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Measuring Untapped Revenue Potential in Developing Countries

Cross-Country Frontier and Panel Data Analysis

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Abstract

Efforts aimed at supporting domestic revenue mobilization in developing countries are often designed and evaluated based on empirical indicators, such as revenue-to-GDP ratios, which capture differences in achieved outcomes across countries. This paper studies a complementary approach to estimate domestic revenue potential that also takes into account differences in countries' fundamental economic structures and constraints associated with different capacities to raise domestic revenues, which are not captured by simple revenue-to-GDP ratios. Specifically, nonparametric data envelopment analysis is applied to estimate domestic revenue potential in a panel of 118 low- and middle-income countries from 2008 to 2019. The analysis addresses the following research questions: (i) How efficient are low-income countries compared with richer countries in mobilizing domestic revenues given the national economic conditions and resources available to each country? (ii) What factors account for the variation in relative domestic revenue mobilization efficiency, that is, the fact that some countries generate more revenues than other countries with comparable economic structures? The paper discusses the policy implications of the findings and demonstrates how the proposed method can be used to identify countries that are already performing close to their limit and those that still feature large untapped potential for further increasing revenues (and thus likely higher marginal benefits to external support for domestic revenue mobilization). Finally, the paper provides insights on the extent to which existing international support for domestic revenue mobilization is targeted at countries with larger untapped revenue potential.

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Measuring Untapped Revenue Potential in Developing Countries: Cross-Country Frontier and Panel Data Analysis

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I. Introduction

For many policy makers in developing countries, improving the effectiveness of domestic revenue mobilization (DRM)—the generation of government revenues from domestic activities—has become a key policy objective to guarantee the financing of the basic functions of their state and provide essential public and infrastructure services (World Bank and IMF 2015; IMF 2018). Moreover, following the 2015 deadline for the attainment of the Millennium Development Goals, there has been a major shift in the importance assigned to DRM by the international development community, originating from the now widely accepted view that official development assistance is unlikely to be adequate to achieve the newly articulated and more ambitious Sustainable Development Goals (SDGs).[1] In this context, it is often argued that governments in developing countries should generate at least 15 percent of GDP in government revenues to finance their development goals in a sustainable and equitable manner (IMF 2018). However, despite the prominence of this goal on the international development agenda, little progress in raising revenue levels has been made. On average, revenue-to-GDP ratios over the past decade in low-income countries, and various countries in Sub-Saharan Africa and Latin America declined (World Bank 2021).[2]

This paper provides a fresh perspective on the efforts performed to raise revenue levels in developing countries by comparing not only the absolute outcomes achieved (such as the achieved revenue-to-GDP ratios), as often done in the literature, but also taking into account differences in countries' fundamental economic structures and constraints that are associated with different capacities to raise domestic revenues. Specifically, we address the following three questions: (i) 'How efficient are low-income countries compared to countries belonging to higher income groups in mobilizing domestic revenue, given the national economic conditions and resources available to each country?'; (ii) 'What factors account for the variation in relative efficiency in DRM across countries, i.e., what factors can explain why some countries generate more revenues than other countries with comparable economic structures?'; (iii) 'Does existing international support for DRM target those countries with higher untapped revenue potential?'

The first question is answered using a non-parametric frontier analysis approach. Specifically, data envelopment analysis (DEA) is used to first estimate the empirical production possibility frontier for government revenues as a function of a set of indicators capturing differences in countries' domestic economic structures and constraints, and then rate countries' performance relative to other countries facing similar economic conditions. Question (ii) is answered based on a panel regression framework using the efficiency estimates obtained from the frontier analysis as the outcome variable and relating them to a set of explanatory variables, including institutional and societal factors as well as quality of tax policy (among others). Question (iii) is answered based on additional evidence from panel regressions focusing on projects aimed at improving DRM financed by the World Bank Group.

Results from the frontier analysis show that countries' relative efficiencies in mobilizing domestic revenue given their economic structures does not exhibit the same strongly positive correlation with income levels as typically observed for achieved revenue-to-GDP ratios. In particular, we find that

[1] The realization that achieving the SDGs would require a more concerted effort on DRM is reflected in several influential reports and statements originating from the international development community, including *Financing for Development Post-2015* (World Bank 2013), *Sustainable Development Goals* (United Nations 2015a), *From Billions to Trillions* (AfDB et al. 2015), and *Addis Ababa Action Agenda* (United Nations 2015b). Effective DRM is also directly relevant to at least two of the 17 SDGs, namely SDG 10 (reducing inequality between and within countries) and SDG 17 (strengthen the means of implementation and revitalize global partnership for sustainable development), with the latter under subsection "Finance" (point 17.1) referencing "Strengthen[ing] domestic resource mobilization, including through international support to developing countries, to improve domestic capacity for tax and other revenue collection."

[2] Factors commonly used to explain why revenue collection lags behind government needs in many low-income countries include narrow tax bases, large informal sectors, and the difficult political economy of tax reform.

countries with low relative efficiency (and thus large untapped potential to further increase revenues) are spread across all income groups and geographical world regions; contrary to some perceptions, it is not the exclusive province of low-income countries. Importantly, this suggests that just looking at the absolute revenue-to-GDP ratio might be misleading for drawing conclusions about how much more revenues a country should aim to raise given its current economic structure.

We also find that relative efficiency in DRM increased in most countries and regions between 2008 and 2019. Moreover, the strongest increase in average relative efficiency was achieved by the group of low-income countries, indicating that many poor countries were able to improve their revenue mobilization performance relative to other countries and catch up with the frontier.

The results obtained from the post-DEA regression analysis indicate that among various potential determinants of efficiency in DRM, the level of technological readiness appears to be the factor that is most robustly correlated with higher efficiency. The panel structure of our data allows us to control for both observable and unobservable, time-invariant country characteristics (e.g., geographical features, history, cultural traits) through the inclusion of country-fixed effects, but we are aware that the observational nature of the underlying data limits our ability to identify causal relationships. We therefore interpret the results as suggestive evidence of the factors that are potentially driving the observed differences in efficiency and argue that these insights can inform further investigation into the underlying root causes of inefficiency in DRM. We also provide insights on the extent to which existing international support for DRM tends to be targeted at countries with larger untapped revenue potential (and thus likely higher marginal benefits to such projects).

Overall, this paper contributes to the literature mainly in the following three ways. First, we provide new evidence on relative efficiency in domestic revenue mobilization across countries based on the most updated and comprehensive data set, covering 118 low- and middle- income countries in the period 2008 to 2019. Second, we identify factors that are associated with higher efficiency in DRM, broadly supporting existing literature. Third, we find support for the conclusion that even countries with low nominal revenue-to-GDP ratios can exhibit high efficiency in revenue mobilization given the limitations of their economic structure. The main policy implication is that revenue-to-GDP ratios—which are commonly used to gauge DRM for policy monitoring and analysis purposes—are a poor indicator of a country's efficiency with which it is able to convert its tax base into revenue. This is important because efficiency-based analysis presented in this paper provides more granular and accurate information needed in evaluating constraints to DRM, and in setting realistic revenue mobilization targets in the context of annual budgets and revenue reforms. Therefore, we argue that such an efficiency approach is useful to inform governments' and international development partners' efforts towards monitoring, evaluating, and policy making efforts towards DRM.

The remainder of the paper is structured as follows. Section II discusses related literature and explains how our analysis both builds on and expands on findings in the existing literature on the determinants of government revenue potential. Section III presents the empirical strategy and describes how data envelopment analysis is used to estimate countries' performance in mobilizing domestic revenues relative to their economic revenue potential. Section IV describes the variables and data sources underlying the empirical analysis. Section V presents the results. Section VI concludes.

II. Related Literature

The analysis presented in this paper relates to three strands of literature. First, we contribute to the literature on revenue potential and revenue effort. Due to limited data availability, existing studies in this literature tend to focus on relatively small samples of countries for which sufficient data on taxation and revenue outcomes were available in the past, typically comprising only few low-income countries. For example, the study by Piancastelli (2001) analyzes a sample of 75 countries in the period 1985-1995. Le et al. (2008) study a sample of 104 countries (including both developing and developed countries)

during the period 1994-2003, Le et al. (2012) study 110 countries during the period 1994-2009, and Khwaja and Iyer (2014) study 61 countries during the period 2000-2010. We contribute to this literature by providing new evidence on relative efficiency in DRM across countries based on a recently launched, comprehensive data set covering 182 countries (including 118 low- and middle- income countries which we focus on as our core sample) in the period 2008 to 2019.[3] As such, our analysis may be considered as providing an updated view of past analyses of revenue potential across countries based on the largest data set available to date.

In addition, by using non-parametric data envelopment analysis to estimate countries' domestic revenue potential, we add a new approach to the range of methodologies used in the existing literature on revenue potential. Using non-parametric frontier analysis to evaluate countries' performance in DRM offers several benefits compared to alternative methods for performance assessments, such as regression-based approaches. In particular, DEA has the advantage that it involves fewer assumptions about the structure of the data than parametric methods (e.g., regression analysis). Consequently, the results generated by DEA tend to be easier to interpret and are not subject to the same econometric challenges that regression-based methods typically face.[4] Moreover, DEA estimates efficiency scores for a given unit (e.g., country) based on the performance of a subset of efficient units in the sample with similar input factors than the considered unit. This differs from the estimates obtained from regression-based approaches, which rely on comparisons relative to the average performance across all units in the sample. If the observed units are heterogeneous—as is clearly the case when analyzing countries from different parts of the world with different sizes and stages of development—then an important advantage of DEA is that the estimates for any given country are not determined by other countries with fundamentally different characteristics and prospects, but only by those countries that feature comparable economic structures.

Second, we add to the growing body of literature that uses DEA for analyzing efficiency in macroeconomic contexts. Various existing studies in this literature apply DEA to assess efficiency of government expenditure (Gupta and Verhoeven 2001; Afonso et al. 2005; Herrera and Pang 2005) or public spending on education (Clements 2002). In contrast, we focus on efficiency in the financing of public spending through domestic revenue mobilization. Other topics in economics which have been studied by applying DEA include agricultural productivity (Latruffe et al. 2004), efficiency in schools (Ray 1991; Bogetić and Chattopadyay 1995), national transportation and commerce (Rashidi and Cullinane 2019; Wang et al. 2020), and regional economic integration (Naeher 2015; Naeher and Narayanan 2020). In a recent study on private capital mobilization, Naeher and Narayanan (2021) perform a similar analysis as presented here but focusing on countries' ability to attract (foreign) private capital flows such as foreign direct investment and portfolio equity investment.

Finally, our analysis relates to the theoretical and empirical literature on the determinants of government revenue potential. We contribute to this literature new evidence on factors that are associated with higher efficiency in DRM (see the performed post-DEA panel regression analysis). In addition, our analysis builds on the findings presented in this literature to inform our selection of variables included as input factors in the DEA. Among the many variables that have been considered in this literature, four economic factors are commonly identified as important determinants of revenue potential (see the survey in Gupta 2007): (i) per-capita income levels, (ii) sectoral composition of output,

[3] Specifically, the analysis is based on data from the UNU-WIDER Government Revenue Dataset which was launched in 2014 and combines government revenue data from various sources (see Section IV for more details).

[4] DEA and regression analysis represent alternative approaches to performance assessments which each feature their own benefits and weaknesses (for a detailed discussion, we refer to Thanassoulis 1993; Sickles and Zelenyuk 2019). Regression analysis features more tools to identify causal relationships in observational data. However, it also involves stronger assumptions on the structure of the underlying data than non-parametric methods, making the results sensitive to econometric challenges such as endogeneity and omitted variable bias.

(iii) international trade relative to GDP, and (iv) demographic composition as captured by the age dependency ratio.

Per-capita income as a proxy of the level of development of a country's economy is positively related to revenue potential. This is so because both the capacity to collect and the ability and willingness of taxpayers to pay taxes tend to increase with higher development (Gupta 2007; Khwaja and Iyer 2014). In addition, higher levels of income are typically associated with greater demand for public goods and services (Le et al. 2008). This, in turn, may strengthen "demand" for higher revenues to finance public services. These views are supported by a large body of empirical evidence of a strong positive relationship between revenues and GDP per capita, including in developing countries (Stotsky and Wolde-Mariam 1997; Ghura 1998; Piancastelli 2001; Le et al. 2008). In our data set, there is a clear positive correlation between revenues and GDP per capita that is consistent with these findings (see Figure 2 in Section III).

The sectoral composition of output matters for revenue mobilization because certain sectors of the economy are easier to tax than others. In particular, the share of agriculture in GDP is considered to be negatively related to revenue potential, especially if it is dominated by a large number of subsistence farmers which are considered a "hard-to-tax" group (Gupta 2007; Le et al. 2008).[5] In accordance with this view, many empirical studies find that the share of agriculture in GDP is significantly negatively related to revenues (Leuthold 1991; Tanzi 1992; Piancastelli 2001; Le et al. 2012) or, alternatively, that the share of industry and service is positively related to revenues (Khwaja and Iyer 2014). As shown in Figure 2, there is a negative correlation between revenues and the share of agriculture in GDP in our data that is consistent with these findings.

In addition, more international trade relative to GDP is commonly considered to be an important determinant of revenue potential. Since taxes from imports and exports represent important sources of revenues that are relatively easy to collect even with weaker tax administrations, trade openness is considered to be positively related to tax base and revenue potential (Gupta 2007; Aizenman and Jinjarak 2009; Khwaja and Iyer 2014).[6] This view is supported by empirical evidence (Leuthold 1991; Tanzi 1992; Gupta 2007; Le et al. 2012) and also consistent with the positive correlation between revenues and trade openness observed in our data (see Figure 2).

Finally, a higher age dependency ratio[7] tends to reduce countries' revenue potential as it indicates a lower share of productive population and, hence, a narrower tax base. In accordance with this view, empirical evidence shows that a higher age dependency ratio is associated with lower levels of revenue mobilization, including in developing countries (Le et al. 2012; Khwaja and Iyer 2014). The correlation in our data shown in Figure 2 (Section III) is consistent with these findings.

III. Empirical Strategy

The analysis uses non-parametric frontier analysis (DEA) to quantify efficiency in domestic revenue collection at the country level. The obtained efficiency scores are then used as the dependent variable in a regression framework based on country panel data.

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[5] Countries with a larger share of agriculture in GDP also tend to have lower demand for public goods and services since most high-value public services are based in cities (Tanzi 1992; Le et al. 2008).

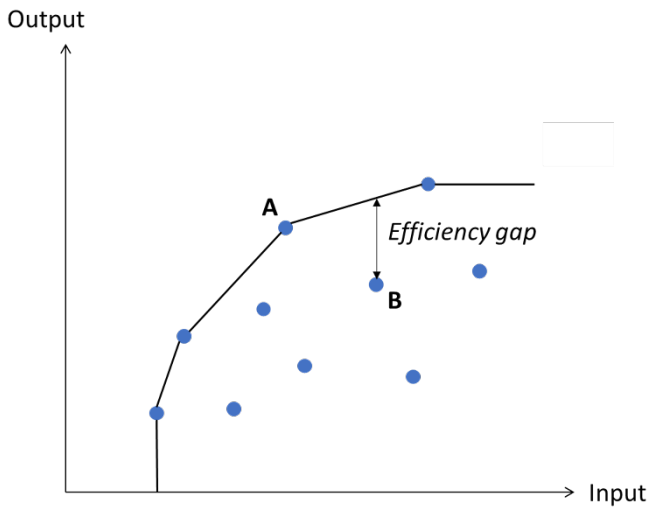
[6] Note that, in general, higher trade openness may have an ambiguous effect on revenue mobilization. On the one hand, trade liberalization often occurs through reductions in tariffs which imply losses in tariff revenue. On the other hand, given that higher trade openness facilitates economic growth, eventually more revenues can be collected in open economies. Many authors argue that the second effect dominates and trade openness has a positive effect on fiscal revenue (Rodrik 1998; Le et al. 2012). In addition, revenue may also increase if trade liberalization occurs mainly through tariffication of quotas, eliminations of exemptions, reduction in tariff peaks, or improvements in customs procedure (Keen and Simone 2004).

[7] The age dependency ratio is the number of people of non-working age (zero to 14 and over 65), compared with the number of those of working age (15 to 64).

A. Data Envelopment Analysis

DEA is a well-established, nonparametric method for estimating production possibility frontiers based on linear programming (see Charnes, Cooper and Rhodes 1978; Coelli et al. 2005). This method is especially suitable for analyzing efficiency represented by the distance of a pool of observations from the maximum performing units of observation, i.e., "the efficiency frontier". The basic logic behind DEA can be described as follows. Suppose there exists a convex production possibility set for a given set of outputs and a given set of inputs. As illustrated in Figure 1, DEA calculates the frontier as the maximum attainable level of output for any level of input. Production units located on the frontier (e.g., unit A) are considered to be efficient. In contrast, unit B in Figure 1 is considered to be inefficient, because other units (including unit A) generate more output using less or an equal amount of inputs. The distance ("efficiency gap") between an observed input-output combination and the estimated frontier is used to quantify each unit's efficiency score.

Figure 1. Illustration of Data Envelopment Analysis



Source: Authors' illustration.

In the context of revenue mobilization, the results obtained from DEA can be interpreted in a straightforward way based on the following intuition. DEA first calculates the empirical production frontier for revenue mobilization (the 'output') given a set of relevant input factors, i.e., countries' fundamental economic characteristics that influence revenue potential (as specified below). The frontier is defined as the maximum possible level of revenue for a given level of input. The revenue mobilization performance of a country is then measured as the distance to the estimated frontier. In essence, this provides an estimate of the revenue each country should be able to achieve based on what other countries with similar economic characteristics are achieving. Thus, countries that generate more revenues as a percentage of GDP with the same economic characteristics (or countries that generate the same level of revenue with less favorable economic characteristics) are considered to be more efficient than others.

The efficiency scores obtained from DEA are normalized to range between 0 and 1, where units located on the frontier are assigned the maximum value of one. Scores close to one thus indicate that a country is achieving relatively high levels of revenue given its economic conditions, i.e., the country is "efficient" in generating revenue. Efficiency scores well below one indicate inefficiency or "untapped potential". For example, an efficiency score of 0.5 indicates that a country is currently only generating

half of the revenue that it should theoretically be able to. In line with this intuition, we define *untapped revenue potential* as the gap between a country's observed level of revenue and the theoretically possible level according to the estimated frontier, quantified as one minus the country's DEA efficiency score.

The variables included as input factors in the DEA are selected based on the theoretical and empirical literature on the determinants of government revenue potential reviewed in Section II (see also the survey by Gupta 2007). Specifically, we focus on the following four economic factors: (i) per-capita income levels, (ii) sectoral composition of output, (iii) international trade relative to GDP, and (iv) the age dependency ratio (capturing a country's demographic composition). There are, of course, many other factors potentially influencing revenue potential, including institutional and societal factors and tax policies. Since our analysis is concerned with estimating countries' *economic* revenue potential (rather than, e.g., their *legal* revenue potential as in Khwaja and Iyer 2014), we focus on those fundamental economic characteristics that have been found to be most relevant according to the empirical literature.[8] The roles of other factors, including institutional and societal variables, quality of tax policy, and level of available technology, are considered as part of the post-DEA regression analysis.

To make the frontier analysis tractable, we aggregate the four economic input factors into a single composite measure, the 'DEA input index'. One can think about this index as a proxy of the fundamental economic structure and economic strength that determine a country's revenue potential. For each considered input factor, we identify an empirical indicator (see Table 2 in Section III) and then aggregate all indicators in the following way. First, we calculate mean values for the three periods 2008-2011, 2012-2015, and 2016-2019 at the country level. The purpose of the first two periods is to serve as the benchmark for the main period of interest, which is 2016-2019. Also, economic structure and revenue potentials are slow-moving variables, so it is important to capture changes over longer periods. Thanks to this, and to minimize potential biases from missing data, we can impute missing values for a given 4-year period with the value of the nearest period available (if any). We drop countries with insufficient information for the period 2016-2019, i.e., countries without data on revenue and at least one of the indicators in the DEA input index.[9] Next, we normalize all indicators so that higher values correspond to more favorable conditions for revenue mobilization. This is achieved by taking the inverse of the original values for those indicators that are negatively associated with revenue (i.e., share of agriculture in GDP and age dependency ratio; see Figure 2). To normalize the ranges of values across indicators, we apply min-max rescaling, which ensures that all indicators range between 0 and 1 (since this normalization method is very sensitive to outliers, we winsorize all variables at the 98-percent level beforehand).[10] Finally, we aggregate the four normalized indicators into a single composite measure using an equal weighting scheme (alternative weighting schemes are explored as part of the robustness checks; see Appendix A).[11]

In estimating countries' (untapped) revenue potential, we consider two different frontiers. The first frontier, representing our main specification, is estimated based on low- and middle-income countries (subject to data availability), i.e., high-income countries (HICs) are excluded. By excluding HICs,

[8] Khwaja and Iyer (2014) distinguish between a country's economic revenue potential (based on economic structure and strength) and legal revenue potential (based on tax policy variables). While we consider tax policy variables in the post-DEA regression analysis, the frontier analysis itself focuses exclusively on quantifying economic revenue potential. We acknowledge that, from a general equilibrium viewpoint, this is a simplification as the economic structure is not fully independent of tax policy and, conversely, influences the choice of tax instruments and tax structure.

[9] In cases where data are available only for a subset of the indicators used in the DEA input index, the index is computed based on the available indicators.

[10] This approach effectively caps the two or three most extreme values in each variable by setting them equal to the third or fourth largest value, which ensures that the aggregated values are not driven by a few outliers.

[11] Using equal weights facilitates the interpretation of the results and is in line with many other studies that construct composite indices, including both popular indices such as the Human Development Index as well as indices constructed with the particular purpose of using them in DEA (e.g., Afonso et al. 2005; Herrera and Pang 2005).

the obtained efficiency scores provide a more adequate picture of revenue mobilization potential in developing countries. In addition, we estimate a second frontier based exclusively on the set of low-income countries (LICs) in our data set. The purpose of this second frontier is to provide an upper bound estimate of the efficiency scores for LICs. In particular, the second frontier assumes that LICs can generate the same revenue levels as other LICs with comparable economic conditions (as captured by the DEA input index) but not necessarily the revenue levels achieved by lower-middle income countries (LMICs) and upper-middle income countries (UMICs) with such conditions, thus accounting for the special challenges to revenue mobilization facing many LICs.

It should be noted that the results derived from DEA are subject to the following limitations. Given that DEA is a non-parametric method of estimating efficiency scores, the derived results are of a descriptive nature and should not be interpreted as identifying causal links between the included variables. Instead, the performed DEA compares revenues among a set of countries at a given time and identifies those countries that, relative to others with similar economic conditions, are currently performing below the level which they should potentially be able to. This also implies that the analysis is based exclusively on current conditions and thus not designed to provide forecasts of revenues under possible scenarios of future changes in economic or other conditions. Finally, it should be noted that the obtained results relate only to the considered outcome in government revenues relative to GDP and do not provide direct implications for potential welfare gains (or losses) associated with increased revenues.

B. Panel Regression Analysis

To investigate the factors that potentially account for variation in efficiency scores across countries, we estimate a panel regression framework using the obtained DEA efficiency scores as dependent variable. The purpose of this analysis is to examine which factors are associated with higher or lower relative performance in achieving domestic revenue potential (as captured by the DEA scores), i.e., why some countries generate more revenues than other countries with comparable domestic economic structures. While the panel structure of our data allows us to control for both observable and unobservable, time-invariant country characteristics (e.g., geographical features, history, cultural traits) through the inclusion of country-fixed effects, we stress that the observational nature of the underlying data clearly limits our ability to identify causal relationships. The (time-variant) factors included as regressors are selected to capture countries' quality of tax policy, size of the informal sector, level of technological readiness, natural resources, control of corruption, and social trust, since these factors are commonly argued to play a role in determining countries' ability to convert their tax base into revenues.

In addition, we estimate a second set of regressions where the DEA efficiency scores enter as an independent variable to potentially explain the allocation of international development cooperation efforts aimed at improving revenue mobilization (focusing on projects related to DRM financed by the World Bank Group) across countries with different performances in DRM efficiency. The purpose behind this specification is to obtain insights on the extent to which these efforts tend to be targeted at countries with large untapped revenue potential (and thus likely higher marginal benefits to such projects).

IV. Data

All data used in this study are publicly available from the sources described in Table 1. The table provides a list of the variables and respective data sources used in the analysis, grouped into four categories. Panel A describes our main outcome variable, government revenue (excluding grants) as a percentage of

GDP, which is based on data from the UNU-WIDER Government Revenue Dataset (GRD), 2020.[12] Panel B in Table 1 describes the four indicators used in the construction of the DEA input index. Panel C lists additional factors which are included in the post-DEA regression analysis (pairwise correlations between these variables are reported in Table A1 in the appendix).

The core sample which is used in the frontier analysis consists of 118 countries, comprising 25 LICs, 45 LMICs, and 48 UMICs. In addition, we have data on 58 HICs as well as 6 countries with revenues above 50 percent of GDP which we exclude as outliers in the frontier analysis, so that the maximum sample size amounts to 182 countries. For most countries, data for the variables listed in Panels A and B of Table 1 are available annually for the years 2008 to 2019. To limit the role of temporary fluctuations and measurement error, most of the analysis is based on values for 4-year periods, which we construct as the mean values of the years 2008-2011, 2012-2015, and 2016-2019 for each country (for ease of exposition, all tables and figures refer to these time periods, even if the data for a particular indicator are only available for a subset of these years).

Table 1. List of Variables and Data Sources

Indicator	Description	Source
Panel A: Revenues (DEA output)		
Revenue	Government revenue, excluding grants (% of GDP)	ICTD/UNU-WIDER, Government Revenue Dataset
Panel B: Economic fundamentals (DEA input index)		
Per-capita income	GDP per capita, PPP (constant 2017 international $)	World Bank
Share of agriculture in GDP	Agriculture, forestry, and fishing, value added (% of GDP)	World Bank
Trade openness	Trade (% of GDP): Sum of exports and imports of goods and services measured as a share of gross domestic product	World Bank
Age dependency ratio	Age dependency ratio (% of working-age population): Ratio of dependents (people younger than 15 or older than 64) to the working-age population (ages 15-64)	World Bank
Panel C: Other factors (used in regression analysis)		
Control of corruption	Score on 'Control of corruption' indicator (values from -2.5=weak to +2.5=good governance)	Worldwide Governance Indicators
Informal sector	Informal employment (% of total non-agricultural employment); harmonized series	International Labour Organization
Natural resources	Total natural resources rents (% of GDP): Sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents	World Bank
Tax policy	Score on 'Efficiency of revenue mobilization' indicator (values from 1=low to 6=high efficiency)	World Bank, Country Policy and Institutional Assessment
Technological readiness	Score on 'Technological Readiness Index (9th Pillar)' (values from 1=low to 7=high readiness)	World Economic Forum, Global Competitiveness Report

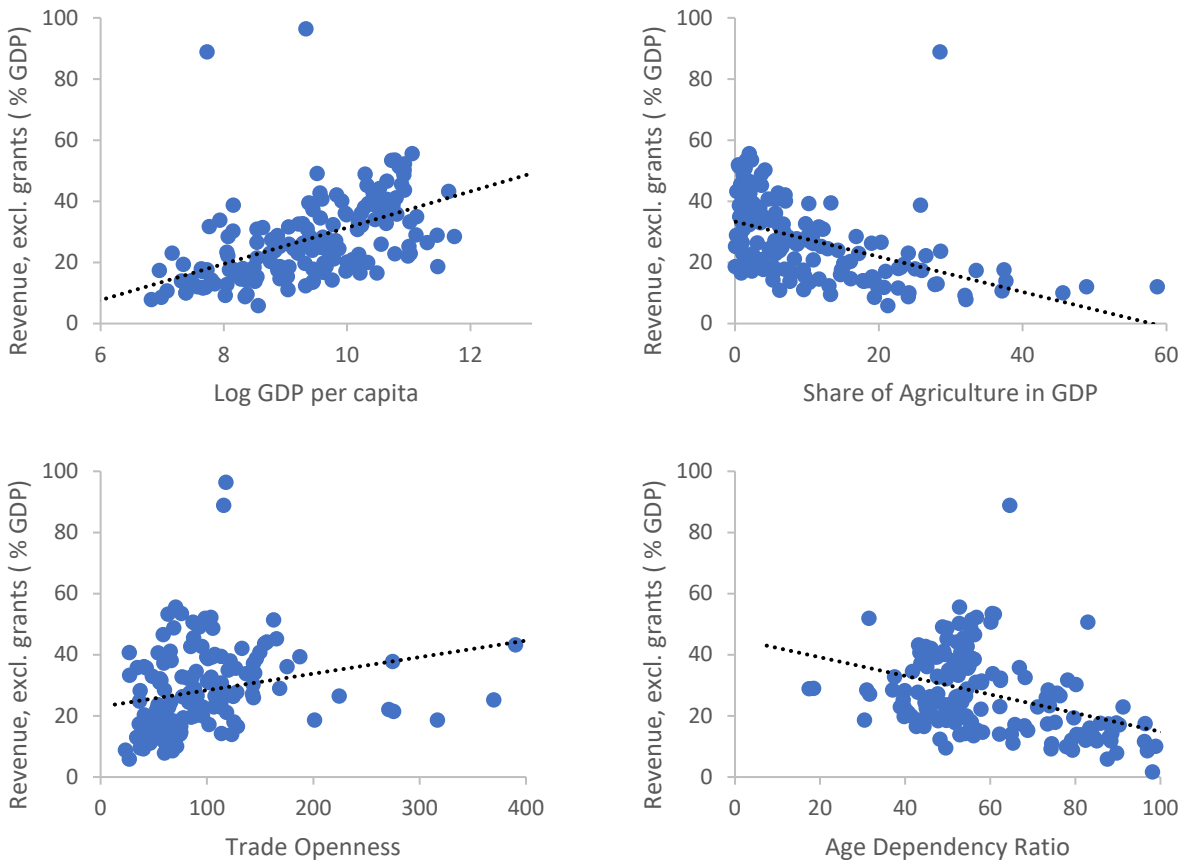
[12] The GRD was launched in 2014 and combines government revenue data from various sources, including OECD Revenue Statistics, IMF Government Finance Statistics, and CEPALSTAT (revenue statistics in Latin America). It is arguably the most updated and comprehensive cross-country data set on government revenues available (for more detailed information on the construction and scope of the data set, see Prichard et al. 2014; McNabb 2017).

Table 1. List of Variables and Data Sources

Indicator	Description	Source
Social trust	Percentage of respondents stating that, "Generally speaking, most people can be trusted"; survey waves mapped to 4-year periods as follows: survey 2005-2009 (period 1), survey 2010-2014 (period 2), survey 2017-2019 (period 3)	World Values Survey
WBG engagement	WBG own commitment (% of GDP): Total amount committed for projects related to domestic resource mobilization by approval fiscal year as a share of the recipient country's GDP (scaled by factor 1,000 for better readability)	World Bank (public and internal data) as reported in Table A3 in the appendix

Source: Authors' compilation.

Figure 2. Economic Fundamentals and Revenues, 2016-2019



Notes: The sample consists of 182 countries. The dotted line represents the result of a bivariate linear regression of revenue on the indicator shown on the x-axis (see Table A2 in the appendix).
Source: Authors' analysis based on the variables and data sources described in Table 1.

The indicator of technological readiness (see Table 1, Panel D) is countries' score on the "Technological Readiness Index" from the World Economic Forum's Global Competitiveness Report.

Since this variable turns out to be quite important, a word on it is in order. Values range from 1 (low) to 7 (high technological readiness) and measure "the agility with which an economy adopts existing technologies to enhance the productivity of its industries, with specific emphasis on its capacity to fully leverage information and communication technologies (ICTs) in daily activities and production processes for increased efficiency and enabling innovation for competitiveness. Whether the technology used has or has not been developed within national borders is irrelevant for its ability to enhance productivity. The central point is that the firms operating in the country need to have access to advanced products and blueprints and the ability to absorb and use them."[13]

As shown in Figure 2, the correlations in our sample between the DEA output variable (revenue) and the variables included in the DEA input index are consistent with the past empirical evidence discussed in Section II. Specifically, there is a clear positive correlation between revenues and per-capita income levels as well as trade openness in our data, while revenues are negatively correlated with the share of agriculture in GDP and with the age dependency ratio (the same holds for earlier periods; see Figures A1 and A2 as well as Table A2 in the appendix). When constructing the DEA input index, we thus use the inverse of the share of agriculture in GDP and the inverse of the age dependency ratio, so that higher values of the input index correspond to more favorable conditions for revenue mobilization.

V. Results

A. Comparison of Revenues across Income Groups and Regions

Figure 3 shows the evolution of revenues over time for each income group (Panel A) and geographical region (Panel B). According to these data, LICs generated considerably less revenues relative to GDP than countries belonging to higher income groups in every year since 1980. Between 1980 and the Global Financial Crisis in 2007, revenues in LMICs and UMICs increased faster than those in HICs, indicating that revenue levels in these two income groups were catching up to the levels in HICs. In contrast, revenues in LICs stagnated, on average, so that the gap between LICs and HICs in 2017 is of the same magnitude as in 1980.

Revenues also vary widely by geographical region. As shown in Panel B of Figure 3, since 1980 the countries in South Asia (SA) and Sub-Saharan Africa (SSA) have generated the lowest levels of revenue, ranging between 10 and 20 percent revenue as a share of GDP, on average. East Asia & Pacific (EAP) and Latin America & Caribbean (LAC) generated between 20 and 30 percent revenue as a share of GDP, on average, in most years. The highest levels of revenues are generated in Europe & Central Asia (ECA) and Middle East & North Africa (MENA), ranging between 30 and 40 percent as a share of GDP in most years since 1980.

Figure 4 provides additional insights on the ranges of revenue levels in each income group for the period 2016-2019. Except for one outlier (South Sudan), revenue levels in LICs show moderate variation, ranging from 2 percent of GDP (Somalia) to 23 percent of GDP (Mozambique). Within the other three income groups, revenue levels are much more dispersed, with a range of up to 39 percentage points in UMICs and HICs.[14]

According to these results, and in view of the IMF's (2018) recommendation for LICs of a minimum of 15 percent of GDP in government revenues in order to ensure the functioning of basic elements of a state, and that 16 out of 26 LICs in our data are below this threshold (only 4 of the 26 LICs have revenues above 20 percent of GDP), it seems plausible to assume that increasing government revenues is a

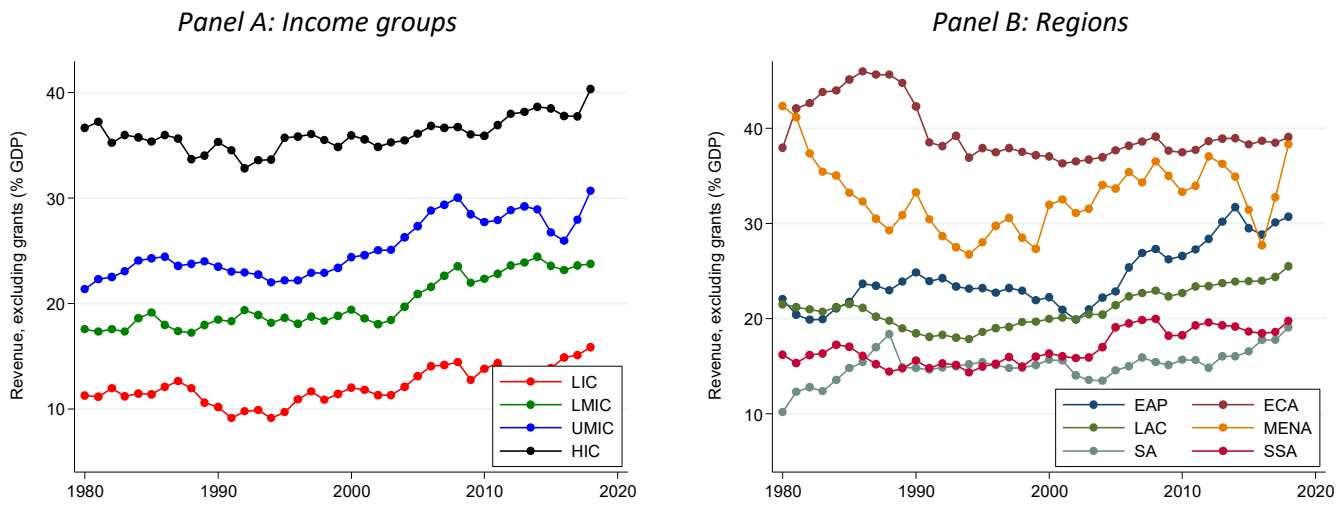
[13] See the documentation of the Global Competitiveness Report available at http://reports.weforum.org/global-competitiveness-index-2017-2018 (last accessed in February 2021).

[14] Standard deviations of revenue levels within each income group are as follows: LIC (8.68), LMIC (12.72), UMIC (10.94), and HIC (13.27).

desirable outcome in most LICs. Of course, it is difficult to determine what the optimal level of revenue should be in each country, and there is no guarantee that more revenues will automatically lead to productive public expenditures and better development outcomes. Nevertheless, given that the governments in many LICs are often unable to meet even the most basic development needs, it seems very unlikely that increasing government revenues (including by raising tax-to-GDP ratios) would not be desirable in most LICs.

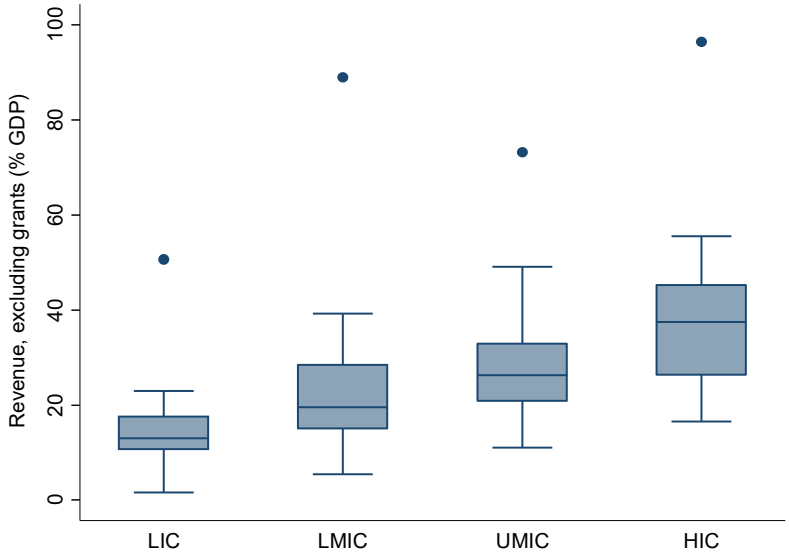
At the same time, it is important to note that countries with lower income levels also tend to feature less favorable economic conditions for generating government revenues. Figure 5 shows the average value of the DEA input index for each income group in 2016-2019 together with the disaggregated values for each of the four included input factors. Unsurprisingly, countries with lower income levels tend to feature smaller values of the DEA input index, indicating less favorable conditions for revenue mobilization. Simple averages of the DEA input index for income groups are: LIC (0.09), LMIC (0.15), UMIC (0.21), and HIC (0.40). Individual economies with the highest values of the DEA input index include Singapore (1.00), Luxembourg (0.90), and Hong Kong SAR, China (0.83). Countries featuring the lowest values of the DEA input index include Niger (0.02), Uganda (0.03), and Tanzania (0.04).

Figure 3. Revenues Over Time, by Income Group and Region



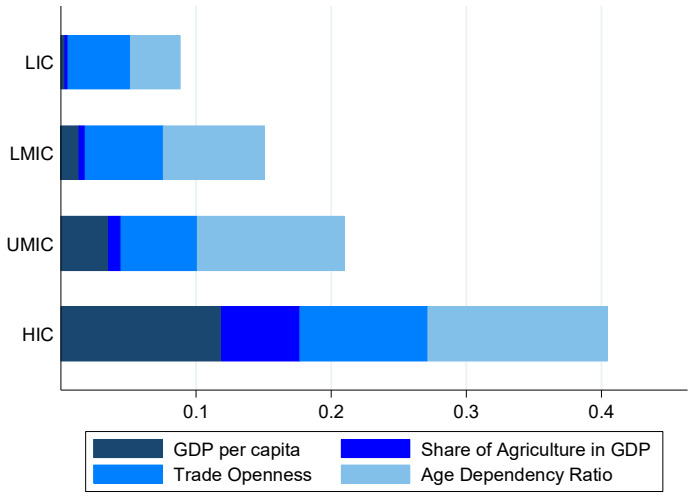
Notes: The sample consists of 182 countries.
Source: Authors' analysis based on the variables and data sources described in Section III.

Figure 4. Ranges of Revenues (incl. Median) by Income Group, 2016-2019



Notes: The sample consists of 182 countries. The boxes represent the range of values between the 25th and 75th percentile (including the median), the ends of the whiskers represent the lower and upper adjacent value, and the dots represent outliers (see Tukey, 1977).
Source: Authors' analysis based on the variables and data sources described in Section III.

Figure 5. DEA Input Index (Measure of the Economic Strength and Capacity to Raise Revenues) by Income Group, 2016-2019



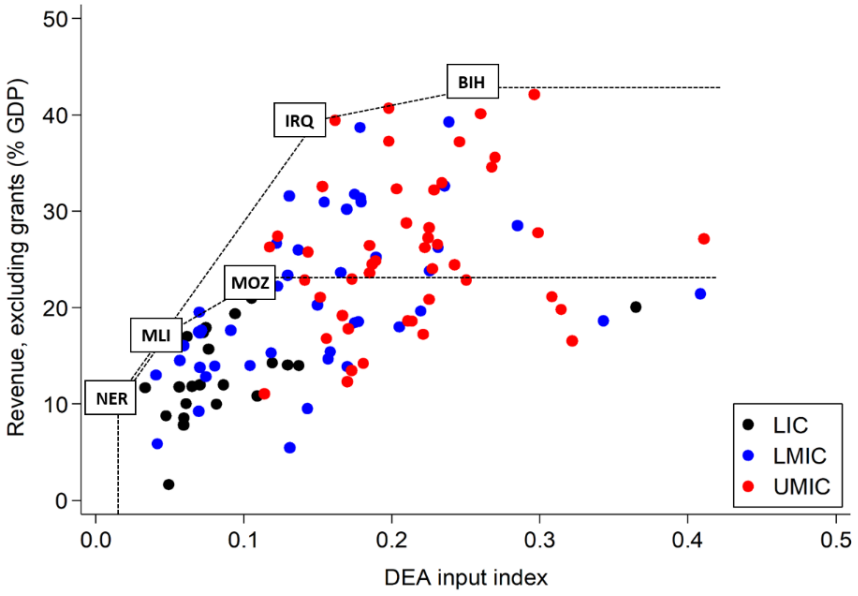
Notes: The sample consists of 182 countries. Depicted values are normalized and aggregated as described in Section II. Details on the indicators and data sources used in the computation of the DEA input index are provided in Section III.
Source: Authors' analysis based on the variables and data sources described in Section III.

B. Frontier Analysis

As described in Section III, non-parametric frontier analysis allows us to account for differences in countries' fundamental economic structure and economic strength that determine each country's revenue potential. The performed DEA uses revenue as a percentage of GDP as the output variable and the constructed composite proxy measure (DEA input index) of relevant economic fundamentals identified in the literature as the input variable. This approach allows us to identify those countries that, relative to other countries facing similar economic conditions and constraints, currently generate relatively high revenues, and those countries that are apparently falling short of their potential.

Figure 6 plots revenues over the DEA input index and shows the resulting production possibility frontier (dotted line) for revenues for the period 2016-2019. For our core sample of 118 countries, the frontier turns out to be determined by three countries. At the lower end of the input index, the frontier is defined by Niger (NER), which during this time period featured the least favorable economic conditions for revenue mobilization (measured by the DEA input index) among the included countries. In the middle of the sample, the frontier is defined by Iraq (IRQ), which generated more revenues than many other countries with similar values of the input index. At the upper end, the frontier is defined by Bosnia & Herzegovina (BIH), which features both higher revenue and stronger economic structure relevant for government revenues than most other countries in the sample.[15] When we compute the DEA only for the set of 25 LICs in our sample, the frontier is determined by Niger (lower end), Mali (midpoint), and Mozambique (high end).[16]

Figure 6. Estimated Frontier for Government Revenues for LICs and MICs, 2016-2019



Notes: The sample consists of 118 countries (high-income countries are excluded). The upper dotted line represents the production possibility frontier for government revenue as a function of countries' economic structure and economic strength (measured by the DEA input index) for the whole sample. The lower dotted line represents the frontier for the subsample of low-income countries only. The DEA input index aggregates information on each country's level of per-capita income, share of agriculture in GDP, trade openness, and age dependency ratio. Details on the methodology and data sources used in the computation of the DEA input index

[15] Bosnia and Herzegovina is a federation with a complex federal structure and several layers of government. In addition to the joint functions of the federal state, there is a federation of Bosniaks and Croats and Republika Srpska, the Serbian entity; finally, there is local government level. It is this sizeable government structure and the legacy of socialism that are some of the underlying reasons for the high government revenues in Bosnia and Herzegovina.

[16] As discussed in Section II, the DEA scores associated with this second frontier should be viewed as providing an upper bound estimate for LICs.

are provided in Sections II and III.
Source: Authors' analysis based on the variables and data sources described in Section III.

The mean DEA score in the sample comprising both low- and middle-income countries equals 0.62, suggesting that revenue levels are at 62 percent of the estimated potential, on average across these countries. Figure 7 provides additional details on the ranges of DEA scores achieved in each income group (Panel A) and region (Panel B) for the period 2016-2019. According to these results, half of the included LICs feature scores between 0.45 and 0.75, with a median score of 0.54 and a mean of 0.58. This suggests that most LICs currently generate between 45 and 75 percent of their potential revenues.

While the median DEA score among LICs (0.54) is lower than the median score of LMICS (0.62) and UMICS (0.63), Figure 7 also shows that LICs cover almost the entire possible range of DEA scores from zero to one. These results demonstrate that accounting for differences in economic conditions (via DEA scores) leads to important, additional insights about revenue potential of countries at different income levels. In particular, a simple comparison of revenue levels across countries suggests that LICs perform worse than countries in higher income groups (recall the results in Figures 3 and 4). In contrast, the DEA results reveal that there are many LICs that, in fact, perform better than countries from higher income groups *given* the economic resources and conditions available to them.[17] Hence, just looking at the absolute revenue-to-GDP ratio might be misleading for drawing conclusions about how much more revenues a country can potentially raise, given its economic structure. This puts the efforts of low-income countries to increase revenue mobilization, i.e., their revenue-to-GDP ratio, in perspective: it may, indeed, be much harder for these countries to raise their revenue mobilization from the low absolute level unless and until their income level rises or economic structure changes substantially, thereby increasing their potential for additional revenue.

Figure 7 also shows that countries with low or high DEA scores are not concentrated in a particular income group or region. Rather, all income groups and regions cover wide ranges of scores, and median scores are relatively similar across income groups and regions (except for ECA and SSA). In particular, these results indicate that in case future efforts to support revenue mobilization were to assign strategic priorities to countries considering their efficiency in DRM as captured by the DEA scores, these priorities would not necessarily end up benefiting countries belonging to a particular income group or geographical region in a disproportional way.[18] Simply put, efficient government revenue mobilization appears to be a challenge across income groups and regions (including across countries with very different revenue-to-GDP ratios).

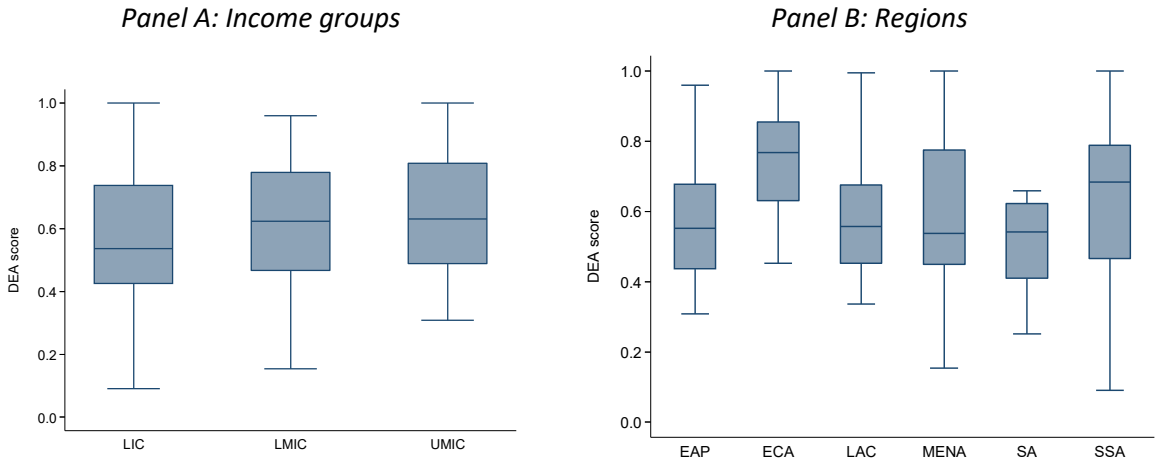
A series of robustness checks reported in Appendix A indicate that the main results of the DEA are robust to changes in the selection of indicators and the aggregation methodology underlying the construction of the variables used in the DEA. Due to imperfect data quality, however, we stress that the

[17] An example is Uganda, a LIC, whose revenue-to-GDP ratio (0.12 in 2016-2019) is much smaller than that of, for example, Botswana (an UMIC with revenue-to-GDP ratio of 0.32 in the same period). Despite its lower revenue level, however, Uganda is achieving 81 percent of its potential revenue according to the estimated frontier, slightly more than Botswana (79 percent). The underlying reason is that Botswana features a much more favorable economic structure for generating revenue than Uganda, as captured by the large gap in the DEA input index across these two countries (0.20 in Botswana and 0.03 in Uganda).

[18] The finding that countries with large untapped revenue potential come from different income groups and geographical regions is generally consistent with the findings of previous studies (Le at al. 2012; Khwaja and Iyer 2014). At the same time, our findings for individual countries differ in several cases from those of previous studies, which is likely due to dynamics over time in these countries that are not captured in previous studies as well as differences in methodology. For example, Le et al. (2012) find that Azerbaijan, Bulgaria, Burkina Faso, Uganda, and Ukraine are part of a group of countries with relatively large potential to increase tax collection, while according to our results these countries are, in the most recent period under study, already achieving revenues close to their potential (above 80 percent of potential revenue in the period 2016-2019).

quantitative magnitudes of the results—especially those for individual countries—should be interpreted with caution.

Figure 7. Ranges of DEA Scores by Income Group and Region, 2016-2019



Notes: The sample consists of 118 countries (high-income countries are excluded). The boxes represent the range of values between the 25th and 75th percentile (including the median), the ends of the whiskers represent the lower and upper adjacent value (see Tukey, 1977). Details on the methodology and data sources used in the computation of the depicted DEA scores are provided in Sections II and III.
Source: Authors' analysis based on the variables and data sources described in Section III.

***Trends over time*.** Our data allow us to track countries' relative efficiency in generating revenues over time by calculating the frontier separately for three subsequent 4-year periods between 2008 and 2019. Table 2 reports the results by income group and world region. Most regions saw improvements in their efficiency score in raising revenues between 2008 and 2019, and most countries were able to improve their efficiency vis-à-vis other countries. In particular, all income groups and all regions except ECA and MENA achieved weakly higher DEA scores in the period 2016-2019 than in 2012-2015, suggesting that efficiency in revenue mobilization tended to improve in past years.

Figure 8 provides some examples of the results for individual countries by showing the evolution of revenues (as a share of GDP) and DEA efficiency scores across the three 4-year periods for four selected countries (chosen solely for illustrative purposes). As can be seen in the first two panels in Figure 8, Chad (a LIC) features significantly lower revenue levels than Colombia (an UMIC) in all three periods but achieves comparable DEA scores. This indicates that Chad was, despite its low revenue-to-GDP ratio, relatively efficient given its limited economic revenue potential (though with a decline between the second and third period). While Colombia features relatively stable DEA scores over time (corresponding to around 60-70 percent of its estimated revenue potential), Pakistan and Rwanda were able to continuously improve their performance relative to other countries over time and catch up with the frontier, achieving almost 80 percent (Rwanda) and 60 percent (Pakistan) of their revenue potential in the period 2016-2019.

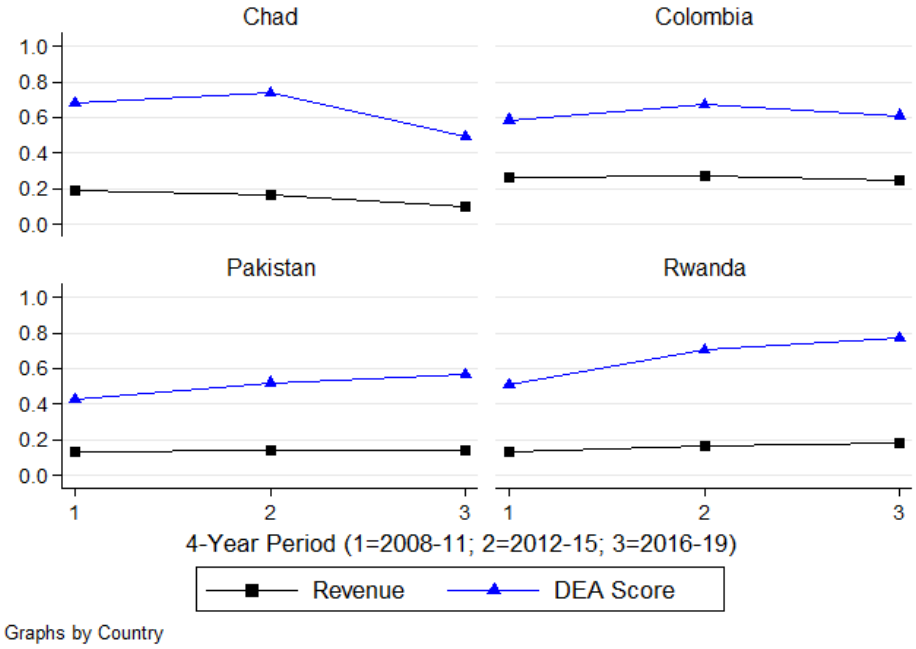
Table 2. DEA Results by Income Group and Region

	2008-2011			**2012-2015**			**2016-2019**			Change in efficiency
	Rev.	DEA	DEA Score	Rev.	DEA	DEA Score	Rev.	DEA	DEA Score	

		Input Index	(upper bound)		Input Index	(upper bound)		Input Index	(upper bound)	since 2012-15
Income Group:										
LIC	13.40	0.07	0.56 (0.61)	13.66	0.07	0.55 (0.71)	13.55	0.09	0.58 (0.69)	+0.03
LMIC	20.75	0.14	0.52	21.43	0.14	0.60	20.77	0.15	0.62	+0.02
UMIC	27.05	0.21	0.60	26.76	0.20	0.65	26.36	0.21	0.65	+0.00
Region:										
EAP	20.85	0.17	0.48	21.93	0.17	0.55	22.21	0.19	0.57	+0.02
ECA	32.25	0.23	0.71	31.34	0.21	0.75	30.46	0.23	0.74	-0.01
LAC	21.84	0.17	0.49	22.61	0.17	0.56	23.51	0.19	0.59	+0.03
MENA	26.39	0.20	0.62	23.93	0.20	0.60	22.75	0.21	0.57	-0.03
SA	15.46	0.14	0.42	16.18	0.15	0.46	17.29	0.17	0.51	+0.05
SSA	17.21	0.09	0.58	17.81	0.09	0.62	16.52	0.09	0.64	+0.02
Average	21.76	0.15	0.56	21.95	0.15	0.61	21.52	0.16	0.62	

Notes: The sample consists of 118 countries (high-income countries are excluded). Details on the methodology and data sources used in the computation of the DEA scores and DEA input index are provided in Sections II and III.
Source: Authors' analysis based on the variables and data sources described in Section III.

Figure 8. Revenues and DEA Scores for Selected Countries



Notes: Details on the methodology used in the computation of the DEA scores are provided in Section II.
Source: Authors' analysis based on the variables and data sources described in Section III.

When interpreting these results, two features of the performed DEA should be kept in mind. First, for any given country there are three possible factors behind an increase in DEA scores: an increase in the country's revenue relative to its GDP, a decline in the DEA input index (corresponding to less favorable economic conditions), and changes in the frontier due to developments in other countries. As can be seen in Table 2, changes in the DEA input index were generally very small over this period. The improvements in efficiency can thus be attributed either to increases in revenues or to changes in the frontier. [19] The fact that there are several cases in Table 2 in which DEA scores increased despite declining revenues (as a percentage of GDP) suggests that changes in the frontier play a crucial role for the changes in DEA scores.

Moreover, when looking at changes in countries' revenue mobilization performance across time, it is important to note that the frontier analysis is designed to track countries' relative performance within the sample (i.e., in comparison to other countries during the same time period) rather than countries' absolute performance over time. This means that the DEA scores (as well as the values of the input index) cannot be directly compared across time. Instead, similar scores in two periods indicate that the *relative* performance of a country within the sample remained about the same. This approach has the advantage that it controls for general time effects, i.e., events that affect all countries simultaneously in a given period. For example, suppose country A achieves a score of 0.4 in the first period and 0.5 in the second period. It might be the case that revenues in fact declined from the first to the second period. This might be the case if a global shock (such as the Financial Crisis) negatively affected revenue mobilization in all countries, but country A managed to cope with the shock relatively better than other countries. In this case, country A would have improved its performance relative to the other countries in the sample despite a decline in its revenue-to-GDP ratio.

Table 3. Regression Results: Dependent Variable—DEA Efficiency Score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Technological readiness	0.074**						0.064***	0.138**	0.066***	0.045
	(0.014)						(0.003)	(0.013)	(0.010)	(0.198)
Natural resources		0.003*					0.001	-0.005	-0.011	0.003
		(0.088)					(0.820)	(0.272)	(0.128)	(0.500)
Control of corruption			0.039*				0.019	0.057	-0.018	-0.027
			(0.096)				(0.733)	(0.496)	(0.833)	(0.770)
Tax policy				0.068*				0.017		
				(0.066)				(0.863)		
Informal sector					-0.003**				0.006	
					(0.014)				(0.225)	
Social trust						0.150				0.079
						(0.387)				(0.553)
Country FE							yes	yes	yes	yes
Observations	240	345	354	213	126	84	237	127	111	78
Countries	86	116	118	75	70	46	85	49	59	42
R-squared	0.055	0.024	0.014	0.032	0.091	0.010				
R-squ. (within)							0.058	0.152	0.241	0.050

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. p-values in parentheses. Estimated via OLS. Standard errors are clustered at the country level.
Source: Authors' analysis based on the variables and data sources described in Section III, Table 1.

[19] Increases in revenues may stem from changes in tax policy and tax administration as well as from other factors (e.g., conflict, natural disasters, or commodity prices) which are not directly captured by the indicators included in the DEA input index.

C. Regression Analysis

Why do some countries generate more revenues than other countries with comparable domestic economic structures? To address this question, we estimate two types of panel regressions based on the sample of 118 countries included in the frontier analysis, and the three 4-year periods considered between 2008 to 2019. These regressions feature the efficiency estimates obtained from the DEA as the outcome variable, relating them to various explanatory variables that can potentially account for the observed variation in efficiency scores across countries. Specifically, countries' quality of tax policy, size of the informal sector, level of technological readiness, natural resources, control of corruption, and social trust are included as regressors.

The results are reported in Table 3. Columns (1) to (6) report the results of bivariate regressions which include each considered factor separately. Columns (7) to (10) report the results of regressions that include different sets of regressors together, and add country-fixed effects (FE) to control for time-invariant country characteristics such as geographical features, history, and cultural traits. [20] According to the results of the bivariate regressions in columns (1) to (6) of Table 3, countries that are closer to achieving their full revenue potential tend to feature higher levels of technological readiness, natural resources, control of corruption, and social trust, as well as better tax policy and a smaller informal sector. Except for the regression on trust, all the respective coefficients are statistically significant at the 10-percent significant level. However, when several of these factors are included at once and time-invariant country characteristics are controlled for using country fixed effects, then only technological readiness remains statistically significant across most specifications (see columns (7) to (10) in Table 3).[21]

Given the observational nature of the data underlying these estimates, our ability to identify causal relationships between the considered variables is, of course, very limited. We therefore interpret the regression results as suggestive evidence of the factors that are potentially driving the observed differences in efficiency and argue that these results can inform further investigation into the underlying root causes of inefficiency in DRM. Moreover, these results suggest that the findings obtained from the DEA are not merely driven by differences in the roles of the informal economy or natural resources across countries (if this was the case, then the coefficients of these factors should be statistically significant in the regressions in Table 3).

D. Does International Support for DRM Target Countries with High Untapped Potential?

We now turn to the question of how international development cooperation efforts aimed at improving revenue mobilization are distributed across countries with different performances in DRM efficiency. In addressing this question, we focus on the engagement of the World Bank Group (WBG) in developing countries. The main reason for this focus is data availability: For the WBG, we have access to information about the full universe of projects related to DRM, which allows us to get a complete picture of how this institution's engagement is distributed across countries with respect to DRM efficiency. In addition, the WBG is one of few development agencies that is active in almost all developing countries, and that plays a significant role in the international support to poor countries related to improving revenue mobilization outcomes (World Bank 2021).

In investigating the WBG's targeting of DRM-related projects across countries, two indicators of engagement are considered. The first indicator is the total amount committed by the WBG for projects

[20] For tax policy, informal sector employment, and social trust, the data available to us cover only a very limited number of countries, and the covered countries differ relatively strongly across these variables. We therefore include these variables only separately in the regressions.

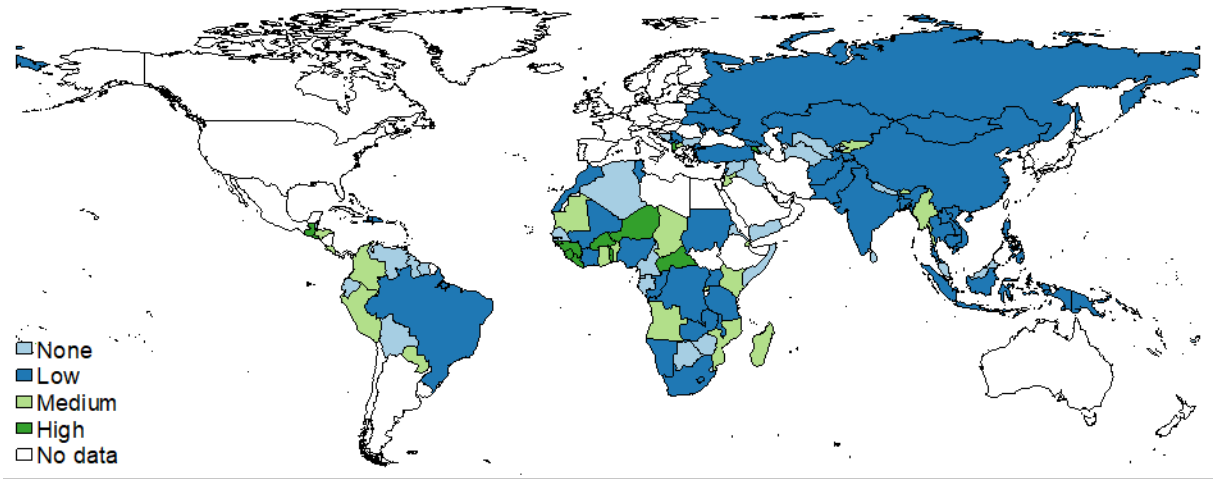
[21] The insignificant coefficient of "Technological readiness" in column (10) of Table 3 may be due to the smaller number of observations included in this regression (due to the limited availability of data on the variable *Social trust*).

related to DRM as a share of the recipient country's GDP (scaled by factor 1,000 for better readability; see Table 1, Panel C). The second indicator is obtained by splitting the average annual values in the period 2008-2019 of the first indicator into the following four categories. 'No engagement': countries without projects related to DRM approved in 2008-2019; 'Low engagement': countries with a committed amount (as a share of GDP) below the 50th percentile; 'Medium engagement': countries with a committed amount between the 50th and 75th percentile; and 'High engagement': countries with a committed amount above the 75th percentile.

Figure 9 shows a map of the magnitudes of WBG engagement in DRM across countries according to the four discrete levels of engagement (HICs, which are not eligible for WBG borrowing, are excluded from the analysis and labeled as 'no data'). A first insight obtained from Figure 9 is that the WBG's engagement in DRM is spread across many countries, with the highest engagement in the Sub-Saharan Africa and Latin America regions, which tend to show smaller revenue-to-GDP ratios than other regions (recall Figure 3).

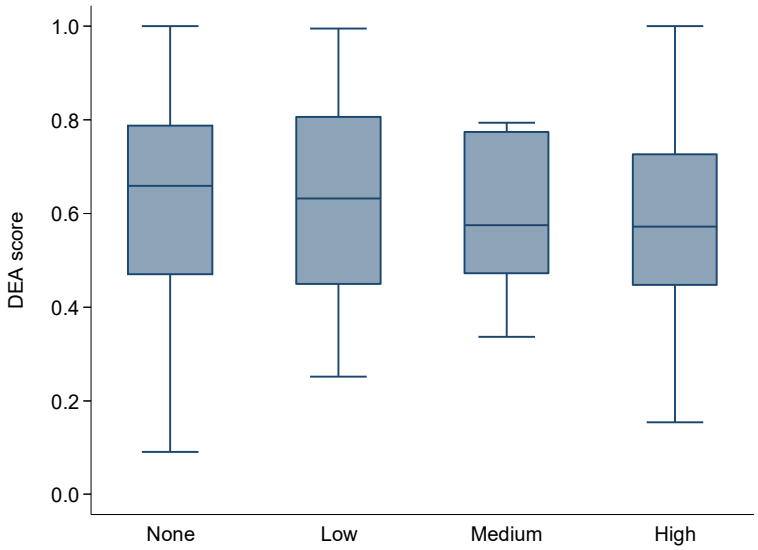
However, as noted above, the fact that a country has a low revenue-to-GDP ratio does not mean that it is not raising revenues close to its potential. Viewed from this prism, there are, indeed, many countries with large untapped revenue potential which receive only very little (often zero) support from WBG engagement explicitly focused on DRM. To illustrate this finding, Figure 10 plots the ranges of achieved DEA scores across countries belonging to the four levels of WBG engagement. The median DEA scores slightly decrease in higher levels of WBG engagement, indicating that WBG engagement in DRM tends to be more prevalent in countries with lower relative efficiency in DRM (or larger untapped potential). At the same time, there is large dispersion and countries with small DEA scores are found in all four categories of WBG engagement, indicating that many countries with large untapped revenue potential feature little or no WBG engagement in DRM.

Figure 9. Levels of WBG Engagement in DRM by Country, 2008-2019



Notes: The sample consists of 118 countries (high-income countries are excluded and labelled as 'No data'). The depicted categories of WBG engagement are defined as follows. No engagement: countries without projects related to DRM in 2008-2019; low engagement: countries with a committed amount (as a share of GDP) below the 50th percentile; medium engagement: countries with a committed amount between the 50th and 75th percentile; high engagement: countries with a committed amount above the 75th percentile.
Source: Authors' analysis based on the variables and data sources described in Section III.

Figure 10. Ranges of DEA Scores (2016-2019) by Level of WBG Engagement



Notes: The sample consists of 118 countries (high-income countries are excluded). The boxes represent the range of values between the 25th and 75th percentile (including the median), the ends of the whiskers represent the lower and upper adjacent value (see Tukey, 1977). Details on the methodology and data sources used in the computation of the depicted DEA scores are provided in Sections II and III.
Source: Authors' analysis based on the variables and data sources described in Section III.

Table 4. Regression Results: Dependent Variable—WBG Engagement

	(1)	(2)	(3)	(4)	(5)
DEA score	-0.392**	-0.679***	-0.385	-1.106***	-0.405
	(0.020)	(0.001)	(0.145)	(0.000)	(0.112)
Technological readiness	-0.110**	-0.095*	-0.087	-0.200*	-0.136*
	(0.010)	(0.096)	(0.275)	(0.076)	(0.062)
Natural resources	0.001	0.002	0.001	0.006	-0.003
	(0.719)	(0.661)	(0.776)	(0.221)	(0.577)
Control of corruption	0.159**	0.228***	0.270**	0.369**	0.226**
	(0.030)	(0.002)	(0.012)	(0.019)	(0.018)
Tax policy			-0.129		
			(0.255)		
Informal sector				0.001	
				(0.717)	
Social trust					0.275
					(0.375)
Income Group:					
LIC		0.090	0.082	-0.164	-0.029
		(0.293)	(0.379)	(0.221)	(0.766)
UMIC		-0.130*	0.006	-0.160	0.048
		(0.096)	(0.978)	(0.313)	(0.606)
Region:					
EAP		-0.134*	-0.098	-0.226**	-0.275**
		(0.067)	(0.211)	(0.048)	(0.012)

ECA		0.218**	0.077	0.473*	-0.003
		(0.035)	(0.532)	(0.054)	(0.983)
LAC		0.129	-0.154	0.083	0.026
		(0.188)	(0.306)	(0.489)	(0.817)
MENA		-0.069	-0.306***	-0.060	-0.145*
		(0.306)	(0.002)	(0.671)	(0.052)
SA		-0.289***	-0.299**	-0.473***	-0.195
		(0.004)	(0.016)	(0.010)	(0.127)
Observations	237	237	127	111	78
Countries	85	85	49	59	42
R-squared	0.061	0.135	0.153	0.216	0.180

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. p-values in parentheses. Estimated via OLS. Standard errors are clustered at the country level. The omitted categories for income group and region are LMIC and SSA.
Source: Authors' analysis based on the variables and data sources described in Section III, Table 1.

Of course, the negative relationship between levels of WBG engagement and median DEA scores observed in Figure 10 only represents a simple association which is unconditional of other factors. To test whether this relationship also holds when controlling for other factors, Table 4 reports the results of regressing WBG engagement on the DEA efficiency scores and other potentially relevant variables. Colum (1) reports the results when technological readiness, natural resources, and control of corruption are included as regressors along with the DEA scores. In column (2), countries' income group and geographical region are added. Columns (3) to (5) further include tax policy, informal sector activity, and social trust. According to the results in Table 4, WBG engagement elated to DRM indeed tends to be stronger in countries that feature lower DRM efficiency (the coefficient is statistically significant in most specifications in Table 4).[22] This finding is consistent with the result in Figure 10 that the median DEA scores tend to decrease with higher levels of WBG engagement (as well as with the result that there are nevertheless many countries with large untapped revenue potential that feature only little WBG engagement).

In addition, Table 4 shows that WBG engagement in DRM tends to be stronger in countries that feature lower levels of technological readiness and better control of corruption. Moreover, there is some evidence that WBG engagement in DRM plays a smaller role in UMICs than in LICs and LMICs (column 2). For regions, the results indicate that WBG engagement tends to be stronger in SSA than in EAP and SA, but not as strong as in ECA (note that SSA is the omitted category for region). Finally, there is no evidence of a significant relationship between WBG engagement in DRM and countries' natural resource endowments, tax policy, informal sector activity, and measures of social trust.[23]

[22] The insignificant coefficient of "DEA score" in column (5) of Table 4 may be due to the smaller number of observations included in this regression (due to the limited availability of data on the variable "Trust").

[23] These results are robust to using an alternative measure of WBG engagement defined relative to recipient countries' government revenues (rather than GDP). Specifically, when we repeat the regressions specified in Table 4 using as dependent variable 'WBG engagement as a share of client countries' total government revenues (excluding grants)', then the coefficients of *DEA score* and *Technology* remain negative and statistically significant across most specifications, the coefficient of *Control of corruption* remains positive and significant, and the coefficients of *Natural resources*, *Tax policy*, *Informal sector*, and *Trust* are always insignificant.

We stress again that, due to the observational nature of our data, these regression results should not be interpreted as identifying causal relationships between the included variables. In particular, our data do not allow us to differentiate between effects from the included regressors in Table 4 on decisions about WBG engagement (e.g., if in countries that are performing poorly in terms of DRM efficiency, projects are more likely to focus on DRM), and potential effects in the opposite direction (e.g., WBG engagement affects countries' relative efficiency in DRM).

VI. Conclusion

This paper uses non-parametric frontier analysis to provide a fresh perspective on the efforts performed to raise revenue levels in developing countries. In addition to generating an updated view of past analyses of revenue potential across countries based on recent and more comprehensive data, we also find support for the conclusion that even countries with low nominal revenue-to-GDP ratios can exhibit high efficiency in revenue mobilization, given the limitations imposed by their economic structure and constraints.

Our results imply that countries' revenue-to-GDP ratios are not an adequate indicator of the efficiency with which governments manage to convert their tax bases into revenues, given the economic structure and associated capacity of each country to raise revenues. When data envelopment analysis is used to take into account differences in economic structure across countries, the results show that untapped potential (corresponding to low efficiency) in DRM exists across all world regions and income groups; it is not the exclusive province of low-income countries. In particular, this finding suggests that looking only at a countries' revenue-to-GDP ratios will be misleading for drawing conclusions about how much more revenues each country should aim to raise given its current economic structure. Therefore, efficiently allocating scarce development financing to support DRM requires both knowledge of current levels of government revenues in each country and insights about which countries are already performing close to their revenue raising potential. Our efficiency estimates generated by DEA can thus be useful for guiding reform priorities.

There also appears to be a robust empirical association between higher magnitudes of WBG engagement targeted at DRM and low efficiency in revenue mobilization, lower levels of technological readiness, and higher levels of control of corruption. At the same time, many countries with large untapped revenue potential feature little or no engagement in DRM. Overall, these results suggest that there may be ways to improve revenue mobilization outcomes globally by targeting efforts at those locations that feature large untapped revenue potential.

The presented results are generally robust against moderate changes in the methodology underling the construction of the variables used in the DEA. Nevertheless, we stress that the results should be interpreted with caution, as data quality for some of the indicators is limited. More empirical research to investigate the performance and determinants of countries' revenue mobilization, and guide policy decisions, is warranted.

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APPENDIX

A. Robustness

This appendix describes the robustness checks performed to assess the sensitivity of the presented results to changes in the composition and aggregation methodology underlying the construction of the variables used in the DEA.

First, we test the robustness of our results to alternative weighting schemes which assign double weight to one of the four indicators included in the DEA input index (recall that our baseline specification uses equal weights).[24] For example, one alternative specification assigns a weight of 2/5 to trade openness while the other three indicators are assigned a weight of 1/5 each (and analogously for the other alternative specifications). To assess the similarity of the resulting outcomes with our baseline

[24] This approach mirrors the robustness checks with respect to weighting performed in Afonso et al. (2005).

specification, we calculate two sets of correlation coefficients. The first set consists of standard Pearson correlation coefficients for continuous variables. These are used to test the similarity between the resulting values under alternative weighting schemes with those of the baseline measure. Second, we calculate Spearman correlation coefficients which measure the similarity between discrete rankings.[25] These are used to assess the similarity between the resulting rankings of countries rather than the associated absolute values. In total, we calculate 24 correlation coefficients: two coefficients for each of the four weighting specifications in each of the three time periods. In all these cases, the correlation between our baseline measure and a given alternative specification is never below 0.95 and is always significant at the 1-percent significance level, suggesting that that our results are robust against moderate changes in the aggregation methodology used in the construction of the DEA input index.

We also test the robustness of our results to changes in the composition of the DEA input index by considering the outcomes when one of the four indicators is dropped from the index. Specifically, we construct for each time period four alternative indices (in each case dropping one of the four indicators included in the baseline measure), compute the corresponding country rankings, and calculate the Pearson and Spearman correlation coefficients as described above. This leads to another 24 correlation coefficients. While some of these correlation coefficients are as low as 0.85, they are always statistically significant at the 1-percent significance level. Overall, this indicates that our results are largely robust to changes in the selection of indicators included in the DEA input index and are unlikely to be driven by a single economic factor included in the DEA input index.

B. Additional Tables and Figures

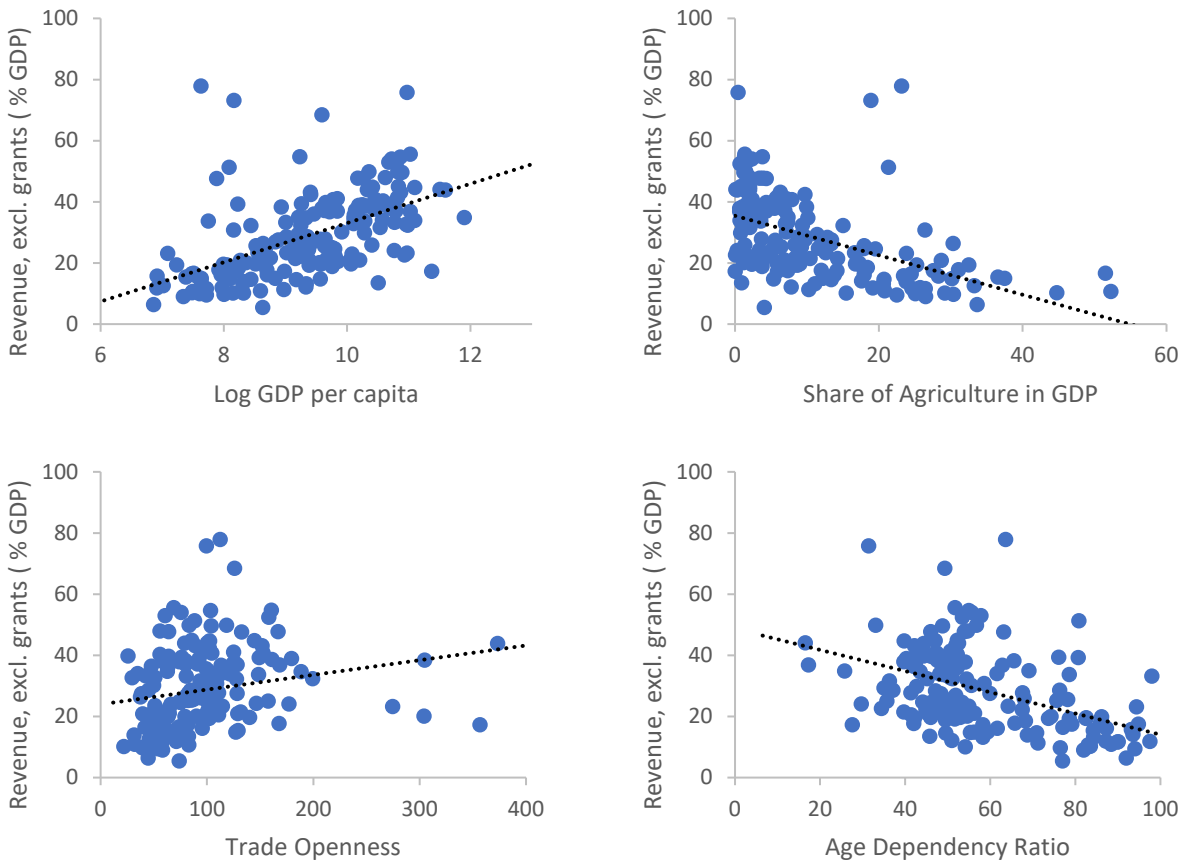
Table A1. Pairwise Correlations

	Tax policy	Control of corruption	Informal sector	Technological readiness	Social trust
Tax policy	1				
Control of corruption	0.452	1			
Informal sector	-0.446	-0.438	1		
Technological readiness	0.334	0.454	-0.788	1	
Social trust	-0.349	0.178	-0.218	0.195	1
Natural resources	-0.152	-0.417	0.214	-0.276	-0.106

Notes: The sample consists of 118 countries (high-income countries are excluded).
Source: Authors' calculation based on the variables and data sources described in Section III.

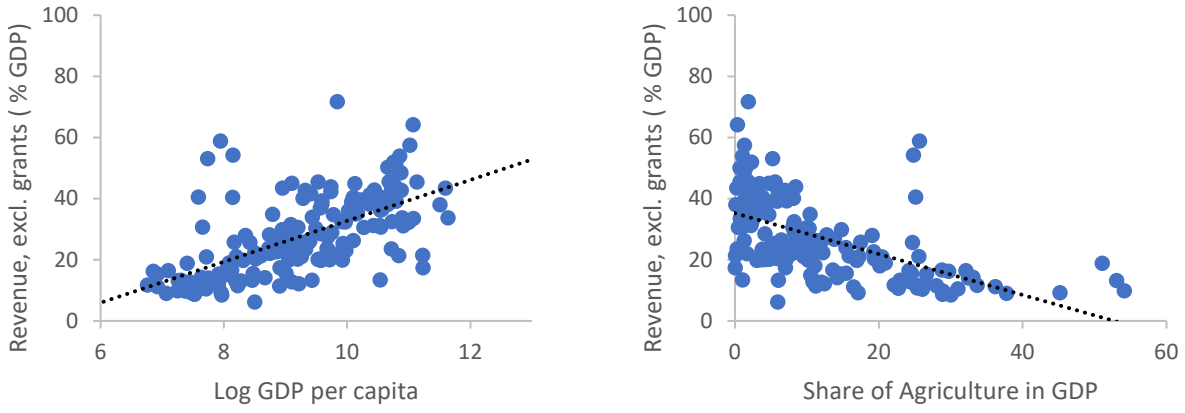
Figure A1. Economic Fundamentals and Revenues, 2012-2015

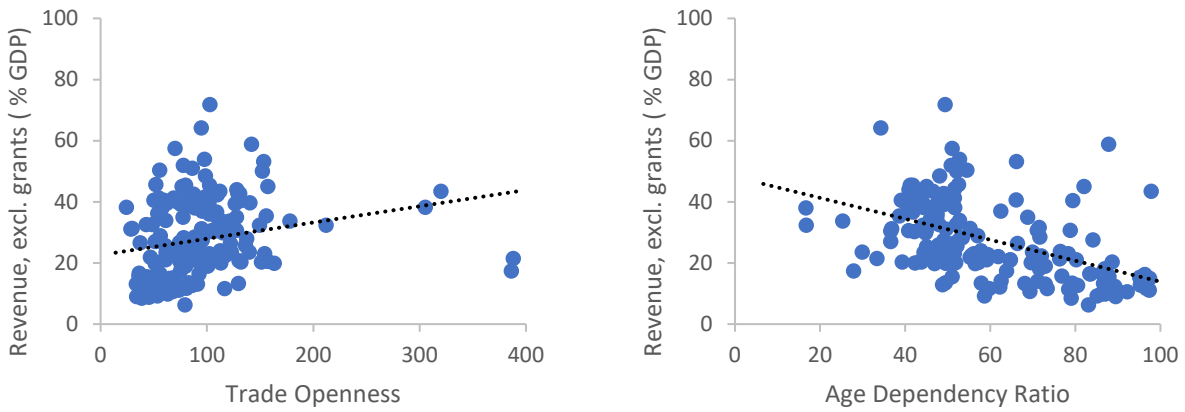
[25] The Spearman correlation coefficient ranges inside the interval [−1,1] and takes the value 1 if the two rankings are identical whereas values smaller than 1 indicate less agreement (a value of 0 indicates that the rankings are completely independent and a value of -1 indicates that one ranking is the reverse of the other).



Notes: The dotted line represents the result of a bivariate linear regression of revenue on the indicator shown on the x-axis.
Source: Authors' calculation based on the variables and data sources described in Section III.

Figure A2. Economic Fundamentals and Revenues, 2008-2011





Notes: The dotted line represents the result of a bivariate linear regression of revenue on the indicator shown on the x-axis.
Source: Authors' calculation based on the variables and data sources described in Section III.

Table A2. Bivariate Linear Regressions of Revenues on Economic Fundamentals

	2008-2011			2012-2015			2016-2019		
	Mean	Slope in Biv. Reg.	Sign.	Mean	Slope in Biv. Reg.	Sign.	Mean	Slope in Biv. Reg.	Sign.
Revenue (% GDPG)	27.7			28.8			27.8		
Log GDP per capita	9.2	6.69	***	9.3	6.42	***	9.4	5.93	***
Share of Agriculture in GDP	11.5	-0.67	***	10.9	-0.65	***	10.8	-0.58	***
Trade Openness	93.1	0.05	***	97.2	0.05	***	95.1	0.05	***
Age Dependency Ratio	60.6	-0.34	***	59.4	-0.35	***	59.3	-0.30	***

Notes: Significance levels (Sign.) correspond to p-values in bivariate regression of revenue on respective indicator: ** p<0.10, ** p<0.05, *** p<0.01.* Samples consist of a maximum of 182 countries (including high-income countries).
Source: Authors' calculation based on the variables and data sources described in Section III.

Table A3. Data on World Bank Group Engagement in DRM

Country	Income Group	Region	WBG Engagement[1]			Level of WBG Engagement[2]
			2009-2011	2012-2015	2016-2019	
Afghanistan	LIC	SA	0.159	0.170	0.077	Low
Albania	UMIC	ECA	0.066	2.553		High
Algeria	LMIC	MENA				None
Angola	LMIC	SSA		0.756		Medium
Armenia	UMIC	ECA	0.930	1.323		High
Azerbaijan	UMIC	ECA				None
Bangladesh	LMIC	SA	0.060	0.028		Low
Belarus	UMIC	ECA	0.312			Low
Belize	UMIC	LAC				None
Benin	LMIC	SSA	0.527		0.389	Medium
Bhutan	LMIC	SA		0.738	0.121	Medium
Bolivia	LMIC	LAC				None
Bosnia and Herzegovina	UMIC	ECA				None
Botswana	UMIC	SSA				None

Brazil	UMIC	LAC	0.060	0.106	0.012	Low
Bulgaria	UMIC	ECA				None
Burkina Faso	LIC	SSA	0.316		1.624	High
Cabo Verde	LMIC	SSA	1.221	1.963		High
Cambodia	LMIC	EAP		0.098		Low
Cameroon	LMIC	SSA				None
Central African Republic	LIC	SSA	1.062		7.333	High
Chad	LIC	SSA			0.867	Medium
China	UMIC	EAP		0.001		Low
Colombia	UMIC	LAC	0.012	0.730	0.252	Medium
Comoros	LMIC	SSA				None
Congo, Dem. Rep.	LIC	SSA	0.458		0.140	Low
Congo, Rep.	LMIC	SSA			0.562	Low
Costa Rica	UMIC	LAC	1.734			Medium
Côte d'Ivoire	LMIC	SSA			0.409	Low
Djibouti	LMIC	MENA			0.775	Medium
Dominica	UMIC	LAC				None
Dominican Republic	UMIC	LAC	0.313			Low
Ecuador	UMIC	LAC				None
El Salvador	LMIC	LAC	3.130			High
Equatorial Guinea	UMIC	SSA				None
Eritrea	LIC	SSA				None
Eswatini	LMIC	SSA				None
Fiji	UMIC	EAP				None
Gabon	UMIC	SSA				None
Gambia, The	LIC	SSA	1.395	0.660		High
Georgia	UMIC	ECA	0.340			Low
Ghana	LMIC	SSA		1.169	0.025	Medium
Grenada	UMIC	LAC	1.692			Medium
Guatemala	UMIC	LAC	1.609	1.133	0.101	High
Guinea	LIC	SSA	1.028		0.837	High
Guinea-Bissau	LIC	SSA	1.114	0.694		High
Guyana	UMIC	LAC				None
Haiti	LIC	LAC	0.191		0.258	Low
Honduras	LMIC	LAC	0.462	0.469		Medium
India	LMIC	SA	0.100		0.004	Low
Indonesia	UMIC	EAP	0.272	0.072	0.110	Low
Iraq	UMIC	MENA				None
Jordan	UMIC	MENA	0.944			Medium
Kazakhstan	UMIC	ECA	0.027			Low
Kenya	LMIC	SSA			1.070	Medium
Kosovo	UMIC	ECA	0.107			Low
Kyrgyz Republic	LMIC	ECA	0.801			Medium
Lao PDR	LMIC	EAP		0.050	0.201	Low
Lebanon	UMIC	MENA	0.011	0.012		Low
Liberia	LIC	SSA	20.869	0.724	0.706	High
Madagascar	LIC	SSA			0.782	Medium
Malawi	LIC	SSA	0.646			Low
Malaysia	UMIC	EAP				None
Maldives	UMIC	SA	0.571			Low
Mali	LIC	SSA	0.098	0.367		Low
Marshall Islands	UMIC	EAP				None
Mauritania	LMIC	SSA			0.868	Medium
Micronesia, Fed. Sts.	LMIC	EAP			7.110	High
Moldova	LMIC	ECA		0.266	0.153	Low
Mongolia	LMIC	EAP	0.596			Low
Montenegro	UMIC	ECA			0.314	Low
Morocco	LMIC	MENA		0.169		Low

Mozambique	LIC	SSA	1.805			Medium
Myanmar	LMIC	EAP		0.581	0.193	Medium
Namibia	UMIC	SSA		0.004		Low
Nepal	LMIC	SA				None
Niger	LIC	SSA	1.557	2.206	2.206	High
Nigeria	LMIC	SSA	0.273	0.093	0.031	Low
North Macedonia	UMIC	ECA	0.275	1.143		Medium
Pakistan	LMIC	SA	0.180	0.298	0.138	Low
Papua New Guinea	LMIC	EAP	0.181			Low
Paraguay	UMIC	LAC	0.400	0.675		Medium
Peru	UMIC	LAC	0.834			Medium
Philippines	LMIC	EAP	0.116			Low
Russian Federation	UMIC	ECA		0.003		Low
Rwanda	LIC	SSA		1.290		Medium
Samoa	UMIC	EAP			4.692	High
São Tomé and Príncipe	LMIC	SSA	3.420		5.494	High
Senegal	LMIC	SSA				None
Serbia	UMIC	ECA		0.101	0.109	Low
Sierra Leone	LIC	SSA	0.280	1.833	0.995	High
Solomon Islands	LMIC	EAP		1.307		Medium
Somalia	LIC	SSA				None
South Africa	UMIC	SSA			0.002	Low
Sri Lanka	LMIC	SA				None
St. Lucia	UMIC	LAC				None
St. Vincent and the Grenadines	UMIC	LAC			5.526	High
Sudan	LIC	SSA		0.008		Low
Suriname	UMIC	LAC				None
Syrian Arab Republic	LIC	MENA				None
Tajikistan	LIC	ECA	0.150	0.207		Low
Tanzania	LMIC	SSA		0.407		Low
Thailand	UMIC	EAP	0.266			Low
Togo	LIC	SSA			2.227	High
Tonga	UMIC	EAP		8.818		High
Tunisia	LMIC	MENA	0.598	0.001		Low
Turkey	UMIC	ECA	0.224	0.080		Low
Turkmenistan	UMIC	ECA				None
Uganda	LIC	SSA	0.007			Low
Ukraine	LMIC	ECA	0.223	0.348		Low
Uzbekistan	LMIC	ECA				None
Vanuatu	LMIC	EAP				None
Venezuela, RB	UMIC	LAC				None
Vietnam	LMIC	EAP	0.136	0.298	0.001	Low
West Bank and Gaza	LMIC	MENA	0.050	1.747	0.393	High
Yemen, Rep.	LIC	MENA				None
Zambia	LMIC	SSA		0.145		Low
Zimbabwe	LMIC	SSA				None

Notes: [1] WBG engagement is the total amount committed for projects related to domestic resource mobilization by approval fiscal year as a share of the recipient country's gross domestic product (scaled by factor 1,000 for better readability). [2] Level of WBG engagement is based on WBG engagement in the period 2008-2019 and defined as follows. 'No engagement': countries without projects related to DRM approved in 2008-2019; 'Low engagement': countries with a committed amount (as a share of GDP) below the 50th percentile; 'Medium engagement': countries with a committed amount between the 50th and 75th percentile; and 'High engagement': countries with a committed amount above the 75th percentile.
Source: Authors' calculation based on the variables and data sources described in Section III.