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A Deep Dive into Tax Buoyancy: Comparing Estimation Techniques in a Large Heterogeneous Panel

Prepared by Antoine Cornevin, Juan Sebastian Corrales, and Juan Pablo Angel

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March 2023

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A Deep Dive into Tax Buoyancy: Comparing Estimation Techniques in a Large Heterogeneous Panel.

Antoine Cornevin* Juan Sebastian Corrales† Juan Pablo Angel‡

March 6, 2023

This paper provides new empirical evidence on tax buoyancy (tax revenues responsiveness to changes in economic activity) over the period 1990-2020 using a large panel of 185 countries. This study compares short-term and long-term buoyancy coefficients for total tax revenues and different individual taxes by reviewing and contrasting a range of estimators. Our results broadly confirm the main body of the literature on long-term buoyancy hovering around one. We find evidence of lower estimates for short-term buoyancy relative to previous literature, suggesting a limited automatic stabilization power of taxes. As a robustness exercise, in addition to changes in tax rates, we introduce novel control variables for tax exemptions and bases to disentangle discretionary from automatic tax revenue changes. The marginal changes in the results when controlling for policy actions suggest that, on average, the economic cycle does not necessarily influence tax reforms.

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1 Introduction

The COVID-19 pandemic demanded unprecedented monetary and fiscal policy measures that contributed to mitigating the negative impact on the economies but simultaneously generated complex challenges for public finance's sustainability. The need to continue supporting the recovery, coupled with tighter global financial conditions, make revenue mobilization a critical element for successful medium-term fiscal consolidation plans. However, credible forecasts of government income depend on having solid answers to the question of how tax revenue responds to changes in economic activity.

The literature has approached this question by estimating two related yet different concepts: tax buoyancy and tax elasticity. Measuring tax buoyancy does not involve controlling for discretionary changes in the tax system or administration. Hence, it captures the effects of both policy changes and automatic revenue growth. Meanwhile, estimating tax elasticity implies controlling for the effects of tax policy measures to isolate the revenue growth due only to changing economic conditions. Tax elasticity is, therefore, considered a better factor for forecasting purposes. Nonetheless, while tax elasticity estimates abound in the literature (see for example Sancak et al. (2010), Fricke and Süssmuth (2014), Boschi and d'Addona (2019), Mourre and Princen (2019)), there are several difficulties to consider when estimating it. First, an enormous amount of very detailed information is necessary to assess developments in the various tax bases. As such data usually does not exist, forecasters rely on proxies for the tax bases (e.g., Gross Domestic Product). Second, even if one could perfectly identify the dynamics of the underlying tax bases, accurate identification of changes in tax rates or exemptions may not be possible. Third, the relationship between tax revenues and their tax bases could be non-linear due to the intricate design and reforms of some taxes. In addition, other elements such as collection lags, tax evasion, and differences in accounting systems (e.g., accrual vs cash-based) further complicate this task (see Lagravinese et al. (2020) for a discussion on issues estimating tax elasticity).

We concentrate on tax buoyancy estimates due to (i) the limited availability of systematic data on changes in tax policy parameters for the large sample of countries (185) included in our database spanning from 1990 to 2020 and (ii) the fact that in a long-run perspective, buoyancy represents a comprehensive measure of the tax systems sustainability, as it accounts for both the soundness of the tax bases and the effectiveness of tax changes. Several studies have estimated short- and long-term tax buoyancy coefficients following a panel data approach. For example, Belinga et al. (2014) analyze OECD countries between 1965 and 2012 and find that for aggregate tax revenues, short-run tax buoyancy does not significantly differ from one in the majority of countries, while long-run buoyancy exceeds one in about half of the countries. Dudine and Jalles (2018) study 107 countries between 1980–2014 and find that for advanced economies both short- and long-run tax buoyancy coefficients are not different from one for total tax revenue. Also, they find long-run tax buoyancy coefficients greater than one for Corporate Income Tax in advanced economies, Personal Income Tax in emerging economies, and Taxes on Goods and Services in low-income countries. Lagravinese et al. (2020), using an alternative estimator (dynamic common correlated effects) with respect to previous literature and a sample of 35 OECD countries over the period 1995–2016, find that both short- and long-run tax responses are lower than one. And Gupta et al. (2022) review the topic in sub-Saharan African (SSA) using a sample of 44 countries during 1980–2017 and find that the long-term tax buoyancy is either one or slightly above one in most cases. Also, while short-term buoyancy hovers around one for total tax revenue, in the case of personal income tax is significantly less than one.

Using a larger database than previous studies, this paper takes stock of recent econometric techniques in the literature to determine how tax buoyancy coefficients differ for different groups of countries and for different types of taxes. Our contribution to the literature is threefold: (i) we construct a more comprehensive tax revenue dataset to estimate tax buoyancy (185 countries); (ii) we review and compare differences in short- and long-term tax buoyancy coefficients resulting from different estimators and accounting for the presence of cross-sectional dependence in panel units [1]; and (iii) we introduce new control variables, taking advantage of information from the Global Tax Expenditure Database and the Tax Policy Reform Database, in an attempt to better disentangle discretionary from automatic tax revenue changes (i.e. obtain estimates closer to elasticity).

The remainder of the paper is organized as follows. Section 2 discusses the empirical methodology and discusses the data and stylized facts. Section 3 presents our estimates of tax buoyancy coefficients for different types of estimators. Section 4 explores the effect

[1] Since we group countries by common characteristics (e.g., level of income) ignoring some weak or strong cross-sectional correlation may lead to biased estimates (Pesaran, 2006; Chudik and Pesaran, 2015b; Lagravinese et al., 2020).

of discretionary tax measures on tax buoyancy coefficients. The last section concludes and elaborates on some policy implications.

2 Empirical methodology

2.1 Data and stylized facts

We collect data on tax revenues from the IMF World Economic Outlook (WEO) when available, and from the OECD Revenue Statistics otherwise. The database includes data on aggregate tax revenues, as well as Personal Income Tax (PIT), Corporate Income Tax (CIT), Taxes on Goods and Services (TGS), Value-Added Tax (VAT), and Social Security Contributions (SSC) for 185 countries, including 35 Advanced Economies (AE), 90 Emerging Market Economies (EME), and 60 Low-Income Countries (LIC) between 1990 and 2020. The panel of tax revenue data is unbalanced, as the number of countries with available data varies by year and tax category. We exclude some countries from the sample, depending on the estimated model, due to a limited time span of some of the timeseries.[2] Figure 25 in the appendix plots the number of countries with available data for aggregated tax revenues. To address potential selection biases towards more developed economies in earlier periods of the sample, we run additional regressions for the period 2001-2019 in Section 3.3.2. GDP and inflation data are also obtained from the WEO. Table 12 in the appendix presents summary statistics for the key variables and their sources.

We combine several data sources to account for discretionary tax policy changes in the regressions. Vegh and Vuletin (2015) provides yearly data on tax rates, covering PIT, CIT, and VAT for a sample of 77 countries from 1960 to 2020. The Tax Policy Reform Database (TPRD) of the IMF (Amaglobeli et al., 2018) supplies data on tax base reforms, including PIT, CIT, VAT, SSC, as well as excise (EXE) and property taxes (PRO) for 23 Advanced Economies (AE) and Emerging Market Economies (EME) from 1930 to 2017. The Global Tax Expenditures Database (GTED) of the Council on Economic Policies and the German Development Institute (Redonda et al., 2022) provides data on tax expenditures (TE), henceforth foregone revenues, for 102 countries between 1990 and 2020.

[2]As a general rule, we exclude timeseries with fewer than 15 years of available observations due to the consumption of a significant number of degrees of freedom by estimation techniques such as the dynamic common correlated effect (DCCE). Section 2.2.3 provides further information on the different estimators.

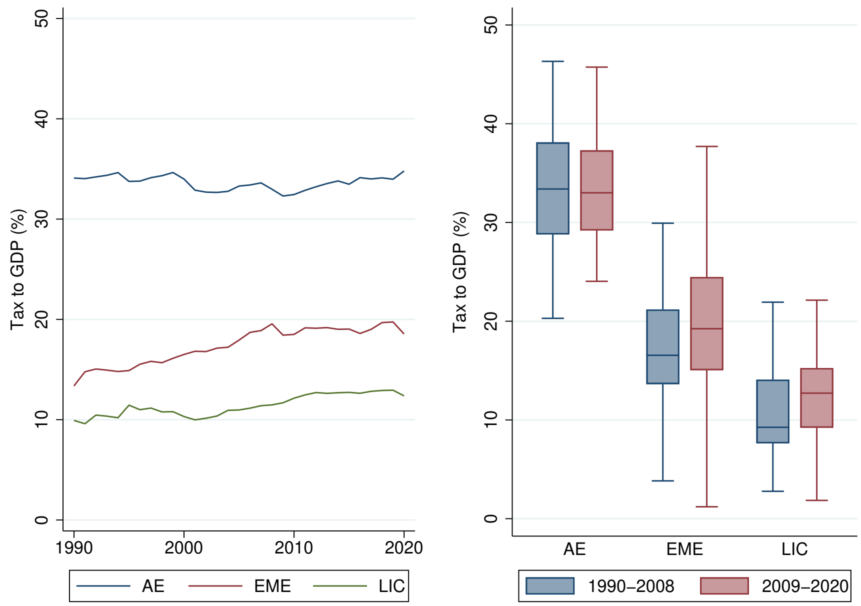


Figure 1: Average tax to GDP ratio by income group

The data, shown in the left panel of figure 1, reveals that the average tax-to-GDP ratio in Advanced Economies (AE) is significantly higher than that in Emerging Market Economies (EME) and Low-Income Countries (LIC), at 33.6% versus 17.3% and 11.4%, respectively, on average over the sample period.[3] While the tax-to-GDP ratio in AE has remained relatively stable from 1990 to 2020, with a modest increase of 0.7 percentage points, EME and LIC have seen significant tax mobilization progress, with the tax-to-GDP ratio increasing by 5.1 and 2.5 percentage points, respectively, from 1990 to 2020.

The right panel of figure 1 and figure 2 also provide two important pieces of information: (i) the tax-to-GDP ratio varies considerably within income groups, in the appendix provide a detailed breakdown of the composition of tax revenues by country. and (ii) the composition of tax revenues varies significantly by country. These sources of heterogeneity motivate the use of panel econometric techniques with heterogeneous coefficients, as well as the separate study of individual tax components, as argued in the following sections. This last point is especially relevant, given the consensus in the literature that tax components respond differently to changes in economic activity (see, for example, Belinga et al., 2014; Deli

[3]Figures 26, 27, and 28 in the appendix provide a detailed breakdown of the tax-to-GDP ratio by country.

et al., 2018; Dudine and Jalles, 2018; Boschi and d'Addona, 2019; Mourre and Princen, 2019; Lagravinese et al., 2020). We exclude social security contributions from total tax revenues, as this item is usually much less elastic than other tax components and may therefore distort estimates of aggregate tax revenues buoyancy in some cases. This study also excludes taxes on goods and services from the analysis as the latter include various types of taxes, including sales and value-added taxes, excise taxes, import duties, and taxes on exports, which may react differently to changes in economic activity.

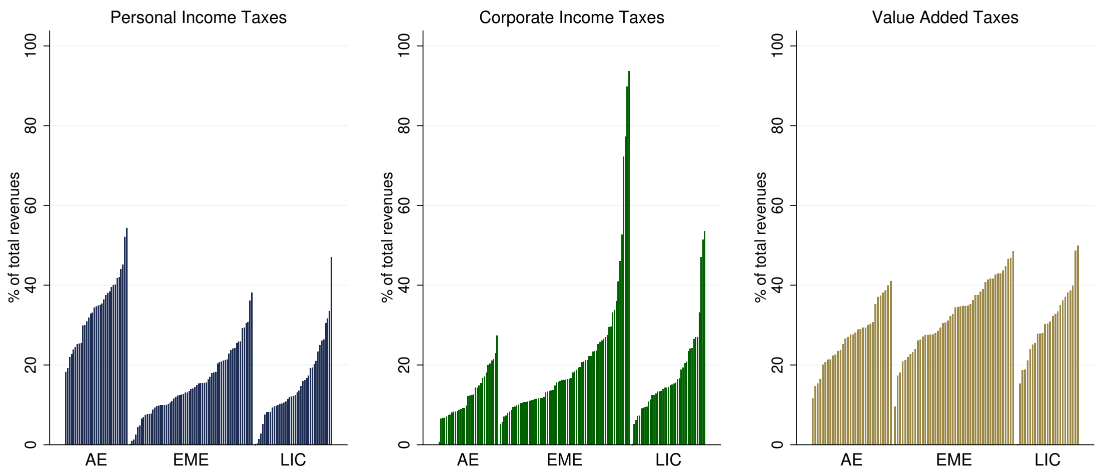


Figure 2: Tax revenues composition by tax category and income group (% of total revenues)

However, we do consider VAT in our analysis because the latter (i) is available for a large number of countries; (ii) accounts on average for 60% of taxes on goods and services in our sample (when data is available) and (iii) has a direct link to consumption. As a result, this paper focuses on PIT, CIT, and VAT, which on average make up more than 80% of total tax revenues.

2.2 Model specification and estimation techniques

2.2.1 Error correction model

We base our analysis on an auto-regressive distributed lags model (ARDL)(p, q) transformed into a single-equation error correction model (ECM) to examine tax buoyancy. We choose an optimal lag length of 1 for both p and q based on recent cross-country studies on tax buoyancy (Dudine and Jalles, 2018; Lagravinese et al., 2020; Gupta et al., 2022). We use a one-step ECM rather than the two-step ECM proposed in Engle and Granger (1987) to ensure comparability[4]. ECM allows for the estimation of both long- and short-term buoyancy estimates in a dynamic setting, assuming that changes in tax revenues and changes in GDP are cointegrated[5]. From a theoretical perspective, a long-term relationship of one between GDP and tax revenues is sensible, as otherwise the tax to GDP ratio would either continuously increase to unsustainable levels (if the long-term buoyancy is above one) or gradually decline to zero (if the long-term buoyancy is below one). However, the long-term coefficient may slightly differ from one depending on the estimation window, reflecting slow adjustments towards a long-term equilibrium[6]. ECM also allow for the short-term coefficient to diverge from the long-term trend and simultaneously estimate the speed at which the time series converge back to their long-term equilibrium. This is particularly relevant for the study of tax buoyancy, as the short-term responses of tax revenues to changes in the tax base may vary depending on the built-in flexibility of different tax systems and tax-specific characteristics[7].

2.2.2 Baseline regression

We estimate the following baseline regression:

$$\Delta ln\, Tax_{c,t} = \lambda_c\, ln\, Tax_{c,t-1} + \gamma_c\, \Delta ln\, GDP_{c,t} + \delta_c\, ln\, GDP_{c,t-1} + \mu_c + \epsilon_{c,t} \tag{1}$$

where $Tax_{c,t}$ is the nominal tax revenue in country c at time t, $GDP_{c,t}$ is the nominal level of GDP at time, and $\epsilon_{c,t}$ is the error term. The coefficient γ_c captures the instantaneous variation in tax revenues following a one percentage change in GDP (i.e the short-term

[4]In a one-step approach, the long-term and short-term buoyancy are estimated simultaneously, while in a two-step approach, the long-term relationship (or "cointegrating regression") is estimated first and the short-term relationship is then obtained from an ECM including the residual of the first regression. In a similar study based on a sample or European countries, Mourre and Princen (2019) find that elasticity coefficients obtained using both methods remain broadly similar.

[5]See table 14 and 15 in the appendix for stationarity and panel cointegration tests results in the appendix

[6]As discussed in the previous section EME and LIC have on average experienced an increase in their tax to GDP ratio since the 1990s. These dynamics may justify an average long-term buoyancy coefficient slightly higher than one in our study for EME and LIC.

[7]For example, the literature has shown that the short-term buoyancy for the corporate income tax (CIT) is often higher than one due to the speed at which corporate profits adjust relative to other, more stable tax bases (see, for example, Lagravinese et al., 2020; Dudine and Jalles, 2018).

buoyancy). The coefficient $\theta_c = -\frac{\delta_c}{\lambda_c}$ measures the long-run effect of a 1 percentage change in GDP (i.e the long-term buoyancy) and λ_c is the speed of adjustment towards the long-run equilibrium. μ_c is a country-specific effect.

2.2.3 Estimation technique: a trade-off

We use panel data methods instead of timeseries techniques to increase the statistical efficiency of the econometric estimation of the short- and long term tax buoyancy in our sample. While panel data methods may impose an unwarranted amount homogeneity on the data, they help mitigating issues related to the lack of degrees of freedom. This argument is particularly relevant in our study due to the inclusion of a significant number of EME and LIC in the sample (92 and 60 respectively) with relatively shorter time-spans. To account for the heterogeneity of tax responses across countries, a novelty of this paper is to estimate equation (1) using several heterogeneous coefficient model estimators (table 1 provides a summary of the estimators). The estimators considered in this study can broadly be classified along two dimensions (i) according to the degree of homogeneity imposed on the data through restrictions on the short-term and long-term parameters (i.e. homogeneous vs heterogeneous coefficients); and (ii) whether the estimator controls for the presence of cross-sectional dependence. While the former dimension addresses concerns related to country heterogeneity, the latter tackles a potential risk of biased and inconsistent estimators due to the presence of common unobserved factors among cross-sectional units in large samples[8]. Table 13 in the appendix provides the results of the cross-sectional dependence tests based on Pesaran (2015) and Pesaran (2021) for total tax revenues, all tax components, and nominal GDP by income groups. Test results reveal two important findings: (i) cross-sectional dependence is present in all variables of interest and across most income groups; (ii) average cross-correlation between pairs of countries are higher for AE compared to EME and LIC. These results suggest that cross-sectional dependence should be properly accounted for in the estimations especially when estimating tax buoyancy for AE.

We define as “first generation”estimators the Mean Group (MG) estimator of Pesaran and Smith (1995), which estimates a separate regression for each country and reports an av-

[8]For a theoretical discussion on the implication of cross-sectional dependence in heterogeneous coefficient models see Pesaran (2006); Chudik et al. (2011); Chudik and Pesaran (2015b,a); Everaert and De Groote (2016); Karabiyik et al. (2017); Chudik and Pesaran (2019); Juodis et al. (2021).

erage of the short-term and long-term coefficients, and the Pooled Mean Group (PMG) estimator of Pesaran et al. (1999), which restricts the long-run relationship between the dependent and independent variable to be homogeneous for all countries but allows heterogeneity in short-term coefficients. Both of these estimators do not take into account the presence of cross-sectional dependence in the data. We then define as "second generation" estimators the class of common correlated effects (CCE) estimators as proposed in Pesaran (2006) with homogeneity restrictions on the long-term coefficients (i.e CCE-PMG) and without homogeneity restrictions on the long-term coefficients (i.e. CCE-MG). The CCE controls for cross-sectional dependence by adding cross-sectional averages of the dependent and independent variables as control variables[9]. Finally, we define as "third generation" estimators the class of dynamic common correlated effects (DCCE) following Chudik and Pesaran (2015b) and implemented in Stata by Ditzen (2018) and Ditzen (2021) with homogeneity restrictions on the long-term coefficients (i.e DCCE-PMG) and without homogeneity restrictions on the long-term coefficients (i.e. DCCE-MG). Compared to CCE, the DCCE adds lags of cross-sectional averages to control for cross-sectional dependence[10]. The estimated equation including cross-sectional averages becomes:

$$\Delta ln\,Tax_{c,t} = \lambda_c\,ln\,Tax_{c,t-1} + \gamma_c\,\Delta ln\,GDP_{c,t} + \delta_c\,ln\,GDP_{c,t-1} + \sum_{l=0}^{p_t} \iota_{c,l}^{'}\,\bar{z}_{t-l} + \mu_c + \epsilon_{c,t} \quad (2)$$

where $\bar{z}_t = (ln\,T\bar{a}x_{c,t},\, ln\,G\bar{D}P_{c,t})^{'}$ are the cross-sectional averages of the dependent and independent variables and $\iota_{c,l}^{'}$ the corresponding estimated coefficients usually treated as nuisance parameters. In addition to the estimators listed above, we also run a dynamic fixed effect model, which imposes coefficient homogeneity both in the short-term and in the long-term and does not control for cross-sectional dependence.

[9]Another approach to control for cross-sectional dependence is through principle components (Bai and Ng, 2002; Bai, 2009). See Westerlund and Urbain (2015) for a comparison.

[10]In a dynamic setting, Chudik and Pesaran (2015b) show that $\sqrt[3]{T}$ lags of cross-sectional average should be included as control variables to obtain consistent estimates using OLS.

Table 1: Parameter restrictions and control for cross-sectional dependence by estimators

Estimator	Homogeneity of short-term coefficients?	Homogeneity of long-term coefficients?	Control for cross-sectional dependence?	Source
MG	No	No	No	Pesaran and Smith (1995)
PMG	No	Yes	No	Pesaran et al. (1999)
CCE-MG	No	No	Yes*	Pesaran (2006)
CCE-PMG	No	Yes	Yes*	Pesaran (2006)
DCCE-MG	No	No	Yes**	Chudik and Pesaran (2015b)
DCCE-PMG	No	Yes	Yes**	Chudik and Pesaran (2015b)

Notes: MG = Mean Group; PMG = Pooled Mean Group; CCE-MG = Common Correlated Effects - Mean Group; CCE-PMG = Common Correlated Effects - Pooled; Mean Group; DCCE-MG = Dynamic Common Correlated Effects - Mean Group; DCCE-PMG = Dynamic Common Correlated Effects - Pooled Mean Group

* Control for cross-sectional dependence using contemporaneous cross-sectional averages.

** Control for cross-sectional dependence using contemporaneous and lagged cross-sectional averages.

From a theoretical standpoint, among available panel data methods, we concur with Lagravinese et al. (2020) that the DCCE-MG should be the preferred estimator in the study of tax buoyancy because it accounts for (i) temporal persistence, (ii) unobserved heterogeneity, and (iii) cross-sectional dependence. However, we argue that the DCCE-MG consumes a lot of degrees of freedom and coefficients may be therefore biased and unreliable especially for countries with limited historical tax revenues data available. This trade-off motivates our decision to run several estimators to assess the buoyancy of tax systems[11].

[11] The literature either provides tax buoyancy or elasticity estimates at the country level (Twerefou et al., 2010; Timsina et al., 2007) or at the regional level (Belinga et al., 2014; Deli et al., 2018; Khadan, 2020; Gupta et al., 2022) and in global panels (Dudine and Jalles, 2018) but using first generation estimation techniques. Only Lagravinese et al. (2020) use the class of common correlated estimators to account for cross-sectional dependence but only for OECD countries.

3 Results

3.1 Baseline results

We estimate equation 1 using the seven estimators discussed in the previous section: Dynamic Fixed Effects (DFE), Mean Group (MG), Pooled Mean Group (PMG), Common-Correlated Effects Mean Group (CCE-MG), Common-Correlated Effects Pooled Mean Group (CCE-PMG), Dynamic Common-Correlated Effects Mean Group (DCCE-MG), and Dynamic Common-Correlated Effects Pooled Mean Group (DCCE-PMG). Figures 5 through 16 present the results for total tax revenues and all tax components' short- and long-run buoyancy estimates, as well as the corresponding kernel distributions of the coefficients[12]. In the appendix, tables 2 through 8 display the regression output and report Pesaran (2015) cross-sectional dependence (CD) tests. The CD tests show that there is a significant reduction in CD statistics between first and second generation estimators for all country income groups and tax components. The decrease in CD statistics is smallest for low-income countries (LIC), consistent with the initial low levels of cross-sectional dependence identified in table 13 in the appendix and discussed in the previous section. However, the decrease in CD statistics from second to third generation estimators is only marginal. These results suggest that the inclusion of contemporaneous cross-sectional averages in the regressions generally enhances the capture of cross-sectional dependence, but the addition of lags does not significantly improve it further and consumes more degrees of freedom.

3.1.1 Total tax revenues

Figures 3-6 show the long-term and short-term buoyancy estimates as well as the related kernel distributions[13] of total tax revenue coefficients in a sample of 174 countries, including 35 AE, 87 EME, and 52 LIC[14]. Our results suggest that long-term buoyancy coefficients, which measure the average long-term reaction of tax revenues to economic activity, hover around one, consistent with previous cross-country studies (Hill et al., 2022; Gupta et al.,

[12]Note that only the MG, CCE-MG, and DCCE-MG estimators have long-term kernel distributions of coefficients as the PMG, CCE-MG, and DCCE-PMG do not allow heterogeneous estimations of long-term parameters by definition. See table 1 for an overview of the parameter restrictions.

[13]The online statistical appendix presents country-level estimates using MG, PMG, CCE-MG, CCE-PMG, DCCE-MG and DCCE-PMG estimators

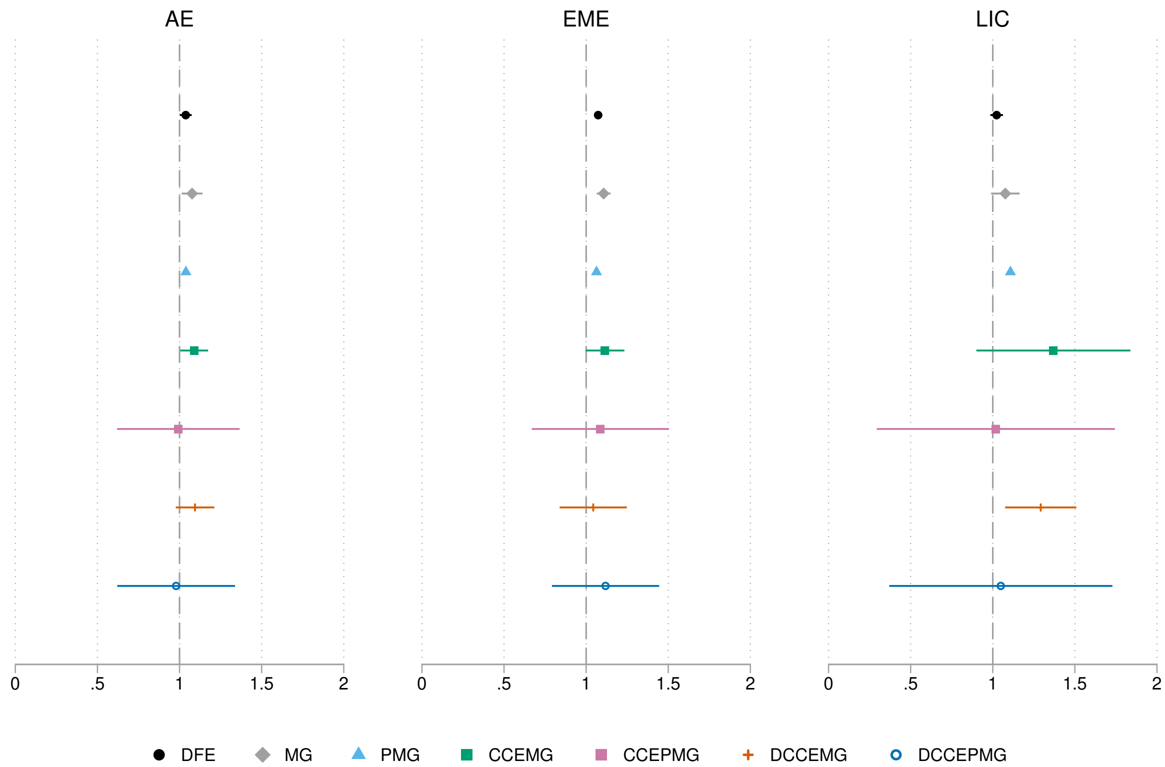
[14]As mentioned earlier, we exclude countries with less than 15 years of available observations and thus drop 11 countries from the initial sample of 185 countries

2022; Deli et al., 2018; Belinga et al., 2014). Our findings hold true across estimators and country income groups, with only marginal variations. As expected, confidence intervals for second and third generation estimators are larger because these estimation methods consume more degrees of freedom. Confidence intervals are also larger for LIC due to the shorter average span of the time series, as previously noted. On average, the coefficients are slightly higher for EME and LIC, possibly due to the gradual tax mobilization progress in these economies as discussed in section 2.1. However, unlike Lagravinese et al. (2020), we do not find long-term coefficients lower than unity when using second and third generation estimators[15]. Our results therefore suggest that controlling for cross-sectional dependence does not significantly impact buoyancy estimates in the long-run.

On the other hand, short-term buoyancy estimates differ more significantly across estimators and diverge from the long-term estimates. While some first generation estimators show that short-term coefficients for AE are not statistically different from 1, consistent with prior cross-country studies using similar estimators (Deli et al., 2018; Belinga et al., 2014; Dudine and Jalles, 2018), second and third generation estimators indicate statistically significantly lower estimates, in line with Lagravinese et al. (2020). These findings suggest that controlling for cross-sectional dependence does significantly impact buoyancy estimates in the short-run. For EME and LIC, short-term buoyancy coefficients are on average lower and statistically significantly below 1 across estimators. These results posit a limited role for taxes as automatic stabilizers, which may be partly due to insufficient cyclical discretionary changes to compensate for low tax elasticity as we argue in section 3.2.

Previous literature has found variance in the buoyancy of tax components. In order to determine whether certain tax items drive this variance in total tax revenue, the next sections replicate the analysis for each component.

[15] It is worth noting that Lagravinese et al. (2020) is the only cross-country study using a third generation estimator, while the others utilize first generation estimators.



Notes: The bars represent 95% confidence intervals. DFE = Dynamic Fixed Effect; MG = Mean Group; PMG= Pooled Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator

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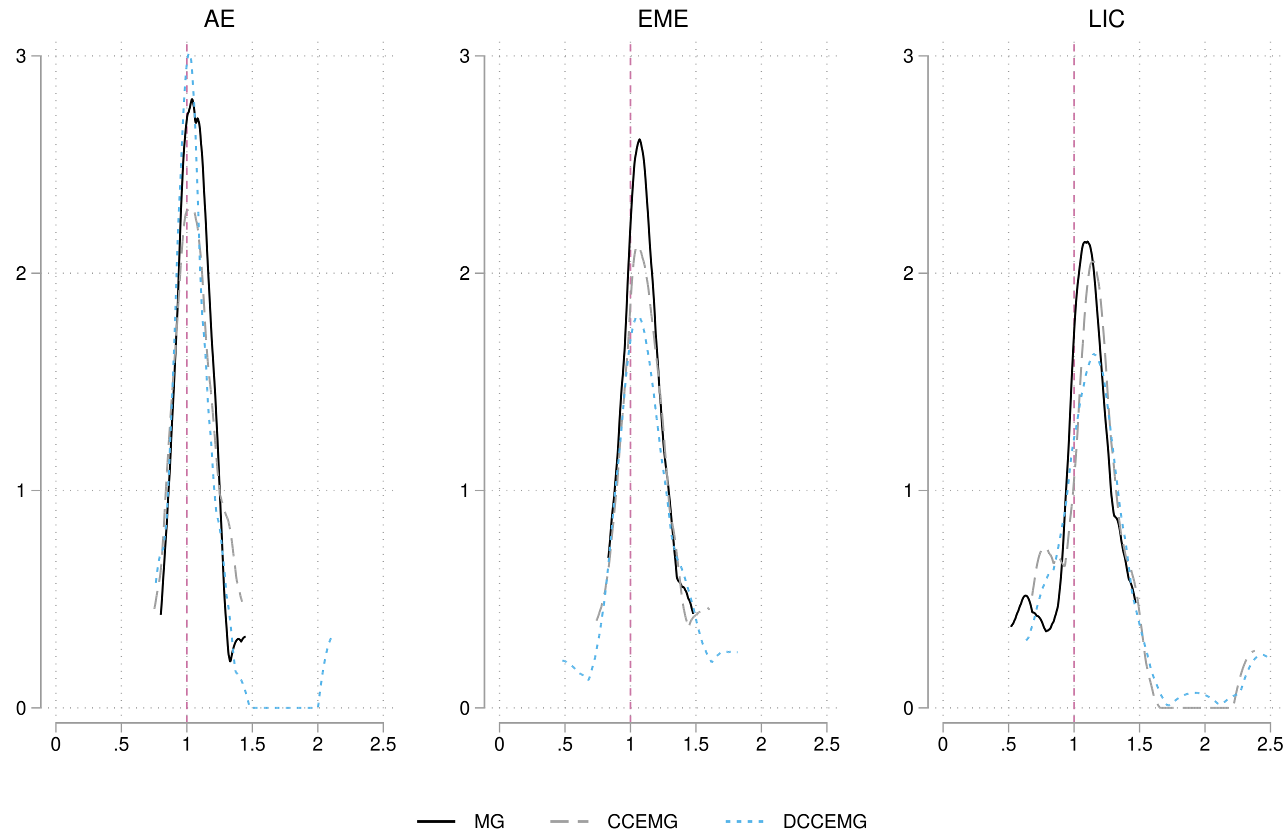
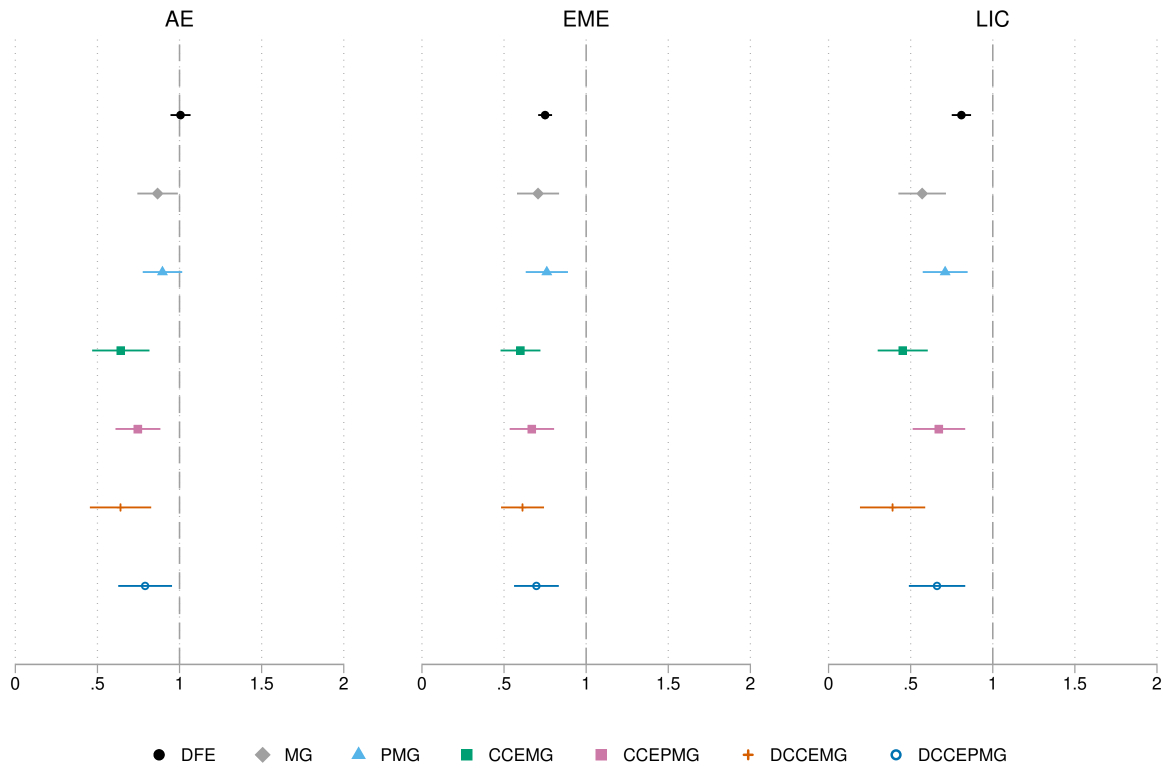
Figure 3: Long-run total tax revenues buoyancy by estimator



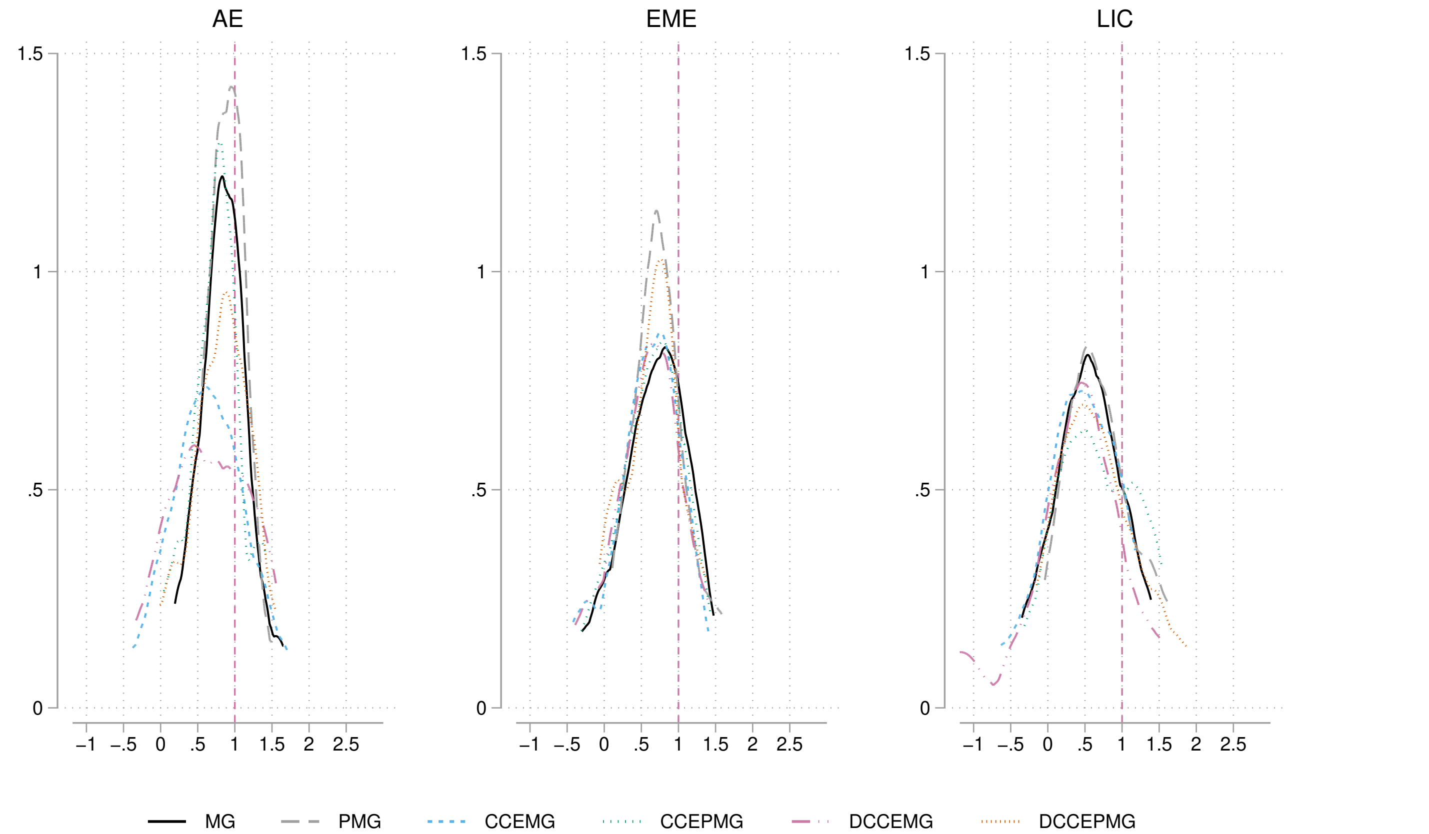
Notes: MG = Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator. We apply a 95% winsorization on coefficients.

Figure 4: Kernel distribution of total tax revenues long-run buoyancy coefficients by estimator



Notes: The bars represent 95% confidence intervals. DFE = Dynamic Fixed Effect; MG = Mean Group; PMG= Pooled Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator

Figure 5: Short-run total tax revenues buoyancy by estimator



Notes: MG = Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator. We apply a 95% winsorization on coefficients.

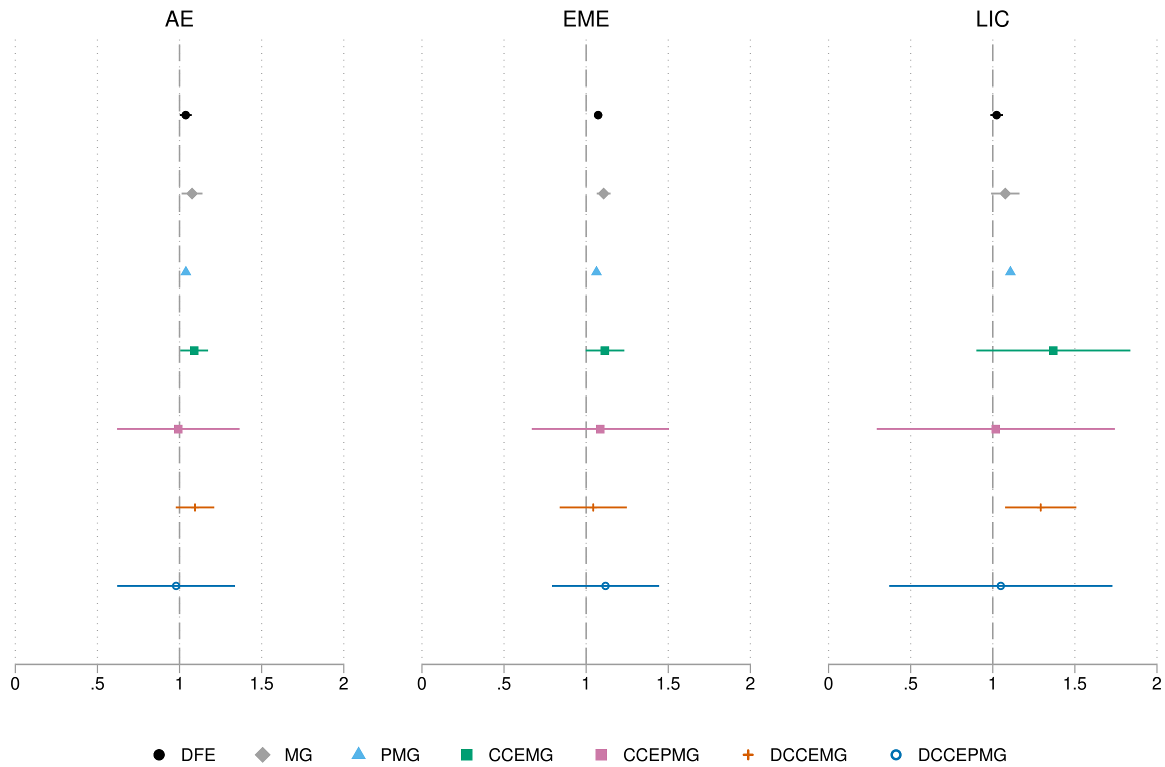
Figure 6: Kernel distribution of total tax revenues short-run buoyancy coefficients by estimator

3.1.2 Personal income taxes

In this section, we study the reaction of PIT revenues to changes in GDP for a sample of 127 countries, including 33 advanced economies (AE), 60 emerging market economies (EME), and 34 low-income countries (LIC). Figures 7-10 present long-term and short-term estimates of buoyancy coefficients for PIT and the corresponding kernel distributions. These countries were selected from our initial sample of 185, with 58 removed due to missing data or inadequate observations (less than 15 years). As of 2019, PIT constituted a significant portion of total tax revenues on average in our sample, particularly in AE where it represents 34% compared to 15% for EME and LIC.

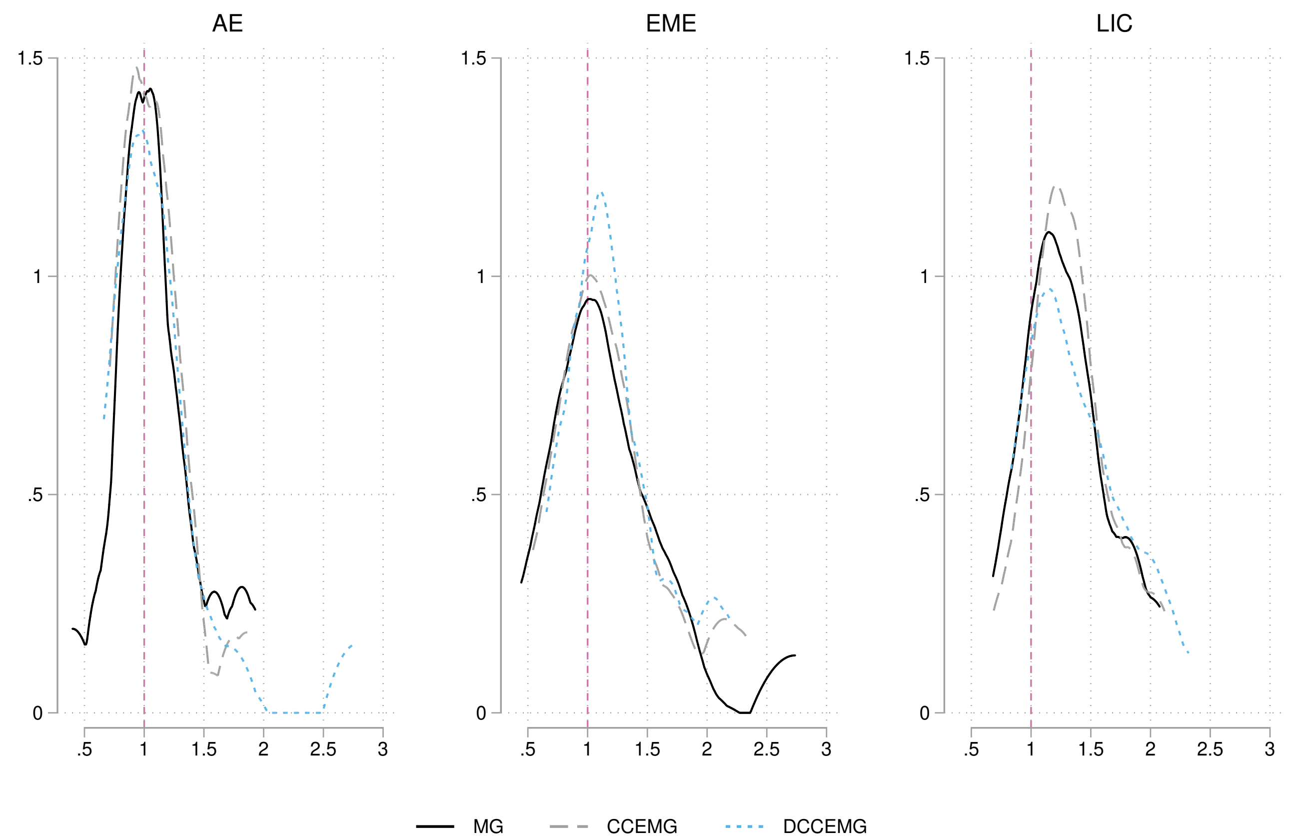
The long-term buoyancy coefficients of PIT are found to be close to one and consistent with total tax revenue buoyancy and previous studies. This holds true across estimators and country income groups, with estimates slightly higher for EME and LIC in line with improved tax revenue mobilization. As noted in the dynamics of total tax revenues, second and third generation of estimators post lower short-run coefficients than first generation estimators suggest that controlling for cross-sectional dependence does significantly impact buoyancy estimates in the short-run. However, short-term buoyancy of PIT is found to be statistically significantly below one for all estimators and income groups, indicating limited role of PIT as automatic stabilizer. These results concur with some previous research such as Boschi and d'Addona (2019) and Dudine and Jalles (2018), but with slightly lower estimates depending on estimator used. They contrast with findings of Lagravinese et al. (2020) and Belinga et al. (2014) of coefficients above unity, but those studies used different time periods and sample of countries. Our results suggest that tight employment protection and wage rigidity may offset the progressive nature of PIT and drive coefficients down in the short-term[16].

[16]The literature has identified several other factors that may influence tax buoyancy such as the quality of institutions, the role of the shadow economy, the share of agriculture in national income, trade-openness, the level of education, output volatility, and other economic behaviors. For a review of the characteristics influencing tax buoyancy, see among other studies Lagravinese et al. (2020) and Dudine and Jalles (2018).



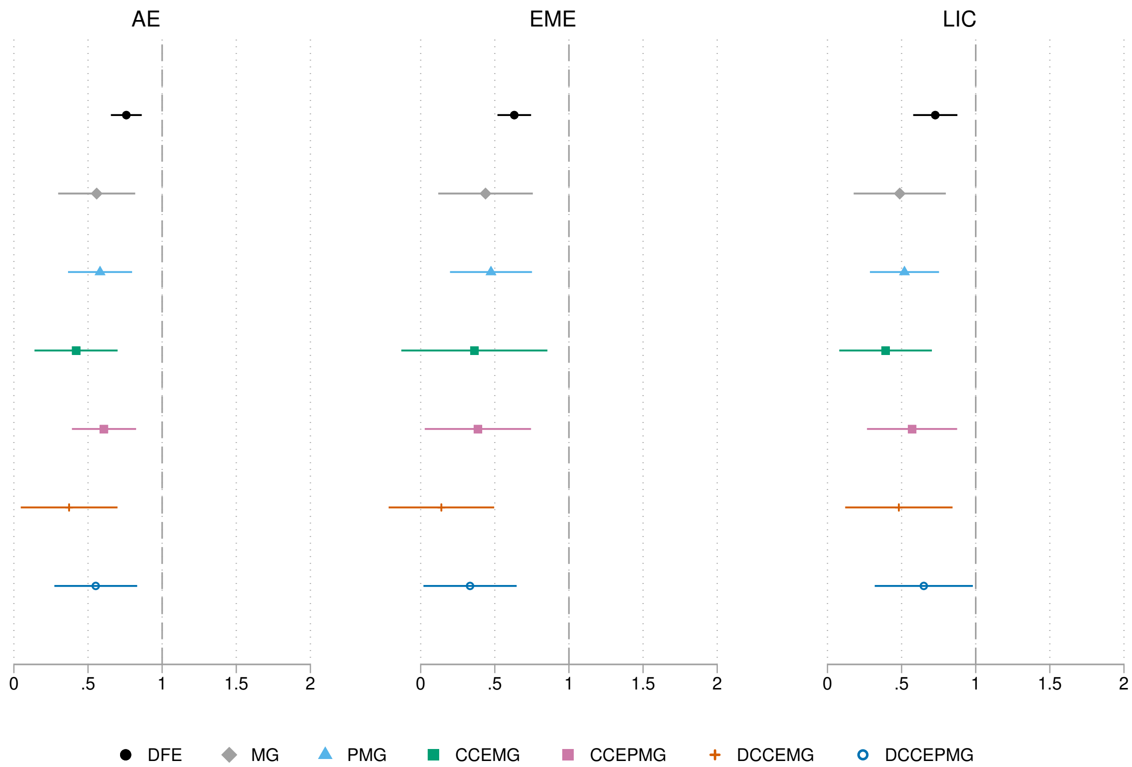
Notes: The bars represent 95% confidence intervals. DFE = Dynamic Fixed Effect; MG = Mean Group; PMG= Pooled Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator

Figure 7: Long-run personal income taxes buoyancy results by estimator



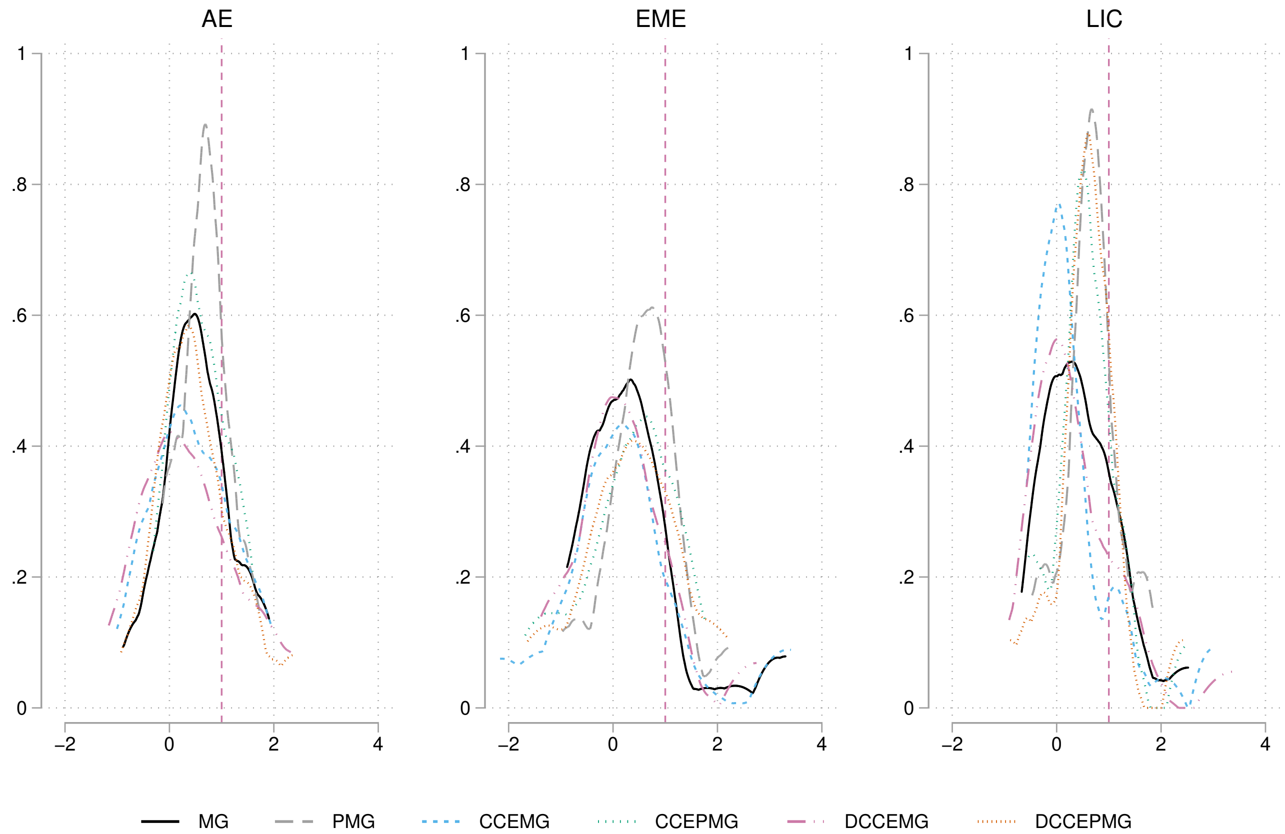
Notes: MG = Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator. We apply a 95% winsorization on coefficients.

Figure 8: Kernel distribution of personal income taxes long-run buoyancy coefficients by estimator



Notes: The bars represent 95% confidence intervals. DFE = Dynamic Fixed Effect; MG = Mean Group; PMG= Pooled Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator

Figure 9: Short-run personal income taxes buoyancy by estimator



Notes: MG = Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator. We apply a 95% winsorization on coefficients.

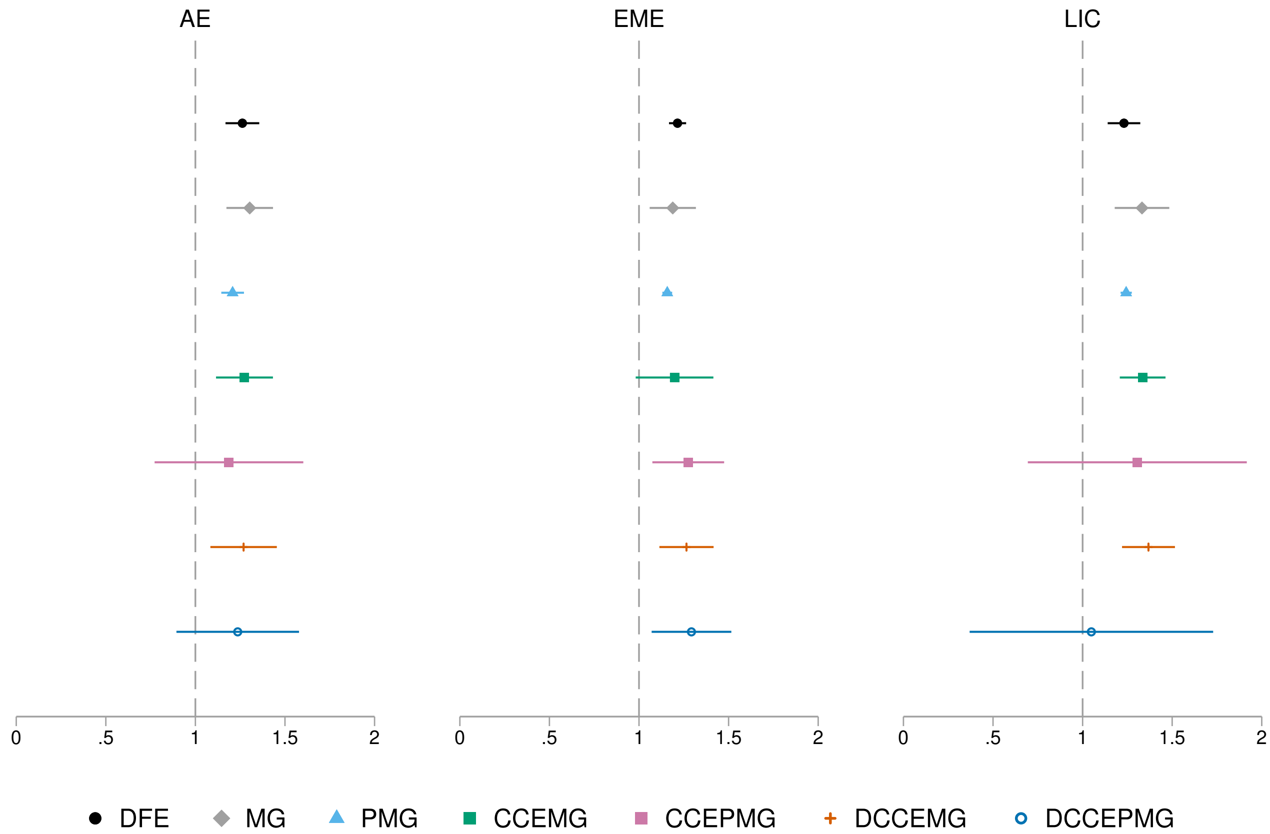
Figure 10: Kernel distribution of personal income taxes short-run buoyancy coefficients by estimator

3.1.3 Corporate income taxes

In this section, we investigate the responsiveness of CIT revenues to changes in GDP for a sample of 135 countries, comprising 33 AE, 68 EME, and 34 LIC. We removed 50 countries from our initial dataset of 185 countries due to missing data or limited observations (less than 15 years). On average, CIT revenues represented 13% of AE total tax revenues compared to 22% for EME and 18% for LIC in our sample as of 2019. The figures 11, 12, 13, and 14 present the results of long-term and short-term buoyancy estimates and their respective kernel distributions.

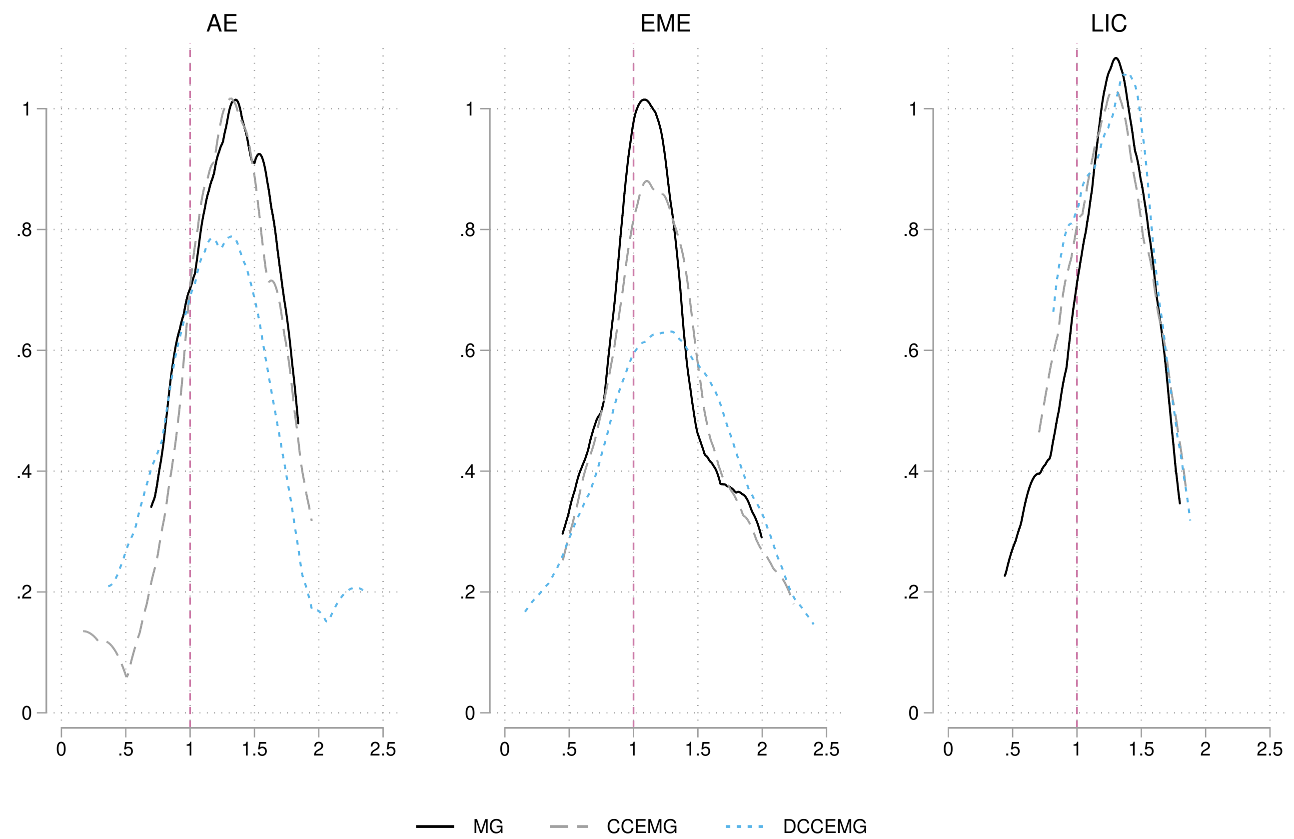
Our findings reveal that, on average, CIT long-term buoyancy exceeds one for all income groups across all estimators, although not statistically significantly in all cases when utilizing second and third generation estimators. These results align with existing cross-country studies utilizing first-generation estimators (Boschi and d'Addona, 2019; Deli et al., 2018; Dudine and Jalles, 2018; Mourre and Princen, 2019; Belinga et al., 2014). However, our results differ from those of Lagravinese et al. (2020), who, using the DCCE-MG estimator, found long-run buoyancy to be lower than unity, albeit with a slightly different sample of countries and time period studied. A long-term buoyancy greater than one for CIT is consistent with the gradual increase in the share of profits in GDP over the period analyzed (Grossman and Oberfield, 2022; Autor et al., 2020; Karabarbounis and Neiman, 2014).

On the other hand our estimates of short-term buoyancy for AE suggest that when using first-generation estimators, the coefficients are found to be statistically greater than one, in line with the results of several other cross-country studies (Boschi and d'Addona, 2019; Deli et al., 2018; Dudine and Jalles, 2018; Mourre and Princen, 2019; Belinga et al., 2014). However, when using second and third-generation estimators, the coefficients are not statistically different from unity. This suggests that the responsiveness of AE's tax revenues to changes in economic activity may differ depending on the estimator used. Overall, the higher short-term buoyancy level for AE indicate that CIT is a more effective source of automatic stabilization, which may be due to the relatively higher speed at which profits adjust during economic cycles. The sharp drop in the buoyancy coefficients of AE when using second and third-generation is sensible as the control for cross-sectional dependence captures discretionary tax policy coordination influenced by supranational constraints within monetary unions, such as European rules on public budgets(Lagravinese et al., 2020) and changes in global economic activity dynamics among AE that enhance domestic CIT revenues movements. Our estimates of short-term buoyancy for EME reveal that, when using first and second generation estimators, the coefficients do not statistically differ from unity. However, when using third generation estimators, the coefficients are found to be statistically lower than unity. Furthermore, the estimates of short-term buoyancy for CIT in LIC suggest a limited role of CIT as an automatic stabilizer, with coefficients below unity across estimators. However, while CIT may not have a substantial role in providing automatic stabilization in LIC, it is still slightly more effective than Personal Income Tax (PIT) in this regard. Finally, the estimates for EME and LIC exhibit less variation when using second and third generation estimators, likely due to the lower levels of tax policy coordination and economic interdependence in these groups of countries.



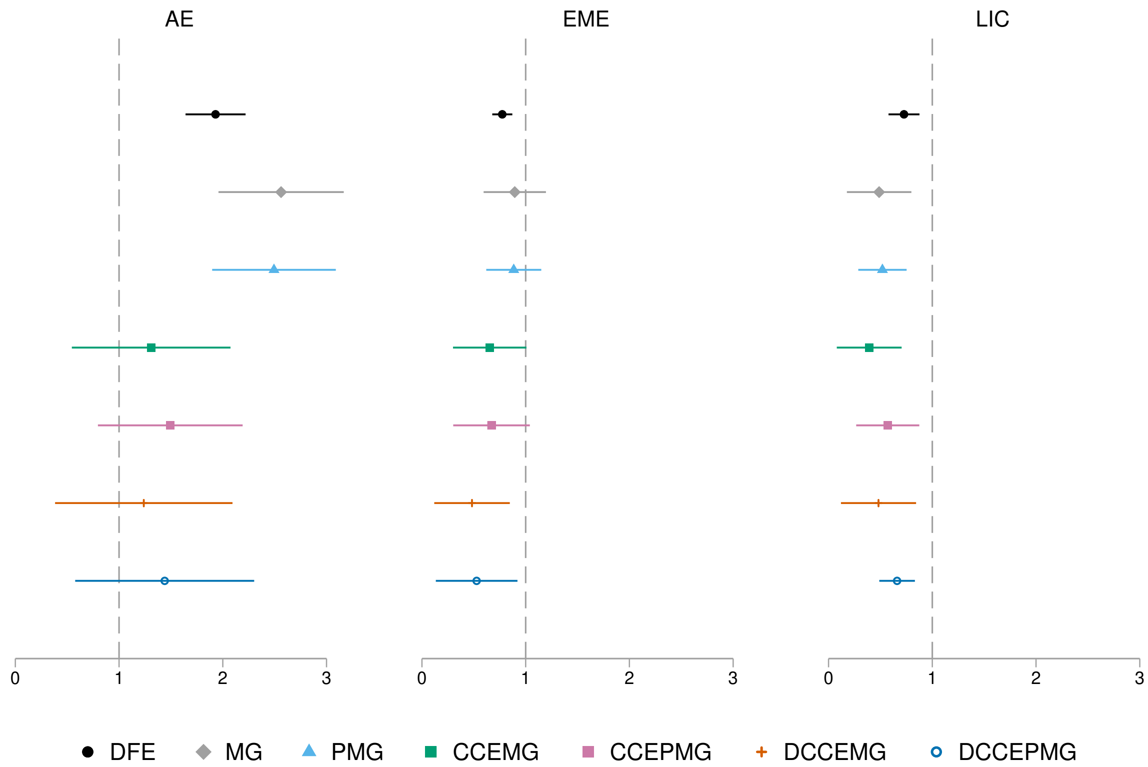
Notes: The bars represent 95% confidence intervals. DFE = Dynamic Fixed Effect; MG = Mean Group; PMG= Pooled Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator

Figure 11: Long-run corporate income taxes buoyancy results by estimator



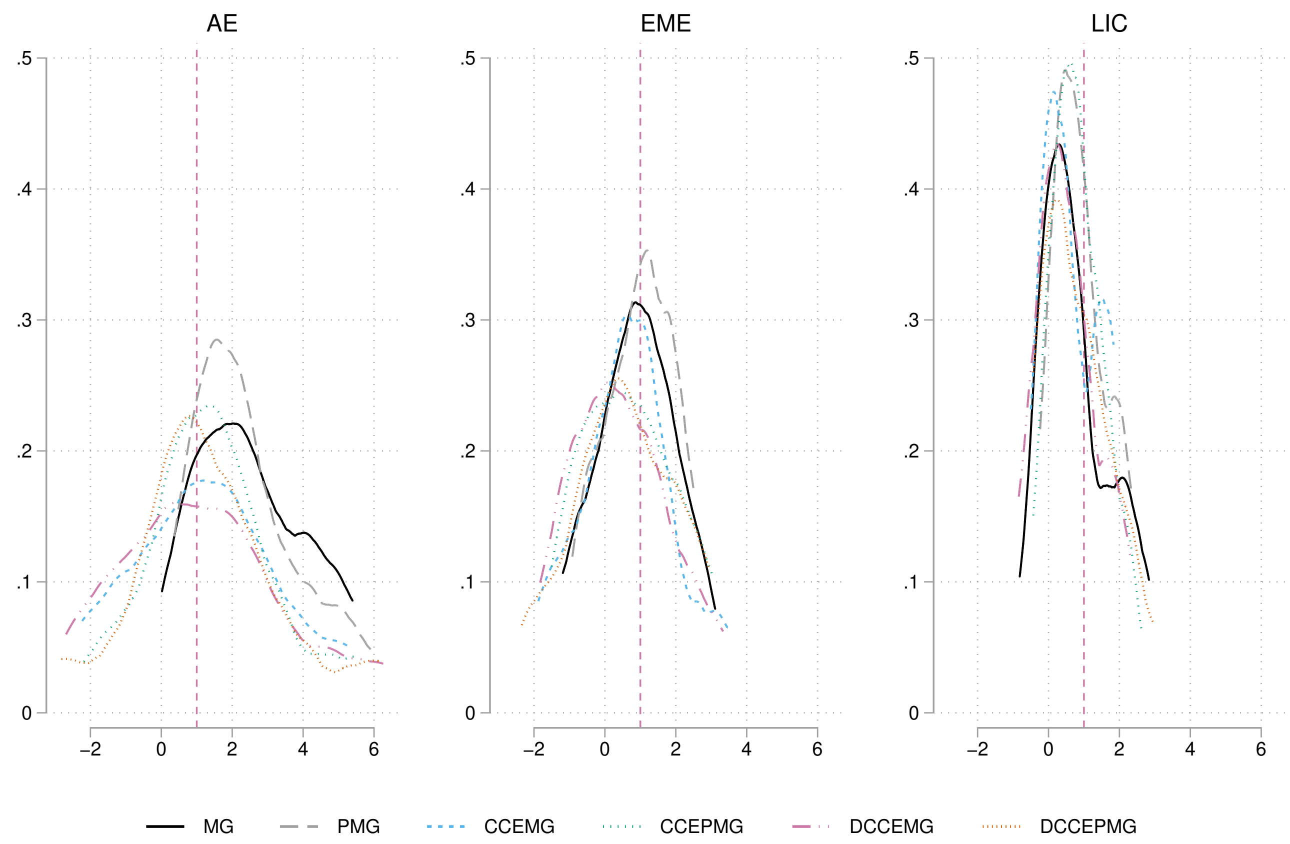
Notes: MG = Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator.We apply a 95% winsorization on coefficients.

Figure 12: Kernel distribution of corporate income taxes long-run buoyancy coefficients by estimator



Notes: The bars represent 95% confidence intervals. DFE = Dynamic Fixed Effect; MG = Mean Group; PMG= Pooled Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator

Figure 13: Short-run corporate income taxes buoyancy by estimator



Notes: MG = Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator. We apply a 95% winsorization on coefficients.

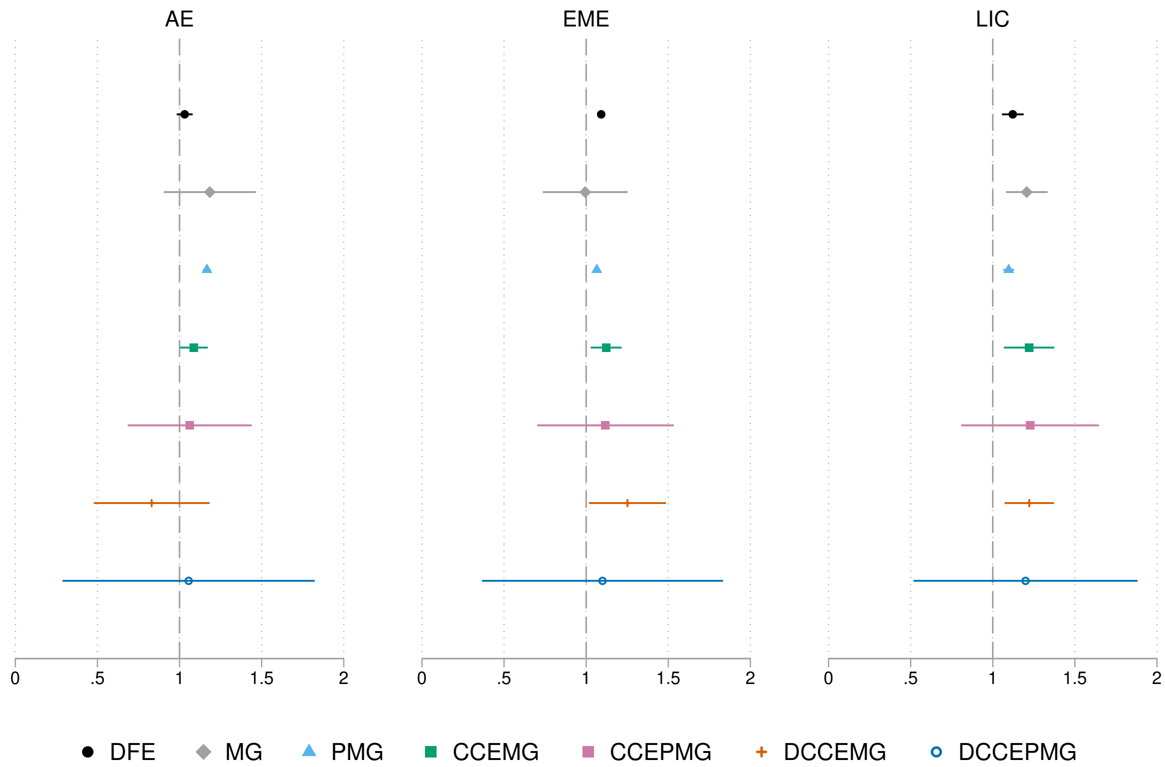
Figure 14: Kernel distribution of corporate income taxes short-run buoyancy coefficients by estimator

3.1.4 Value added taxes

In this section, we examine the reaction of VAT revenues in relation to GDP fluctuations in a sample of 88 countries, which includes 32 AE, 36 EME, and 20 LIC. We excluded 97 countries from our initial dataset of 185 countries due to missing time series or limited observations (less than 15 years). Our findings are not directly comparable to those of other cross-country studies, which typically examine the responsiveness of TGS to changes in economic activity. The TGS tax category includes VAT as well as other taxes, such as excise taxes, import duties, and taxes on exports. The dissimilar responsiveness of these various tax items to GDP changes motivated our focus on VAT, given that (i) VAT data is available for a large number of countries; (ii) it accounts for a significant share of TGS in our sample with an average of 60% when data is available; and (iii) it has a direct relationship with consumption. The figures 15, 16, 17, and 18 present the results of long-term and short-term buoyancy estimates and their respective kernel distributions. On average, VAT revenues represented 27% of AE total tax revenues compared to 32% for EME and 28% for LIC in our sample as of 2019.

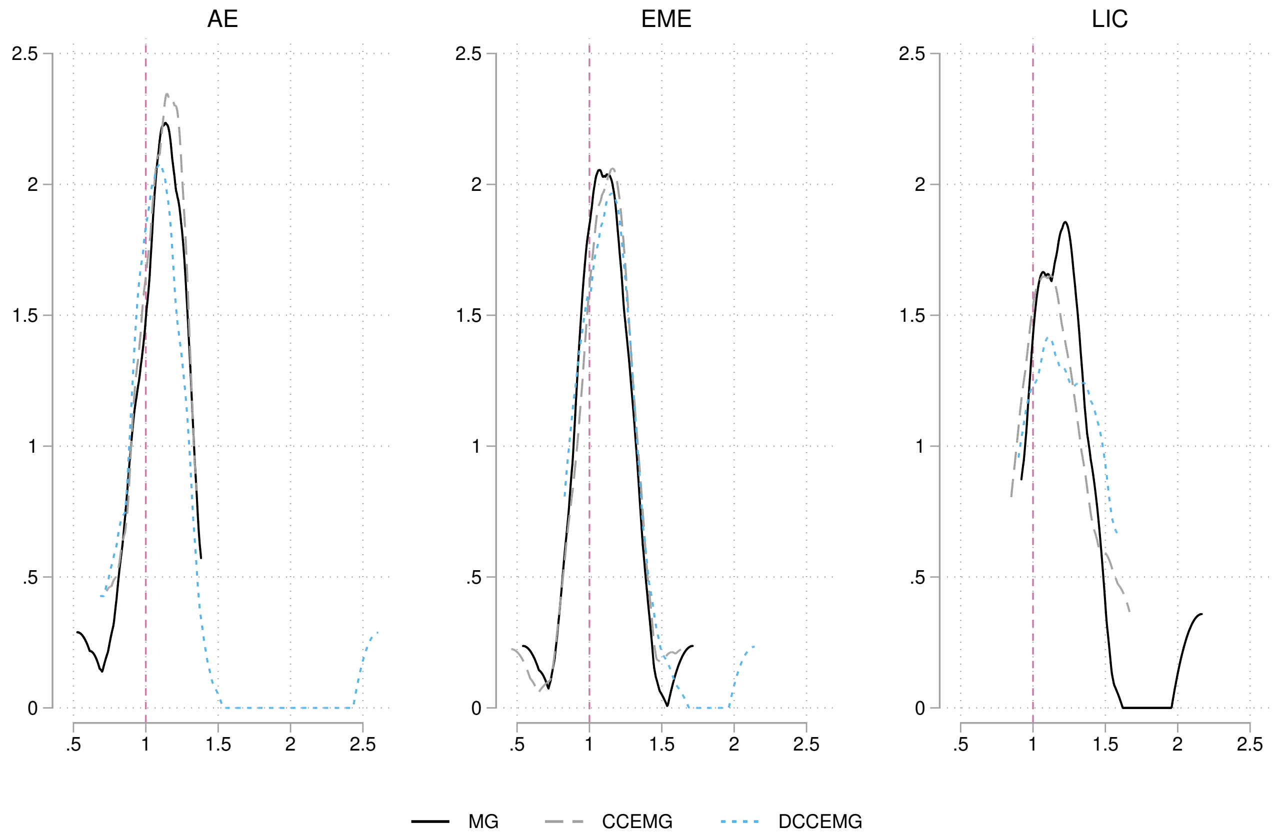
Our estimates of long-term elasticity of VAT revenues are similar to those we found for PIT, with estimates generally falling around unity for all income groups and across all estimators. These results are in line with the majority of estimates for TGS in existing cross-country studies, with the exception of those obtained by Lagravinese et al. (2020) and Khadan (2020), who report coefficients significantly below unity. The low coefficients reported by Khadan (2020) may be specific to the restricted focus on Caribbean countries, while the low estimates reported by Lagravinese et al. (2020) may be attributed to the use of the DCCE-MG estimator, which is computationally demanding in terms of degrees of freedom, and the limited time span of the study (1995-2016).

On the other hand, estimates of short-term elasticity of VAT revenues are mixed and depend on the estimator used and the income group of the country in question, which is consistent with the mixed findings in the literature. For example, Lagravinese et al. (2020) and Boschi and d'Addona (2019) report coefficients that are statistically significantly lower than unity and lower than our own estimates, while Hill et al. (2022), Gupta et al. (2022), Mourre and Princen (2019), and Belinga et al. (2014) report coefficients that are equal to or greater than unity. It is worth noting that these studies focus on taxes on goods and services, which are composed of taxes that may respond differently to changes in economic activity, and the estimates may also vary due to the different sample of countries and time period covered compared to our study. Interestingly, our study finds that short-term VAT buoyancy estimates generally remain lower and statistically significantly below one fo rAE and LIC across first and second generation estimators. Third generation estimators, however, do not indicate a statistically significant difference from one. In contrast, for EME, nearly all estimators point towards short-run buoyancy coefficients that are not statistically different from one across all estimators. These findings suggest that VAT generally does not perform well as an automatic stabilizer, particularly in AE and LIC. While more integrated financial markets and better access to credit in AE may explain higher levels of consumption smoothing and provide an explanation for the lower short-term buoyancy (Brady (2008); Cecchetti et al. (2006)), the imperfect implementation of VAT systems during the trade liberalization process in some LIC, notably through the provision of excessive exemptions, could explain relatively lower short-run buoyancy (Baunsgaard and Keen (2010)).



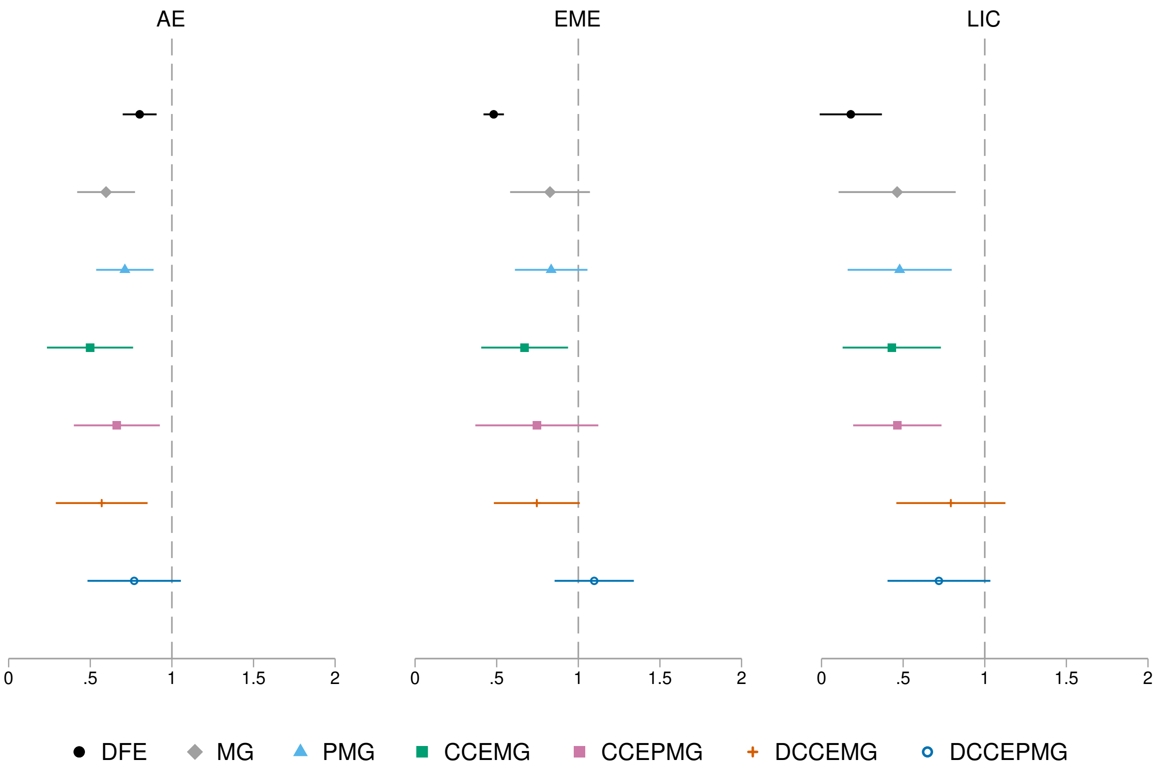
Notes: The bars represent 95% confidence intervals. DFE = Dynamic Fixed Effect; MG = Mean Group; PMG= Pooled Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator

Figure 15: Long-run value added taxes buoyancy results by estimator



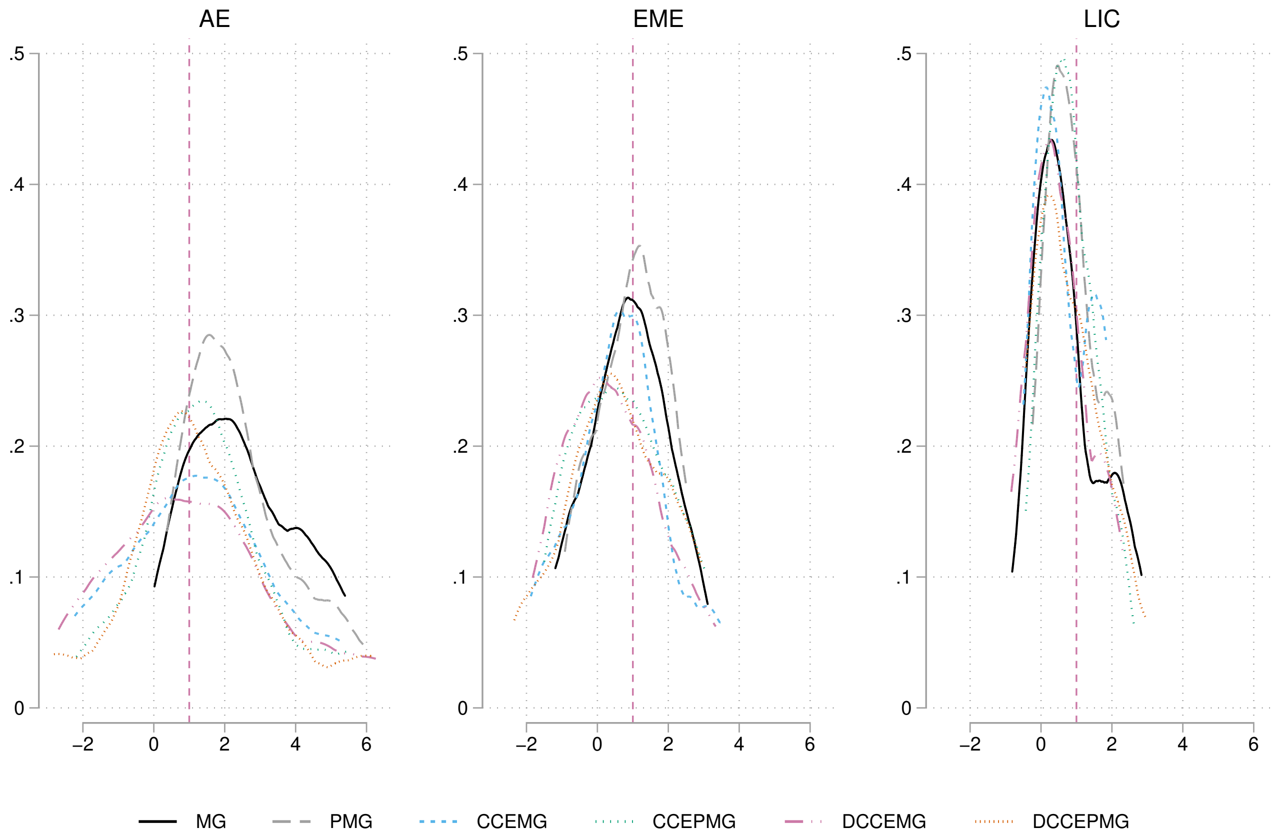
Notes: MG = Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator.We apply a 95% winsorization on coefficients.

Figure 16: Kernel distribution of value added taxes long-run buoyancy coefficients by estimator



Notes: The bars represent 95% confidence intervals. DFE = Dynamic Fixed Effect; MG = Mean Group; PMG= Pooled Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator

Figure 17: Short-run value added taxes buoyancy by estimator



Notes: MG = Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator. We apply a 95% winsorization on coefficients.

Figure 18: Kernel distribution of value added taxes short-run buoyancy coefficients by estimator

3.2 Tax buoyancy versus tax elasticity

In this section, we investigate whether tax buoyancy (i.e., the measure of how taxes respond to economic growth through both automatic changes and discretionary measures) and tax elasticity (i.e., a measure that ignores the impact of discretionary measures) differ by introducing several control variables. Both measures provide important information. While tax buoyancy gives a comprehensive understanding of the sustainability of tax systems, tax elasticity is typically viewed as the relevant indicator for forecasting purposes (Lagravinese et al., 2020). Prior cross-country studies have typically controlled for variations in tax rates and examined whether buoyancy coefficients vary[17]. This approach assumes that buoyancy and elasticity estimates only differ if both changes in tax rates and changes in GDP are correlated with tax policy reforms, suggesting the presence of an omitted variable bias. However, both of these correlations have limited empirical evidence or are a matter of debate. In terms of the correlation between tax policy reforms and GDP, while empirical evidence is limited[18], Vegh and Vuletin (2015) find that the conduct of tax rate reforms varies across countries over the economic cycle, with tax policy being broadly acyclical in industrial countries but largely procyclical in developing countries[19]. On the other hand, the correlation between tax policy reforms and tax revenues is debated and depends on several factors including the instrument adopted (Mertens and Ravn, 2013; Kawano and Slemrod, 2016; Amaglobeli et al., 2022) as well as behavioural responses to tax reforms affecting the tax base (Kleven and Schultz, 2014; Aarbu and Thoresen, 2001).

This study extends previous research by controlling for tax base reforms and exemptions in addition to tax rate changes using multiple data sources. Although it would be optimal to control for all variables in a single model, the limited number of available observations for each country and year with all control variables necessitates the presentation of results in separate tables. We employ the PMG estimator in this section as it offers a suitable

[17] See for example Dudine and Jalles (2018); Lagravinese et al. (2020); Gupta et al. (2022). Other studies disentangle the effect of discretionary tax changes on changes in tax revenues from automatic changes in economic conditions by collecting detailed information on national tax policy changes and the impact of discretionary measures using the proportional adjustment method, as originally proposed by Prest (1962). However, this approach is not feasible in our study due to the large number of countries in our sample and the limited comparability of national accounting systems.

[18] On the contrary, studies about the conduct of government spending over the business cycle abound in the literature (see for example Kaminsky et al. (2004); Alesina et al. (2008); Frankel et al. (2013))

[19] To the best of our knowledge, no study investigates how policymakers conduct other tax policy reforms such as tax exemptions and tax base reforms during the economic cycle.

compromise between avoiding imposing excessive homogeneity on the data and conserving degrees of freedom. Results obtained using other estimators are also robust and can be obtained from the authors upon request. Furthermore, we focus on the short-term impacts of control variables on coefficients, as there is no evidence of long-term relationships between tax policy reforms and changes in tax revenues. This lack of cointegration implies that in our ECM tax policy reforms should not impact the long-run relation between changes in GDP and changes in tax revenues.

3.2.1 Controlling for changes in tax rates

In order to control for the effect of changes in tax rates on our results, we utilize yearly data on PIT, CIT, and VAT from Vegh and Vuletin (2015) for a sample of 77 countries from 1960 to 2020[20]. Figure 19 plots the short-run buoyancy estimates with and without control for tax rates, and Table 9 presents the regression output. We find only minor differences in the short-run buoyancy coefficients across all income groups and tax components after accounting for changes in tax rates. Assuming that tax rate reforms are correlated with tax revenues, these results suggest that changes in PIT, CIT, and VAT rates are not significantly correlated with changes in GDP in our study period. These findings are consistent with recent cross-country studies on tax buoyancy (Deli et al., 2018; Lagravinese et al., 2018; Gupta et al., 2022), but contrast with earlier research such as Dudine and Jalles (2018) and Belinga et al. (2014), which found that some coefficients increased, albeit slightly, depending on the country income group and the tax component after controlling for tax rates. However, these earlier studies covered different time periods (1980-2014 and 1965-2012, respectively, compared to 1990-2020 in our study), which may suggest that the correlation with GDP changes has decreased over time.

3.2.2 Controlling for discretionary changes in the tax base

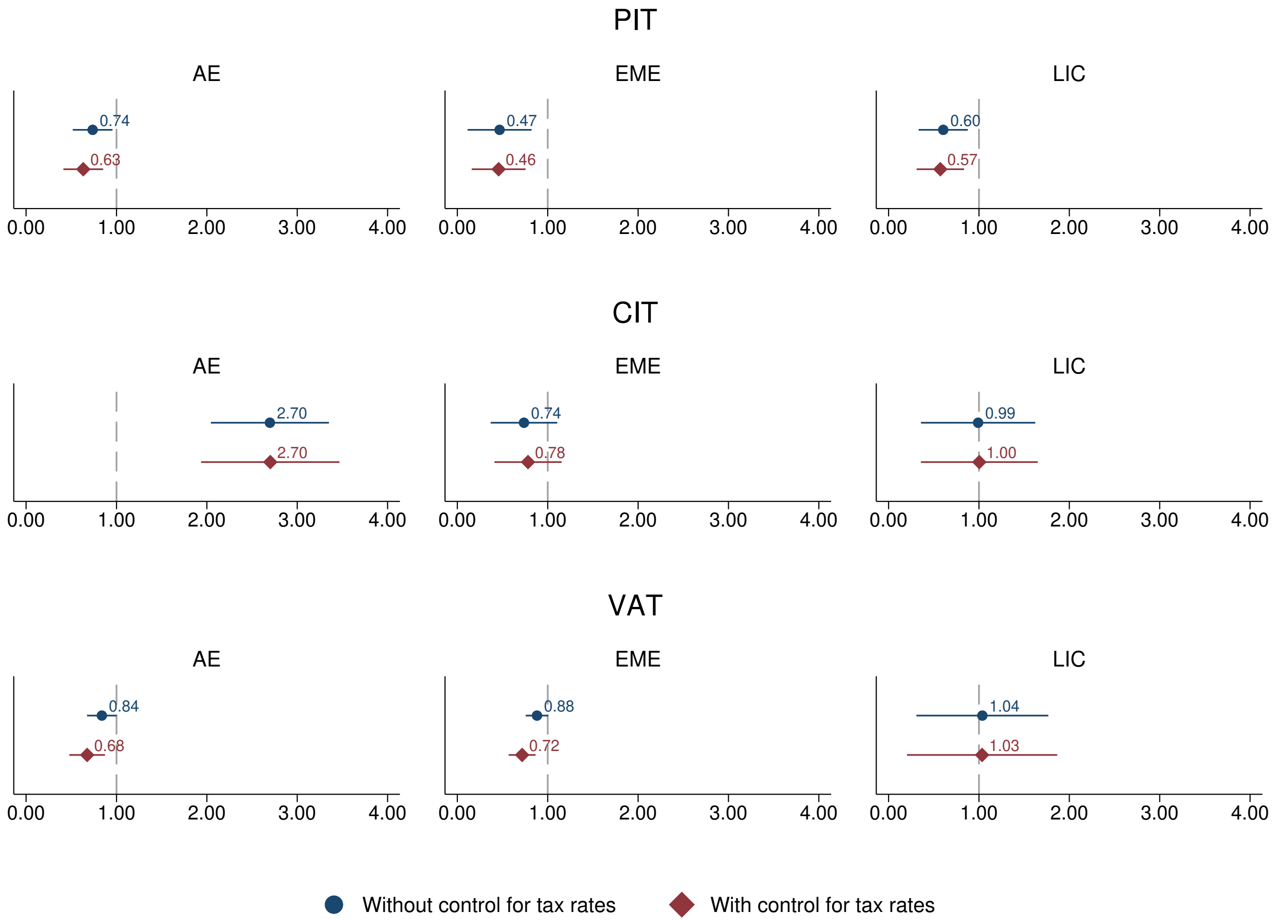
To control for tax base reforms, we use the Tax Policy Reform Database (TPRD) of the IMF (Amaglobeli et al., 2018), which covers 23 AE and EME. The TPRD comprises yearly

[20]The number of countries used in our analyses is smaller than this due to the availability of observations for each tax component. A previously mentioned, we exclude countries with less than 15 years of consecutive observations. The number of countries included for each model is reported in Table 9 in the appendix

data on personal income tax, corporate income tax, value-added tax, excise, and property taxes from 1930 to 2017. However, for the purpose of this study, we only consider PIT, VAT, and CIT. We adopt a similar approach to Gechert and Groß (2019) and Amaglobeli et al. (2022), where we count the number of major tax base reforms implemented within a year but we introduce two dummy variables to account for tax base expansion and tax base narrowing. The tax base expansion dummy variable takes a value of 1 if there are more major tax base expansion reforms than major tax base narrowing reforms in a given year, and 0 otherwise. The opposite is true for the tax base narrowing dummy variable. By construction, both dummy variables cannot simultaneously have a value of 1 in a given year. It is important to note that dummy variables, while useful for controlling for tax base reforms, do not capture the magnitude of such reforms. Unfortunately, the inherent design of the TPRD dataset prevents us from addressing this limitation. The short-run buoyancy estimates with and without control for discretionary changes in the tax base are presented in Figure 20, and the regression output is shown in Table 10. The results suggest that controlling for tax base reforms does not have a significant impact on the short-term coefficients, indicating that there is no significant correlation between tax base reforms and GDP

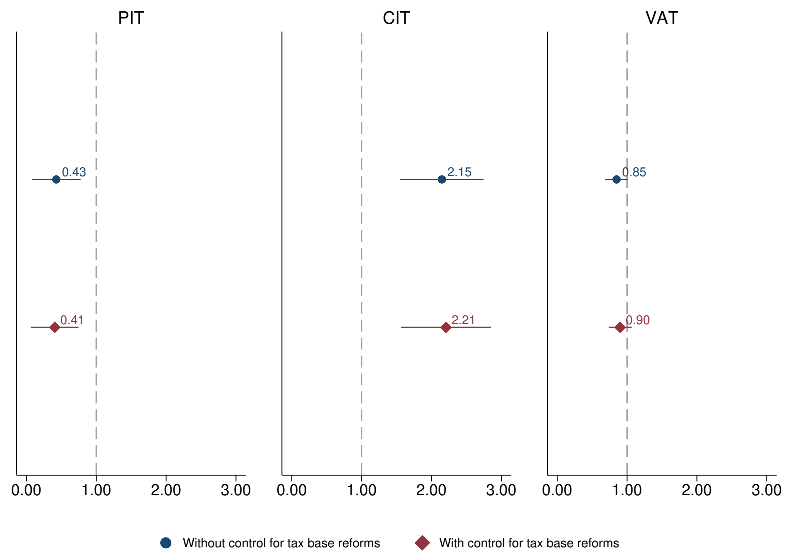
3.2.3 Controlling for changes in tax exemptions

To control for changes in tax exemptions, we utilize the Global Tax Expenditures Database (GTED) of the Council on Economic Policies and the German Development Institute (Redonda et al., 2022). The GTED comprises all publicly available data on tax expenditures published by national governments worldwide from 1990 onwards, covering 102 countries. In this study, we consider "tax expenditures" and "tax exemptions" to be synonymous, referring to provisions in the tax code that allow taxpayers to reduce their tax liability through exemptions, deductions, credits, or other types of tax preferences. Given that the GTED does not provide data on tax exemptions by tax component, we limit our analysis to aggregated tax revenues but provide estimations by country income group. The short-run buoyancy estimates with and without control for tax exemptions are presented in Figure 21, and the regression output is shown in Table 11. The results indicate that controlling for tax exemptions has only a marginal impact on the short-term coefficients, suggesting once again a lack of significant correlation between tax exemptions and GDP.



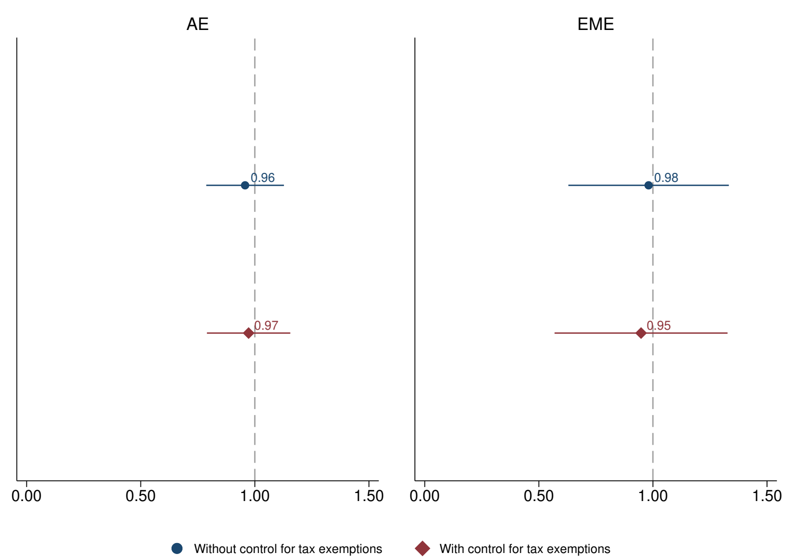
Notes: The estimator is PMG.

Figure 19: Tax components short-run buoyancy estimates controlling for tax rates



Notes: The estimator is PMG.

Figure 20: Tax components short-run buoyancy estimates controlling for tax base reforms



Notes: The estimator is PMG. LIC is not reported because of a lack of sufficient historical data on tax exemption.

Figure 21: Total tax revenues short-run buoyancy estimates controlling for tax exemptions

3.3 Robustness checks

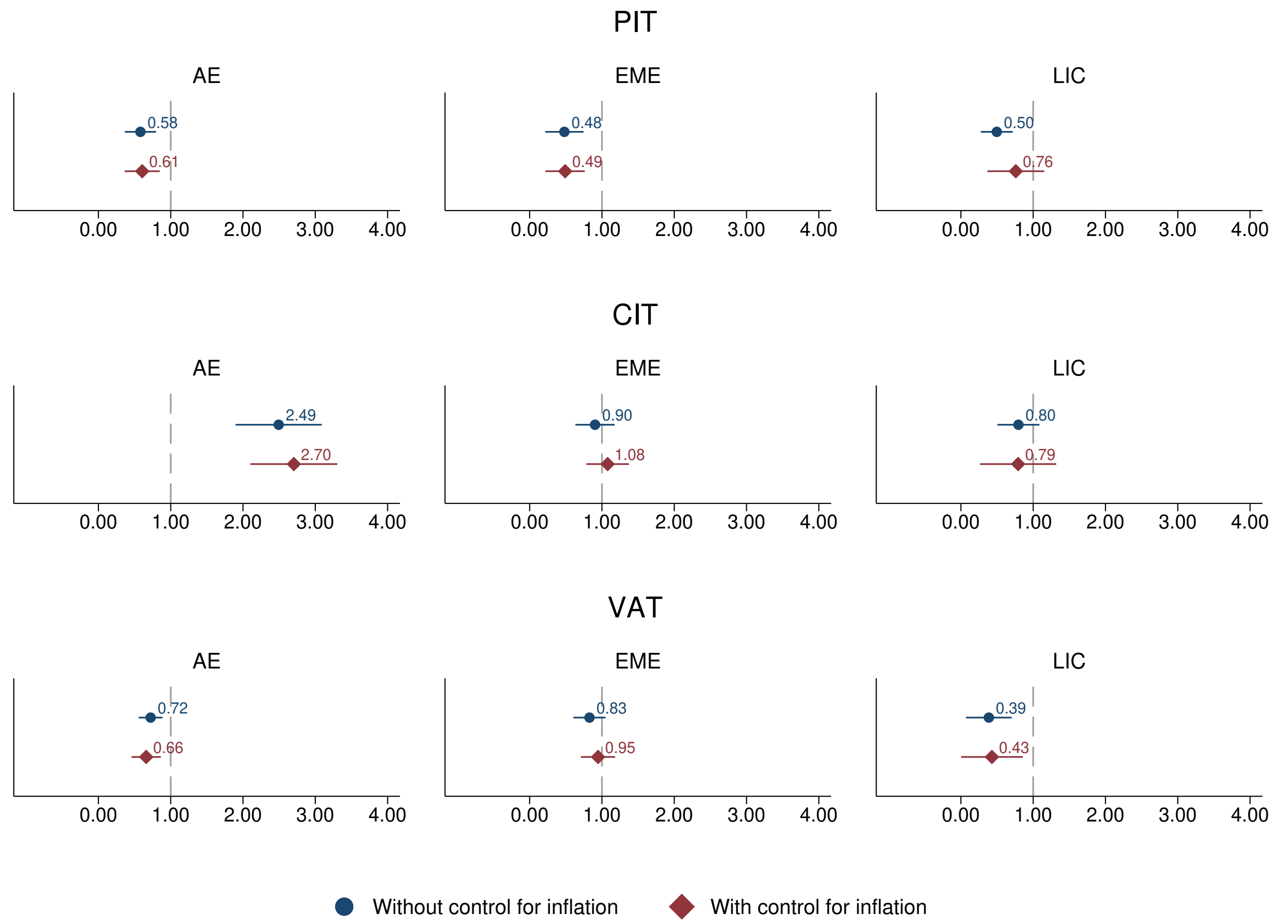
3.3.1 Controlling for inflation

Tax systems that do not account for inflation may face a "fiscal drag" during periods of high inflation Mourre and Princen (2019). This occurs when tax authorities collect more revenue due to higher prices, but do not adjust the tax base (e.g. by not adjusting income brackets for personal income tax). Under such circumstances, the tax buoyancy coefficients should become lower after controlling for inflation. Therefore, by controlling for inflation, it is possible to determine whether tax buoyancy is independent of price changes and compare tax buoyancy in real terms to tax buoyancy in nominal terms. Figure **??** presents our estimates of short-run buoyancy with and without controlling for inflation. Our results suggest that tax buoyancy is neutral with respect to inflation across tax components and country income groups. This finding differs from those of some previous cross-country studies (Belinga et al., 2014; Dudine and Jalles, 2018). However, the robustness of the coefficients in our study may be due to lower levels of inflation in the time period covered (beginning in the 1990s) compared to earlier periods in the previous studies, and the introduction of the indexing of tax brackets to inflation in both advanced and developing economies since the mid-1980s[21].

3.3.2 Balanced panel

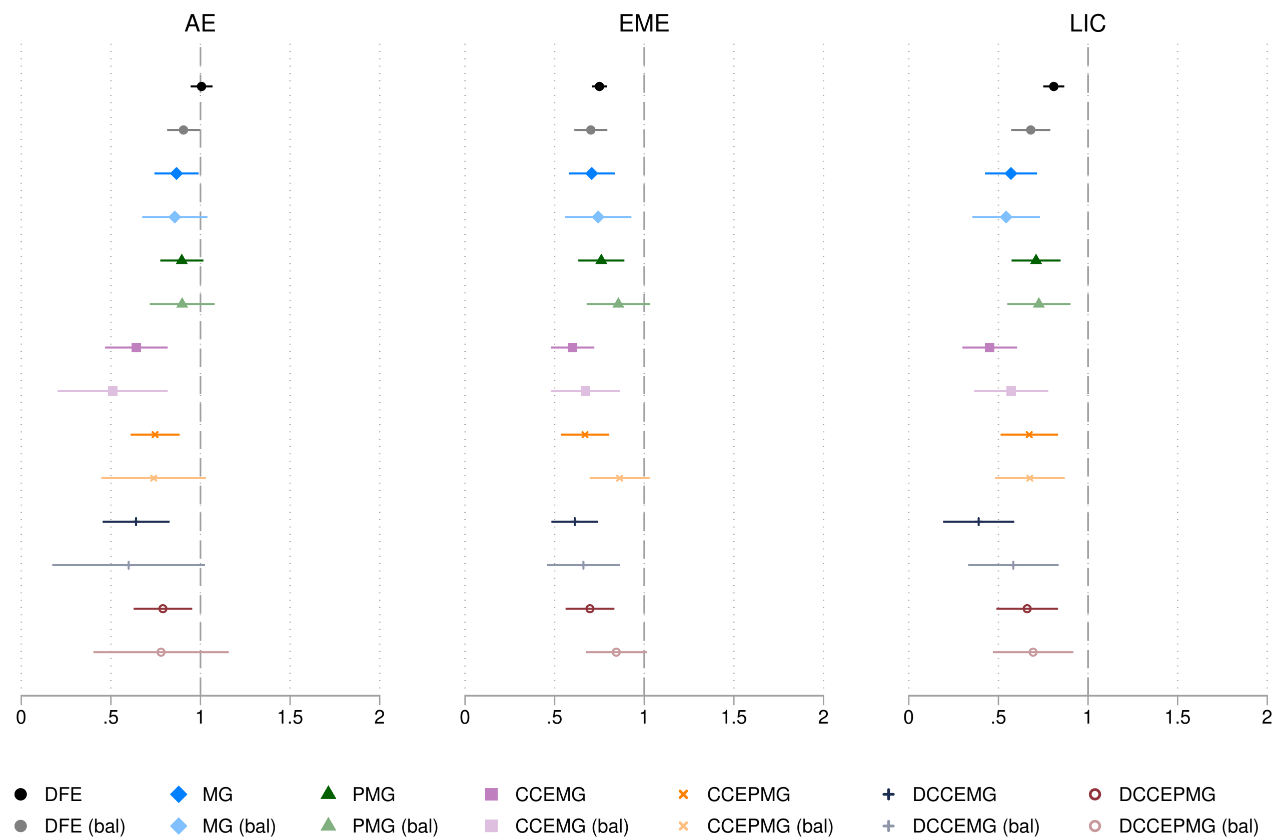
To address a potential selection bias towards more developed economies in the earlier periods of the sample, we also run additional regressions for 2001-2019 using a reduced sample to obtain a more balanced panel. A bias towards more developed economies may occur as we place more weight on countries with longer historical time series and typically stronger institutional structures, potentially neglecting countries with shorter time series. In this section, we present results for total tax revenues but results for other tax components yield similar outputs and are available upon request. Figures 22 and 23 respectively display estimates for short-run and long-run buoyancy across all estimators using both the full sample and the balanced panel. Overall, our estimates of short-run and long-run tax buoyancy remain robust, with long-term buoyancy for total tax revenue hovering around one and short-run buoyancy being lower than one, particularly for EME and LIC.

[21]For example in the USA, the indexing of tax brackets to inflation was introduced in the Tax Reform Act of 1986. Prior to this, tax brackets were not automatically adjusted for inflation.



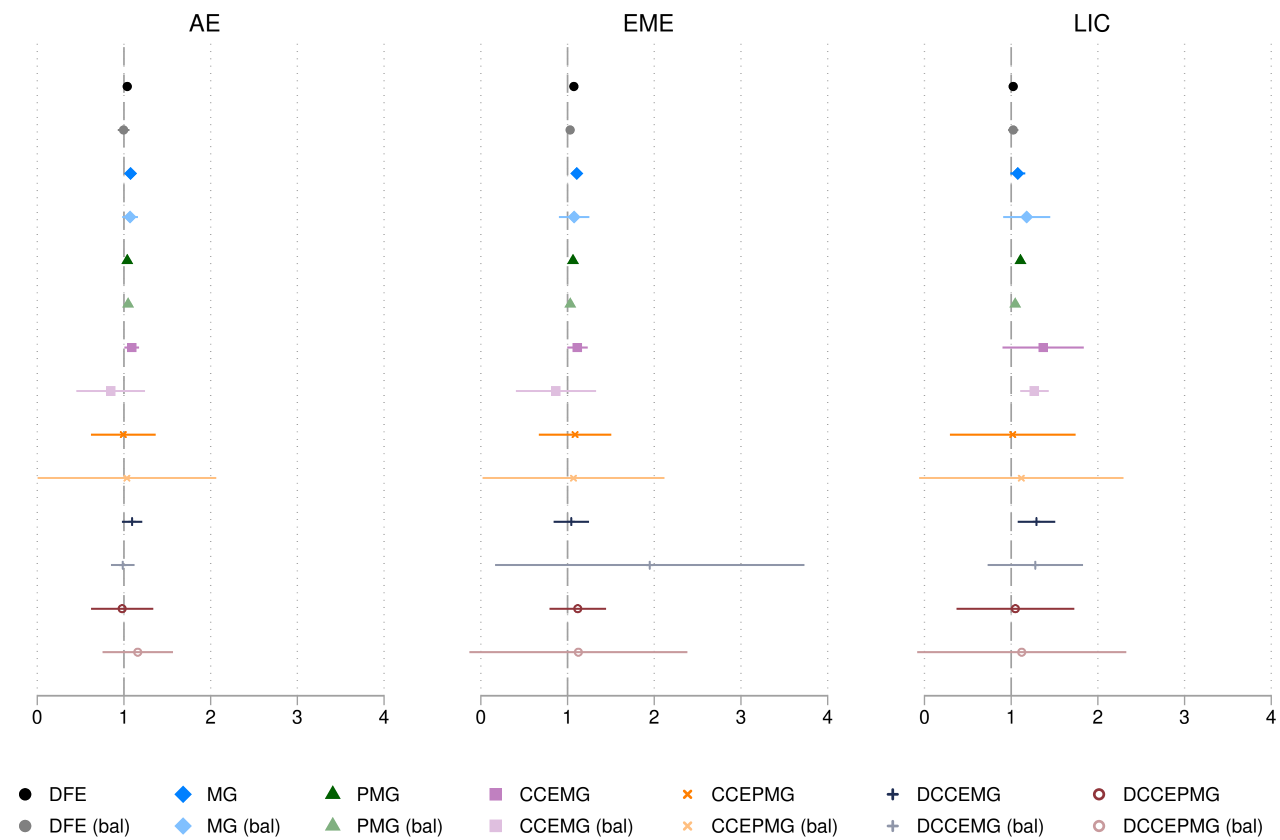
Notes: The estimator is PMG.

Figure 22: Robustness check: Controlling for inflation



Notes: The bars represent 95% confidence intervals. DFE = Dynamic Fixed Effect; MG = Mean Group; PMG= Pooled Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator. The balanced panel consists of 162 countries from 2011 until 2019

Figure 23: Robustness check: Short-run total tax revenues buoyancy by estimator with a balanced panel



Notes: The bars represent 95% confidence intervals. DFE = Dynamic Fixed Effect; MG = Mean Group; PMG= Pooled Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator. The balanced panel consists of 162 countries from 2011 until 2019

Figure 24: Robustness check: Long-run total tax revenues buoyancy by estimator with a balanced panel

4 Conclusion and policy implications

This paper provides estimates of short- and long-run tax buoyancy coefficients for total tax revenue, personal income tax, corporate income tax, and value added tax using a panel of 185 countries, grouped by level of income, over the period 1990-2021 using six different estimators. The use of different estimators contrast with previous literature commonly using only one. The analysis suggests that, overall, tax systems seem to be consistently buoyant in the long-run across methodologies, tax components, and country income group. In the short-run, buoyancy estimates are consistently below 1 for aggregated tax revenue but vary by tax components. Short-term buoyancy is broadly higher in Advanced Economies than in Emerging Market Economies and Low-Income Countries. However, significant intra-group variability exist suggesting that the estimation technique, the pooling of countries, and the mix of tax revenues are key elements to consider when estimating tax buoyancy. Finally, controlling for discretionary changes in tax rates, tax base reforms, and tax exemptions does not seem to alter significantly the buoyancy estimates, hinting that, on average, tax policy is acyclical. These results imply that there is room for fiscal authorities to improve the automatic stabilization power of tax systems (i.e., increasing short-term tax buoyancy), to better align tax revenues with the business cycle considering more pro-active cyclical tax policy interventions.

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5 Appendix

5.1 Buoyancy estimates by country income groups and tax types for all estimators

Table 2: Buoyancy estimates by country income groups and tax type - DFE estimator

Advanced economies	Total Taxes	PIT	CIT	VAT
Short-term buoyancy	1.007***	0.759***	1.930***	0.835***
	(0.0312)	(0.0531)	(0.148)	(0.0519)
Speed of adjustment	-0.175***	-0.119***	-0.318***	-0.153***
	(0.0168)	(0.0154)	(0.0226)	(0.0179)
Long-term buoyancy	1.039***	1.069***	1.262***	1.018***
	(0.0186)	(0.0451)	(0.0481)	(0.0350)
Observations	981	936	936	890
Number of Countries	35	33	33	32
Emerging economies	Total taxes	PIT	CIT	VAT
Short-term buoyancy	0.738***	0.616***	0.774***	0.482***
	(0.0215)	(0.0567)	(0.0494)	(0.0319)
Speed of adjustment	-0.291***	-0.226***	-0.345***	-0.588***
	(0.0134)	(0.0147)	(0.0145)	(0.0164)
Long-term buoyancy	1.072***	1.075***	1.215***	1.092***
	(0.0102)	(0.0424)	(0.0244)	(0.00940)
Observations	2321	1466	1704	913
Number of Countries	87	60	68	36
Low income countries	Total taxes	PIT	CIT	VAT
Short-term buoyancy	0.821***	0.740***	0.784***	0.208**
	(0.0293)	(0.0722)	(0.0773)	(0.0945)
Speed of adjustment	-0.194***	-0.211***	-0.259***	-0.262***
	(0.0145)	(0.0179)	(0.0225)	(0.0317)
Long-term buoyancy	1.031***	1.221***	1.157***	1.117***
	(0.0185)	(0.0432)	(0.0384)	(0.0365)
Observations	1282	790	790	435
Number of Countries	52	34	34	20

Notes: Standard errors in parenthesis. PIT = Personal Income Tax; CIT = Corporate Income Tax VAT = Value Added Tax. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Buoyancy estimates by country income groups and tax type - MG estimator

Advanced economies	Total Taxes	PIT	CIT	VAT
Short-term buoyancy	0.866***	0.559***	2.562***	0.607***
	(0.0629)	(0.133)	(0.308)	(0.0852)
Speed of adjustment	-0.325***	-0.302***	-0.442***	-0.414***
	(0.0290)	(0.0403)	(0.0295)	(0.0475)
Long-term buoyancy	1.076***	1.012***	1.303***	1.398***
	(0.0324)	(0.125)	(0.0663)	(0.256)
Observations	981	936	936	890
Number of Countries	35	33	33	32
R^2	0.206	0.525	0.544	0.443
CD	16.10	12.30	9.723	6.049
CD p-value	0	0	0	0

Emerging economies	Total taxes	PIT	CIT	VAT
Short-term buoyancy	0.707***	0.438***	0.951***	0.827***
	(0.0654)	(0.163)	(0.158)	(0.125)
Speed of adjustment	-0.398***	-0.426***	-0.464***	-0.466***
	(0.0274)	(0.0261)	(0.0318)	(0.0467)
Long-term buoyancy	1.107***	1.111***	1.212***	0.994***
	(0.0215)	(0.137)	(0.0605)	(0.132)
Observations	2321	1466	1704	913
Number of Countries	87	60	68	36
R^2	0.189	0.538	0.347	0.0614
CD	42.37	7.885	22.40	14.17
CD p-value	0	0	0	0

Low income countries	Total taxes	PIT	CIT	VAT
Short-term buoyancy	0.570***	0.488***	0.773***	0.437**
	(0.0739)	(0.159)	(0.202)	(0.176)
Speed of adjustment	-0.393***	-0.449***	-0.470***	-0.463***
	(0.0282)	(0.0436)	(0.0423)	(0.0671)
Long-term buoyancy	1.076***	1.332***	1.240***	2.322**
	(0.0442)	(0.0777)	(0.0756)	(1.117)
Observations	1282	790	790	435
Number of Countries	52	34	34	20
R^2	0.305	0.511	0.508	0.512
CD	1.804	5.886	0.472	-0.706
CD p-value	0.0712	0	0.637	0.480

Notes: Standard errors in parenthesis. PIT = Personal Income Tax; CIT = Corporate Income Tax VAT = Value Added Tax. CD is the Pesaran (2015) test for weak cross-sectional dependence of residuals. CD p-value is the related p-value to the CD test.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Buoyancy estimates by country income groups and tax type - PMG estimator

Advanced economies	Total Taxes	PIT	CIT	VAT
Short-term buoyancy	0.942***	0.713***	2.457***	0.819***
	(0.0496)	(0.0975)	(0.287)	(0.0647)
Speed of adjustment	-0.181	-0.145	-0.322***	-0.151
	(0.160)	(0.401)	(0.0860)	(0.973)
Long-term buoyancy	1.012***	1.038**	1.243***	1.023
	(0.174)	(0.505)	(0.138)	(1.405)
Observations	981	936	936	890
Number of Countries	35	33	33	32
R^2	0.244	0.596	0.617	0.585
CD	16.64	11.44	8.855	5.457
CD p-value	0	0	0	0
Emerging economies	Total taxes	PIT	CIT	VAT
Short-term buoyancy	0.799***	0.580***	1.032***	0.583***
	(0.0615)	(0.130)	(0.145)	(0.133)
Speed of adjustment	-0.279***	-0.243*	-0.368***	-0.612**
	(0.0979)	(0.135)	(0.102)	(0.279)
Long-term buoyancy	1.080***	1.146***	1.266***	1.103***
	(0.142)	(0.108)	(0.107)	(0.330)
Observations	2321	1466	1704	913
Number of Countries	87	60	68	36
R^2	0.238	0.642	0.510	0.181
CD	43.43	7.675	33.04	14.30
CD p-value	0	0	0	0
Low income countries	Total taxes	PIT	CIT	VAT
Short-term buoyancy	0.716***	0.656***	0.860***	0.538***
	(0.0693)	(0.106)	(0.142)	(0.131)
Speed of adjustment	-0.194	-0.212	-0.262	-0.254
	(0.151)	(0.193)	(0.167)	(2.397)
Long-term buoyancy	0.983***	1.228***	1.156***	1.162
	(0.191)	(0.300)	(0.253)	(2.854)
Observations	1282	790	790	435
Number of Countries	52	34	34	20
R^2	0.370	0.637	0.645	0.661
CD	1.647	1.534	-0.822	0.199
CD p-value	0.0996	0.125	0.411	0.843

Notes: Standard errors in parenthesis. PIT = Personal Income Tax; CIT = Corporate Income Tax VAT = Value Added Tax. CD is the Pesaran (2015) test for weak cross-sectional dependence of residuals. CD p-value is the related p-value to the CD test.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Buoyancy estimates by country income groups and tax type - CCEMG estimator

Advanced economies	Total Taxes	PIT	CIT	VAT
Short-term buoyancy	0.642^{***}	0.419^{***}	1.310^{***}	0.532^{***}
	(0.0890)	(0.143)	(0.390)	(0.119)
Speed of adjustment	-0.291^{***}	-0.326^{***}	-0.414^{***}	-0.406^{***}
	(0.0273)	(0.0390)	(0.0328)	(0.0455)
Long-term buoyancy	1.089^{***}	1.072^{***}	1.274^{***}	1.415^{***}
	(0.0431)	(0.164)	(0.0809)	(0.335)
Observations	981	936	936	890
Number of Countries	35	33	33	32
R^2	0.313	0.642	0.641	0.533
CD	1.318	-0.804	2.615	-1.551
CD p-value	0.188	0.421	0	0.121
Emerging economies	Total taxes	PIT	CIT	VAT
Short-term buoyancy	0.600^{***}	0.362	0.637^{***}	0.671^{***}
	(0.0619)	(0.251)	(0.183)	(0.135)
Speed of adjustment	-0.390^{***}	-0.426^{***}	-0.452^{***}	-0.490^{***}
	(0.0281)	(0.0268)	(0.0332)	(0.0416)
Long-term buoyancy	1.115^{***}	1.236^{***}	1.247^{***}	1.122^{***}
	(0.0601)	(0.0814)	(0.0884)	(0.0481)
Observations	2321	1466	1704	913
Number of Countries	87	60	68	36
R^2	0.254	0.604	0.383	0.151
CD	4.216	4.056	2.162	4.368
CD p-value	0	0	0.0306	0
Low income countries	Total taxes	PIT	CIT	VAT
Short-term buoyancy	0.452^{***}	0.392^{**}	0.647^{***}	0.435^{***}
	(0.0777)	(0.159)	(0.177)	(0.153)
Speed of adjustment	-0.417^{***}	-0.455^{***}	-0.462^{***}	-0.421^{***}
	(0.0332)	(0.0475)	(0.0488)	(0.0636)
Long-term buoyancy	1.369^{***}	1.335^{***}	1.307^{***}	1.188^{***}
	(0.239)	(0.0650)	(0.0782)	(0.0824)
Observations	1282	790	790	435
Number of Countries	52	34	34	20
R^2	0.346	0.512	0.546	0.606
CD	4.732	1.902	-1.554	-2.529
CD p-value	0	0.0571	0.120	0.0115

Notes: Standard errors in parenthesis. PIT = Personal Income Tax; CIT = Corporate Income Tax VAT = Value Added Tax. CD is the Pesaran (2015) test for weak cross-sectional dependence of residuals. CD p-value is the related p-value to the CD test.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Buoyancy estimates by country income groups and tax type - CCEPMG estimator

Advanced economies	Total Taxes	PIT	CIT	VAT
Short-term buoyancy	0.747***	0.608***	1.494***	0.705***
	(0.0697)	(0.110)	(0.355)	(0.113)
Speed of adjustment	-0.167	-0.171	-0.274**	-0.172
	(0.169)	(0.546)	(0.112)	(0.335)
Long-term buoyancy	0.993***	0.989	1.187***	1.064***
	(0.190)	(0.670)	(0.211)	(0.387)
Observations	981	936	936	890
Number of Countries	35	33	33	32
R^2	0.366	0.751	0.735	0.702
CD	0.610	-2.510	-1.220	-2.470
CD p-value	0.542	0.0121	0.223	0.0135

Emerging economies	Total taxes	PIT	CIT	VAT
Short-term buoyancy	0.669***	0.386**	0.664***	0.746***
	(0.0691)	(0.183)	(0.199)	(0.192)
Speed of adjustment	-0.308*	-0.256*	-0.430***	-0.379*
	(0.168)	(0.134)	(0.108)	(0.220)
Long-term buoyancy	1.087***	1.193***	1.282***	1.117***
	(0.213)	(0.151)	(0.0979)	(0.212)
Observations	2321	1466	1704	913
Number of Countries	87	60	68	36
R^2	0.314	0.704	0.538	0.287
CD	4.622	-3.320	7.033	2.450
CD p-value	0	0	0	0.0143

Low income countries	Total taxes	PIT	CIT	VAT
Short-term buoyancy	0.672***	0.571***	0.808***	0.497***
	(0.0816)	(0.155)	(0.152)	(0.135)
Speed of adjustment	-0.238	-0.228	-0.256	-0.247
	(0.265)	(0.197)	(0.181)	(0.193)
Long-term buoyancy	1.018***	1.305***	1.189***	1.235***
	(0.370)	(0.311)	(0.255)	(0.208)
Observations	1282	790	790	435
Number of Countries	52	34	34	20
R^2	0.446	0.633	0.710	0.808
CD	3.402	-1.446	-3.263	-2.864
CD p-value	0	0.148	0	0

Notes: Standard errors in parenthesis. PIT = Personal Income Tax; CIT = Corporate Income Tax VAT = Value Added Tax. CD is the Pesaran (2015) test for weak cross-sectional dependence of residuals. CD p-value is the related p-value to the CD test.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Buoyancy estimates by country income groups and tax type - DCCEMG estimator

Advanced economies	Total Taxes	PIT	CIT	VAT
Short-term buoyancy	0.641***	0.373**	1.238***	0.545***
	(0.0951)	(0.166)	(0.436)	(0.120)
Speed of adjustment	-0.304***	-0.342***	-0.414***	-0.391***
	(0.0309)	(0.0442)	(0.0387)	(0.0474)
Long-term buoyancy	1.094***	1.197***	1.269***	3.629*
	(0.0598)	(0.125)	(0.0945)	(2.067)
Observations	946	903	903	857
Number of Countries	35	33	33	32
R^2	0.313	0.642	0.665	0.586
CD	1.287	-0.646	2.377	-0.764
CD p-value	0.198	0.518	0.0174	0.445
Emerging economies	Total taxes	PIT	CIT	VAT
Short-term buoyancy	0.613***	0.140	0.508***	0.746***
	(0.0667)	(0.181)	(0.188)	(0.134)
Speed of adjustment	-0.402***	-0.434***	-0.508***	-0.513***
	(0.0301)	(0.0307)	(0.0356)	(0.0423)
Long-term buoyancy	1.043***	1.223***	1.493***	1.252***
	(0.104)	(0.227)	(0.213)	(0.119)
Observations	2234	1405	1636	877
Number of Countries	87	60	68	36
R^2	0.288	0.577	0.421	0.219
CD	-0.424	5.764	4.680	2.069
CD p-value	0.671	0	0	0.0386
Low income countries	Total taxes	PIT	CIT	VAT
Short-term buoyancy	0.390***	0.482***	0.606***	0.848***
	(0.101)	(0.184)	(0.191)	(0.189)
Speed of adjustment	-0.422***	-0.462***	-0.510***	-0.474***
	(0.0375)	(0.0518)	(0.0497)	(0.0715)
Long-term buoyancy	1.292***	1.368***	1.326***	1.202***
	(0.110)	(0.0752)	(0.0691)	(0.0752)
Observations	1230	755	755	415
Number of Countries	52	34	34	20
R^2	0.346	0.519	0.606	0.576
CD	5.007	1.746	-0.885	-2.863
CD p-value	0	0.0809	0.376	0

Notes: Standard errors in parenthesis. PIT = Personal Income Tax; CIT = Corporate Income Tax VAT = Value Added Tax. CD is the Pesaran (2015) test for weak cross-sectional dependence of residuals. CD p-value is the related p-value to the CD test. We use one lag of cross-sectional averages for the DCCE.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Buoyancy estimates by country income groups and tax type - DCCEPMG estimator

Advanced economies	Total Taxes	PIT	CIT	VAT
Short-term buoyancy	0.790***	0.552***	1.440***	0.803***
	(0.0835)	(0.142)	(0.439)	(0.128)
Speed of adjustment	-0.168	-0.195	-0.260**	-0.134
	(0.160)	(0.466)	(0.114)	(2.772)
Long-term buoyancy	0.979***	0.961**	1.236***	1.055
	(0.183)	(0.482)	(0.174)	(1.456)
Observations	946	903	903	857
Number of Countries	35	33	33	32
R^2	0.363	0.767	0.744	0.706
CD	-0.537	-2.128	-0.704	-2.198
CD p-value	0.591	0.0334	0.481	0.0280
Emerging economies	Total taxes	PIT	CIT	VAT
Short-term buoyancy	0.697***	0.333**	0.543**	1.097***
	(0.0695)	(0.160)	(0.212)	(0.124)
Speed of adjustment	-0.289**	-0.262***	-0.407**	-0.194
	(0.132)	(0.0491)	(0.188)	(0.361)
Long-term buoyancy	1.118***	1.087***	1.302***	1.100***
	(0.166)	(0.146)	(0.190)	(0.374)
Observations	2234	1405	1636	877
Number of Countries	87	60	68	36
R^2	0.363	0.651	0.615	0.307
CD	0.257	7.935	1.505	3.648
CD p-value	0.797	0	0.132	0
Low income countries	Total taxes	PIT	CIT	VAT
Short-term buoyancy	0.661***	0.650***	0.765***	0.734***
	(0.0875)	(0.169)	(0.182)	(0.150)
Speed of adjustment	-0.223	-0.274	-0.267	-0.290
	(0.305)	(0.268)	(0.191)	(0.238)
Long-term buoyancy	1.049***	1.298***	1.264***	1.207***
	(0.346)	(0.390)	(0.297)	(0.301)
Observations	1230	755	755	415
Number of Countries	52	34	34	20
R^2	0.437	0.648	0.744	0.755
CD	2.248	-1.376	-2.610	-3.125
CD p-value	0.0246	0.169	0	0

Notes: Standard errors in parenthesis. PIT = Personal Income Tax; CIT = Corporate Income Tax VAT = Value Added Tax. CD is the Pesaran (2015) test for weak cross-sectional dependence of residuals. CD p-value is the related p-value to the CD test. We use one lag of cross-sectional averages for the DCCE.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Robustness checks: Controlling for tax policy changes

Table 9: Buoyancy estimates by country income groups and tax type - controlling changes in tax rates

	PIT		CIT		VAT	
Advanced economies	No control	Control	No control	Control	No control	Control
Short-term buoyancy	0.736***	0.632***	2.698***	2.702***	0.838***	0.676***
	(0.112)	(0.112)	(0.333)	(0.390)	(0.0836)	(0.101)
Speed of adjustment	-0.165	-0.233	-0.320***	-0.339**	-0.153	-0.419***
	(0.252)	(0.203)	(0.0918)	(0.155)	(0.331)	(0.130)
Long-term buoyancy	1.051***	1.107***	1.240***	1.278***	1.134***	1.053***
	(0.319)	(0.191)	(0.184)	(0.356)	(0.407)	(0.162)
Observations	718	718	727	727	674	674
Number of Countries	25	25	25	25	24	24
R^2	0.579	0.546	0.618	0.589	0.576	0.431
CD	7.742	6.702	4.503	4.302	4.100	3.040
CD p-value	0	0	0	0	0	0

	PIT		CIT		VAT	
Emerging economies	No control	Control	No control	Control	No control	Control
Short-term buoyancy	0.467***	0.457***	0.737***	0.782***	0.881***	0.717***
	(0.181)	(0.152)	(0.187)	(0.190)	(0.0636)	(0.0757)
Speed of adjustment	-0.236	-0.265	-0.382**	-0.403**	-0.292	-0.452***
	(0.233)	(0.279)	(0.180)	(0.180)	(0.482)	(0.105)
Long-term buoyancy	1.202***	1.211***	1.186***	1.175***	1.098**	1.073***
	(0.252)	(0.249)	(0.251)	(0.259)	(0.545)	(0.285)
Observations	742	742	818	818	598	598
Number of Countries	30	30	33	33	23	23
R^2	0.372	0.338	0.317	0.305	0.155	0.118
CD	1.456	1.507	12.14	11.71	12.37	12.67
CD p-value	0.145	0.132	0	0	0	0

	PIT		CIT		VAT	
Low income countries	No control	Control	No control	Control	No control	Control
Short-term buoyancy	0.605***	0.573***	0.991***	1.004***	1.038***	1.035**
	(0.137)	(0.132)	(0.320)	(0.326)	(0.365)	(0.416)
Speed of adjustment	-0.251	-0.316	-0.241	-0.243	-0.181	-0.240
	(0.709)	(0.558)	(0.476)	(0.470)	(0.455)	(0.410)
Long-term buoyancy	1.142	1.193**	1.164*	1.189*	1.153**	1.075**
	(0.942)	(0.518)	(0.681)	(0.643)	(0.534)	(0.445)
Observations	118	118	136	136	77	77
Number of Countries	6	6	7	7	4	4
R^2	0.636	0.603	0.694	0.675	0.613	0.545
CD	2.395	3.305	1.016	0.874	0.900	0.844
CD p-value	0.017	0	0.310	0.382	0.368	0.399

Notes: S.E in parenthesis. PIT: Personal Income Tax; CIT: Corporate Income Tax; VAT: Value Added Tax. Tax rates from Vegh and Vuletin (2015). PMG estimator but conclusions are robust for other estimators. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Buoyancy estimates by country income groups and tax type - controlling for discretionary changes in the tax base

	PIT		CIT		VAT	
	No control	Control	No control	Control	No control	Control
Short-term buoyancy	0.428**	0.406**	2.149***	2.207***	0.850***	0.901***
	(0.177)	(0.173)	(0.304)	(0.328)	(0.0846)	(0.0835)
Speed of adjustment	-0.494	-0.513	-0.289**	-0.288**	-0.145	-0.128
	(0.346)	(0.373)	(0.141)	(0.145)	(1.318)	(0.529)
Long-term buoyancy	1.047***	1.046**	1.217***	1.209***	1.047	1.060
	(0.385)	(0.459)	(0.171)	(0.180)	(1.712)	(0.664)
Observations	644	644	649	649	564	564
Number of Countries	23	23	23	23	20	20
R^2	0.352	0.327	0.601	0.545	0.361	0.341
CD	16.11	15.47	8.660	6.458	4.047	3.484
CD p-value	0	0	0	0	0	0

Notes: Standard errors in parenthesis. PIT = Personal Income Tax; CIT = Corporate Income Tax VAT = Value Added Tax. Tax base reforms are from the Tax Policy Reform Database (TPRD) of the IMF. The estimator is PMG but conclusions are robust using other estimators (regression tables for other estimators are available from authors upon request). The number of countries is limited to the the 23 countries covered in the TPRD which are mostly AE and some EME.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Total tax revenues buoyancy estimates by country income groups - controlling for tax exemptions

	AE		EME	
	No control	Control	No control	Control
Short-term buoyancy	0.957***	0.973***	0.981***	0.948***
	(0.0865)	(0.0928)	(0.178)	(0.192)
Speed of adjustment	-0.280	-0.272	-0.283	-0.329
	(0.391)	(0.343)	(0.312)	(0.364)
Long-term buoyancy	0.972**	1.003***	1.046***	1.062***
	(0.386)	(0.364)	(0.370)	(0.388)
Observations	341	341	219	219
Number of Countries	15	15	13	13
R^2	0.533	0.472	0.239	0.217
CD	-0.425	-0.458	4.243	4.668
CD p-value	0.670	0.647	0	0

Notes: Standard errors in parenthesis. Data on tax exemptions is from the Global Tax Expenditure Database (GTED) (Redonda et al., 2022). The estimator is PMG but conclusions are robust using other estimators (regression tables for other estimators are available from authors upon request). LIC is not reported because of a lack of sufficient historical data on tax exemption.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Summary statistics

Table 12: Summary statistics (1990-2020 in billions of USD)

	Obs	Mean	Std. Dev.	Min	Max	Source
Total tax revenue	4697	87	351	< 1	5337	WEO and OECD
PIT revenue	3369	31	140	< 1	2192	WEO and OECD
CIT revenue	3561	12	41	< 1	634	WEO and OECD
Value added tax revenue	2521	21	61	< 1	1018	OECD
Forgone tax revenue	1152	43	158	< 1	1603	GTED
Nominal GDP	5494	286	1266	< 1	21373	WEO

5.4 Tests for cross-sectional dependence

The presence of dependence between cross-sectional units in an OLS regression model violates the assumption of independent and identically distributed error term, thus compromising the accuracy of the estimation results. Pesaran (2015) develops a test to identify cross sectional dependence based on the correlation coefficient between units. The null hypothesis is the presence of weak cross-sectional dependence, which indicates that the correlation between units at each point in time tends to zero as the number of cross sections increases to infinity. Instead, strong cross-sectional dependence suggest that the correlation converges to a constant. The test statistic for an unbalanced panel as in our case is:

$$CD = \sqrt{\frac{2}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left[\sqrt{T_{ij}} \hat{\rho_{ij}} \right] \right)$$

where $\rho(ij)$ is the correlation coefficient of country i and j and $T(ij)$ is the number of common observations between i and j. Table 13 reports cross-sectional test statistic for the first difference of the logarithm of all variables of interest, the average correlation correlation coefficient and the average absolute correlation coefficient. The test statistics suggest the presence of cross-sectional dependence across all variables of interest and across most income groups. Average cross-correlation between pairs of countries are higher for AE compared to EME and LIC.

Table 13: Pesaran (2015) cross-sectional dependence tests and average correlation coefficient of all variables

	Pesaran CD-test			Correlation			Correlation (abs)		
Variable	AE	EME	LIC	AE	EME	LIC	AE	EME	LIC
Δ Total Tax Revenues	60.78***	50.76***	1.24	0.316	0.101	0.004	0.318	0.147	0.271
	(0.000)	(0.000)	(0.216)						
Δ PIT	21.58***	8.42***	11.59***	0.127	0.03	0.08	0.165	0.110	0.124
	(0.000)	(0.000)	(0.000)						
Δ CIT	24.48***	14.34***	6.31***	0.144	0.04	0.044	0.165	0.102	0.100
	(0.000)	(0.000)	(0.000)						
Δ VAT	20.65***	6.51***	5.14***	0.129	0.04	0.085	0.161	0.130	0.136
	(0.000)	(0.000)	(0.000)						
Δ GDP	83.82***	166.45***	47.17***	0.436	0.330	0.142	0.438	0.420	0.267
	(0.000)	(0.000)	(0.000)						

Notes: p-value in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.5 Panel unit root and cointegration tests

Table 14: Pesaran (2007) panel unit root tests

	Lags = 0			Lags = 1			Lags = 2		
Variable	AE	EME	LIC	AE	EME	LIC	AE	EME	LIC
Levels									
Total Tax Revenues	-1.852	-1.659	-1.92	-1.53	-1.663	-1.952	-1.523	-1.676	-1.972
PIT	-1.803	-2.15**	-2.256**	-1.537	-1.964	-2.185**	-1.332	-1.738	-1.638
CIT	-1.998	-2.061*	-2.365***	-1.527	-1.642	-2.097*	-1.642	-1.701	-1.626
VAT	-1.761	-1.818	-2.192*	-1.896	-1.803	-2.324**	-1.558	-1.435	-2.057
GDP	-1.323	-1.727	-1.986	-1.499	-1.661	-1.947	-1.363	-1.619	-1.823
First-difference									
Δ Total Tax Revenues	-3.477***	-3.676***	-3.764***	-2.38***	-2.569***	-2.826***	-1.695	-1.864	-2.252***
Δ PIT	-3.565***	-3.789***	-4.227***	-2.261***	-2.805***	-3.04***	-1.662	-2.122**	-1.957
Δ CIT	-3.869***	-4.247***	-4.056***	-2.518***	-2.663***	-3.154***	-1.952	-2.147**	-2.341***
Δ VAT	-3.586***	-3.97***	-4.017***	-2.79***	-3.064***	-2.955***	-2.212**	-2.084*	-1.966
Δ GDP	-2.834***	-3.233***	-3.377***	-2.367***	-2.465***	-2.653***	-2.045*	-2.03*	-2.175**

Notes: We use Pesaran (2007) panel unit root test as it properly takes into account the presence of cross-sectional dependence identified in table 13. The test requires a balanced panel so we use a reduced sample covering 2001-2019. The null hypothesis assumes that all series are non-stationary. To eliminate cross-sectional dependence, the test relies on a cross-sectionally augmented Dickey-Fuller distribution. We include 0,1, and 2 lags of the cross-section averages and report the results. Critical values are available in Pesaran (2007). The results suggest that the variables are non-stationary. All variables are in logarithm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Kao (1999) cointegration tests for GDP and tax revenues

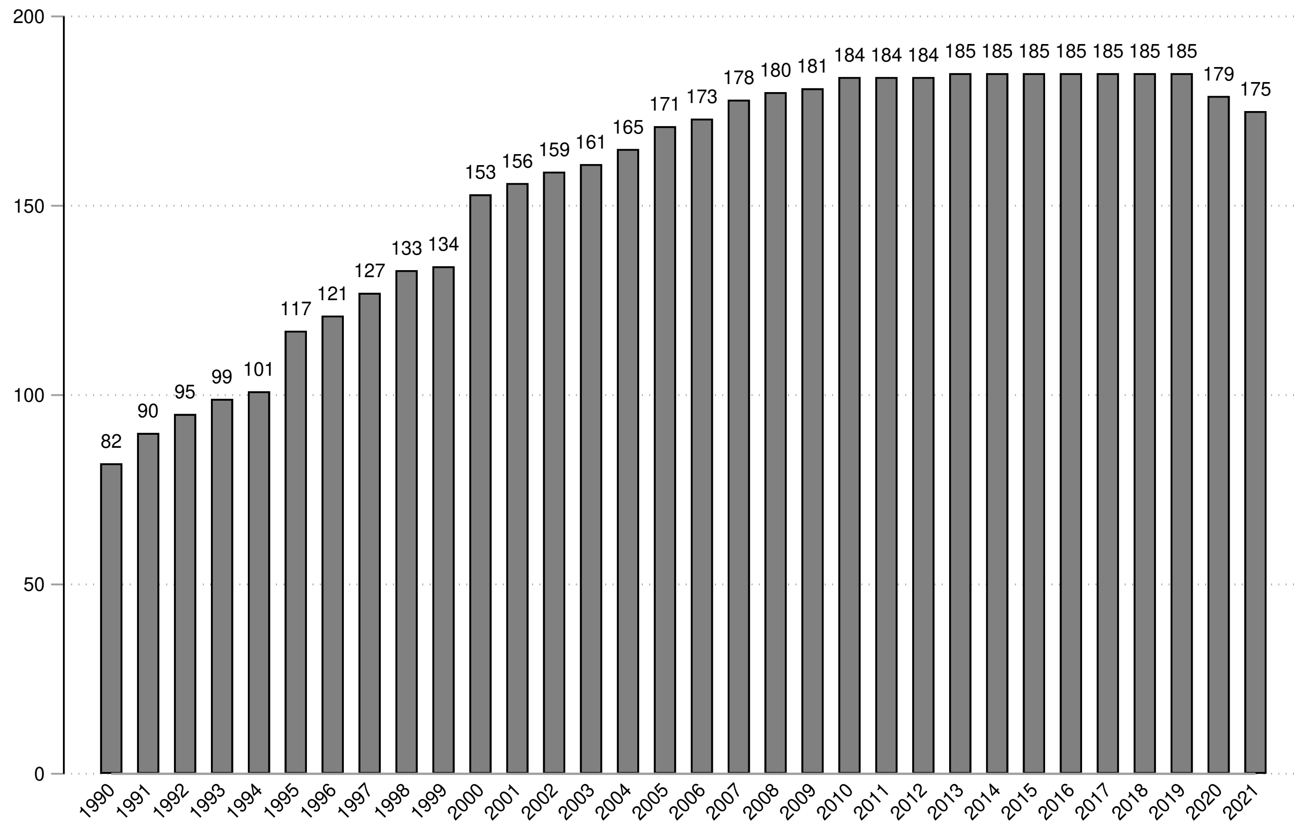
	Total Tax Revenues			PIT		
Test type	AE	EME	LIC	AE	EME	LIC
Modified Dickey-Fuller t	-3.573***	-6.211***	-2.128**	-0.372	-2.118**	-1.401*
	(0.000)	(0.000)	(0.017)	(0.355)	(0.017)	(0.080)
Dickey-Fuller t	-3.610***	-7.590***	-4.044***	-0.636	-5.313***	-4.266***
	(0.000)	(0.000)	(0.000)	(0.262)	(0.000)	(0.000)
Augmented Dickey-Fuller t	-3.067***	-4.038***	-5.410***	-1.706**	-9.948***	-1.715**
	(0.001)	(0.000)	(0.000)	(0.044)	(0.000)	(0.043)
Unadjusted modified Dickey-Fuller t	-4.041***	-12.860***	-3.159***	-0.634	-6.961***	-3.614***
	(0.000)	(0.000)	(0.001)	(0.261)	(0.000)	(0.000)
Unadjusted Dickey-Fuller t	-3.818***	-10.39***	-4.605***	-0.816	-7.882***	-5.481***
	(0.000)	(0.000)	(0.000)	(0.207)	(0.000)	(0.000)

(Continued)

Test type	CIT			VAT		
	AE	EME	LIC	AE	EME	LIC
Modified Dickey-Fuller t	-3.349***	-7.705***	-3.379***	-2.791***	-7.924***	-2.945***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Dickey-Fuller t	-3.576***	-8.656***	-3.795***	-3.272***	-7.243***	-3.463***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Augmented Dickey-Fuller t	-4.461***	-2.917***	-3.504***	-3.138***	-2.985***	-3.976***
	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)
Unadjusted modified Dickey-Fuller t	-9.073***	-11.15***	-5.308***	-7.754***	-6.738***	-3.751***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unadjusted Dickey-Fuller t	-6.049***	-9.914***	-4.684***	-5.535***	-6.882***	-3.816***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

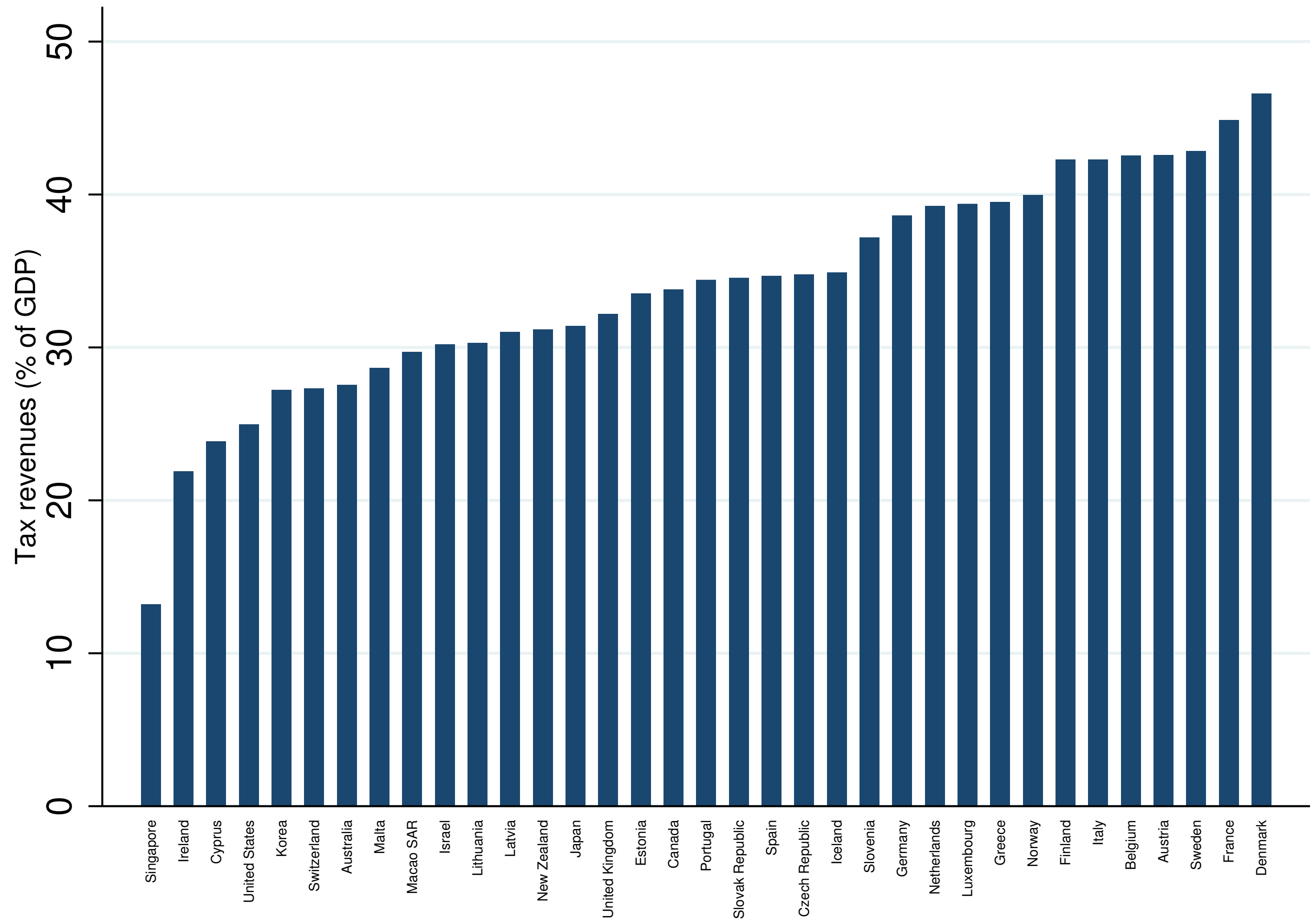
Notes: The null hypothesis assumes no cointegration. The alternative hypothesis is that the variables are cointegrated in all panels. All tests reject the null hypothesis of no cointegration except four out of five tests for GDP and PIT. We also ran Pedroni (1999) and Westerlund (2005) cointegration tests in which all null hypothesis are rejected (results for these tests available upon request). p-value in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.6 Additional data plots



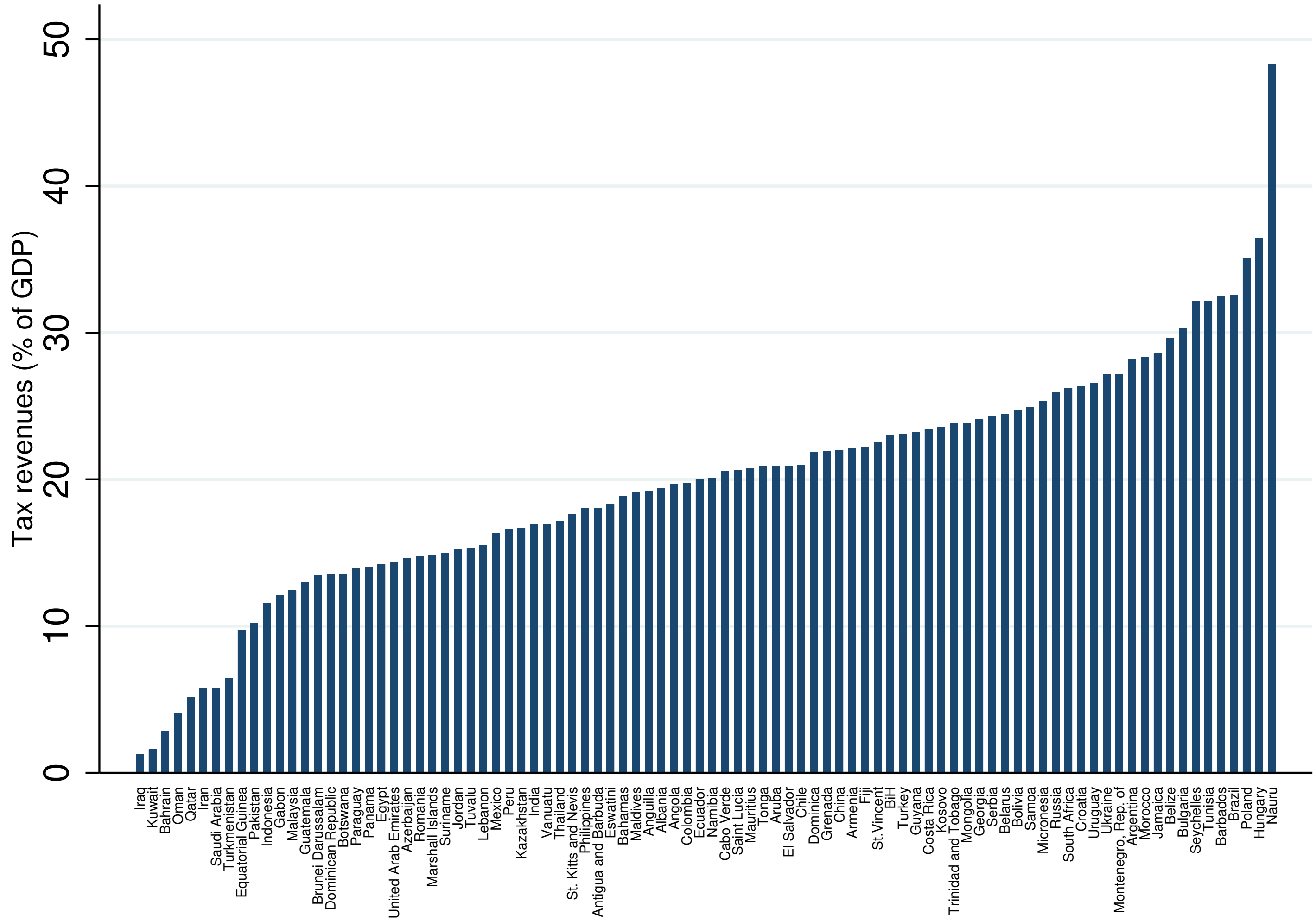
Source: Authors own calculations based on OECD and IMF WEO.

Figure 25: Number of countries with available aggregated tax revenues data per year.



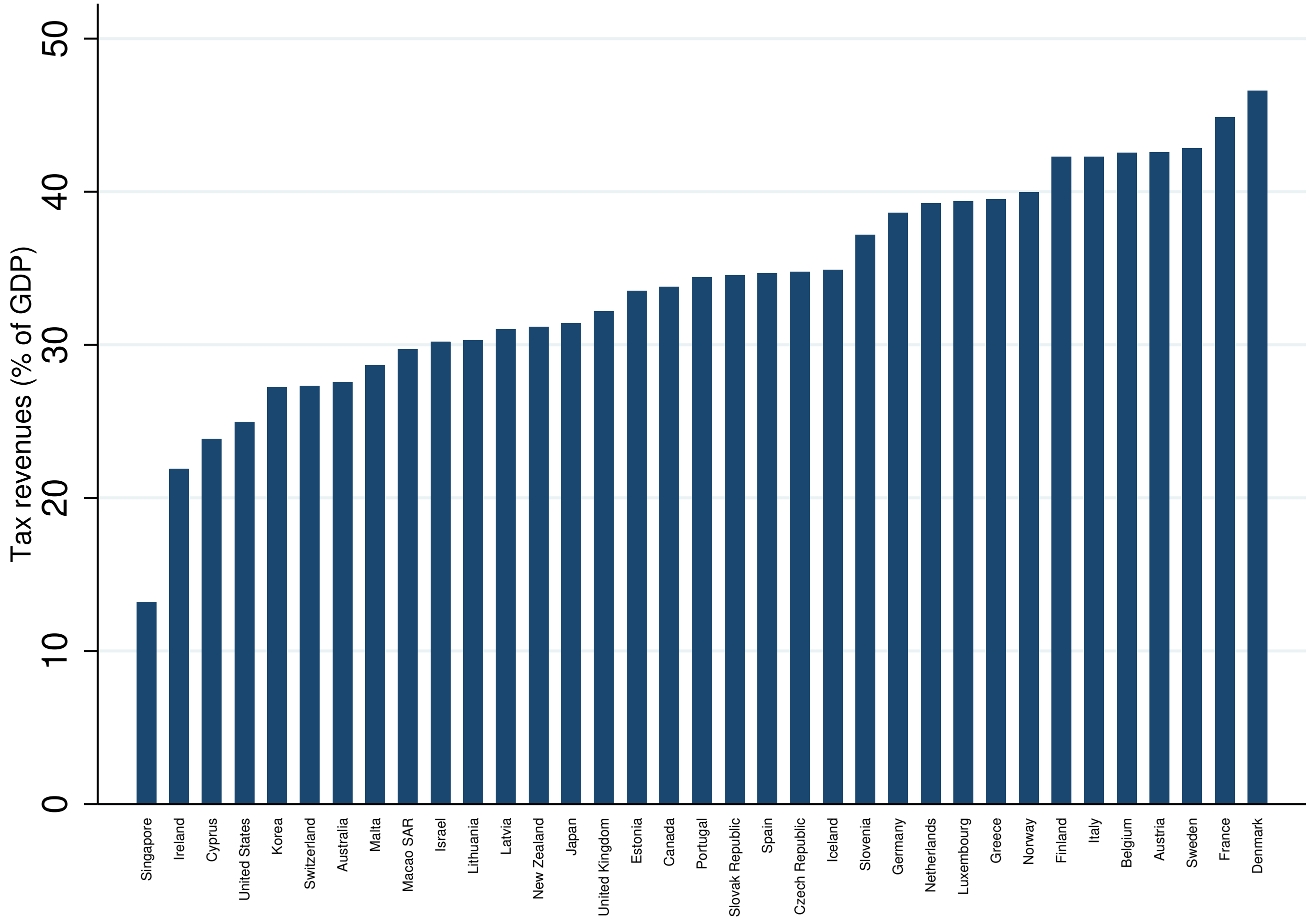
Source: Authors own calculations based on OECD and IMF WEO.

Figure 26: Advanced economies tax to GDP ratio as of 2019.



Source: Authors own calculations based on OECD and IMF WEO.

Figure 27: Emerging economies tax to GDP ratio as of 2019.



Source: Authors own calculations based on OECD and IMF WEO.

Figure 28: Low income countries tax to GDP ratio as of 2019.