# The State Capacity Ceiling on Tax Rates: Evidence from Randomized Tax Abatements in the DRC

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**Abstract**

How can developing countries increase the tax revenue they collect? In collaboration with the Provincial Government of Kasaï-Central, we evaluate an experiment in the D.R. Congo that randomly assigned 38,028 property owners to different property tax liabilities. We find that status quo tax rates are above the revenue-maximizing (Laffer) tax rate. *Reducing* the tax rate by approximately 34% would maximize government revenue by increasing tax compliance. We then investigate how responses to tax rates interact with enforcement. We exploit two sources of variation in enforcement – randomized enforcement letters and random assignment of tax collectors – and show that the Laffer rate increases with enforcement. Replacing tax collectors in the bottom 25th percentile of enforcement capacity by average collectors would raise the Laffer rate by 42%. Tax rates and enforcement are thus complementary levers. According to our estimates, a government that adjusts tax rates and increases enforcement independently would increase revenue by 61%, while a government that takes their complementarity into account and adjusts both optimally would instead raise revenue by 77%. These findings provide experimental evidence that low government enforcement capacity sets a binding ceiling on the Laffer tax rate in some developing countries, thereby demonstrating the value of increasing tax enforcement in tandem with tax rates to expand fiscal capacity.

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# 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. In absolute terms, the gap is even more stark: the Democratic Republic of the Congo (DRC) raises US$63 in tax revenue per person, compared to US$17,100 per person in France.[1] Low-quality public services and infrastructure stemming from the lack of government revenue are thought to be important deterrents to economic growth (Kaldor, 1965; Besley and Persson, 2013). How can developing countries increase tax revenues? Can they simply increase tax rates?

To answer this question, governments must consider behavioral responses — e.g., in noncompliance or labor supply — which could offset revenue gains from tax rate increases. Canonical models of optimal taxation assume perfect enforcement. But in developing countries, enforcement is far from perfect, and tax *delinquency* is the first-order behavioral response governments must contend with when setting tax rates (Besley and Persson, 2009) and choosing the tax base (Best et al., 2015). Indeed, a growing theoretical literature emphasizes that behavioral responses to tax rates are shaped by the enforcement environment, and thus the revenue-maximizing (Laffer) rate should be thought of as a policy choice, not an immutable parameter (Slemrod, 1994; Slemrod and Kopczuk, 2002; Kopczuk, 2005; Saez et al., 2012; Slemrod, 2019).[2] Investments in enforcement capacity could, in theory, shift up the Laffer rate (Keen and Slemrod, 2017).

This paper tackles these issues empirically and provides experimental evidence that low government enforcement capacity can impose a ceiling on the Laffer rate in poor countries. We study random variation in tax rates and in tax enforcement in the DRC, an extremely poor and low-capacity state. 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 Laffer tax rate. 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 Laffer rate responds to changes in the enforcement environment.

[1]These estimates come from combining data on tax revenues from the International Centre for Tax and Development with population data from the World Bank for the period 2010-2015.

[2]In this paper, we use the term "Laffer tax rate" as a shorthand for the tax rate that maximizes government revenue in the context we study, in which the first-order behavioral response is tax delinquency.

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.

Tax compliance is low in Kananga: on average, 8.8% of property owners paid the property tax in 2018.[3] 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 12.9% for owners assigned reductions of 17%, 33%, and 50%, respectively. The property tax in Kananga is a flat fee and partial payments were not permitted, so these responses translate into a large, negative elasticity of tax compliance with respect to the tax rate (–1.246). The fact that this elasticity is greater than one in absolute value means that lowering tax rates would increase tax revenue. Indeed, we estimate that a 1% increase in the property tax rate reduces revenues by 0.243%. In short, the status quo tax rates appear to be above the Laffer rate in this setting.

Before estimating the Laffer rate explicitly, and investigating its interaction with the enforcement environment, we evaluate the validity of our treatment effects and elasticities by (*i*) ruling out alternative explanations concerning taxpayer and collector behavior, and (*ii*) providing evidence on the mechanism through which lower rates increase revenue.

An important concern is whether property owners' responses could be biased by knowledge of others' tax rates, anchoring on past tax rates, expectations about future rates, or by collectors exerting enforcement effort differentially across tax rates. Knowledge of others' rates, for instance, could bias our estimated elasticities if owners' behavior in part reflects fairness considerations (Besley et al., 2019; Best et al., 2020; Nathan et al., 2020). 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 (Thaler, 1985). Yet few property owners were aware that they received a discount, and those who were behaved similarly to the rest. Compliance responses to tax rates could also be biased upward if property owners who received a tax reduction expected

[3] Property tax compliance is similar in other low-capacity settings: about 7% in Haiti (Krause, 2020), 7.7% in Liberia (Okunogbe, 2019), 12% in Senegal (Cogneau et al., 2020), and 25% in Ghana (Dzansi et al., 2020).

the reduction to be temporary and the rate to increase in the future.[4] However, we provide evidence that property owners in this context expect assigned tax rates to apply again in subsequent rounds of collection. Finally, if tax collectors made more frequent visits after registration to households assigned to low rates, then the elasticities of compliance we estimate could be explained in part by differential enforcement effort across rates. We examine this issue by (*i*) controlling for the number of times collectors visited households, and (*ii*) exploiting exogenous variation in collectors' incentives to exert effort differentially by rate.[5] Our estimated elasticities of compliance and revenue are essentially unchanged when we take collectors' enforcement effort into account.

What drives the revenue response to lower tax rates? The reduced-form estimates have already revealed that the decrease in tax delinquency — or, put differently, the increase in compliance on the extensive margin — explains the higher revenues observed among properties assigned to lower tax rates. Although the public finance literature has focused on intensive margin responses, this extensive margin tax delinquency response is a first-order consideration in low- and middle-income countries.[6] We estimate heterogeneous treatment effects to shed further light on why compliance increases as tax rates fall. This exercise reveals that the elasticity of compliance with respect to rates is largest among property owners facing cash-on-hand constraints. The compliance response we observe thus appears to reflect cash-constrained individuals entering the tax net only when tax rates are sufficiently low.[7]

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 affect citizens' decisions to comply or not with the property tax. Using a formula for the revenue-maximizing (Laffer) tax rate from this framework, we estimate that the Laffer rate is 66% of the status quo rate. In other words, consistent with our reduced-form results, in this low-enforcement environment the provincial government

[4] For instance, if owners assigned to a rate reduction expected to instead face the full rate in future arrears, then they might have been more likely to pay in 2018.

[5] Specifically, collectors' compensation varied randomly on the household level between (*i*) a proportion of the amount of tax they collected — eliminating the incentive to target tax visits to low rates — and (*ii*) a constant amount independent of the rate.

[6] While Besley and Persson (2009) make this point theoretically, recent empirical work in Brazil (Best et al., 2020) and Mexico (Brockmeyer et al., 2020) similarly finds high rates of property tax delinquency.

[7] This conclusion is consistent with recent evidence from Mexico (Brockmeyer et al., 2020) and the United States (Wong, 2020) about the importance of liquidity constraints in property tax compliance. This mechanism is thus not unique to low-income countries, nor is it a reflection of the particular form of tax collection used in this setting as we discuss below.

would maximize revenue by reducing the statutory property tax rate by 34%.

We then examine how the Laffer rate evolves as a function of enforcement. The first source of variation in enforcement we study comes from 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 penalties for tax delinquency or a control message noting that paying taxes is important.[8] The estimated Laffer rate is 41% higher among owners assigned to the enforcement message. In fact, the Laffer rate is only 22% less than the status quo rate in the enforcement message group, compared to 45% less in the control message group.

A second source of variation in enforcement comes from random assignment of tax collectors to neighborhoods. 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. Tax collectors vary in their intrinsic enforcement ability, and thus neighborhoods were subject to exogenous variation in enforcement depending on which tax collectors were randomly assigned to work there. Moreover, tax collectors vary in their ability to collect at different tax rates, allowing us to estimate the Laffer rate for each tax collector, again using a fixed effect model.[9] The tax collector approach yields similar results to the tax letter approach: the Laffer rate increases with enforcement capacity. Specifically, replacing tax collectors in the bottom 25$^{\text{th}}$ percentile of enforcement capacity with average collectors would increase the Laffer rate by 42%.[10]

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 will increase the Laffer rate, compared to a naive government that manipulates rates and enforcement independently. The naive government that sequentially implements the Laffer rate and then increases enforcement — again by replacing the bottom

[8] A large literature finds that enforcement messages on tax letters generally increase compliance at the margin (Blumenthal et al., 2001; Pomeranz, 2015; Hallsworth et al., 2017).

[9] While the random assignment of tax collectors to neighborhoods and of tax rates within neighborhoods means that our estimates of tax collector enforcement capacities and Laffer rates are unbiased, the relatively small sample introduces noise in our estimates. We use multivariate Empirical Bayes methods to correct our estimates for noise due to sampling error.

[10] We also consider alternative policies the government could use to increase enforcement capacity, such as hiring tax collectors with observable characteristics predictive of high enforcement capacity (including education, income, and tax morale).

25th percentile of collectors with average collectors — would raise revenue by 61% relative to the status quo. By contrast, the sophisticated government that prospectively chooses the new Laffer rate corresponding to its higher enforcement capacity — would instead raise revenue by 77%.

Finally, we consider whether the government might have set tax rates above the Laffer rate for reasons that are unrelated to enforcement capacity. In particular, a government might choose to set tax rates above the Laffer rate if lowering rates backfires on other margins, such as generating negative fiscal externalities by lowering citizens' propensity to pay other taxes, increasing bribery, or undermining citizens' views of the government's capacity. We investigate these possibilities using survey data and find little evidence of adverse effects. In fact, property tax abatements reduced bribery on the extensive and intensive margins; they also led citizens to view the property tax as more fair.

This paper contributes to three literatures. First, it offers experimental evidence of a state capacity ceiling on the revenue-maximizing (Laffer) tax rate. A large theoretical literature argues that individuals' responses to tax rates depend on the enforcement environment (Slemrod, 2019), and thus that the Laffer rate is a policy choice not a structural parameter (Slemrod and Kopczuk, 2002; Kopczuk, 2005; Saez et al., 2012; Keen and Slemrod, 2017). The idea that Laffer rates move in tandem with enforcement capacity has escaped empirical scrutiny given the challenge of finding exogenous variation in both tax rates and enforcement.[11] The field experiment we study enables us to make progress on this issue. Consistent with this theoretical literature, tax rates and enforcement appear to be complementary levers in our setting.

We also contribute to a growing empirical literature studying optimal tax rates. Most of this literature focuses on high-income countries (Saez et al., 2012) and middle-income countries (Basri et al., 2019; Brockmeyer et al., 2020), where tax rates often lie below the Laffer rate.[12] We contribute evidence from a low-income country with weak enforcement capacity, where we find that tax rates are *above* the Laffer rate. Moreover, while most past work is quasi-experimental, we estimate the elasticity of tax revenue using random variation in tax liabilities generated by a field experiment. Finally, we advance this literature by leveraging rich administrative and survey data to explore mechanisms through which rate changes affect total revenues and to consider other policy-relevant response margins, such

[11] The interaction between the Laffer rate and other tax policy parameters, such as the tax base, has been studied in the context of corporation taxation (Kawano and Slemrod, 2016; Serrato and Zidar, 2018).

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

as fiscal externalities, corruption, and citizens' views of the government.

Finally, we contribute to the literature on taxation in developing countries, which has focused on third-party reporting (Pomeranz, 2015; Naritomi, 2019; Jensen, 2019), pecuniary and non-pecuniary motivations for compliance (Del Carpio, 2013; Pomeranz, 2015), tax administration (Basri et al., 2019), and tax design (Kleven and Waseem, 2013; Best et al., 2015). In particular, we add to a small but growing literature on property taxation in developing countries, where property taxes are significantly underexploited. Past work examines social norms (Del Carpio, 2013), technologies to increase enforcement (Okunogbe, 2019), and tax collector incentives (Khan et al., 2015). By contrast, we focus on tax rates, which have received relatively less attention in the literature on public finance and development. A key exception is Brockmeyer et al. (2020), which compares tax rates and enforcement as independent tools to raise revenues in a middle-income country (Mexico).[13] By contrast, we focus on the *interaction* between tax rates and enforcement in the context of a low-income country with weak state capacity.[14] Finally, we note low-cost policies that governments can use to increase their Laffer rates: (*i*) making more salient the penalties for tax delinquency on tax letters, and (*ii*) hiring tax collectors with characteristics associated with high enforcement ability.

This paper is organized as follows. Sections 2 and 3 review the setting and design, respectively. Section 4 summarizes the data and balance tests, before the presentation of treatment effects on tax compliance and revenue in Section 5. Section 6 then introduces a simple theoretical framework to generate a formula for the Laffer tax rate, which we estimate in the data. Section 7 explores how the Laffer rate responds to changes in enforcement. Finally, Section 8 examines other behavioral responses to randomly assigned property tax rates in our setting, before concluding in Section 9.

# 2 Setting

The DRC is one of the largest and most populous countries in Africa, and yet also one of the poorest. Median 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

[13] In the context of corporate income taxation in Indonesia, Basri et al. (2019) also independently compares tax rates and tax administration but does not explore the interaction between the two.

[14] Brockmeyer et al. (2020) also focuses on liquidity constraints as a driver of responses to tax rate changes and government provision of liquidity as a policy tool. Their framework and results reinforce our analysis of liquidity constraints as a plausible mechanism behind the elasticity of compliance with respect to tax rates.

"failed" or "fragile" states, the country has been beleaguered by misrule and conflict since King Leopold took control in the late 19th century and allowed private rubber companies to plunder as they pleased (Lowes and Montero, 2020; Sanchez de la Sierra, 2020). The country today has low state capacity, especially in terms of tax enforcement. From 2000-2017, the DRC finished in 188$^{\text{th}}$ place of 200 countries in terms of its tax-GDP ratio.[15]

Kananga, a city of roughly 1 million inhabitants (the fourth largest in the DRC), is the seat of the Provincial Government of Kasaï-Central. Government tax revenues are extremely low: roughly US$0.30 per person per year (or US$2 million in a province of 6 million people).[16] The majority of these tax revenues come from trade taxes, commercial permits, and various fees levied on a handful of firms in downtown Kananga, such as mobile-phone companies. Although there are many taxes on the books, few are enforced among private citizens. At baseline, about 20% of citizens in Kananga reported paying any taxes in the previous year.[17] Low tax revenue is a key challenge facing governments across the developing world (Gordon and Li, 2009).

Heeding international advice, the Provincial Government of Kasaï-Central has turned to the property tax in an effort to raise revenues.[18] 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.[19] 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 partic-

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

[16]Annual provincial tax revenue per capita in Kasaï-Central is thus considerably lower than national tax revenue per capita (US$63) in the DRC.

[17]The most commonly reported taxes paid are: the bicycle tax (11.27% of citizens), property and/or rental tax (3.81%), firm permits and registration (3.58%), social security tax (3.49%), toll tax (2.66%), vehicle tax (1.13%) and market vendor fees (0.65%). The low share of citizens who report paying formal taxes is partially offset by contributions to informal labor taxes (Olken and Singhal, 2011), called *salongo*, in which citizens engage in local public goods provision. About 37% of citizens reported that a household member participated in *salongo* in the past two weeks.

[18]Tax experts often recommend that local governments focus on the property tax because revenues stay local and it is thought to be efficient — because it is levied on an immobile asset (Fjeldstad et al., 2017). Indeed, we confirm that assignment to tax abatements is not associated with differential rates of property investment or moving to different neighborhoods or properties (Table A9).

[19]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 58% of Kananga's neighborhoods were randomly selected to receive the campaign in 2016. The variation in tax liabilities studied in this paper occurs *within* neighborhoods, and we explore heterogeneous responsiveness to rate reductions by exposure to the 2016 campaign in Section 5.3.

ular, the governor noted 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 tax ministry leadership also anticipated longer term revenue gains by widening the tax net as citizens develop a "fiscal culture" and feel more of an obligation to pay in future years.[20] Recent work confirms this assumption that tax payment is habit-forming (Dunning et al., 2015). These ideas about the short- and long-run revenue benefits of lower rates lie at the root of the tax abatement intervention we study and describe in detail in the next section.

# 3 Experimental Design

## 3.1 Property Tax Campaign

The experiment is 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.[21] 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 house is in the low- or high-value band, a distinction based on the type of materials used to build the walls and roof.[22] They also determined exemptions from the property tax during this visit.[23] Next, collectors issued a taxpayer ID (written on the door or wall) and gave the property owner a tax letter. This letter contained the tax rate assigned to the property, as described in Section 4.2.[24] Collectors also solicited payment of

[20] In other words, the government assumed that once citizens enter the formal tax net, even if they pay a reduced amount, there is a discrete shift in their role as *contribuables*, citizens who contribute to the public good by funding the government.

[21] The identity of the tax collector varied across neighborhoods between state agents and city chiefs (or a combination of the two). We describe tax collector types in Section A1.3 and study their impacts on compliance in a companion paper (Balan et al., 2020). We show that this tax collector variation does not impact the results presented in this paper in Table A8.

[22] Houses made of non-durable materials (sticks, palm, mud bricks) are classified in the low-value band, while those made of durable materials (bricks or concrete) are classified in the high-value band.

[23] Exempted 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.

[24] During property registration, collectors were required to take a linear, house-by-house route through neighborhoods, which eliminated the possibility of manipulating the randomization of tax abatements during registration. We validate that collectors complied with these instructions using the time stamps and GPS coordinates taken during registration (Figure A1).

the property tax during this initial registration visit. Independent surveyors trained to use GPS devices accompanied tax collectors during registration in order to verify and record property locations.

Upon completion of the property register, collectors made follow-up tax visits throughout the neighborhood. They had roughly 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 handheld receipt printer to issue receipts, with the transaction recorded in the device's memory. Collectors were responsible for any discrepancies between the money they submitted to the state and the sum recorded in the receipt printer. Partial payments were not permitted.[25] Consistent with standard practices at the tax ministry, collectors received a piece-rate wage for their work on the campaign.[26] The structure and magnitude of collector compensation is analogous to that received by property tax collectors in other developing countries (Khan et al., 2015; Amodio et al., 2018).

Property owners who failed to pay the property tax by the end of the one-month tax collection period were considered tax delinquents. The official penalty set forth by the Provincial Government of Kasaï-Central for tax delinquency was a fine of 1.5 times the original tax liability, due within 30 days. After this, delinquent owners could be summoned to court and face further penalties. In reality, such sanctions were rare among residential property owners. 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 collector-level enforcement capacity.

## 3.2 Tax Abatement Randomization

### 3.2.1 Tax Rate Description

Rather than a property tax schedule that applies marginal tax rates to property value, as is common in high- and middle-income countries (Khan et al., 2015; Brockmeyer et al.,

[25] We suspect the provincial tax ministry did not accept partial payments because (*i*) transaction costs of collectors making multiple trips to households might have outweighed the revenue gains, and (*ii*) it could have created opportunities for bribery by effectively making the amount due negotiable between collector and property owner (Khan et al., 2015).

[26] Specifically, collectors received 30 Congolese Francs (CF) per property registered plus a piece rate corresponding to tax payments. As discussed in Section A1.2, 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. This variation in wages allows us to examine (and hold constant) collector effort levels across different rates, as shown in Table A7.

2020), properties in Kananga face a fixed annual tax liability. Before the 2018 campaign, properties in the low-value band (89% of total properties) faced tax rate of 3,000 Congolese Francs (CF), or roughly US$2. Properties in the high-value band (11% of properties) faced tax rate of 13,200 CF (US$9) for properties in the high-value band (built in durable materials).[27,28]. Figure A2 contains examples of low- and high-value properties.

The use of fixed annual fees for the property tax — rather than applying a marginal tax rate to property values — reflects the absence of an up-to-date property valuation roll for the city of Kananga. This is not a problem specific to the DRC. The high costs of creating and maintaining valuation rolls mean that, out of the 159 non-OECD countries in the World Bank's *Doing Business Survey*, only one third have registered and mapped their largest city's private plots (Lall et al., 2017). The absence of a working cadastre also makes it difficult for governments to collect arrears.[29] Simplified property tax schedules involving fixed fees and no arrears are common in low-income countries with weak tax enforcement capacity (Franzsen and McCluskey, 2017).[30]

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 A5, 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.[31]

#### 3.2.2 Tax Abatement Randomization

In the 2018 property tax campaign, randomly selected properties received tax abatements (i.e. tax liability reductions). When collectors assigned taxpayer IDs and issued the corresponding tax letter during property registration, they randomly assigned each property to the status quo annual tax rate (3,000 CF for low-value properties and 13,200 CF for high-value properties) or to reductions of 17% (2,500 CF and 11,000 CF), 33% (2,000 CF and 8,800 CF), or 50% (1,500 CF and 6,600 CF). Table 1 summarizes the different tax abatement treatment groups by property value band. The randomization of abatements was

[27] There are indeed clear differences in the property values in the low- and high-value bands, as shown in histograms of estimated property values using machine learning (Figure A24). The difference between these distributions to some extent validates the government's use of this building quality tag in setting tax rates. For details on the machine learning estimates of property values, see Section A5.

[28] 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.

[29] The exception is the 285 *villa* properties, for which the government does track past liabilities.

[30] 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.

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

stratified at the neighborhood level (351 in total).[32]

Taxpayer IDs and liabilities (inclusive of randomized abatements) were pre-populated on tax letters. As long as tax collectors completed the property registration in a systematic fashion, then properties were assigned to rate reductions at random. 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 in some way (Figure A1). We also check balance in Section 4.2.

Importantly, tax letters mentioned the property's annual liability without reference to the status quo rate or to tax abatements. Taxpayers in the rate reduction treatment groups were thus only informed about their annual rate with no mention that they had received a reduction.[33] Figure A3 provides examples of tax letters for each of the rate treatments.[34]

# 4 Data and Balance

## 4.1 Data

As summarized in Table A1, data come from five sources.

**1. Administrative Data**: For our 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.[35]

**2. Baseline Survey**: Baseline survey enumeration occurred between July and December 2017, before the tax campaign. Enumerators randomly sampled compounds following skip patterns while walking down each avenue in a neighborhood: e.g., visit every $X^{\text{th}}$ 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 3,358

[32] 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 (a pure control in Balan et al. (2020)). We show robustness to including these neighborhoods in Table A5.

[33] That abatements were not made salient to households simplifies interpretation of treatment effects by minimizing the impacts of fairness considerations or "transactional utility," as we discuss in Section 5.3.

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

[35] There are 46,290 registered properties in all of Kananga. For the analysis, we exclude the 1,132 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. (2020)). We also exclude the 6,333 (14%) exempted 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 exempted properties in Table A5.

respondents, to examine balance and study heterogeneity in treatment effects.[36]

**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. It also collected secondary outcome data, such as bribe payment and contributions to other taxes. Enumerators sought to conduct this survey with the property owner, who was available in 22,667 cases. Alternatively, enumerators conducted the survey with another adult family member or simply recorded property characteristics — such as the quality of the walls, roof, and fence — in the absence of any available respondent, in an additional 6,967 cases.[37,38]

**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 2,760 respondents, such as payment of other taxes, views of the government, and the perceived fairness of the tax system.[39]

**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.[40] As described in detail in Section A5, we trained several machine learning algorithms (linear regression, elastics net, SVR, random forest, boosting, and ensemble model) using a sample of 1,654 property values as well as survey and GPS data. The market value of each property in the training sample derives from

[36] The baseline survey was conducted with a total of 4,331 respondents. But, as noted, in the main analyses we exclude respondents in pilot neighborhoods, pure control neighborhoods of Balan et al. (2020), and exempted respondents, which brings the number of total baseline respondents to 3,358. Table A5 re-estimates the main analysis in alternate samples that include these excluded sub-groups as a robustness check. Moreover, in analyses that require us to match baseline surveys with tax rates assigned during the 2018 campaign, we further restrict the sample to the households enumerators were able to resurvey at endline (about whom we observe tax rate information with a high degree of confidence).

[37] The midline survey was conducted with a total of 36,314 respondents. As noted, in the main analyses, we exclude neighborhoods from the logistics pilot, the pure control in Balan et al. (2020), and exempted households — a total of 6,680 midline surveys. We show robustness to including these excluded subgroups in Table A5.

[38] Attrition from the property register into the midline survey (22%) is balanced across treatments (Table 2). Attrition also appears unrelated to property value (Figure A4, Panel A) or monthly income (Panel B).

[39] Enumerators were able to survey 3,883 of the total 4,331 baseline sample respondents at endline (89.66%). Attrition is uncorrelated with property value, monthly income, or past tax compliance. The final sample size after restricting to non-pilot neighborhoods exposed to door-to-door collection, and excluding exempted households, is 2,760.

[40] In a companion paper, Bergeron et al. (2020a), we discuss these machine learning and computer vision methods in depth and describe how these predicted property values could be used by the Provincial Government of Kasaï-Central to improve the design of the property tax.

in-person property appraisal visits conducted by government land surveyors. The features we consider include property characteristics from household surveys as well as geographic characteristics (Table A31). For instance, survey-based features include different dimensions of house quality, and geographic features include the distance of a house to the city center, schools, government buildings, and other important locations. Figure A23 reports the feature importance in terms of data splits for the best algorithm.

### 4.2 Balance

In Table 2, we examine balance across treatment groups for a range of property and property owner characteristics. Panel A considers all the characteristics of the property, drawing on geographic data, midline survey data on house quality, and property values as estimated using machine learning. Panel B considers basic characteristics of the property owner collected at midline that are unlikely to be affected by the treatments. Panel C considers additional characteristics of the property owners collected at baseline, including attitudes about the government and tax ministry.

Overall, 2 of the 90 differences reported in Panels A–C of Table 2 are significant at the 5% level, and 3 of the 90 differences are significant at the 10% level based on $t$-tests that do not adjust for multiple comparisons. This is in line with what one would expect under random assignment. We also test the omnibus null hypothesis that the treatment effects for the variables in Table 2 are all zero using parametric $F$-tests (Table A2). We fail to reject the omnibus null hypothesis for the property characteristics reported in Panel A as well as for the property owner characteristics reported in Panels B and C.

## 5 Treatment Effects on Tax Compliance and Revenue

### 5.1 Empirical Specifications

We first estimate the effect of being assigned to each of the tax rate abatement treatment groups using the following OLS regression:

$$\begin{aligned} y_{i,n} = \beta_0 + \beta_1 17\%\ Abatement_{i,n} + \beta_2 33\%\ Abatement_{i,n} \\ + \beta_3 50\%\ Abatement_{i,n} + \gamma_{i,n} + \delta_n + \epsilon_{i,n} \end{aligned} \tag{1}$$

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). $\gamma_{i,n}$ is an indicator for properties in the high-value band. $\delta_n$ are neighborhood (randomization stratum) fixed effects, and $\epsilon_{i,n}$ is the error term. Exempted properties are excluded from the analysis.[41] Given that the tax reduction treatments were assigned at the property level, we follow Abadie et al. (2017) and report robust standard errors.

We estimate the elasticities of tax compliance and revenue with respect to the tax rate — which we denote $\hat{\varepsilon}_{y,T}$ — using the following OLS regression:

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

with $Tax\ Rate_{i,n} \in \{1500\,CF, 2000\,CF, 2500\,CF, 3000\,CF\}$ for properties in the low-value band, and $Tax\ Rate_{i,n} \in \{6600\,CF, 8800\,CF, 11000\,CF, 13200\,CF\}$ for properties in the high-value band. $\gamma_{i,n}$ and $\delta_n$ 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.[42] Because $\hat{\beta}$ and $\overline{y_{i,n}}$ are estimated separately, we compute bootstrapped standard errors for the elasticity $\hat{\varepsilon}_{y,T}$.[43]

## 5.2 Results

We first examine the causal effect of rate reductions on tax compliance. As in other low-capacity settings,[44] compliance is low across all treatments: on average 8.8% of property

[41] In Table A3, we use the tax rate these exempted properties would have been assigned had they not been exempted to show balance of exemption status by tax rate.

[42] Goldberg (2016) uses a similar approach to estimate the elasticity of employment with respect to wages in rural Malawi.

[43] Specifically, we construct $1,000$ samples (with replacement) and repeat the estimation procedure for each sample, yielding $SE_{\hat{\varepsilon}_{y,T}}$ as the standard deviation of these bootstrap iterations.

[44] For example, recent estimates include 7% in Haiti (Krause, 2020), 7.7% in Liberia (Okunogbe, 2019), 12% in Senegal (Cogneau et al., 2020), and 25% in Ghana (Dzansi et al., 2020). In fact, each of these

owners in Kananga paid the property tax in 2018. Nonetheless, rate reductions substantially increased the share of taxpayers (Figure 1). Only 5.6% of the property owners assigned to the status quo tax rate paid the property tax, while 6.7%, 10%, and 12.9% of owners assigned to reductions of 17%, 33%, and 50% paid, respectively (Table 3, Column 1). The results are robust to including neighborhood fixed effects (Column 2) — our preferred specification — and to restricting the sample to low- or high-value band properties (Columns 3–4). As noted, the property tax in Kananga is a flat fee, and collectors did not accept partial payments; these treatment effects therefore translate into a large negative elasticity of tax compliance with respect to the tax rate: $\hat{\varepsilon}_{C,T}$ =–1.246 ($SE_{\hat{\varepsilon}_{y,T}}$ =0.061) (Column 2). A 1% increase in the property tax rate is associated with a 1.246% decline in property tax compliance.

Importantly, the increases in compliance from rate reductions lead to higher revenue. This result is clearest in Panel B of Figure 1: tax revenue was higher for individuals assigned to the 50% and 33% reduction treatments than for individuals assigned to the 17% reduction or the control group. Again, these results hold when we include neighborhood fixed effects or estimate the results in the two value band sub-samples separately (Table 3, Columns 6–8). The elasticity of tax revenue with respect to the property tax rate is thus also negative: $\hat{\varepsilon}_{R,T}$ =–0.243 ($SE_{\hat{\varepsilon}_{y,T}}$ =0.081). A 1% increase in the tax rate is associated with a 0.24% decline in property tax revenues. In this context, status quo tax rates were thus *above* the revenue-maximizing (Laffer) rate.

We explore a range of robustness checks in Table A5, 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 2), (*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. (2020)), and (*vi*) including exempted properties (using the rate they would have been assigned had they not been exempted).

Finally, to make the results comparable with settings with a property tax based on underlying property value, we re-estimate the elasticities of compliance and revenue while expressing the property tax rate as a percentage of property value. We rely on predicted property values using machine learning estimates (cf. Section A5). This approach yields similar results, with compliance and revenue decreasing in the tax rate (Figure A5). To

studies was conducted in national capitals, where property tax compliance is typically higher (Franzsen and McCluskey, 2017).

quantify the magnitude of this decline, we estimate elasticities using an instrumental variable (IV) approach:

$$y_{i,n} = \alpha + \beta log(\tau_{i,n}) + \gamma_{i,n} + \delta_n + \nu_{i,n} \tag{4}$$

$$\begin{aligned} log(\tau_{i,n}) = \beta_0 + \beta_1 17\%\ Abatement_{i,n} + \beta_2 33\%\ Abatement_{i,n} \\ + \beta_3 50\%\ Abatement_{i,n} + \gamma_{i,n} + \delta_n + \epsilon_{i,n} \end{aligned} \tag{5}$$

where $\tau_{i,n} = Tax\ Rate_{i,n} / Property\ Value_{i,n}$. In other words, we instrument for the tax rate expressed as a percentage of property value using the tax abatement treatment indicators. We estimate Equations (4) and (5) using two-stage least squares and summarize the results in Table A4. The elasticities, $\hat{\varepsilon}_{C,\tau}$ =-1.278 ($SE_{\hat{\varepsilon}_{C,\tau}}$=0.066) for compliance and $\hat{\varepsilon}_{R,\tau}$ =-0.253 ($SE_{\hat{\varepsilon}_{R,\tau}}$ =0.084) for revenue, are similar to those reported in Table 3.

## 5.3 Alternative Explanations

Before estimating the Laffer rate in Section 6, we confirm the validity of the treatment effects on tax compliance and revenue by considering whether the estimates could be biased 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 collector enforcement effort across tax rates. We find little evidence that these factors biased our estimates.

### 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 bias our results if the decision to comply or not with the property tax was in part driven by fairness considerations (Besley et al., 2019; Best et al., 2020; Nathan et al., 2020). To investigate this possibility, we re-estimate the reduced-form results controlling for the tax rates of each property owner's 5 and 10 closest neighbors, respectively (Tables 4 and A6, Columns 1–2). The effects on tax compliance and revenue are essentially unaffected by adding these controls.

Additionally, we re-estimate the results comparing the set of property owners who reported knowing any of their neighbors' tax rates. 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.[45] The results are similar among owners who reported knowing, and not knowing, their neighbors' rates (Tables

[45]For instance, Lowes (2017) notes that adults often avoid discussing financial matters even with their spouse, consistent with redistributive pressures in many parts of sub-Saharan Africa (Jakiela and Ozier, 2016).

4 and A6, Columns 3–4).[46]

Awareness of others' tax rates could also bias our results if owners assigned to lower rates were more likely to pay because of "transactional utility" — the sense of getting a good deal — associated with receiving a tax reduction (Thaler, 1985). There are several reasons why transactional utility is unlikely to be present in this setting. First, tax notices only informed owners about their tax liability, without any mention of the status quo liability, others' liability, or any mention of a reduction (Figure A3). Second, only 2.8% of property owners were aware that the government was issuing any property tax abatements in 2018, according to midline survey data. Owners who had and had not heard of reductions had statistically indistinguishable elasticities (Tables 4 and A6, Columns 5–6).[47]

Relatedly, tax collectors might have have been more likely to mention tax abatements to property owners who received larger tax reductions in order to convince them to pay, in which case awareness and the size of reductions would be positively correlated. Yet we find no evidence that owners assigned to larger reductions were more likely to have heard of tax abatements, or to be more aware of their neighbors' rates (Table A10, Columns 1–2). Moreover, we use endline survey data to examine if collectors' persuasion tactics — i.e., their messaging about the tax, reported by owners at endline — varied by tax rate treatment.[48] We find little evidence of such heterogeneity (Table A10, Columns 3–11).

#### 5.3.2 Anchoring on Past Tax Rates

A second concern is that property owners' responses could be biased if their expectations of current tax rates were anchored on past rates. For instance, if owners expected the same rate in real terms as 2016 — equivalent to status quo rates — but were assigned to a reduction, they could also experience "transactional utility," described above as the feeling of getting a good deal. Such anchoring could make owners assigned to rate reductions more inclined to pay than they otherwise would have been.

For anchoring to meaningfully impact our estimates, precise knowledge of status quo property tax rates would need to be widespread. Yet, only 16.23% of property owners were able to report the exact status quo rate corresponding to their property value band

[46] Table A12 alternatively shows heterogeneous treatment effects by owners' knowledge of neighbors' rates.

[47] Estimating heterogeneous treatment effects returns a marginally significant coefficient using compliance as the outcome, but insignificant results for revenue (Table A12).

[48] Common messages used by tax collectors to try to convince households to pay included emphasizing: sanctions (Columns 3–4), public good provision (Columns 5–6), showing trust in the government (Column 7), the importance of paying tax (Column 8), the legal obligation to pay (Column 9), the potential social embarrassment of evading taxes (Column 10), and other threats for tax delinquents (Column 11).

in the baseline survey.[49] Moreover, those who knew the status quo rate did not respond differently to the treatment (Table 4, Columns 8–9).[50] This result suggests that anchoring is an unlikely source of bias in this setting.

As an additional test, we re-estimate the results in neighborhoods that were randomly assigned to door-to-door tax collection in 2016 compared to neighborhoods where no such collection occurred (Weigel, 2020).[51] At baseline, owners were more likely to accurately report the status quo tax rate in neighborhoods that received the 2016 tax campaign, and thus should have been more likely to anchor on past rates.[52] However, we find similar compliance and revenue responses to tax abatements in both types of neighborhoods (Table 4, Columns 9–10, and Table A6, Columns 9–10).[53] Our results thus do not appear to be unique to settings in which the government is introducing a new tax — but rather extend to low-compliance settings in which governments lower existing tax rates.[54]

#### 5.3.3 Beliefs about Future Tax Rates

A third concern is that property owners may have expected tax rate reductions to be temporary, which could enhance the perceived benefit of paying in 2018. For example, if owners assigned to a rate abatement in 2018 expected to instead face the full rate in future arrears, then they might have been more likely to pay this year.

Given that less than 3% of citizens knew of tax reductions, it seems unlikely that such beliefs over future rates could be influencing behavior in this context. A standard result from models of decision-making under uncertainty is that rational actors assign more weight to factors whose outcomes they are sure about than to those about which they are more uncertain (Anscombe et al., 1963). Taxpayers would thus likely focus on this year's liability when making their compliance decision, rather than considering future liabilities about which they are uncertain.

Moreover, according to this logic, property owners would most likely expect persis-

[49] Although citizens are often inattentive to specific tax rates (Chetty et al., 2009), inflation in the DRC likely further impeded knowledge of the status quo rate. The value of the Congolese Franc declined by about 80% against the dollar in 2017 and 2018, and the government inconsistently updated the various fees and taxes it collects, leading to variation in the changes in the real prices of government services faced by citizens.

[50] Table A6 reports results with revenue as the outcome, and Table A12 examines heterogeneous treatment effects by knowledge of the status quo rate.

[51] In neighborhoods where no door-to-door tax collection occurred during the 2016 campaign, property owners were expected to pay at the tax ministry in 2016.

[52] Specifically, 17.9% of owners accurately reported the status quo rate in neighborhoods that experienced door-to-door collection in 2016 compared to 13.8% elsewhere.

[53] We also find no heterogeneous treatment effects by assignment to the 2016 tax campaign (Table A12).

[54] In other words, we believe our results are comparable to quasi-experimental estimates leveraging changes in statutory rates, albeit in a considerably lower-compliance setting.

tence of tax rates over time. We investigate this proposition empirically in Table A11 by examining whether property owners solicited to pay the tax in 2016 expected the same rate in 2018. This was indeed the case. Owners who paid in 2016 were especially likely to accurately report the status quo rate in 2018.[55] These empirical patterns are most consistent with property owners in Kananga expecting future tax rates to mirror current rates.

#### 5.3.4 Tax Collector Effort

A fourth concern is whether the elasticities of compliance by tax rate we estimate are driven not by taxpayer responses but by collectors exerting enforcement effort differentially across tax rates. For instance, with a constant piece-rate wage, collectors might have targeted their tax visits toward lower rates if they anticipated property owners' higher willingness to pay, potentially magnifying the compliance and revenue elasticities we observe.[56]

Anticipating this possibility, collectors' piece-rate wages were cross-randomized on the property level between a constant amount — 750 CF per collection, irrespective of the rate — and a proportional amount — 30% of the amount collected.[57] This wage structure introduced exogenous variation in collectors' incentives to target by rate. If collectors expected property 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 not have been present in the proportional wage group. To test this intuition, we estimate the elasticity of visits with respect to rate in the two wage groups. Specifically, Table A7 uses midline survey measures of collector visits on the intensive and extensive margin as outcomes. As expected, we find evidence that collectors were more likely to visit households assigned to the lowest tax liability, but only in the constant wage group (Columns 2 and 5), not the proportional wage group (Columns 3 and 6).

To investigate if the differential targeting by rate in the constant wage groups may influence our main estimated elasticities of compliance and revenue, Table A7 re-estimates the main results while controlling for visits on the extensive and intensive margin (Columns

[55] The fact that (*i*) expectations over future rates reflect past rates, yet (*ii*) we find no evidence that anchoring on past rates affects responsiveness to rate reductions may at first appear contradictory. However, these results are not, in fact, incompatible. Knowledge of past rates and anchoring are conceptually distinct: property owners may well remember the tax rate applied in a previous tax campaign, and yet not have any kind of transactional utility term in their utility function.

[56] Recall that choosing which households to visit after registration, and how many visits to make, was at the discretion of each tax collector. This is thus the crucial margin of collector effort that could influence household compliance. Fortunately, we observe which households received visits after registration — and how many visits — in our surveys.

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

7–8). The resulting elasticities of compliance (–1.191 and –1.203) are statistically indistinguishable from the main results presented in Table 3. We also analyze each wage group separately (Columns 9–10), and the results are similar. If anything, including fixed effects for wage groups increases responses to tax abatements and results in elasticities larger in absolute value (Column 11). This combination of results makes it unlikely that our main elasticities of compliance and revenue are driven by differential collector effort rather than by household responses.

## 5.4 Mechanisms

What drives the revenue response to lower tax rates? On one level, the results discussed above already answer this question: lowering tax rates increases revenue by bringing more property owners into the tax net — that is, by increasing extensive margin tax compliance. To explore this compliance response further, we estimate heterogeneity in treatment effects and elasticities by proxies for socio-economic status. This exercise reveals that the elasticity of tax compliance with respect to rates is larger in absolute value among property owners with lower incomes or with cash-on-hand constraints (Tables A13 and A14). This heterogeneity in part reflects the fact that the liability is a fixed fee within property bands while house values vary. Yet if we run the same heterogeneity analysis using variation in the property tax rate expressed as a percentage of property value, we observe very similar results (Tables A15 and A16). The compliance response we observe thus appears to reflect cash-constrained individuals entering the tax net only when tax rates are sufficiently low.[58]

One may wonder if the importance of liquidity constraints in shaping the compliance response to rate changes is specific to the door-to-door nature of tax collection in our setting. Property owners might have been less responsive to changes in tax liability if they could pay whenever they had cash on hand. However, owners were in fact informed that they could always pay at the provincial tax ministry, if they preferred.[59] Moreover, after registration, tax collectors made appointments with property owners at times of their choosing (within the one month window), allowing them time to find the money to pay the tax. The tax campaign procedures were thus designed to lessen the impact of time-varying cash-on-hand constraints. Finally, we can directly test whether the unexpected nature of collector visits is driving our results by re-estimating the main results while excluding tax payments during property registration. Registration visits were indeed likely unexpected,

[58]This interpretation is bolstered by the fact that partial payments were not accepted.

[59]In total, 38 property owners — about 1% of taxpayers — paid at the ministry, even though paying in this manner increased the transaction costs of tax compliance.

in contrast to scheduled follow-up tax visits. We find similar elasticities of compliance and revenue (Table A17). Cash-on-hand constraints appear to be a fundamental determinant of tax compliance, rather than specific to door-to-door collection.

The role of liquidity constraints as a factor in property tax compliance is not unique to low-income settings. Recent work from Mexico (Brockmeyer et al., 2020) and the United States (Wong, 2020) emphasizes how liquidity constraints shape payment behavior in the context of property taxes. The importance of liquidity constraints is also policy-relevant, as the government could potentially increase compliance by allowing partial property tax payments.[60]

# 6 The Laffer Rate

The previous section provided evidence that the status quo tax rate is above the revenue-maximizing (Laffer) rate in this setting. In this section, we estimate the Laffer rate directly. We begin by outlining a simple theoretical framework that illustrates how the levers empirically assessed in this paper — tax rates and tax enforcement — affect citizens' decisions to comply or not with the property tax and the government's tax revenues.[61] We then derive a formula for the Laffer tax rate that we take to the data. We also use this theoretical framework to discuss how government's enforcement capacity affects the Laffer rate, a topic we explore empirically in Section 7.

## 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 $\pi$ is the associated fine. We refer

[60] As noted, we suspect the government chose not to allow partial payment because it might increase the transaction costs of collection and potentially create opportunities for bribe-taking. In the future, the tax ministry seeks to establish a mobile payment platform, which could eliminate these issues and make partial payment possible. Brockmeyer et al. (2020) provides further detail on policies that could relax liquidity constraints limiting property tax compliance in Mexico City.

[61] Another potential lever available to a government seeking to raise revenues is to adjust the tax base. For instance, the government could impose a progressive property tax based on the value of the property. Although an important policy lever, we do not focus on this margin because maintaining an up-to-date property valuation roll likely requires a threshold level of state capacity that the Provincial Government of Kasaï-Central lacks. As noted above, simplified property tax instruments are common in settings of low state capacity (Franzsen and McCluskey, 2017).

to $\alpha$ 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 property owner's decision to comply or not with the property tax can be written as:

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

Therefore, the fraction of owners who pay the property tax is a function of $T$ and $\alpha$:

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

### 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., to train auditors or create a database of third-party information on potential taxpayers). The government thus chooses the property tax rate, $T$, and the level of enforcement, $\alpha$. In this section, we assume that the government's goal is simply to maximize tax revenue:[62,63]

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

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, $\alpha$, it trades off the higher revenue stemming from increasing compliance, $\mathbb{P}(T, \alpha)$, at rate $T$ and the higher enforcement costs, $\mathbb{C}(\alpha)$.

### 6.1.3 Revenue-Maximizing (Laffer) Rate

To obtain the revenue-maximizing (Laffer) tax rate, $T^*$, we consider a small increase, $dT$, in the fixed annual tax rate. As noted above, a rate change increases revenue mechanically

[62] In theory, tax delinquency is sanctioned by a fine but in practice such fines are rarely enforced. We thus ignore the fine revenues, $(1 - \mathbb{P})p\pi$, from the expression for government's revenue $\mathbb{R}(T, \alpha)$.

[63] We discuss the implications of welfare maximization by the government and the welfare-maximizing tax rate in Section 6.4.

but also indirectly reduces it because of the behavioral compliance margin.

**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 response**: The behavioral effect, $dB$, represents the reduction in tax receipts due to property owners dropping out of the tax net as the tax rate increases, $d\mathbb{P}(T, \alpha)$. The total behavioral effect $dB$ is thus:

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

**Laffer Rate**: To maximize revenue, the government should use the tax rate that maximizes the sum of the mechanical and behavioral effects, i.e, such that $dM + dB = 0$. Substituting in the above expression for $dM$ and $dB$, and rearranging terms, we obtain an implicit expression for the revenue-maximizing (Laffer) rate.

**Proposition 1.** *The revenue-maximizing (Laffer) tax rate, $T^*$, is defined by:*

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

#### 6.1.4 Enforcement Capacity

To obtain the revenue-maximizing level of enforcement capacity, $\alpha^*$, we similarly consider a small increase $d\alpha$.[64] This increase in $\alpha$ 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.

**Proposition 2.** *The revenue-maximizing level of enforcement capacity, $\alpha^*$, is defined by:*

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

[64] As above, we follow Besley and Persson (2009) in conceptualizing enforcement capacity as the outcome of costly government investments.

Additionally, the government's enforcement capacity, $\alpha$, is a determinant of the revenue-maximizing (Laffer) tax rate. The Laffer rate increases with the government's enforcement capacity.

**Proposition 3.** *The revenue-maximizing (Laffer) tax rate $T^*$ increases with the government's enforcement capacity, $\alpha$.*

By Topkis's monotonicity theorem, if $R(T,\alpha)$ is supermodular in $(T,\alpha)$, then $T^*(\alpha) = \underset{T}{argmax} R(T,\alpha)$ is nondecreasing in $\alpha$.[65]

## 6.2 Estimation

We follow Proposition (1) to estimate the Laffer rate in linear and non-linear specifications.

**Linear Specifications:** We first assume that property tax compliance is linear in the property tax rate, i.e., $\mathbb{P}(T,\alpha) = \beta_0(\alpha) + \beta_1(\alpha)T$, which the data appears to support (Figure A7). Under this assumption, the revenue-maximizing (Laffer) tax rate, $T^*$, in Proposition (1) is:[66]

$$T^* = \frac{\beta_0(\alpha)}{-2 \times \beta_1(\alpha)} \tag{6}$$

In this section, we take enforcement capacity as constant, $\alpha = \bar{\alpha}$, when estimating $\beta_0(\alpha)$ and $\beta_1(\alpha)$. In Section 7, we introduce variation in enforcement capacity and allow $\beta_0(\alpha)$ and $\beta_1(\alpha)$ to vary with $\alpha$. We can then estimate Equation (6) with the following regression:

$$Compliance_{i,n} = \beta_0 + \beta_1 Tax\ Rate_{i,n} + \gamma_{i,n} + \delta_n + \epsilon_{i,n} \tag{7}$$

where $Compliance_{i,n}$ is an indicator for the tax compliance status of property owner $i$ in

[65] Given that $\mathbb{R}(T,\alpha)$ is twice continuously differentiable, a sufficient condition for $\mathbb{R}(T,\alpha)$ to be supermodular in $(T,\alpha)$ 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 is increasing in enforcement capacity, $\alpha$, at all rates: i.e., $\frac{\partial \mathbb{P}(T,\alpha)}{\partial \alpha} = f(T-\alpha) \geq 0$. Additionally, we assume that increasing enforcement capacity weakly attenuates the negative compliance response to tax rate increases — i.e., $\frac{\partial}{\partial \alpha}[\frac{\partial \mathbb{P}(T,\alpha)}{\partial T}] \geq 0$ — 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 non-payment 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 $\frac{\partial \mathbb{P}(T,\alpha)}{\partial \alpha} < -T\frac{\partial}{\partial \alpha}[\frac{\partial \mathbb{P}(T,\alpha)}{\partial T}]$).

[66] Under the assumption that $\mathbb{P}(T,\alpha) = \beta_0(\alpha) + \beta_1(\alpha)T$, we obtain the Laffer rate, $T^*$, in Proposition (1) by solving the linear equation: $\beta_0(\alpha) + 2\beta_1(\alpha)T^* = 0$. This leads to the solution in Equation (6).

neighborhood $n$, and $Tax\ Rate_{i,n}$ is the tax rate expressed as a percentage of the status quo rate. $\gamma_{i,n}$ are property value band fixed effects, and $\delta_n$ are neighborhood fixed effects. We use $\widehat{\beta_0}$ and $\widehat{\beta_1}$ to construct an unbiased estimator of the Laffer rate: $\widehat{T^*} = \frac{\widehat{\beta_0}}{-2\times\widehat{\beta_1}}$.[67] Since the numerator and denominator of this expression are estimated from the same regression, we use the delta method to compute standard errors.

**Non-Linear Specifications:** Linearity of tax compliance with respect to the tax rate appears to be a plausible assumption given the responses we observe. Figure A7 shows that a linear fit as well as a quadratic or a cubic fit are all within the confidence interval of the treatment effects for every tax rate treatment group. Nonetheless, for completeness, we also relax the linearity assumption by modeling compliance as a quadratic function of the tax rate, i.e., $\mathbb{P}(T,\alpha) = \beta_0(\alpha) + \beta_1(\alpha)T + \beta_2(\alpha)T^2$. Under this assumption, the revenue-maximizing (Laffer) tax rate, $T^*$, in Proposition (1) is:[68]

$$T^* = \frac{-2\beta_1(\alpha) - \sqrt{(2\beta_1(\alpha))^2 - 4\times\beta_0(\alpha)\times 3\beta_2(\alpha))}}{-2\times 3\beta_2(\alpha)} \tag{8}$$

Again, taking enforcement capacity as constant, $\alpha = \bar{\alpha}$, we can then estimate Equation (8) in the data using the following regression:

$$Compliance_{i,n} = \beta_0 + \beta_1 Tax\ Rate_{i,n} + \beta_2 Tax\ Rate^2_{i,n} + \gamma_{i,n} + \delta_n + \xi_{i,n} \tag{9}$$

where $Compliance_{i,n}$, $Tax\ Rate_{i,n}$, $\gamma_{i,n}$, $\delta_n$ are defined as above, and $\xi_{i,n}$ is the error term. We again use $\widehat{\beta_0}$, $\widehat{\beta_1}$ and $\hat{\beta_2}$ to compute $\widehat{T^*}$ and the delta method to obtain standard errors. We also report results when assuming a cubic relationship between tax compliance and tax rates in Figure A8 and Table A19.[69] We are constrained in examining higher order polynomials because there are four tax rate treatment groups.

[67]Our estimator is unbiased given that tax rates were randomly assigned to property owners.

[68]Under the assumption that $\mathbb{P}(T,\alpha) = \beta_0(\alpha) + \beta_1(\alpha)T + \beta_2(\alpha)T^2$, we can obtain the Laffer tax rate, $T^*$, in Proposition (1) by solving the following quadratic equation: $\beta_0(\alpha) + 2\beta_1(\alpha)T^* + 3\beta_2(\alpha)T^{*2} = 0$. The two roots of this quadratic equation are given by Equation (8). We ignore the root arising from this functional form that corresponds to the part of the function in which compliance implausibly increases with tax rates.

[69]Under the assumption that $\mathbb{P}(T,\alpha) = \beta_0(\alpha) + \beta_1(\alpha)T + \beta_2(\alpha)T^2 + \beta_3(\alpha)T^3$ we can obtain the Laffer tax rate, $T^*$, in Proposition (1) by solving the following cubic equation: $\beta_0(\alpha) + 2\beta_1(\alpha)T^* + 3\beta_2(\alpha)T^{*2} + 4\beta_3(\alpha)T^{*3} = 0$, which has three roots that we solve for numerically. We ignore roots arising from this functional form that correspond to parts of the function in which compliance implausibly increases with tax rates.

## 6.3 Results

Starting with the linear specification, we find that the Laffer tax rate is about 66% of the status quo tax rate with or without neighborhood fixed effects (Figure 2 and Table 5, Columns 1–2). A 34% cut in the status quo rate would maximize revenues. This estimate echoes our reduced-form results, in which the 33% tax abatement treatment maximized tax revenues. If we repeat the analysis by value bands, we find that a 33% (36%) reduction would maximize revenues in the low (high) value bands (Figure A6 and Table A18).

The quadratic specification delivers similar results (Figure 2 and Table 5, Columns 3–4). The estimated Laffer rate is even lower: 55% of the status quo rate. According to this specification, the government would maximize revenues by cutting property tax rates by 43% and 61% in the low- and high-value bands, respectively (Figure A6 and Table A18). The results are similar when imposing a cubic relationship between tax compliance and the tax rate (Figure A8 and Table A19). We repeat the robustness checks considered in Section 5.3, such as controlling for neighbors' rates, awareness of tax abatements, and knowledge of past rates, and find similar results (Table A20).

The Laffer rate is also well below the status quo tax rate at all levels of property value, income, and liquidity (Tables A21 and A22). Consistent with the mechanism results in Section 5.4, the Laffer rate is higher for households with more predicted cash on hand. For instance, among households with above-median expenditures in the previous week, the Laffer rate is 76% of the current rate, while among below-median households it is 61% of the current rate (Table A22, Columns 7–8). The Laffer rate is also higher for higher-value properties: about 75% of the current rate in the 10$^{\text{th}}$ decile of property value compared to 63% of the current rate in the 1$^{\text{st}}$ decile of property value (Table A21). 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.

## 6.4 Welfare Implications

The results presented in Sections 6.1–6.3 assume that the government's goal is to maximize revenue. In Section A2.1, we extend the theoretical framework to assume the government maximizes welfare. We show that the welfare-maximizing (i.e., optimal) tax rate is even lower than the revenue-maximizing (Laffer) tax rate as long as the government places positive social welfare weights on taxpayers and the only costs of non-compliance are lost government revenues.[70,71]

To quantify the welfare implications of tax abatements, Section A2.2 reports the marginal value of public funds (MVPF) for each tax abatement. For policy changes that are not budget neutral, the MVPF is a simple "benefit/cost" ratio equal to the marginal social welfare impact of the policy per unit of government revenue expended (Hendren, 2016; Hendren and Sprung-Keyser, 2020).[72] We denote the MVPF of each tax abatement as $MVPF_{17\%}$, $MVPF_{33\%}$, and $MVPF_{50\%}$. Using the tax revenue results presented in Section 5.1, we find that $MVPF_{50\%} = MVPF_{33\%} = \infty$ and $MVPF_{17\%}$ =1.84 (Table A23). So long as the tax rate exceeds the Laffer rate, the MVPF of tax abatements is infinite, and reducing tax rates represents a Pareto improvement.

# 7 Can Enforcement Increase the Laffer Tax Rate?

At current levels of enforcement capacity, a revenue-maximizing government in Kananga would cut property tax rates. But could that government also invest in its enforcement capacity to shift up the Laffer rate? As noted, a growing theoretical literature emphasizes that, because individuals' responses to tax rates depend on the enforcement environment, the Laffer rate is potentially endogenous to government policies (Slemrod and Kopczuk, 2002; Kopczuk, 2005; Saez et al., 2012; Keen and Slemrod, 2017; Slemrod, 2019). We replicated this intuition in Section 6.1 by showing that the Laffer rate should increase with government enforcement capacity (Proposition (3)).

This section explores this proposition empirically using two sources of exogenous variation in enforcement: random assignment of enforcement messages embedded in tax letters and random assignment of tax collectors. Both interventions increase enforcement capacity by raising the perceived probability of sanctions for tax delinquency while leaving the magnitude of fines unchanged.[73]

[70] 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.

[71] As discussed in Chetty (2009), the assumption that costs of tax delinquency are limited to lost revenues to the government might not hold when delinquency imposes externalities on other citizens or on individuals themselves. Examining such cases strays beyond the scope of this paper.

[72] The marginal value of public funds is defined by Hendren (2016) and Hendren and Sprung-Keyser (2020) as $MVPF = \frac{WTP}{Net\ Cost}$ where $WTP$ is the willingness to pay (in local monetary units) of the policy recipients and $Net\ Cost$ is the policy's net cost to the government. We explicitly compute the $WTP$ and the $Net\ Cost$ associated with tax rate reductions in Section A2.2.

[73] Specifically, in Section 6.1, we defined enforcement capacity as the product of the perceived probability of sanctions for tax delinquents and the fine, $\alpha = p \cdot \pi$. The enforcement messages and collector variation we study affect the former (perceived probability) margin while holding the latter (fine) margin constant.

## 7.1 Randomized Enforcement Letters

We first examine how the estimated Laffer rate interacts with the random assignment of enforcement messages embedded in tax letters.[74] 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 written at the bottom.[75] Collectors were instructed to read the message out-loud, along with the rest of the tax letter, to make them more salient to taxpayers.[76]

The first of the two enforcement messages we examine, termed *central enforcement*, read "refusal to pay the property tax entails the possibility of audit and investigation by the provincial tax ministry" (Figure A9, Panel A). A second message, *local enforcement*, was identical except the phrase "provincial tax ministry" was replaced by "chef de quartier" (Figure A9, Panel B), a city authority who helps oversee local governance.[77] We compare these enforcement messages to an active *control* message: "paying the property tax is important" (Figure A9, Panel C).[78] We pool the enforcement message treatments to maximize power. The random assignment of these letters achieved balance across property and property owner characteristics (Table A24).[79]

Compared to the control message, enforcement messages increased tax compliance by 1.6 percentage points (Table A25, Columns 1–3) and tax revenues by 36 CF per person (Columns 4–6). These results are robust to including neighborhood fixed effects. We find evidence that the mechanism behind these increases in tax payment stems from higher perceived probability of sanctions for non-compliers. 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

[74] As noted, this approach builds on past work noting that enforcement letters from tax authorities can marginally increase compliance (Blumenthal et al., 2001; Pomeranz, 2015; Hallsworth et al., 2017).

[75] For this analysis, we restrict the sample to the 2,665 properties subject to one of the three randomized messages of interest (*central enforcement*, *local enforcement*, *control*) on their tax letter. The message randomization was introduced in the last phase of the tax campaign, hence the smaller sample.

[76] According to data collected by enumerators, collectors indeed read the messages in over 95% of cases.

[77] In some randomly selected neighborhoods, similar chiefs were responsible for tax collection, as noted above and analyzed in Balan et al. (2020).

[78] In total, 893 owners were assigned to the *control* message, 906 to the *central enforcement message*, and 866 to the *local enforcement message*. There were also trust and public goods messages, which we do not examine here but describe in Section A1.4 and study in Bergeron et al. (2020b).

[79] Overall, 2 of the 58 differences reported in Table A24 are significant at the 1% level, 4 are significant at the 5% level, and 6 are significant at the 10% level based on $t$-tests, in line with what one would expect under random assignment. Moreover, we show in Table A27 that the results are unaffected by controlling for the property and property owner characteristics that are imbalanced in Table A24.

were "likely" or "very likely" (Columns 7–9). In light of these results, we leverage the random assignment of enforcement messages to test if households have a higher Laffer rate when they perceive the government to have greater enforcement capacity.

The results are consistent with this prediction. According to the linear specification, the estimated Laffer tax rate is 77.9% of the status quo rate among properties assigned to enforcement messages compared to 55.4% of the status quo rate among properties assigned to the control message (Figure 3 and Table 6).[80] Responses to tax rates by type of message display some non-linearities, as shown in Figures A10 and A11. We therefore repeat the analysis using a quadratic specification in Panel B of Figure 3 and Columns 3–4 and 7–8 of Table 6. The gap between the estimated Laffer rate among properties assigned to enforcement (77.2% of the status quo rate) and control messages (35.4%) is even larger according to this specification. In this setting, tax rates and enforcement appear to be complementary levers for raising government revenue.

## 7.2 Random Assignment of Tax Collectors

A second source of exogenous variation in enforcement capacity stems from the random assignment of tax collectors to neighborhoods during the 2018 campaign.[81] Collectors vary in their intrinsic enforcement capacity, i.e., their skill at collecting taxes. In low-capacity settings, the degree to which taxpayers view compliance as obligatory and non-compliance as likely to be punished is shaped by the specific tax collectors who arrive at their doorstep, inform them of their annual liability, and demand payment. In Kananga, tax collectors explain as much as 36% of the variation in tax compliance across neighborhoods (Bergeron et al., 2020c).[82] Each neighborhood was thus subject to exogenous variation in enforcement capacity depending on which tax collectors were randomly assigned to work there.

In total, we study 44 state tax collectors working in 233 neighborhoods of Kananga.[83]

[80] If we analyze the *central* and *local enforcement* messages separately, we find similar results (Table A26).

[81] This approach is similar to recent work examining teacher quality (Chetty et al., 2014) and bureaucrat quality (Best et al., 2019).

[82] This is a larger share of outcome variance than has been typically found in the literature on bureaucrat quality (Best et al., 2019; Fenizia, 2020). Random assignment of collectors thus offers an appealing (and exogenous) source of variation in enforcement capacity.

[83] The tax campaign was in fact active in 363 neighborhoods, but we exclude from this analysis: (*i*) 8 neighborhoods where a logistics pilot took place, (*ii*) 110 neighborhoods in which city chiefs collected taxes — chief collectors were not randomly assigned to neighborhoods and did not typically collect in multiple neighborhoods, which means it is not possible to causally estimate their enforcement capacity — studied in Balan et al. (2020), (*iii*) 5 neighborhoods with no door-to-door collection (the pure control in Balan et al. (2020)), and (*iv*) 7 neighborhoods in which the assigned collectors worked in no other neighborhoods because they stopped working in the first wave of the campaign.

Each neighborhood is randomly assigned two state tax collectors who work there for one month. The pairs of tax collectors are re-randomized each month. Over the course of the 2018 campaign, each collector worked in an average of 10 neighborhoods covering 1,200 properties. In Figure A12, we show balance across assigned collectors in the property and owner characteristics examined in Table 2 using parametric $F$-tests.

#### 7.2.1 Collector-Specific Enforcement Capacity

In this section, we proxy each tax collector's enforcement capacity as the average level of compliance they achieved across the set of neighborhoods to which they were randomly assigned. Specifically, we estimate tax collector enforcement capacities, $E_c$, with a fixed effect specification:

$$y_{i,n} = \sum_c E_c 1[c(n) = c] + \delta_{i,n} + \epsilon_{i,n} \tag{10}$$

where $y_{i,n}$ is an indicator for the tax compliance of property owner $i$ living in neighborhood $n$, $c(n)$ denotes the tax collectors assigned to neighborhood $n$, $\delta_{i,n}$ are property value band fixed effects, and $\epsilon_{i,n}$ denotes the error term. Because the collectors were randomly assigned to work in pairs, and the pair was then randomly assigned to work in a neighborhood, the $\hat{E}_c$ are unbiased estimates of collector enforcement capacities. We cluster standard errors by collector pair (allowing for common error components across collectors) because randomization occurred at the collector pair level. We describe the estimation procedure in more detail in Section A3, and we report the distribution of the estimated $\widehat{E}_c$ in Panel A of Figure A13.[84]

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 citizens' beliefs about the probability of sanctions for tax delinquents. Figure A14 demonstrates that collector enforcement capacity is strongly correlated with the frequency with which they made tax visits — on the extensive and intensive margin (Panels A and B). It is also positively correlated with households' perceptions of the probability of sanctions

[84]Some of the estimates of $E_c$ are negative (Figure A13, Panel A). This is because $E_c$ should be interpreted as the predicted additional compliance brought by collector $c$ when paired with a randomly chosen tax collector and assigned to a randomly selected neighborhood. The fact that some $\widehat{E_c}$ are negative reflects that low-performing collectors on average lowered the compliance achieved in collector pairs to which they were randomly assigned. By contrast, when we estimate enforcement capacity at the collector-pair level, rather than the collector level, the estimates can be interpreted as the predicted compliance associated with the collector pair when randomly assigned to a neighborhood, and consequently all of them are positive (Panel A of Figure A18).

for the delinquent, as measured in the midline survey (Panel C). The relationship between collector enforcement capacity and household perceptions of the probability of sanctions remains strong even when controlling for the frequency of collector visits (Panel D), which suggests that these are two independent channels. In sum, though collector enforcement capacity may also have other dimensions, two key components include the frequency of tax visits and the ability to alter households' beliefs about the probability of sanctions for tax delinquency.

#### 7.2.2 Collector-Specific Laffer Rates

Collectors also vary in their ability to collect taxes at different rates (Figure A15), which means we can define for each tax collector an individual revenue-maximizing (Laffer) tax rate, $T^*_c$. We first assume a linear relationship between tax rates and compliance, and estimate the following fixed effect specification:

$$y_{i,n} = \sum_c \beta^0_c 1[c(n) = c] + \sum_c \beta^1_c 1[c(n) = c] \times Tax\ Rate_{i,n} + \delta_{i,n} + \epsilon_{i,n} \tag{11}$$

where $TaxRate_{i,n}$ is the tax rate assigned to property owner $i$, expressed as a percentage of the status quo tax rate, and $y_{i,n}$, $\delta_{i,n}$, and $\epsilon_{i,n}$ are the same as in Equation (10). Owing to random assignment of tax liabilities and tax collectors, we can use the estimated coefficients from Equation (11) to construct an unbiased estimate of collector $c$'s Laffer tax rate, $T^*_c = \frac{\beta^0_c}{-2\times\beta^1_c}$. Because the tax abatement treatments (randomized at the property level) are interacted with the tax collector treatments (randomized at the neighborhood level), we cluster the standard errors of $\beta^0_c$ and $\beta^1_c$ at the collector pair level. We obtain standard errors for $\widehat{T}^*_c$ using the delta method.

Collectors' responses to tax rates display some non-linearities (Figure A15), so we also impose a quadratic specification and estimate $T^*_c = \frac{-2\beta^c_1 - \sqrt{(2\beta^c_1)^2 - 4\times\beta^c_0\times 3\beta^c_2)}}{-2\times 3\beta^c_2}$ using the following fixed effect specification:

$$\begin{aligned} y_{i,n} = \sum_c \beta^0_c 1[c(n) = c] + \sum_c \beta^1_c 1[c(n) = c] \times Tax\ Rate_{i,n} \\ + \sum_c \beta^2_c 1[c(n) = c] \times Tax\ Rate^2_{i,n} + \delta_{i,n} + \epsilon_{i,n} \end{aligned} \tag{12}$$

As above, the standard errors of $\beta^0_c$, $\beta^1_c$, and $\beta^2_c$ are clustered at the collector pair level and the standard error of each $\widehat{T}^*_c$ is obtained using the delta method.[85]

[85] We describe the estimation procedure in more detail in Section A3 and we report the distribution of the

Why are some collectors capable of achieving compliance across all tax rates, including the higher ones, therefore having a higher Laffer rate? We show that this is unlikely to be explained by collectors' visit strategies by tax rates since the elasticity of visits with respect to tax rates is flat across collector-level enforcement capacity (Figure A21, Panels A and B). Collectors' ability to collect across all rates is therefore more likely to reflect their ability to persuade households to pay — perhaps by more credibly conveying compliance as a legal obligation and delinquency as punishable — conditional on having visited them (Figure A14, Panels C and D).

#### 7.2.3 Empirical Bayes Adjustment

The fixed effect estimates $\widehat{E}_c$ and $\widehat{T^*_c}$ provide unbiased but noisy estimates of collectors' performance. To improve precision, we use a multivariable empirical Bayes model (Gelman et al., 2013) and shrink our estimates of $\widehat{E}_c$ and $\widehat{T^*_c}$ towards the mean of the true underlying distribution to reduce prediction errors.[86,87] Consider $q_c$, the true performance vector of tax collector $c$, which is given by $q_c = (E_c, T^*_c)'$, and $\widehat{q}_c$, the estimated performance of collector $c$, which equals true performance plus an error vector $\eta_c$:

$$\underbrace{\begin{pmatrix} \widehat{E}_c \\ \widehat{T^*_c} \end{pmatrix}}_{\widehat{q}_c} = \underbrace{\begin{pmatrix} E_c \\ T^*_c \end{pmatrix}}_{q_c} + \underbrace{\begin{pmatrix} \eta_{E_c} \\ \eta_{T^*_c} \end{pmatrix}}_{\eta_c}$$

Suppose that the estimated performance is independently distributed around the true performance, $q_c$, following a bivariate normal distribution $\widehat{q}_c | q_c, \Lambda \sim \mathcal{N}(q_c, \Lambda_c)$ and that the true performance of collector $c$ is independently bivariate normal with mean $\bar{q}$ and covariance matrix $\Omega$. The prior distribution of collector $c$'s performance is the bivariate normal distribution:

$$q_c | \bar{q}, \Omega \sim \mathcal{N}(\bar{q}, \Omega)$$

and the posterior distribution for $q_c$ is

$$q_c | \hat{q}_c, \bar{q}, \Omega, \Lambda \sim \mathcal{N}(Q_c, \Omega_c)$$

estimated $\widehat{T^*_c}$ in Panels B and C of Figure A13.

[86]The empirical Bayes approach was introduced by Morris (1983) and has been used in economics to estimate the causal effects of: teachers on students test scores (Gordon et al., 2006), hospitals on patients' health (Chandra et al., 2006), and neighborhoods on intergenerational mobility (Chetty and Hendren, 2018).

[87]We use a multivariate empirical Bayes model rather than the more standard univariate empirical Bayes model since Section 7.2.4 focuses on the relationship between collectors' enforcement capacity, $E_c$, and collectors' Laffer tax rate, $T^*_c$.

where $Q_c$ and $\Lambda_c$ are defined as

$$
\begin{aligned}
Q_c &= (\Omega^{-1} + \Lambda_c^{-1})^{-1}(\Omega^{-1}\bar{q} + \Lambda_c^{-1}\hat{q}) \\
\Omega_c^{-1} &= \Omega^{-1} + \Lambda_c^{-1}
\end{aligned}
$$

which we can estimate in the data after first estimating the covariance matrices $\Omega$ and $\Lambda_c$:[88]

$$
\begin{aligned}
\widehat{\Omega} &= \frac{1}{C}\sum_{i=1}^{c=C}(\hat{q}_c - \bar{q}_c)(\hat{q}_c - \bar{q}_c)^T - \widehat{\Lambda} \\
\widehat{\Lambda} &= \frac{1}{C}\sum_{i=1}^{c=C}\hat{\Lambda}_c \\
\hat{\Lambda}_c &= \begin{bmatrix} SE^2_{\widehat{E_c}} & Cov(\widehat{E_c}, \widehat{T_c^*}) \\ Cov(\widehat{E_c}, \widehat{T_c^*}) & SE^2_{\widehat{T_c^*}} \end{bmatrix}
\end{aligned}
$$

The interpretation of the multivariate empirical Bayes model (Gelman et al., 2013) is analogous to the interpretation of the univariate normal model (Morris, 1983): the posterior mean is a weighted average of the prior mean and the data, and the weights are equal to corresponding precision matrices, $\Lambda_c^{-1}$ and $\Omega^{-1}$, respectively. The precision of the posterior is equal to the sum of the prior and data precisions. We report the distribution of the empirical Bayes estimates of collectors' enforcement capacity, $E_c^{EB}$, and of the Laffer rate, ${T^*}_c^{EB}$, in Figure A16.

#### 7.2.4 Raising the (Collector-Specific) Laffer Rate

Consistent with Proposition (3), we find a positive and statistically significant relationship between tax collector enforcement capacities, $E_c$, and their collector-specific Laffer rates, $T_c^*$. This positive relationship holds when assuming a linear relationship between compliance and rates, and estimating Equation (11) (Panel A of Figure 4), or a quadratic relationship and estimating Equation (12) (Panel B of Figure 4). To be more precise about the magnitude of this relationship, Table A28 reports the elasticity of collector Laffer rates, $T_c^*$, with respect to collector enforcement capacity, $E_c$. A 1% increase in collector enforcement capacity is associated with a 0.62% increase in the Laffer tax rate using the linear

[88] When estimating the covariance matrix $\Lambda_c$, $SE_{\widehat{E_c}}$ comes from estimating Equation (10) and computing the standard errors of each coefficient using the delta method. $SE_{\widehat{T_c^*}}$ comes from estimating (11) or (12) and computing the standard errors of each coefficient using the delta method, and $Cov(\widehat{E_c}, \widehat{T_c^*})$ is estimated by computing the covariance between $\widehat{E_c}$ and $\widehat{T_c^*}$ across $1,000$ bootstrap samples with replacement at the collector pair level.

specification, and a $0.35\%$ increase using the quadratic specification.

We conduct several robustness checks. First, the results are analogous when using the empirical Bayes estimates, $E_c^{EB}$ and $T^{*EB}_c$ (Figure A17). Second, they are robust to splitting the sample in two and estimating $E_c$ on the first sample split and $T_c^*$ on the second split (Figure A19, Panels A and B). The results are therefore unlikely to be driven by positively correlated measurement error in $E_c$ and $T_c^*$. Third, the results are similar when estimated at the collector pair level, which suggests that they are unlikely to be affected by complementarities between collectors in each pair (Figure A20).[89] Finally, the results are very similar if we re-estimate the relationship between collector enforcement capacity and collector-level Laffer rates controlling for the number of visits households received by collectors (Figure A21, Panels C–F), confirming that the results do not stem from collectors with higher enforcement capacities differentially visiting households assigned to certain rates (Figure A21, Panels A–B).

Overall, these results suggest that the Laffer rate is well below the status quo rate for "low enforcers," who achieve lower compliance as tax rates increase. By contrast, the Laffer rate is closer to the status quo rate for "high enforcers," who do not experience the same decline in compliance as tax rates increase. Anticipating this complementarity between enforcement capacity and tax rates, governments would ideally be able to predict which potential tax collectors are likely to be high enforcers.

#### 7.2.5 Collector Characteristics Associated with Enforcement Capacity

As a policy-relevant extension, we explore if governments might be able to identify "high enforcer" tax collectors — capable of raising more revenue and of sustaining higher tax rates — ex ante. We examine which collector characteristics, measured in a survey with collectors before the tax campaign, are positively associated with higher enforcement capacity and a higher Laffer rate.[90]

Collectors with more education, income, and wealth appear to have higher enforcement capacity (Table A29). Perhaps more interestingly, collectors with higher tax morale and stronger preferences for redistribution appear to have a higher enforcement capacity.[91] Although these correlations do not imply a causal relationship between these collector char-

[89] We analyze potential complementarities between tax collectors in more detail in a companion paper (Bergeron et al., 2020c).

[90] This analysis builds on recent work studying how bureaucrat characteristics impact policy outcomes (Xu, 2018; Callen et al., 2018; Ashraf et al., 2020; Best et al., 2019).

[91] These characteristics are also associated with a higher Laffer rate, but most correlation coefficients are not statistically significant (Table A30).

acteristics and enforcement capacity, they provide suggestive evidence that a sophisticated government could potentially both increase revenue and create space to raise tax rates by recruiting tax collectors with higher socio-economic status and more intrinsic motivation to work in the public sector.[92]

### 7.3 Rates and Enforcement as Complements: Revenue Implications

The observed relationship between enforcement capacity and the Laffer rate implies that governments should treat these levers as complementary. To illustrate this point, we predict the revenue gains that a sophisticated government would realize by anticipating how enforcement investments will increase the Laffer rate, compared to a naive government that manipulates rates and enforcement independently.

To do so, we estimate "Laffer curves" at different levels of enforcement capacity. Specifically, we predict tax revenues, $T \cdot \widehat{\mathbb{P}(T, \alpha)}$, at different tax rates, $T$, using Equation (7). The resulting graph shows the familiar hump-shaped relationship between tax rates and total revenue (Figure 5, Panel A).

We then consider a hypothetical policy in which the government increases its enforcement capacity by replacing collectors in the bottom 25th percentile of the enforcement capacity distribution with average collectors. We estimate the new Laffer curve at the resulting (higher) level of enforcement capacity (Figure 5, Panel B). It lies up and to the right of the initial Laffer curve, which is consistent with the complementarities discussed in Sections 7.1 and 7.2. Specifically, while the Laffer tax rate was 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 25th percentile of enforcement capacity by average collectors would raise the Laffer rate by 42%.

Imagine that the naive government sequentially implements the Laffer rate and then increases enforcement. Lowering tax rates would raise revenue by 32% (Figure 5, Panel A), and additionally replacing the bottom 25th percentile of collectors with average collectors would result in a total revenue increase of 61% (Figure 5, Panel B). By contrast, a sophisticated government that increases enforcement and prospectively chooses the new Laffer rate corresponding to its higher enforcement capacity, would raise revenue by 77% (Figure 5, Panel B). These revenue predictions are similar using the tax letter variation in

[92] Selection of tax collectors with high intrinsic motivation to work in the public sector has long been recognized as optimal for states. In Tunisia under Ottoman rule, for instance, tax collectors were selected from "preachers of the faith" to ensure individuals of high integrity and dedication (Khaldun, 1978).

enforcement rather than the collector-level variation (Figure A22).[93] 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 Treatment Effects on Secondary Outcomes

Governments might set tax rates above the Laffer rate for reasons unrelated to enforcement capacity. In particular, a low-capacity government might worry that lowering rates could backfire on other margins — for instance, by fueling bribe payments, crowding out other tax payments, or eroding the perceived legitimacy of the government. This section explores these possibilities, but finds little evidence that tax rate reductions had adverse effects. If anything, they reduced bribery and led citizens to view property tax rates as more fair.

## 8.1 Bribe Payments

Lowering tax rates could potentially backfire by leading tax collectors to extract more bribes.[94] For instance, collectors might have asked property owners in the tax abatement treatment groups to pay part of the difference between the status quo rate and the reduced rate as a bribe in order to receive a tax receipt.

We test this possibility using survey data on bribe payments to property tax collectors in the midline survey. Enumerators asked respondents if they paid the "transport" of the collectors — a colloquial expression for bribes — and if so, the amount of the payment. While these measures of bribe payments are self-reported and should therefore be interpreted with caution, reporting petty bribes is not taboo in Kananga.[95] According to these measures, we find no evidence that lowering tax rates increased bribe payments. If anything, lower tax rates are associated with fewer bribe payments on the extensive margin (Table 7, Panel A, Row 1). Although the negative effects on bribe payments are only statistically significant when analyzing the 50% reduction treatment, the elasticity of bribe payments with respect to the tax rate, and bootstrapped standard error, is $\hat{\varepsilon}_{B,T} = 0.706$ (0.180). On the intensive margin, the magnitude of the equilibrium bribe also appears to decrease among households assigned to the 50% and 33% rate reduction treatments (Table 7, Panel A, Row 2), yielding

[93] Estimates using variation in collector enforcement capacity rely on a larger sample (23,777 properties) compared to those using variation in exposure to enforcement letters (2,665 properties while those), thus we report the latter as our preferred estimates.

[94] Khan et al. (2015) demonstrate the importance of examining how bribes respond to tax policy changes.

[95] For instance, Reid and Weigel (2019) find that nearly half of motorcycle taxi drivers openly admitted to paying bribes at Kananga's roadway tolls using similar local codes for bribes. The authors also show a high correlation between more and less overt bribe elicitation mechanisms.

an elasticity of $\hat{\varepsilon}_{B,T} = 1.604$ (0.210).

Although we prefer the midline bribe measures because of the large sample, we also explore alternative measures of bribes and other informal payments to tax collectors collected in the endline survey, including (*i*) the gap between self-reported payments and payment according to the administrative data (Table 7, Panel A, Row 3), and (*ii*) self-reported bribe payments (Table 7, Panel A, Rows 4–6). Re-estimating treatment effects and elasticities using these measures, the results are qualitatively similar though not statistically significant. Thus, although there is some evidence that property owners switched from bribes to tax payments when the rate was sufficiently low, this conclusion is suggestive at best.

## 8.2 Payment of Other Taxes

Lowering property tax rates could also backfire, from the government's point of view, if it crowds out payment of other taxes. For example, higher tax compliance in response to lower property tax rates could reduce payment of other taxes if citizens have a fixed budget or a mental model in which enforcement risk declines sharply for the partially compliant.[96]

In Kananga, the most common "tax" to which citizens contribute is actually an informal labor levy called *salongo*. *Salongo* is organized on a weekly basis by neighborhood chiefs and involves citizens contributing labor (or occasionally cash or in-kind contributions) to local public good projects, such as road repair and trash collection. In our midline data, 37.6% of citizens reported participating in *salongo* in the past two weeks, with those participating contributing 4.2 hours on average over this period. We estimate treatment effects of property tax rate reductions on reported *salongo* participation in (Table 7, Panel B, Rows 1–2). There are no significant effects on the extensive or intensive margin.

Other formal taxes paid by citizens in Kananga include the vehicle tax (3.6% of endline respondents reported paying), market vendor fees (18.5%), the business tax (5.3%), and the income tax (11.5%). Although these measures are self-reported, our questionnaire included an obsolete poll tax included to gauge possible reporting bias. Estimating treatment effects in the familiar specification, we find no evidence that property tax rate reductions crowded out payment of other formal taxes (Table 7, Panel B, Rows 3–7).

## 8.3 Views of the Government

Finally, tax rate reductions could backfire if they cause citizens to update negatively about the government. This could be the case if lowering tax rates were perceived by citizens as

[96]This section builds on the literature on fiscal externalities across tax instruments (Waseem, 2018).

signaling that property tax payment is less important or obligatory than they had previously thought, or if it signals a lack of state capacity to enforce compliance at higher rates.[97]

We investigate this possibility using endline survey data on citizens' trust in the provincial government, perceptions of the performance of the government, and perceptions of government corruption — as well as corresponding measures for the provincial tax ministry. As shown in Panel C of Table 7, we find no evidence that reductions in tax rates affected views of the provincial government (Rows 1–3) or of the provincial tax ministry (Rows 5–7). Distributing property tax abatements does not appear to have eroded citizens' attitudes about the government.

Finally, we examine citizens' perceptions of the fairness of the property tax, an important component of tax morale (Luttmer and Singhal, 2014; Best et al., 2020). The endline survey included questions about citizens' perceptions of the fairness of property tax collection, property tax rates, and tax collectors. Lower rates do not appear to have affected respondents' perception of the fairness of the property tax (Table 7, Panel C, Row 7) or of the property tax collectors (Row 9). They did, however, increase how fair citizens viewed property tax rates, with a sizable elasticity of –0.100 (0.048) (Row 8).

# 9 Conclusion

This paper studied random variation in property tax rates and tax enforcement in the DRC, a low-capacity state. We found that status quo tax rates were above the revenue-maximizing (Laffer) tax rate. Due to higher compliance as tax liabilities decrease, the government would maximize revenues by reducing rates by 34%. Exploiting two sources of variation in enforcement — randomized enforcement letters and random assignment of tax collectors — we demonstrated that the Laffer rate increases with government enforcement capacity. Tax letters containing enforcement messages caused a 41% increase in the Laffer rate compared to control letters. Similarly, replacing tax collectors in the bottom 25$^{\text{th}}$ percentile of enforcement capacity by average collectors would raise the Laffer rate by an estimated 42%.

Governments in low-capacity settings can exploit these complementarities between enforcement and responses to tax rates to better counter the revenue deficits they face. While sequentially implementing the Laffer rate and increasing enforcement would raise revenue by 61% in our setting, prospectively choosing the post-enforcement Laffer rate would in-

[97]This vein of analysis is motivated by recent work documenting how tax collection shapes citizens' views of the legitimacy and capacity of the government (Jibao and Prichard, 2016; Weigel, 2020).

stead increase revenue by 77%. That said, these complementarities are likely limited to low-capacity settings. In countries with near-perfect enforcement (e.g., with high coverage of third-party reporting) and high tax rates, increasing enforcement could lower the Laffer rate and tax revenues by eroding tax morale, fueling delinquency, and potentially causing costly tax protests (Besley et al., 2019).

Nonetheless, in light of the observed complementarities we document, 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 Laffer rate given their low enforcement capacities, as we found in the DRC. One plausible explanation is that low-capacity governments simply lack information about the Laffer rate and set rates by mimicking those in other countries. Alternatively, forward-looking governments may strategically set tax rates above the Laffer rate if they anticipate making investments in enforcement capacity and thus shifting up the Laffer rate (knowing 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. Adjudicating between these (and other) explanations would be fertile ground for future research.

**TABLE 1: TAX ABATEMENT TREATMENT ALLOCATION**

| Tax Rate Abatement Treatment Groups | Tax Rates by Type of Property | | | |
|---|---|---|---|---|
| | Low-value band properties | | High-value band properties | |
| | Rate | N | Rate | N |
| Status Quo Tax Rate | 3,000 CF | 8,282 | 13,200 CF | 971 |
| 17% Reduction in Tax Rate | 2,500 CF | 8,569 | 11,000 CF | 1,047 |
| 33% Reduction in Tax Rate | 2,000 CF | 8,372 | 8,800 CF | 1,113 |
| 50% Reduction in Tax Rate | 1,500 CF | 8,633 | 6,600 CF | 1,041 |

*Notes:* This table shows the number of properties assigned to each tax abatement treatment. Property owners in the low-value band were randomly assigned to an annual status quo property tax rate of 3,000 CF or to tax abatements of 17% (2,500 CF), 33% (2,000 CF), or 50% (1,500 CF). Similarly, property owners in the high-value band were randomly assigned to an annual status quo property tax rate of 13,200 CF or to tax abatements of 17% (11,000 CF), 33% (8,800 CF), or 50% (6,600 CF). We discuss these treatments in Section 3.2.2.

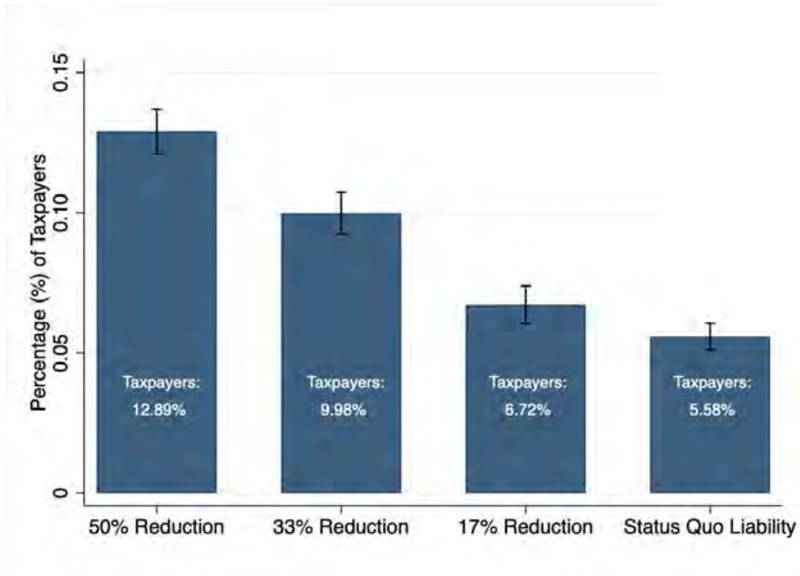
# TABLE 2: RANDOMIZATION BALANCE

| | Sample (1) | Obs. (2) | Status quo Mean (3) | 17% Reduction (4) | 33% Reduction (5) | 50 % Reduction (6) |
|---|---|---|---|---|---|---|
| Panel A: Property Characteristics | | | | | | |
| Distance to city center (in km) | Registration | 37,790 | 3.204 | 0.000 | -0.002 | 0.001 |
| | | | | (0.002) | (0.002) | (0.002) |
| Distance to market (in km) | Registration | 37,790 | 0.809 | -0.002 | -0.004* | -0.002 |
| | | | | (0.002) | (0.002) | (0.002) |
| Distance to gas station (in km) | Registration | 37,790 | 1.924 | 0.001 | -0.001 | 0.004 |
| | | | | (0.002) | (0.002) | (0.002) |
| Distance to health center (in km) | Registration | 37,790 | 0.350 | 0.002 | 0.001 | 0.003 |
| | | | | (0.002) | (0.002) | (0.002) |
| Distance to government building (in km) | Registration | 37,790 | 0.998 | -0.000 | -0.001 | 0.003 |
| | | | | (0.002) | (0.002) | (0.002) |
| Distance to police station (in km) | Registration | 37,790 | 0.801 | -0.000 | -0.001 | 0.001 |
| | | | | (0.002) | (0.002) | (0.002) |
| Distance to private school (in km) | Registration | 37,790 | 0.322 | -0.001 | 0.002 | 0.002 |
| | | | | (0.002) | (0.002) | (0.002) |
| Distance to public school (in km) | Registration | 37,790 | 0.425 | 0.001 | 0.001 | 0.001 |
| | | | | (0.002) | (0.002) | (0.002) |
| Distance to university (in km) | Registration | 37,790 | 1.314 | 0.001 | - 0.001 | 0.001 |
| | | | | (0.002) | (0.002) | (0.002) |
| Distance to road (in km) | Registration | 37,237 | 0.427 | 0.001 | 0.001 | 0.002 |
| | | | | (0.002) | (0.002) | (0.002) |
| Distance to major erosion (in km) | Registration | 37,237 | 0.128 | 0.000 | 0.000 | -0.001 |
| | | | | (0.001) | (0.001) | (0.001) |
| Roof Quality | Midline | 29,740 | 0.970 | -0.004 | -0.006** | -0.006** |
| | | | | (0.003) | (0.003) | (0.003) |
| Walls Quality | Midline | 29,413 | 1.163 | -0.005 | -0.006 | -0.004 |
| | | | | (0.005) | (0.005) | (0.005) |
| Fence Quality | Midline | 27,071 | 1.391 | -0.003 | -0.006 | -0.011 |
| | | | | (0.007) | (0.007) | (0.007) |
| Erosion Threat | Midline | 29,634 | 0.402 | -0.002 | -0.007 | 0.004 |
| | | | | (0.008) | (0.008) | (0.008) |
| Property value (in USD) | Registration | 38,028 | 1338 | -6.304 | 3.094 | -34.503 |
| Machine Learning estimate | | | | (23.484) | (23.918) | (23.409) |
| Panel B: Property Owner Characteristics | | | | | | |
| Employed Indicator | Midline | 20,441 | 0.793 | 0.006 | -0.000 | 0.013 |
| | | | | (0.008) | (0.008) | (0.008) |
| Salaried Indicator | Midline | 20,441 | 0.265 | 0.003 | -0.006 | -0.003 |
| | | | | (0.009) | (0.009) | (0.009) |
| Work for Government Indicator | Midline | 20,441 | 0.157 | 0.006 | -0.002 | 0.004 |
| | | | | (0.007) | (0.007) | (0.007) |
| Relative Work for Government. Indicator | Midline | 22,667 | 0.229 | 0.008 | -0.004 | 0.012 |
| | | | | (0.008) | (0.008) | (0.008) |
| Panel C: Property Owner Characteristics | | | | | | |
| Gender | Baseline | 2,760 | 1.339 | -0.013 | -0.022 | -0.001 |
| | | | | (0.027) | (0.027) | (0.027) |
| Age | Baseline | 2,753 | 47.763 | -1.158 | 0.232 | -0.138 |
| | | | | (0.880) | (0.854) | (0.872) |
| Main Tribe Indicator | Baseline | 2,760 | 0.750 | 0.023 | 0.022 | 0.014 |
| | | | | (0.024) | (0.024) | (0.025) |
| Years of Education | Baseline | 2,751 | 10.745 | -0.112 | -0.055 | -0.085 |
| | | | | (0.239) | (0.240) | (0.244) |
| Has Electricity | Baseline | 2,760 | 0.152 | -0.016 | -0.005 | -0.017 |
| | | | | (0.020) | (0.021) | (0.020) |
| Log Monthly Income (CF) | Baseline | 2,735 | 10.687 | -0.006 | -0.005 | -0.209 |
| | | | | (0.133) | (0.133) | (0.148) |
| Trust Chief | Baseline | 2,760 | 3.151 | -0.013 | -0.014 | -0.031 |
| | | | | (0.059) | (0.060) | (0.060) |
| Trust National Government. | Baseline | 2,611 | 2.569 | -0.036 | -0.095 | -0.095 |
| | | | | (0.073) | (0.075) | (0.074) |
| Trust Provincial Government | Baseline | 2,628 | 2.493 | -0.060 | -0.030 | -0.026 |
| | | | | (0.071) | (0.073) | (0.072) |
| Trust Tax Ministry | Baseline | 2,600 | 2.353 | 0.040 | 0.011 | 0.044 |
| | | | | (0.070) | (0.072) | (0.071) |
| Panel D: Attrition | | | | | | |
| Registration to Midline | Registration | 38,028 | 0.213 | -0.001 | -0.002 | -0.003 |
| | | | | (0.004) | (0.004) | (0.004) |

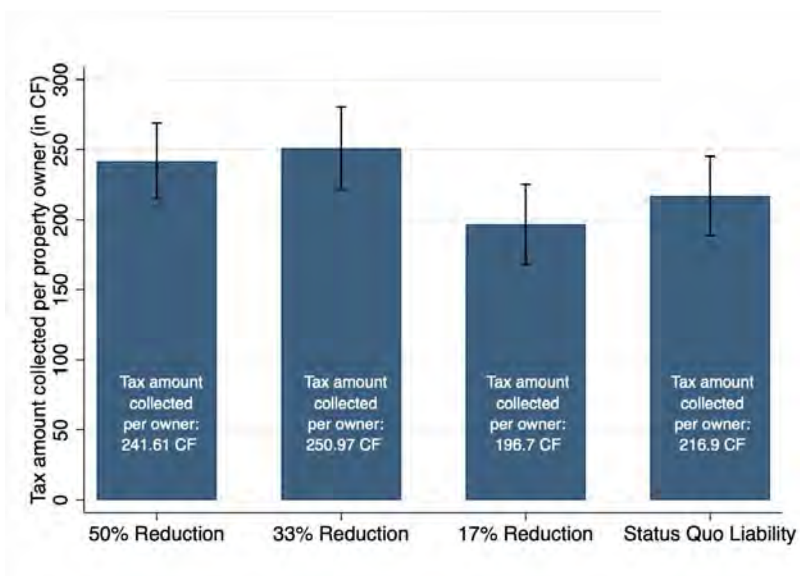
*Notes:* This table reports coefficients from balance tests conducted by regressing baseline and midline characteristics for properties (Panel A) and property owners (Panels B and C) on treatment indicators, with property value band and randomization stratum (neighborhood) fixed effects. Robust standard errors are reported. All balance checks are conducted in the same samples of the primary analysis, which excludes neighborhoods from the logistics pilot, pure control group of Balan et al. (2020) in which no door-to-door collection took place, and exempted households (with robustness to alternative samples shown in Table A5). Specifically, Panel A considers the sample of 38,028 non-exempted properties. Rows 1–11 exclude 238 properties with missing GPS information; Rows 12–15 use midline surveys conducted with 29,634 property owners; and Row 16 uses the predicted property value for the 38,028 non-exempted properties. Panels B and C use 22,667 midline surveys and 2,760 baseline surveys with property owners, respectively. Variable-level missingness in Panels B–C reflect non-response to individual survey questions. The results are summarized in section 4.2. The variables are described in detail in Section A6.

## FIGURE 1: TREATMENT EFFECTS ON TAX COMPLIANCE AND REVENUE

A: Tax Compliance




B: Tax Revenue




*Notes:* This figure reports estimates from Equation (1), comparing property tax compliance and revenue in the tax abatement treatment groups relative to the status quo property tax rate (the excluded category). Panel A uses an indicator for tax compliance as the dependent variable while Panel B uses tax revenue (in Congolese Francs). All estimations include property value band and randomization stratum fixed effects. Panel A corresponds to the results in Column 2 of Table 3 (Panel A), while Panel B corresponds to the results in Column 6. The black lines show the 95% confidence interval for each of the estimates using robust standard errors. The data include all non-exempt properties registered by tax collectors merged with the government's property tax database. We discuss these results in Section 5.2.

## Table 3: Treatment Effects on Tax Compliance and Revenue

| | Tax Compliance (Indicator) | | | | 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: Reduced Form 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 |
| | (0.063) | (0.061) | (0.063) | (0.232) | (0.083) | (0.081) | (0.065) | (0.247) |
| Observations | 38028 | 38028 | 33856 | 4172 | 38028 | 38028 | 33856 | 4172 |
| Sample | All properties | All properties | Low-value properties | High-value properties | All properties | All properties | Low-value properties | High-value properties |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | No | Yes | Yes | Yes | No | Yes | Yes | Yes |

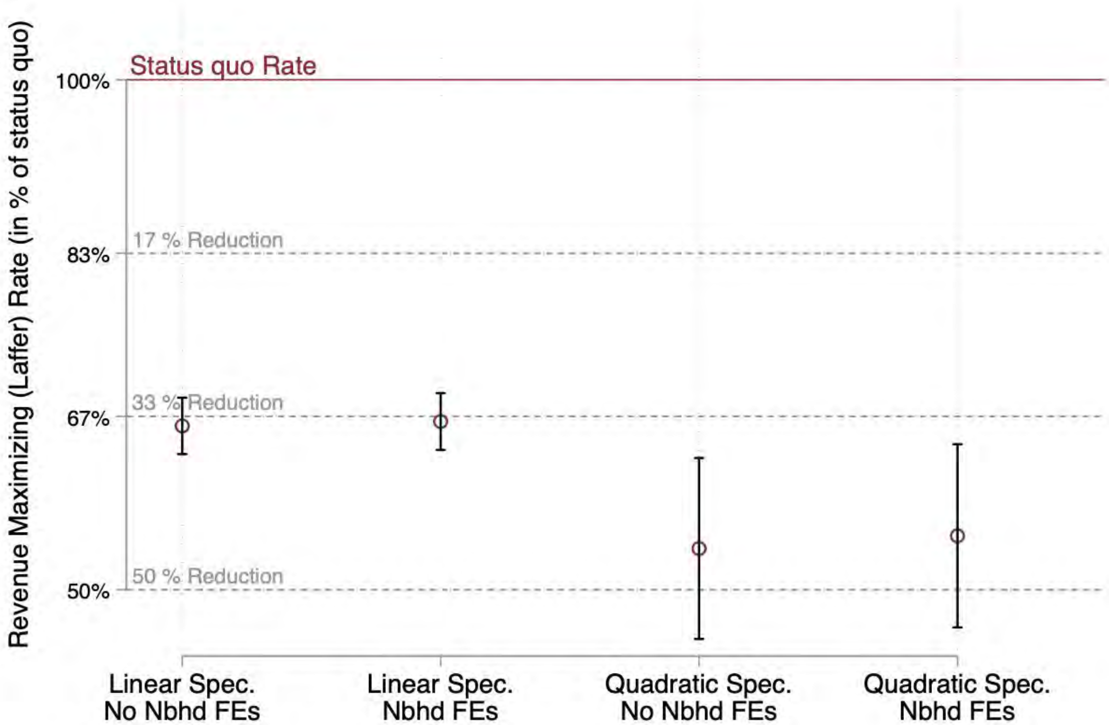
*Notes:* This table reports estimates from Equations (1), (2), and (3). The dependent variable is an indicator for compliance in Columns 1–4 and tax revenues (in Congolese Francs) in Columns 5–8. Panel A reports treatment effects from Equation (1), comparing property tax compliance and revenue for the 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). All regressions include fixed effects for property value band, and Columns 2–4 and 6–8 include fixed effects for randomization stratum (neighborhood). Panels A and B report robust standard errors. Standard errors in Panel C are bootstrapped (with 1,000 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 non-exempt properties registered by tax collectors merged with the government's property tax database. We discuss these results in Section 5.2.

## Table 4: Treatment Effects on Compliance — Robustness: Accounting for Knowledge of Others' Rates, Past Rates, Expectations of Future Rates, and Past Exposure to Tax Collection

| | Outcome: Tax Compliance Indicator | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Controls for 5 neighbors' rate (1) | Controls for 10 neighbors' rate (2) | Doesn't know neighbors' rate (3) | Knows neighbors' rate (4) | Doesn't know discounts (5) | Knows discounts (6) | Doesn't know past rates (7) | Knows past rates (8) | No 2016 door-to-door tax campaign (9) | Door-to-door 2016 tax campaign (10) |
| Panel A: Reduced Form Effects | | | | | | | | | | |
| 50% Reduction | 0.072*** | 0.072*** | 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 | 0.045*** | 0.045*** | 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 |
| Panel B: Marginal Effects | | | | | | | | | | |
| ln(Tax Rate in CF) | -0.109*** | -0.109*** | -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 |
| Panel C: Elasticities | | | | | | | | | | |
| Elasticity | -1.241 | -1.241 | -1.202 | -1.117 | -1.111 | -2.286 | -1.471 | -1.507 | -1.369 | -1.176 |
| | (0.061) | (0.061) | (0.148) | (1.906) | (0.166) | (1.928) | (0.254) | (0.713) | (0.099) | (0.079) |
| Observations | 37211 | 37211 | 13046 | 2158 | 5098 | 147 | 2069 | 401 | 14590 | 23296 |
| Sample | All properties | All properties | Midline Sample | Midline Sample | Midline Sample | Midline Sample | Baseline Sample | Baseline Sample | All properties | All properties |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighbor Rate Controls | Yes | Yes | No | No | No | No | No | No | No | No |

*Notes:* This table explores alternative explanations concerning taxpayers' responses to randomized tax abatements that could introduce bias into our estimated treatment effects. 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). 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 fixed effects for property value and for randomization stratum (neighborhood). Panels A and B report robust standard errors. Standard errors in Panel C are bootstrapped (with 1,000 iterations). Columns 1 and 2 control for the property tax rate assigned to 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 A6. 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 1–2 is slightly smaller than the total properties registered because of missing GPS data in $<3\%$ of cases. 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 analyses with revenue as the outcome. We discuss these results in Section 5.3.

**FIGURE 2: THE REVENUE-MAXIMIZING (LAFFER) TAX RATE**




*Notes:* This figure reports estimates of the revenue-maximizing (Laffer) tax rate using the expression in Proposition (1). The first two estimates assume linearity of tax compliance with respect to the tax rate and correspond to the estimation of Equation (6) using regression specification (7), while the following two estimates assume a quadratic relationship between tax compliance and tax rate and correspond to the estimation of Equation (8) using regression specification (9). All estimates of the Laffer rate are expressed as a percentage of the status quo tax rate. All regressions include property value band fixed effects, and the second and fourth point estimates also include randomization stratum (i.e., neighborhood, or "Nbhd") fixed effects. The black lines show the 95% confidence interval for each estimate using the standard errors obtained from the delta method applied to Equations (6) and (8). The coefficients and confidence intervals correspond to the point estimates and standard errors reported in Table 5 (Panel B). The data include all non-exempt properties registered by tax collectors merged with the government's property tax database. We discuss these results in Section 6.3.

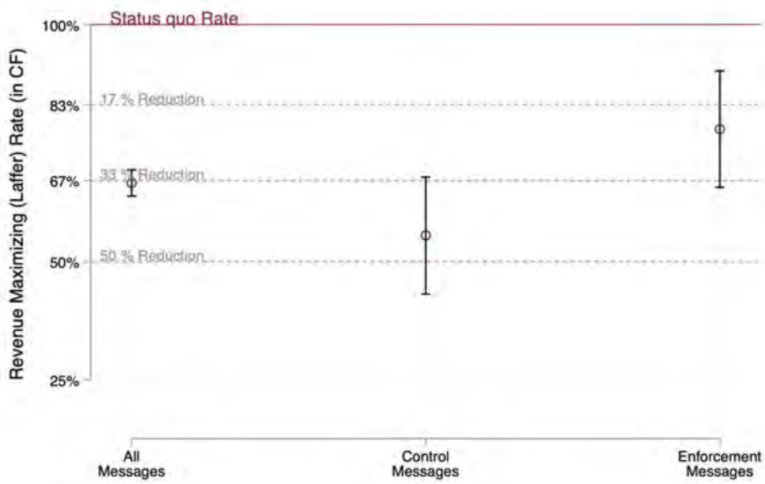
**TABLE 5: THE REVENUE-MAXIMIZING (LAFFER) TAX RATE**

| | 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** |
| | | | (0.051) | (0.049) |
| Constant | 0.203*** | 0.202*** | 0.293*** | 0.293*** |
| | (0.006) | (0.006) | (0.029) | (0.028) |
| *Panel B: Laffer Tax Rate* | | | | |
| Laffer Rate (in % 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 | 38028 | 38028 | 38028 | 38028 |
| Sample | All properties | All properties | All properties | All properties |
| House FE | Yes | Yes | Yes | Yes |
| Neighborhood FE | No | Yes | No | Yes |
| Quadratic Tax Rate Term | No | No | Yes | Yes |

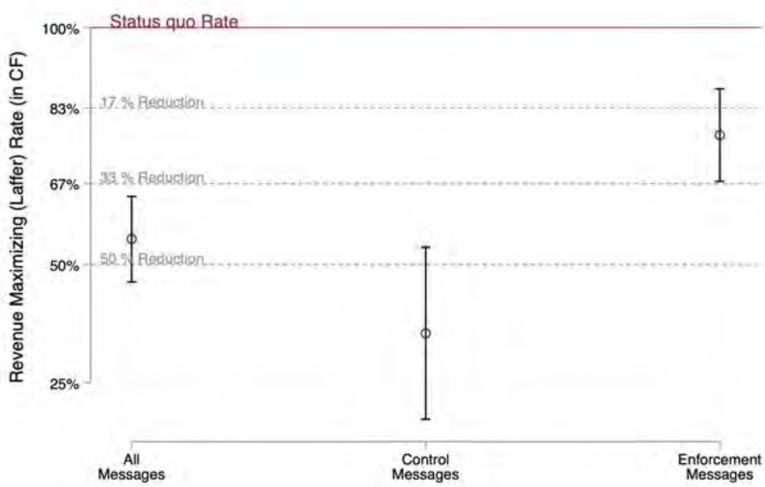
*Notes:* This table reports estimates of the revenue-maximizing (Laffer) tax rate using the expression in Proposition (1). Columns 1 and 2 assume linearity of tax compliance with respect to the tax rate. Panel A reports estimates from regression specification (7), and Panel B reports the corresponding Laffer rate from Equation (6). Columns 3 and 4 assume a quadratic relationship between tax compliance and tax rate. Panel A reports estimates from regression specification (9), and Panel B reports the Laffer rate from Equation (8). All estimates in Panels A and B are expressed as a percentage of the status quo tax rate. All regressions include fixed effects for property value band, and Columns 2 and 4 also include fixed effects for randomization stratum (neighborhood). In Panel A, we report robust standard errors. Standard errors in Panel B are computed using the delta method. The data include all non-exempt properties registered by tax collectors merged with the government's property tax database. We discuss these results in Section 6.3.

## FIGURE 3: LAFFER RATES BY ENFORCEMENT CAPACITY (TAX LETTERS)

A: Linear Specification




B: Quadratic Specification




*Notes:* This figure examines how the revenue-maximizing (Laffer) tax rate, given by Proposition (1), varies by enforcement capacity using the variation in messages embedded in tax letters. The estimates in Panel A assume linearity of tax compliance with respect to the tax rate and correspond to the estimation of Equation (6) using regression specification (7), while the estimates in Panel B assume a quadratic relationship between tax compliance and tax rate and correspond to the estimation of Equation (8) using regression specification (9). All estimates of the Laffer rate are expressed as a percentage of the status quo tax rate. All regressions include fixed effects for property value band and for randomization stratum (neighborhood). The black lines show the 95% confidence interval for each estimate using the standard errors obtained from the delta method applied to Equations (6) and (8). The coefficients and confidence intervals correspond to the point estimates and standard errors reported in Table 6 (Panel B). The data are restricted to the sample of 2,665 properties exposed to randomized messages on tax letters. In each panel, the first point estimates pool all the recipients of a message, the second point estimates are for owners who received the *control* message, and the third point estimates are for owners who received an enforcement message (*central enforcement* or *local enforcement*). We discuss these results in Section 7.1.

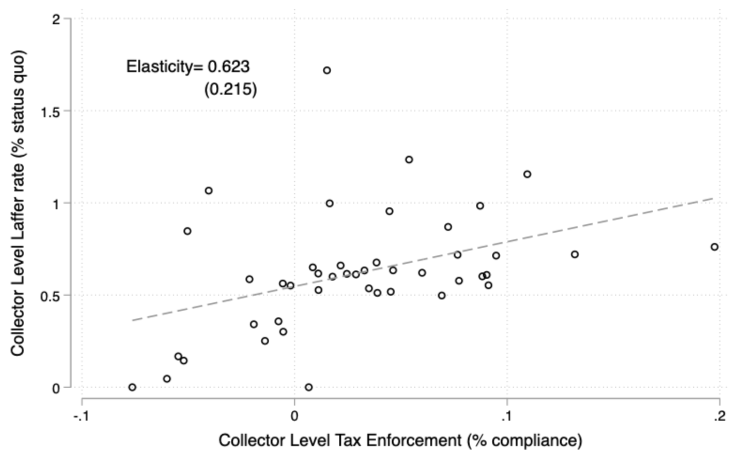
## Table 6: Laffer Rates by Enforcement Capacity (Tax Letters)

| | Control Message | | | | Enforcement Message | | | |
|---|---|---|---|---|---|---|---|---|
| | Linear Specification | | Quadratic Specification | | Linear Specification | | Quadratic Specification | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Panel A: Effect of Tax Rates on Tax Compliance** | | | | | | | | |
| Tax Rate (in % of status quo) | -0.082** | -0.083** | -0.379 | -0.399 | -0.061** | -0.053** | 0.192 | 0.210 |
| | (0.032) | (0.033) | (0.336) | (0.327) | (0.025) | (0.025) | (0.266) | (0.261) |
| Tax Rate Squared (in % of status quo) | | | 0.196 | 0.210 | | | -0.169 | -0.175 |
| | | | (0.211) | (0.209) | | | (0.172) | (0.170) |
| Constant | 0.091*** | 0.092*** | 0.197 | 0.203* | 0.088*** | 0.082*** | -0.001 | -0.010 |
| | (0.028) | (0.028) | (0.128) | (0.123) | (0.020) | (0.021) | (0.097) | (0.096) |
| **Panel B: Laffer Tax Rate** | | | | | | | | |
| Laffer Rate (in % Status quo Rate) | 0.557 | 0.554 | 0.361 | 0.354 | 0.724 | 0.779 | 0.756 | 0.772 |
| | (0.061) | (0.063) | (0.101) | (0.093) | (0.138) | (0.190) | (0.052) | (0.050) |
| Implied Reduction in Tax Rate | 44.32% | 44.57% | 63.91% | 64.57% | 27.63% | 22.12% | 24.35% | 22.75% |
| Observations | 893 | 893 | 893 | 893 | 1772 | 1772 | 1772 | 1772 |
| Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample |
| Neighborhood FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Quadratic Tax Rate Term | No | No | Yes | Yes | No | No | Yes | Yes |

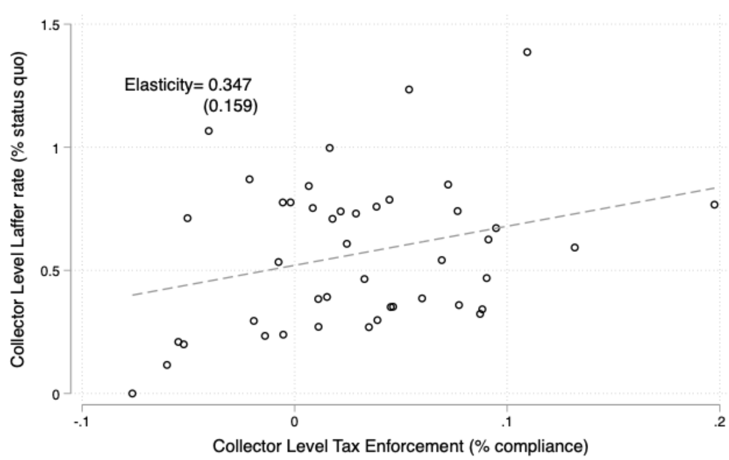
*Notes:* This table examines how the revenue-maximizing (Laffer) tax rate, given by Proposition (1), varies by enforcement capacity using the variation in messages embedded in tax letters. Columns 1–2 and 5–6 assume linearity of tax compliance with respect to the tax rate; Panel A reports results from estimating Equation (7), and Panel B reports the corresponding Laffer rate from Equation (6). Columns 3–4 and 7–8 assume a quadratic relationship between tax compliance and tax rate; Panel A reports results from estimating Equation (9), and Panel B reports the Laffer rate from Equation (8). All estimates in Panels A and B are expressed as a percentage of the status quo tax rate. All regressions include fixed effects for property value band, and Columns 2, 4, 6, and 8 also include randomization stratum (neighborhood) fixed effects. In Panel A, we report robust standard errors. In Panel B, we reported standard errors computed using the delta method. The data are restricted to the sample of 2,665 properties exposed to randomized messages on tax letters. Columns 1–4 further restrict the sample to owners who received the *control* message and Columns 5–8 to owners who received an enforcement message (*central enforcement* or *local enforcement*). We discuss these results in Section 7.1.

## FIGURE 4: LAFFER RATES BY ENFORCEMENT CAPACITY (COLLECTORS)

A: Laffer Rate (linear spec.) by Enforcement Capacity



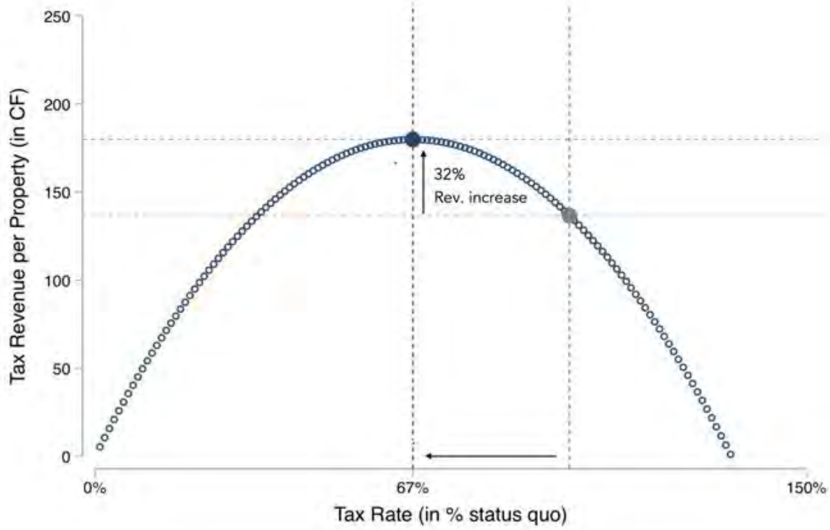

B: Laffer Rate (quadratic spec.) by Enforcement Capacity



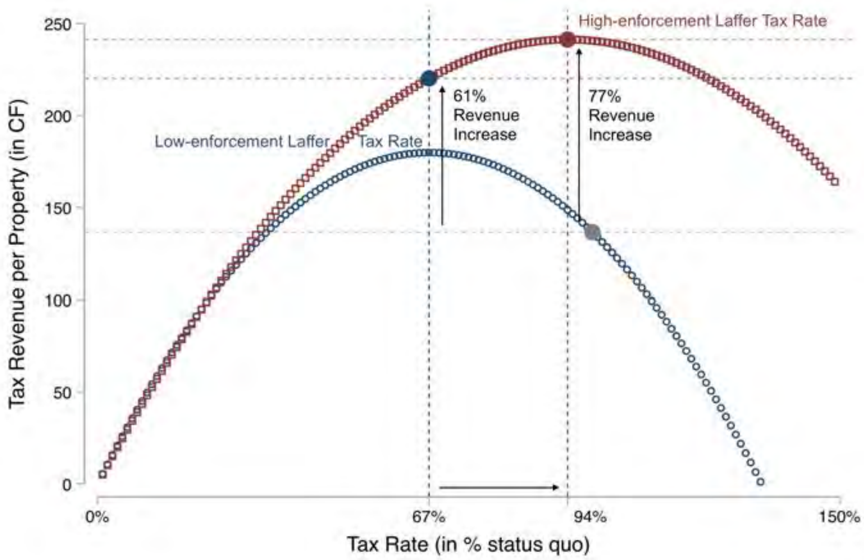

*Notes:* This figure shows the relationship between collector-level revenue-maximizing (Laffer) rates and collector enforcement capacities. The x-axis contains estimates of collector enforcement capacities from Equation (10). The y-axis reports the collector-specific Laffer rates in Proposition (1). In Panel A, the estimated Laffer rate assumes linearity of tax compliance with respect to the tax rate and is obtained from estimating Equation (11). In Panel B, the estimated Laffer rate assumes a quadratic relationship between tax compliance and the tax rate and is obtained from estimating Equation (12). All estimates of enforcement capacity are expressed as the percentage of owners who pay the property tax, and all estimates of the Laffer rate are expressed as a percentage of the status quo tax rate. The best fit line and the corresponding regression coefficient of the x-axis on the y-axis are reported with the corresponding robust standard errors. These estimates correspond to those in Table A28. We discuss these results in Section 7.2.

**FIGURE 5: RATES AND ENFORCEMENT AS COMPLEMENTS: REVENUE IMPLICATIONS — COLLECTOR VARIATION**

A: Setting Tax Rates at the Laffer Rate




B: Increasing Enforcement Capacity
Naive vs Sophisticated Government




*Notes:* This figure reports estimates of the relationship between tax rates (x-axis) and tax revenue per property owner (y-axis). We predict tax revenues at different hypothetical tax rates using the regression coefficients obtained when estimating Equation (7). Panel A estimates this relationship in the current enforcement environment in Kananga. Panel B then compares the predicted relationship between tax rates and tax revenues in the current enforcement environment (black dotted line) and after the government increases its enforcement capacity by replacing collectors in the bottom 25$^{\text{th}}$ percentile of enforcement capacity by average tax collectors (gray dotted line). 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 Laffer rate and increase revenue by 77%. Figure A22 conducts the analogous analysis using the tax letter enforcement variation. We discuss these results in Section 7.3.

**TABLE 7: TREATMENT EFFECTS ON SECONDARY OUTCOMES: BRIBE PAYMENTS, PAYMENT OF OTHER TAXES, VIEWS OF THE GOVERNMENT**

| | **Treatment Effects** | | | | | | | **Marginal Effects** | | | **Elasticity** | | **Sample** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 50% Reduction | | 33% Reduction | | 17% Reduction | | Status Quo | ln(Tax Rate in CF) | | | Elasticity | | | |
| *Dependent variable* | $\hat{\beta}$ | $SE$ | $\hat{\beta}$ | $SE$ | $\hat{\beta}$ | $SE$ | $\bar{y}$ | $\hat{\beta}$ | $SE$ | $\bar{y}$ | $\hat{\beta}$ | $SE$ | Obs. | Sample |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| Panel A: Bribes | | | | | | | | | | | | | | |
| Paid Bribe | -0.007** | 0.002 | -0.002 | 0.002 | 0.001 | 0.002 | 0.019 | 0.012*** | 0.003 | 0.017 | 0.706 | 0.180 | 25,558 | Midline |
| Bribe Amount | -28.209*** | 5.182 | -17.455** | 5.820 | -8.232 | 6.438 | 39.467 | 40.553*** | 6.480 | 25.286 | 1.604 | 0.210 | 25,558 | Midline |
| Gap Self v. Admin | -0.005 | 0.006 | -0.010* | 0.006 | -0.003 | 0.006 | 0.103 | 0.008 | 0.008 | 0.098 | 0.082 | 0.084 | 19,146 | Midline |
| Paid Bribe | 0.000 | 0.020 | -0.015 | 0.018 | -0.004 | 0.022 | 0.027 | 0.002 | 0.027 | 0.034 | 0.059 | 0.847 | 951 | Endline |
| Bribe Amount | -0.538 | 22.376 | -27.530 | 19.693 | -8.189 | 22.339 | 27.232 | 4.000 | 31.355 | 29.715 | 0.135 | 1.122 | 949 | Endline |
| Other Payments | -0.019 | 0.019 | -0.038** | 0.018 | -0.018 | 0.019 | 0.136 | 0.029 | 0.026 | 0.118 | 0.246 | 0.219 | 2753 | Endline |
| Panel B: Payments of Other Taxes | | | | | | | | | | | | | | |
| Participation to Salongo | 0.009 | 0.009 | 0.007 | 0.009 | 0.007 | 0.009 | 0.374 | -0.012 | 0.013 | 0.376 | -0.032 | 0.034 | 18,924 | Midline |
| Hours of Salongo | 0.145 | 0.142 | 0.077 | 0.099 | -0.033 | 0.085 | 1.510 | -0.245 | 0.196 | 1.539 | -0.159 | 0.128 | 18,426 | Midline |
| Paid Vehicle Tax | 0.005 | 0.011 | -0.005 | 0.010 | -0.003 | 0.011 | 0.038 | -0.008 | 0.014 | 0.036 | -0.222 | 0.396 | 2,752 | Endline |
| Paid Market Vendor Fee | -0.031 | 0.022 | -0.033 | 0.022 | -0.007 | 0.022 | 0.208 | 0.049 | 0.030 | 0.185 | 0.265 | 0.172 | 2,757 | Endline |
| Paid Business Tax | -0.009 | 0.013 | -0.018 | 0.013 | -0.015 | 0.013 | 0.067 | 0.010 | 0.018 | 0.053 | 0.189 | 0.324 | 2,753 | Endline |
| Paid Income Tax | 0.002 | 0.018 | 0.009 | 0.019 | 0.000 | 0.018 | 0.116 | -0.006 | 0.025 | 0.115 | -0.052 | 0.226 | 2,751 | Endline |
| Paid Obsolete Tax | 0.002 | 0.007 | 0.002 | 0.007 | 0.013* | 0.008 | 0.013 | 0.003 | 0.010 | 0.017 | 0.176 | 0.592 | 2,725 | Endline |
| Panel C: Views of the Government | | | | | | | | | | | | | | |
| Trust in Provincial Government | -0.069 | 0.049 | -0.033 | 0.051 | -0.013 | 0.050 | 1.770 | 0.100 | 0.066 | 1.761 | 0.057 | 0.037 | 2,739 | Endline |
| Provincial Government Performance | 0.028 | 0.067 | 0.043 | 0.068 | 0.074 | 0.067 | 3.878 | -0.010 | 0.089 | 3.924 | -0.003 | 0.023 | 2,687 | Endline |
| Provincial Government Corruption | 3.212 | 20.012 | 18.631 | 19.989 | 1.080 | 19.668 | 567.274 | -9.591 | 27.225 | 572.370 | -0.017 | 0.049 | 2,760 | Endline |
| Trust in Tax Ministry | -0.027 | 0.055 | -0.003 | 0.056 | 0.026 | 0.055 | 2.038 | 0.055 | 0.074 | 2.035 | 0.027 | 0.037 | 2,743 | Endline |
| Tax Ministry Performance | -0.120 | 0.070 | -0.064 | 0.071 | -0.019 | 0.071 | 4.138 | 0.178* | 0.097 | 4.080 | 0.044 | 0.024 | 2,691 | Endline |
| Tax Ministry Corruption | 34.549* | 18.617 | 20.410 | 18.473 | 34.927 | 18.598 | 399.903 | -35.066 | 25.367 | 422.366 | -0.083 | 0.061 | 2,743 | Endline |
| Fairness Prop. Tax | -0.021 | 0.033 | -0.010 | 0.032 | 0.021 | 0.034 | 2.021 | 0.044 | 0.045 | 2.008 | 0.022 | 0.023 | 2,745 | Endline |
| Fairness Tax Rates | 0.121** | 0.049 | 0.121** | 0.049 | 0.123** | 0.048 | 1.293 | -0.138** | 0.066 | 1.384 | -0.100 | 0.048 | 2,513 | Endline |
| Fairness Tax Coll. | 0.005 | 0.042 | -0.027 | 0.042 | 0.005 | 0.041 | 1.687 | 0.004 | 0.057 | 1.688 | 0.002 | 0.035 | 2,466 | Endline |

*Notes:* Each row summarizes the estimation of Equations (1), (2), and (3). Columns 1–7 summarize the OLS estimation of Equations (1). All regressions include fixed effects for property value band and randomization stratum. The $\hat{\beta}$ are the coefficients on the treatment indicators (in Columns 1, 3, and 5 for the 50%, 33%, and 17% tax abatements, respectively) followed by robust standard errors (in Columns 2, 4, and 6). $\bar{y}$ indicates the mean outcome in the control — status quo tax rate — group (Column 7). Columns 8–10 summarize the OLS estimation of Equation (2). $\hat{\beta}$ is the marginal effect of property tax rates (in CF) on the outcome of interest (Column 8), followed by the robust standard error (Column 9) and $\bar{y}$, the mean outcome in the sample (Column 10). Columns 11–12 summarize the estimation of Equation (3) and present the elasticity of the outcome of interest with respect to the tax rate (Column 11) and the bootstrapped standard errors (Column 12), using the standard deviation across 1,000 bootstrap samples with replacement. Finally, the last two columns provide the number of observations (Column 13) and the sample used, midline or endline (Column 14). In Panel A, the outcome in Rows 1 and 4 are indicators for self-reported bribe payment in the midline and endline surveys, respectively. Rows 2 and 5 report results for the corresponding amount of bribe paid. The outcome in Row 3 indicates property owners who reported paying the tax during the midline survey but who were not recorded as having paid in the administrative data. The outcome in Row 6 is self-reported payment of any informal fee at endline. In Panel B, the outcome in Rows 1 and 2 are indicators for participation in *salongo* and the number of hours devoted to *salongo* at midline, respectively. The outcome in Rows 3–7 are indicators from the endline survey for the payment of the vehicle tax (Row 3), the market vendor fee (Row 4), the business tax (Row 5), the income tax (Row 6), or a fake tax (Row 7). In Panel C, the outcomes are standardized indices measuring trust, perceived performance, and corruption of the provincial government (Rows 1–3) and of the provincial tax ministry (Rows 4–6), followed by the perceived fairness of property tax collection (Row 7), tax rates (Row 8), and tax collectors (Column 9). The number of observations varies across variables in the same survey due to nonresponse. Additionally, analysis of the gap between self-reported and administratively verified tax payments (Row 3) restricts the sample to households deemed noncompliant in the admin data, while analysis of endline bribe measures (Rows 4–5) restricts to the set of households reporting any post-registration visits from collectors (who had opportunities to pay bribes). Midline and endline survey data collection is described in Section 4.1, and the variables used in this table are described in Section A6. We discuss these results in Section 8.

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# Supplementary Data and Appendix
## For Online Publication

# A1 Additional Campaign Details

## A1.1 Logistics Pilot

Before the tax campaign, a logistics pilot took place in March-April 2018. During the pilot, collectors tested the receipt printers for the different tax abatement treatments. They also piloted the protocols for property registration and the delivery of tax letters that were used in the campaign. The pilot took place in eight neighborhoods of Kamilabi, in northwest Kananga. Kamilabi is isolated from the rest of Kananga by a series of steep ravines. This area was selected strategically due to its remote location to minimize potential informational spillovers. We exclude the pilot neighborhoods from our main estimations. But in Table A5, we show that the main results are robust to including these pilot neighborhoods

## A1.2 Collector Compensation

Consistent with standard practices at the tax ministry, all tax collectors received piece-rate compensation for their work on the campaign. Tax collectors received 30 Congolese Francs per property in the register plus a piece rate for the amount of property tax that they collected. The compensation for tax payments was randomly assigned at the property level, orthogonal to tax rates, between a proportional wage of 30% and a constant wage of 750 CF.[98] The size of the piece-rate wage in this context is analogous to incentives paid to property tax collectors in other low-income countries (Khan et al., 2015; Amodio et al., 2018).

> **B1. Proportional Wage.** Half of the properties in the low-value band were randomly assigned to the proportional wage group equal to 30% of the amount of property tax collected. Thus, compensation is 900 CF for taxed properties assigned to the status quo tax rate, 750 CF for properties in the 17% tax abatement treatment, 600 CF for the properties in the 33% tax abatement treatment, and 450 CF for properties in the 50% tax abatement treatment.
>
> **B2. Constant Wage.** Half of the properties in the properties in the low-value band were randomly assigned to a constant piece-rate wage of 750 CF per taxed property.

The treatment effects on tax compliance and revenue as well as the elasticities of tax compliance and revenue with respect to the tax rate are very similar across collector wage groups (Table A7).

## A1.3 Types of Tax Collector

During the 2018 property tax campaign, the provincial government simultaneously randomized different types of tax collector at the neighborhood level. We provide more details about these tax collector types and analyze their effects on tax compliance and tax revenue in a companion paper (Balan et al., 2020), but here we provide a brief summary.

[98] One exception is for properties in the high-value band, which were all assigned to a fixed collector wage of 2,000 CF per taxed property.

**1. State Collectors (Central)**. In 110 "Central" neighborhoods, agents of the provincial tax ministry were charged with all campaign responsibilities. Central collectors were unsalaried contractors who frequently undertake work for the tax ministry and other parts of the provincial government. Some of these agents had worked on the 2016 property tax campaign; others had prior experience collecting firm taxes. The most productive collectors could expect to be competitive for full-time (salaried) positions at the tax ministry.

**2. Chief Collectors (Local).** In 111 "Local" neighborhoods, city chiefs were charged with campaign responsibilities. These chiefs are locally embedded elite leaders whose main responsibilities include: (*i*) mediating local disputes, especially over property; (*ii*) acting as an intermediary between citizens in the neighborhood and the authorities; and (*iii*) organizing a weekly informal labor tax in which citizens undertake local public good provision (*salongo*). The position is technically approved by city government authorities, but chiefs have indefinite and often lifelong tenure, which at times passes through families. Although they share many characteristics with customary chiefs — including land dispute mediation, informal labor tax administration, and long-lasting, sometimes heritable tenure — city chiefs are a distinct institution that is common across Francophone Africa. Known as *chefs d'avenue* or *chefs de localité,*, such chiefs frequently play a role in property tax collection.

**3. Central + Local Information (CLI).** In 80 "Central + Local Information" neighborhoods, after completing the registry, but before follow-up tax visits, state collectors met with the neighborhood chief for a consultation about potential taxpayers. During this meeting, the chief and central collectors went line-by-line through the property register with accompanying photos of each compound (shown on a tablet) taken during registration. For each property, the chief indicated the household's ability and willingness to pay.

**4. Central X Local (CXL).** In 50 "Central X Local" neighborhoods, one state and one chief collector worked together on the campaign. The other rules and procedures of tax collection remained as above.

**5. Pure Control.** 5 "Pure Control" neighborhoods kept the old "declarative" system (the status quo until 2016), in which individuals were supposed to pay themselves at the tax ministry. In this arm, two agents from the tax ministry conducted the property register, assigned tax IDs, and distributed tax letters as in other neighborhoods. The exception was that property owners were informed that they could only pay at the tax ministry rather than paying field-based collectors.

Because the tax rate abatements were randomized at the household level (stratifying on the neighborhood level), we pool neighborhoods assigned to these different tax collector treatments in most of the analysis in this paper. However, we show in Table A8 that the treatment effects in terms of tax compliance and tax revenue as well as the elasticities of tax compliance and revenue with respect to the tax rate are similar across types of tax collector.

### A1.4 Tax Letter Messages

Tax letters contained six cross-randomized messages read out loud by collectors during taxpayer registration:

**M1. Central enforcement.** This message says that refusal to pay the property tax entails the possibility of audit and investigation by the provincial tax ministry.

**M2. Local enforcement.** The local version of the deterrence message says that refusal to pay the property tax entails the possibility of audit and investigation by the quartier chief.[99]

**M3. Central public goods.** This message says that the provincial government will be able to improve infrastructure in the city of Kananga only if citizens pay the property tax.

**M4. Local public goods.** The local version of this message is exactly the same, expect that it mentions each citizen's locality instead of Kananga.[100]

**M5. Trust.** The trust message reminds citizens that paying the property tax is a way of showing that they trust the state and its agents.

**M6. Control.** Control letters say "It is important to pay the property tax."

Figure shows examples of the messages written on the tax letters. We show in Table A24 that the random assignment of these letters achieved balance across property and property owner characteristics. Table A25 shows that compared to the control message, the enforcement messages (M1 or M2) increased tax compliance and revenue. Finally, Figure 3 and Table 6 show that the Laffer rate is lower among property owners assigned to the control message than among those assigned to enforcement messages. Table A27 shows that this is true when controlling for characteristics of the property and of the property owner that appear to be imbalanced across tax messages in Table A24.

## A2 Welfare Implications

### A2.1 Optimal Tax Rate

In this section, we consider the case where the government maximizes social welfare. To define the welfare-maximizing rate, consider a small increase, $dT$, in the fixed annual tax rate. This change in the tax rate has three effects:

[99] This is a higher-rank chief than the chiefs who are collecting taxes in Local neighborhoods.

[100] Localities are the smallest administrative unit in Kananga. The neighborhoods (polygons on a satellite map of the city) used for randomization are roughly analogous to localities.

1. **Mechanical effect**: The mechanical effect, $dM$, represents the mechanical increase in tax revenue.

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

2. **Welfare effect**: The welfare effect, $dW$, represents the social welfare loss due to the additional taxes paid.

$$dW = -\bar{g}\mathbb{P}(T, \alpha)dT$$

   where $\bar{g}$ is the average social welfare weights for tax compliers and so $\bar{g} \in [0, 1]$. There is no change in welfare for marginal payers — who pay the tax only if the tax rate decreases — assuming they are optimizing and the envelope theorem holds.

3. **Behavioral effect**: The behavioral effect, $dB$, represents the fiscal externality due to behavioral responses.

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

The optimal tax rate is characterized by $dM + dW + dB = 0$ and is therefore

$$\begin{aligned} \mathbb{P}(T, \alpha)dT - \bar{g}\mathbb{P}(T, \alpha)dT + T\frac{d\mathbb{P}(T, \alpha)}{dT}dT = 0 \\ \Rightarrow T^{Optimal} = \frac{(1-\bar{g})\mathbb{P}(T^{Optimal}, \alpha)}{-\frac{d\mathbb{P}(T,\alpha)}{dT}\Big|_{T=T^{Optimal}}} \end{aligned}$$

The optimal tax rate decreases with $\bar{g}$, the average social welfare weight attributed to taxpayers. Moreover, for any $\bar{g} > 0$, the welfare-maximizing tax rate is strictly lower than the revenue-maximizing tax rate.

The easiest way to see this is to consider the case where the relationship between tax compliance and the tax rate is linear. In this case, the welfare-maximizing tax rate is

$$T^{Optimal} = \frac{1-\bar{g}}{2-\bar{g}} \times \frac{\beta_0(\alpha)}{-2\beta_1(\alpha)}$$

while the revenue-maximizing tax rate is

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

for $\bar{g} \in [0, 1]$, $\frac{1-\bar{g}}{2-\bar{g}} < 1$. As a consequence, the welfare-maximizing tax rate is always strictly lower than the revenue-maximizing tax rate:

$$T^{Optimal} = \frac{1-\bar{g}}{2-\bar{g}} \times \frac{\beta_0(\alpha)}{-2\beta_1(\alpha)} < \frac{\beta_0(\alpha)}{-2\beta_1(\alpha)} = T^*$$

### A2.2 Marginal Value of Public Funds (MVPF)

For policy changes that are not budget neutral, the marginal value of public funds can be defined following Hendren (2016) and Hendren and Sprung-Keyser (2020) as a simple "benefit/cost" ratio equal to the marginal social welfare impact of the policy per unit of government revenue expended:

$$MVPF = \frac{WTP}{Net\ Cost}$$

where $WTP$ is the willingness to pay (in local monetary units) of the policy recipients and $Net\ Cost$ is the policy's net cost to the government.

- **Willingness to Pay (WTP):** Based on the results with respect to tax revenue presented in Figure 1 and Table 3, taxpayers would be willing to pay $WTP_{17\%} = 0.17 \times 216.9 = 37$ Congolese Francs (CF) for a $17\%$ reduction, $WTP_{33\%} = 0.33 \times 216.9 = 72$ CF for a $33\%$ reduction, and $WTP_{50\%} = 0.50 \times 216.9 = 108$ CF for a $50\%$ reduction in the status quo tax rate. Behavioral responses to marginal policy changes do not affect utility directly by the envelope theorem and so marginal payers — who pay the tax when the tax rate decreases — do not enter into the expression of the willingness to pay.

- **Net Cost:** Based on the results with respect to tax revenue presented in Figure 1 and Table 3, the net cost associated with the 50% and the 33% reduction — $Net\ Cost_{50\%}$ and $Net\ Cost_{33\%}$ — is 0 (it is, in fact, negative since the $50\%$ and the $33\%$ tax reductions increase tax revenues) while $Net\ Cost_{17\%} = 216.9 - 196.70 = 20.2$ CF for the 17% reduction.

Table A23 summarizes this information and reports the willingness to pay, net cost, and marginal value of public funds associated with each tax reduction.

## A3 Estimation of Collector-Lever Enforcement Capacity and Laffer Rate

To estimate $E_c$, the enforcement capacity of collector $c$, we use OLS and regress an indicator for tax compliance of property owner $i$ living in neighborhood $n$, denoted $y_{i,n}$, on a matrix $G$ that consists of indicators for each tax collector and include property value band fixed effects, $\theta_{i,n}$:

$$y_{i,n} = G\vec{E} + \theta_{i,n} + \eta_{i,n}$$

The matrix $G$ is constructed as follows: for each property owner $i$, living in neighborhood $n$, the column corresponding to collector $c$ is assigned a value of +1 if this collector worked as a tax collector in the neighborhood and a value of 0 otherwise. Tax collectors work in pairs in our setting and as a consequence for each row, which represents a property owner, two of the columns — corresponding to the two tax collectors working in neighborhood $n$ — take the value of +1 and the other columns take the value of 0.

Consider an example where collectors $c_1$ and $c_3$ are assigned to collect in neighborhood $n = 1$ (which has a population of $n_1$ property owners) and collectors $c_1$ and $c_2$ are assign to collect taxes in neighborhood $n = 2$ (which has a population of $n_2$ property owners). In this example, the matrix G has the following form:

$$G = \begin{array}{cc} & \begin{array}{ccccc} c1 & c2 & c3 & c4 & c5 \end{array} \\ \begin{array}{c} y_{1,1} \\ \vdots \\ y_{n_1,1} \\ y_{1,2} \\ \vdots \\ y_{n_2,2} \end{array} & \begin{bmatrix} +1 & 0 & +1 & 0 & 0 \\ +1 & 0 & +1 & 0 & 0 \\ +1 & 0 & +1 & 0 & 0 \\ +1 & +1 & 0 & 0 & 0 \\ +1 & +1 & 0 & 0 & 0 \\ +1 & +1 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

The approach is similar when estimating $T_c^*$. For the specification that assumes that tax compliance is linear with respect to the tax rate, we use OLS and regress $y_{i,n}$ on the matrix G as well as the interaction of matrix G with the property tax rate faced by property owner $i$ living in neighborhood $n$, $Tax\ Rate_{i,n}$:

$$y_{i,n} = G\vec{\beta_0} + Tax\ Rate' \times G \times \vec{\beta_1} + \theta_{i,n} + \eta_{i,n}$$

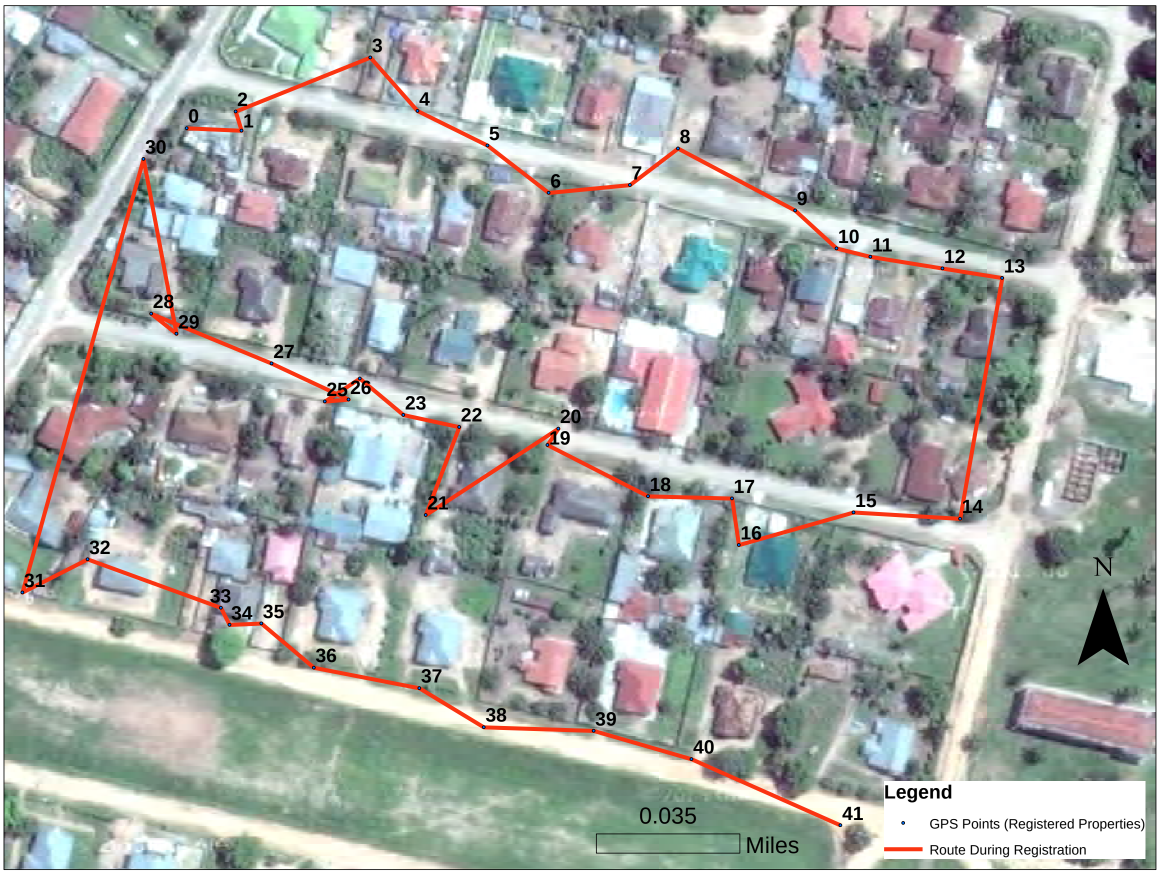
For the specification that assumes that tax compliance is quadratic with respect to the tax rate, we add the interaction of matrix G and the property tax rate squared, $Tax\ Rate^2_{i,n}$:

$$y_{i,n} = G\vec{\beta_0} + Tax\ Rate' \times G \times \vec{\beta_1} + Tax\ Rate^{2'} \times G \times \vec{\gamma} + \theta_{i,n} + \mu_{i,n}$$

# A4 Additional Tables and Figures

## A4.1 Additional Exhibits for Paper Section 3 — Setting

FIGURE A1: COLLECTORS' ROUTES DURING PROPERTY REGISTRATION.




*Notes*: This map shows the linear, property-by-property route taken by collectors in a sample neighborhood in the Quartier of Malanji. Due to slight error in GPS measures, some points appear slightly outside of the neighborhood (across the street). These points would have been, in fact, within the neighborhood boundary. We discuss this figure in Section 3.1.

## Figure A2: Low- and High-Value Property Bands — Examples

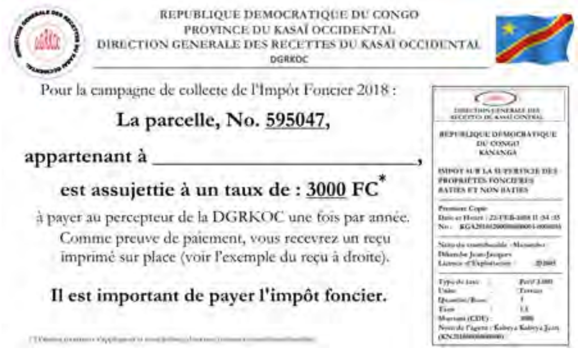
A: Low-value band property

B: High-value band property

*Notes:* This figure shows pictures of a property in the low-value band (Panel A) and of a property in the high-value band (Panel B). The distinction is based on whether the main building on the property is constructed with non-durable materials, such as mudbricks (low-value band), or is built in cement or other durable materials (high-value band). Further details about the property value bands and their importance in the tax campaign are discussed in Section 3.

**FIGURE A3: TAX LETTERS: EXAMPLES BY TREATMENT GROUP**

A: Status Quo Tax Rate



REPUBLIQUE DEMOCRATIQUE DU CONGO
PROVINCE DU KASAÏ OCCIDENTAL
DIRECTION GENERALE DES RECETTES DU KASAÏ OCCIDENTAL
DGRKOC

Pour la campagne de collecte de l'Impôt Foncier 2018 :

**La parcelle, No. 595047,**

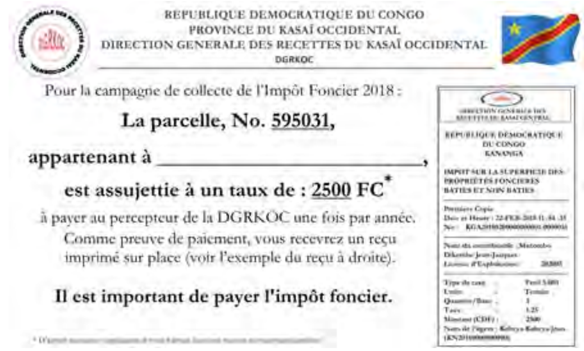
**appartenant à ______________________,**

**est assujettie à un taux de : 3000 FC***

à payer au percepteur de la DGRKOC une fois par année.
Comme preuve de paiement, vous recevrez un reçu imprimé sur place (voir l'exemple du reçu à droite).

**Il est important de payer l'impôt foncier.**

B:17% Reduction in the Status Quo Rate



REPUBLIQUE DEMOCRATIQUE DU CONGO
PROVINCE DU KASAÏ OCCIDENTAL
DIRECTION GENERALE DES RECETTES DU KASAÏ OCCIDENTAL
DGRKOC

Pour la campagne de collecte de l'Impôt Foncier 2018 :

**La parcelle, No. 595031,**

**appartenant à ______________________,**

**est assujettie à un taux de : 2500 FC***

à payer au percepteur de la DGRKOC une fois par année.
Comme preuve de paiement, vous recevrez un reçu imprimé sur place (voir l'exemple du reçu à droite).

**Il est important de payer l'impôt foncier.**

C: 33% Reduction in the Status Quo Rate

REPUBLIQUE DEMOCRATIQUE DU CONGO
PROVINCE DU KASAÏ OCCIDENTAL
DIRECTION GENERALE DES RECETTES DU KASAÏ OCCIDENTAL
DGRKOC

Pour la campagne de collecte de l'Impôt Foncier 2018 :

**La parcelle, No. 595069,**

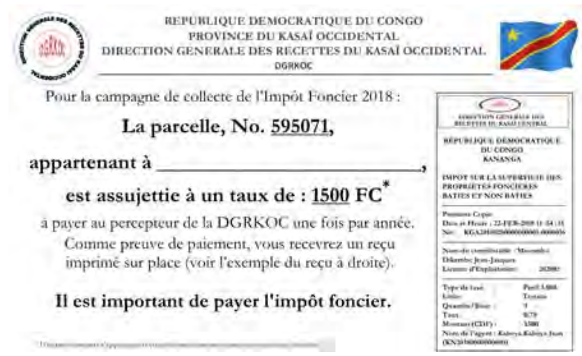
**appartenant à ______________________,**

**est assujettie à un taux de : 2000 FC***

à payer au percepteur de la DGRKOC une fois par année.
Comme preuve de paiement, vous recevrez un reçu imprimé sur place (voir l'exemple du reçu à droite).

**Il est important de payer l'impôt foncier.**

D: 50% Reduction in the Status Quo Rate



REPUBLIQUE DEMOCRATIQUE DU CONGO
PROVINCE DU KASAÏ OCCIDENTAL
DIRECTION GENERALE DES RECETTES DU KASAÏ OCCIDENTAL
DGRKOC

Pour la campagne de collecte de l'Impôt Foncier 2018 :

**La parcelle, No. 595071,**

**appartenant à ______________________,**

**est assujettie à un taux de : 1500 FC***

à payer au percepteur de la DGRKOC une fois par année.
Comme preuve de paiement, vous recevrez un reçu imprimé sur place (voir l'exemple du reçu à droite).

**Il est important de payer l'impôt foncier.**

*Notes:* This figure shows examples of tax letters for owners of properties in the low-value band for each of the tax abatement treatment groups. Panel A shows a picture of a letter for a property owner assigned to the status-quo annual tax rate (control), and Panels B, C and D show the letter for a property owner assigned to a 17%, 33%, and 50% tax abatement, respectively. The main text of the fliers (from *"Pour la campagne ..."* to *"... droite)."*) translates in English as: "For the 2018 property tax collection campaign, the property Number [Property ID] belonging to [Property Owner Name] is subject to a tax rate of [Tax Rate] CF to pay to the DGRKOC collector once a year. As proof of payment, you will receive a printed receipt on the spot (see the example of the receipt at right)." The footnote indicated by an asterisk reads: "Other amounts apply if you live in a house made of durable materials." The randomization of property tax abatements is discussed in Section 3.

## A4.2 Additional Exhibits for Paper Section 4 — Data and Balance

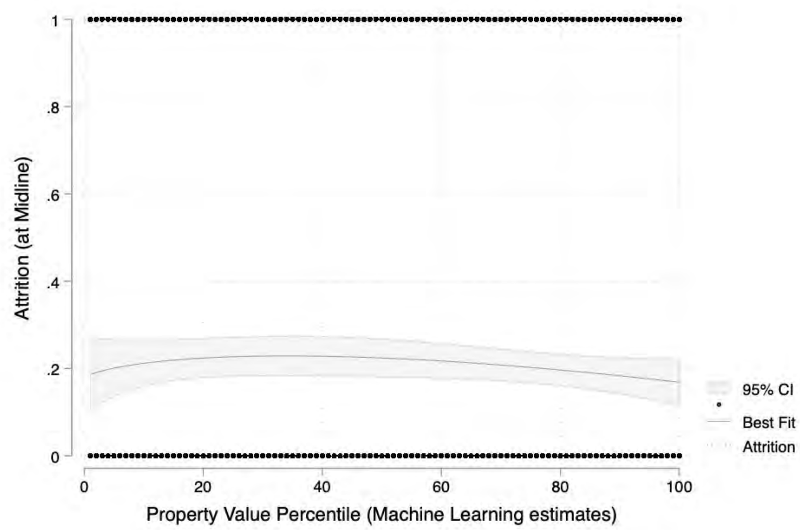
**TABLE A1: ACTIVITIES OF COLLECTORS, ENUMERATORS AND LAND SURVEYORS**

| Activity | Timing | Observations | Neighborhoods |
|---|---|---|---|
| **Tax Campaign - Collectors** | | | |
| Property registration | May-Dec 2018 | 44,361 | 351 |
| Tax collection | May-Dec 2018 | 38,028 | 351 |
| **Household Surveys - Enumerators** | | | |
| Baseline survey | Jul-Dec 2017 | 3,358 | 351 |
| Midline survey | Jun '18-Feb '19 | 29,634 | 351 |
| Endline survey | Mar-Sep 2019 | 2,760 | 351 |
| **Collector Surveys - Enumerators** | | | |
| Baseline survey | Jan-Apr 2018 | 44 | NA |
| Endline survey | Feb-Apr 2019 | 33 | NA |
| **Other Data - Land Surveyors** | | | |
| Property value estimation | Aug-Dec 2019 | 1,654 | 364 |

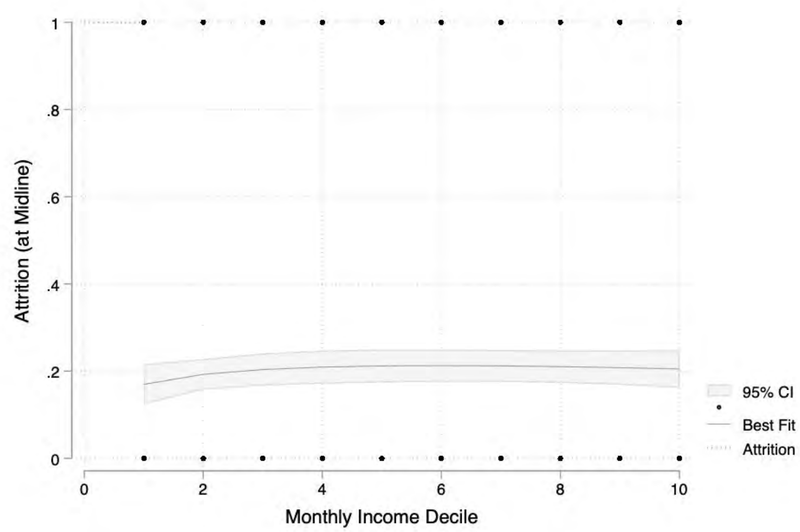
*Notes:* This table reports the components of the 2018 property tax campaign and its evaluation. The tax campaign was implemented by tax collectors, the household and collector surveys by enumerators, and the property value estimation by land surveyors. The numbers of observations and neighborhoods in this table reflect the sample used in the main analysis, in which we exclude the 8 neighborhoods where the logistics pilot took place, the 5 pure control neighborhoods in Balan et al. (2020) where no door-to-door collection took place, and exempted households (with robustness to alternative samples shown in Table A5). Thus, of the 44,361 properties registered (Row 1), only 38,028 properties were non-exempt. As explained in detail in Section 4.1, the midline sample consists of 29,634 (77.93%) of the 38,028 non-exempted households that the enumerators managed to survey at midline. Attrition from baseline and endline was roughly 10% and is uncorrelated with predicted property value, household income, or past tax compliance status. Enumerators conducted pre-campaign surveys with the 44 tax collectors studied in Section 7.2, and again with 33 of them at endline. Finally, the property value estimation was conducted with 1,654 randomly chosen property owners from the 364 total neighborhoods of Kananga (including those chosen for the logistics pilot and the pure control group in Balan et al. (2020)). These data sources are discussed in Section 4.1.

**FIGURE A4: ATTRITION AT MIDLINE BY PROPERTY VALUE AND INCOME**

A: Attrition by Property Value (ML Estimates)




B: Attrition at Midline by Monthly Income




*Notes:* This figure shows how attrition between the initial property registration and the midline survey varies with the percentile of the predicted property values in USD (Panel A) and with the decile of the baseline measure of household monthly income (Panel B). Property values were estimated using the best performing machine learning algorithm as described in Section A5. These relationships are estimated using a fractional polynomial regression of degree 2 and the best fit curve is displayed in dark gray. Standard errors are clustered at the neighborhood level, and the 95 percent confidence interval is displayed in light gray. We discuss the results in Section 4.1.

## TABLE A2: F-TEST OF THE OMNIBUS NULL

| Sample and Test | F-test | p-value |
|---|---|---|
| **Panel A: Property Characteristics (Registration, Midline)** | | |
| Status quo rate vs 17% reduction | 0.370 | 0.989 |
| Status quo rate vs 33% reduction | 0.981 | 0.474 |
| Status quo rate vs 50% reduction | 0.883 | 0.590 |
| **Panel B: Property Owner Characteristics (Midline)** | | |
| Status quo rate vs 17% reduction | 0.535 | 0.710 |
| Status quo rate vs 33% reduction | 0.160 | 0.958 |
| Status quo rate vs 50% reduction | 1.727 | 0.141 |
| **Panel C: Property Owner Characteristics (Baseline)** | | |
| Status quo rate vs 17% reduction | 1.273 | 0.241 |
| Status quo rate vs 33% reduction | 0.537 | 0.865 |
| Status quo rate vs 50% reduction | 0.668 | 0.755 |

*Notes:* This table tests the omnibus null hypothesis that the treatment effects for the variables listed in Table 2 are all zero using parametric $F$-tests. Panel A reports the omnibus null hypothesis for each tax abatement treatment against the status quo treatment for property characteristics from the registration and midline sample. Panels B and C repeat this exercise using characteristics from the midline and endline surveys, respectively. The results are summarized in Section 4.2.

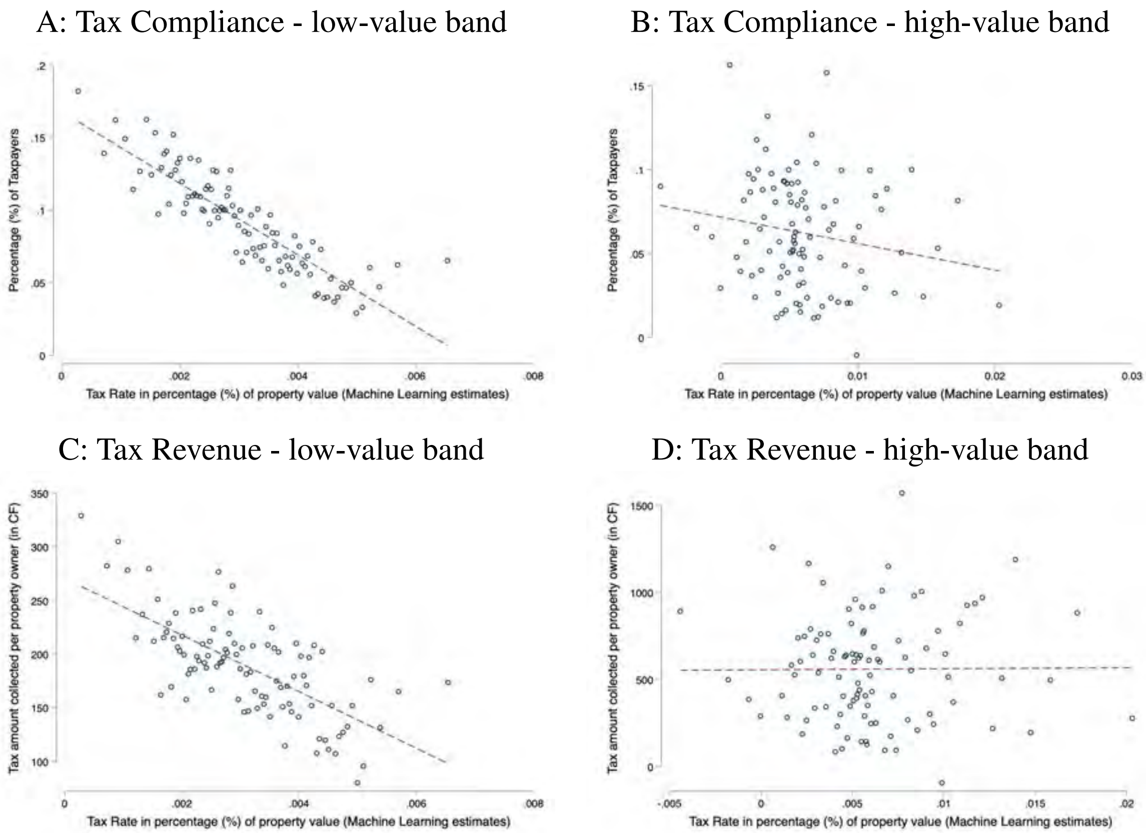
## Table A3: Randomization Balance - Exemption Status

| | Sample (1) | Obs. (2) | Status quo Mean (3) | 17% Reduction (4) | 33% Reduction (5) | 50 % Reduction (6) |
|---|---|---|---|---|---|---|
| Exempted | Registration | 44,361 | 0.147 | -0.007 | 0.001 | -0.009 |
| | | | | (0.005) | (0.005) | (0.005) |
| Senior | Registration | 44,361 | 0.071 | 0.005 | 0.002 | -0.002 |
| | | | | (0.003) | (0.003) | (0.003) |
| Widow | Registration | 44,361 | 0.062 | -0.005 | -0.001 | -0.006** |
| | | | | (0.003) | (0.003) | (0.003) |
| Government Pension | Registration | 44,361 | 0.007 | 0.000 | -0.000 | -0.000 |
| | | | | (0.001) | (0.001) | (0.001) |
| Handicap | Registration | 44,361 | 0.002 | 0.000 | 0.001 | 0.000 |
| | | | | (0.001) | (0.001) | (0.001) |
| Other | Registration | 44,361 | 0.005 | -0.000 | -0.001 | -0.000 |
| | | | | (0.001) | (0.001) | (0.001) |

*Notes:* This table reports results from estimating Equation (1) using different official exemption categories as the outcome. This table uses the final registration sample that consists of 44,361 properties. The status quo tax rate is the excluded category. Row 1 examines balance of any official exemption status by tax abatement treatments. Rows 2–6 report balance by categories of exemption. The results are discussed in Sections 4.2 and 5.2. The variable comes from property registration and are described in Section A6.

## A4.3 Additional Exhibits for Paper Section 5 — Treatment Effects on Tax Compliance and Revenue

**FIGURE A5: TAX COMPLIANCE AND REVENUE BY TAX RATE (AS A PERCENTAGE OF PROPERTY VALUE)**




*Notes:* This table reports binned scatterplots of the relationship between tax rates, expressed as a percentage of property value, and tax compliance (Panels A and B) or tax revenue (Panels C and D). All binned scatterplots include fixed effects for randomization stratum (neighborhood). The data include all non-exempt properties registered by tax collectors merged with the government's property tax database. Panels A and C restrict the sample to properties in the low-value band, while Panels B and D restrict the sample to properties in the high-value band. The prediction of property values in Kananga using machine learning is described briefly in Section 4.1 and in more detail in Section A5. We discuss these results in Section 5.2.

## Table A4: Effects of Tax Rates (in % of property value) on Tax Compliance and Revenue

| | Tax Compliance Indicator | | | | 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: IV Specification - First Stage | | | | | | | | |
| 50% Reduction | -0.658*** | -0.674*** | -0.667*** | -0.708*** | -0.658*** | -0.674*** | -0.667*** | -0.708*** |
| | (0.013) | (0.009) | (0.008) | (0.040) | (0.013) | (0.009) | (0.008) | (0.040) |
| 33% Reduction | -0.397*** | -0.408*** | -0.404*** | -0.442*** | -0.397*** | -0.408*** | -0.404*** | -0.442*** |
| | (0.013) | (0.009) | (0.009) | (0.039) | (0.013) | (0.009) | (0.009) | (0.039) |
| 17% Reduction | -0.181*** | -0.180*** | -0.173*** | -0.237*** | -0.181*** | -0.180*** | -0.173*** | -0.237*** |
| | (0.013) | (0.009) | (0.008) | (0.039) | (0.013) | (0.009) | (0.008) | (0.039) |
| Mean (control) | -5.995 | -5.995 | -6.021 | -5.777 | -5.995 | -5.995 | -6.021 | -5.777 |
| F-Test | 961 | 1187 | 2418 | 116 | 961 | 1187 | 2418 | 116 |
| p-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Panel B: IV Specification - Second Stage | | | | | | | | |
| ln(Tax Rate in % property value) | -0.118*** | -0.113*** | -0.118*** | -0.081*** | -65.576*** | -58.035** | -49.395*** | -141.088 |
| | (0.006) | (0.006) | (0.006) | (0.016) | (19.763) | (18.796) | (12.709) | (144.781) |
| Mean (sample) | 0.088 | 0.088 | 0.092 | 0.062 | 229.662 | 229.662 | 188.888 | 560.547 |
| Panel C: Elasticities | | | | | | | | |
| Elasticity | -1.332 | -1.278 | -1.284 | -1.311 | -0.286 | -0.253 | -0.262 | -0.252 |
| | (0.071) | (0.066) | (0.067) | (0.257) | (0.088) | (0.084) | (0.069) | (0.266) |
| Observations | 38028 | 38028 | 33856 | 4172 | 38028 | 38028 | 33856 | 4172 |
| Sample | All properties | All properties | Low-value properties | High-value properties | All properties | All properties | Low-value properties | High-value properties |
| House FE | Yes | Yes | No | No | Yes | Yes | No | No |
| Neighborhood FE | No | Yes | Yes | Yes | No | Yes | Yes | Yes |

*Notes:* This table reports estimates from the instrumental variable approach described in Equations (4) and (5). The dependent variable is an indicator for tax compliance in Columns 1–4 and tax revenue (in Congolese Francs) in Columns 5–8. Panel A reports the first stage of the instrumental variable model (Equation (5)) and the corresponding $F$-test and $p$-value. Panel B reports the second stage of the instrumental variable model (Equation (5)). Panel C reports the corresponding elasticity of tax compliance and revenue with respect to the tax rate from Equation (3). All regressions include fixed effects for property value band and Columns 2–4 and 6–8 include fixed effects for randomization stratum (neighborhood). Panels A and B report robust standard errors, while Panel C reports bootstrapped standard errors (with 1,000 iterations). Results are reported for all properties in Columns 1–2 and 5–6, while Columns 3 and 7 restrict the sample to low-value properties, and Columns 4 and 8 restrict to high-value properties. The data include all non-exempt properties registered by tax collectors merged with the government's property tax database. We discuss these results in Section 5.2.

## TABLE A5: ROBUSTNESS — INCLUDING CONTROLS, PILOT NEIGHBORHOODS, PURE CONTROL NEIGHBORHOODS, AND EXEMPTED PROPERTIES

| | Tax Compliance Indicator | | | | | | Tax Revenue (in CF) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Panel A: Reduced Form Effects | | | | | | | | | | | | |
| 50% Reduction | 0.073$^{***}$ | 0.073$^{***}$ | 0.073$^{***}$ | 0.075$^{***}$ | 0.072$^{***}$ | 0.064$^{***}$ | 24.769$^{*}$ | 24.565$^{*}$ | 23.707$^{*}$ | 27.975$^{**}$ | 24.809$^{*}$ | 24.876$^{**}$ |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (13.819) | (13.841) | (13.826) | (13.568) | (13.589) | (11.970) |
| 33% Reduction | 0.044$^{***}$ | 0.044$^{***}$ | 0.044$^{***}$ | 0.045$^{***}$ | 0.043$^{***}$ | 0.038$^{***}$ | 33.328$^{**}$ | 33.807$^{**}$ | 33.891$^{**}$ | 36.914$^{**}$ | 33.417$^{**}$ | 28.958$^{**}$ |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.003) | (14.936) | (14.953) | (14.933) | (14.690) | (14.646) | (12.874) |
| 17% Reduction | 0.011$^{***}$ | 0.011$^{***}$ | 0.012$^{***}$ | 0.012$^{***}$ | 0.011$^{***}$ | 0.010$^{**}$ | -20.795 | -20.311 | -19.175 | -18.161 | -20.037 | -16.924 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (14.418) | (14.423) | (14.423) | (14.171) | (14.156) | (12.453) |
| Mean (control) | 0.056 | 0.056 | 0.056 | 0.055 | 0.055 | 0.048 | 216.903 | 216.903 | 216.903 | 214.874 | 212.696 | 186.066 |
| Panel B: Marginal Effects | | | | | | | | | | | | |
| ln(Tax Rate in CF) | -0.110$^{***}$ | -0.110$^{***}$ | -0.109$^{***}$ | -0.113$^{***}$ | -0.108$^{***}$ | -0.097$^{***}$ | -56.040$^{**}$ | -55.642$^{**}$ | -53.862$^{**}$ | -60.187$^{***}$ | -55.712$^{**}$ | -52.779$^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.005) | (18.256) | (18.294) | (18.257) | (17.936) | (17.966) | (15.837) |
| Mean (sample) | 0.088 | 0.088 | 0.088 | 0.089 | 0.087 | 0.076 | 229.662 | 229.662 | 229.662 | 229.515 | 225.588 | 198.548 |
| Panel C: Elasticities | | | | | | | | | | | | |
| Elasticity | -1.247 | -1.245 | -1.236 | -1.267 | -1.248 | -1.263 | -0.239 | -0.244 | -0.235 | -0.262 | -0.247 | -0.266 |
| | (0.084) | (0.070) | (0.060) | (0.060) | (0.062) | (0.062) | (0.109) | (0.090) | (0.122) | (0.079) | (0.082) | (0.081) |
| Controls: | | | | | | | | | | | | |
| Age, Age-squared, Gender | Yes | No | Yes | No | No | No | Yes | No | Yes | No | No | No |
| Roof Quality, Distance to Market (Imbalanced) | No | Yes | Yes | No | No | No | No | Yes | Yes | No | No | No |
| Employed, Salaried | No | No | Yes | No | No | No | No | No | Yes | No | No | No |
| Government Job (Self & Fam.) | No | No | Yes | No | No | No | No | No | Yes | No | No | No |
| Adjustments: | | | | | | | | | | | | |
| Includes Pilot Nbdhs. | No | No | No | Yes | No | No | No | No | No | Yes | No | No |
| Includes Pure Control Nbdhs. | No | No | No | No | Yes | No | No | No | No | No | Yes | No |
| Includes Exempted Properties | No | No | No | No | No | Yes | No | No | No | No | No | Yes |
| Observations | 38028 | 38028 | 38028 | 38899 | 38744 | 44361 | 38028 | 38028 | 38028 | 38899 | 38744 | 44361 |
| Sample | Midline sample | Midline sample | Midline sample | All properties | All properties | All properties | Midline sample | Midline sample | Midline sample | All properties | All properties | All properties |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table explores a series of robustness checks concerning the main treatment effects on compliance and revenue. It reports estimates from Equations (1), (2), and (3). In Columns 1–6, the dependent variable is an indicator for compliance, while in Columns 7–12, the dependent variable is tax revenue (in Congolese Francs). Panel A reports treatment effects from Equation (1) comparing property tax compliance and property tax 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 property tax rates (in CF) on tax compliance and revenue from Equation (2). These two estimates are used in Panel C to compute the elasticity of tax compliance and revenue with respect to the tax rate following Equation (3). All regressions include fixed effects for property value band and fixed effects for randomization stratum (neighborhood). Panels A and B report robust standard errors. Standard errors in Panel C are bootstrapped (with 1,000 iterations). Columns 1 and 7 control for basic covariates (age, age squared, and gender), measured at baseline; Columns 2 and 8 add controls for roof quality and distance to the nearest market (the imbalanced covariates in Table 2); Columns 3 and 9 add controls for having any job, a salaried job, and a government job, and a family member with a government job. When including controls, we replace missing values in control variables with the mean for the entire sample and include a separate dummy (for each control variable) for the value being missing. Columns 4 and 10 include pilot neighborhoods; Columns 5 and 11 include pure control neighborhoods; and Columns 6 and 12 include exempted properties. The data include all properties registered by tax collectors merged with the government's property tax database. We discuss these results in Section 5.2.

**Table A6: Treatment Effects on Revenue — Robustness: Accounting for Knowledge of Others' Rates, Past Rates, Expectations of Future Rates, and Past Exposure to Tax Collection**

| | Outcome: Tax Revenue (in Congolese Francs) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Controls for 5 neighbors' rate (1) | Controls for 10 neighbors' rate (2) | Doesn't know neighbors' rate (3) | Knows neighbors' rate (4) | Doesn't know discounts (5) | Knows discounts (6) | Doesn't Know past rates (7) | Knows past rates (8) | No 2016 door-to-door tax campaign (9) | Door-to-door 2016 tax campaign (10) |
| <u>Panel A: Reduced Form Effects</u> | | | | | | | | | | |
| 50% Reduction | 22.923 | 22.709 | 31.000 | 2.066 | -2.676 | -64.522 | 51.831 | 133.677 | 39.711 | 15.271 |
| | (13.939) | (13.952) | (24.196) | (63.235) | (35.987) | (680.464) | (77.198) | (176.085) | (24.254) | (16.647) |
| 33% Reduction | 36.918** | 37.064** | 42.073 | 42.736 | 71.435* | -621.510 | -32.192 | 72.279 | 23.625 | 40.434** |
| | (15.137) | (15.134) | (25.663) | (61.768) | (39.649) | (1129.941) | (80.482) | (211.148) | (25.358) | (18.432) |
| 17% Reduction | -20.668 | -20.549 | -38.543 | -28.680 | -42.812 | -372.198 | -97.065 | 27.455 | -28.553 | -16.780 |
| | (14.602) | (14.602) | (24.935) | (66.992) | (37.663) | (642.694) | (81.063) | (207.580) | (24.764) | (17.602) |
| Mean (control) | 217.154 | 217.154 | 258.357 | 330.055 | 227.411 | 634.286 | 301.250 | 428.571 | 225.726 | 211.524 |
| <u>Panel B: Marginal Effects</u> | | | | | | | | | | |
| ln(Tax Rate in CF) | -54.429** | -54.110** | -76.148** | -30.241 | -41.952 | 294.168 | -119.342 | -195.964 | -78.392** | -42.766* |
| | (18.432) | (18.461) | (32.165) | (87.645) | (46.021) | (1174.460) | (107.128) | (232.279) | (31.950) | (22.013) |
| Mean (sample) | 229.411 | 229.411 | 272.444 | 317.748 | 225.010 | 399.320 | 328.565 | 329.177 | 239.047 | 223.150 |
| <u>Panel C: Elasticities</u> | | | | | | | | | | |
| Elasticity | -0.237 | -0.236 | -0.280 | -0.095 | -0.186 | 0.737 | -0.363 | -0.595 | -0.328 | -0.192 |
| | (0.082) | (0.082) | (0.169) | (2.455) | (0.198) | (3.023) | (0.354) | (0.733) | (0.132) | (0.102) |
| Observations | 37211 | 37211 | 13046 | 2158 | 5098 | 147 | 2069 | 401 | 14590 | 23296 |
| Sample | All properties | All properties | Midline Sample | Midline Sample | Midline Sample | Midline Sample | Baseline Sample | Baseline Sample | All properties | All properties |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighbor Rate Controls | Yes | Yes | No | No | No | No | No | No | No | No |

*Notes:* This table explores alternative explanations concerning taxpayers' responses to randomized tax abatements that could introduce bias into our estimated treatment effects. It reports estimates from Equations (1), (2), and (3). The dependent variable is tax revenues (in Congolese Francs). Panel A reports treatment effects from Equation (1) comparing property tax revenue for the tax abatement treatment groups relative to the status quo property tax rate (the excluded category). Panel B reports the mean tax revenue in the sample as well as the marginal effect of property tax rates (in CF) on tax revenue from Equation (2). These two estimates are used in Panel C to compute the elasticity of tax revenue with respect to the tax rate following Equation (3). All regressions include fixed effects for property value and for randomization stratum (neighborhood). Panels A and B report robust standard errors. Standard errors in Panel C are bootstrapped (with 1,000 iterations). 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 (indicated in the bottom panel of the table) and are described in Section A6. Columns 9 and 10 estimate treatment effects for neighborhoods where door-to-door tax collection took place during the previous (2016) property tax campaign and neighborhoods where no door-to-door collection took place, using the treatment assignment from Weigel (2020). The sample in Columns 1–2 is slightly smaller than the total properties registered because of missing GPS data in $<3\%$ of cases. 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). We discuss these results in Section 5.3.

## TABLE A7: ROBUSTNESS — ACCOUNTING FOR DIFFERENTIAL TAX COLLECTOR ENFORCEMENT EFFORT BY RATE

| | Outcome: Visit Indicator | | | Outcome: Number of Visits | | | Outcome: Tax Compliance | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | All<br>(1) | Constant Wage<br>(2) | Proportional Wage<br>(3) | All<br>(4) | Constant Wage<br>(5) | Proportional Wage<br>(6) | Visit Ind. Ctrl<br>(7) | Nb of Visits Ctrl<br>(8) | Constant Wage<br>(9) | Proportional Wage<br>(10) | Wage Amount Fixed Effects<br>(11) |
| Panel A: Reduced Form Effects | | | | | | | | | | | |
| 50% Reduction | 0.026** | 0.038** | 0.015 | 0.027* | 0.043** | 0.015 | 0.079*** | 0.080*** | 0.070*** | 0.078*** | 0.089*** |
| | (0.009) | (0.012) | (0.012) | (0.014) | (0.022) | (0.020) | (0.005) | (0.005) | (0.005) | (0.006) | (0.006) |
| 33% Reduction | 0.016* | 0.015 | 0.016 | 0.001 | -0.012 | 0.014 | 0.047*** | 0.048*** | 0.042*** | 0.048*** | 0.050*** |
| | (0.009) | (0.012) | (0.012) | (0.014) | (0.021) | (0.020) | (0.005) | (0.005) | (0.005) | (0.006) | (0.005) |
| 17% Reduction | 0.013 | 0.016 | 0.011 | 0.014 | -0.001 | 0.025 | 0.009* | 0.009* | 0.007 | 0.018*** | 0.021*** |
| | (0.009) | (0.012) | (0.012) | (0.015) | (0.021) | (0.022) | (0.004) | (0.004) | (0.005) | (0.005) | (0.004) |
| Mean (control) | 0.407 | 0.409 | 0.404 | 0.56 | 0.579 | 0.541 | 0.066 | 0.066 | 0.055 | 0.057 | 0.056 |
| Panel B: Marginal Effects | | | | | | | | | | | |
| ln(Tax Rate in CF) | -0.034** | -0.049** | -0.020 | -0.031 | -0.056* | -0.012 | -0.120*** | -0.122*** | -0.107*** | -0.115*** | -0.129*** |
| | (0.012) | (0.017) | (0.016) | (0.020) | (0.029) | (0.027) | (0.007) | (0.007) | (0.008) | (0.009) | (0.008) |
| Mean (sample) | 0.422 | 0.429 | 0.416 | 0.570 | 0.586 | 0.554 | 0.101 | 0.101 | 0.085 | 0.093 | 0.088 |
| Panel C: Elasticities | | | | | | | | | | | |
| Elasticity | -0.081 | -0.114 | -0.049 | -0.055 | -0.095 | -0.021 | -1.191 | -1.203 | -1.271 | -1.235 | -1.464 |
| | (0.028) | (0.041) | (0.040) | (0.034) | (0.051) | (0.048) | (0.068) | (0.068) | (0.086) | (0.089) | (0.088) |
| Observations | 23054 | 11411 | 11643 | 22893 | 11335 | 11558 | 25520 | 25340 | 21042 | 16986 | 38028 |
| Sample | Midline Sample | Midline Sample | Midline Sample | Midline Sample | Midline Sample | Midline Sample | Midline Sample | Midline Sample | All Properties | All Properties | All Properties |
| House FE | No | No | No | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Visit Controls | No | No | No | No | No | No | Yes | Yes | No | No | No |
| Wage FE | No | No | No | No | No | No | No | No | No | No | Yes |

*Notes:* This table explores the possibility that collectors exerted enforcement effort differentially across rates, which could magnify the estimated taxpayer responses to rate reductions. It reports estimates from Equations (1), (2), and (3). In Columns 1–3, the dependent variable is an indicator for the property owner reporting any visits by tax collectors after property registration. In Columns 3–6, the dependent variable is the number of visits by tax collectors after property registration reported by property owners. In Columns 7–11, the dependent variable is an indicator for property tax compliance. Columns 1 and 3 consider all properties. Columns 2 and 5 restrict the sample to properties randomly assigned to the constant tax collector wage group, while Columns 3 and 6 restrict to properties assigned to the proportional collector wage group. Collector compensation is discussed in Section A1.2. In Columns 7–8, all cases of tax compliance are considered, and we control for a visit indicator (Column 8) and for number of visits (Column 9). Column 9 restricts the sample to properties assigned a constant wage (750 FC per collection) and Column 10 to properties assigned a proportional wage (30% of the amount collected). Column 11 considers all properties but introduces fixed effects for the wage amount in the familiar specification. Panel A reports treatment effects from Equation (1) comparing visits or property tax compliance for the tax abatement treatment groups relative to the status quo property tax rate (the excluded category). Panel B reports the mean visits or property tax compliance as well as the marginal effect of property tax rates (in CF) on visits or property tax compliance from Equation (2). These two estimates are used in Panel C to compute the elasticity of visits and tax compliance with respect to the tax rate following Equation (3). The data include all non-exempt properties registered by tax collectors merged with the government's property tax database. We discuss these results in Section 5.3.4.

## Table A8: Heterogeneous Treatment Effects on Compliance and Revenue by Collector Type

| | Central Collectors | | Local Collectors | | Central Collectors (+ Local Info) | | Central x Local Collectors | |
|---|---|---|---|---|---|---|---|---|
| | Tax Compliance | Tax Revenue | Tax Compliance | Tax Revenue | Tax Compliance | Tax Revenue | Tax Compliance | Tax Revenue |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Reduced Form Effects | | | | | | | | |
| 50% Reduction | 0.057*** | 4.195 | 0.085*** | 8.573 | 0.079*** | 68.986*** | 0.077*** | 43.062 |
| | (0.007) | (25.365) | (0.008) | (28.422) | (0.008) | (19.856) | (0.011) | (32.428) |
| 33% Reduction | 0.035*** | 11.777 | 0.057*** | 47.506 | 0.037*** | 46.232** | 0.048*** | 37.073 |
| | (0.006) | (27.552) | (0.007) | (31.265) | (0.007) | (20.972) | (0.010) | (33.723) |
| 17% Reduction | 0.009 | -24.676 | 0.012* | -59.054** | 0.013* | 38.155* | 0.015* | -16.143 |
| | (0.006) | (27.187) | (0.007) | (28.567) | (0.007) | (22.754) | (0.009) | (32.173) |
| Mean (control) | 0.052 | 219.31 | 0.069 | 282.721 | 0.048 | 142.786 | 0.047 | 173.226 |
| Panel B: Marginal Effects | | | | | | | | |
| ln(Tax Rate in CF) | -0.086*** | -22.664 | -0.130*** | -57.658 | -0.115*** | -90.529** | -0.115*** | -80.133* |
| | (0.009) | (33.298) | (0.011) | (37.139) | (0.012) | (27.926) | (0.015) | (42.766) |
| Mean (sample) | 0.078 | 220.921 | 0.107 | 285.889 | 0.081 | 182.62 | 0.081 | 188.84 |
| Panel C: Elasticities | | | | | | | | |
| Elasticity | -1.096 | -0.103 | -1.216 | -0.202 | -1.422 | -0.496 | -1.424 | -0.424 |
| | (0.112) | (0.149) | (0.096) | (0.134) | (0.139) | (0.153) | (0.175) | (0.225) |
| Observations | 12514 | 12514 | 12232 | 12232 | 8251 | 8251 | 5018 | 5018 |
| Sample | All properties | All properties | All properties | All properties | All properties | All properties | All properties | All properties |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table examines heterogeneity in the main treatment effects by the cross-randomized tax collector treatments, assigned at the neighborhood level, examined in Balan et al. (2020). It reports estimates from Equations (1), (2), and (3). In Columns 1, 3, 5, and 7 the dependent variable is an indicator for compliance, while in Columns 2, 4, 6, and 8 the dependent variable is tax revenues (in Congolese Francs). Panel A reports treatment effects from Equation (1) comparing property tax compliance and property tax 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 property tax rates (in CF) on tax compliance and revenue from Equation (2). These two estimates are used in Panel C to compute the elasticity of tax compliance and revenue with respect to the tax rate following Equation (3). All regressions include fixed effects for property value band and Columns 2–4 and 6–8 include fixed effects for randomization stratum (neighborhood). Panels A and B report robust standard errors. Standard errors in Panel C are bootstrapped (with 1,000 iterations). Results are reported for neighborhoods assigned to "Central" tax collection in Columns 1–2, "Local" tax collection in Columns 3–4, "Central + Local Information" tax collection in Columns 5–6, and "Central x Local" tax collection in Columns 7–8. The treatment groups are described in Section A1.3 and in further detail in Balan et al. (2020). The data include all non-exempt properties registered by tax collectors merged with the government's property tax database. We discuss these results in Section 3.1.

## TABLE A9: TREATMENT EFFECTS ON PROPERTY QUALITY AND MOVING TO NEW PROPERTIES

| | House Characteristics | | | Moving from Property | | |
|---|---|---|---|---|---|---|
| | Wall Quality (1) | Roof Quality (2) | Fence Quality (3) | Any (4) | Different Nbhd (5) | Same Nbhd (6) |
| Panel A: Reduced Form Effects | | | | | | |
| 50% Reduction | 0.042 | 0.103 | 0.024 | 0.004 | 0.010 | -0.006 |
| | (0.217) | (0.390) | (0.163) | (0.012) | (0.009) | (0.008) |
| 33% Reduction | -0.103 | -0.602 | 0.021 | -0.004 | -0.006 | 0.002 |
| | (0.202) | (0.419) | (0.176) | (0.011) | (0.008) | (0.008) |
| 17% Reduction | 0.085 | -0.282 | 0.186 | 0.007 | 0.008 | -0.001 |
| | (0.213) | (0.389) | (0.150) | (0.011) | (0.008) | (0.008) |
| Mean (control) | 2.888 | 5.313 | 1.313 | 0.035 | 0.015 | 0.02 |
| Panel B: Marginal Effects | | | | | | |
| ln(Tax Rate in CF) | 0.019 | -0.112 | 0.060 | -0.000 | -0.007 | 0.007 |
| | (0.288) | (0.533) | (0.231) | (0.016) | (0.012) | (0.010) |
| Mean (sample) | 3.04 | 5.143 | 1.371 | 0.037 | 0.020 | 0.017 |
| Panel C: Elasticities | | | | | | |
| Elasticity | 0.006 | -0.022 | 0.044 | -0.008 | -0.373 | 0.414 |
| | (0.091) | (0.098) | (0.167) | (0.448) | (0.645) | (0.627) |
| Observations | 329 | 329 | 329 | 2656 | 2656 | 2656 |
| Sample | Endline Sample | Endline Sample | Endline Sample | Endline Sample | Endline Sample | Endline Sample |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table explores if the tax abatement treatments caused real effects, i.e., whether households invested differentially in the quality of their existing properties or whether they chose to move to new properties. It reports estimates from Equations (1), (2), and (3). In Columns 1–3 the dependent variables are proxies for house quality: walls materials (Column 1), roof materials (Column 2), and fence materials (Column 3). In Columns 4–6 the dependent variables are indicators for the property owner moving to a different property between the baseline and the endline sample. Column 4 examines any such move, Column 5 when an owner moved to a different neighborhood, and Column 6 when an owner moved within the same neighborhood. Panel A reports treatment effects from Equation (1) comparing each outcome for the tax abatement treatment groups relative to the status quo property tax rate (the excluded category). Panel B reports the mean for each outcome as well as the marginal effect of property tax rates (in Congolese Francs) on each outcome using Equation (2). These two estimates are used in Panel C to compute the elasticity of each outcome with respect to the tax rate following Equation (3). All regressions include fixed effects for property value band and fixed effects for randomization stratum (neighborhood). Panels A and B report robust standard errors. Standard errors in Panel C are bootstrapped (with 1,000 iterations). Results are limited to set of households in the endline sample for which we observe the outcomes of interest. We discuss these results in Section 5.2.

## TABLE A10: TREATMENT EFFECTS ON OWNERS' KNOWLEDGE AND COLLECTORS' STRATEGIES

| | Knowledge | | Collector Messages | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Knows Nb Rate | Knows Reductions | Sanctions Chief | Sanctions Tax Ministry | Public goods Neighborhood | Public goods Kananga | Show Trust in Gov | It's Important | Legal Obligation | Avoid Social Embarrassment | Other Threat |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| 50% Reduction | -0.011 | -0.004 | 0.008 | -0.003 | -0.003 | 0.018 | -0.014 | -0.064** | -0.003 | 0.008 | -0.005 |
| | (0.008) | (0.007) | (0.025) | (0.026) | (0.025) | (0.025) | (0.026) | (0.026) | (0.025) | (0.023) | (0.022) |
| 33% Reduction | -0.014* | 0.003 | 0.029 | 0.030 | 0.051* | 0.035 | -0.006 | -0.022 | 0.008 | 0.015 | 0.022 |
| | (0.008) | (0.007) | (0.024) | (0.026) | (0.026) | (0.025) | (0.026) | (0.026) | (0.025) | (0.023) | (0.023) |
| 17% Reduction | -0.005 | 0.002 | -0.033 | -0.021 | 0.014 | 0.037 | -0.012 | -0.036 | -0.009 | -0.015 | -0.007 |
| | (0.008) | (0.007) | (0.024) | (0.025) | (0.025) | (0.025) | (0.025) | (0.026) | (0.025) | (0.022) | (0.023) |
| Mean (control) | 0.149 | 0.029 | 0.256 | 0.278 | 0.263 | 0.232 | 0.324 | 0.452 | 0.383 | 0.203 | 0.230 |
| Observations | 15072 | 5245 | 2743 | 2743 | 2743 | 2743 | 2743 | 2743 | 2743 | 2743 | 2743 |
| Sample | Midline Sample | Midline Sample | Endline Sample | Endline Sample | Endline Sample | Endline Sample | Endline Sample | Endline Sample | Endline Sample | Endline Sample | Endline Sample |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table examines treatment effects on owners' knowledge of tax rates and abatements as well as the different possible messages used by collectors when demanding payment, as measured in the midline and endline surveys. It reports the treatment effects from Equation (1) comparing the outcome of interest for the tax abatement treatment groups relative to the status quo property tax rate (the excluded category). The dependent variable in Column 1 is an indicator for knowing the neighbors' property tax rate. In Column 2 it is an indicator for knowing about the existence of tax abatements. In Columns 3–11 the outcomes are indicators for the different messages used by the property tax collectors during tax collection: sanctions by the chief (Column 3), sanctions by the tax ministry (Column 4), provision of public goods in the neighborhood (Column 5) or in Kananga (Column 6), showing trust in the government (in Column 7), the importance of paying the property tax (Column 8), tax compliance as a legal obligation (Column 9), social embarrassment associated with tax delinquency (Column 10), and any other threats in the case of tax delinquency (Column 11). All regressions include fixed effects for property value band and for randomization stratum (neighborhood). We report robust standard errors. The variables are described in Section A6. We discuss these results in Section 5.3.

**TABLE A11: KNOWLEDGE OF STATUS QUO TAX RATE BY PAST ASSIGNMENT TO DOOR-TO-DOOR PROPERTY TAX COLLECTION**

| *Outcome:* | Accurately reported status quo tax rate | | |
|---|---|---|---|
| *Sample:* | 2016 Treatment Vs Control | Paid in 2016 Treatment Vs Control – self reported | Paid in 2016 Treatment Vs Control – administrative data |
| | (1) | (2) | (3) |
| Past door-to-door collection | $0.033^{**}$ | $0.078^{***}$ | $0.134^{***}$ |
| | (0.016) | (0.023) | (0.040) |
| Control Mean | 0.142 | 0.142 | 0.142 |
| Observations | 2424 | 1465 | 1101 |
| Sample | Baseline Sample | Baseline Sample | Baseline Sample |
| House FE | Yes | Yes | Yes |
| Stratum FE | Yes | Yes | Yes |

*Notes:* This table examines the treatment effects of assignment to door-to-door tax collection in the 2016 property tax campaign, using the treatment assignment from Weigel (2020), on an indicator for the property owner accurately reporting the status quo tax rate at baseline in 2017. Column 1 reports the results when considering all baseline respondents. Columns 2–3 includes everyone in the control group from Weigel (2020), where no door-to-door tax collection took place in 2016, compared to tax compliant households in the treatment group from Weigel (2020), where tax collection did occur in 2016. In Column 2, tax compliance status is self reported, while in Column 3 it is measured using administrative data. All regressions include fixed effects for property value band and the randomization strata from Weigel (2020). Standard errors are clustered at the neighborhood level, the unit of randomization in Weigel (2020). The data include all property owners surveyed at baseline merged with the government's property tax databases. We discuss these results in Section 5.3.

**Table A12: Heterogeneous Treatment Effects by Knowledge of Neighbors' Tax Rates, Status Quo Tax Rates, Tax Reductions, and Exposure to Past Tax Collection**

| | Tax Compliance Indicator | | | | Tax Revenue (in CF) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ln(Tax Rate in CF) | -0.130*** | -0.100*** | -0.185*** | -0.119*** | -62.430* | -32.563 | -124.156 | -72.196** |
| | (0.010) | (0.016) | (0.032) | (0.007) | (33.459) | (45.883) | (103.334) | (32.174) |
| ln(Tax Rate in CF) x Knows Neighbors' Rate | -0.022 | | | | -28.878 | | | |
| | (0.015) | | | | (104.330) | | | |
| Knows Neighbors' Rate | 0.193 | | | | 273.372 | | | |
| | (0.122) | | | | (798.787) | | | |
| ln(Tax Rate in CF) x Knows About Reductions | | -0.077* | | | | -36.410 | | |
| | | (0.046) | | | | (394.187) | | |
| Knows About Reductions | | 0.673* | | | | 419.863 | | |
| | | (0.373) | | | | (3036.938) | | |
| ln(Tax Rate in CF) x Knows Status Quo Rate | | | 0.072 | | | | 254.871 | |
| | | | (0.081) | | | | (194.257) | |
| Knows Status Quo Rate | | | -0.529 | | | | -1875.112 | |
| | | | (0.627) | | | | (1485.650) | |
| ln(Tax Rate in CF) x Exposure to 2016 Collection | | | | 0.015** | | | | 25.556 |
| | | | | (0.007) | | | | (40.345) |
| Exposure to 2016 Collection | | | | -0.008 | | | | -17.213 |
| | | | | (0.058) | | | | (315.733) |
| Constant | 1.016*** | 0.767*** | 1.427*** | 0.931*** | 524.885** | 239.794 | 940.023 | 586.081** |
| | (0.079) | (0.122) | (0.246) | (0.055) | (260.462) | (354.332) | (799.083) | (248.235) |
| Observations | 15072 | 5245 | 2470 | 37886 | 15072 | 5245 | 2470 | 37886 |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table examines how the effect of tax liabilities varies by owners' knowledge of neighbors' tax rates, status quo tax rates (at baseline), the existence of property tax abatements in Kananga, and the exposure to past door-to-door tax collection in 2016. It reports the marginal effect of property tax rates (in Congolese Francs) on tax compliance (in Columns 1–4) and tax revenue in CF (in Columns 5–8). The property tax rate (in Congolese Francs) is interacted with an index for knowledge of the neighbors' tax rates in Columns 1 and 5, with an index for knowledge of tax reductions in Kananga in Columns 2 and 6, with an indicator for accurately reporting the status quo property tax rate at baseline in Columns 3 and 7, and with an indicator for assignment to door-to-door tax collection during the 2016 property tax campaign (studied in Weigel (2020)) in Columns 4 and 8. All regressions include fixed effects for property value band and for randomization stratum (neighborhood). We report robust standard errors. The variables coming from the baseline and midline survey used in Columns 1–3 and 5–7 are described in Section A6. We discuss these results in Section 5.3.

# TABLE A13: HETEROGENEOUS TREATMENT EFFECTS ON COMPLIANCE BY PROXIES FOR LIQUIDITY

| | Outcome: Tax Compliance Indicator | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Employment Status | | Works for the Gov | | Income | | Transport | | Lacks 3,000 CF Today | | Lacked 3,000 CF this Month | |
| | Unemployed | Employed | No | Yes | below median | above median | below median | above median | Yes | No | Yes | No |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Panel A: Reduced Form Effects | | | | | | | | | | | | |
| 50% Reduction | 0.078*** | 0.082*** | 0.088*** | 0.070*** | 0.141*** | 0.090** | 0.131*** | 0.081** | 0.076** | 0.119*** | 0.119*** | 0.102** |
| | (0.013) | (0.007) | (0.006) | (0.012) | (0.031) | (0.029) | (0.032) | (0.028) | (0.031) | (0.031) | (0.027) | (0.038) |
| 33% Reduction | 0.039*** | 0.054*** | 0.048*** | 0.050*** | 0.066** | 0.028 | 0.058** | 0.004 | 0.080** | 0.011 | 0.062** | -0.009 |
| | (0.012) | (0.006) | (0.006) | (0.012) | (0.028) | (0.028) | (0.029) | (0.025) | (0.030) | (0.027) | (0.025) | (0.035) |
| 17% Reduction | 0.014 | 0.008 | 0.012** | 0.007 | 0.037 | -0.038 | 0.007 | -0.042* | 0.009 | -0.033 | -0.016 | -0.014 |
| | (0.011) | (0.006) | (0.005) | (0.011) | (0.026) | (0.025) | (0.027) | (0.024) | (0.025) | (0.026) | (0.022) | (0.033) |
| Mean (control) | 0.054 | 0.071 | 0.062 | 0.076 | 0.069 | 0.101 | 0.069 | 0.097 | 0.076 | 0.113 | 0.085 | 0.096 |
| Panel B: Marginal Effects | | | | | | | | | | | | |
| ln(Tax Rate in CF) | -0.114*** | -0.127*** | -0.132*** | -0.110*** | -0.198*** | -0.157*** | -0.202*** | -0.137*** | -0.192*** | -0.115** | -0.198*** | -0.153** |
| | (0.017) | (0.009) | (0.009) | (0.016) | (0.042) | (0.040) | (0.045) | (0.039) | (0.034) | (0.052) | (0.037) | (0.053) |
| Mean (sample) | 0.085 | 0.108 | 0.101 | 0.107 | 0.138 | 0.128 | 0.132 | 0.131 | 0.129 | 0.136 | 0.137 | 0.121 |
| Panel C: Elasticities | | | | | | | | | | | | |
| Elasticity | -1.335 | -1.177 | -1.316 | -1.026 | -1.438 | -1.224 | -1.526 | -1.039 | -1.492 | -0.850 | -1.446 | -1.264 |
| | (0.193) | (0.084) | (0.083) | (0.151) | (0.314) | (0.325) | (0.350) | (0.306) | (0.280) | (0.410) | (0.272) | (0.441) |
| Observations | 4145 | 16296 | 17390 | 5277 | 1348 | 1485 | 1317 | 1544 | 1816 | 944 | 1769 | 991 |
| Sample | Midline Sample | Midline Sample | Midline Sample | Midline Sample | Baseline Sample | Baseline Sample | Baseline Sample | Baseline Sample | Endline Sample | Endline Sample | Endline Sample | Endline Sample |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table investigates how the effect of tax abatements on compliance varies by household liquidity. 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). 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 fixed effects for property value band and for randomization stratum (neighborhood). Panels A and B report robust standard errors. Standard errors in Panel C are bootstrapped (with 1,000 iterations). Column 1 restricts the sample to unemployed property owners and Column 2 to owners who are employed. Column 3 restricts to respondents who do not work for the government and Column 4 for those who do. Columns 5 and 7 restrict to respondents with below-median monthly household income and transport expenditures, respectively. Columns 6 and 8 restrict to respondents with above-median income and transport, respectively. Columns 9–10 restrict to respondents who declared having and not having 3,000 CF in cash today. Columns 11–12 restrict to respondents who declared ever lacking (or not ever lacking) 3,000 CF in cash at some point in the past 30 days. The variables come from the baseline, midline, and endline surveys and are described in Section A6. We discuss these results in Section 5.4.

## Table A14: Heterogeneous Treatment Effects on Revenue by Proxies for Liquidity

| | Outcome: Tax Revenues (in CF) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Employment Status | | Works for the Gov | | Income | | Transport | | Lacks 3,000 CF Today | | Lacked 3,000 CF this Month | |
| | Unemployed | Employed | No | Yes | below median | above median | below median | above median | Yes | No | Yes | No |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Panel A: Reduced Form Effects | | | | | | | | | | | | |
| 50% Reduction | 95.250$^{**}$ | 16.845 | 45.713$^{**}$ | 11.102 | 71.688 | 26.514 | 111.085 | 3.042 | 110.943 | -105.025 | 51.432 | 30.188 |
| | (41.715) | (21.865) | (20.204) | (42.113) | (87.999) | (95.677) | (79.620) | (91.617) | (67.707) | (164.700) | (75.855) | (137.123) |
| 33% Reduction | 12.324 | 46.449$^{**}$ | 29.249 | 58.266 | -6.071 | 5.527 | 43.882 | -89.182 | 65.845 | -120.566 | 31.664 | -124.863 |
| | (41.370) | (23.214) | (20.746) | (45.725) | (80.965) | (110.040) | (78.531) | (102.475) | (64.647) | (193.147) | (75.655) | (167.034) |
| 17% Reduction | 0.005 | -37.555$^{*}$ | -24.578 | -38.002 | 15.657 | -110.807 | 56.875 | -209.486$^{**}$ | 25.427 | -184.973 | -44.960 | -177.611 |
| | (43.827) | (22.079) | (20.223) | (43.047) | (100.635) | (98.965) | (78.872) | (98.062) | (75.991) | (146.793) | (77.765) | (134.503) |
| Mean (control) | 202.326 | 258.053 | 228.289 | 293.101 | 275.248 | 332.948 | 205.776 | 372.632 | 252.323 | 429.73 | 304.478 | 332.751 |
| Panel B: Marginal Effects | | | | | | | | | | | | |
| ln(Tax Rate in CF) | -136.507$^{**}$ | -57.148$^{**}$ | -86.043$^{**}$ | -52.646 | -90.641 | -100.628 | -136.409 | -86.593 | -162.423$^{*}$ | 79.912 | -109.667 | -114.052 |
| | (55.904) | (28.601) | (26.729) | (56.092) | (118.118) | (128.514) | (114.727) | (123.949) | (95.774) | (228.604) | (105.246) | (187.235) |
| Mean (sample) | 231.701 | 266.673 | 244.491 | 290.373 | 326.113 | 335.96 | 301.139 | 351.943 | 312.004 | 366.949 | 333.861 | 325.328 |
| Panel C: Elasticities | | | | | | | | | | | | |
| Elasticity | -0.589 | -0.214 | -0.352 | -0.181 | -0.278 | -0.3 | -0.453 | -0.246 | -0.521 | 0.218 | -0.328 | -0.351 |
| | (0.238) | (0.106) | (0.111) | (0.194) | (0.385) | (0.408) | (0.408) | (0.365) | (0.336) | (0.646) | (0.325) | (0.587) |
| Observations | 4145 | 16296 | 17390 | 5277 | 1348 | 1485 | 1317 | 1544 | 1816 | 944 | 1769 | 991 |
| Sample | Midline Sample | Midline Sample | Midline Sample | Midline Sample | Baseline Sample | Baseline Sample | Baseline Sample | Baseline Sample | Endline Sample | Endline Sample | Endline Sample | Endline Sample |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table investigates how the effect of tax abatements on revenue varies by household liquidity. It reports estimates from Equations (1), (2), and (3). The dependent variable is tax revenues (in Congolese Francs). Panel A reports treatment effects from Equation (1) comparing property tax revenues for the tax abatement treatment groups relative to the status quo property tax rate (the excluded category). Panel B reports the mean revenue as well as the marginal effect of property tax rates (in CF) on tax revenue from Equation (2). These two estimates are used in Panel C to compute the elasticity of tax revenue with respect to the tax rate following Equation (3). All regressions include fixed effects for property value band and for randomization stratum (neighborhood). Panels A and B report robust standard errors. Standard errors in Panel C are bootstrapped (with 1,000 iterations). Column 1 restricts the sample to unemployed property owners and Column 2 to owners who are employed. Column 3 restricts to respondents who do not work for the government and Column 4 for those who do. Columns 5 and 7 restrict to respondents with below-median monthly household income and transport expenditures, respectively. Columns 6 and 8 restrict to respondents with above-median income and transport, respectively. Columns 9–10 restrict to respondents who declared having and not having 3,000 CF in cash today. Columns 11–12 restrict to respondents who declared ever lacking (or not ever lacking) 3,000 CF in cash at some point in the past 30 days. The variables come from the baseline, midline, and endline surveys and are described in Section A6. We discuss these results in Section 5.4.

# TABLE A15: HETEROGENEOUS TREATMENT EFFECTS ON COMPLIANCE BY PROXIES FOR LIQUIDITY — TAX RATE AS PERCENTAGE OF PROPERTY VALUE

| | Outcome: Tax Compliance Indicator | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Employment Status | | Works for the Gov | | Income | | Transport | | Lacks $3,000$ CF Today | | Lacked $3,000$ CF this Month | |
| | Unemployed | Employed | No | Yes | below median | above median | below median | above median | Yes | No | Yes | No |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Panel A: IV Specification - First Stage | | | | | | | | | | | | |
| 50% Reduction | -0.669*** | -0.663*** | -0.660*** | -0.665*** | -0.694*** | -0.656*** | -0.698*** | -0.689*** | -0.726*** | -0.634*** | -0.707*** | -0.595*** |
| | (0.027) | (0.012) | (0.012) | (0.024) | (0.047) | (0.063) | (0.055) | (0.057) | (0.045) | (0.085) | (0.046) | (0.083) |
| 33% Reduction | -0.407*** | -0.391*** | -0.398*** | -0.371*** | -0.404*** | -0.316*** | -0.384*** | -0.371*** | -0.391*** | -0.466*** | -0.389*** | -0.291*** |
| | (0.028) | (0.012) | (0.012) | (0.024) | (0.047) | (0.058) | (0.052) | (0.055) | (0.041) | (0.088) | (0.044) | (0.080) |
| 17% Reduction | -0.153*** | -0.174*** | -0.165*** | -0.189*** | -0.191*** | -0.126** | -0.177*** | -0.159** | -0.234*** | -0.135* | -0.143** | -0.148* |
| | (0.027) | (0.012) | (0.012) | (0.024) | (0.047) | (0.058) | (0.050) | (0.054) | (0.043) | (0.077) | (0.045) | (0.077) |
| Mean (control) | -6.173 | -6.132 | -6.129 | -6.255 | -5.992 | -6.207 | 6.029 | -6.176 | -6.070 | -6.183 | -6.058 | -6.198 |
| F-Test | 240 | 1112 | 1147 | 289 | 80 | 40 | 63 | 54 | 93 | 24 | 93 | 19 |
| p-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Panel B: IV Specification - Second Stage | | | | | | | | | | | | |
| ln(Tax Rate in CF) | -0.116*** | -0.133*** | -0.138*** | -0.114*** | -0.200*** | -0.171*** | -0.202*** | -0.142*** | -0.186*** | -0.116** | -0.194*** | -0.193** |
| | (0.018) | (0.010) | (0.009) | (0.017) | (0.043) | (0.042) | (0.045) | (0.039) | (0.034) | (0.052) | (0.036) | (0.063) |
| Mean (sample) | 0.085 | 0.108 | 0.101 | 0.107 | 0.138 | 0.128 | 0.132 | 0.131 | 0.129 | 0.136 | 0.137 | 0.121 |
| Panel C: Elasticities | | | | | | | | | | | | |
| Elasticity | -1.355 | -1.231 | -1.371 | -1.07 | -1.446 | -1.338 | -1.527 | -1.083 | -1.441 | -.853 | -1.421 | -1.592 |
| | (0.203) | (0.090) | (0.092) | (0.166) | (0.312) | (0.381) | (0.360) | (0.328) | (0.453) | (0.642) | (0.277) | (0.602) |
| Observations | 4145 | 16296 | 17390 | 5277 | 1348 | 1485 | 1317 | 1544 | 1816 | 944 | 1769 | 991 |
| Sample | Midline Sample | Midline Sample | Midline Sample | Midline Sample | Baseline Sample | Baseline Sample | Baseline Sample | Baseline Sample | Endline Sample | Endline Sample | Endline Sample | Endline Sample |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table explores how the treatment effect of tax liabilities on compliance varies by liquidity using the instrumental variable approach described in Equations (4) and (5). In all columns, the dependent variable is an indicator for tax compliance. Panel A reports the first stage of the instrumental variable model (Equation (5)) and the corresponding first stage $F$-test and $p$-value. Panel B reports the second stage of the instrumental variable model (Equation (5)). Panel C reports the corresponding elasticity of tax compliance with respect to the tax rate from Equation (3). All regressions include fixed effects for property value band and for randomization stratum (neighborhood). Panels A and B report robust standard errors. Standard errors in Panel C are bootstrapped (with 1,000 iterations). Column 1 restricts the sample to unemployed property owners and Column 2 to owners who are employed. Column 3 restricts to respondents who do not work for the government and Column 4 for those who do. Columns 5 and 7 restrict to respondents with below-median monthly household income and transport expenditures, respectively. Columns 6 and 8 restrict to respondents with above-median income and transport, respectively. Columns 9–10 restrict to respondents who declared having and not having 3,000 CF in cash today. Columns 11–12 restrict to respondents who declared ever lacking (or not ever lacking) 3,000 CF in cash at some point in the past 30 days. The variables come from the baseline, midline, and endline surveys and are described in Section A6. We discuss these results in Section 5.4.

## TABLE A16: HETEROGENEOUS TREATMENT EFFECTS ON REVENUE BY PROXIES FOR LIQUIDITY — TAX RATE AS PERCENTAGE OF PROPERTY VALUE

| | Outcome: Tax Revenue | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Employment Status | | Works for the Gov | | Income | | Transport | | Lacks $3,000$ CF Today | | Lacked $3,000$ CF this Month | |
| | Unemployed | Employed | No | Yes | below median | above median | below median | above median | Yes | No | Yes | No |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Panel A: IV Specification - First Stage | | | | | | | | | | | | |
| 50% Reduction | -0.669*** | -0.663*** | -0.660*** | -0.665*** | -0.694*** | -0.656*** | -0.698*** | -0.689*** | -0.726*** | -0.634*** | -0.707*** | -0.595*** |
| | (0.027) | (0.012) | (0.012) | (0.024) | (0.047) | (0.063) | (0.055) | (0.057) | (0.045) | (0.085) | (0.046) | (0.083) |
| 33% Reduction | -0.407*** | -0.391*** | -0.398*** | -0.371*** | -0.404*** | -0.316*** | -0.384*** | -0.371*** | -0.391*** | -0.466*** | -0.389*** | -0.291*** |
| | (0.028) | (0.012) | (0.012) | (0.024) | (0.047) | (0.058) | (0.052) | (0.055) | (0.041) | (0.088) | (0.044) | (0.080) |
| 17% Reduction | -0.153*** | -0.174*** | -0.165*** | -0.189*** | -0.191*** | -0.126** | -0.177*** | -0.159** | -0.234*** | -0.135* | -0.143** | -0.148* |
| | (0.027) | (0.012) | (0.012) | (0.024) | (0.047) | (0.058) | (0.050) | (0.054) | (0.043) | (0.077) | (0.045) | (0.077) |
| Mean (control) | -6.173 | -6.132 | -6.129 | -6.255 | -5.992 | -6.207 | 6.029 | -6.176 | -6.070 | -6.183 | -6.058 | -6.198 |
| F-Test | 240 | 1112 | 1147 | 289 | 80 | 40 | 63 | 54 | 93 | 24 | 93 | 19 |
| p-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Panel B: IV Specification - Second Stage | | | | | | | | | | | | |
| ln(Tax Rate in CF) | -137.759** | -60.189** | -90.876** | -49.985 | -91.583 | -114.833 | -137.191 | -101.433 | -157.933* | 70.671 | -110.441 | -158.793 |
| | (56.724) | (29.901) | (27.791) | (59.116) | (118.579) | (132.567) | (114.207) | (123.026) | (92.770) | (241.071) | (101.662) | (213.297) |
| Mean (sample) | 231.701 | 266.673 | 244.491 | 290.373 | 326.113 | 335.96 | 301.139 | 351.943 | 312.004 | 366.949 | 333.861 | 325.328 |
| Panel C: Elasticities | | | | | | | | | | | | |
| Elasticity | -0.595 | -0.226 | -0.372 | -0.172 | -0.281 | -0.342 | -0.456 | -0.288 | -0.506 | 0.193 | -0.331 | -0.488 |
| | (0.251) | (0.117) | (0.114) | (0.215) | (0.388) | (0.434) | (0.412) | (0.376) | (0.540) | (1.089) | (0.320) | (0.708) |
| Observations | 4145 | 16296 | 17390 | 5277 | 1348 | 1485 | 1317 | 1544 | 1816 | 944 | 1769 | 991 |
| Sample | Midline Sample | Midline Sample | Midline Sample | Midline Sample | Baseline Sample | Baseline Sample | Baseline Sample | Baseline Sample | Endline Sample | Endline Sample | Endline Sample | Endline Sample |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table explores how the treatment effect of tax liabilities on revenue varies by liquidity using the instrumental variable approach described in Equations (4) and (5). In all columns, the dependent variable is tax revenue (in Congolese Francs). Panel A reports the first stage of the instrumental variable model (Equation (5)) and the corresponding first stage $F$-test and $p$-value. Panel B reports the second stage of the instrumental variable model (Equation (5)). Panel C reports the corresponding elasticity of tax revenue with respect to the tax rate from Equation (3). All regressions include fixed effects for property value band and for randomization stratum (neighborhood). Panels A and B report robust standard errors. Standard errors in Panel C are bootstrapped (with 1,000 iterations). Column 1 restricts the sample to unemployed property owners and Column 2 to owners who are employed. Column 3 restricts to respondents who do not work for the government and Column 4 for those who do. Columns 5 and 7 restrict to respondents with below-median monthly household income and transport expenditures, respectively. Columns 6 and 8 restrict to respondents with above-median income and transport, respectively. Columns 9–10 restrict to respondents who declared having and not having 3,000 CF in cash today. Columns 11–12 restrict to respondents who declared ever lacking (or not ever lacking) 3,000 CF in cash at some point in the past 30 days. The variables come from the baseline, midline, and endline surveys and are described in Section A6. We discuss these results in Section 5.4.

## TABLE A17: HETEROGENEOUS TREATMENT EFFECTS ON COMPLIANCE AND REVENUE BY CAMPAIGN TIMING

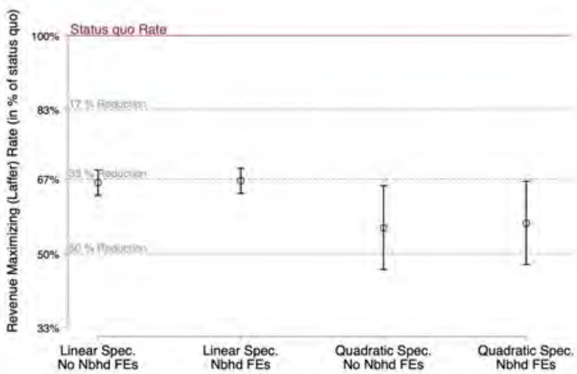
| | Outcome: Tax Compliance Indicator | | | Outcome: Tax Revenue (in Congolese Francs) | | |
|---|---|---|---|---|---|---|
| | Full period of tax collection (1) | Excluding day 1 of tax collection (2) | Excluding day 1-3 of tax collection (3) | Full period of tax collection (4) | Excluding day 1 of tax collection (5) | Excluding day 1-3 of tax collection (6) |
| Panel A: Reduced Form Effects | | | | | | |
| 50% Reduction | 0.073*** | 0.069*** | 0.066*** | 24.711* | 20.940 | 19.840 |
| | (0.004) | (0.004) | (0.004) | (13.828) | (13.593) | (13.454) |
| 33% Reduction | 0.044*** | 0.042*** | 0.041*** | 34.069** | 33.385** | 34.270** |
| | (0.004) | (0.004) | (0.004) | (14.937) | (14.788) | (14.662) |
| 17% Reduction | 0.011*** | 0.012*** | 0.011*** | -20.202 | -18.141 | -16.428 |
| | (0.003) | (0.003) | (0.003) | (14.420) | (14.213) | (14.028) |
| Mean (control) | 0.056 | 0.053 | 0.051 | 216.903 | 206.744 | 199.261 |
| Panel B: Marginal Effects | | | | | | |
| ln(Tax Rate in CF) | -0.110*** | -0.103*** | -0.099*** | -55.870** | -49.297** | -47.144** |
| | (0.006) | (0.006) | (0.005) | (18.274) | (17.973) | (17.826) |
| Mean (sample) | 0.088 | 0.084 | 0.080 | 229.662 | 218.853 | 211.388 |
| Panel C: Elasticities | | | | | | |
| Elasticity | -1.246 | -1.238 | -1.234 | -0.243 | -0.225 | -0.223 |
| | (0.061) | (0.062) | (0.064) | (0.081) | (0.083) | (0.085) |
| Observations | 38028 | 37830 | 37689 | 38028 | 37830 | 37689 |
| Sample | All properties | All properties | All properties | All properties | All properties | All properties |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighbor Rate Controls | No | No | No | No | No | No |

*Notes:* This table explores whether households' responses to rate reductions vary by different time periods during the month in which tax collectors worked in each neighborhood. It reports estimates from Equations (1), (2), and (3). In Columns 1–3 the dependent variable is an indicator for compliance, while in Columns 4–6 the dependent variable is tax revenue (in Congolese Francs). Panel A reports treatment effects from Equation (1) comparing property tax compliance and property tax 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 property tax rates (in CF) on tax compliance and revenue from Equation (2). These two estimates are used in Panel C to compute the elasticity of tax compliance and revenue with respect to the tax rate following Equation (3). All regressions include fixed effects for property value band, and Columns 2–4 and 6–8 include fixed effects for randomization stratum (neighborhood). Panels A and B report robust standard errors. Standard errors in Panel C are bootstrapped (with 1,000 iterations). Results are reported for the full month-long period of tax collection for each neighborhood in Columns 1 and 4, while Columns 2 and 5 exclude payments made on the first day of the month, and Columns 3 and 6 exclude the first three days. Collectors' visits to households would have been unexpected during the initial days of the campaign in each neighborhood, while subsequent visits were typically made by appointment. The data include all non-exempt properties registered by tax collectors merged with the government's property tax database. We discuss these results in Section 5.4.

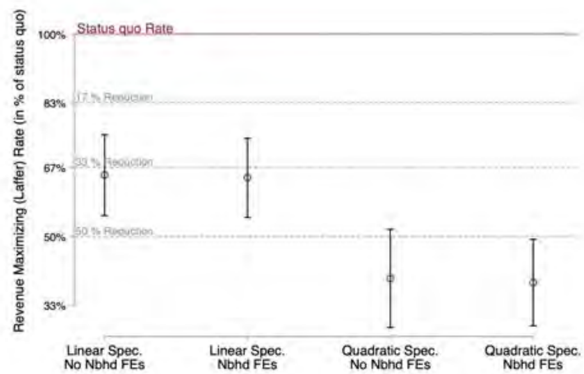
## A4.4 Additional Exhibits for Paper Section 6 — The Laffer Rate

### FIGURE A6: LAFFER TAX RATES BY PROPERTY VALUE BAND

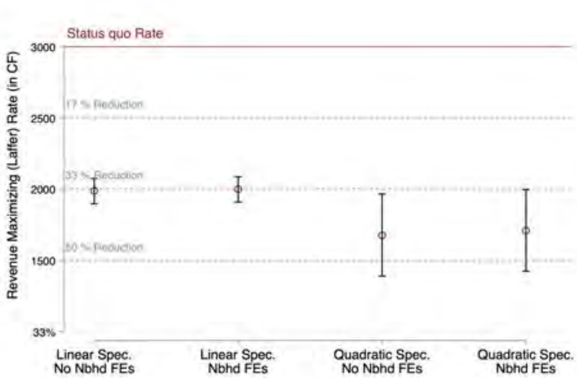
A: Properties in the low-value band
(in % of status quo rate)



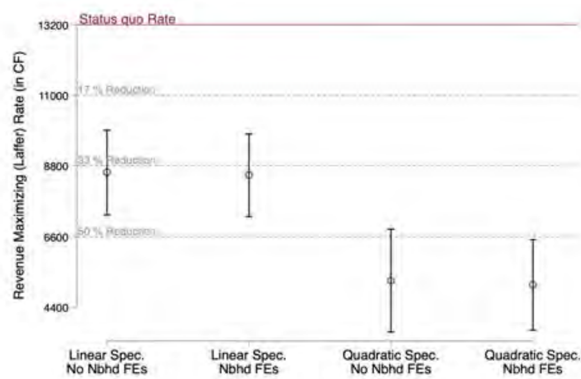

B: Properties in the high-value band
(in % of status quo rate)




C: Properties in the low-value band
(in Congolese Francs)



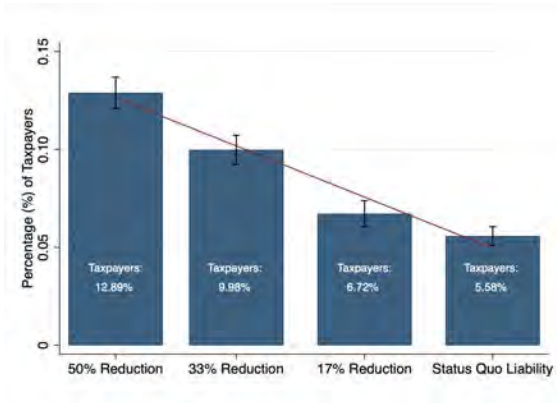

D: Properties in the high-value band
(in Congolese Francs)



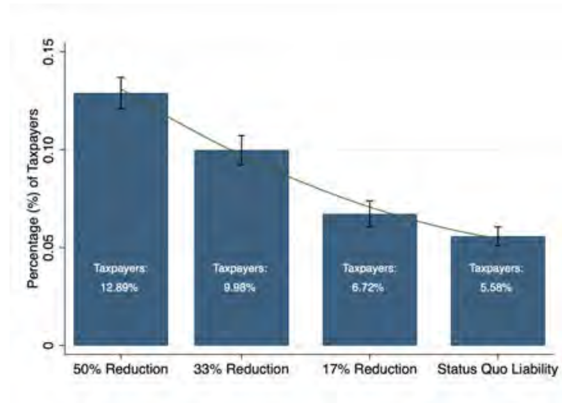

*Notes:* This figure reports estimates of the revenue-maximizing (Laffer) tax rate in Proposition (1) in different property value bands. Panels A and C restrict the sample to properties in the low-value band, and Panels B and D to properties in the high-value band. In Panels A and B, we estimate the Laffer rate as a percentage of the status quo tax rate, while in Panels C and D we estimate it in tax amounts expressed in Congolese Francs. In each panel, the first two estimates assume linearity of tax compliance with respect to the tax rate and correspond to the estimation of Equation 6 using regression specification (7) while the following two estimates assume a quadratic relationship between tax compliance and rate and correspond to the estimation of Equation (8) using regression specification (9). All regressions include fixed effects for property value band, and the second and fourth point estimates in each figure also include fixed effects for randomization stratum (neighborhood). 95% confidence intervals are reported for each estimate using the standard errors obtained from the delta method applied to Equations (6) and (8). The coefficients and confidence intervals in Panels A and B of Figure A6 correspond to the point estimates and standard errors reported in Panel B of Table A18. The data include all non-exempt properties registered by tax collectors merged with the government's property tax database. We discuss these results in Section 6.3.

### Figure A7: Treatment Effects on Tax Compliance — Linear, Quadratic and Cubic Fits

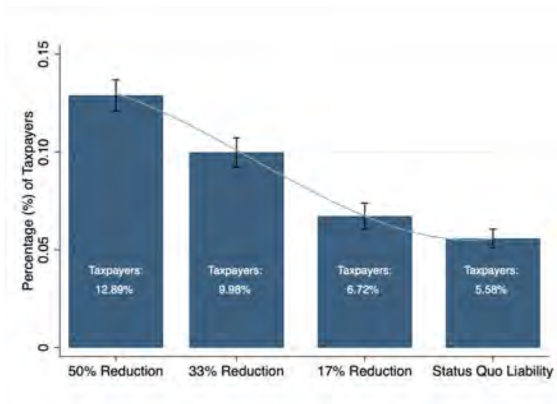
A: Linear Fit



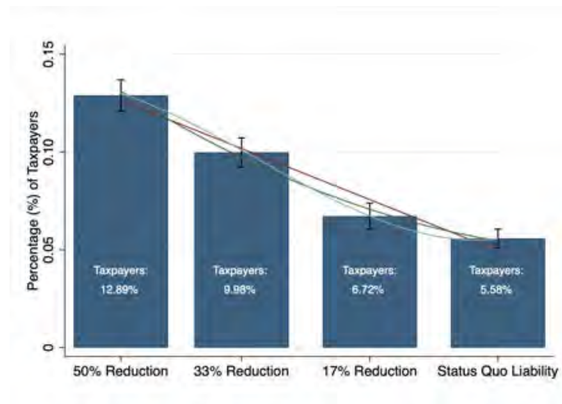

B: Quadratic Fit




C: Cubic Fit




D: All



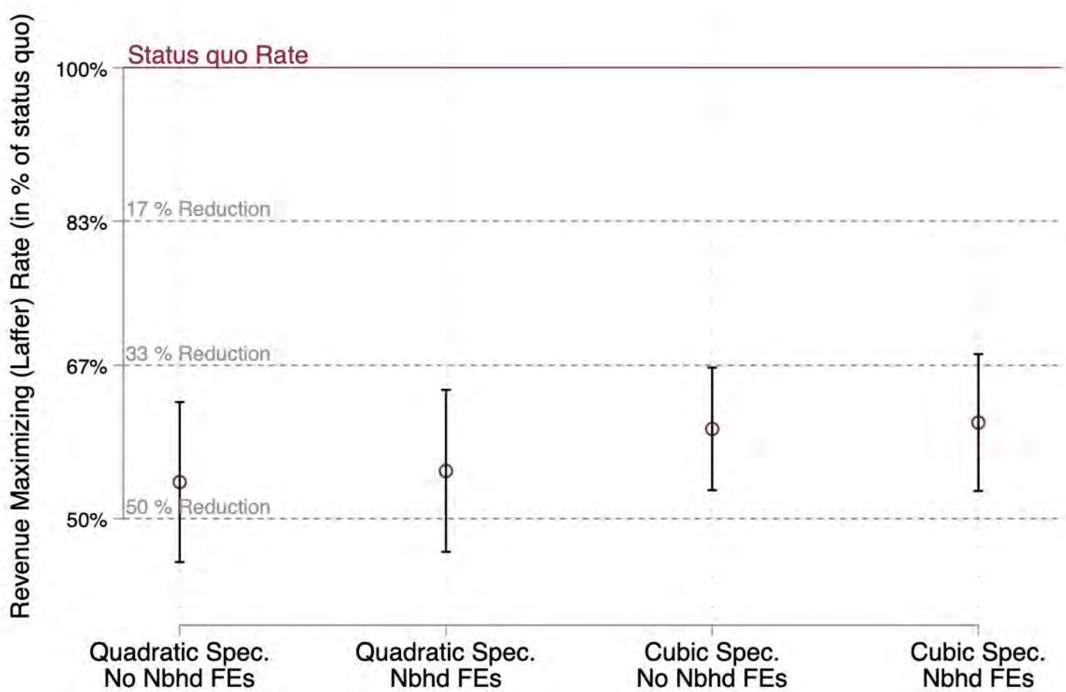

*Notes:* This figure reports estimates from Equation (1) comparing property tax compliance for the tax abatement treatment groups relative to the status quo property tax rate (the excluded category). Panel A displays the best linear fit, Panel B the best quadratic fit, Panel C the best cubic fit, and Panel D all fits. All panels report results including fixed effects for property value band and for randomization stratum (neighborhood). The black lines show the 95% confidence interval for each of the estimates using robust standard errors. The treatment effects correspond to the results in Figure 1 and Table 3. The data include all non-exempt properties registered by tax collectors merged with the government's property tax database. We discuss these results in Section 5.2.

## TABLE A18: LAFFER TAX RATES BY PROPERTY VALUE BAND

| | Low-value band properties | | | | High-value band properties | | | |
|---|---|---|---|---|---|---|---|---|
| | Linear Specification | | Quadratic Specification | | Linear Specification | | Quadratic Specification | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Panel A: Effect of Tax Rates on Tax Compliance** | | | | | | | | |
| Tax Rate (in % of status quo) | -0.159*** | -0.157*** | -0.391*** | -0.375*** | -0.111*** | -0.114*** | -0.561** | –0.600** |
| | (0.008) | (0.008) | (0.086) | (0.083) | (0.021) | (0.021) | (0.206) | (0.208) |
| Tax Rate Squared (in % of status quo) | | | 0.155** | 0.146** | | | 0.300** | 0.324** |
| | | | (0.056) | (0.054) | | | (0.134) | (0.135) |
| Constant | 0.210*** | 0.209*** | 0.292*** | 0.286*** | 0.145*** | 0.147*** | 0.303*** | 0.318*** |
| | (0.007) | (0.007) | (0.032) | (0.031) | (0.017) | (0.017) | (0.076) | (0.076) |
| **Panel B: Laffer Tax Rate** | | | | | | | | |
| Laffer Rate (in % Status quo Rate) | 0.662 | 0.666 | 0.559 | 0.570 | 0.651 | 0.645 | 0.396 | 0.386 |
| | (0.015) | (0.015) | (0.049) | (0.048) | (0.051) | (0.050) | (0.062) | (0.055) |
| Implied Reduction in Tax Rate | 33.82% | 33.40% | 44.10% | 43.01% | 34.90% | 35.55% | 60.37% | 61.40% |
| Observations | 33856 | 33852 | 33856 | 33852 | 4172 | 4147 | 4172 | 4147 |
| Sample | low-value band properties | low-value band properties | low-value band properties | low-value band properties | high-value band properties | high-value band properties | high-value band properties | high-value band properties |
| House FE | No | No | No | No | No | No | No | No |
| Neighborhood FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Quadratic Tax Rate Term | No | No | Yes | Yes | No | No | Yes | Yes |

*Notes:* This table reports estimates of the revenue-maximizing (Laffer) tax rate in Proposition (1). Columns 1–2 and 5–6 assume linearity of tax compliance with respect to the tax rate. For these columns, Panel A contains estimates of regression specification (7), and Panel B reports the corresponding Laffer rate from Equation (6). Columns 2–3 and 7–8 assume a quadratic relationship between tax compliance and tax rate. For these columns, Panel A estimates regression specification (9), and Panel B reports the Laffer rate from Equation (8). All estimates in Panels A and B are expressed as a percentage of the status quo tax rate. All regressions include fixed effects for property value band and Columns 2, 4, 6, and 8 also include fixed effects for randomization stratum (neighborhood). In Panel A, we report robust standard errors. Standard errors in Panel B are computed using the delta method. Columns 1–4 restrict the sample to properties in the low-value band, while Columns 5–8 restrict the sample to properties in the high-value band. We discuss these results in Section 7.

**FIGURE A8: LAFFER TAX RATE — QUADRATIC AND CUBIC SPECIFICATION**




*Notes:* This figure reports estimates of the revenue-maximizing (Laffer) tax rate in Proposition (1). The first two estimates assume linearity of tax compliance with respect to the tax rate and correspond to the estimation of Equation (6) using regression specification (7), while the following two coefficients assume a quadratic relationship between tax compliance and tax rate and correspond to the estimation of Equation (8) using regression specification (9). All estimates of the Laffer tax rate are expressed as a percentage of the status quo tax rate. All regressions include fixed effects for property value band, and the second and fourth also include fixed effects for randomization stratum (neighborhood). The black lines show the 95% confidence interval for each of the estimates. For the quadratic specification, the 95% confidence interval is estimated using the standard errors from the delta method applied to Equation (8). For the cubic specification, the standard errors are bootstrapped (with 100 iterations). The coefficients and confidence intervals correspond to the point estimates and standard errors reported in Table 5, Panel B. The data include all non-exempt properties registered by tax collectors merged with the government's property tax database. We discuss these results in Section 6.3.

**TABLE A19: LAFFER TAX RATE — QUADRATIC AND CUBIC SPECIFICATION**

| | Quadratic Specification | | Cubic Specification | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: Effect of Tax Rates on Tax Compliance* | | | | |
| Tax Rate (in % of status quo) | -0.410*** | -0.391*** | 1.045 | 1.054 |
| | (0.080) | (0.077) | (0.764) | (0.739) |
| Tax Rate Squared (in % of status quo) | 0.171*** | 0.160** | -1.837* | -1.833* |
| | (0.052) | (0.050) | (1.038) | (1.004) |
| Tax Rate Cubed (in % of status quo) | | | 0.893* | 0.886** |
| | | | (0.456) | (0.441) |
| Constant | 0.293*** | 0.286*** | -0.045 | -0.050 |
| | (0.029) | (0.028) | (0.181) | (0.175) |
| *Panel B: Laffer Tax Rate* | | | | |
| Laffer Rate (in % Status quo Rate) | 0.541 | 0.553 | 0.599 | 0.606 |
| | (0.045) | (0.046) | (0.035) | (0.039) |
| Implied Reduction in Tax Rate | 45.95% | 44.71% | 40.06% | 39.35% |
| Observations | 38028 | 38028 | 38028 | 38028 |
| Sample | All properties | All properties | All properties | All properties |
| House FE | Yes | Yes | Yes | Yes |
| Neighborhood FE | No | Yes | No | Yes |
| Quadratic Tax Rate Term | Yes | Yes | Yes | Yes |
| Cubic Tax Rate Term | No | Yes | No | Yes |

*Notes:* This table reports estimates of the revenue-maximizing (Laffer) tax rate in Proposition (1). Columns 1 and 2 assume linearity of tax compliance with respect to the tax rate. Panel A contains estimates of regression specification (7), and Panel B reports the corresponding Laffer rate from Equation (6). Columns 3 and 4 assume a quadratic relationship between tax compliance and tax rate. Panel A contains estimates from regression specification (9), and Panel B reports the Laffer rate from Equation (8). All estimates in Panels A and B are expressed as a percentage of the status quo tax rate. All regressions include fixed effects for property value band, and Columns 2 and 4 also include fixed effects for randomization stratum (neighborhood). In Panel A, we report robust standard errors. Standard errors in Panel B are computed using the delta method applied to Equation (8) for the quadratic specification. For the cubic specification the standard errors are bootstrapped (with 100 iterations). The data include all non-exempt properties registered by tax collectors merged with the government's property tax database. We discuss these results in Section 6.3.

## Table A20: Laffer Rate Robustness: Accounting for Knowledge of Others' Rates, Past Rates, Expectations of Future Rates, and Past Exposure to Tax Collection

| | Controls for 5 neighbors' rate (1) | Controls for 10 neighbors' rate (2) | Doesn't know neighbors' rate (3) | Knows neighbors' rate (4) | Doesn't know discounts (5) | Knows discounts (6) | Doesn't Know past rates (7) | Knows past rates (8) | No 2016 door-to-door tax campaign (9) | Door-to-door 2016 tax campaign (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| **<u>Panel A</u>: Effect of Tax Rates on Tax Compliance** | | | | | | | | | | |
| Tax Rate (in % of status quo) | -0.151*** | -0.151*** | -0.182*** | -0.209*** | -0.137*** | -0.466 | -0.246*** | -0.326** | -0.167*** | -0.143*** |
| | (0.008) | (0.008) | (0.014) | (0.042) | (0.022) | (0.296) | (0.045) | (0.138) | (0.013) | (0.010) |
| Constant | 0.193*** | 0.188*** | 0.245*** | 0.292*** | 0.191*** | 0.503** | 0.309*** | 0.390*** | 0.214*** | 0.195*** |
| | (0.007) | (0.008) | (0.012) | (0.033) | (0.018) | (0.225) | (0.035) | (0.105) | (0.010) | (0.008) |
| **<u>Panel B</u>: Laffer Tax Rate** | | | | | | | | | | |
| Laffer Rate (in % Status quo Rate) | 0.640 | 0.626 | 0.674 | 0.700 | 0.698 | 0.539 | 0.628 | 0.599 | 0.640 | 0.681 |
| | (0.019) | (0.021) | (0.023) | (0.064) | (0.051) | (0.112) | (0.045) | (0.100) | (0.019) | (0.020) |
| Implied Reduction in Tax Rate | 36.05% | 37.45% | 32.55% | 29.97% | 30.24% | 46.05% | 37.23% | 40.09% | 35.96% | 31.90% |
| Observations | 37209 | 37209 | 13042 | 2126 | 5093 | 87 | 2066 | 300 | 14589 | 23295 |
| Sample | All properties | All properties | Midline Sample | Midline Sample | Midline Sample | Midline Sample | Baseline Sample | Baseline Sample | All properties | All properties |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighbor Rate Controls | Yes | Yes | No | No | No | No | No | No | No | No |

*Notes:* This table examines whether the revenue-maximizing (Laffer) tax rate could be biased by owners' knowledge of others' rates, past rates, expectations of future rates, or past exposure to tax collection. It reports estimates of the Laffer rate in Proposition (1), assuming linearity of tax compliance with respect to the tax rate. Panel A contains estimates of regression specification (7), and Panel B reports the corresponding Laffer rate from Equation (6). All estimates in Panels A and B are expressed as a percentage of the status quo tax rate. All regressions include fixed effects for property value band and for randomization stratum (neighborhood). In Panel A, we report robust standard errors. Standard errors in Panel B are computed using the delta method. Columns 1 and 2 control for the property tax rate assigned to nearest 5 and nearest 10 properties (using the GPS location of all properties in Kananga), respectively. Columns 3 and 4 restrict the sample to owners who reported not knowing or knowing their neighbors' rate. Columns 5 and 6 then restrict the sample to owners who reported knowing or not knowing about the existence of tax abatements in Kananga. Columns 7 and 8 restrict the sample to owners who accurately reported the status quo rate or not. The variables that define these subsamples come from the baseline and midline survey (indicated in the bottom panel of the table) and are described in Section A6. Columns 9 and 10 estimate treatment effects for neighborhoods where door-to-door tax collection took place during the previous (2016) property tax campaign and neighborhoods where no door-to-door collection took place, using the treatment assignment from Weigel (2020). We discuss these results in Section 6.3.

## Table A21: Laffer Rates by Decile of Estimated Property Value

| | Property Value (in 2018 USD) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $1^{st}$ Decile | $2^{nd}$ Decile | $3^{rd}$ Decile | $4^{th}$ Decile | $5^{th}$ Decile | $6^{th}$ Decile | $7^{th}$ Decile | $8^{th}$ Decile | $9^{th}$ Decile | $10^{th}$ Decile |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| **<u>Panel A</u>: Effect of Tax Rates on Tax Compliance** | | | | | | | | | | |
| Tax Rate (in % of status quo) | -0.160*** | -0.166*** | -0.168*** | -0.195*** | -0.144*** | -0.155*** | -0.109*** | -0.190*** | -0.127*** | -0.111*** |
| | (0.024) | (0.025) | (0.026) | (0.025) | (0.025) | (0.024) | (0.023) | (0.025) | (0.026) | (0.025) |
| Constant | 0.201*** | 0.221*** | 0.222*** | 0.233*** | 0.196*** | 0.196*** | 0.159*** | 0.237*** | 0.189*** | 0.167*** |
| | (0.019) | (0.020) | (0.021) | (0.020) | (0.020) | (0.019) | (0.019) | (0.021) | (0.021) | (0.020) |
| **<u>Panel B</u>: Laffer Tax Rate** | | | | | | | | | | |
| Laffer Rate (in % Status quo Rate) | 0.628 | 0.665 | 0.663 | 0.597 | 0.677 | 0.630 | 0.731 | 0.625 | 0.746 | 0.748 |
| | (0.036) | (0.043) | (0.042) | (0.028) | (0.050) | (0.038) | (0.074) | (0.032) | (0.074) | (0.080) |
| Implied Reduction in Tax Rate | 37.19% | 33.53% | 33.71% | 40.31% | 32.29% | 37.04% | 26.95% | 37.53% | 25.41% | 25.17% |
| Observations | 3777 | 3788 | 3791 | 3778 | 3787 | 3780 | 3771 | 3750 | 3767 | 3788 |
| Sample | All properties | All properties | All properties | All properties | All properties | All properties | All properties | All properties | All properties | All properties |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table explores how the estimated Laffer rate varies as a function of predicted property value. It reports estimates of the revenue-maximizing (Laffer) tax rate in Proposition (1), assuming linearity of tax compliance with respect to the tax rate. Panel A contains estimates of regression specification (7), and Panel B reports the corresponding Laffer rate from Equation (6). All estimates in Panels A and B are expressed as a percentage of the status quo tax rate. All regressions include fixed effects for property value band and for randomization stratum (neighborhood). In Panel A, we report robust standard errors. Standard errors in Panel B are computed using the delta method. Each column restricts the sample to one of the deciles of property value in Kananga, as estimated using using machine learning and described in Section 4.1 as well as in Bergeron et al. (2020a). We discuss these results in Section 6.3.

# Table A22: Laffer Rates by Proxies for Liquidity

| | Employment Status | | Works for the Gov | | Income | | Transport | | Lacks 3,000 CF Today | | Lacked 3,000 CF this Month | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Unemployed | Employed | No | Yes | below median | above median | below median | above median | Yes | No | Yes | No |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| **<u>Panel A</u>: Effect of Tax Rates on Tax Compliance** | | | | | | | | | | | | |
| Tax Rate (in % of status quo) | -0.156*** | -0.176*** | -0.181*** | -0.152*** | -0.273*** | -0.205*** | -0.274*** | -0.173** | -0.261*** | -0.150** | -0.267*** | -0.195** |
| | (0.024) | (0.013) | (0.012) | (0.022) | (0.057) | (0.055) | (0.061) | (0.053) | (0.047) | (0.069) | (0.051) | (0.071) |
| Constant | 0.202*** | 0.239*** | 0.236*** | 0.220*** | 0.343*** | 0.283*** | 0.335*** | 0.262*** | 0.324*** | 0.243*** | 0.337*** | 0.267*** |
| | (0.019) | (0.010) | (0.010) | (0.018) | (0.046) | (0.043) | (0.048) | (0.041) | (0.037) | (0.053) | (0.040) | (0.055) |
| **<u>Panel B</u>: Laffer Tax Rate** | | | | | | | | | | | | |
| Laffer Rate (in % Status quo Rate) | 0.650 | 0.680 | 0.651 | 0.722 | 0.629 | 0.690 | 0.611 | 0.757 | 0.619 | 0.807 | 0.630 | 0.685 |
| | (0.041) | (0.022) | (0.018) | (0.051) | (0.053) | (0.085) | (0.052) | (0.117) | (0.044) | (0.199) | (0.048) | (0.115) |
| Implied Reduction in Tax Rate | 35.01% | 31.96% | 34.88% | 27.77% | 37.09% | 30.98% | 38.94% | 24.26% | 38.08% | 19.28% | 37.01% | 31.47% |
| Observations | 4126 | 16292 | 17387 | 5266 | 1316 | 1458 | 1286 | 1526 | 1808 | 882 | 1735 | 930 |
| Sample | Midline sample | Midline sample | Midline sample | Midline sample | Baseline sample | Baseline sample | Baseline sample | Baseline sample | Endline sample | Endline sample | Endline sample | Endline sample |
| House FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table explores how the estimated revenue-maximizing (Laffer) tax rate varies by several proxies of household liquidity. It reports estimates of the Laffer rate in Proposition (1), assuming linearity of tax compliance with respect to the tax rate. Panel A contains estimates of regression specification (7), and Panel B reports the corresponding Laffer rate from Equation (6). All estimates in Panels A and B are expressed as a percentage of the status quo tax rate. All regressions include fixed effects for property value band and for randomization stratum (neighborhood). In Panel A, we report robust standard errors. Standard errors in Panel B are computed using the delta method. Column 1 restricts the sample to unemployed property owners and Column 2 to owners who are employed. Column 3 restricts to respondents who do not work for the government and Column 4 for those who do. Columns 5 and 7 restrict to respondents with below-median monthly household income and transport expenditures, respectively. Columns 6 and 8 restrict to respondents with above-median income and transport, respectively. Columns 9–10 restrict to respondents who declared having and not having 3,000 CF in cash today. Columns 11–12 restrict to respondents who declared ever lacking (or not ever lacking) 3,000 CF in cash at some point in the past 30 days. The variables come from the baseline, midline, and endline surveys and are described in Section A6. We discuss these results in Section 6.3.

**TABLE A23: MARGINAL VALUE OF PUBLIC FUNDS (MVPF)**

| Policy | WTP | Net Cost | MVPF |
|---|---|---|---|
| 17% reduction | CF 37 | CF 20.2 | 1.84 |
| 33% reduction | CF 72 | CF 0 (<0) | $\infty$ |
| 50% reduction | CF 108 | CF 0 (<0) | $\infty$ |

*Notes:* This table reports the willingness to pay, net cost, and marginal value of public funds associated with each tax reduction using the results with respect to tax revenue presented in Figure 1 and Table 3. The results are discussed in Section A2.

## A4.5 Additional Exhibits for Paper Section 7 — Can Enforcement Increase the Laffer Tax Rate?

### FIGURE A9: TAX LETTER MESSAGES — ENFORCEMENT AND CONTROL

A: Central Enforcement Message


REPUBLIQUE DEMOCRATIQUE DU CONGO
PROVINCE DU KASAÏ OCCIDENTAL
DIRECTION GENERALE DES RECETTES DU KASAÏ OCCIDENTAL
DGRKOC

Pour la campagne de collecte de l'Impôt Foncier 2018 :

**La parcelle, No. 595013,**

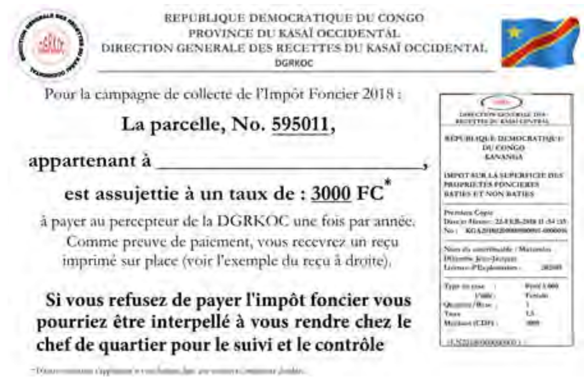
**appartenant à ______________________,**

**est assujettie à un taux de : 3000 FC***

à payer au percepteur de la DGRKOC une fois par année. Comme preuve de paiement, vous recevrez un reçu imprimé sur place (voir l'exemple du reçu à droite).

**Si vous refusez de payer l'impôt foncier vous pourriez être interpellé à la DGRKOC pour le suivi et le contrôle**

B: Local Enforcement Message


REPUBLIQUE DEMOCRATIQUE DU CONGO
PROVINCE DU KASAÏ OCCIDENTAL
DIRECTION GENERALE DES RECETTES DU KASAÏ OCCIDENTAL
DGRKOC

Pour la campagne de collecte de l'Impôt Foncier 2018 :

**La parcelle, No. 595011,**

**appartenant à ______________________,**

**est assujettie à un taux de : 3000 FC***

à payer au percepteur de la DGRKOC une fois par année. Comme preuve de paiement, vous recevrez un reçu imprimé sur place (voir l'exemple du reçu à droite).

**Si vous refusez de payer l'impôt foncier vous pourriez être interpellé à vous rendre chez le chef de quartier pour le suivi et le contrôle**

C: Control Message


REPUBLIQUE DEMOCRATIQUE DU CONGO
PROVINCE DU KASAÏ OCCIDENTAL
DIRECTION GENERALE DES RECETTES DU KASAÏ OCCIDENTAL
DGRKOC

Pour la campagne de collecte de l'Impôt Foncier 2018 :

**La parcelle, No. 595047,**

**appartenant à ______________________,**

**est assujettie à un taux de : 3000 FC***

à payer au percepteur de la DGRKOC une fois par année. Comme preuve de paiement, vous recevrez un reçu imprimé sur place (voir l'exemple du reçu à droite).

**Il est important de payer l'impôt foncier.**

*Notes:* This figure shows examples of tax letters for owners of properties in the low-value band. The main text of the fliers (from *"Pour la campagne ..."* to *"... droite)."*) translates in English as: "For the 2018 property tax collection campaign, the property Number [Property ID] belonging to [Property Owner Name] is subject to a tax rate of 3000 CF to pay to the DGRKOC collector once a year. As proof of payment, you will receive a printed receipt on the spot (see the example of the receipt at right)." The footnote indicated by an asterisk reads: "Other amounts apply if you live in a house made of durable materials." Examples of the message treatments examined in the paper appear in the last large-font, bolded sentence in each letter. Panel A shows a letter with the *control* message, Panel B the *central enforcement* message, and Panel C the *local enforcement* message. The English translation of these messages and the details of their randomization on tax letters is discussed in Section 7.1.

## TABLE A24: RANDOMIZATION BALANCE OF TAX LETTER MESSAGES

| | Sample | Obs. | Control Mean | Local Enforcement | Central Enforcement |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Panel A: Property Characteristics | | | | | |
| Distance to city center (in km) | All Properties | 2,665 | 2.878 | 0.008 | 0.001 |
| | | | | (0.007) | (0.006) |
| Distance to market (in km) | All Properties | 2,665 | 0.638 | -0.001 | -0.007 |
| | | | | (0.006) | (0.006) |
| Distance to gas station (in km) | All Properties | 2,665 | 1.855 | 0.008 | -0.003 |
| | | | | (0.006) | (0.006) |
| Distance to health center (in km) | All Properties | 2,665 | 0.356 | -0.000 | -0.005 |
| | | | | (0.006) | (0.005) |
| Distance to government building (in km) | All Properties | 2,665 | 0.874 | -0.003 | -0.015** |
| | | | | (0.006) | (0.006) |
| Distance to police station (in km) | All Properties | 2,665 | 0.884 | -0.004 | -0.011* |
| | | | | (0.007) | (0.006) |
| Distance to private school (in km) | All Properties | 2,665 | 0.313 | 0.006 | 0.003 |
| | | | | (0.006) | (0.005) |
| Distance to public school (in km) | All Properties | 2,665 | 0.420 | 0.001 | -0.002 |
| | | | | (0.005) | (0.005) |
| Distance to university (in km) | All Properties | 2,665 | 1.302 | 0.006 | -0.008 |
| | | | | (0.007) | (0.006) |
| Distance to road (in km) | All Properties | 2,664 | 0.371 | 0.004 | 0.005 |
| | | | | (0.006) | (0.005) |
| Distance to major erosion (in km) | All Properties | 2,664 | 0.154 | -0.003 | -0.002 |
| | | | | (0.003) | (0.003) |
| Roof Quality | Midline Sample | 1,634 | 0.961 | -0.010 | -0.003 |
| | | | | (0.011) | (0.011) |
| Walls Quality | Midline Sample | 1,628 | 1.145 | 0.016 | 0.011 |
| | | | | (0.018) | (0.017) |
| Fence Quality | Midline Sample | 1,641 | 1.308 | 0.026 | 0.024 |
| | | | | (0.024) | (0.022) |
| Erosion Threat | Midline Sample | 2,106 | 0.392 | -0.006 | -0.006 |
| | | | | (0.028) | (0.027) |
| Property value (in USD) | All Properties | 2,665 | 1230 | 10.929 | -5.329 |
| Machine Learning estimate | | | | (68.748) | (65.513) |
| Panel B: Property Owner Characteristics | | | | | |
| Employed Indicator | Midline Sample | 1,627 | 0.712 | 0.073*** | 0.058** |
| | | | | (0.025) | (0.025) |
| Salaried Indicator | Midline Sample | 1,627 | 0.222 | 0.073*** | 0.051* |
| | | | | (0.027) | (0.026) |
| Work for Government Indicator | Midline Sample | 1,627 | 0.147 | 0.013 | 0.032 |
| | | | | (0.022) | (0.022) |
| Relative Work for Government. Indicator | Midline Sample | 1,780 | 0.235 | -0.002 | 0.026 |
| | | | | (0.025) | (0.025) |
| Panel C: Property Owner Characteristics | | | | | |
| Gender | Midline Sample | 193 | 1.250 | 0.071 | 0.056 |
| | | | | (0.087) | (0.091) |
| Age | Midline Sample | 193 | 49.697 | -1.082 | 0.441 |
| | | | | (3.096) | (2.734) |
| Main Tribe Indicator | Midline Sample | 193 | 0.842 | -0.220*** | -0.072 |
| | | | | (0.085) | (0.086) |
| Years of Education | Baseline Sample | 193 | 11.211 | -0.099 | 0.552 |
| | | | | (0.838) | (0.763) |
| Has Electricity | Baseline Sample | 193 | 0.263 | -0.106 | -0.069 |
| | | | | (0.087) | (0.098) |
| Log Monthly Income (CF) | Baseline Sample | 193 | 11.366 | -0.275 | -0.277 |
| | | | | (0.392) | (0.260) |
| Trust Chief | Baseline Sample | 193 | 2.961 | 0.113 | -0.250 |
| | | | | (0.248) | (0.257) |
| Trust National Government. | Baseline Sample | 183 | 2.521 | -0.112 | -0.028 |
| | | | | (0.271) | (0.265) |
| Trust Provincial Government | Baseline Sample | 183 | 2.357 | 0.210 | 0.390 |
| | | | | (0.261) | (0.259) |
| Trust Tax Ministry | Baseline Sample | 183 | 2.282 | 0.139 | 0.085 |
| | | | | (0.252) | (0.249) |

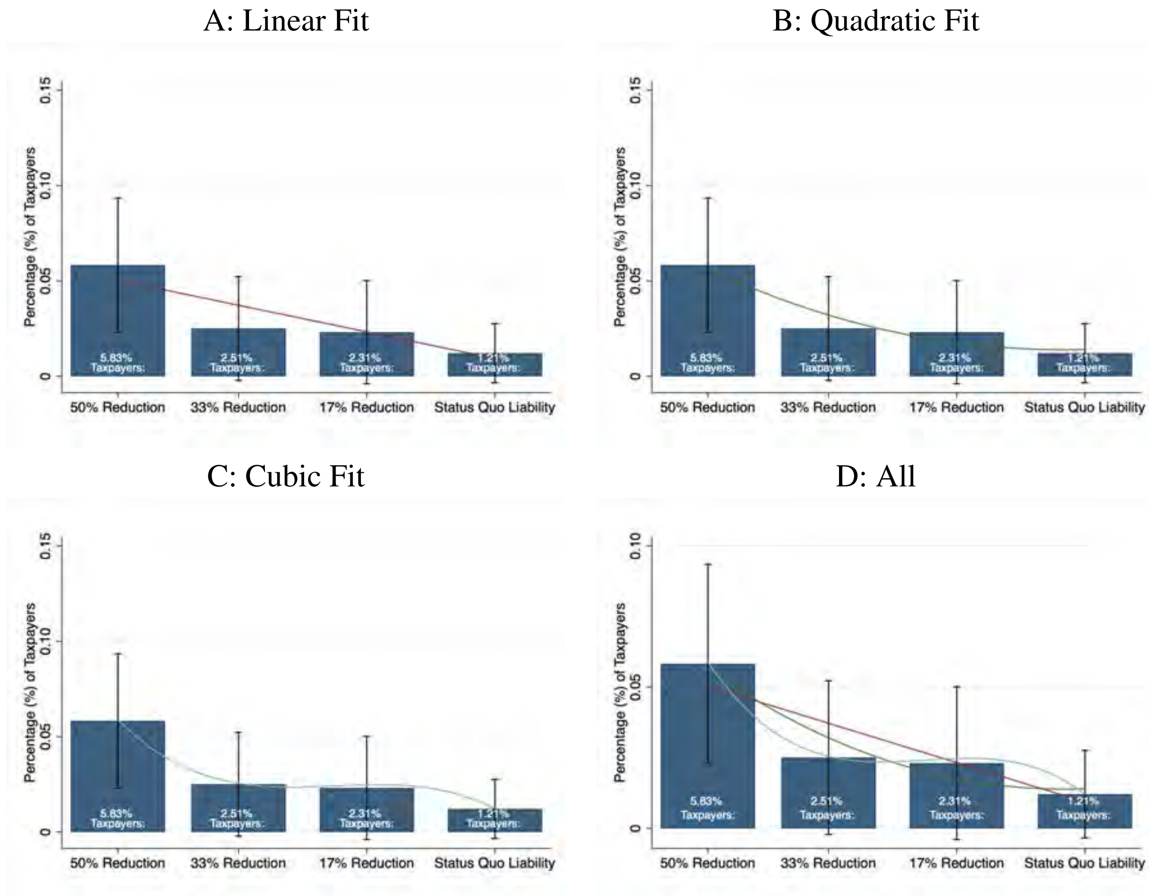
*Notes:* This table reports the coefficients regressing baseline and midline characteristics for properties (Panel A) and property owners (Panels B and C) on treatment indicators, including property value band fixed effects and randomization stratum (neighborhood) fixed effects. The control message is the excluded category. We report robust standard errors. The results are discussed in Section 7.1. The variables comes from the baseline, registration, and midline surveys and are described in Section A6.

**TABLE A25: EFFECTS OF TAX LETTER MESSAGES ON TAX COMPLIANCE, REVENUES, AND PERCEIVED SANCTIONS**

| | Tax Compliance | | | Tax Revenue (in CF) | | | Likelihood of Sanctions | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Central Enforcement | 0.014 | 0.016* | | 32.837* | 36.510** | | 0.064** | 0.058** | |
| | (0.009) | (0.009) | | (18.610) | (18.453) | | (0.031) | (0.029) | |
| Local Enforcement | 0.014 | 0.016* | | 31.244* | 35.545* | | 0.019 | 0.022 | |
| | (0.009) | (0.009) | | (18.723) | (18.783) | | (0.032) | (0.030) | |
| Pooled Enforcement | | | 0.016** | | | 36.038** | | | 0.041 |
| | | | (0.007) | | | (15.589) | | | (0.025) |
| Neighborhood FE | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Observations | 2665 | 2665 | 2665 | 2665 | 2665 | 2665 | 1553 | 1553 | 1553 |
| Mean | .029 | .029 | .029 | 57.671 | 57.671 | 57.671 | .478 | .478 | .478 |

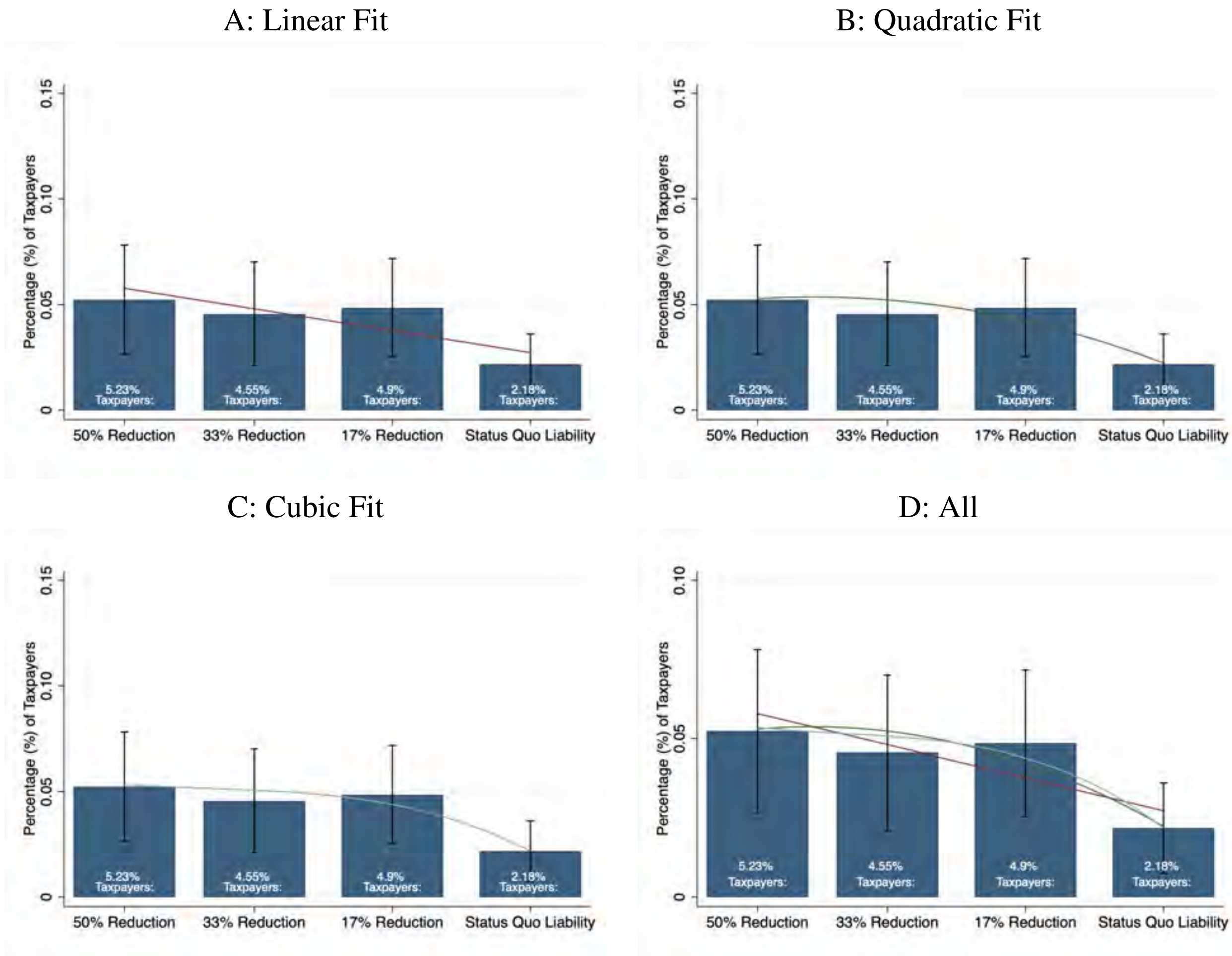
This table examines treatment effects of randomized tax letter enforcement messages on compliance, revenues, and perceived sanctions for tax delinquents. It reports estimates from a regression of tax compliance (Columns 1–3), tax revenue (Columns 4–6), and a dummy indicating high perceived probability of sanctions for delinquents (Columns 7–9) on treatment dummies for households assigned to enforcement messages on tax letters distributed during property registration. Sections 7.1 and A1.4 describe these tax letters and the message randomization. The excluded category is the control message in all regressions. Columns 2–3, 5–6, and 8–9 introduce randomization stratum (neighborhood) fixed effects. Columns 3, 6, and 9 pool households assigned to the *central enforcement* message and the *local enforcement* message. The data are restricted to the sample of 2,665 properties subject to randomized messages on tax letters, which were introduced toward the end of the tax campaign. The sample in Columns 7–9 is smaller because the outcome comes from the midline survey, rather than the administrative data.

### FIGURE A10: TREATMENT EFFECTS ON TAX COMPLIANCE (WITH LINEAR, QUADRATIC, AND CUBIC FITS) — CONTROL MESSAGE GROUP




*Notes:* This figure reports estimates from Equation (1) comparing property tax compliance for the tax abatement treatment groups relative to the status quo property tax rate (the excluded category). Panel A displays the best linear fit, Panel B the best quadratic fit, Panel C the best cubic fit, and Panel D all fits. All panels report results including fixed effects for property value band and for randomization stratum (neighborhood). The black lines show the 95% confidence interval for each of the estimates using robust standard errors. The treatment effects correspond to the results in Figure 1 and Table 3. The data include all non-exempt property owners who received a *control* message and are merged with the government's property tax database. We discuss these results in Section 7.1.

FIGURE A11: TREATMENT EFFECTS ON TAX COMPLIANCE (WITH LINEAR, QUADRATIC, AND CUBIC FITS) — ENFORCEMENT MESSAGE GROUP




*Notes:* This figure examines treatment effects among households randomly assigned to the tax letter control message. It reports estimates from Equation (1) comparing property tax compliance for the tax abatement treatment groups relative to the status quo property tax rate (the excluded category). Panel A displays the best linear fit, Panel B the best quadratic fit, Panel C the best cubic fit, and Panel D all fits. All panels report results including fixed effects for property value band and for randomization stratum (neighborhood). The black lines show the 95% confidence interval for each of the estimates using robust standard errors.The treatment effects correspond to the results in Figure 1 and Table 3. The data include all non-exempt property owners who received the *central enforcement* or *local enforcement* message and are merged with the government's property tax database. We discuss these results in Section 7.1.

## TABLE A26: LAFFER TAX RATES BY TAX LETTER ENFORCEMENT MESSAGES

| | Central Enforcement Message | | | | Local Enforcement Message | | | |
|---|---|---|---|---|---|---|---|---|
| | Linear Specification | | Quadratic Specification | | Linear Specification | | Quadratic Specification | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Panel A: Effect of Tax Rates on Tax Compliance** | | | | | | | | |
| Tax Rate (in % of status quo) | -0.061* | -0.049 | 0.297 | 0.282 | -0.061* | -0.058 | 0.084 | 0.189 |
| | (0.034) | (0.037) | (0.374) | (0.387) | (0.036) | (0.036) | (0.379) | (0.359) |
| Tax Rate Squared (in % of status quo) | | | -0.239 | -0.221 | | | -0.097 | -0.165 |
| | | | (0.242) | (0.250) | | | (0.247) | (0.235) |
| Constant | 0.089** | 0.080** | -0.037 | -0.037 | 0.088** | 0.086** | 0.037 | -0.002 |
| | (0.028) | (0.030) | (0.137) | (0.142) | (0.030) | (0.029) | (0.138) | (0.131) |
| **Panel B: Laffer Tax Rate** | | | | | | | | |
| Laffer Rate (in % Status quo Rate) | 0.728 | 0.814 | 0.761 | 0.780 | 0.718 | 0.738 | 0.748 | 0.761 |
| | (0.191) | (0.326) | (0.055) | (0.061) | (0.200) | (0.218) | (0.112) | (0.074) |
| Implied Reduction in Tax Rate | 27.18% | 18.61% | 23.90% | 21.99% | 28.15% | 26.24% | 25.25% | 23.94% |
| Observations | 906 | 906 | 904 | 904 | 866 | 866 | 866 | 866 |
| Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample |
| Neighborhood FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Quadratic Tax Rate Term | No | No | Yes | Yes | No | No | Yes | Yes |

*Notes:* This table examines how the revenue-maximizing (Laffer) tax rate, from Proposition (1), varies among households randomly assigned to tax letter enforcement messages. Columns 1–2 and 5–6 assume linearity of tax compliance with respect to the tax rate. For these columns, Panel A contains estimates of regression specification (7), and Panel B reports the corresponding Laffer rate from Equation (6). Columns 3–4 and 7–8 assume a quadratic relationship between tax compliance and tax rate. For these columns, Panel A reports estimates of regression specification (9) and Panel B reports the Laffer rate from Equation (8). All estimates in Panels A and B are expressed as a percentage of the status quo tax rate. All regressions include fixed effects for property value band and Columns 2, 4, 6, and 8 also include fixed effects for randomization stratum (neighborhood). In Panel A, we report robust standard errors. Standard errors in Panel B are computed using the delta method. The data are restricted to the sample of 2,665 properties exposed to randomized messages on tax letters. Columns 1–4 further restrict the sample to owners who received the *local enforcement* message, and Columns 5–8 to owners who received the *central enforcement* message. We discuss these results in Section 7.1.

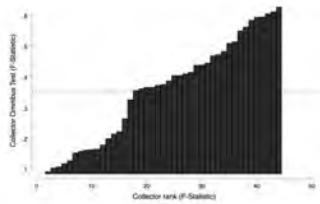
## TABLE A27: LAFFER TAX RATES BY TAX LETTER ENFORCEMENT MESSAGES — INCLUDING IMBALANCED COVARIATES

| | Control Message | | | | Enforcement Message | | | |
|---|---|---|---|---|---|---|---|---|
| | Linear Specification | | Quadratic Specification | | Linear Specification | | Quadratic Specification | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Panel A: Effect of Tax Rates on Tax Compliance** | | | | | | | | |
| Tax Rate (in % of status quo) | -0.081** | -0.088** | -0.424 | -0.444 | -0.058** | -0.050** | 0.243 | 0.225 |
| | (0.032) | (0.033) | (0.346) | (0.328) | (0.025) | (0.025) | (0.268) | (0.263) |
| Tax Rate Squared (in % of status quo) | | | 0.227 | 0.237 | | | -0.201 | -0.184 |
| | | | (0.218) | (0.210) | | | (0.174) | (0.171) |
| Constant | 0.079** | -0.013 | 0.200 | 0.109 | 0.099*** | 0.064 | -0.008 | -0.033 |
| | (0.032) | (0.042) | (0.129) | (0.127) | (0.026) | (0.040) | (0.101) | (0.102) |
| **Panel B: Laffer Tax Rate** | | | | | | | | |
| Laffer Rate (in % Status quo Rate) | 0.489 | 0.076 | 0.315 | 0.138 | 0.849 | 0.634 | 0.791 | 0.734 |
| | (0.111) | (0.254) | (0.078) | (0.083) | (0.237) | (0.362) | (0.054) | (0.114) |
| Implied Reduction in Tax Rate | 51.09% | 92.44% | 68.50% | 86.23% | 15.07% | 36.59% | 20.93% | 26.64% |
| Controls: | | | | | | | | |
| Dist. state building (imbalanced) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Dist. police station (imbalanced) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Employed (imbalanced) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Salaried (imbalanced) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 893 | 893 | 893 | 893 | 1772 | 1772 | 1772 | 1772 |
| Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample | Tax Message Sample |
| Neighborhood FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Quadratic Tax Rate Term | No | No | Yes | Yes | No | No | Yes | Yes |

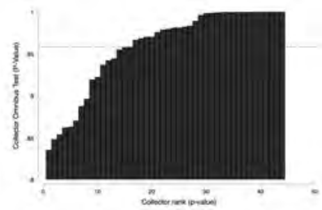
*Notes:* This table reports estimates of the revenue-maximizing (Laffer) tax rate in Proposition (1). Columns 1–2 and 5–6 assume linearity of tax compliance with respect to the tax rate. For these columns, Panel A contains estimates of regression specification (7), and Panel B reports the corresponding Laffer rate from Equation (6). Columns 3–4 and 7–8 assume a quadratic relationship between tax compliance and tax rate. For these columns, Panel A reports estimates of regression specification (9), and Panel B reports the Laffer rate from Equation (8). All estimates in Panels A and B are expressed as a percentage of the status quo tax rate. All regressions include fixed effects for property value band and Columns 2, 4, 6, and 8 also include fixed effects for randomization stratum (neighborhood). In Panel A, we report robust standard errors. Standard errors in Panel B are computed using the delta method. In all specifications, we add controls for distance to the nearest state building and police stations as well as indicators for having any job and a salaried job (the imbalanced covariates in Table A24). When including controls, we replace missing values in control variables with the mean for the entire sample and include a separate dummy (for each control variable) for the value being missing. The data are restricted to the sample of 2,665 properties exposed to randomized messages on tax letters. Columns 1–4 further restrict the sample to owners who received the *control* message, and Columns 5–8 to owners who received the *central enforcement* or *local enforcement* message. We discuss these results in Section 7.1.

## Figure A12: Tax Collector Assignment — Omnibus Balance Tests

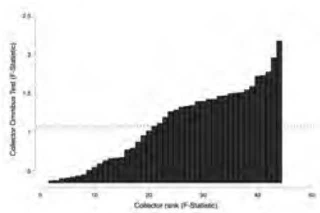
A: $F$-statistic - Property Characteristics



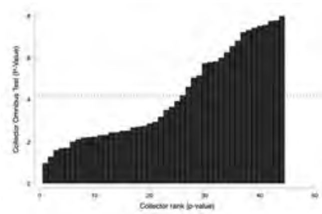
B: $p$-value - Property Characteristics



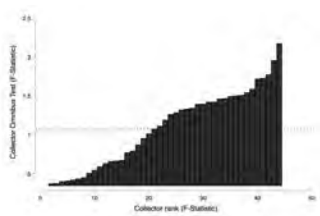
C: $F$-statistic - Property Owner Characteristics



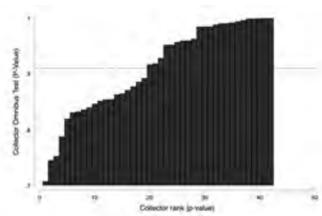
D: $p$-value - Property Owner Characteristics



E: $F$-statistic - Property Owner Characteristics



F: $p$-value - Property Owner Characteristics



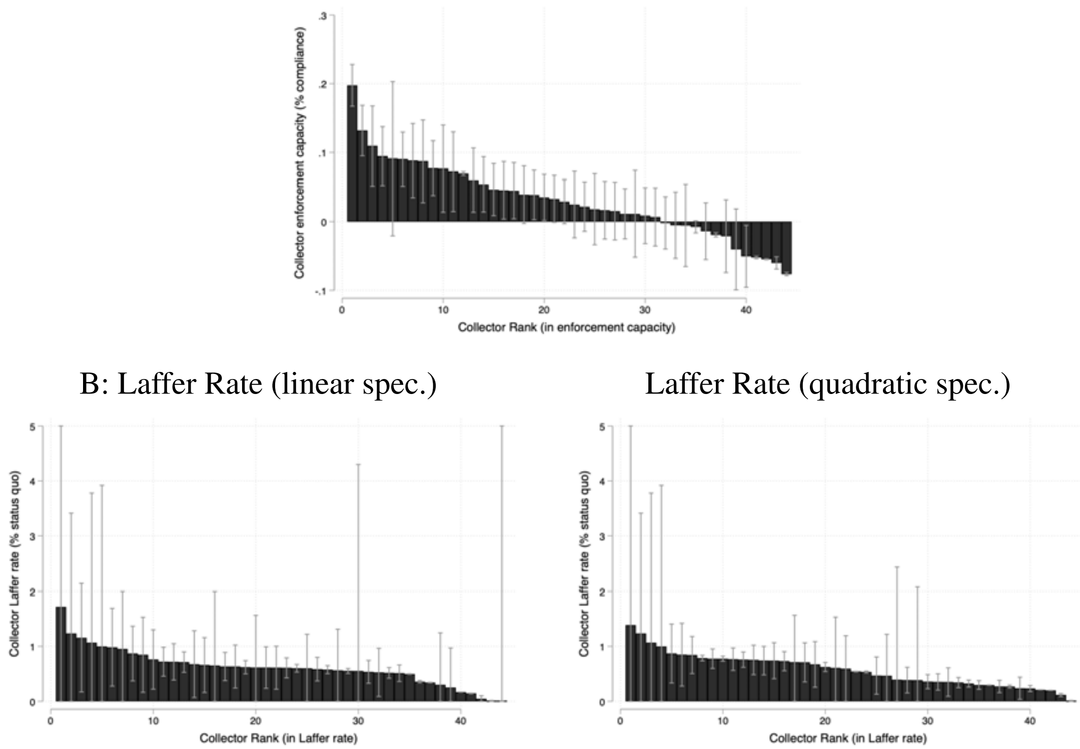
*Notes:* In this figure, we test the omnibus null hypothesis that the treatment effects of random tax collector assignments are zero for all of the variables studied in Table 2 using parametric $F$-tests. For each tax collector, we test the omnibus null for property characteristics in Panels A and B (which correspond to Panel A of Table 2) and for property characteristics in Panels C, D, E, and F (which correspond to Panels B and C of Table 2). Panels A, C, and E report the $F$-statistic associated with the omnibus null test for each tax collector, as well as the mean of the $F$-statistic across collectors. Panels B, D, and F report the $p$-value associated with the omnibus null test for each tax collector, as well as the mean of the $p$-value across collectors. We discuss these results in Section 7.2.

## FIGURE A13: TAX COLLECTOR ENFORCEMENT CAPACITIES AND LAFFER RATES

A: Enforcement Capacity

B: Laffer Rate (linear spec.)

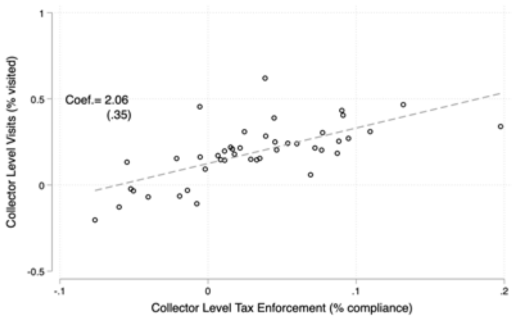
Laffer Rate (quadratic spec.)



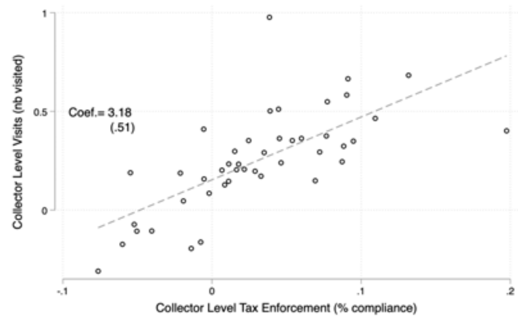

*Notes:* This figure shows estimated collector-specific enforcement capacities and revenue-maximizing (Laffer) rates. Panel A contains estimates of each tax collector's enforcement capacity following regression specification (10). The estimated enforcement capacity is expressed as the percentage of owners who pay the property tax on average among neighborhoods to which each collector is randomly assigned. Some of the estimates of $E_c$ are negative, reflecting the fact that $E_c$ should be interpreted as the predicted additional compliance brought by collector $c$ when paired with a randomly chosen tax collector and assigned to a randomly selected neighborhood. That some $\widehat{E_c}$ are negative reflects that low-performing collectors on average lowered the compliance achieved in collector pairs to which they were randomly assigned. By contrast, when we estimate enforcement capacity at the collector-pair level, rather than the collector level, the estimates can be interpreted as the predicted compliance associated with the collector pair when randomly assigned to a neighborhood, and consequently all of them are positive (Panel A of Figure A18). Panels B and C report the collector-specific Laffer rate in Proposition (1). In Panel B, the estimated Laffer rate assumes linearity of tax compliance with respect to the tax rate and is obtained from estimating Equation (11). In Panel C, the estimated Laffer rate assumes a quadratic relationship between tax compliance and the tax rate and is obtained from estimating Equation (12). All estimates of the Laffer rate are expressed as a percentage of the status quo tax rate. We discuss these results in Section 7.2.

**FIGURE A14: COLLECTOR ENFORCEMENT CAPACITIES VS. FREQUENCY OF COLLECTOR VISITS AND PERCEPTIONS OF SANCTIONS**

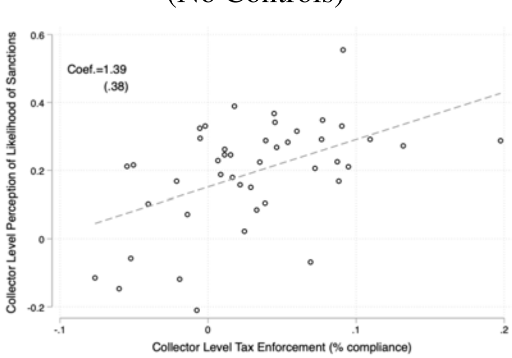
A: Visit Indicator



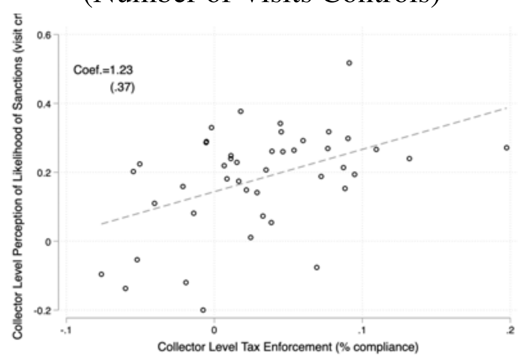

B: Number of Visits




C: Perceptions of Sanctions
(No Controls)

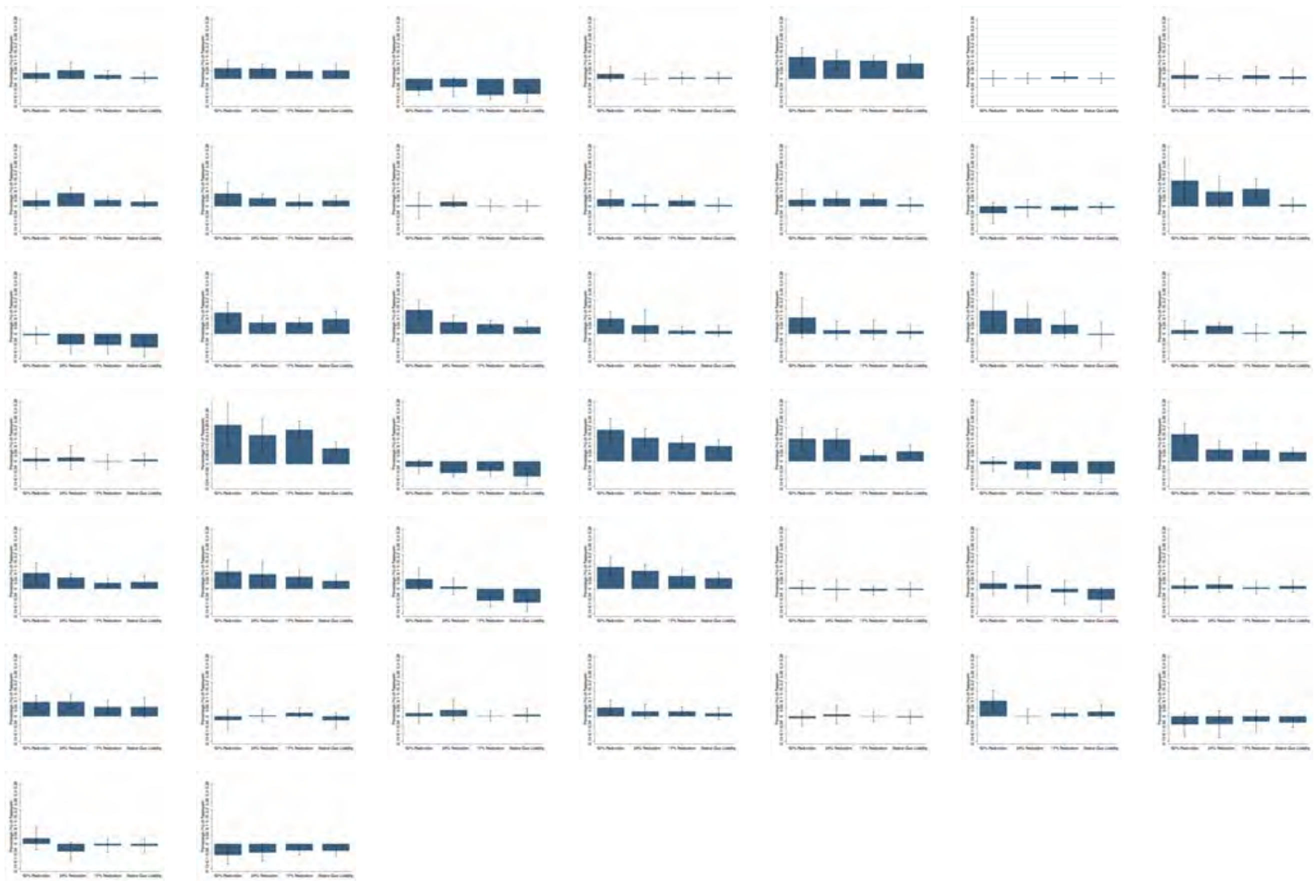



D: Perceptions of Sanctions
(Number of Visits Controls)




*Notes:* This figure shows correlations between the collector-specific enforcement capacities and average reported visits (or beliefs about the probability of sanctions for tax delinquents) in neighborhoods to which collectors were randomly assigned. The x-axis reports estimates of tax collector enforcement capacity using regression specification (10), expressed as the percentage of owners who pay the property tax in all neighborhoods to which a collector was randomly assigned. In Panels A and B, the y-axis reports the collector-level visits on the extensive and intensive margins as reported by households in the midline survey. In Panels C and D, the y-axis reports the collector-level midline perception of sanctions for tax delinquency. This variable is measured as an indicator for households reporting that sanctions for tax delinquency are "likely" or "very likely". All y-axis estimates are from empirical specification (10). We discuss these results in Section 7.2.

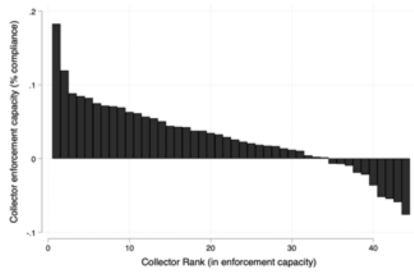
## FIGURE A15: TREATMENT EFFECTS ON TAX COMPLIANCE — HETEROGENEITY BY TAX COLLECTOR



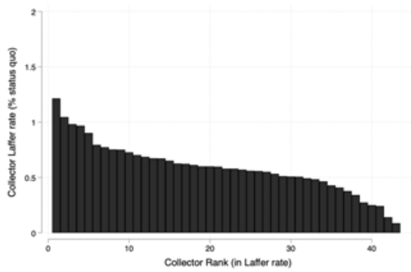
*Notes:* This figure reports estimates from equation $y_{i,n} = \sum_c \alpha_c^0 1[c(n) = c] + \sum_c \alpha_c^1 1[c(n) = c] Reduction17\%_{i,n} + \sum_c \alpha_c^2 1[c(n) = c] Reduction33\%_{i,n} + \sum_c \alpha_c^3 1[c(n) = c] Reduction50\%_{i,n} + \theta_{i,n} + \epsilon_{i,n}$ for each of the 45 provincial government tax collectors considered in Section 7.2. $y_{i,n}$ is an indicator for tax compliance of property owner $i$ living in neighborhood $n$, $c(n)$ denotes the tax collectors assigned to neighborhood $n$, $\theta_{i,n}$ are property value band fixed effects, and $\epsilon_{i,n}$ denotes the error term. Because the collectors were randomly assigned to work in pairs, and the pair was then randomly assigned to work in a neighborhood, we cluster standard errors at the tax collector pair level. We discuss these results in Section 7.2.

## FIGURE A16: TAX COLLECTOR ENFORCEMENT CAPACITIES AND LAFFER RATES — EMPIRICAL BAYES ESTIMATES

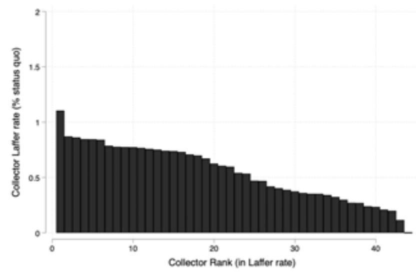
A: Enforcement Capacity




B: Laffer Rate (linear spec.)



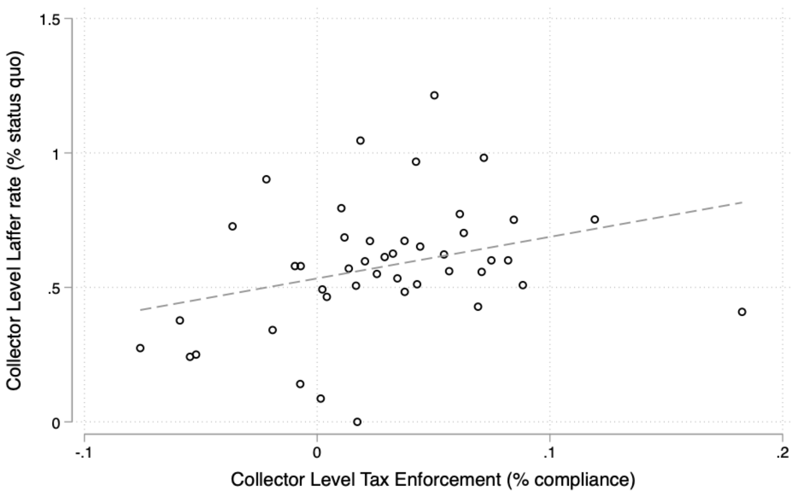

Laffer Rate (quadratic spec.)



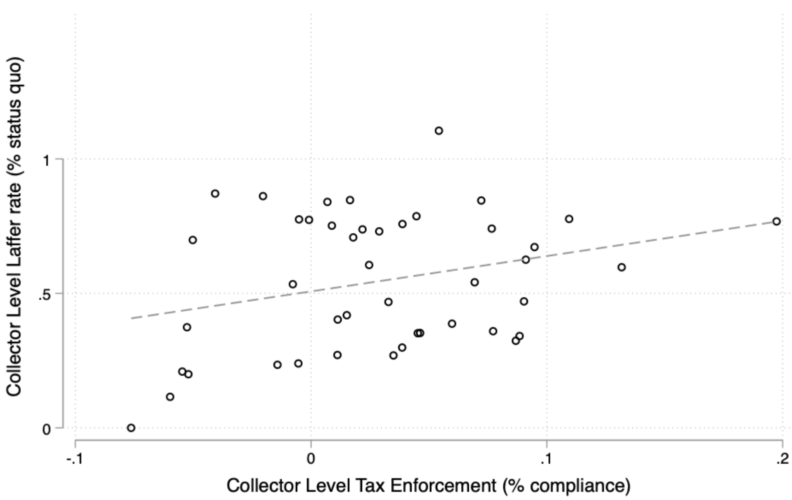

*Notes:* This figure shows estimated collector-specific enforcement capacities and revenue-maximizing (Laffer) rates with all estimates adjusted using the empirical Bayes approach presented in Section 7.2.3. Panel A contains estimates of each tax collector's enforcement capacity following regression specification (10). The estimated enforcement capacity is expressed as the percentage of owners who pay the property tax on average among neighborhoods to which each collector is randomly assigned. Some of the estimates of $E_c$ are negative, reflecting the fact that $E_c$ should be interpreted as the predicted additional compliance brought by collector $c$ when paired with a randomly chosen tax collector and assigned to a randomly selected neighborhood. That some $\widehat{E_c}$ are negative reflects that low-performing collectors on average lowered the compliance achieved in collector pairs to which they were randomly assigned. By contrast, when we estimate enforcement capacity at the collector-pair level, rather than the collector level, the estimates can be interpreted as the predicted compliance associated with the collector pair when randomly assigned to a neighborhood, and consequently all of them are positive (Panel A of Figure A18). Panels B and C report the collector-specific Laffer rate in Proposition (1). In Panel B, the estimated Laffer rate assumes linearity of tax compliance with respect to the tax rate and is obtained from estimating Equation (11). In Panel C, the estimated Laffer rate assumes a quadratic relationship between tax compliance and the tax rate and is obtained from estimating Equation (12). All estimates of the Laffer rate are expressed as a percentage of the status quo tax rate. We discuss these results in Section 7.2.

**FIGURE A17: COLLECTOR LAFFER RATES BY ENFORCEMENT CAPACITY — EMPIRICAL BAYES ESTIMATES**

A: Laffer Rate (linear spec.) by Enforcement Capacity



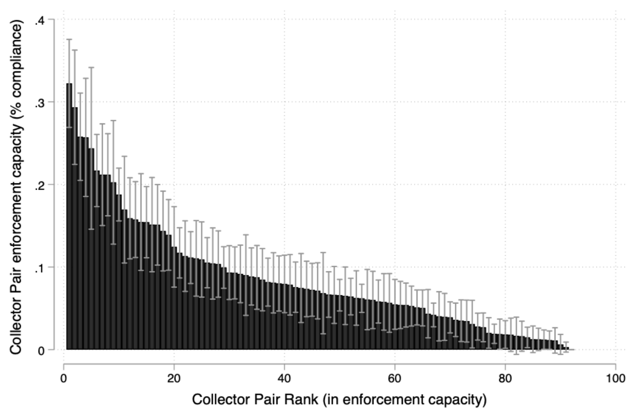

B: Laffer Rate (quadratic spec.) by Enforcement Capacity



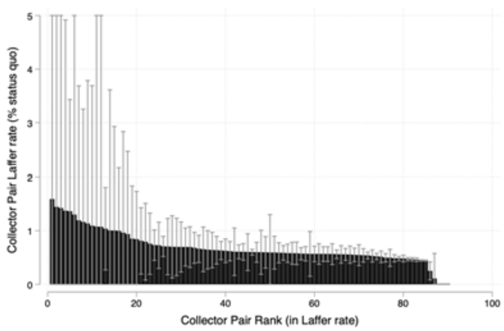

*Notes:* This figure shows the relationship between collector-level revenue-maximizing (Laffer) rates and collector enforcement capacities with all estimates adjusted using the empirical Bayes approach presented in Section 7.2.3. The x-axis contains estimates of collector enforcement capacity from Equation (10). The y-axis reports the collector-specific Laffer rates in Proposition (1). In Panel A, the estimated Laffer rate assumes linearity of tax compliance with respect to the tax rate and is obtained from estimating Equation (11). In Panel B, the estimated Laffer rate assumes a quadratic relationship between tax compliance and the tax rate and is obtained from estimating Equation (12). All estimates of enforcement capacity are expressed as the percentage of owners who pay the property tax, and all estimates of the Laffer rate are expressed as a percentage of the status quo tax rate. The best fit line and the corresponding regression coefficient of the x-axis on the y-axis are reported with the corresponding robust standard errors. These estimates correspond to those in Table A28. We discuss these results in Section 7.2.

## **FIGURE A18: COLLECTOR PAIR ENFORCEMENT CAPACITIES AND LAFFER RATES**

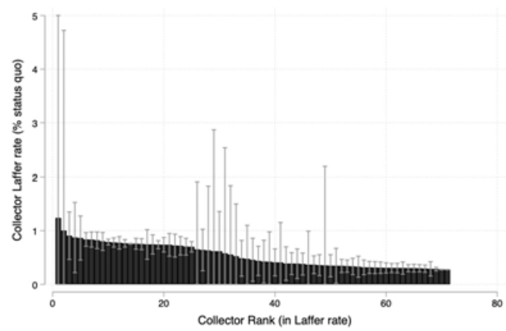
A: Enforcement Capacity




B: Laffer Rate (linear spec.)



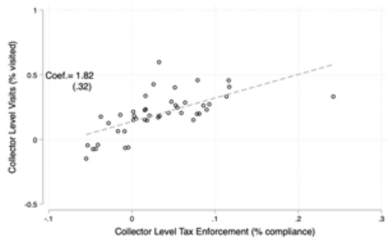

C: Laffer Rate (quadratic spec.)



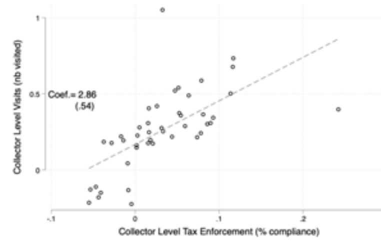

*Notes:* This figure shows the distribution of collector-pair-level enforcement capacities and revenue-maximizing (Laffer) rates, rather than the collector-level quantities reported in Figure A13. Panel A reports estimates *?*of collector pair enforcement capacity estimated using regression specification (10) but replacing dummies for each collector by dummies for collector pairs. Estimated enforcement capacities are expressed as the percentage of owners who pay the property tax. Panels B and C report the collector-pair Laffer rate in Proposition (1). In Panel B, the estimated Laffer rate assumes linearity of tax compliance with respect to the tax rate and is obtained from estimating empirical specification (11) but replacing dummies for each collector by dummies for collector pairs and using robust standard errors. In Panel C, the estimated Laffer rate assumes a quadratic relationship between tax compliance and the tax rate and is obtained from empirical specification (12) but replacing dummies for each collector by dummies for collector pairs and using robust standard errors. All estimates of the Laffer rate are expressed as a percentage of the status quo tax rate. We discuss these results in Section 7.2.

### FIGURE A19: COLLECTOR-LEVEL ANALYSIS — ROBUSTNESS TO SPLIT SAMPLE APPROACH

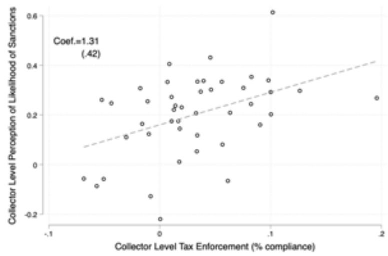
A: Visit Indicator
by Enforcement Capacity



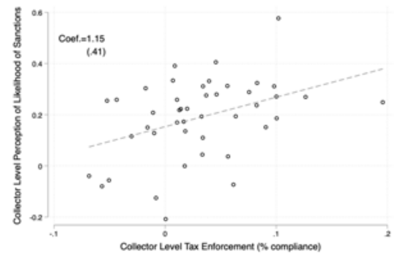

B: Number of Visits
by Enforcement Capacity



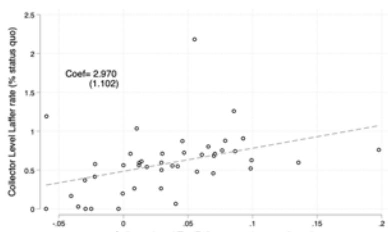

C: Perceptions of Sanction
(No Controls)



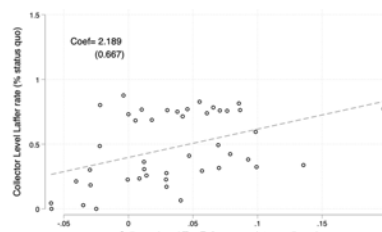

D: Perceptions of Sanction
(Number of Visits Controls)



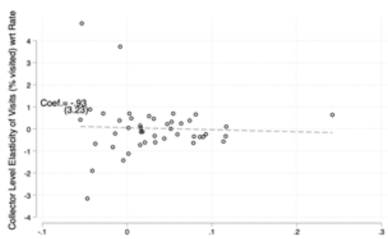

E: Laffer Rate (linear spec.)
by Enforcement Capacity



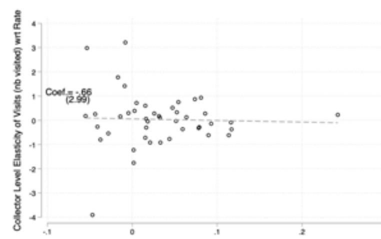

F: Laffer Rate (quadratic spec.)
by Enforcement Capacity




G: Elasticity of Visit Indicator
wrt Tax Rates by Enforcement Capacity



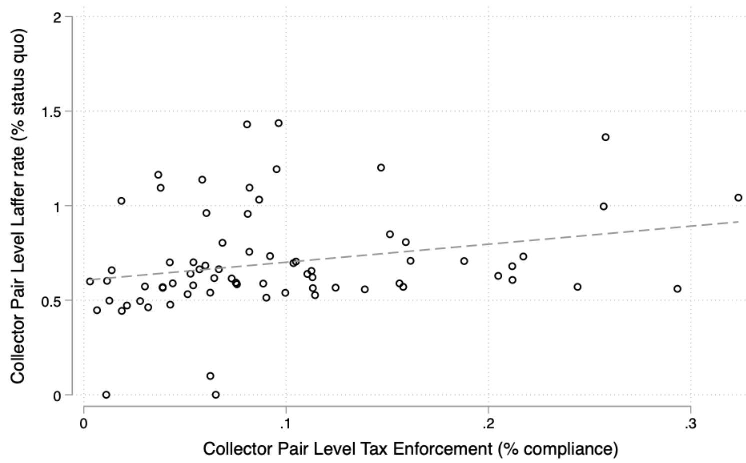

H: Elasticity of Number of Visits
wrt Tax Rates by Enforcement Capacity



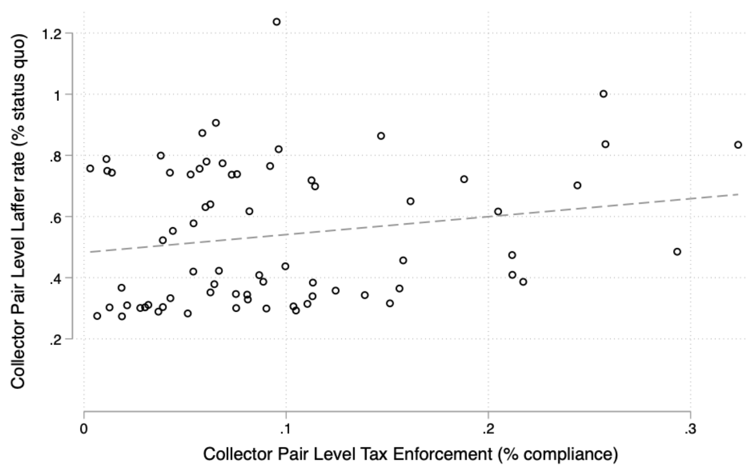

*Notes:* This figure demonstrates robustness of the collector-based analysis to a split-sample approach, in which we split the sample in two and estimate collector enforcement capacities (on the x-axis) using the first sample and then the different variables on the y-axis using the second sample. We repeat this analysis to replicate the results in Figure A14 (Panels A–D), Figure 4 (Panels E and F), and Figure A21 (Panels G and H). We discuss these results in Section 7.2.

## FIGURE A20: COLLECTOR PAIR LAFFER RATES BY ENFORCEMENT CAPACITY

A: Linear Specification




B: Quadratic specification




*Notes:* This figure explores the relationship between collector enforcement capacity and revenue-maximizing (Laffer) tax rates — all on the collector pair level. The x-axis reports estimates of tax collector pair enforcement capacity from Equation (10) but replacing collector dummies with collector pair dummies. The y-axis reports collector-specific Laffer rates in Proposition (1). In Panel A, the estimated Laffer rate assumes linearity of tax compliance with respect to the tax rate and is obtained from estimating Equation (11), replacing dummies for each collector by dummies for collector pairs. In Panel B, the estimated Laffer rate assumes a quadratic relationship between tax compliance and the tax rate and is obtained from estimating Equation (12), replacing dummies for each collector by dummies for collector pairs. All estimates of enforcement capacity are expressed as the percentage of owners who pay the property tax, and all estimates of the Laffer rate are expressed as a percentage of the status quo tax rate. We also report the best fit line. We discuss these results in Section 7.2.

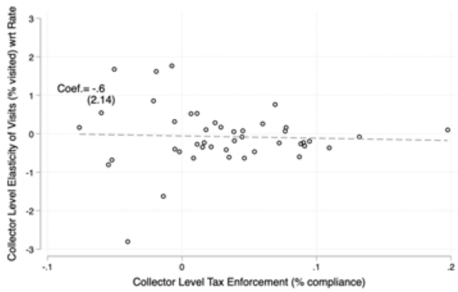
## TABLE A28: COLLECTOR ENFORCEMENT CAPACITIES AND LAFFER RATES

| | Level-Level | | Log-Log | |
|---|---|---|---|---|
| | Raw | Shrunk | Raw | Shrunk |
| | (1) | (2) | (3) | (4) |
| Panel A: Linear Specification | | | | |
| Enforcement Capacity | 2.421** | 1.545* | | |
| | (0.819) | (0.811) | | |
| ln(Enforcement Capacity) | | | 0.623** | 0.345** |
| | | | (0.215) | (0.108) |
| Observations | 44 | 44 | 42 | 42 |
| Panel B: Quadratic Specification | | | | |
| Enforcement Capacity | 1.587* | 1.684** | | |
| | (0.831) | (0.702) | | |
| ln(Enforcement Capacity) | | | 0.347** | 0.129** |
| | | | (0.159) | (0.049) |
| Observations | 44 | 44 | 43 | 43 |
| Sample | All state tax collectors | All state tax collectors | All state tax collectors | All state tax collectors |

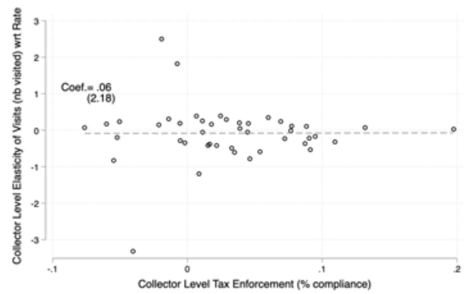
*Notes:* This table examines the relationship between tax collectors' revenue-maximizing (Laffer) tax rates and their enforcement capacities. Collector-specific enforcement capacities are estimated using regression specification (10). In Columns 1–4, the collector-specific Laffer rate assumes linearity of tax compliance with respect to the tax rate and is obtained from estimating Equation (11). In Columns 5–8, the collector-specific Laffer rate assumes a quadratic relationship between tax compliance and the tax rate and is obtained from estimating regression specification (12). Columns 1, 3, 5, and 7 report the fixed effect estimates, while Columns 2, 4, 6, and 8 report the empirical Bayes estimates described in Section 7.2.3. Columns 1–2 and 5–6 report the results of a level-level regression, while Columns 3–4 and 7–8 use the log-log specification $ln(\widehat{T_c^*}) = \alpha + \beta ln(\widehat{E}_c) + \nu_c$ and can be interpreted as an elasticity. We discuss these results in Section 7.2.

## FIGURE A21: COLLECTOR ENFORCEMENT CAPACITIES AND VISITS BY RATE

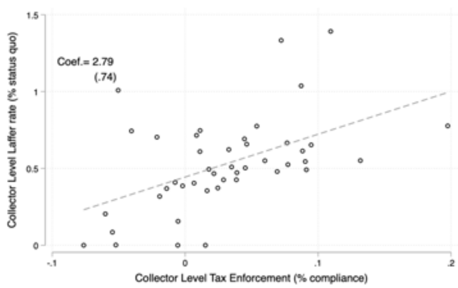
A: Elasticity of Visit Indicator
wrt Tax Rates v. Enforcement Capacity



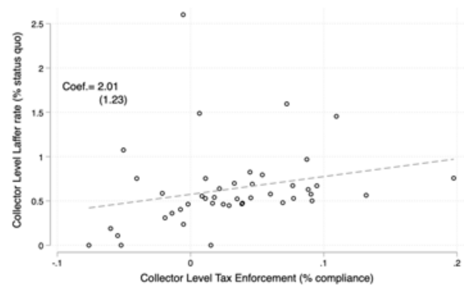

B: Elasticity of Number of Visits
wrt Tax Rates v. Enforcement Capacity



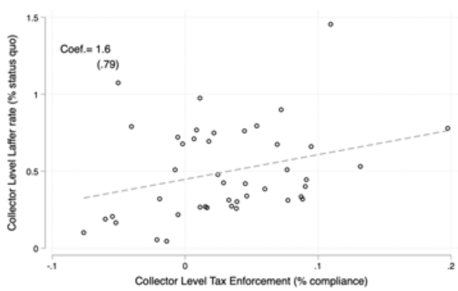

C: Enforcement Capacities v. Laffer Rates
Controlling for Visit Indicator
(linear spec.)



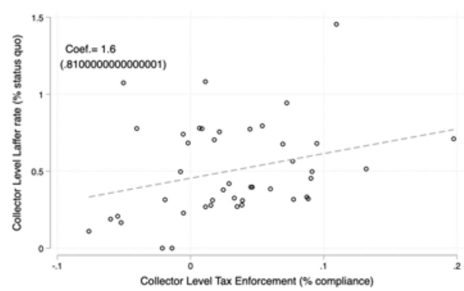

D: Enforcement Capacities v. Laffer Rates
Controlling for Number of Visits
(linear spec.)




E: Enforcement Capacities v. Laffer Rates
Controlling for Visit Indicator
(quadratic spec.)




F: Enforcement Capacities v. Laffer Rates
Controlling for Number of Visits
(quadratic spec.)




*Notes:* This figure examines whether high-enforcement collectors exhibit differential elasticity of tax visits by rate, and whether controlling for tax visits impacts the observed relationship between collector Laffer rates and enforcement capacities. The x-axis of this figure aways reports estimates of tax collector enforcement capacity using regression specification (10), expressed as the percentage of owners who pay the property tax. In Panels A and B, the y-axis reports the collector-level elasticity of visits on the extensive (Panel A) and intensive margin (Panel B) with respect to tax rates. In Panels C–F, the y-axis reports the collector-specific Laffer rate in Proposition (1) controlling for visits on the extensive margin (Panels C and D) and extensive margin (Panels E and F). When estimating the collector-specific Laffer rate, we assume linearity in Panels C and D and estimate Equation (11), while in Panels E and F we assume a quadratic relationship and estimate Equation (12). We discuss these results in Section 7.2.

## TABLE A29: CORRELATES OF COLLECTOR ENFORCEMENT CAPACITY

| | Coef. (1) | SE (2) | p-value (3) | Mean (4) | R-squarred (5) | Obs. (6) |
|---|---|---|---|---|---|---|
| Panel A: Demographics | | | | | | |
| Female | -0.056 | 0.069 | 0.423 | 0.068 | 0.003 | 44 |
| Age | 0.247 | 0.153 | 0.114 | 30.535 | 0.062 | 43 |
| Main Tribe | -0.117 | 0.178 | 0.514 | 0.250 | 0.014 | 44 |
| Years of Education | 0.193* | 0.110 | 0.086 | 3.674 | 0.038 | 43 |
| Math Score | 0.204 | 0.130 | 0.124 | -0.052 | 0.042 | 43 |
| Literacy (Tshiluba) | 0.135 | 0.156 | 0.393 | 0.042 | 0.019 | 43 |
| Literacy (French) | 0.258* | 0.145 | 0.082 | 0.013 | 0.068 | 43 |
| Monthly Income | 0.447*** | 0.124 | 0.001 | 98.562 | 0.203 | 43 |
| Possessions | 0.323*** | 0.095 | 0.002 | 1.698 | 0.106 | 43 |
| Born in Kananga | 0.061 | 0.155 | 0.694 | 0.488 | 0.004 | 43 |
| Panel B: Trust in the Government | | | | | | |
| Trust Nat. Gov. | 0.027 | 0.159 | 0.864 | 2.841 | 0.001 | 44 |
| Trust Prov. Gov. | 0.033 | 0.141 | 0.817 | 2.955 | 0.001 | 44 |
| Trust Tax Min. | 0.195 | 0.155 | 0.216 | 3.500 | 0.038 | 44 |
| Index | 0.109 | 0.152 | 0.479 | 0.065 | 0.012 | 44 |
| Panel C: Perceived Performance of Government | | | | | | |
| Prov. Gov. Capacity | -0.085 | 0.132 | 0.521 | 0.364 | 0.007 | 44 |
| Prov. Gov. Responsiveness | -0.246* | 0.142 | 0.091 | 1.795 | 0.060 | 44 |
| Prov. Gov. Performance | 0.067 | 0.121 | 0.583 | 4.545 | 0.004 | 44 |
| Prov. Gov. use of Funds | 0.058 | 0.192 | 0.764 | 0.624 | 0.003 | 44 |
| index | -0.085 | 0.134 | 0.531 | 0.077 | 0.007 | 44 |
| Panel D: Government Connections | | | | | | |
| Job through Connections | 0.032 | 0.167 | 0.849 | 0.275 | 0.001 | 40 |
| Relative work for Prov. Gov. | -0.106 | 0.143 | 0.462 | 0.209 | 0.011 | 43 |
| Relative work for Tax Ministy | -0.104 | 0.142 | 0.470 | 0.209 | 0.011 | 43 |
| Index | -0.083 | 0.164 | 0.615 | -0.095 | 0.007 | 43 |
| Panel E: Tax Morale | | | | | | |
| Taxes are Important | 0.265* | 0.136 | 0.058 | 2.750 | 0.070 | 44 |
| Work of Tax Min. is Important | 0.118 | 0.181 | 0.517 | 3.727 | 0.014 | 44 |
| Paid Taxes in the Past | 0.087 | 0.168 | 0.610 | 0.367 | 0.010 | 30 |
| Index | 0.217 | 0.141 | 0.132 | 0.013 | 0.047 | 44 |
| Panel F: Redistributive Preferences | | | | | | |
| Imp. of Progressive Taxes | 0.018 | 0.132 | 0.891 | 1.682 | 0.000 | 44 |
| Imp. of Progressive Prop. Taxes | -0.101 | 0.125 | 0.421 | 1.227 | 0.010 | 44 |
| Imp. to Tax Employed | 0.343** | 0.165 | 0.044 | 3.318 | 0.118 | 44 |
| Imp. to Tax Owners | 0.187 | 0.130 | 0.156 | 3.000 | 0.035 | 44 |
| Imp. to Tax Owners w. title | 0.310** | 0.119 | 0.013 | 3.227 | 0.096 | 44 |
| Index | 0.008 | 0.128 | 0.948 | -0.081 | 0.000 | 44 |
| Panel G: Motivation | | | | | | |
| Intrinsic Motivation | -0.204 | 0.147 | 0.177 | -0.092 | 0.050 | 27 |
| Extrinsic Motivation | -0.303* | 0.160 | 0.069 | 0.022 | 0.111 | 27 |
| Gap: Intrinsic - Extrinsic | 0.091 | 0.181 | 0.619 | -0.097 | 0.010 | 27.000 |

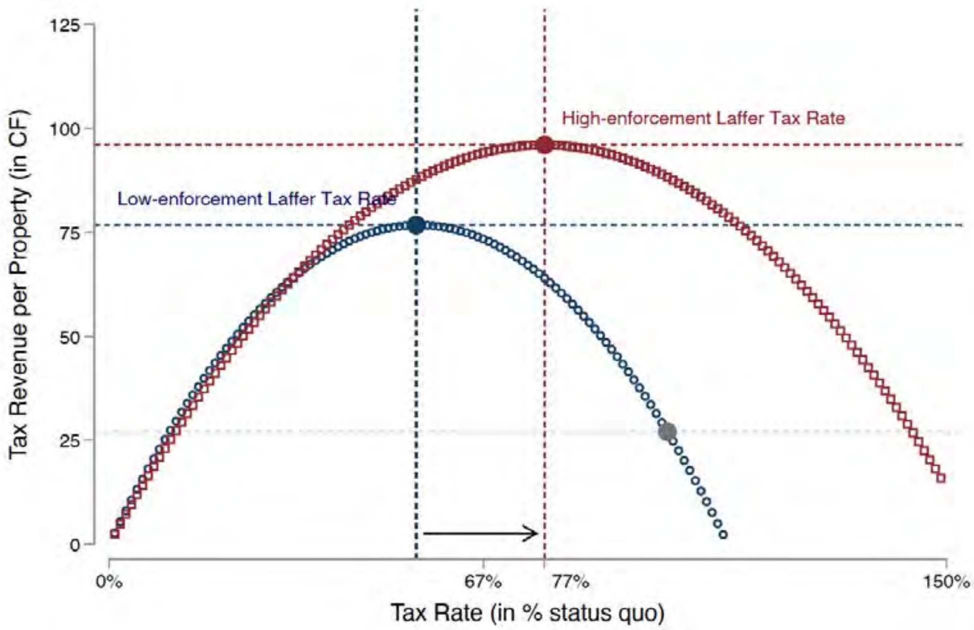
*Notes:* This table reports the correlations between collector enforcement capacities and other collector characteristics, measured from surveys conducted with each collector. The columns report the correlation coefficient, robust standard error, $p$-value, mean of the characteristic among collectors, R-squared, and total number of collectors about whom we observe the characteristic. The variables come from surveys with tax collectors and are described in Section A6. We discuss these results in Section 7.2.

## TABLE A30: CORRELATES OF COLLECTOR LAFFER RATES

| | Laffer Rate: Linear Specification | | | | | | Laffer Rate: Quadratic Specification | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coef.<br>(1) | SE<br>(2) | p-value<br>(3) | Mean<br>(4) | R-squarred<br>(5) | Obs.<br>(6) | Coef.<br>(7) | SE<br>(8) | p-value<br>(9) | Mean<br>(10) | R-squarred<br>(11) | Obs.<br>(12) |
| Panel A: Demographics | | | | | | | | | | | | |
| Female | 0.071 | 0.091 | 0.439 | 0.068 | 0.005 | 44 | 0.172*** | 0.045 | 0.000 | 0.068 | 0.030 | 44 |
| Age | -0.114 | 0.193 | 0.556 | 30.535 | 0.013 | 43 | 0.138 | 0.190 | 0.470 | 30.535 | 0.020 | 43 |
| Main Tribe Indicator | -0.045 | 0.181 | 0.807 | 0.250 | 0.002 | 44 | -0.046 | 0.200 | 0.821 | 0.250 | 0.002 | 44 |
| Years of Education | -0.033 | 0.139 | 0.816 | 3.674 | 0.001 | 43 | -0.257** | 0.119 | 0.037 | 3.674 | 0.069 | 43 |
| Math Score | 0.253* | 0.140 | 0.078 | -0.052 | 0.065 | 43 | 0.089 | 0.167 | 0.598 | -0.052 | 0.008 | 43 |
| Literacy (Tshiluba) | 0.037 | 0.115 | 0.749 | 0.042 | 0.001 | 43 | 0.177 | 0.139 | 0.209 | 0.042 | 0.033 | 43 |
| Literacy (French) | 0.106 | 0.136 | 0.440 | 0.013 | 0.011 | 43 | 0.147 | 0.150 | 0.334 | 0.013 | 0.022 | 43 |
| Monthly Income | 0.291*** | 0.088 | 0.002 | 98.562 | 0.087 | 43 | 0.151 | 0.118 | 0.208 | 98.562 | 0.024 | 43 |
| Possessions | 0.155 | 0.134 | 0.253 | 1.698 | 0.025 | 43 | -0.010 | 0.146 | 0.948 | 1.698 | 0.000 | 43 |
| Born in Kananga | 0.283* | 0.149 | 0.064 | 0.488 | 0.082 | 43 | 0.191 | 0.151 | 0.212 | 0.488 | 0.038 | 43 |
| Panel B: Trust in the Government | | | | | | | | | | | | |
| Trust Nat. Gov. | 0.010 | 0.107 | 0.926 | 2.841 | 0.000 | 44 | -0.122 | 0.133 | 0.367 | 2.841 | 0.015 | 44 |
| Trust Prov. Gov. | 0.048 | 0.116 | 0.681 | 2.955 | 0.002 | 44 | -0.075 | 0.155 | 0.633 | 2.955 | 0.006 | 44 |
| Trust Tax Min. | 0.079 | 0.201 | 0.695 | 3.500 | 0.006 | 44 | -0.192 | 0.180 | 0.293 | 3.500 | 0.037 | 44 |
| Index | 0.059 | 0.132 | 0.659 | 0.065 | 0.003 | 44 | -0.170 | 0.140 | 0.231 | 0.065 | 0.029 | 44 |
| Panel C: Perceived Performance of Government | | | | | | | | | | | | |
| Prov. Gov. Capacity | 0.161 | 0.165 | 0.333 | 0.364 | 0.026 | 44 | 0.075 | 0.158 | 0.639 | 0.364 | 0.006 | 44 |
| Prov. Gov. Responsiveness | 0.159 | 0.207 | 0.447 | 1.795 | 0.025 | 44 | -0.059 | 0.197 | 0.768 | 1.795 | 0.003 | 44 |
| Prov. Gov. Performance | 0.005 | 0.154 | 0.976 | 4.545 | 0.000 | 44 | -0.079 | 0.183 | 0.670 | 4.545 | 0.006 | 44 |
| Prov. Gov. use of Funds | 0.172 | 0.151 | 0.261 | 0.624 | 0.030 | 44 | 0.321** | 0.133 | 0.020 | 0.624 | 0.103 | 44 |
| index | 0.201 | 0.163 | 0.224 | 0.077 | 0.040 | 44 | 0.100 | 0.175 | 0.571 | 0.077 | 0.010 | 44 |
| Panel D: Government Connections | | | | | | | | | | | | |
| Job through Connections | -0.025 | 0.179 | 0.889 | 0.275 | 0.001 | 40 | -0.035 | 0.194 | 0.858 | 0.275 | 0.001 | 40 |
| Relative work for Prov. Gov. | 0.083 | 0.154 | 0.592 | 0.209 | 0.007 | 43 | 0.037 | 0.167 | 0.828 | 0.209 | 0.001 | 43 |
| Relative work for Tax Ministry | 0.210 | 0.242 | 0.391 | 0.209 | 0.045 | 43 | 0.234 | 0.214 | 0.279 | 0.209 | 0.057 | 43 |
| Index | 0.135 | 0.196 | 0.496 | -0.095 | 0.018 | 43 | 0.119 | 0.208 | 0.571 | -0.095 | 0.015 | 43 |
| Panel E: Tax Morale | | | | | | | | | | | | |
| Taxes are Important | 0.009 | 0.191 | 0.961 | 2.750 | 0.000 | 44 | -0.145 | 0.198 | 0.468 | 2.750 | 0.021 | 44 |
| Work of Tax Min. is Important | 0.207 | 0.131 | 0.120 | 3.727 | 0.043 | 44 | 0.086 | 0.149 | 0.565 | 3.727 | 0.007 | 44 |
| Paid Taxes in the Past | -0.237 | 0.174 | 0.183 | 0.367 | 0.048 | 30 | -0.099 | 0.187 | 0.603 | 0.367 | 0.008 | 30 |
| Index | 0.019 | 0.175 | 0.916 | 0.013 | 0.000 | 44 | -0.065 | 0.183 | 0.724 | 0.013 | 0.004 | 44 |
| Panel F: Redistributive Preferences | | | | | | | | | | | | |
| Imp. of Progressive Taxes | -0.102 | 0.155 | 0.516 | 1.682 | 0.010 | 44 | 0.195 | 0.129 | 0.137 | 1.682 | 0.038 | 44 |
| Imp. of Progressive Prop. Taxes | -0.191 | 0.120 | 0.118 | 1.227 | 0.037 | 44 | -0.138 | 0.127 | 0.282 | 1.227 | 0.019 | 44 |
| Imp. to Tax Employed | -0.094 | 0.138 | 0.498 | 3.318 | 0.009 | 44 | -0.095 | 0.199 | 0.636 | 3.318 | 0.009 | 44 |
| Imp. to Tax Owners | -0.129 | 0.184 | 0.487 | 3.000 | 0.017 | 44 | 0.022 | 0.144 | 0.880 | 3.000 | 0.000 | 44 |
| Imp. to Tax Owners w. title | -0.079 | 0.112 | 0.485 | 3.227 | 0.006 | 44 | -0.048 | 0.109 | 0.659 | 3.227 | 0.002 | 44 |
| Index | -0.148 | 0.130 | 0.260 | -0.081 | 0.022 | 44 | -0.001 | 0.143 | 0.993 | -0.081 | 0.000 | 44 |
| Panel G: Motivation | | | | | | | | | | | | |
| Intrinsic Motivation | -0.205 | 0.182 | 0.271 | -0.092 | 0.029 | 27 | -0.122 | 0.219 | 0.583 | -0.092 | 0.011 | 27 |
| Extrinsic Motivation | 0.450* | 0.253 | 0.088 | 0.022 | 0.141 | 27 | 0.192 | 0.187 | 0.314 | 0.022 | 0.028 | 27 |
| Gap: Intrinsic - Extrinsic | -0.553** | 0.248 | 0.035 | -0.097 | 0.213 | 27 | -0.265 | 0.203 | 0.204 | -0.097 | 0.054 | 27 |

*Notes:* This table reports the correlations between collectors' revenue-maximizing (Laffer) tax rates and other collector characteristics. In Columns 1–6, we assume linearity of tax compliance with respect to the tax rate and use empirical specification (11), while in Columns 7–12 we assume a quadratic relationship and use empirical specification (12). The columns report the correlation coefficient, robust standard error, *p*-value, mean of the characteristic among collectors, R-squared, and total number of collectors about whom we observe the characteristic. The variables come from surveys with tax collectors and are described in Section A6. We discuss these results in Section 7.2.

**FIGURE A22: RATES AND ENFORCEMENT AS COMPLEMENTS: REVENUE IMPLICATIONS — TAX LETTER 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 revenues at different hypothetical tax rates using the regression coefficients obtained when estimating Equation (7). We compare the estimated relationship among households assigned to the *control* message on their tax letter (blue dotted line) to households assigned to an enforcement message (red dotted line). For the latter, we pool the *central enforcement* and *local enforcement* messages. Vertical lines indicate different potential tax rates, while horizontal lines indicate the corresponding revenue levels. The data are restricted to the sample of 2,665 properties subject to randomized messages on tax letters. We discuss these results in Section 7.3

# A5 Predicting Property Value with Machine Learning

This section discusses how we estimate the value of each property in the sample using machine learning methods. More detail is provided in Bergeron et al. (2020a).

## A5.1 Data Collection

### A5.1.1 Training Sample

To train our Machine Learning and Computer Vision algorithms, we constructed a training sample of 1,654 property values. These 1,654 properties were randomly chosen from our baseline sample. To estimate their market value, land surveyors from the Provincial Government of Kasaï-Central conducted appraisal field visits on these properties between August and September 2019.

During these field appraisal visits, the government land surveyors estimated the market value of each property based on the neighborhood, the property's land area and fruit trees, the property built area and the materials used in construction as well as their depreciation. The median (mean) property value in the training sample was US$797 (US$3,125).

Estimating the market value of properties in Kananga is one of the key components of the training of the provincial governments' land surveyors with whom we worked. These surveyors are often employed by formal banks in Kananga to value the properties of clients who apply for mortgages or loans.[101]

### A5.1.2 Feature Vector

To train our machine learning algorithms, we constructed a vector of features using survey data, GPS information, and the value of the properties in the training sample:

- **Property Features.** Property-level features come from the midline survey conducted with property owners in Kananga between July 2018 and February 2019 as described in Section 4.1. The midline survey recorded the GPS location of the property, the materials and quality of the walls, roof and fence of the main house as well as the quality of the street road and whether the property and road are threatened by erosion. These variables are described in Table A31.

- **Geographic Features.** Geographic information comes from combining the GPS location of every property from the registration survey described in Section 4.1 and the GPS location of important buildings/infrastructure in Kananga. In September 2019, enumerators recorded the GPS location of all the following in Kananga: (1) hospitals and health centers, (2) public and private schools, (3) universities, (4) markets, (5) gas stations, (6) government buildings (communal, provincial, and national), and (7) police stations. Maps of the (8) main roads and (9) large ravines (sources of erosion) were also digitized by our research team. For each property in Kananga, we compute the distance to the nearest of these geographic features as described in Table A31.

[101] One of the surveyors is the former head of the Provincial Cadastral Division and the other is the Chief Technical Officer of the Cadastral Division.

- **Neighborhood Property Value Features.** Additional information about the average value of nearby properties comes from the property values of the 1,654 properties in our training sample. We use this information to create several additional features: average property value in the neighborhood and in the geographical strata, average property value within a close radius (200, 500, and 1000 meters), and the average price of the nearest 3 and 5 houses. These additional features are also summarized in Table A31.

## A5.2 Machine Learning Predictions

### A5.2.1 Algorithms

Our goal is to use the training sample of 1,654 property values and the vector of features to predict as accurately as possible the value of the remaining properties in Kananga using the following machine learning algorithms:

1. **Penalized linear models (LASSO, Ridge, and Elastic Net) -** Penalized linear models are widely used by econometricians, LASSO (Tibshirani, 1996), Ridge (Hoerl and Kennard, 1970) and Elastic Net (Zou and Hastie, 2005) methods allow creating a linear model that is penalized for having too many variables in the model, by adding a constraint in the equation, and are also known for this reason as shrinkage or regularization methods.

2. **Kernel models (SVM and SVR).** SVM and its regression equivalent, SVR, usually perform well on small datasets due to their nonparametric nature and the flexibility of kernel functions (Bierens, 1987). A kernel is essentially a feature map of the input data to a higher dimensional space. While data may not be linear on the original input space, moving to a higher dimensional space may help finding a linear line of best fit. In SVR, the linear regression function is fit in the kernel space and often turns out to be a non-linear function in the original input space. We tested the two most commonly use kernels, Linear and Radial Basis Function (RBF).

3. **Regression Trees and Forests.** Regression trees (Breiman et al., 1984) and their extension, random forests (Breiman, 2001), have also become very popular and effective methods for flexibly estimating regression functions in settings where out-of-sample predictive power is important. They are considered to have great out-of-the box performance without requiring subtle regularization.

4. **Boosting.** Boosting is a general-purpose technique to improve the performance of simple supervised learning methods. In the context of tree-based models, boosting works as tree ensembles that are grown sequentially, with a new tree fitted on residuals of the previous model. Tree are not full grown, and as such are considered

"weak learners." The combination of multiple rounds of sequential weak learners has been show to deliver a "strong learner," characterized by high predictive performance (Schapire and Freund, 2012).

5. **Ensemble modeling.** Another key feature of the machine learning literature is the use of model averaging and ensemble methods (e.g., Dietterich (2000)). In many cases, a single model or algorithm does not perform as well as a combination of different models, averaged using weights obtained by optimizing out-of-sample performance. Here we investigate the out-of-sample performance of a combination of boosting algorithms with different loss functions for different types of properties.

#### A5.2.2 Results

Each machine learning model has well-known advantages and drawbacks (Hastie et al., 2001). The advantage of machine learning is that it allows to systematically compare the performance of different algorithms by assessing their out-of-sample accuracy. We use 10-fold cross validation to compare the performance of our machine learning algorithms for the task of assigning a property value to each property in our sample.

Table A32 assesses the out-of-sample accuracy of each machine learning algorithm using several evaluation metrics.[102] Table A32 shows that the boosted trees models outperform penalized linear models, kernel models, and tree models. This is in line with recent studies that have found that in many contexts, boosting algorithms tend to perform better than other machine learning algorithms (Schapire and Freund, 2012).

The performance of the boosting algorithm is greatly affected by the choice of loss function.[103] The best performing algorithm uses a boosted tree algorithm with MAPE loss function for properties we predict as "low-value" and with MAE loss function for property we predict as "high-value."[104] This algorithm performs better than a boosted tree algorithm with MAPE loss function or a boosted tree algorithm with MAE loss function.[105] It is

[102] In Column 1, we report the *Mean Absolute Error (MAE)*, which is defined as the average of absolute difference between the target value and the predicted value and is a commonly used evaluation metric for regression models. It has the advantage of penalizing large errors and being robust to outliers. In Column 2, we report the *Mean Absolute Percentage Error (MAPE)*, defined as the average absolute difference between the target value and the predicted value expressed in percentage of the actual value, which is also a commonly used evaluation metric for regression models due to its scale-independency and interpretability, though it has the inconvenience of producing infinite or undefined values for close-to-zero actual values. In Columns 3, 4 and 5 we use the share of prediction within a 20%, 50% and 150%, band of the target value.

[103] In the case of random forest or tree-based boosting, the loss function is the function used by the algorithm to decide tree splits.

[104] To differentiate between "low-value"' and "high-value" properties, we fit a random forest classifier. The random classifier predicts whether a house is worth less than US$1,000 ("low-value") or more than US$1,000 USD ("high-value").

[105] This is because with a MAPE loss function, the prediction procedure will overweight "low-value" proper-

this ensemble modeling approach that yields what we refer to as our preferred measure of predicted property value in the paper.

While machine learning models' predictive performance typically comes at the cost of explainability, we can describe how our preferred machine learning algorithm based its prediction by looking at the features that were used most often for prediction.[106] Figure A23 presents the results. It shows that the value of neighboring properties, which constitutes 7 of the most 15 important features, is the most effective at predicting the value of a property in Kananga. Then comes relative location (distance to nearest ravine, distance to the nearest road, to the city center, or to any major infrastructure) with 4 of the 15 most important features. Finally the remaining important features are the characteristics of the property such as quality of the walls, roof, and the road.

ties and all the property value predictions will be pushed downwards. Similarly, with a MAE loss function, the prediction procedure will overweight "high-value" properties and all the property value predictions will be pushed upwards.

[106]The number of tree splits made on this feature in the learning process.

**TABLE A31: FEATURES USED TO TRAIN MACHINE LEARNING MODELS**

| Category | Description |
|---|---|
| **Property Features** | Property latitude |
| | Property longitude |
| | Communes (1-5 indicator) |
| | Geographic stratum (1-12 indicator) |
| | Materials of the fence - 1-4 scale |
| | Materials of the roof - 1-4 scale |
| | Roof quality - 1-4 scale |
| | Wall quality - 1-7 scale |
| | Road quality - 1-5 scale |
| | Erosion threat - 1-3 scale |
| **Geographic Features** | Distance of the property to the city center |
| | Distance of the property to the nearest commune building |
| | Distance of the property to the nearest gas station |
| | Distance of the property to the nearest health center |
| | Distance of the property to the nearest hospital |
| | Distance of the property to the nearest market |
| | Distance of the property to the nearest police station |
| | Distance of the property to the nearest private school |
| | Distance of the property to the nearest public school |
| | Distance of the property to the nearest university |
| | Distance of the property to the nearest government building |
| | Distance of the property to the nearest road |
| | Distance of the property to the nearest ravine |
| | Cumulative distance |
| **Neighborhood Property Value Features** | K-Fold target encoded geographic stratum property value |
| | K-Fold target encoded neighborhood property value |
| | Average property value in a 200 m radius |
| | Average property value in a 500 m radius |
| | Average property value in a 1 km radius |
| | Average price of the 3 closest properties |
| | Average price of the 5 closest properties |

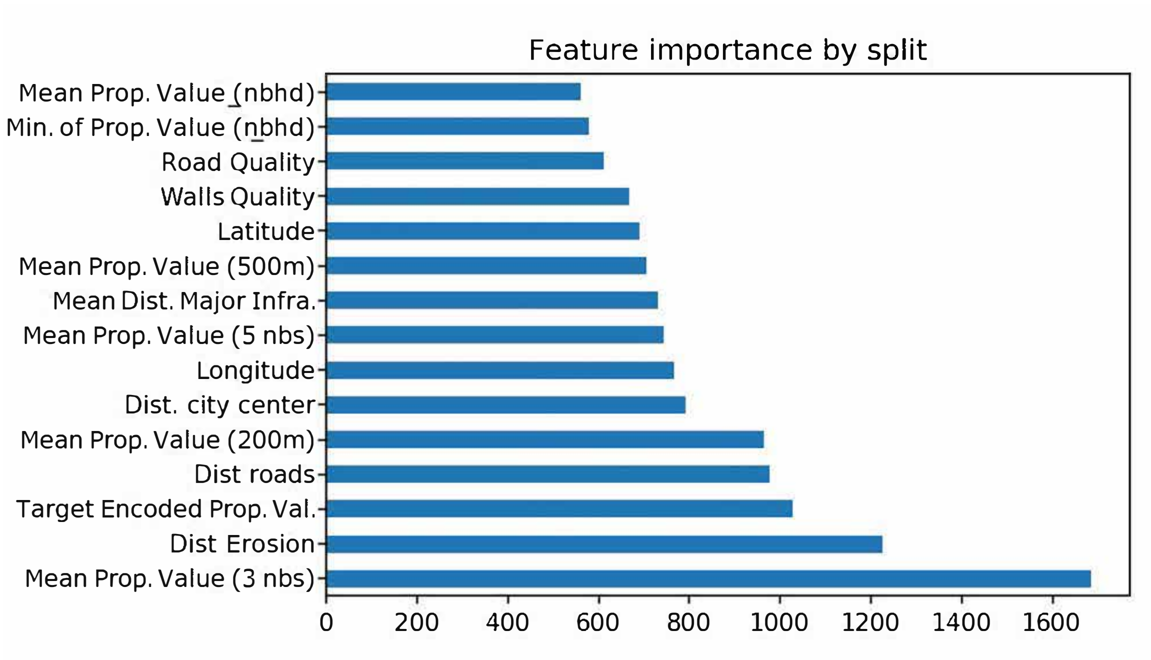
*Notes:* This table shows the features used to train the machine learning models. The property features come from registration and midline surveys and from administrative data about the boundaries of the five communes in Kananga. Geographic strata are those used in Balan et al. (2020), reflecting slightly finer geographic units than communes. The geographic features were computed as the crow-flies distance between the GPS location of the house and the nearest (noted) building/infrastructure from a city census conducted in September 2019. The neighborhood property value features were computed using the training sample of 1,654 property values. The variables are described in Section A6. The prediction procedure is described above and in depth in Bergeron et al. (2020a).

TABLE A32: PERFORMANCE OF MACHINE LEARNING MODELS

| Model | MAE Score | MAPE | Within 20% | Within 50% | Share $\leq$ 150% |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Linear regression | 2687.9458 | 241.33% | 11.30% | 26.96% | 53.60% |
| Elastic Net | 2871.1446 | 265.33% | 10.87% | 27.20% | 50.43% |
| SVR - Linear kernel | 2687.9458 | 241.33% | 11.30% | 26.96% | 53.60% |
| SVR - RBF Kernel | 2567.4541 | 154.49% | 6.40% | 21.86% | 49.81% |
| Random Forest | 2259.1849 | 154.31% | 17.83% | 41.30% | 55.03% |
| Boosting - MAPE loss | 2227.2905 | 55.95% | 17.64% | 48.88% | 89.38% |
| Boosting - MAE loss | 1983.1291 | 116.13% | 18.88% | 43.23% | 59.32% |
| Ensemble modeling | 1912.2261 | 69.57% | 22.11% | 53.54% | 79.88% |

*Notes:* This table assesses the out-of-sample accuracy of each machine learning model used in Bergeron et al. (2020a) to predict property values in Kananga. We examine the following algorithms: penalized linear model (Lasso, Ridge, and Elastic Net), kernel models (SVR), regression trees and forests (random forest), and boosting algorithms. Column 1 reports the mean absolute error (MAE), the average of absolute difference between the target value and the predicted value. Column 2 reports the absolute percentage error (MAPE), the average absolute difference between the target value and the predicted value expressed in percentage of the actual target value. In Columns 3, 4, and 5, we use the share of predictions within a 20%, 50%, and 150% band of the target value. The prediction procedure is described above and in depth in Bergeron et al. (2020a).

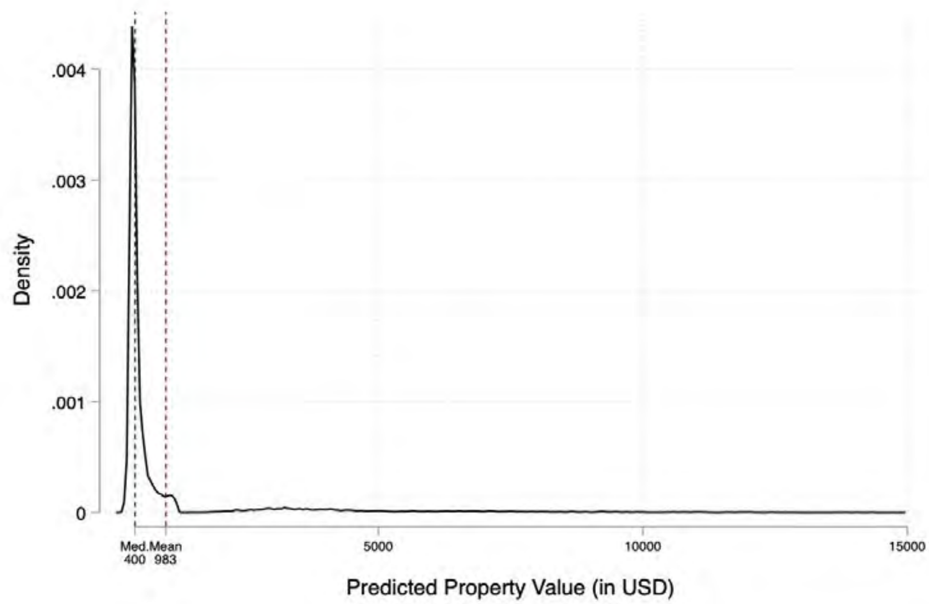
**FIGURE A23: FEATURE IMPORTANCE BY SPLIT**



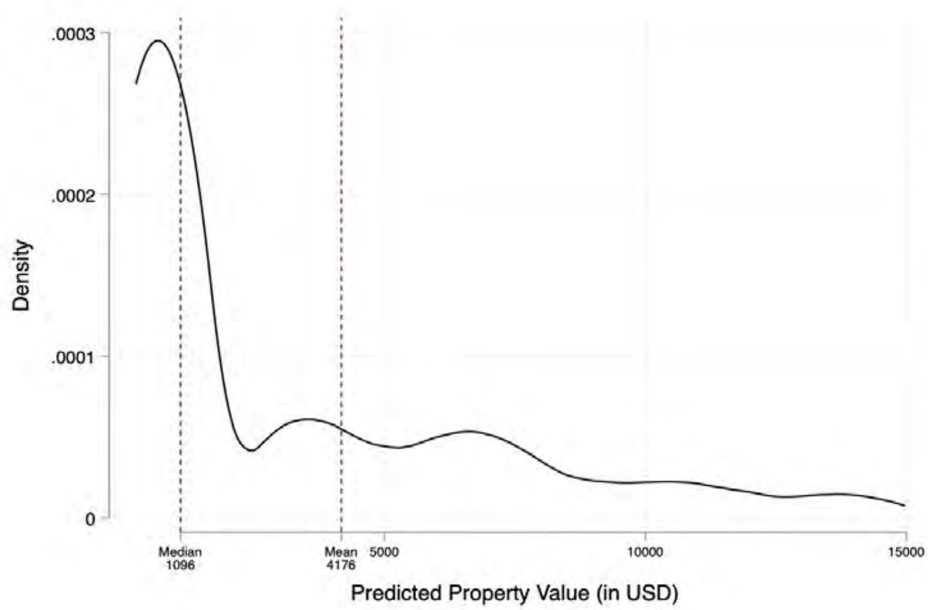

*Notes:* This figure shows how the preferred machine learning model in Bergeron et al. (2020a) based its prediction by showing the features that were used most often, i.e., the number of tree splits made on each feature in the learning process. These features are described in Table A31. The prediction procedure is described above and in more detail in Bergeron et al. (2020a).

**FIGURE A24: DISTRIBUTION OF ESTIMATED PROPERTY VALUES BY VALUE BANDS**

A: Estimated Property Value (in USD): Low-Value Band




B: Estimated Property Value (in USD): High-Value Band




*Notes:* This figure shows the distributions of the predicted property values (in USD) for the best performing algorithm. Panel A concerns properties in the low-value band, and Panel B properties in the high-value band. The median property value is represented by a blue dotted line, and the mean property value by a red dotted line. The prediction procedure is described above and in depth in Bergeron et al. (2020a).

# A6 Detailed Survey-Based Variable Descriptions

This section provides the exact text of the questions used to construct all survey-based variables examined in this paper.

## A6.1 Property and Property Owner Surveys

1. *Roof Quality.* This is a Likert scale variable, increasing in the quality of the roof of the respondent's house. It was recorded in the midline and endline survey in response to the prompt: 'Observe the principal material of the roof.' [thatch/ straw, mat, palms/ bamboos, logs (pieces of wood), concrete slab, tiles/slate/eternit, sheet iron]

2. *Wall Quality.* This is a Likert scale variable, increasing in the quality of the walls of the respondent's house. It was recorded in the midline and endline survey in response to the prompt: 'Observe the principal material of the walls of the main house.' [sticks/palms, mud bricks, bricks, cement]

3. *Fence Quality.* This is a Likert scale variable, increasing in the quality of the fence of the respondent's house. It was recorded in the midline and endline survey in response to the prompt: 'Does this compound have a fence? If so, select the type of fence.' [no fence, bamboo fence, brick fence, cement fence]

4. *Erosion Threat.* This is a Likert scale variable, increasing in the threat to the respondent's house caused by erosion. It was recorded in the midline survey in response to the prompt: 'Is this compound threatened by a ravine?' [no, yes - somewhat threatened, yes - gravely threatened]

5. *Distance of the property to the city center/ to the nearest commune building/ to the nearest gas station/ to the nearest health center/ to the nearest hospital/ to the nearest market/ to the nearest police station/ to the nearest private school/ to the nearest public school/ to the nearest university/ to the nearest government building.* These distances were based on a survey that recorded the GPS locations of all the important buildings in Kananga. The shortest distance between the respondent's property and each type of location was then computed using ArcGIS.

6. *Distance of the property to the nearest road / to the nearest ravine.* These distances were also measured using GIS. The locations of roads and ravines were digitized on GIS by the research office enabling computation of the distance between the respondent's property and the nearest road or ravine.

7. *Gender.* This is a variable reporting the respondent's gender. It was recorded in the midline survey in response to the prompt: 'Is the owner a man or a woman? '

8. *Age.* This is a variable reporting the respondent's age. It was recorded in the midline survey in response to the question: 'How old were you at your last birthday?'

9. *Main Tribe Indicator.* This is a dummy variable that equals 1 the respondent reports being Luluwa, the main tribe in Kananga. It was recorded in the midline survey in response to the question: 'What is your tribe?' [Bindi, Bunde, Dekese, Dinga, Kefe, Kele, Kete, Kongo, Kuba, Kuchu, Kusu, Lele, Lualua, Luba, Lubakat, Luluwa, Lunda/Rund, Luntu, Lusambo, Mbala, Mfuya, Mongo, Ndumbi, Ngwandji, Nyambi, Nyoka, Pende, Rega, Sakata, Sala, Shi, Songe, Tetela, Tshokwe, Tutsi, Utu, Uvira, Wongo, Yaka, Yeke, Other]

10. *Employed Indicator.* This is a dummy variable that equals 1 if the respondent reports any job (i.e., is not unemployed). It was recorded in the midline survey in response to the question: 'What type of work do you do now?' [Unemployed-no work, Medical assistant, Lawyer, Cart pusher, Handyman, Driver (car and taxi moto), Tailor, Diamond digger, Farmer, Teacher, Gardner, Mason, Mechanic, Carpenter, Muyanda, Military officer/soldier or police officer, Fisherman, Government personnel, Pastor, Porter, Professor, Guard, Work for NGO, Seller (in market), Seller (in a store), Seller (at home), Student, SNCC, Other]

11. *Salaried Indicator.* This is a dummy variable that equals 1 if the respondent reports one of the following jobs: medical assistant, lawyer, teacher, military officer/soldier or police officer, government personnel, professor, guard, NGO employee, bank employee, brasserie employee, Airtel (telecommunication services) employee, SNCC (national railway company of the Congo) employee. It was recorded in the midline survey in response to the question 'what type of work do you do now?' [responses noted above]

12. *Work for the Government Indicator.* This is a dummy variable that equals 1 if the respondent reports having one of the following jobs: military officer/soldier or police officer, government personnel, or SNCC (national railway company of the Congo) employee. It was recorded in the midline survey in response to the question 'what type of work do you do now?' [responses noted above]

13. *Relative Work for the Government Indicator.* This is a dummy variable that equals 1 if the respondent reports that someone in her/his family works for the government. It was recorded in the midline survey in response to the question: 'Does a close member of the family of the property owner work for the provincial government, not including casual labor?' [no, yes]

14. *Years of Education.* This is variable reports the respondent's years of education. It was calculated using responses to two baseline survey questions:

    - 'What is the highest level of school you have reached?' [never been to school, kindergarten, primary, secondary, university]
    - 'What is the last class reached in that level?' [1, 2, 3, 4, 5, 6, >6]

15. *Has electricity.* This is a dummy variable that equals 1 if the household reports in the baseline survey that they have access to electricity. It was recorded in the baseline survey in response to the question: 'Do you have any source of electricity at your home?' [no, yes]

16. *Log Monthly Income.* This variable is the self-reported income of the respondent, transformed by taking the natural logarithm. It was recorded in the baseline survey in response to the question: 'What was the household's total earnings this past month?'

17. *Trust in Provincial Government / National Government / Tax Ministry.* This is a Likert scale variable, increasing in the level of trust the respondent reports having in different organizations. It was recorded in the baseline and endline survey in response to the question:

    - 'I am going to name a number of organizations. For each one, could you tell me how much confidence you have in them: no confidence at all, not much confidence, quite a lot of confidence, a great deal of confidence?'
    - Organizations:
      (a) 'NGOs'
      (b) 'Local leaders'
      (c) 'The national government (in Kinshasa)'
      (d) 'The provincial government'
      (e) 'The tax ministry'
      (f) 'Foreign research organizations'.

18. *Knows Neighbors' Rate.* This is a dummy variable that equals 1 if the respondent knows the property tax rates his neighbors were assigned to during the property tax campaign. It was recorded in the midline survey in response to the question: 'Do you know how much the collectors asked your neighbors or friends to pay?' [no, yes]

19. *Knows about Reductions.* This is a dummy variable that equals 1 if the respondent is aware of anyone receiving a tax reduction during the property tax campaign. It was recorded in the midline survey in response to the question: 'Have you heard of anyone receiving an official reduction in the amount they were supposed to pay for the property tax in 2018?' [no, yes]

20. *Knows Past Rate.* This is a dummy variable that equals 1 if the respondent guessed correctly the 2016 tax rate. It was recorded in the midline survey in response to the question: 'According to you, how much does one pay for the property tax?' [amount in Congolese Francs]

21. *Exemption Status.* We construct dummy variables that equal 1 if a property owner was declared exempted by the tax collectors. It was recorded at property registration in response to the questions:

- ‘Is this household exempted? [no, yes]
- ‘Why is it exempted? [elderly, government pensioner, handicapped, widow, orphanage, convent, church, school]

22. *Migration Status.* We construct a dummy variables that equals to 1 if the property owner changed property between the baseline and the endline survey, a dummy variables that equals to 1 if the property owner moved to a different neighborhood between the baseline and the endline survey, and a dummy variable that equals to 1 if the property owner changed property but remained in the same neighborhood between the baseline and the endline survey. We use the endline survey question: ‘Did the respondent move since the last survey?’ [no, yes - within polygon, yes - to different polygon]

23. *Collector Messages.* We construct dummy variables that equal 1 if a message was used by the tax collectors during property tax collection, according to household self reports. It was recorded in the midline survey in response to the question: ‘Now let’s talk about the messages used by the property tax collectors in 2018 to convince property owners to pay the property tax. For each of the following messages, please indicate if you heard the tax collectors say this, or if you heard that they said this to other people.’

    - ‘If you refuse to pay the property tax, you may be asked to go to the chief for monitoring and control.’ [no, yes]
    - ‘If you refuse to pay the property tax, you may be asked to go to the provincial tax ministry for monitoring and control.’ [no, yes]
    - ‘The Provincial Government will only be able to improve public infrastructure in your community if its residents pay property taxes.’ [no, yes]
    - ‘The Provincial Government will only be able to improve public infrastructure in Kananga if residents pay property tax.’ [no, yes]
    - ‘Pay the property tax to show that you have confidence in the state and its officials.’ [no, yes]
    - ‘It is important.’ [no, yes]
    - ‘Payment is a legal obligation.’ [no, yes]
    - ‘Many households are paying; you should pay to avoid embarrassment in your community.’ [no, yes]
    - ‘If you don’t pay, there could be violent consequences.’ [no, yes]

24. *Past Payment.* This is a dummy variable that equals 1 if the household reports that they paid the property tax during the 2016 property tax campaign. It was recorded in the baseline survey in response to the questions: ‘Have you ever paid the property tax?’ [no, yes]

25. *Above Median Income.* This is a dummy variable that equals 1 if the household reports an income that is above the median monthly income in the baseline sample. It was recorded in the baseline survey in response to the questions: 'What was the household's total earnings this past month?' [amount in Congolese Francs]

26. *Above Median Transport.* This is a dummy variable that equals 1 if the respondent reports an income that is above the median amount spend on transport in the past week in the baseline sample. It was constructed using the baseline survey question: 'How much money have you spent on transport in the past seven days?' [amount in Congolese Francs]

27. *Lacks 3,000 CF Today.* This is a dummy variable that equals 1 if the respondent reports not having 3,000 Congolese Francs today. It was recorded in the endline survey in response to the question: 'Imagine that today you learn that you need to pay an additional 3000 FC for a school fee in order for your child to continue in school. Could you find this money in the next 4 days?' [no, yes]

28. *Lacks 3,000 CF This Month.* This is a dummy variable that equals 1 if the respondent reports not having 3,000 Congolese Francs at some point in the past month. It was recorded in the endline survey in response to the question: 'In the past 30 days, were there days in which you could not have paid this fee?' [no, yes]

29. *Perception of Enforcement.* This is a variable reporting the respondent's perception of likelihood of sanctions for evading the property tax. The exact endline survey question is as follows: 'Now, imagine that next week a tax collector comes and visits one of your neighbors. Imagine he absolutely refuses to pay the property tax. In this case, what is the probability that the government will pursue and enforce sanctions?' [he is very unlikely to be pursued and punished, he is unlikely to be pursued and punished, he is very likely to be pursued and punished, he will definitely be pursued and punished]

30. *Likelihood of Sanction Indicator.* This is a dummy variable that equals 1 if the respondent reports that sanctions for tax delinquency are likely. It was recorded in the midline survey in response to the question: 'In your opinion, do you think a public authority will pursue and enforce sanctions among households that did not pay the property tax in 2018?' [they will definitely not sanction them, they will probably not sanction them, they will probably sanction them, they will definitely sanction them]

31. *Bribe Payment Indicator.* This is a dummy variable that equals 1 if the respondent reports paying a bribe to the tax collectors. It was recorded in the midline and midline survey in response to the question: 'Did you (or a family member) pay the "transport" of the collector?' [no, yes]

32. *Bribe Amount.* This is a variable that indicate the amount of bribe paid to the tax collectors by the respondent. It was recorded in the midline and midline survey in re-

sponse to the question: ‘How much “transport” did you pay?’ [amount in Congolese Francs]

33. *Paid Self Indicator.* This is a dummy variable that equals 1 if the respondent reports paying the property tax during the 2018 property tax campaign. It was recorded in the midline survey in response to the question: ‘To date, has your household paid the property tax in 2018?’ [no, yes]

34. *Other Informal Payments.* This a variable that indicate the amount of informal payments paid to state agents in the past six months. It was recorded in the endline survey in response to the question: ‘Now, I’d like to talk about small payments made to government officials such as small amounts paid for transport, water, tea, etc. Please count up all the total such informal payments you made in the last 6 months. How much do you think you paid in total?’ [amount in Congolese Francs]

35. *Participation to Salongo.* This is a dummy variable that equals 1 if the respondent reports participation in informal taxation (Salongo) in the past two weeks. It was recorded in the endline survey in response to the question: ‘Did someone from your household participate in Salongo in the past two weeks?’ [no, yes]

36. *Hours of Salongo.* This is a variable reporting the number of hours spend participating in informal taxation (Salongo) in the past two weeks. It was recorded in the endline survey in response to the question: ‘For how many hours did you participate in Salongo in the past two weeks?’ [number of hours]

37. *Paid Vehicle Tax.* This is a dummy variable that equals 1 if the respondent reports that his household paid the vehicle tax in 2018. It was recorded in the endline survey in response to the question: ‘Let’s discuss the vehicle tax. Did you pay this tax in 2018?’ [no, yes]

38. *Paid Market Vendor Fee.* This is a dummy variable that equals 1 if the respondent reports that his household paid the market vendor fee in 2018. It was recorded in the endline survey in response to the question: ‘Let’s discuss the market vendor fee. Did you pay this tax in 2018?’ [no, yes]

39. *Paid Business Tax.* This is a dummy variable that equals 1 if the respondent reports that his household paid the business tax in 2018. It was recorded in the endline survey in response to the question: ‘Let’s discuss the business tax (patente, registre de commerce). Did you pay this tax in 2018?’ [no, yes]

40. *Paid Income Tax.* This is a dummy variable that equals 1 if the respondent reports that his household paid the income tax in 2018. It was recorded in the endline survey in response to the question: ‘Let’s discuss the income tax. Did you pay this tax in 2018?’ [no, yes]

41. *Paid Fake Tax.* This is a dummy variable that equals 1 if the respondent reports that his household paid a fictitious poll tax in 2018. It was recorded in the endline survey in response to the question: 'Let's discuss the poll tax. Did you pay this tax in 2018?' [no, yes]

42. *Provincial Government Peformance.* This is a Likert scale variable increasing in the respondent's perception of the performance of the Provincial Government. The exact endline survey question was: 'How would you rate the performance of the provincial government in Kananga?' [terrible, very poor, poor, fair, very good, excellent]

43. *Provincial Government Corruption.* This is a variable that reports how much, according to the respondent, the Provincial Government diverted from the tax revenues of the 2018 property tax campaign. The exact endline survey question is as follows: 'Now I would like to ask you what you think the provincial government will do with the money it receives from this 2018 property tax campaign. Imagine that the provincial government of Kasaï-Central receives $1000 thanks to this campaign. How much of this money will be diverted or wasted?' [0-1000]

44. *Tax Ministry Performance.* This is a Likert scale variable increasing in the respondent's perception of the performance of the Provincial Tax Ministry. The exact endline survey question was: 'How would you rate the performance of the provincial tax ministry in Kananga?' [terrible, very poor, poor, fair, very good, excellent]

45. *Tax Ministry Corruption.* This is a variable that reports how much, according to the respondent, the tax collectors of the Provincial Tax Ministry diverted from the tax revenues of the 2018 property tax campaign. The exact endline survey question is as follows: 'In general, think of what the property tax collectors did with the money they collected this year. Imagine the tax collectors collect $1000. How much of this money did they put in their pockets?' [0-1000]

46. *Fairness of Property Taxation.* This is a Likert scale variable that reports the respondent's perceived fairness of property tax collection in Kananga in 2018. The exact endline survey question was: 'In your opinion, how fair is it that households in your neighborhood must pay the property tax?' [very unfair, unfair, fair, very fair]

47. *Fairness of Property Tax Rates.* This is a Likert scale variable that reports the respondent's perceived fairness of property tax rates in Kananga in 2018. The exact endline survey question was: 'In your opinion, how fair were the tax amounts asked during the 2018 property tax?' [very unfair, unfair, fair, very fair]

48. *Fairness of Property Tax Collectors.* This is a Likert scale variable that reports the respondent's perceived fairness of property tax collectors in Kananga in 2018. The exact endline survey question was: 'In your opinion, how fair were the collectors who worked on the property tax campaign of 2018?' [very unfair, unfair, fair, very fair]

## A6.2 Tax Collectors Surveys

1. *Female.* This is a dummy variable that equals 1 if the respondent is female. It was recorded in the baseline collector survey in response to the prompt: 'Select the sex of the interviewee.' [female, male]

2. *Age.* This is a variable reporting the respondent's age. It was recorded in the baseline collector survey in response to the question: 'How old were you at your last birthday?'

3. *Main Tribe Indicator.* This is a dummy variable that equals 1 the respondent reports being Luluwa, the main tribe in Kananga. It was recorded in the baseline collector survey in response to the question: 'What is your tribe?' [Bindi, Bunde, Dekese, Dinga, Kefe, Kele, Kete, Kongo, Kuba, Kuchu, Kusu, Lele, Lualua, Luba, Lubakat, Luluwa, Lunda/Rund, Luntu, Lusambo, Mbala, Mfuya, Mongo, Ndumbi, Ngwandji, Nyambi, Nyoka, Pende, Rega, Sakata, Sala, Shi, Songe, Tetela, Tshokwe, Tutsi, Utu, Uvira, Wongo, Yaka, Yeke, Other].

4. *Years of Education.* This variable reports the respondent's years of education. It was calculated using responses to two baseline collector survey questions:

   - 'What is the highest level of school you have reached?' [never been to school, kindergarten, primary, secondary, university]
   - 'What is the last class reached in that level?' [1, 2, 3, 4, 5, 6, >6]

5. *Math Score.* This variable is a standardized index increasing in the respondent's math ability. The exact baseline collector survey questions used to create the standardized index are: 'Now we would like to ask you some math problems. Don't worry if you are not sure of the answer, just do your best to answer them.'

   - 'Can you tell me what 2 plus 3 equals?'
   - 'Can you tell me what 2 plus 3 equals?'
   - 'Can you tell me what 2 plus 3 equals?'
   - 'Can you tell me what 10 percent of 100 is?'

6. *Literacy* . This variable is a standardized index increasing in the respondent's ability to read Tshiluba. The exact baseline collector survey questions used to create the standardized index are: 'Now we would like to ask you if you could read two separate paragraphs about tax collection by the provincial government. The first paragraph is in Tshiluba and the second paragraph is in French. Don't worry if you're not sure of certain words, just do your best to read the paragraphs.'

   - 'How well did they read the Tshiluba paragraph?' [could not read, read with lots of difficult

- ‘How confidently did they read the Tshiluba paragraph?’ [not at all confident, not very confident, a bit confident, very confident]
- ‘How well did they read the French paragraph?’ [could not read, read with lots of difficult
- ‘How confidently did they read the French paragraph?’ [not at all confident, not very confident, a bit confident, very confident]

7. *Monthly Income.* This variable is the self-reported income of the respondent. It was recorded in response to the baseline collector survey question: ’What was the household’s total earnings this past month?’ [amount in USD]

8. *Number of Possessions.* This variable report the number of possessions owned by the collector’s household. The exact baseline collector survey question is as follows: ‘In your household, which (if any) of the following do you own?

    - A motorbike [no, yes]
    - A car or a truck [no, yes]
    - A radio [no, yes]
    - A television [no, yes]
    - An electric generator [no, yes]
    - A sewing machine [no, yes]
    - None.’ [no, yes]

9. *Born in Kananga.* This is a dummy variable that equals 1 if the respondent was born in Kananga. The exact baseline collector survey question is as follows: ‘Were you born in Kananga?’ [no, yes]

10. *Trust in Provincial Government / National Government / Tax Ministry.* This is a Likert scale variable increasing in the level of trust the respondent reports having in each organization. The exact baseline collector survey question is as follows:

    - ‘I am going to name a number of organizations. For each one, could you tell me how much confidence you have in them: no confidence at all, not much confidence, quite a lot of confidence, a great deal of confidence?’
    - Organizations:
        (a) ‘The national government (in Kinshasa)’
        (b) ‘The provincial government’
        (c) ‘The tax ministry’

    The values were reversed to code this variable.

11. *Provincial Government Capacity.* This is a dummy variable equal to 1 if the collector believes that the government has the capacity to respond to an urgent situation. The exact baseline collector survey question is as follows: 'Imagine that many of the roads in central Kananga have been badly damaged due to bad weather. Do you think the local government would fix this problem within three months?' [no, yes]

12. *Provincial Government Responsiveness.* This is a Likert scale variable increasing in the respondent's perception of how responsive the provincial government is. The exact baseline collector survey question is as follows: 'To what degree does the provincial government respond to the needs of your avenue's inhabitants?' [Not very hard working, Hard working, Somewhat hard working, Not hard working]

13. *Provincial Government Performance.* This is a variable increasing in the respondent's perception of the overall performance of the provincial government. The exact baseline collector survey question is as follows: 'How would you rate the performance of the provincial government in Kananga?' [terrible, very poor, poor, fair, very good, excellent]

14. *Provincial Government Corruption.* This is a variable that reports what fraction of the tax revenues from the 2018 property tax campaign the respondent thinks the Provincial Government will put to good use. The exact baseline collector survey question is as follows: 'Now I would like to ask you what you think the provincial government will do with the money it receives from the property tax campaign this year. Imagine that the Provincial Government of Kasaï-Central receives $1000 thanks to this campaign. How much of this money will be put to good use, for example providing public goods?' [0-1000]

15. *Employed Through Connections.* This is a dummy variable equals to 1 if the respondent got his job as a tax collector for the Provincial Tax Ministry through a personal connection. The exact baseline collector survey question is as follows: 'How did you know that a position was available at the Provincial Tax Ministry?' [through a connection at the Provincial Tax Ministry, through a connection in the Provincial Government, I responded to job announcement from the Provincial Tax Ministry, I applied without knowing that the Provincial Tax Ministry was hiring]

16. *Relatives are Provincial Tax Ministry Employees.* This is a dummy variable that equals 1 if the respondent has a family member working at the Provincial Tax Ministry. The exact baseline collector survey question is as follows: 'Do you have a family member who is a Provincial Tax Ministry employee?' [no, yes]

17. *Relatives are Provincial Government Employee.* This is a dummy variable that equals 1 if the respondent has a family member working for the provincial government. The exact baseline collector survey question is as follows: 'Do you have a family member who is a Provincial Government employee?' [no, yes]

18. *Taxes are Important.* This is a Likert scale variable increasing in how important the respondent considers taxes to be. The exact baseline collector survey question is as follows: 'To what degree do you think that paying the property and rent taxes are important for the development of the province?' [not important, important, somewhat important, important, very important]

19. *Provincial Tax Ministry is Important.* This is a Likert scale variable increasing in how important the respondent considers the work of the Provincial Tax Ministry to be. The exact baseline collector survey question is as follows: 'To what degree do you think the work of the Provincial Tax Ministry is important for the development of the province?' [not important, important, somewhat important, important, very important]

20. *Paid Property Tax in the Past.* This is a dummy variable that equals 1 if if the respondent declared having paid the property tax in the past. The exact baseline collector survey question is as follows: 'Have you (or your family) paid your own property tax this year?' [no, yes]

21. *Importance of Progressive Taxes.* This is a dummy variable that equals 1 if the respondent reports that taxes in general should be progressive. The exact baseline collector survey question is as follows: 'Do you think all individuals should be taxed the same amount or should taxes be proportional to someone's income/wealth?' [everyone should pay the same amount, taxes should be proportional to someone's income/wealth]

22. *Importance of Progressive Property Taxes.* This is a dummy variable that equals 1 if the respondent reports that property tax rates should be progressive. The exact baseline collector survey question is as follows: 'According to you who should pay more property tax?' [only the poorest, mostly the poorest but also a little bit the rest of society, everyone should contribute the same amount, mostly the wealthiest but also a little bit the rest of society, only the wealthiest]

23. *Important to Tax Employed Individuals.* This is a Likert scale variable reporting respondent's view of the importance of taxing individuals with salaried jobs in Kananga. The exact baseline collector survey question is 'How important do you think it is to pay the property tax for property owners who are employed?' [not important, somewhat important, important, very important]

24. *Important to Tax Property Owners.* This is a Likert scale variable increasing in respondent's view of the importance of taxing property in Kananga. The exact baseline collector survey question is 'How important do you think it is to pay the property tax for property owners who have lived in a compound for many years?' [not important, somewhat important, important, very important]

25. *Important to Tax Property Owners with a Title.* This is a Likert scale variable reporting respondent's view of the importance of taxing property owners in Kananga. The exact baseline collector survey question is 'How important do you think it is to pay the property tax for property owners who have a formal land title?' [not important, somewhat important, important, very important]

26. *Intrinsic Motivation.* This variable is a standardized index increasing in respondents' intrinsic motivation to work as a tax collection. The exact endline collector survey questions used to create the standardized index are: 'Now, I want you to reflect on why you worked as a tax collector for the IF campaign of 2018. I am going to give you a series of possible reasons for why you did this work. For each reason, indicate if you strongly disagree, disagree, neutral, agree, strongly agree that this is a reason why you worked on the property tax campaign of 2018.' Responses:

    - 'I did this work because I derived much pleasure from learning new things.'
    - 'I did this work for the satisfaction I experienced from taking on interesting challenges.'
    - 'I did this work for the satisfaction I experienced when I was successful at doing difficult tasks.'

27. *Extrinsic Motivation.* This variable is a standardized index increasing in respondents' extrinsic motivation to work as a tax collection. The exact endline collector survey questions used to create the standardized index are: 'Now, I want you to reflect on why you worked as a tax collector for the IF campaign of 2018. I am going to give you a series of possible reasons for why you did this work. For each reason, indicate if you strongly disagree, disagree, neutral, agree, strongly agree that this is a reason why you worked on the property tax campaign of 2018. Responses:

    - 'I did this work because of the income it provided me.'
    - 'I did this work because it allowed me to earn money.'
    - 'I did this work because it provided me financial security.'