BACKGROUND PAPER

How do Tax Revenues Respond to GDP Growth? Evidence from Developing Asia, 1998–2020

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DISCLAIMER

HOW DO TAX REVENUES RESPOND TO GDP GROWTH? EVIDENCE FROM DEVELOPING ASIA, 1998–2020

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Abstract

How did developing Asian economies perform with respect to tax revenue mobilization before and during the coronavirus disease (COVID-19) pandemic? An analysis of data from developing Asia suggests that both short-run and long-run tax buoyancies, a measure of how tax revenue responds to GDP, were close to one before COVID-19, which is indicative of fiscal sustainability. COVID-19 had a negative impact on the region's gross domestic product (GDP) and thus its tax base, and spurred significant fiscal stimulus including tax measures. At a regional level, the pandemic subtracted a tenth of a percentage point from tax revenue growth after controlling for changes in GDP. Using estimated country-level tax buoyancy coefficients, a counterfactual analysis is undertaken to estimate excess tax revenue losses in 2020 because of COVID-19. The average GDP-weighted excess tax revenue loss is about half a percentage point of pre-pandemic GDP.

JEL Classification

E32; H12; H20; H71

Keywords

tax collection, business cycles, pandemic crisis

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I. INTRODUCTION

In many developing economies, additional tax revenue is needed to meet growing demands for public goods and services, and support development goals. For example, Gaspar et al. (2019) estimate that achieving the Sustainable Development Goals (SDGs) in key areas requires additional spending by 2030 of US$0.5 trillion for low-income developing countries and US$2.1 trillion for emerging market economies. The coronavirus disease (COVID-19) pandemic has battered government finances, adding to the challenge (Benedek et al. 2021).

Much of this additional spending will need to be financed by tax revenue. To shed light on how well governments are positioned to meet this challenge, it is important to understand the responsiveness and efficiency of tax collection in developing economies, informed by empirically assessing the links between the tax base and tax revenues. In particular, tax buoyancy measures the response of tax revenues to gross domestic product (GDP), and is therefore a key metric for understanding tax system performance and the outlook for revenues. A buoyancy coefficient greater than one implies that tax revenues grow faster than GDP, and less than one the opposite. In this study, we focus on developing economies in Asia, where tax revenue is comparatively low, and estimate the short-run and long-run association between tax revenue and output with panel and time-series analyses. Our research questions, testing hypotheses, and their relevance are:

(i) How buoyant was tax revenue before the COVID-19 crisis? Were tax buoyancy coefficients greater than one indicative of fiscal sustainability, strongly rising revenues, and effective tax collection?

(ii) What was the impact of the COVID-19 pandemic on tax buoyancy? How large are the actual tax revenue losses in 2020 compared to the model estimates?

(iii) What can we infer about the recovery in revenues after the crisis? What are the implications of a country's COVID-19 fiscal measures on its tax buoyancy?

Our estimation of tax buoyancy uses both time-series and panel data. Using error-correction models (ECMs), we take the natural logarithm of tax revenues and GDP, test the hypothesis that there exists a cointegrating relationship, and allow for the short-run and long-run tax buoyancies coefficients to differ. Our data covers 24 developing economies in Asia and the Pacific from 1998 to 2020, sourced from the Organisation for Economic Co-operation and Development (OECD), the International Monetary Fund (IMF), and the Asian Development Bank (ADB), and carefully cross-validated. Overall, the sample covers 23 years and 24 countries, giving us a total of 552 observations.

The panel results suggest that both short-run and long-run tax buoyancies coefficients are above one. We then apply the regression coefficients to obtain estimates of revenue loss because of COVID-19. Specifically, we first estimate a time-series model with 1998–2019 data. We then compare model predictions of revenues from 2015 to 2020 with actual data to assess the impact of COVID-19 over and above what would normally be expected, given the GDP downturn. We find that tax revenue fell more than the model's predictions in many economies, while in a few economies predicted actual revenues are very close. Averaged and GDP weighted across 24 economies, the estimated excess revenue loss of developing Asia amounted to -0.5% of 2019 GDP in 2020.

The final part of our analysis projects the tax revenue-to-GDP ratio in the 24 economies to 2030, the target year for the SDGs. We find that the model estimates are insignificant for some economies. In addition, the projection is sensitive to growth forecasts and model specification. Nevertheless, the different model specifications are largely in agreement on the 2030 projection. We find that tax-to-GDP ratios are projected to improve toward 2030 in a majority of developing Asian countries, other things held constant.

Section II presents the testing hypotheses. We then describe data and estimate tax buoyancy coefficients in section III, while section IV concludes with key takeaways and policy implications.

II. TESTING HYPOTHESES

This section describes the hypotheses motivating our analysis of tax buoyancy in developing Asia. Broadly defined as how tax revenues (either in aggregate and/or by individual types of taxes) vary with changes in nominal GDP, tax buoyancy estimates inform fiscal sustainability and the extent to which taxes are an effective "automatic stabilizer," and provide a formal metric of structural changes in tax revenues.

The testing hypothesis is informed by, and builds on, previous tax buoyancy studies. In a sample of 30 Asia and Pacific economies spanning 1980–2017, Jalles et al. (2021) assess tax buoyancy of total tax revenue, personal income taxes, corporate income taxes, general sales taxes, and trade taxes. They control for inflation and tax rates, and draw on data from the World Bank's World Development Indicators, and the IMF's World Economic Outlook (WEO) and Tax Policy Division databases. Applying an ECM specification with panel data and using

the pooled mean group estimator, they estimate short-run tax buoyancy of one and long-run buoyancy greater than one. For advanced economies, Lagravinese et al. (2020) examine 35 OECD countries for the period 1995–2016, assessing the buoyancy of total revenue (excluding social security contributions), total taxes, personal income taxes, corporate income taxes, and general sales taxes. They control for unemployment, inflation, various policy variables, using data from OECD revenue statistics, and OECD national accounts. They too apply an ECM specification with panel data, and use a Dynamic Common Correlated Effects estimator, and IV. They report estimates of short-run and long-run tax buoyancies generally less than one.

As tax buoyancy estimates have multiple uses and can inform a variety of policies, our testing hypotheses focus on assessing the overall progress with tax revenue mobilization, the impact of the COVID-19 pandemic, and the longer-term implications implied by projections.

A. Interpretation of Coefficients of Short-Run and Long-Run Tax Buoyancies

Our estimation tests the response of tax revenues to GDP. Where tax buoyancy is estimated to be greater than one, tax revenues are rising more than proportionately to an increase in GDP. In this scenario, tax revenues are structurally increasing and sufficiently buoyant to support fiscal sustainability, even allowing for some increases in the spending share of GDP. However, this is not a stable long-run equilibrium, as taxes cannot continue to grow faster than GDP—the tax base—indefinitely. The tax system is also playing an automatic stabilizer role, providing a countercyclical fiscal impulse.

In contrast, when tax buoyancy is less than one, tax revenues are structurally decreasing and weak taxes pose a risk to fiscal sustainability in the absence of spending cuts. The tax system also works against short-run macroeconomic stabilization.

Finally, a buoyancy of one implies tax revenues are structurally stable, rising in tandem with GDP. Taxes are sufficiently buoyant to support fiscal sustainability so long as spending is not rising as a share of GDP, and the tax system has a neutral influence on short-run changes in output. However, it does not guarantee overall fiscal sustainability, which depends on debt dynamics.

B. COVID-19 crisis is associated with an excess tax loss over and above what would normally be expected, given the gross domestic product downturn.

By estimating tax buoyancy with data up to and including 2020, it is possible to formally examine the impact of COVID-19 on tax revenues using the country's tax buoyancy estimate. More specifically, to test this hypothesis, we need to assess excess tax losses, which requires comparing actual tax revenues in 2020 with those expected based on 2020 GDP outturns. The causal impact of COVID-19 is thus a comparison between the actual tax revenue in 2020 and the model predictions of 2020 tax revenue.

C. Large-scale tax relief measures may explain the decline in estimated tax buoyancy.

In response to the COVID-19 pandemic, many countries implemented fiscal stimulus in the form of tax cuts and exemptions. These were often intended to be temporary measures and, if they turn out to be temporary, then pre–COVID-19 estimates of tax buoyancy are a

reasonable starting point for judgments about revenue mobilization during and post–COVID-19 pandemic. However, there may be sound economic reasons or political pressure for governments to extend or even entrench measures. If tax cuts become permanent, then tax revenues will be structurally lower, and the starting point for improving revenue mobilization worse.

Given the COVID-19 pandemic, we can then assess what happens when countries implement large-scale tax relief, as has happened during the pandemic in many countries. The association between discretionary fiscal policy support during the pandemic and the tax-buoyancy coefficients can help explain changes in estimated buoyancy during 2020.

III. EMPIRICAL STRATEGY AND FINDINGS

In its simplest form, the estimation of tax buoyancy includes the growth of tax revenues as the dependent variable and the growth of nominal GDP and lags of both variables as the determinants. From here the equation can be augmented to include other control variables, including proxies for changes in policy variables, the business cycle, and exogenous shocks.

Tax buoyancy is typically estimated following an ECM approach that is preferred for two reasons (Dudine and Jalles 2018, and Lagravinese et al. 2020). First, the natural logarithm of both tax revenues and GDP are integrated series and it is hypothesized that there exists a cointegrating relationship between them. Second, the approach allows for the separate estimation of short-run and long-run tax buoyancies which may naturally differ. It is reasonable to assume that tax buoyancy will be one over a sufficiently long horizon, given that taxes cannot indefinitely grow faster or slower than GDP. However, in the short run, tax

policy features, such as allowances to carry forward losses, may result in revenues deviating from changes in activity (Creedy and Gemmel 2008).

In the ECM equation, a common interpretation of short-run tax buoyancy is how effectively taxes act as an automatic stabilizer, while the long-run coefficient is an indicator of fiscal sustainability. The literature on fiscal policy over the business cycles draws a distinction between estimating the "tax elasticity" and "tax buoyancy". Whereas the former is commonly used to refer to the direct impact of discretionary changes in tax revenue because of changes in GDP (or a specific tax base), the latter captures other influences including discretionary policy changes. By including a time dummy variable for 2020 in our analysis, it is possible to infer how government responses to COVID-19 affected tax revenues and draw some conclusions on the outlook for revenue mobilization in the medium to long term.

A. Data and Descriptive Statistics

To maximize country and temporal coverage, including observations for 2020, our data are drawn from a variety of sources, mainly IMF, OECD, and ADB databases. As outlined in the Appendix and described in more detail in Co Go et al. (2022), tax revenue data are carefully validated for consistency across countries and through time. Tax revenue in domestic currency is drawn primarily from OECD Revenue Statistics, supplemented by IMF Government Financial Statistics. GDP data is from the IMF's WEO database.

Given our focus on tax-buoyancy dynamics, our sample is restricted to economies for which tax revenue and GDP data are continuously available up to and including 2020. The final sample covers 25 developing economies in Asia and the Pacific from 1998 to 2020, giving us a total of 575 observations.

We convert nominal taxes and nominal GDP in domestic currency to their growth rates, using log differences, i.e. $z_{i,t}$ growth: $lnz_{i,t} - lnz_{i,t-1} = \Delta lnz_{i,t}$. Both series in the log-differences passed the panel unit-root tests (Im et al., 2003; Levin et al., 2002).

B. Estimation

To estimate tax buoyancy in developing Asia, an ECM of total tax revenue and nominal GDP, both in time-series and panel, is estimated using data for 25 developing Asian economies for the period 1998–2020. The estimation yields two sets of coefficients, the instantaneous impact of changes in GDP on tax revenues (short-run tax buoyancy), and the long-run relationship between GDP and taxes (long-run tax buoyancy). During a major downturn like the pandemic, tax buoyancy may be affected differently, including due to increased tax evasion or changes in policy (Sancak, Xing, and Velloso 2010). To investigate the impact of COVID-19, the baseline specification is augmented to include a dummy variable DUM2020, which takes the value of 1 for the year 2020 and zero otherwise.

1. Panel Results: Mean-Group Estimator

Denoting country i and year t, we estimate the short-run and long-run tax buoyancies using the balanced panel data, applying the mean-group (MG) estimator. Following Pesaran et al. (1997, 1999), the mean-group estimator allows the intercept, the short-run coefficients, the error variances, and the long-run coefficients to differ across groups (economies).

Mean-group estimator

$$\Delta lnTaxes_{i,t} = c_i - \alpha_i\left(lnTaxes_{i,t-1} - \theta lnGDP_{i,t}\right) + \Sigma_{j=1}^{p-1}\psi_{lnTaxes,i}\Delta lnTaxes_{i,t-j} + \Sigma_{j=0}^{q-1}\psi'_{lnGDP,i}\Delta lnGDP_{i,t-j} + u_{i,t}$$

, where $\alpha_i = 1 - \Sigma_{j=1}^{p}\phi_{i,j}$ is the speed of adjustment coefficient, and the long-run coefficient $\theta_i = \frac{\Sigma_{j=0}^{q}\beta_{i,j}}{\alpha_i}$.

Table 1 provides the mean-group estimates. The short-run tax coefficient is 1.2 in column I, and, accounting for the pandemic crisis, 1.1 in column II. The long-run tax coefficient is 1.1, suggesting fiscal sustainability in our sample of economies during 1998–2020.

Regression results reported show that both estimated short-run and long-run tax buoyancies in developing Asia is very close to one and statistically significant. The results also indicate that the pandemic had both direct and indirect negative impacts on the region's tax revenue. The coefficient on the dummy variable for 2020 is statistically significant and indicates that, after controlling for the economic downturn for the region as whole, the pandemic subtracted a tenth of a percentage point from tax revenue growth.

2. Time-Series Results: Autoregressive Distributed Lag Model

Next, we use the autoregressive distributed lag (ARDL) model to assess tax buoyancy in individual economies, again separating the long-run from the short-run dynamics. The model allows for cointegration of nonstationary variables, which is the case for tax revenue and GDP in our sample. This approach is equivalent to an error correction model, with a

corresponding reparameterization. Bounds testing provides inference on whether the two variables are integrated of order zero [I(0)] or one [I(1)]

Following Engel and Granger (1987) and Pesaran et al. (1998), for each economy i, we estimate the short-run buoyancy as follows:

$$lnTaxes_t = c_0 + \Sigma_{i=1}^{p} \phi_{lnTaxes,i} lnTaxes_{t-i} + \Sigma_{i=0}^{q} \beta'_{lnGDP,i} lnGDP_{t-i} + u_t$$

$$\Delta lnTaxes_t = c_0 - \alpha(lnTaxes_{t-1} - \theta lnGDP_{t-1}) + \Sigma_{i=1}^{p-1} \psi_{lnTaxes,i} \Delta lnTaxes_{t-i} + \Sigma_{i=1}^{q-1} \psi'_{lnGDP,i} \Delta lnGDP_{t-i} + u_t$$

, where $\alpha = 1 - \Sigma_{j=1}^{p} \phi_i$ is the speed of adjustment coefficient, and the long-run coefficient $\theta = \frac{\Sigma_{i=0}^{q} \beta_j}{\alpha}$.

Our baseline analysis uses a specification of unrestricted intercept and unrestricted trend, with Bayesian Information Criterion with a maximum lag order of 4. It does not fix the lag order for any variables in the estimation; the Newey-West standard errors can be obtained with the optimal lag order.

In the specification, GDP, allowed to be $I(0)$ or $I(1)$ is weakly exogenous for taxes, thus yielding at most one cointegrating relationship. The analysis uses Pesaran, Shin, and Smith (2001) bounds test. The test assesses the statistical evidence of a cointegrating relationship between taxes and GDP according to all three of the following testing steps:

(i) start with F-test if α and β are jointly significant from zero,

(ii) follow with t-test if α is significant from zero, and

(iii) then with z-test if θ is significant from zero.

There are variations (finite sample; asymptotic) in the distributions of the test statistics of steps 1 and 2 (Kripfganz and Scheneider 2018; Pesaran, Shin, Smith 2001; and Narayan 2005), depending on the number of independent variables, integration order, short-run coefficients, and intercept and time trend.

The variables of interest include:

(i) The negative adjustment coefficients, $-\alpha$, measuring the strength of tax response to the one-period deviation from its equilibrium association with GDP. For most economies this is found to take on the expected negative value.

(ii) The long-run coefficients, θ, measuring the equilibrium effects of GDP on taxes, suggesting cointegration relationships between the variables across countries. The estimates are above one for many economies, but below one for a few.

(iii) The short-run coefficients, ψ, measuring the dynamics not accounted by the deviation from the long-run equilibrium, which are all positive and statistically significant.

3. Tax Buoyancy Coefficients: Taking Stock

To test our first hypothesis, we study tax buoyancy at the country level and in the panel data, using the ECMs on 25 developing Asian economies. Figure 1 plots the long-run tax buoyancy coefficients, displaying the range of estimates from both the autoregressive distributed lag model (AR) and the mean-group model (MG). The results show that estimated long-run tax buoyancy is greater than one in most economies, indicative of fiscal sustainability. We note

that the estimates are relatively large for some small economies, where GDP and tax revenue are often volatile.

IV. IMPACT OF COVID-19 ON TAX REVENUES

In this section, we further explore the impact of COVID-19 on tax revenue, reporting the estimated excess tax revenue loss in 2020, and consider the impact of COVID-19 fiscal measures on tax buoyancy.

A. Estimated Excess Tax Revenue Loss from COVID-19

Using the coefficients from country level equations, a simple counterfactual analysis is undertaken to estimate excess tax revenue lost in 2020 as a share of GDP, as outlined in the second testing hypothesis above. Predicted tax revenues are estimated by applying 2020 GDP outturns to the estimated models, and then deducted from actual tax revenues.

Specifically, our analysis involves the following steps:

(i) run the time-series model for each economy with 1998–2019 data,

(ii) estimated model predicted revenues for 2020 (tax_f), and

(iii) deduct predicted revenues from actual revenues to assess the impact of COVID-19 over and above what would normally be expected given the GDP downturn.

Excess tax revenue losses are thus defined as:

$$Excess\ Tax\ Loss = \frac{100 \times \left(ln(Tax_{2020}) - ln\left(Tax_{f,2020}\right)\right) \times Tax_{2019}}{GDP_{2019}}$$

i.e., $ln(Tax_{2020}) - ln\left(Tax_{f,2020}\right) = \frac{Tax_{2020} - Tax_{f,2020}}{Tax_{f,2020}}$, and approximately, $Tax_{2020} = e^{Gap} Tax_{f,2020}$.

Figure 2 shows for the economies in our sample the gap between actual and model estimated 2020 tax revenue, expressed as a percentage of 2019 GDP. In most but not all economies, the decline in tax revenues in 2020 is greater than predicted by the model estimates. On average (GDP weighted), it is estimated that developing Asian economies endured excess lost tax revenues, over and above what was expected because of the decline in GDP, equal to half a percentage point of 2019 GDP because of COVID-19.

B. COVID-19 Fiscal Measures and Tax Buoyancy

Turning to the third testing hypothesis, we consider whether the fiscal stimulus measures deployed during the COVID-19 pandemic, including large-scale tax relief, are associated with lower estimated buoyancy. Fiscal policy responses are measured as announced above the line COVID-19 stimulus measures from the IMF. While COVID-19 fiscal packages differed in size, design, and timing across countries, in many cases these packages were several percentage points of GDP.

As shown in Figure 3, COVID-19 fiscal policy responses appear to be associated with lower tax buoyancy in developing Asian economies. Specifically, we observe a negative correlation (-0.15) between the size of the fiscal policy response, expressed as a share of GDP, and the

size of the estimated tax buoyancy coefficients. While the negative association is suggestive, more data post-pandemic is required to support the test.

V. PROJECTION OF TAX/GROSS DOMESTIC PRODUCT IN 2030

As a by-product of tax buoyancy analysis, we can analyze whether a country is on the path of increasing tax revenue as a share of GDP over the long run. By estimating tax buoyancy with the data up to and including 2019, we could answer the question: Were countries making progress in mobilizing revenues prior to the pandemic? If the answer is yes, then one might infer that, post-pandemic, when economies recover, progress with revenue mobilization would continue.

Having derived estimates of tax buoyancy, a simple forecasting exercise is undertaken to estimate tax revenue in the long-run, specifically in 2030, the target date for achievement of the SDGs.

Given tax/GDP of 2019, growth forecasts, and the estimated long-term tax buoyancy coefficients, we calculate tax revenue from 2019 and 2030. Following Gupta and Liu (2021):

$$\left(\frac{tax}{GDP}\right)_{i,T} = \left(\frac{tax}{GDP}\right)_{i,t} \times \Pi_{\tau=t+1}^{T}\left(\frac{(1 + \left(LRtaxBuoyancy_i \times gdpGrowth_{i,\tau}\right))}{1 + gdpGrowth_{i,\tau}}\right); \tau = t+1, \ldots, T$$

In our calculation, $t = 2019; T = 2030$. We use GDP forecasts for 2020–2026 and a 10-year moving average (2017–2026) as the growth projection after 2026. Both historical and forecasted values of GDP are drawn from the 2019 IMF WEO database. In the scenario analysis of section IV, we use the 2019 forecast of 2020–2026 GDP to assess the pandemic effect on tax buoyancy on GDP.

Table 2 reports projected tax-to-GDP ratios in 2030. We note that the model estimates are not significant for some economies (t-values) and that the projection is sensitive to growth forecasts and the model specified. Nevertheless, different model specification is largely in agreement on the projection. Tax-to-GDP ratios are projected to increase in most economies in our sample, other things held constant. However, in some cases the projected increase is modest, leaving countries with still low tax revenues. This underscores the importance of bolstering efforts to mobilize taxes to support development in Asia (ADB 2022).

VI. CONCLUSIONS

Tax buoyancy, which captures how tax revenues vary in response to changes in GDP, is crucial to understanding tax revenue performance and fiscal sustainability. Tax buoyancy provides estimates of the extent to which tax revenues rise and fall during cyclical upturns and downturns, shedding light on the stabilizing role of taxes over the business cycle. Tax buoyancy also helps assess how tax revenue evolves over the long run. In light of the pronounced economic impact of COVID-19, now is an especially opportune time to visit this issue. During a major downturn like the COVID-19 pandemic, tax buoyancy may be affected because of policy changes or greater tax evasion. Therefore, we are interested in both the impact of the pandemic on revenues and the prospects for the recovery of revenues as the pandemic recedes.

Tax buoyancy greater than one implies that tax revenues are rising more than proportionately to an increase in GDP. Therefore, tax revenues are structurally increasing and sufficiently buoyant to support fiscal sustainability, even with some increases in public spending. The tax system is also helping to stabilize short-run output. During upturns, tax

revenues increase disproportionately, providing a countercyclical impulse which dampens demand and prevents overheating. During downturns, tax revenues decrease disproportionately, which is analytically equivalent to a tax cut which boosts economic activity. In contrast, if tax buoyancy is less than one, tax revenues are structurally decreasing, and insufficiently buoyant tax revenues pose a risk to fiscal sustainability in the absence of spending cuts (Creedy and Gemmel 2008; Dudine and Jalles 2018; Gupta, Jalles, and Liu forthcoming; and Lagravinese et al. 2020).

To estimate tax buoyancy in developing Asia, an ECM of total tax revenue and nominal GDP is estimated for a sample of 24 developing Asian economies for the period 1998–2020, using both time-series and panel data approaches. The estimation yields two sets of coefficients: the instantaneous impact of changes in GDP on tax revenues or short-run tax buoyancy; and the long-run relationship between GDP and taxes or long-run tax buoyancy. To investigate the impact of COVID-19, the analysis includes a dummy variable, which takes the value of 1 for 2020 and zero otherwise.

Regression results from our panel data analysis show that both short-run and long-run tax buoyancies in developing Asia as a whole is very close to one and statistically significant. The results also indicate that the pandemic subtracted a tenth from tax revenue growth after controlling for changes in GDP. To explore tax buoyancy at the country level, the same model is estimated for individual economies. Consistent with our regional level analysis, we find that long-run tax buoyancy coefficients are close to one in most economies.

Using coefficients from country-level equations, a simple counterfactual analysis is performed to estimate excess tax revenue lost in 2020 because of the pandemic, reflecting

the decline in revenue over and above what would normally be expected given the GDP downturn. We first estimate predicted revenues for 2020 and then deduct this from actual revenues. Based on GDP-weighted figures, it is estimated that, on average, developing Asian economies endured excess tax revenues losses equal to half a percentage point of 2019 GDP because of COVID-19. This is consistent with an observed negative association between the size of COVID-19 fiscal stimulus measures and our estimates of tax buoyancy.

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Table 1: Pooled Mean-Group Estimator

Panel A: Base Specification

D.lny	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
ec						
lnx	1.10338	.0110827	99.56	0.000	1.081659	1.125102
SR						
ec	-.2745811	.0542916	-5.06	0.000	-.3809906	-.1681715
lnx						
D1.	1.269343	.1840026	6.90	0.000	.9087045	1.629981
_cons	4.893768	.9315188	5.25	0.000	3.068025	6.719511

Panel B: Including the Dummy Variable for 2020

D.lny	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
ec						
lnx	1.111206	.011562	96.11	0.000	1.088545	1.133867
SR						
ec	-.2659643	.0525299	-5.06	0.000	-.368921	-.1630077
lnx						
D1.	1.073585	.1588511	6.76	0.000	.7622425	1.384928
d1	-.1094677	.0336261	-3.26	0.001	-.1753737	-.0435618
_cons	4.743125	.8912466	5.32	0.000	2.996314	6.489936

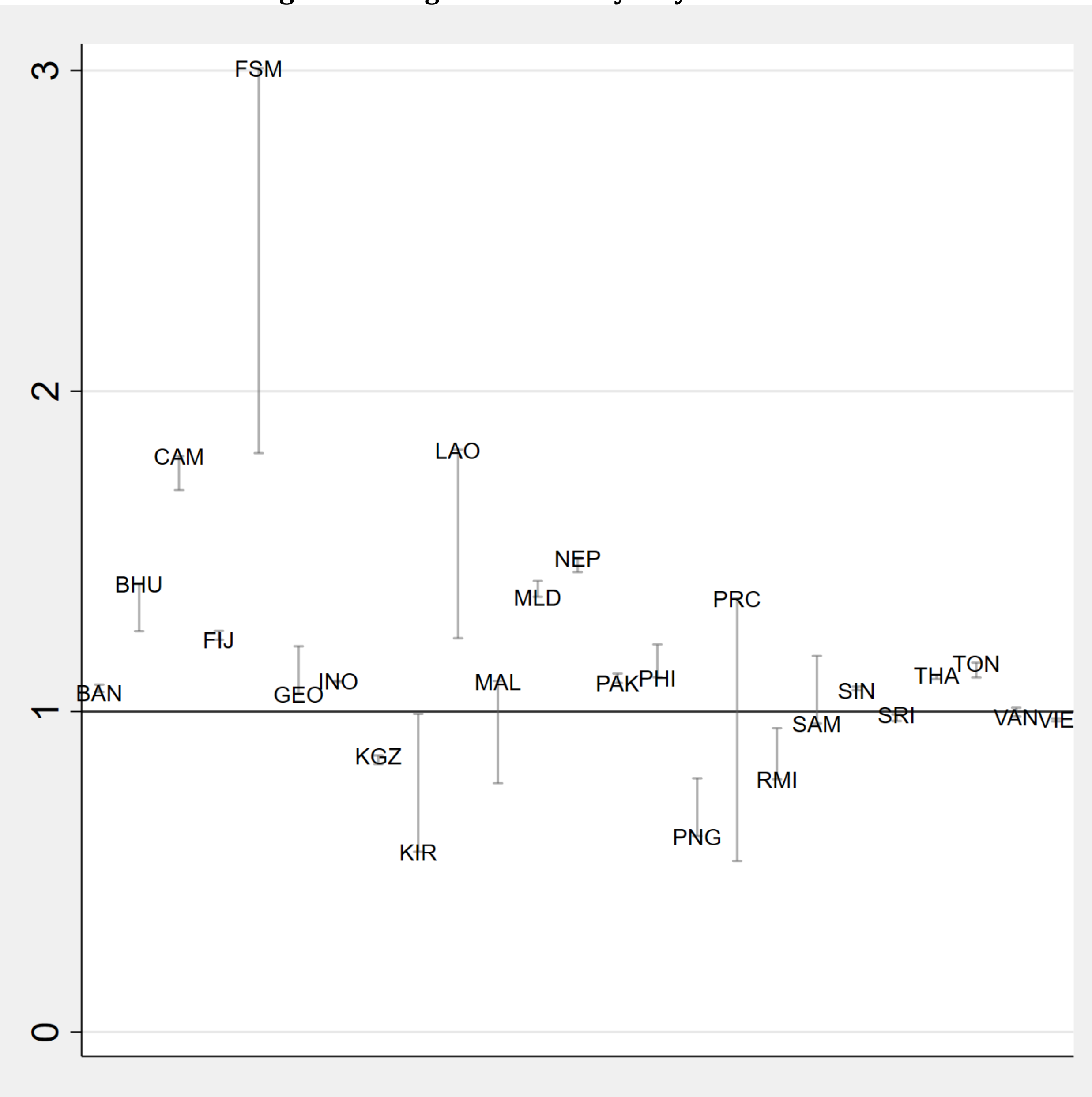
Note: Asian Development Bank estimates from the Organisation for Economic Co-operation and Development Revenue statistics (accessed 15 September 2021); International Monetary Fund Government Finance Statistics (accessed 22 October 2021). The sample covers 25 economies from 1998 to 2020. The dependent variables, lny, is natural log of tax revenues in local currency unit. The explanatory variable, lnx, is the natural log of gross domestic product in local currency unit. The dummy variable, d1, is for the year 2020. ec denotes the error correction and SR denotes short run.
Source(s): ADB staff estimates.

Table 2: Projection of Tax/Gross Domestic Product in 2030 and Changes from 2019

Country	GDP_Growth	Tax_Buoyancy	taxGDP2030	Change	t_stat
Bangladesh	10.2	1.1	9.7	0.8	34.36
Bhutan	9.1	1.3	20.3	4.1	13.90
Cambodia	6.8	1.7	34.3	12.4	7.87
Sri Lanka	6.8	1.0	11.3	-0.2	19.70
Indonesia	6.1	1.1	11.7	0.6	41.71
Lao People's Democratic Republic	7.2	1.2	12.8	1.9	0.64
Malaysia	4.9	0.8	10.8	-1.3	5.11
Maldives	6.1	1.4	24.4	5.4	9.18
Nepal	6.7	1.4	24.9	5.1	28.81
Pakistan	8.5	1.1	13.0	1.2	59.53
Philippines	6.1	1.2	16.4	1.9	9.62
Singapore	2.1	1.1	13.5	0.2	6.87
Thailand	3.5	1.1	16.7	0.6	15.97
Viet Nam	4.1	1.0	14.6	-0.1	28.18
Fiji	4.8	1.3	26.5	3.1	44.69
Kiribati	2.4	1.0	17.4	-0.0	2.28
Vanuatu	4.0	1.0	17.8	0.1	16.32
Papua New Guinea	3.6	0.8	12.0	-1.0	3.54
Samoa	4.5	1.2	27.8	2.2	4.26
Tonga	3.0	1.1	21.6	0.7	8.65
Marshall Islands	1.3	0.9	17.3	-0.1	3.05
Micronesia, Federated States of	1.1	1.8	26.7	1.9	4.49
Georgia	4.7	1.2	26.2	2.2	3.39
Kyrgyz Republic	5.9	0.8	18.6	-1.9	2.29
China, People's Republic of	5.2	0.5	12.5	-3.5	0.29

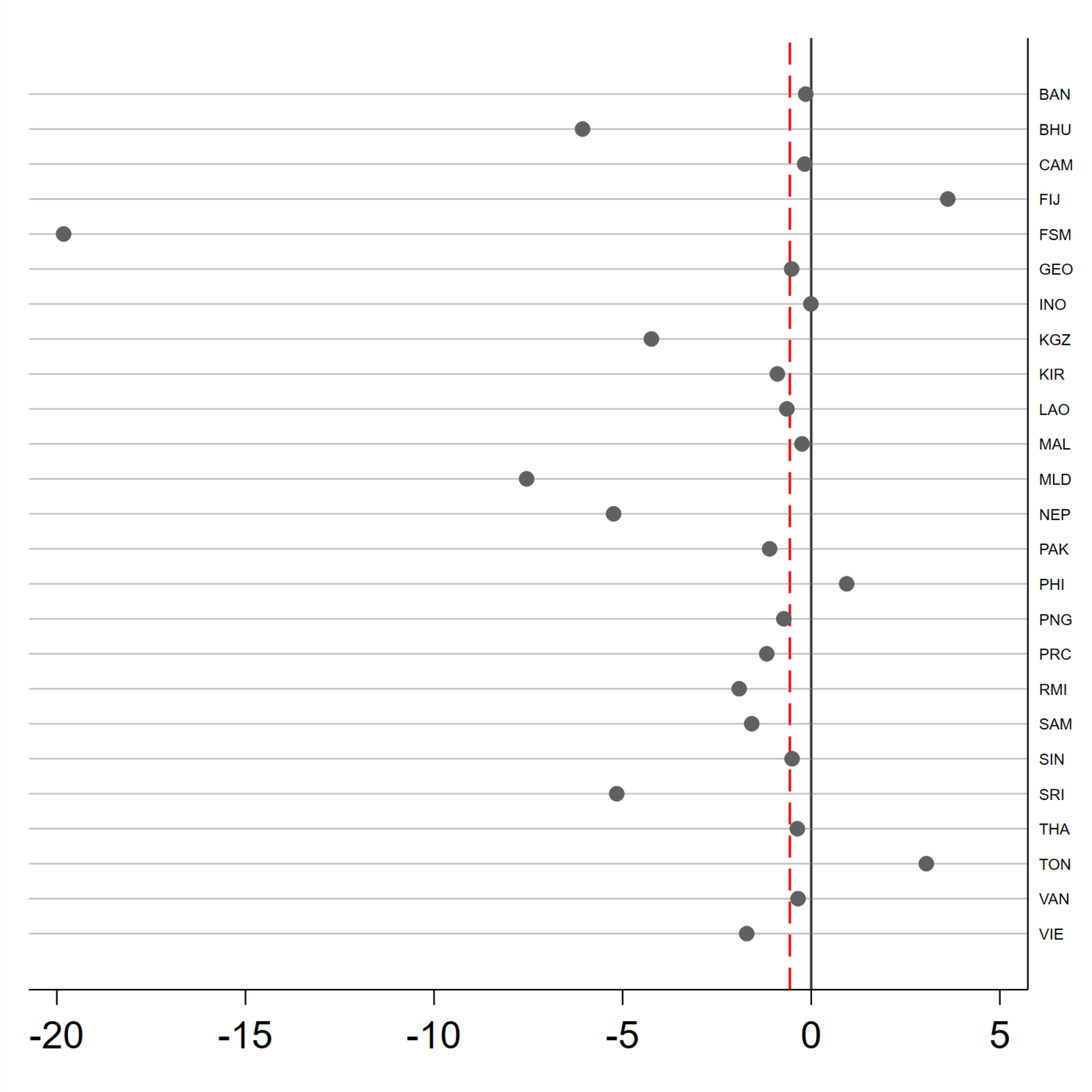
GDP = gross domestic product.
Note: Long-run estimates of the mean-group estimator (MG); those of the autoregressive distributed lags model are available upon request. Tax buoyancy coefficients from the estimation on 1998–2019 data. Asian Development Bank estimates from the Organisation for Economic Co-operation and Development Revenue statistics (accessed 15 September 2021); International Monetary Fund Government Finance Statistics (accessed 22 October 2021).
Source(s): ADB staff estimates.

Figure 1: Long-Run Tax Buoyancy Coefficients



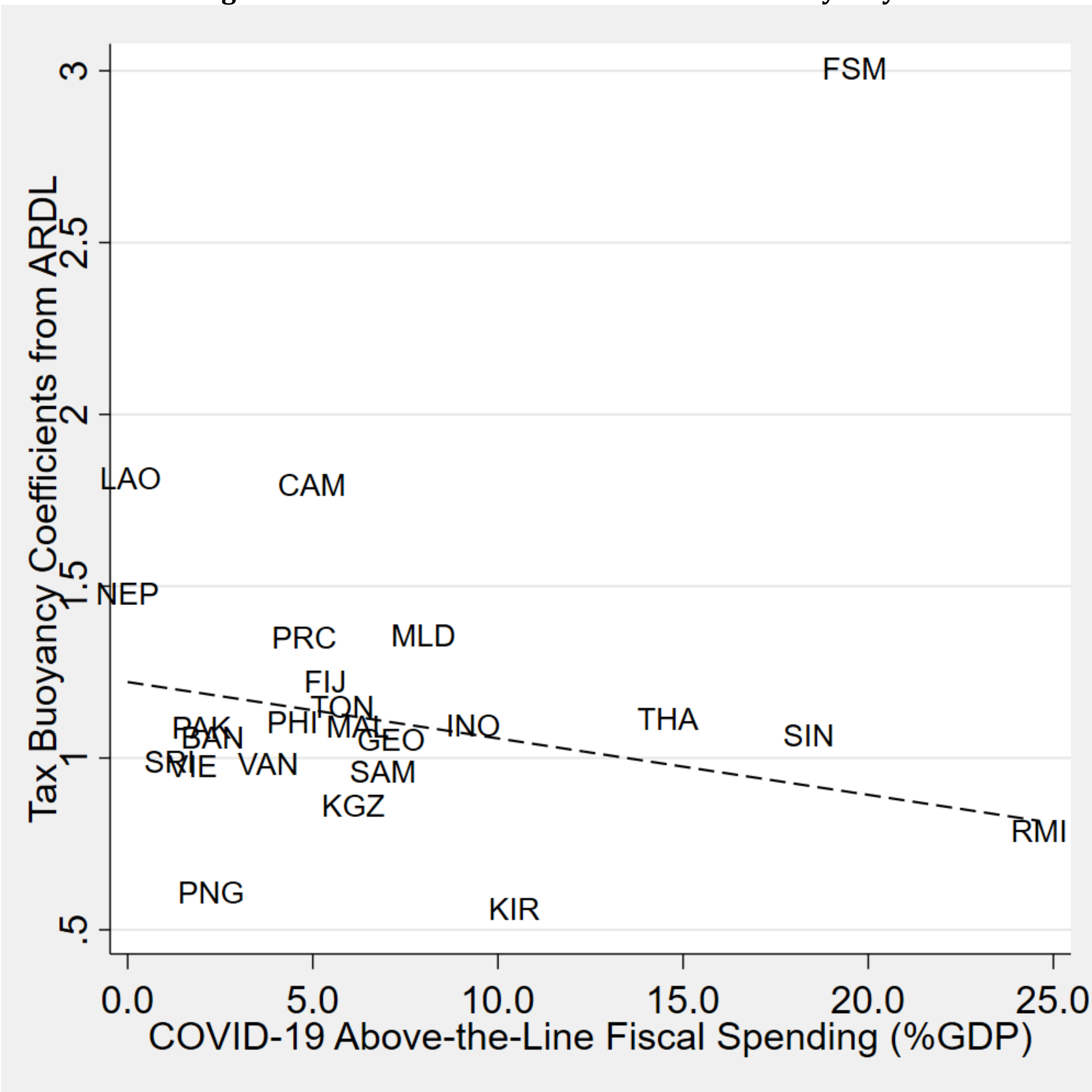
ARDL = autoregressive distributed lag, BAN = Bangladesh, BHU = Bhutan, CAM = Cambodia, FIJ = Fiji, FSM = Federated States of Micronesia, GEO = Georgia, INO = Indonesia, KGZ = Kyrgyz Republic, KIR = Kiribati, LAO = Lao People's Democratic Republic, MAL = Malaysia, MLD = Maldives, NEP = Nepal, PAK = Pakistan, PHI = Philippines, PNG = Papua New Guinea, PRC = People's Republic of China, RMI = Marshall Islands, SAM = Samoa, SIN = Singapore, SRI = Sri Lanka, THA = Thailand, TON = Tonga, VAN = Vanuatu, VIE = Viet Nam.
Note: Upper and lower bounds of estimates from time-series ARDL and panel mean-group estimator.
Source(s): ADB staff estimates.

Figure 2: Excess (Actual Values Minuses Model Estimates) Tax Losses in 2020
(% GDP in 2019)



BAN = Bangladesh, BHU = Bhutan, CAM = Cambodia, FIJ = Fiji, FSM = Federated States of Micronesia, GDP = gross domestic product, GEO = Georgia, INO = Indonesia, KGZ = Kyrgyz Republic, KIR = Kiribati, LAO = Lao People's Democratic Republic, MAL = Malaysia, MLD = Maldives, NEP = Nepal, PAK = Pakistan, PHI = Philippines, PNG = Papua New Guinea, PRC = People's Republic of China, RMI = Marshall Islands, SAM = Samoa, SIN = Singapore, SRI = Sri Lanka, THA = Thailand, TON = Tonga, VAN = Vanuatu, VIE = Viet Nam.
Note: Negative values are excess tax losses over and above what would normally be expected, given the GDP downturn.
Source(s): ADB staff estimates.

Figure 3: COVID-19 Fiscal Measures and Tax Buoyancy.



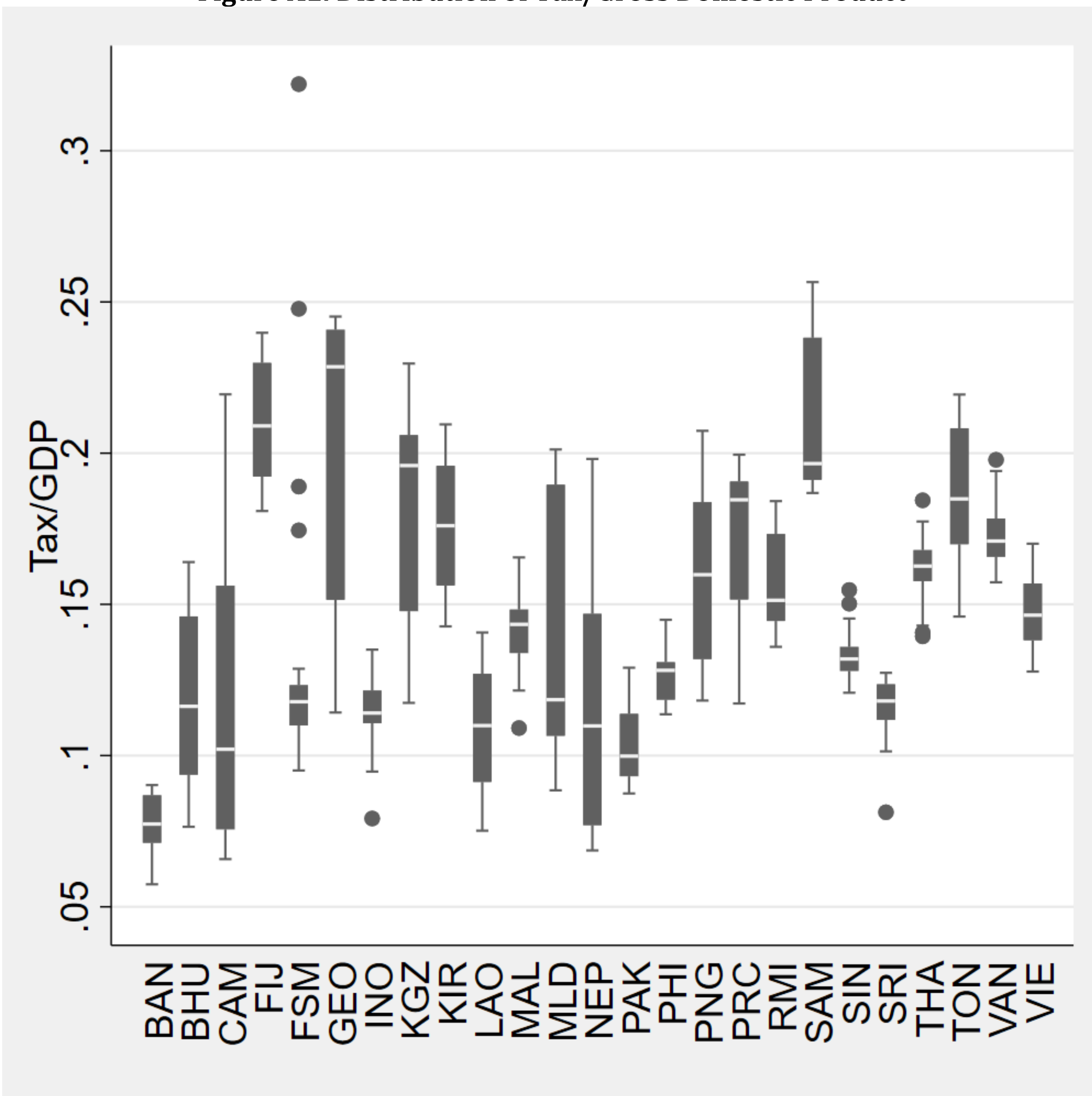
ARDL = autoregressive distributed lag, BAN = Bangladesh, CAM = Cambodia, COVID-19 = coronavirus disease, FIJ = Fiji, FSM = Federated States of Micronesia, GDP = gross domestic product, GEO = Georgia, INO = Indonesia, KGZ = Kyrgyz Republic, KIR = Kiribati, LAO = Lao People's Democratic Republic, MAL = Malaysia, MLD = Maldives, NEP = Nepal, PAK = Pakistan, PHI = Philippines, PNG = Papua New Guinea, PRC = People's Republic of China, RMI = Marshall Islands, SAM = Samoa, SIN = Singapore, SRI = Sri Lanka, THA = Thailand, TON = Tonga, VAN = Vanuatu, VIE = Viet Nam.

Note: Asian Development Bank estimates of tax buoyancy coefficients, and International Monetary Fund Fiscal Monitor: Database of Country Fiscal Measures in Response to the COVID-19 Pandemic; measures since January 2020 and covers measures for implementation in 2020, 2021, and beyond. Above-the-line refers to measures directly affecting revenue and expenditure; for example, deferral of taxes and cash transfers.

Source(s): ADB staff estimates.

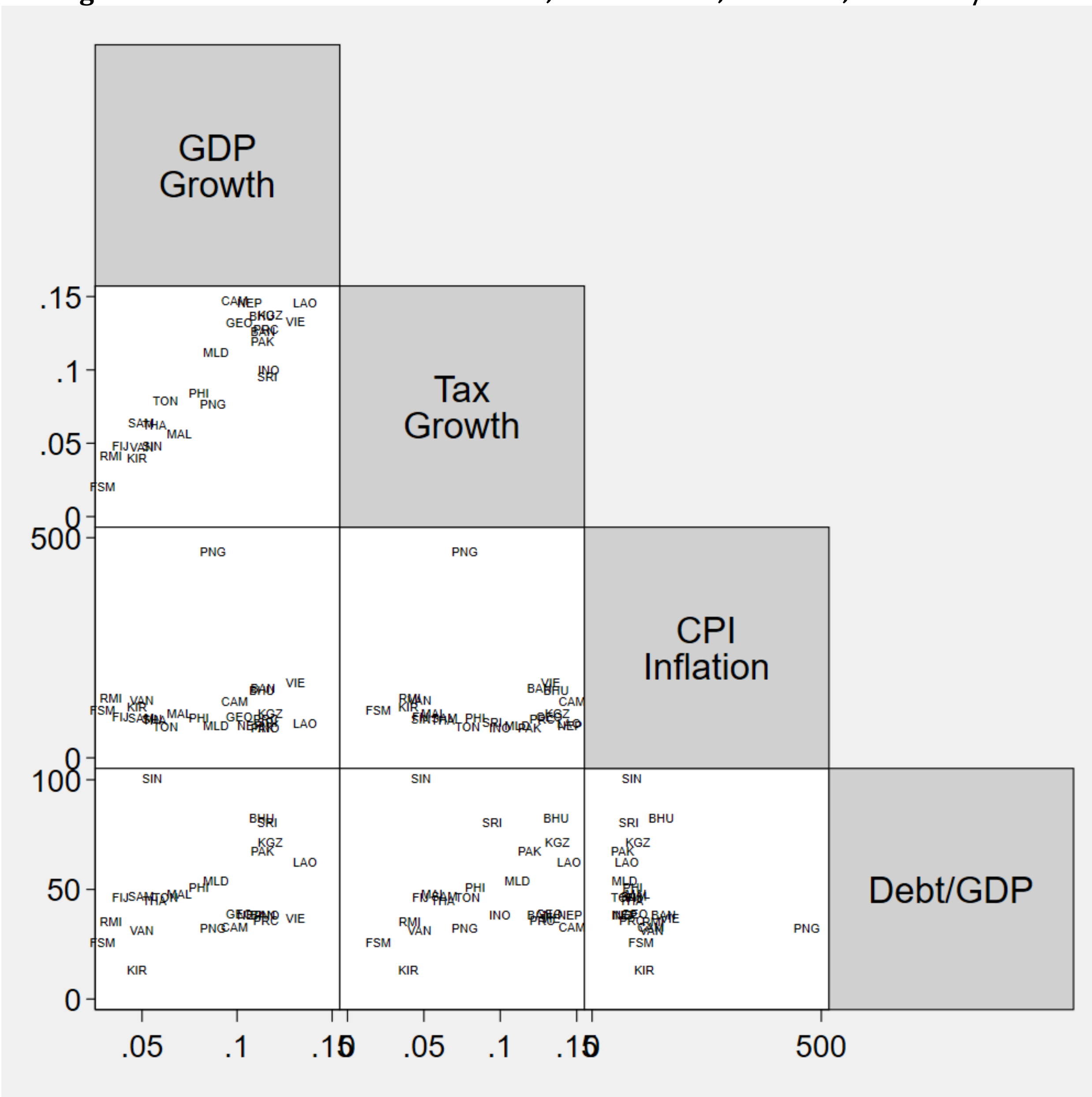
APPENDIX

Figure A1: Distribution of Tax/Gross Domestic Product



BAN = Bangladesh, BHU = Bhutan, CAM = Cambodia, FIJ = Fiji, FSM = Federated States of Micronesia, GDP = gross domestic product, GEO = Georgia, INO = Indonesia, KGZ = Kyrgyz Republic, KIR = Kiribati, LAO = Lao People's Democratic Republic, MAL = Malaysia, MLD = Maldives, NEP = Nepal, PAK = Pakistan, PHI = Philippines, PNG = Papua New Guinea, PRC = People's Republic of China, RMI = Marshall Islands, SAM = Samoa, SIN = Singapore, SRI = Sri Lanka, THA = Thailand, TON = Tonga, VAN = Vanuatu, VIE = Viet Nam.
Note: Asian Development Bank estimates from the Organisation for Economic Co-operation and Development Revenue statistics (accessed 15 September 2021); International Monetary Fund Government Finance Statistics (accessed 22 October 2021). The sample covers 25 economies from 1998 to 2020.
Source(s): ADB staff estimates.

Figure A2: Correlations of Tax Growth, GDP Growth, Inflation, and Debt/GDP.



CPI = consumer price index, GDP = gross domestic product.
Note: Asian Development Bank estimates from the Organisation for Economic Co-operation and Development Revenue statistics (accessed 15 September 2021); International Monetary Fund Government Finance Statistics (accessed 22 October 2021). The sample covers 25 economies from 1998 to 2020.
Source(s): ADB staff estimates.