Revisiting Tax Effort in Emerging Markets*

Gustavo Canavire-Bacarreza† Maria Cecilia Deza‡
Osmel Manzano§ and Alejandro Puerta¶

ABSTRACT

Insufficient tax revenues has been one of the most pervasive restrictions on investment in the social and economic infrastructure needed to close the development gaps in emerging markets (EM). To assess the potential for increasing tax collection, the literature has emphasized the concept of tax capacity and tax effort. Conceptually, tax effort is modeled as an inefficiency term with both time-varying and time-invariant components. These are commonly estimated through OLS or stochastic frontier analysis techniques. However, these strategies provide only point estimates and are limited in their ability to break down tax effort into time-varying and time-invariant components. We estimate tax effort for a balanced panel of 108 countries for which data were available from 2002 to 2017, using a Bayesian strategy that allows us to calculate the invariant inefficiency as an upper bound for a country's tax effort. We also show that the GTRE model from Tsionas and Kumbhakar (2014) allows for more precise estimates, providing powerful tools for more informed fiscal planning.
Keywords: Tax Effort, Tax Revenue, Stochastic Frontier Analysis, Bayesian Econometrics
JEL CODES:C23, C51, H2, H21

*The opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the World Bank, the Inter-American Development Bank, the board of directors of either entity, or the countries they represent.

†The World Bank, Washington, DC, USA. and Universidad Privada Boliviana, La Paz, Bolivia Email: gcanavire@gmail.com

‡Inter-American Development Bank, Washington, DC, USA. Email: mdeza@iadb.org

§Inter-American Development Bank, Washington, DC, USA. Email: osmelm@iadb.org

¶Department of Economics, Universidad Carlos III, Madrid, Spain, E-mail: alpuerta@eco.uc3m.es

1 Introduction

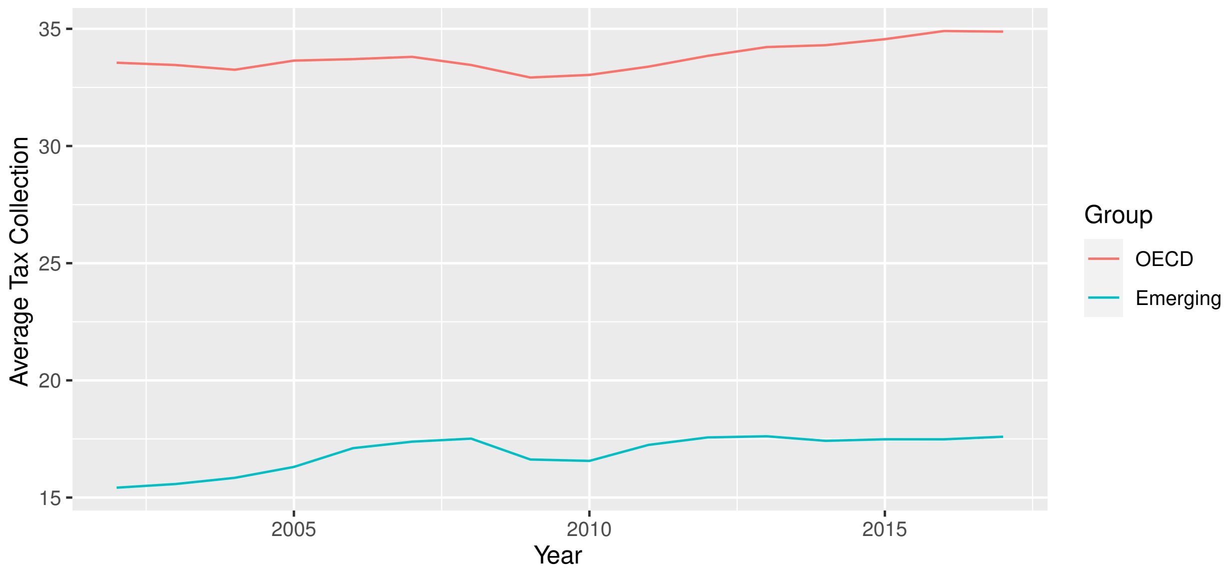
During the commodity supercycle of the mid-2000s, emerging markets (EMs) found themselves benefitting from windfall revenues (see Figure 2), which were used, to a greater or lesser extent, to finance both current and capital expenditures. The global financial crisis of 2008–2009 interrupted this upward trend only briefly and a steep recovery was seen after 2010. However, the supercycle seems to have reached an end in mid-2014, leaving many oil producer countries with significantly lower fiscal revenues, permanently high expenditures and, consequently, wide fiscal deficits and rising debt ratios.

The response of several countries has been to implement fiscal adjustments. The magnitude of the consolidation plans differed depending on each country's circumstances and initial conditions; however, it is fair to say that most implemented expenditures reductions and only a handful of approved revenue increases. According to Inter-American Development Bank (2019), expenditures adjustment was done basically through cutting capital expenditures, which jeopardizes future economic growth.

While it is a fact that there is a lag in fiscal revenue collection relative to international standards (see Section 2), only a few countries have implemented significant tax reforms. One of the reasons for this unwillingness is that countries lack knowledge about their true tax effort and, therefore, their tax capacity, and how much of that capacity is lost by technical inefficiencies in their tax collection, which is within their control. However, the most commonly employed theoretical approaches fail to provide an explicit breakdown of the inefficiency term into its time-invariant and time-varying components. Isolating the former has value from the policy perspective since, depending on their nature, it may be less difficult to correct, compared to time-varying inefficiencies that could be related to the particular economic cycle. For instance, time-invariant inefficiencies might stem from weak tax administrations, low enforcement capabilities, general government ineffectiveness and a lack of underlying institutional strength.

This paper attempts to address this gap, providing several estimates of countries' tax effort and tax capacity, taking as a starting point previous efforts by Fenochietto and Pessino (2013), but with methodological improvements in the estimation of the inefficiency, relying on the Bayesian model from Tsionas and Kumbhakar (2014). The mainstream estimates of the tax effort use the approximation of Jondrow et al. (1982) or Battese and Coelli (1988), both of which rely on single point estimates of inefficiency. The Bayesian strategy proposed in this paper enables identification of the whole posterior distribution and approximation of the expected value of the tax effort

FIGURE 1: Tax collection by economic group (2002–2017)



Source: Stat (2019)

with the sample average of the exponential of the inefficiencies' chains. Additionally, by disentangling inefficiency into time-invariant and transient components, we can find an upper bound for tax collection, which is currently not possible using the mainstream frequentist models.

The reminder of the paper unfolds as follows: section 2 describes the context, the recent evolution of tax revenues and social security contributions in EMs, and the data used. Section 3 provides a description of the methodological approach. Section 4 presents and comments on the results. Section 5 concludes and discusses.

2 Context and data

2.1 Context

The lower tax collection in EMs compared to developed economies has been a stylized fact, as Figure 1 depicts. The average OECD country collected 34.88% of GDP in 2017, while the average EM collected around half of that—17.59% of GDP. Except for the transitory upward pattern of tax collection during the commodity price upswing, the trend of tax revenues and social security contributions (SSC) in EMs has remained fairly constant in the last decade of the period under

FIGURE 2: Tax revenue by economic group and concept (2002–2017)

Source: Stat (2019)[a]

[a]The data set did not have information available for China, Egypt, Syrian Arab Republic, India, Pakistan, Qatar, Russian Federation, Saudi Arabia, and Thailand.

study (it was 17.38% in 2017).

Figure 2 shows the breakdown of tax revenues by concept. Looking at the structure of tax collection in EMs and OECD countries, we see that the gap in revenues in developing countries is mostly explained by a lower reliance on personal income taxes and SSC. Even though there has been catch-up in individual income taxes, in 2017 the gap in revenues was around 1% of GDP (4.45% of GDP in OECD countries and 3.55% of GDP in EMs), which has been compensated by overtaxation of corporates. In terms of property and payroll taxes, the gap has become smaller over time. During the commodity supercycle of the mid-2000s, revenues from taxes on goods and services grew vastly in EMs but dropped after 2008, leaving a small gap of 0.26%. Over the past decade, tax collection in EM has relied basically on indirect taxes, which are relatively easier to collect, rather than on individual direct taxation, as is the case in more-advanced economies. The gap in direct taxation at the individual level is, in part, a consequence of the economic structure in emerging economies, which is characterized by lower wages, informality, and the existence of sectors that are hard to tax.

Related to direct taxation is the gap in terms of SSC, which has been consistent over time. In 2002, OECD countries collected 4.33% of GDP while EMs just 1.52% of GDP. For 2017, revenue from this concept has remained almost unchanged (4.21% and 1.85% of GDP, respectively), leading to a current gap of around 2.3%. This difference in SSC collection can be explained by the prevalent informality that keeps most workers outside the tax regime and labor regulations, as well as by the generosity of the design of the personal income tax in EMs. In 2016, informality was 67% of total employment in EMs and 18% in developed countries. If agriculture is excluded, the level of informal employment falls to 59% of total employment in EMs and to 17% in developed countries (Bonnet, Vanek and Chen, 2019).

The evidence shows that the levels of tax revenues collected in EMs are clearly insufficient for closing those countries' infrastructure gaps and meeting their social needs. The questions that follow naturally are: What is the potential tax collection those countries could achieve, given their macroeconomic and social conditions? How far are the current tax revenues away from that potential? In other words, what tax effort do the EMs exercise? How variable is that tax effort? How are the differences in tax effort explained?

Since commodity revenue windfalls like those observed in the 2006–2014 period are unlikely to repeat in the coming years, it is key for EM governments to increase their tax effort by looking at domestic sources of revenue to finance their social and infrastructure gaps. A greater tax effort will be achieved with strengthened tax systems, which, in turn, depend on improving the effectiveness of their tax administrations in fighting evasion and better design of their tax and revenue policies. While the formula to boost tax effort will depend on each country's economic, political, and social environment, in general, increasing tax revenues to bring EMs closer to their potential should be a key fiscal policy priority. Tax reforms in this context should consider a composition of tax revenues that is pro-growth, in the sense that it is sufficient, neutral, and efficient. Finally, any tax reform should also address equity concerns and be accompanied by efforts to modernize the tax administration.

The literature on tax effort and its determinants is vast. In an influential work, Tanzi and Davoodi (1997) find that higher corruption is associated with lower government revenues, which lays out the foundations to formally assess the potential tax collection and compare it against actual revenues. In this line, Bird, Martinez-Vazquez and Torgler (2008) study that institutional factors such as perception of corruption, voice and accountability are as important as supply factors in explaining tax effort in developing and high income countries. On another contribution, Cyan, Martinez-Vazquez and Vulovic (2013) explore different approaches and conclude that any attempt to estimate revenue potential taken should depend upon a country's specific developmental needs, budgetary ambitions and feasibility of potential tax reforms; also, they argue that the sufficiency of tax effort should be linked to particular expenditure and welfare gains goals. The authors also attempt to account for time-invariant inefficiency in tax collection.

Similarly, Bird and Martinez-Vazquez (2014) discuss that tax issues should take into account not only the level and structure of economic development, but also historical, geographical and political aspects. Beyond that, economic and political perceptions, such as the expectation and magnitude of debt forgiveness, could also influence incentives to improve tax effort (Brown and Martinez-Vazquez (2019)). Le, Moreno-Dodson and Bayraktar (2012) expand the empirical methodology applied by Tanzi and Davoodi (1997) and Bird, Martinez-Vazquez and Torgler (2008) to include proxies of a country's macroeconomic condition, as well as demographic and institutional features. Using a similar setup, Boukbech, Bousselhamia and Ezzahid (2018) estimate two separate panel data models for tax capacity and tax effort, following the usual determinants in the literature, such as per capita GDP, value added of agriculture and trade openness. Pessino and Fenochietto (2010) and Fenochietto and Pessino (2013) undertake a methodological advancement to usual cross-section or panel data techniques using stochastic frontier analysis to approach tax effort, based on the theoretical idea that each country has a maximum that could be achieved using a set of inputs efficiently. Finally, Brun and Diakite (2016) attempt to disentangle the time-varying and time-invariant inefficiency, which has been a shortcoming of traditional models. Despite the theoretical and methodological improvements, as Tanzi and Zee (2000) point out, estimates of tax capacity or potential usually fail to capture all the dimensions that explain ability to mobilize revenue. As such, they should not be seen as an optimal level of taxation a country should aspire to achieve, given the complexities of different economic and political structures.

2.2 Data

The dataset consists of a balanced panel of 108 countries with information from 2002 to 2017. Countries of all levels of income and regions are included; in this paper we only report the results for EMs, but results for other countries are available upon request. We use the Standard and Poor's (S&P) classification of a country as EM. For the variables used, the main source of information is the World Bank's World Development Indicators (WDI) database. Other sources of information include the International Monetary Fund's World Economic Indicators (WEO) database, the UNU-WIDER's World Income Inequality database, and the World Governance Indicators (WGI) database.

The criteria to select the variables to be included in the model follows those considered in previous research as structural determinants of a country's tax capacity, such as the degree of development, trade openness, macroeconomic conditions, institutional capacity, and the existence of sectors that are hard to tax, among others (see, for instance, Fenochietto and Pessino (2013) and Le, Moreno-Dodson and Bayraktar (2012)).

We follow Fenochietto and Pessino (2013) in determining the variables to be included in the model. Due to a lack of comparable data, we do not use public expenditure on education and the Gini coefficient in this version of the paper. The size of the informal economy and the magnitude of informal employment are key variables that explain the differences in tax collection between EMs and advanced economies, and in EMs' actual and potential collection. However, harmonized worldwide time series are not available so far. In fact, to estimate the model including informality we would only have 261 observations instead of 1728. Therefore we try to mitigate for this lack of data by controlling for our set of variables (including wage and salaried workers as a percentage of total employment) and specifying varying betas for resource and non-resource rich countries.

The variables used in our paper are (i) the ratio of tax revenues and social security contributions to GDP (in logs), which is the dependent variable[1]; and several explanatory variables, such as (ii) GDP *per capita* in 2011 international dollars; (iii) trade openness, measured as the ratio of exports and imports of goods and services to GDP, both as proxies of the level of development of a country; (iv) value added of agriculture to GDP, as an activity that is hard to tax; (v) annual average inflation rate, as a proxy of macroeconomic conditions; (vi) Control of Corruption; (vii) wage and salaried workers as a percentage of total employment; and (viii) a dummy variable indicating whether the country is resource rich or not.

3 Methodology

We apply the Bayesian GTRE algorithm from Tsionas and Kumbhakar (2014) with the prior modifications from Makieła (2017). To motivate the reasons to pick such a model, we will illustrate its advantages with respect to the mainstream. First, consider the model from Battese and Coelli (1992), that estimated by Fenochietto and Pessino (2013). For the frequentist estimation of tax effort, consider a two-part disturbance given by

$$\epsilon_{it} = v_{it} - u_{it}; \quad v_{it} \sim \mathcal{N}(0, \sigma_v^2) \;\; u_{it} \sim |\mathcal{N}(0, \sigma_u^2)|$$

Then, according to Theorem 1 in Jondrow et al. (1982),

$$\mathbb{E}(u|\epsilon) = \frac{\sigma_u^2 \sigma_v^2}{\sigma^2}\left[\frac{f(\epsilon\lambda/\sigma)}{1 - F(\epsilon\lambda/\sigma)} - \frac{\epsilon\lambda}{\sigma}\right] \tag{1}$$

[1]To fill in missing values for the dependent variable, the annual change in the ratio taken from other sources was considered. However, only a limited number of countries benefited from this adjustment.

where f and F are the standard normal density and cdf, respectively, and $\sigma^2 = \sigma_u^2 + \sigma_v^2$. The mainstream approach is to calculate tax effort using (1) or with the approximation from Battese and Coelli (1988). Both approximations rely on a point estimate. However, a Bayesian approach achieves a substantially superior estimation, enabling the retrieval of the entire posterior distribution, and the expected value is approximated with the average of the exponential of the inefficiency chains. The model from Tsionas and Kumbhakar (2014) has the following structure:

$$y_{it} = x'_{it}\beta + \alpha_i + v_{it} + u_{it}^{+} + \eta_i^{+} \tag{2}$$

where, originally, the dependent variable y_{it} is (log) cost and the independent variables x_{it} are input prices and outputs (log), α_i represents firm heterogeneity, η_i^{+} is the inefficiency associated with persistent management,u_{it}^{+} is the inefficiency associated with transient management, and v_{it} is the idiosyncratic stochastic shock. It is possible to disentangle the time-varying and persistent components via data augmentation (Tanner and Wong, 1987), due to the fact that even thought both components have the same mean and posterior distribution, they have different scale parameters, and one of them is constant across time. This result is shown in (Tsionas and Kumbhakar, 2014) (see Table III). Even thought they use two reparametrizations, we employ data augmentation and assign different types of priors, since it can potentially make it easier to separate the two inefficiency terms Makieła (2017).

In our case, u_{it}^{+} and η_i^{+} will follow a truncated normal distribution that is truncated at $(-\infty, 0)$ instead of $(0, \infty)$[2]. y_{it} is (log) sum of tax revenues and SSC collected by central and subnational governments as a percentage of GDP, and the independent variables x_{it} are the aforementioned covariates: α_i represents country heterogeneity, η_i^{+} is the inefficiency associated with a persistent country (in)capacity to collect the potential tax revenue, u_{it}^{+} is the inefficiency associated with the transient country (in)capacity to collect the potential tax revenue, and v_{it} is an idiosyncratic stochastic shock. Let $u_{it}^{+(s)}$ and $\eta_i^{+(s)}$ be the draws from the conditional distributions of the transient and persistent inefficiencies for the s-th pass of a Markov Chain Monte Carlo (MCMC) scheme. Then, the posterior estimate of the tax effort is:

$$\frac{1}{S}\sum_{s=1}^{S} \exp(u_{it}^{+(s)} + \eta_i^{+(s)}) \tag{3}$$

In this regard, our contribution is twofold. First, instead of using one observation (the point estimate of inefficiency) and equation (1) to produce an estimate of tax effort, we use S samples from the

[2]This model was developed in a cost function framework. Since companies engage in higher costs than they should, the inefficiency is usually truncated at $(0, \infty)$. However, since countries collect less taxes than they should, in our case it is truncated at $(-\infty, 0)$

posterior distribution, and the Law of Large Numbers to estimate $\mathbb{E}\big[\exp(u_{it}^{+} + \eta_i^{+})\big]$, which, for a sufficiently large S, is a very good approximation. Second, by disentangling the inefficiency into transient and persistent components we also estimate an upper bound for tax effort. Notice that since u_{it}^{+} and $\eta_i^{+} \in \mathbb{R}^{-}$, an upper bound for tax effort is $\mathbb{E}\big[\exp(\eta_i^{+})\big]$. Therefore, we can calculate the expected value of the highest tax effort a country can achieve, given the covariates. In a frequentist framework there is no straightforward way to identify u_{it}^{+} and η_i^{+} separately, and at this time, to the best of our knowledge, there is no frequentist model in the SFA literature that can achieve this.

Letting $\boldsymbol{\theta} = (\boldsymbol{\phi}', \sigma_\alpha^2, \sigma_v^2, \sigma_\eta^2, \sigma_u^2)'$ and using data augmenting (Tanner and Wong, 1987), the augmented vector is $\boldsymbol{\Theta} = (\boldsymbol{\theta}', u_{it}^{+}, \eta_i^{+})$. Therefore, the model in equation (2) yields a likelihood of the form

$$
\begin{aligned}
f(\boldsymbol{y}|\boldsymbol{x}, \boldsymbol{\Theta}) \propto \prod_{i=1}^{N} \exp\Big\{ -\frac{1}{2\sigma_v^2} \big(\boldsymbol{y}_i - \boldsymbol{x}_i'\phi - \alpha_i \boldsymbol{i}_T + \boldsymbol{u}_{it}^{+} + \eta_i^{+}\boldsymbol{i}_T\big)' \big(\boldsymbol{y}_i - \boldsymbol{x}_i'\boldsymbol{\phi} - \alpha_i \boldsymbol{i}_T + \boldsymbol{u}_{it}^{+} + \eta_i^{+}\boldsymbol{i}_T\big) \Big\} \\
\times I(\boldsymbol{u}_{it}^{+} < 0) \left(\frac{2}{\pi}\right)^{-\frac{T}{2}} (\sigma_u^2)^{-\frac{T}{2}} \exp\Big\{ -\frac{1}{2\sigma_u^2} \boldsymbol{u}_{it}^{+\prime} \boldsymbol{u}_{it}^{+} \Big\} \\
\times I(\eta_i^{+} < 0) \left(\frac{2}{\pi}\right)^{-\frac{T}{2}} (\sigma_\eta^2)^{-\frac{T}{2}} \exp\Big\{ -\frac{1}{2\sigma_\eta^2} \eta_i^{+\prime} \eta_i^{+} \Big\}
\end{aligned}
\tag{4}
$$

4 Results

4.1 Simulations

Consider the model proposed by Battese and Coelli (1992):

$$
\begin{aligned}
y_{it} &= \alpha + \mathbf{x}_{it}'\beta + \epsilon_{it} \\
\epsilon_{it} &= v_{it} - u_{it} \\
v_{it} &\sim \mathcal{N}(0, \sigma_v^2) \\
u_{it} &= \mathbf{exp}(-\eta(t - T_i)) \times u_i
\end{aligned}
$$

Setting α to be invariant across units could produce biased results, because the effect of these factors may be captured by the inefficiency term (Belotti et al., 2013). Therefore, Greene (2005) proposes the model

$$y_{it} = \alpha_i + \mathbf{x}'_{it}\beta + \epsilon_{it}$$

However, a similar issue could arise if there is a persistent inefficiency. In fact, the Greene (2005) formulation is likely to produce a downward bias in the estimate of overall inefficiency (Tsionas and Kumbhakar, 2014). Hence, Tsionas and Kumbhakar (2014) propose the model in equation (2):

$$y_{it} = x'_{it}\beta + \alpha_i + v_{it} + u^+_{it} + \eta^+_i$$

To motivate the use of the model from Tsionas and Kumbhakar (2014), we perform simulations with different sample sizes and compare the tax effort estimates. We consider the following data generating process (DGP):

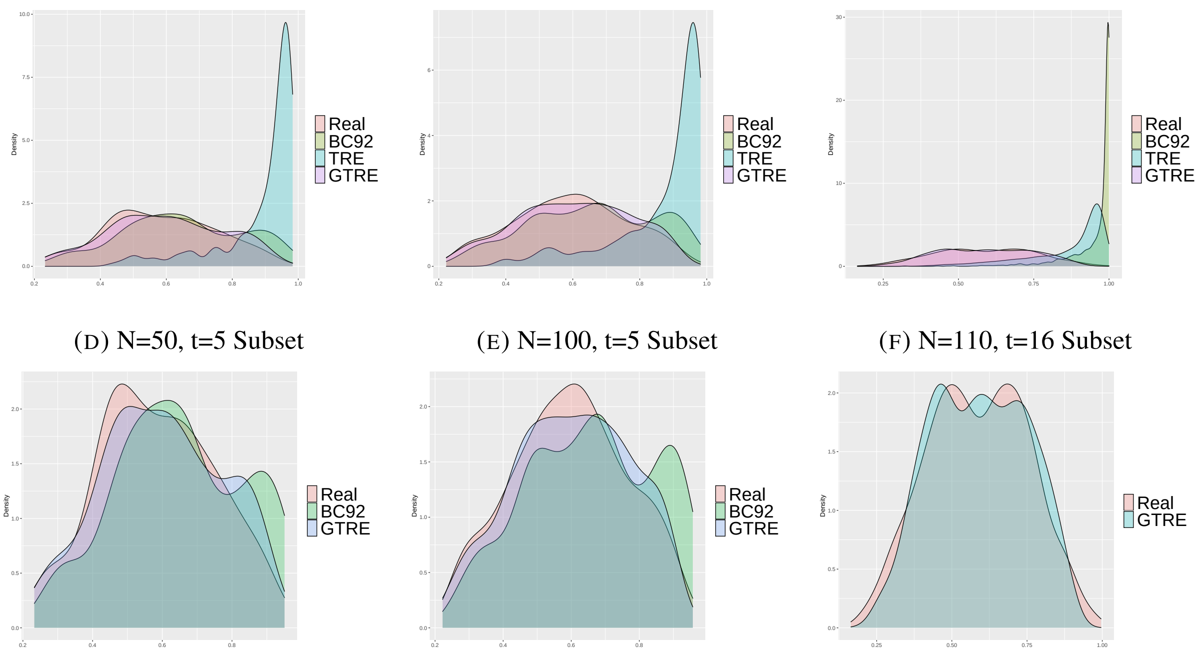
$$y_{it} = \alpha_i + x_{i1,t} - x_{i2,t} + \eta^-_i + v_{it} + u^-_{it}$$

where $x_{i1,t}$ and $x_{i2,t}$ are generated from a standard normal distribution, $\sigma^2_u = 0.2$, $\sigma^2_\eta = 0.5$, and $\sigma^2_v = \sigma^2_\alpha = 0.1$. This implies that the real values for β are $\beta = (\beta_0 = 0, \beta_1 = 1, \beta_2 = -1)'$. We perform three simulations: N=50 and t=5, N=100 and t=5 and t=15,and N=110 and t=16. Densities for the tax effort estimates are reported in Figure 3. Labels indicate the method (BC92 stands for Battese and Coelli (1992), TRE for Greene (2005), and GTRE for Tsionas and Kumbhakar (2014)). By means of simulations we reinforce what Tsionas and Kumbhakar (2014) assert: the TRE model from Greene (2005) is likely to underestimate the inefficiency and therefore overestimate the expected value. Additionally, in every subfigure in the top panel of Figure 3 the GTRE model is always closer to the real density than the others. However, to have a more informed idea of how alike they are, we perform a Kolmogorov-Smirnov test (Kolmogorov, 1933; Smirnov, 1939) for comparing each density estimate with the real density. In Table 1 we summarize the p-value corresponding to this test and the correlation with the real tax effort[3]. The only model that does not have any null hypothesis rejected at any standard level of significance is the GTRE. Since the null hypothesis is that the sample (inefficiencies of each model) is drawn from the reference distribution (the one corresponding to the real inefficiencies, labeled “Real” in 3), there is evidence that the model with the best fit is the one from Tsionas and Kumbhakar (2014). Additionally, in all the simulations, the highest and most stable correlation is the one from the GTRE model.

In Table 2 point estimates are reported for each model. The constant is not included in the Bayesian model, since we are already controlling for α_i. Additionally, an improper prior could be specified

[3]When a value of 0 appears in Table 1, it means that the p-value was smaller than 2.2e-16

FIGURE 3: Simulations for tax effort



(A) N=50, t=5 All (B) N=100, t=5 All (C) N=110, t=16 All

(D) N=50, t=5 Subset (E) N=100, t=5 Subset (F) N=110, t=16 Subset

Source: Authors' calculations

for the constant and its sampling could interfere with the one from α_i. The coefficients reported in the third column of Table 2 correspond to the mean of the posterior distribution for each parameter, and the credible intervals are estimated with the highest posterior density intervals (HPDI)[4]. Note that the constant term in the BC92 and TRE models is always significant, and particularly for the biggest sample size is non-negligible. This could explain the underestimation of the inefficiencies and the corresponding overestimation of the tax effort in Figure 3. Even though point estimates are relevant for the analysis, the focus of our paper is tax effort. Therefore, as the results in Figure 3 and Table 1 suggest, the most appropriate model is the GTRE.

4.2 RESULTS

We estimate the model

$$\begin{aligned} log(tot)_{it} =& \beta_0 + \beta_{1,j} LGD_{it} + \beta_{2,j} PVR_{it} + \beta_{3,j} CCR_{it} + \beta_{4,j} CPI_{it} + \beta_{5,j} TR_{it} + \beta_{6,j} AVA_{it} \\ &+ \beta_{7,j} LEMP_{it} + \beta_{8,j} OIL_i + \alpha_i + v_{it} + u_{it}^{+} + \eta_i^{+} \quad i = 1, 2, ..., 110, \;\; t = 1, 2, ..., 16, \;\; j = 1, 2. \end{aligned} \tag{5}$$

[4]This corresponds to 95% of the mass of the posterior, excluding both tails, which is "comparable" to the frequentist confidence intervals at a 95% confidence level.

TABLE 1: KS test and correlations

	N=50, t=5		N=100, t=5		N=110, t=16	
	ρ	p–value	ρ	p–value	ρ	p–value
BC92	0.875	6.2e-03	0.854	6.1e-08	0.245	0
TRE	0.776	0	0.808	0	0.823	0
GTRE	0.912	0.536	0.902	0.612	0.923	0.426

Source: Authors' calculations

where

- $log(tot)$ is the (log) sum of tax and SSC collected by central and subnational governments as percentage of GDP
- LGD is the (log) GDP per capita
- PVR is (log) Political Stability and Absence of Violence/Terrorism, percentile rank (0–100)
- CCR is Control of Corruption, percentile rank (0–100)
- CPI is the percentage change in the Consumer Price Index
- TR is trade (imports plus exports as a percentage of GDP)
- AVA is the value added of the agriculture sector as a percentage of GDP
- LEMP is the (log) wage and salaried workers as a percentage of total employment
- OIL is a dummy variable equal to 1 if the country is resource rich and 0 otherwise

We first diverge from Fenochietto and Pessino (2013) regarding the covariate set in the following way: we include neither the quadratic form of the GDP[5] nor the GINI[6], and we include a variable

[5]We have performed back-testing exercises including the quadratic form of the GDP (available upon request) and find that even thought the results change slightly, as expected, there are no substantial discrepancies regarding the results. Even thought it is the common view that the relationship between tax effort and GDP is non-linear, our objective is prediction. Inclusion of polynomials might induce over-fitting, and excluding the quadratic form is a first order approximation.

[6]When including the GINI or any variable related to inequality measures (such as percentage of income held by the lowest 10%), the frequentist models do not converge. The GTRE does converge, but there is very little variability in u^+_{it}, implying that the efficiency would be akin to time invariant. Due to these issues, and because it is a highly correlated control, we decided not to include it

TABLE 2: Estimates

β	BC92	TRE	GTRE
		N=50, t=5	
1	1.009***	1.008***	1.009***
	[0.991,1.026]	[0.990,1.025]	[0.993,1.028]
-1	-0.996***	-0.994***	-0.997***
	[-1.018,-0.974]	[-1.016,-0.973]	[-1.019,-0.975]
0	-0.0809*	-0.486***	
	[-0.170,0.00825]	[-0.566,-0.406]	
		N=100, t=5	
1	0.987***	0.989***	0.989***
	[0.972,1.001]	[0.975,1.004]	[0.975,1.003]
-1	-1.008***	-1.007***	-1.008***
	[-1.023,-0.992]	[-1.022,-0.992]	[-1.024,-0.994]
0	-0.0849***	-0.459***	
	[-0.147,-0.0226]	[-0.528,-0.390]	
		N=110, t=16	
1	1.003***	1.005***	1.003***
	[0.979,1.027]	[0.998,1.012]	[0.997,1.010]
-1	-1.004***	-0.999***	-0.999***
	[-1.028,-0.980]	[-1.006,-0.992]	[-1.006,-0.992]
0	-0.499***	-0.472***	
	[-0.525,-0.474]	[-0.513,-0.431]	

95% confidence intervals in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Authors' calculations

to control for formal employment, which is one of the main drivers of tax capacity in EMs[7]. We naturally expect that employment being formal has a significant and positive effect on tax collection. It would be ideal to control for tax rates to disentangle what part of a country's tax revenue gap is due to inefficiency, and what part is due to public choice. Nonetheless, a long time series on statutory or effective tax rates for a large panel of countries are not available. They are available for (i) a sub-sample of countries, such as advanced economies and Latin American countries, and (ii) specific taxes, such as the VAT, corporate tax rates or personal income taxes. However, the scope of our study excludes advanced economies and is broader than the sub-sample of Latin American countries, attempting to include the rest of emerging economies. Conditional on having the data, there is a potential challenge, due to that fact that countries have different tax regimes, for instance, in different VAT rates for certain products as well as minimum and maximum rates. Moreover, considering a broader spectrum of effective tax rates, including the Personal Income Tax, imposes the challenge of significant differences in brackets among countries, and additional brackets if the country is federal, among other details, making harder to construct a single measure of effective tax rates.

The main difference of equation (5) with the mainstream is the subscript of the location parameters. As Fenochietto and Pessino (2013) observe, "natural resource dependent countries have very different economic structures that affect the comparison among them and with other countries". Therefore, we propose to capture such diversity in dynamics by allowing the marginal effects to vary among resource-rich countries and the rest of the sample. Hence $\beta_{k,1}$ will correspond to the marginal effect of the $k-th$ covariate for the resource rich-countries and $\beta_{k,2}$ for the rest of the sample. This apparent subtle difference has a nontrivial theoretical difference: even though all the countries have the same data generating process, the marginal effect of every covariate depends on whether a country is resource rich or not. In practice, this implies that resource-rich countries will have their own equation to calculate their tax effort and its corresponding upper bound.

We estimate three variants of equation (5), two restricted models and one unrestricted: (i) setting $\beta_{k,1} = \beta_{k,2}$ for $k = 1, 2, .., 8$ and $\beta_{8,j} = 0$ for $j = 1, 2$, (ii) setting $\beta_{k,1} = \beta_{k,2}$ for $k = 1, 2, .., 8$, and (iii) a model without restrictions, but setting $\beta_{8,j} = 0$ for $j = 1, 2$ because we are already assuming two different sets of location parameters, so there is no point in controlling for OIL. In the first one, we assume that the marginal effects are the same regardless of whether a country is resource rich or not, so there is no effect of being a resource-rich country other than the implied heterogeneity in the covariates set. In the second one, we maintain the assumption of invariant marginal effects, but

[7] We also perform exercises including variables of political stability and regulatory quality, but neither is significant once corruption has been controlled for. The resulting estimates and tax efforts remain almost the same. We omit such robustness checks for the sake of brevity, but they are available upon request.

we include a dummy to control for whether a country is resource rich or not. In the third model we relax both assumptions of the first specification.

Results are reported in Tables 3 and 4. For the Gibbs sampler, we obtain posterior chains of dimension 2,500 (total iterations 50,000, burn-in 25,000, and thin parameter of 10). The significance of Bayesian estimates depends on the HPDI passing through zero. It is straightforward to analyze the difference between the two columns in Table 3; results are very similar, and even though the OIL variable is positive it fails to be significant at any standard confidence level.

Higher levels of development come with more demand for public expenditure, as expressed in Tanzi (1983) and a higher level of tax capacity to pay for the higher expenditure, as mentioned in Fenochietto and Pessino (2013). Therefore, it makes sense that the coefficient associated with lgd is positive. Control of Corruption has a positive and significant effect, as expected. As Fenochietto and Pessino (2013) notes, countries that obtain their resources from printing money have a negative efficiency for collecting taxes, which explains the negative sign in CPI in all models. Also, because inflation is a proxy of macroeconomic stability, we can expect tax revenues to be diminished during inflationary episodes that reduce wages and income in real terms. Since collection increases from more economic activity and trade (i.e., tariffs) (Fenochietto and Pessino, 2013; Baunsgaard and Keen, 2010), TR should have a positive and significant sign, which is the case. The difficulty of controlling small producers and the exemption of agricultural products from the VAT (Fenochietto and Pessino, 2013) supports the negative sign of AVA. Finally, we find that the proportion of wage and salaried workers has a significant positive effect on tax collection.

Table 4 shows that resource-rich and non-resource-rich countries have similar dynamics in terms of tax collection determinants. The only structural differences are that neither control of corruption nor proportion of wage and salaried workers are significant for resource-rich countries, but are for non-resource-rich countries. Another important result is that the marginal effect of GDP is twice as large for countries that are resource rich as for countries that are not. The results from Table 4 indicate that it is not enough to control for a dummy variable indicating whether a country is resource rich or not. In fact, the dynamics of these two groups of countries appear different, and the impacts that our determinants have are very heterogeneous.

Rather than calculating marginal effects, our aim is to calculate tax effort. We report the posterior mean of the tax effort for the three specifications in Table 5[8] (the first column reports the tax effort corresponding to the first restricted model, the second column does the same for the second

[8]As we mention, our sample comprehends 108 countries. We report results only for Emerging Economies as they are the object of interest and for the sake of brevity. Nonetheless, results for the full sample are available upon request.

TABLE 3: Regression Results: Common marginal effects

	$log(tot)$	$log(tot)$
LGD	0.1602***	0.1611***
	[0.1121,0.2094]	[0.1054,0.212]
CCR	0.0249*	0.0242*
	[-0.0017,0.0496]	[-7e-04,0.05]
CPI	-0.0022***	-0.0022***
	[-0.0031,-0.0011]	[-0.0033,-0.0012]
TR	0.0013***	0.0013***
	[9e-04,0.0017]	[9e-04,0.0017]
AVA	-0.0113***	-0.0114***
	[-0.0141,-0.0089]	[-0.0144,-0.0086]
LEMP	0.1047***	0.1141***
	[0.0352,0.1833]	[0.0436,0.1855]
OIL		0.1445
		[-0.0409,0.3328]
Cons	1.6851***	1.6284***
	[1.2895,2.0693]	[1.2182,2.0826]
N	1728	1728

95% HPDI in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Authors' calculations

TABLE 4: Regression Results: Varying marginal effects

	$log(tot)$
LGD_{rr}	0.2114***
	[0.1553,0.2792]
LGD_{nrr}	0.1087***
	[0.0585,0.1577]
CCR_{rr}	-0.0095
	[-0.0454,0.0289]
CCR_{nrr}	0.0373***
	[0.0059,0.067]
CPI_{rr}	-0.0016**
	[-0.0029,-1e-04]
CPI_{nrr}	-0.0023***
	[-0.0038,-8e-04]
TR_{rr}	0.0025***
	[0.0019,0.0033]
TR_{nrr}	5e-04**
	[0,9e-04]
AVA_{rr}	-0.0098***
	[-0.0127,-0.0068]
AVA_{nrr}	-0.0186***
	[-0.0229,-0.0145]
LEMP_{rr}	-0.0737
	[-0.189,0.038]
LEMP_{nrr}	0.174***
	[0.0967,0.2655]
Cons	1.9696***
	[1.568,2.3509]
N	1728

95% HPDI in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Authors' calculations

restricted model, and the third likewise for the unrestricted model, respectively). These results correspond to the upper bound. Even though there are non-negligible differences between the third model and the first two, as shown by Table 5, tax effort estimates are very similar for the entire set of countries. This means that, despite the location parameters being very different across resource-rich and non-resource-rich countries, assuming constant parameters does not greatly affect our tax effort estimates. However, if statistical inference is performed (as usual), it is restrictive and unrealistic to assume constant location parameters, as suggested by Table 4. One relevant (and intuitive) result is that the persistent component of the inefficiency is the dominant one by far. On average it comprehends around 87% of the inefficiency component, as suggested by Table 4. This number corresponds to the ratio between the average upper bound (55%) and the average lower bound (48%).

TABLE 5: Tax effort posterior means comparison

	Lower Bound			Upper Bound		
Country	(1)	(2)	(3)	(1)	(2)	(3)
Argentina	0.73	0.75	0.70	0.77	0.79	0.74
Brazil	0.68	0.67	0.62	0.77	0.77	0.70
Chile	0.44	0.39	0.46	0.52	0.46	0.53
China	0.61	0.63	0.60	0.66	0.69	0.65
Colombia	0.57	0.49	0.55	0.63	0.55	0.61
Czech Republic	0.62	0.61	0.61	0.69	0.69	0.68
Egypt, Arab Rep.	0.44	0.43	0.42	0.54	0.52	0.52
Greece	0.68	0.70	0.66	0.71	0.73	0.70
Hungary	0.66	0.67	0.69	0.76	0.76	0.78
India	0.62	0.63	0.64	0.71	0.72	0.74
Indonesia	0.34	0.29	0.32	0.43	0.37	0.39
Korea, Rep.	0.36	0.35	0.33	0.39	0.38	0.36
Mexico	0.28	0.24	0.27	0.29	0.25	0.28
Pakistan	0.46	0.46	0.47	0.48	0.48	0.49
Peru	0.43	0.37	0.40	0.54	0.47	0.51
Philippines	0.48	0.48	0.46	0.53	0.53	0.52
Poland	0.67	0.66	0.65	0.75	0.75	0.72
Qatar	0.08	0.07	0.07	0.10	0.08	0.09
Russian Federation	0.67	0.59	0.69	0.78	0.69	0.80
Saudi Arabia	0.07	0.06	0.06	0.07	0.06	0.07
South Africa	0.55	0.56	0.51	0.61	0.62	0.56
Thailand	0.40	0.41	0.43	0.47	0.48	0.50
Turkey	0.54	0.53	0.53	0.66	0.65	0.64

Source: Authors' calculations

Tax effort mean estimates for the sample of EMs are presented in Table 6. As we mentioned, we identify an upper bound for tax effort with $\exp(\eta_i^+)$. This bound is time invariant and denotes the highest tax collection of a country conditional on the covariates.

On average, the EMs have an upper bound tax effort—considering only the time-invariant inefficiency—of 55% in 2017, which implies that they collected around half of their potential[9]. The average lower bound is 48%. In general, the median is fairly similar to the mean, indicating that with few exceptions, the distribution of the tax effort estimates behaves roughly like a normal distribution.

Based on Table 6 we observe that Latin America countries show a considerable heterogeneity, with countries spreading between a range of around 70% mean tax effort, such as Argentina, to less than 30%, as in Mexico. Emerging European countries seem to have a more uniform behavior, with tax effort ranging between around 60% and 70%. African and Asian countries seem to have a wider variety of tax effort, with a minimum of 39% in Indonesia and a maximum of 74% in India. Finally, countries in the Middle East seem to have very low percentages: tax effort in Saudi Arabia and Qatar is 7% and 9%, respectively. As expected, advanced economies have a higher tax effort, around 61% on average, while emerging markets (excluding those that belong to OECD) have on average a 46% tax effort, and the remaining countries have a mean tax effort of 51%. From this perspective, although the maximum level of tax effort is 100%, it is unlikely that countries will reach that level, and it is potentially not advisable from an efficiency and equity point of view. Thus, the indicator of tax capacity reported in Table 7 should be taken as a theoretical reference only.

Our results are similar to those found in the literature, although the variability of the estimates is fairly high. For instance, Fenochietto and Pessino (2013) estimate a tax effort of around 70%, 80%, 57%, 45%, and 7% in Argentina, Brazil, Colombia, Indonesia, and Saudi Arabia, respectively. On the other hand, Cyan, Martinez-Vazquez and Vulovic (2013) and Le, Moreno-Dodson and Bayraktar (2012) use a similar stochastic frontier analysis, but found across-the-board higher tax effort percentages for their sample of countries. Also, in our view Brun and Diakite (2016) is one of the few efforts to estimate tax effort and attempt to disentangle time-varying inefficiency from the time-invariant one in relation to policy decisions. These authors find that non-resource-persistent tax efforts are higher for low-income countries than for middle- or upper- income countries; other scholars have found a similar pattern for the VAT.

[9] Notice that our results must not be mistaken with tax rate optimality. This is due to the fact that our dependent variable is tax collection, which is quite more endogenous than tax rate. Therefore, our model does not allow us to extrapolate results regarding efficiency in tax collection to optimality of countries' tax rate.

Another hypothesis that can be proposed from these results is that resource-rich countries—such as Chile, Mexico, Peru, Qatar, and Saudi Arabia—tend to have lower levels of tax effort. According to the literature on the features of natural-resource-rich countries (Frankel, 2010; Sachs and Warner, 2001), the availability of resource revenues is linked to a reduced capacity of domestic tax collection, or "fiscal laziness" due to limited institutional capacity, weaker tax administrations, the displacement of sectors with higher tax potential, a more ad-hoc tax policy, corruption, and ultimately lower average GDP growth rates. Of course, this is just preliminary evidence, and more formal proof is beyond the scope of this paper. However, Fenochietto and Pessino (2013) put forth evidence that this might be the case. Also, Crivelli and Gupta (2014) finds that each additional percentage point of resource revenue leads to a corresponding reduction in non-resource revenue of around 0.3 percentage points. The effect is particularly high for taxes on good and services, such as the VAT.

TABLE 6: Tax effort for EM (2017)

	$\exp(u_{it}^{+} + \eta_i^{+})$				$\exp(\eta_i^{+})$			
			HDI 95%				HDI 95%	
Country	Mean	Median	Lower	Upper	Mean	Median	Lower	Upper
Argentina	0.70	0.70	0.57	0.86	0.74	0.74	0.62	0.91
Brazil	0.62	0.62	0.50	0.76	0.70	0.69	0.58	0.85
Chile	0.46	0.45	0.35	0.57	0.53	0.52	0.42	0.66
China	0.60	0.59	0.48	0.73	0.65	0.64	0.54	0.80
Colombia	0.55	0.54	0.43	0.74	0.61	0.59	0.49	0.82
Czech Republic	0.61	0.61	0.49	0.76	0.68	0.67	0.55	0.83
Egypt, Arab Rep.	0.42	0.42	0.34	0.53	0.52	0.51	0.43	0.65
Greece	0.66	0.66	0.53	0.80	0.70	0.69	0.56	0.83
Hungary	0.69	0.69	0.57	0.85	0.78	0.77	0.65	0.93
India	0.64	0.63	0.52	0.78	0.74	0.73	0.63	0.91
Indonesia	0.32	0.31	0.24	0.41	0.39	0.38	0.31	0.49
Korea, Rep.	0.33	0.33	0.27	0.41	0.36	0.36	0.30	0.44
Mexico	0.27	0.26	0.21	0.35	0.28	0.27	0.22	0.36
Pakistan	0.47	0.46	0.39	0.56	0.49	0.48	0.41	0.59
Peru	0.40	0.39	0.31	0.53	0.51	0.49	0.41	0.68
Philippines	0.46	0.46	0.37	0.56	0.52	0.51	0.45	0.63
Poland	0.65	0.64	0.52	0.79	0.72	0.71	0.60	0.86
Qatar	0.07	0.07	0.05	0.10	0.09	0.08	0.06	0.12
Russian Federation	0.69	0.69	0.55	0.85	0.80	0.79	0.66	0.97
Saudi Arabia	0.06	0.06	0.05	0.08	0.07	0.06	0.05	0.09
South Africa	0.51	0.51	0.41	0.63	0.56	0.55	0.46	0.69
Thailand	0.43	0.42	0.34	0.54	0.50	0.49	0.41	0.64
Turkey	0.53	0.52	0.42	0.65	0.64	0.63	0.53	0.77
Average	0.48	0.48	0.39	0.60	0.55	0.54	0.45	0.67

Source: Authors' calculations

As mentioned, one of the most important contributions of our Bayesian strategy is the possibility of obtaining the posterior distributions of the tax effort. Knowing the shape of that distribution gives important information regarding where the location of the true value of the unknown tax effort might be. Such inferences cannot be made in a frequentist framework, where only point estimates and an estimate of the confidence interval are reported. In Figure 4 the posterior distributions for the tax effort are depicted for our sample of EMs. Countries are grouped into quartiles according to their tax effort posterior means as shown in Table 6. As mentioned earlier, in most cases the distribution of tax effort in EMs resembles a left-skewed normal distribution, in particular for countries with low tax effort. A remarkable observation from Figure 4 is that as tax effort increases, the skewness disappears and the distribution is more akin to a normal distribution. This has important implications: two countries having similar tax effort posterior means are not necessarily equally likely to have a given value of tax effort in a year. Consider the case of Pakistan and the Philippines: the mean tax effort for Pakistan is one percentage point bigger than that for the Philippines (47% and 46%, respectively). However, Pakistan's posterior distribution shows a bigger skew than the Philippines, which implies that the former is less likely to have a tax effort greater than the latter. Moreover, the mean estimate of the upper bound of the tax effort for the Philippines (52%) is three percentage points bigger than that for Pakistan (49%). In general, the fact that the posterior distributions are either left skewed, in case of countries in the first and second quartiles, or fairly symmetric in the case of those in the third and fourth quartiles (see Table 7) makes us believe that in several cases the true tax effort is lower than what point estimates of the mean tax effort might suggest. Fiscal planning should incorporate this information.

Looking just at the estimates of tax effort, we identify the set of EMs that need to improve their tax collection: Saudi Arabia, Qatar, Mexico, Indonesia, South Korea, and Peru (which are located in the lowest quartile). However, Egypt, Thailand, Chile, Philippines, Pakistan, and South Africa (countries in the second-lowest quartile) have a tax effort smaller than 50% (except for South Africa, which has a tax effort mean of 56%), and they should also implement policies to improve collection. However, this assessment should be considered in light of these countries' actual level of tax collection. In Figure 5 we present a comparison of the mean upper-bound tax effort and actual tax revenues. As expected, there is a positive association between these two indicators. As a benchmark, we take the average tax collection (24% of GDP) and the tax effort (53%) for the entire sample and locate countries in the associated quadrants. We see that countries in the bottom left (low effort and low collection) should prioritize tax reforms to bring their domestic revenues closer to their potential, and have enough room to do so; this is the case for Mexico, Indonesia, Thailand, Saudi Arabia, and Qatar. Countries located in the opposite (upper-right) quadrant are already close to their potential tax collection with a higher tax effort; for these countries—such as Argentina, Brazil, Russian Federation, and Greece—the priority should be to evaluate their tax systems from the perspective of efficiency and equity against sufficiency. Countries like India and the Philippines, along with other lower-income countries (such as Haiti, Honduras, and Nicaragua) are located in the high effort-low collection zone, which means that, due to their economic structure, those countries have a lower tax potential, which is likely easier to achieve. The low effort-high collection quadrant does not appear to have any countries.

TABLE 7: Tax effort, tax collection, and tax capacity for EMs (2017)

Country[a]	Tax Effort[b]	Tax Collection	Tax Capacity
Saudi Arabia	0.06	3.38	54.30
Qatar	0.07	4.85	68.47
Mexico	0.27	13.08	49.15
Indonesia	0.32	11.09	34.71
Korea, Rep.	0.33	18.71	56.01
Peru	0.40	15.49	38.66
Egypt, Arab Rep.	0.42	14.51	34.33
Thailand	0.43	17.31	40.64
Chile	0.46	20.66	45.25
Philippines	0.46	17.49	37.69
Pakistan	0.47	12.42	26.66
South Africa	0.51	24.57	47.88
Turkey	0.53	23.66	44.94
Colombia	0.55	21.37	38.73
China	0.60	24.60	41.16
Czech Republic	0.61	35.24	57.33
Brazil	0.62	27.01	43.74
India	0.64	17.76	27.65
Poland	0.65	34.97	53.85
Greece	0.66	34.70	52.28
Hungary	0.69	38.34	55.58
Russian Federation	0.69	31.26	45.30
Argentina	0.70	32.01	45.44
Emerging[c]	0.46	18.36	42.59
OECD	0.61	34.88	57.19
Other	0.51	18.17	37.84

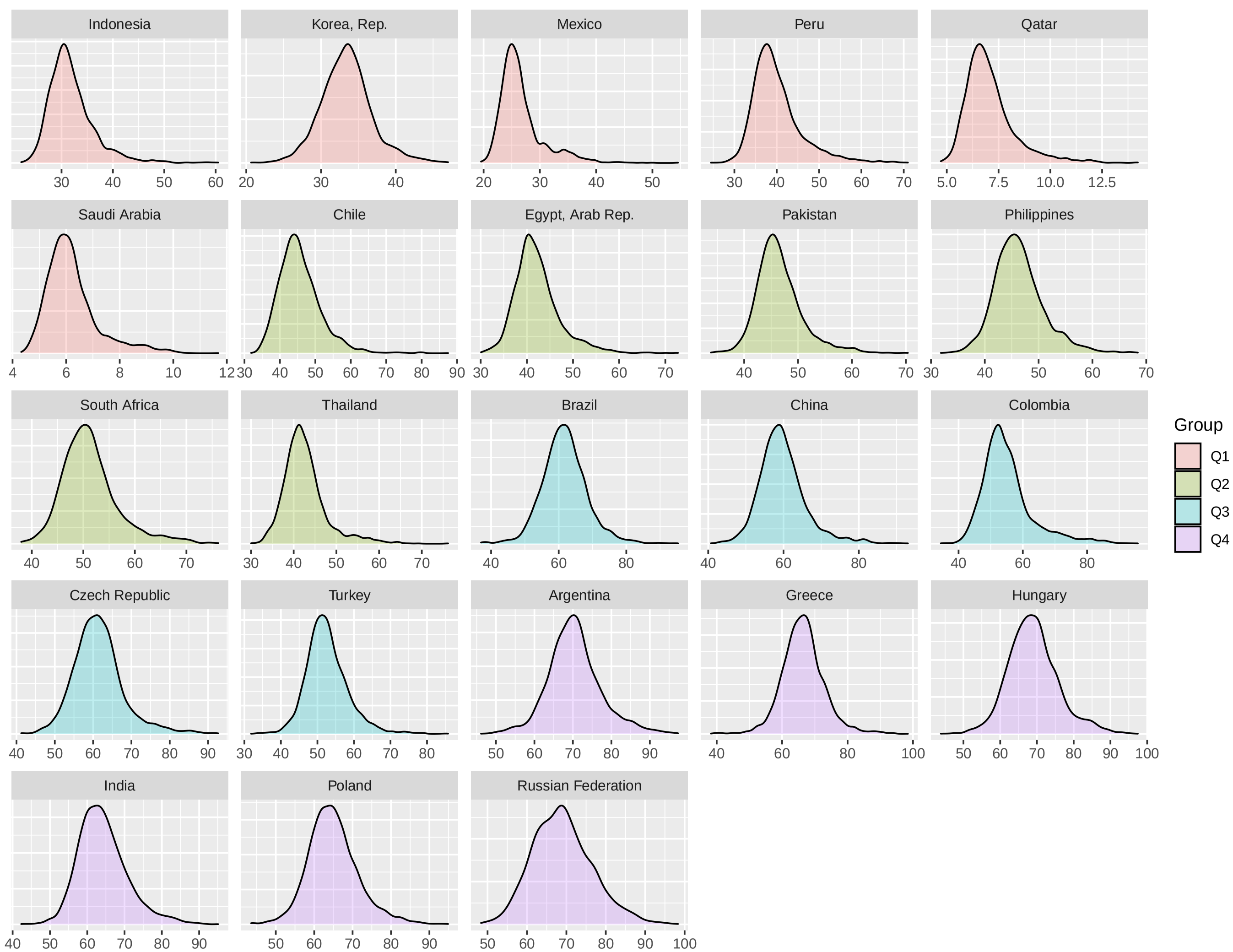
Source: Authors' calculations

[a]Horizontal columns separate countries by quartiles.

[b]Which is calculated as $\exp(u_{it}^{+} + \eta_i^{+})$.

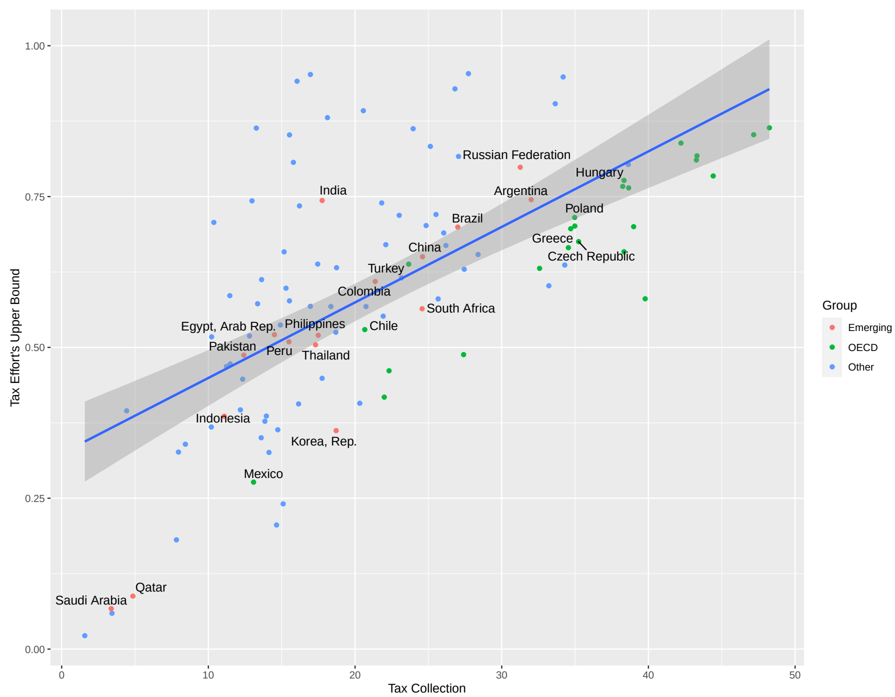
[c]The Emerging Economies Average excludes Chile, Czech Republic, Greece, Hungary, Mexico, Poland, and Turkey, because they are considered OECD Countries.

FIGURE 4: Tax Effort for EMs (2017)



Source: Authors' calculations

FIGURE 5: Tax Effort's Upper Bound and Tax Collection



Source: Authors' calculations

5 CONCLUSIONS

The inability of emerging economies to bring actual tax collection ratios close to their potential is a stylized fact. It has also become a common discussion on economic policy grounds, since these countries face pressing infrastructure and social needs and lack the necessary fiscal space to address them decisively. Yet, little is known about EM's true tax effort and tax potential and, ideally, its distribution.

In this paper, we attempt to bridge that gap by providing tax effort estimates for a sample of EM using the GTRE model from Tsionas and Kumbhakar (2014) with the prior corrections from Makieła (2017), as opposed to the mainstream, which estimates the model from Battese and Coelli (1992) in producing point estimates. Our reasons for doing so are related to having a better estimate of tax effort, the availability of an upper bound, and the posterior distributions along with their corresponding Highest Density Posterior Intervals. With such estimates, fiscal policy planning will be better informed and more likely to achieve the desired outcomes. Even thought both our simulations and the robustness of our estimates suggest that the GTRE performs soundly, our approach comes with limitations. The model requires distributional assumptions: we assume both inefficiences come from a truncated normal distribution with zero mean. Consistently, the means (which could potentially be different from zero) are not estimated along with the other parameters. Our simulation results indicate that the model underestimates tax effort in the tails of the distribution, that is, as the tax effort approaches zero or one, the estimates are less accurate. Moreover, it is relevant to remark that since tax rates are not included as controls, we are not able to disentangle what part of a country's tax revenue gap is due to inefficiency, and what part is due to public choice. Consistently, interpretation of our results should bear this in mind.

On average, our results indicate that EM collect around half of their potential, although heterogeneity is present. We find heterogeneity in tax effort among Latin America countries as well as among African and Asian countries, whereas emerging European countries behave more similarly. Specifically, Middle Eastern countries tend to show quite low levels of tax effort. We also identify the countries in need of fiscal policies aiming for a greater tax collection, which would strengthen countries' fiscal space and their ability to implement proactive short-, medium-, and long- term policies. Of course, countries should not target 100% tax effort and it is probably not feasible to do so; even advanced economies have a tax effort of around 60%, according to our estimates.

Tax reforms oriented to boosting tax collection and strengthening tax administrations will depend on specific country features and initial conditions. As such, tax reforms with the goal of increasing tax collection should be pursued in countries that observe low tax effort and tax collection. On the other hand, countries with high tax effort and already high tax ratios over GDP should carefully revise their tax systems from the perspective of efficiency and equity. Having a more efficient and equitable tax system will increase tax collection itself by boosting sustainable growth and thus bringing it closer to its potential.

Finally, we show preliminary evidence that resource-rich countries tend to have a lower level of tax effort, consistent with the postulates of the "natural resource curse" literature. Considering that it is unlikely that we will observe a revenue windfall similar to that of the 2006–2014 period and that natural resources are expected to be depleted in the next few decades, it is vital that these countries diversify their domestic revenue bases in order to finance their infrastructure and social needs with more sustainable streams of revenue and a more stable budget. An ample domestic revenue base also increases accountability, solidifies institutions, and deepens the social contract between citizens and government.

References

Battese, George E, and Tim J Coelli. 1988. "Prediction of firm level technical inefficiencies with a generalized frontier production function." *Journal of econometrics*, 38: 387–399.

Battese, George E, and Tim J Coelli. 1992. "Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India." *Journal of productivity analysis*, 3(1-2): 153–169.

Baunsgaard, Thomas, and Michael Keen. 2010. "Tax revenue and (or?) trade liberalization." *Journal of Public Economics*, 94(9-10): 563–577.

Belotti, Federico, Silvio Daidone, Giuseppe Ilardi, and Vincenzo Atella. 2013. "Stochastic frontier analysis using Stata." *The Stata Journal*, 13(4): 719–758.

Bird, Richard, and Jorge Martinez-Vazquez. 2014. *Taxation and Development: The Weakest Link?* Edward Elgar Publisher.

Bird, Richard, Jorge Martinez-Vazquez, and Benno Torgler. 2008. "Tax effort in Developing Countries and High Income Countries: The Impact of Corruption, Voice and Accountability." *Economic Analysis and Policy*, 38(1).

Bonnet, Florence, Joann Vanek, and Martha Chen. 2019. "Women and men in the informal economy: a statistical brief." *International Labour Office, Geneva*, 20.

Boukbech, Rachid, Ahmed Bousselhamia, and Elhadj Ezzahid. 2018. "Determinants of tax revenues: Evidence from a sample of Lower Middle Income countries." *MPRA Paper*, I(90268).

Brown, Leanora, and Jorge Martinez-Vazquez. 2019. "Addiction to debt forgiveness in developing countries: Consequences and who gets picked." *Review of Development Economics*, 23.

Brun, Jean Francois, and Maimouna Diakite. 2016. "Tax Potential and Tax Effort: An Empirical Estimation for Non-resource Tax Revenue and VAT's Revenue." *Études et Documents 10, CERDI*.

Crivelli, Ernesto, and Sanjeev Gupta. 2014. "Resource blessing, revenue curse? Domestic revenue effort in resource-rich countries." *European Journal of Political Economy*, 35: 88–101.

Cyan, Musharraf, Jorge Martinez-Vazquez, and Violeta Vulovic. 2013. "Measuring tax effort: Does the estimation approach matter and should effort be linked to expenditure goals?" *ICEEP Working Papers*.

Fenochietto, Mr Ricardo, and Ms Carola Pessino. 2013. *Understanding countries' tax effort.* International Monetary Fund.

Frankel, Jeffrey A. 2010. "The natural resource curse: a survey." National Bureau of Economic Research.

Greene, William. 2005. "Reconsidering heterogeneity in panel data estimators of the stochastic frontier model." *Journal of econometrics*, 126(2): 269–303.

Inter-American Development Bank, IADB. 2019. *Latin America and the Caribbean Macroeconomic Report.* Inter-American Development Bank.

Jondrow, James, CA Knox Lovell, Ivan S Materov, and Peter Schmidt. 1982. "On the estimation of technical inefficiency in the stochastic frontier production function model." *Journal of econometrics*, 19(2-3): 233–238.

Kolmogorov, A.N. 1933. "Sulla determinazione empírica di uma legge di distribuzione." *Giornale dell' Istituto Italianodegli Attuari*, 4: 83–91.

Le, Tuan Minh, Blanca Moreno-Dodson, and Nihal Bayraktar. 2012. *Tax capacity and tax effort: Extended cross-country analysis from 1994 to 2009.* The World Bank.

Makieła, Kamil. 2017. "Bayesian inference and Gibbs sampling in generalized true random-effects models." *Central European Journal of Economic Modelling and Econometrics*, 69–95.

Pessino, Carola, and Ricardo Fenochietto. 2010. "Determining countries' tax effort." *Hacienda Pública Española*, 195(4).

Sachs, Jeffrey D, and Andrew M Warner. 2001. "The curse of natural resources." *European economic review*, 45(4-6): 827–838.

Smirnov, Nikolai V. 1939. "Estimate of deviation between empirical distribution functions in two independent samples." *Bulletin Moscow University*, 2(2): 3–16.

Stat, OECD. 2019. "Global Revenue Statistics Database."

Tanner, M. A., and W. H. Wong. 1987. "The Calculation of Posterior Distributions by Data Augmentation." *Journal of the American Statistical Association*, 82(398): 528–540.

Tanzi, Vito. 1983. *Quantitative characteristics of the tax systems of developing countries.* IMF International Monetary Fund.

Tanzi, Vito, and Hamid Davoodi. 1997. "Corruption, Public Investment, and Growth." *IMF Working Paper*, 1(WP/97/139).

Tanzi, Vito, and Howell Zee. 2000. "Tax Policy for Emerging Markets: Developing Countries." *National Tax Journal*, 53(2).

Tsionas, Efthymios G, and Subal C Kumbhakar. 2014. "Firm Heterogeneity, Persistent And Transient Technical Inefficiency: A Generalized True Random-Effects model." *Journal of Applied Econometrics*, 29(1): 110–132.