Econometrica, Vol. 92, No. 4 (July, 2024), 1163–1193

THE STATE CAPACITY CEILING ON TAX RATES: EVIDENCE FROM RANDOMIZED TAX ABATEMENTS IN THE DRC

AUGUSTIN BERGERON
Department of Economics, University of Southern California

GABRIEL TOUREK
Department of Economics, University of Pittsburgh

JONATHAN L. WEIGEL
Haas School of Business, U.C. Berkeley

This paper investigates how tax rates and tax enforcement jointly impact fiscal capacity in low-income countries. We study a policy experiment in the D.R. Congo that randomly assigned 38,028 property owners to the status quo tax rate or to a rate reduction. This variation in tax liabilities reveals that the status quo rate lies *above* the revenue-maximizing tax rate (RMTR). Reducing rates by about one-third would maximize government revenue by increasing tax compliance. We then exploit two sources of variation in enforcement—randomized enforcement letters and random assignment of tax collectors—to show that the RMTR increases with enforcement. Including an enforcement message on tax letters or replacing tax collectors in the bottom quartile of enforcement capacity with average collectors would raise the RMTR by about 40%. Tax rates and enforcement are thus complementary levers. Jointly optimizing tax rates and enforcement would lead to 10% higher revenue gains than optimizing them independently. These findings provide experimental evidence that low government enforcement capacity sets a binding ceiling on the revenue-maximizing tax rate in some developing countries, thereby demonstrating the value of increasing tax rates in tandem with enforcement to expand fiscal capacity.

KEYWORDS: State capacity, tax rates, revenue-maximizing tax rates, tax enforcement, tax compliance, tax revenue, property tax, Democratic Republic of the Congo.

1. INTRODUCTION

GOVERNMENTS IN THE WORLD'S POOREST COUNTRIES FACE SEVERE revenue constraints. They collect only 10% of GDP in taxes compared to 40% in rich countries. This lack of

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Augustin Bergeron: augustin.bergeron@usc.edu
Gabriel Tourek: gabriel.tourek@pitt.edu
Jonathan L. Weigel: jweigel@berkeley.edu

We thank Pablo Balán, Jacob Bastian, Pedro Bessone, Michael Best, Emily Breza, Anne Brockmeyer, Raj Chetty, Lucas De Lima, Monica Farid, Edward Glaeser, Blake Heller, Nathan Hendren, Anders Jensen, Larry Katz, Adnan Khan, Henrik Kleven, Wojciech Kopczuk, Asim Khwaja, Gabriel Kreindler, Juliana Londoño-Vélez, Omeed Maghzian, Mateo Montenegro, Joana Naritomi, Nathan Nunn, Dina Pomeranz, Gautam Rao, Tzachi Raz, Juan Carlos Suárez Serrato, Mazhar Waseem, David Yang, Noam Yuchtman as well as participants at the BREAD/NBER Conference 2020, DEVPEC 2020, NEUDC 2019, NTA 2019, PacDev 2020, the 2nd World Bank Tax Conference, and numerous seminars for invaluable suggestions. For outstanding research assistance, we thank Michele Mary Bernadine, Manon Delvaux, Samih Ferrah, Arnaud Fournier, Alix Leroy, Florence Oberholzer, Stephen Mathew, and David Mast. For excellent program management, we thank Elie Kabue Ngindu and the rest of the Odeka team. We are grateful for the collaboration with the Provincial Government of Kasaï-Central and the Direction Générale des Recettes du Kasaï-Central (DGRKAC). We gratefully acknowledge funding from the EGAP Metaketa II Taxation Initiative and the J-PAL Governance Initiative. This study has been approved by the Harvard Institutional Review Board: Protocol IRB17-0724. The Pre-Analysis Plan was submitted to the AEA RCT Registry on January 28, 2019: AEARCTR-0003818.

tax revenue is associated with low-quality public services and infrastructure and is thought to undermine economic growth (Besley and Persson (2013)).

To increase revenue, can low-income countries simply raise tax rates? To answer this question, governments must consider behavioral responses, for example, in labor supply or tax delinquency, which could offset the revenue gains from tax rate increases. In low-income countries with weak states, enforcement is far from perfect (Pomeranz (2015)), and tax delinquency is the first-order behavioral response that governments must contend with when setting tax rates (Besley and Persson (2014)) or choosing the tax base (Best, Brockmeyer, Kleven, Spinnewijn, and Waseem (2015)). The magnitude of behavioral responses—and thus the revenue-maximizing tax rate (RMTR)—is likely shaped by government policy and the enforcement environment, as noted in a large theoretical literature (e.g., Slemrod and Kopczuk (2002), Keen and Slemrod (2017)). Investments in enforcement capacity could, in theory, shift up the RMTR in weak states (Besley and Persson (2009)).

This paper quantifies the impact of tax enforcement activities on the revenue-maximizing tax rate, and in doing so empirically illustrates that low enforcement capacity can set a ceiling on the RMTR. We exploit random variation in the joint distribution of tax rates and tax enforcement in the Democratic Republic of the Congo (DRC), a very low capacity state and one of the world's poorest countries. There are two steps to the analysis. First, we analyze (to our knowledge) the first field experiment generating random variation in tax rates. In its 2018 property tax campaign, the Provincial Government of Kasaï-Central randomly assigned tax abatements at the property level. We use this variation to estimate the elasticity of tax compliance and revenue with respect to the tax rate as well as the RMTR. Second, we leverage two exogenous sources of variation in enforcement—randomized enforcement messages on tax notices and random assignment of tax collectors to neighborhoods—to study how the RMTR responds to changes in the enforcement environment.

The field experiment we study was embedded in a 2018 property tax campaign in the city of Kananga, implemented by the Provincial Government of Kasaï-Central. The 38,028 properties in the city were randomly assigned to the status quo annual tax liability (control) or a reduction of 17%, 33%, or 50%. In these three treatment groups, taxpayers were only informed about their liability, printed on a government tax notice, and were not informed about receiving a reduction.

As in other low-income countries, tax compliance is low in Kananga: on average, 8.8% of property owners paid the property tax in 2018. However, lower tax rates substantially increased compliance. Only 5.6% of the owners assigned to the status quo tax rate paid the property tax, compared to 6.7%, 10%, and 13% for owners assigned to reductions of 17%, 33%, and 50%, respectively. Because the property tax in Kananga is a flat fee and partial payments were not permitted, this increase in compliance led to significantly higher revenue at lower rates. The elasticities of tax compliance and revenue with respect to the tax rate are -1.246 and -0.243, respectively. In other words, a 1% increase in the tax rate reduces compliance by 1.246% and revenue by 0.243%. The treatment effects on compliance and revenue and the associated elasticities therefore suggest that the status quo tax rates lie above the RMTR in this setting.

Before estimating the revenue-maximizing tax rate and investigating its interaction with enforcement, we evaluate the validity of our treatment effects and elasticities by considering alternative explanations concerning taxpayer and collector behavior. An important concern is whether property owners' responses could be biased by their information and beliefs about tax rates. Owners' knowledge of others' rates, for instance, could bias our estimated elasticities if owners' behavior in part reflects fairness considerations. However, our estimates are robust to controlling for neighbors' tax rates, or restricting the sample by knowledge of others' rates, as measured in surveys. Our results would also be biased if owners assigned to lower rates were more likely to pay because they anchored on past rates, and thus received "transactional utility"—the sense of getting a deal—from rate abatements. Yet by design very few property owners (2.8%) were aware that they received a discount. Another concern is if tax collectors made more frequent visits to households assigned to low rates, the treatment effects could be explained in part by differential enforcement effort across rates. We examine this issue by (i) exploiting exogenous variation in collectors' incentives to exert effort differentially by rate, and (ii) controlling for the number of times collectors visited households. The treatment effects are essentially unchanged when we take collectors' enforcement effort into account.

In the second part of the paper, we explore how responses to tax rates interact with enforcement. First, we outline a simple theoretical framework focused on how tax rates and tax enforcement jointly impact citizens' decisions to comply or not with the property tax. We use this framework to obtain a formula for the RMTR that we can estimate in the data. The estimated RMTR is 66% of the status quo rate when assuming a linear relationship between tax rates and compliance. In other words, consistent with the estimated treatment effects, in this low-enforcement environment the provincial government would maximize revenue by reducing the statutory property tax rate by 34%.

We then examine the impact of tax enforcement activities on the revenue-maximizing tax rate. According to the theoretical framework, the RMTR should increase with government enforcement capacity. We rely on two sources of variation in enforcement to test this prediction. First, we study messages embedded in government tax letters distributed by collectors to property owners during property registration. Property owners were randomly assigned to receive an enforcement message noting the consequences for tax delinquency or a control message noting that paying taxes is important. The estimated RMTR is 41% higher among owners assigned to the enforcement message.

A second source of variation in enforcement comes from the random assignment of tax collectors to neighborhoods. Tax collectors vary in their enforcement capacity—that is, their ability to make property owners pay the tax—and we can use their random assignment to neighborhoods to estimate how collector enforcement capacity impacted the RMTR. We use a fixed effects model to estimate each collector's enforcement ability, proxied by the average tax compliance they achieved across all assigned neighborhoods and rates. Additionally, tax collectors vary in their ability to collect at different tax rates, allowing us to estimate the RMTR for each tax collector, again using a fixed effects model. The tax collector approach yields similar results to the tax letter approach: the RMTR increases with enforcement capacity. Specifically, replacing tax collectors in the bottom quartile of enforcement capacity with average collectors would increase the RMTR by 42%.

These results suggest that tax rates and enforcement are complementary levers. Investments in enforcement capacity could allow developing countries to shift up their revenue-maximizing tax rates. To illustrate this idea in revenue terms, we use our estimates to predict the gains that a sophisticated government would realize by anticipating how enforcement investments would increase the RMTR, compared to a naive government that manipulates rates and enforcement independently. A naive government that sequentially implements the RMTR and then increases enforcement—by replacing the bottom quartile of collectors with average collectors—would raise revenue by 61% relative to the status quo. By contrast, a sophisticated government that prospectively chooses the new

RMTR corresponding to its higher enforcement capacity would instead raise revenue by 77%. In short, jointly optimizing tax rates and enforcement would lead to 10% higher revenue gains than optimizing them independently.[1]

This paper contributes to the literature by providing experimental evidence of a state capacity ceiling on the revenue-maximizing tax rate. To our knowledge, this is the first paper to provide a rigorous empirical illustration of this idea, which is how Besley and Persson (2009) conceptualize state capacity in their seminal framework. More generally, a large theoretical literature argues that individuals' responses to tax rates depend on the enforcement environment, and thus that the RTMR is a policy choice not a structural parameter (e.g., Slemrod and Kopczuk (2002), Keen and Slemrod (2017)). The idea that the RMTR moves in tandem with enforcement capacity is challenging to test because one needs exogenous variation in both tax rates and enforcement.[2] Two related papers are Basri, Felix, Hanna, and Olken (2019) and Brockmeyer, Estefan, Serrato, and Ramirez (2023), which compare tax rates and tax enforcement as independent policy levers but do not explore their interaction.[3] The policy experiment we study enables us to make progress on this issue. Consistent with the theoretical literature, tax rates and enforcement appear to be complementary levers in this setting.

We also contribute to a growing empirical literature on optimal tax rates by experimentally illustrating the importance of extensive-margin taxpayer compliance responses in low-income countries. Most of this literature focuses on high-income countries (Saez, Slemrod, and Giertz (2012)) and middle-income countries (Basri et al. (2019), Brockmeyer et al. (2023)), where tax rates often lie below the RMTR.[4] We contribute evidence from a low-income country with weak enforcement capacity, where tax rates have received less attention.[5] In contrast to most of the literature in high- and middle-income settings, we find that tax rates are *above* the RMTR due to greater extensive-margin noncompliance as rates increase. This is important for policy because tax revenues are sorely needed in fragile state settings (Besley and Persson (2013)), yet we have little evidence of policies capable of boosting compliance in such settings. Moreover, while most past work is quasi-experimental, we use random variation in tax liabilities generated by a policy experiment implemented by the government to estimate the elasticity of tax compliance and revenue with respect to the tax rate as well as the RMTR.

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[1]The Supplemental Appendix, (Bergeron, Tourek, and Weigel (2024a)), provides additional details about the sample and intervention. It also includes additional robustness checks and analyses of the mechanisms and the effect of tax abatements on nontax outcomes. Appendix B of the working paper version, Bergeron, Tourek, and Weigel (2024b), provides additional details about the tax campaign (B1), discusses the welfare implications of the results (B2), provides additional details about the estimation of the collector-level results (B3–B5), additional results (B6), and describes the estimation of property value (B7) and the survey variables used in the study (B8).

[2]The closest paper might be Mishra, Subramanian, and Topalova (2008), which, while lacking exogenous variation in enforcement, shows that the evasion elasticity with respect to tariff rates in India is more pronounced (i) for products where evasion is easier because of differentiation or price variation, and (ii) in ports compared to airports, potentially due to less computerization. The interaction between the RMTR and other tax policy parameters, such as the tax base, has also been studied in the context of income (Kopczuk (2005)) and corporate taxation (e.g., Serrato and Zidar (2018)).

[3]Basri et al. (2019) mention the cross-elasticity in passing, but focus instead on comparing how increasing tax rates or staff-to-taxpayer ratios independently impact revenue.

[4]An exception is Bachas and Soto (2019), which finds that the highest tax rates on corporate profits are above the RMTR in a middle-income country (Costa Rica).

[5]Generally, the literature on public finance in developing countries has focused more on enforcement and third-party reporting (Pomeranz (2015), Naritomi (2019), Jensen (2019)), tax administration (Khan, Khwaja, and Olken (2015, 2019), Basri et al. (2019)), and tax design (Kleven and Waseem (2013), Best et al. (2015)).

2. SETTING

The DRC is one of the largest and most populous countries in Africa, yet it is also one of the poorest. The average monthly household income in Kananga, the provincial capital of the Kasaï-Central Province, is roughly US$106 (or PPP US$168). Often high on the list of "failed" or "fragile" states, the country has extremely low state capacity, especially in terms of tax enforcement. From 2000–2017, the DRC finished in 188th place of 200 countries in terms of its tax-GDP ratio.[6]

Kananga, a city with 1.6 million inhabitants (the fourth largest in the DRC), is the seat of the Provincial Government of Kasaï-Central. Tax revenues are extremely low: roughly US$0.30 per person per year. The majority of these revenues come from trade taxes, property and rental taxes, and various fees levied on a handful of firms in downtown Kananga, such as mobile-phone companies. Taxes are seldom enforced among private citizens: only 20% of citizens in Kananga reported paying any formal taxes in 2017.

In an effort to raise revenue, the Provincial Government of Kasaï-Central has turned to the property tax, which currently represents about 26% of provincial tax revenue.[7] Beginning in 2016, the government has organized a series of door-to-door property tax collection campaigns in Kananga. The first campaign raised property tax compliance from less than 1% to 11% (Weigel (2020)). We study the second property tax campaign run by the government.[8] When the results of the 2016 property tax campaign were presented to the governor, the officials present discussed whether lowering rates could expand the tax net sufficiently to increase revenues. In particular, the governor mentioned a recent voluntary development fund he organized in 2015–2016, which asked citizens to contribute roughly 50% of the modal property tax liability. The perceived success of this initiative led the government to suspect that marginally lowering rates could increase compliance enough to raise revenue. The potential revenue benefits of lower rates lie at the root of the tax abatement intervention we study and describe in detail in the next section.

In sum, we study a setting of extremely low state capacity in which the government is trying to initiate broad-based compliance with formal taxation. The fact that the government is at this early stage of building tax capacity is likely one reason why it is experimenting with key dimensions of tax policy, such as the use of tax abatements.[9] This presents a rare opportunity to study how the use of key levers—tax rates and tax enforcement, in our case—interact in the context of real-world policy experiments. That said, it also limits the external validity of our results to similar low-capacity and fragile state settings with very little compliance with formal taxes.[10] Although many developing countries do not share these characteristics, fragile states present some of the greatest development and

[6]See: https://data.worldbank.org/indicator/gc.tax.totl.gd.zs.

[7]This decision is consistent with international advice about promising sources of revenue for local governments in Africa because the property tax is thought to be efficient and relatively easy to collect, and urbanization in Africa is driving up property values while fueling demand for urban infrastructure (Franzsen and McCluskey (2017), Fjeldstad, Ali, and Goodfellow (2017)).

[8]Nearly all tax collection was discontinued in 2017 due to a violent conflict in the province between the Kamuina Nsapu militia and the national army. The 2016 and 2018 campaigns were largely coextensive, though only 59% of Kananga's neighborhoods were randomly selected to receive the campaign in 2016, as we discuss in Section 5.3.

[9]The willingness to experiment with tax policy is not uncommon in low-capacity settings. Rulers in early modern Europe faced information frictions and other forms of uncertainty over optimal policy such that they frequently engaged in "experimentation"—over tax instruments, rates, and administration policies—in order to learn how best to raise revenue (Kiser (1994)).

[10]The World Bank noted 39 fragile states in 2021: http://pubdocs.worldbank.org/en/888211594267968803/FCSList-FY21.pdf.

governance challenges today (Collier, Besley, and Khan (2018)), and they are in great need of tax revenue (Besley and Persson (2013)). Yet, the literature on the public finance of developing countries has focused more extensively on middle-income countries with higher-capacity states and higher initial levels of tax compliance.[11] Understanding how to extend the tax net and raise revenue at the margin in fragile and weak state settings is thus of great importance.

3. EXPERIMENTAL DESIGN

3.1. *Property Tax Campaign*

The experiment was embedded in the 2018 property tax campaign in Kananga. In every neighborhood, the campaign had two steps. First, tax collectors, paired in teams of two, went door-to-door to construct a property register.[12] Because the government did not have an existing cadastre, or property valuation roll, collectors essentially created one in this first step. During the registration visit, tax collectors informed property owners about the property tax, including if their plot is in the low- or high-value band, a distinction based on the building type of the principal construction, as discussed below. They also determined exemptions from the property tax during this visit.[13] Next, collectors issued a taxpayer ID (written on the door or wall) and gave the property owner a tax letter, which contained the tax rate (Section 4.1). Collectors also solicited payment of the property tax during this initial registration visit, which lasted 3–4 minutes for the median property.

Upon completion of the property register, collectors made follow-up tax visits throughout the neighborhood. They had one month to complete a neighborhood, after which they would begin work in another. Each collector had a paper copy of the property register, containing taxpayer IDs, names, rates, and exemptions. When a property owner paid the tax, the collector used a hand-held receipt printer to issue receipts, with the transaction recorded in the device's memory. Collectors were responsible for discrepancies between the money submitted to the state and the sum recorded by the printer. As in many settings with in-person tax collection, partial payments were not permitted in order to reduce opportunities for collusion between collectors and households (Franzsen and McCluskey (2017)). According to household surveys, the median property owner who paid the tax spent roughly ten more minutes with collectors during this visit. Consistent with standard practices at the tax ministry, collectors received a piece-rate wage for their work on the campaign.[14] The structure and magnitude of the collector wage is analogous to that received by property tax collectors in other developing countries (e.g., Khan, Khwaja, and Olken (2015)).

Property owners who failed to pay the tax during the one-month collection period were considered delinquents and then owed 250% of the original tax liability, due within 30

[11] Important recent exceptions include Okunogbe (2021), Almunia, Hjort, Knebelmann, and Tian (2019), and Krause (2020).

[12] As discussed in Section B1.3 and Balan, Bergeron, Tourek, and Weigel (2022), in some (randomly selected) neighborhoods, state agents worked as collectors, while in others, city chiefs worked as collectors. Running the analysis separately in neighborhoods with different collector types does not qualitatively alter our results (Table B7).

[13] Exempt properties — 14.27% of total properties in Kananga — include: (1) properties owned by the state; (2) school, churches, and scientific/philanthropic institutions; (3) properties owned by widows, the disabled, or individuals 55 years or older; and (4) properties with houses under construction.

[14] Specifically, collectors received 30 Congolese Francs (CF) per property registered plus a piece rate corresponding to tax payments. As discussed in Section B1.2, this piece rate varied between 30% of the household liability and a flat 750 CF, randomly assigned at the property level and orthogonal to tax rates.

days. After this, delinquent owners could be summoned to court and face further penalties. In reality, such sanctions were rarely pursued among residential property owners.[15] Nonetheless, there is considerable variation in citizens' beliefs about the probability of sanctions for tax delinquency, and, as we explore in Section 7.2.1, shaping these beliefs is a key source of collectors' enforcement capacity.

3.2. *Status Quo Tax Rates*

Rather than a schedule of tax rates expressed in percentage of property value, properties in Kananga face a fixed annual tax liability.[16] Before the 2018 campaign, properties in the low-value band (built with nondurable materials, 89% of total properties) faced a tax rate of 3000 Congolese Francs (CF), or roughly US$2. Properties in the high-value band (built with durable materials, 11% of properties) faced a tax rate of 13,200 CF (US$9).[17]

The use of fixed annual fees for the property tax—rather than applying a rate to property values—reflects the absence of an up-to-date property valuation roll. This is not a problem specific to the DRC.[18] Simplified property tax schedules involving flat fees are common in low-income countries with weak tax enforcement capacity (Franzsen and McCluskey (2017)).[19] Though the tax rates in Kananga might seem low, they are not so different from those in richer countries when expressed as a share of property value. According to machine learning estimates, discussed in Section B7, the average property tax rate in Kananga is 0.34% of the property value, which in fact exceeds the rate in certain U.S. states.[20]

3.3. *Tax Abatement Randomization*

In the 2018 property tax campaign, randomly selected properties received tax abatements (i.e., tax liability reductions). During property registration, collectors assigned properties sequential taxpayer IDs. They then delivered the corresponding pre-populated tax letter for each ID, which contained the randomly assigned tax liability (inclusive of abatements): either the status quo annual tax rate (3000 CF for low-value properties and 13,200 CF for high-value properties) or reductions of 17% (2500 CF and 11,000 CF), 33% (2000 CF and 8800 CF), or 50% (1500 CF and 6600 CF). Collectors were instructed to read aloud the content of the tax letter, including the tax liability, to property owners and

[15] Although we lack administrative data on sanctions, conversations with tax authority staff make us confident that they did not pursue sanctions against most delinquent owners in 2018. By contrast, they impose highly salient sanctions—locking the front door with a sign noting tax delinquency—on stores and large properties rented by NGOs that fail to meet their tax obligations. Such visible enforcement actions likely sustain beliefs regarding the consequences of residential property tax delinquency.

[16] Strictly speaking, this property tax therefore does not have *rates* but fixed liabilities. In a slight abuse of terminology, we at times use the term "tax rates" to refer to these fixed liabilities.

[17] There are indeed clear differences in the property values between the low- and high-value bands, according to machine learning estimates (Figure B22) discussed in Section B7, which to some extent validates the use of this building quality "tag" in setting tax rates. A last category of properties consists of 285 higher-value properties called *villas*. They were not part of the tax campaign and were taxed according to a different tax schedule by different collectors.

[18] Due to the cost of maintaining valuation rolls, only one-third of 159 non-OECD countries in the World Bank's *Doing Business Survey* have mapped and valued their largest city's private plots (Lall, Henderson, and Venables (2017)).

[19] Similar property tax schemes exist in India, Tanzania, Sierra Leone, Liberia, and Malawi (Franzsen and McCluskey (2017)), and were in place in the U.K. from 1989–1993 and Ireland until 2013.

[20] Real-estate property tax rates varied from 0.27% in Hawaii to 2.47% in New Jersey in 2020.

did so in more than 95% of cases. Table A1 summarizes the different tax abatement treatment groups by property value band. The randomization of abatements was stratified at the neighborhood level (351 in total).[21]

The randomization of abatements before property registration and pre-population of liabilities on tax letters restricted scope for manipulation. Independent surveyors accompanied collectors during registration to take the GPS coordinates of each property, which allows us to confirm that collectors did not try to game the assignment of tax rates by assigning codes nonsequentially (e.g., Figure B1). We check balance in Section 4.1, including robustness checks for interactions between the assigned tax liability and exemptions or value band designations.

To reduce scope for anchoring or comparisons with other taxpayers, tax letters mentioned the property's annual liability without reference to the status quo rate, tax abatements, or anything about randomization. Figure A1 provides examples of tax letters for each of the rate treatments.[22]

4. DATA AND BALANCE

As summarized in Table A2, we use five sources of data.

1. **Administrative Data**: For the main tax outcomes, we use the universe of payments in the government's tax database. This database was managed by a company, KS InfoSystems, which integrated raw data from tax collectors' receipt printers with bank data. We link the official tax record for the 38,028 properties in our sample to survey data using the unique taxpayer IDs assigned during property registration.[23]
2. **Baseline Survey**: Baseline survey enumeration occurred before the tax campaign, between July and December 2017. Enumerators randomly sampled compounds following skip patterns while walking down each avenue in a neighborhood; for example, visiting every Xth property in the neighborhood, where X was determined by the estimated number of properties and a target of 12 per neighborhood. We primarily use this survey, conducted with 3358 respondents, to examine balance and study heterogeneity in treatment effects.[24]
3. **Midline Survey**: Enumerators conducted a midline survey in all compounds on average 4–6 weeks after tax collection ended in a given neighborhood. The midline survey measured characteristics of the property and property owner that we use to study heterogeneous treatment effects—as well as secondary outcomes, such as payment of bribes and other taxes. Enumerators sought to conduct this survey with the

[21]There are 364 neighborhoods in total. Our analysis excludes 8 neighborhoods that were part of a logistics pilot and 5 neighborhoods randomly selected to have no door-to-door tax collection (the pure control in Balan et al. (2022)). We show robustness to including these neighborhoods in Table A4.

[22]Letters also contained randomized messages as described in Section 7.1.

[23]There are 46,290 registered properties in all of Kananga. For the analysis, we exclude the 1132 properties located in the neighborhoods where the logistics pilot took place and the 797 properties in the neighborhoods where no door-to-door tax collection took place (the pure control group of Balan et al. (2022)). We also exclude the 6333 (14%) exempt properties in the remaining neighborhoods. Our final sample size is therefore 38,028 properties. We show robustness of our results to including these excluded neighborhoods and exempt properties in Table A4.

[24]The baseline survey was conducted with a total of 4331 respondents. But, as noted, in the main analyses we exclude respondents in pilot neighborhoods, pure control neighborhoods of Balan et al. (2022), and exempt properties. Our baseline sample is thus 3358. Table A4 reestimates the main analysis in alternate samples that include these excluded subgroups as a robustness check.

property owner, who was available in 22,667 cases. Alternatively, enumerators surveyed another adult family member or simply recorded property characteristics—such as wall, roof, and fence quality—in the absence of an available respondent, in an additional 6967 cases.[25]

4. **Endline Survey**: Endline survey enumeration occurred between March and September 2019, after tax collection had ended. We draw outcomes from this survey, conducted with 2760 respondents, such as payment of other taxes, views of the government, and the perceived fairness of the tax system.[26]
5. **Property Value**: We predicted the market value of the 38,028 properties in our sample using machine learning in order to calculate the effective tax rate as a share of property value, among other analyses. As described in detail in Section B7 (and in Bergeron, Fournier, Kabeya, Tourek, and Weigel (2023)), we trained several algorithms using a sample of 1654 expert-assessed property values as well as survey and GIS data.

4.1. *Balance*

In Table A3, we examine balance across treatment groups for a range of property and property owner characteristics. Panel A considers property characteristics, drawing on geographic data, midline survey data on house quality, and property values as estimated using machine learning. Panel B considers property owner characteristics collected at midline that are unlikely to be affected by the treatments. Panel C considers property owner characteristics collected at baseline, including attitudes about the government and tax ministry.

Overall, 2 of the 90 differences reported in panels A–C of Table A3 are significant at the 5% level, and 3 are significant at the 10% level based on independent t-tests—as one would expect under random assignment. We also test the omnibus null that the treatment effects for the variables in Table A3 are all zero using parametric F-tests (Table B1). We fail to reject this omnibus null for each of these sets of characteristics. Exemption status is also balanced across treatments (Table B3).

5. TREATMENT EFFECTS ON TAX COMPLIANCE AND REVENUE

5.1. *Empirical Specifications*

We first estimate the effect of assignment to the tax rate abatement treatments using OLS:

$$y_{i,n} = \beta_0 + \beta_1 17\%Abatement_{i,n} + \beta_2 33\%Abatement_{i,n} + \beta_3 50\%Abatement_{i,n} + X'_{i,n}\gamma + \delta_n + \epsilon_{i,n} \tag{1}$$

[25] The midline survey was conducted with 36,314 respondents, but after excluding the logistics pilot neighborhoods, the pure control in Balan et al. (2022), and exempt properties, the sample drops by 6680 (with robustness checks again shown in Table A4). Attrition between registration and the midline survey (22%) is balanced across treatments (Table A3) and appears unrelated to property or owner characteristics (Table B2 and Figure B3).

[26] Enumerators were able to survey 3887 of the 4331 baseline respondents at endline. We cannot test whether attrition between baseline and endline (10%) is balanced across treatments because the assignment status and compound code of baseline respondents were recovered at endline and are thus missing for attritors. The sample size after excluding pilot neighborhoods, the pure control in Balan et al. (2022), and exempt properties is 2760.

where $y_{i,n}$ measures the outcome of interest (tax compliance, C, or revenue, R) for individual i living in neighborhood n. The variables 17% $Abatement_{i,n}$, 33% $Abatement_{i,n}$, and 50% $Abatement_{i,n}$ are indicators for being assigned to a rate reduction of 17%, 33%, or 50%. The control group is households assigned to the status quo rate (no reduction). In our main specification, $X_{i,n}$ is an indicator for the property value band, but we also report results using a broad set of characteristics of the property and owner as controls. δ_n are neighborhood (randomization stratum) fixed effects, and $\epsilon_{i,n}$ is the error term. Exempt properties are excluded from the analysis. Given that the abatement treatments were assigned at the property level, we report robust standard errors.

We then summarize the information contained in the treatment effects by estimating the elasticity of tax compliance and revenue with respect to the tax liability, which we denote $\hat{\varepsilon}_{P,T}$ and $\hat{\varepsilon}_{R,T}$.[27] Because tax compliance and revenue are equal to zero for delinquent properties, we cannot estimate these elasticities using a log-log specification. Instead, we adopt the approach of Goldberg (2016) using the following OLS regression:

$$y_{i,n} = \alpha + \beta \log(Tax\ Rate_{i,n}) + X'_{i,n}\gamma + \delta_n + \nu_{i,n} \tag{2}$$

with $Tax\ Rate_{i,n} \in \{1500CF, 2000\ CF, 2500\ CF, 3000\ CF\}$ for properties in the low-value band, and $Tax\ Rate_{i,n} \in \{6600\ CF, 8800\ CF, 11{,}000\ CF, 13{,}200\ CF\}$ for properties in the high-value band. $X_{i,n}$ and δ_n are defined as before, and $\nu_{i,n}$ is the error term. As above, we report robust standard errors.

The coefficient, $\hat{\beta}$, is the marginal effect of a 1 log-point, or approximately 1%, change in the tax rate on the outcome of interest $y_{i,n}$. This marginal effect can be converted into an elasticity using the standard elasticity formula:

$$\begin{aligned} \hat{\varepsilon}_{y,T} &= \frac{\partial y}{\partial T} \times \frac{T}{y} = \frac{\partial y}{\frac{\partial T}{T}} \times \frac{1}{y} \\ &\approx \hat{\beta}/\overline{y_{i,n}} \end{aligned} \tag{3}$$

where T denotes the property tax rate (in Congolese Francs), y denotes the outcome of interest, and $\overline{y_{i,n}}$ is the mean value of the outcome of interest. Because $\hat{\beta}$ and $\overline{y_{i,n}}$ are estimated separately, we compute bootstrapped standard errors for the elasticity $\hat{\varepsilon}_{y,T}$.[28]

5.2. *Results*

We first examine the causal effect of rate reductions on tax compliance. As in other low-capacity settings,[29] compliance is low across all treatments: on average, 8.8% of property

[27]When the property tax is a fixed fee, the policy-relevant elasticities are the elasticity of tax compliance and revenue with respect to the tax liability—$\varepsilon_{P,T}$ and $\varepsilon_{R,T}$—because these elasticities determine whether the tax liability is above or below the RMTR (Section 6). These elasticities differ from the standard elasticities used in the optimal taxation literature (e.g., Saez (2001)). For example, if the property tax rate were a percentage of the property value, the key policy-relevant elasticity would instead be the elasticity of taxable property value with respect to the net-of-tax rate.

[28]Specifically, we construct 1000 samples (with replacement) and repeat the estimation procedure for each sample, yielding $SE_{\hat{\varepsilon}_{y,T}}$ as the standard deviation of $\varepsilon_{y,T}$ across these bootstrap iterations.

[29]Recent estimates include 7% in Haiti (Krause (2020)), 8% in Liberia (Okunogbe (2021)), 12% in Senegal (Cogneau, Gurgand, Knebelmann, Pouliquen, and Sarr (2020)), and 25% in Ghana (Dzansi, Jensen, Lagakos, and Telli (2022)). Moreover, these studies were conducted in national capitals, where property tax compliance is typically higher (Franzsen and McCluskey (2017)).

owners in Kananga paid the property tax in 2018. Nonetheless, rate reductions substantially increased the share of taxpayers (Figure A2, panel A). Only 5.6% of the property owners assigned to the status quo tax rate paid the property tax, while 6.7%, 10%, and 13% of owners assigned to reductions of 17%, 33%, and 50% paid, respectively (Table I, column 1). The results are robust to including neighborhood fixed effects (Table I, column 2)—our preferred specification—and to restricting the sample to low- or high-value band properties (Table I, columns 3–4). The elasticity of tax compliance with respect to the tax rate is thus large and negative: $\hat{\varepsilon}_{C,T} = -1.246$ ($SE_{\hat{\varepsilon}_{y,T}} = 0.062$) (Table I, column 2). A 1% increase in the tax rate is associated with a 1.246% decline in compliance.

Because the property tax is a flat fee with no possibility of partial payments, the treatment effects on compliance lead to higher tax revenue at lower rates. In particular, tax revenue was significantly higher for owners assigned to 50% ($p = 0.04$) and 33% reductions ($p = 0.02$) compared to control (Figure A2, panel B and Table I, column 5).[30] The results hold when we include neighborhood fixed effects (Table I, column 6) or estimate the results in the two value band subsamples separately (columns 7–8). The elasticity of tax revenue with respect to the property tax rate is thus negative: $\hat{\varepsilon}_{R,T} = -0.243$ ($SE_{\hat{\varepsilon}_{y,T}} = 0.081$). In this context, status quo tax rates were *above* the revenue-maximizing tax rate.

We explore a range of additional robustness checks in Table A4, including (i) controlling for basic covariates (age, age squared, and gender), (ii) controlling for roof quality and distance to the nearest market (the imbalanced covariates in Table A3), (iii) controlling for further socioeconomic covariates, (iv) including neighborhoods where the logistics pilot took place, (v) including neighborhoods where no door-to-door tax collection took place (the pure control group in Balan et al. (2022)), and (vi) including exempt properties (using the rate they would have been assigned had they not been exempted).

To make the results comparable with settings with a property tax based on underlying property value, we reestimate the elasticities of compliance and revenue while expressing the property tax rate as a percentage of property value (using our machine learning estimates, cf. Section B7). To quantify the magnitude of the decrease in compliance and revenue as the tax rate increases (Figure B4), we estimate elasticities by instrumenting for the tax rate (as a percentage of property value) using the tax abatement treatment indicators in a standard two-stage least squares set up (Table B4). The elasticities, $\hat{\varepsilon}_{C,\tau} = -1.278$ ($SE_{\hat{\varepsilon}_{C,\tau}} = 0.062$) for compliance and $\hat{\varepsilon}_{R,\tau} = -0.253$ ($SE_{\hat{\varepsilon}_{R,\tau}} = 0.079$) for revenue, are similar to those reported in Table I.

What drives the revenue response to lower tax rates? Lowering tax rates increases revenue by bringing more property owners into the tax net, that is, by increasing extensive-margin tax compliance. While the public finance literature has focused on the intensive margin,[31] our paper thus adds to growing evidence that extensive-margin delinquency is a first-order problem in low- and middle-income countries (e.g., Brockmeyer et al. (2023), Dzansi et al. (2022)). We also provide suggestive evidence that property owners with cash-on-hand constraints are more responsive to tax rate reductions (Table A12 and Section B6.3.1). The compliance and revenue responses we observe are thus consistent with liquidity-constrained individuals entering the tax net only when their tax liability is sufficiently low.

Finally, we exploit our survey data to examine whether tax rate reductions adversely impacted other margins of importance to the government: bribe collection, payment of

[30] The revenue difference between the 17% treatment and control is not statistically significant ($p = 0.16$).

[31] There are exceptions, of course, including work on nonfiling "ghosts" in developed countries, such as Meiselman (2018).

TABLE I

TREATMENT EFFECTS ON TAX COMPLIANCE AND REVENUE.

	Outcome: Tax Compliance (Indicator)				Outcome: Tax Revenue (in CF)			
	All Properties		Low-Value Properties	High-Value Properties	All Properties		Low-Value Properties	High-Value Properties
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Treatment Effects								
50% Reduction	0.074	0.073	0.076	0.050	28.675	24.711	28.270	16.743
	(0.004)	(0.004)	(0.004)	(0.012)	(14.145)	(13.828)	(9.201)	(109.071)
33% Reduction	0.044	0.044	0.046	0.026	35.616	34.069	35.327	17.659
	(0.004)	(0.004)	(0.004)	(0.010)	(15.316)	(14.937)	(9.837)	(113.175)
17% Reduction	0.011	0.011	0.014	−0.013	−20.518	−20.202	6.404	−253.891
	(0.003)	(0.003)	(0.004)	(0.009)	(14.750)	(14.420)	(10.034)	(109.150)
Mean (control)	0.056	0.056	0.057	0.046	216.903	216.903	170.611	611.74
Panel B: Marginal Effects								
ln(Tax Rate in CF)	−0.112	−0.110	−0.114	−0.085	−62.089	−55.870	−47.027	−170.321
	(0.006)	(0.006)	(0.006)	(0.016)	(18.669)	(18.274)	(12.267)	(142.544)
Mean (sample)	0.088	0.088	0.092	0.062	229.662	229.662	188.888	560.547
Panel C: Elasticities								
Elasticity	−1.266	−1.246	−1.241	−1.37	−0.270	−0.243	−0.249	−0.304
	(0.064)	(0.062)	(0.064)	(0.245)	(0.083)	(0.081)	(0.067)	(0.259)
p-value (elasticity = 0)					0.0011	0.0026	0.0002	0.2405
Observations	38,028	38,028	33,856	4172	38,028	38,028	33,856	4172
Sample	All properties	All properties	Low-value properties	High-value properties	All properties	All properties	Low-value properties	High-value properties
FE: Property Value Band	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Neighborhood	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Note: This table reports estimates from equations (1), (2), and (3). The dependent variable is an indicator for compliance in columns 1–4 and tax revenues (in Congolese Francs) in columns 5–8. Panel A reports treatment effects from equation (1), comparing property tax compliance and revenue for the tax abatement treatment groups relative to the status quo property tax rate (the excluded category). Panel B reports the mean tax compliance and revenue as well as the marginal effect of changes in tax rates (in CF) on tax compliance and revenue from equation (2). These two estimates are used in panel C to compute the elasticities of tax compliance and revenue with respect to the tax rate following equation (3) and to calculate the p-value associated with the elasticity of tax revenue. All regressions include an indicator for the property value band, and columns 2–4 and 6–8 include randomization stratum (neighborhood) fixed effects. Panels A and B report robust standard errors. Standard errors in panel C are bootstrapped (with 1000 iterations). Results are reported for all properties in columns 1–2 and 5–6. Results for properties in the low (high) value band are reported in columns 3 and 7 (columns 4 and 8). The data include all nonexempt properties registered by tax collectors merged with the government's property tax database.

other taxes, and the perceived legitimacy of the government. As we discuss in Section A1, tax rate reductions do not appear to have increased bribe payment, crowded out payment of other taxes, or eroded perceptions of the government, at least according to our survey measures (Table A5). If anything, they may have slightly reduced bribery and led citizens to view property tax rates as more fair.

5.3. *Alternative Explanations*

Before estimating the revenue-maximizing tax rate in Section 6, we examine whether other components of the experimental design could have influenced taxpayers' responses to treatments in ways that could affect the internal or external validity of our estimates of the causal effect of tax rates on tax compliance—the key policy parameter. We provide evidence that taxpayer behavior does not appear to have been significantly affected by (i) knowledge of other property owners' tax rates, (ii) anchoring on past tax rates, (iii) expectations about future property tax rates, or (iv) variation in collectors' enforcement effort across tax rates.

5.3.1. *Knowledge of Other Owners' Tax Rates*

A first concern is whether property owners were aware that other property owners faced different tax rates, which could introduce fairness considerations into the decision to comply (Besley, Jensen, and Persson (2019), Best, Gerard, Kresch, Naritomi, and Zoratto (2020), Nathan, Ricardo, and Zentner (2020)). To investigate this possibility, we reestimate the treatment effects controlling for the tax rates of each property owner's 5 and 10 closest neighbors, respectively. The estimates are not noticeably affected (Tables II and A6, columns 1–2), and none of the closest neighbors' tax rates appear to impact compliance or revenue (Table A7).

Additionally, knowledge of neighbors' tax rates does not appear to have been affected by tax rate reductions (Table A10, column 1). Only 14.19% of midline survey respondents reported any knowledge of their neighbors' rates, which likely reflects the fact that financial matters—including taxes—tend to be private in Kananga.[32] The treatment effects are not statistically different for owners who reported knowing, and not knowing, their neighbors' rates (Tables II and A6, columns 3 and 4, and Table B5, columns 1 and 5).

Awareness of others' tax rates could also give treated owners "transactional utility"—the sense of getting a good deal—from payment if they were aware of receiving a reduction (Thaler (1985)). However, transactional utility is unlikely in this setting because tax notices only informed owners about their tax liability, without any mention of the status quo liability, others' liability, or a reduction (Figure A1). Moreover, the treatments did not affect citizens' knowledge that the government was issuing abatements (Table A10, column 2). In fact, only 2.8% of midline survey respondents were aware that the government was issuing abatements. This group of owners may have been somewhat more responsive to treatments, but most differences are not statistically significant (Tables II and A6, columns 5–6, and Table B5, columns 2 and 6). The low level of awareness of abatements makes this explanation of our main results appear implausible.

[32]For instance, Lowes (2017) notes that adults often avoid discussing financial matters even with their spouse, in part due to redistributive pressures.

TABLE II

TREATMENT EFFECTS ON COMPLIANCE—ROBUSTNESS: ACCOUNTING FOR KNOWLEDGE OF OTHERS' RATES, PAST RATES, AND PAST TAX COLLECTION.

	Outcome: Tax Compliance (Indicator)									
	Neighbors' Rate		Neighbors' Rate		Discounts		Past Rates		Past Tax Campaign	
	Ctrl for 5 (1)	Ctrl for 10 (2)	Doesn't Know (3)	Knows (4)	Doesn't Know (5)	Knows (6)	Doesn't Know (7)	Knows (8)	No (9)	Yes (10)
Panel A: Treatment Effects										
50% Reduction	0.073	0.073	0.084	0.093	0.062	0.241	0.113	0.159	0.081	0.069
	(0.004)	(0.004)	(0.008)	(0.022)	(0.012)	(0.221)	(0.023)	(0.085)	(0.007)	(0.005)
33% Reduction	0.044	0.044	0.055	0.067	0.043	0.094	0.046	0.084	0.042	0.045
	(0.004)	(0.004)	(0.007)	(0.022)	(0.011)	(0.195)	(0.022)	(0.089)	(0.006)	(0.005)
17% Reduction	0.011	0.011	0.006	−0.002	0.002	−0.013	−0.016	0.027	0.008	0.013
	(0.003)	(0.003)	(0.006)	(0.020)	(0.010)	(0.161)	(0.019)	(0.088)	(0.005)	(0.004)
Mean (control)	0.056	0.056	0.071	0.104	0.064	0.114	0.079	0.143	0.055	0.056
Tests of coef. equality:										
50% Reduction			$p_{50\%} = 0.687$		$p_{50\%} = 0.617$		$p_{50\%} = 0.455$		$p_{50\%} = 0.102$	
33% Reduction			$p_{33\%} = 0.562$		$p_{33\%} = 0.565$		$p_{33\%} = 0.551$		$p_{33\%} = 0.855$	
17% Reduction			$p_{17\%} = 0.679$		$p_{17\%} = 0.769$		$p_{17\%} = 0.487$		$p_{17\%} = 0.768$	
All Reductions			$p_{All\%} = 0.780$		$p_{All\%} = 0.785$		$p_{All\%} = 0.873$		$p_{All\%} = 0.265$	
Panel B: Marginal Effects										
ln(Tax Rate in CF)	−0.110	−0.110	−0.132	−0.152	−0.099	−0.358	−0.184	−0.237	−0.122	−0.103
	(0.006)	(0.006)	(0.010)	(0.030)	(0.016)	(0.282)	(0.032)	(0.114)	(0.009)	(0.007)
Mean (sample)	0.088	0.088	0.110	0.136	0.089	0.156	0.125	0.157	0.089	0.088

(*Continues*)

TABLE II

TREATMENT EFFECTS ON COMPLIANCE—ROBUSTNESS: ACCOUNTING FOR KNOWLEDGE OF OTHERS' RATES, PAST RATES, AND PAST TAX COLLECTION.

	Outcome: Tax Compliance (Indicator)									
	Neighbors' Rate		Neighbors' Rate		Discounts		Past Rates		Past Tax Campaign	
	Ctrl for 5 (1)	Ctrl for 10 (2)	Doesn't Know (3)	Knows (4)	Doesn't Know (5)	Knows (6)	Doesn't Know (7)	Knows (8)	No (9)	Yes (10)
Panel C: Elasticities										
Elasticity	−1.247	−1.247	−1.202	−1.117	−1.111	−2.286	−1.471	−1.507	−1.369	−1.176
	(0.061)	(0.061)	(0.139)	(1.890)	(0.171)	(1.958)	(0.263)	(0.726)	(0.093)	(0.077)
Observations	38,028	38,028	13,046	2158	5098	147	2069	401	14,590	23,296
Sample	All properties	All properties	Midline Sample	Midline Sample	Midline Sample	Midline Sample	Baseline Sample	Baseline Sample	All properties	All properties
FE: Property Value Band	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Neighborhood	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Neighbor Rate Controls	Yes	Yes	No	No	No	No	No	No	No	No

Note: This table explores whether other components of the experimental design could have influenced taxpayers' responses to tax abatements. It reports estimates from equations (1), (2), and (3). The dependent variable is an indicator for tax compliance. Panel A reports treatment effects from equation (1) comparing property tax compliance for the tax abatement treatment groups relative to the status quo property tax rate (the excluded category). It also reports the p-values associated with F-tests for equality of the treatment effects when considering heterogeneity by knowledge of others' rates (columns 3–4), tax reduction (columns 5–6), past rates (columns 7–8), and by past exposure to tax collection (columns 9–10). Panel B reports the mean tax compliance as well as the marginal effect of property tax rates (in Congolese Francs) on tax compliance from equation (2). These two estimates are used in panel C to compute the elasticity of tax compliance with respect to the tax rate following equation (3). All regressions include an indicator for the property value band and for randomization stratum (neighborhood). Panels A and B report robust standard errors. Standard errors in panel C are bootstrapped (with 1000 iterations). Columns 1 and 2 control for the property tax rate assigned to the nearest 5 and nearest 10 properties (using the GPS location of all properties in Kananga), respectively. The effects are reported for: owners who reported not knowing or knowing their neighbors' rate in columns 3–4; owners who reported knowing or not knowing about the existence of tax abatements in Kananga in columns 5–6; and owners who accurately reported the status quo rate or not in columns 7–8. The variables that define these subsamples come from the baseline and midline survey and are described in Section B8. Columns 9–10 estimate treatment effects in neighborhoods where door-to-door tax collection took place during the previous property tax campaign and in neighborhoods where no door-to-door collection took place, using the treatment assignment from Weigel (2020). The sample in columns 3–6 is smaller than the total midline sample because these questions were introduced after midline enumeration began, and the question about knowledge of discounts randomly appeared for a subset of respondents (to increase the pace of survey administration). Table A6 provides analogous results with revenue as the outcome.

5.3.2. *Anchoring on Past Tax Rates*

Treated owners might have also experienced transactional utility—and thus been more likely to pay—if their tax rate expectations were anchored on past rates. For anchoring to meaningfully impact our estimates, knowledge of status quo property tax rates would need to be widespread. Yet, only 16.23% of baseline survey respondents were able to report the status quo rate corresponding to their property value band. Although citizens are often inattentive to tax rates (Chetty, Looney, and Kroft (2009)), low knowledge of rates in this context additionally reflects (i) the fact that this was only the second-ever citywide property tax campaign in Kananga (and the first covered only 59% of the city), and (ii) rapid inflation before the campaign—the value of the Congolese Franc declined by about 80% against the dollar in 2017 and 2018—and the government's inconsistent updating of tax rates during this time. Moreover, according to our evidence, knowledge of the status quo rate was unaffected by tax rate reductions (Table A10, column 3), and responses to treatment among those who knew the status quo rate were not statistically different (Table II and A6, columns 7–8, and Table B5, columns 3 and 7). The results are similar if we count as correct tax rates that are close but not exactly the status quo tax rate (Table B6).

As an additional test, we reestimate the results in neighborhoods that were randomly assigned to door-to-door tax collection in 2016 compared to neighborhoods where no collection occurred (Weigel (2020)). At baseline, owners were 3.3 percentage points more likely to accurately report the status quo tax rate in neighborhoods that received the 2016 tax campaign (Table A11, column 3), and thus should have been more likely to anchor on past rates. However, we find similar responses to tax abatements in both types of neighborhoods (Table II and A6, columns 9–10, and Table B5, columns 4 and 8). There is thus little evidence that anchoring on past rates influenced taxpayer behavior.

5.3.3. *Beliefs About Future Tax Rates*

Property owners might have expected tax rate reductions to be temporary, enhancing the perceived benefit of paying in 2018. For example, owners assigned to a rate abatement in 2018 might have been more likely to pay this year because they expected to face the full rate in future arrears. However, less than 3% of citizens even knew of tax abatements, and generally citizens faced a high degree of uncertainty about future tax rates in this setting because citywide collection of the property tax was a new phenomenon. (This was the second such campaign.) If anything, we find suggestive evidence that citizens expect short-term stability in tax rates: owners solicited to pay the property tax in 2016 were more likely to report that the same rate would apply in this tax campaign (Table A11, columns 3–5). It thus appears implausible that the anticipation of higher future rates would have differentially spurred treated owners to pay.

5.3.4. *Tax Collector Effort*

The treatment effects might be partly driven by collectors exerting enforcement effort differentially across tax rates. For instance, with a piece-rate wage per collection, collectors might anticipate property owners' higher willingness to pay at lower rates and target their visits accordingly. Such targeting of tax visits—at collectors' discretion—could magnify the treatment effects on compliance and revenue.

Anticipating this possibility, collectors' piece-rate wages were cross-randomized on the property level between a constant amount—750 CF per collection—and a proportional amount—30% of the amount collected.[33] This wage structure introduced exogenous variation in collectors' incentives to target by rate. If collectors expected owners who received tax abatements to be more likely to pay, then they would have had an incentive to target treated individuals in the constant wage group. By contrast, this incentive would have been significantly dampened in the proportional wage group because the higher likelihood of collection among lower-rate households was counterbalanced by larger wage payments for collecting from higher-rate households. To test this intuition, we estimate the elasticity of post-registration visits—measured in the midline survey—with respect to rate in both wage groups. Collectors were indeed more likely to visit households assigned to the lowest tax liability in the constant wage group (Table A8, columns 2 and 5), but not in the proportional wage group (columns 3 and 6)—though an F-test fails to reject equality of effects ($p = 0.182$).

We investigate if differential targeting by rate in the constant wage groups could influence our treatment effects by re-estimating the main results by wage group (Table A9, columns 1–2 and 6–7). The elasticities for the constant wage group and the proportional wage group are statistically indistinguishable from each other and from the main results (Table I).[34] Similarly, including a wage group indicator does not appear to affect responses to tax abatements (columns 3 and 8). Finally, controlling for visits on the extensive and intensive margin does not noticeably change the results (columns 4–5 and 9–10). Overall, these results suggest that the treatment effects are more likely the result of households' compliance responses than differential collector effort.

A more subtle possibility is that tax collectors might have changed their persuasion tactics among households who received abatements. For instance, they might have been more likely to mention tax abatements to convince owners to pay. Yet we find no evidence that owners assigned to reductions were more likely to know their neighbors' rates or to have heard of abatements (Table A10, columns 1–3). Alternatively, collectors might have felt emboldened by lower rates to use more forceful messaging to demand tax payment. We examine this possibility using endline survey data about the types of messages owners reported being used by the collectors, such as sanctions, public goods provision, legal obligation, etc. Although this is admittedly challenging to measure, we find little evidence that collectors used different messages across treatments (Table A10, columns 4–12).

6. THE REVENUE-MAXIMIZING TAX RATE

Building on the evidence that the status quo tax rate is above the revenue-maximizing tax rate (RMTR) in this setting, we now estimate the RMTR directly. We first outline a simple theoretical framework that illustrates how the levers empirically assessed in this paper—tax rates and tax enforcement—affect citizens' compliance decisions and total revenue. We then derive a formula for the RMTR that we take to the data. The framework also clarifies how the government's enforcement capacity shapes the RMTR, a topic we explore empirically in Section 7.

[33] As noted, the property-specific wage was listed along with the tax rate and owner information on the property register used by collectors.

[34] It may be surprising that tax compliance and revenue do not vary across wage groups given that collectors' visit strategies do appear to vary by wage groups. The likely explanation is that (i) given the effect of an additional visit on compliance (0.03), the effect of rate reductions on collector visits is likely too small in magnitude to generate a substantial increase in compliance and revenue; and (ii) the effect of rate reductions on visits is likely small in magnitude because collectors target their visits primarily based on other property and owner characteristics that essentially overpower the (weaker) targeting based on tax rates.

6.1. *Theoretical Framework*

6.1.1. *Property Owners*

First, consider the decision to comply or not with the property tax for a representative owner. She faces the choice between paying the fixed annual tax rate, T, or not paying and incurring the expected cost of tax delinquency, $\alpha = p \cdot \pi$ where p is the perceived probability of being sanctioned for tax delinquency and π is the perceived associated fine. We refer to α as the government's enforcement capacity because it captures the degree to which citizens believe that tax delinquency will be detected and punished.

The owner also derives utility from tax compliance, denoted by $\Lambda \sim F(.)$, with pdf $f(.)$, which captures "tax morale" motivations to pay, such as intrinsic motivation, reciprocity, or social pressure (Luttmer and Singhal (2014)). The owner's decision is thus

$$\begin{cases} \text{Compliance if } \Lambda > T - \alpha \\ \text{Delinquency if } \Lambda \leq T - \alpha \end{cases}$$

and the fraction of owners who pay the property tax is a differentiable function of T and α:

$$\mathbb{P}(T, \alpha) = 1 - F(T - \alpha) = \int_{T-\alpha}^{\infty} f(\lambda)\, d\lambda$$

6.1.2. *Government Revenue*

We follow Besley and Persson (2009) in conceptualizing enforcement capacity as the product of deliberate and costly government investments (e.g., training auditors or accumulating third-party information on taxpayers). The government thus chooses the property tax rate, T, and the level of enforcement capacity, α. Given that the property tax is intended for local public goods provision (rather than redistribution), we assume that the government's goal is to maximize tax revenue:[35,36]

$$\mathbb{R}(T, \alpha) = T \cdot \mathbb{P}(T, \alpha) - \mathbb{C}(\alpha)$$

When choosing the tax rate, the government faces a trade-off because a higher tax rate, T, mechanically increases revenue but also has an indirect negative effect on revenue by reducing compliance, $\mathbb{P}(T, \alpha)$. When deciding how much to invest in enforcement capacity, α, it trades off the higher revenue stemming from increasing compliance, $\mathbb{P}(T, \alpha)$, at rate T and the higher enforcement costs, $\mathbb{C}(\alpha)$.[37]

[35]In Section B2.1, we instead assume the government maximizes welfare. The welfare-maximizing (i.e., optimal) tax rate is lower than the revenue-maximizing tax rate as long as the government places positive social welfare weights on taxpayers and the only costs of noncompliance are lost government revenues. When the tax rate decreases by a small amount, taxpayers derive a welfare gain from the lower tax rate, and there is no change in welfare for marginal payers—who pay the tax only if the tax rate decreases—as long as they are optimizing, and thus the envelope theorem holds.

[36]Since fines are rarely implemented in practice, we assume that α captures a utility loss from tax delinquency that does not result in revenue gains from the government. We thus ignore fine revenues, $(1 - \mathbb{P})p\pi$, from the government revenue expression, $\mathbb{R}(T, \alpha)$.

[37]The costs of tax enforcement in Kananga primarily involve personnel costs of hiring and managing collectors and, in extreme cases, pursuing legal action against tax delinquents. As these outlays reflect inputs into the apparatus of tax enforcement as whole—irrespective of the tax rate—we assume that enforcement costs, $\mathbb{C}(\alpha)$, do not depend on the tax rate, T. Although this assumption could be restrictive in settings in which collector incentives are a function of tax rates, we think it is plausible in our setting given the cross-randomized wage variation and our analysis in Section 5.3.4.

6.1.3. *Revenue-Maximizing Tax Rate (RMTR)*

To obtain the revenue-maximizing tax rate, T^*, we consider a small increase, dT, in the fixed annual tax rate. This increase has two effects.

Mechanical effect. The mechanical effect, dM, represents the increase in tax receipts if there were no behavioral (compliance) responses. In the absence of behavioral responses, property owners who comply with the property tax—which we have denoted $\mathbb{P}(T, \alpha)$—would pay dT additional taxes, making the total mechanical effect:

$$dM = \mathbb{P}(T, \alpha)\, dT$$

Behavioral effect. The behavioral effect, dB, is the reduction in revenue from owners dropping out of the tax net as the rate increases, $d\mathbb{P}(T, \alpha)$:

$$dB = T \frac{d\mathbb{P}(T, \alpha)}{dT}\, dT$$

Revenue-Maximizing Tax Rate. To maximize revenue, the government should use the tax rate that maximizes the sum of the mechanical and behavioral effects, that is, such that $dM + dB = 0$. Substituting in the above expression for dM and dB, and rearranging terms, we obtain an implicit expression for the RMTR, T^*:

$$T^* = \frac{\mathbb{P}(T^*, \alpha)}{-\frac{d\mathbb{P}(T, \alpha)}{dT}\big|_{T=T^*}} \tag{4}$$

In other words, at the RMTR, the elasticity of tax compliance with respect to the tax rate would be equal to -1 and the elasticity of tax revenue to 0, respectively.[38]

6.1.4. *Enforcement Capacity*

To obtain the revenue-maximizing level of enforcement capacity, α^*, we similarly consider a small increase $d\alpha$. This increase in α results in an increase in revenues by $T\frac{d\mathbb{P}(T,\alpha)}{d\alpha}\, d\alpha$, due to increased compliance. But it also increases the cost of enforcement by $\frac{d\mathbb{C}(\alpha)}{d\alpha}\, d\alpha$. To maximize revenue, the government chooses the level of enforcement capacity to equate its marginal benefit and cost. The revenue-maximizing level of enforcement capacity, α^*, is defined by

$$T\frac{d\mathbb{P}(T, \alpha)}{d\alpha}\bigg|_{\alpha=\alpha^*} = \frac{d\mathbb{C}(\alpha)}{d\alpha}\bigg|_{\alpha=\alpha^*}$$

Additionally, the government's enforcement capacity, α, is a determinant of the revenue-maximizing tax rate. By Topkis's monotonicity theorem, if $R(T, \alpha)$ is supermodular in (T, α), then $T^*(\alpha) = \arg\max_T R(T, \alpha)$ is nondecreasing in α.[39] Thus, if $R(T, \alpha)$ is supermodular in (T, α), the revenue-maximizing tax rate T^* increases with the government's enforcement capacity, α.

[38]At the RMTR, $\varepsilon_{P,T}$ and $\varepsilon_{R,T}$ introduced in Section 5.1 are characterized by $\varepsilon_{P,T} = \frac{d\mathbb{P}(T,\alpha)/dT}{\mathbb{P}(T,\alpha)/T} = -1$ or $\varepsilon_{R,T} = \frac{d\mathbb{R}(T,\alpha)/dT}{\mathbb{R}(T,\alpha)/T} = 0$.

[39]Given that $\mathbb{R}(T, \alpha)$ is twice continuously differentiable, a sufficient condition for $\mathbb{R}(T, \alpha)$ to be supermodular in (T, α) is $\frac{\partial^2\mathbb{R}}{\partial T\partial\alpha} \geq 0$. In our framework, $\frac{\partial^2\mathbb{R}}{\partial T\partial\alpha} = \frac{\partial\mathbb{P}(T,\alpha)}{\partial\alpha} + T\frac{\partial}{\partial\alpha}[\frac{\partial\mathbb{P}(T,\alpha)}{\partial T}]$. By definition, tax compliance

6.2. *Estimation*

To estimate equation (4), we first assume that property tax compliance is linear in the property tax rate, that is, $\mathbb{P}(T,\alpha) = \beta_0(\alpha) + \beta_1(\alpha)T$. Substituting into the expression for revenue and taking the derivative, we find that the revenue-maximizing tax rate is

$$T^* = \frac{\beta_0(\alpha)}{-2 \times \beta_1(\alpha)} \tag{5}$$

For now, we consider enforcement capacity as constant when estimating $\beta_0(\alpha)$ and $\beta_1(\alpha)$—though we relax this in Section 7—and estimate equation (5) with the regression:

$$\mathit{Compliance}_{i,n} = \beta_0 + \beta_1 \mathit{Tax\ Rate}_{i,n} + \gamma X_{i,n} + \delta_n + \epsilon_{i,n} \tag{6}$$

where $\mathit{Compliance}_{i,n}$ is an indicator for the tax compliance status of property owner i in neighborhood n, and $\mathit{Tax\ Rate}_{i,n}$ is the tax rate expressed as a percentage of the status quo rate. $X_{i,n}$ is an indicator for the property value band, and δ_n are neighborhood fixed effects.[40] We use $\widehat{\beta_0}$ and $\widehat{\beta_1}$ to compute $\widehat{T^*} = \frac{\widehat{\beta_0}}{-2\times\widehat{\beta_1}}$. Since the numerator and denominator are estimated in the same regression, we compute standard errors using the delta method.[41] We also relax the linearity assumption by modeling tax compliance as a quadratic or cubic function of the tax rate (Figure B5).[42]

6.3. *Results*

Starting with the linear specification, we find that the revenue-maximizing tax rate is about 66% of the status quo rate with or without neighborhood fixed effects (Figure A3 and Table III, columns 1–2). In other words, a 34% tax cut would maximize revenue. With the quadratic and cubic specifications, the RMTR is even lower: 55% (Figure A3 and Table III, columns 3–4) and 61% of the status quo rate (Figure B7 and Table B13), respectively. In the rest of the analysis, we only report results from the linear and quadratic

is increasing in enforcement capacity, α, at all rates; that is, $\frac{\partial \mathbb{P}(T,\alpha)}{\partial \alpha} = f(T-\alpha) \geq 0$. Additionally, we assume that increasing enforcement capacity weakly attenuates the negative compliance response to tax rate increases that is, $\frac{\partial}{\partial\alpha}[\frac{\partial \mathbb{P}(T,\alpha)}{\partial T}] \geq 0$—which reflects the intuition that enhancing general enforcement capacity should raise compliance equally across rates or differentially more at higher rates (e.g., if fines for nonpayment are increasing in liability). This assumption rules out the case where $\frac{\partial}{\partial\alpha}[\frac{\partial \mathbb{P}(T,\alpha)}{\partial T}] < 0$, which could arise if, for instance, enforcement efforts were only effective at lower rates and in fact exacerbated the marginal drop in compliance from tax rate increases. In such a case, the revenue-maximizing tax rate does not necessarily increase with enforcement capacity (if it is also true that $\frac{\partial \mathbb{P}(T,\alpha)}{\partial \alpha} < -T\frac{\partial}{\partial\alpha}[\frac{\partial \mathbb{P}(T,\alpha)}{\partial T}]$).

[40]The results presented in Figure A3 and Table III report results with the property value band indicator and neighborhood fixed effects, but the results are reformulated so that the reported intercept is the average of the indicator and fixed effects. Consequently, the results are representative of the average property in Kananga. Results are similar when these fixed effects are omitted (Table B10).

[41]Inference remains unchanged when computing bootstrapped standard errors instead (Table B11).

[42]When tax compliance is a quadratic function of the tax rate, that is, $\mathbb{P}(T,\alpha) = \beta_0(\alpha) + \beta_1(\alpha)T + \beta_2(\alpha)T^2$, the revenue-maximizing tax rate is $T^* = (-2\beta_1(\alpha) \pm \sqrt{(2\beta_1(\alpha))^2 - 4\times\beta_0(\alpha)\times 3\beta_2(\alpha)})/(2\times 3\beta_2(\alpha))$, which we estimate in the data using the regression $\mathit{Compliance}_{i,n} = \beta_0 + \beta_1 \mathit{Tax\ Rate}_{i,n} + \beta_2 \mathit{Tax\ Rate}^2_{i,n} + \gamma X_{i,n} + \delta_n + \xi_{i,n}$ where $\mathit{Compliance}_{i,n}$, $\mathit{Tax\ Rate}_{i,n}$, $X_{i,n}$, δ_n are defined as above, and $\xi_{i,n}$ is the error term. We use $\widehat{\beta_0}$, $\widehat{\beta_1}$, and $\widehat{\beta_2}$ to compute $\widehat{T^*}$ and the delta method to obtain standard errors. To obtain T^*, we ignore the root that corresponds to the part where $\mathbb{P}(T,\alpha)$ implausibly increases with T. We also consider the case where tax compliance is a cubic function of the tax rate and solve for the revenue-maximizing tax rate numerically and similarly ignore the nonsensical roots.

TABLE III

THE REVENUE-MAXIMIZING TAX RATE.

	Linear Specification		Quadratic Specification	
	(1)	(2)	(3)	(4)
Panel A: Effect of Tax Rates on Tax Compliance				
Tax Rate (in % of status quo)	−0.154	−0.152	−0.410	−0.391
	(0.008)	(0.008)	(0.080)	(0.077)
Tax Rate Squared (in % of status quo)			0.171	0.160
			(0.052)	(0.050)
Constant	0.203	0.202	0.293	0.286
	(0.006)	(0.006)	(0.029)	(0.028)
Panel B: Revenue-Maximizing Tax Rate (RMTR)				
RMTR (in % of status quo rate)	0.661	0.665	0.541	0.553
	(0.014)	(0.014)	(0.045)	(0.046)
Implied Reduction in Tax Rate	33.93%	33.50%	45.95%	44.71%
Observations	38,028	38,026	38,028	38,026
Sample	All properties	All properties	All properties	All properties
FE: Property Value Band	Yes	Yes	Yes	Yes
FE: Neighborhood	No	Yes	No	Yes
Quadratic Tax Rate Term	No	No	Yes	Yes

Note: This table reports estimates of the revenue-maximizing tax rate (RMTR) using the expression in equation (4). Columns 1 and 2 assume linearity of tax compliance with respect to the tax rate. Panel A reports estimates from regression specification (6), and panel B the corresponding RMTR estimates from equation (5). Columns 3 and 4 assume a quadratic relationship between tax compliance and tax rate. Panel A reports estimates from a quadratic regression specification, and panel B reports the corresponding RMTR estimates. All estimates in panels A and B are expressed as a percentage of the status quo tax rate. All regressions include an indicator for the property value band, and columns 2 and 4 also include randomization stratum (neighborhood) fixed effects. In panel A, we report robust standard errors. Standard errors in panel B are computed using the delta method. In this and all subsequent tables in Sections 6.3 and 7.1 that report the RMTR, we use the Stata command *reghdfe*, which allows several levels of fixed effects and reformulates the output so that the reported intercept, which is used to compute the RMTR, is the average value of the fixed effects. The command *reghdfe* drops singleton observations, resulting in two observations being dropped when including property value band and neighborhood fixed effects in columns 2 and 4. The data include all nonexempt properties registered by tax collectors merged with the government's property tax database.

specification because likelihood ratio tests find improvements in fit from the quadratic ($p = 0.007$) but not the cubic model ($p = 0.137$). We repeat the robustness checks considered in Section 5.3 and find similar results (Table B14).

The RMTR is well below the status quo tax rate in both value bands (Figure B6 and Table B12) and at all levels of liquidity, income, and property value (Tables B15 and B16). However, the RMTR is higher for households with more liquidity and higher value property: 75% of the status quo rate in the top decile versus 63% in the bottom decile (Table B16, columns 1 and 10).[43] Such heterogeneity suggests that, separate from fairness or redistributive concerns, a progressive rate schedule would maximize revenue—though all rates would still lie below the status quo rate. Given that status quo tax rates exceed the RMTR, the abatements we study represent a Pareto improvement. In this context, implementing the RMTR would increase welfare (see Section B2.1).

[43]This echoes the mechanism discussed in Section B6.3.1.

7. DOES ENFORCEMENT INCREASE THE RMTR?

At current levels of enforcement capacity, a revenue-maximizing government in Kananga would cut property tax rates. But a large theoretical literature emphasizes that the magnitude of behavioral responses—and thus the RMTR—is a function of government enforcement efforts (e.g., Slemrod and Kopczuk (2002), Keen and Slemrod (2017)). As suggested in our theoretical framework, could the government invest in its enforcement capacity to shift up the RMTR? This section explores this question empirically by quantifying the impact of tax enforcement activities on the RMTR. We use two sources of exogenous variation in enforcement: random assignment of enforcement messages embedded in tax letters and random assignment of tax collectors to neighborhoods.

7.1. *Randomized Enforcement Letters*

We first examine how randomly assigned enforcement letters impacted the RMTR.[44] As noted in Section 3, during property registration, owners received a tax letter with information about the property tax and rate. A subset of these tax letters contained randomly assigned messages, which collectors were instructed to read aloud to property owners and did so in over 95% of cases.[45] The first enforcement message, *central enforcement*, stated "refusal to pay the property tax entails the possibility of audit and investigation by the provincial tax ministry" (Figure B8, panel A). A second message, *local enforcement*, was identical except "provincial tax ministry" was replaced by "chef de quartier" (panel B), a city authority who oversees local governance.[46] We compare these enforcement messages to an active *control* message: "paying the property tax is important" (panel C). To maximize power, we pool the enforcement message treatments. The random assignment of messages achieved balance across property and owner characteristics (Table B18).[47]

Compared to the control message, enforcement messages increased tax compliance by 1.6 percentage points and tax revenue by 36 CF per property (Table A13). We find suggestive evidence that the increases in tax payments stems from higher perceived probability of sanctions for tax delinquency. In response to a midline survey question asking households to estimate this probability, the *central enforcement* messages caused a roughly 6 percentage point increase in the frequency with which households said sanctions were "likely" or "very likely" (Table A14, columns 1–3).[48] We can therefore leverage the random assign-

[44] A large literature finds that enforcement letters from tax authorities can marginally increase compliance (e.g., Blumenthal, Christian, Slemrod, and Smith (2001), Pomeranz (2015)).

[45] For this analysis, we restrict the sample to the 2665 properties subject to one of the three randomized messages of interest (*central enforcement*, *local enforcement*, *control*) on their tax letter. There were also trust and public goods messages, which we do not examine here but describe in Section B1.4. The message randomization was introduced in the last phase of the tax campaign, which had two consequences: (i) a smaller sample size, (ii) lower levels of tax compliance and revenue, due to a secular decline in compliance over the course of the study, as described in Balan et al. (2022).

[46] In some randomly selected neighborhoods, similar chiefs were responsible for tax collection, as noted above and analyzed in Balan et al. (2022).

[47] Overall, 3 of the 58 differences reported in Table B18 are significant at the 1% level, 5 are significant at the 5% level, and 6 are significant at the 10% level based on t-tests. Moreover, we show in Table B20 that the results are unaffected by controlling for the property and property owner characteristics that are imbalanced in Table B18.

[48] That said, the effect of the *local enforcement* message on beliefs about sanctions is not significant. When we pool the enforcement messages the point estimate is positive but not statistically significant at conventional levels ($p = 0.109$). For completeness, Table B19 shows results separately for each message. Table A14 also clarifies that enforcement messages are not associated with improved beliefs about overall state capacity (columns

ment of enforcement messages to test if raising perceptions of government enforcement capacity shifts up the RMTR.

The results are consistent with this prediction. According to the linear specification, the RMTR is 55.4% of the status quo rate among properties assigned to the control message compared to 77.9% among properties assigned to enforcement messages (panel A of Figure 1 and columns 1–2 and 5–6 of Table A15). Using the quadratic specification (panel B of Figure 1 and columns 3–4 and 7–8 of Table A15) suggests an even larger difference in RMTR for properties assigned to the control (35.4% of the status quo rate) and enforcement messages (77.2%). The estimated RMTR is consistent with the treatment effects in Figure B9, which show that tax revenue is maximized by the 50% tax abatement for the control message and by the 17% tax abatement for the enforcement messages. These results suggest that tax enforcement activities, such as reminding taxpayers about the consequences of delinquency, can raise the RMTR. Tax rates and enforcement thus appear to be complementary levers for raising government revenue.

7.2. *Random Assignment of Tax Collectors*

A second source of variation in tax enforcement capacity stems from the random assignment of tax collectors to neighborhoods. In low-capacity settings, the degree to which taxpayers view tax delinquency as likely to be sanctioned is shaped by the specific tax collectors who arrive at their doorstep, inform them of their annual liability, and demand payment. Indeed, tax collectors explain 21% of the variation in tax compliance across neighborhoods (Bergeron, Bessone, Kabeya, Tourek, and Weigel (2022)). Because collectors vary in their enforcement capacity—that is, their ability to make property owners pay the tax—overall and by tax rate, we can use their random assignment to study if higher enforcement capacity raises the RMTR.

During the 2018 tax campaign, state tax collectors were assigned to team up with another collector every month at random. Each pair of collectors was then randomly assigned to two neighborhoods, where they were in charge of tax collection for the month. In total, 44 state tax collectors worked in 233 neighborhoods of Kananga spanning 23,777 properties.[49] The median collector worked with 6 teammates in 12 neighborhoods. Random assignment of collectors achieved balance across property and owner characteristics (Figure B10).

4–6) and that tax collectors did not target their visits toward owners who received an enforcement message (columns 7–9).

[49]The tax campaign was active in 363 neighborhoods. We only consider the 190 neighborhoods where teams of two state tax collectors worked in pairs (the 110 "Central" and 80 "Central + Local information" neighborhoods in Balan et al. (2022)) and 43 neighborhoods where state tax collectors teamed up with city chiefs to collect taxes ("Central X Local" neighborhoods in Balan et al. (2022)). More specifically, we exclude from the analysis (i) 8 neighborhoods where a logistics pilot took place, (ii) 5 neighborhoods with no door-to-door collection (pure control neighborhoods in Balan et al. (2022)), (iii) 110 neighborhoods where city chiefs collected taxes—chiefs are not randomly assigned to neighborhoods preventing us from obtaining an unbiased estimate of their enforcement capacity—("Local" neighborhoods in Balan et al. (2022)), (iv) 7 "Central + Local Information" neighborhoods where state tax collectors never worked in other neighborhoods, preventing us from obtaining an unbiased estimate of their enforcement capacity.

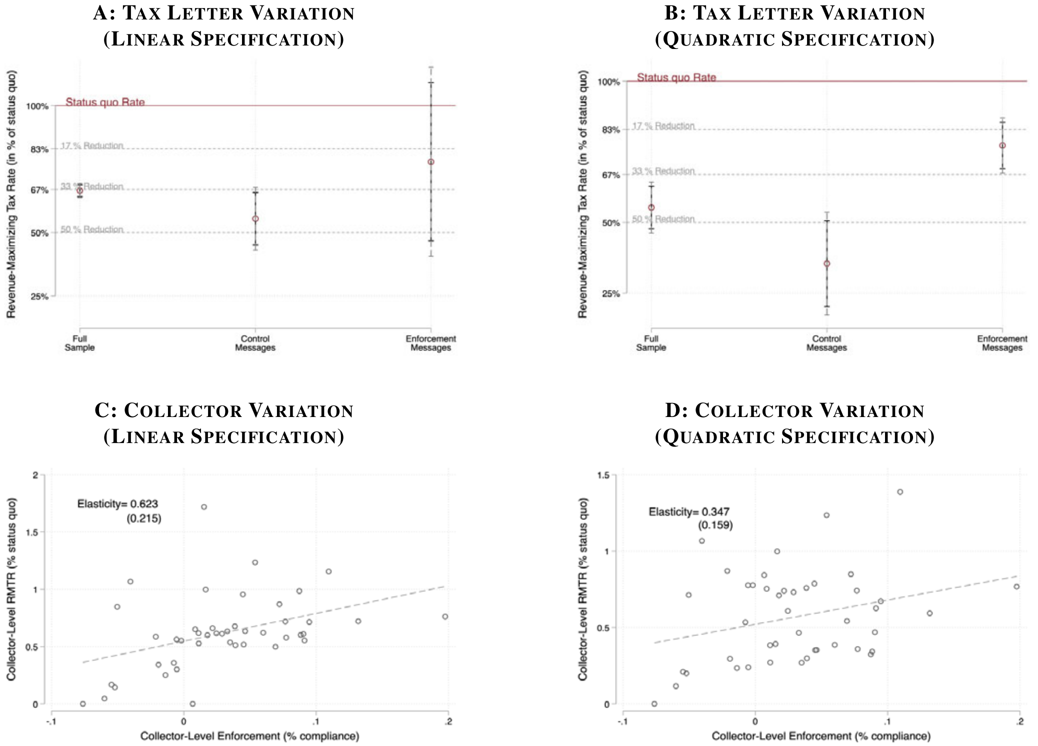

FIGURE 1.—Revenue-Maximizing Tax Rate by Enforcement Capacity. *Notes*: This figure examines how the revenue-maximizing tax rate (RMTR) varies by enforcement capacity. Panel A and B use the variation in the messages embedded in the tax letters. Panel A assumes that tax compliance is linear with respect to the tax rate so the RMTR is given by Equation (5) and estimated using regression specification (6). The quadratic analog is shown in Panel B. All estimates of the RMTR are expressed as a percentage of the status quo tax rate. All regressions include an indicator for the property value band and for randomization stratum (neighborhood). The dashed lines show the 90% confidence interval and the solid lines the 95% confidence interval for each estimate using the standard errors obtained from the delta method. The coefficients and confidence intervals correspond to the point estimates and standard errors reported in Table A15 (Panel B). The first point estimate corresponds to the full sample, the second to owners who received the *control* message, and the third to owners who received an enforcement message (*central enforcement* or *local enforcement*). For the second and third point estimates, the sample is restricted to the 2665 properties exposed to randomized messages on tax letters. In this and all subsequent Figures in Sections 6.3 and 7.1 that report the RMTR, we use the Stata command *reghdfe*, which allows several levels of fixed effects and reformulates the output so that the reported intercept, which is used to compute the RMTR, is the average value of the fixed effects. Panel C and D uses variation in collector enforcement capacity. The x-axis contains estimates of collector enforcement capacity from Equation (7). In Panel C, the y-axis reports the collector-specific RMTR assuming that tax compliance is linear with respect to the tax rate so the RMTR is obtained from estimating Equation (8). In Panel D, the y-axis reports the quadratic analog collector-specific RMTR. Estimates of enforcement capacity are expressed as the percentage of owners who pay the property tax. Estimates of the RMTR are expressed as a percentage of the status quo tax rate. The best-fit line and the regression coefficient of the log of the x-axis on the log of the y-axis are reported with the corresponding robust standard errors. These estimates correspond to those in Table A16.

7.2.1. *Collector-Specific Enforcement Capacity*

We proxy tax collectors' enforcement capacity, E_c, by the average level of compliance they achieved across randomly assigned neighborhoods using a fixed-effects specification:

$$y_{i,n} = \sum_c E_c 1\big[c(n) = c\big] + X'_{i,n}\gamma + \epsilon_{i,n} \tag{7}$$

where $y_{i,n}$ is an indicator for tax compliance of property owner i living in neighborhood n, $c(n)$ denotes the tax collectors assigned to neighborhood n, $X_{i,n}$ is a vector containing an indicator for the property value band and indicators for the neighborhood-level interventions described in Balan et al. (2022), and $\epsilon_{i,n}$ denotes the error term. Due to random assignment, $\widehat{E}_c$ are unbiased estimates of collectors' enforcement capacities. Because randomization occurred at the collector pair level, we cluster standard errors by collector pair. We describe the estimation procedure in more detail in Section B3, and we report the distribution of the estimated $\widehat{E}_c$ in panel A of Figure B13.[50]

Why do some collectors have greater enforcement capacity than others? We provide evidence of two (related) mechanisms: more frequent tax visits and the ability to shape beliefs about the probability of sanctions for tax delinquency.

Collectors with high enforcement capacity appear to conduct more visits on the extensive and intensive margin (Figure A4, panels A and B). Extensive margin visits mechanically raise compliance by allowing more property owners to pay. Intensive margin visits could increase compliance by relaxing time-varying cash-on-hand constraints—because the collector is present at different points in time[51]—or by having a causal effect on beliefs about enforcement—because, with each visit, the owners might update their belief about the necessity of payment. We find evidence consistent with the latter explanation: the number of visits reported by households is positively correlated with their perceptions of the probability of sanctions for delinquency ($\rho = 0.101$, $p < 0.001$).

Relatedly, collectors with high enforcement capacity appear to be more persuasive in convincing owners that payment is mandatory as collector enforcement capacity is positively correlated with owners' perceived probability of sanctions for tax delinquency, measured in the midline survey (Figure A4, panel C). This relationship holds even when controlling for collector visits (panel D), suggesting that high enforcers raise compliance partly by persuading owners that payment is necessary.

7.2.2. *Collector-Specific RMTRs*

Because we have random variation in tax rates within each collector's set of assigned neighborhoods, we can estimate the collector-specific treatment effects (Figures B11 and B12) and revenue-maximizing tax rate, T^*_c. We begin with the linear specification:

$$y_{i,n} = \sum_c \beta^0_c 1\big[c(n) = c\big] + \sum_c \beta^1_c 1\big[c(n) = c\big] \times \mathit{Tax\ Rate}_{i,n} + X'_{i,n}\gamma + \epsilon_{i,n} \tag{8}$$

[50]This estimation procedure imposes an additional linear restriction that the average collector effect is zero. E_c should thus be interpreted with reference to the average collector, and some of the estimated $\widehat{E}_c$ are negative (Figure B13, panel A) for collectors with low enforcement capacity. By contrast, enforcement capacity at the collector-pair level, $E_{(c_1,c_2)}$, captures the compliance associated with the pair (c_1, c_2) when randomly assigned to a neighborhood, and the estimates, $\widehat{E}_{(c_1,c_2)}$, are always positive (Figure B18, panel A).

[51]We unfortunately cannot test this first mechanism because we lack data on the exact timing of cash-on-hand constraints and collector visits.

where *Tax Rate*$_{i,n}$ is the tax rate assigned to property owner i, expressed as a percentage of the status quo tax rate, and $y_{i,n}$, $X_{i,n}$, and $\epsilon_{i,n}$ are the same as in equation (7). Owing to random assignment of tax liabilities and tax collectors, the estimates of β_c^0 and β_c^1 are unbiased and can be used to construct an informative estimate of collector c's RMTR, $T_c^* = \frac{\beta_c^0}{-2\times\beta_c^1}$. We cluster the standard errors of β_c^0 and β_c^1 at the collector pair level, and we obtain standard errors for $\widehat{T_c^*}$ using the delta method. We also estimate an analogous quadratic specification. We describe the estimation procedure in more detail in Section B3 and we report the distribution of the estimated $\widehat{T_c^*}$ in panels B and C of Figure B13.

The fixed effects estimates $\widehat{E}_c$, $\widehat{\beta_c^0}$, and $\widehat{\beta_c^1}$ provide unbiased but noisy estimates of collectors' performance. We show robustness to shrinking $\widehat{E}_c$ and $\widehat{T_c^*} = \frac{\widehat{\beta_c^0}}{-2\times\widehat{\beta_c^1}}$ toward the mean of the true underlying distribution using a multivariable empirical Bayes (EB) model. We describe the EB adjustment in Section B4, and show the distribution of the EB estimates of collectors' enforcement capacity and RMTR in Figure B14.

7.2.3. *Raising the (Collector-Specific) RMTR*

Consistent with our theoretical prediction, we find a positive and statistically significant relationship between tax collectors' enforcement capacity, E_c, and their RMTR, T_c^*, regardless of whether we assume that tax compliance is linear in the tax rate (Figure 1, panel C) or quadratic in the tax rate (Figure 1, panel D). A 1% increase in collector enforcement capacity is associated with a 0.623% increase in the RMTR using the linear specification, and a 0.347% increase using the quadratic specification (Table A16). The positive relationship between E_c and T_c^* suggests that the RMTR is well below the status quo rate for "low enforcers," while the RMTR is closer to the status quo rate for "high enforcers."[52]

The results are analogous when using the empirical Bayes estimates of collectors' enforcement capacity and RMTR (Figure B15). They are also robust to splitting the sample in two and estimating E_c on the first sample split and T_c^* on the second split and are therefore unlikely to be driven by positively correlated measurement error in E_c and T_c^* (Figure B16, panels A and B). They are also robust to controlling for characteristics of the properties and their owner and are thus unlikely to be driven by differences in the characteristics of the neighborhoods the tax collectors are assigned to (Figure B17). Finally, the results are similar when estimated at the collector pair level, which suggests that they are unlikely to be affected by violations of the linearity assumption implicit in equations (7) and (8) and by potential complementarities between collectors in each pair (Figure B19).[53]

Section 5.3.4 presented evidence that the effects of tax abatements on compliance and revenue did not stem from collectors exerting effort or deploying persuasion techniques differentially across rates. This section shows that collectors who have a high enforcement

[52]Anticipating the positive relationship between collectors' enforcement capacity and RMTR, governments would ideally recruit high enforcers ex ante. Section B5 shows that collectors' enforcement capacity is positively correlated with their socioeconomic status and their intrinsic motivation to work in the public sector. That said, less than 10% of collectors have an RMTR that exceeds the status quo tax rate, which makes it unlikely that even the optimal recruitment policy could maximize revenue without corresponding reductions to tax rates.

[53]Given the small number of neighborhoods randomly assigned to each collector pair, these results could be influenced by differences in neighborhood characteristics. But in fact the relationship between the RMTR and enforcement capacity is more pronounced when controlling for property characteristics (Figure B20).

capacity have a higher RMTR. Although these two findings might at first appear contradictory, they can be reconciled by the fact that collectors appear to raise the RTMR by increasing compliance across all rates—that is, by increasing the intercept in equation (5)—rather than by moderating how household compliance responds to lower tax rates—that is, changing the slope in equation (5). Consistent with this interpretation, we find that there is more variation in collectors' intercepts than slopes (Figure A5),[54] and that high-enforcement collectors have larger intercepts but similar slopes compared to low-enforcement collectors (Table A17).[55] Moreover, the elasticities of collectors' visits and persuasion tactics with respect to rate are essentially flat across collector enforcement capacity (Figure A6, panels A–B and Figure A7).[56] In other words, according to our evidence, collectors with high enforcement capacity are not differentially targeting visits or using more persuasive tactics for households with rate reductions relative to collectors with low enforcement capacity. Instead, high-enforcement collectors appear to shift the RMTR by raising average compliance across all tax rates.

7.3. *Rates and Enforcement as Complements: Revenue Implications*

The positive impact of tax enforcement activities on the RMTR implies that governments should treat tax rates and enforcement as complementary policy levers. To illustrate this point, we predict the revenue gains that a sophisticated government would achieve by anticipating that investments in its enforcement capacity will increase the RMTR, compared to a naive government that manipulates rates and enforcement independently.

To do so, we estimate tax revenue by tax rates ("Laffer curves") at different levels of enforcement capacity. Specifically, we predict tax revenue, $T \cdot \widehat{\mathbb{P}(T, \alpha)}$, at different tax rates, T, using equation (6) to estimate $\widehat{\mathbb{P}(T, \alpha)}$.[57,58] The resulting graph shows the familiar hump-shaped relationship between tax rates and total revenue (Figure 2, panel A).

We then consider a hypothetical policy in which the government increases its enforcement capacity by replacing collectors in the bottom quartile of the enforcement capacity distribution with average collectors. The estimated revenue curve shifts up and to the right at this higher level of enforcement capacity (Figure 2, panel B), echoing the positive impact of tax enforcement activities on the RMTR discussed in Sections 7.1 and 7.2. Specifically, while the RMTR is 67% of the status quo tax rate in the baseline enforcement scenario, it rises to 95% of the status quo rate after the hypothetical enforcement policy. Thus, replacing tax collectors in the bottom quartile of enforcement capacity by average collectors would raise the RMTR by 42%.

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[54] Using regression specification (8), collector-level intercepts—that is, β_c^0—have higher variance ($\text{Var}(\beta_c^0) = 0.011$) than the collector-level slopes, that is, β_c^1—($\text{Var}(\beta_c^1) = 0.008$).

[55] We estimate the regression specification $y_{i,n} = \beta_1 1[c_1(n) = H \text{ or } c_2(n) = H] + \beta_2 \textit{Tax Rate}_{i,n} + \beta_3 1[c_1(n) = H \text{ or } c_2(n) = H] \times \textit{Tax Rate}_{i,n} + X'_{i,n}\gamma + \epsilon_{i,n}$, where $1[c_1(n) = H \text{ or } c_2(n) = H]$ is an indicator for either or both of the collectors' fixed effects—estimated in equation (7)—being above median, and everything else is defined as above. Table A17 summarizes the results.

[56] Furthermore, if we reestimate the relationship between collector enforcement capacity and collector-level RMTRs controlling for the number of visits households received from collectors, we find a similar positive slope (Figure A6, panels C–F).

[57] Figure A8 shows the fit of the predicted tax revenue by tax rate and the treatment effects on tax revenue described in Section 5.

[58] We use the same sample restriction as in Section 7.2 given that we consider the increase in enforcement capacity associated with replacing collectors in the bottom quartile of the enforcement capacity distribution with average collectors. This explains the difference in tax compliance levels in Figures A2 and A8.

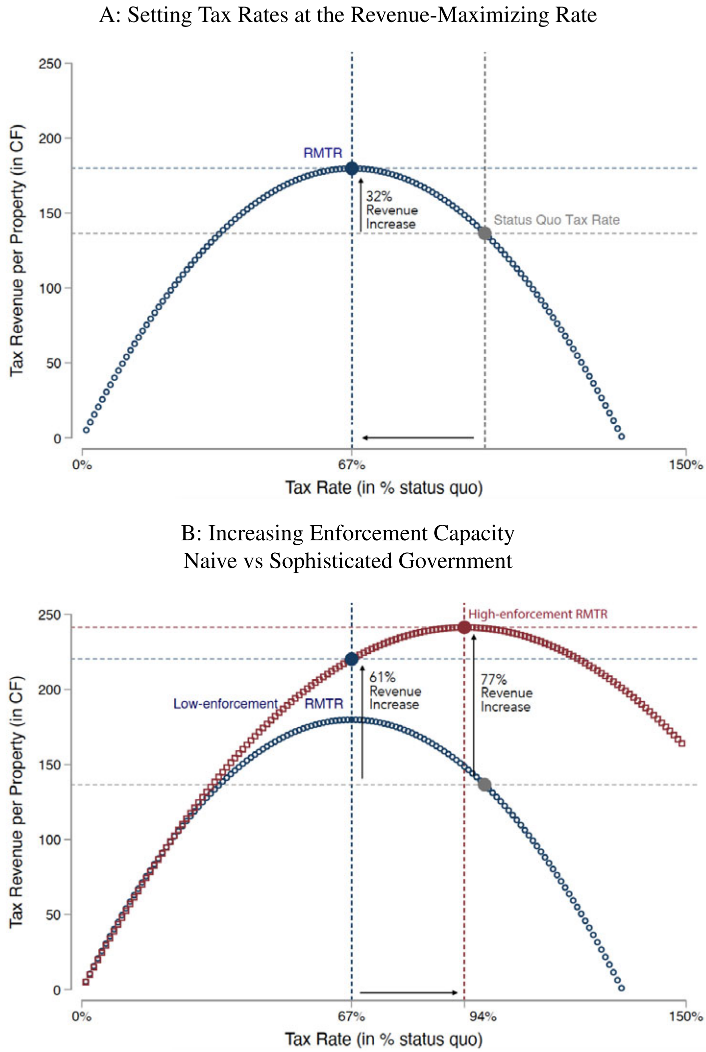

FIGURE 2.—Rates and Enforcement as Complements: Revenue Implications (Collector Variation). *Notes*: This figure reports estimates of the relationship between tax rates (x-axis) and tax revenue per property owner (y-axis). We predict tax revenue $T \cdot \widehat{\mathbb{P}(T, \alpha)}$ by predicting $\mathbb{P}(T, \alpha)$ at every tax rate T using Equation (6). Panel A estimates this relationship in the current enforcement environment in Kananga. Panel B then compares the predicted relationship between tax rates and tax revenue in the current enforcement environment (curve made up of circles) and after the government increases its enforcement capacity by replacing collectors in the bottom quartile of enforcement capacity with average tax collectors (curve made up of squares). In both panels, vertical lines indicate different potential tax rates, while horizontal lines indicate the corresponding revenue levels. In our example, a naive government would sequentially increase rates and increase enforcement, increasing total revenue by 61%, while a sophisticated government would prospectively choose the post-enforcement revenue-maximizing tax rate (RMTR) and increase revenue by 77%. We restrict the data to the properties subject to tax collection by teams of two state tax collectors. Figure A9 conducts the analogous analysis using the tax letter enforcement variation.

Imagine that the naive government sequentially implements the RMTR and then increases enforcement. Implementing the RMTR would raise revenue by 32% (Figure 2, panel A), and additionally replacing the bottom quartile of collectors with average collectors would result in a total revenue increase of 61% (Figure 2, panel B). By contrast, a sophisticated government could increase enforcement and prospectively choose the new RMTR corresponding to its higher enforcement capacity, which would raise revenue by 77% (Figure 2, panel B).[59] Jointly optimizing tax rates and enforcement would therefore lead to 10% higher revenue gains than adjusting these levers independently.[60] In short, governments are leaving tax dollars on the table if they fail to exploit the complementarities between enforcement and tax rates as policy tools.

8. CONCLUSION

Using random variation in property tax rates and enforcement in the DRC, this paper provides evidence that the revenue-maximizing tax rate increases with government enforcement capacity. The paper thus highlights the importance of endogenizing government enforcement activities as well as taxpayer compliance decisions (on the intensive and extensive margin) when conceptualizing the revenue-maximizing tax rate. Governments in low-capacity settings can exploit the complementarity between tax rates and enforcement to counter the revenue deficits they face. Compared to independently implementing the RMTR and increasing enforcement, prospectively implementing the post-enforcement RMTR would lead to 10% higher revenue gains.

In light of the observed complementarities between tax rates and enforcement, it is puzzling that many low-capacity governments adopt tax rates on par with high-capacity countries (Besley and Persson (2013)). Tax rates in some of these countries could be above the RMTR, as we found to be the case in the DRC, given their low enforcement capacities. One plausible explanation is that low-capacity governments simply lack information about the RMTR and set rates by mimicking those in other countries. Alternatively, forward-looking governments may strategically set tax rates above the RMTR if they anticipate investing in enforcement capacity—and thus shifting up the RMTR—in the future and if they know that tax rate increases are unpopular. Still another possibility is that officials choose higher-than-optimal tax rates to signal effort in raising revenues when other tax policy levers are less observable to their principals (e.g., politicians, voters, international donors). Adjudicating between these (and other) explanations would be fertile ground for future research.

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[59]These revenue predictions are similar when using the tax letter variation in enforcement instead of the collector-level variation (Figure A9).

[60]Independently optimizing rates and enforcement leads to 1.61 times more revenue than the status quo, while jointly optimizing rates and enforcement leads to 1.77 times, that is, 10% ($1.77/1.61 = 1.10$), more revenue.

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Co-editor Dave Donaldson handled this manuscript.

Manuscript received 12 July, 2021; final version accepted 27 February, 2024; available online 1 March, 2024.

The replication package for this paper is available at https://doi.org/10.5281/zenodo.10593883. The Journal checked the data and codes included in the package for their ability to reproduce the results in the paper and approved online appendices.