Globalization and Factor Income Taxation*

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Abstract

Exploiting a new global macro-historical database of effective tax rates, we uncover an intriguing pro-tax-capacity effect of international trade. While effective capital tax rates have fallen in developed countries, they have risen in developing countries since the mid-1990s. Event studies of trade liberalization shocks and instrumental variable regressions show that a significant share of this rise can be explained by trade integration, which increases the share of output produced in large corporations, where effective taxation of capital is higher. In contrast to a widely held view, globalization appears in many countries to have supported the ability of government to tax capital.

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1 Introduction

How has globalization affected the relative taxation of labor and capital, and why? Has international economic integration uniformly eroded the amount of taxes paid by capital owners, shifting the tax burden to workers? Or have some countries managed to increase effective capital tax rates, and if so through which mechanisms? Answering these questions is critical to better understand the macroeconomic effects and long-run social sustainability of globalization.

This paper makes some progress on these issues by uncovering an intriguing pro-tax-capacity effect of international trade. Thanks to a new global database of effective tax rates on labor and capital, we document that in developing countries, effective capital tax rates have increased in the post-1995 era of hyper-globalization. Consistently across a variety of research designs, we find that a significant part of this rise can be explained by trade liberalization. By expanding economic activity in larger, formal corporate structures relative to smaller informal businesses, trade liberalization improves the effective collection of taxes, particularly of corporate taxes. The effect is sizable: trade liberalization can explain 17-37% of the rise in effective capital tax rates in developing countries. Of course, globalization has also had widely noted negative effects on capital taxation, in particular because of international tax competition. On balance, we find that the negative race-to-the-bottom effect has dominated in high-income countries, but the pro-tax-capacity effect of trade we uncover has prevailed in developing economies. In contrast to a widely held view, globalization has not uniformly eroded the ability of governments to tax capital, and in fact appears to have supported it 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 labor (ETR_L) and capital (ETR_K) covering 155 countries with over half starting in 1965. Each ETR divides all actual 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 statutory tax rules and, importantly in a development context, tax evasion and tax avoidance. In contrast to existing series that focus on high-income countries, this global database allows us to systematically characterize the evolution of effective tax rates in developing economies, and thus to compare the trends of tax structures across development levels.

A simple and striking fact emerges from this database. We uncover an asymmetric evolution of capital taxation in the era of hyper-globalization. In high-income countries, effective capital tax rates declined, from 36-38% in the post-World War II decades to about 30% in 2018. For instance, in the United States, ETR_K collapsed from more than 40% in the 1960s to 25% in 2018. By contrast, in developing countries, effective capital tax rates have been on a rising trend since the 1990s, albeit starting from a low level. Effective capital tax rates rose from about 10% in the 1990s to 19% in 2018, with more pronounced increases in larger economies. Between the early 1990s and 2018, for example, ETR_K rose from 5% to 25% in China, 10% to 27% in Brazil, 6% to 12% in India, and 5% to 10% in Mexico.

This rise of capital taxation in low- and middle-income countries had not been noted in the literature before, due to the limited data on the evolution of tax structures in developing countries. The finding appears to be robust. It holds when we exclude China and oil-rich countries; when we restrict the analysis to a balanced sample of countries; and under different weighting schemes. It holds with alternative approaches to computing capital and labor income in non-corporate businesses, where factor shares are not directly observable. It is also robust to alternative ways of assigning the personal income tax to capital versus labor.

What can explain the asymmetric evolution of capital taxation across development levels? Our second contribution is to formulate and test a new hypothesis that sheds light on this puzzle. Our hypothesis is motivated by the observation that the increase in ETR_K in developing countries coincides with their trade liberalization. Between the late 1980s and the early 2000s, many countries opened their markets and reduced tariffs. These reforms, combined with technological innovations, led to a boom in international trade and reshaped the economy of countries such as Mexico, India, and China. We hypothesize that openness exerts a positive effect on developing countries' capacity to raise taxes, as trade leads to the expansion of larger firms relative to smaller ones, and firm-level ETR_K rises with size (revenue). By disproportionately benefiting larger firms, trade increases the share of economic activity in firms more likely to be incorporated and formalized, where effective taxation of capital (and labor) is higher.[1]

[1]Improved effective taxation in the corporate sector stems from both stronger enforcement and higher statutory tax burdens than in the non-corporate sector. The ability to impose a higher statutory tax burden is endogenous to stronger enforcement. Our notion of tax capacity is that these co-determined forces jointly lead to higher ETR_K as a function of firm size.

To test this hypothesis, we implement three research designs. First, we run non-parametric estimations of within-country associations between changes in ETR and changes in trade openness. Second, we analyze major trade liberalization events which occurred in seven large developing countries, including the often-discussed WTO accession of China in 2001 (Brandt, Biesebroeck, Wang, & Zhang, 2017; Goldberg & Pavcnik, 2016). These events caused large and sharp reductions in trade barriers. We use synthetic control methods and present event-study results. Last, we extend the instruments for trade openness presented in Egger, Nigai, and Strecker (2019).

In each case we find that trade openness leads to a large rise in effective capital taxation in developing countries (and a smaller increase in effective labor taxation). On the contrary, trade integration has a null or negative effect on capital taxation in high-income countries (and a positive effect on labor taxation). Although the identification strategies are different in our three empirical designs, the results are consistent across them and robust to a range of sensitivity checks.

To better understand these results, we study potential mechanisms using the event studies and IV. Consistent with our tax-capacity mechanism, in developing countries we find that trade increases the share of domestic output that originates from the corporate sector, relative to the non-corporate business sector. This leads to a larger share of output being produced in a sector with more effective tax collection (Slemrod & Velayudhan, 2018) and a higher effective tax rate. The corporate share of domestic output increased from 55% to 65% in developing countries between 1995 and 2018.

Trade also increases the average effective tax rate on capital in the corporate sector, consistent with the trade-induced additional corporate revenue accruing to firms where ETR_K increases in size (revenue). Importantly, this occurs despite trade causing a decrease in the statutory corporate income tax (CIT) rate, which reflects the race-to-bottom mechanism. To unpack these effects in the corporate sector, we provide a firm-level analysis in Rwanda by merging several administrative datasets. Using an IV based on the shift-share design of Hummels, Jørgensen, Munch, and Xiang (2014), we find that increased integration to international trade at the corporate firm level causes an increase in both the firm's ETR_K and its size. These results provide firm-level evidence for trade's positive impact on ETR_K and support the tax-capacity mechanism interpretation that the impact is mediated by a positive size-ETR_K gradient.

We find that trade has no significant impact on outcomes related to the tax-capacity mechanism in developed countries,[2] yet causes a decrease in the CIT rate. On net, the trade-induced increase in tax capacity dominates the CIT reduction in developing countries and increases ETR_K, but not in developed countries where the race-to-the-bottom effects that exert downward pressure on capital taxation prevail.

Over the sample period in our study, developing countries have implemented policies to increase domestic tax enforcement.[3] We find trade's positive impacts on ETR_K and tax-capacity mechanism outcomes hold without these policies, but increased domestic enforcement enhances the benefits of the tax-capacity effect. We also find larger effects of trade on ETR_K in countries with restrictions on capital flows and with larger populations. This finding suggests that countries managing their capital accounts and with larger markets are less exposed to race-to-bottom effects.

We conclude by discussing implications for public finance and globalization in developing countries. Despite potential revenue losses at the border, we find that trade's positive impacts on the domestic tax bases of capital and labor are sufficiently large that openness causes an increase in overall tax revenues (as a % of GDP). This is a policy relevant result, as potential revenue losses from trade liberalization remain an important concern amongst policy-makers (World Bank, 2020).[4] Moreover, we find that the positive impact of trade on effective taxation is systematically larger for capital than for labor. Given the higher concentration of capital income relative to labor income, the evolution of ETR_K and ETR_L provides one of several inputs necessary to study the changes caused by globalization in tax progressivity and, in turn, in the distribution of disposable income. (Goldberg, 2023)

In the following section, we relate our work to the existing literature. Section 3 describes the methodology and data. Section 4 presents findings on the long-run evolution of effective tax rates. Section 5 presents results on the impacts of trade on effective tax rates, and Section 6 investigates mechanisms. Section 7 concludes.

[2]Where the corporate output-share has remained stable at a high level since the 1970s, which may suggest that constraints on effective taxation have been steady and are not as binding in these countries.

[3]Including large taxpayer units (Almunia & Lopez-Rodriguez, 2018) and integrated customs-tax agencies. The literature has yet to establish a causal link between these policies and globalization.

[4]While prominent amongst practitioners, the concern over losses in total tax revenue arising from trade openness has little empirical basis in developing countries. Studies in these countries on trade's net total tax impact find differing results, perhaps owing to differences in measures, methods, and samples (including Baunsgaard & Keen, 2009; Buettner & Madzharova, 2018; Cagé & Gadenne, 2018). We complement this body of work by drawing on multiple identification strategies and the most comprehensive sample to date, and robustly find that trade leads to a net increase in overall revenues.

2 Related literature

Globalization and tax structure Our paper contributes to the macro-oriented literature on globalization and tax structure (Alesina & Wacziarg, 1998), reviewed in Adam, Kammas, and Rodriguez (2013). The 'race to the bottom' hypothesis postulates that governments reduce taxes on factors that become more mobile (e.g., capital) following trade liberalization (Clausing, 2016; Slemrod, 2004). To achieve revenue-neutrality, governments raise taxes on the less mobile factor (e.g., labor).[5] The 'social insurance' hypothesis postulates governments raise revenue to provide insurance for workers displaced by international competition (Rodrik, 1998). These studies mainly concern high-income countries. By expanding the scope to developing countries, we formulate and test a new mechanism, where trade increases ETR by expanding firms with higher effective tax collection. In contrast to a prevalent view in the literature, we find that globalization has supported the effective taxation of capital in many countries.

Our results are based on a new global dataset of effective tax rates, which complements existing datasets (including Carey & Rabesona, 2018; Kostarakos & Varthalitis, 2020; McDaniel, 2007) by expanding coverage to developing countries (Section 3).[6] Our ETR measure is complementary to the literature on forward-looking measures of capital tax rates (including Devereux & Griffith, 1999), which models the statutory tax burden faced by firms in greater detail, but does not account for tax evasion and other behavioral responses that determine actual effective tax rates. This literature finds that the statutory tax burden on capital has fallen over the long-run in both developed and developing countries, consistent with the 'race to bottom' mechanism.[7] In developing countries, several studies have noted a 'puzzle' in corporate tax systems – namely, that the aggressive reduction in statutory tax burdens on firms has not been accompanied by a reduction in corporate tax revenue as a share of GDP. Consistent with our tax-capacity mechanism, Abbas and Klemm (2013) conjecture that this puzzle could be resolved by the growing importance of the corporate sector in these economies, which Mansour and Keen (2009) suggest may be related to globalization.[8]

[5]Within labor, Egger et al. (2019) find that globalization in the post-1994 era led to a reduction in income taxes for the top 1% of workers and an increase in income taxes for middle class workers.

[6]This was achieved through archival work to digitize numerous countries' historical public finance records. We complement other work in economic history on taxation (including Cogneau, Dupraz, Knebelmann, & Mesplé-Somps, 2021), by providing long-run measures of factor effective tax rates.

[7]Including Steinmüller, Thunecke, and Wamser (2019), Loretz (2008) and Keen and Simone (2004).

[8]See also Quinn (1997), Kumar and Quinn (2012) and Abramovsky, Klemm and Phillips (2014).

Effective taxation and trade in developing countries Our paper contributes to the micro-oriented literature on trade and public finance in developing countries. Most studies focus on evasion of *border taxes* (e.g., Fisman & Wei, 2004; Javorcik & Narciso, 2017) or cross-border income-shifting by firms and individuals (e.g., Bilicka, 2019; Londoño-Vélez & Tortarolo, 2022; Wier, 2020). Our paper focuses instead on the impacts of trade on domestic economic structure and *domestic tax bases* of capital and labor.[9] Our results are intuitive when considering that the trade literature finds positive effects on domestic outcomes including market shares (McCaig & Pavcnik, 2018), firm size (Alfaro-Ureña, Manelici, & Vasquez, 2022), and local development (Méndez & Van Patten, 2022), which the public finance literature has separately identified as important determinants of effective taxation (Besley & Persson, 2014; Best, Shah, & Waseem, 2021).[10] Our contribution is to link these two bodies of work by directly and rigorously studying trade's impacts on domestic tax bases.

These impacts are mediated by our novel tax capacity mechanism, which is rooted in two separately established insights from the trade and public finance literatures in developing countries. First, a large class of models predicts that trade leads to the expansion of large firms relative to small firms (Mrázová & Neary, 2018); for empirical evidence, see Bernard, Jensen, Redding, and Schott (2007). Second, small firms are largely informal, and effective taxation increases with firm size (Basri, Felix, Hanna, & Olken, 2021).[11] Effective tax collection is stronger in larger firms such as corporations due to visibility, complex production structures, and employment of many workers (Almunia & Lopez-Rodriguez, 2018; Waseem, 2020). This results in information trails that improve enforcement (Gordon & Li, 2009; Naritomi, 2019; Pomeranz, 2015), though with limits (Carillo, Pomeranz, & Singhal, 2017).[12] Stronger enforcement also permits higher statutory tax burdens. We focus on a specific mechanism based on size, but many links between international trade, firm structure, and taxation remain to be explored in developing countries (Atkin & Khandelwal, 2020; Parenti, 2018).

[9]A theoretical literature focuses on analyzing trade's impact on the optimal indirect tax mix between border taxes and domestic consumption taxes (e.g., Emran & Stiglitz, 2005), but has abstracted from the role of direct taxes on capital and labor. Benzarti and Tazhitdinova (2021) empirically study the impact of domestic consumption taxes on trade flows.

[10]Our 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 6).

[11]See also Kopczuk and Slemrod (2006), Kleven, Knudsen, Kreiner, Pedersen, and Saez (2011), La Porta and Shleifer (2014), Bachas, Fattal, and Jensen (2019) and Best et al. (2021).

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

3 Construction of Effective Tax Rates

This section presents our new database of effective tax rates (ETR) on labor and capital, which covers 155 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 B.

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:

$$ETR_L = \frac{T_L}{Y_L} \quad \text{and} \quad ETR_K = \frac{T_K}{Y_K} \tag{1}$$

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

$$T_L = \sum_j \lambda_j \cdot \tau_j \quad \text{and} \quad T_K = \sum_j (1 - \lambda_j) \cdot \tau_j \tag{2}$$

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 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 5.3). Table B2 provides a detailed allocation summary.

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

$$Y = Y_L + Y_K = \underbrace{CE + \phi \cdot OS_{PUE}}_{Y_L} + \underbrace{(1-\phi) \cdot OS_{PUE} + OS_{CORP} + OS_{HH}}_{Y_K} \tag{3}$$

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}).[13]

The ETRs are macroeconomic effective tax rates that capture the total and economically relevant tax wedges on each factor of production (i.e., the wedges that matter for production decisions), such as the difference between the cost to employ a worker and what the worker receives. Since national account statistics are compiled following harmonized standards and methods, these ETRs are conceptually comparable over time and across countries, although a number of data limitations (discussed below) need to be kept in mind. By relying on taxes effectively collected, the ETRs incorporate the net past effects of all tax rules—including base reductions, exemptions, and tax credits. The ETRs also incorporate all avoidance and evasion behavior; this 'de facto' incidence of actual payment is particularly important in a development context, where evasion is widespread and information on current statutory tax rules provides only a partial insight into the actual tax burden.

In sum, the ETRs provide a comprehensive, homogeneous, backward-looking measure of which factor of production has effectively paid what amount in taxes. An important body of work, pioneered by Devereux and Griffith (1999), constructs forward-looking average tax burdens on capital, based on the simulated present value of returns and costs of a new investment. These measures model in detail the statutory tax schedule faced by firms, while our ETR measure remains aggregate in nature; however, by solely relying on the tax code, these measures do not capture the actual effective tax burden.[14] Driven by their differing objectives, the backward-looking and forward-looking measures are naturally distinct, but also complementary.

Our macroeconomic ETRs rely on several conventions and assumptions (see Carey & Rabesona, 2018). First, as is done in the literature, they do not factor in economic incidence in the sense 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

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

[14] This literature refers to 'effective tax rates' as those which incorporate the tax code, and 'implicit rates' as those which are based on collected tax revenues (which we refer to as 'effective tax rates').

allocated to capital. Second, the tax revenue streams need to be comparable to their macroeconomic tax bases measured in the national accounts. This generates two key challenges for our ETRs: (i) for the numerator, what share of personal income tax revenues to allocate to capital versus labor; and (ii) for the denominator, what share of mixed income to allocate to capital versus labor. We outline below our benchmark assumptions, while an in-depth discussion is provided in Appendix B.2.

Allocation of personal income taxes (PIT) The main empirical difficulty in assigning taxes to labor or capital concerns the allocation of the 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, 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. 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 United States, 75% of labor income was subject to PIT in 2015, versus a third of capital income (Piketty, Saez, & Zucman, 2018). This suggests allocating 15% of the personal income tax to capital and 85% to labor.[15]

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 35% 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.

The labor share of mixed income The labor share of mixed income (unincorporated enterprises) is hard to measure.[16] For our benchmark series we assume $\phi = 75\%$, i.e.,

[15] If 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.

[16] The UN's national accounts framework outlines the combination of multiple, exhaustive methods to overcome challenges of measuring the *level* of mixed income in economies with widespread informality. While information on the methods used is not readily available on a country-year basis, a careful inspection of the published frameworks over time suggests no change in outlined methodologies, for mixed income or more generally, which coincides with the LMIC-trends in Section 4.

25% of mixed income is considered capital income.[17] In the absence of a consensus over alternatives, this assumption is transparent. We implement two robustness checks, which create time-year varying measures of ϕ. The first method, based on ILO (2019), uses micro-data to estimate the labor income of self-employed based on the observable characteristics of these workers and their comparison with employees.[18] Second, we assign to ϕ the observed labor share of the corporate sector (as in Gollin, 2002).

The exact ETR formulas which integrate the above adjustments are in Appendix B.2, including details on time-variant and invariant components.

3.2 Data sources

3.2.1 National income

To measure factor incomes for 155 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 begin by using the 2008 SNA online repository that has global coverage in more recent decades. In turn, the UN Statistics Division provided access to the 1968 SNA offline data which covers historical observations from the 1960s and 1970s for most countries. To the best of our knowledge, our paper is the first to harmonize and integrate the 2008-SNA and 1968-SNA datasets. To estimate factor incomes requires information on all the components of national income (equation 3). Whenever we have national income for a country-year in an SNA dataset but information on a component is missing, we attempt to recover it using both information from the second SNA dataset as well as national accounting identities with non-missing values for the other income components. In the remaining cases, we impute component values using methods developed in the DINA guidelines (Blanchet et al., 2021). Details are in Appendix B.1.[19]

[17] This is slightly lower than the 30% used in Distributional National Accounts (DINA) guidelines (Blanchet, Chancel, Flores, & Morgan, 2021), but given that the global average of the capital share in the corporate sector is 27%, assuming that the capital share of unincorporated enterprises is slightly lower seems reasonable (see Guerriero, 2019).

[18] Details are in Appendix B.2. A challenge with this estimation method is that it can create implausible estimates of the level of mixed income that are much larger than their actual values in national accounts. We implement an adjustment to help with this limitation but also choose, for this reason, to use ILO (2019) as a robustness check.

[19] Relative to recent work (including Guerriero, 2019; Karabarbounis & Neiman, 2014), our national accounts data expands coverage in space and time and systematically attempts to measure factor incomes for total domestic output (vs. only for the corporate sector).

3.2.2 Tax revenue

We construct a new tax revenue dataset that dis-aggregates revenues 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 our preferred source, as it covers all types of tax revenues and goes back to 1965 for OECD countries. It accounts for 2,866 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 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 it often lacks social security/payroll taxes. ICTD adds 1,249 country-year observations (18.3% of the sample). To complement these pre-existing sources, we conducted an archival data-collection to digitize and harmonize data from historical public budgets and national statistical yearbooks.[20] We supplemented the archival data-collection with countries' online publications and offline data from the IMF Government Finance Statistics (1972-1989). These new data-sources add 2,681 observations (39.4% of the sample), of which 2,011 come from our archival work.

We follow three principles to create each country's time series. First, we aim to only combine two data sources by country. OECD is the preferred starting point. 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 that best matches the OECD data in overlapping time-periods. Second, we only interpolate up to 4 years of gaps in coverage. Third, we draw on country-specific studies to gauge the credibility of the historical archival data. Appendix B.1 provides more details.

3.3 Data coverage of effective tax rates

Our final effective tax rates sample contains 6,816 country-year observations in 155 countries (Figure A1). The number of countries starts at 78 in 1965 and grows to 110

[20]These archives were accessed in the Government Section of the Lamont Library (website link).

by 1975 (due to independence or country creation). The key jump in coverage —from 117 to 148 countries— corresponds to the entry of ex-communist countries in 1994, including China when it arguably built a modern tax system (see World Bank, 2008 and box in Appendix B.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 98% of world GDP. Figure A1 shows coverage by development level. We use the World Bank income classification in 2018, assigning low and middle-income countries (LMICs) as developing countries and high-income countries (HICs) as developed countries. We will interchangeably refer to LMICs as developing countries and HICs as developed countries. Our sample contains 5,198 observations in LMICs and 1,618 observations in HICs.

Our database complements previous ETR series by expanding coverage to developing countries, both for recent and historical time periods. Table B3 summarizes the coverage of the main pre-existing ETR series, which focus mainly on OECD countries (Carey & Rabesona, 2018; Kostarakos & Varthalitis, 2020; McDaniel, 2007; Mendoza et al., 1994). Table B3 also details the methodological differences with our series.[21]

4 Stylized Facts on Global Taxation Trends

4.1 Evolution of effective tax rates on capital and labor

Figure 1 documents the global evolution of effective tax rates on capital and labor from 1965 to 2018. These time series follow our benchmark assumptions. Aggregates are dollar-weighted, i.e., the global effective tax rate on capital equals worldwide capital tax revenues divided by worldwide capital income. This series can 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 trends between 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%.

[21] Figure B1 shows that, when holding the sample constant, our data produces similar trends for ETR_K and ETR_L as these studies, albeit with some moderate differences in levels. The variation in levels is accounted for by the methodological differences which are explained in Table B3.

The decline in capital taxation is driven by the corporate sector: the global effective tax rate on corporate profits fell from 27% in 1965 to 18% in 2018.

The global trends mask heterogeneity by development levels. While labor taxation rose everywhere, the decline in capital taxation is concentrated in HICs, where the effective tax rate on capital fell from 36-38% to about 30% between 1965 and 2018. In contrast, ETR_K increased in LMICs, albeit from a low baseline: it rose from 10% to 19%, with the increase happening entirely since the 1990s. The secular decline in ETR_K in HICs has been documented before (Dyreng, Hanlon, Maydew, & Thornock, 2017; Garcia-Bernardo, Janský, & Tørsløv, 2022), but the rise in ETR_K in LMICs starting in the 1990s is novel. We thus need to establish that this result is robust to the assumptions used to construct the ETR series.

4.2 The rise of capital taxation in developing countries

When creating our ETR series, we make four key methodological decisions: (1) how to allocate personal income tax revenue to capital vs labor; (2) how to allocate mixed income to capital vs labor; (3) whether to present results for a balanced vs. unbalanced panel of countries; (4) how to weight individual countries when aggregating them. Our benchmark series: (1) allocates personal income taxes to capital vs. labor for each country-year using data on tax exemption thresholds and differential tax treatment of dividends relative to wages; (2) allocates 25% of mixed income to capital and 75% to labor; (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 using 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.

Figure 2 tests the robustness of the ETR_K trend in LMICs.[22] Panel (a) varies the allocation of personal income tax (PIT) revenue. While our benchmark assignment is based on a country-year varying allocation, we consider two simple robustness scenarios where the share allocated to capital is fixed over time, at either 0% or 30% (low and high-end scenarios, respectively). Due to high PIT exemption thresholds in developing countries, the benchmark country-specific assignment is closer in levels to the 30% than to the 0% allocation. Though the capital share allocated to PIT does change over time (Section 3.1), the time-invariant robustness series track the trends in

[22]Figure A2 shows the robustness checks for ETR_L in LMICs and ETR_L and ETR_K in HICs.

the benchmark series closely. This occurs because the PIT remains limited in scope in LMICs, meaning its split into labor vs. capital makes little difference for our results.

Panel (b) shows the effect of varying our assumptions on the labor share of mixed income (unincorporated enterprises). We implement two robustness checks, creating country-year varying mixed income labor share based on either the ILO (2019) method or the labor share in the corporate sector. Both robustness series are slightly below the benchmark ETR_K in terms of levels but track its evolution closely over time.

Panel (c) quantifies the effect of country entry into the panel. In our benchmark series, China, Russia, and other former command economies enter in 1994. In this robustness check, we balance the panel by imputing missing country observations between 1965 and 1993; we use the observed value of ETR_K for that country in 1994 and the trends in ETR_K observed for LMICs with data 1965-1993. This imputation raises ETR_K between 1965 and 1993, since the new entrants (especially Russia) have relatively high ETR_K and a high global weight when they enter the sample in 1994.

Panel (d) aggregates countries using net domestic product (NDP) weights, instead of capital income weights. The NDP weights are either time varying or fixed in 2010. The figure shows that the weighting procedure has limited impact on the results.

Finally, panel (e) considers all 54 combinations of the 4 methodological choices: the rise in ETR_K in LMICs between 1994 and 2018 is clearly apparent in all 54 series. How wide is the range of increases and how does our benchmark series compare? Computing the 1994-2018 change in the 54 series, we obtain a meaningfully tight range of ETR_K increases between 5.6% and 8.9%, with our benchmark series in the middle at 7.6% (with larger increases in 21 series and smaller increases in 32 series).[23]

4.3 Where has capital taxation risen the most?

Figure 3 shows the evolution of ETR_K for major developing countries and subsamples of countries. Panel (a) plots the ETR_K series for the four largest LMICs: Brazil, China, India, Indonesia. All display a marked increase in ETR_K since the early 1990s: from 10% to 27% in Brazil, 5% to 25% in China, 6% to 12% in India,

[23]Setting 1994 as the base year is partly arbitrary, but at that time all countries have entered the sample and, as argued later, the 1990s correspond to a period of rapid trade liberalization. If we instead compute the change in ETR_K between 2018 and the lowest point in a given series, the range of changes is 6.9%-11.6% across the 54 series, with our benchmark series at 9.3% (low point in 1989).

and 10% to 15% in Indonesia. China's global income weight implies that it plays an important role in the aggregate rise in ETR_K in developing countries.

Panel (b) plots ETR_K in sub-samples of developing countries. When excluding China, the rise in ETR_K is more muted, going from 10% in 1989 to 14% in 2018. Oil-rich countries (defined as deriving at least 7% of GDP from oil in 2018) have volatile corporate tax revenues. Excluding oil-rich countries yields a more pronounced ETR_K rise (from 10% in 1989 to 23% in 2018), and a flatter ETR_K series pre-1989 as the revenue impacts of the 1970s oil shocks are removed. If we exclude both China and oil-rich countries, we again observe a substantial rise in ETR_K.

Panel (c) shows that, among non oil-rich countries, the ETR_K rise is stronger in the 19 largest LMICs (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 17% between 1989 and 2018; in smaller countries, ETR_K rose from 9 to 14%.[24] The ETR_K has risen by more than 5 percentage points in 13 of the 19 largest LMICs in the past 30 years, and has only fallen in one country (Russia).[25] In short, the rise in effective capital taxation in LMICs is more pronounced in larger economies, including China, but appears to be a general pattern in developing countries.

4.4 Suggestive evidence for the role of globalization

We found that while ETR_K has fallen in HICs, it actually has risen in LMICs. The rise in ETR_K in LMICs is robust to our assumptions, and while more pronounced in larger countries, it is a widespread phenomenon. Importantly, this rise occurred in the 1990s to early 2000s, during the period of "hyper-globalization" which should a priori have made capital more mobile and hence harder to tax. Instead, could globalization have caused a rise in ETR_K in LMICs? In this subsection, we take a first pass at investigating the role that trade globalization may have played in impacting the differential trends of capital taxation in LMICs vs HICs.

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 over NDP), after residualizing all variables against year fixed effects. Figure 4 depicts these within-country associations, which condition on global time trends. Mirroring the heterogeneity in long-run trends, we observe large differences by development

[24] As discussed below, we find larger trade-impacts on ETR_K in more populous countries (Section 6.5).
[25] The supplementary appendix (link) shows the individual countries' ETR_K and ETR_L time series.

level in the association between trade and ETR_K: rising trade openness is associated with increases in ETR_K in LMICs, but with decreases in ETR_K in HICs.[26] In sum, from a global and historical perspective, the correlational evidence suggests that trade liberalization may have contributed to the newly documented rise in effective capital taxation in developing countries. In the next sections, we try to causally investigate this hypothesis and study potential mechanisms.

5 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.

5.1 Event-studies for trade liberalization

5.1.1 Empirical design

In the first design, we implement event studies of trade liberalization events in key developing countries. To discern sharp breaks from trends in our outcomes, our selection criteria was to select events which 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.[27] Appendix C.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,

[26] Figure A3 probes the trade-ETR_K correlation in LMICs further by separating the countries into two groups based on their trade level pre-1995. 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-1995 saw a rise in trade and ETR_K in the 1995-2018 period.

[27] The 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.

as in Abadie, Diamond, and Hainmueller (2010).[28] 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 (Table A1).[29] We plot the average levels of the outcome variable for treated countries vs. synthetic control countries by relative time to the event. We also estimate the event-study model in the 10 years before and 10 years after the events:

$$y_{ct} = \sum_{e=-10, e\neq -1}^{10} \beta_e \cdot \mathbb{1}(e=t)_t \cdot D_c + \theta_t + \kappa_c + \pi_{Year(t)} + \epsilon_{ct} \tag{4}$$

where we include fixed effects for event-time, θ_t, country κ_c, and calendar year, $\pi_{Year(t)}$ (the latter control for shocks to outcomes that may 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. Finally, in Table A2 we estimate both the simple difference-in-differences, which captures the average treatment effect in the 10 years post-liberalization, as well as the imputed treatment effect based on Borusyak, Jaravel, and Spiess (2021), which addresses challenges from two-way fixed effects and heterogeneous event-times.

5.1.2 Event-study results

Figure 5 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 rises in the year of the event and its trend changes in post-reform years compared to pre-liberalization years.[30] Turning to our outcomes of interest, we see that ETR_K sharply rises following the liberalization event. Both ETR_K and ETR_L break from stable pre-trends at the time of liberalization, but the effect on capital taxation is double that on labor. Despite the small sample size, the dynamic post-treatment coefficients are often significant at the 5% level. The p-values for the joint significance

[28] For 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.

[29] Table A1 details the synthetic control matching for each event and each outcome.

[30] The 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.

of all post-reform dummies are well below 0.05. Panel A of Table A2 reports the DiD results, showing that the liberalization events led to a 6.4 percentage point rise in trade openness over 10 years, and a 4.5 (2.0) percentage point rise in ETR_K (ETR_L); results are marginally more precise when estimating the imputed treatment effects. Panel B shows the effects remain comparable when we jointly match on all outcomes for each country-event (corresponding event-study graphs in the supplementary appendix).

The identifying assumption is that there are no changes in confounding determinants of ETR which 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 C.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.[31] Such reforms do, however, sometimes occur in the post-event years; for example, Mexico joined NAFTA and removed capital inflow restrictions, Argentina and Brazil joined MERCOSUR, and India liberalized its FDI rules (Appendix C.1). These cross-border reforms occurred several years after the trade events,[32] yet ETRs sharply rise in the immediate post-event years. This discussion highlights that the interpretation of trade centered macroeconomic reforms requires caution. A plausible interpretation is that the short-run increases in ETRs with sharp breaks from stable pre-trends reflect the impact of trade liberalization, but that the medium-run coefficients also reflect the impacts of additional, mainly cross-border, reforms.

We conduct further analyses to probe the identification and robustness of our results. First, given the limited number of liberalization events, we verify that the average effects are not unduly influenced by one particular event. Figure A5 removes one treated country at a time: the dynamic treatment effects for all subsets of events are similar to the full sample. Second, the limited set of events arose from our specific selection criteria (Section 5.1.1). In Appendix C.3, we study the robustness to using (very) different selection criteria for trade liberalization; we re-estimate the event-study using the 68 liberalization events in LMICs from Wacziarg and Welch (2008) and find comparable impacts on ETR. Third, in Table A2 we address concerns related to the control group. We find similar results when we remove from the donor pool

[31] Only Mexico had a concurrent domestic reform, and results hold without it (Figure A5).
[32] Only Brazil and Colombia implemented domestic reforms in the post-liberalization years.

each liberalizing country's 5 major export and import trading partners (measured in the immediate pre-event years), alleviating concerns of spill-over to countries in the synthetic control.[33] Results are comparable when the donor pool excludes countries that have already liberalized (based on Wacziarg & Welch, 2008), to guard against the concern that the trends in the synthetic control group reflect 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).

5.2 Regressions with instrumental variables for trade

5.2.1 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. Moreover, while it is harder to directly inspect the identifying assumptions than in the event-study, the IV permits a precise investigation of mechanisms (Section 6). We estimate the following model in developing countries:

$$y_{ct} = \mu \cdot trade_{ct} + \Theta \cdot X_{ct} + \pi_c + \pi_t + \epsilon_{ct} \quad (5)$$

where y_{ct} is the ETR in country c in year t, $trade_{ct}$ is the share of import and exports in NDP and π_c and π_t are country and year fixed effects.[34] 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 & Ito, 2006; Rodrik, 1998). ETR time-series are sometimes volatile (Figure 3), so we winsorize ETR at the 5%-95% level by year separately for LMICs and HICs.

OLS estimation of equation (5) may be biased due to reverse causality and unobservable confounding factors which correlate with trade. To try to address these issues, we use the two instruments for trade from Egger et al. (2019). The first instrument, denoted $Z^{gravity}$, relies on the structure of general equilibrium models of

[33] We also verify that none of the main countries in the synthetic control (Table A1) had external or domestic reforms in the event-year or in the post-event periods (using the data in Wacziarg & 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.

[34] We include fixed effects for imputed and interpolated values, as well as for each tax and national account data-source (Section 3.2), to ensure results are not driven by changes in data-quality. Results also hold without imputed/interpolated values and within each data-source (Table A4).

trade. Under the standard gravity model assumptions, it 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 Appendix D).

In LMICs, Figure A4 shows the 1^{st}-stage is stronger in the 2000s and at higher income levels for Z^{oil}, and in earlier periods and at lower income levels for $Z^{gravity}$. Restricting the analysis to sub-samples where one of the instruments has a strong first-stage introduces bias (Mogstad, Torgovitsky, & 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 A3 shows the 1^{st}-stage.[35]

5.2.2 Instrumental variable results

Table 1 presents the results in LMICs for ETR_K in Panel A and ETR_L in Panel B.[36] In column (1), OLS uncovers positive, significant associations between trade and both ETRs. In column (2), we employ the two instruments. The 1^{st}-stage Kleibergen-Paap F-statistic is 24.57. The IV shows that trade causes an increase in both effective tax rates, but the magnitude is twice as large for ETR_K (0.109) than for ETR_L (0.056).

In the remaining columns, we conduct three sets of robustness checks. In the first set, we modify the specification. Column (3) shows that the results remain

[35] Table E2 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.

[36] There is a 4% drop in sample size relative to ETR coverage (Section 3.3) due to availability of instruments. Relative to previous versions of this paper, recent access to trade data from Harvard Growth Lab increased the sample size for the instruments and led to updated results.

unchanged when we use non-winsorized ETRs. Column (4) re-estimates the IV with NDP weights (used in Section 4 for representativity), which increases magnitudes but decreases statistical significance. Results remain similar in column (5) when we include country-year varying controls in X_{ct}. In column (6), our results are robust to allowing oil-rich countries to be on a separate non-parametric time path. This addresses the concern that the identifying variation for $Z^{oil-dist}$ is correlated with trends in effective tax rates specific to oil-rich countries (Figure 3). In column (7), results remain similar when we winsorize the trade variable.

In the second robustness set, we implement the alternative capital vs labor assignments from Section 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; results remain comparable. Results also remain similar when we assign the K-share of PIT to be 0% (column 10) or 30% (column 11). In the third robustness set (columns 12-13), we estimate IVs using each instrument separately. The 1^{st}-stage F-statistic is 45.17 for $Z^{gravity}$ and 10.80 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 A3) 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 and multiple data-sources (Section 3.2- 3.3). In Table A4, we find that the results are qualitatively similar within each data-source for taxes and national accounts, as well as in both quasi-balanced panels (pre and post-1994) and in a strongly balanced panel (1965-2018).[37]

Taking stock How much of the ETR_K rise in LMICs since the 1990s can be accounted for by increased trade? Between 1994 and 2018, ETR_K rose by 7.6ppt (Section 4.2) and trade by 12.8ppt. The NDP-weighted IV for trade's impact (col.4 of Table 1) is arguably most comparable, since the ETR_K trends in Section 4 are also weighted by national income. Using this estimate would imply that trade openness can account for 37% of the rise in ETR_K ($0.222 * 0.128/0.076 = 0.374$). Considering all estimates in Table 1 generates a range of 17%-37% (main specification in col.2 at 19%).[38]

[37]Variation between coefficients may reflect data-quality or 1^{st}-stage and treatment heterogeneity.
[38]For reasons discussed in 5.1.2, we do not rely on the event-study estimates for this exercise.

5.3 Impacts of trade openness on overall taxation

We find positive effects on capital and labor taxes, but what are the implications for trade's impact on *overall* revenues? This is a relevant question, as trade-induced revenue losses remain an important concern amongst practitioners (World Bank, 2020).[39]

We investigate trade's impacts on total tax revenue (% of NDP) in developing countries in Table 2, with OLS in Panel A and IV in Panel B. Total taxes include direct taxes on capital and labor and indirect taxes (sum of taxes on trade and domestic consumption).[40] Both in OLS and IV, the trade-coefficient for total tax collection is positive and statistically significant (column 1). Focusing on the IV, the next columns show the increase in total revenue is mainly driven by corporate income taxes and social security, the two main sources of effective capital and labor taxation. The final column shows a statistically insignificant impact of openness on indirect taxes (trade and consumption taxes); the coefficient is also quantitatively small in comparison to the coefficients on direct labor and capital taxes. Trade's impact on total taxes is robust to: using NDP weights for estimation; including various controls; winsorizing the trade variable; and, estimating the IV using each instrument separately (Table A5).

We can also study the impact of the trade liberalization events from Section 5.1 on total tax revenue. Using the event-study methodology, Figure A6 shows that the trade events led to an increase in overall tax collection, with a break from stable pre-trend.[41]

In summary, although the identifying assumptions differ, the IV and event-studies yield consistent findings showing that trade causes increases in capital and labor taxation, which result in a net positive impact of openness on overall tax revenues. Our emphasis on direct domestic taxes leads to a comprehensive analysis of trade's impact on tax systems in developing countries, with findings that run somewhat counter to a persistent revenue-concern amongst policy-makers.

In the next section, we investigate mechanisms for trade's impact on ETR.

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[39] For example, fiscal concerns were a dominant theme during the WTO's Doha Round (Hallaert, 2010).

[40] Our data does not permit a systematic breakdown into trade and domestic consumption taxes. Long-run trends in taxation by type and development level are in the supplementary appendix (link).

[41] Based on multiple identification strategies and the largest sample to date in LMICs, our results contribute to the literature on trade's net impact on total tax collection, which has produced mixed findings (Section 1). A seminal study in this literature, Baunsgaard and Keen (2009) write in their 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."

6 Mechanisms

6.1 Outlining the tax capacity mechanism

The *tax capacity* mechanism combines two separate insights from the trade and public finance literatures: trade leads to the expansion of large firms relative to small firms; effective taxation increases with firm size (measured by revenue).[42] To study this mechanism we focus on corporations, given the evidence on effective taxation in these larger firms (Section 2) and because outcomes related to corporations are consistently defined and measured in national accounts and tax data.[43] The role of corporations can be seen in the following decomposition of ETR^K (in a given country-year):

$$ETR^K = \int_{i \in C} ETR_i^K f(i)\, di + \int_{i \in NC} ETR_i^K f(i)\, di \tag{6}$$

$$= \mu_C^K \cdot \overline{ETR}_C^K + (1 - \mu_C^K) \cdot \overline{ETR}_{NC}^K \tag{7}$$

where μ_C^K is the corporate share of (capital) national income of agents i with density $f(i)$, and $\overline{ETR}_C^K$ and $\overline{ETR}_{NC}^K$ are the average effective tax rates on capital in the corporate (C) and non-corporate (NC) sectors, respectively.

In national accounts, $\overline{ETR}_C^K$ is the average effective tax rate on corporate profits, which is measurable in our data.[44] In LMICs, $\overline{ETR}_C^K$ is 50% larger than the overall ETR^K (19.9% versus 13.3%). This improved effective taxation in the corporate sector stems from both stronger enforcement and higher statutory tax burdens than in the non-corporate sector. The ability to levy higher statutory taxes is endogenous to stronger enforcement (Bergeron et al., 2023). The tax capacity mechanism considers that these co-determined elements jointly lead to higher ETR^K as a function of size.

In equation (6), trade can impact the corporate share of national income (μ_C), through two distinct channels (see Dix-Carneiro, Goldberg, Meghir, & Ulyssea, 2021).

[42] See studies cited in Section 2. For example, Best et al. (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 Gordon & Li, 2009; Kleven et al., 2016; Kopczuk & Slemrod, 2006).

[43] Several theories predict heterogeneous trade impacts on ETR across industries (including Romalis, 2004). However, testing these predictions is challenging as data on taxes collected by industry is infrequently reported in official publications (and not harmonized across countries).

[44] To accommodate additional notation, ETR on capital is interchangeably referred to with a K subscript or superscript in this section. $\overline{ETR}_{NC}^K$ contains a heterogeneous set of non-corporate agents (taxes on self-employed, property and wealth), for which our data does not contain a systematic breakdown.

First, trade openness can lead to increased market opportunities that disproportionately benefit large exporters (Melitz, 2003), causing an increase in the market income-share of firms that are initially larger and likely to be corporations (McCaig & Pavcnik, 2018). Second, trade can expand the availability of intermediate goods and lower their prices, which may also disproportionately benefit initially larger firms (for example due to fixed costs as in Kugler & Verhoogen, 2009), and similarly cause an increase in the income-share of formal and incorporated firms. All else equal, trade increases ETR^K by raising the income-share of the sector with higher effective taxation.

In equation (6), trade can impact $\overline{ETR}_C^K$. All else equal, $\overline{ETR}_C^K$ will rise if the trade-induced corporate income accrues to firms where the ETR^K-size gradient is positive. Bachas, Brockmeyer, Dom, and Semelet (2023) use administrative data from 13 LMICs and find that the ETR^K-size gradient for corporate firms is positive until the very top of the size distribution, where it becomes negative due to the take-up of statutory deductions and exemptions.[45] If some of the trade-induced corporate income accrues to these largest firms, this will, all else equal, tend to reduce $\overline{ETR}_C^K$. Related, trade's potential negative impact on the CIT rate ('race to bottom') will, all else equal, reduce $\overline{ETR}_C^K$. The net effect of trade on $\overline{ETR}_C^K$ is therefore ambiguous. Even if trade reduced $\overline{ETR}_C^K$, it could still have a net positive effect on ETR^K via μ_C.[46]

Trends in corporate sector share To gauge this novel mechanism's plausibility, Figure 6 plots the evolution since 1965 of the share of domestic income that originates from the corporate sector μ_C (corporate income is the sum of corporate profits and employee compensation). We observe a sizeable uptick in the corporate-share in LMICs in the mid-1990s, from 55% to 65%, which coincides with trade liberalization and the rise in ETR^K. Meanwhile, the share of mixed income (i.e., income of self-employed individuals and unincorporated businesses) sharply falls around that time, consistent with an expansion of formal income relative to informal activities. Thus, since the

[45]In South Africa and Ethiopia, Mascagni and Mengistu (2016) and Carreras et al. (2017) find that corporate ETR^K rises with size towards the top, but is largest for the smallest corporations. Wier and Erasmus (2022) find that profit shifting in South Africa is concentrated among the very largest firms; this would impact the ETR^K-size gradient if the difference for these profit-shifting firms in corporate taxes paid is disproportionate to the difference in underlying domestic reported profits.

[46]Positive impacts on μ_C and $\overline{ETR}_C^K$ could also occur if trade led to uniform growth for firms of different initial sizes - so long as the growth occurs where the size-gradients for ETR^K and the likelihood of incorporating are positive. Uniform trade-benefits can arise if the foreign inputs are widely accessible and encourage all firms to become more productive (Nataraj, 2011).

1990s, a growing fraction of output is produced in corporations in LMICs and the timing of this rise suggests that it could be linked to trade liberalization. In HICs, μ_C has been stable around 70% since the early 1970s.

6.2 Main results on mechanism outcomes

We investigate the tax capacity mechanism, as well as the 'race-to-the-bottom' and 'social insurance' mechanisms (Section 2), in developing countries. Table 3 shows OLS in Panel A and IV in Panel B. Consistent with a race to the bottom, in column (1) trade causes a decrease in the statutory corporate income tax (CIT) rate (significant at 10% in the IV).[47] Columns (2)-(3) show that trade causes a significant increase in the corporate share of national income (μ_C), and a significant reduction of equivalent magnitude in mixed income.[48] This is consistent with the tax capacity mechanism, whereby trade disproportionately benefits larger firms and causes an expansion of market income in more formal firms relative to smaller, more informal firms. In column (6), trade raises $\overline{ETR}_C^K$, consistent with the trade-induced corporate income accruing to firms where the ETR_K-size gradient is positive.

How is the additional corporate income allocated between capital and labor? Columns (4)-(5) show that the corporate sector rise is driven by an increase in capital corporate income (corporate profits), while the growth in labor corporate income (employee compensation) is smaller in magnitude and statistically insignificant.[49] This, in turn, causes trade to have a positive impact on the capital-share, both of national income and inside the corporate sector (columns 7-8).[50]

[47]The outcome is the first-differenced tax rate (Romer & Romer, 2010). Table A5 shows results with the level of the CIT rate. We combine data from Végh and Vuletin (2015), Egger et al. (2019), Tax Foundation (link) and country-specific sources. The CIT rate is an imperfect proxy for a firm's capital tax incentives (Kawano and Slemrod, 2016), but is observable in our full sample. Going forward, it would be interesting to study trade's impact on the detailed forward-looking measures (Section 2), which have recently been extended to LMICs (Steinmüller et al., 2019). Reassuringly, the long-run trends in CIT rates in LMICs track these more comprehensive statutory measures (supp. appendix).

[48]The scope and quality of data-sources used by national statistics offices can affect the measurement of mixed income in LMICs (Section 3.1). Using information collected by the World Bank (link), we find no impact of trade on countries' statistical capacity (results available).

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

[50]This may occur if rising markups drive the growth in the corporate sector's income share. De Loecker and Eeckhout (2021) find markups have risen in most regions over the past 40 years. De Loecker, Goldberg, Khandelwal, and Pavcnik (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 strong increase in corporate profits, and limited change in employee compensation,

Table A5 shows that the mechanism IV-results are robust to several checks: using NDP representative weights; including different controls; winsorizing the trade variable; and, estimating IVs separately based on each instrument. The CIT rate result remains less robust than the other mechanism results in these checks.

Finally, Figure A6 shows the same mechanism-outcomes but using the event-study design (Section 5.1). Relative to stable pre-trends, the trade-liberalization events led to a decrease in the CIT rate as well as increases in both corporate income (μ_C) and the average effective corporate tax rate ($\overline{ETR}_C^K$). Although they are based on different identifying variation in openness, the event-study and IV therefore both provide evidence consistent with the tax-capacity and race-to-bottom mechanisms.

6.3 Firm-level analysis

Section 6.1 highlights that trade's net impact on the average effective corporate tax rate ($\overline{ETR}_C^K$) is ex ante ambiguous, as it combines multiple potential channels. To unpack trade's effects inside the corporate sector, in Appendix E.1 we conduct a firm-level analysis in Rwanda between 2015-2017, to study the impact of trade on the individual corporate firm's effective tax rate. We use corporate income tax returns to measure each firm's effective tax rate as the ratio of corporate taxes paid divided by net profit. Net profit is revenue minus material, labor, operational, depreciation and financial costs. This firm-level corporate ETR_K decreases due to lower compliance and a lower statutory tax burden (through reduced rates, specialized exemptions or deductions).

We merge with customs data, which record firms' direct trade exposure. Following recent work (reviewed in Atkin and Khandelwal, 2020, Bernard & Moxnes, 2018), we measure a firm's total exposure to trade by accounting for the firm's indirect exposure through its linkages to domestic suppliers that use traded goods in their production process.[51] We merge administrative data which record transaction linkages between formal firms.[52] To measure a firm's total trade exposure in a network setting, we

may also arise if trade increases corporate firms' labor market power (Felix, 2022). Finally, it may arise if trade benefits more capital-intensive production in developing countries.

51 Recent papers document the existence of domestic transaction linkages in LMICs (e.g. Almunia, Hjort, Knebelmann, & Tian, 2023) and the role of these linkages in propagating trade-shocks to domestic firms that transact with importing firms (Fieler, Eslava, & Xu, 2018; Javorcik, 2004)

52 The transaction data is meant to improve the enforcement of corporate taxes and VAT, and the reporting of linkages is comprehensive for the relatively larger firms that are registered for these tax bases; for smaller firms that are instead registered to simplified tax bases (flat-amount or turnover), the linkage reporting is less strong. Moreover, calculating the effective capital tax rate for these non-

follow the methodology in Dhyne, Kikkawa, Mogstad, and Tintelnot (2021) who use similar datasets to measure Belgian firms' exposure to trade. While under 30% of firms import directly, 93% of Rwandan firms obtain foreign inputs either directly or indirectly through domestic suppliers that use imports. Thus, most formal firms in Rwanda are dependent on imports, but a significant share of this dependence comes from the domestic linkages to importing firms. Our measure of total trade exposure is the share of input costs spent on goods that are imported directly or indirectly; for the median formal Rwandan firm, this exposure to trade is 48%.[53]

We estimate firm-level panel regressions in the sample of corporate firms. The OLS reveals that a within-firm increase in trade exposure is associated with an increase in the firm's corporate effective tax rate. The IV generates firm-level variation in trade exposure through the shift-share design from Hummels et al. (2014): the identifying variation is trade shocks from changes in world export supply of specific country-product combinations in which a Rwandan firm had a previous import relationship. 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 trade exposure, generating a strong 1^{st}-stage. Using the IV, we find that an increase in trade causes an increase in the individual firm's effective tax rate on capital. The IV also shows that trade causes an increase in firm size (proxied by revenue), while OLS regressions show a positive association between firm size and ETR_K. We find no impact of trade exposure on the take-up of statutory tax deductions or exemptions.[54]

These results serve two purposes. First, they provide firm-level identified evidence on trade's positive impact on ETR_K in a developing country, which complements our country-level results in LMICs.[55] Second, they support the mechanism interpretation that trade's impact on ETR_K is mediated by a positive size-ETR_K gradient.[56]

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corporate firms with less information on costs requires additional assumptions on the relationship between turnover and profit. With these data-challenges in mind, we can include these non-corporate but tax-registered firms in the analysis; we find qualitatively similar results (available upon request).

[53] We focus on firms' exposure to imports through their supply network; in an extension, we investigate firms' exposure to exports through their client network and find similar results (available).

[54] The absence of a change in the firm's statutory tax burden could suggest that, in this setting, trade's positive impact on ETR_K is mediated by improved compliance as the firm grows in size.

[55] By virtue of being an estimation strategy within the corporate sector, these results cannot directly determine trade's net impact on sector-level $\overline{ETR}_C^K$. We also found impacts of trade on tax policies at the corporate sector level (statutory CIT rate). These firm-level results on corporate ETR_K are therefore complementary to the country-level results on $\overline{ETR}_C^K$.

[56] The network linkage measures are derived from administrative data which, by construction, only exist for tax registered firms. This sample restriction, which is common to network studies in developing

6.4 Discussion

In this subsection we discuss how the tax capacity mechanism relates to governments' enforcement policies and the trade-formalization literature.

Enforcement reforms Over the sample period in our study, governments in LMICs have implemented policies to improve domestic tax enforcement. A challenge for the mechanism interpretation is that openness, potentially due to concerns over border revenue losses, prompted governments to implement enforcement reforms which increased ETR_K (and ETR_L). To investigate this, we measure the year of adoption (if any) in LMICs of four policies which raise domestic tax enforcement: (i) introduction of a large taxpayer unit; (ii) integration of the customs and domestic tax authorities into a unified revenue agency; (iii) implementation of a VAT; (iv) adoption of international accounting standards (IAS).[57]

Using the IV, in Table A6 we find positive effects of trade on ETR_K without the enforcement measures in place, but (qualitatively) larger effects with them in place.[58] The impacts on mechanism outcomes help clarify these heterogeneous results: trade has precisely the same impact on the corporate income-share (μ_C) in both settings, but the positive impact of trade on $\overline{ETR}_C^K$ is significantly amplified with the enforcement measures.[59] In other words, the trade induced expansion of the corporate sector (which increases ETR_K) occurs regardless, but the extent to which the additional corporate income translates into higher effective corporate capital taxation is reinforced with domestic tax enforcement policies (which further increases ETR_K).[60]

countries (Atkin & Khandelwal, 2020), implies that while this firm-level regression may be appropriate to study trade's impacts on the size of corporate and formal firms, it is not suited to study the impacts on the size of informal firms.

[57]Evidence shows that the additional enforcement focus on firms and individuals above a size-threshold increases tax collection (Almunia & Lopez-Rodriguez, 2018; Basri et al., 2021). The customs-tax unification can improve domestic audit capacity through enhanced information-sharing and economies of scale (IMF, 2022). The transition from a general sales tax to a VAT can improve domestic enforcement by creating additional information trails on business partners (Almunia, Henning, Knebelmann, Nakyambadde, & Tian, 2023; Waseem, 2020). Relative to national accounting practices, IAS can improve the scope and depth of accounting requirements for firms (Wolk, Francis and Tearney, 1989; Barth, Landsman and Lang, 2008) and curb the possibility of tax mis-reporting (Kleven et al., 2016).

[58]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).

[59]Of the four administrative reforms, only the VAT was in place in all countries (except for India) by the time of the liberalization events studied in Section 5.1.

[60]Intuitively, the enforcement policies all (weakly) disproportionately raise enforcement on larger firms, thereby increasing the slope of the ETR_K-size gradient inside the corporate sector.

In sum, the positive effects of trade on the tax capacity mechanism and ETR_K do not hinge upon investments in tax enforcement, but are magnified by them.[61] These investments may themselves have been triggered by globalization; assessing their quantitative importance in determining ETR-trends is left for future research.

Links to trade-formality literature We find positive effects of trade on outcomes linked to formalization. Recent studies focused on the number of formal versus informal firms or formal versus informal workers and found mixed evidence that trade liberalization increases formality by these measures (see reviews in Engel & Kokas, 2021; Ulyssea, 2020).[62] One way to reconcile our results with these studies is to note that our focus is on the share of output produced in formal versus informal firms: the expansion of output in larger, formal firms may occur without changes to the number of formal or informal firms, and does not necessarily imply an increase in the number of formal workers, since informal workers may work in formal firms and contribute to their output (Ulyssea, 2018).

Moreover, trade models highlight that impacts on formality depend on the nature of the trade shock. In Appendix E.2, we investigate if the ETR and mechanism impacts differ along two dimensions of trade shocks (Dix-Carneiro et al., 2021). Using both instruments in the LMIC sample, 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 negative demand shock for domestic firms, disproportionately affecting larger ones. In additional IV regressions, trade in *intermediate G-S* increases ETR_K and the corporate income-share, while trade in *final G-S* decreases both outcomes.[63] 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, formal firms. These findings suggest that the impacts of trade on the tax-capacity mechanism, and ultimately on ETR, depend on the nature of the trade shock.

[61] Trade-induced revenue loss concerns may prompt governments to increase enforcement in other, unobservable ways. To gauge this possibility, in supplementary appendix (link) we use the measures of trade-induced tariff revenue loss episodes from Cagé and Gadenne (2018). We find that the positive impacts of trade on ETR and tax-capacity mechanism outcomes hold outside of these episodes.

[62] Goldberg and Pavcnik (2003), Bosch et al. (2012), Cruces et al. (2018), Dix-Carneiro and Kovak (2019).

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

6.5 Heterogeneity: Developing vs developed countries

We have provided supporting evidence for the tax capacity mechanism in LMICs. We now expand our sample to HICs to test if trade's impact on this and other mechanisms, and ultimately on ETR, differs across development levels. If so, then openness may have contributed to the divergent trends in ETR_K between HICs and LMICs (Figure 1). We conjecture that the tax capacity mechanism is unlikely to operate in HICs, where constraints on effective taxation are not as binding and stable (e.g. Figure 6 shows the corporate income share has been stable in HICs over the past 40 years). In contrast, the race-to-the-bottom and social insurance mechanisms are likely active in HICs, given previous research. We estimate heterogeneous IV effects by development level, by including an interaction term with a high-income country dummy:

$$y_{ct} = \mu \cdot trade_{ct} + \kappa \cdot trade_{ct} \cdot \mathbb{1}(HighIncome)_c + \Theta \cdot X_{ct} + \pi_c + \pi_t + \epsilon_{ct} \tag{8}$$

To increase comparability, the IV uses NDP weights so the regression results are representative similarly to the descriptive trends in Figure 1. The IV estimates in the full sample of countries are reported in Table 4, with the 1^{st}-stage regression in Table A3. The Kleibergen-Paap 1^{st}-stage F-statistic is 14.39.[64]

Column (1) of Table 4 reveals clear heterogeneity: trade causes ETR_K to increase in LMICs but to decrease in HICs.[65] The coefficient for HICs is not statistically significant, however. Column (2) reveals a positive effect of trade on ETR_L everywhere, but the magnitude is (slightly) larger in HICs. Column (3) shows the negative race-to-bottom effect on the CIT rate is more pronounced in HICs, which likely contributed to trade's impact on ETR_K. In the final columns, we find that the positive impacts of trade on tax capacity outcomes (μ_C, $\overline{ETR}_C^K$) are limited to LMICs, with largely null effects in HICs. While Table 4 reveals qualitative differences in coefficients between development levels, we cannot statistically reject their equality for several outcomes.

[64]With multiple endogenous regressors, the Kleibergen-Paap F-statistic depends on whether the instruments generate sufficiently distinct variation in the endogenous regressors. In Table A3, we also report the Sanderson-Windmeijer weak multiple instruments F-statistic. See Andrews, Stock and Sun (2019) for a discussion of effective first-stage F-statistics with multiple endogenous regressors.

[65]The IV-coefficients for developing countries qualitatively differ between Table 4 and Tables 1 and 3 (though they are not statistically different). This is mainly because the two instruments' strength change in the 1^{st}-stage regression in the expanded sample relative to the sample of developing countries (compare column 1 to columns 4-5 in Table A3). Moreover, the overall first-stage strength is somewhat weaker in the expanded sample, which impacts the estimated coefficients in both developing and developed countries (Sanderson and Windmeijer, 2016).

These results are consistent with the existence of countervailing mechanisms which differ by development level. Trade's impact on ETR_K is negative in HICs, perhaps due to tax competition's downward pressure, but this force is counteracted by increased tax capacity in LMICs where trade's net impact on ETR_K is positive. Through these heterogeneous and counteracting mechanisms, trade openness can rationalize the divergent long-run ETR_K trends by development level in Figure 1. Trade's positive impact on ETR_L in LMICs is likely due to tax capacity and social insurance.[66] The positive trade-impact on ETR_L in HICs may be due to social insurance demand and revenue compensation needs following the CIT cuts.

Table A7 provides additional heterogeneity results in LMICs and HICs. Panel A shows trade's negative impact on the CIT rate is larger in less populous countries and in countries with fewer capital restrictions (Alesina & Wacziarg, 1998), where capital flight concerns are stronger (Hines, 2006). Mirroring this result, Panel B shows trade's positive impact on ETR_K is limited to populous countries with more capital restrictions. These results support the conjecture that the tax capacity and race-to-bottom mechanisms occur simultaneously: countries with larger markets and limited capital mobility are better situated to reap the positive tax-capacity effects of trade.

6.6 Capital openness

To finish the analysis, we note that our focus throughout the paper has been on one key dimension of globalization: trade openness. Given our interest in capital taxation, another relevant dimension is capital openness (Ilzetzki, Reinhart, & Rogoff, 2019; Van Patten, 2022). However, due to differences in countries' reporting requirements, data on capital openness is not as available and comparable as trade data. Finding credible exogenous variation for capital openness is also challenging. Notwithstanding these challenges, in Appendix F we try to investigate the impact of capital openness on ETR. We rely on the capital inflow liberalization events for 25 developing countries from Chari, Henry, and Sasson (2012), which capture the first time when foreign investment in the domestic stock market is allowed. Employing the same event-study design as in Section 5.1, we find that the events lead to both increased capital openness and higher ETR_K, which is qualitatively consistent with the trade-liberalization results. This suggests that the positive impact of globalization on ETR_K in LMICs may be

[66]Corporations serve as third-party reporters and withholding agents for employees' income, which increases the effective taxation of labor income on employees relative to self-employed workers.

robust to using capital instead of trade openness. However, given the limitations with the measurement of capital flows, we consider that our trade results provide more robust insights into globalization's impacts on effective taxation.

7 Conclusion

This paper provides evidence on trends and causal effects of globalization on tax structures. We make two main contributions. First, we build and analyze a global macro-historical database of effective tax rates on labor and capital covering 155 countries, with over half starting in 1965. The key novel fact is the asymmetric evolution of capital taxation by development level in the era of hyper-globalization: while ETR_K fell in rich countries, it rose in developing ones since the 1990s. Our second contribution is to formulate and test a new hypothesis that sheds light on this asymmetric evolution. Across multiple research designs, we find evidence of a pro-tax capacity effect of international trade in LMICs: trade increases ETR_K (and ETR_L), by expanding larger firms where effective taxation is higher. We provide evidence for trade's positive impact on ETR_K at the country, corporate sector and firm level. The pro-tax capacity effect prevails in developing countries, while the well-known negative effect of international competition on ETR_K appears to have dominated in rich countries.

This paper's findings have implications for public finance and globalization in developing countries. By improving effective taxation and positively impacting domestic taxes, trade increases overall revenue. This result runs counter to a persistent policy-concern over tax losses from trade liberalization, and previous academic work has mainly abstracted from investigating trade's impacts on domestic capital and labor taxes. By incorporating domestic tax bases, we make a step towards a comprehensive analysis of the revenue consequences of globalization. We focus on a specific mechanism, but many links remain to be explored between trade, firms, and taxation.

Across our research designs, the positive effect of trade is systematically larger for ETR_K than ETR_L in LMICs. As capital income is more concentrated than labor income, this result is a relevant input for the broader study of the distributional effects of globalization on post-tax income in LMICs. While we adopted a macro perspective on tax systems, a next step could be to combine our ETRs with individual-level estimates of the progressivity of labor and capital taxes. This would make it possible to compare the distributional effects of globalization on pre-tax versus post-tax income (Goldberg, 2023; Pavcnik, 2017), and raises empirical questions for future research.

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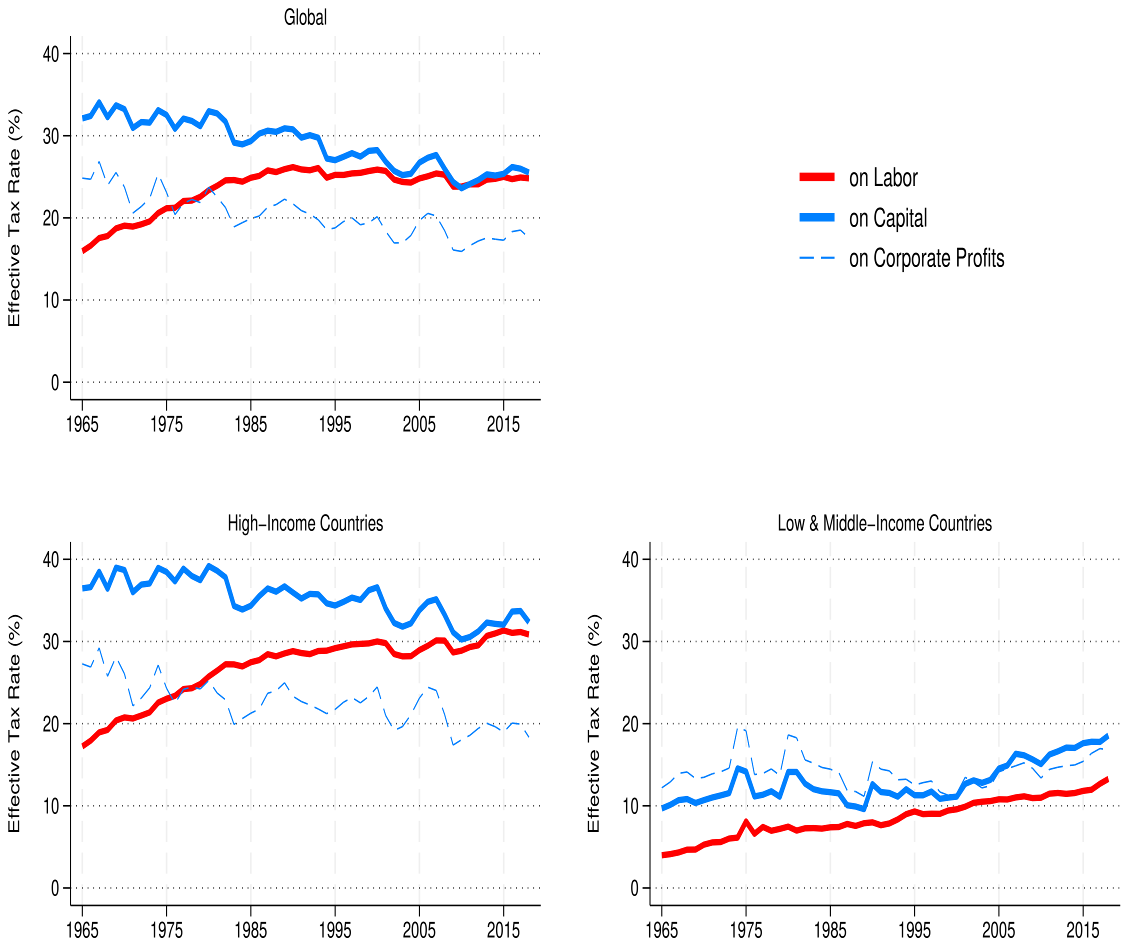
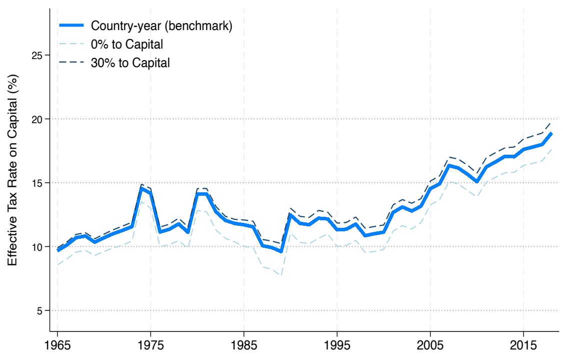
Figure 1: Effective Taxation of Capital and Labor



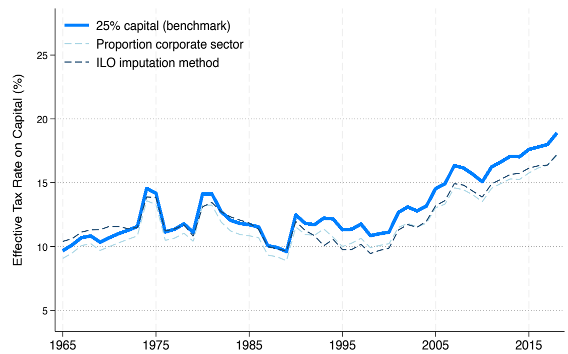
Notes: This figure plots the time series of average effective tax rates on labor (red) and capital (blue), as well as the average effective tax rate on corporate profits (blue dashed line). The top-left panel corresponds to the global average, weighting country-year observations by their share in that year's total factor income, in constant 2019 USD (N=155). 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=118). 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 4.1.

Figure 2: Robustness of Effective Capital Taxation in Developing Countries

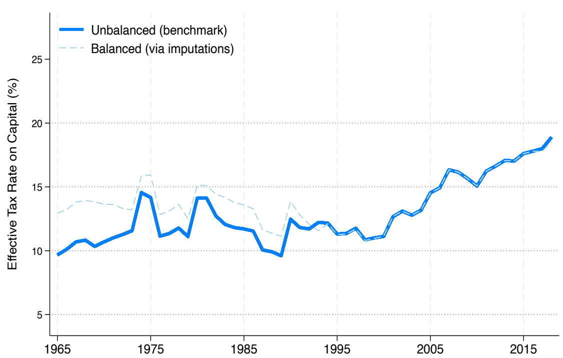
(a) PIT revenue allocation



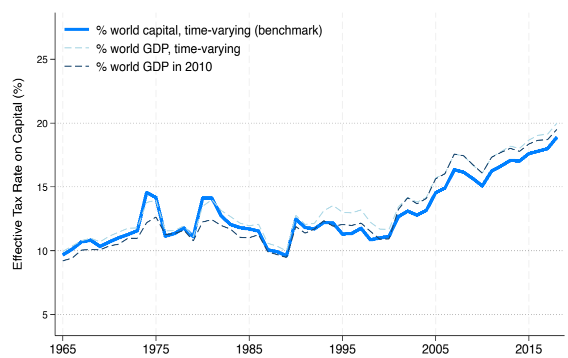
(b) Mixed-income allocation



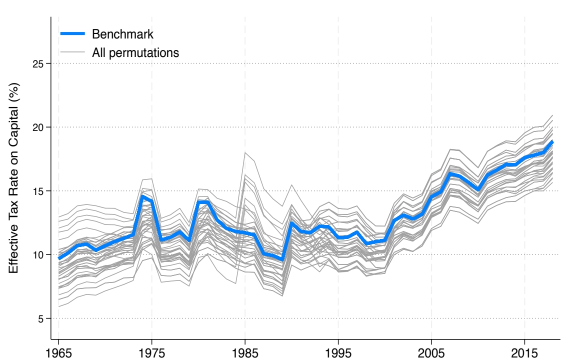
(c) Panel balancedness



(d) Weights for aggregation



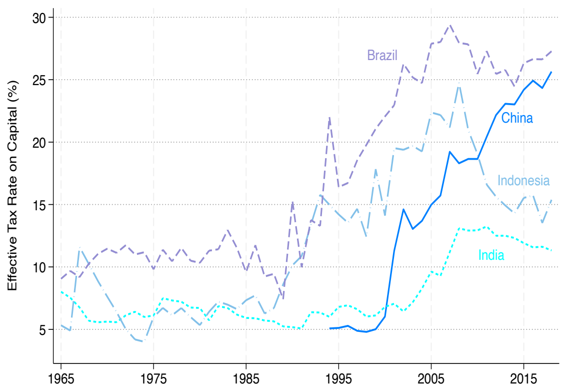
(e) All combinations



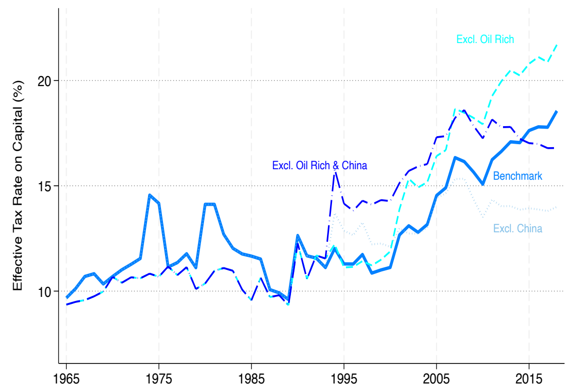
Notes: These panels show trends in the effective tax rate on capital in the 118 developing countries in our sample. The panels vary our four key methodological choices: the allocation of personal income tax revenue to capital vs labor (panel a); the allocation of mixed income to capital vs labor (panel 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 4.2.

Figure 3: Heterogeneity of Effective Capital Taxation in Developing Countries

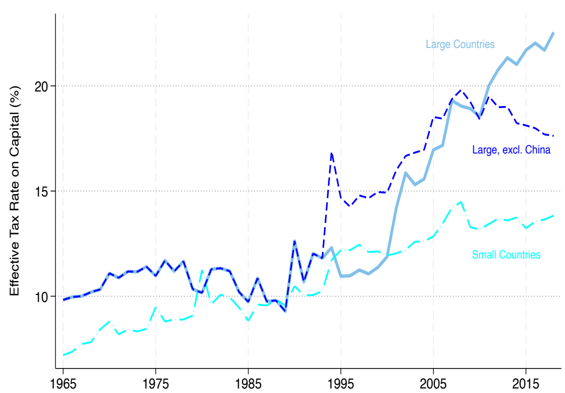
(a) Four largest countries



(b) Oil rich countries and China

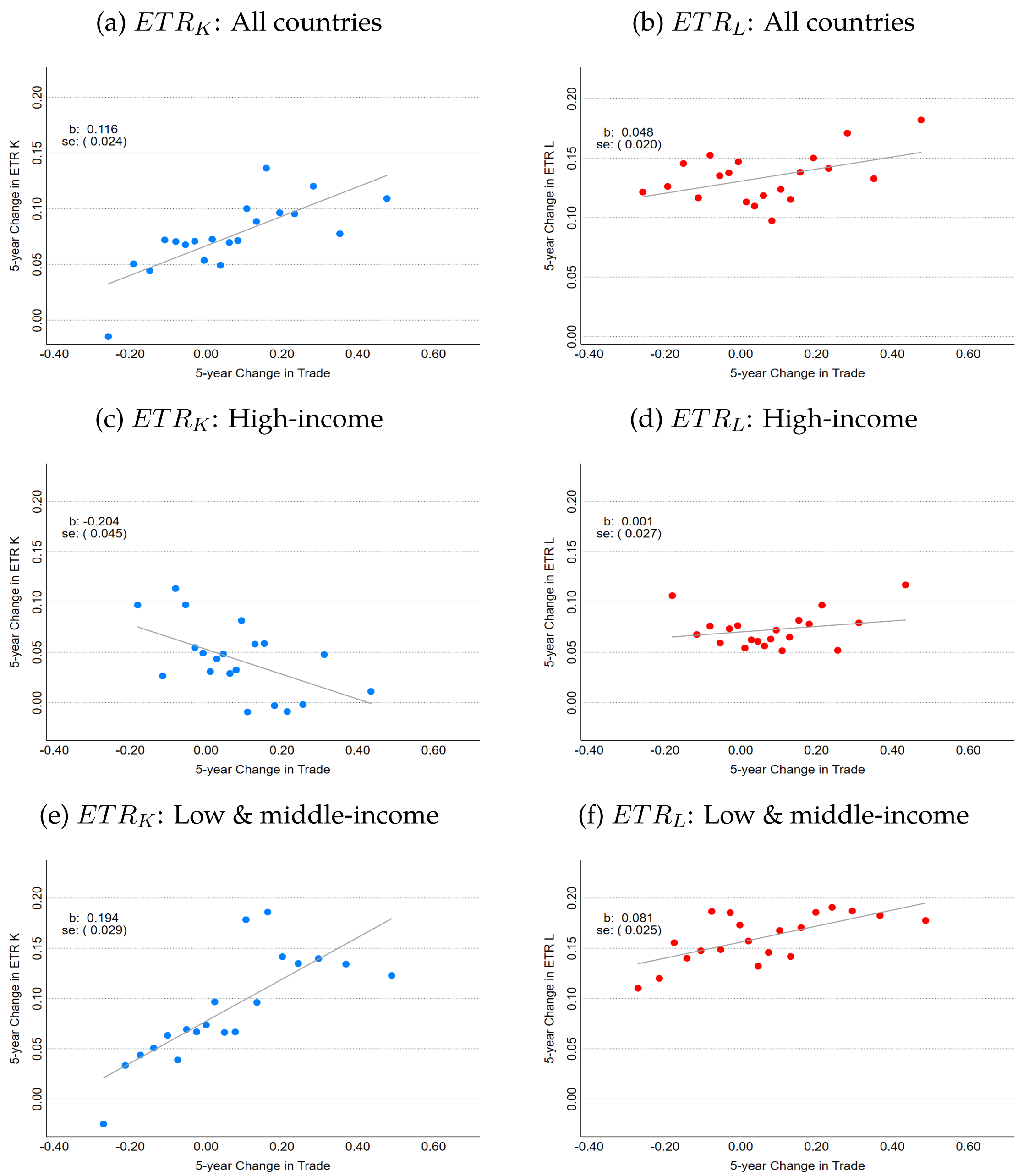


(c) Large vs small countries



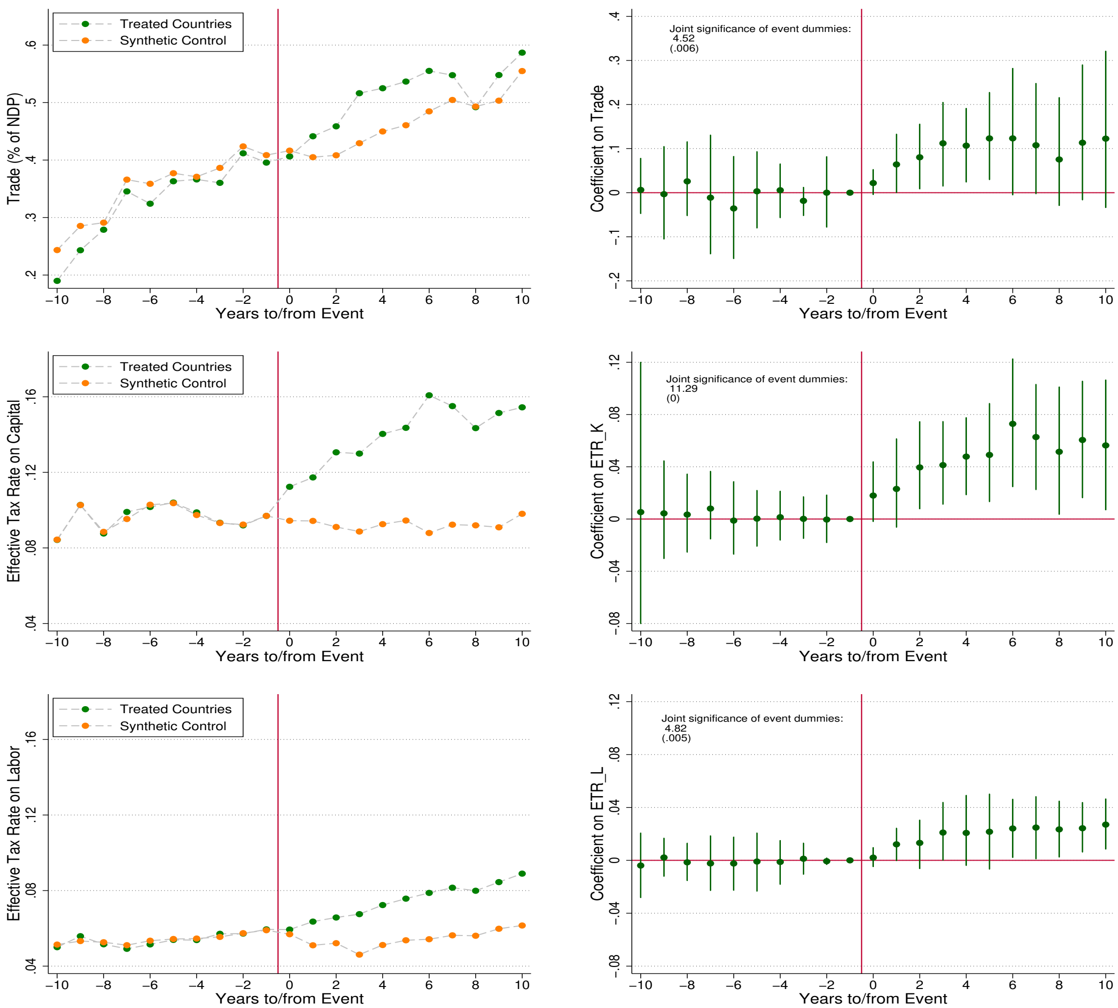
Notes: These panels show the evolution of the effective tax rate on capital, ETR_K, for major developing countries and sub-samples of developing countries. Developing countries are low and middle-income countries according to the World Bank income classification in 2018. Panel (a) plots the ETR_K series for the four largest developing countries: Brazil, China, India, Indonesia. Panel (b) compares our benchmark series to: a series without China; a series without oil-rich countries (countries with more than 7% of GDP from oil in 2018); and, a series without China and oil-rich countries. Within the sample of non-oil rich developing countries, panel (c) 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 4.3.

Figure 4: Within-Country Associations between Effective Tax Rates and Trade



Notes: These panels shows 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 4.4.

Figure 5: 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 (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 5.1.1.

Figure 6: Corporate Sector Income and Mixed Income, by Development Level

Notes: These panels plot the time series of corporate sector income and of mixed income between 1965 and 2018 and by level of development. Both outcomes are expressed as a percent of net domestic product and weighted by country-year net domestic product in constant 2019 USD. Corporate income is the sum of corporate profits and corporate employee compensation. The left panels show the results for high-income countries (N=37), and the right panels show the results for low- and middle-income countries (N=118), based on the World Bank income classification in 2018. 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. For more details, see Section 6.

Table 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	0.032***	0.109***	0.118***	0.222*	0.106**	0.102***	0.115***	0.150***	0.100**	0.116***	0.124***	0.108***	0.164*
	(0.010)	(0.033)	(0.041)	(0.120)	(0.046)	(0.033)	(0.032)	(0.048)	(0.039)	(0.039)	(0.042)	(0.034)	(0.087)
Panel B: ETR_L													
Trade	0.011**	0.056***	0.049***	0.062	0.046**	0.058***	0.059***	0.041***	0.053***	0.052***	0.045***	0.054***	0.140**
	(0.004)	(0.016)	(0.015)	(0.042)	(0.020)	(0.017)	(0.016)	(0.015)	(0.016)	(0.016)	(0.015)	(0.016)	(0.061)
Specification	OLS	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
1^{st} stage Kleibergen-Paap F-statistic		24.57	24.57	31.24	14.24	23.09	34.83	24.57	24.57	24.57	24.57	45.17	10.80
Modifications to IV in col. (2)			No 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	4970	4970	4970	4970	3984	4970	4970	4970	4970	4970	4970	4970	4970

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 (5). All other columns use IV; at the bottom of each column, we report the 1^{st}-stage Kleibergen-Paap F-statistic. The benchmark IV specification is in column (2), with the corresponding 1^{st}-stage regression reported in Table A3. 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 5.2.1. 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 (2019) 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 5.2. * p<0.10 ** p<0.05 *** p<0.01. Standard errors in parentheses are clustered at the country level.

Table 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	0.033***	0.018***	-0.001	0.003	0.002	0.009
	(0.011)	(0.003)	(0.001)	(0.003)	(0.002)	(0.006)
Panel B: IV						
Trade	0.098***	0.047***	0.004	0.010*	0.015**	0.019
	(0.033)	(0.013)	(0.003)	(0.005)	(0.006)	(0.022)
1^{st}-stage Kleibergen-Papp F-statistic	24.57	24.57	24.57	24.57	24.57	24.57
N	4970	4970	4970	4970	4970	4970

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 5.2. At the bottom of each column, we report the 1^{st}-stage Kleibergen-Paap F-statistic. The corresponding 1^{st}-stage regression is reported in Table A3. 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 B2 and Appendix B.1. For more details on the IV, see Section 5.2. * p<0.10 ** p<0.05 *** p<0.01. Standard errors in parentheses are clustered at the country level.

Table 3: Trade Impacts on Mechanism Outcomes in Developing Countries

		National income components					Factor shares	
	First-diff. CIT rate (1)	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***	0.040***	-0.017	0.027***	0.006	0.063***	0.021**	0.031**
	(0.001)	(0.013)	(0.011)	(0.009)	(0.010)	(0.019)	(0.008)	(0.012)
Panel B: IV								
Trade	-0.012*	0.183***	-0.193***	0.184***	0.014	0.142*	0.161***	0.206***
	(0.006)	(0.043)	(0.041)	(0.036)	(0.032)	(0.074)	(0.034)	(0.048)
1^{st} stage Kleibergen-Paap F-Statistic	24.57	24.57	24.57	24.57	24.57	24.57	24.57	24.57
N	4970	4970	4970	4970	4970	4970	4970	4970

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 5.2. At the bottom of each column in Panel B, we report the 1^{st}-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 3.1 and Section 6.1. For more details on the instrumental variables, see Section 5.2. * p<0.10 ** p<0.05 *** p<0.01. Standard errors in parentheses are clustered at the country level.

Table 4: Heterogeneous Impacts of Trade by Development Level

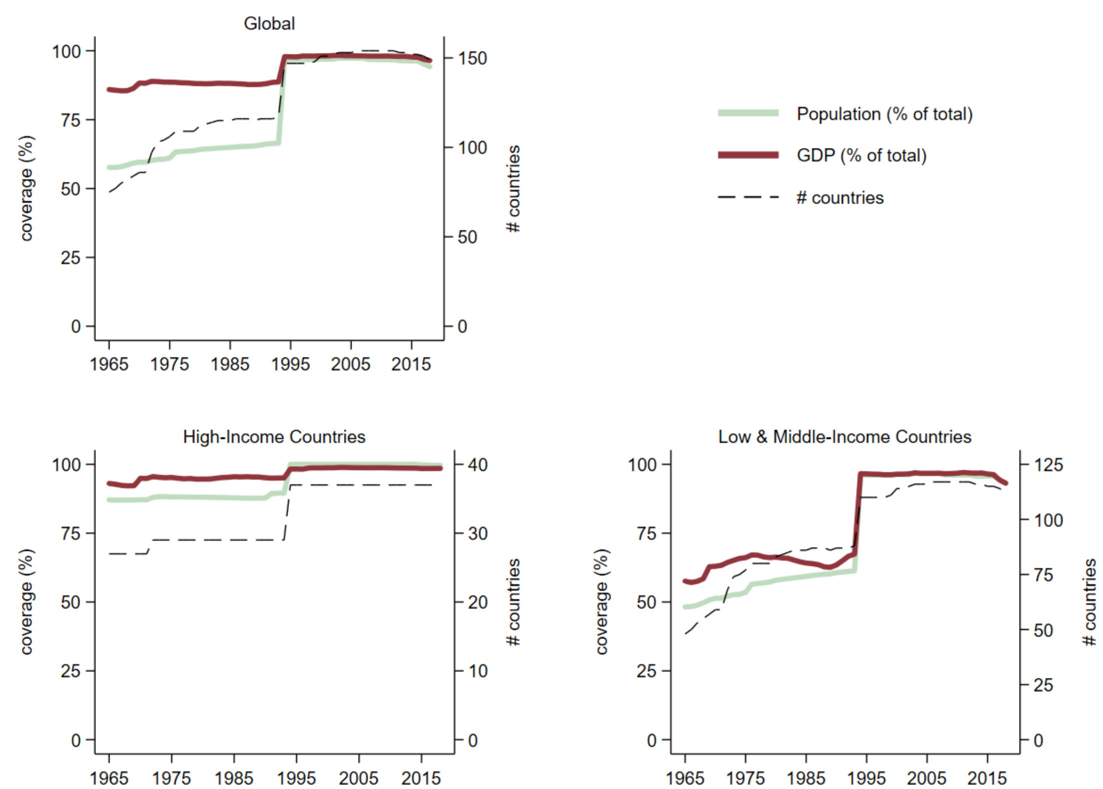
	ETR_K (1)	ETR_L (2)	First-diff. CIT Rate (3)	Corp. Totl. Income (4)	Mixed Income (5)	Corp. Profits (6)	Employee Comp. (7)	Corp. ETR_K (8)	Natl. K-Share (9)	Corp. K-Share (10)
Trade	0.267**	0.123**	-0.015	0.340**	-0.200*	0.211***	0.088	0.341**	0.132***	0.167***
	(0.134)	(0.050)	(0.020)	(0.133)	(0.116)	(0.057)	(0.098)	(0.134)	(0.048)	(0.051)
Trade$*\mathbb{1}$(High-inc.)	-0.315	0.012	-0.070**	-0.545***	0.340**	-0.333***	–0.239**	-0.142	-0.194**	-0.238**
	(0.231)	(0.110)	(0.032)	(0.174)	(0.141)	(0.103)	(0.116)	(0.261)	(0.076)	(0.095)
Implied coef. for Trade in High-inc.	-0.047	0.135	-0.085***	-0.204	0.140	-0.121*	-0.150	0.198	-0.061	-0.071
	(0.134)	(0.090)	(0.020)	(0.141)	(0.135)	(0.071)	(0.125)	(0.156)	(0.055)	(0.077)
1^{st}-stage Kleibergen-Papp F-statistic	14.39	14.39	14.39	14.39	14.39	14.39	14.39	14.39	14.39	14.39
N	6544	6544	6544	6544	6544	6544	6544	6544	6544	6544

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 estimate the IV described in equation 8. The first-stage regression is reported in Table A3. 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 $Trade * \mathbb{1}$(High-inc.) coefficients. High-income is based on the World Bank income classification in 2018. We also report the 1^{st}-stage Kleibergen-Paap F-statistic. Across the columns, the outcome differs: 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 (CIT) 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 the outcomes, see Section 3.1 and Section 6.1. For more details on the instrumental variables, see Section 5.2. * p<0.10 ** p<0.05 *** p<0.01. Standard errors in parentheses are clustered at the country level.

Appendix

Appendix A Additional Figures and Tables

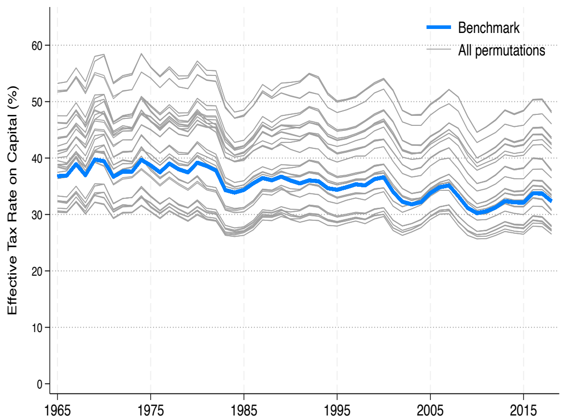
Figure A1: Data Coverage of Effective Tax Rates



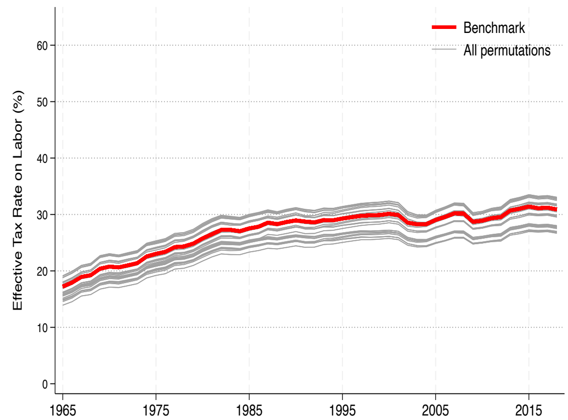
Notes: These panels show the coverage of our effective tax rate data between 1965 and 2018 at the global level (top left panel), in high income countries (bottom left panel), and in low- and middle-income countries (bottom right panel). Low, middle and high-income countries are based on the World Bank 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 3.3 for more details.

Figure A2: Robustness of ETR_K and ETR_L Trends by Development Levels

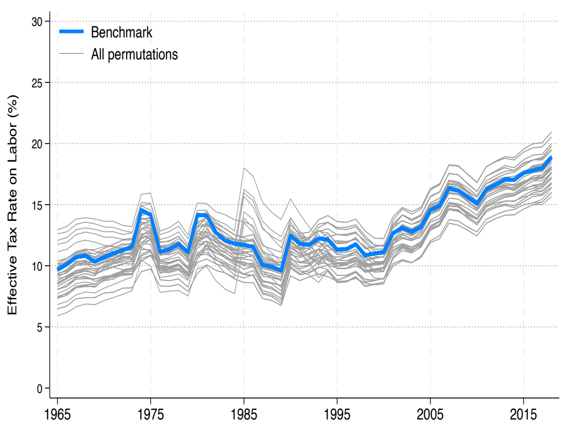
(a) ETR_K in HICs



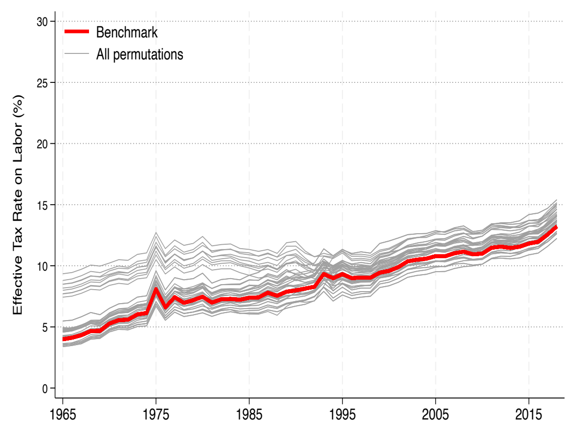
(b) ETR_L in HICs



(c) ETR_K in LMICs

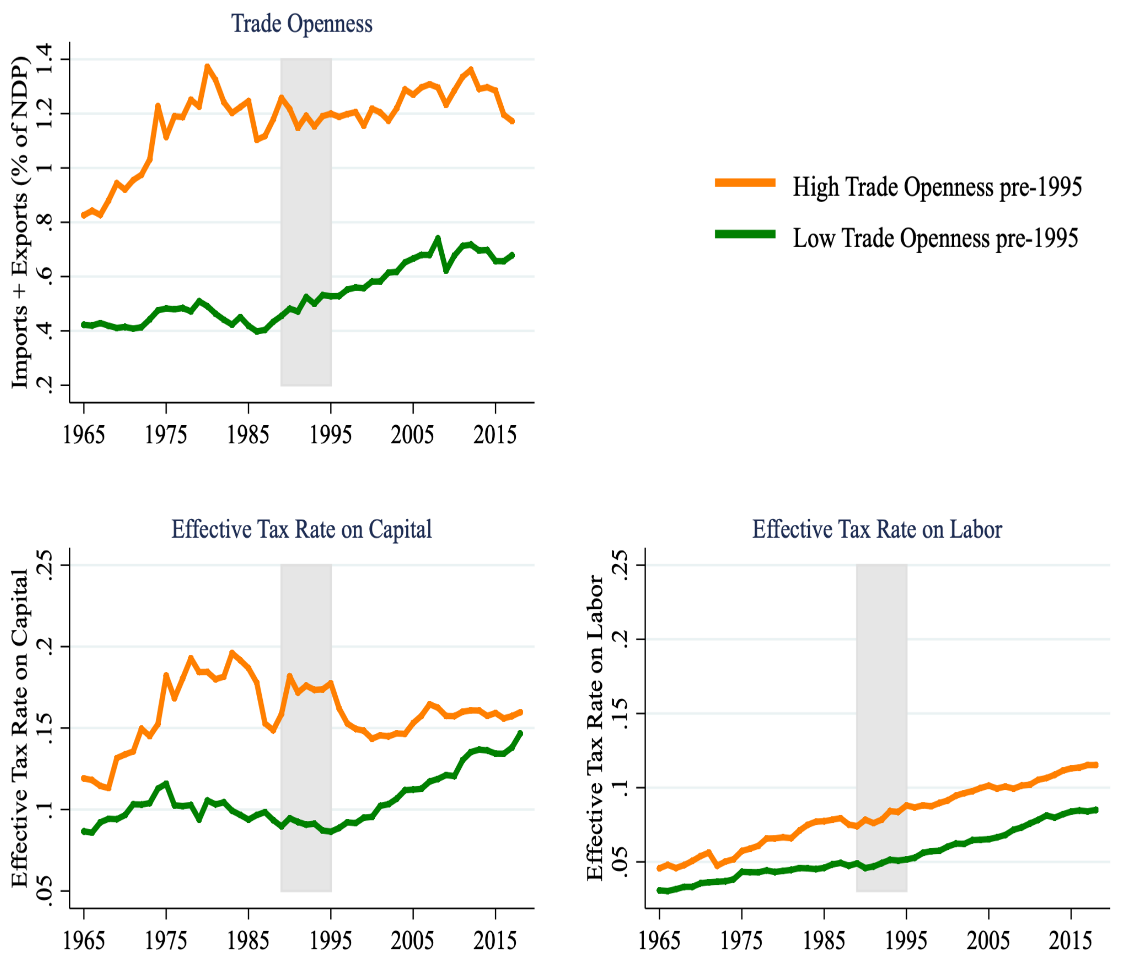


(d) ETR_L in LMICs



Notes: These panels show trends in the effective taxation of capital and labor for high-income countries (HICs, top panels) and low and middle-income countries (LMICs, bottom panels). Low, middle and high-income countries' classification are based on the World Bank income classification in 2018. The benchmark series are denoted by the thick colored lines and the grey lines denote all 54 possible permutations of the series when varying the four key methodological choices (detailed in Section 4.2): the allocation of personal income tax revenue to capital vs labor; the allocation of mixed income to capital vs labor; presenting results for an unbalanced panel of countries vs a balanced panel via imputations; and, how to weight individual countries' series when aggregating them. Panel (c) corresponding to the ETR_K for low and middle-income countries is further decomposed in Figure 2.

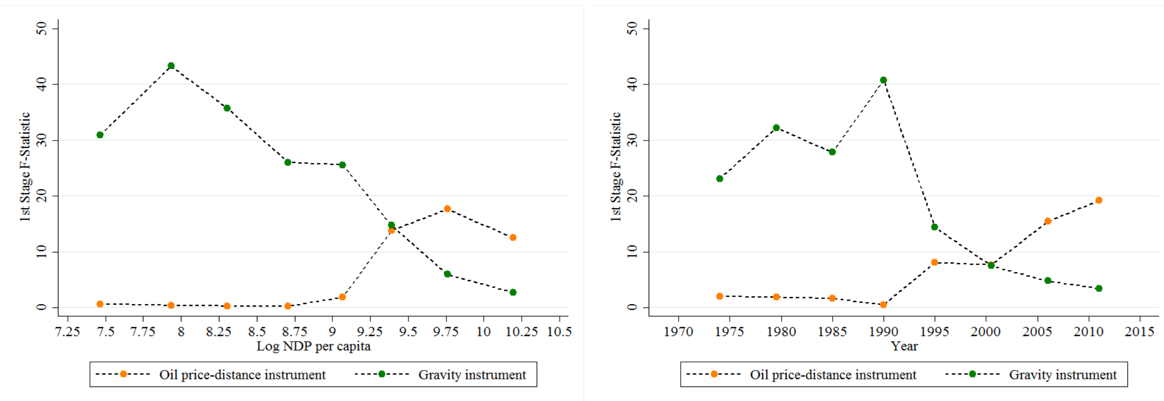
Figure A3: Trends by Initial Trade Openness in Developing Countries



Notes: These panels plot the time series of trade openness (top-left panel), effective tax rate on capital (bottom-left panel) and effective tax rate on labor (bottom-right panel). The sample is limited to low- and middle-income countries, according to the World Bank income classification in 2018. Within each panel, the orange line (green line) traces the evolution of the group which had relatively high (low) trade openness prior to 1995. Specifically, high (low) trade openness is defined as having average trade openness which lies above (below) the global average between 1965 and 1995. Trade openness is measured as the share of imports and exports in national domestic product; note that this share can exceed a value of 1. Each line plots the year fixed effects from an OLS regression in the relevant sub-sample of the outcome on country and year fixed effects. The inclusion of country fixed effects limits the influence of countries entering and leaving the sample. The fixed effects are normalized to equal the level of the outcome variable in the relevant sub-sample in 1965. The shaded area highlights the notable 1990-1995 period, which marks the beginning of the 'second wave' of globalization that featured a proliferation of bilateral and multilateral trade agreements (Egger, Nigai, & Strecker, 2019).

Figure A4: Strength of Individual Instruments Across Subsamples

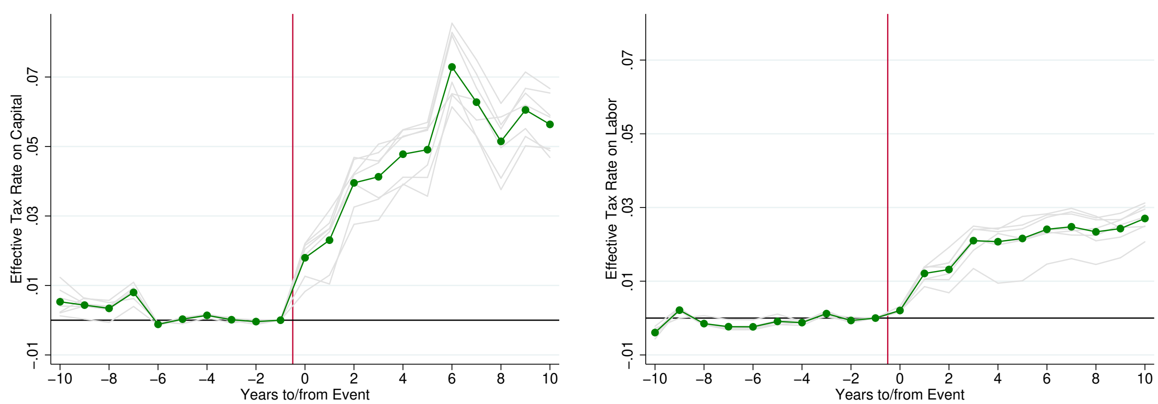
(a) Sub-samples of NDP per capita (b) Sub-samples of time-periods



Notes: These figures show the statistical strength of the instruments $Z^{oil-distance}$ and $Z^{gravity}$ in developing countries (low and middle-income countries based on World Bank classification in 2018, $N = 4970$). The outcome is the first-stage F-statistic from a regression of trade openness on each individual instrument, in subsamples of log NDP per capita (panel a) and years (panel b). The x-axis variable is partitioned into ten deciles, and the estimation is done in increments of one decile with a bandwidth of one additional decile of on either side. To maintain equal sample sizes, estimation centered on the first and the tenth decile are dropped. More details in Section 5.2.

Figure A5: Robustness of Trade Liberalization to Changing Events-Sample

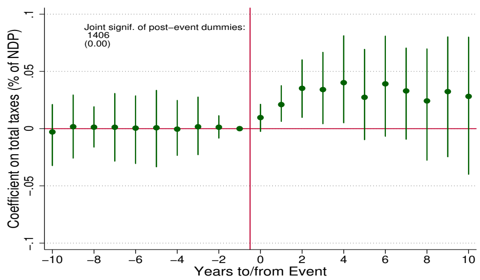
(a) Effective tax rate on capital (b) Effective tax rate on labor



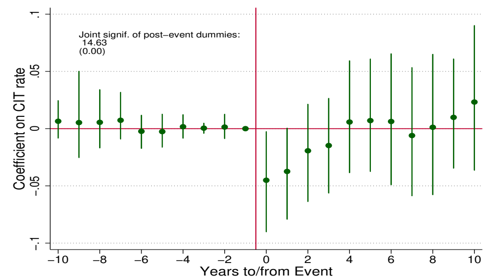
Notes: These figures show event study impacts of trade liberalization on the effective tax rate on capital (panel a) and the effective tax rate on labor (panel b). The solid green line displays the dynamic event-study coefficients β_e estimated in the full sample of 7 liberalization event-countries (Figure 5); the gray lines present the event-study coefficients estimated in samples that remove one event-country one at a time. More details in Section 5.1.1.

Figure A6: Mechanism Impacts in Trade Liberalization Event Studies

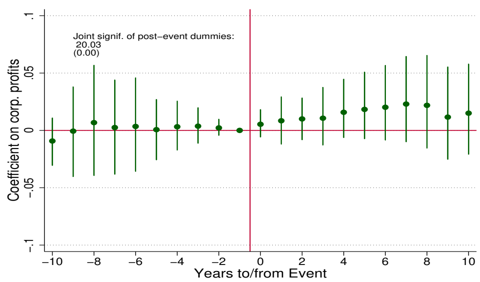
(a) Total taxes (% of NDP)



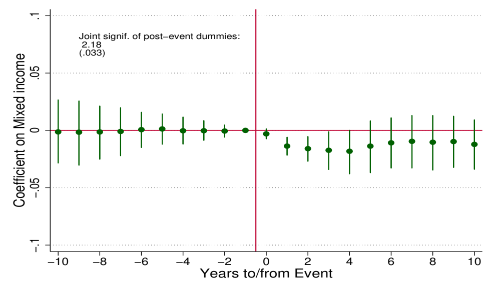
(b) Corp. income tax rate (first-diff.)



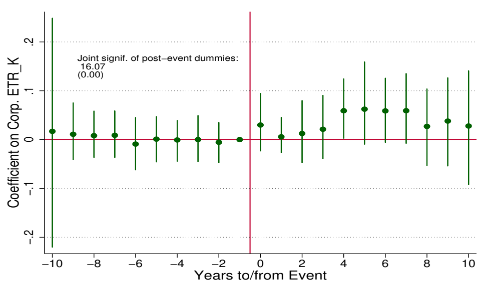
(c) Corporate income (% of NDP)



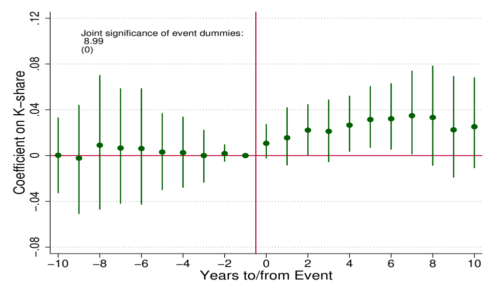
(d) Mixed income (% of NDP)



(e) Corporate ETR_K



(f) Capital income (% of NDP)



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 5.1, and similarly to Figure 5. 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.

Table A1: Weights in Synthetic Control for Trade Liberalization Events

Treated Country	Event Year	Trade Openness	Weight	ETR_K	Weight	ETR_L	Weight	Reference
		Bangladesh	97.3	% Bangladesh	41.6 %	Chile	35.9 %	
Argentina	1989	United States	2.7 %	Haiti	14.1 %	Togo	31.6 %	Goldberg and Pavcnik (2006)
		.	.	Bolivia	13.4 %	Jordan	16.8 %	
		.	.	...	...	...	...	
		Bangladesh	59.8 %	Jordan	35.7 %	Panama	25.7 %	Goldberg and Pavcnik (2006),
Brazil	1988	United States	32.2	% Sudan	21.2 %	Guyana	21.7 %	Dix-Carneiro and Kovak (2017)
		Japan	6.1 %	Zimbabwe	12.7 %	Chile	14.5 %	
		...	...	...	...	...	...	
		United States	36.2 %	Congo	41.8 %	Kuwait	31.1 %	
China	2001	Bangladesh	36.0 %	Nicaragua	26.3 %	Pakistan	22.9 %	Brandt et al. (2017)
		Dominican Rep.	12.2 %	Gabon	14.2 %	Uganda	20.2 %	
		...	...	...	...	...	...	
		Bangladesh	50.7 %	Kuwait	67.9 %	Paraguay	45.5 %	
Colombia	1985	Iran	22.6 %	Gabon	14.6 %	Sudan	15.0 %	Goldberg and Pavcnik (2006; 2016)
		Guatemala	12.5 %	Sierra Leone	12.6 %	Cameroon	11.5 %	
		...	...	...	...	...	...	
		United States	76.4 %	Uganda	41.4 %	Lebanon	37.9 %	Goldberg and Pavcnik (2006, 2016);
India	1991	Bangladesh	23.6 %	Bolivia	14.0 %	Oman	17.6 %	Topalova et al. (2009)
		.	.	Haiti	4.6 %	Jordan	16.2 %	
		.	.	...	...	...	...	
		Bangladesh	72.0 %	Sierra Leone	33.2 %	Tunisia	31.1	Feenstra and Hanson (1997);
Mexico	1985	Uruguay	9.6 %	Bahrain	23.6 %	Zimbabwe	25.8 %	Goldberg and Pavcnik (2006, 2016)
		Spain	8.0 %	Bolivia	14.7 %	Uruguay	15.9 %	
		...	...	...	...	...	...	
		Thailand	42.4 %	Korea	45.8 %	Bangladesh	72.8 %	Goldberg and Pavcnik (2016),
Vietnam	2001	Ghana	22.6 %	Luxembourg	19.2 %	Myanmar	22.6 %	McCaig and Pavcnik (2018)
		Venezuela	21.7 %	Trinidad & Tob.	17.3 %	Haiti	4.6 %	
		...	...	...	...	.	.	

Notes: This table shows the seven treated countries and the three countries with the largest weight in the synthetic control group for each treated country and outcome (trade openness, ETR_K, ETR_L). For each outcome, the pool of possible donor countries consists of all non-treated countries with a balanced panel over all the pre-event periods that are used in the matching procedure.

Table A2: Synthetic Difference-in-Difference of Trade Liberalization

	Trade (1)	ETR_K (2)	ETR_L (3)
Panel A: *Synthetic control for each outcome separately*			
Post*Treat	0.064	0.0457***	0.020**
	(0.047)	(0.015)	(0.009)
Imputed treatment effect	0.070*	0.047***	0.020***
	(0.039)	(0.009)	(0.005)
Panel B: *Synthetic control for all outcomes jointly*			
Post*Treat	0.092*	0.033*	0.012
	(0.044)	(0.016)	(0.008)
Imputed treatment effect	0.101***	0.033***	0.012***
	(0.028)	(0.006)	(0.004)
Panel C: *Donor pool excluding major trading partners*			
Post*Treat	0.0733	0.0470***	0.0187**
	(0.0558)	(0.0151)	(0.00852)
Imputed treatment effect	0.0821**	0.0481***	0.0186***
	(0.0357)	(0.00912)	(0.00450)
Panel D: *Donor pool restricted to not-yet liberalized*			
Post*Treat	0.0544	0.0541***	0.0136
	(0.0582)	(0.0144)	(0.0088)
Imputed treatment effect	0.0625*	0.0548***	0.0135***
	(0.0348)	(0.0096)	(0.0051)
Panel E: *Donor pool restricted to same region*			
Post*Treat	0.0490	0.0341*	0.0074
	(0.0606)	(0.0192)	(0.0087)
Imputed treatment effect	0.0586*	0.0357***	0.0173***
	(0.0319)	(0.0124)	(0.0050)
Panel F: *Donor pool restricted to LMICs*			
Post*Treat	0.0768	0.0405**	0.0169*
	(0.0529)	(0.0167)	(0.00930)
Imputed treatment effect	0.0854**	0.0419***	0.0167***
	(0.0345)	(0.00846)	(0.00523)
N	294	294	294

Notes: This table shows the results from estimating the difference-in-difference effect and the imputed treatment effect - see Appendix C.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 & 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 A3: First-Stage and Reduced Form Regressions

	1^{st}-stage	Reduced form		1^{st}-stage		Reduced form	
	Trade	ETR_K	ETR_L	Trade	Trade$*\mathbb{1}$(High-inc.)	ETR_K	ETR_L
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Z^{gravity}$	0.068***	0.007***	0.003***	0.017	0.037***	0.016*	0.003
	(0.010)	(0.002)	(0.001)	(0.018)	(0.014)	(0.008)	(0.003)
$Z^{oil-distance}$	-0.115***	-0.017***	-0.013**	-0.089***	-0.023	-0.017**	-0.011***
	(0.036)	(0.006)	(0.006)	(0.015)	(0.014)	(0.007)	(0.003)
1^{st}-stage F-statistic	24.57			23.27	11.10		
1^{st}-stage Sanderson-Windmeijer Weak Instruments F-statistic	24.57			41.43	25.75		
1^{st}-stage Kleibergen-Paap F-statistic	24.57			14.39			
Sample	Developing countries only			Developing and developed countries			
N	4970	4970	4970	6544	6544	6544	6544

Notes: This regression table shows the first stage and the reduced form results. The sample is developing countries ($N = 4970$) in cols. (1)-(3), and developing and developed countries ($N = 6544$) 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 1-2-3. 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 4. We report several 1^{st}-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 A4: 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	0.113***	0.123***	0.112**	0.075**	0.108**	0.094*	0.120***	0.092*	0.130**	0.103**
	(0.037)	(0.043)	(0.055)	(0.032)	(0.043)	(0.052)	(0.045)	(0.051)	(0.061)	(0.040)
Panel B: ETR_L										
Trade	0.064***	0.031***	0.094*	0.023**	0.039**	0.036*	0.050**	0.035**	0.066**	0.072***
	(0.018)	(0.010)	(0.053)	(0.011)	(0.015)	(0.018)	(0.020)	(0.014)	(0.030)	(0.022)
Modifications to bench-mark sample in Table 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	4612	2296	1194	1480	2783	1002	1781	2151	2819	2479

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; 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 (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 3 and Appendix B.

Table A5: Robustness of Results for Total Taxes and Mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Total taxes (% of NDP)						
Trade	0.108*	0.091**	0.093***	0.103***	0.096***	0.176**
	(0.063)	(0.039)	(0.032)	(0.032)	(0.033)	(0.077)
1^{st} stage K-P F-stat	31.24	14.24	23.09	34.83	45.17	10.80
N	4970	3984	4970	4970	4970	4970
Panel B: CIT rate (first-diff.)						
Trade	0.004	-0.008	-0.012*	-0.013*	-0.012*	-0.031*
	(0.011)	(0.009)	(0.007)	(0.007)	(0.007)	(0.016)
1^{st} stage K-P F-stat	31.24	14.24	23.09	34.83	45.17	10.80
N	4970	3984	4970	4970	4970	4970
Panel C: $log(1+$CIT rate$)$						
Trade	-0.009*	-0.006	-0.009*	-0.010*	-0.009*	-0.027*
	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)	(0.015)
1^{st} stage K-P F-stat	31.24	14.24	23.09	34.83	45.17	10.80
N	4970	3984	4970	4970	4970	4970
Panel D: Corp. income (% of NDP)						
Trade	0.225***	0.210***	0.180***	0.193***	0.183***	0.181**
	(0.052)	(0.046)	(0.043)	(0.044)	(0.044)	(0.090)
1^{st} stage K-P F-stat	31.24	14.24	23.09	34.83	45.17	10.80
N	4970	3984	4970	4970	4970	4970
Panel E: Mixed income (% of NDP)						
Trade	-0.199***	-0.175***	-0.191***	-0.201***	-0.191***	-0.112
	(0.048)	(0.041)	(0.041)	(0.038)	(0.041)	(0.116)
1^{st} stage K-P F-stat	31.24	14.24	23.09	34.83	45.17	10.80
N	4970	3984	4970	4970	4970	4970
Panel F: Capital share of NDP						
Trade	0.121***	0.112**	0.157***	0.170***	0.163***	0.111**
	(0.034)	(0.043)	(0.033)	(0.032)	(0.034)	(0.050)
1^{st} stage K-P F-stat	31.24	14.24	23.09	34.83	45.17	10.80
N	4970	3984	4970	4970	4970	4970
Panel G: Corp. ETR_K						
Trade	0.237*	0.163	0.129*	0.149*	0.138*	0.399**
	(0.131)	(0.104)	(0.075)	(0.076)	(0.075)	(0.188)
1^{st} stage K-P F-stat	31.24	14.24	23.09	34.83	45.17	10.80
N	4970	3984	4970	4970	4970	4970
Modifications to IV in Panel B of Table 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 1^{st}-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 $(1+CITrate)$. 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 - 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 A6: Heterogeneous Impacts of Trade in Developing Countries

	ETR_K (1)	ETR_L (2)	Corp. income (3)	Corp. ETR_K (4)
Panel A: Large Taxpayer Unit				
Trade	0.100**	0.039*	0.183***	0.088*
	(0.046)	(0.022)	(0.055)	(0.050)
Trade∗𝟙(LTU)	0.024	0.041**	-0.000	0.129
	(0.056)	(0.020)	(0.049)	(0.132)
Implied coef. for	0.125***	0.081***	0.183***	0.218**
Trade with LTU	(0.041)	(0.019)	(0.040)	(0.095)
Panel B: Customs-Tax Integration				
Trade	0.099**	0.040*	0.182***	0.135*
	(0.043)	(0.024)	(0.052)	(0.077)
Trade∗𝟙(Customs-Tax)	0.066	0.101*	0.005	0.228
	(0.124)	(0.059)	(0.111)	(0.262)
Implied coef. for	0.166	0.142***	0.187**	0.363*
Trade with Customs-Tax	(0.101)	(0.050)	(0.087)	(0.208)
Panel C: Value-Added Tax				
Trade	0.099**	0.040**	0.182***	0.130
	(0.044)	(0.020)	(0.054)	(0.096)
Trade∗𝟙(VAT)	0.031	0.048**	0.002	0.103
	(0.060)	(0.022)	(0.053)	(0.112)
Implied coef. for	0.131***	0.089***	0.185***	0.234***
Trade with VAT	(0.045)	(0.021)	(0.043)	(0.083)
Panel D: International Accounting Standards				
Trade	0.102***	0.039**	0.185***	0.140*
	(0.038)	(0.017)	(0.050)	(0.081)
Trade∗𝟙(IAS)	0.037	0.052**	-0.007	0.151
	(0.070)	(0.025)	(0.056)	(0.144)
Implied coef. for	0.140**	0.092***	0.178***	0.291***
Trade with IAS	(0.056)	(0.023)	(0.049)	(0.113)
N	4970	4970	4970	4970

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

$$y_{ct} = \mu \cdot trade_{ct} + \kappa \cdot trade_{ct} \cdot \mathbb{1}(A)_{ct} + \theta \cdot \mathbb{1}(A)_{ct} + \pi_c + \pi_t + \epsilon_{ct}$$

where $\mathbb{1}(A)_{ct}$ 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 $trade_{ct} \cdot \mathbb{1}(A)_{ct}$ using the two instruments (Section 5.2). The coefficient on $\mathbb{1}(A)_{ct}$ 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 internationl 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 $trade_{ct} \cdot \mathbb{1}(A)_{ct}$ coefficients. * p<0.10 ** p<0.05 *** p<0.01. Standard errors in parentheses are clustered at the country level.

Table A7: Additional Heterogeneity Impacts of Trade

Heterogeneity H_c :	Small population (1)	Capital openness (2)
Panel A: CIT rate (first-diff).		
Trade	-0.065***	0.006
	(0.016)	(0.038)
Trade$*H_c$	-0.025	-0.121**
	(0.064)	(0.054)
Implied coef. for Trade in H_c	-0.090	-0.115***
	(0.055)	(0.028)
1^{st}-stage Kleibergen-Papp F-statistic	7.01	9.96
N	6544	6017
Panel B: ETR_K		
Trade	0.294	0.456**
	(0.207)	(0.224)
Trade$*H_c$	-0.696	-0.410
	(0.511)	(0.296)
Implied coef. for Trade in H_c	-0.401	0.045
	(0.373)	(0.104)
1^{st}-stage Kleibergen-Papp F-statistic	7.01	9.96
N	6544	6017
Panel C: ETR_L		
Trade	0.155**	0.112
	(0.070)	(0.111)
Trade$*H_c$	-0.006	0.126
	(0.230)	(0.178)
Implied coef. for Trade in H_c	0.149	0.239**
	(0.199)	(0.095)
1^{st}-stage Kleibergen-Papp F-statistic	7.01	9.96
N	6544	6017

Notes: This table presents results from estimating heterogeneous effects of trade on outcomes in the full sample of developed and developing countries. Trade is the sum of exports and imports divided by net domestic product. We estimate an IV similar to equation 8, but where the interaction term H_c is an indicator for small population (column 1), or an indicator for capital openness (column 2). Small population takes a value of 1 if the country's population in 2018 was below 40 million. Capital openness takes a value of 1 if the country's average value of the Chinn-Ito index (Chinn & Ito, 2006) lies above the median value of all country-years. Both of these heterogeneity dimensions are therefore country-specific but time-invariant. The sample size is smaller in column (2) due to data-availability of the Chinn-Ito variable. The panels differ by outcome: panel a) is the first-differenced corporate income tax (CIT) rate; panel b) is the effective tax rate on capital, ETR_K; panel c) is the effective tax rate on labor, ETR_L. At the bottom of each column and panel, we report the implied coefficient and estimated standard error based on the linear combination of the $Trade$ and the $Trade$*H_c coefficients. We also report the 1^{st}-stage Kleibergen-Paap F-statistic. For more details on the IV, see Section 5.2 and 6.5. * p<0.10 ** p<0.05 *** p<0.01. Standard errors in parentheses are clustered at the country level.

Appendix B 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 B.1). Additionally, we discuss the methodology to measure effective tax rates (Section B.2).

B.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. To complement hard-copy archival data, we retrieved countries' online reports, usually published by their national statistical office or finance ministry. We relied on individual country studies to help corroborate the levels and trends of tax revenues in more historical periods. These country-by-country reviews are contained in a forthcoming case studies guide. 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).

Constructing long panels of tax revenue series across sources requires making decisions about harmonization. We maintained the following guiding rules:

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 income taxes. We also study if ICTD has the better match in overlapping time-periods with OECD data. We aim to use no more than two data sources per country. If discrepancies exist when data sources overlap, we inspect the accuracy of each source with additional academic studies.

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 arguably corresponds to China's establishment of a modern tax system (World Bank, 2008) (discussed below).

3. When none of the data sources separate PIT from CIT, we use academic sources and tax legislation to assign values.

4. To guard against omitting decentralized tax revenues, we use the OECD database on subnational government finance (link) to find the countries with significant state and local taxes, and collect further data for these countries if necessary.

5. We linearly interpolate data when a given tax type is missing between observed values, but for no more than 4 years in a time-series and without extrapolation. We check for important socio-economic changes that could cast doubt on the continuity and credibility of tax revenue series, and do not interpolate between years characterized by such events.

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 there 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 ETR.

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.[67] This allows us to meaningfully expand the coverage of factor incomes across space and time.

To estimate capital and labor factor incomes requires information on the 4 main sub-components that make up net domestic product (see equation 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 5-6 include dummy variables for these composite cases; our main results also hold without the imputed values (Table A4). For the imputation, we follow the procedure from Blanchet et al. (2021). The

[67] A new concept in the 2008 SNA is the separation of mixed income from imputed rent. In the 1968 SNA, these concepts were subsumed under 'entrepreneurial income of private unincorporated enterprises' in the household sector. We maintain the 2008 SNA distinction and use accounting identities and imputations to measure OS_{PUE} and OS_{HH} where required.

World Inequality Database uses this procedure to impute consumption of fixed capital (depreciation) when it is missing in countries' national income 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 B1 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.

Table B1: Main Data Sources

	Country-year obs.	%
Panel A: Tax revenue data		
OECD	2866	42.3%
Archives	2681	39.4%
ICTD	1249	18.3%
N	*6816*	*100%*
Panel B: Factor income data		
Complete SNA2008	2463	36.1%
Complete SNA1968	1362	20.0%
Composite	2991	43.9%
N	*6816*	*100%*

Notes: For the 6816 country-year observations in which we estimate effective tax rates on capital and labor, Panel A presents the sources of our tax revenue data while Panel B presents the sources of our factor income data. For details, see Section B.1.

B.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 and 2 in Section 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 B2, 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-year level, based on either the ILO (2019) method or the country-year varying labor share in the corporate sector. In our benchmark assignment, replacing the invariant parameters with their fixed numerical values, we therefore have:

$$ETR_{L,ct} = \frac{T_{L,ct}}{Y_{L,ct}} = \frac{\lambda_{PIT,ct} \cdot T_{1100,ct} + T_{2000,ct}}{CE_{ct} + 0.75 \cdot OS_{PUE,ct}}$$

$$ETR_{K,ct} = \frac{T_{K,ct}}{Y_{K,ct}} = \frac{(1-\lambda_{PIT,ct}) \cdot T_{1100,ct} + T_{1200,ct} + T_{4000,ct}}{0.25 \cdot OS_{PUE,ct} + OS_{CORP,ct} + OS_{HH,ct}}$$

Below, we describe the parameter values in detail in Table B2, both for the tax revenue numerator and the national income denominator. We then provide more details on two key parameters: λ_{PIT}, the share of personal income tax revenue assigned to labor; and ϕ, the labor share of mixed income.

Table B2: Main Tax Revenue and National Accounts Concepts

Panel A: Tax Revenue

OECD revenue classification	type of tax j	incidence λ_j on labor	notes
1100	personal income tax (PIT)	$65\% \leq \lambda_{PIT} \leq 93\%$	Taxes on individuals (wages, capital income, capital gains). $\lambda_{PIT,ct}$ varies by country and year: see Section B.2 for details.
1200	corporate income tax (CIT)	$\lambda_{CIT} = 0\%$	Taxes on corporate profits. [Note: Unallocable income taxes (OECD category *1300*) are split proportionally between PIT and CIT; rare in occurence and quantitatively small.]
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 occurence and quantitatively small
7000	non-tax revenue	excluded	Does not meet definition of taxation, can be quantitatively significant

Panel B: National Accounts

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 ETR are expressed net of 'consumption of fixed capital'

Labor share of personal income taxes: λ_{PIT} As discussed in Section 3.1, the level of PIT revenue that derives from capital versus labor income is rarely directly observed.[68] Thus, within personal income tax (PIT), an important parameter is the share of revenue assigned to labor, denoted λ_{PIT}. In the United States, Piketty et al. (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 ($\lambda_{PIT} = 85\%$), to which we make two country-year specific 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 similarly assign 85% of PIT to labor in countries for which the PIT covers half or more 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 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

[68]PIT 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).

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 seems 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, $\phi_{ct} = \frac{CE_{ct}}{CE_{ct}+OS_{CORP,ct}}$. This procedure follows Gollin (2002).

Second, we implement the ILO (2019) method which relies on harmonized household surveys and labor force surveys across many years in developing countries. To match our ETR sample coverage, we extend the ILO's sample with as much additional data as we can retrieve from complementary sources. Estimation of the relative labor income of self-employed is based on the observable 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 national accounts, 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.[69] Intuitively, ILO (2019) does not rely on the SNA observed values of mixed income; instead, it estimates factor shares through a regression framework which computes 'shadow wages' of self-employed based on their overlap in observable characteristics with employees. It provides country-year varying measures of ϕ based on variation across space and time in w_{emp}, γ_q and b_q.

[69] After expanding data-coverage through additional sources, in the remaining cases where b_q and γ_q are missing, we impute observations using the same procedure as in Section B.1 above. This is particularly relevant in the years before 1991.

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 $\sum_q w_{emp} \cdot \gamma_q \cdot b_q > OS_{PUE}$ - such that estimated labor mixed income is larger than the SNA actually observed entire mixed income. This would, implausibly, imply that $\phi^{ILO} > 100\%$. By extension, this also implies the need to correct values of other national account components, in order for the accounting identity to hold whereby the sum of these components add up to the observed SNA value of total national income Y. It is unclear which labor or capital components would have to be revised downwards, and to what extent.

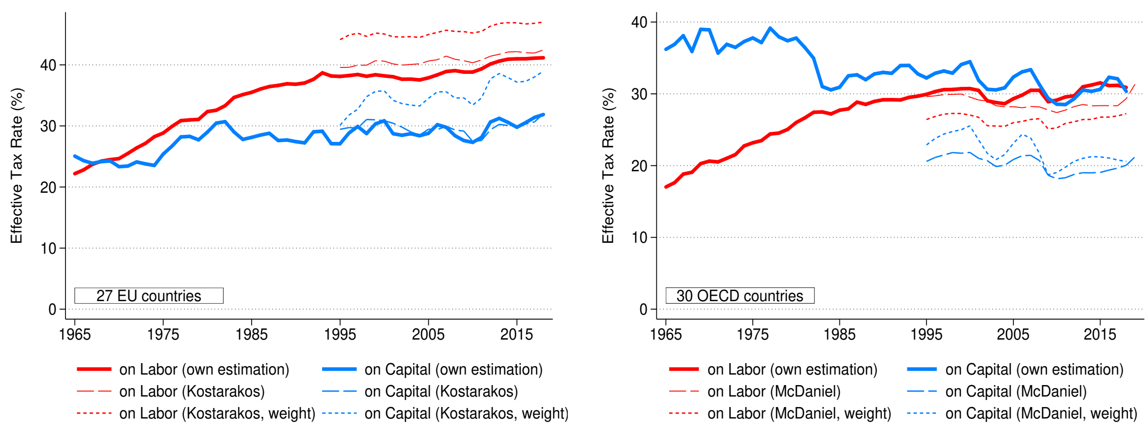
By estimating labor's *share* of mixed income, the method can generate estimated values of the *level* of mixed income which are at odds with observed ones, and which require revisions to other national income components. To remedy this concern, we winsorize ϕ^{ILO} at 100%. In cases where γ_q and b_q are not from ILO (2019), we also winsorize ϕ^{ILO} from below with the lowest observed country-year value in ILO (2019), which is 35%. This latter case occurs in 5% of the full sample. By imposing $35\% < \phi^{ILO} < 100\%$, we allow mixed income's labor share to be country-year varying and take on plausible values, while ensuring that SNA aggregate values remain intact and consistent with national accounting identities. In practice, while the ILO (2019) method generates important country-year variation, the global average value for ϕ^{ILO} does not differ much from our benchmark value $\phi = 75\%$.

Mixed income in China and the US We make minor mixed-income adjustments to the benchmark series for China and the United States. First, for China, Piketty, Yang and Zucman (2019) show that the income of many self-employed agricultural workers is attributed to employee compensation in the SNA 2008 data and not to mixed income (as in other countries). They conclude that Chinese national accounts systematically underestimate mixed income but overestimate compensation of employees. We therefore estimate mixed income according to ILO (2019) for China.

We use the factor shares from Piketty et al. (2018) for the US. The authors show that some large businesses (including listed firms) are organized as partnerships and are classified as non-corporate businesses and not corporations (as in other countries). The SNA of the US lists their income as mixed income (rather than corporate profits). The revised US series therefore (i) assumes a higher capital share of income for partnerships vs. other non-corporate businesses; and (ii) factors in the rising capital intensity of partnerships since the 1980s.

Figure B1: ETR Evolution and Previous Literature

(a) Kostarakos and Varthalitis (2020) (b) McDaniel (2020)



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 updated dataset in McDaniel (2020) that includes 30 OECD countries from 1995 to 2018. This extension is based on McDaniel (2007) (Table B3), and covers the largest OECD countries, including the US, as well as Mexico and Turkey. 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. The differences in ETR, mainly in levels rather than trends, can be due to i) the computation of the personal income tax, ii) the assumptions for factor income shares, iii) the definition of mixed income, and iv) the data sources used. In particular, our ETR measures differ from Kostarakos and Varthalitis (2020) and McDaniel (2007) in terms of the PIT allocation and the mixed-income definition, as detailed in Table B3.

Table B3: Effective Tax Rates: Pre-Existing Databases

Paper	Time	Countries	Source	Methodological note on differences with our approach
Mendoza et al (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 biggest members	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, extensions consider preferential tax treatment of pension funds and dividends. Minor differences regarding the inclusion of social security contributions.
McDaniel (2007) (McDaniel 2020)	1950-2003 (updated: 1995-2018)	15 OECD biggest members (updated 30 OECD biggest members)	OECD	Difference: Mixed income imputed to capital based on economy-wide share. Difference: Labor and capital in PIT are taxed at the same rate Difference: Uses some tax data from national accounts
Kostarakos and Varthalitis (2020)	1995-2019	EU-27 members	Eurostat	Follows Carey and Rabesona (2004)

Appendix C Trade Liberalization Event Studies

C.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 our 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.

Selection of events 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 licence 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 & Pavcnik, 2016). The timing of the events and academic references are provided in Table A1.

Timing of events 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 and unexpectedly abolished the list of suspended import licences and removed nearly all of the remaining special customs regimes."

- **Columbia** 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 India's balance of payment crisis, which was triggered by "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 in Vietnam was implemented as a broad trade agreement that did not involve negotiations over specific tariffs (McCaig & Pavcnik, 2018). The reform was driven by the American government's decision to reclassify Vietnam from 'Column 2' of the US tariff schedule to the '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. McCaig and Pavcnik (2018) show that there are no differential trends between Vietnamese exports to the US vs other high-income countries.

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 in the 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. These additional reforms also reduced cross-border barriers and may have contributed to the medium-run effects observed in Figure 5.

C.2 Event study methodology

Sample construction 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 (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 also estimate the difference-in-differences (DiD) model:

$$y_{ct} = \beta^{DiD} \cdot \mathbb{1}(e \geq 0)_t \cdot D_c + \theta_t + \kappa_c + \pi_{Year(t)} + \epsilon_{ct} \tag{9}$$

which uses the same notation as equation (4). Moreover, we use the imputation method by Borusyak et al. (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 (link). All the DiD average treatment effects are reported in Table A2.

Simultaneously matching on main outcomes We test that our results hold up with a more restrictive synthetic control. Specifically, we use our three main outcomes—trade, ETR_K and ETR_L—to construct one synthetic control group per treated country. This still allows us run separate regressions for each outcome, but the composition of the control group is now held constant across regressions. The results are reported in Panel B of Table A2.

C.3 Alternative trade liberalization event study

In this subsection, we present event-study results based on an alternative measure of trade liberalization events. In particular, we use the liberalization events from Wacziarg and Welch (2008), who extended the Sachs-Warner (1995) study to cover 141 countries at all levels of development between the early 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 5.1 and C.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, which was one of our main event criteria, was the remaining event-condition to be satisfied in Wacziarg and Welch (2008). Based on a within-country event-study design, the authors find that the trade liberalization events led to higher trade openness, investment and GDP growth.

We estimate the effects of the liberalization events using the DiD model

$$y_{ct} = \beta^{DiD} \cdot E_{ct} + \theta_t + \theta_c + \epsilon_{ct} \tag{10}$$

where 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. The standard error ϵ_{ct} is clustered at the country level. Given the large number of liberalization events ($N = 68$), estimation issues arising from heterogeneous treatment-timing are likely to be important. For this reason, we report and focus on the imputed treatment effects based on Borusyak et al. (2021). We do not use synthetic controls. We restrict the sample to developing countries between 1965 and 2008 (permitting a 10-year post-event horizon for all events, like in our main event-study in Section 5.1).

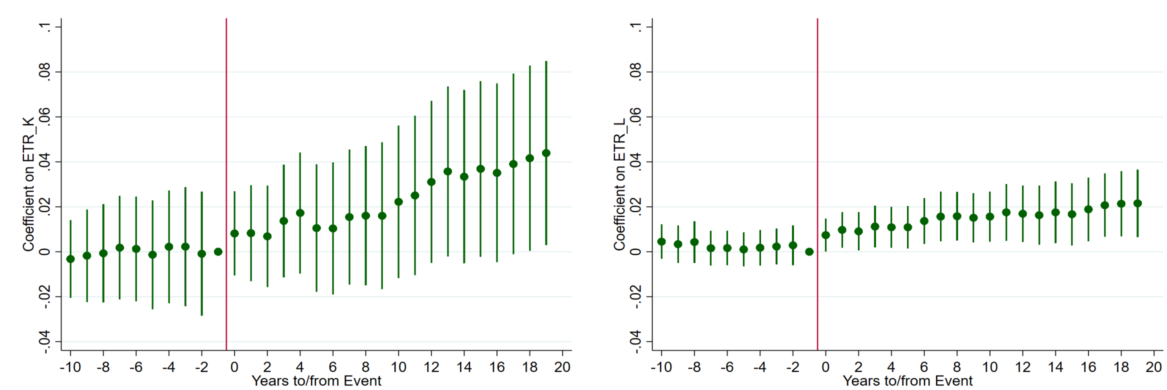
Panel A of Table C1 reports the β^{DiD} impacts on trade openness, ETR_K and ETR_L. Imputed treatment effects are more precisely estimated than the simple DiD coefficients, possibly due to the above-mentioned issue. Despite being based on broader event-definition criteria, the trade liberalization events produce qualitatively similar results to the main event-study (Section 5.1): we find positive impacts on openness and both ETRs, and a larger magnitude-impact on ETR_K than ETR_L. Figure C1 estimates the dynamic event-study regression with the method of Borusyak et al. (2021). Liberalized and control countries are on parallel trends until the event onset; both ETRs see marked increases that begin in the immediate post-event years.

The remaining panels of Table C1 conduct robustness checks similar to those for the main liberalization events (Section 5.1). In Panel B, the results are robust to estimating the effects in a fully balanced panel 10-years post-reform (matching the sample construction and post-event horizon for the main events). In Panel C, the results hold when the control group is formed within-region. To alleviate concerns over concurrent external reforms, Panel D shows the results are robust to excluding countries which have cross-border capital liberalization events at any point during the sample-period (based on Bekaert, Harvey and Lundblad, 2000). Finally, to alleviate concerns about confounding domestic reforms that impact ETRs, Panel E shows the results hold when we exclude countries with concurrent domestic reforms (as coded in Wacziarg & Wallack, 2004).

Figure C1: Event-Study of Trade Liberalization Based on Wacziarg & Welch (2008).

(a) Effective tax rate on capital

(b) Effective tax rate on labor



Notes: These graphs show the event-study impacts of the trade liberalization events from Wacziarg and Welch (2008) on the effective tax rate on capital (left panel) and the effective tax rate on labor (right panel). The graphs show the event-study coefficients on the to/since event dummies, based on estimating the dynamic event-study regression with the method developed by Borusyak, Jaravel, and Spiess (2021). The bars represent the 95% confidence intervals. Standard errors are clustered at the country level. For more details on the liberalization events, see Appendix C.3.
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Table C1: Trade Liberalization Event-Study Based on Wacziarg & Welch (2008)

	Trade	ETR_K	ETR_L
	(1)	(2)	(3)
Panel A: *Benchmark*			
Post*Treat	0.030	0.016	0.006
	(0.048)	(0.017)	(0.006)
Imputed treatment effect	0.088*	0.039**	0.021***
	(0.049)	(0.016)	(0.005)
N	4032	4032	4032
Panel B: *Fully balanced panel, 10 year post-reform*			
Imputed treatment effect	0.110**	0.031**	0.018***
	(0.054)	(0.014)	(0.005)
N	3082	3082	3082
Panel C: *With region-year fixed effects*			
Imputed treatment effect	0.082**	0.040**	0.021***
	(0.040)	(0.016)	(0.005)
N	4032	4032	4032
Panel D: *Excluding countries with capital liberalization*			
Imputed treatment effect	0.101*	0.029*	0.014**
	(0.057)	(0.016)	(0.006)
N	2651	2651	2651
Panel E: *Excluding countries with domestic reforms*			
Imputed treatment effect	0.053	0.038**	0.017***
	(0.050)	(0.016)	(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 (2008), 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 equation 10. 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 C.3. * p<0.10 ** p<0.05 *** p<0.01.

Appendix D Instrumental Variables for Trade

In this section, we outline the construction of the two instrumental variables. Both instruments are drawn from Egger et al. (2019), who provide further details.

Instrument based on quantitative trade models The first instrument leverages the structure of gravity models in general equilibrium. These models permit calibration of country pair-year-specific trade costs from trade data, relying on three key assumptions: (i) producers are perfectly competitive and make zero profits or charge a constant markup; (ii) trade costs take the iceberg form; and (iii) aggregate expenditure and its allocation across products are separable. These assumptions imply that bilateral consumption shares towards country o by consumers in country c in year t, denoted π_{cot}, have multiplicative components that are exporter-year-specific (ψ_{ot}), importer-year-specific (ι_{ct}) and pair-year-specific (β_{cot}):

$$\pi_{cot} = \psi_{ot} \times \iota_{ct} \times \beta_{cot}$$

The component ψ_{ot} is proportional to country o's supply potential and captures production costs and gross-of-tax factor income—and might be influenced by both capital and labor taxation. The component ι_{ct} depends on the consumer price index, which varies across years and countries.[70] β_{cot} captures trade frictions across country-pairs and time.[71] The product of the normalized shares gives the bilateral frictions of importing-exporting country-pairs at a point in time:

$$\frac{\pi_{cot}}{\pi_{cct}} \cdot \frac{\pi_{oct}}{\pi_{oot}} = \beta_{cot} \cdot \beta_{oct}$$

Finally, we use $\beta_{cot} \cdot \beta_{oct}$ to compute the average ct-specific costs of exporting and importing, which constitutes the instrument:

$$Z_{ct}^{gravity} = \sum_{o \neq c} [\beta_{cot} \cdot \beta_{oct}]$$

[70] Both ψ_{ot} and ι_{ct} may capture country-year-specific trade costs, but the pair-specific component β_{cot} is free of such country-year specific influence.

[71] Egger et al. (2019) exploit the multiplicative model structure about π_{cot} to recover measures of β_{cot}. They assume that transaction costs between domestic sellers and customers are zero, such that $\beta_{cct} = 1$. Both the importer-year component and exporter-year component can then be eliminated by normalizing import and export trade shares by the importer and exporters' consumption from domestic sellers.

Note that all exporter-year and importer-year factors are removed from the instrument. This instrument is valid so long as the *distribution* of trade costs among country-pairs (not its level) is not influenced by the level of factor incomes or effective tax burdens. Constructing this instrument requires data on country-pair trade flows: we use UN COMTRADE data to construct a large sample of bilateral consumption shares.[72] First-stage regressions with $Z_{ct}^{gravity}$ are shown in Table A3.

Instrument based on global oil prices & transport distances The second instrument exploits spatial heterogeneity across countries in a way that interacts with oil price shocks. This instrument is based on global oil price changes over time and within-country transportation distances from cities to the nearest port.[73] The instrument is the variance of the product oil price p_t^{oil} $\times$ distance d_c^k across cities k in country c in year t:

$$Z_{ct}^{oil-dist} = \frac{1}{2}\sum_{k=1}^{3}[(p_t^{oil}d_c^k - p_t^{oil}\overline{d_c})^2]$$

where $\overline{d_c}$ is the average city-port distance in country c. This variance increases in countries whose main cities are far from the nearest port and far from each other, which implies a larger change to transportation costs following a global oil price shock in spread-out countries than in countries with concentrated populations. It is this transportation-cost shock that the instrument captures.[74]

This second instrument does not hinge on theoretical assumptions. Instead, this instrument is valid so long as the country-specific distribution of trade-costs, induced by the interaction between global oil price shocks and a country's fixed spatial concentration, is not correlated with contemporaneous changes in factor incomes and effective tax rates. First-stage results for $Z_{ct}^{oil-dist}$ are presented in Table A3.

[72]We augment our raw data from COMTRADE with data from Harvard Growth Lab, who harmonized importer- and exporter-reported trade flows to expand the coverage and improve the precision of country-partner-year trade flow estimates.

[73]For the former, we retrieve the OPEC Reference Basket benchmark world price of crude oil. For the latter, we measure road distances from the three largest cities (according to UN population statistics) to their nearest port, using SeaRates international shipping logistics calculators.

[74]Alternatively, one could measure the variance in distance and then multiply it by the global oil price. The distribution of the variance instrument $Z_{ct}^{oil-dist}$ across country-years would not change; the only impact would be a level-shift by the price. We consider the main approach to more closely capture the sensitivity of transport costs to spatial concentration, but results based on this alternative variance measure are similar.

Appendix E Additional Analyses of Tax Capacity

E.1 Firm-level analysis in Rwanda

In this section, we investigate the relationship between trade exposure and the effective capital tax rate for corporate firms in Rwanda.

Data Our analysis draws on three administrative data sources from Rwanda, accessible at 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, as well as information on industry codes and geographical location. We use these data to measure firms' effective tax rate on profits. 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 install and use (Eissa and Zeitlin, 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' direct and indirect trade exposure. Importantly, since the network data is based on tax-IDs to link firms, this implies that 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 (Huneeus, 2020); Costa Rica (Alfaro-Ureña et al.); Ecuador (Adao et al., 2022); India (Gadenne et al., 2022); Turkey (Demir et al., 2021); and Uganda (Almunia et al, 2023a, 2023b).

Our sample is firms registered for CIT which 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 (6), as the ratio of corporate taxes paid divided by net profit. Net profit is revenue minus material, labor, operational, depreciation and financial costs.

It is in principle also possible to measure ETR_i^K amongst firms that are registered for simplified taxes (and pay a flat amount or a rate on turnover). However, since the information on their tax returns regarding cost items is less detailed than for CIT, the measure of profit in the denominator of ETR_i^K is less precise. Moreover, only a small number of these firms are also registered for VAT (due to eligibility criteria, size and segmented trading networks: Gadenne et al., 2022). This implies that these firms are most likely to be recorded in the EBM data as clients in a particular transaction; as a consequence, reporting of transactions on these firms is less comprehensive than for corporate firms. Keeping these data challenges in mind, we can include these firms in the main analysis; the results are qualitatively similar (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:

$$s_i^{Total} = s_{Fi} + \sum_{l \in V_i} s_{li} \cdot [s_{Fl} + \sum_{r \in V_l} s_{rl} \cdot (s_{Fr} + ...)] \quad (11)$$

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 the definition of 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}). In other words, 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 international imports through their supplier network; in an extension, we find qualitatively similar results when we study firms' exposure to exports through their client network (results available).

Figure E1 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 suppliers which use foreign inputs in their production process. Indeed, most formal firms are strongly dependent on foreign trade, but only a limited number show that dependence through the direct foreign inputs observed in customs data: in the median firm, for example, the total foreign input share is 48% (it is 39% for the median Belgian firm in Dhyne et al., 2021).

Impacts of trade exposure on ETR^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 E2, 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 E2 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 the robustness of this association in Panel A of Table E1, where we estimate regressions of the form

$$ETR_{itg}^K = \mu \cdot s_{it}^{Total} + \Theta \cdot X_{it} + \pi_t + \pi_g + \epsilon_{itg} \tag{12}$$

where ETR_{itg}^K and s_{it}^{Total} are the corporate effective tax rate and trade exposure of firm i in year t in industry-geography group g, and π_t and π_g are fixed effects for year and industry-geography. ϵ_{itg} is clustered at the industry-geography level (robust to clustering at firm-level). Column (1) corresponds to the association in Figure E2. Column (2) adds 561 industry-geography interactive fixed effects between industry categories and geographical locations. In column (3), we add time-varying controls, including a firm's age, number of employees, and total number of clients and suppliers. In column (4), we include firm fixed effects (and cluster at the firm-level). The variation in trade exposure is now within-firm over time and can come, for example, from new linkages with suppliers that import directly or rely significantly on foreign inputs. The positive association between trade and ETR_i^K holds in these specifications.

In column (5), we employ an instrumental variable that creates trade shocks from changes in world export supply of country-product combinations in which a firm had a previous import relationship. Previous studies have used this strategy, arguing that the shocks are plausibly exogenous and vary significantly across firms because firms do not have all inputs in common (Hummels et al., 2014). Specifically, we follow the design in Dhyne et al. (2021) that extends the shift-share approach of Hummels et al. (2014) to a setting with shock pass-through via network linkages. To construct the direct import shock for firm i, we use information about the firm's product-country-level imports in year $t-1$ (the share variable capturing firm-specific shock exposure) and the aggregate shift in world export supply for each country and product:

$$logM_{it}^{D} = log\sum_{a,c} s_{ic,t-1}^{a,M} \cdot WES_{a,c,t} \tag{13}$$

where $s_{ic,t-1}^{a,M}$ is the share of imports of firm i in the initial 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. For firm i's suppliers, we construct the weighted average of their import shocks, using i's input share from each supplier in the previous year as the weights. We also construct the weighted average of the trade shocks of the suppliers to the suppliers of firm i, using the recursive formulation in equation (11). This gives us three instruments, namely import trade shocks direct to firm i, $logM_{it}^{D}$, as well as shocks to its suppliers, $logM_{it}^{S}$, and shocks to the suppliers of its suppliers, $logM_{it}^{SS}$. The 1^{st}-stage regression is then:

$$s_{it}^{Total} = \beta_1 \cdot logM_{it}^{D} + \beta_2 \cdot logM_{it}^{S} + \beta_3 \cdot logM_{it}^{SS} + \kappa_t + \kappa_i + \epsilon_{it} \tag{14}$$

and the 2^{nd}-stage is equation (12). Standard errors are clustered at the firm-level.

In column (5), we find that increases in a firm's trade exposure, when instrumented by the import shocks, cause an increase in the effective corporate tax rate ETR_i^K. The instruments are relevant, with a 1^{st}-stage Kleibergen-Paap F-statistic of 18.17.[75]

In Section 6, we argued that trade may positively impact ETR^K through its effect on size (as effective taxation is higher in larger firms). We investigate this in Panels B and C of Table E1. In Panel B, we find, across the various specifications including IV, that more exposure to international trade increases a firm's size. We proxy for size with annual revenue. Panel C reveals a positive association between a firm's size and

[75]Our results are robust to controlling for two additional types of trade shocks. First, we can control for shocks to the potential suppliers of firm i, defined as the set of firms that operate in the same industry and geographical area as i's current suppliers but that are not currently supplying to i. Second, we can control for shocks to firm i's horizontal suppliers, defined as the set of firms that are suppliers to firm i's current clients.

its effective corporate tax rate in the different specifications, though we cannot employ the IV due to the exclusion restriction. Finally, we find no impact of trade on a firm's take-up of statutory deductions, reduced rates or exemptions (results available).

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.

These results provide firm-level identified evidence linking trade to ETR^K in Rwanda, which is complementary to the country-level results in developing countries (Tables 1-3). The results also support the tax-capacity mechanism interpretation, where the positive impact on ETR^K is mediated by trade's expansion of income in larger firms where effective taxation is higher.

E.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 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 1^{st}-stage regressions are

$$log(imp_{ct}) = \beta_1 \cdot Z_{ct}^{gravity} + \beta_2 \cdot Z_{ct}^{oil-dist} + \mu_c + \mu_t + \epsilon_{ct}$$
$$log(exp_{ct}) = \pi_1 \cdot Z_{ct}^{gravity} + \pi_2 \cdot Z_{ct}^{oil-dist} + \eta_c + \eta_t + \iota_{ct}$$

where $log(imp_{ct})$ and $log(exp_{ct})$ 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 1^{st}-stage (results without logs are qualitatively similar). The 2^{nd}-stage is

$$y_{ct} = \theta_1 \cdot log(imp_{ct}) + \theta_2 \cdot log(exp_{ct}) + \kappa_c + \kappa_t + \phi_{ct}$$

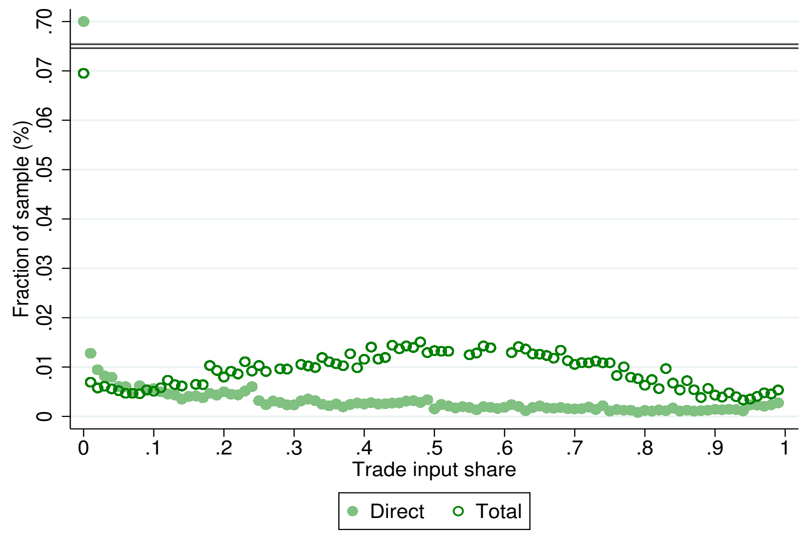
The set-up is similar for the second IV (intermediate G-S vs final G-S) where we replace $log(imp_{ct})$ and $log(exp_{ct})$ with the log of total trade in intermediate G-S to

NDP and the log of total trade in final G-S to NDP. IV results for developing countries are in Panel A of Table E2, with 1^{st}-stage regressions in Panel B. Two comments are in order. First, the two IVs could in theory impact the different types of trade (Bergstrand and Egger, 2010). In practice, $Z^{gravity}$ significantly predicts all types of trade, while $Z^{oil-dist}$ significantly predicts imports and final G-S but not exports or intermediate G-S (Panel B). It is unclear if the 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 (10.18 and 7.39). 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). Second, 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.

Focusing on the IV results, col. (1) shows exports increase ETR_K while imports decrease it; col. (2) shows trade in intermediate G-S increases ETR_K while trade in final G-S decreases it. In each IV, the coefficients imply a positive overall effect of trade openness on ETR_K even if the two trade-types had equal shares of NDP. In practice, many LMICs run trade surpluses (UNCTAD, 2014) and trade more in intermediate G-S than final G-S (Miroudot, Lanz and Ragoussis, 2009). We can statistically reject that the different trade-types have the same impact on ETR_K, at 10% for exports vs imports and at 1% for intermediate G-S vs final G-S. Similar patterns hold for ETR_L (cols. 3 and 4). The remaining columns focus on mechanism outcomes. Exports cause an increase in the corporate income share (μ_C in equation 6), while imports decrease it. Trade in intermediate G-S increases μ_C while trade in final G-S decreases it. Results are similar for the average corporate effective tax rate ($\overline{ETR}_C^K$ in equation 6).

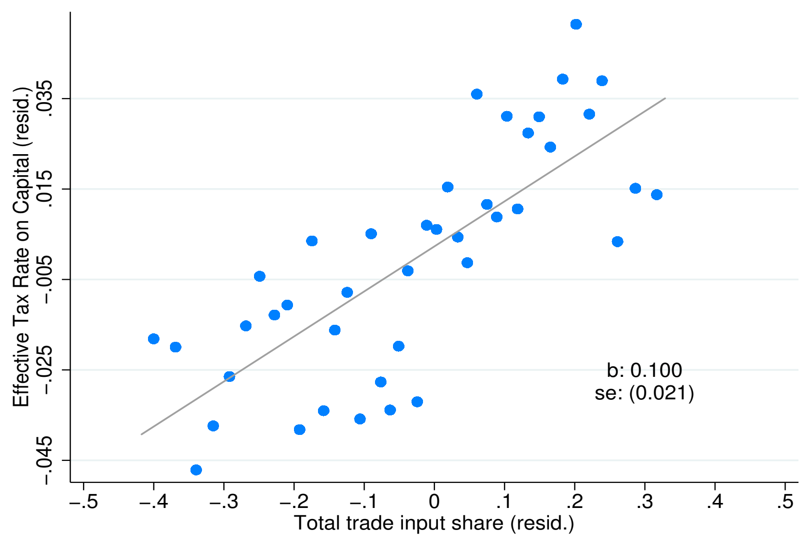
Since we only have 2 instruments, we cannot decisively conclude on the impacts for the 4 types of trade (imports of intermediate G-S, exports of intermediate G-S, imports of final G-S, exports of final G-S). Notwithstanding, the signs of the four estimated IV coefficients are consistent with imports of final G-S decreasing ETR_K and mechanism outcomes (μ_C,$\overline{ETR}_C^K$), and imports of intermediate G-S increasing them.

Figure E1: 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 represent a scale break in the vertical axis. More details in Section E.1.

Figure E2: 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 E1.

Table E1: Firm-Level Regressions in Rwanda: ETR^K, Trade and Size

	(1)	(2)	(3)	(4)	(5)
Panel A outcome: ETR^K					
S^{Total}	0.100***	0.087***	0.075***	0.025*	0.133**
	(0.021)	(0.017)	(0.017)	(0.014)	(0.060)
Panel B outcome: Log revenue					
S^{Total}	1.362***	1.351**	1.078**	0.202*	1.444***
	(0.466)	(0.542)	(0.475)	(0.107)	(0.233)
Panel C outcome: ETR^K					
Log revenue	0.040*	0.092***	0.077**	0.029***	-
	(0.023)	(0.029)	(0.027)	(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	
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^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 (12): Column (1) includes year fixed effects; column (2) adds industry-geography fixed effects; column (3) adds firm-year controls (firm age, 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, Jørgensen, Munch, and Xiang (2014). The instruments are described in detail in equation (13) in Section E.1. In column (5), we also report the 1^{st}-stage Kleibergen-Paap F-statistic from estimating the 1^{st}-stage in equation (14). * 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).

Table E2: 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	0.406		0.184**		0.374**		-0.227*		0.475	
	(0.258)		(0.092)		(0.181)		(0.136)		(0.287)	
	[0.079]		[0.019]		[0.092]		[0.119]		[0.053]	
Import of G-S	-0.295*		-0.153***		-0.265**		0.136		-0.345**	
	(0.151)		(0.049)		(0.108)		(0.089)		(0.149)	
	[0.075]		[0.008]		[0.097]		[0.125]		[0.051]	
Intermediate G-S		0.270***		0.115***		0.252***		-0.162***		0.316***
		(0.100)		(0.042)		(0.072)		(0.060)		(0.101)
		[0.039]		[0.013]		[0.046]		[0.033]		[0.033]
Final G-S		-0.204***		-0.105***		-0.185***		0.096**		-0.239***
		(0.065)		(0.026)		(0.049)		(0.046)		(0.050)
		[0.037]		[0.006]		[0.019]		[0.119]		[0.006]
F-test: Equality of coefficients [p-value]	2.99	8.45	5.75	10.88	5.01	13.49	2.68	6.08	3.59	13.77
	[0.086]	[0.004]	[0.018]	[0.001]	[0.027]	[0.000]	[0.104]	[0.015]	[0.060]	[0.000]
N	4572	4572	4572	4572	4572	4572	4572	4572	4572	4572

Panel B: 1^{st}-stage	Import of G-S	Export of G-S	Intermediate G-S	Final G-S
	(1)	(2)	(3)	(4)
$Z^{gravity}$	0.277***	0.248***	0.274***	0.269***
	(0.037)	(0.058)	(0.035)	(0.055)
$Z^{oil-distance}$	-0.085***	0.013	0.019	-0.121***
	(0.014)	(0.019)	(0.013)	(0.023)
1^{st}-stage F-statistic	131.83	21.29	65.03	82.09
1^{st}-stage Sanderson-Windmeijer Weak Instrument F-statistic	35.70	33.25	51.78	55.50
1^{st}-stage Kleibergen-Papp F statistic	7.39		10.18	
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 1^{st}-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 and 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-Windmeer multivariate F-test of excluded instruments; and, the Kleibergen-Paap 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 E.2.

Appendix F Capital Liberalization Events

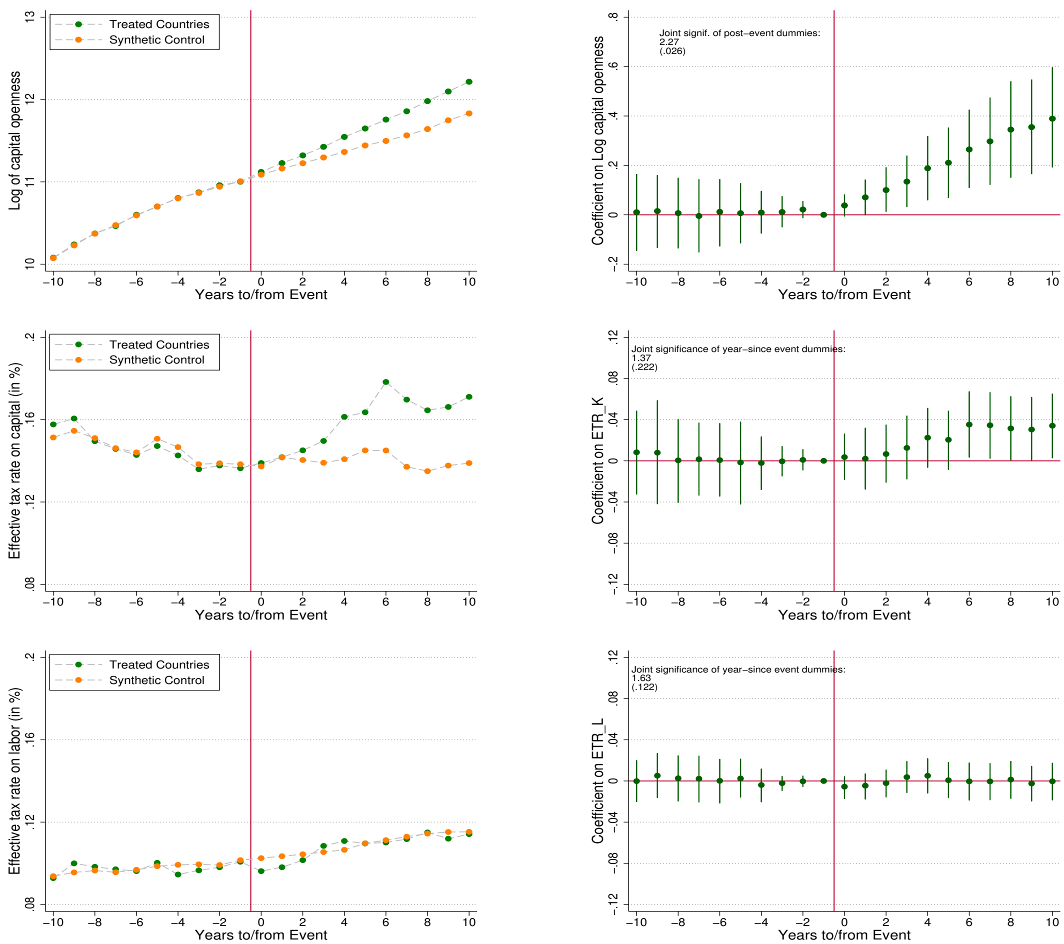
To attempt to investigate the impact of capital liberalization on effective tax rates, we draw on Chari et al. (2012). The authors measure capital liberalization events in 25 developing countries as the date when foreign investment in the domestic stock market was first allowed. They show that these events significantly increase foreign capital inflows, including foreign direct investment (FDI) and import of capital goods.[76] 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 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 (Gygli et al., 2019). We find similar results when using alternative measures of capital openness, including portfolio equity assets and liabilities and the KOF financial globalization index (Gygli et al., 2019).

Figure F1 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 the growth of firms and/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 income-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 which impact cross-border capital flows in developing countries and their effects on ETR.

[76] FDI includes green field investments (building plants from scratch) and cross-border mergers and acquisitions (M&A). Chari et al. (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.

Figure F1: 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 (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 F.