Central Bank of Armenia

Working Paper



Estimating Tax Effort: New Evidence from a Heterogeneous Panel

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November 4, 2022

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Abstract

We provide new evidence on countries' tax effort based on a self-constructed heterogeneous panel of 114 countries, covering the period from 1995 to 2020. We apply the stochastic frontier model of Kumbhakar et al. (2014) to disentangle country-specific fixed effects from persistent and time-varying components of tax effort. This allows us to mitigate the misspecification bias of other studies that treat persistent effort as either individual heterogeneity or a time-varying phenomenon. Furthermore, we control for tax rate differences across countries, improving accuracy and interpretation of the previous estimates. We find that 1) the level of development, trade volume, education, income inequality, and the ease of tax collection are important determinants for tax collection; 2) countries with historically strong indicators of governance, rule of law, and control of corruption have a higher level of persistent effort; 3) there is a non-linear relationship between time-varying inefficiency and statutory tax rates.

JEL classification:H21, H22, H26, C23, G40
Keywords: Stochastic Frontier Analysis, Tax Effort, Tax Rate Dataset

The views expressed in this paper are those of the authors and do not necessarily represent the views or policies of the Central Bank of Armenia.

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1 Introduction

Institutional and macroeconomic conditions limit the amount of taxes a country can reasonably raise. A natural question to ask is, therefore, how much additional revenue can be generated through taxation at a particular time, and what factors determine this maximum tax capacity? Gaining insights into this is important for at least two reasons. First, it helps identify the level of taxation beyond which additional taxes cannot be raised and informs the administration against overstepping these bounds. Second, the estimates of tax effort can be used as a rational basis to compare tax performance over time and across countries with similar characteristics. The existing literature has developed different approaches to measure tax effort, including traditional econometric techniques and stochastic frontier (SF) analysis. The first strand of literature focuses on linear regression models and aims at explaining a country's tax performance based on the predicted values of tax revenues. However, the estimates obtained in this manner cannot be interpreted as a maximum tax capacity since tax effort is greater than one whenever the actual collection is greater than the regression prediction. Therefore, they have a limited value for policy advice. The SF approach, on the other hand, effectively captures the notion of potential by determining the maximum level of tax revenues a country could achieve given its own characteristics relative to other countries in the sample.

In this paper, we provide new evidence on countries' tax effort based on SF analysis, contributing to the existing literature in several ways. First, we develop a comprehensive and internationally comparable dataset that contains granular information on top statutory personal income tax (PIT), corporate income tax (CIT), and value-added tax (VAT) rates for 114 countries from 1995 to 2020. Although several institutions and individual researchers have constructed similar datasets, they mainly focus on a particular type of tax or a specific period, limiting the scope of empirical research on taxation issues. Another common limitation of existing datasets is that coverage is often limited, especially for lower-income countries. We extend the data span of the currently available datasets and supplement them with detailed information on countries' PIT schedules, which allows us to have a better understanding of national individual tax systems.

Second, we apply the SF model of Kumbhakar et al. (2014) to disentangle country-specific fixed effects from persistent and time-varying tax effort. Most of the earlier studies are based on specifications, in which country heterogeneity (e.g., tax morale, geography, and cultural attitudes) is viewed as a persistent trend. As a consequence, these models are misspecified and tend to produce a downward bias in the estimates of tax effort, conflating country-specific fixed effects with overall inefficiency. Other studies effectively separate country heterogeneity from tax effort but do not take into consideration the presence of factors that might have permanent effects on tax performance. Therefore, these models are also misspecified and are likely to produce an upward bias in the resulting estimates, confounding persistent inefficiency with country-specific fixed effects. In this paper, we employ an alternative approach and split the general error term into four separate components – a country's latent heterogeneity, time-varying inefficiency, persistent inefficiency, and random shocks. This allows us to mitigate the misspecification bias of other studies and obtain more reliable measures of tax effort.

Third, we control for tax rate differences across countries in the sample, improving the accuracy and interpretation of the previous estimates. More specifically, we take the unweighted average of the top PIT, CIT, and VAT rates of each country and use this composite to parameterize the distribution of time-varying inefficiency. The premise is that tax rates contain useful information for this purpose because they are among the very few policy instruments that can change relatively quickly. For example, in many cases, countries choose to change tax rates in order to ease tax administration and increase tax effort. A large number of empirical studies (Piculescu & Douglas, 2010; Romer & Romer, 2014) support this argument as they show that keeping tax rates at a reasonable level is important to encourage the formalization of businesses and mitigate the incentives through which tax rates affect tax collection. This allows us to better understand one of the main limitations of other studies: our approach tells us what part of a country's tax gap is due to non-compliance and what part arises because of policy choice.

Our findings suggest that the level of development, trade, education, income inequality, and the ease of tax collection are important in determining tax effort. Most advanced countries with a high level of per capita GDP are on the constructed frontier while developing countries are far away from it. Several exceptions exist among countries with a dominant role of natural resources that have a low level of development but operate near the frontier, or vice versa. Nevertheless, the estimates of tax effort are on average higher in the specification that excludes resource-rich countries from the sample.

We also show that countries with strong indicators of governance, rule of law, and control of corruption have a lower level of persistent inefficiency than those with underdeveloped institutions. The implication is that countries with advanced institutions can further improve their tax effort mostly by addressing base-related problems, while in countries with weaker institutions improvements in national tax systems might not be enough to achieve substantial tax collection. In addition, we find that there is a non-linear relationship between time-varying inefficiency and tax rates. Thus, when controlling for tax rate differences, we rule out overestimation (underestimation) of tax effort in countries with relatively high (low) tax rates, improving accuracy and interpretation of the previous estimates.

The remainder of the paper is organized as follows. Section 2 presents a brief review of related empirical literature. Section 3 explains the methodology applied. Section 4 describes the main variables of the SF model and data. Section 5 summarizes the most significant findings. Section 6 illustrates the contributions of the paper. Section 7 analyses the sensitivity of the results. Section 8 concludes and discusses the major limitations of the study.

2 Literature Review

There are two main branches of empirical literature that study countries' tax effort. The first branch relies on traditional regression techniques and stretches back to Lotz & Morss (1967). These studies apply linear regression models and aim at identifying the determinants of taxation, including per capita GDP (Tanzi, 1987; Fox and Gurley, 2005; Gupta, 2007), sectoral composition of the economy (Jewell et al., 2005), degree of openness (Agbeyegbe et al, 2006; Baunsgaard & Keen, 2010), education level (Cyan, 2013), and income distribution (Bird et al., 2006; Gupta, 2007). Grigorian & Davoodi (2007) extended the main determinants of tax collection to include measures of institutional quality and informality. Bird et al. (2008) and Le et al. (2012) explored this strand of literature further, showing that factors such as governance, rule of law, and corruption play an important role in achieving a high level of tax collection. Drummond & Wendell (2012) provide a comprehensive review of the existing literature on the main factors affecting countries' tax performance.

The second part of the literature moved beyond the traditional regression methods and used SF analysis. Unlike the regression approach, which is more akin to estimating the average level of tax collection, the SF approach aims at determining the true tax potential. The intuitive interpretation of tax potential, in this case, is the maximum level of tax revenues that a country could achieve given its own characteristics relative to other countries in the sample. In other words, under the first approach tax capacity is interpreted as the predicted tax ratio from the estimated model, so tax effort can be greater than one whenever the actual collection is higher than the regression prediction. For that reason, as argued by Langford & Ohlenburg (2015), it provides little information on the ability of a country to raise additional revenues. By contrast, the SF tax capacity is identified as a measure of some true maximum, therefore, tax effort indicates the size of additional revenues that can be generated. Cyan et al. (2013) discuss this and other aspects of regression-based and SF models in more detail.

Jha et al. (2000) were the first to apply the SF approach in the estimation of tax effort for the Indian states. Several studies followed thereon, including the SF analysis of tax effort in Indonesia (Alfirman, 2003), Mexico (Castaneda & Pardinas, 2012), West African States (Ndiaye & Korsu, 2014), and Brazil (Antonio & Postali, 2015). Pessino & Fenochietto (2013) extended existing literature of cross-sectional analysis by employing the SF method for a panel of advanced and emerging countries. They applied the simplest formulation of the Battese & Coelli (1992) model, which assumed a deterministic trend for tax effort. Langford & Ohlenburg (2015) ran a similar analysis based on the novel ICTD government revenue dataset and the Battese & Coelli (1995) specification to sift out unobserved heterogeneity from tax effort. Canavire-Bacarreza et al. (2021) used the Bayesian model of Tsionas & Kumbhakar (2014) to obtain the upper bounds of tax effort instead of conventional single-point estimates.

The abovementioned studies do not distinguish between persistent and time-varying inefficiencies, resulting in biased estimates of tax effort. Moreover, they do not take into account tax policy differences across countries, thus insufficiently specifying which part of a country's tax gap results because of non-compliance and which part is due to policy choice. Our paper contributes to the literature in two main directions. First, we disentangle country-specific fixed effects from persistent and time-varying components of tax inefficiency by applying the Kumbhakar et al. (2014) model and avoiding the misspecification bias of previous studies.

Second, we control for tax rate differences across countries, improving accuracy and interpretation of the estimates. These methodological improvements are discussed in the following section.

3 Methodology

Our estimation strategy is built around the reduced form representation of the SF model discussed in the previous section:

$$y_{it} = \beta_0 - \alpha_i + \beta' x_{it} + v_{it} - \eta_i - u_{it} \tag{3.1}$$

where y_{it} represents the log of tax revenue-to-GDP ratio of country i at time t; x_{it} is the vector of variables affecting tax collection; u_{it} and η_i are non-negative time-varying and persistent inefficiency components that hold countries back from attaining full tax capacity; α_i are random country-specific fixed effects; and v_{it} is the standard two-sided error term with a symmetric distribution.

The analysis aims at measuring tax effort as the ratio between actual and the corresponding SF tax revenue predicted from equation 3.1:

$$TE_{it} = \frac{exp(\beta_0 - \alpha_i + \beta' x_{it} + v_{it} - \eta_i - u_{it})}{exp(\beta_0 - \alpha_i + \beta' x_{it} + v_{it})} = exp(-\eta_i - u_{it}) \tag{3.2}$$

To this end, Kumbhakar et al. (2014) provide a simple three-stage procedure by first transforming the baseline model in the form

$$y_{it} = \beta_0^* + \beta' x_{it} + \mu_i + \epsilon_{it} \tag{3.3}$$

where $\beta_0^* = \beta_0 - E[\eta_i] - E[u_{it}]$; $\epsilon_{it} = v_{it} - u_{it} + E[u_{it}]$ and $\mu_i = \alpha_i - \eta_i + E[\eta_i]$. The new representation is a standard panel data framework. In the first step, a simple random-effects model is applied to estimate β', which also provides the predicted values of the error terms μ_i and ϵ_{it} ($\hat{\mu_i}$ and $\hat{\epsilon_{it}}$ respectively). In the second step, time-varying inefficiency (u_{it}) is estimated, using the predicted values of ϵ_{it} from step 1 and assuming that $u_{it} \sim N^+(\mu_u, \sigma_u^2)$ and $v_{it} \sim N(0, \sigma_v^2)$.In the third step, a similar procedure is employed to estimate time-invariant inefficiency (η_i).[1] We use the formulation of Kumbhakar et al. (2014) because even though the previous models (Battese & Coelli, 1995; Greene, 2005a; 2005b; Wang and Ho, 2010; etc.) effectively separate country-specific fixed effects from time-varying inefficiency, none of these models take into consideration the presence of factors that have permanent effects on a country's overall tax inefficiency. As such, these models are misspecified and tend to produce an upward bias in the estimates of tax effort, confounding persistent inefficiency within country-specific time-invariant effects. From a practical point of view, however, it is more sensible to suppose that a country can eliminate part of its inefficiency by removing some of the short-run rigidities, while other sources of inefficiency might stay with it over time. With the proposed specification, we address this limitation by disentangling the general error term into a country's latent heterogeneity, time-varying inefficiency, persistent inefficiency, and random shocks (Appendix A1 discusses the evolution of SF models and the peculiarities of each approach in detail).

Identifying the magnitude of persistent inefficiency is important because it reflects the effects of a country's structural parameters (e.g., corruption, governance, and rule of law) on its tax performance. Such a decomposition is also useful for effective policymaking because time-varying and persistent components of inefficiency have different implications. For example, if a country has a relatively large time-varying component of inefficiency in a particular year, it could be argued that the overall inefficiency is caused by something, which is unlikely to repeat in the future. On the other hand, a larger persistent component of inefficiency indicates inertia in overall inefficiency, which will prevail unless some institutional changes take place.

To identify persistent inefficiency, we construct a composite governance index (CGI) based on the unweighted average of the World Bank's control of corruption, government effectiveness, and rule of law indicators. We then use the historical country-level averages of this composite to parameterize the distribution of persistent inefficiency. There are two reasons behind this approach. First, existing empirical evidence suggests that institutional variables are important in determining a country's tax effort (Bird et al, 2008; Le et al., 2012; Akanbi, 2019; etc.). Second, these variables usually do not change abruptly, especially in short panels.

[1] In both cases, the Jondrow et al. (1982) procedure was applied to obtain time-varying ($RTE = exp(-\hat{u_{it}})$) and persistent ($PTE = exp(-\hat{\eta_i})$) inefficiency terms. Then the overall inefficiency was derived as the product of the two: $OTE = RTE * PTE$.

For time-varying inefficiency, we use the unweighted average of the top PIT, CIT, and VAT rates of each country to parameterize the distribution of the corresponding error term. In addition, we use the squared term of this variable to capture the possible non-linear relationship between statutory rates and tax effort. This captures the idea that if two countries collect similar tax revenues, then the country with higher tax rates is more likely to have inefficient tax collection. A caveat is that the reason behind low tax revenue despite high statutory rates may be the difference in exemptions, deductions, and other specific features of national tax systems. Unfortunately, effective tax rates are available only for a small number of advanced economies and for a short period.

An alternative approach would be to include the information on statutory tax rates in the main regression as an additional explanatory variable rather than in the parametrization of time-varying inefficiency. This, however, would miss the information that tax rates contain for disentangling the time-varying and persistent tax inefficiency. The premise is that tax rates are useful for the identification of time-varying inefficiency because the rates are one of very few tax policy instruments, which can change relatively quickly. For example, countries in many cases choose to change tax rates in order to ease tax administration and increase tax effort. The World Bank's Enterprise Surveys support this argument as they show that firms, which identify tax rates as a major constraint for their business, usually are also dissatisfied with tax administration (appendix A2). At the same time, a large number of empirical studies (Piculescu & Douglas, 2010; Romer & Romer, 2014) claim that keeping tax rates at a reasonable level is important to encourage the formalization of businesses and mitigate the incentives through which tax rates affect tax collection. It is also worth mentioning that this specification does not preclude tax rates to affect the overall tax capacity but rather allows tax rates to affect the capacity indirectly.

4 Variables and Data

Our estimation strategy is built around the reduced form representation of the SF model discussed in the previous section:

$$ltax = f(lpcgdp, lpcgdp2, ltr, lava, ei, gini, gov, rate, rate2, cgi)$$

where ltax is the log of tax revenue-to-GDP ratio; lpcgdp is the log of per capita GDP at 2010 prices; lpcgdp2 is the squared term of per capita GDP; ltr is the log of trade-to-GDP ratio; lava is the log of agricultural sector value added-to-GDP ratio; ei is the UN education index; gini is the coefficient of income inequality; gov is a dummy variable that is equal to 1 for general and 0 for central governments[2] ; rate is the unweighted average of countries' PIT, CIT, and VAT rates; rate2 is the squared term of rate; and CGI is the unweighted average of the World Bank's control of corruption, government effectiveness, and rule of law indicators.

The first explanatory variable included in the model is per capita GDP, based on the hypothesis that a high level of development brings more demand for public expenditures and higher tax revenue (Tanzi, 1987; Fox and Gurley, 2005; Gupta, 2007). Trade volume reflects the degree of openness of an economy, which is likely to increase tax collection in the medium term (Agbeyegbe et al, 2006; Baunsgaard & Keen, 2010). The expected effect of value added of the agricultural sector, on the other hand, is negative because it is usually harder to collect taxes from that sector and also many countries have multiple tax exemptions for agriculture (Langford & Ohlenburg, 2015). The UN education index is included in the model since an educated population is more likely to understand how and why it is necessary to pay taxes (Cyan, 2013; Pessino & Fenochietto, 2013). The GINI coefficient is expected to have a negative effect on tax collection, as perception of unfairness in more unequal societies may reduce voluntary taxpayer compliance (Bird et al., 2006; Gupta, 2007).

The tax data we constructed is a heterogeneous panel, which includes top statutory PIT, CIT, and VAT rates of 114 countries from 1995 to 2020 and expands the currently available datasets in two important directions. First, it extends the time series for top statutory tax rates, especially for developing economies. More specifically, 38.2% of the countries included in our database are classified as high-income, 50.4% as middle-income, and 11.3% as low-income countries. Second, our PIT database in addition to the top rates

[2]For some countries, data is available only at the central government level.

contains information on the corresponding tax schedules, allowing us to have a better understanding of country-specific individual tax systems.

The consolidated dataset of statutory tax rates was assembled from multiple distinct sources, among which the most important ones were the tax summaries of the Big Four accounting firms (PwC, Deloitte, EY, and KPMG), as well as publications of international organizations (e.g., OECD, World Bank, CEPAL, IMF, ADB), public policy centers (e.g., Michigan University's World Tax Database, Economist Intelligence Unit, Georgia State University's Tax Database, Fraser Institute), and national tax authorities.

There are several publicly available databases for countries' tax revenues, such as IMF Government Finance Statistics, OECD Revenue Statistics, CEPAL Revenue Statistics on Latin America, and ICTD Government Revenue Dataset. However, the range of datasets that include systematic information on statutory rates in time-series format is limited. Some of the institutions and individual researchers that have constructed such datasets include Fraser Institute, Michigan University, Heritage Foundation, Georgia State University, Economist Intelligence Unit, Oxford Centre for Business Taxation, and Vegh & Vuletin (2015). However, all these datasets focus on a particular type of tax or a specific time period, limiting the scope of empirical research on taxation issues. For example, Georgia State University and Fraser Institute provide information only on PIT rates, while Michigan University's database is available for the period until the year 2005. Another common limitation of existing datasets is the gap in coverage, especially for lower-income countries. The most recent example is the dataset of Vegh & Vuletin (2015), which includes granular data on both individual and corporate tax rates; the number of countries in this dataset, however, is limited to 62.

Common drawbacks of collecting data from different sources include definitional errors, country-specific peculiarities, and editorial omissions. While we have made our best effort to reconcile and produce a consistent database, we recognize that it may still have some limitations. These are carefully discussed in appendix B together with data sources and descriptive statistics of the variables.

5 Empirical Findings

Before estimating the SF model described in Section 3, we follow the recommendation of Kumbhakar et al. (2015) and conduct a likelihood-ratio (LR) test on the existence of inefficiency. If no evidence for one-sided errors is found, the model reduces to a standard regression framework for which a simple ordinary least squares (OLS) estimation would be sufficient. Otherwise, the estimation should be conducted via a maximum likelihood (ML) approach to ensure the unbiasedness and consistency of the estimates.

For a half-normal model, the LR test simply amounts to testing the hypothesis that $\sigma_u^2 = 0$. The complication is that the null hypothesis of $\sigma_u^2 = 0$ is on the boundary of the corresponding parameter's permissible space and the LR test statistic does not have a standard chi-square distribution. Coelli (1995) shows that in such cases the test has a mixture of chi-square distributions and its critical values should be taken from the reference model of Kodde & Palm (1986). As shown in Table 1, the value of the LR test statistic is 86.6 in our specification, which is much higher than the 0.1 percent critical value of 9.5. This implies that we can reject the null hypothesis of an OLS formulation in favor of the ML estimation of the SF model.

Table 1: Log-Likelihood (LR) Test Results

DoF	LR Test Statistic	Significance Level						
1	86.597	0.250	0.100	0.050	0.025	0.010	0.005	0.001
		0.455	1.642	2.705	3.841	5.412	6.635	9.500

Source: Kodde & Palm (1986) and authors' calculations

Given the results of the LR test, we then estimate our baseline specification, disentangling country-specific effects from time-varying and persistent inefficiencies. Table 2 summarizes the estimation results of the frontier and inefficiency models, where we assumed a half-normal distribution for both time-varying and persistent inefficiency components. All the coefficients are statistically significant at a 5 percent level and have the expected signs. In particular, the level of development, education, and trade volume are found to be positively correlated with countries' tax performance, while the agricultural sector value added and income inequality have a negative association with it. This is consistent with the findings of Grigorian & Davoodi (2007), Pessino & Fenochietto (2013), and Langford & Ohlenburg (2015) who observed similar trends for these variables.

We also provide evidence of a non-linear relationship between statutory tax rates and time-varying inefficiency, supporting the hypothesis that the level of statutory tax rates might have real effects on the economy, especially in the short run. This has the policy implication that when tax rates are very low, a country can moderately increase them and improve its tax collection without any substantial disturbance in its tax system. On the other hand, when tax rates are high enough, their further increase can have adverse effects on overall tax collection. A large number of empirical studies (Romer & Romer, 2014; Piculescu & Douglas, 2010) support this argument, showing that keeping tax rates at a reasonable level is important to encourage the formalization of businesses and mitigate the incentive channels through which tax rates affect the overall tax performance.

Finally, we obtain a negative coefficient for the CGI in the inefficiency model, meaning that high levels of governance effectiveness, rule of law, and control of corruption indices are associated with a lower level of persistent inefficiency. This is in line with the findings of Bird et al. (2008), Le et al. (2012), & Akanbi (2019), who also found a strong long-run relationship between the quality of institutions and the estimates of tax effort.

Figure 1 shows the estimates of tax effort (see Appendix C for details) based on the formula of Jondrow et al. (1982). It is apparent that most emerging countries with a lower level of per capita GDP are far away from their tax capacity, while the advanced countries are generally on the frontier. For example, Denmark, Netherlands, Luxembourg, Finland, and Norway have more than 90 percent of tax effort, while countries such as the Republic of Congo, Venezuela, Bangladesh, Mexico, and the Dominican Republic operate at less than 60 percent of their tax capacity.

Table 2: Kumbhakar, Lien, & Hardaker (2014) Model Estimation Results

	Coefficient	Standard Error	p >|z|
	FRONTIER MODEL		
lpcgdp	1.3100	0.0678	0.000
lpcgdp2	-0.0744	0.0041	0.000
lava	-0.0473	0.0120	0.000
ltr	0.0698	0.0126	0.000
ei	0.6044	0.0644	0.000
gini	-0.0101	0.0007	0.000
gov	0.1572	0.0748	0.036
Intercept	-2.8860	0.2991	0.000
	INEFFICIENCY MODEL		
Persistent Inefficiency			
Usigmas			
Intercept	-2.8621	0.1668	0.000
cgi	-1.3691	0.1230	0.000
Vsigmas			
Intercept	-2.7964	0.0529	0.000
Time-Varying Inefficiency			
Usigmas			
Intercept	-0.8012	0.8865	0.366
rate1	-0.3311	0.0562	0.000
rate2	0.0056	0.0015	0.000
Vsigmas			
Intercept	-4.7239	0.0562	0.000

Figure 1 illustrates that the variance of tax effort is quite high for the same level of income. In other words, for the same level of development, we observe countries with both high and low levels of tax effort. For example, Mali, Namibia, and Senegal have a low level of development but operate near the constructed frontier, while Azerbaijan, Kazakhstan, and Venezuela have a relatively high level of development but a low level of tax effort. A possible explanation is that some of these resource-dependent countries have managed to develop their tax systems before exploiting natural resources, while others lack well-developed tax systems (Pessino & Fenochietto, 2013). Nevertheless, consistent with other studies (Fabian et al., 2009; Thomas & Trevino, 2013; Crivelli & Gupta, 2014), we show that the estimates of tax effort are on average higher in the specification that excludes resource-dependent countries from the sample. To be more specific, the unweighted average of the estimated tax effort is 78.8 percent for the whole sample but it increases to 81.2 percent when we drop the countries with a large reliance on natural resources (see Table 3).[3]

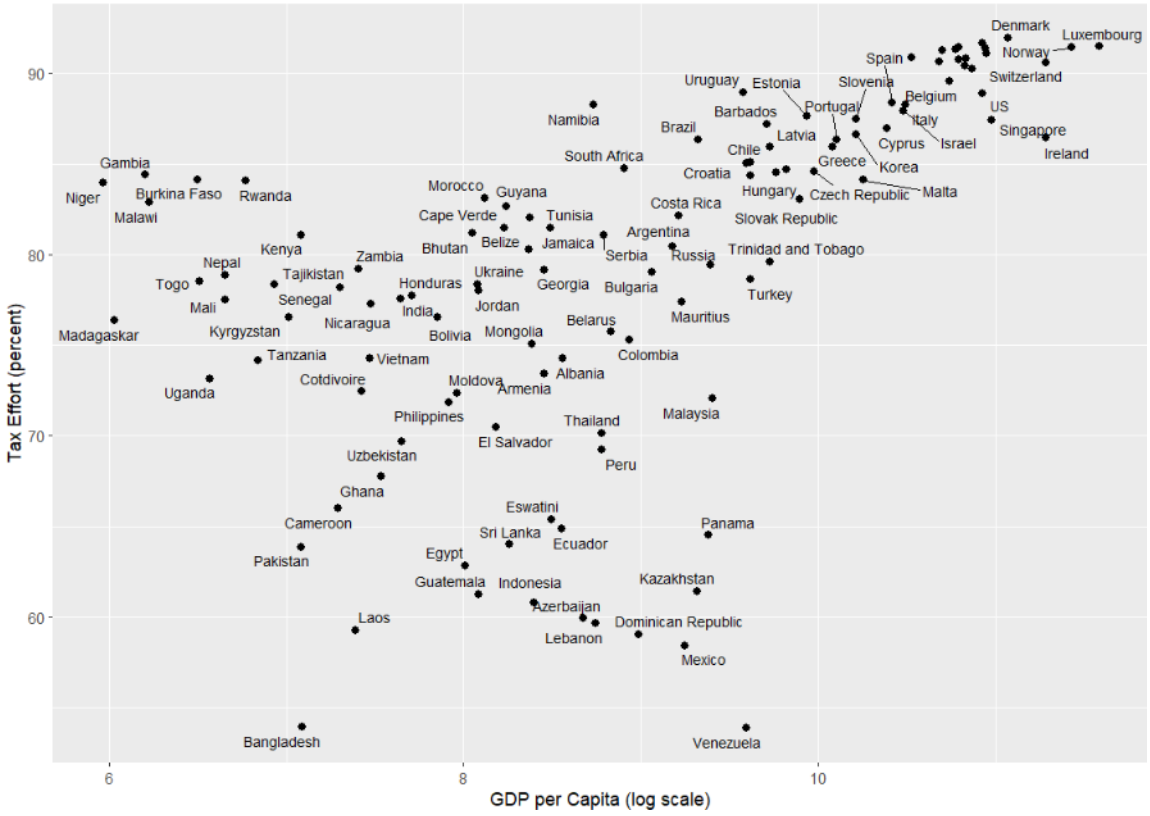
Table 3: Tax Effort with and without Natural Resource-Dependent Countries

With Resource-Dependent Countries				Without Resource-Dependent Countries			
Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
78.8	10.4	30.8	92.8	81.2	8.0	54.0	92.7

Figure 2a illustrates the relationship between CGI and persistent tax effort, while Figure 2b shows the marginal effects of CGI on this component. The results suggest that countries with historically strong

[3]The choice of the resource-rich countries is based on Ghura et al. (2012) and IMF Article IV reports. The list includes Azerbaijan, Bolivia, Cameroon, Republic of Congo, Cotdivoire, Ghana, Guyana, Indonesia, Kazakhstan, Mexico, Mongolia, Niger, Norway, Russia, Venezuela, and Zambia.

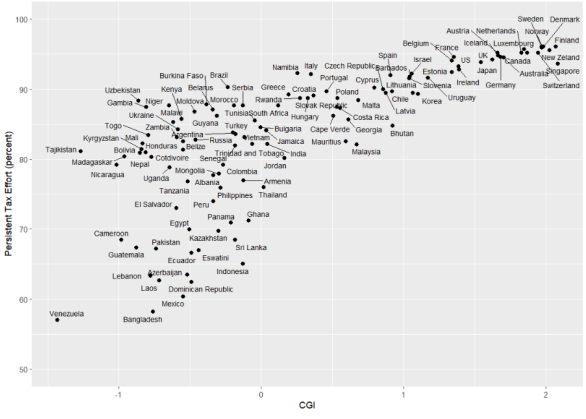
Figure 1: Estimates of Tax Effort vs the Level of Development



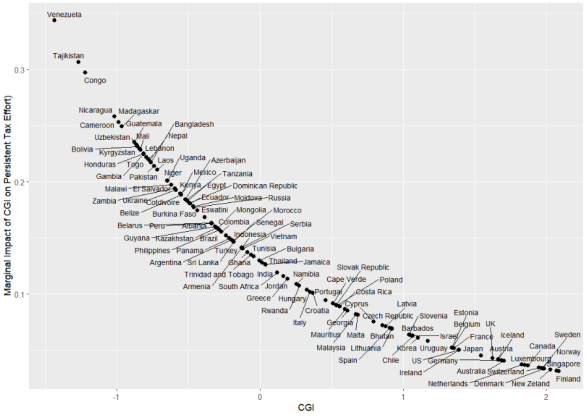
indicators of governance, rule of law, and control of corruption have a lower level of persistent inefficiency than those with underdeveloped institutions. Moreover, the estimated marginal effects of structural factors on persistent tax effort are much larger for developing countries than for advanced ones. This implies that countries with relatively strong institutions, such as Denmark, Sweden, or Finland, can further improve their tax effort mostly by optimizing existing taxes, revisiting tax exemptions, or addressing other base-related issues. On the other hand, for countries with weak institutions (e.g., Venezuela, Tajikistan, or Cambodia) improvements in the functioning of national tax systems might not be enough to achieve substantial tax collection because the underlying structural factors would still act as major constraints.

Figure 2

(a) Persistent Tax Effort vs CGI



(b) Marginal Impact of CGI

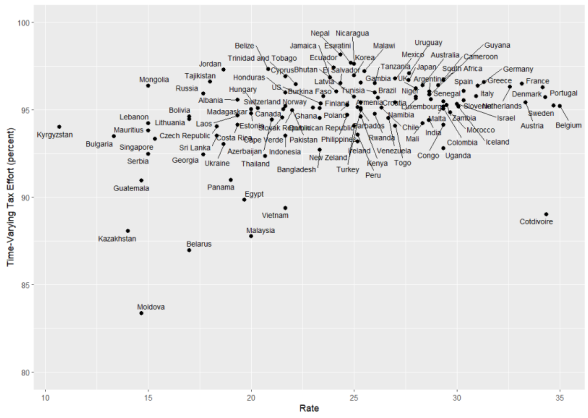


Similarly, Figure 3a shows the relationship between average tax rates and the estimates of time-varying tax effort, while Figure 3b depicts the marginal effects of tax rates. First of all, one can observe that there is a non-linear relationship between time-varying inefficiency and statutory tax rates, meaning that higher tax rates do not necessarily lead to higher tax effort. Moreover, at some point they might even have negative effects on it. Second, countries that are ranked lowest in terms of statutory tax rates also tend to have the highest marginal impact estimates, with the policy implication that some efficiency gains can be achieved in these countries through upward revisions of current tax rates. In contrast, for countries with high tax rates, the trend line of the estimated marginal effects has a positive slope, which implies that most of these countries can further improve their time-varying tax effort by cutting current tax rates.

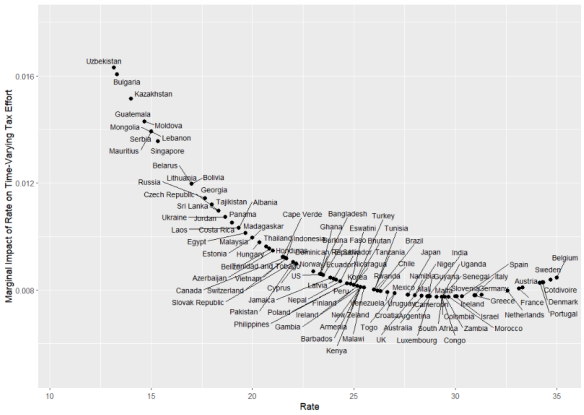
Of course, any change in a country's tax rates will affect not only its actual tax collection but also tax capacity. One might argue that it is not reasonable to claim that countries with a hypothetical 10 percent tax rate should have higher tax effort than others where the rate is, for example, 5 percent. However, it is important to note that in SF frameworks the magnitude of tax capacity is driven not only by tax rates but also by macroeconomic and institutional fundamentals. Thus, in the short run when tax rates are low and there are no massive risks of change in compliance, the increase in tax rates would entail actual tax revenues to grow faster than tax capacity, resulting in a higher level of time-varying tax effort. On the other hand, when the rates are high and some concerns on the side of non-compliant behavior exist, the downward revision of tax rates can help mute the incentive channels of tax evasion. At the same time, it is important to highlight that these patterns may not apply to all countries as the incidence of low or high tax rates can simply be a matter of public choice as in the case of Singapore, Sweden or Denmark. Thus, one needs to be careful in generalizing the findings of this paper and fully understand the local context before making certain conclusions.

Figure 3

(a) Time-Varying Effort vs Tax Rates



(b) Marginal Impact of Tax Rates

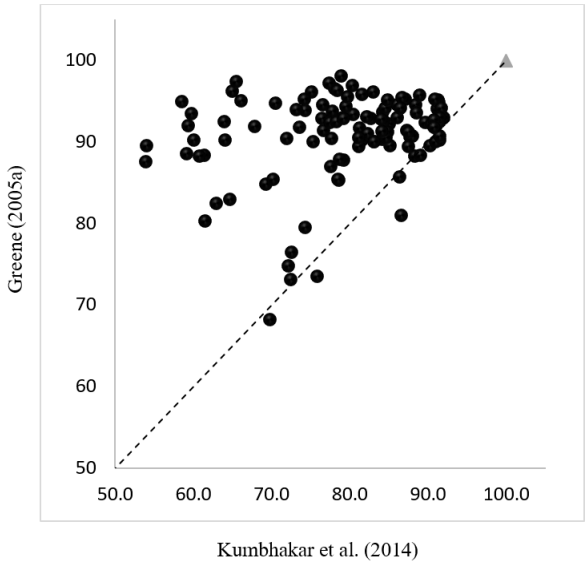


6 Illustration of the Main Contributions

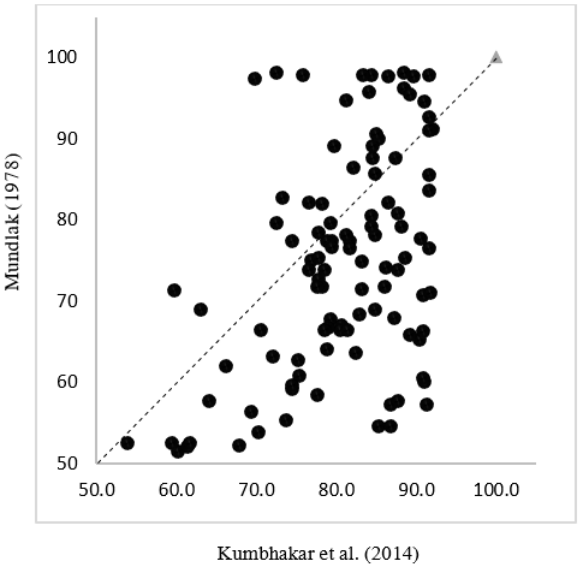
Our approach of estimating countries' tax effort has several advantages over the traditional SF models. First, the disentanglement of country-specific fixed effects from persistent and time-varying components of inefficiency mitigates the misspecification bias of other models. To illustrate this, in Figure 4a and Figure 4b (see Appendix D for details), we compare our findings with the estimates obtained using two extreme cases - Greene (2005a) and Mundlak (1978). The former treats persistent tax effort as a part of country-specific fixed effects, whereas the latter does the exact opposite, viewing individual heterogeneity as tax inefficiency. As a result, in Greene (2005a) most countries have an upward bias in their tax effort estimates, as opposed to Mundlak (1978), where the estimates of tax effort are mostly downward biased.

Figure 4: Tax Effort

(a) Greene vs Kumbhakar



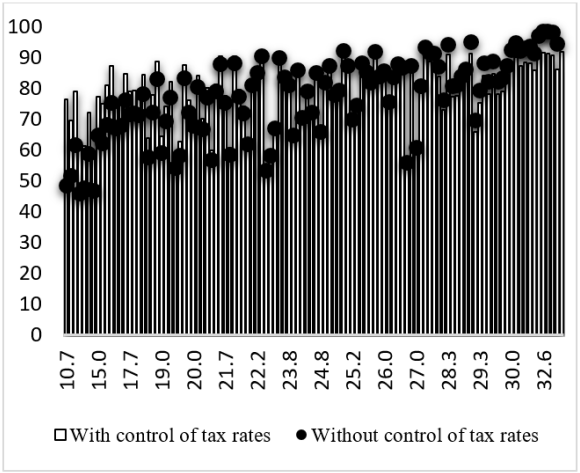
(b) Mundlak vs Kumbhakar



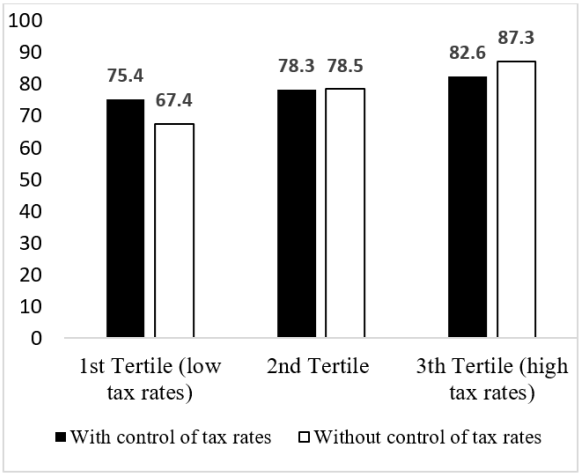
Second, by controlling for tax rates across countries, we improve the accuracy and interpretation of other studies, because, for example, low tax collection can be a result of public choice of a smaller government rather than a lack of tax performance. This is shown in Figure 5a and Figure 5b, which compare the estimates of tax effort with and without controlling for tax rates (see Appendix D for details). It is apparent that when we incorporate tax rates into our baseline specification, the estimates of tax effort improve for countries with relatively low tax rates while decreasing for those with relatively high tax rates. For example, the average tax effort of countries with the highest tax rates in the sample is 87.3 percent when the differences in tax rates are not controlled. However, the figure decreases to 82.6 percent once we include tax rates in the model. On the other hand, the average tax effort for countries with the lowest tax rates in the sample is 67.4 percent without controlling for tax rates but the figure increases to 75.4 percent when tax rates are taken into account.

Figure 5: Tax Effort with and w/o Control of Tax Rates

(a) Country-Specific Estimates

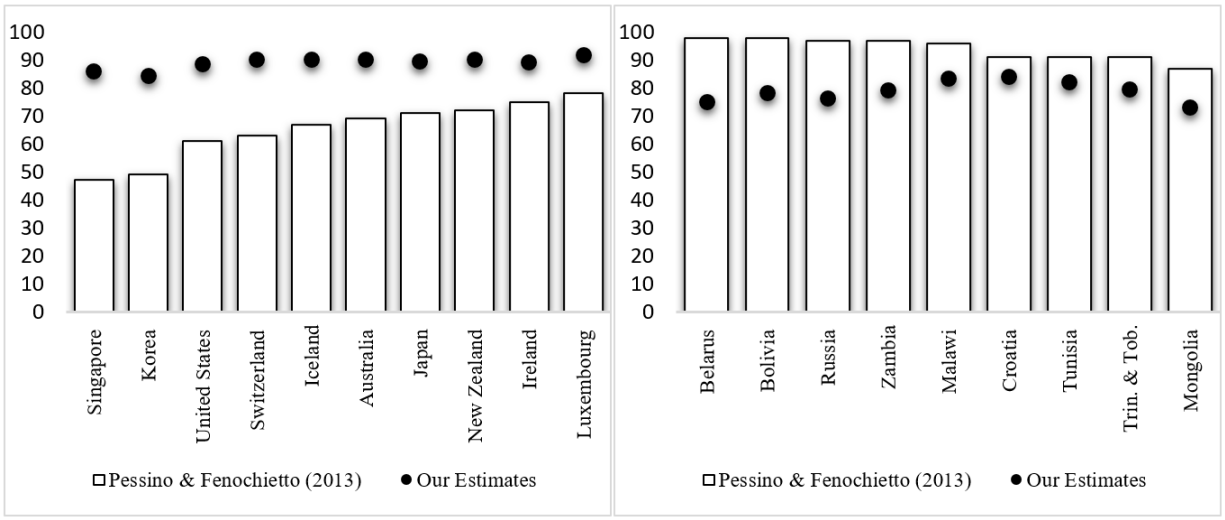


(b) Average Estimates



We also make a cross-country comparison between our estimates and the findings of other empirical studies. For example, as shown in Figure 6, Pessino & Fenochietto (2013) obtain unusually small estimates of tax effort for a number of advanced countries (e.g., Japan (71%), Singapore (47%), or Korea (49%)) and unusually large estimates for some developing countries (e.g., Belarus (98%), Russia (97%), or Bolivia (98%)). For the first group of countries, the authors argue that this is partly because of relatively low tax rates in these countries, while for the second group of countries no explanation is provided,. By contrast, our estimates for the same sample and for the same period of time seem to be more intuitive, given the final ranking of countries and their actual tax revenues. For example, Japan, Singapore, and Korea are now ranked among the highest-performing countries, while Belarus, Russia, and Bolivia have modest tax effort consistent with their macroeconomic and institutional foundations.

Figure 6: Comparison of Tax Effort: Our Estimates vs Pessino & Fenochietto (2013)



7 Sensitivity Analysis

To examine the sensitivity of the findings, we first estimate our baseline specification without the three countries with the highest per capita GDP (Luxembourg, Norway, and Switzerland) and then without the three countries with the lowest per capita GDP (Niger, Malawi, and Togo). Table 4 shows that these changes do not have a significant impact on the results.

Table 4: Sensitivity Analysis: Different Scenarios

	Average	Std. Dev.	Min	Max
Baseline model	80.0	10.3	32.3	94.2
Without the three highest-income countries	80.2	10.1	32.9	94.6
Without the three lowest-income countries	81.0	10.4	35.2	94.9
Increase in the GINI coefficient by 20 percent	80.0	10.3	32.3	94.2
Truncated distribution	80.5	10.4	32.5	95
Controlling for informal GDP	81.2	9.4	35.3	94.5
With lagged lpcgdp and lpcgdp2	80.2	10.3	31.6	94.6
Tax effort of non-resource countries: Resource-rich countries included in the sample	81.7	8.7	53.4	94.2
Tax effort of non-resource countries: Resource-rich countries excluded from the sample	82.3	7.9	53.5	94.1
Estimates for the period 2003-2020	Average	Std. Dev.	Min	Max
Baseline model	69.8	14.6	26.6	90.6
Governance index from FHD	71.2	14.3	27.0	90.6

Next, we carry out an alternative assessment of the baseline model by increasing the GINI coefficient of

all countries by 20 percent. The intuition is that such a consideration should not have any notable impact on the findings since the entire framework is based on comparative analysis. The estimates of tax effort, indeed, do not differ across the countries in the sample when we run the model with the original or modified series of the income distribution.

We also estimate the baseline specification with different distributions. Greene (2008) notes that adopting alternative assumptions for the distribution of u_{it}, such as half-normal, gamma, or exponential, tends to have a minimal impact on the size of inefficiency estimates. To support this argument, we do our analysis both for half-normal and truncated-normal distributions. As expected, the differences are negligible, with average tax effort being 80.0 and 80.5 percent for the two distributions respectively.

In another exercise, we control for informal GDP to see whether there is an omitted variable bias in the baseline model. However, as shown in Table 4, average tax effort changes only marginally due to this exercise. One explanation could be the inclusion of the agricultural sector value added in the original specification, which proxies for the non-taxable sector of the economy.

It is natural to think that potential endogeneity might arise coming from reverse causality of the tax-to-GDP ratio to various dependent variables, inducing a bias in the estimation. For the structural factors on the right-hand side (e.g., income inequality, agriculture value added, education), such concerns are minimal, as these variables are slow-moving and there is little simultaneous comovement with tax revenues. For other variables, such as per capita GDP, we address this issue by adding the lagged values in the analysis. Again, we see no major changes in the results.

Moreover, we bring evidence that the average tax effort of non-resource-rich countries does not change with or without the inclusion of resource-dependent countries in the sample. Lastly, to check the sensitivity of the findings with respect to the constructed CGI composite, we estimate the model using the governance index of the Freedom House Database (FHD) for the period 2003-2020. The results show that the estimates of tax effort do not differ significantly in both specifications.

8 Conclusion

In this paper, we bring new evidence on countries' tax effort, contributing to the existing literature in several ways. First, we develop a comprehensive and internationally comparable dataset that contains granular information on top statutory PIT, CIT, and VAT rates of 114 countries for the period 1995-2020. We extend the data span of currently available databases and collect data on countries' PIT schedules in addition to their top rates. Second, we apply the SF model of Kumbhakar et al. (2014), disentangling country-specific effects from persistent and time-varying components of tax effort, thereby mitigating the misspecification bias of other studies. Lastly, we control for tax rate differences across countries, which allows us to improve the accuracy and interpretation of the estimates.

Our findings suggest that the level of development, trade, education, income inequality, and the ease of tax collection are essential in determining a country's tax effort. Most developing countries with a lower level of per capita GDP are far away from their tax capacity, while advanced countries are generally close to the frontier. Several exceptions exist among countries with a dominant role of natural resources. Nevertheless, the estimates of tax effort are on average higher in the specification that excludes resource-rich countries from the sample.

Countries with historically sound indicators of governance, rule of law, and control of corruption have a lower level of persistent inefficiency than countries with underdeveloped institutions. This implies that countries with relatively strong institutions can further improve their tax effort mostly by addressing base-related issues. On the other hand, for countries with weaker institutions, improvements in national tax systems might not be enough to achieve substantial tax collection because the underlying structural factors would still act as major constraints. Lastly, we show that there is a non-linear relationship between time-varying inefficiency and statutory tax rates. In other words, when controlling for tax rates, we rule out overestimation of tax effort in countries with relatively high tax rates, and its underestimation in countries with lower tax rates. In simpler terms, countries may have lower tax collection because of public choice of a smaller government rather than inefficient tax collection. Thus, distinguishing between policy and inefficiency contributions to estimated tax gaps allows us to overcome one of the main limitations of other studies.

The accuracy of tax effort estimates heavily depends on the quality of underlying databases, which is always one of the main limitations of such studies. This refers to both technical and conceptual aspects. Technical problems include definitional errors, country-specific peculiarities, and editorial omissions. The main conceptual problem, on the other hand, is that statutory tax rates do not necessarily comprise the differences in exemptions and deductions of national tax systems. Therefore, further improvements in both aspects would materially improve the quality of future research in the field.

References

[1] Agbeyegbe, T., Stotsky, J., & WoldeMariam, A. (2006). Trade liberalization, exchange rate changes and tax revenue in Sub-Saharan Africa. Journal of Asian Economics, 17(2), 261-284.

[2] Aigner, D., Lovell, K., & Schmidt, P. (1977). Formulation & estimation of stochastic frontier production function models. Journal of Econometrics, 6, 21–37.

[3] Akanbi, O. (2019). State institutions & tax capacity: An empirical investigation of causality. International Monetary Fund. WP/19/177.

[4] Alfirman, L. (2003). Estimating stochastic frontier tax potential: Can Indonesian local governments increase tax revenues under decentralization? University of Colorado at Boulder. WP/03/19.

[5] Antonio, F., & Postali, S. (2015). Tax effort and oil royalties in the Brazilian municipalities. EconomiA. 16(3), 395-405.

[6] Battese, G. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics. 20(2), 325-332.

[7] Battese, G. & Coelli, T. (1988). Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. Journal of Econometrics. 38, 387–99.

[8] Battese, G., & Coelli, T. (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.

[9] Baunsgaard, T. & Keen, M. (2010). Tax revenue and (or?) trade liberalization. Journal of Public Economics. 94(9-10), 563-577.

[10] Bird, R., Martinez-Vazquez, J., & Torgler, B. (2006). Societal institutions and tax effort in developing countries. The challenges of tax reform in a global economy. 283.

[11] Bird, R. & Martinez-Vazquez, J. (2014). Taxation and development: The weakest link?. Essays in Honor of Roy Bahl.

[12] Bird, R., Martinez-Vazquez, J., & Torgler, B. (2008). Tax effort in developing countries and high income countries: The impact of corruption, voice, and accountability. Economic Analysis and Policy. 38(1), 55-71.

[13] Castaneda, L. & Pardinas, J. (2012). Sub-National revenue mobilization in Mexico. Inter-American Development Bank. WP/354.

[14] Canavire-Bacarreza, G., Deza, M. C., Manzano, O., & Puerta, A. (2021). Revisiting tax effort in emerging markets. Public Finance Review. 49(6), 845-873.

[15] Coelli, T. (1995). Estimators and hypothesis tests for a stochastic frontier function: A Monte Carlo analysis. Journal of Productivity Analysis. 6, 247-267.

[16] Cornwell, C., Schmidt, P., & Sickles, R. (1990). Production frontiers with cross-sectional and time-series variation in efficiency levels. Journal of Econometrics. 46, 185-200.

[17] Crivelli, E. & Gupta, S. (2014). Revenue substitution in resource-rich economies: Evidence from a new dataset. VoxEU.

[18] Cyan, M., Martinez-Vazquez, J., & Vulovic, V. (2013). Measuring tax effort: Does the estimation approach matter and should effort be linked to expenditure goals? International Center for Public Policy. WP 13-08.

[19] Drummond, P. & Wendell, D. (2012). Mobilizing revenue in Sub-Saharan Africa: Empirical norms and key determinants. International Monetary Fund. WP/12/108.

[20] Fabian, B., Gupta, S., & Thornton, J. (2009). Natural resource and endowments and the domestic revenue effort. European Journal of Political Economy. 25, 439–446.

[21] Fox, W. F., & Gurley, T. (2005). An exploration of tax patterns around the world. Tax Notes International. 37(9), 793-805.

[22] Ghura, D., Pattillo, C. et al.(2012). Macroeconomic policy frameworks for resource-rich developing countries. International Monetary Fund. Background Paper 1.

[23] Greene, W. (2005a). Fixed and random effects in stochastic frontier models. Journal of Productivity Analysis. 23, 7–32.

[24] Greene, W. (2005b). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. Journal of Econometrics. 126, 269–303.

[25] Grigorian, M. & Davoodi, M. (2007). Tax potential vs. tax effort: A cross-country analysis of Armenia's stubbornly low tax collection. International Monetary Fund, WP/07/106 .

[26] Gupta, A. (2007). Determinants of tax revenue efforts in developing countries. International Monetary Fund, WP/07/184.

[27] Jewell, C., Flanagan, R., & Cattell, K. (2005). The effects of the informal sector on construction. In Construction Research Congress 2005: Broadening Perspectives (pp. 1-10).

[28] Jha, R., Mohanty, M., Chatterjee, S., & Chitkara, P. (2000). Tax efficiency in selected Indian states. Advances in Public Economics. 91-104.

[29] Jondrow , J., Lovell, C., Materov , I., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. Journal of Econometrics. 19(2-3), 233-238.

[30] Kodde, D. & Palm, F. (1986). Wald criteria for jointly testing equality and inequality restrictions. Econometrica. 54, 1243–1248.

[31] Kumbhakar, S., Lien, G., & Hardaker, J. (2014). Technical efficiency in competing panel data models: A study of Norwegian grain farming. Journal of Productivity Analysis. 41(2), 321-337.

[32] Kumbhakar, S. (1990). Production frontiers, panel data, and time-varying technical inefficiency. Journal of Econometrics. 46, 201–11.

[33] Kumbhakar, S., Wang, H., & Horncastle, A. (2015). A practitioner's guide to stochastic frontier analysis using Stata. Cambridge University Press.

[34] Langford, B. & Ohlenburg, T. (2015). Tax revenue potential and effort. International Growth Centre Working Paper.

[35] Le, T., Moreno-Dodson, B., & Bayraktar, N. (2012). Tax capacity and tax effort: Extended cross-country analysis from 1994 to 2009. World Bank.

[36] Lee, Y. & Schmidt, P. (1993). A production frontier model with flexible temporal variation in technical efficiency. The Measurement of Productive Eefficiency: Techniques and Applications. 237-255.

[37] Lotz, J. & Morss, E. (1967). Measuring tax effort in developing countries. Staff Papers. 14(3), 478-499.

[38] Mundlak, Y. (1978). On the pooling of time series and cross section data. Econometrica, 46(1), 69-85.

[39] Meeusen, W. & J. van den Broeck (1977). Efficiency estimation from Cobb–Douglas production functions with composed error. International Economic Review, 18, 435–444.

[40] Ndiaye, M. & Korsu, R. (2014). Tax effort in ECOWAS countries. Regional Economic Integration in West Africa, 137-158.

[41] Pessino, C. & Fenochietto, R. (2010). Determining countries' tax effort. Hacienda Pública Española. 195(4), 65-87.

[42] Pessino, C. & Fenochietto, R. (2013). Understanding countries' tax effort. International Monetary Fund. WP/13/244.

[43] Piculescu, V. & Douglas, H. (2010). Tax toleration and tax compliance: How government affects the propensity of firms to enter the unofficial economy. American Journal of Political Science. 54(1), 18-33.

[44] Pitt, M. & Lee, L. (1981). The measurement and sources of technical inefficiency in the Indonesian weaving industry. Journal of Development Economics. 9(1), 43-64.

[45] Romer, C. & Romer, D. (2014). The incentive effects of marginal tax rates: Evidence from the interwar era. American Economic Journal. 6(3), 242-81.

[46] Schmidt, P. & Sickles, R. (1984). Production frontiers and panel data. Journal of Business & Economic Statistics. 2, 367–74.

[47] Tanzi, V. (1987). Quantitative characteristics of the tax systems of developing countries. In the theory of taxation for developing countries. New York: Oxford University.

[48] Tanzi, V. & Davoodi, H. (1998). Corruption, public investment, and growth. International Monetary Fund. WP/97/139.

[49] Thomas, M. & Trevino, M. (2013). Resource dependence and fiscal effort in Sub-Saharan Africa. International Monetary Fund. WP/13/188.

[50] Tsionas, E. & Kumbhakar, C. (2014). Firm heterogeneity, persistent and transient technical inefficiency: A generalized true random-effects model. Journal of Applied Econometrics. 29(1), 110-132.

[51] Vegh, A. & Vuletin, G. (2015). How is tax policy conducted over the business cycle?. American Economic Journal: Economic Policy. 7(3), 327-70.

[52] Wang, H. J. & Ho, C. W. (2010). Estimating fixed-effect panel stochastic frontier models by model transformation. Journal of Econometrics. 157(2), 286-296.

9 Appendix A

9.1 A1. Evolution of SF models

SF analysis became a popular tool in estimating countries' tax effort since its introduction by Aigner et al. (1977) and Meeusen & van den Broeck (1977). A panel version of the basic setup can be formulated as follows:

$$y_{it} = \beta_0 + \beta' x_{it} + v_{it} - u_{it} \tag{9.1}$$

where $y_i t$ represents the log of tax revenue-to-GDP ratio of country i at time t; $x_i t$ is the vector of variables that affect tax collection; $u_i t$ is the magnitude of inefficiency to achieve a maximum level of tax revenue; $v_i t$ is the standard two-sided error term with a symmetric distribution.

The literature in recent years has been enriched by different methodologies to estimate equation 10.1 . The first generation models (Pitt and Lee, 1981; Schmidt and Sickles, 1984; and Battese and Coelli, 1988) assume that inefficiency is country-specific and time-invariant, which makes the unobservable individual effects the base from which inefficiency is measured. In this case, the model becomes the same as the one-way error component model widely discussed in panel data literature, except that individual effects are made one-sided ($u_i > 0$) with half- or truncated-normal distributions:

$$y_{it} = \beta_0 + \beta' x_{it} + v_{it} - u_i \tag{9.2}$$

The assumption that the inefficiency might be different for different countries but should not change over time simply implies that countries never learn over time. This can be the case in some situations when there is no change in tax administration or if the time period of the panel is particularly short. However, from a practical point of view, it is more plausible to accommodate the notion of productivity improvement over time. This is achieved through the second-generation SF models, which treat tax inefficiency as a function of time (G_t):

$$y_{it} = \beta_0 + \beta' x_{it} + v_{it} - u_{it} \tag{9.3}$$

$$u_{it} = G_t u_i \tag{9.4}$$

Cornwell et al. (1990) suggested to replace $\beta_0 - u_i t$ by $\beta_{it} = \beta_{0i} + \beta_{1i} t + \beta_{2i} t^2$ where β_{0i}, β_{1i}, and β_{2i} are country-specific parameters and t is the time trend. A more parsimonious model was proposed by Lee and Schmidt (1993), in which $u_i t$ is modeled as $\lambda_t u_i$, where λ_t are the coefficients of time dummies to be estimated. Following a different strategy, Battese and Coelli (1992) specified $G(t)$ as $exp^{\eta}(t - T)$, with η being the time decay and T - the terminal period. Kumbhakar (1990) modeled $u_i t$ as $u_i(1 + e^{\gamma_1 t + \gamma_2 t^2})^{-1}$, where depending on the values of γ_1 and γ_2, the deterministic function of time can be concave or convex.

The common feature of these models is that individual heterogeneity is not distinguishable from time-varying inefficiency. As such, these models are misspecified and tend to produce a downward bias in the estimates of tax effort. Greene (2005a; 2005b) approached this issue through a model with unit-specific intercepts, replacing with the following specification:

$$y_{it} = \beta_0 - \alpha_i + \beta' x_{it} + v_{it} - u_{it} \tag{9.5}$$

Another approach to capture country-specific effects was proposed by Battese AND Coelli (1995), which is based on the assumption that these effects matter for mean inefficiency:

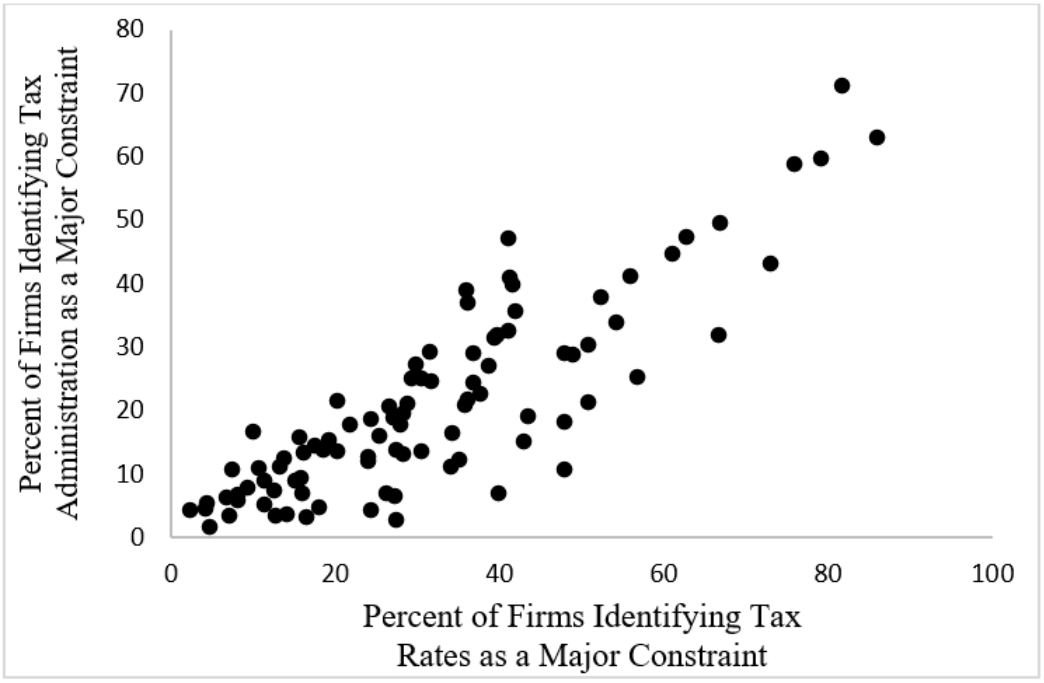
$$y_{it} = \beta_0 + \beta' x_{it} + v_{it} - u_{it} \tag{9.6}$$

$$u_{it} \sim N^{+}(\mu_u, \sigma_u^2) \tag{9.7}$$

$$\mu_i = \mu_0 + \mu_1' w_i \tag{9.8}$$

Although these models can effectively disentangle country-specific fixed effects from time-varying inefficiency, none of them takes into account the possible presence of factors that might have permanent effects on countries' overall tax inefficiency. Therefore, these models are also miss-specified and are likely to produce an upward bias in the estimates of tax effort by confounding persistent inefficiency with country-specific time-invariant effects. For this reason, we employ the Kumbhakar et al. (2014) model, which allows to split the error term into a country's heterogeneity, time-varying inefficiency, persistent inefficiency, and two-sided random shocks.

9.2 A2. Firm Perceptions of Tax Rates and Tax Administration



Source: World Bank Enterprise Surveys 2020

10 Appendix B

10.1 B1. Notes on database construction and main caveats

Acquiring clean and consistent panel data from multiple sources is a difficult task. There were three broad categories of problems that we had to pay a particular attention to – definitional errors, country-specific peculiarities, and editorial omissions.

Definitional errors refer to cases where data sources use different definitions or reporting style for same variables. For example, the top statutory rates may or may not include a national surtax. A related problem is when central and general governments have different tax rates, whereas the reference sources do not differentiate between them. We address these problems by collecting tax rates at the general government level where possible; in cases where such data is not available, we use a dummy variable to control for the differences between central and general governments.

The second group of problems is associated with country-specific peculiarities that require subjective decisions about data selection. One of the main questions is handling the tax rates when countries enact tax laws retroactively or make them effective on dates other than January 1. In our database, we take the rates that were effective during the longest period of a year. For example, if a tax change is enacted in August, we assume it will become effective on January 1 of the next year. An equally important country specific cause for errors is the use of multiple tax schedules for different types of activities and/or subgroups of taxpayers. In such cases, we broke down tax rates into their component parts to understand the largest source of tax revenue across all schedules and chose the rate of the largest schedule.

The last group of problems is related to editorial errors and decisions that are publication specific. In addition to outright reporting errors, this category includes a broad variety of issues such as tardy updating, missing data, breaks in publication series, and changing presentation formats. The incidence of publication specific errors and random editorial changes left crucial breaks in the data that had to be filled in by other reputable sources. One of the main limitations of the constructed database is that for CIT and VAT, we provide only the standard rates, whereas most countries also have reduced rates. Another major drawback of the database is the lack of information on exemptions, deductions, and other similar features of national tax systems, which could give a better understanding of countries' tax policy differences. Lastly, although we have increased the coverage of existing datasets with new observations for uncovered periods and countries, there is still much room for improvement, including collection of effective tax rates.

10.2 B2. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
tax	23.7	10.2	4.3	51.6
pcgdp	14559.4	19620.4	285.3	111968
ava	10.9	10.1	0.03	56.6
tr	85.3	52.2	15.2	437.3
rate	25.9	5.7	10.7	41.7
cgi	0.2	1.0	-1.9	2.3
ei	0.6	0.2	0.1	0.9
gini	38.7	8.9	20.2	65.8

10.3 B3. Data sources

Variable name	Description	Source
lpcgdp	Log of per capita GDP (constant 2010 US$)	World Bank, https://data.worldbank.org/indicator/NY.GDP.PCAP.KD
ltr	Log of trade-to-GDP ratio	World Bank https://data.worldbank.org/indicator/NE.TRD.GNFS.ZS
lava	Log of agricultural sector value added-to-GDP ratio	World Bank https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS
gini	GINI coefficient of income distribution	World Bank https://data.worldbank.org/indicator/SI.POV.GINI
cgi	Unweighted average of the control of corruption, government effectiveness, and rule of law indicators	World Bank https://databank.worldbank.org/source/worldwide-governance-indicators
ei	Education index	UN Human Development Reports https://data.humdata.org/dataset/education-index
ltax	Log of tax revenue-to-GDP ratio	IMF Government Finance Statistics, IMF Country Reports, OECD, EUROSTAT, CEPALSTAT, ADB, AfDB, National Statistical Offices, Ministries of Finance, Tax Authorities, Central Banks, etc.
rate	Unweighted average of top PIT, CIT, and VAT rates	PwC, Deloitte, EY, KPMG, OECD, World Bank, IMF, ADB, CEPAL, Michigan University's World Tax Database, Economist Intelligence Unit, Georgia State University's Tax Database, Fraser Institute, National Tax Authorities, etc.
Informal GDP	Multiple Indicators, Multiple Causes (MIMIC) model-based estimates of informal output	Elgin, C., Kose, M. A., Ohnsorge, F., & Yu, S. (2021). Understanding informality. C.E.P.R. Discussion Paper 16497, Centre for Economic Policy Research, London

11 Appendix C. Estimates of Tax Effort and Tax Capacity

ID	Country	Year	Tax Revenue (% of GDP)	Overall Tax Effort (%)	Time-Varying Tax Effort (%)	Persistent Tax Effort (%)	Tax Capacity (%)
1	Albania	2019	25.1	73.3	95.6	76.7	34.3
2	Argentina	2019	28.6	80.3	96.0	83.6	35.7
3	Armenia	2019	22.7	71.7	95.4	75.2	31.6
4	Australia	2018	29.4	92.1	96.4	95.5	31.9
5	Austria	2019	43.1	91.6	95.4	96.0	47.0
6	Azerbaijan	2019	18.0	56.7	94.5	60.1	31.7
7	Bangladesh	2018	7.9	53.1	92.7	57.3	14.9
8	Barbados	2016	29.6	88.8	95.0	93.5	33.4
9	Belarus	2019	34.6	74.9	87.0	86.1	46.2
10	Belgium	2017	44.6	90.5	95.2	95.0	49.3
11	Belize	2019	31.0	81.7	97.3	84.0	37.9
12	Bhutan	2017	13.3	79.3	95.8	82.8	16.7
13	Bolivia	2019	24.7	77.5	94.6	81.9	31.9
14	Brazil	2019	34.4	86.7	95.7	90.6	39.7
15	Bulgaria	2018	29.7	79.3	93.5	84.8	37.5
16	Burkina Faso	2016	18.8	84.2	95.8	87.9	22.3
17	Cameroon	2016	14.2	65.8	96.4	68.3	21.5
18	Canada	2016	32.7	91.0	95.0	95.8	35.9
19	Cape Verde	2018	21.3	82.2	94.6	87.0	25.9
20	Chile	2019	20.9	87.6	95.1	92.1	23.8
21	Colombia	2017	18.8	75.6	95.1	79.5	24.8
22	Congo	2018	7.4	37.6	94.1	40.0	19.7
23	Costa Rica	2019	22.9	82.7	94.1	87.9	27.7
24	Cotdivoire	2018	13.0	71.3	89.0	80.0	18.2
25	Croatia	2016	37.1	84.9	95.4	89.0	43.7
26	Cyprus	2019	35.3	89.1	96.5	92.4	39.7
27	Czech Republic	2019	35.0	85.0	94.0	90.4	41.1
28	Denmark	2019	46.7	92.7	95.7	96.8	50.4
29	Dominican Republic	2019	13.5	58.4	94.5	61.8	23.2
30	Ecuador	2018	19.5	62.6	97.4	64.2	31.2
31	Egypt	2019	13.8	63.8	89.8	71.1	21.7
32	El Salvador	2019	21.0	72.0	96.5	74.6	29.2
33	Estonia	2019	33.3	87.2	94.8	92.0	38.2
34	Eswatini	2018	17.6	65.1	97.7	66.7	27.1
35	Finland	2019	42.3	92.1	95.2	96.8	46.0
36	France	2019	47.2	91.9	96.5	95.3	51.3
37	Gambia	2016	16.7	85.0	96.6	88.0	19.6
38	Georgia	2019	23.2	74.1	92.4	80.1	31.3
39	Germany	2019	39.0	92.2	96.6	95.4	42.4
40	Ghana	2019	12.3	69.1	95.1	72.6	17.8
41	Greece	2019	39.6	87.3	96.4	90.6	45.3
42	Guatemala	2019	13.1	62.1	90.9	68.3	21.0
43	Guyana	2016	23.6	82.6	95.9	86.2	28.6
44	Honduras	2019	21.7	77.9	96.0	81.2	27.9
45	Hungary	2016	39.2	86.3	95.1	90.7	45.4
46	Iceland	2019	35.1	91.3	95.2	95.9	38.5
47	India	2018	17.0	77.1	94.4	81.7	22.1
48	Indonesia	2018	11.6	55.8	93.5	59.7	20.7
49	Ireland	2019	22.7	88.1	93.2	94.5	25.8

50	Israel	2019	31.1	88.6	95.3	92.9	35.1
51	Italy	2019	42.7	88.7	95.8	92.6	48.1
52	Jamaica	2019	28.6	81.2	96.9	83.8	35.2
53	Japan	2018	31.6	91.0	96.7	94.2	34.7
54	Jordan	2018	23.2	79.4	97.3	81.6	29.2
55	Kazakhstan	2018	17.9	57.9	88.1	65.7	31.0
56	Kenya	2018	16.7	80.7	94.6	85.3	20.7
57	Korea	2019	27.3	86.0	97.0	88.7	31.7
58	Kyrgyzstan	2019	25.8	76.3	94.0	81.2	33.8
59	Laos	2016	12.4	57.5	94.7	60.7	21.6
60	Latvia	2019	31.6	85.0	96.1	88.5	37.2
61	Lebanon	2017	16.1	61.8	94.2	65.6	26.1
62	Lithuania	2019	30.4	84.0	94.5	88.9	36.2
63	Luxembourg	2016	38.1	92.0	95.6	96.3	41.4
64	Madagascar	2016	11.0	77.6	95.0	81.7	14.1
65	Malawi	2016	15.4	83.5	97.2	85.9	18.5
66	Malaysia	2018	12.5	72.6	87.8	82.7	17.2
67	Mali	2018	14.0	78.2	94.2	83.0	17.9
68	Malta	2019	31.4	87.2	95.2	91.6	36.0
69	Mauritius	2017	19.8	80.0	93.8	85.2	24.8
70	Mexico	2018	16.1	63.3	96.8	65.4	25.5
71	Moldova	2019	27.8	72.3	83.4	86.7	38.5
72	Mongolia	2019	28.8	75.3	96.4	78.1	38.2
73	Morocco	2018	27.8	83.5	94.9	88.0	33.3
74	Namibia	2017	30.8	88.4	95.7	92.4	34.9
75	Nepal	2017	21.3	79.4	98.2	80.9	26.8
76	Netherlands	2019	39.8	92.5	96.3	96.1	43.0
77	New Zealand	2016	31.6	91.4	95.1	96.2	34.5
78	Nicaragua	2019	25.9	78.4	97.6	80.3	33.0
79	Niger	2016	14.3	84.0	95.7	87.7	17.0
80	Norway	2019	39.9	92.0	95.1	96.7	43.3
81	Pakistan	2019	11.8	63.8	95.0	67.1	18.5
82	Panama	2019	13.8	66.9	91.0	73.6	20.6
83	Peru	2019	17.0	69.3	93.6	74.0	24.6
84	Philippines	2016	17.0	72.1	94.7	76.1	23.6
85	Poland	2019	35.2	85.5	95.3	89.8	41.1
86	Portugal	2019	36.8	89.4	96.3	92.8	41.2
87	Russia	2019	33.2	78.6	95.9	81.9	42.2
88	Rwanda	2019	17.1	82.6	94.8	87.1	20.8
89	Senegal	2017	16.2	78.6	95.5	82.3	20.6
90	Serbia	2017	35.9	80.4	92.5	87.0	44.7
91	Singapore	2019	13.2	88.3	93.3	94.6	15.0
92	Slovak Republic	2017	32.9	83.7	95.0	88.2	39.3
93	Slovenia	2019	37.6	88.0	95.5	92.1	42.8
94	South Africa	2019	29.0	86.0	96.7	88.9	33.7
95	Spain	2019	35.3	89.8	96.1	93.5	39.3
96	Sri Lanka	2017	12.7	65.9	93.5	70.5	19.3
97	Sweden	2017	44.0	92.0	95.2	96.6	47.8
98	Switzerland	2019	27.4	91.4	95.2	96.0	30.0
99	Tajikistan	2017	21.6	78.6	96.6	81.4	27.5
100	Tanzania	2017	12.1	74.5	96.5	77.2	16.2
101	Thailand	2019	17.2	71.1	92.3	77.0	24.1
102	Togo	2018	14.6	78.1	94.1	83.0	18.7
103	Trinidad and Tobago	2015	29.9	81.3	96.9	83.9	36.8

104	Tunisia	2017	31.2	82.8	96.0	86.3	37.7
105	Turkey	2019	23.1	80.2	94.1	85.2	28.8
106	UK	2019	34.3	85.8	96.2	89.2	39.9
107	US	2019	25.0	90.3	95.4	94.7	27.7
108	Uganda	2018	11.1	73.2	92.8	78.9	15.2
109	Ukraine	2019	32.5	81.8	93.0	87.9	39.7
110	Uruguay	2017	30.9	89.9	97.1	92.6	34.4
111	Uzbekistan	2019	24.0	69.5	78.9	88.1	34.5
112	Venezuela	2013	14.4	54.6	94.5	57.7	26.4
113	Vietnam	2016	17.9	73.2	89.4	81.9	24.5
114	Zambia	2019	16.7	79.5	95.3	83.5	21.0

12 Appendix D. Tax Effort Estimates of Different Specifications

ID	Country	Year	Kumbhakar (2014), with tax rates	Kumbhakar (2014), w/o tax rates	Greene (2005a)	Mundlak (1978)
1	Albania	2019	73.3	73.7	94.4	58.7
2	Argentina	2019	80.3	80.1	93.5	66.4
3	Armenia	2019	71.7	71.6	93.0	55.6
4	Australia	2018	92.1	91.9	94.3	63.1
5	Austria	2019	91.6	91.4	92.2	96.0
6	Azerbaijan	2019	56.7	57.0	91.7	49.3
7	Bangladesh	2018	53.1	53.2	91.0	38.5
8	Barbados	2016	88.8	88.7	90.8	83.4
9	Belarus	2019	74.9	78.4	77.8	98.2
10	Belgium	2017	90.5	90.5	92.0	94.1
11	Belize	2019	81.7	81.8	97.0	75.3
12	Bhutan	2017	79.3	79.2	92.5	67.8
13	Bolivia	2019	77.5	78.3	92.6	77.9
14	Brazil	2019	86.7	86.5	92.1	97.1
15	Bulgaria	2018	79.3	81.0	93.0	78.9
16	Burkina Faso	2016	84.2	84.2	93.9	97.9
17	Cameroon	2016	65.8	65.7	94.8	62.3
18	Canada	2016	91.0	91.3	92.4	77.1
19	Cape Verde	2018	82.2	82.6	91.5	79.8
20	Chile	2019	87.6	87.4	90.5	56.6
21	Colombia	2017	75.6	75.3	91.0	62.1
22	Congo	2018	37.6	37.5	84.3	42.4
23	Costa Rica	2019	82.7	83.5	92.0	67.5
24	Cotdivoire	2018	71.3	71.2	78.8	79.1
25	Croatia	2016	84.9	84.7	92.1	87.5
26	Cyprus	2019	89.1	89.2	95.4	71.9
27	Czech Republic	2019	85.0	85.9	91.7	74.6
28	Denmark	2019	92.7	92.6	93.2	96.5
29	Dominican Republic	2019	58.4	58.5	90.6	44.7
30	Ecuador	2018	62.6	62.5	96.6	47.3
31	Egypt	2019	63.8	65.2	83.9	65.7
32	El Salvador	2019	72.0	72.0	95.4	64.6
33	Estonia	2019	87.2	87.7	91.8	74.5
34	Eswatini	2018	65.1	65.1	97.4	52.0
35	Finland	2019	92.1	92.0	91.8	90.3
36	France	2019	91.9	91.8	94.0	97.8
37	Gambia	2016	85.0	84.9	95.0	84.4
38	Georgia	2019	74.1	75.5	89.6	67.9
39	Germany	2019	92.2	92.0	94.7	76.9
40	Ghana	2019	69.1	69.1	93.3	52.9
41	Greece	2019	87.3	87.1	94.6	78.3
42	Guatemala	2019	62.1	64.3	89.7	53.9
43	Guyana	2016	82.6	82.4	93.5	67.6
44	Honduras	2019	77.9	78.0	94.6	82.4
45	Hungary	2016	86.3	86.7	92.9	88.6
46	Iceland	2019	91.3	91.0	89.1	77.8
47	India	2018	77.1	76.8	90.5	69.0
48	Indonesia	2018	55.8	56.1	89.2	42.3
49	Ireland	2019	88.1	87.9	84.2	63.8

50	Israel	2019	88.6	88.3	91.5	76.1
51	Italy	2019	88.7	88.5	92.9	97.3
52	Jamaica	2019	81.2	81.1	96.1	76.5
53	Japan	2018	91.0	90.9	95.5	65.8
54	Jordan	2018	79.4	79.6	96.9	57.7
55	Kazakhstan	2018	57.9	61.0	82.9	51.4
56	Kenya	2018	80.7	80.6	90.3	71.1
57	Korea	2019	86.0	85.9	96.1	53.8
58	Kyrgyzstan	2019	76.3	77.9	94.8	82.8
59	Laos	2016	57.5	57.9	92.2	52.4
60	Latvia	2019	85.0	84.9	93.9	71.2
61	Lebanon	2017	61.8	62.8	92.4	64.4
62	Lithuania	2019	84.0	85.0	92.6	69.9
63	Luxembourg	2016	92.0	91.8	92.7	96.1
64	Madagascar	2016	77.6	78.0	93.2	71.7
65	Malawi	2016	83.5	83.4	96.4	70.1
66	Malaysia	2018	72.6	74.5	78.6	47.9
67	Mali	2018	78.2	77.8	88.9	76.7
68	Malta	2019	87.2	86.9	91.5	76.1
69	Mauritius	2017	80.0	81.4	93.1	57.5
70	Mexico	2018	63.3	63.2	95.6	43.2
71	Moldova	2019	72.3	78.3	77.3	98.3
72	Mongolia	2019	75.3	75.8	96.4	64.0
73	Morocco	2018	83.5	83.1	90.7	98.0
74	Namibia	2017	88.4	88.2	91.5	98.3
75	Nepal	2017	79.4	79.4	98.2	59.4
76	Netherlands	2019	92.5	92.4	94.3	79.1
77	New Zealand	2016	91.4	91.3	91.4	71.0
78	Nicaragua	2019	78.4	78.3	97.3	76.1
79	Niger	2016	84.0	83.7	93.2	95.0
80	Norway	2019	92.0	92.1	92.7	88.8
81	Pakistan	2019	63.8	64.0	92.7	53.3
82	Panama	2019	66.9	68.3	84.5	50.8
83	Peru	2019	69.3	69.1	86.8	55.6
84	Philippines	2016	72.1	72.1	91.5	65.3
85	Poland	2019	85.5	85.5	91.0	79.6
86	Portugal	2019	89.4	89.3	94.6	80.7
87	Russia	2019	78.6	79.0	94.9	73.9
88	Rwanda	2019	82.6	82.4	92.1	82.1
89	Senegal	2017	78.6	78.3	92.5	80.7
90	Serbia	2017	80.4	82.4	91.9	94.3
91	Singapore	2019	88.3	90.0	91.5	40.0
92	Slovak Republic	2017	83.7	84.0	91.6	75.4
93	Slovenia	2019	88.0	87.7	92.2	78.5
94	South Africa	2019	86.0	85.8	95.2	84.8
95	Spain	2019	89.8	89.6	93.8	78.5
96	Sri Lanka	2017	65.9	66.8	89.7	40.7
97	Sweden	2017	92.0	92.0	91.8	95.3
98	Switzerland	2019	91.4	91.7	93.3	63.8
99	Tajikistan	2017	78.6	78.9	96.3	68.8
100	Tanzania	2017	74.5	74.4	95.3	52.4
101	Thailand	2019	71.1	71.9	87.3	56.4
102	Togo	2018	78.1	77.8	87.7	80.8
103	Trinidad and Tobago	2015	81.3	81.4	96.1	75.7

104	Tunisia	2017	82.8	82.7	94.0	86.6
105	Turkey	2019	80.2	80.1	89.0	67.2
106	UK	2019	85.8	85.6	94.1	72.2
107	US	2019	90.3	90.4	92.6	63.4
108	Uganda	2018	73.2	72.7	85.6	66.8
109	Ukraine	2019	81.8	82.9	88.9	92.3
110	Uruguay	2017	89.9	89.8	96.1	68.8
111	Uzbekistan	2019	69.5	78.3	74.6	97.7
112	Venezuela	2013	54.6	54.4	88.5	53.0
113	Vietnam	2016	73.2	74.2	81.7	81.4
114	Zambia	2019	79.5	79.3	92.7	70.2