income distribution (Atkinson, 2017; Kuznets and Jenks, 1953; Pareto, 1897), Blanchet and Fournier and Piketty developed the nonparametric generalized Pareto curve in order to recover an entire distribution according to varying inverted Pareto coefficients $b(p)$ that are similar but not precisely identical over the course of the smooth distribution function.

Following Fournier (2015) and Atkinson, Piketty, and Saez (2011), the Pareto distribution can be expressed as:

$$F(y) = 1 - \left(\frac{k}{y}\right)^\alpha$$

where $k > 0$ is the scale parameter, income is $y > k$, and $\alpha > 1$ is the Pareto parameter determining the shape of the distribution. In the classical Paretian distribution, the ratio of the average income above y to y itself does not depend on the threshold level of y . This ratio $b(p)$ is the inverted Pareto coefficient, given by:

$$b(p) = \frac{a}{a - 1}$$

While this Pareto coefficient $b(p)$ can be considered as a constant parameter throughout the distribution, it can also be modeled more flexibly to match empirically observed data. This is one of the most interesting contributions of the theory of generalized Pareto curves (Blanchet, Fournier and Piketty 2017), as the technique allows the parameter $b(p)$ to change over the course of the distribution. In turn, this allows to model an entire income distribution based on no more than a few pieces of information sampled from the population: several income levels (e.g., thresholds at cumulative population density $p = 10\%$, 50% , 90% and 99%), and the average income of earners within those brackets. The interpolation method creates a polynomial spline function from these pieces of information. Tests of the method show that an estimation error of less than 1% (on top incomes shares) can be achieved with income information on as little as three brackets, and that the error can be reduced to less than 0.05% with seven brackets (Blanchet, Fournier, and Piketty, 2022).

However, the information on these brackets needs to be well placed over the income distribution in order to yield the most precise results. Fortunately, the income data from American tax records after 1944 meets that criterion, and is granular enough to provide information across the entire distribution—for the years in which tax returns are representative of the population (or close to a full population sample). Unfortunately, before 1945, we do not observe a full population sample filing tax returns. We will turn to this question below. As I will discuss, when we do not have information below the 90th percentile, then it is difficult at best (speculative at worst) to infer the levels and shares of income for middle-class earners. Therefore, we must infer or impute as much information as possible about income levels throughout the population, before setting the generalized Pareto curve distribution function to smooth out the cumulative distribution function and rigorously model income shares accruing to the middle-class and poorest households.

In fine, when I model the cumulative distribution function,² I infer the entire taxpayer income distribution based on available information from tax brackets and complementary information that I have imputed and assigned accordingly.

A3.1.3 Missing income and missing people: two approaches

One of the greatest challenges of this approach, then, is what to infer about missing information: the people and the income that go unreported in the annual SOI tabulations.

Harmonizing this procedure with the original Piketty and Saez (2003) analysis and more recent Piketty, Saez, and Zucman (2018) datasets, we know the total number of tax units in the population thanks to US Census and historical data on the marital structure of the population. And from the same source I use the total income of the population (beyond only the tax filers) computed from national accounts data. Piketty and Saez (2003) found that tax return gross income (adjusted gross income, plus transfers, minus capital gains) remained between 77 and 83 percent of national accounts' personal income from 1944 through 1998, after adjustments for non-filers, and imputed this fraction at exactly 80 percent from 1913 to 1944. There were fewer non-filers after 1944, so the amount imputed to non-filers equals only 2-3% of the total income.³ By contrast, non-filers before 1944 represented a much greater proportion of the population (up to 90 percent or more), so the challenge is how to allocate their imputed income across the income distribution. (See Figure A3.3.)

To determine the full income distribution including non-filers, I test two approaches. One approach is to simply allocate all missing income on the left side of the income distribution, below a certain threshold where it is assumed that all earners faithfully report their income to the tax authorities. That is the filing threshold of IRS returns. This would not be an unheard-of solution, especially if most of the unreported income was due to a “filing requirement” below which point of income a person or household was not required to file a tax return.

However, it is possible that this line may be too arbitrary: either (a) many non-filers would be spread along the “true” income distribution even above this amount—and to draw the legal line below which to assign all missing income would be to overestimate the bottom portion of the income distribution; or (b), we would be drawing a threshold so high as to be analytically meaningless and lose valuable information about the income distribution below that point.

Instead, in a second approach, I could remain agnostic about the reasons for non-filing,⁴ and compare another solution: to allocate all missing tax units with a simple proportional split from the bottom of the distribution up the 90th percentile. Garbinti, Goupille-Lebret, and Piketty (2018) applied this solution to missing

²An excellent tool is available online at <http://wid.world/gpinter>.

³After 1945, missing tax units were assumed to average 30% of the non-missing tax units' average income; they were imputed 50% of that average in 1944-45.

⁴Tax avoidance and tax evasion represent another possible source of missing income, according to which I would underestimate the income at the top of the distribution (Zucman, 2015). In the case of hidden high incomes, the new estimates on inequality here would become the lower bound, and true incomes at the top of the distribution may be even higher than those supposed in the recent scholarly literature. I leave that concern aside for now and rely on tax data as, at least, a more reliable source for top income information than would be, say, survey data.

income data in the distributional national accounting framework from French data. That is, I would first assume there are no missing units from the tax data whose income would place them in the top 10% of the income distribution. Beyond that, I would not presume to know where along the cumulative distribution function the missing observations would fall.

Under that approach, I would thereby preserve the shape of the income distribution that is given by the original tax data, and simply re-weight the existing observations from 0 to the 90th percentile of the overall population, such that the total number of observations in the tax data is equal to the total number of tax units in the earlier demographic calculations from Census data. According to this methodology, for income brackets below the 90th percentile (after inclusion of missing tax units), I would impute a number of missing tax returns per bracket in exact proportion to the number of tax returns that are not missing.

After we assign “missing” tax units (the non-filers) along the overall income distribution from zero to 90th percentiles—whether at the far left, or equal-split—our generalized Pareto curve technique is able to automatically determine the amount of “missing” income that is apportioned to each tax unit (or tax bracket), based on the existing SOI information on average bracket income and the overall average for the distribution.

It should be noted that this method is not intended to give a precise estimate of the poverty line or a poverty headcount (especially when the number of missing observations is particularly high), but rather at least on orders of magnitude to reproduce a rough distribution of income in the population, such that we can observe top shares of income, and furthermore to draw inferences about the middle class share of income. It would not be possible to provide a histogram or income distribution function at the far left of the distribution, without much more information on non-filers (see Saez, 2016).

In fact, a method for allocating missing tax units via simple proportional split can be viewed as either an upper-bound or a lower-bound estimate on inequality. There is a compelling argument that households are less likely to file taxes if their income is lower; but as above, without any data on such households we might not want to assume a concentration of non-filers at the left-hand side of the distribution. In that case, we might view it as the safest assumption to say nothing about the non-filers except that we do not place them among the top 10% of the income distribution. In particular, the IRS “filing requirement” meant that non-filers were more likely to be found below \$2000 net income or \$5000 gross income before World War II, because below this level of income they were not required to file a tax return.⁵ In any case, I draw this level as the lowest income threshold to include in generalized Pareto interpolation. After World War II, the filing threshold was lowered to \$600 in gross income, regardless of marital/filing status.⁶

⁵Checking in the data after 1945, after almost all tax units in the population begin filing, I observe that this level corresponds to the 90th percentile of the income distribution.

⁶Regarding this filing requirement and the left side of the distribution, I should also note that 1951 is the first year in which filers are allowed to claim “no adjusted gross income.” I have bottom-coded negative income post-1965 at zero. Before 1951 all filers reported positive income. The exemption levels below which taxpayers would not have filed a return creates the problem of a truncated distribution when studying returns only above the amount giving by the filing requirement. However, it may be for many reasons, not just this one, that we observe a limited distribution until the post-war period, so the truncated distribution at the left-hand side of the

To proportionally split missing tax units might make more sense when there are fewer tax units missing, and when the missing data can be construed as more of a “random” process (and less to do with a “filing requirement” and likely poverty). Therefore, the simple proportional split might make more sense in the dataset after World War II or more recently, and we would have to look for another method to make sense of the full income distribution in the years prior to World War II.

The results from these two approaches are compared in Appendix [A3.2](#).

From these results, we see that the more robust approach is to impute the non-filers as low-income—as below the filing threshold—and not as equally spread throughout the lower 90 percent of the distribution. I also show several visualizations on this comparison in the same appendix section.

From those comparisons, I moved forward with the imputation method that placed missing income and missing tax returns on the lefthand side of the distribution, below the filing threshold, rather than the imputation that allocates non-filers equally among the entire bottom 90 percentiles of the distribution.

Unfortunately not applicable to the current context, a third approach would have been to impute the income of non-filers using disaggregated data about the determinants of their non-filing status. Saez (2016) and Rohaly, Carasso, and Saleem (2005) studied the recent IRS samples of non-filers since 1999 to predict which income levels (and other demographic characteristics) would determine the absence of an individual record in the SOI statistics. From that function, one can then create a pseudo-sample of non-filing tax units. Indeed, this is the approach selected by Piketty, Saez, and Zucman (2018) to infer the distribution of non-filers’ income, using micro data on filers and adding an imputed set of observations and income for non-filers.⁷

However, micro data from the Statistics of Income were not available until 1962, so I cannot pursue the same approach here. And before 1945 there are not enough observed tax units on which to anchor a predicted distribution for the unobserved tax units. It would be a stretch of external validity to infer that precisely the same determinants of non-filing after 1999 would hold for non-filing before 1962, or that the same relative distribution of income among non-filing tax units after 1999 would hold for the earlier eras.

A3.1.4 Equal-split adults

Although the United States and other countries often report tabulations in terms of tax units (the unit of observation filing the return—conceptually similar to a household, if on average slightly smaller), to report income inequality statistics on the basis of tax units could give a misleading impression of true inequality. For example, tax units at the top of the income distribution may have a greater propensity to be filing jointly rather than as single individuals. In the top tax brackets, it might rare to observe a single adult rather than a complete household. In the lower tax brackets, the reverse could be true. Therefore, if I report income

distribution may a lesser concern. We return to the question of imputing pre-1945 data in Appendix [A3.2](#).

⁷For a visual comparison of the new results to Piketty, Saez, and Zucman (2018) microestimates, please refer to Appendix [A3.3](#).

distribution statistics on the basis of tax units, I would overstate the disparity of income at the top.

Instead, the preferred benchmark series is to report income inequality on the basis of equal-split adults. Whenever we observe a married couple tax unit filing their return jointly, I split the total income in two. While this is still not a perfect approximation of income distribution among individuals—we would need to know to what extent there are economies of scale within a household; and to what extent income is actually shared equally between the married couple filing jointly—it more closely represents the distribution of income among adults than it would to, say, compare a high-earning individual to the combined income of a middle-income married couple. Therefore I choose to represent an individualized (but equal-split among household earners) income distribution as the benchmark series.

Before I could split tax units into an individualized income distribution, it was necessary to retrieve from the SOI archive data the entire record of joint vs. nonjoint tax return filing status, per bracket.

Each year, the SOI reports listed for each income bracket (“net income” pre-1944; “adjusted gross income” since then) the number of returns for “joint” married couples filing as a single household tax units, distinguishing these from married couples filing separately or from single adults. I brought all of this information into the long-run dataset.⁸

To equally split the joint incomes in the dataset is accomplished by dividing into two the married couples filing jointly, and then joining the full income distribution as if all earners are single or nonjoint.⁹ By construction, the levels and averages of this resulting distribution are lower than is the tax-unit distribution, which is undifferentiated by joint or single filing status.

Non-filers’ joint tax-return status depends on methods for imputation (discussed above). In the method that proportionally splits all missing income among the distribution, non-filers would be assumed the same “propensity to file jointly” as is true of the income bracket into which the tax unit is imputed. By contrast, when I impute the missing tax units as uniformly below the filing threshold, I do not make any assumption about whether they would have filed jointly, if they had filed. Instead, I use the overall average number of adults per tax unit (calculated in *ibid.*, from historical demographic statistics) and re-weight that average to exclude the

⁸In some years, the brackets of income in which joint vs. nonjoint returns were reported varied from the thresholds in which tax unit income itself was reported (with either more or fewer stepwise brackets reported for marital filing status), so it was necessary to correct with linear averages the imputed number of married vs. non-married tax units based on the bracketwise reporting. Furthermore, the “taxable” and “nontaxable” returns were often categorized differently below a certain threshold: The filing requirement could be lower than the exemption level, so within lower income brackets there could be returns that were required to file but were not required to pay any tax. Taxability status was one level of disaggregation of reported statistics during the period of archival reports I examined, as were “optional” taxes and separate filing formats during the World War II era. Finally, I aggregate joint vs. nonjoint returns from differing taxability, to create a unified bracketwise percentage of single filers, by which to split the tax units and individualize the income distribution among all adults

⁹First, the generalized Pareto curve smoothing function takes into account the income thresholds and bracket averages; and then, on the basis of the percentage of joint vs. nonjoint tax returns per bracket, creates a set of adults with incomes either consistent with the level of the bracket (singles), or of the bracket divided by two (if married). Combining these together again yields the individualized cumulative distribution function.

joint-filing propensity of observed tax units. In this way, I arrive at a proportion of imputed “joint” tax units among unobserved non-filers below the filing threshold. While it is simply a record of the number of adults per tax unit among missing tax units, this “imputed propensity to file jointly” is actually considerably higher than the proportion of joint tax units just above the filing threshold. However, the result is a plausible—and likely represents a more robust imputation of “adults per tax unit” than would be the assumption that non-filing tax units follow the same pattern of “joint” households and tax units who do file (even or especially at the precise threshold of the filing requirement—given the changing incentives). In practice, the results on overall shares of income distribution are not greatly affected, since this imputation takes place at the level of the lowest tax brackets. However, it is still worth noting this rationale for the relatively high proportion of would-be “joint” tax units among non-filer tax units at the base of the income distribution.

A3.1.5 Toward a harmonized income concept over time

As in Piketty and Saez (2003), it was necessary here to adjust the “net income” and “adjusted gross income” concepts to create a harmonized fiscal income concept for comparability over time. To create a harmonized fiscal income concept has been a chimera since Scheuren and McCubbin (1989) attempted the effort, and still has not been resolved even by the efforts of Statistics of Income scholars at the IRS (Bryant et al., 2010). The changing nature of exemptions and deductions codified into law has meant that net income and adjusted gross income are not the same across time. But I do make some calculations to retrieve a gross income concept, before the tax and transfer system, without pensions, and including capital gains.

As the SOI report for 1939 puts it, “It is not possible... to adjust the ‘Total income,’ ‘Total deductions,’ and ‘Net income’ so that they will be comparable with these items as tabulated for prior years” (SOI, 1942). Even the definition of what was deductible changed over time. More significantly, in 1944 the IRS changed their definition of the tabulated income statistic, from “net income” to “adjusted gross income”:

The income concept applicable to 1951 through 1986 is adjusted gross income (AGI). Introduced in 1944, AGI is generally defined as gross income less (1) allowable trade and business deductions, (2) travel, lodging and other reimbursed expenses connected with employment, (3) deductions attributable to rents and royalties, (4) deductions for depreciation and depletion allowable to beneficiaries of property held in trust, and (5) allowable losses from sales of property. (Personal deductions, such as those for medical expenses, personal interest paid and charitable contributions, are not subtracted from income until later, when the net income of itemizers is computed.)

The precise definition of AGI did change fairly often during this period, as various tax laws were enacted. The treatment of capital gains and losses was altered the most frequently, although other sources of income were included or exempted from time to time, as well. SOI data suggest, that the definitional changes that occurred in the gross income concept did not greatly affect the distribution of returns with income of \$25,000 or more in 1986 dollars in the 1916 to 1950 period. However, the

increasing frequency of significant tax law changes in the 1950 to 1986 period make these assertions more problematic. (Scheuren and McCubbin, 1989)

The new “adjusted gross income” concept of 1944 was meant to allow a harmonization between self-employment and salary/wage income concepts, as more taxpayers entered the IRS system and SOI reporting framework. However, the income concepts are not immediately comparable over time, even if they are comparable within a given year. According to the 1944 SOI report on the nature of the new AGI concept and its itemized deductions:

One group, deductible from gross income in computing adjusted gross income, consists of expenses incurred in trade or business, deductions attributable to the production of rents and royalties, expenses of travel and lodging in connection with employment, reimbursed expenses in connection with employment, deductions for depreciation and depletion allowable to a life tenant or an income beneficiary of property held in trust, and allowable losses from sales or exchanges of property. These deductions, except losses from sales of property, are not tabulated. The income or loss to which such deductions relate is reported as a net amount.

The second group of deductions consists of the allowable expenses of a nontrade or nonbusiness character, such as contributions, medical expenses, taxes, interest, and casualty losses, which are deductible from the adjusted gross income for the computation of net income. . . (SOI, 1950)

Not only there many more missing returns pre-1944 when “net income” as opposed to “adjusted gross income” was the main fiscal income concept, but the income concepts themselves are very difficult to reconcile. Nonetheless, I tabulate the deductions for each year, within each income bracket, in order to infer a gross income concept.

Revised bracket thresholds and bracket averages are expressed as:

$$s^* = \frac{s}{1 - d}$$

where s is the original threshold level or bracket average of net income or AGI, and d is the deduction as a percentage of the overall gross income, so s^* gives the new threshold or bracket average for gross income prior to deductions and other adjustments.

The amount of deductions per bracket varied from as much as 40 percent of gross income in the lowest net income brackets to as little as 10 percent of gross income in the highest net income brackets. Fortunately, there is no effect of re-ranking,¹⁰ as the proportion of deductions changes rather smoothly, but I have accounted for the percentage and amount of deductions in the overall gross income for each bracket, for each year.

¹⁰Re-ranking would occur if the filers in a lower net income bracket had deducted so much more on average than a higher income bracket so as to become in effect higher earners in overall gross income. Such an issue of re-ranking would make it necessary to merge the brackets, at which point I would lose valuable information about the shape of the cumulative distribution function.

One further adjustment was necessary in the income tax returns for the years 1941-43. For some filers whose net income was below \$3000, it was not necessary to file a return, but rather optional. These taxpayers were accounted for separately in the SOI annual reports, as they had filed a separate return, the simplified 1040A instead of the 1040. Since the overall data from the IRS did not include these “optional” taxpayers within the net income brackets below \$3000, instead listing them separately, I codified their gross income from the archive data that listed them separately, and folded them into homologous income brackets with similar earners in the years 1941-43.

A3.1.6 Treatment of capital gains

Beyond these specific tweaks, the notion of capital gains represented a final remaining issue for the treatment of gross income over time.

Treatment of capital gains in tax law (and, therefore, tax return data) changed over time. To deal with this issue, Piketty and Saez (2003) calibrated the resulting effect on net income, in order to calculate a gross income concept prior to the differential reporting of capital gains. In fact, they computed several variants of capital gains treatment in their dataset, including one which excludes capital gains, one which excludes but re-ranks top incomes according to capital gains, and finally a series that fully accounts for capital gains.¹¹ In general, they found that the adjustments for capital gains could be given as a 4 percent adjustment upward for the top 0.01% of income earners, a 2 percent adjustment upward for the remaining top 0.5% of earners, and a 1 percent increase to adjust for capital gains in the income of remaining top 5% tax unit earners. These capital gains adjustments (from *ibid.*) are stable over the period of this study. I revise threshold levels and bracket averages to reflect income from capital gains; in practice the adjustment only affects the top of the distribution.

Of course, capital gains are a lesser source of income for those below the top percentiles, and indeed negligible on average, so it was not necessary to make adjustments below the top thresholds. Using the Piketty and Saez (*ibid.*) capital gains adjustment multipliers allows to create a harmonized gross income concept that is relatively uniform across years. As will be discussed below, I also end up with results that are consistent with the earlier findings of that paper and of Piketty, Saez, and Zucman (2018).

With these corrections the issue of re-ranking can be overcome. For income from capital gains, the re-ranking problem would have arisen as follows: Incomes without capital gains can appear greater on “net” than incomes with capital gains, if the latter are not included in the SOI income concept in certain years (due to a changing definition of net income or AGI). As we are looking for a harmonized time series on “gross” income, of course, it becomes important to adjust net income and AGI upward by the same as the proportion of missing capital income.

In fact, there is little capital gains correction to be made below the 90th percentile of income earners, as capital gains makes up a very small proportion of income for the average middle class tax unit, and there is almost zero income from capital among the poorest households. Adjustments for the changing definition of

¹¹All of this is despite the variable tax treatment of capital gains—including some levels of exclusion of this income source post-1934—or, rather, after adjusting for that variation.

capital gains have a greater effect above the 90th percentile, and particularly above the 95th and then 99th percentiles. I adjust accordingly and in tune with the corrections of Piketty and Saez (2003).

More recently, Piketty, Saez, and Zucman (2018) and Saez and Zucman (2016) have adjusted post-1962 top incomes based on observations from the Survey of Consumer Finances (SCF) from 1989 to present. While I have not attempted to extrapolate SCF results to pre-1962 data, the smoothing function of Piketty-Saez-Zucman means that the top 99.999th (or 0.001) percentile of income earners shows more volatility in the raw SOI data than in their results.¹² In principle, this does not affect the results on the middle class share of earned income, but is worth bearing in mind as we consider pre-1962 results.

The notion of deductions changes slightly for post-war data (as the IRS changes its benchmark concept from “net” to “adjusted gross” income), and especially post-1962. Again, I make the same adjustments as Piketty and Saez (2003) in order to re-adjust the IRS adjusted gross income into the more complete and comparable-over-time gross income concept. After World War II, these adjustments for deductions are less important than they had been beforehand.

A3.1.7 Wage income series

As the largest component of fiscal income among middle class households, wage and salary income is worthy of our particular attention.

In addition to the benchmark series on overall income inequality, I have extended the Piketty and Saez (*ibid.*) series on wage income, to track the patterns of gain and loss of the lower 50% and middle 40% shares of wages and salaries, and in particular among equal-split adults in addition to tax units.

Many of the same adjustments from the fiscal income series (above) were also necessary in order to create a long-run wage series. I also use the same generalized Pareto curves technique as discussed above. However, the definition of wage income is more constant over time, as this source of income does not admit as many variations of tax status and definition as does overall income (see above).

In general, in most years, the SOI reports list the number of tax returns with wages earned per bracket of net income (or, later, AGI). The reports also list amount of wages earned per income bracket. And the reports list the number of returns by wage bracket. Only in early years (pre-1935), however, do the reports list the amount of wages by wage bracket.

Therefore, I generalize a wage income distribution on the basis of a general imputation and interpolation following the procedure of Piketty and Saez (*ibid.*). For the lower zero to 90th percentiles of the wage income distribution, I infer that the average wage income distribution (which we do not observe) follows the overall income distribution (which we do). This is a safe inference: More than 90% of returns in these income brackets report wage income, and the average size of wage income (among wage earners) in these brackets is very similar to the average size of

¹²This is discussed further in Appendix A3.3.

gross income (among all earners) in these brackets.¹³ We can observe these patterns in the chart in Figure A3.4.

The ratio of wage returns to total returns, and average wages to average net income, is stable within the bottom 90 percentiles of net income distribution, and stable over time. I adjust the income bracket averages and thresholds by this ratio (average wage income to average overall income, within the income bracket), along the entire income distribution until the 90th percentile. This gives imputed wage brackets up to the 90th percentile.

It is at the 90th percentile or above when wages begin to appear in fewer than 90 percent of returns, and to represent less than 90 percent of the average income of the bracket. At this point, the issue of re-ranking would become too important to ignore.¹⁴ We would no longer be faithfully following the wage distribution if we assumed its shape were the same as the overall income distribution (e.g., higher earners have great proportion of income from capital gains, rent, royalties, etc.). Therefore, I follow Piketty and Saez (2003) and turn back to the limited information on the wage distribution.

At the 90th percentile of the wage distribution, that is, I turn away from the net income distribution (with imputed wages per net income bracket) and now interpolate the wage distribution based on two pieces of data: the number of tax units in and above the 90th percentile, *by wage bracket*, which we observe in the SOI report; and the amount of wage income per wage bracket among the highest returns, which we do not observe in the reports. This is solved in the same way as in Piketty and Saez (*ibid.*). From the Pareto distribution function above, they solved:

$$k = (s) * (p)^{\frac{1}{\alpha}}$$

and

$$k = (t) * (q)^{\frac{1}{\alpha}}$$

where k and α are the Pareto parameters and can change from one wage bracket to another, and s and t are the lower and upper income thresholds of the wage bracket, while p is the proportion of the population above s and q is the proportion above t . The parameter α is related to the inverted Pareto coefficient b mentioned earlier, simply as:

$$\alpha = \frac{b}{b - 1}$$

The amount of wage income in the wage bracket can then be given by:

¹³Note that average wage income within an SOI net income bracket can exceed the average net income of that bracket in one of two ways: Either the average wage income of tax returns with wages (more than 90 percent of the filers, within lower brackets) can exceed the average gross income of tax returns without wages (the remaining less than 10 percent of filers, within lower brackets); or the average wage income is similar to average gross income, which is of course higher than the average net income of the bracket, regardless of any difference between wage earners and non-wage earners within the net income bracket.

¹⁴That is, if a household has a high income but does not report much wage income, it would actually be lower on the *wage income* distribution than a household that is lower in the *overall income* distribution whose proportion of income from wages is much higher. This issue of re-ranking could cause us to misidentify the proportion of households at given levels of wage income.

$$Y = N \int_s^t y dF(y)$$

with N as the number of tax returns in the wage bracket. This is also related to the methods of Kuznets and Jenks (1953) and Feenberg and Poterba (1993). Scheuren and McCubbin (1989) use a “spline-fitting” approach, but that is not necessary here, as I fit the Pareto distribution to top wage income brackets.

With this procedure, then, I calculate the same top 10% wage shares and wage income levels as Piketty and Saez (2003) observe.

With this imputed and interpolated information on the complete distribution of wage income thresholds and bracket averages, we are now in position to use the generalized Pareto curve technique to estimate the levels and shares of wage income among the entire wage-earning population from zero through the 90th percentiles of the wage income distribution.

For missing wage income and missing wage-earning tax units: As in the overall income series above, and as in Piketty and Saez (*ibid.*), the total wage bill and the total number of tax units with wages are estimated from national accounts data 1929-present, and interpolated from Kuznets and Jenks (1953) prior to that. From these totals, we know the amount of missing income and missing tax units that are not found in the annual SOI reports. We may know very little about missing wage returns (specifically, we do not know where they would fall along the overall income distribution), but I insert missing wage income and missing wage returns according to the first (and more robust) of the two imputations procedures for overall income discussed above. That is, I allocate missing wage-earning tax units below the filing threshold. This again relies on the observation that most income earners below the 90th percentile threshold earn wages, and most income below the 90th percentile is wage income. Therefore, in the interpolation technique, I set the lowest wage income bracket as the one corresponding to the overall income filing requirement, and I assign all missing wage income to the lowest bracket.

When Piketty and Saez (2003) estimated wage inequality among tax units, they made sure to account for the proportion of working wives in the population of married couple tax units. We are now able to disaggregate the wage-earning population into equal-split adults as above, by returning to the SOI reports archive for data on joint vs. nonjoint tax returns. For each income bracket of the wage-earning population, for each year, I record the propensity to file singly or jointly. The SOI did not report the number of wage returns among married couples filing jointly for wage income brackets, but only according to net income brackets, and only after 1954.

For equal-split adults among wage-earning tax units, I follow a similar line of reasoning as above. For the lowest zero to 90th percentiles, I again make use of the fact that there would be little re-ranking between income earners and wage earners. This is especially true when we are only looking at the number of joint returns that filed with wage income. Before 1947, I take the percentage of wage returns for each net income bracket, among joint vs. nonjoint returns, to split equally the (imputed average wage) income of those brackets. Later, when we have information on wage returns specifically within joint returns, I analyze according to the “propensity to file jointly” among wage returns specifically.

For the top 10 percent of wage earners, considering the significant re-ranking among wage returns and returns overall, it would not be safe to assume that the bracket averages among net income returns apply in the same way to wage income returns (which have distinct bracket thresholds, in any case, as derived above)—nor that the top net income brackets look similar to the top wage income brackets in terms of “propensity to file jointly.” Rather, I take the average of wage returns filing jointly among all top-ten percent earners, and set this equal in each top-ten (imputed) wage income bracket. It may be the case that top 1% or top 0.01% wage earners actually filed jointly at a greater percentage than would top 10 or top 5% income earners, but the reverse might also be true, so I do not want to make any assumption. In practice, usually an average of 90% of returns are filed jointly within the top ten percent of the distribution (see Figure A3.5).

I make one further correction to joint vs. single wage income returns: For the period 1947-1953, the number of wage returns filing jointly vs. separate/singly is not reported, and all we have is the overall number of joint vs. single returns per bracket, without knowing whether these varied by wage vs. nonwage returns. Therefore, I study the ratio for filing jointly within wage vs. overall returns from 1954-75, and find constant multipliers for the lower 50th percentiles, the middle 50-90 percentiles, and the top 10 percentiles. I impute the propensity to file jointly among wage earners in 1947-53, from the fraction among earners overall, according to the same ratio in years 1954-75. In practice, the correction is negligible among the lower net income (and wage) brackets, but becomes a more necessary correction among the top 10% of wage earners.

Unfortunately, for the years prior to 1947 I do not want to make the same imputation because the incentives to filing singly or jointly were very different. As discussed in Piketty and Saez (2003), before 1947 there was a single tax schedule applying to all tax units (whether filing jointly or separately, if married), so married couples had an incentive to file separately. This incentive may have impacted filing behavior of wage-earning couples distinctly from the way it impacted nonwage-earning couples, but I do not speculate and instead impute the overall propensity to file jointly among all couples, to be the same propensity as among wage-earning couples. That is, pre-1947 I assign to wage returns the same proportion of single vs. joint returns as is observed overall, per net income bracket, without any adjustment except the one for the top 10% of the distribution, discussed above.

A3.1.8 Incorporating Goldsmith-OBE data into new estimates

The final labor to prepare this new data series consisted of merging survey data from another distribution, into the SOI data.

As we have seen, the central challenge to interpolate the fiscal and wage income distributions prior to World War II is that we do not have many tax returns—often as few as 10 percent of the overall population. On top of this, even when we do have more than 10 percent of the population filing tax returns, the high filing requirements (discussed above) make it hard to say whether the returns that we do have are representative of any subsample of the population beyond the top 10 percent of earners. I assume that the highest income earners observed in the tax data are the highest income earners overall, but we cannot be sure where the

remaining earners fall on the total distribution that includes missing returns (non-filers). When there are many non-filers—as is the case in the early decades of American income tax data—we do not have enough of a distribution on which to anchor any imputation of missing tax units, even (or especially) if we wanted to split the non-filers equally from zero through 90th income percentiles.

Since we do not have reliable income data below the 90th percentile of tax units in the time period prior to World War II, I supplement the administrative tax data with survey data from the same period. The US Department of Commerce, Office of Business Economics (OBE, what would later become the Bureau of Economic Analysis) produced a periodic *Survey of Current Business* which tabulated the entire income distribution of family “consumer units.” This survey gathered data in 1929, 1935-36,¹⁵ 1941, 1944, 1946, 1947 and then annually from 1950 (see Fitzwilliams, 1964).

While the survey data was harmonized to a large extent by Selma Goldsmith et al. (1954), it remained imperfectly comparable, particularly for 1929:

Unlike 1935-1936, 1941, and postwar years, there was no nationwide sample field survey of family incomes in 1929 on which to base the income distribution estimates. Instead, the Brookings Institution constructed a 1929 distribution for families and unattached individuals by combining a variety of different sets of income statistics for persons (for example, for wage earners and farmers) and then converting them to a family-unit basis. The Brookings distribution is admittedly rough, particularly for the lower end of the income scale. (Goldsmith, 1958)

The Brookings Institution data for 1929 was harmonized by Goldsmith and colleagues for use in the long-run OBE income distribution series. They removed capital gains and losses, after which adjustments the top income shares and top tail of the distribution began to resemble those from the SOI data of that time for top earners. The 1935-36 data is from the Consumer Purchases Study undertaken by the National Resources Committee and “did not have the benefit of subsequent advances in sampling techniques” (ibid.). The 1941 data is from the Bureau of Labor Statistics, and the 1944 and 1946 and 1947 surveys were carried out by the Census Bureau, with complementary inputs from the Federal Reserve Board. The Commerce Department Office of Business Economics (OBE) reworked these datasets to bring them into line with their own “personal income” concept of total money income (see Goldsmith, 1951).

In discussing the trends of income distribution and the comparability of income concepts over time, Goldsmith felt that an increasing share of top incomes were given as in-kind benefits, deferred compensation and business expense accounts (1957).¹⁶ The OBE estimates also did not quite agree with Census/CPS estimates of the bottom quintile of the distribution in the year of their comparison, i.e., with data for 1954 (Goldsmith, 1958). For higher incomes, however, the two datasets began to match, which to Goldsmith served as testament to their fidelity to the true population parameters.

¹⁵OBE data represents an average for the two years of survey fieldwork, 1935-36.

¹⁶If income components and income concepts that change over time, by bracket, this highlights one significant part of the appeal of creating a distributional national accounts measure—such that 100 percent of national income is allocated according to its distribution, regardless of whether it accrues to households as salaries, capital gains, benefits, or other forms of income.

Even if these Goldsmith-OBE survey estimates prior to IRS comprehensive tax data are admittedly “rough,” as Goldsmith (1958) put it, they remain our best source of information on nationwide income distribution below the 90th percentile, prior to World War II.¹⁷

Since this OBE series is the only known survey of the *full* distribution of income prior to the mid-1940s expansion of comprehensive SOI data, I will use this source to draw some inferences about the shape of the distribution. Specifically, I use the SOI data above the 90th percentile, and the OBE data below the 90th percentile, and harmonize the estimates at this juncture. Figure A3.6 illustrates.

I rescale the bottom 90 percent distribution of the OBE distribution according to the known average income level (and total income) from SOI statistics and the national accounts (discussed above), so that the OBE bottom 90 average and levels match that of the SOI bottom 90. Then I reweight the OBE distribution to accommodate missing tax units, such that family units of the OBE distribution match the tax units of the SOI distribution, with an imputed propensity of joint vs. single filers to seamlessly fit the calculation of a series for equal-split adults. I can only assume that the number of tax units per household is constant over the income distribution from zero to the 90th percentile, and that the propensity to file jointly among OBE households would be that of the SOI population average (making no distinction for tax bracket).

Since we have observed from SOI that the majority of income among below-90th percentile income earners comes from wages and salaries, I can repeat the above exercise among the OBE below-90th percentile distribution to move from overall income to wage income. That is, I rescale the OBE income averages according to the known averages of the bottom-90 wage distribution, and I reweight the distribution up to the 90th percentile according to the known population of wage earners.

After these adjustments and the above method of interpolation, we now have estimates for 1929, 1935-36,¹⁸ 1941, and 1944 that cover the whole population, for overall income and for wage income, for both tax units and equal-split adults.

First, it is important to show that these estimates agree with the benchmark series on top shares. In Figure A3.7 I compare these on a tax-unit basis, which is the only comparison available, as previous estimates could not examine equal-split adults.

Indeed, the data from Selma Goldsmith and the US Commerce Department OBE do match Piketty and Saez (2003) and Piketty, Saez, and Zucman (2018) on the top 10% shares of fiscal income, which should not be surprising because I am using SOI data on top 10% shares to harmonize the OBE data. Estimates from the Goldsmith-OBE series are by necessity very rough, given the limitations of the source material, but at the same time they appear to be in the appropriate range to scrutinize further their depth and substance. I have also tested the fidelity of Goldsmith-OBE estimates in 1946, 1955 and 1962, to ensure the similarity with Piketty and Saez (2003), Piketty, Saez, and Zucman (2018) and these new estimates. These results are shown in Appendix Tables A3.1 and A3.2.

¹⁷A few scholars have examined state-level income distributions for the era, a possibility I will return to in discussing further research below.

¹⁸As the Goldsmith-OBE dataset is averaged for calendar years 1935-36, I have done the same with the SOI administrative tax records for those years.

These pre-1945 results can tie seamlessly together with the annual estimates of post-1945 income and wage inequality for the full distribution of equal-split adults. Furthermore, for the pre-1945 years we observe top 10% shares every year, so I can extrapolate shares within the bottom 90% in years for which we do not have survey data, by way of a simple ratio. That is, I take the ratio of distributions within the bottom 90%, to the top 10%, in years for which we do have data, and extend these backward for the bottom 90% in years for which we only have top 10% data.

In this way I show tabulations for bottom 90 percentiles, and a representation of their income distribution, for several years even before the comprehensive SOI data series began in the 1940s. For the post-war years, we have much more solid evidence from the entire population of tax filers. In all cases, we now can draw inferences on the entire adult population, as well, and not only the tax units. We can now look inside the bottom 90th percentiles of fiscal and wage income distributions for the years 1913-75.¹⁹

That said, with respect to the data that precedes the Goldsmith-OBE survey data era, caveats are in order. For the period 1929-1944, I am able to complement the SOI information on top shares (p90p100) with Goldsmith-OBE survey data for the remainder of the distribution (p0p90), interpolating between the survey years of 1929, 1935-36, 1941 and 1944. As SOI converges to its minimal level of non-filers by 1945,²⁰ I am able to use only the SOI data for all years after 1944. (Using the Goldsmith-OBE survey data beyond 1944 would not change much.) Before 1929,²¹ however, I make a simple assumption that the *within*-p0p90 splits do not change, even if with SOI data we can observe that the bottom 90% (p0p90) and top 10% (p90p100) shares do change. From 1913-1916, we only observe the top 1% of the fiscal income distribution. For these reasons, we may have more confidence in the reliability of the estimates from 1945 throughout the postwar period, and estimates prior to 1929 (1917) are particularly (most) fragile.

A3.1.9 From fiscal income to pre-tax national income

Once I have a reliable estimate of fiscal income distribution, it is only a small step to infer the distribution of national income. I do so here on a pre-tax basis, i.e., before the redistributive actions of the tax-and-transfer system (but including pension contributions and receipts among pre-tax income flows).

Specifically, the procedure to move from fiscal income to pre-tax national income is neatly summarized in a recent technical note from Piketty, Saez, and Zucman (2019), and I make the following assumptions: (1) Non-fiscal labor income is distributed like fiscal labor income; (2) non-fiscal capital income from pensions is distributed like fiscal labor income; and (3) non-fiscal capital income (from all other sources) is distributed like fiscal capital income.²² The authors show that this

¹⁹Further research could extend these results from SOI raw tabulated data even into the 21st century, although I show below that this method already matches closely with the Piketty-Saez-Zucman microdata estimates for the period of overlap from 1962-75. Microdata files are available from 1962.

²⁰Approximately 10-15% of estimated tax units do not file; a level that remains stable through the rest of the study period.

²¹Wages are only observed beginning in 1927.

²²We also assume zero or negligible re-ranking from the differences between fiscal and non-fiscal income distributions.

method produces a reliable estimate of pre-tax national income distribution to a first-order approximation, even without the more complex calculations that are feasible with their microdata after 1962 (*ibid.*). Therefore, even despite the aforementioned limitations in the available data and the associated caveats, we can be confident that the new fiscal income estimates equally allow an estimation of pre-tax national income.

We are able to move from fiscal income to pre-tax income, then, because we know the components of fiscal and pre-tax income. That is, we know from which sources tax units earned their income—so we have an estimate of labor (and capital) income within the share of income that is reported to the SOI. Taking the difference of this fiscal labor (capital) income from the total amount of labor (capital) income in the economy as a whole—an amount which can be calculated from national accounts²³—we distribute the residual non-fiscal labor (capital) income according to the principles outlined above.

From this basis and the procedures above, I estimate the full distribution of national income (and its components) for the years 1913-62. While the pre-tax national income estimates are interesting in their own right (see Figure 3.3) and perhaps deserve further discussion, the main focus of this paper has been the treatment of fiscal and wage income distributions—which, of course, comprise the majority of earnings among the lower 90 percent of the income distribution. Therefore, the fiscal and wage income distributions are the backbone of this analysis, in both the statistical procedure above and in the economic reality it reflects (in both the data- and the income-generating processes, one might say). For this reason, although the new data and new results here do extend more broadly to cover all of national income and its component parts, for the full income distribution from 1913-62, I will focus this discussion here on fiscal and wage inequality patterns for poor and middle-class households at midcentury, and especially in the postwar period.

A3.2 Robustness and sensitivity analysis

To assess the validity of these findings, and select one method rather than another for the imputation of missing income and missing tax units, it is useful to compare the new results to those of Piketty, Saez, and Zucman (2018, hereafter PSZ) in the years that they were able to calculate inequality estimates using microdata and IRS public use files. That is, I calibrate the new results against PSZ the years after 1962. I show my new estimates, then, comparing to the benchmark series, for the years 1962-1975. The imputation method that matches microdata after 1962 would be the better method for imputing data pre-1962, when there is no microdata.

If I assign all “non-filing” tax units to the lefthand side of the income distribution as discussed above, I observe the following pattern (in blue) of top 10% fiscal income shares during the period 1945-75. By contrast, when I allocate a simple proportional split of non-filing tax units across the income distribution, then I observe a lower level of inequality (in red), albeit a similar pattern. My comparison of the two methods shows that one follows PSZ microdata estimates

²³These macroeconomic components are reported in the appendix materials to Piketty, Saez, and Zucman (2018).

much more closely on top 10% shares of the income distribution. In Figure [A3.8](#) I zoom in on the post-war period to make this comparison.

According to these results comparing imputation to microdata estimates, it would seem to make more sense to assign the missing tax units to the leftmost side of the income distribution, and not proportionally split them among all tax units in the distribution of filers. This imputation strategy which allocates missing income and missing people to the leftmost side of the distribution as opposed to simple proportional split throughout the distribution, also shows a goodness of fit that can be observed in the top 1% shares of fiscal income (see Figure [A3.9](#)).

These lefthand-allocation results are also a closer match to microdata estimates of the bottom 50% and middle 40% shares of fiscal income between 1962 and 1975, as well (Figures [A3.10](#) and [A3.11](#)).

In fact, the method where I impute all non-filers to below the filing threshold is almost a perfect match for bottom 50% income share. No matter which method of imputation I choose for the nonfilers, I do see that PSZ find a higher share of income going to the middle 40%. However, if I assign nonfilers to the lefthand side of the distribution, the estimate is closer than if I assign according to a simple proportional split. The remaining difference is within the range of methodological difference: sampling error combined with the small range of error from generalized Pareto curves from bracket tabulations (Blanchet, Fournier, and Piketty, [2022](#)). The microdata public use files are a sample, while the bracket tabulations are interpolated to yield a smooth income distribution function. Some discrepancy is reasonable, and 1% is likely not unreasonable, but it would be interesting in further research to consider the difference between the result here and the PSZ result.

In any case, from the results above, I see that the more robust approach is to impute the non-filers as low-income—as below the filing threshold—and not as equally spread throughout the lower 90 percent of the distribution. From these comparisons, I moved forward with the imputation method that placed missing income and missing tax returns on the lefthand side of the distribution, below the filing threshold, rather than the imputation that allocates non-filers equally among the entire bottom 90 percentiles of the distribution.

A3.3 Tabulated data vs. microdata, 1962-75

As in the text, it is clear that we have a good match at the top 10% share, but it worth showing and exploring this in more detail.

To compare the two methods of non-filer imputation, it is also important to take stock of what is happening at the different thresholds of the income distribution. Here in Figure [A3.12](#) I look at the overall average, and again find that imputing non-filers below the filing threshold is a better match with microdata estimates.

While the method of imputing non-filers as low-income (placing them at the lefthand side of the distribution) decreases the overall average, it does not do so by much, and in some years not at all. In fact, the only reason it should do this would be by the mechanics of the smoothing function. In principle, the 90th percentile should be the same income level in both distributions, and so should the overall average, but when I assume non-filers have a very low income, the generalized Pareto curve income distribution function notes the overall income of the distribution and imputes more of it to the lowest earners. The smoothing function has to adjust some of the percentile thresholds and bracket averages of the distribution, based on the parameter I have attributed to the distribution (in the discussion above), and fitted to the information about the number of tax units in each bracket.

Once I have selected the method that imputes non-filers below the filing threshold, it is also worthwhile to examine comparisons and estimates further. First in Figure [A3.13](#), we can see that the 90th percentile is almost an exact fit between newly tabulated and disaggregated data, and the benchmark PSZ series.

I can also show that the Pareto coefficient is very similar between both estimates, at the 90th percentile (Figure [A3.14](#)).

However, we begin to see some differences in the very top 1%, not much in the top percentile threshold, nor in the top 1% share of overall income, but in the Pareto coefficient (Figure [A3.15](#)).

In fact, this probably has less to do with the imputation strategy than with the particular method of calculating income at the very top. The disparity can be seen in closest detail at the 99.999th percentile. Even there, the threshold levels are similar between both series' estimates, as can be seen in Figure [A3.16](#).

The estimates up to this point are close. However, the income levels above this point are much more volatile. (See Figure [A3.17](#).) While the top Pareto coefficient of the PSZ estimates remains steady, that of the new series swings up and down between years.

This can likely be explained by the different treatment of income at the very top. While the PSZ series creates a more nuanced and multiply imputed top-income measure from use of the Survey of Consumer Finances and asset capitalization methods drawn from Saez and Zucman ([2016](#)), the new estimate here from tabulated tax data relies solely on that source and benefits neither from microdata nor from any similar refinement as in the former case. These adjustments would bring the two series into harmony at the top 0.001%, and in so doing a more perfect overlap on the entire annual income distribution.

There is no such similar question for the wage distribution, which agrees at the very top as it does all along the distribution in the percentiles farther below.

Appendix 3 Tables

Table A3.1 – Fiscal income, tax units, for comparison years 1946, 1955, 1962

| series | Bottom 90% | | Bottom 50% | | Middle 40% | | Top 10% | | Top 1% | |
|--------|-------------------|-------------------|------------|-----|------------|-----|---------|-----|--------|-----|
| | OBE ²⁴ | SOI ²⁵ | OBE | SOI | OBE | SOI | OBE | SOI | OBE | SOI |
| 1946 | 63% | 63% | 21% | 18% | 42% | 45% | 37% | 37% | 15% | 14% |
| 1955 | 65% | 65% | 22% | 17% | 44% | 48% | 35% | 35% | 12% | 12% |
| 1962 | 67% | 66% | 21% | 15% | 45% | 51% | 33% | 34% | 9% | 10% |

²⁴refers to Goldsmith-OBE harmonized series

²⁵SOI only

Table A3.2 – Fiscal income, equal-split adults, for comparison years 1946, 1955, 1962

| series | Bottom 90% | | Bottom 50% | | Middle 40% | | Top 10% | | Top 1% | |
|---------------|-------------------|------------|-------------------|------------|-------------------|------------|----------------|------------|---------------|------------|
| Year | OBE | SOI | OBE | SOI | OBE | SOI | OBE | SOI | OBE | SOI |
| <i>1946</i> | 61% | 62% | 19% | 17% | 42% | 45% | 39% | 38% | 16% | 16% |
| <i>1955</i> | 66% | 67% | 20% | 20% | 46% | 47% | 34% | 33% | 12% | 12% |
| <i>1962</i> | 68% | 68% | 20% | 19% | 48% | 49% | 32% | 32% | 9% | 10% |

Table A3.3 – Fiscal income shares, tax units

| series | Bottom 90% | | Bottom 50% | | Middle 40% | | Top 10% | | Top 1% | |
|--------|------------|-----|------------|-----|------------|-----|---------|-----|--------|-----|
| | PSZ (2018) | new | PSZ | new | PSZ | new | PSZ | new | PSZ | new |
| 1913 | 59% | 61% | | 18% | | 43% | 41% | 39% | 18% | 18% |
| 1914 | 59% | 61% | | 18% | | 43% | 41% | 39% | 18% | 18% |
| 1915 | 60% | 61% | | 18% | | 43% | 40% | 39% | 18% | 18% |
| 1916 | 58% | 59% | | 18% | | 42% | 42% | 41% | 18% | 18% |
| 1917 | 59% | 61% | | 18% | | 43% | 41% | 39% | 18% | 18% |
| 1918 | 60% | 62% | | 18% | | 44% | 40% | 38% | 16% | 16% |
| 1919 | 60% | 61% | | 18% | | 43% | 40% | 39% | 16% | 16% |
| 1920 | 61% | 62% | | 18% | | 44% | 39% | 38% | 15% | 15% |
| 1921 | 57% | 57% | | 17% | | 41% | 43% | 43% | 16% | 16% |
| 1922 | 56% | 57% | | 17% | | 41% | 44% | 43% | 17% | 17% |
| 1923 | 59% | 59% | | 17% | | 42% | 41% | 41% | 16% | 16% |
| 1924 | 56% | 56% | | 16% | | 40% | 44% | 44% | 17% | 17% |
| 1925 | 54% | 53% | | 15% | | 38% | 46% | 47% | 20% | 20% |
| 1926 | 54% | 54% | | 16% | | 38% | 46% | 46% | 20% | 19% |
| 1927 | 53% | 53% | | 15% | | 37% | 47% | 47% | 21% | 20% |
| 1928 | 51% | 51% | | 15% | | 36% | 49% | 49% | 24% | 23% |
| 1929 | 53% | 52% | | 15% | | 37% | 47% | 48% | 22% | 23% |
| 1930 | 56% | 53% | | 15% | | 38% | 44% | 47% | 17% | 18% |
| 1931 | 55% | 52% | | 15% | | 37% | 45% | 48% | 15% | 17% |
| 1932 | 54% | 51% | | 15% | | 36% | 46% | 49% | 16% | 16% |
| 1933 | 54% | 50% | | 15% | | 36% | 46% | 50% | 16% | 17% |
| 1934 | 54% | 53% | | 15% | | 38% | 46% | 47% | 16% | 16% |
| 1935 | 56% | 56% | | 16% | | 39% | 44% | 44% | 17% | 21% |
| 1936 | 53% | 55% | | 16% | | 38% | 47% | 45% | 19% | 18% |
| 1937 | 56% | 57% | | 17% | | 40% | 44% | 43% | 17% | 16% |
| 1938 | 56% | 57% | | 17% | | 40% | 44% | 43% | 16% | 15% |
| 1939 | 54% | 57% | | 17% | | 40% | 46% | 43% | 16% | 15% |
| 1940 | 55% | 57% | | 17% | | 40% | 45% | 43% | 16% | 16% |
| 1941 | 58% | 57% | | 17% | | 40% | 42% | 43% | 16% | 19% |
| 1942 | 64% | 65% | | 21% | | 44% | 36% | 35% | 13% | 13% |
| 1943 | 66% | 68% | | 22% | | 45% | 34% | 32% | 12% | 12% |
| 1944 | 67% | 66% | | 22% | | 44% | 33% | 34% | 11% | 12% |
| 1945 | 66% | 64% | | 16% | | 47% | 34% | 36% | 13% | 14% |
| 1946 | 63% | 63% | | 18% | | 45% | 37% | 37% | 13% | 14% |
| 1947 | 66% | 66% | | 20% | | 46% | 34% | 34% | 12% | 12% |
| 1948 | 65% | 64% | | 17% | | 47% | 35% | 36% | 12% | 14% |
| 1949 | 65% | 64% | | 17% | | 48% | 35% | 36% | 12% | 13% |
| 1950 | 64% | 63% | | 17% | | 47% | 36% | 37% | 13% | 14% |
| 1951 | 66% | 65% | | 17% | | 47% | 34% | 35% | 12% | 13% |
| 1952 | 67% | 66% | | 18% | | 48% | 33% | 34% | 11% | 12% |
| 1953 | 68% | 67% | | 18% | | 49% | 32% | 33% | 10% | 10% |
| 1954 | 66% | 66% | | 17% | | 49% | 34% | 34% | 11% | 12% |
| 1955 | 66% | 65% | | 17% | | 48% | 34% | 35% | 11% | 12% |
| 1956 | 67% | 66% | | 17% | | 49% | 33% | 34% | 11% | 12% |
| 1957 | 67% | 66% | | 17% | | 49% | 33% | 34% | 10% | 11% |
| 1958 | 66% | 65% | | 16% | | 50% | 34% | 35% | 10% | 11% |
| 1959 | 66% | 65% | | 16% | | 49% | 34% | 35% | 11% | 12% |
| 1960 | 67% | 66% | | 16% | | 50% | 33% | 34% | 10% | 11% |
| 1961 | 66% | 65% | | 15% | | 49% | 34% | 35% | 11% | 12% |
| 1962 | 66% | 66% | 15% | 15% | 51% | 51% | 34% | 34% | 10% | 10% |
| 1963 | 66% | 65% | 15% | 15% | 51% | 50% | 34% | 35% | 10% | 11% |
| 1964 | 66% | 65% | 14% | 15% | 51% | 50% | 34% | 35% | 10% | 11% |
| 1965 | 65% | 64% | 15% | 15% | 51% | 49% | 35% | 36% | 11% | 13% |
| 1966 | 66% | 65% | 15% | 15% | 51% | 50% | 34% | 35% | 10% | 11% |

| series | Bottom 90% | | Bottom 50% | | Middle 40% | | Top 10% | | Top 1% | |
|---------------|-------------------|------------|-------------------|------------|-------------------|------------|----------------|------------|---------------|------------|
| <i>Year</i> | PSZ (2018) | new | PSZ | new | PSZ | new | PSZ | new | PSZ | new |
| <i>1967</i> | 66% | 64% | 15% | 15% | 50% | 49% | 34% | 36% | 11% | 13% |
| <i>1968</i> | 65% | 64% | 15% | 15% | 50% | 48% | 35% | 36% | 11% | 13% |
| <i>1969</i> | 66% | 65% | 16% | 16% | 50% | 49% | 34% | 35% | 10% | 12% |
| <i>1970</i> | 67% | 67% | 16% | 17% | 51% | 50% | 33% | 33% | 9% | 10% |
| <i>1971</i> | 67% | 66% | 15% | 16% | 51% | 50% | 33% | 34% | 9% | 10% |
| <i>1972</i> | 66% | 66% | 15% | 16% | 51% | 50% | 34% | 34% | 10% | 10% |
| <i>1973</i> | 67% | 67% | 15% | 16% | 51% | 51% | 33% | 33% | 9% | 8% |
| <i>1974</i> | 67% | 66% | 15% | 16% | 51% | 50% | 33% | 34% | 9% | 10% |
| <i>1975</i> | 67% | 65% | 15% | 15% | 51% | 50% | 33% | 35% | 9% | 10% |

Table A3.4 – Fiscal income shares, equal-split adults

| series | Bottom 90% | | Bottom 50% | | Middle 40% | | Top 10% | | Top 1% | |
|-------------|-------------------|-----|------------|-----|------------|-----|------------|-----|------------|-----|
| <i>Year</i> | PSZ (2018) | new | PSZ | new | PSZ | new | PSZ | new | PSZ | new |
| 1913 | | 58% | | 15% | | 43% | | 42% | | 18% |
| 1914 | | 58% | | 15% | | 42% | | 42% | | 18% |
| 1915 | | 58% | | 15% | | 43% | | 42% | | 17% |
| 1916 | | 56% | | 15% | | 41% | | 44% | | 19% |
| 1917 | | 57% | | 15% | | 42% | | 43% | | 17% |
| 1918 | | 60% | | 16% | | 44% | | 40% | | 15% |
| 1919 | | 60% | | 16% | | 44% | | 40% | | 16% |
| 1920 | | 61% | | 16% | | 45% | | 39% | | 15% |
| 1921 | | 57% | | 15% | | 41% | | 43% | | 16% |
| 1922 | | 57% | | 15% | | 41% | | 43% | | 17% |
| 1923 | | 59% | | 16% | | 43% | | 41% | | 16% |
| 1924 | | 55% | | 15% | | 40% | | 45% | | 17% |
| 1925 | | 51% | | 14% | | 37% | | 49% | | 19% |
| 1926 | | 52% | | 14% | | 38% | | 48% | | 19% |
| 1927 | | 51% | | 14% | | 37% | | 49% | | 20% |
| 1928 | | 49% | | 13% | | 36% | | 51% | | 23% |
| 1929 | | 50% | | 13% | | 36% | | 50% | | 22% |
| 1930 | | 51% | | 14% | | 37% | | 49% | | 18% |
| 1931 | | 50% | | 13% | | 37% | | 50% | | 17% |
| 1932 | | 50% | | 13% | | 36% | | 50% | | 16% |
| 1933 | | 49% | | 13% | | 36% | | 51% | | 17% |
| 1934 | | 52% | | 14% | | 38% | | 48% | | 16% |
| 1935 | | 54% | | 15% | | 39% | | 46% | | 21% |
| 1936 | | 52% | | 14% | | 38% | | 48% | | 18% |
| 1937 | | 55% | | 15% | | 40% | | 45% | | 17% |
| 1938 | | 56% | | 15% | | 40% | | 44% | | 15% |
| 1939 | | 55% | | 15% | | 40% | | 45% | | 16% |
| 1940 | | 57% | | 16% | | 42% | | 43% | | 16% |
| 1941 | | 56% | | 16% | | 41% | | 44% | | 20% |
| 1942 | | 65% | | 20% | | 45% | | 35% | | 13% |
| 1943 | | 67% | | 21% | | 46% | | 33% | | 12% |
| 1944 | | 65% | | 20% | | 45% | | 35% | | 13% |
| 1945 | | 62% | | 15% | | 47% | | 38% | | 15% |
| 1946 | | 62% | | 17% | | 45% | | 38% | | 16% |
| 1947 | | 64% | | 18% | | 46% | | 36% | | 13% |
| 1948 | | 65% | | 19% | | 46% | | 35% | | 13% |
| 1949 | | 66% | | 18% | | 47% | | 34% | | 12% |
| 1950 | | 65% | | 19% | | 46% | | 35% | | 14% |
| 1951 | | 66% | | 20% | | 47% | | 34% | | 12% |
| 1952 | | 68% | | 20% | | 48% | | 32% | | 11% |
| 1953 | | 69% | | 21% | | 48% | | 31% | | 10% |
| 1954 | | 67% | | 20% | | 48% | | 33% | | 11% |
| 1955 | | 67% | | 20% | | 47% | | 33% | | 12% |
| 1956 | | 68% | | 20% | | 47% | | 32% | | 11% |
| 1957 | | 68% | | 20% | | 48% | | 32% | | 11% |
| 1958 | | 67% | | 19% | | 48% | | 33% | | 11% |
| 1959 | | 67% | | 19% | | 48% | | 33% | | 11% |
| 1960 | | 68% | | 19% | | 49% | | 32% | | 11% |
| 1961 | | 67% | | 18% | | 48% | | 33% | | 12% |
| 1962 | 68% | 68% | 18% | 19% | 50% | 49% | 32% | 32% | 9% | 10% |
| 1963 | 68% | 67% | 19% | 18% | 50% | 48% | 32% | 33% | 9% | 11% |
| 1964 | 68% | 67% | 19% | 19% | 49% | 49% | 32% | 33% | 9% | 11% |
| 1965 | 68% | 66% | 19% | 19% | 49% | 47% | 32% | 34% | 10% | 12% |
| 1966 | 68% | 68% | 20% | 20% | 49% | 48% | 32% | 32% | 10% | 11% |

| series | Bottom 90% | | Bottom 50% | | Middle 40% | | Top 10% | | Top 1% | |
|---------------|-------------------|------------|-------------------|------------|-------------------|------------|----------------|------------|---------------|------------|
| <i>Year</i> | PSZ (2018) | new | PSZ | new | PSZ | new | PSZ | new | PSZ | new |
| <i>1967</i> | 68% | 67% | 20% | 20% | 48% | 47% | 32% | 33% | 10% | 12% |
| <i>1968</i> | 67% | 66% | 20% | 19% | 48% | 47% | 33% | 34% | 11% | 13% |
| <i>1969</i> | 69% | 67% | 20% | 20% | 48% | 47% | 31% | 33% | 10% | 11% |
| <i>1970</i> | 69% | 69% | 20% | 21% | 50% | 49% | 31% | 31% | 8% | 9% |
| <i>1971</i> | 69% | 69% | 19% | 20% | 50% | 49% | 31% | 31% | 9% | 9% |
| <i>1972</i> | 69% | 68% | 19% | 20% | 50% | 49% | 31% | 32% | 9% | 10% |
| <i>1973</i> | 69% | 70% | 19% | 20% | 50% | 50% | 31% | 30% | 9% | 8% |
| <i>1974</i> | 69% | 69% | 19% | 20% | 50% | 49% | 31% | 31% | 8% | 9% |
| <i>1975</i> | 69% | 68% | 18% | 18% | 51% | 50% | 31% | 32% | 8% | 10% |

Table A3.5 – Wage income shares, tax units

| series | Bottom 90% | | Bottom 50% | Middle 40% | Top 10% | | Top 1% | |
|-------------|------------------|-----|------------|------------|----------------|-----|----------------|-----|
| <i>Year</i> | PS (2003) | new | new | new | PS 2003 | new | PS 2003 | new |
| 1927 | 72% | 72% | 22% | 50% | 28% | 28% | 9% | 9% |
| 1928 | 71% | 71% | 22% | 49% | 29% | 29% | 9% | 9% |
| 1929 | 71% | 71% | 21% | 49% | 29% | 29% | 9% | 9% |
| 1930 | 71% | 71% | 22% | 49% | 29% | 29% | 9% | 9% |
| 1931 | 71% | 71% | 22% | 49% | 29% | 29% | 8% | 8% |
| 1932 | 70% | 70% | 21% | 48% | 30% | 30% | 8% | 8% |
| 1933 | 70% | 70% | 22% | 48% | 30% | 30% | 8% | 8% |
| 1934 | 70% | 70% | 22% | 49% | 30% | 30% | 8% | 8% |
| 1935 | 70% | 70% | 22% | 49% | 30% | 30% | 8% | 8% |
| 1936 | 70% | 70% | 22% | 49% | 30% | 30% | 9% | 9% |
| 1937 | 70% | 70% | 21% | 49% | 30% | 30% | 8% | 8% |
| 1938 | 70% | 70% | 21% | 49% | 30% | 30% | 8% | 8% |
| 1939 | 69% | 69% | 21% | 48% | 31% | 31% | 8% | 8% |
| 1940 | 69% | 69% | 21% | 48% | 31% | 31% | 8% | 8% |
| 1941 | 71% | 73% | 25% | 48% | 29% | 27% | 8% | 7% |
| 1942 | 73% | 74% | 30% | 44% | 27% | 26% | 7% | 7% |
| 1943 | 74% | 76% | 35% | 41% | 26% | 24% | 6% | 6% |
| 1944 | 75% | 76% | 35% | 41% | 25% | 24% | 6% | 5% |
| 1945 | 76% | 77% | 36% | 40% | 24% | 23% | 6% | 6% |
| 1946 | 75% | 76% | 35% | 41% | 25% | 24% | 6% | 6% |
| 1947 | 75% | 76% | 35% | 41% | 25% | 24% | 6% | 6% |
| 1948 | 75% | 76% | 33% | 42% | 25% | 24% | 6% | 6% |
| 1949 | 75% | 76% | 34% | 42% | 25% | 24% | 6% | 6% |
| 1950 | 75% | 76% | 33% | 43% | 25% | 24% | 6% | 6% |
| 1951 | 75% | 76% | 33% | 43% | 25% | 24% | 6% | 6% |
| 1952 | 76% | 76% | 32% | 44% | 24% | 24% | 6% | 6% |
| 1953 | 76% | 76% | 33% | 44% | 24% | 24% | 6% | 6% |
| 1954 | 76% | 76% | 33% | 43% | 24% | 24% | 6% | 6% |
| 1955 | 76% | 76% | 33% | 43% | 24% | 24% | 6% | 5% |
| 1956 | 75% | 76% | 33% | 43% | 25% | 24% | 6% | 5% |
| 1957 | 75% | 76% | 33% | 43% | 25% | 24% | 5% | 5% |
| 1958 | 75% | 76% | 33% | 43% | 25% | 24% | 5% | 5% |
| 1959 | 75% | 76% | 32% | 43% | 25% | 24% | 5% | 5% |
| 1960 | 75% | 75% | 32% | 43% | 25% | 25% | 5% | 5% |
| 1961 | 75% | 76% | 33% | 43% | 25% | 24% | 5% | 5% |
| 1962 | 75% | 75% | 33% | 43% | 25% | 25% | 5% | 5% |
| 1963 | 75% | 75% | 33% | 43% | 25% | 25% | 5% | 5% |
| 1964 | 75% | 76% | 31% | 44% | 25% | 24% | 5% | 5% |
| 1965 | 75% | 75% | 32% | 44% | 25% | 25% | 5% | 5% |
| 1966 | 75% | 76% | 31% | 44% | 25% | 24% | 5% | 5% |
| 1967 | 74% | 75% | 31% | 44% | 26% | 25% | 5% | 5% |
| 1968 | 74% | 75% | 31% | 44% | 26% | 25% | 5% | 5% |
| 1969 | 74% | 75% | 32% | 43% | 26% | 25% | 5% | 5% |
| 1970 | 74% | 75% | 32% | 43% | 26% | 25% | 5% | 5% |
| 1971 | 74% | 75% | 32% | 43% | 26% | 25% | 5% | 5% |
| 1972 | 74% | 75% | 32% | 43% | 26% | 25% | 5% | 5% |
| 1973 | 74% | 75% | 32% | 43% | 26% | 25% | 5% | 5% |
| 1974 | 73% | 75% | 32% | 43% | 27% | 25% | 6% | 5% |
| 1975 | 74% | 74% | 33% | 42% | 26% | 26% | 6% | 5% |

Table A3.6 – Wage income shares, equal-split adults

| series | Bottom 90% | Bottom 50% | Middle 40% | Top 10% | Top 1% |
|---------------|-------------------|-------------------|-------------------|----------------|---------------|
| <i>Year</i> | new | new | new | new | new |
| 1927 | 70% | 20% | 50% | 30% | 8% |
| 1928 | 69% | 19% | 50% | 31% | 9% |
| 1929 | 66% | 19% | 48% | 34% | 9% |
| 1930 | 68% | 20% | 49% | 32% | 9% |
| 1931 | 68% | 20% | 48% | 32% | 8% |
| 1932 | 68% | 20% | 49% | 32% | 8% |
| 1933 | 68% | 20% | 49% | 32% | 8% |
| 1934 | 69% | 20% | 49% | 31% | 8% |
| 1935 | 66% | 19% | 47% | 34% | 9% |
| 1936 | 68% | 20% | 48% | 32% | 9% |
| 1937 | 67% | 20% | 47% | 33% | 8% |
| 1938 | 67% | 20% | 48% | 33% | 8% |
| 1939 | 67% | 20% | 47% | 33% | 8% |
| 1940 | 67% | 20% | 47% | 33% | 8% |
| 1941 | 72% | 24% | 48% | 28% | 7% |
| 1942 | 74% | 29% | 45% | 26% | 7% |
| 1943 | 74% | 28% | 45% | 26% | 6% |
| 1944 | 75% | 29% | 46% | 25% | 6% |
| 1945 | 75% | 31% | 44% | 25% | 6% |
| 1946 | 74% | 31% | 43% | 26% | 7% |
| 1947 | 73% | 31% | 42% | 27% | 7% |
| 1948 | 76% | 30% | 46% | 24% | 6% |
| 1949 | 77% | 31% | 46% | 23% | 6% |
| 1950 | 77% | 31% | 46% | 23% | 6% |
| 1951 | 77% | 31% | 46% | 23% | 5% |
| 1952 | 78% | 31% | 47% | 22% | 5% |
| 1953 | 77% | 31% | 47% | 23% | 5% |
| 1954 | 78% | 31% | 47% | 22% | 5% |
| 1955 | 78% | 32% | 46% | 22% | 5% |
| 1956 | 78% | 32% | 46% | 22% | 5% |
| 1957 | 78% | 32% | 46% | 22% | 5% |
| 1958 | 78% | 33% | 45% | 22% | 5% |
| 1959 | 78% | 31% | 46% | 22% | 5% |
| 1960 | 77% | 31% | 46% | 23% | 5% |
| 1961 | 78% | 32% | 46% | 22% | 5% |
| 1962 | 78% | 31% | 47% | 22% | 5% |
| 1963 | 78% | 32% | 46% | 22% | 5% |
| 1964 | 78% | 31% | 47% | 22% | 4% |
| 1965 | 78% | 32% | 46% | 22% | 5% |
| 1966 | 78% | 32% | 46% | 22% | 5% |
| 1967 | 78% | 32% | 46% | 22% | 5% |
| 1968 | 78% | 30% | 47% | 22% | 5% |
| 1969 | 77% | 30% | 47% | 23% | 5% |
| 1970 | 78% | 32% | 46% | 22% | 4% |
| 1971 | 78% | 32% | 46% | 22% | 5% |
| 1972 | 78% | 32% | 46% | 22% | 5% |
| 1973 | 77% | 31% | 47% | 23% | 5% |
| 1974 | 77% | 30% | 46% | 23% | 5% |
| 1975 | 76% | 30% | 46% | 24% | 5% |

Table A3.7 – Fiscal income inequality, 1950, equal-split adults

| cumulative population density | threshold level (current \$US) | share of income > threshold | average income > threshold | bracket average income | Pareto coefficient $b(p)$ |
|-------------------------------|--------------------------------|-----------------------------|----------------------------|------------------------|---------------------------|
| 0% | - | 100% | 1,879 | 14 | - |
| 1% | 27 | 100% | 1,898 | 41 | 69.6 |
| 2% | 55 | 100% | 1,917 | 68 | 35.0 |
| 3% | 82 | 100% | 1,936 | 95 | 23.6 |
| 4% | 108 | 100% | 1,955 | 121 | 18.1 |
| 5% | 133 | 100% | 1,974 | 145 | 14.8 |
| 6% | 156 | 100% | 1,994 | 166 | 12.8 |
| 7% | 176 | 100% | 2,013 | 185 | 11.4 |
| 8% | 193 | 100% | 2,033 | 200 | 10.5 |
| 9% | 206 | 99% | 2,053 | 211 | 10.0 |
| 10% | 216 | 99% | 2,074 | 219 | 9.6 |
| 11% | 222 | 99% | 2,095 | 225 | 9.4 |
| 12% | 227 | 99% | 2,116 | 230 | 9.3 |
| 13% | 234 | 99% | 2,138 | 239 | 9.1 |
| 14% | 245 | 99% | 2,160 | 253 | 8.8 |
| 15% | 263 | 99% | 2,182 | 275 | 8.3 |
| 16% | 290 | 99% | 2,205 | 306 | 7.6 |
| 17% | 325 | 98% | 2,228 | 345 | 6.9 |
| 18% | 367 | 98% | 2,251 | 390 | 6.1 |
| 19% | 415 | 98% | 2,274 | 439 | 5.5 |
| 20% | 464 | 98% | 2,297 | 487 | 5.0 |
| 21% | 509 | 98% | 2,319 | 530 | 4.6 |
| 22% | 549 | 97% | 2,342 | 570 | 4.3 |
| 23% | 590 | 97% | 2,365 | 611 | 4.0 |
| 24% | 632 | 97% | 2,389 | 651 | 3.8 |
| 25% | 670 | 96% | 2,412 | 690 | 3.6 |
| 26% | 710 | 96% | 2,435 | 731 | 3.4 |
| 27% | 752 | 96% | 2,458 | 773 | 3.3 |
| 28% | 792 | 95% | 2,482 | 812 | 3.1 |
| 29% | 833 | 95% | 2,505 | 854 | 3.0 |
| 30% | 874 | 94% | 2,529 | 893 | 2.9 |
| 31% | 912 | 94% | 2,552 | 930 | 2.8 |
| 32% | 948 | 93% | 2,576 | 966 | 2.7 |
| 33% | 985 | 93% | 2,600 | 1,003 | 2.6 |
| 34% | 1,021 | 92% | 2,625 | 1,038 | 2.6 |
| 35% | 1,056 | 92% | 2,649 | 1,073 | 2.5 |
| 36% | 1,091 | 91% | 2,674 | 1,108 | 2.5 |
| 37% | 1,126 | 90% | 2,698 | 1,142 | 2.4 |
| 38% | 1,158 | 90% | 2,724 | 1,173 | 2.4 |
| 39% | 1,189 | 89% | 2,749 | 1,205 | 2.3 |
| 40% | 1,221 | 89% | 2,775 | 1,237 | 2.3 |
| 41% | 1,253 | 88% | 2,801 | 1,268 | 2.2 |
| 42% | 1,282 | 87% | 2,827 | 1,297 | 2.2 |
| 43% | 1,312 | 87% | 2,854 | 1,327 | 2.2 |
| 44% | 1,342 | 86% | 2,881 | 1,357 | 2.1 |
| 45% | 1,372 | 85% | 2,909 | 1,387 | 2.1 |
| 46% | 1,401 | 84% | 2,937 | 1,415 | 2.1 |
| 47% | 1,429 | 84% | 2,966 | 1,442 | 2.1 |
| 48% | 1,456 | 83% | 2,995 | 1,470 | 2.1 |
| 49% | 1,485 | 82% | 3,025 | 1,498 | 2.0 |
| 50% | 1,512 | 81% | 3,056 | 1,525 | 2.0 |
| 51% | 1,538 | 81% | 3,087 | 1,551 | 2.0 |
| 52% | 1,563 | 80% | 3,119 | 1,576 | 2.0 |

| cumulative population density | threshold level (current \$US) | share of income > threshold | average income > threshold | bracket average income | Pareto coefficient $b(p)$ |
|-------------------------------|--------------------------------|-----------------------------|----------------------------|------------------------|---------------------------|
| 53% | 1,589 | 79% | 3,152 | 1,602 | 2.0 |
| 54% | 1,615 | 78% | 3,185 | 1,628 | 2.0 |
| 55% | 1,642 | 77% | 3,220 | 1,656 | 2.0 |
| 56% | 1,670 | 76% | 3,256 | 1,684 | 1.9 |
| 57% | 1,699 | 75% | 3,292 | 1,714 | 1.9 |
| 58% | 1,729 | 74% | 3,330 | 1,744 | 1.9 |
| 59% | 1,758 | 74% | 3,368 | 1,772 | 1.9 |
| 60% | 1,786 | 73% | 3,408 | 1,800 | 1.9 |
| 61% | 1,813 | 72% | 3,450 | 1,827 | 1.9 |
| 62% | 1,840 | 71% | 3,492 | 1,854 | 1.9 |
| 63% | 1,868 | 70% | 3,537 | 1,883 | 1.9 |
| 64% | 1,898 | 69% | 3,582 | 1,913 | 1.9 |
| 65% | 1,929 | 68% | 3,630 | 1,945 | 1.9 |
| 66% | 1,961 | 67% | 3,680 | 1,978 | 1.9 |
| 67% | 1,994 | 66% | 3,731 | 2,010 | 1.9 |
| 68% | 2,026 | 64% | 3,785 | 2,042 | 1.9 |
| 69% | 2,058 | 63% | 3,841 | 2,074 | 1.9 |
| 70% | 2,090 | 62% | 3,900 | 2,107 | 1.9 |
| 71% | 2,124 | 61% | 3,962 | 2,142 | 1.9 |
| 72% | 2,160 | 60% | 4,027 | 2,178 | 1.9 |
| 73% | 2,197 | 59% | 4,096 | 2,216 | 1.9 |
| 74% | 2,235 | 58% | 4,168 | 2,255 | 1.9 |
| 75% | 2,274 | 56% | 4,244 | 2,294 | 1.9 |
| 76% | 2,314 | 55% | 4,326 | 2,334 | 1.9 |
| 77% | 2,355 | 54% | 4,412 | 2,376 | 1.9 |
| 78% | 2,398 | 53% | 4,505 | 2,421 | 1.9 |
| 79% | 2,445 | 51% | 4,604 | 2,469 | 1.9 |
| 80% | 2,493 | 50% | 4,711 | 2,518 | 1.9 |
| 81% | 2,544 | 49% | 4,826 | 2,570 | 1.9 |
| 82% | 2,596 | 47% | 4,951 | 2,623 | 1.9 |
| 83% | 2,651 | 46% | 5,088 | 2,680 | 1.9 |
| 84% | 2,709 | 45% | 5,239 | 2,741 | 1.9 |
| 85% | 2,773 | 43% | 5,405 | 2,809 | 1.9 |
| 86% | 2,847 | 42% | 5,591 | 2,886 | 2.0 |
| 87% | 2,926 | 40% | 5,799 | 2,969 | 2.0 |
| 88% | 3,013 | 39% | 6,035 | 3,061 | 2.0 |
| 89% | 3,112 | 37% | 6,305 | 3,167 | 2.0 |
| 90% | 3,224 | 35% | 6,619 | 3,284 | 2.1 |
| 91% | 3,346 | 33% | 6,990 | 3,413 | 2.1 |
| 92% | 3,483 | 32% | 7,437 | 3,566 | 2.1 |
| 93% | 3,656 | 30% | 7,990 | 3,757 | 2.2 |
| 94% | 3,863 | 28% | 8,695 | 3,987 | 2.3 |
| 95% | 4,130 | 26% | 9,637 | 4,310 | 2.3 |
| 96% | 4,508 | 23% | 10,968 | 4,792 | 2.4 |
| 97% | 5,127 | 21% | 13,027 | 5,661 | 2.5 |
| 98% | 6,357 | 18% | 16,710 | 7,716 | 2.6 |
| 99% | 9,739 | 14% | 25,705 | 10,062 | 2.6 |
| 99.1% | 10,401 | 13% | 27,444 | 10,786 | 2.6 |
| 99.2% | 11,196 | 13% | 29,526 | 11,660 | 2.6 |
| 99.3% | 12,153 | 12% | 32,078 | 12,708 | 2.6 |
| 99.4% | 13,303 | 11% | 35,306 | 14,001 | 2.7 |
| 99.5% | 14,763 | 11% | 39,568 | 15,690 | 2.7 |
| 99.6% | 16,720 | 10% | 45,537 | 18,035 | 2.7 |
| 99.7% | 19,551 | 9% | 54,704 | 21,662 | 2.8 |
| 99.8% | 24,232 | 8% | 71,225 | 28,572 | 2.9 |

| cumulative population density | threshold level (current \$US) | share of income > threshold | average income > threshold | bracket average income | Pareto coefficient $b(p)$ |
|-------------------------------------|--------------------------------------|-----------------------------------|----------------------------------|------------------------------|---------------------------------|
| 99.9% | 34,801 | 6% | 113,879 | 35,805 | 3.3 |
| 99.91% | 36,871 | 6% | 122,554 | 38,085 | 3.3 |
| 99.92% | 39,384 | 6% | 133,112 | 40,883 | 3.4 |
| 99.93% | 42,501 | 5% | 146,288 | 44,414 | 3.4 |
| 99.94% | 46,510 | 5% | 163,267 | 49,061 | 3.5 |
| 99.95% | 51,888 | 5% | 186,108 | 55,445 | 3.6 |
| 99.96% | 59,506 | 5% | 218,774 | 64,960 | 3.7 |
| 99.97% | 71,415 | 4% | 270,045 | 81,076 | 3.8 |
| 99.98% | 93,344 | 4% | 364,530 | 116,327 | 3.9 |
| 99.99% | 150,915 | 3% | 612,732 | 156,608 | 4.1 |
| 99.991% | 162,665 | 3% | 663,412 | 169,572 | 4.1 |
| 99.992% | 176,976 | 3% | 725,142 | 185,558 | 4.1 |
| 99.993% | 194,843 | 3% | 802,226 | 205,838 | 4.1 |
| 99.994% | 217,878 | 3% | 901,624 | 232,550 | 4.1 |
| 99.995% | 248,884 | 3% | 1,035,438 | 269,604 | 4.2 |
| 99.996% | 293,235 | 3% | 1,226,897 | 325,098 | 4.2 |
| 99.997% | 362,847 | 2% | 1,527,496 | 419,350 | 4.2 |
| 99.998% | 491,105 | 2% | 2,081,569 | 625,557 | 4.2 |
| 99.999% | 827,919 | 2% | 3,537,582 | 3,537,582 | 4.3 |

Notes: This table presents an example g-percentile table for the year 1950. The corresponding tables are available for all years 1913-2014, for fiscal and pre-tax income (and wage income from 1927), by tax units and equal-split adults.

Appendix 3 Figures

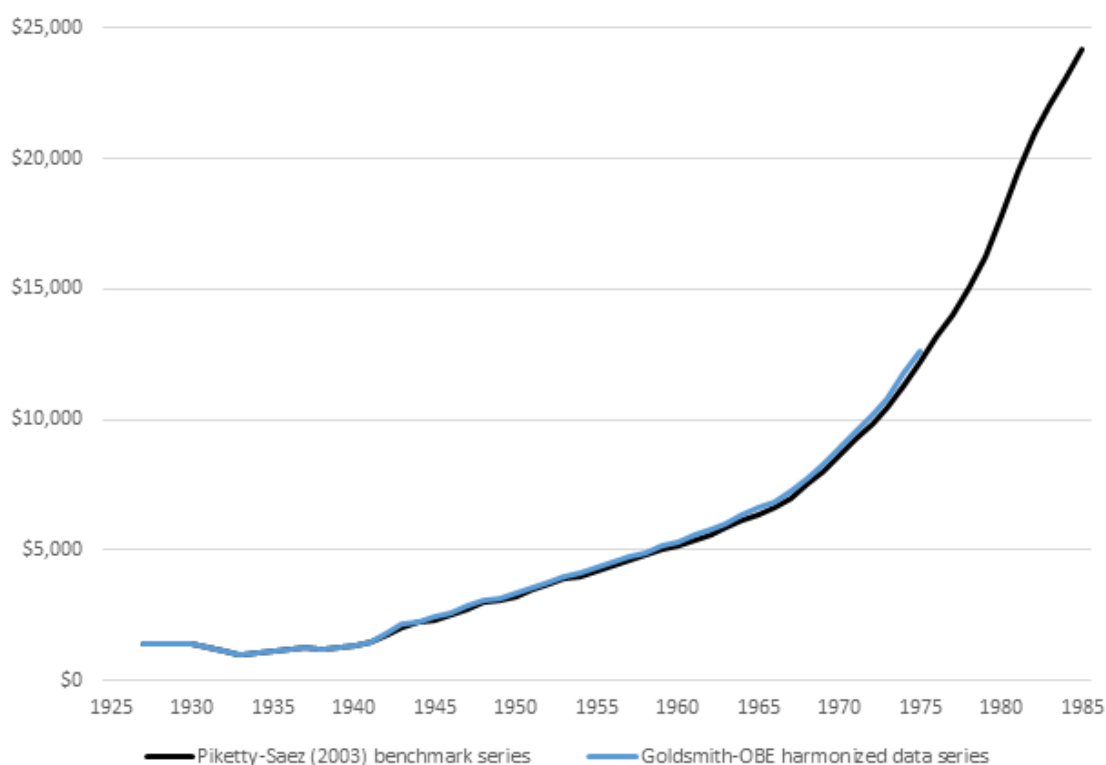


Figure A3.1 – Overall average fiscal wage income

Notes: This figure compares Goldsmith-OBE harmonized data series (see Goldsmith, 1951) to Piketty and Saez (2003) benchmark series. The match of existing to new estimates on overall income is not quite perfect, as the smoothing function needs to make some adjustments to accommodate the observed distribution and impute non-filers into the lefthand side of the distribution, but it comes very close. All dollar figures are in current terms from the era Series are tax units, 1927-2011. Currency is current United States dollars.

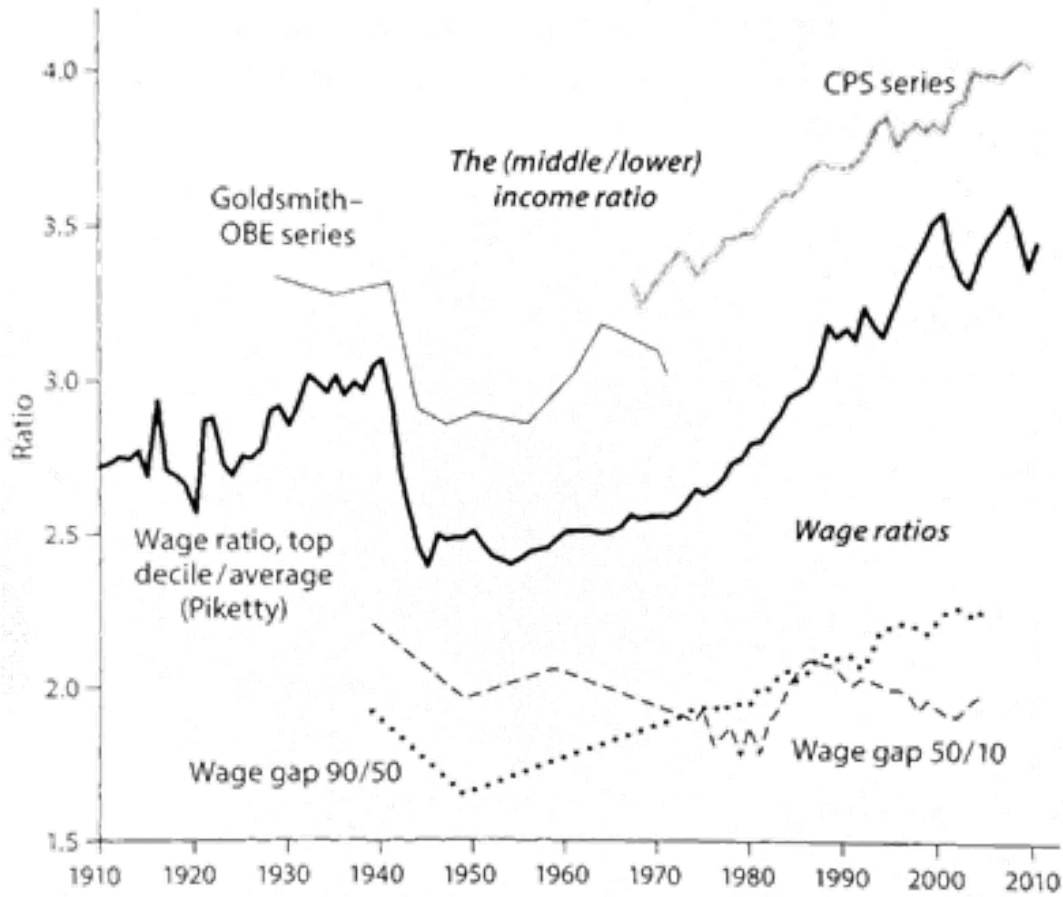


Figure A3.2 – A catalog of historical income data in the United States, 1910-2010

Notes: Reprinted from Lindert and Williamson ([ibid.](#)). Figure presents several comparable but distinct ratio measures of inequality.

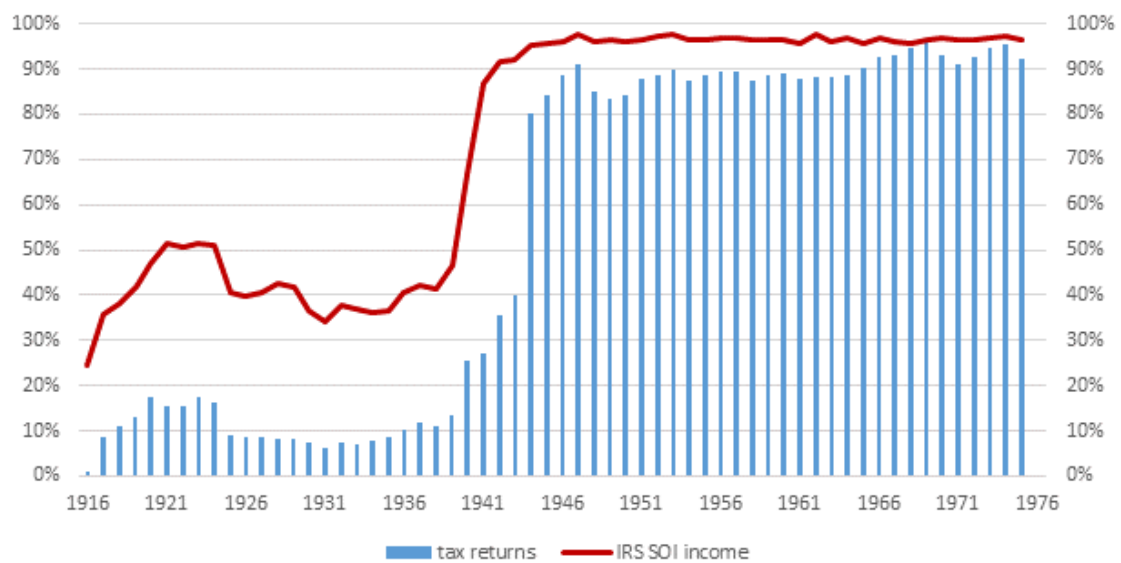


Figure A3.3 – Data availability from tax archives, 1916-75

Notes: The blue bars show tax returns filed, as a percentage of estimated total tax units. The red line shows income on tax returns filed to the IRS, as a percentage of estimated total personal income.



Figure A3.4 – Wage income as a proportion of net income, by net income bracket, 1952

Notes: 1952 is taken as a representative year. The pattern is stable over time.

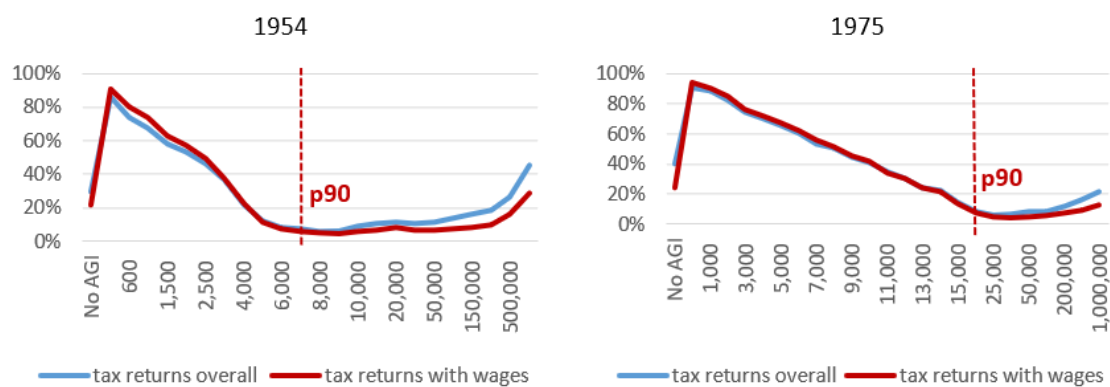


Figure A3.5 – Single filers as a proportion of tax returns, by tax bracket

Notes: The distribution of single filer status—in tax returns with wages, vs. in tax returns overall—diverges only in net income brackets above the 90th percentile of earners. 1954 and 1975 are selected as representative years. Currency is current United States Dollars.

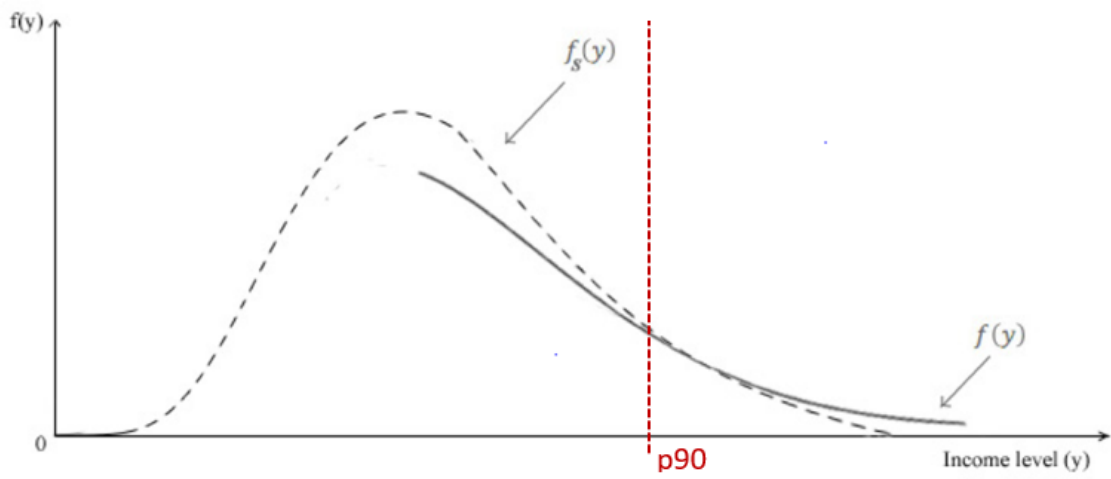


Figure A3.6 – Harmonizing survey data with tax data

Notes: Adapted from Blanchet, Flores, and Morgan (2022).

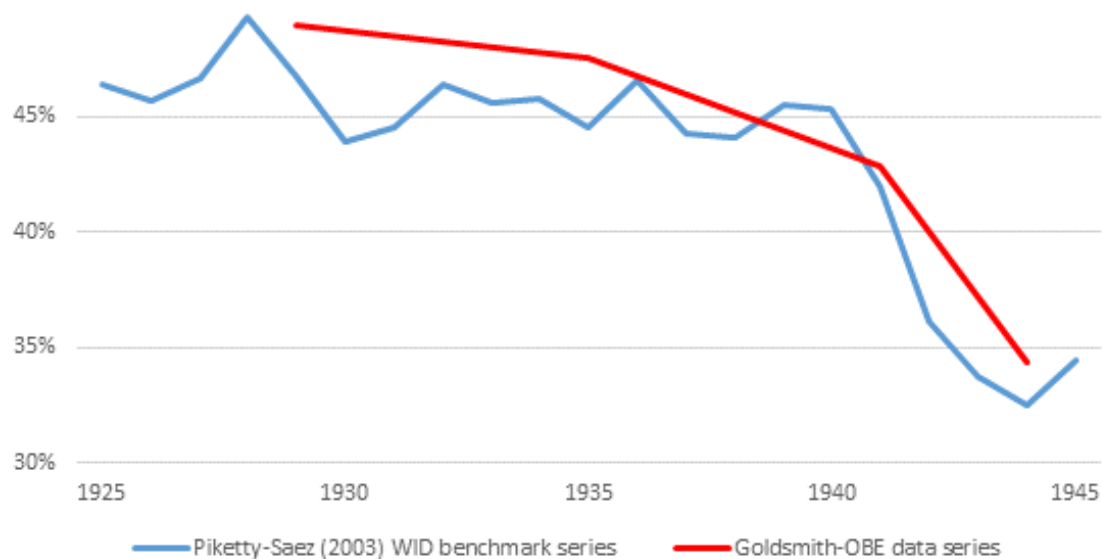


Figure A3.7 – Top 10% share of total fiscal income, tax units, 1925-45

Notes: Goldsmith-OBE (see Goldsmith, 1951) pre-World War II interpolations are compared to Piketty and Saez (2003) benchmark estimates.

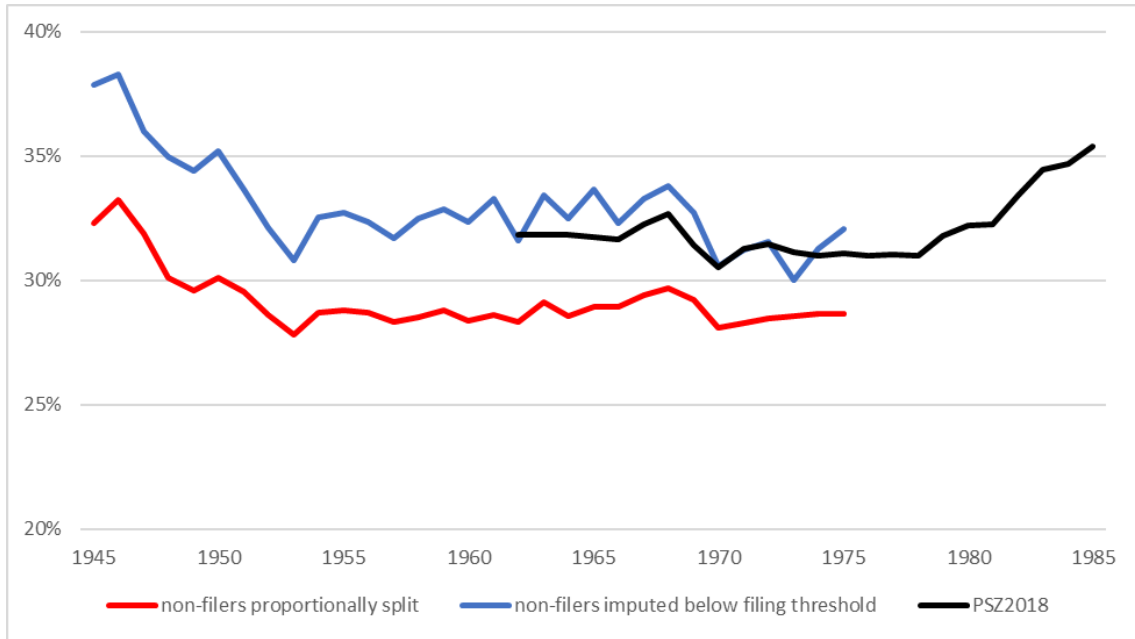


Figure A3.8 – Imputing non-filers: Top 10% fiscal income shares

Notes: This figure compares imputing non-filers to the lefthand side of the income distribution, vs. imputing non-filers with a proportional split along the entire income distribution (to p90)—both compared to Piketty, Saez, and Zucman (*ibid.*) microestimates. Series are equal-split adults, 1945-85.

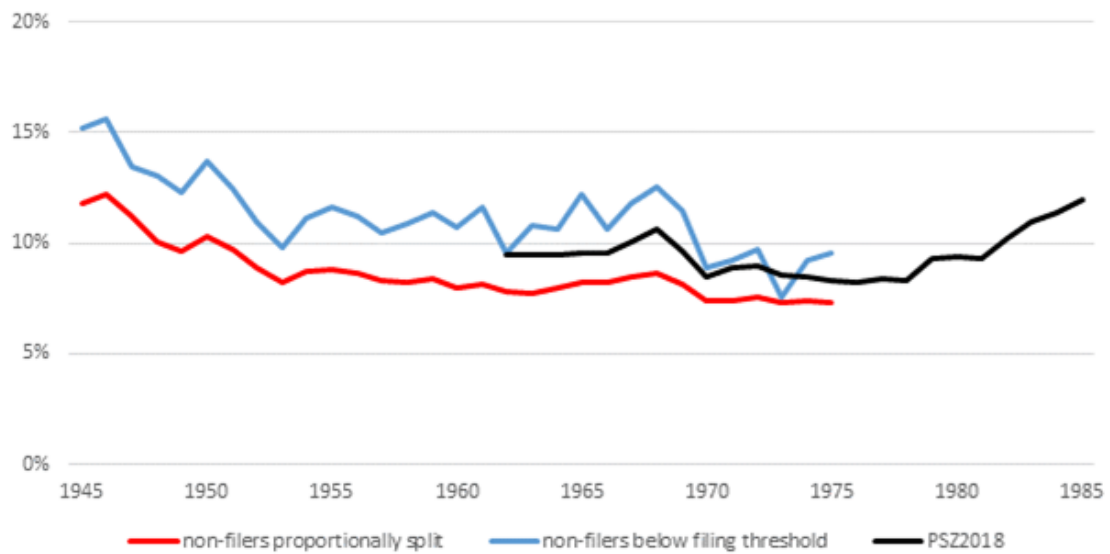


Figure A3.9 – Imputing non-filers: Top 1% share of total fiscal income

Notes: This figure compares imputing non-filers with a proportional split along the entire income distribution (to p90), vs. imputing non-filers as low-income—both compared to Piketty, Saez, and Zucman (2018) microestimates. Series are equal-split adults, 1945-85.

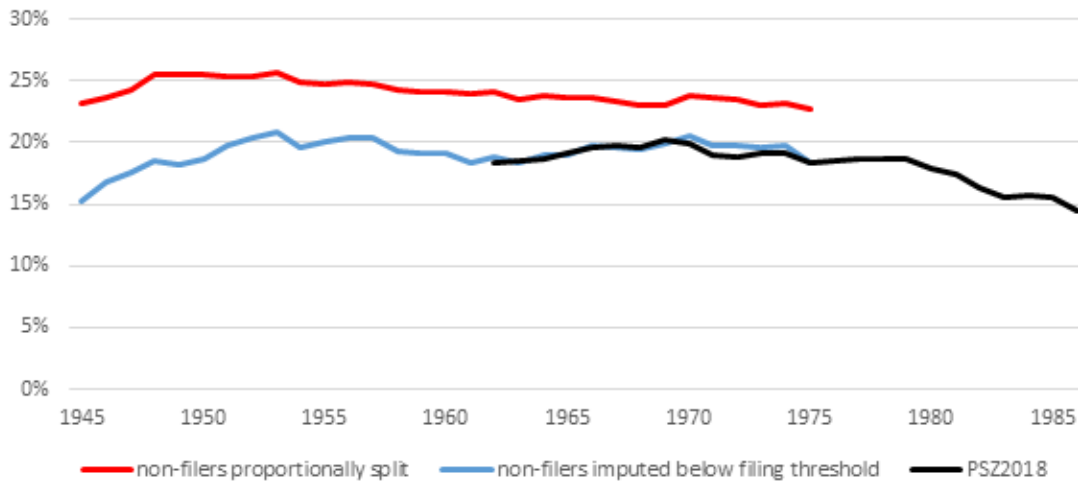


Figure A3.10 – Imputing non-filers: Bottom 50% share of total fiscal income

Notes: This figure compares imputing non-filers with a proportional split along the entire income distribution (to p90), vs. imputing non-filers as low-income—both compared to Piketty, Saez, and Zucman (*ibid.*) microestimates. Series are equal-split adults, 1945-85.

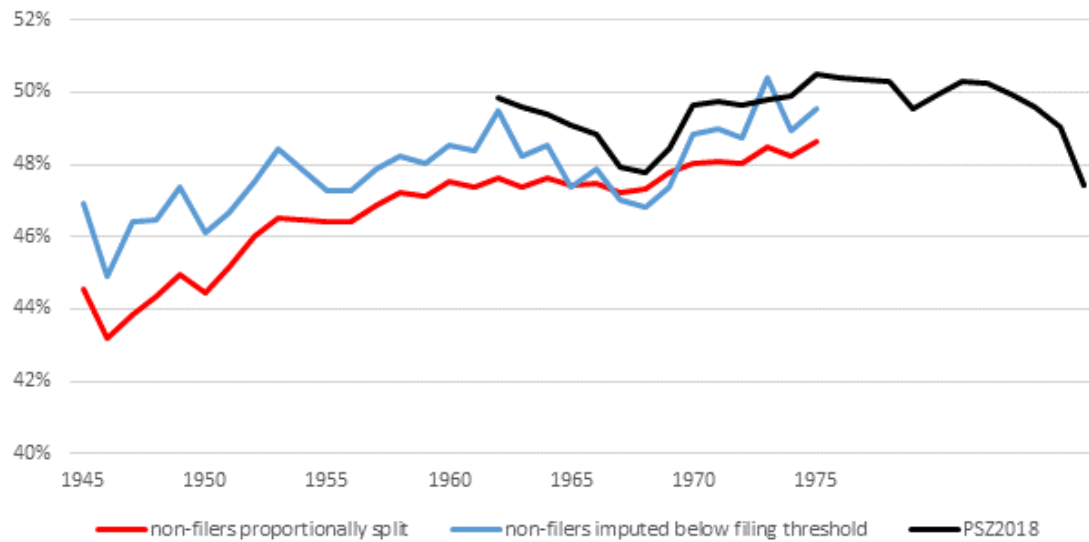


Figure A3.11 – Imputing non-filers: Middle 40% share of total fiscal income

Notes: This figure compares imputing non-filers with a proportional split along the entire income distribution (to p90), vs. imputing non-filers as low-income—both compared to Piketty, Saez, and Zucman (2018) microestimates. Series are equal-split adults, 1945-85.

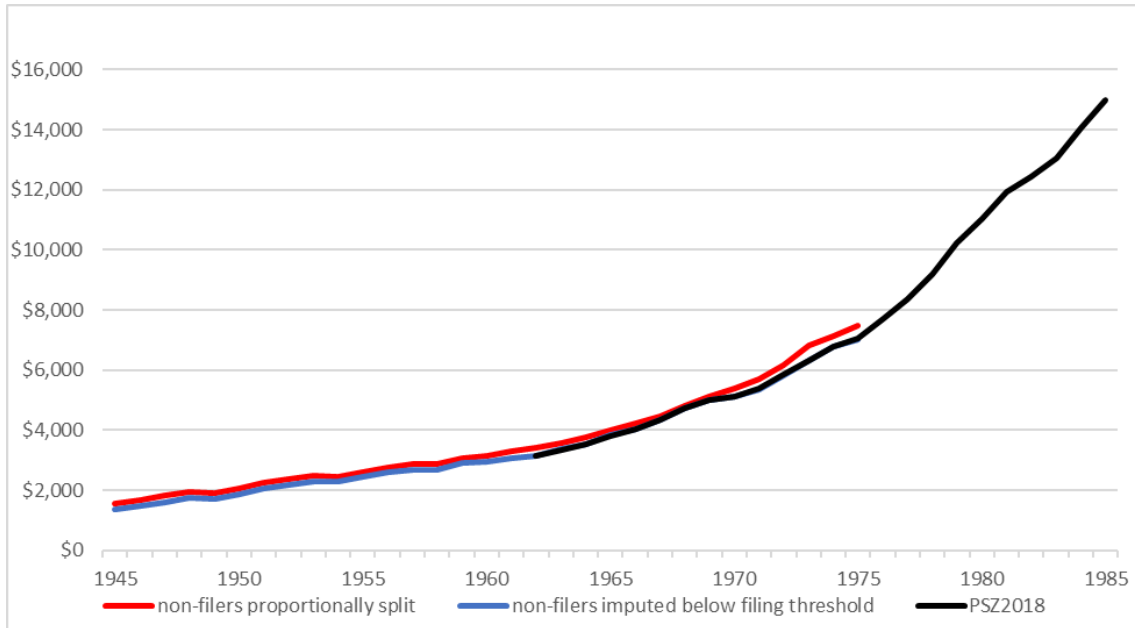


Figure A3.12 – Imputing non-filers: Overall average fiscal income

Notes: This figure compares imputing non-filers with a proportional split along the entire income distribution (to p90), vs. imputing non-filers as low-income—both compared to Piketty, Saez, and Zucman (*ibid.*) microestimates. Series are equal-split adults, 1945-85. Currency is current United States dollars.

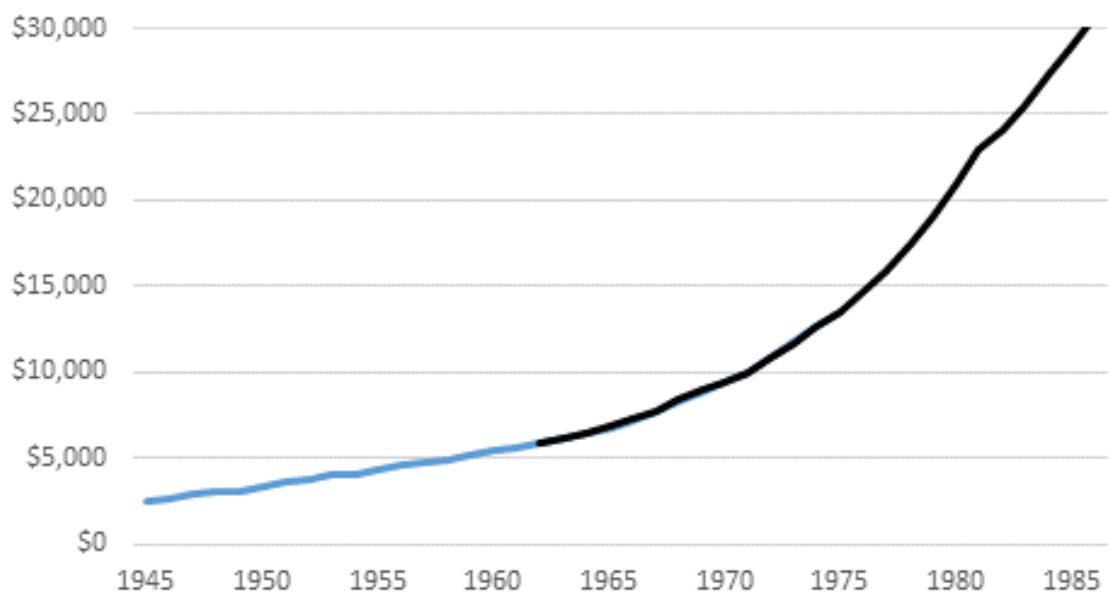


Figure A3.13 – Robustness: Top 10% threshold of total fiscal income

Notes: This figure compares new estimates to Piketty, Saez, and Zucman (2018) microestimates during the period of overlap 1962-75. Series are equal-split adults, 1945-85. Currency is current United States dollars.

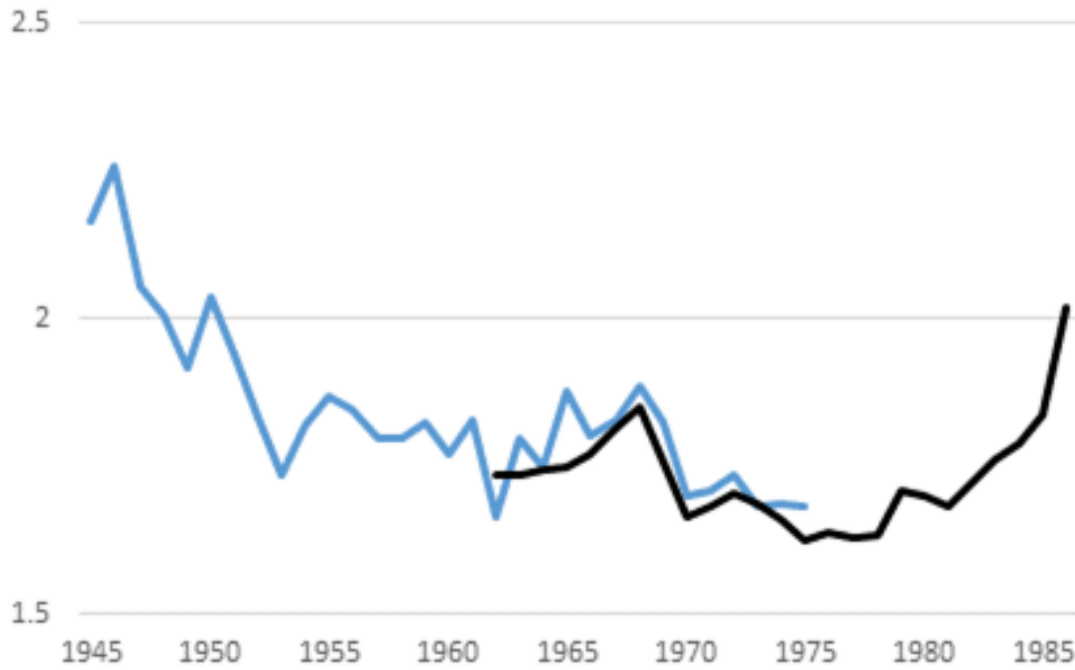


Figure A3.14 – Pareto coefficient $b(p)$ above top 10% threshold of fiscal income

Notes: This figure compares new estimates to Piketty, Saez, and Zucman ([ibid.](#)) microestimates during the period of overlap 1962-75. Series are equal-split adults, 1945-85.

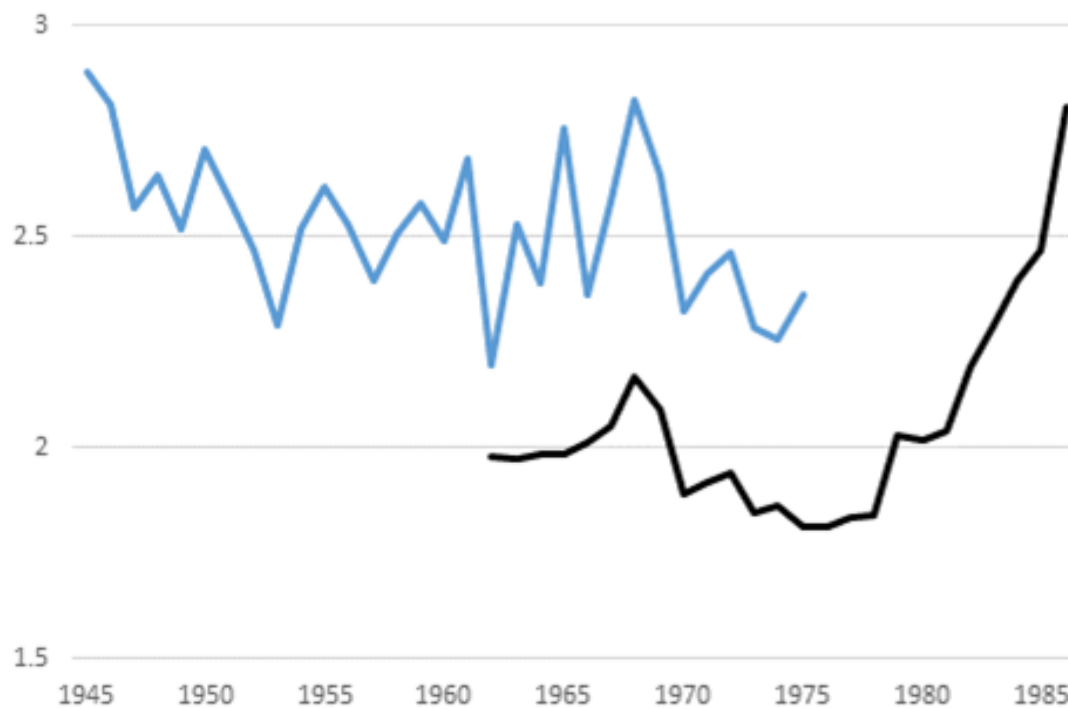


Figure A3.15 – Pareto coefficient $b(p)$ above top 1% threshold of fiscal income

Notes: This figure compares new estimates to Piketty, Saez, and Zucman (2018) microestimates during the period of overlap 1962-75. Series are equal-split adults, 1945-85.

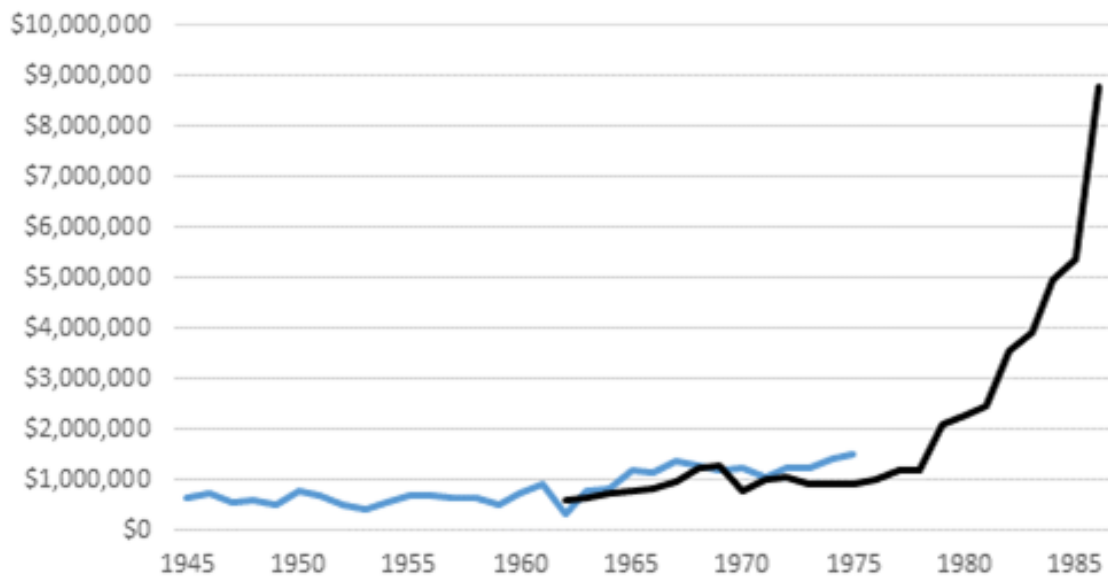


Figure A3.16 – Level of top 0.001% threshold of fiscal income

Notes: This figure compares new estimates to Piketty, Saez, and Zucman ([ibid.](#)) microestimates during the period of overlap 1962-75. Series are equal-split adults, 1945-85. Currency is current United States dollars.



Figure A3.17 – Pareto coefficient $b(p)$ above top 0.001% threshold of fiscal income

Notes: This figure compares new estimates to Piketty, Saez, and Zucman (2018) microestimates during the period of overlap 1962-75. Series are equal-split adults, 1945-85.

Appendix A4

Appendix to Chapter 4

Distributional National Accounts for Australia, 1991-2018

A4.1 Preliminary adjustments to top 1% in ALife

A few adjustments are performed in ALife before it is combined with survey data for the top 1%.

Incomes and income components are not top coded in ALife, with one exception: in each year, the 24 largest ‘employment termination’ (redundancy) payments in the entire tax filer population are reduced to the level of the 25th-largest payment value. Between 1991 and 2017, this represented a total adjustment of between \$8 million and \$57 million in total and (noting that ALife is a 10% sample) affected between 0 and 7 individuals in ALife each year (see Table A4.1). We distribute the portion of Employment Termination Payment that was cut due to top-coding: we take 10% of the total shortfall and divide it between all top-coded observations in ALife.

As ALife is a 10% random sample of tax filers, it is subject to sampling error. We address this issue by reconciling top income outliers (defined here the top 100 individuals in terms of taxable gross income in Australia each year) with the ATO full population for which the ATO has provided us mean income values (separately for the top 100 to 50 and the top 50 individuals). We average income for top 100 to 50 and top 50 individuals in Australia to adjust incomes of the top 10 and top 5 individuals in ALife. All income components are scaled up by a constant factor. This approach fixes the top 0.001% but sampling error may still affect income groups below the top 0.001%, with the issue likely to be more important the smaller the income group. In practice, top income shares for groups smaller than 0.1% of the population and above the top 0.1% may not be reliable.

A4.2 Construction of the DINA by income component and income concept

Up until 2015-16, the SIH unit record data contain measures of both annual income (for the preceding financial year, 1 July to 30 June) and ‘current weekly’ income. We use the annual income estimates for these surveys. However, in the 2017-18 SIH, only current weekly income is available. We therefore use an annualised measure of this income measure for this survey.

A4.2.1 Pre-tax factor income

Labour income Grossing up of labour incomes is required because of potential under-reporting in SIH as well as the failure of the SIH to capture (all of) salary sacrificed employment income, fringe benefits and fringe benefits tax, and ‘employer social contributions’ (i.e., employers’ superannuation contributions and workers’ compensation premiums). Employee incomes are grossed up by a constant factor so that total employee income in the SIH equals total employment income in the National Accounts.

Mixed income is grossed up separately, also by a constant factor. ABS National Accounts data do not report net mixed income. We therefore estimate net mixed income based on gross mixed income, which is reported in the National Accounts data, by applying net-to-gross ratios for mixed income sourced from the WID for Australia.

All grossing-up factors are provided in Appendix Table A4.2 Total employee incomes have to be increased by between 10% and 26% to ensure consistency with National Accounts. The required increase is much larger and more variable for mixed income, ranging from 25% to 226%, depending on the year.

Capital income Capital income is estimated based on reported business and investment income and imputed rent. A ‘grossing up’ adjustment is done separately for each of superannuation, imputed rent and other capital income. The principle is that superannuation income is imputed based on observed or estimated superannuation balances. Net operating surplus of households and non-profit institutions serving households (NOSH) is distributed based on imputed rent. The remaining (i.e., non-pension non-imputed-rent) capital incomes not captured by the SIH are distributed according to reported non-pension non-imputed-rent capital incomes (hereafter called ‘other capital income’).

From the total capital stock (“National net wealth”) as measured in the National Accounts, we compute the share of the capital stock in superannuation funds (“Pension funds & life insurance”) and then use that share to allocate the appropriate proportion of total private capital income (other than NOSH) accruing to superannuation funds. The implicit assumption is that returns on superannuation are the same as the overall return on the national private capital stock. Total private capital income is obtained here from the National Accounts by adding “total net property income of households and non-profit institutions serving households” and “total net primary income of corporations.” Superannuation income, NOSH and other capital incomes are thus allocated to each individual separately.

Superannuation income We impute superannuation income proportionally to each individual’s superannuation balance. We use superannuation balances from the SIH for all years for which they are available (2003/04, 2005/06, 2009/10, 2011/12, 2013/14, 2015/16 and 2017/2018). For the years not covered by the SIH, we estimate superannuation balances separately for those aged 60 and over and those aged under 60.

For those aged under 60, we estimate a regression model of superannuation balances on age, labour income and sex (as well as interactions). For those aged 60 and over, the model is enriched by including superannuation income. The coefficient estimates (see Appendix Tables A4.3 and A4.4) are then used to impute superannuation balances in the SIH data for years with no information, by using the set of estimated coefficients from the closest year available. This means that superannuation balances from 1991 to 2002 are all estimated based on the 2003 model. This approach is likely to generate some prediction errors. However, we note that superannuation wealth was limited in the 1990s, since compulsory contributions only commenced in 1992, initially at only 3% of gross earnings and gradually increased up to 9% as of 1 July 2002.¹ Moreover, it is the relative distribution of superannuation balances that matters for imputation and not the absolute values, and relativities by labour income, age and sex are likely to have remained relatively stable between 1991 and 2003.

Net operating surplus of households and non-profit institutions serving households (NOSH) ABS National Accounts data report only gross and not net operating

¹The minimum contribution rate is now 10% and is scheduled to gradually increase up to 12% by 1 July 2025.

surplus of households and non-profit institutions serving households. We use the share of the consumption of fixed capital attributable to operating surplus in NOSHN from the WID Australian National Accounts data (see footnote 5 above) to derive net operating surplus from the ABS National Accounts data on gross operating surplus.

We then impute NOSHN proportionally to each household's net imputed rent. Where a household comprises more than one adult, the income is equally split. Gross and net imputed rents are directly provided in the SIH from 2005 onwards.² For earlier years, we predict gross and net imputed rents. Using 2005 values, we estimate a model to predict gross imputed rents based on reported tenure type, state of residence, area of residence, number of bedrooms, household gross income decile and landlord type. The approach draws heavily on the approach developed by the ABS (2008a). For net imputed rent, all covariates listed above are interacted with (predicted) gross imputed rent and we add mortgage repayments and predicted gross imputed rent to the list of covariates. Coefficient estimates are reported in Appendix Table A4.5. All models are estimated with and without tenure type as this variable was not available before 1995 in the SIH and thus cannot be used for imputation before that year. These models fit the data well with the adjusted R-square 0.97 for gross imputed rent and 0.69 for net imputed rent.

Other capital income Other capital income has two components: that captured by SIH and that not captured by SIH, the latter of which is a residual equal to total capital income³ from the National Accounts minus superannuation income from the National Accounts minus non-pension capital income as measured in SIH. This non-captured capital income will primarily comprise corporate retained earnings. We distribute it assuming it has the same distribution as observed other (non-superannuation non-imputed rent) capital income. We take the same approach for adding foreign income received from tax havens and reinvested earnings on foreign portfolio investment. The latter captures retained earnings in foreign firms accruing to Australians whose shares comprise less than the 10% foreign direct investment threshold required to appear in the National Accounts. We use WID estimates of foreign income received from tax havens and reinvested earnings on foreign portfolio investment (see Zucman, 2015).

Grossing-up factors reported in Appendix Table A4.2 indicate that this captured capital income has to be multiplied by a factor of between 2 and 4.3 to match National Accounts totals.

Taxes on production As Blanchet et al. (2021) show, a pre-tax income measure not only requires that income taxes are not deducted from capital and labour income, but that taxes on production (and taxes on wealth, if they exist) need to be *added* to incomes to ensure all of national income is distributed to individuals. As per the guidelines, taxes on production are assumed to have the same distribution as total factor income. This is somewhat arbitrary, but means pre-tax income

²According to the ABS (2008b, p.3), 'Gross imputed rent is the market value of the rental equivalent, and has been estimated using hedonic regression. Net imputed rent for owner occupiers has been derived by subtracting the housing costs normally paid by landlords (i.e., council rates, mortgage interest, building insurance premiums, repairs and maintenance) from gross imputed rent.'

³Total capital income is defined here as 'total net property income of households and non-profit institutions serving households' plus 'total net primary income of corporations.'

distributions among those with factor incomes are unaffected by these taxes other than via a scaling up factor applied to all incomes. Inequality measured over the total population increases, however, because people with zero factor incomes become relatively poorer.

A4.2.2 Pre-tax national income

Following the approach adopted for the French DINA by Garbinti, Goupille-Lebret, and Piketty (2018) and US DINA by Piketty, Saez, and Zucman (2018), as well as the DINA Guidelines (Blanchet et al., 2021), we include the Age Pension as income to produce pre-tax national income. This presents no major difficulty as the Age Pension is reported in the SIH.⁴ We distribute the total cost of Age Pension payments as a flat percentage of income tax liabilities. That is, we assume each individual's contribution to the funding of the Age Pension is in proportion of their income tax liabilities.

A4.2.3 Post-tax disposable income

To move from pre-tax national income to post-tax disposable income requires deducting all taxes and adding all government cash transfers to individuals' pre-tax incomes. Deducting income taxes and adding cash transfers is straightforward since both are recorded in the SIH and ALife data. However, both income taxes and cash transfers need to be scaled up to match National Accounts totals.

As noted in the DINA guidelines (*ibid.*, p.53), the aim is “to describe post-tax, post transfer inequality for the population's actual perceived budget constraints, while excluding in-kind transfers such as health and education and other public spending (as these may impact purchasing power and disposable income only indirectly). For this reason, aggregate post-tax disposable income can be substantially less than aggregate national income.”

Government pensions and allowances, as well as income taxes, are distributed according to the survey (and tax) data. For taxes on production (indirect taxes), which were distributed proportionally to factor income in pre-tax series, the DINA Guidelines advocate they are removed in proportion to consumption, proxied by disposable income (before the deduction of taxes on production) minus saving (where savings rates are based on external sources). In the absence of data on savings rates by level of income, we simply remove production taxes proportionally to household disposable income (as defined in the SIH).⁵ Corporate taxes are imputed proportionally to capital incomes after excluding imputed rent.

⁴Age Pension income is not directly reported in ALife, but we can combine information on receipt of government pensions and age to infer it. In addition, we use ALife only for the top 1%, a group almost certain not to receive the Age Pension given that it is subject to both an income test and an asset test.

⁵A potential refinement for future work is to estimate expenditure regression models using the ABS Household Expenditure Survey data (collected in 1993, 1998, 2003, 2009 and 2015) to impute household expenditure as a function of income (and perhaps other factors) and use this to distribute taxes on production.

A4.2.4 Post-tax national income

Moving from post-tax disposable income to post-tax national income requires distributing government expenditure to individuals. This corresponds to total expenditure of the government adjusted for the surplus or deficit of the government (Blanchet et al., 2021, p.64). The DINA Guidelines' definition of government surplus or deficit differs from the usual definition "due to the exclusion of other current transfers and capital transfers" (*ibid.*, p.51). Thus the government surplus or deficit is defined as net saving plus net other current transfers.

Three alternative approaches to distributing government expenditure are recommended by the DINA Guidelines: (1) assume health expenditures benefit all adults equally but that the benefits of other expenditures are proportional to disposable income; (2) assume everyone benefits equally from all government expenditure; and (3) assume the benefits of government spending are distributed in the same way as disposable income. The third approach means government spending can effectively be ignored since it doesn't affect the distribution other than to scale up everyone's income by the same fraction. Interestingly, the Guidelines do not allow for a scenario where government spending is more redistributive than (2).

In Australia, the biggest expenditure items—health and education—are somewhat redistributive to lower-income individuals (ABS, 2018, Table 1.1). Consequently, of the approaches the guidelines recommend, the most appropriate approach for the Australian context is approach (2). This means average government expenditure per adult is added to disposable income. This acts to lower measured inequality compared with post-tax disposable income, but nonetheless is likely to overstate benefits to high-income earners and understate benefits to low-income earners and thus not reduce measured inequality as much as it should.

Appendix 4 Tables

Table A4.1 – ATO adjustment of Employment Termination Payments, 1991-2017

| Tax year | Total adjustment | Mean adjustment |
|----------|------------------|-----------------|
| 1991 | -8,241,221 | -343,384 |
| 1992 | -14,613,357 | -608,890 |
| 1993 | -11,291,962 | -470,498 |
| 1994 | -15,332,505 | -638,854 |
| 1995 | -15,336,185 | -639,008 |
| 1996 | -10,649,353 | -443,723 |
| 1997 | -16,235,498 | -676,479 |
| 1998 | -16,477,313 | -686,555 |
| 1999 | -27,519,147 | -1,146,631 |
| 2000 | -42,319,718 | -1,763,322 |
| 2001 | -15,676,018 | -653,167 |
| 2002 | -27,836,179 | -1,159,841 |
| 2003 | -24,939,858 | -1,039,161 |
| 2004 | -18,548,200 | -772,842 |
| 2005 | -20,565,614 | -856,901 |
| 2006 | -21,123,878 | -880,162 |
| 2007 | -32,612,964 | -1,358,874 |
| 2008 | -47,913,907 | -1,996,413 |
| 2009 | -51,932,913 | -2,163,871 |
| 2010 | -51,184,871 | -2,132,703 |
| 2011 | -56,628,558 | -2,359,523 |
| 2012 | -34,672,593 | -1,444,691 |
| 2013 | -20,742,471 | -864,270 |
| 2014 | -36,156,344 | -1,506,514 |
| 2015 | -14,594,126 | -608,089 |
| 2016 | -23,385,390 | -974,391 |
| 2017 | -19,181,113 | -799,213 |

Notes: Employment termination payment is a lump sum payment made as a result of the termination of a person's employment. Amounts are in current Australian dollars.

Source: ATO (private communication).

Table A4.2 – Grossing-up factors from survey to National Accounts, 1991-2018

| Year | Employee income | Mixed income | Non-pension capital income | Personal income tax | Cash benefits |
|------|-----------------|--------------|----------------------------|---------------------|---------------|
| 1991 | 1.11 | 1.74 | 2.93 | 1.14 | 0.98 |
| 1992 | 1.10 | 1.40 | 3.18 | 1.05 | 1.12 |
| 1993 | 1.14 | 1.58 | 3.51 | 1.06 | 1.20 |
| 1994 | 1.17 | 1.54 | 3.76 | 1.12 | 1.28 |
| 1995 | 1.18 | 1.24 | 3.87 | 1.14 | 1.25 |
| 1996 | 1.18 | 1.40 | 3.24 | 1.18 | 1.25 |
| 1997 | 1.19 | 1.32 | 3.51 | 1.19 | 1.26 |
| 1998 | 1.17 | 1.56 | 3.24 | 1.16 | 1.25 |
| 1999 | 1.18 | 1.41 | 2.69 | 1.17 | 1.28 |
| 2000 | 1.16 | 1.56 | 3.15 | 1.16 | 1.29 |
| 2001 | 1.16 | 1.02 | 3.34 | 1.02 | 1.38 |
| 2002 | 1.16 | 1.83 | 3.43 | 1.12 | 1.39 |
| 2003 | 1.17 | 1.49 | 3.40 | 1.12 | 1.33 |
| 2004 | 1.17 | 1.64 | 3.25 | 1.12 | 1.45 |
| 2005 | 1.18 | 1.86 | 2.70 | 1.12 | 1.44 |
| 2006 | 1.19 | 1.85 | 2.68 | 1.19 | 1.52 |
| 2007 | 1.23 | 1.47 | 2.60 | 1.15 | 1.53 |
| 2008 | 1.27 | 2.00 | 2.43 | 1.23 | 1.65 |
| 2009 | 1.16 | 2.02 | 3.36 | 1.22 | 1.46 |
| 2010 | 1.16 | 2.17 | 3.14 | 1.16 | 1.36 |
| 2011 | 1.17 | 2.24 | 3.35 | 1.16 | 1.44 |
| 2012 | 1.19 | 2.12 | 3.07 | 1.17 | 1.46 |
| 2013 | 1.19 | 2.09 | 2.40 | 1.14 | 1.47 |
| 2014 | 1.19 | 2.09 | 2.48 | 1.11 | 1.46 |
| 2015 | 1.17 | 2.80 | 2.34 | 1.12 | 1.39 |
| 2016 | 1.14 | 2.56 | 1.88 | 1.09 | 1.39 |
| 2017 | 1.14 | 2.90 | 2.19 | 1.11 | 1.34 |
| 2018 | 1.12 | 2.50 | 2.01 | 1.10 | 1.30 |

Notes: Constant factors by which each income component has to be multiplied in the survey data (complemented by tax data for the top 1%) to restore consistency with National Accounts. For instance, a factor of 2 means that incomes have to be doubled.

Table A4.3 – Superannuation balance regression estimates (adults under 60 years of age)

| | 2003 | | 2005 | | 2009 | | 2011 | | 2013 | | 2015 | | 2018 | |
|-----------------------------|------------|-------|------------|-------|------------|-------|------------|-------|------------|-------|------------|-------|------------|-------|
| | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| Age | 872*** | 66.3 | 992*** | 86.5 | 1,241*** | 80.3 | 1,496*** | 101.5 | 1,635*** | 109.4 | 2,266*** | 106.8 | 2,385*** | 122.3 |
| Labour income (in \$1,000s) | -1,092*** | 69.1 | -1,316*** | 77.1 | -1,307*** | 61.7 | -1,306*** | 68.5 | -1,439*** | 69.8 | -1,458*** | 70.2 | -1,147*** | 67.1 |
| Labour income squared | -1.589*** | 0.15 | -1.026*** | 0.07 | -0.925*** | 0.04 | -0.577*** | 0.04 | -1.219*** | 0.05 | -0.214*** | 0.01 | -0.346*** | 0.02 |
| Age x labour income | 52.1*** | 1.6 | 58.5*** | 1.7 | 55.7*** | 1.4 | 57.0*** | 1.5 | 63.9*** | 1.6 | 56.4*** | 1.5 | 52.3*** | 1.4 |
| Female | 19,138*** | 3,023 | 16,908*** | 4,113 | 15,137*** | 3,729 | 20,744*** | 4,870 | 16,960*** | 5,171 | 23,683*** | 5,166 | 9,736* | 5,901 |
| Female x age | -755*** | 77.5 | -617*** | 104.3 | -618*** | 94.6 | -770*** | 122.7 | -632*** | 130.3 | -946*** | 129.1 | -463*** | 148.3 |
| Zero labour income | 9,600*** | 1,426 | 13,820*** | 1,854 | 7,525*** | 1,635 | 18,261*** | 2,215 | 12,849*** | 2,327 | 4,912** | 2,209 | 9,153*** | 2,680 |
| Constant | -23,828*** | 2,584 | -27,555*** | 3,439 | -29,054*** | 3,162 | -39,385*** | 4,049 | -41,409*** | 4,336 | -46,995*** | 4,372 | -54,929*** | 4,991 |
| Sample size | 17,491 | | 14,800 | | 23,666 | | 20,896 | | 19,783 | | 23,072 | | 18,883 | |
| Adjusted R2 | 0.273 | | 0.287 | | 0.271 | | 0.273 | | 0.322 | | 0.303 | | 0.347 | |

Notes: Ordinary Least Square estimates. 'x' denotes interaction terms. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4.4 – Superannuation balance regression estimates (adults over 59 years of age)

| | 2003 | | 2005 | | 2009 | | 2011 | | 2013 | | 2015 | | 2018 | |
|-------------------------------------|-------------|--------|------------|--------|-----------|--------|-----------|--------|-----------|--------|------------|--------|-----------|--------|
| | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| Age | -2,066*** | 351.3 | -2,999*** | 496.8 | -2,677*** | 391.1 | -3,848*** | 577.8 | -5,273*** | 570.1 | -4,190*** | 492.3 | -4,743*** | 609.2 |
| Superannuation income (in \$1,000s) | 30,463*** | 1793.7 | 19,297*** | 2282.3 | 17,273*** | 1676.9 | 11,652*** | 1765.3 | 7,598*** | 1632.4 | 11,144*** | 1478.7 | 24,516*** | 1431.4 |
| Superannuation income squared | -14.27*** | 2.66 | 5.69*** | 2.09 | -4 | 3.95 | -31.72*** | 1.65 | -24.73*** | 1.21 | -16.22*** | 2.16 | -17.38*** | 0.89 |
| Age x superannuation income | -358*** | 25.2 | -202*** | 33 | -132*** | 24.6 | -7 | 25.8 | 26 | 23.7 | -12 | 21.1 | -186*** | 20.3 |
| Female | -114,578*** | 30,515 | -105,355** | 42,529 | -26962 | 34,548 | -93,112* | 49,348 | -83,279* | 49,324 | -35430 | 43,155 | -96,150* | 53,620 |
| Female x age | 1,467*** | 434 | 1,369** | 603 | 273 | 488 | 1,159* | 705 | 1054 | 704 | 482 | 607 | 1,347* | 757 |
| Zero labour income | 461 | 4,461 | 18,713*** | 6,927 | 3658 | 4,477 | 5796 | 6,834 | -12,831* | 6,628 | -22,210*** | 6,474 | -17,068** | 8,117 |
| Labour income (in \$1000s) | 1,804*** | 82 | 3,089*** | 146 | 2,027*** | 73 | 2,227*** | 93 | 1,841*** | 77 | 1,744*** | 84 | 2,035*** | 82 |
| Sample size | 4,792 | | 4,386 | | 10,265 | | 7,307 | | 7,479 | | 10,811 | | 7,952 | |
| Adjusted R2 | 0.314 | | 0.298 | | 0.307 | | 0.357 | | 0.356 | | 0.366 | | 0.468 | |

Notes: Ordinary Least Square estimates. 'x' denotes interaction terms. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4.5 – Weekly imputed rent regression estimates (2005-06)

| | Gross imputed rent | | | | Net imputed rent | | | |
|--|--------------------|-------|-----------|-------|------------------|-------|-----------|-------|
| | (1) | | (2) | | (1) | | (2) | |
| | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| Tenure type (ref. is owner without a mortgage) | | | | | | | | |
| Owner with a mortgage | -0.003 | 0.010 | | | -0.198*** | 0.009 | | |
| Renter | -1.361*** | 0.095 | | | 0.450*** | 0.096 | | |
| Other | -0.048* | 0.028 | | | 0.218*** | 0.023 | | |
| Has a mortgage | 0.000 | | 0.009 | 0.010 | | | -0.274*** | 0.010 |
| State of residence (ref. is NSW) | | | | | | | | |
| VIC | -0.121*** | 0.012 | -0.119*** | 0.012 | -0.001 | 0.01 | -0.003 | 0.010 |
| QLD | -0.093*** | 0.012 | -0.092*** | 0.012 | 0.004 | 0.01 | 0.006 | 0.010 |
| SA | -0.205*** | 0.013 | -0.204*** | 0.013 | -0.046*** | 0.012 | -0.049*** | 0.012 |
| WA | -0.244*** | 0.013 | -0.242*** | 0.013 | -0.013 | 0.012 | -0.017 | 0.012 |
| Tas | -0.184*** | 0.016 | -0.179*** | 0.016 | -0.016 | 0.016 | -0.021 | 0.016 |
| ACT & NT | 0.008 | 0.018 | 0.008 | 0.018 | 0.056*** | 0.013 | 0.057*** | 0.013 |
| Area of residence (ref. is Capital city) | | | | | | | | |
| Balance of State | -0.198*** | 0.009 | -0.198*** | 0.009 | -0.033*** | 0.008 | -0.035*** | 0.008 |
| Number of bedrooms | 0.128*** | 0.005 | 0.131*** | 0.005 | 0.028*** | 0.004 | 0.025*** | 0.004 |
| Household gross income decile (ref. is 1) | | | | | | | | |
| 2 | -0.005 | 0.017 | -0.001 | 0.017 | -0.001 | 0.016 | -0.004 | 0.016 |
| 3 | -0.043** | 0.017 | -0.036** | 0.017 | -0.017 | 0.016 | -0.026 | 0.016 |
| 4 | -0.018 | 0.017 | -0.019 | 0.017 | -0.037** | 0.016 | -0.042*** | 0.016 |
| 5 | 0.001 | 0.018 | 0.000 | 0.018 | -0.044*** | 0.016 | -0.052*** | 0.016 |
| 6 | 0.004 | 0.018 | 0.005 | 0.018 | -0.054*** | 0.016 | -0.057*** | 0.016 |
| 7 | -0.007 | 0.018 | -0.011 | 0.018 | -0.073*** | 0.016 | -0.080*** | 0.016 |
| 8 | 0.015 | 0.018 | 0.012 | 0.019 | -0.050*** | 0.016 | -0.055*** | 0.016 |
| 9 | 0.051*** | 0.019 | 0.048** | 0.019 | -0.058*** | 0.016 | -0.072*** | 0.016 |
| 10 | 0.109*** | 0.019 | 0.109*** | 0.019 | -0.022 | 0.016 | -0.042*** | 0.016 |
| Landlord type (ref. is real estate agent) | | | | | | | | |
| No landlord | 3.962*** | 0.095 | 5.313*** | 0.013 | 2.311*** | 0.381 | 1.862*** | 0.379 |
| State housing authority | 5.140*** | 0.020 | 5.167*** | 0.020 | 1.596*** | 0.391 | 1.590*** | 0.379 |
| Parent | 5.300*** | 0.034 | 5.307*** | 0.035 | 1.423*** | 0.392 | 1.420*** | 0.380 |
| Other person | 0.053*** | 0.019 | 0.058*** | 0.019 | 1.682*** | 0.419 | 1.621*** | 0.418 |
| Other | 3.941*** | 0.029 | 3.946*** | 0.029 | 1.492*** | 0.392 | 1.492*** | 0.380 |
| Mortgage weekly repayments | | | | | -0.439*** | 0.005 | -0.396*** | 0.006 |
| Gross imputed rent | | | | | -1.636*** | 0.381 | -1.170*** | 0.379 |
| Sample size | 9,857 | | 9,857 | | 9,857 | | 9,857 | |
| Adjusted R2 | 0.969 | | 0.968 | | 0.690 | | 0.692 | |

Notes: Notes: Ordinary Least Square estimates. Model (1) is with tenure type, model (2) is without tenure type. In the net imputed rent models all variables are interacted with gross imputed rent, with the exception of mortgage weekly repayments and gross imputed rent. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4.6 – Mean pre-tax adult income by income group, 1991-2018

| | Income group | | | | |
|------|--------------|---------------|---------------|---------|--------|
| | Bottom 50% | Top 50 to 10% | Top 10% to 1% | Top 1% | All |
| 1991 | 10,197 | 30,406 | 58,550 | 162,852 | 24,141 |
| 1992 | 10,823 | 30,620 | 58,278 | 161,773 | 24,511 |
| 1993 | 11,337 | 32,337 | 62,629 | 182,177 | 26,037 |
| 1994 | 11,927 | 33,992 | 66,201 | 201,152 | 27,528 |
| 1995 | 12,532 | 35,053 | 69,946 | 195,753 | 28,523 |
| 1996 | 13,324 | 36,809 | 73,666 | 225,678 | 30,266 |
| 1997 | 13,812 | 38,918 | 76,736 | 221,114 | 31,538 |
| 1998 | 14,223 | 40,462 | 80,723 | 248,906 | 33,043 |
| 1999 | 14,561 | 42,077 | 83,216 | 269,915 | 34,283 |
| 2000 | 15,439 | 44,256 | 89,952 | 284,875 | 36,361 |
| 2001 | 16,834 | 46,084 | 92,993 | 308,709 | 38,301 |
| 2002 | 16,670 | 48,744 | 99,508 | 349,734 | 40,277 |
| 2003 | 17,251 | 50,659 | 105,894 | 379,418 | 42,199 |
| 2004 | 18,409 | 53,773 | 114,852 | 427,802 | 45,316 |
| 2005 | 18,658 | 56,123 | 121,404 | 455,394 | 47,248 |
| 2006 | 20,238 | 59,310 | 128,463 | 472,402 | 50,114 |
| 2007 | 22,497 | 63,609 | 137,018 | 558,410 | 54,534 |
| 2008 | 23,864 | 68,142 | 147,157 | 579,469 | 58,208 |
| 2009 | 23,765 | 69,375 | 157,164 | 634,094 | 60,103 |
| 2010 | 23,821 | 70,147 | 156,412 | 622,404 | 60,258 |
| 2011 | 25,685 | 75,252 | 168,774 | 689,945 | 65,029 |
| 2012 | 26,993 | 79,637 | 182,466 | 706,888 | 68,830 |
| 2013 | 27,259 | 81,324 | 187,210 | 685,060 | 69,827 |
| 2014 | 28,025 | 82,976 | 186,245 | 709,438 | 71,037 |
| 2015 | 27,842 | 84,142 | 185,418 | 671,095 | 70,946 |
| 2016 | 27,451 | 83,336 | 181,216 | 640,997 | 69,765 |
| 2017 | 29,186 | 88,220 | 195,828 | 712,084 | 74,601 |
| 2018 | 30,125 | 89,235 | 196,108 | 702,775 | 75,417 |

Notes: All values expressed in current Australian dollars.

Table A4.7 – Mean post-tax national adult income by income group, 1991-2018

| | Income group | | | | All |
|------|--------------|---------------|---------------|---------|--------|
| | Bottom 50% | Top 50 to 10% | Top 10% to 1% | Top 1% | |
| 1991 | 15,131 | 27,911 | 47,320 | 123,522 | 24,221 |
| 1992 | 15,621 | 28,254 | 47,442 | 120,227 | 24,582 |
| 1993 | 16,318 | 29,867 | 51,326 | 136,344 | 26,079 |
| 1994 | 17,411 | 31,344 | 53,972 | 150,189 | 27,596 |
| 1995 | 18,227 | 32,333 | 55,481 | 159,939 | 28,630 |
| 1996 | 19,601 | 34,009 | 59,151 | 166,351 | 30,386 |
| 1997 | 20,590 | 35,840 | 60,493 | 163,170 | 31,694 |
| 1998 | 21,451 | 37,459 | 63,788 | 179,679 | 33,237 |
| 1999 | 22,352 | 38,890 | 65,559 | 187,608 | 34,487 |
| 2000 | 23,819 | 40,992 | 69,169 | 202,323 | 36,552 |
| 2001 | 25,090 | 42,992 | 73,715 | 214,010 | 38,511 |
| 2002 | 25,464 | 45,333 | 80,060 | 246,504 | 40,526 |
| 2003 | 27,016 | 47,331 | 82,365 | 252,877 | 42,380 |
| 2004 | 29,096 | 50,453 | 89,305 | 281,936 | 45,578 |
| 2005 | 30,174 | 52,799 | 93,993 | 291,275 | 47,576 |
| 2006 | 32,171 | 56,219 | 99,703 | 293,952 | 50,476 |
| 2007 | 35,292 | 60,995 | 106,681 | 333,825 | 54,975 |
| 2008 | 36,634 | 65,215 | 116,352 | 362,085 | 58,488 |
| 2009 | 36,442 | 66,421 | 125,183 | 428,971 | 60,319 |
| 2010 | 36,171 | 66,782 | 126,392 | 438,939 | 60,544 |
| 2011 | 39,284 | 71,313 | 135,625 | 483,792 | 65,201 |
| 2012 | 41,446 | 75,736 | 146,016 | 477,770 | 68,926 |
| 2013 | 42,121 | 77,541 | 149,839 | 455,603 | 70,114 |
| 2014 | 43,167 | 79,345 | 150,176 | 486,384 | 71,673 |
| 2015 | 43,100 | 80,091 | 149,701 | 459,942 | 71,645 |
| 2016 | 42,973 | 78,695 | 144,544 | 425,162 | 70,217 |
| 2017 | 45,552 | 83,598 | 156,873 | 479,191 | 75,107 |
| 2018 | 47,380 | 84,389 | 154,612 | 456,248 | 75,918 |

Notes: All values expressed in current Australian dollars.

Table A4.8 – Mean post-tax disposable adult income by income group, 1991-2018

| | Income group | | | | |
|------|--------------|---------------|---------------|---------|--------|
| | Bottom 50% | Top 50 to 10% | Top 10% to 1% | Top 1% | All |
| 1991 | 9,327 | 22,107 | 41,517 | 117,719 | 18,417 |
| 1992 | 10,291 | 22,925 | 42,113 | 114,898 | 19,252 |
| 1993 | 10,986 | 24,536 | 45,995 | 131,012 | 20,747 |
| 1994 | 11,522 | 25,454 | 48,082 | 144,299 | 21,706 |
| 1995 | 11,765 | 25,871 | 49,019 | 153,476 | 22,167 |
| 1996 | 12,630 | 27,037 | 52,179 | 159,379 | 23,415 |
| 1997 | 13,055 | 28,304 | 52,957 | 155,635 | 24,159 |
| 1998 | 13,301 | 29,309 | 55,637 | 171,529 | 25,087 |
| 1999 | 13,652 | 30,190 | 56,859 | 178,908 | 25,787 |
| 2000 | 14,297 | 31,470 | 59,647 | 192,801 | 27,030 |
| 2001 | 16,004 | 33,906 | 64,628 | 204,923 | 29,424 |
| 2002 | 15,890 | 35,759 | 70,486 | 236,930 | 30,952 |
| 2003 | 16,587 | 36,902 | 71,936 | 242,448 | 31,951 |
| 2004 | 18,028 | 39,384 | 78,236 | 270,868 | 34,510 |
| 2005 | 18,264 | 40,889 | 82,083 | 279,365 | 35,667 |
| 2006 | 19,290 | 43,338 | 86,822 | 281,070 | 37,594 |
| 2007 | 21,260 | 46,963 | 92,650 | 319,793 | 40,944 |
| 2008 | 22,282 | 50,862 | 102,000 | 347,733 | 44,135 |
| 2009 | 24,656 | 54,635 | 113,397 | 417,185 | 48,533 |
| 2010 | 23,769 | 54,381 | 113,990 | 426,537 | 48,142 |
| 2011 | 25,825 | 57,854 | 122,167 | 470,334 | 51,743 |
| 2012 | 27,327 | 61,617 | 131,897 | 463,651 | 54,806 |
| 2013 | 27,571 | 62,990 | 135,288 | 441,052 | 55,563 |
| 2014 | 28,194 | 64,373 | 135,203 | 471,410 | 56,701 |
| 2015 | 27,619 | 64,610 | 134,219 | 444,461 | 56,163 |
| 2016 | 26,855 | 62,577 | 128,426 | 409,045 | 54,099 |
| 2017 | 27,995 | 66,040 | 139,315 | 461,633 | 57,550 |
| 2018 | 28,219 | 65,227 | 135,450 | 437,086 | 56,756 |

Notes: All values expressed in current Australian dollars.

Appendix 4 Figures

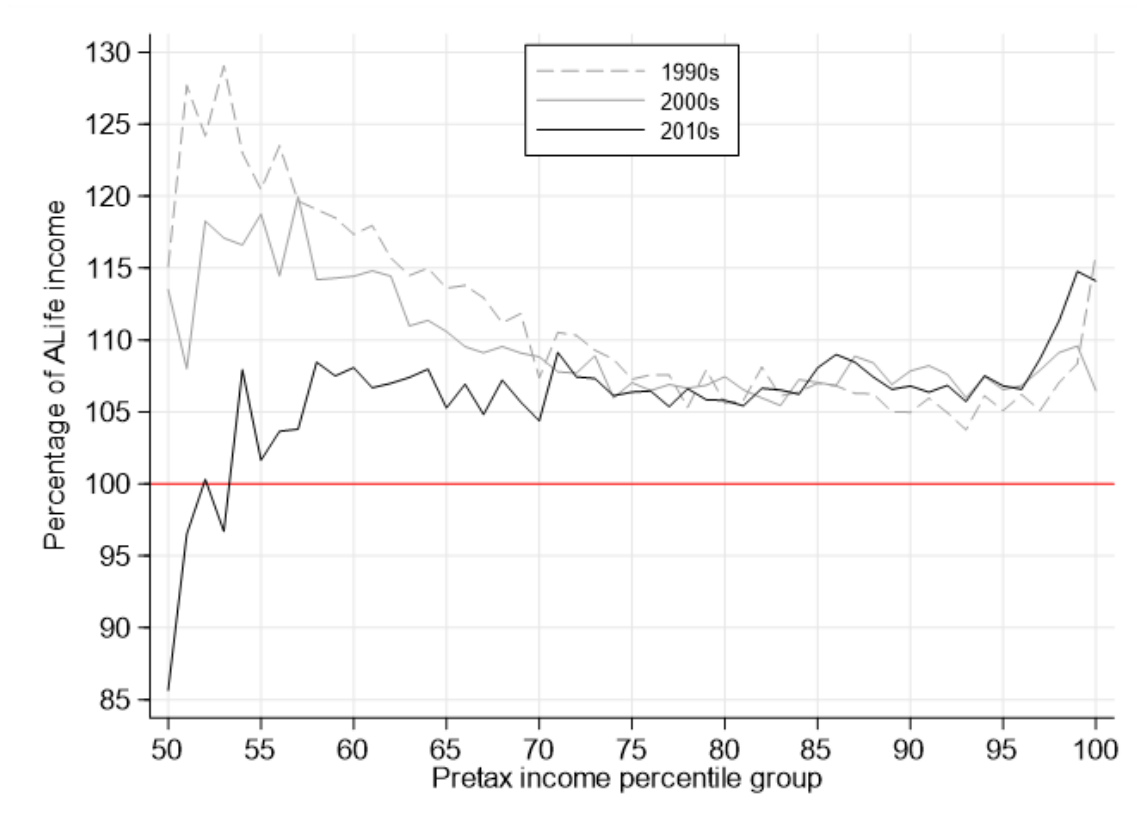


Figure A4.1 – SIH survey vs. ALife tax data by percentile - Labour income

Notes: Individuals are ranked based on pre-tax income.

Source: Authors' calculations based on ALife and SIH data.

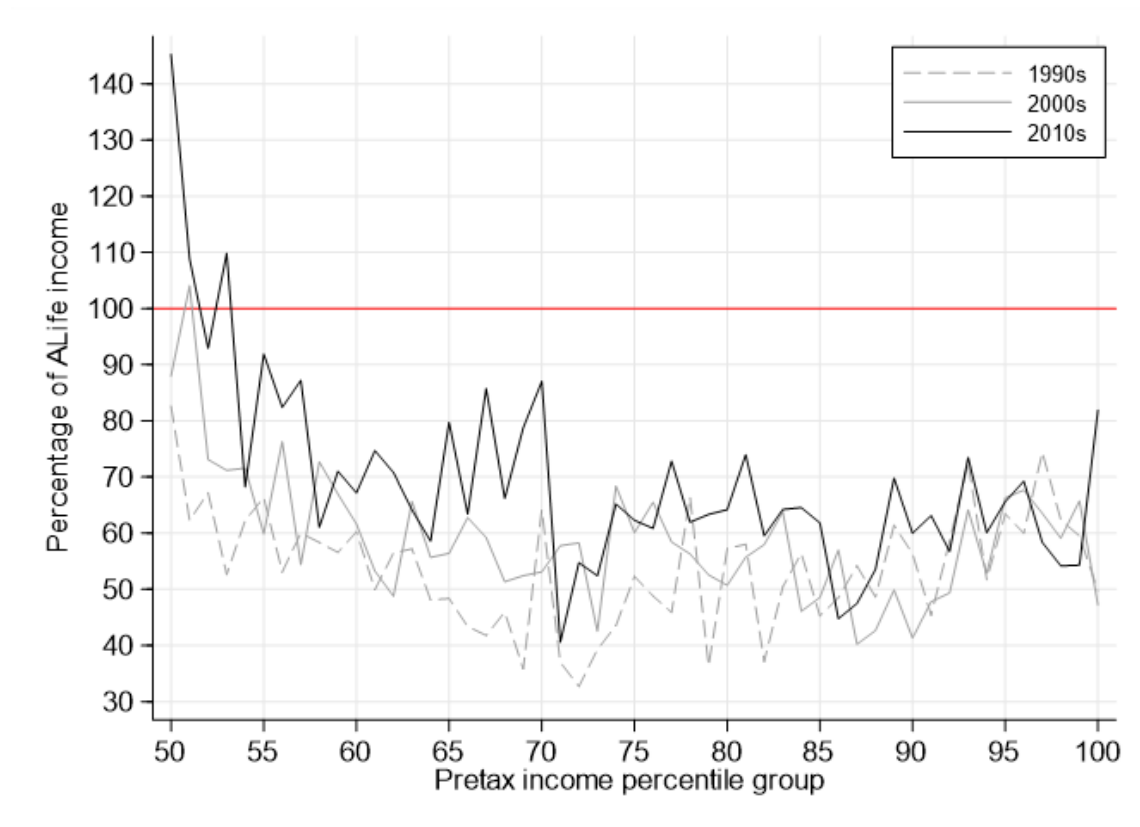


Figure A4.2 – SIH survey vs. ALife tax data by percentile – Non-labour income

Notes: Individuals are ranked based on pre-tax income.

Source: Authors' calculations based on ALife and SIH data.

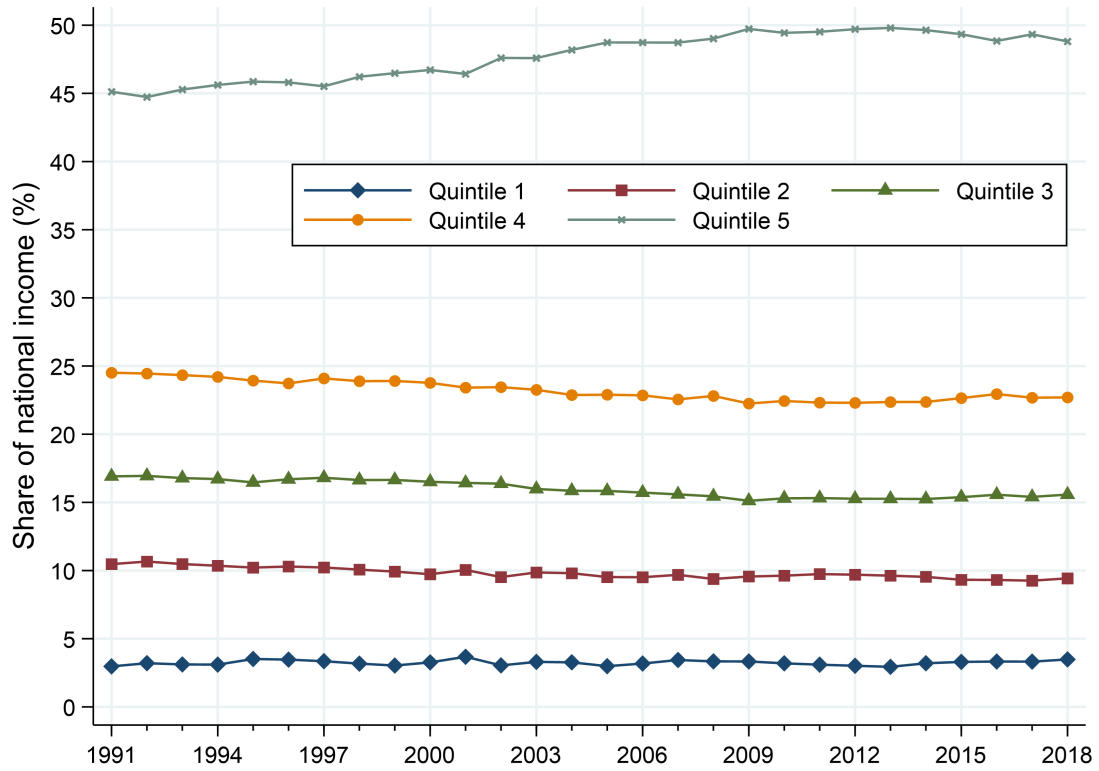


Figure A4.3 – Pre-tax national income quintile shares, 1991-2018

Notes: Distribution of pre-tax national income (before all taxes and transfers, except age pensions) among adults. Broad equal-split adults series (household income equally split among adults).

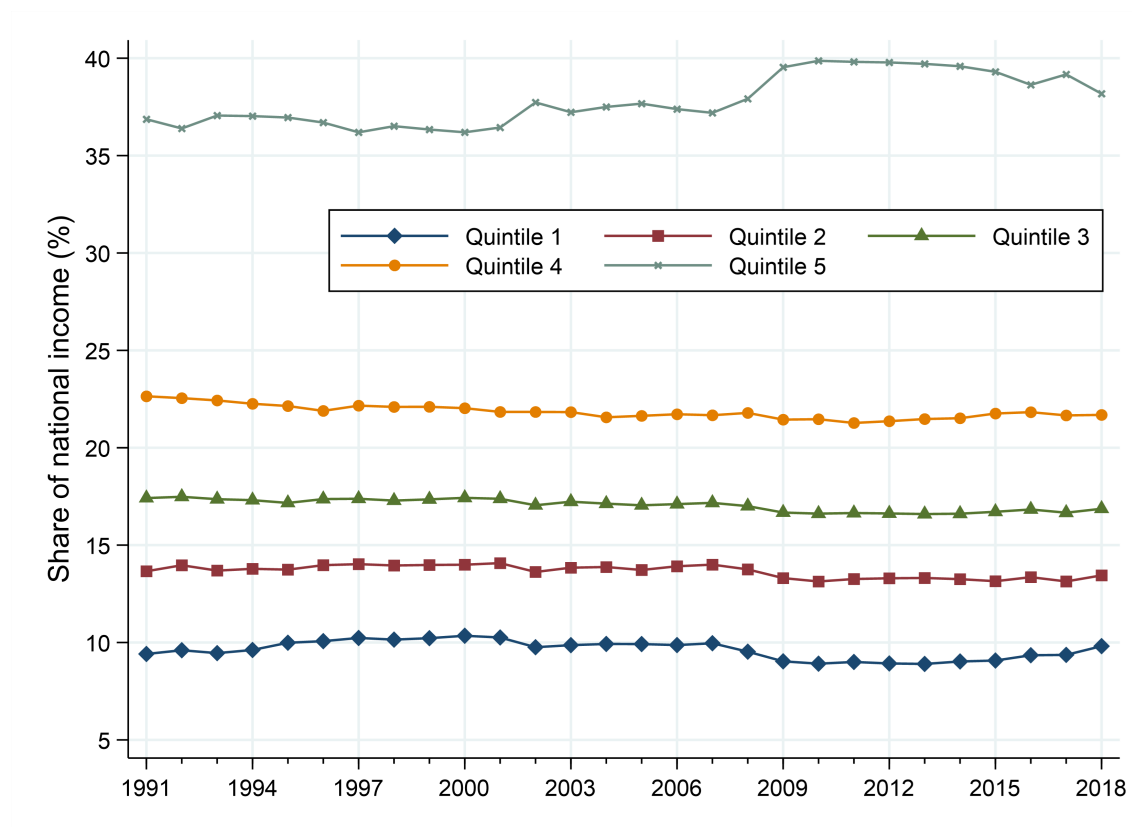


Figure A4.4 – Post-tax national income quintile shares, 1991-2018

Notes: Distribution of pre-tax national income (before all taxes and transfers, except age pensions) among adults. Broad equal-split adults series (household income equally split among adults).

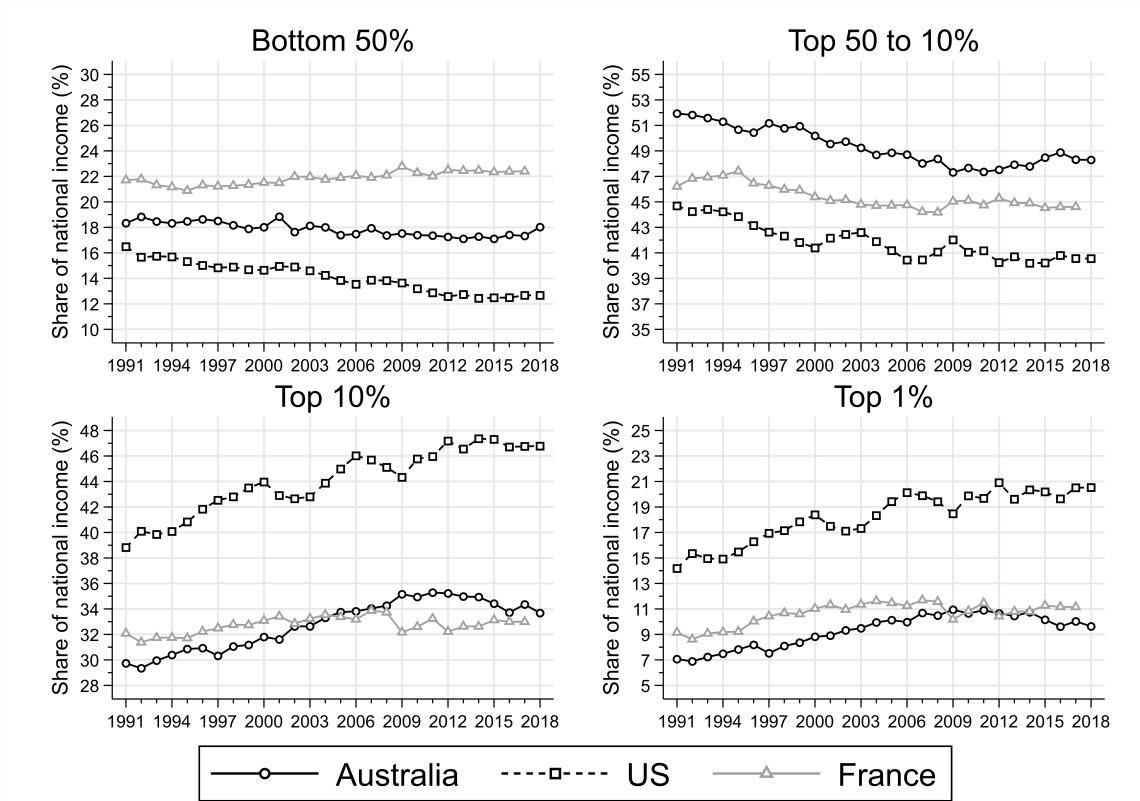


Figure A4.5 – Pre-tax income shares: Australia, US and France, 1991-2018

Notes: Distribution of pre-tax national income (before all taxes and transfers, except age pensions) among adults. Narrow equal-split adults series (income of married couples divided by two).

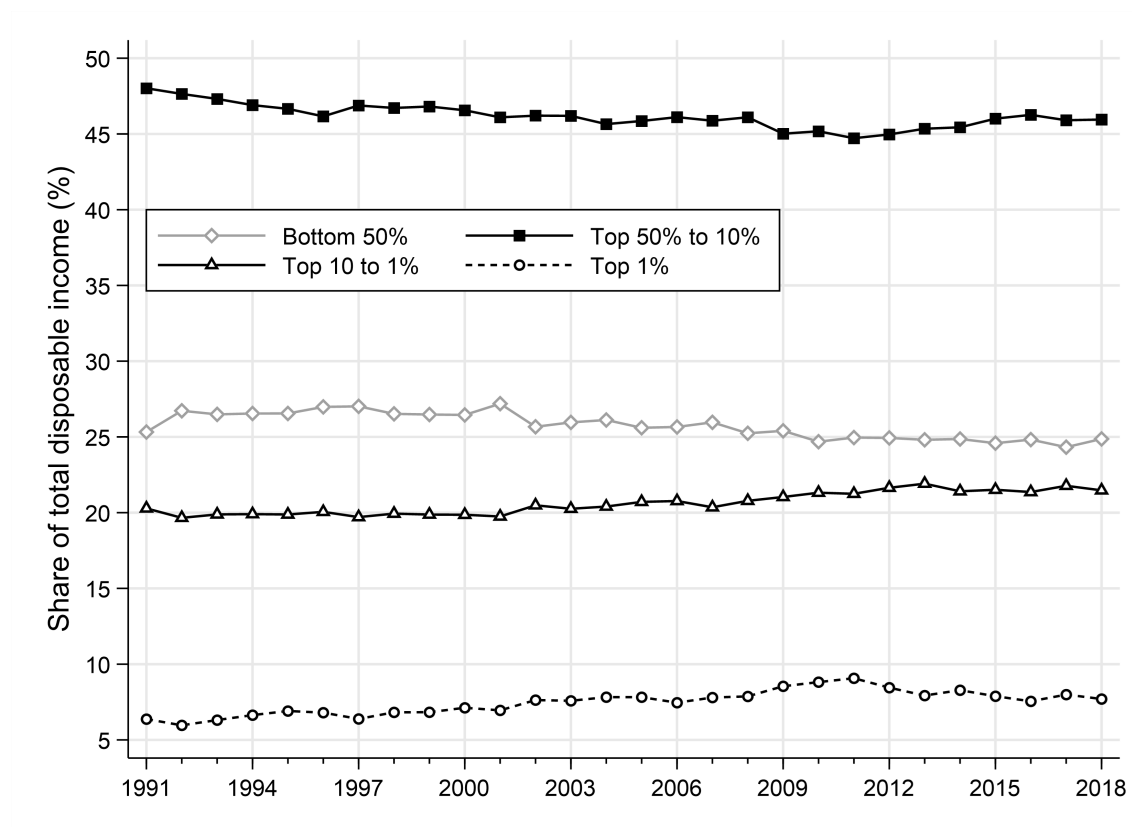


Figure A4.6 – Income shares, 1991-2018

Notes: Distribution of post-tax disposable income (after all taxes and transfers) among adults. Broad equal-split adults series (household income equally split among adults).

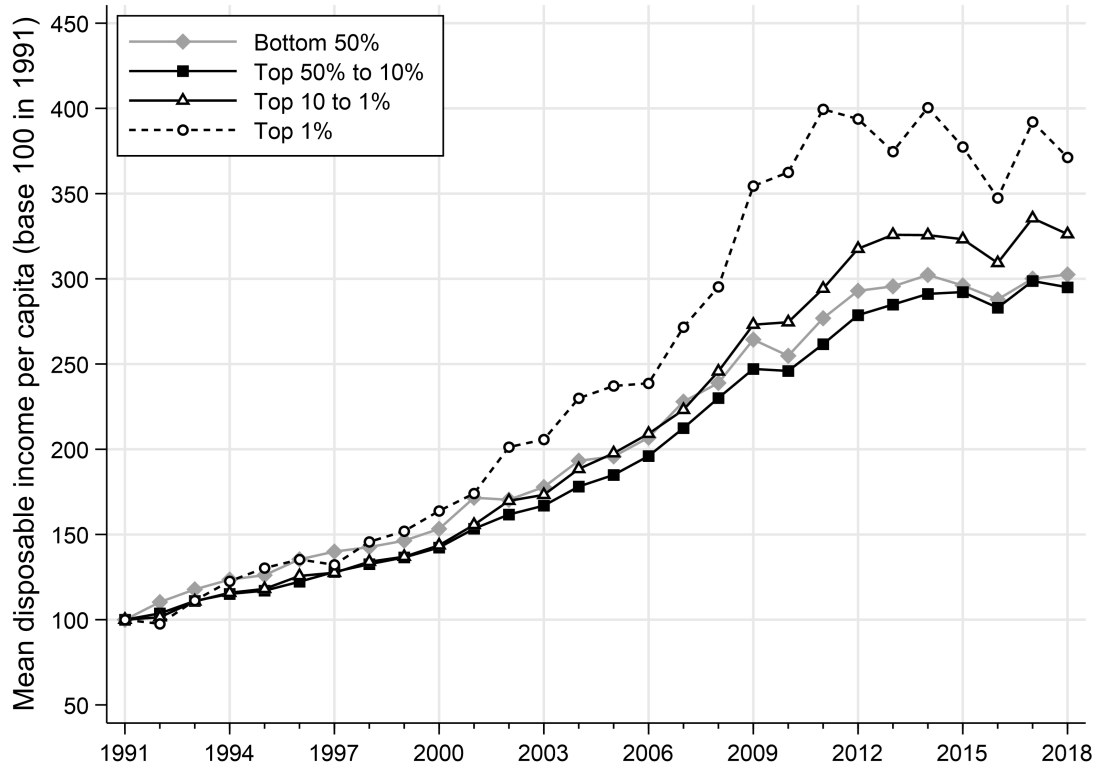


Figure A4.7 – Mean adult income by income group, 1991-2018

Notes: Distribution of post-tax disposable income (before all taxes and transfers, except age pensions) among adults. Broad equal-split adults series (household income equally split among adults). Index based on mean incomes in current dollars.

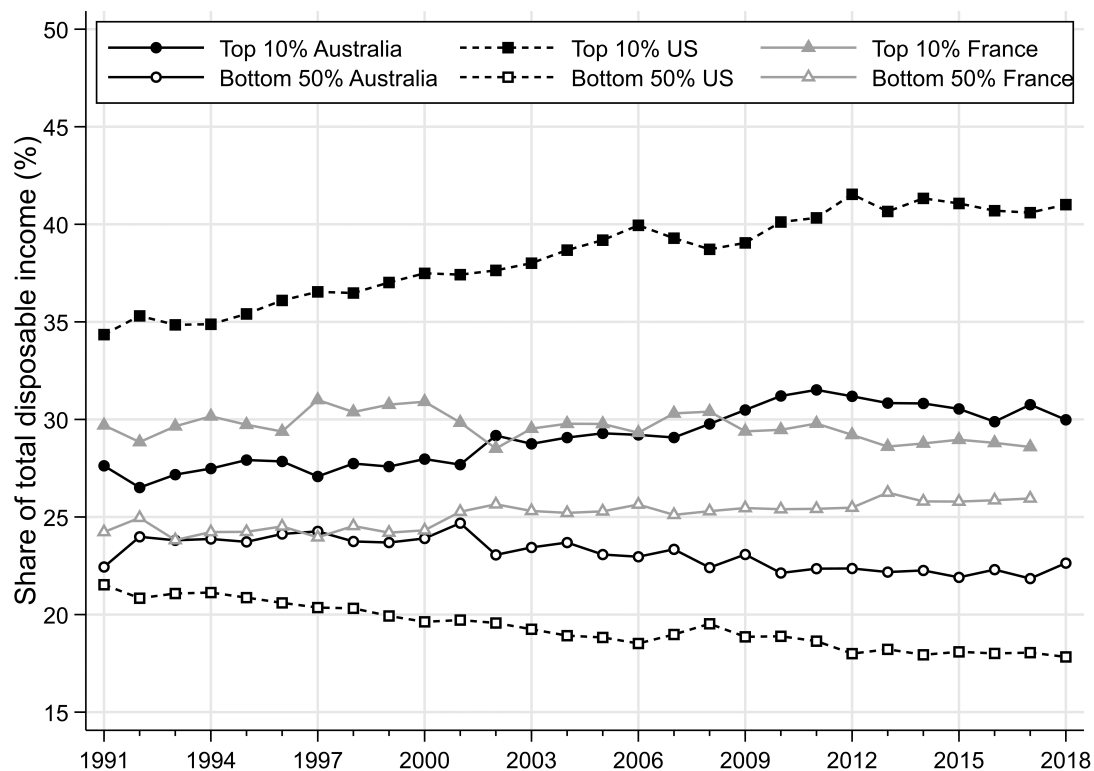


Figure A4.8 – Top 10% and bottom 50% shares: Australia, US and France, 1991-2018

Notes: Distribution of post-tax disposable income (after all taxes and transfers) among adults. Narrow-equal-split adults series (income of married couples divided by two).

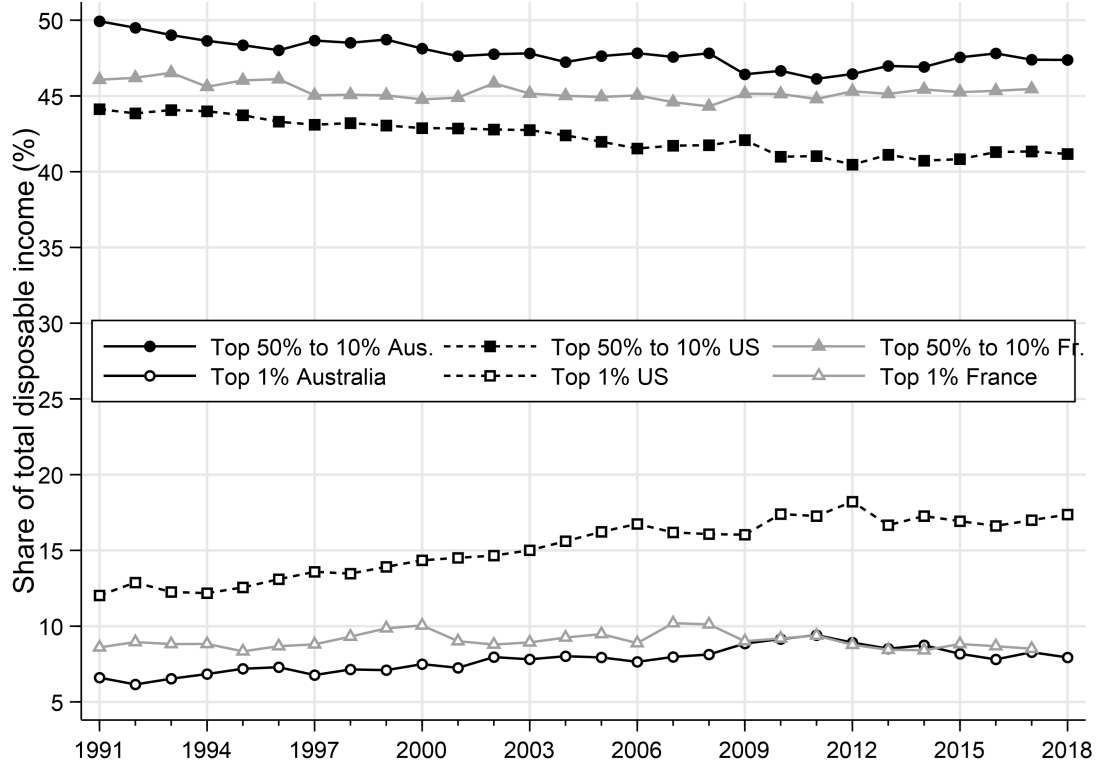


Figure A4.9 – Top 1% & Top 50 to 10% shares: Australia, US and France, 1991-2018

Notes: Distribution of post-tax disposable income (after all taxes and transfers) among adults. Narrow-split-adults series (income of married couples divided by two).