Shifting the Laffer Rate in Developing Countries: Evidence from Randomized Tax Rates in the DRC

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Abstract

This paper studies individual responses to tax rates and tax enforcement in the DRC, a low-capacity state. In collaboration with the Provincial Government of Kasaï Central, we evaluate a property tax campaign that randomly assigned 48,000 property owners to the status quo annual tax rate or to a tax reduction of 17%, 33% or 50%. We find that tax rates are above the revenue maximizing ("Laffer") tax rate: a 1% increase in the tax rate leads to a 0.26% decrease in tax revenue. Machine-learning estimates of heterogeneous treatment effect suggests that liquidity constraints likely explain this large response to tax rates. Beyond higher revenues, lowering tax rates reduces bribe payment to tax collectors and increases citizens' perception that the property tax is fair. Finally, we exploit two sources of variation in the enforcement environment – randomized enforcement letters and random assignment of tax collectors – to show that the elasticity of tax revenue with respect to the tax rate increases with enforcement. Investments in government enforcement capacity can therefore shift up the revenue maximizing tax rate.

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1 Introduction

A rudimentary level of state capacity is thought to be a precondition for economic development (Besley and Persson, 2009, 2013). Tax capacity, in particular enables states to provide public goods and is also associated with more accountable and responsive governance (Besley and Persson, 2009, 2013; Paler, 2013; Weigel, 2019; Martinez, 2019). But the transition to becoming a "tax state" is perhaps the greatest challenge of state capacity building (Schumpeter, 1918).

How should governments in the world's poorest countries set tax rates to maximize their tax capacity? The so-called "Laffer Curve" suggests that above a certain rate, increases in the tax rate will produce lower revenue due to behavioral responses (e.g. through evasion or changes in labor supply, taxable income, wealth) and as a consequence there exists a revenue maximizing ("Laffer") rate. A nascent empirical literature has shown that tax rates are in general below this revenue maximizing tax rate in high-income countries (Saez et al. (2012)) as well as in middle-income countries (Basri et al., 2019; Brockmeyer et al., 2019). In low-income countries, where tax revenues are directly needed to support investment in public goods and infrastructures, there exist very little evidence on whether tax rates are below or above the "Laffer" rate, beyond theoretical work suggesting that with low tax enforcement, high non-compliance rates can set a ceiling on the revenue maximizing tax rate (Besley and Persson, 2009; Slemrod, 1994; Keen and Slemrod, 2017).

In settings where tax compliance is low, how individuals respond to tax rates additionally depends on the enforcement environment (Slemrod, 2019). Thus the revenue maximizing tax rate can therefore be thought of as a policy choice rather than an immutable parameter of the economy (Slemrod and Kopczuk, 2002; Kopczuk, 2005; Saez et al., 2012; Keen and Slemrod, 2017). In theory, it has been argued that increasing enforcement capacity in low-enforcement countries could shift up the revenue maximizing ("Laffer") tax rate (Slemrod, 1994; Slemrod and Kopczuk, 2002; Keen and Slemrod, 2017). However, there is surprisingly scant evidence on how responses to tax rates in low tax capacity vary with stronger enforcement, partly because sources of exogenous variation in both tax rates and enforcement in low tax capacity countries have been so far elusive.

This paper breaks new grounds on these questions by examining how tax revenues respond to experimental variations in tax rates and enforcement in the Democratic Republic of the Congo, an extremely poor and low tax capacity state. In the first part of the paper we exploit what is to our knowledge the first field experiment to randomize tax rates combined with administrative tax data on tax payments to estimate the elasticity of tax revenue with respect to the tax rate. In the second part of the paper we study how this elasticity responds to changes in the enforcement environment, leveraging exogenous shocks in enforcement threats and tax collector capacity. Both pieces of evidence are crucial to evaluate how tax

rates should be set in our setting but also more generally in low tax capacity countries.

In collaboration with the provincial government of Kasaï Central, in the Democratic Republic of the Congo, we conduct the first field experiment to randomize tax rates. Property tax rates were randomized at the property level as part of the 2018 door-to-door city-wide property tax campaign covering 48,000 properties in the city of Kananga. Property owners randomly face the status quo tax liability or a reduction of 17%, 33% or 50% in their annual tax liability. Using the randomly generated variations in the tax rate faced by property owners we show that lowering tax rates increases tax revenues. The random variations in tax rates also allow us to estimate the elasticity of tax revenue with respect to the tax rate. We find that the elasticity is $\hat{\varepsilon}_{R,\tau} = -0.26$, which implies that a 1% increase in the property tax rate leads to a decrease in tax revenue of 0.26%. A negative elasticity implies that the Provincial Government of Kasaï Central could increase tax revenue by lowering the property tax rate. In other words, the property tax rate is above the revenue maximizing ("Laffer") rate.

To explore the possible mechanisms behind the large effects of random assignment to a reduction in the status quo tax rate on tax compliance and tax revenue, we exploit the generic machine learning inference methodology developed by Chernozhukov et al. (2018) to study heterogeneous treatment effects in randomized experiments. Using this approach we find that the large effect of assignment to tax rates on tax compliance and revenue are likely to be explained by variations in liquidity constraints: assignment to a reduction in the status quo tax rate has the most effect on the compliance of individuals with low levels of cash on hand.

Beyond generating higher tax revenues, we find that lowering the property tax rate results in significantly lower amounts of bribes extracted by tax collectors ($\hat{\varepsilon}_{B,\tau} = 1.64$). Part of the increase in tax compliance associated with lower tax rates can therefore be attributed to citizens deciding to substitutes tax payments in place of bribes when the tax rate decreases. We do not find evidence that assignment to a lower property tax rate affects payment of other taxes, neither formal (firm tax, vehicle tax, market tax) nor informal, or changes citizens' overall view of the state. However, we do find evidence that assignment to a lower tax rate increases citizens' perception that property tax collection and property tax rates are fair.

While we find that status quo property tax rates in our context are above the revenue maximizing tax rate, recent theoretical work suggests that the government could shift up the revenue maximizing tax rate by strengthening its enforcement efforts (Keen and Slemrod, 2017). In the last section of the paper we exploit two exogenous sources of variations in enforcement to offer empirical evidence on this question. First, we exploit variation in enforcement from tax letter messages. On the tax notices distributed to taxpayers containing the tax rate were randomly assigned messages. We compare the enforcement message, which reminded taxpayers about the penalties and legal processes for tax evaders, to a placebo message. The estimated elasticity of tax revenue with respect to the tax rate increases significantly with exposure to the enforcement message.

Second, we use the random assignment of tax collectors to neighborhoods as a second shock to the enforcement environment. Tax collectors vary in their intrinsic enforcement ability, which we measure as the total tax revenue they collect, irrespective of rates. Neighborhoods receive enforcement shocks of different magnitudes based on the individual enforcement abilities of the tax collectors to which they are assigned. This approach yields comparable estimates to the tax letter approach: at the collector level, the elasticity of tax revenue to the rate also increases with enforcement capacity. These results suggest that tax enforcement and high tax rates are complements. State investments in enforcement capacity can shift up the revenue-maximizing tax rate in low-income countries.

Finally, we explore what tax collector qualities are correlated with enforcement capacity. We ask this question because governments may seek to enhance tax enforcement by recruiting certain types of individuals as collectors. We find that high tax morale and trust in the government predicts enforcement capacity and a higher elasticity of tax revenue with respect to the tax rate. Hiring collectors with these characteristics, or instilling them through training, may allow governments to increase their Laffer rate.

This paper contributes to three main literatures. First, there is the aforementioned empirical literature documenting that tax rates are below the revenue-maximizing tax rate in developed countries (Saez et al., 2012) as well as in middle-income countries (Basri et al., 2019; Brockmeyer et al., 2019). We make several contributions to this literature. First, we show that tax rates can be above the revenue-maximizing tax rates in low-income and low-enforcement settings. Second, we are able to shed some light on the mechanism explaining why tax compliance are above the revenue-maximizing rate in our setting: lower tax rates increase government revenue through a large increase in compliance which appears to be driven by liquidity constrained individuals entering the tax base only when tax rates are sufficiently low. Third, unlike previous studies, we are able to measure other behavioral responses to changes in tax rates such as bribe payments to tax collectors, payments of other taxes (formal or informal) and views of the government.

Second, we contribute to the literature that argues that individuals' responses to tax rates depend on the enforcement environment (Slemrod, 2019) and that the revenue-maximizing tax rate should therefore be thought of as a policy choice rather than an immutable parameter of the economy (Slemrod and Kopczuk, 2002; Kopczuk, 2005; Saez et al., 2012; Keen and Slemrod, 2017). We make several contributions to this literature. First, we exploit two exogenous shocks to the enforcement environment to show that the elasticity of tax revenue with respect to the tax rate increases with enforcement. We are therefore able to show that government's enforcement efforts can shift up the revenue-maximizing tax rate and that tax rates and enforcement are complements in our setting. Second, we show that investments in tax collectors with high level of tax morale or trust in the state through training or recruitment, can shift up the Laffer rate.

Third, we broadly contribute to the literature on tax design and compliance in the developing world, which has chiefly examined middle-income countries. Past work examines how government can raise compliance and revenue through third-party reporting (Pomeranz, 2015; Naritomi, 2019; Jensen, 2019), providing information about peer behavior or enforcement (Del Carpio, 2013; Pomeranz, 2015), changes in tax administation (Basri et al., 2019) and reducing bureaucratic barriers to compliance (Best et al., 2015; Kleven and Waseem, 2013). In particular, we contribute to a small but growing literature on property taxation in low income countries, where property taxes are vastly underexploited. Several tools to increase property tax compliance have been discussed in the literature: Del Carpio (2013) studies the effect of social norms in Peru, Okunogbe (2019) test the impact of improved enforcement capacity in Liberia, Khan et al. (2015) evaluates the impact of performance incentives on tax inspectors in the context of property taxation in Pakistan and Brockmeyer et al. (2019) broadly discuss how to optimally design property tax schedules in Mexico. We contribute to this literature by providing evidence from a low-capacity state and by focusing on the role played by tax rates in increasing tax compliance and revenue and how this role depends on the enforcement environment.

The remainder of this paper is organized as follows. Section 2 reviews the setting. Section 3 introduces the experimental design. Section 4 describes our data. Section 5 presents responses to randomly assigned property tax rates in terms of tax compliance and revenue. Section 6 discusses potential mechanisms. Section 7 presents other behavioral responses to randomly assigned property tax rates. Section 8 discusses how the responses to randomly assigned tax rates varies with the enforcement environment. Finally, section 9 concludes.

2 Setting

The DRC is the fourth most populous country in Africa, and one of the five poorest in the world[2]. Our study takes place in the Kasaï Central province, one of the poorest in the DRC. Median monthly household income in the study site is roughly $ 70, PPP $111 (Lowes et al., 2017; Weigel, 2019). The country is often termed a 'kleptocracy' due to the corrupt rule of long time president Mobutu Sese Seko or a 'failed state' due to its history of civil conflict (Sanchez de la Sierra, 2019). It has low capacity across all dimensions, and especially in terms of tax capacity. In tax revenue as a percent of GDP, the DRC ranks 188 out of 200 countries for the period 2000 to 2017[3].

Kananga where our study takes place, is a city of roughly 1 million inhabitant (the fourth largest in the DRC) and the seat of the Provincial Government of Kasaï Central. Its tax revenues are extremely low: roughly $2 million USD per year for a province of 6 million people.

[2]see http://wdi.worldbank.org/table/1.2

[3]see https://data.worldbank.org/indicator/gc.tax.totl.gd.zs

The majority of these tax revenues come from trade and rental taxes levied on a handful of firms in downtown Kananga, such as mining and mobile-phone companies. Although there are many taxes on the books, few are enforced among private citizens in Kananga. At baseline, about 20 % of the citizens reported paying any taxes in the previous year[4]. The lack of a broad tax base is a challenge to the provincial government of Kasaï Central and more generally to governments in developing countries (Gordon and Li, 2009).

Due to unexpected shortfalls in tax revenue in 2015, the Provincial Government of Kasaï Central decided to systematically collect property taxes door-to-door in Kananga[5]. It thus followed suit with other local governments in developing countries who have adopted property taxation because of its efficiency and its ability to capture some of the rapid growth in real state values (Fjeldstad et al., 2017). Prior to 2016, property owners were supposed to visit the tax ministry themselves to pay and as a consequence compliance was near zero[6]. Beginning in 2016 property taxes were collected by agents of the provincial tax ministry door-to-door. While door-to-door tax collection resulted in a 10 percentage point increase in property tax payments, nearly 90% of property owners did not pay and were simply non compliant since less than 1% of the property owners reported paying a bribe instead of the property tax (Weigel, 2019). Property tax collection was discontinued by the Provincial Government in 2017 due to a conflict between the Kamuina Nsapu militia and the national army but was resumed in 2018 when our experiment takes place. Because door-to-door tax collection is very recent, only occurred once and resulted in a low level of tax compliance, knowledge of the property tax is still relatively low in Kananga. While at baseline 89% of the respondents had heard the name of the provincial tax ministry, only 29% had heard of the property tax and only 2.16% could accurately tell to the enumerators the property tax rate they should pay given their house type.

In sum, Kananga is a good setting in which to investigate how randomly assigned tax rates affect individuals' compliance decision as well as tax revenues. First, understanding

[4]The most common taxes reported to be paid are: the bike tax (reported by 11.27% of the citizens), the property and rental tax (reported by 3.81% of the citizens), the firm tax (reported by 3.58% of the citizens), the insurance tax (reported by 3.49% of the citizens), the toll tax (reported by 2.66% of the citizens), the transportation tax (reported by 1.73% of the citizens), the vehicle tax (reported by 1.13% of the citizens) and the market tax (reported by 0.65% of the citizens). The low percentage of citizens who report paying taxes is partially offset by contributions in informal taxes (Olken and Singhal, 2011). In Kananga, informal taxation (or *salongo*) is organized by local notables (avenue chiefs) regularly (in theory on a weekly basis). During *Salongo* citizens most often clean the streets and sometimes engage in more substantive activities such as trying to prevent erosion from damaging properties or improving a well or a water source . About 37% of our midline respondents reported that a household member participated in informal taxation in the past two weeks.

[5]As mentioned in Weigel (2019), the 2015 *découpage* (administrative splitting) of the 11 old provinces into 26 new provinces meant that the diamond-rich region around Tshikapa, a large source of revenue for the Kananga-based tax ministry, was no longer part of the province. Facing tax revenue shortfalls, the governor turned to property taxes.

[6]According to Weigel (2019), there were less than 300 property tax payments recorded in 2015 and 86% were made by firms

how tax rates affect compliance and revenue is especially key in a context where government revenues are low, which in turns results in citizens having little access to running water, electricity, roads, public education or public health. Second, the lack of knowledge by citizens about the property tax rates prior to the intervention allowed the provincial government to randomize property tax rates without having to worry about peoples' prior about the tax rate affecting their response.

3 Experimental Design

In this section we describe our research design. We first describe property tax collection during the 2018 campaign when our experiment took place. We then provide some background on property tax rates in Kananga and describe how the randomization of property tax rates was conducted.

3.1 Property Tax Campaign

The experiment took place during the 2018 property tax campaign in the city of Kananga. Before the start of the tax campaign, collectors were trained by the tax ministry and by members of the research team. Training sessions, conducted at the tax ministry, introduced tax collectors to the door-to-door taxation protocol and taught the future tax collectors how to manipulate the handheld receipt printers used during tax collection, how to identify the different types of properties in Kananga and what the property tax exemption criteria are.

The first step of the property tax campaign consisted in the construction of the property register, which took place on the first few days of each month. During this step, teams of tax collectors visited every house in each neighborhood, accompanied by an independent enumerator (who work for the research team) trained to use tablets with GPS capabilities. The property registration visit served four purposes. First, tax collectors informed property owners about the tax campaign, which includes determining if the house is built in durable or non-durable materials - which are taxed differently as described in section 3.2.1 - and whether a property owner is exempt. Second, properties are assigned a unique code and are given a tax letter containing their randomly assigned tax rate as described in section 3.2.2. These codes effectively produce a cadastral map of the city and enable subsequent door-to-door tax visits. Third, collectors can collect taxes from property owners during this visit. Finally, independent enumerators fill out a short survey recording details about the property that we will use in our analysis.

Upon completion of the property registration visit, tax collectors begin door-to-door tax collection which is the second step of the tax campaign and lasts for the rest of each month. The collection team receives a paper copy of the property register for the neighborhood where

they are assigned to collect taxes. This property register contains the property code, name of the property owners, whether the owner is exempted from the property tax, and the tax rate randomly assigned to the property as described in section 3.2.2. During tax collection, collectors work without being accompanied by an enumerator. Collectors are equipped with handheld receipt printers to issue receipts to taxpayers. When a property owner pays the tax, two receipts are automatically printed in the field, one for the taxpayers and one of the collector. Collectors bring the money weekly to the provincial tax ministry, account for the money they deposit, and need to justify any discrepancy between the total sum on their report (from their copy of the paper receipts and from the handheld printers which stored each printed receipt in their memory) and the money they have with them.

Consistent with standard practices at the tax ministry, all tax collectors receive a bonus for working on the campaign. First, they receive a bonus for constructing the property register, equal to 30 CF per property visited. Second, they receive a performance-based bonus for collecting taxes. The amount of this performance-based bonus was randomly assigned at the property level before tax collection, which was made possible by the Provincial Government's desire to evaluate the effect of collectors' compensation on their performance, which we study in a companion paper (Bergeron et al., 2020). Non-durable properties were randomly assigned to a proportional collector bonus equal to 30% of the amount of tax collected or to a fixed collector bonus of 750 CF. For durable properties the collector bonus was not randomized but fixed at 2,000 CF per property. The size of the collection bonus in our context is analogous to incentives paid to property tax collectors in other low income countries (Khan et al., 2015; Amodio et al., 2019). Finally all tax collectors are given transport funds on a weekly basis for hiring motorcycle taxis to visit the neighborhoods where they are assigned to work and for their weekly visit to the tax ministry to deposit money form tax collection[7].

3.2 Experimental Design

3.2.1 Tax Rates Description

Rather than facing a property tax schedule that applies marginal tax rates to property value, as is common in both high and middle-income countries (Khan et al., 2015; Brockmeyer et al., 2019) properties in Kananga face a fixed annual tax liability. The status quo tax rate for properties built in non-durable materials is therefore 3,000 CF (or about $2 USD) while it is 13,200 CF (or about $9 USD) for properties built in non-durable materials. There are 47,157 properties in Kananga. Among these, 40,958 (or 86.44% of the properties) are built in non-durable materials and face a status quo tax rate of 3,000 CF, while the remaining 5,914 (or 12.56% of the properties) are built in durable materials and face a status quo tax rate is 13,200

[7]Transport costs, which vary by neighborhood, were carefully estimated by the enumerators as well as through interviews with motorcycle taxi operators.

CF[8]. See Appendix Figure A1 for an example of properties built in non-durable and durable materials.

The use of fixed annual fees by the provincial tax ministry - rather than applying a marginal tax rate to a property value - is mostly explained by 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 associated with the constitution of property valuation rolls mean that out of the 159 non-OECD countries in the World Banks' *Doing Business Survey*, only a third have registered and mapped their main city's private plots (Lall et al., 2017). Some low income countries -particularly in Sub-Saharan Africa - have adopted fixed annual fees for property taxation as is the case in our setting (Franzsen and McCluskey, 2017).

Though the tax rates might seem low when expressed in USD, we can use the predicted property value for all the properties in Kananga using Machine Learning - as described in section 4 - to estimate the property tax rate in percentage of the property value. We find an average property tax rate of 0.22% of the property value in Kananga, which is not substantially different from the property tax rates levied by local governments in high and middle-income countries. For example, in the Unites States the effective property tax rate in percent of property value vary from 0.27% in Hawaii to 2.44% in New Jersey.

3.2.2 Tax Rates Randomization

As part of its 2018 property tax campaign in Kananga, the Provincial Government of Kasaï Central randomized the amount of the fixed annual tax rate faced by each property owner. Why did the Provincial Government of Kasaï Central randomize property tax rates in 2018? While the 2016 property tax campaign substantially increased provincial tax revenue, tax compliance and revenues remained low (10% of the property owners paid the property tax in 2016). One consequence of this low level of compliance was that the Provincial Government was keen on having a better understanding of the effects of tax rates on tax compliance and revenues, which could be achieved through randomizing tax rates. In particular, the former minister of taxation argued that too high property tax rates were part of the reason why tax compliance and revenue were low and as a consequence it was decided to randomize reductions in the fixed annual property tax rate.

Property owners were thus randomly assigned to the status-quo annual tax rate (3,000 CF for non-durable properties and 13,200 CF for durable properties) or to reductions of 17% (2,500 CF for non-durable properties and 11,000 CF for durable properties), 33% (2,000 CF for non-durable properties and 8,800 CF for durable properties) or 50% (1,500 CF for non-durable properties and 6,600 CF for durable properties) in the status quo annual tax rate.

[8] A last category of properties consist in 285 (or 1.06% of the properties) extremely high value properties called "villas". They are not included in our sample since they are taxed according to a different tax schedule and by different tax collectors

The tax liability randomly faced by a property owner for 2018 was directly printed on the tax letter received by each owner during property registration to minimize transaction utility effects (Thaler, 1983) as discussed in section 5.3. See Appendix Figure A2 for examples of tax letters for property owners assigned to each of the tax rate treatments.

Assignment to a tax rate treatment was randomized at the property level and stratified at the neighborhood level[9]. There are 351 randomization strata (i.e. neighborhoods) in our final sample [10]. In Table 1 we report summary statistics and balance test for selected baseline and midline property and property owner characteristics. In Panel A we consider all the property characteristics collected during the midline survey: walls quality, roof quality and erosion threat. In Panel B we consider all the property owners' characteristics collected during the midline survey: gender, age, years lived on the avenue, an indicator for being of the main tribe (luluwa), an indicator for being salaried, for being employed, for working for the government and for having a relative who works for the government. Finally in Panel C we consider a few selected characteristics of the property owners collected during the baseline survey: number of years of education, an indicator for having access to electricity, the logarithm of the monthly income in Congolese Francs, trust in the chief, in the national government, in the provincial government and in the provincial tax ministry.

Overall, 1 of the 54 differences reported in Table 1 is significant with $p < 0.05$ and 2 of the 54 are significant with $p < 0.1$ based on t-tests that do not adjust for multiple comparisons, in line with what one would expect under random assignment. We also test the omnibus null hypothesis that the treatment effects for the covariates studied in Table 1 are all zero using parametric F tests. As one would expect under random assignment, we fail to reject the null for the midline survey variables (status quo rate vs 17% reduction: $F = 0.897$ and $p = 0.542$; status quo rate vs 33% reduction: $F = 0.491$ and $p = 0.910$; status quo rate vs 50% reduction: $F = 0.816$ and $p = 0.624$) as well as for the baseline survey variables (status quo rate vs 17% reduction: $F = 0.989$ and $p = 0.437$; status quo rate vs 33% reduction: $F = 0.334$ and $p = 0.939$; status quo rate vs 50% reduction: $F = 0.877$ and $p = 0.524$), thus giving us further reassurance that the randomization was successful.

[9]each neghborhood was identified on a satellite map using natural boundaries like roads, ravines, or other natural features that would be easily identifiable from the ground.

[10]There are 364 neighborhoods in total in Kananga. We excluded the 8 neighborhoods that were part of a logistic pilot that the provincial government of Kasaï Central conducted several weeks before the launch of the 2018 property tax collection and 5 neighborhood where no door-to-door tax collection took place as described in Balan et al. (2020).

TABLE 1: RANDOMIZATION BALANCE

	Sample (1)	Obs. (2)	Status quo Mean (3)	17% Reduction (4)	33% Reduction (5)	50 % Reduction (6)
Panel A: Property Characteristics						
Roof Quality	Midline	25,407	4.967	-0.003	-0.013*	-0.009
				(0.006)	(0.007)	(0.007)
Walls Quality	Midline	25,410	2.177	-0.010	-0.020	-0.035**
				(0.014)	(0.014)	(0.014)
Erosion Threat	Midline	31,091	0.403	-0.001	-0.005	0.003
				(0.008)	(0.008)	(0.008)
Panel B: Property Owner Characteristics						
Gender	Midline	19,579	0.773	-0.009	0.003	-0.002
				(0.008)	(0.008)	(0.008)
Age	Midline	17,321	54.171	0.237	-0.051	-0.085
				(0.287)	(0.288)	(0.288)
Years Lived on Avenue	Midline	14,308	16.373	0.156	-0.415	-0.049
				(0.346)	(0.338)	(0.335)
Main Tribe Indicator	Midline	19,910	0.795	0.003	0.007	-0.007
				(0.008)	(0.008)	(0.008)
Employed Indicator	Midline	21,528	0.736	0.003	-0.001	0.011
				(0.008)	(0.008)	(0.008)
Salaried Indicator	Midline	21,533	0.244	0.002	-0.006	-0.005
				(0.008)	(0.008)	(0.008)
Work for Government Indicator	Midline	21,531	0.148	0.006	-0.002	0.005
				(0.007)	(0.007)	(0.007)
Relative Work for Government. Indicator	Midline	23,855	0.225	0.007	-0.006	0.011
				(0.008)	(0.008)	(0.008)
Panel C: Property Owner Characteristics						
Years of Education	Baseline	2,807	10.298	-0.118	-0.098	-0.142
				(0.234)	(0.236)	(0.243)
Has Electricity	Baseline	2,816	0.131	-0.014	-0.002	-0.016
				(0.019)	(0.020)	(0.019)
Log Monthly Income (CF)	Baseline	2,816	10.527	-0.013	-0.001	-0.240
				(0.131)	(0.130)	(0.146)
Trust Chief	Baseline	2,805	3.180	-0.022	-0.031	-0.067
				(0.058)	(0.059)	(0.059)
Trust National Government.	Baseline	2,665	2.525	-0.009	-0.070	0.028
				(0.072)	(0.074)	(0.074)
Trust Provincial Government	Baseline	2,683	2.452	-0.039	-0.013	-0.020
				(0.071)	(0.072)	(0.071)
Trust Tax Ministry	Baseline	2,654	2.333	0.051	0.028	0.062
				(0.070)	(0.071)	(0.071)

Notes: This table reports the coefficients from balance tests estimated by regressing midline property characteristics (Panel A), midline property owner characteristics (Panel B) and baseline property owner characteristics (Panel C) on all the tax rate treatment indicators. Each row shows the estimates from a separate regression of the characteristics on the the tax rates treatment indicators. All measures are drawn from midline and baseline surveys described in Section 4. Wall quality is a 0–4 Likert scale rating the materials of the walls of the property. Roof quality is a 1–7 Likert scale rating the materials of the roof of the property. Erosion threat is a 0-2 Likert scale rating how threatened the property is by erosion. Male, age, years of education, age, and male are characteristics of the property owner. Electricity, whether the walls and roof of the households are in good conditions, and an indicator for whether a property are affected by erosion describe property characteristics. Log monthly income (in Congolese francs) is for the entire household. Connected to chief is an index of measures including whether a property is related to the chief, knows the chief, has his or her phone number, and attends the same church. The trust measures are 1–4 Likert scales rating the property owner's trust of distinct entities.

4 Data

Data come from five sources: (1) administrative data on property tax payment, (2) a baseline survey before the campaign, (3) a midline survey during the campaign, (4) an endline survey after the campaign, (5) estimated property values using machine learning.

Administrative Data - Administrative data come from the government's official tax database. This database was managed by a company, KS, which integrated raw data from tax collector's hand receipt printers with the existing bank data[11]. We link official tax records to survey data using the unique household tax identification number assigned during property registration.

Baseline Survey - Baseline survey enumeration occurred between July and December 2017, before tax collection started. Independent enumerators randomly sampled compounds following skip patterns while walking down each avenue in a neighborhood: e.g. visit every Xth property in the neighborhood, where X was determined by the estimated number of properties and a target of 12 per neighborhood. We use a selected group of baseline characteristics to assess balance of the randomized tax rate treatment in Table 1. We use a different selected group of baseline characteristics to study heterogeneity of the treatment effects in section 6.

Midline Survey - Enumerators conducted a midline survey in all compounds on average 4-6 weeks after tax collection ended in that neighborhood[12]. The midline survey aimed at measuring characteristics of the property and of the property owner that we use to assess balance of the randomized tax rate treatment in Table 1. We also use these characteristics to study heterogeneity of the treatment effects in section 6. The midline survey also aimed at measuring whether tax collectors engaged in bribery as well as households contributions to informal taxes which we use as secondary outcomes in section 7. Because the population to survey was large and the survey had to be implemented a few weeks after talk collection ended in each neighborhood, it was not possible to conduct more than one visit per property. Yet, we were able to find 36,495 of the 49,921 property owners in the registration sample (i.e. 73% of

[11]The printers record the collector's name and ID number, date and time stamps, neighborhood number, the code assigned to each property during property registration, the property category (durable vs non-durable), the applied tax rate, and the amount paid.

[12]During property registration, we also administered a short survey for all the 49,921 properties in our sample. This registration survey recorded the code assigned to each property, its GPS location, the name of the property owner, whether the main house in the property is built in durable vs non-durable materials, the property owner's exemption status, the tax rate assigned to each property owner as described in section 3.2.2. The survey also contained the protocol read by the tax collectors to inform the property owner about the property tax campaign and recorded wether the property tax was collected during the registration visit.

the property owners in the registration sample). We show that attrition in the midline sample is not explained by the randomized tax rate treatment assignment in the Online Appendix.

Endline Survey - Endline survey enumeration occurred between March and September 2019, after tax collection had ended. The endline survey instrument covered a wide range of property owner's characteristics and allowed to measure if our intervention affected households' propensity to pay other formal taxes (market tax, firm tax, vehicle tax) as well as owners' trust in and perceived performance of the national government, the provincial government and the provincial tax ministry. We also ask respondents to assess how fair they thought the overall property tax collection process was and ask them the same fairness question about the property tax rates and the property tax collectors. We use these survey questions as secondary outcomes in section 7. We were able to survey 3,950 respondents of our baseline sample of 4,343 respondents (or 90.95% of them) at endline. We show that attrition in the endline sample is not explained by the randomized tax rate treatment assignment in the Online Appendix.

Predicting Property Value using Machine Learning - We constructed the predicted value of every property in our sample using Machine Learning. As described in details in Bergeron et al. (2020a), we trained several machine learning algorithms on a training sample of 1,950 properties for which the value of property replacement was estimated by government land surveyors following in-person property appraisal visits. As discussed in the Online Appendix the best algorithm is LightGMB, a gradient boosting model that uses tree based learning algorithms. When training each algorithm, we only include the 15 most important property and neighborhood characteristics from the baseline and midline survey to avoid overfitting. Using 10-fold cross-validation, Light GBM achieves an out-of-sample mean absolute percentage error (MAPE) of 44% which is much lower than when using other standard machine learning methods such as k-nearest neighbor (MAPE=167%), ridge regression (MAPE=142%) support vector regression (SVR) (MAPE=120% with a linear kernel and MAPE=83% with a radial basis function kernel) or random forest (MAPE=99%). We use the predicted property value for each property in our sample in section 5, 7 and 8.

Summary - Table 2 summarizes the activities of the collectors, the enumerators and the land surveyors. All research components of the study - baseline, midline, and endline survey - were constant across tax rate treatment groups . What varied across treatment groups was assignment to a tax rate treatment group.

TABLE 2: ACTIVITIES OF COLLECTORS, ENUMERATORS AND LAND SURVEYORS

Activity	Timing	N	J
Tax collectors			
Property register	May-Dec 2018	49,921	356
Tax collection	May-Dec 2018	49,921	356
Enumerators			
Baseline citizen survey	Jul-Dec 2017	4,343	356
Midline citizen survey	Jun '18-Feb '19	36,495	356
Endline citizen survey	Mar-Sep 2019	4,343	356
Both			
Baseline collector survey	Jan-Apr 2018	493	N/A
Endline collector survey	Feb-Apr 2019	490	N/A
Land Surveyors			
Property value estimation	Aug-Oct 2019	1950	356

N= Number of observations, J= number of clusters.

5 Responses of Tax Revenues to Tax Rates

5.1 Reduced Form Results

We first show the reduced form effects of being assigned to the different tax rates and estimate the following regression:

$$y_{in} = \beta_0 + \beta_1 Reduction17\%_{in} + \beta_2 Reduction33\%_{in} + \beta_3 Reduction50\%_{in} + \gamma_{in} + \delta_n + \epsilon_{in} \quad (1)$$

where y_i measures the outcome of interest (tax revenue and tax compliance) for indivudal i in neighborhood n. The variables $Reduction17\%_{ip}$, $Reduction33\%_{ip}$ and $Reduction50\%_{ip}$ are indicators for being assigned to a reduction of 17%, 33% or 50% in the status quo annual tax rate, which is considered here as the control group. γ_{in} is an indicator for whether the house house is built in durable or non-durable materials - which in turns determines the property tax they face as described in section 3.2.1 and 3.2.2, δ_n are the randomization strata (neighborhood) fixed effects and δ_{in} is the error term. Given that the treatment was randomized at the individual level, we follow (Abadie et al., 2017) and report robust standard errors.

We show the reduced form results in Figure 1. Panel A presents the results when using tax revenue as the outcome. Surprisingly, we find that tax revenue decrease as the tax rate increases. Tax revenues for the 33% and 50% reduction in the status quo tax rate are significantly higher than for the 17% reduction and the status quo tax rate treatment groups. The

results presented in Panel A of Figure 1 thus shows that tax rates in our context are above the revenue maximizing tax rate and that the government could increase its revenue by lowering the status quo tax rate. In particular, tax revenue are maximized for the 33% reduction in the status quo tax rate treatment group.

The decrease in tax revenue as a result of a change in tax rates is in our context entirely driven by changes in tax compliance. As explained in section 3.2.1, in our setting the tax rate is a fixed fee (rather than a percentage of the property value) and the tax amounts has to be paid in full by the property owner in order to receive a tax receipt. Panel B of Figure 1 presents the results when using tax compliance as the outcome. Tax compliance decreases monotonically with tax rates: from 12.6% compliance for the 50% reduction in the status-quo tax rate to 6.55% compliance for the status quo tax rate.

5.2 The Elasticity of Tax Revenue with Respect to the Tax Rate

We can summarize the magnitude of the response to changes in the tax rates by computing the elasticity of tax revenue with respect to the tax rate τ - which we denote $\hat{\varepsilon}_{R,\tau}$ - which is obtained by estimating the following two-stage least square specification :

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

$$\begin{aligned} log(\tau_{i,n}) = \beta_0 + \beta_1 Reduction17\%_{i,n} + \beta_2 Reduction33\%_{i,n} \\ + \beta_3 Reduction50\%_{i,n} + \gamma_{i,n} + \delta_n + \epsilon_{i,n} \end{aligned} \tag{3}$$

where $\tau_{i,n}$ is equal to the fixed tax rate assigned to property i divided by the predicted property value using Machine Learning, as described in section 4[13]. Equation (3) is the first stage of the instrumental variable model and Equation (2) is the second stage. The coefficient β is the marginal effect of a one log-point, or approximately one percent, change in the average tax rate τ_{in} on the outcome of interest y_{in}. This marginal effect is not an elasticity, but it can easily be transformed into one using the standard formula $\frac{\partial R}{\partial \tau} \times \frac{\tau}{R}$. Because we are using log of the tax rate as the independent variable, we can compute $\hat{\varepsilon}_{R,\tau} = \frac{\beta}{mean(R_{in})}$[14].

The elasticity of tax revenue with respect to the tax rate can be interpreted as the percent change in tax revenue when the tax liability increases by 1 %. Conveniently, it gives us a measure of whether tax rates are above or below the revenue maximizing rate. A positive elasticity of tax revenue with respect to the tax rate, $\hat{\varepsilon}_{R,\tau} > 0$ implies that tax rates are below the revenue maximizing rate and the government can increase its revenue by increasing tax

[13]Our estimates of the elasticity of tax revenue with respect to the average property tax rate are expressed in percentage of the property value, which allows us to relate our estimates to cases where the property tax rate is expressed in percentage of the property value (Brockmeyer et al., 2019).

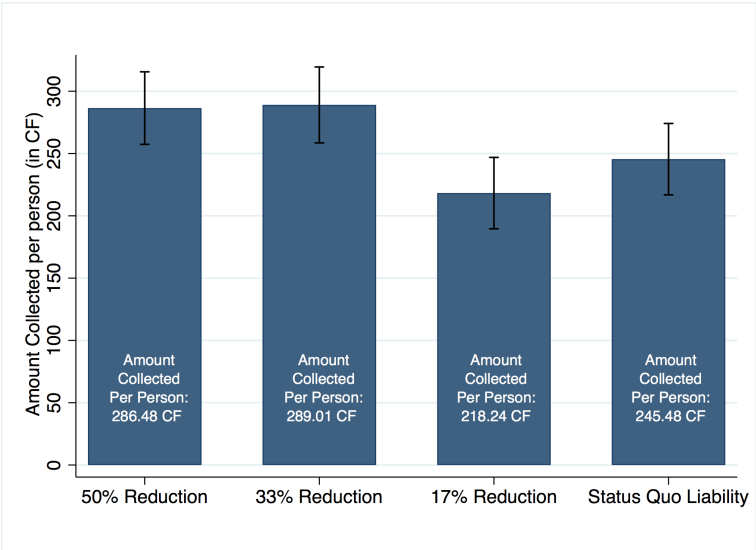
[14]Goldberg (2016) uses the same regression specification to estimate the elasticity of employment with respect to wages in rural Malawi

rates. Conversely, a negative elasticity $\hat{\varepsilon}_{R,\tau} < 0$ implies that tax rates are below the revenue maximizing rate and the government can increase its revenue by lowering tax rates.

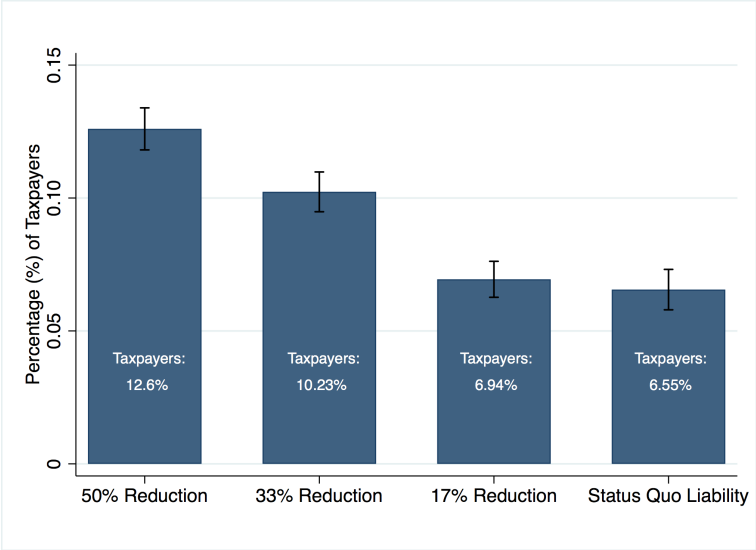
We summarize our results in Table 3. Overall, we confirm the reduced-form results presented in section 5.1 that tax rates are above the revenue maximizing tax rate, meaning that the government could increase it's revenue by reducing the tax rate in our setting. The average elasticity of tax revenue with respect to the tax rate is $e_{R,T} = -0.26$, which means that overall the government looses 0.26 % of revenue when it increases its tax rate by 1 %[15].

FIGURE 1: REDUCED FORM RESULTS

A: Tax Revenue



B: Tax Compliance



[15]We can also use the regression framework to estimate the elasticity of tax compliance with respect to the tax rate. We find $e_{C,T} = -1.19$.

TABLE 3: ELASTICITY OF TAX REVENUE AND COMPLIANCE WITH RESPECT TO THE TAX RATE

	Tax Compliance			Tax Revenue		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Tax Liability)	-0.105***	-0.103***	-0.100***	-61.816**	-59.642**	-47.421*
	(0.008)	(0.008)	(0.008)	(28.769)	(28.289)	(27.968)
Observations	38379	35648	3633	38379	35648	3633
Sample	All	All	All	All	All	All
House	Pooled	Periphery	Midrange	Pooled	Periphery	Midrange
Strata	363	363	363	363	363	363
Mean	.09	.09	.09	234.11	222.77	222.77
Elasticity	-1.19	-1.18	-1.14	-.26	-.27	-.21

5.3 Robustness Checks

A major concern is that our estimates might be biased if property owners know that their tax rate differs from their neighbors' tax rate. This could bias our estimate of the elasticity of tax revenue with respect to the tax rate for at least two reasons. First, if the decision to pay the property tax is determined by taxpayer's preferences for a fair tax system (Besley et al., 2019). Second, if the transaction utility (Thaler, 1988) associated with receiving a reduction in the status quo tax rate is a determinant of tax compliance. In the first case, a property owner assigned the status quo tax rate who knows that her neighbors have been assigned a lower tax rate might have a lower propensity to pay than a property owner who is assigned the status quo tax rate and doesn't know her neighbor's tax rate. In the second case, a property owner who is assigned a lower tax rate than his neighbor might decide to pay the tax because she knows that she received a reduction in the status quo tax rate but would not have paid had she not known that she had received a tax reduction.

It is worth mentioning that the design of the tax rate randomization aimed at minimizing such concerns: As shown in Appendix Figure A2, the tax rate faced by each property owner was directly printed on the tax letter received during property registration. For owners who received a 17%, 33% or 50% reduction in the status quo liability, no reference was made to receiving a reduction or to the status-quo tax rate.

To directly test whether we should potentially worry about these concerns, we conduct three robustness checks. In Appendix Table A1 we estimate the elasticity of tax compliance and directly control for neighbors' tax rates. In Appendix Table A2 we estimate the elasticity of tax compliance and revenue for property owners who declare knowing heir neighbors' tax rate as well as for property owners who declare not knowing their neighbors' tax rate. Finally, in Appendix Table A3 we estimate the elasticity of tax compliance and revenue for property owners who report knowing that they receiving a tax reduction and for owners who report not knowing that they receiving a tax reduction. While in some of the specifications the

significance of the estimate is affected due to the reduced sample size the sign and magnitude of the elasticity of tax revenue is left unchanged: in all specifications $\hat{\varepsilon}_{C,\tau} \approx -0.26$.

5.4 Discussion

We've shown in Figure 5.1 and in Table 3 that tax rates are above the revenue maximizing ("Laffer") rate: tax revenue decrease with the tax rate and that $\hat{\varepsilon}_{R,\tau} = -0.26$, i.e. a 1% increase in the tax rate leads to a 0.26% decrease in tax revenue. While we cannot generalize our findings to other contexts that the DRC, several recent studies have also found that tax rates are above or close to the revenue maximizing tax rates in settings characterized by low tax enforcement. Waseem (2018) shows that a change in the income tax rates faced by firms in Pakistan lead treated firms to report significantly lower earnings, migrated into informality, and switch business form. The revenue loss caused by these behavioral responses was so large that by the third year after the reform, the government was collecting less revenue than it would have without the tax increase, showing that the new tax rate was on the wrong side of the Laffer curve. Similarly, Bachas and Soto (2019) focus on changes in corporate income tax among firms in Costa Rica and find find that the large elasticity of profits for firms subject to the corporate income tax in Costa Rica means that the corporate income tax rates in Costa Rica are above the revenue maximizing tax rate.

6 Mechanisms

This section examines possible mechanisms behind the effects of random assignment to tax rates treatment groups on tax compliance and tax revenue: (1) lower tax rates brings in the tax base people who were not able to pay at the previous tax rate due to liquidity constraints, (2) lower tax rates brings in the tax base people who have negative views of the government and are only willing to pay at a low enough tax rate. To make progress on mechanisms, we study heterogeneous treatment effects by proxies for liquidity constraints as well as views of the government. Although the evidence in this section is more suggestive, it seems to support the first hypothesis.

To study heterogeneity in the treatment effects of being assigned to a higher tax rate we use the generic machine learning inference strategy developed in Chernozhukov et al. (2018) The main advantage of the authors' methodology is that it relies on data splitting to avoid overfitting and achieve validity. As a result it allows us to explore different dimensions of heterogeneity without having to worry about usual multiple hypothesis testing concerns (List et al., 2019)[16]. A second advantage of this methodology is that it allows to compare the

[16]We submitted our Pre-Analysis Plan to the American Economic Association's registry for randomized controlled trials (AEA RCT Registry) on January 28th 2019. The pre-analysis plan did pre-specify heterogeneous

characteristics of the most and least affected population in a much simpler way than when using other machine learning methods for estimating heterogeneous causal effects (Imai and Ratkovic, 2003; Athey and Imbens, 2015, 2016; Davis and Heller, 2017; Wager and Athey, 2019).

Conditional Average Treatment Effect (CATE) - We are interested in the Conditional Average Treatment Effect (CATE)

$$s_0(Z) = \mathbb{E}[Y|D = 1, Z] - \mathbb{E}[Y|D = 0, Z] \tag{4}$$

Since we care about understanding the determinants of tax compliance we focus on the case where Y is tax compliance. Our treatment of interest is change in tax rates so we consider the case where D=0 is assignment to a high tax rate treatment group and D=1 is assignment to a low tax rate treatment group. More specifically, to maximize power we focus on the case where $D = 0$ if the property owner is assigned to the status quo tax rate and $D = 1$ if the property owner is assigned to a 50% reduction in the status quo tax rate. Z are demographic characteristics of the property owner as well as proxies for liquidity constraints and views of the government from our baseline and midline survey. To proxy for liquidity constraints we use indicators for the respondents (or her relatives) having a regular source of income (an indicator for being salaried, for being employed, for working for the government and for having a relative who works for the government) and characteristics of the property (an index of quality / materials of the walls, an index of quality / materials of the roof and an index of erosion threatening the property). To proxy for views of the government we use measures of trust in the provincial government and satisfaction with the performance of the provincial government. We follow Chernozhukov et al. (2018) and report the Best Linear Predictor (BLP), the Group Average Treatment Effects (GATES) and the Classiffication analysis (CLAN) of the Conditional Average Treatment Effect (CATE).

Comparison of Machine Learning Methods - Table 4 compares three Machine Learning methods – Elastic Net, Boosting and Random Forest – for producing the best Best Linear Predictors (BLP) and the best Sorted Group Average Treatment Effects (GATES) of the effects in the auxiliary sample [17]. In this case, boosting comes out as the winner based on GATES targeting of CATE, followed closely by random forest. As a consequence, we focus on these

treatment effects but discussed using Chernozhukov et al. (2018) to characterize heterogeneous treatment effects.

[17]For BLP, the best Machine Learning method can be chosen in the main sample by maximizing $\Lambda = Corr^2(S_0(Z), S(Z))Var(S_0(Z))$ where $S_0(Z)$ is the average treatment effect (ATE) and $S(Z)$ is the Machine Learning proxy predictor of $S_0(Z)$. For GATES, the best ML method can be chosen in the main sample by maximizing $\bar{\Lambda} = \mathbb{E}\left(\sum \gamma_k 1_{\{S \in I_k\}}\right)^2$ where $\gamma_k = \mathbb{E}[S_0(Z)|G_k]$ are the GATES parameter and I_k are non-overlapping intervals that divide the support of S.

two ML methods for the rest of the analysis.

TABLE 4: COMPARISON OF MACHINE LEARNING METHODS

	Elastic Net (1)	Boosting (2)	Random Forest (3)
Best BLP	0.003	0.003	0.003
Best GATES	0.006	0.017	0.007

Notes: Medians over 1,000 splits in half.

Best Linear Predictor (BLP) - Table 5 presents results for the Best Linear Predictor (BLP) coefficients. In parentheses, we report confidence intervals adjusted for variability across the sample splits using the median method, and in brackets we report adjusted p-values. The average conditional treatment effect of a 50% decrease in the status quo property tax rate is a 5 percentage point increase in tax compliance and comes close to the unconditional treatment effect reported in Figure 1 as expected by virtue of the randomization. However, the slope of the BLP uncovers substantial heterogeneity across property owners. In particular, we reject the hypothesis that HET is zero at the 10% level for the tax payment indicator with the random forest and boosting methods, suggesting the presence of heterogeneity in the effect of assignment to lower tax rates on tax compliance.

TABLE 5: BEST LINEAR PREDICTOR

Random Forest		Boosting	
ATE (1)	HET (2)	ATE (3)	HET (4)
0.050	0.167	0.050	0.089
(0.033,0.067)	(0.005,0.334)	(0.033,0.067)	(0.005,0.173)
[0.000]	[0.098]	[0.000]	[0.096]

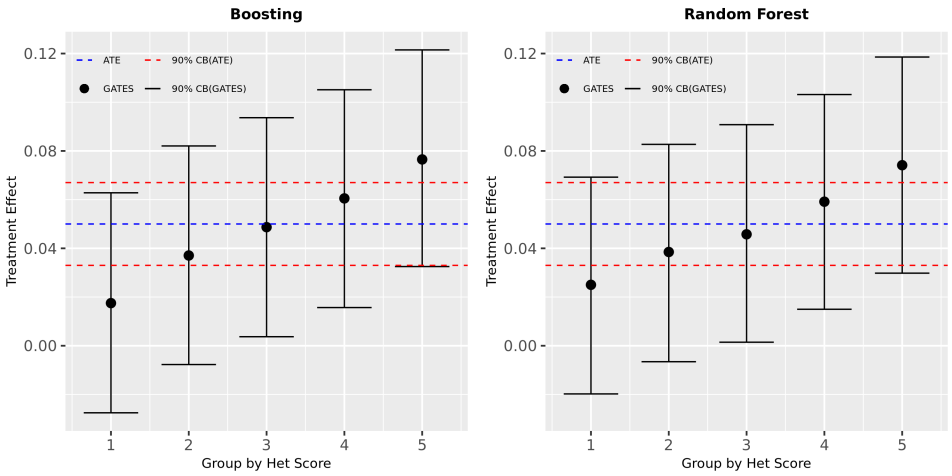
Notes: Medians over 100 splits. 90% confidence interval in parenthesis. P-values for the hypothesis that the parameter is equal to zero in brackets.

Group Average Treatment Effects (GATES) - To estimate the Group Average Treatment Effects (GATES), we divide the sample in $K = 5$ groups defined by the quintiles of the Machine Learning proxy proxy of the CATE, $S(Z)$ and estimate the average effect for each group. Figure 2 shows the estimated GATES coefficients $\gamma_k = \mathbb{E}[S_0(Z)|G_k]$ along with their joint confidence bands. We also report the ATE and its confidence interval that were obtained in the BLP analysis for comparison. Figure 2 confirms the amount of heterogeneity across property owners: the average conditional treatment effect of a 50% decrease in the status quo property tax rates ranges from about a 2 percentage point increase in tax compliance to a 8 percentage point increase in tax compliance across the groups.We also find that there are some groups

for which the GATES on the indicator for paying the property tax are significantly different from zero. These groups are likely to drive the heterogeneity in the treatment effect that we find in the BLP analysis. All the results for the GATES are fairly robust to the ML method.

FIGURE 2: REDUCED FORM RESULTS

A: GATES - Amount of Taxes Paid



Classification Analysis (CLAN) - We conclude by looking at the average characteristics of the most and least affected groups in the classification Analysis Table 6, which reports the Classification Analysis (CLAN) for the 20% least and the 20% most affected groups defined by the deciles of the CATE proxy $S(Z)$ as well as the difference between the two. We find that assignment to a 50% reduction in the status quo property tax rate has a stronger effect on tax compliance for individuals who are more likely to face liquidity constraints. This is true when using lack of access to a stable job as a proxy for liquidity constraints: individuals who respond more to the 50% reduction in the status quo property tax rate are significantly more likely to be unemployed, less likely to be salaried, less likely to work for the government or to have a relative who works for the government than individuals who respond less to the 50% reduction in the status quo property tax rate. This is also true when using property quality as a proxy for liquidity constraints: individuals who respond more to the 50% reduction in the status quo property tax rate live in a property with lower wall quality, lower roof quality, and more erosion threat than individuals who respond less to the 50% reduction in the status quo property tax rate. At the same time we fail to find evidence that assignment to a 50% reduction in the status quo property tax rate has a stronger effect on tax compliance for individuals who have more negative views of the state: individuals who respond more to the 50% reduction in the status quo property tax rate are less likely to trust the provincial government than individuals who respond less to the 50% reduction in the status quo property tax rate, but not significantly so.

Table 6: Taxes Paid Indicator - Classification Analysis

	Random Forest			Boosting		
	20 % Most Affected	20 % Least Affected	Difference	20 % Most Affected	20 % Least Affected	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Demographics:						
Male	0.864	0.792	0.077	0.865	0.819	0.043
	(0.843,0.884)	(0.772,0.812)	(0.047,0.107)	(0.844,0.885)	(0.799,0.840)	(0.015,0.071)
			[0.000]			[0.006]
Age	52.27	51.58	1.397	51.88	52.21	-0.219
	(51.49,53.07)	(50.80,52.37)	(0.241,2.526)	(51.10,52.65)	(51.44,52.99)	(-1.292,0.850)
			[0.036]			[1.000]
Ethnic Majority	0.724	0.829	-0.111	0.787	0.830	-0.047
	(0.701,0.746)	(0.806,0.852)	(-0.142,-0.079)	(0.765,0.808)	(0.809,0.852)	(-0.078,-0.017)
			[0.000]			[0.005]
Source of Income:						
Employed	0.786	0.816	-0.038	0.814	0.828	-0.013
	(0.764,0.809)	(0.794,0.839)	(-0.070,-0.007)	(0.793,0.836)	(0.807,0.849)	(-0.043,0.017)
			[0.035]			[0.786]
Salaried	0.256	0.345	-0.089	0.232	0.340	-0.120
	(0.231,0.281)	(0.320,0.370)	(-0.124,-0.053)	(0.207,0.257)	(0.315,0.365)	(-0.155,-0.085)
			[0.000]			[0.000]
Work for Gov. Self	0.119	0.251	-0.132	0.122	0.250	-0.132
	(0.098,0.140)	(0.231,0.271)	(-0.161,-0.103)	(0.100,0.143)	(0.229,0.272)	(-0.162,-0.102)
			[0.000]			[0.000]
Work for Gov. Self or Relatives	0.229	0.334	-0.104	0.196	0.346	-0.149
	(0.204,0.254)	(0.309,0.359)	(-0.139,-0.068)	(0.171,0.220)	(0.322,0.370)	(-0.183,-0.115)
			[0.000]			[0.000]
Property Chars.:						
Roof Quality	6.918	6.955	-0.029	6.762	6.995	-0.237
	(6.885,6.951)	(6.922,6.985)	(-0.079,0.016)	(6.715,6.807)	(6.949,7.042)	(-0.301,-0.173)
			[0.421]			[0.000]
Walls Quality	2.042	2.450	-0.413	1.984	2.382	-0.400
	(1.982,2.101)	(2.391,2.508)	(-0.499,-0.328)	(1.925,2.043)	(2.323,2.441)	(-0.483,-0.318)
			[0.000]			[0.000]
Erosion Threat	0.530	0.416	0.144	0.448	0.382	0.058
	(0.491,0.569)	(0.378,0.454)	(0.091,0.197)	(0.410,0.486)	(0.345,0.420)	(0.005,0.110)
			[0.000]			[0.063]
View of Gov.:						
Trust in Gov.	1.58	2.27	-1.397	2.21	1.88	0.219
	(0.80,2.37)	(1.49,3.07)	(0.241,2.526)	(1.44,2.99)	(1.10,2.65)	(-1.292,0.850)
			[0.036]			[1.000]

Notes: This table reports the average characteristics of the 20% most and least affected units defined by deciles of the conditional average treatment proxy, for applications of random forest and boosting approaches. Columns 3 and 6 report the difference between the most and least affected units and the corresponding confidence interval and p-values. Medians over 1000 split. 90% confidence interval in parenthesis. P-values for the hypothesis that the parameter is equal to zero in brackets.

Although only suggestive the classification analysis provide evidence that the large effect on tax compliance and revenue of randomly assigning property owners to a lower tax rates documented in section 5 are more likely to be explained by liquidity constraints than by view of the government. In other words, a reduction in the status quo tax rate brings in the tax base property owners who are not able to pay at a lower tax rate and does not bring into the tax base property owners who are more dissatisfied with the government and would only be willing to pay the property tax rate if set sufficiently low.

7 Secondary Outcomes

Changes in tax rates might result in additional behavioral responses that should be considered when evaluating the total fiscal impacts of changes in tax rates. In this section, we consider the effect of changes in tax rates on bribe payments and payments of other taxes (formal and informal). We also consider the effect of changes in tax rates on citizens' perception of the government.

7.1 Responses of Bribe Payments to Tax Rates

We first considers to what extent assignment of property owners to lower tax rates affects bribe payments to the property tax collectors. Bribe payments to collectors are an important issue in contexts when tax collection is done door-to-door (Khan et al., 2015). However the relationship between tax rates and bribes paid to tax collectors is a priori ambiguous. On the one hand, a reduction in tax rates could lower the capacity of tax collectors to extract bribes if citizens are now willing to substitute tax payments in place of bribes. On the other hand it could be the case that when the tax rate is lower tax collectors ask for bribes more often – e.g. they agree to collect a low tax rate only if they are given an additional bribe or succeed more often when the tax rate is lower - e.g. if the bribe asked is strictly increasing in tax rate.

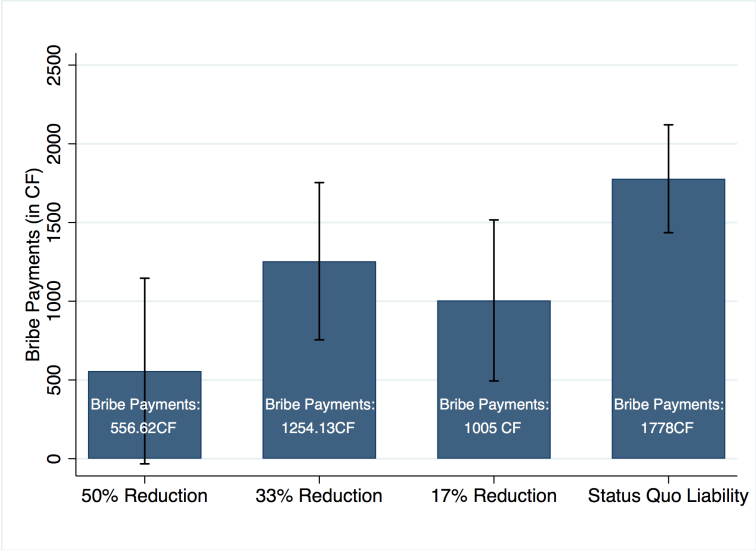
To study the relationship between tax rates and bribes paid, we collected data on bribes paid to the tax collectors during our midline survey. More specifically, we measured whether the respondent paid a bribe to the tax collectors (extensive margin) as well as the amount of bribe paid to the tax collectors (extensive and intensive margin). While our survey measures are self reported and the results should therefore be interpreted with caution, it is worth mentioning that reporting petty bribes is not taboo in Kananga. As an example, Reid and Weigel (2019) show that half of the motorcycle taxi drivers in their study of the toll tax openly admitted paying bribes instead of the tax. The authors also show a high correlation between more and less overt bribe elicitation mechanisms.

Figure 3 shows the reduced form effect of assignment to reduction in the status quo tax rate on bribe payments on the extensive margin (Panel A) and on the intensive mar-

gin (Panel B). We summarize the information from Figure 3 by estimating the elasticity of bribe payments with respected to the tax rate, which we report in Table 7. Overall, we find that bribe payments increase with the tax rate both on the extensive and intensive margin. The corresponding elasticities of bribe payments with respect to the tax rate are large: $e_{B,T} = 0.64$ when we use an indicator for paying a bribe as the outcome (extensive margin) and $e_{B,T} = 1.64$ when we use amounts of bribe paid as the outcome (extensive and intensive margin). Par of the increase in tax compliance associated with lower tax rates could therefore potentially be due to property owners deciding to substitute tax payments in place of bribes when tax rates decrease.

FIGURE 3: REDUCED FORM RESULTS

A: Amounts of Bribe Paid



B: Bribe Payment Indicator

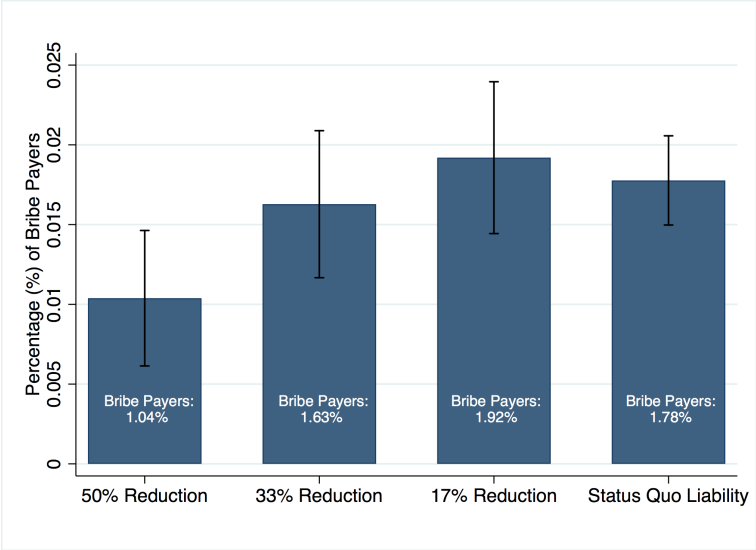


TABLE 7: ELASTICITY OF BRIBE PAYMENTS WITH RESPECT TO THE TAX RATE

	Bribe Payment	Bribe Payment	Bribe Payment	Bribe Amount	Bribe Amount	Bribe Amount
	All Houses	Periphery Houses	Midrange Houses	All Houses	Periphery Houses	Midrange Houses
	(1)	(2)	(3)	(4)	(5)	(6)
ln(tax liability)	0.011***	0.009**	0.026**	27.290***	17.547***	119.846***
	(0.003)	(0.003)	(0.012)	(4.261)	(2.897)	(34.478)
Observations	26328	23831	2497	39183	34984	4199
Sample	All	All	All	All	All	All
House	Pooled	Periphery	Midrange	Pooled	Periphery	Midrange
Strata	363	363	363	363	363	363
Mean	.02	.02	.02	16.65	12.25	47.54
Elasticity	.64	.58	1.21	1.64	1.43	2.52

7.2 Responses of Other Tax Payments to Tax Rates

We now turn to estimating wether the property tax rate faced by a property owner affects compliance with other taxes. The sign of the effect of an increase in property tax rates on compliance with other taxes is a priori ambiguous: compliance with the property tax induced by a decrease in the property tax rate could crowd-in or crowd-out contributions to other taxes.

In Kananga, the primary form of contribution consist in informal taxation (or *salongo*) which is in principle organized by local notables (avenue chiefs) on a weekly basis. During *Salongo* citizens most often clean the streets and sometimes engage in more substantive activities such as trying to prevent erosion from damaging properties or improving a well or a water source. We use our midline survey to measure whether a household member contributed to *salongo* in the past two weeks ("extensive margin") as well as the number of hours contributed ("intensive margin"). About 37% of our midline respondents reported that a household member participated in informal taxation in the past two weeks and household who participate contribute on average for 5.5 hours per week. We report the extensive margin elasticity of *salongo* contributions with respect to the property tax rate in column (1) of Table 8 and the intensive margin elasticity in column (2) of Table 8. We find that the elasticity of informal taxation with respect to the property tax rate is essentially zero, $\hat{\varepsilon}_{Informal,\tau} \approx 0$.

Other taxes commonly paid by citizens in Kananga include the firm tax, the vehicle tax and the market tax[18]. We report the elasticity of tax compliance with these other taxes in columns (3), (4) and (5) of Table 8. While some of the estimated elasticities are large, none of the coefficients are statistically significant from zero

[18] At baseline the most common taxes reported to be paid were: the bike tax (reported by 11.27% of the citizens), the property and rental tax (reported by 3.81% of the citizens), the firm tax (reported by 3.58% of the citizens), the insurance tax (reported by 3.49% of the citizens), the toll tax (reported by 2.66% of the citizens), the transportation tax (reported by 1.73% of the citizens)

TABLE 8: ELASTICITY OF OTHER TAX PAYMENTS WITH RESPECT TO THE TAX RATE

	Salongo	Salongo Hours	Paid Market Tax	Paid Firm Tax	Paid Vehicle Tax
	(1)	(2)	(3)	(4)	(5)
ln(Tax Liability)	-0.006	-0.340	0.100	0.121	0.007
	(0.012)	(0.487)	(0.072)	(0.083)	(0.102)
Observations	19999	7462	1077	653	487
Sample	Midline	Midline	Endline	Endline	Endline
House	Pooled	Pooled	Pooled	Pooled	Pooled
Strata	358	358	360	360	360
Mean	.37	4.9	.44	.22	.19
Elasticity	-.01	-.07	.23	.55	.04

7.3 Changes in Tax Rates and Perception of the Government

This section investigates if assignment to tax rates affects citizen's perception of the government. This is an important outcome to consider since it might in turn affect future tax payments as well as governance. The results in this section thus contribute to the recent literature studying the relationship between taxation and governance (Paler, 2013; Martinez, 2019; Weigel, 2019)

To study the relationship between perception of the government and tax rates, we collected data on three proxies for citizens' self-reported view of the government during our endline survey: (1) their trust in the government, (2) their perception of the government's performance, (3) their perception of tax revenues diversions by the government. The respondents are asked to answer these questions with respect to the provincial government as well as the tax ministry. The elasticity of citizen's view of the provincial government with respect to the property tax rate are reported in columns (1)-(3) of Table 9. Column (1) uses reported trust as the outcome, column (2) uses reported performance as the outcome and column (3) uses reported diversion of tax revenue as the outcome. Columns (4)-(6) report the elasticity of citizen's view of the tax ministry with respect to the property tax rate. Overall we find little evidence that assignment to a different tax rate changes citizens' view of the government and $\hat{\varepsilon}_{View\ Prov\ Gov.,\tau} \approx \hat{\varepsilon}_{Tax\ Min.,\tau} \approx 0$.

we also collected data on citizens perception of the fairness of the property tax campaign, the property tax rates and the property tax collectors during our endline survey. Clumns (7)-(9) of Table 9 uses each of these variables as outcome. We do not find evidence that assignment to a higher tax rate changes citizens' view of the property tax campaign or the property tax collectors $\hat{\varepsilon}_{Fair\ Tax\ Collection,\tau} \approx \hat{\varepsilon}_{Fair\ Tax\ Collectors,\tau} \approx 0$. However, as we would have expected, assignment to a higher tax rate significantly lowers citizens' view that property tax rates are fair $\hat{\varepsilon}_{Fair\ Tax\ Rates,\tau} = -0.11$

TABLE 9: ELASTICITY OF PERCEPTION OF THE GOVERNMENT WITH RESPECT TO THE TAX RATE

	Prov. Gov.			Tax Ministry			Fair Prop. Tax		
	Trust	Performance	Perceived USD Stolen	Trust	Performance	Perceived USD Stolen	Collection	Rates	Collectors
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(Tax Liability)	0.066	-0.006	-5.447	0.023	0.180*	-30.589	0.037	-0.151**	-0.001
	(0.065)	(0.089)	(27.022)	(0.074)	(0.096)	(25.092)	(0.045)	(0.065)	(0.056)
Observations	2783	2732	2806	2787	2735	2789	2790	2554	2509
Sample	Endline	Endline	Endline	Endline	Endline	Endline	Endline	Endline	Endline
House	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled
Strata	363	363	363	363	363	363	363	363	363
Mean	1.77	3.91	576.4	2.04	4.07	426.99	2	1.38	1.69
Elasticity	.04	0	-.01	.01	.04	-.07	.02	-.11	0

8 Responses of the Elasticity of Tax Revenue to the Enforcement Environment

We documented in section 5 that property tax rates are already above the revenue maximizing tax rate. But could this change if the government were to increase enforcement? Because individuals' responses to tax rates depends on the enforcement environment (Slemrod, 2019), the elasticity of tax revenue with respect to the tax rate is not an immutable parameter and can be influence by government policies (Slemrod and Kopczuk, 2002; Kopczuk, 2005; Saez et al., 2012; Keen and Slemrod, 2017; Slemrod, 2019). In this section we provide what is, to our knowledge, the first empirical test of complementarity between enforcement and tax rates. To show complementarity, we use two exogenous sources of variations in enforcement. First, we exploit threat of enforcement letters that were randomly sent to a subsample of property owners during property registration. Second, we use the random assignment of tax collectors - who vary in their enforcement capacity - to different neighborhoods. In both cases we find that that the elasticity of tax revenue with respect to the tax rate - as estimated in section 5 - increases with government's enforcement capacity [19]. Both results taken together provide strong evidence of the complementarity between enforcement and tax rates: while tax rates are already above the revenue maximizing tax rate in our setting government's enforcement effort can shift up the Laffer rate.

8.1 Randomized Threat of Enforcement Letters

8.1.1 Experimental Design

During the 2018 property tax campaign, property owners were randomly assigned to different tax message groups. These tax messages were written on the tax letters delivered by the

[19] In the framework introduced by Keen and Slemrod (2017) complementarity between enforcement and tax rates is captured by the elasticity of net of tax income decreasing with net of tax rate. Here we focus on the elasticity of tax revenue with respect to the tax rate as explained in section 5 and complementarity between enforcement and tax rate is therefore captured by the elasticity increasing with enforcement.

tax collectors to the property owners during property registration. The tax collectors were also instructed to read out loud the message written on the tax letter which they did in 95% of the cases according to enumerators' reports from the registration survey. Some property owners were randomly assigned to receive a status-quo message that read "paying the property tax is important" while other property owners received a central enforcement message that read "refusal to pay the property tax entails the possibility of audit, investigation and sanctions by the provincial tax ministry" or a local enforcement message that read "refusal to pay the property tax entails the possibility of audit, investigation and sanctions by the local chief"[20]. See Appendix Figure A3 for an example of the status-quo message and the enforcement message tax letters. In the online Appendix we report balance test for assignment to the enforcement message relative to the status quo message for selected baseline and midline property and property owner characteristics and confirm that the randomization was successful.

8.1.2 Are Enforcement and Tax Rates Complements?

Table 10 investigates whether assignment to the enforcement message increases the elasticity of tax revenue with respect to the tax rate, which would suggest that enforcement and tax rates are complementary in our setting. Column 1 shows that property owners receiving are characterized by a strong negative elasticity of tax revenue ($e_{R,T} = -1.34$). This suggest that for individuals who received the status quo message, tax rates are above the revenue maximizing tax rates and the government could increase its revenue by decreasing the tax rate. On the other hand Column 2 shows that for property owners who received the enforcement threat message the elasticity of tax revenue with respect to the tax rate is now positive ($e_{R,T} = 0.17$), though not significantly different from zero, suggesting that tax rates are now below the revenue maximizing rate and the government can increase revenue by increasing tax rates. Columns 3 and 4 show the corresponding elasticity of tax compliance for property owners who received the status quo message or the enforcement threat message. The comparison of column 1 and 2 therefore suggest that the elasticity of tax revenue is increasing with enforcement threat, providing evidence that enforcement and tax rates work as complement in our setting.

[20]The remaining property owners were assigned to three other messages: a central public good message that read "the provincial government will be able to improve infrastructure in the city of Kananga only if citizens pay the property tax", a local public goods message that read "the provincial government will be able to improve infrastructure in locality [name of the respondent's locality] only if citizens pay the property tax" and a trust message that read "paying the property tax is a way of showing that you trust the state and its agents". We do not use assignment to these other messages in this analysis and they'll be the subject of another paper (Bergeron et al., 2020b)

TABLE 10: ELASTICITY OF TAX REVENUE AND COMPLIANCE WITH RESPECT TO THE TAX RATE BY FLIERS

	Status Quo Message Tax Revenue (1)	Enforcement Threat Message Tax Revenue (2)	Status Quo Message Tax Compliance (3)	Enforcement Threat Message Tax Compliance (4)
ln(Tax Rate in %)	-292.615*	33.965	-0.099***	-0.071***
	(157.975)	(76.989)	(0.023)	(0.019)
Observations	6386	6386	6386	6386
House	Pooled	Pooled	Pooled	Pooled
Mean	217.64	197.1	.06	.1
Elasticity	-1.34	.17	-1.63	-.75

8.2 Random Assignment of Tax Collectors

8.2.1 Experimental Design

During the 2018 property tax collection campaign, 48 tax collectors from the provincial tax ministry were assigned to collect taxes in 243 of the 363 neighborhoods of Kananga (see Balan et al. (2020) for more details on the methods of property tax collection introduced during the 2018 property tax campaign in Kananga). Every month each collector from the provincial tax ministry was randomly assigned to work with another collector from the provincial tax ministry and the pair of collectors was then randomly assigned to a neighborhood where they would collect taxes for the entire month. Over the entire duration of the 2018 property tax campaign 243 pairs of tax collectors were therefore constituted from the 48 provincial tax ministry tax collectors, therefore representing an average of about 10 neighborhoods and 1,200 properties per tax collector.

8.2.2 Collectors' enforcement and elasticity of revenue estimation

Because collectors from the provincial tax ministry were first randomly assigned to work in pairs and second randomly assigned to work in a given neighborhood, we can use a fixed effect specification to estimate tax collector c's enforcement capacity, which we denote R_c:

$$y_{i,n} = R_{c_1} 1[c(n) = c_1] + R_{c_2} 1[c(n) = c_2] + \epsilon_{i,n} \tag{5}$$

where $y_{i,n}$ is the tax revenue collected from property owner i living in neighborhood n, $c(n)$ denotes the tax collectors working in neighborhood n where property owner i lives and $\epsilon_{i,n}$ denotes the error term. The fixed effect estimates of R_c, $(\hat{R}_1, \ldots, \hat{R}_{48})$ provide unbiased estimates of collector's enforcement capacity measured as the amount of tax revenue per property owner collected by each tax collector. The thought experiment corresponding to our

estimates of R_c is that if we were to randomly assign tax collector c to work in pair with a randomly picked tax collectors in a randomly selected neighborhood of Kananga, tax collector c would be predicted to collect R_c Congolese Francs per property owner.

Because the tax rates faced by each property owner are randomly assigned within each neighborhood, we can also use a fixed effect specification to measure tax collector c's elasticity of tax revenue with respect to the tax rate, which we denote e_c

$$\begin{aligned} y_{i,n} = \beta_{c_1} log(T_{i,n}) 1[c(n) = c_1] + \beta_{c_2} log(T_{i,n}) 1[c(n) = c_2] \\ + \alpha_1 1[c(n) = c_1] + \alpha_2 1[c(n) = c_2] + \epsilon_{ip} \end{aligned} \tag{6}$$

where $y_{i,n}$ is the tax revenue collected from property owner i living in neighborhood n, $c(n)$ denotes the tax collectors working in neighborhood n where property owner i lives and $log(T_{i,n})$ is the logarithm of the tax rate randomly assigned to property owner i living in neighborhood n. β_c represents the marginal effect of an increase in tax liability on tax revenue for tax collector c. As mentioned in section 5, it can be converted into the elasticity of tax revenue with respect to the tax liability for collector c, which we denote e_c, by normalizing β_c by the mean of y_{i,n_c} over all the neighborhoods n_c where collector c worked.

8.2.3 Empirical Bayes Adjustment

The fixed effect estimates $\hat{R}_c$ and $\hat{e}_c$ provide unbiased but imprecise estimates of collectors' performance. To obtain more precise forecasts of collectors' performance, we construct empirical Bayes estimates. By shrinking our estimates of $\hat{R}_c$ and $\hat{e}_c$ towards the mean of the true underlying distribution, the empirical Bayes estimates substantially reduce prediction errors. The empirical Bayes approach that we describe below was introduced by Morris (1983) and has been widely used in economics, for example to estimate the causal effect of teachers on students test scores (Gordon et al., 2006; Jacob and Lefgren, 2007; Kane and Staiger, 2008; Kane et al., 2008), to measure the causal effect of hospitals on patients' health (Chandra et al., 2006) or to estimate the causal effects of neighborhoods on intergenerational mobility (Chetty and Hendren, 2018). Formally, let's denote q_c tax collector c's performance (tax collector c's enforcement capacity R_c or elasticity of tax revenue with respect to the tax rate e_c). We denote by $\hat{q}_c$ the estimate of tax collector c's performance; it equals tax collector c's true performance q_c plus an error term η_c:

$$\hat{q}_c = q_c + \eta_c$$

Suppose that the estimated performance is independently normally distributed around the true quality with known variance π_c^2 which one can think of as the variance of the measure-

ment error of the estimate

$$\hat{q}_c | q_c, \pi_c^2 \sim \mathcal{N}(q_c, \pi_c^2)$$

Let's also assume that the true performance is independently normal with underlying mean $\bar{q}$ and underlying variance σ^2. The *prior distribution* of performance q_c, the distribution before conditioning on the estimated performance, is therefore:

$$q_c | \bar{q}, \sigma^2 \sim \mathcal{N}(\bar{q}, \sigma^2)$$

Conditioning on the estimated performance $\hat{q}_c$ produces the *posterior distribution* q_c:

$$q_c | \hat{q}_c, \bar{q}, \sigma^2, \pi_c^2 \sim \mathcal{N}(q_c^{EB}, \pi_c^2(1 - b_c))$$

q_c^{EB} denotes the empirical Bayes adjusted performance. It is the expected value of q_c conditional on the estimated value $\hat{q}_c$ and the parameters $\bar{q}$, σ_c^2, and π_c^2 and is given by the formula:

$$\begin{aligned} q_c^{EB} &= (1 - b_c)\hat{q}_c + b_c \bar{q} \\ b_c &= \tfrac{\pi_c^2}{\pi_c^2 + \sigma^2} \end{aligned} \tag{7}$$

This empirical Bayes estimator is sometimes known as the "shrinkage" estimator because the adjustment essentially shrinks the estimate $\hat{q}_c$ towards the prior mean $\bar{q}$. As the variance of the measurement error π_c^2 rises, the empirical Bayes correction increasingly disregards the value of the estimate and closes in on the prior mean.

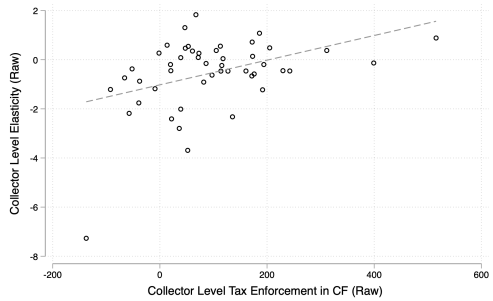
To construct our empirical Bayes estimates, we need to estimate the mean of the performance of the tax collectors, $\bar{q}$, the variance of the tax collectors' performance distribution, σ^2, as well as the variance of the error term π_c^2, which are not generally known. We estimate the mean of the performance of the tax collectors $\bar{q}$ using the mean of the estimated performance $\hat{q}_c$, i.e. $\bar{q} = \mathbb{E}[\hat{q}_c]$. The raw variance of collectors' performance $\sigma_{\hat{q}_c}^2$ overstates the true (signal) variance of collectors' performance σ^2 because part of the variation in the estimates $\hat{\mu}_c$ is due to sampling error. To estimate σ^2, we use the decomposition of collector performance estimates into the collector performance effect q_c and sampling error η_c: $\hat{q}_c = q_c + \eta_c$ where η_c is orthogonal to q_c) ($\mathbb{E}[\eta_c | q_c] = 0$). This decomposition implies that we can estimate $\sigma_{q_c}^2$ by subtracting the variance induced by sampling error, $\sigma_{\eta_c}^2$, from the variance in the observed estimates, $\sigma_{\hat{q}_c}^2$: $\sigma_{q_c}^2 = \sigma_{\hat{q}_c}^2 - \sigma_{\eta_c}^2$ and we can estimate the noise variance $\sigma_{\eta_c}^2$ as the average squared standard error: $\sigma_{\eta_c}^2 = \mathbb{E}[s_c^2]$ where s_c denotes the standard error of $\hat{\mu}_c$ or $\hat{e}_c$ and the expectation is taken across collectors. We estimate $\bar{q}$ and σ^2 weighting by the precision of the performance of the tax collectors' estimates ($1/s_c^2$ to maximize efficiency. Finally, we can estimate the noise variance π_c^2 by squaring the standard error of $\hat{q}_c$.

8.2.4 Are Enforcement and Tax Rates Complements at the Collector Level?

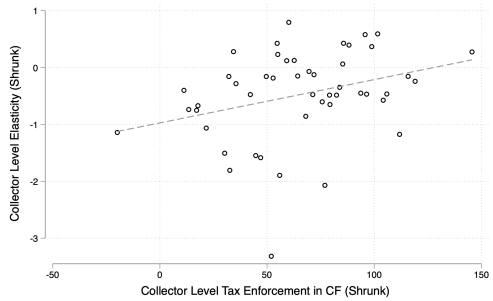
For each tax collector in our sample Figure 4 presents their enforcement capacity (x-axis) and their elasticity of tax collection with respect to the tax rate (y-axis). Panel A shows the fixed effect estimates, panel B the empirical Bayes estimates and Panel C presents both estimates together. Overall we find that the collectors' elasticity of tax revenue with respect to the tax rate is increasing with collectors' enforcement capacity. This positive relationship suggests that tax rates and enforcement capacity are complements in our settings. In other words, tax collectors with the lowest enforcement capacity in our sample (those who collect the lowest amount when assigned to work in a neighborhood) are characterized by a large negative elasticity of tax revenue with respect to the tax rates. This result suggests that for "low enforcers" tax rates are above the revenue maximizing rate and the government could increase revenue by lowering the tax rate. On the other hand tax collectors with the highest enforcement capacity in our sample (those who collect the highest amount when assigned to work in a neighborhood) are characterized by a positive elasticity of tax revenue with respect to the tax rates. This suggests that for "high enforcers" tax rates are below the revenue maximizing rate and the government can increase revenue by increasing the tax rate. Because in Panel B,C and D we shrink both collectors' enforcement capacity and collectors' elasticity of revenue, in Panel D we report the relationship between the shrinking parameters of both estimates. The negative and statistically non-significant relationship between both shrinking parameters is reassuring as it rules out the possibility that the positive relationship between collectors' enforcement capacity and elasticity of revenue is mechanically induced by the shrinking procedure.

FIGURE 4: TAX COLLECTORS - ELASTICITY OF TAX REVENUE BY ENFORCEMENT CAPACITY

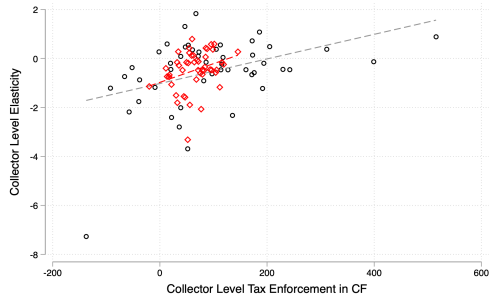
A: Elasticity of tax revenue (raw) vs enforcement capacity (raw)



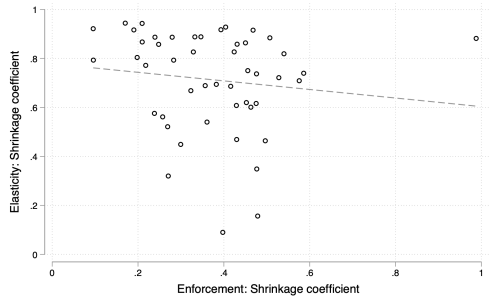
B: Elasticity of tax revenue (shrunk) by enforcement capacity (shrunk)



C: Elasticity of tax revenue (raw & shrunk) vs enforcement capacity (raw & shrunk)



D: shrinkage coefficients



8.3 Tax Collectors' Characteristics

We have shown that the elasticity of tax revenue with respect to the tax rate increases with government's enforcement threat in section 8.1 as well as with government's enforcement capacity in section 8.2. Both results suggest that government's enforcement efforts can shift up the revenue maximizing ("Laffer") tax rate and that tax rates and enforcement are complements in our setting. How can low income countries potentially increase both their enforcement capacity as well as the revenue maximizing tax rate? One such tool consist in the recruitment of tax collectors.

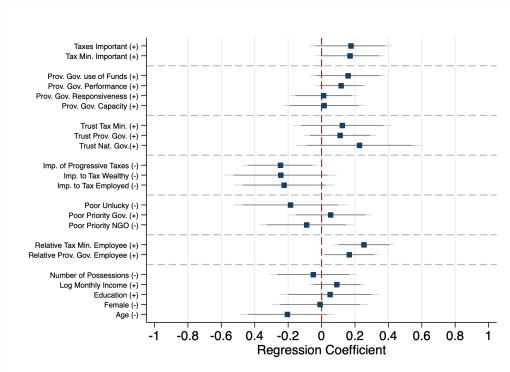
In Figure 5 we report the characteristics of the tax collectors that are associated with a higher enforcement capacity (panel C and D) and a higher elasticity of tax revenue with respect to the tax rate (Panel A and B). Tax collectors' characteristics are from a baseline collector survey that was conducted prior to the tax campaign and with all the tax collectors who worked on the 2018 property tax campaign. The collector survey aimed at measuring tax collectors' demographics (age, gender), education, income, possessions as well as collectors' tax morale (proxied by their view about the importance of paying the property tax), trust in the government (national, provincial and tax ministry), perception of the performance and

responsiveness of the provincial government and their view about redistribution and the importance of progressive taxation.

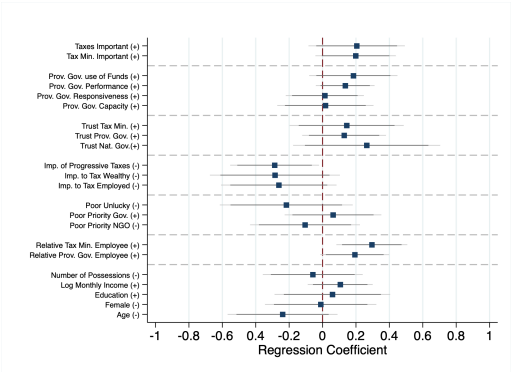
Figure 5 shows that tax collectors with a high tax morale and high trust in the government are associated with both higher enforcement capacity and a higher elasticity of tax revenue with respect to the tax rate. Hiring tax collectors with high levels of tax morale and trust is thus a policy toll that developing countries can use to effectively shift up both their enforcement capacity as well as their revenue maximizing ("Laffer") rate.

FIGURE 5: CORRELATES OF ELASTICITY OF TAX REVENUE AND ENFORCEMENT CAPACITY

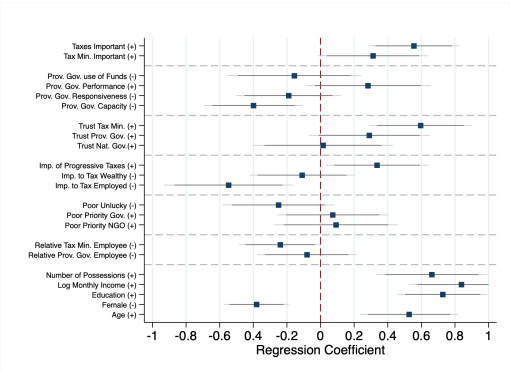
A: Correlates of elasticity of tax revenue (raw)



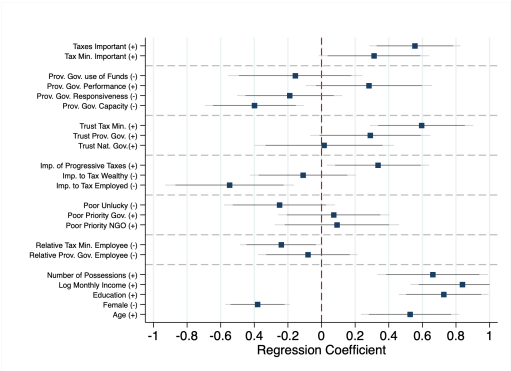
B: Correlates of elasticity of tax revenue (shrunk)



C: Correlates of enforcement capacity (raw)



D: Correlates of enforcement capacity (shrunk)



9 Conclusion

This paper studies individual responses to tax rates and tax enforcement in the DRC, a low-capacity and low-compliance state. In collaboration with the provincial government of Kasaï Central we evaluate the effect of randomizing property tax rates at the individual level during the 2018 city-wide property tax campaign in Kananga. During the property tax campaign, 48,000 property owners were randomly assigned to the status quo annual tax rate or to a reduction of 17%, 33% or 50% in the status quo tax rate. We find that tax rates are above the revenue maximizing ("Laffer") tax rate: a 1% increase in the tax rate leads to a 0.26% decrease in tax revenue. Beyond higher tax revenues, lowering tax rates results in lower bribes to tax

collectors and increases citizen's perception that the property tax is fair.

We use Machine Learning to estimate heterogeneous treatment effects and find evidence that the large response to lower tax rates loads is partly driven by individuals with low levels of cash-on-hand entering the tax base only when tax rates are sufficiently low. Our results thus point to the potentially large importance of lack of cash-on-hand as a deterrent to tax collection in developing countries.

Finally, we use two sources of exogenous variations in the enforcement environment - randomized threats of enforcement and assignment of tax collectors - to show that the elasticity of tax revenue increases with enforcement. Government's enforcement efforts can therefore shift up the revenue maximizing tax rate. We discuss policy tools such as tax collectors recruitment and training that can increase both enforcement and the revenue maximizing tax rate.

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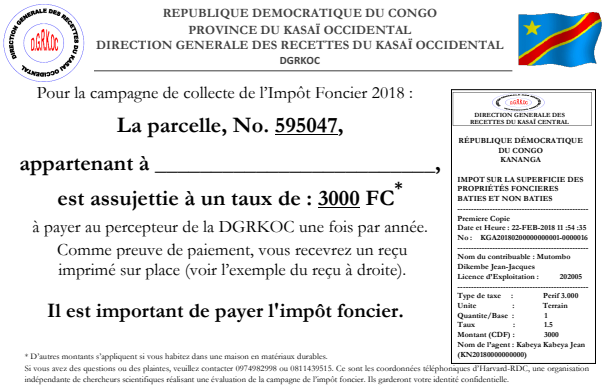
FIGURE A1: EXAMPLE OF PROPERTY TYPES IN KANANGA

A: Property Built in Non-durable Materials

B: Property Built in Durable Materials

FIGURE A2: STATUS QUO TAX RATE AND 17%, 33%, 50% REDUCTIONS

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.

DIRECTION GENERALE DES RECETTES DU KASAÏ CENTRAL

RÉPUBLIQUE DÉMOCRATIQUE DU CONGO
KANANGA

IMPOT SUR LA SUPERFICIE DES PROPRIÉTÉS FONCIERES BATIES ET NON BATIES

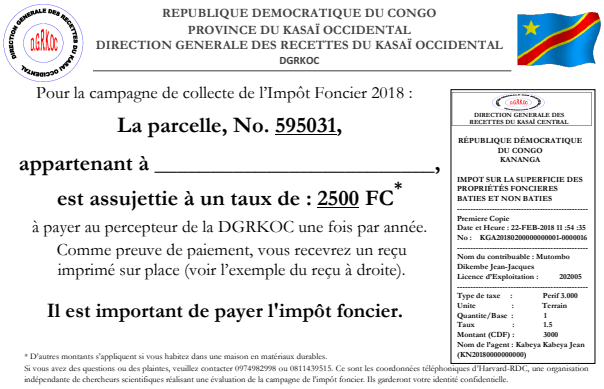
Premiere Copie
Date et Heure : 22-FEB-2018 11 :54 :35
No : KGA201802000000000001-0000016

Nom du contribuable : Mutombo Dikembe Jean-Jacques
Licence d'Exploitation : 202005

Type de taxe :	Perif 3.000
Unite :	Terrain
Quantite/Base :	1
Taux :	1.5
Montant (CDF) :	3000
Nom de l'agent :	Kabeya Kabeya Jean (KN20180000000000)

* D'autres montants s'appliquent si vous habitez dans une maison en matériaux durables.
Si vous avez des questions ou des plaintes, veuillez contacter 0974982998 ou 0811439515. Ce sont les coordonnées téléphoniques d'Harvard-RDC, une organisation indépendante de chercheurs scientifiques réalisant une évaluation de la campagne de l'impôt foncier. Ils garderont votre identité confidentielle.

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.

DIRECTION GENERALE DES RECETTES DU KASAÏ CENTRAL

RÉPUBLIQUE DÉMOCRATIQUE DU CONGO
KANANGA

IMPOT SUR LA SUPERFICIE DES PROPRIÉTÉS FONCIERES BATIES ET NON BATIES

Premiere Copie
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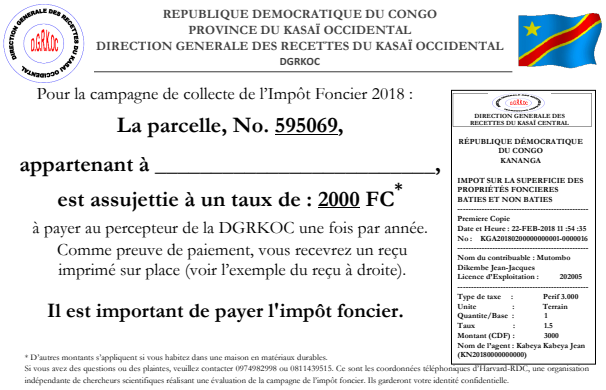
No : KGA201802000000000001-0000016

Nom du contribuable : Mutombo Dikembe Jean-Jacques
Licence d'Exploitation : 202005

Type de taxe :	Perif 3.000
Unite :	Terrain
Quantite/Base :	1
Taux :	1.5
Montant (CDF) :	3000
Nom de l'agent :	Kabeya Kabeya Jean (KN20180000000000)

* D'autres montants s'appliquent si vous habitez dans une maison en matériaux durables.
Si vous avez des questions ou des plaintes, veuillez contacter 0974982998 ou 0811439515. Ce sont les coordonnées téléphoniques d'Harvard-RDC, une organisation indépendante de chercheurs scientifiques réalisant une évaluation de la campagne de l'impôt foncier. Ils garderont votre identité confidentielle.

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.

DIRECTION GENERALE DES RECETTES DU KASAÏ CENTRAL

RÉPUBLIQUE DÉMOCRATIQUE DU CONGO
KANANGA

IMPOT SUR LA SUPERFICIE DES PROPRIÉTÉS FONCIERES BATIES ET NON BATIES

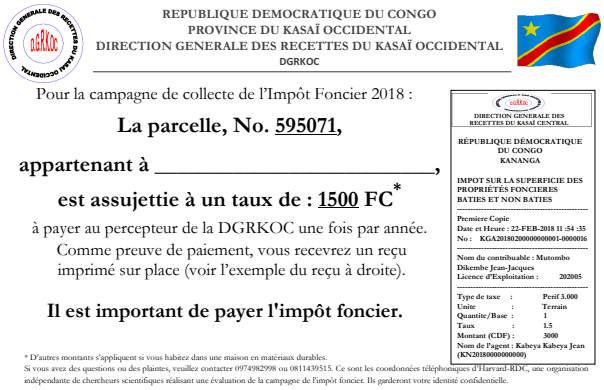
Premiere Copie
Date et Heure : 22-FEB-2018 11 :54 :35
No : KGA201802000000000001-0000016

Nom du contribuable : Mutombo Dikembe Jean-Jacques
Licence d'Exploitation : 202005

Type de taxe :	Perif 3.000
Unite :	Terrain
Quantite/Base :	1
Taux :	1.5
Montant (CDF) :	3000
Nom de l'agent :	Kabeya Kabeya Jean (KN20180000000000)

* D'autres montants s'appliquent si vous habitez dans une maison en matériaux durables.
Si vous avez des questions ou des plaintes, veuillez contacter 0974982998 ou 0811439515. Ce sont les coordonnées téléphoniques d'Harvard-RDC, une organisation indépendante de chercheurs scientifiques réalisant une évaluation de la campagne de l'impôt foncier. Ils garderont votre identité confidentielle.

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.

DIRECTION GENERALE DES RECETTES DU KASAÏ CENTRAL

RÉPUBLIQUE DÉMOCRATIQUE DU CONGO
KANANGA

IMPOT SUR LA SUPERFICIE DES PROPRIÉTÉS FONCIERES BATIES ET NON BATIES

Premiere Copie
Date et Heure : 22-FEB-2018 11 :54 :35
No : KGA201802000000000001-0000016

Nom du contribuable : Mutombo Dikembe Jean-Jacques
Licence d'Exploitation : 202005

Type de taxe :	Perif 3.000
Unite :	Terrain
Quantite/Base :	1
Taux :	1.5
Montant (CDF) :	3000
Nom de l'agent :	Kabeya Kabeya Jean (KN20180000000000)

* D'autres montants s'appliquent si vous habitez dans une maison en matériaux durables.
Si vous avez des questions ou des plaintes, veuillez contacter 0974982998 ou 0811439515. Ce sont les coordonnées téléphoniques d'Harvard-RDC, une organisation indépendante de chercheurs scientifiques réalisant une évaluation de la campagne de l'impôt foncier. Ils garderont votre identité confidentielle.

FIGURE A3: STATUS QUO MESSAGE AND ENFORCEMENT MESSAGE

A: Status Quo 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.

DIRECTION GENERALE DES RECETTES DU KASAÏ CENTRAL

RÉPUBLIQUE DÉMOCRATIQUE DU CONGO
KANANGA

IMPOT SUR LA SUPERFICIE DES PROPRIÉTÉS FONCIERES BATIES ET NON BATIES

Premiere Copie
Date et Heure : 22-FEB-2018 11 :54 :35
No : KGA20180200000000001-0000016

Nom du contribuable : Mutombo Dikembe Jean-Jacques
Licence d'Exploitation : 202005

Type de taxe : Perif 3.000
Unite : Terrain
Quantite/Base : 1
Taux : 1.5
Montant (CDF) : 3000
Nom de l'agent : Kabeya Kabeya Jean (KN20180000000000)

* D'autres montants s'appliquent si vous habitez dans une maison en matériaux durables.
Si vous avez des questions ou des plaintes, veuillez contacter 0974982998 ou 0811439515. Ce sont les coordonnées téléphoniques d'Harvard-RDC, une organisation indépendante de chercheurs scientifiques réalisant une évaluation de la campagne de l'impôt foncier. Ils garderont votre identité confidentielle.

B: 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

DIRECTION GENERALE DES RECETTES DU KASAÏ CENTRAL

RÉPUBLIQUE DÉMOCRATIQUE DU CONGO
KANANGA

IMPOT SUR LA SUPERFICIE DES PROPRIÉTÉS FONCIERES BATIES ET NON BATIES

Premiere Copie
Date et Heure : 22-FEB-2018 11 :54 :35
No : KGA20180200000000001-0000016

Nom du contribuable : Mutombo Dikembe Jean-Jacques
Licence d'Exploitation : 202005

Type de taxe : Perif 3.000
Unite : Terrain
Quantite/Base : 1
Taux : 1.5
Montant (CDF) : 3000

(KN20180000000000)

* D'autres montants s'appliquent si vous habitez dans une maison en matériaux durables.
Si vous avez des questions ou des plaintes, veuillez contacter 0974982998 ou 0811439515. Ce sont les coordonnées téléphoniques d'Harvard-RDC, une organisation indépendante de chercheurs scientifiques réalisant une évaluation de la campagne de l'impôt foncier. Ils garderont votre identité confidentielle.

Table A1: Robustness Check 1: Elasticity of Tax Compliance Controlling for Neighbor's Tax Rate

	No Nbr Ctrls (1)	1 Nearest Nbr Ctrls (2)	2 Nearest Nbrs Ctrls (3)	3 Nearest Nbrs Ctrls (4)	4 Nearest Nbrs Ctrls (5)	5 Nearest Nbrs Ctrls (6)	6 Nearest Nbrs Ctrls (7)	7 Nearest Nbrs Ctrls (8)	8 Nearest Nbrs Ctrls (9)	9 Nearest Nbrs Ctrls (10)	10 Nearest Nbrs Ctrls (11)
ln(tax liability)	-0.104***	-0.104***	-0.104***	-0.104***	-0.104***	-0.104***	-0.104***	-0.104***	-0.104***	-0.104***	-0.104***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
ln(tax liability) Nearest Nbr		0.001	0.001	0.001	0.000	0.000	0.000	-0.000	-0.000	0.000	-0.000
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln(tax liability) 2nd Nearest Nbr			0.004	0.004	0.004	0.003	0.003	0.003	0.003	0.003	0.003
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln(tax liability) 3rd Nearest Nbr				0.004	0.003	0.003	0.003	0.003	0.003	0.003	0.003
				(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln(tax liability) 4th Nearest Nbr					0.003	0.002	0.002	0.002	0.002	0.002	0.002
					(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln(tax liability) 5th Nearest Nbr						0.006*	0.006*	0.006*	0.006*	0.006*	0.006
						(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln(tax liability) 6th Nearest Nbr							-0.000	-0.001	-0.001	-0.000	-0.001
							(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ln(tax liability) 7th Nearest Nbr								0.002	0.002	0.002	0.002
								(0.004)	(0.004)	(0.004)	(0.004)
ln(tax liability) 8th Nearest Nbr									0.000	0.001	0.000
									(0.004)	(0.004)	(0.004)
ln(tax liability) 9th Nearest Nbr										-0.003	-0.003
										(0.003)	(0.003)
ln(tax liability) 10th Nearest Nbr											0.007*
											(0.004)
Observations	34567	34567	34567	34567	34567	34567	34567	34567	34567	34567	34567
House	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled
Mean	.09	.09	.09	.09	.09	.09	.09	.09	.09	.09	.09
Elasticity	-1.19	-1.19	-1.19	-1.19	-1.19	-1.19	-1.19	-1.19	-1.19	-1.19	-1.19

Table A2: Robustness Check 2: Elasticity of Tax Compliance by Knowledge of Neighbor's Tax Rate

	Main Spec (1)	Knows Nbr Rate (2)	Doesn't Know Nbr Rate (3)	Main Spec (4)	Knows Nbr Rate (5)	Doesn't Know Nbr Rate (6)
ln(tax liability)	-0.136***	-0.151***	-0.137***	-70.843	5.926	-86.293*
	(0.013)	(0.045)	(0.014)	(46.232)	(117.514)	(51.544)
Observations	15637	1811	13355	15637	1811	13355
House	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled
Mean	.11	.14	.11	284.11	318.11	282.23
Elasticity	-1.2	-1.11	-1.23	-.25	.02	-.31

Table A3: Robustness Check 3: Elasticity of Tax Compliance by Awareness of Reduction

	Main Spec (1)	Know Discount (2)	Doesn't Know Discount (3)	Main Spec (4)	Know Discount (5)	Doesn't Know Discount (6)
ln(tax liability)	-0.100***	-0.255**	-0.099***	-48.928	-133.726	-57.497
	(0.015)	(0.079)	(0.015)	(52.733)	(167.578)	(53.781)
Observations	13559	9508	13333	13559	9508	13333
House	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled
Mean	.08	.07	.07	241.04	248.94	248.94
Elasticity	-1.34	-3.82	-1.48	-.2	-.54	-.23