Economic Modelling 140 (2024) 106867

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.journals.elsevier.com/economic-modelling

Do tax revenues track economic growth? Comparing panel data estimators

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ARTICLE INFO

Dataset link: https://doi.org/10.17632/dyspdzxpzz.1

JEL classification:
E60
H20
H30

Keywords:
Tax buoyancy
Tax elasticity
Cross-sectional dependence
Economic growth
Fiscal sustainability
Automatic stabilization

ABSTRACT

Determining how economic growth affects tax revenues is crucial for fiscal sustainability, economic stabilization, and policy design. The current literature on tax buoyancy presents contrasting estimates, highlighting the need for a systematic discussion of the trade-offs associated with different estimators. This paper provides new empirical evidence by reviewing a range of panel data estimators in a large sample of 172 countries from 1990 to 2019. We find evidence of lower estimates for tax responses to economic activity in the short term relative to previous literature, suggesting a limited automatic stabilization power of tax systems. The heterogeneity in our results within and across income groups underscores the importance of choosing the appropriate estimator. Our results remain broadly unchanged when we introduce new control variables to disentangle discretionary from automatic tax revenue variations, indicating that economic cycles do not significantly influence the timing of tax policies.

1. Introduction

In the aftermath of the Covid-19 pandemic, governments are revising their fiscal policy frameworks to tackle public finance sustainability challenges (Blanchard et al., 2021; Caselli et al., 2022). Record levels of public debt and pressures arising from the green transition, ageing population, and sustainable development goals, have created an environment with limited space for policy errors and the need for governments to produce fiscal frameworks with well calibrated parameters (Beetsma et al., 2021; Benedek et al., 2021). In this context, understanding how tax revenues respond to changes in national income is key for the design of fiscal policy plans.

The literature has approached this question by estimating two related, yet different, concepts: tax buoyancy and tax elasticity. Tax buoyancy refers to the total percentage change in tax revenues to the percentage change in the tax base, typically proxied by GDP (Mansfield, 1972). Tax buoyancy therefore captures both the automatic changes in tax revenues due to changes in economic conditions and the adjustments in tax revenues caused by changes in tax policy. In contrast, tax elasticity isolates the automatic component of revenue changes by controlling for the effects of tax policy measures (Musgrave and Miller, 1948). Therefore, tax elasticity is usually considered a better indicator compared to tax buoyancy for informing tax policies and forecasting tax revenues (OECD, 2023). However, while attempts to estimate tax elasticity abound in the literature (see for example Fricke and Süssmuth, 2014; Boschi and d'Addona, 2019; Mourre and Princen, 2019), tax buoyancy is often preferred due to several major challenges that prevent the use of the elasticity approach. First, an enormous amount of detailed information is necessary to assess developments in the various tax bases especially when analysing multiple countries over a long period (OECD, 2023). 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 (Dudine and Jalles, 2018). Third, other elements such as collection lags, tax evasion, and differences in accounting systems further complicate this task (Lagravinese et al., 2020).

While a significant share of the literature provides tax buoyancy or elasticity estimates at the country level (Creedy and Gemmell, 2009; Twerefou et al., 2010; Timsina et al., 2007), regional (Belinga et al., 2014; Deli et al., 2018; Khadan, 2020; Gupta et al., 2022) and global (Dudine and Jalles, 2018) tax buoyancy estimations have recently flourished due to a wider availability of panel datasets and the benefits of using panel data over traditional cross-sectional or time

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[1] We discuss this point in more details in Section 2.2.3.
[2] We define estimation issues related to the presence of cross-sectional dependence in Section 2.2.3.

https://doi.org/10.1016/j.econmod.2024.106867
Received 12 September 2023; Received in revised form 17 August 2024; Accepted 17 August 2024
Available online 20 August 2024
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series approaches.[1] Panel data models have also significantly evolved over time to address key limitations including the rationality of pooling heterogeneous panel units together (Pesaran and Smith, 1995) and the presence of cross-sectional dependence (Pesaran, 2006; Chudik and Pesaran, 2015a).[2]

In light of these evolutions, previous cross-country studies have found conflicting tax buoyancy estimates using alternative panel data models. For example, using heterogeneous coefficients panel data models in a global unbalanced panel of 107 countries from 1980 to 2017, Dudine and Jalles (2018) broadly find that both short- and long-run tax buoyancy coefficients for total tax revenues are not different from or slightly larger than one. Gupta et al. (2022) and Deli et al. (2018) confirm such results using similar heterogeneous coefficients panel data models respectively in an unbalanced sample of 44 sub-Saharan African (SSA) countries from 1980–2017 and in a panel of OECD countries from 1995 to 2015. However, using an alternative panel data model accounting for cross-sectional dependence, Lagravinese et al. (2020) find that both short- and long-run tax responses are significantly lower than one in a sample of 35 OECD countries over the period 1995–2016. Yet, the current literature lacks a systematic discussion of the potential trade-offs that come with using different panel data estimators across a consistent set of countries.

Using a large sample of 172 countries from 1990 to 2019, this paper compares estimators to assess tax buoyancy across country income groups and tax components. Our contribution to the literature is threefold: (i) we construct a more comprehensive tax revenue dataset to estimate tax buoyancy ; (ii) we compare and discuss differences in short- and long-term tax buoyancy obtained from different panel estimators; and (iii) we introduce new control variables related to tax exemptions and changes in tax bases in an attempt to better disentangle discretionary from automatic tax revenues changes (i.e. obtain estimates closer to elasticity).

The remainder of the paper is organized as follows. Section 2 explains the empirical methodology and introduces the panel data estimators. Section 3 presents our tax buoyancy estimates across several panel estimators and alternative controls for tax policy changes. Section 4 concludes.

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. Tax data includes aggregate tax revenues, Personal Income Tax (PIT), Corporate Income Tax (CIT), Taxes on Goods and Services (TGS), Value-Added Tax (VAT), and Social Security Contributions (SSC) for 172 countries, including 35 Advanced Economies (AE), 86 Emerging Market Economies (EME), and 51 Low-Income Countries (LIC) between 1990 and 2019. 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 time series.[3] Figure 10 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 also consider a strongly balanced dataset for the period 2001–2019 that we discuss in section 1.8. GDP and inflation data are also obtained from the IMF WEO. Table 1 in the appendix presents summary statistics for the key variables and their sources.

[3] As a general rule, we exclude time series with fewer than 15 years of observations because several panel estimators consume a significant number of degrees of freedom. Section 2.2.3 provides further information on the different estimators.

We combine several data sources to control for tax policy changes. Vegh and Vuletin (2015) provides yearly data on tax rates, covering PIT, CIT, and VAT for a sample of 77 countries from 1960 to 2019. 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 exemptions, for 102 countries between 1990 and 2019.

The data, shown in the left panel of Fig. 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. While the tax-to-GDP ratio in AE has remained relatively stable from 1990 to 2019, 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 2019.

The right panel of Figs. 1 and 2 also provide two important pieces of information: (i) the tax-to-GDP ratio varies considerably within income groups, and (ii) the composition of tax revenues varies significantly by country. As further elaborated in Section 2.2.1, these sources of heterogeneity motivate our consideration of several panel data estimators and justify a detailed investigation into individual tax components. This last point is especially relevant given the consensus in the literature that tax components respond differently to changes in economic activity (Belinga et al., 2014; Deli 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 (Lagravinese et al., 2020). This study also excludes taxes on goods and services from the analysis as the latter include various types of taxes such as sales and value-added taxes, excise taxes, import duties, and taxes on exports, which may react differently to changes in economic activity.

However, we do consider VAT in our analysis because this tax (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 account for more than 80% of total tax revenues.

2.2. Model specification and panel estimators

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 across studies.[4] ECM allows for the estimation of both long- and short-term buoyancy estimates in a dynamic setting, assuming that changes in tax

[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 of European countries, Mourre and Princen (2019) find that elasticity coefficients obtained using both methods are broadly similar.

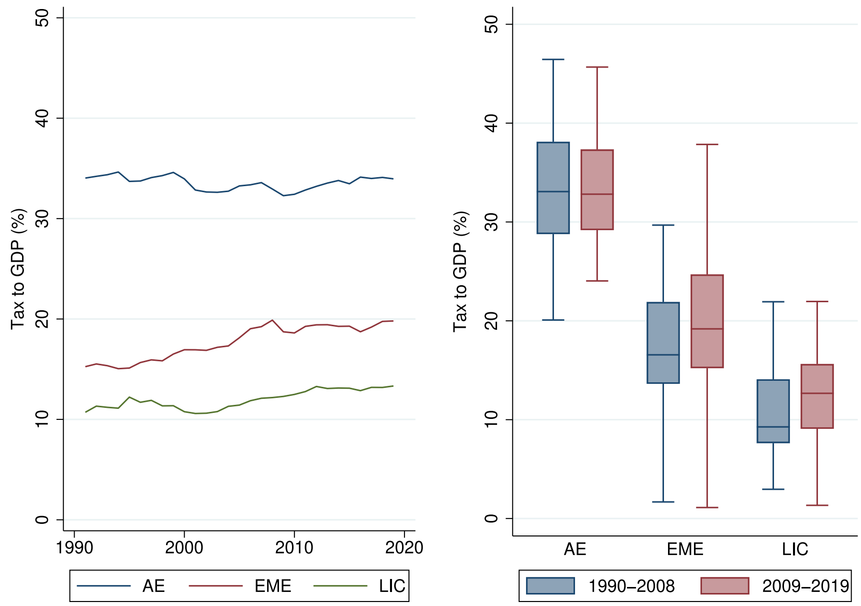

Fig. 1. Average tax-to-GDP ratio by income group.
Source: Authors own calculations based on OECD and IMF data.

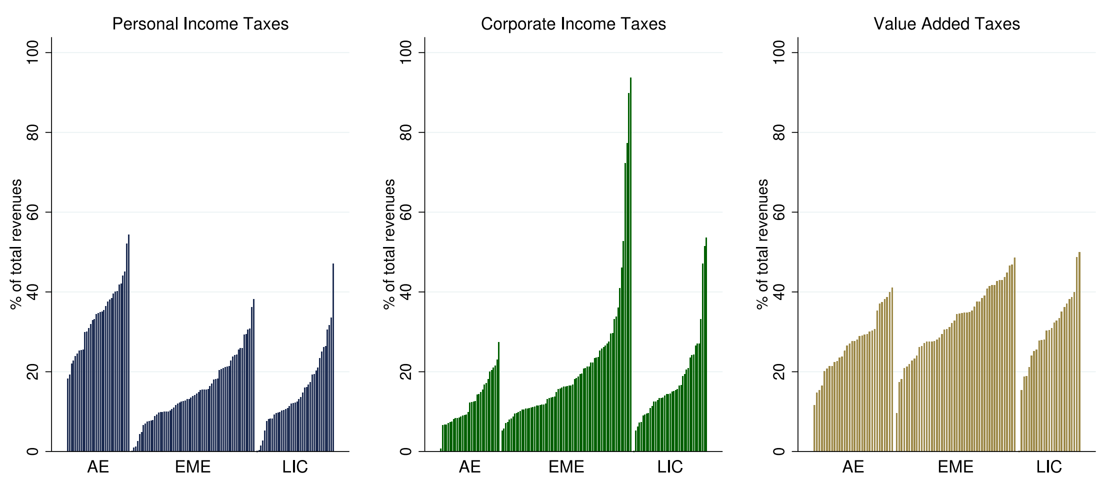

Fig. 2. Tax revenues composition by tax category and income group (% of total revenues)
Source: Authors own calculations based on OECD and IMF data.

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 the tax-to-GDP ratio would otherwise 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 to 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:

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

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 buoyancy). The coefficient $\theta_c = -\frac{\delta_c}{\lambda_c}$ measures the long-run effect of a 1 percentage

[5] Tables 23 and 24 in the appendix show the results for stationarity and panel cointegration tests. The results suggest that the GDP and tax variables are non-stationary and co-integrated.

[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).

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

Estimator	Degrees of freedom consumed	Homogeneity of short-term coefficients?	Homogeneity of long-term coefficients?	Control for cross-sectional dependence?	Source
FE	Minimal	✓	✓	–	–
PMG	Low	–	✓	–	Pesaran et al. (1999)
CCE-PMG	Moderate	–	✓	✓[a]	Pesaran (2006)
DCCE-PMG	Higher	–	✓	✓[b]	Chudik and Pesaran (2015a)
MG	Substantial	–	–	–	Pesaran and Smith (1995)
CCE-MG	Large	–	–	✓[a]	Pesaran (2006)
DCCE-MG	Maximum	–	–	✓[b]	Chudik and Pesaran (2015a)

Notes: FE = Fixed Effects; 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

[a] Control for cross-sectional dependence using contemporaneous cross-sectional averages.

[b] Control for cross-sectional dependence using contemporaneous and lagged cross-sectional averages.

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. Panel data estimators for tax buoyancy: a trade-off?

The benefits and limitations of panel data have been extensively discussed in the literature (Pesaran, 2015b; Wooldridge, 2010; Baltagi, 2021; Hsiao, 2022). Key benefits compared to pure cross-sectional or time series analysis include (i) more accurate inference of model parameters due to increased degrees of freedom and lower multicollinearity concerns; (ii) a better suitability to study the dynamics of adjustment; and (iii) the ability to identify effects that are otherwise not detectable. In contrast, major challenges involve: (i) the rationality of pooling together heterogeneous units, (ii) the neglect of cross-sectional dependence, and (iii) dealing with weakly exogenous explanatory variables notably in dynamic panel data models.

The literature on panel data econometrics has significantly evolved over the past decades to address some of these challenges. However, an ongoing debate still exists on the selection of estimators in different empirical applications.[8] In this section, we discuss potential trade-offs associated with panel data estimators for the study of tax buoyancy along three sources of biases: (i) biases from a reduced accuracy of model parameters linked to the degrees of freedom consumed by each estimator, (ii) biases from the assumption that tax systems are homogeneous across countries, and (iii) biases from not adequately addressing cross-sectional dependence.[9] The estimators selected for this study are classified based on their theoretical effectiveness in addressing these biases and include Fixed Effects (FE), 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) estimators. Table 1 provides a summary of the estimators and how they theoretically fare across these sources of biases.

Among the considered estimators, a primary distinction lies in their approach to pooling tax systems. While pooling countries saves degrees of freedom and lowers multicollinearity concerns, it also assumes that tax systems are homogeneous and that tax revenues across countries respond similarly to changes economic activity. In panel data studies with a large N and small T, the literature typically argues that the benefits of pooling observations outweigh the negatives of combining heterogeneous units (Baltagi et al., 2008). However, the choice is no longer clear cut as the time dimension T becomes larger as is the case in our study (Robertson and Symons, 1992; Pesaran and Smith, 1995; Pesaran et al., 1996; Pesaran, 2015a). In our ECM setting, our estimators can be classified into three distinct groups along this dimension. The FE estimator fully pools individual tax systems by assuming short-term and long-term coefficients of the ECM model to be homogeneous, while only allowing the intercepts to differ. On the other extreme, the MG-type of estimators (MG, CCE-MG, and DCCE-MG) estimate N time series regressions and average the resulting coefficients (Pesaran and Smith, 1995; Pesaran, 2006; Chudik and Pesaran, 2015a). Finally, the PMG-type of estimators rely on a combination of pooling long-term coefficients and averaging short-term coefficients (Pesaran et al., 1999, 1996; Chudik and Pesaran, 2015a). In the context of our study, the use of the PMG estimator constrains the long-run response coefficients of tax revenue responses to GDP to be equal among the pooled countries but allows short-term response coefficients to be estimated individually.

A second significant distinction among the estimators lies in their respective approaches to addressing the presence of cross-sectional dependence. Cross-sectional dependence implies a potential risk of biased and inconsistent estimators due to the presence of common unobserved factors among cross-sectional units in large samples (Pesaran, 2006). In the context of our study, possible common factors include shared economic fiscal policies linked to economic integration (Lagravinese et al., 2020), structural changes in tax revenue composition (Huizinga and Laeven, 2008; Dowd et al., 2017), and global shocks. In theory, tax buoyancy estimates obtained after controlling for cross-sectional dependence should reflect a more accurate relationship between changes in economic activity and tax revenue changes. This is because accounting for external influences that might affect multiple countries simultaneously helps isolating the specific impact of GDP changes on tax revenues. The seminal work of Pesaran (2006) introduced the Common Correlated Effects (CCE) estimator as a solution to this issue in static heterogeneous coefficients panel models. By incorporating the contemporaneous cross-sectional averages of all variables in the model, the CCE method effectively proxies the unobserved common factors and ensures a consistent estimation.[10] However, Chudik and Pesaran (2015a) show that the CCE estimator is only consistent in non-dynamic panels. In dynamic panel data models with presence of common factors, the lagged dependent variable is

[8] Baltagi (2006) and Mátyás and Sevestre (2008) provide insightful discussions on choosing panel estimators in varying empirical setups.

[9] Note that we do not consider the small sample time series bias in this paper given our moderately large albeit varying time dimension (ranging from 15 to 30 years). See Chudik and Pesaran (2015a) for a theoretical discussion about correction measures to mitigate small sample time series bias in dynamic heterogeneous panel data models.

[10] Other approaches to control for the presence of cross-sectional dependence including the principal components (PC) factors of Bai and Ng (2002) exist. Both PC and CCE approaches assume that both N and T are large. We focus on the CCE approach because (i) it fares better in small samples (Chudik et al., 2011; Westerlund and Urbain, 2015); (ii) it is robust to significant divergence in data-generating processes (Kapetanios et al., 2011; Westerlund, 2018); and (iii) it is very easy to implement, making it appealing for real-world applications (Westerlund et al., 2019).

correlated with past realizations of the error term, leading to endogeneity and inconsistency of the estimators. Chudik and Pesaran (2015a) propose the Dynamic Common-Correlated Effects (DCCE) estimator, which includes lagged cross-sectional averages of the dependent and independent variables. They show that $\sqrt[3]{T}$ lags of cross-sectional average should be included as control variables to obtain consistent estimates using OLS.[11] In our study, the estimated equation including cross-sectional averages becomes:

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

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.

Table 22 in the appendix provides the results of the cross-sectional dependence tests based on Pesaran (2015a) 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 models especially when estimating tax buoyancy for AE. However, adding cross-sectional averages to our baseline model results in fewer available degrees of freedom, which can affect the estimation accuracy of model parameters. This is especially relevant for MG-types of estimators, which already consume a significant amount of degrees of freedom by estimating N time series regressions.

In our empirical setup, our estimators can again be classified into three distinct groups along this dimension. The FE, PMG, and MG estimators do not account for the presence of cross-sectional dependence. On the other extreme, the DCCE-type of estimators (DCCE-MG and DCCE-PMG) stand-out as the theoretically preferred estimators to control for cross-sectional dependence in a dynamic panel like ours. Finally, the CCE-type of estimators (CCE-MG and CCE-PMG) do not include lagged cross-sectional averages and are theoretically inconsistent in dynamic panels. However, Everaert and De Groote (2016) and Westerlund (2018) show that CCE-type of estimators perform well in dynamic panel data models even when T is relatively small. Given our moderately large but varying time dimensions, the CCE-type of estimators are therefore considered as potential candidates.

From a theoretical standpoint, among available panel data estimators, the DCCE-MG would be preferred over other estimators in the study of tax buoyancy if T was infinitely large as it accounts for cross-sectional dependence and slope heterogeneity. However, the varying time dimension of our dataset, especially for countries with limited historical tax revenue data, does not discount the preference for simpler methods. In their review of empirical applications comparing homogeneous and heterogeneous panel data estimators, Baltagi et al. (2008) point to a good overall performance of homogeneous panel data estimators due to their simplicity, parsimonious representation, and stable parameter estimates. Conversely, they find that average heterogeneous estimators tend to perform poorly due to the instability of parameter estimates caused by estimating several parameters when the time dimension is relatively small. In any tax buoyancy analysis using panel data, determining which countries to pool is undeniably a central question. Our strategy incorporates a broad spectrum of countries to ensure an adequate number of cross-sectional units across different income levels. However, a refined strategy aimed at creating more uniform groups could prove valuable depending on the objectives of the study. For example, pooling countries subject to common institutional arrangements for fiscal policies, such as in the European Union, might increase the homogeneity of the sample, thereby reducing the benefits from heterogeneous coefficients estimators. At the same time, a more homogeneous pool of countries might result in higher levels of cross-sectional dependence, thereby favouring estimators that specifically control for this cross-sectional dependence. These trade-offs motivate our decision to run several estimators to assess the buoyancy of tax systems.

3. Main results

3.1. Baseline results

Our ECM model allows us to discuss tax buoyancy both in the long-run and in the short-run. On the one hand, long-run buoyancy measures changes in tax revenues resulting from long-term changes in economic activity and is considered a useful indicator for understanding the relationship between economic growth and long-term fiscal sustainability (Belinga et al., 2014). A long-run tax buoyancy of 1, where a 1% GDP growth leads to a 1% growth in tax revenues, indicates that tax revenues are keeping pace with economic growth. A long-run tax buoyancy above 1 can signal improvements in tax revenue mobilization or a need to meet increasing public service demands. Finally, a long-run tax buoyancy below 1 suggests the tax system is not fully capturing the growth benefits of an economy, possibly requiring policy adjustments to avoid long-term fiscal pressures. On the other hand, short-run tax buoyancy reflects the tax system's ability to stabilize the economy over economic cycles (Deli et al., 2018). A short-run tax buoyancy greater than 1 indicates that tax revenues rise more than GDP during economic expansions and fall more than GDP during recessions, which suggests that the tax system functions as an effective automatic stabilizer from the revenues side. A short-run tax buoyancy below 1 suggests the opposite.[12]

We estimate short-run and long-run tax buoyancy from Eqs. (1) and (2) using the seven estimators discussed in the previous section: Fixed Effects (FE), 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).

3.1.1. Cross-sectional dependence

In the appendix, Tables 2 to 8 display the regression output and report (Pesaran, 2015a) cross-sectional dependence (CD) tests. The CD tests indicate that estimators not adjusting for cross-sectional dependence (DFE, MG, PMG) show significantly higher CD statistics compared to those that do adjust for CD (CCE and DCCE-type of 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 22 in the appendix and discussed in the previous section. However, the decrease in CD statistics from CCE-type to DCCE-type of estimators is only marginal. These results suggest that incorporating contemporaneous cross-sectional averages helps address cross-sectional dependence, but adding lags offers little further improvement in our tax buoyancy analysis while consuming more degrees of freedom.

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

[12] As discussed in the introduction, short-run buoyancy estimates may not necessarily be interpreted as reflecting only the effect of automatic stabilizers but also captures discretionary policy changes. Section 3.2 introduces novel control variables for tax exemptions and tax base changes to disentangle discretionary from automatic tax revenue change.

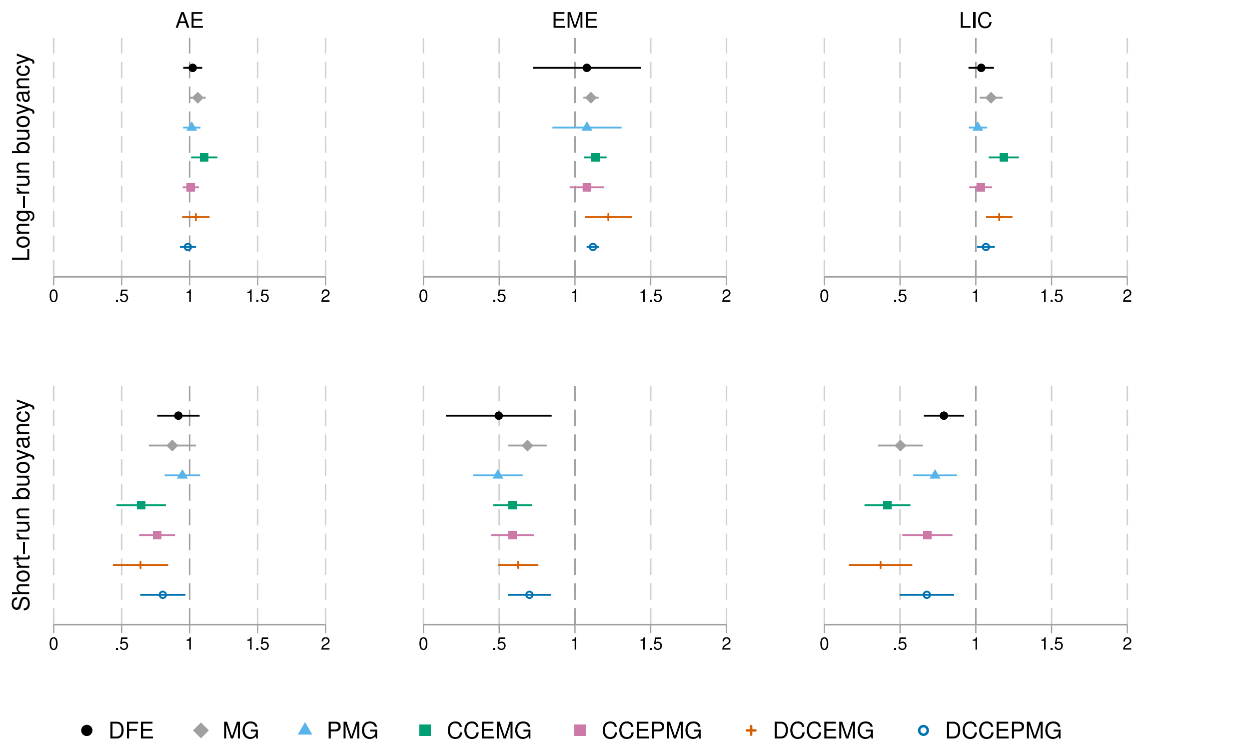

Fig. 3. Total tax buoyancy by estimator. *Notes:* The bars represent 95% confidence intervals. FE = Fixed Effects; MG = Mean Group; PMG= Pooled Mean Group; CCE = Common Correlated Estimator; DCCE = Dynamic Common Correlated Estimator.
Source: Authors own calculations based on OECD and IMF data.

3.1.2. Long-run tax buoyancy

The top panel of Fig. 3 displays the long-run total tax buoyancy estimates across all estimators in our sample of 172 countries, including 35 AE, 86 EME, and 51 LIC. Figure 4 in the appendix provides the related coefficients' kernel distributions.[13]

Our results suggest that long-term tax buoyancy, which measures the average long-term reaction of tax revenues to economic activity, hovers around one, consistent with previous cross-country studies (Gupta et al., 2022; Deli et al., 2018; Belinga et al., 2014). Our findings hold true across estimators and country income groups, with only marginal variations. Confidence intervals are also larger for LIC due to the shorter average span of the tax time series. On average, the point estimates are slightly higher for EME and LIC, possibly due to a gradual progress in tax mobilization in some economies as discussed in Section 2.1. However, unlike (Lagravinese et al., 2020), we do not find long-run tax buoyancy coefficients' lower than unity when using estimators accounting for the presence of cross-sectional dependence (i.e. CCE and DCCE-type of estimators) suggesting that, in the long-run, total tax revenues tend to track economic growth as is found in other cross-country studies (Dudine and Jalles, 2018; Gupta et al., 2022; Belinga et al., 2014).[14] Our results also suggest that unobserved common factors (i.e. external influences that might affect tax revenues of multiple countries simultaneously) do not significantly impact the relationship between changes in economic activity and tax revenues in the long-run and lowers the benefits of using more sophisticated and data consuming CCE-type or DCCE-type of estimators. Table 9 to 15 in the appendix also provide country level estimates for long-run total tax buoyancy extracted from the MG estimator for AE, EME, and LIC.[15] For AE and LIC, none of the countries post long-run tax buoyancy statistically significantly different than 1 at least at the 10% significance level, while only 1 EME has a coefficient statistically significantly higher than one. We further explore which tax components influence these outcomes by analysing the long-run tax buoyancy of each component in section 1.2 of the appendix. As a general result, the long-run buoyancy for PIT and VAT hovers around one like total taxes. However, the long-term buoyancy for CIT exceeds one for all income groups across virtually all estimators and in line with previous cross-country studies (Dudine and Jalles, 2018; Gupta et al., 2022; Belinga et al., 2014).[16] A long-run buoyancy greater than one for CIT is consistent with a gradual increase in the share of profits in GDP over the studied period (Grossman and Oberfield, 2022; Autor et al., 2020; Karabarbounis and Neiman, 2014).

3.1.3. Short-run tax buoyancy

The bottom panel of Fig. 3 displays the short-run total tax buoyancy estimates across all estimators in our sample of 172 countries, including 35 AE, 86 EME, and 51 LIC. Figure 4 in the appendix provides the related coefficients' kernel distributions.

Our short-run tax buoyancy estimates vary significantly across estimators and differ from the long-run tax buoyancy coefficients. Estimators not accounting for cross-sectional dependence (i.e. DFE, MG,

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

[14] It is worth noting that Lagravinese et al. (2020) is the only cross-country study using a the DCCE estimator, while other studies predominantly use estimators not accounting for cross-sectional dependence such as DFE, PMG, and MG.

[15] Country level estimates extracted from the CCEMG and DCCEMG estimators are available from authors upon request.

[16] Only the DCCE-MG estimator for EME suggests that CIT is not statistically significantly different from one at the 5% significance level. The confidence bands around the point estimates are large possibly because of the relatively shorter historical coverage of CIT time series for some EME and the fact that the DCCE-MG estimator consumes a significant amount of degrees of freedom.

and PMG) suggest AE's short-term total tax buoyancy is not statistically different from 1, consistent with conclusions drawn in prior studies that employed these estimators (Deli et al., 2018; Belinga et al., 2014; Dudine and Jalles, 2018). Conversely, CCE-type and DCCE-type of estimators yield significantly lower estimates, aligning with recent findings from Lagravinese et al. (2020). For EME and LIC, short-run tax buoyancy coefficients are on average lower and statistically significantly below 1 with limited variability across estimators. Table 9 to 15 in the appendix also provide country level estimates for short-run total tax buoyancy extracted from the MG estimator for AE, EME, and LIC. For AE, the MG model has 22 countries out of 35 posting short-run tax buoyancy lower than one, including 10 statistically significantly at least at the 10% significance level. For EME and LIC, respectively 61 of 86 and 42 of 51 countries exhibit short-run tax buoyancy below one, with respectively 27 and 25 statistically significantly at least at the 10% significance level. The smaller wedge in buoyancy estimates between estimators accounting for cross-sectional dependence and those that do not in EME and LIC compared to AE likely reflects a higher level of homogeneity and the presence of more common unobserved factors among the pooled countries in the later group. As previously discussed, common unobserved factors might include shared economic fiscal frameworks such as in the European Union (Lagravinese et al., 2020), and possible common structural changes in tax revenue composition (Huizinga and Laeven, 2008; Dowd et al., 2017). Table 22 in the appendix presents (Pesaran, 2015a) cross-sectional dependence tests and confirms that the average cross-correlation between pairs of countries for total tax revenues is 1.74 times higher for AE compared to EME (0.316 vs 0.182) and 105 times than LIC (0.003). Theses findings suggest that common unobserved factors (i.e. external influences that might affect tax revenues of multiple countries simultaneously) significantly alter the underlying relationship between changes in economic activity and tax revenues in the short-run for AE. Therefore, despite using more degrees of freedom, the advantages of CCE-type or DCCE-type estimators stand out for AE but not for EME and LIC. More generally, our results also suggest a limited automatic stabilization power of tax systems from the revenues side and may suggest that discretionary changes are not enough to compensate for a low tax elasticity (Lagravinese et al., 2020). We also provide an analysis of short-run tax buoyancy estimates for all tax components in section 1.2 in the appendix. Our results align with prior cross-country studies, showing that PIT and VAT have lower short-run buoyancy compared to CIT, which is generally attributed to profits being more volatile compared to other national income streams in different phases of the business cycle (Creedy and Gemmell, 2009). Sections 1.7 and 1.8 show that our findings are robust when controlling for inflation and when using a strongly balanced panel dataset.

3.2. Tax buoyancy versus tax elasticity

As discussed previously, tax buoyancy captures both the automatic changes in tax revenues due to changes in economic conditions and the adjustments in tax revenues caused by changes in tax policy. In contrast, tax elasticity isolates the automatic component of revenue changes by controlling for the effects of tax policy measures (Musgrave and Miller, 1948). To obtain measures closer to tax elasticity, prior cross-country studies have typically controlled for changes 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, thereby introducing an omitted variable bias. However, both of these correlations have limited empirical evidence or are a matter of debate. On 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 section builds upon prior research by incorporating novel data sources to account for tax base reforms and tax exemptions. Although ideally all control variables would be included in one model, the scarcity of observations for each country and year across all controls requires presenting the results in separate models. Throughout the section, we employ the PMG estimator as it provides an optimal balance between minimizing heterogeneity concerns and avoiding the excessive consumption of degrees of freedom by the model.[20] In our ECM model, we allow the control variables to affect short-run buoyancy coefficients only as we cannot assume a long-run relationship between tax policy reforms and tax revenues growth.

3.2.1. Controlling for changes in tax rates

To determine the impact of changes in tax rates on our buoyancy estimates, we leverage historical PIT, CIT, and VAT tax rates data from Vegh and Vuletin (2015) covering a sample of 77 countries from 1960 to 2019.[21] Fig. 4 plots the short-run buoyancy estimates with and without controlling for changes in tax rates, and table 18 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 changes in tax rates are at least marginally positively correlated with tax revenues,[22] our results suggest that changes in PIT, CIT, and VAT rates are not significantly correlated with changes in GDP within 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 from Dudine and Jalles (2018) and Belinga et al. (2014), which find that some coefficients increased, albeit slightly, depending on the country income group and the tax component considered. However, these earlier studies cover different time periods (1980–2014 and 1965–2012, respectively, compared to 1990–2019 in our study), which may suggest that the correlation between tax rate reforms and changes in economic activity has declined over time with political factors possibly having more influence than economic variables. (Castanheira et al., 2012).

[17] See for example (Dudine and Jalles, 2018; Lagravinese et al., 2020; Gupta et al., 2022) Other studies disentangle the effect of discretionary and automatic tax changes by collecting detailed information on national tax policy changes and by isolating 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.

[20] Results for other estimators are robust and available from authors upon request.

[21] 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 18 in the appendix.

[22] Assuming the theoretical relationship between the tax rate and the government's tax revenues follows a Laffer curve, an increase in the tax rate leads to higher tax revenues assuming the tax rate is below the tax rate t^* maximizing tax revenues.

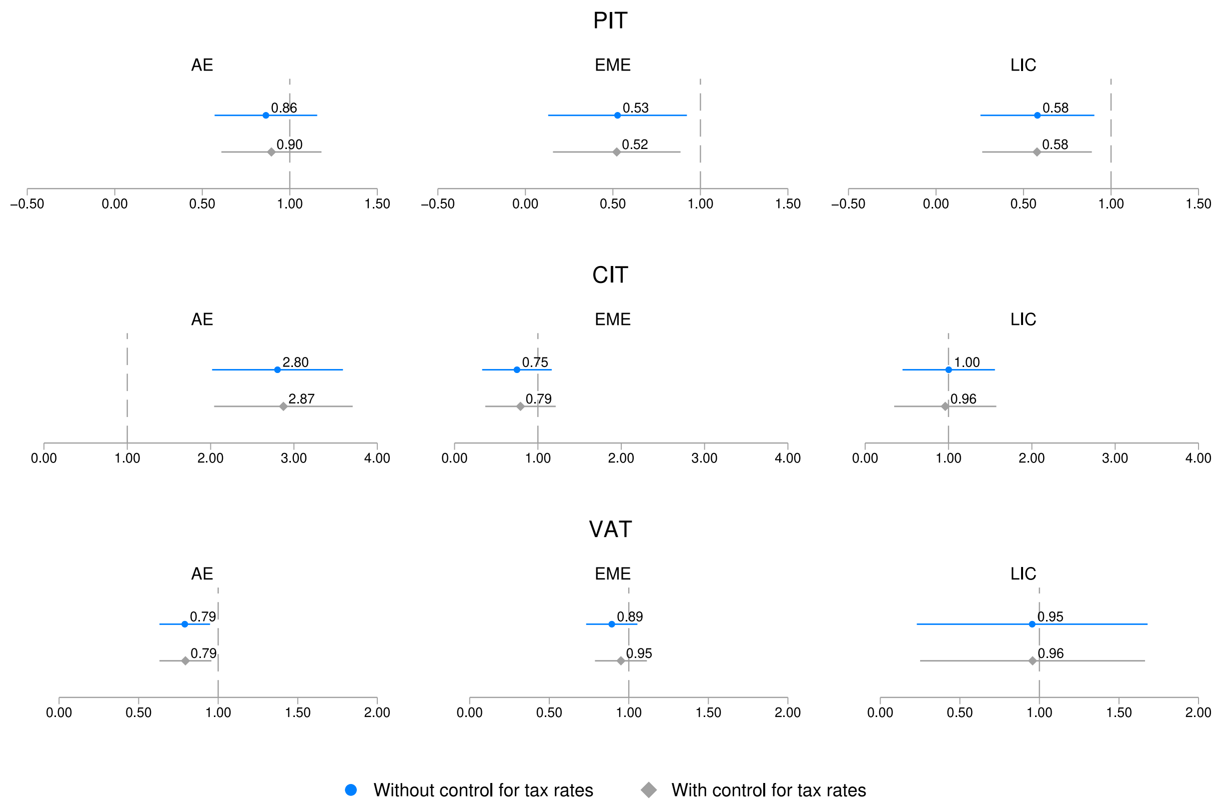

Fig. 4. Tax components buoyancy estimates controlling for tax rates. *Notes:* The estimator is PMG.
Source: Authors own calculations based on Vegh and Vuletin (2015), OECD, and IMF data.

3.2.2. *Controlling tax base reforms*

To determine the impact of changes in the tax base on our buoyancy estimates, we use the Tax Policy Reform Database (TPRD) of the IMF (Amaglobeli et al., 2018), which covers 23 countries, predominantly AE. The TPRD comprises yearly data on PIT, CIT, VAT, 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 Amaglobeli et al. (2022), where we count the number of major tax base reforms implemented within a year and we introduce two dummy variables to account for tax base expansions and tax base narrowings. 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 Fig. 5, and the regression output is shown in Table 19. The results suggest that controlling for tax base reforms does not have a significant impact on the short-run buoyancy we obtained in our baseline model. Assuming that changes in the tax base are at least marginally correlated with tax revenues, our results indicate again that tax base reforms are not significantly correlated with changes in economic activity within our study period.

3.2.3. *Controlling for changes in tax exemptions*

To determine the impact of changes in tax exemptions on our buoyancy coefficients, we resort to 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 exemptions published by national governments worldwide from 1990 onwards and covers 102 countries. The GTED defines tax exemptions as 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 the breakdown of tax exemptions by tax components, we limit our analysis to aggregated tax revenues across income groups. We conduct this exercise for AE and EME but results for LIC are not reported because of a lack of sufficient historical data on tax exemptions. The short-run buoyancy estimates with and without control for tax exemptions are presented in Fig. 6, and the regression output is shown in Table 20. Again, assuming that changes in the tax exemptions are at least marginally correlated with tax revenues,[23] our results indicate that tax exemptions are not significantly correlated with changes in economic activity within our study period.

4. Concluding remarks

This paper re-examines the reaction of tax revenues to changes in economic activity (or tax buoyancy) by reviewing and contrasting seven panel data estimators in a sample of 172 countries split into income groups over the period 1990–2019. Our study contributes two key insights to the literature.

Our first contribution to the literature is to show that trade-offs in the choice of panel estimators for tax buoyancy arise within large heterogeneous panels with moderate historical data. We define these trade-offs along three dimensions: (i) the rationality of pooling together tax systems likely to respond differently to changes in economic activity, (ii) the reduced accuracy of model parameters linked to the

[23] von Haldenwang et al. (2023) find that tax exemptions average 3.8% of global GDP and 23% of global tax revenues globally.

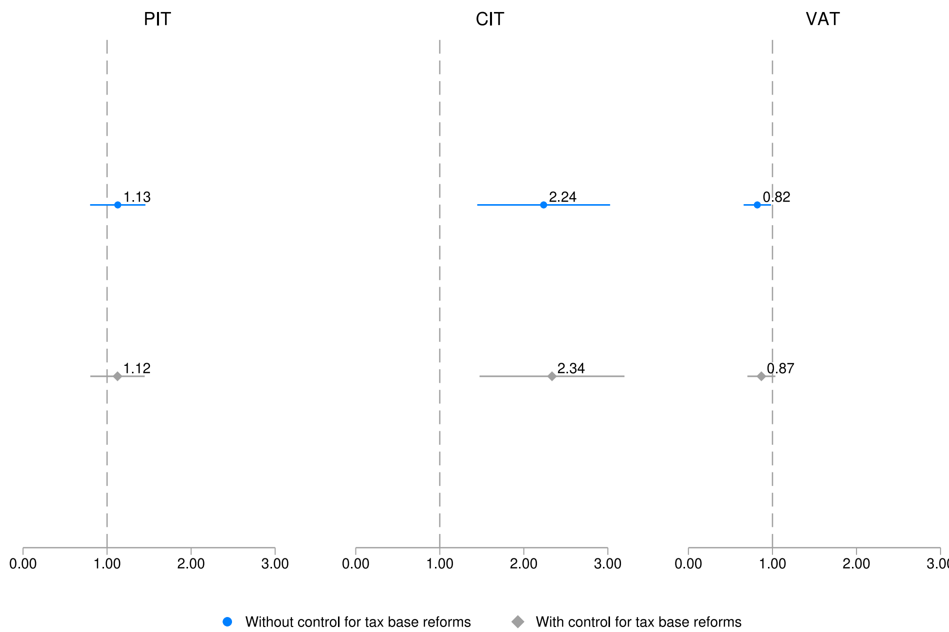

Fig. 5. Tax components estimates controlling for tax base reforms. *Notes:* The estimator is PMG. *Source:* Authors own calculations based on Amaglobeli et al. (2018), OECD, and IMF data.

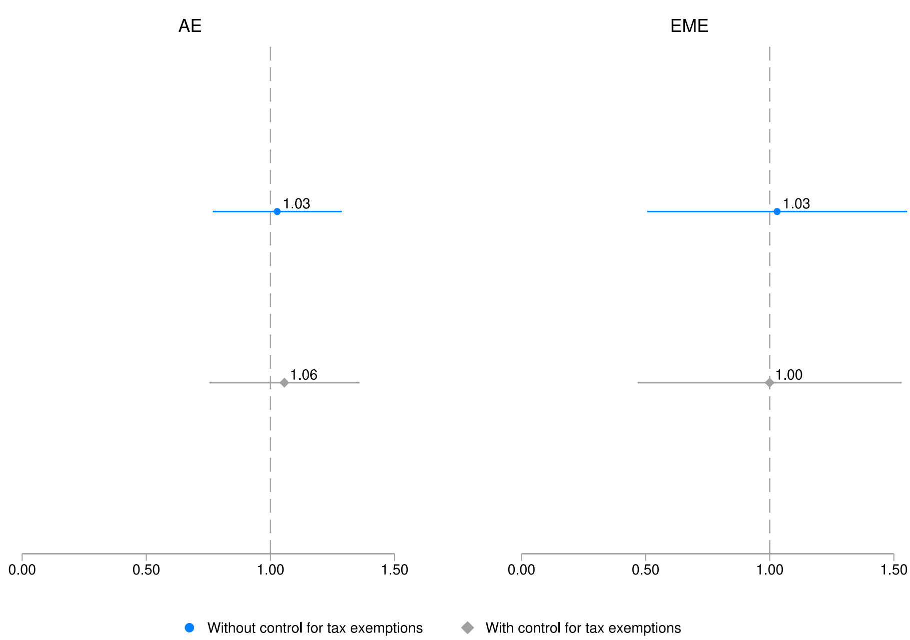

Fig. 6. Total tax buoyancy controlling for tax exemptions. *Notes:* The estimator is PMG. LIC is not reported because of a lack of sufficient historical data on tax exemption. *Source:* Authors own calculations based on GTED, OECD, and IMF data.

degrees of freedom consumed by each estimator, and (iii) the neglect of cross-sectional dependence.

We show that more sophisticated heterogeneous coefficients models accounting for cross-sectional dependence do not necessarily outperform simpler panel models when studying tax buoyancy. For long-run tax buoyancy, which is a useful indicator to understand the relationship between economic growth and long-term fiscal sustainability, we find that total tax revenues, PIT, CIT, and VAT track economic growth across all income groups and with little variations between estimators. For short-run tax buoyancy, which is a useful indicator for assessing the automatic stabilization capacity of tax systems, we find values significantly below 1 across all income groups despite higher variations between estimators. Lower buoyancy is most pronounced in the case of VAT and PIT, whereas CIT displays better automatic stabilization properties. Importantly, we show that the short-run tax buoyancy obtained from estimators accounting for cross-sectional dependence differ significantly from those that do not, particularly in country groups posting strong levels of cross-sectional dependence.

In our study, ignoring cross-sectional dependence may erroneously suggest a good automatic stabilization capacity of tax systems in AE. More generally, our results imply that unobserved common factors (i.e. external influences that might affect tax revenues of multiple countries simultaneously) do not significantly impact the relationship between changes in economic activity and tax revenues in the long-run. However, they do have a significant impact in the short-run. This suggests that the benefits of using more sophisticated and data consuming CCE-type or DCCE-type of estimators is only relevant when the focus is on the automatic stabilization capacity of tax systems.

This first set of findings has two important theoretical and policy implications. First, the low short-run tax buoyancy suggests that discretionary changes are not enough to compensate for a low tax elasticity. This indicates that fiscal authorities, particularly in EME and LIC, have room to improve the automatic stabilization power of tax systems and to make revenue streams more predictable and sustainable. Implementing more progressive taxation, reducing tax systems' inefficiencies such as administrative delays and tax evasion, and rebalancing the tax mix towards more buoyant components such as corporate income taxes would result in more responsive tax systems. In an environment characterized by high levels of public debt and rising spending pressures, our results indicate that fiscal authorities in all income groups should be cautious in presuming that growth in tax revenues will perfectly align with economic growth projections in the short-run. On the other hand, consistent results of a long-term tax buoyancy coefficient close to one indicates that, over time, tax revenues tend to grow proportionally with the economy. This suggests a more stable and sustainable tax system in the long run, as the tax base adjusts and tax policies are fine-tuned to better capture economic growth.

A second important implication is for professional tax forecasters. When using panel data models, forecasters should carefully select the countries to pool to ensure the selection aligns with their specific forecasting purposes. Our methodology includes a broad range of countries to maintain sufficient cross-sectional units across various income levels. However, a more refined strategy could involve grouping tax systems based on similarities in fiscal policy frameworks or tax revenue composition, followed by an assessment of cross-sectional dependence to select the optimal panel estimator. Developing systematic guidelines for selecting tax systems and choosing the corresponding optimal estimator is a task we leave for future research.

Our second contribution to the literature is to demonstrate that controlling for various discretionary changes in revenue-based tax policies, including tax rates, tax base reforms, and tax exemptions, does not significantly alter our buoyancy estimates. These findings suggest that, on average, tax policy is acyclical and that stronger countercyclicality in revenue-based tax policy would enhance short-run economic stabilization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All replication materials are available here: DOI: https://doi.org/10.17632/dyspdzxpzz.1.

Acknowledgments

We are grateful to the Editor, Prof. Sushanta Mallick, PhD, Associate Editor, Prof. Max Gillman, PhD, and two anonymous reviewers for their insightful suggestions and valuable advice that have significantly improved our paper. We also would like to thank Dr. Andrew Berg, Dr. Ali Alichi, Prof. Ugo Panizza, Prof. Cédric Tille, Prof. Jan Ditzen, Prof. João Jalles, and Prof. Agnese Sacchi for their valuable contributions to an earlier version of this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econmod.2024.106867.

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