How do political connections affect property tax compliance? *

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Abstract

How does being connected to a local elected leader affect property tax compliance? Using a close election difference-in-discontinuities design, we quantify the effect of being connected to a local elected leader on tax liability and compliance. We use novel administrative data on property taxation from an Indian district and find that citizens connected to local elected leaders are 45 percentage points more likely to remit taxes and remit 351% more in taxes. We also find that these results are partially driven by enforcement as those who are connected are 30.8 percentage points more likely to face fines and face 247% more in fines. Among those who are connected to the local elected leader, we find that these results are driven by poorer property owners.

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1 Introduction

Developing countries generally raise lower revenues as a share of GDP compared to developed countries. Brockmeyer et al. (2021) show that this is particularly true for property taxes. For example, India, raises 0.2% of GDP as property taxes compared to U.S which raises 2.5%. This is puzzling since tax base for property taxes is immovable and easily visible, reducing the scope for evasion in theory. While there could be many reasons for this huge discrepancy in property tax collection between developed and developing countries, like outdated tax rates for example, the role of fiscal capacity is worth studying.

In our paper, we ask how does being connected to a local elected leader affect tax compliance. There are many reasons why we may expect the tax remitting behavior of those connected to the local leader to be different compared to other citizens. It's possible that those who align themselves with the local leaders may lower their tax evasion or be more likely to voluntarily comply with taxes as documented in Cullen et al. (2021). This is also in line with one of the responses we got on field, *"There is also politics involved. Some people say that if a particular Sarpanch [Elected president of village government] is there then they won't pay the tax."* On the other hand, it's also possible that political leaders have more information about those who they share a social connection with and as a result direct the tax collector to property owners who have higher propensities to pay. This channel is examined in Balan et al. (2022) where local elites collect more property taxes compared to state appointed agents as local elites have more information on which citizens have higher payment propensities.

Alternatively, as documented by vast clientelism literature (Anderson et al., 2015; Khwaja and Mian, 2005; Burgess et al., 2015), political leaders may want to direct transfers towards their connections to secure votes from their "clients" in future elections. Since property taxes can be thought of as negative transfers, leaders may tax their connections less or enforce taxes less stringently, to gain favor with their voters and maximize probability of re-election. One of the findings of Finan and Schechter (2012) is that politicians target reciprocal individuals for vote-buying in exchange for transfers. If higher levels of reciprocity are expected from citizens connected to the leader, then we would expect to find lower tax compliance and enforcement in exchange for votes. Which channels are dominant in our setting likely depends on the ability to enforce taxes, discretion over total revenues, ability to build and target public goods, beliefs about re-election probability and expected levels of reciprocity, among other things.

We argue that this question is also of general policy interest as these tax revenues are used for provision of public goods that are crucial for driving anti-poverty efforts. While it is widely acknowledged that these local governments are important for poverty alleviation programs, across many countries these lower levels of governments overwhelmingly rely on upper levels of government for devolved funds. If these devolved funds are tied to specific purposes, as is the case in India, then it reduces the discretion of local governments on how these funds can be spent. Inability to raise sufficient own revenues constrains the ability of local governments to design and implement policies that are representative of local preferences.

We study our question in the context of Indian Gram Panchayats (village governments) in Pune, Maharashtra in India. We study property taxes as these are the main source of revenue for Gram Panchayats. Our setting is characterized by low property tax compliance. On average, in our sample villages, 49% remit any property taxes and 26% completely remit their property taxes. On average, conditional on remitting something, citizens remit 64% of their taxes. We study connections to local elected leaders of these Gram Panchayats (GPs) and define someone to be connected if they share the same last name as the leader.

In our context, sharing the same last name with the elected leader signifies that the leader shares the same caste (*jati*) as the citizen. A lot of prior work talks about the reliance on caste networks in India (surveyed in Munshi (2019)), for numerous activities, like borrowing credit (Munshi and Rosenzweig, 2016), gaining access to public resources (Duflo et al., 2005; Besley et al., 2004), voting in local elections (Anderson et al., 2015) etc. It's also highly likely that those who share the same last name in a GP share a familial connection.[1] This way of defining family connections is similar to the methodology in Galletta and Giommoni (2023). In that paper, if an individual shares the same surname (similar to last name) as someone else from the same municipality, they are defined as sharing a family connection. We argue that sharing the same last name as a political leader in a GP implies at best being related to the leader and at the very least sharing the same caste.

In order to study our question causally, we exploit GP ward member elections with narrow margins and compare the tax compliance of those connected to the winner versus those connected to the loser. Those who are connected to the winner of a narrow ward member election, are considered to be our treated group and those connected to the loser of narrow ward member election are considered to be the control group. In the rest of the text, local elected leader refers to an individual who contested in a GP ward member election and was declared the winner. We use novel administrative property tax data at the property owner level for an Indian district to conduct our analysis. We use difference-in-discontinuities design proposed by Grembi et al. (2016) to study how being connected to local leaders affects tax compliance.

We find that those who are connected to the GP ward member are 44.9 percentage points more

[1] We are studying individuals who share the same last name in GPs comprising around 400 - 500 households.

likely to remit any property taxes and are 30 percentage points less likely to remit their taxes completely post election[2]. In terms of tax amounts, citizens connected to ward members face 100% more in taxes and remit 351% more in taxes. We find that these results are at least partially driven by enforcement as connected citizens face 247% more in fines and are 30.8 percentage points more likely to be fined post election. In our heterogeneity analysis, we further find that these results are driven by relatively poorer property owners who are connected to the GP ward member instead of the wealthier connections. In fact, we find that wealthier connections are likely (though not always statistically significantly) to display clientelistic behaviour when it comes to taxes.

Our paper contributes to three main strands of literature. The first strand of literature our paper contributes to relates to study of property taxation in developing countries. Prior studies on this topic usually focus on taxes levied on firms such as value added taxes (Gadenne et al., 2018; Pomeranz, 2015), profit taxes (Best et al., 2015) and income taxes (Best, 2014; Holz et al., 2020) in developing countries. Balan et al. (2022) and Dzansi et al. (2022) study property taxation on households in Democratic Republic of Congo and Ghana respectively, but in an urban context. To this literature, we contribute by studying novel property tax data on rural property taxes. With rapid urbanization in developing countries, while it is important to study urban taxation, most of the poor population in the developing world still live in rural area. We contribute by understanding how the rural populations who are politically connected are taxed.

The second strand of literature this study contributes to relates to political connections and transfers. Vast prior literature shows that citizens and firms who are politically connected receive favourable treatment in their interactions with the state. Khwaja and Mian (2005), for example, find that lenders favour firms who are politically connected in Pakistan. Similarly, Fisman and Wang (2015) find that worker fatalities in politically connected firms are two to three times higher than in non-connected firms hinting at low compliance for politically connected firms. We contribute to this literature by documenting a result where those connected to local elected leaders face higher compliance and enforcement in property taxes. Similar result has been documented by Kasara (2007) in the context of agricultural taxes in Africa. To the best of our knowledge, we are the first paper to document this result in the Indian context. It's possible that once we take other transfers into account, like access to public goods, the net benefits for connected citizens are positive. We hope to incorporate other types of transfers in a future version.

The third strand of literature our study contributes to relates to distributional consequences of taxation in developing countries (Bachas et al., 2020; Londoño-Vélez and Ávila-Mahecha, 2021). This is an emerging strand of literature as reviewed in Bachas et al. (2024). We contribute to this

[2] Conditioning on remitting something, those who are connected to the elected leader are associated with a 22 percentage points decline in probability of remitting taxes completely. Similarly, conditional on paying something those who are connected are associated with a 7% decline in fraction of tax that is remitted. Neither of the above are statistically significant.

burgeoning literature on distributional consequences of taxation in developing countries by finding that property taxes in rural India, are potentially regressive once we account for connections to local politicians.

The rest of the paper is organized as follows. In Section 2, we provide institutional background on local governments, property tax assesssment and collection in the Indian context. In Section 3, we discuss our sources of data. In Section 4, we describe our empirical strategy and discuss our results in Section 5. Section 6 concludes.

2 Institutional Background

2.1 Gram Panchayat

Recognizing the need for self-governance to solve problems at the grass root level, the 73rd amendment of the Constitution of India devolved more powers to the rural local bodies (RLBs). These RLBs are a three-tier system with elected local bodies at the village, sub-district (taluk) and district level. The village elected bodies are referred to as Gram Panchayats (GPs henceforth) which will be the focus of our study.

These GPs comprise a cluster of villages. In our setting, a GP usually consists of 1-3 villages. A GP is divided into 2-3 wards. Each of the wards are further divided into seats for electoral purposes. Candidates contest in elections to be elected to the GP seats and the elected representatives of ward seats are referred to as ward members. After the election for the ward member position, all the citizens vote for one of the ward members to be the head of the GP (Sarpanch). The ward members then vote amongst themselves to elect one of the ward members as Deputy Sarpanch[3]. The layout of the GP government is as shown in figure 1. Elections for GP positions happen once every 5 years.

[3]We think this is the main channel through which ward members will be able to control tax collection and enforcement. Deputy Sarpanch is accountable to the ward members as she is elected by them and may rely on ward members regarding who should be targeted for taxes.

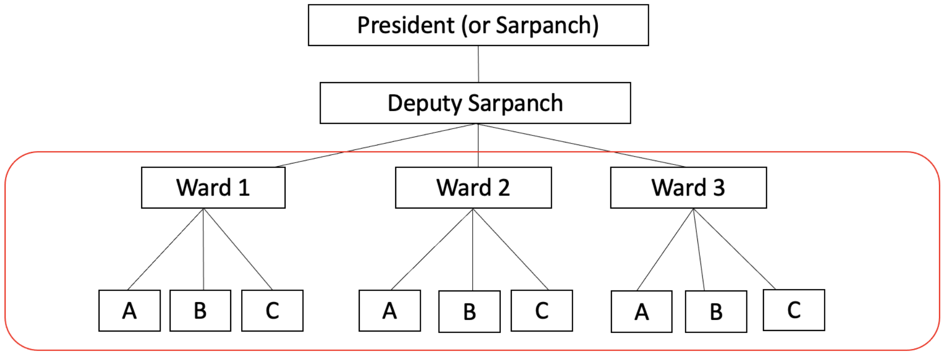


Figure 1: Gram Panchayat Electoral Setup

The main function of GPs is to provide basic public goods and services like irrigation, water and sanitation facilities, and facilitate the implementation of anti-poverty and development programs like MNREGS (Mahatma Gandhi National Rural Employment Guarantee Scheme) (Dodge et al., 2023). To support these initiatives, GPs have the power to raise their own revenues. Their main source of revenue is from residential building taxes and commercial taxes. According to 2018 Economic Survey of India, even in the best performing states in terms of tax collection, GPs raise less than 33% of the their estimated revenue potential. Moreover, GPs own revenue (mostly consisting of property taxes) contributes to only 5% of their total budget. The remaining 95% comes from the state and central governments. However these devolved funds are ear-marked for specific purposes and constrain the types of expenditures that a GP can undertake. As a result, high reliance on state funds may lead the GPs to under serve public goods that are representative of local preferences.

2.2 Property Tax Assessment

Property taxes are supposed to be assessed once every 4 years by a tax assessment committee which is comprised of Sarpanch, Deputy Sarpanch, Gram Sevak, Extension Officer and Junior Engineer. Extension Officer and Junior Engineer are officers appointed at a higher administrative level i.e., at the district level. As mentioned in section 2.1, Sarpanch and Deputy Sarpanch are elected officials of the GP. Gram Sevak is a bureaucrat appointed at the district level (i.e. higher administrative level than the GP) responsible for the development of the assigned GP and draws a salary from the district fund. The Gram Sevak, apart from being a part of tax assessment committee, is also responsible for collecting taxes directly from the property owners.

To assess property tax for a property, first the tax base is assessed. This is done by computing the capital value of the building as (area of building $\times$ annual value rate of land) + (area of building $\times$ rate of construction as per type of construction of building $\times$ rate of depreciation) +

weightages of buildings as per its usages[4]. Next, the capital value of land has to be computed which is calculated as area of land $\times$ annual value rate of land. The applicable annual rates are taken from the Annual Statement of Rates for Maharashtra state. After calculating the capital value of building, different tax rates are applied depending on the type of construction. For example, 0.03% minimum tax rate is applicable for every 1000 INR (12 USD) of capital value of building if the building is a hut or made of mud. If it's a cement building, then the minimum tax rate is 0.075% for every 1000 INR of capital value of building. A flat minimum tax rate of 0.15% is applied to every 1000 INR capital value of land.

Every property owner is notified of the property tax they owe in the beginning of the financial year which starts on April 1st of that year (In India, the financial year runs from April 1st to March 31st of the successive year). If the tax is remitted within the first 6 months of the financial year, i.e., before September 30th, a 5% discount is applied on the tax. If the property owner fails to remit before the end of the financial year, a 5% fine is levied on the outstanding (unpaid) amount of property tax. The property tax schedule incentivizes property owners to remit taxes as soon as possible. It also incentivizes property owners to remit whatever taxes they can, if not completely, to reduce the fine amount that's levied on the outstanding tax amount.

In the raw data, as shown in table 1, we find that 5% fine is levied on the outstanding tax amounts for citizens in general, conditional on there being some tax outstanding and a fine being levied. However, for those that are connected to the the winner or loser of a ward member election the fine levied is around 3%. This is indicative of those being connected to an election contestant receiving some favourable treatment when it comes to enforcing penalties for tax delinquency. In the raw data we do not see a further significant difference in fines levied as a function of tax outstanding depending on whether a citizen is connected to an elected ward member or not. Along the same lines, in figure 2, we see that the distribution of fines levied as a percent of outstanding tax amount is to the left for those who share a connection with winner or loser of a ward election compared to the distribution for citizens who don't share any such connection.

3 Data

3.1 Data sources

We use three sources of data. The first data source is a novel administrative property tax panel dataset covering the years 2017-2023 for Pune district in Maharashtra. This dataset covers (on average) 553,376 properties per financial year and covers about 70% (981) of all Gram Panchayats

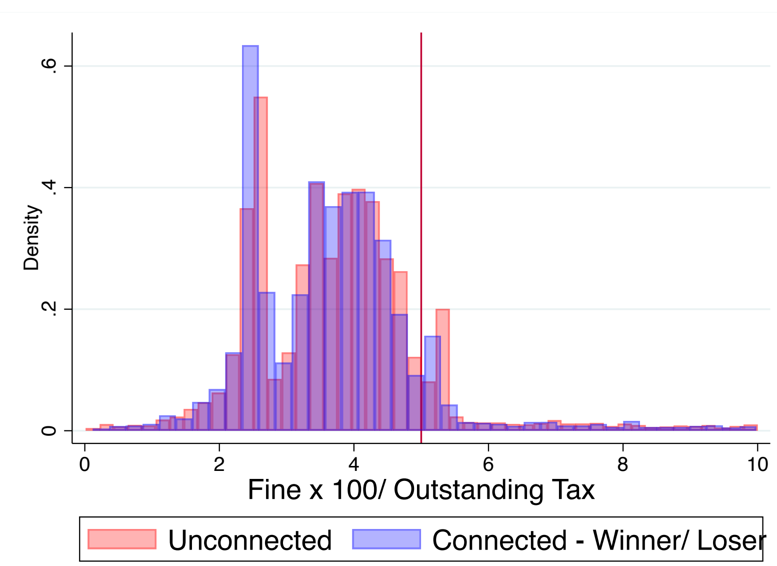
[4]Residential properties are assigned a weight of 1. Industrial properties are assigned weight 1.2 and commerical properties, weight 1.25.

Table 1: Fines and political connectedness

VARIABLES	(1) Fine Amount
Tax Outstanding	0.0578***
	(0.0115)
Tax Outstanding × Connected	-0.0212**
	(0.00952)
Tax Outstanding × Connected - Winner	-0.00164
	(0.00561)
Observations	90,688
GP FE	YES
Year FE	YES
Dependent variable mean	136.8

Notes: The dependent variable is the amount of fine levied. Column 1 of table 1 displays the regression coefficients on the amount of tax outstanding, tax outstanding interacted with connected (with either winner or loser of a ward election) and tax outstanding interacted with being connected to the winner of a ward election. This regression conditions on there being some amount of tax outstanding and receiving a positive fine. Connected is a binary indicator for whether a citizen shares the same last name as the winner or loser of a ward member election. Connected - Winner is a binary indicator for whether a citizen shares the same last name as an elected ward member or not. The regression includes GP fixed effects, year fixed effects and standard errors are clustered at the GP level. *p<0.1, **p<0.05, ***p<0.01

Figure 2: Distribution of percent of fines levied



Notes: This figures shows the distribution of percent of fines levied for those that share a connection with the winner or loser of a ward member election and distribution of percent of fines for those that don't share any connection. The vertical red line indicates the percent of fines that should be levied according to the tax law (5%) on amount of tax outstanding. Percent of fine is calculated as $\frac{\text{Fine Amount} \times 100}{\text{Tax Outstanding}}$. In the graph, to show the existing variation, we restrict the observations to those citizens for whom there is a positive amount of tax outstanding, positive amount of fine levied and the percent of fines fall between 0 and 10%.

in Pune district. This dataset has information on amount of property taxes, and water and electricity bills owed by property owners from the previous year, amounts owed for the current year, and total amount owed (which is the sum of amount owed from previous year and current year).

We also see data on fines that are levied on property owners due to non-payment of property taxes. In addition, this data gives us information on property owner names and property numbers[5]. The property owner names in the tax dataset are in Marathi, which is the official language in state of Maharashtra.

In the property tax dataset, we *mostly* observe that property owners are recorded separately; even though multiple property owners live in the same property in a given year, we observe each of the property owners in separate rows. In some cases, property owners living in the same property in a financial year are levied the same amount of property taxes. For example, John Smith and Jane Doe living in property 1 have 500 INR recorded next to each of them. In some other cases the property owners in the same property have different amounts of property taxes recorded next to them. For example, John Smith living in property 1 has 500 INR tax recorded next to him and Jane Doe in the same apartment has 100 INR tax recorded next to her. At this point, we will assume that the property tax recorded next to a property owner is the amount the owner is individually liable to remit. With further field work, we hope to understand if a single tax amount is levied on the property as a whole (and is then recorded in separate rows for each of the property owners) or whether each individual property owner within a given property is liable to remit the tax that's levied on them. We bottom code our main outcomes of interest, i.e., property tax levied, property tax owed, property tax outstanding, property tax remitted and fine amounts such that the amounts recorded to be less than 0 are recoded to be 0. The summary statistics for our main outcome variables are shown in table 2.

The second data source gives us data on Gram Panchayat elections in Pune. We have this data for 916 GP elections out of a total of 1386 GPs in Pune. We scraped this data from Maharashtra election website. As mentioned in section 2, there is one Sarpanch per GP and six to seven ward member seats per GP. In our election data, we observe elections for 348 Sarpanch elections and 5,846 ward member elections. Since we leverage a close elections regression difference-in-discontinuities design, for statistical power we need data for many elections. For this purpose, we restrict our analysis to ward member elections. This dataset contains information on the names of contestants who ran for a ward member election between 2017 and 2023 in English. In addition, we see the date of the election, the ward seat for which the election is being contested, valid votes polled for each of the contestants, and the candidate who was declared the winner.

The goal of the empirical exercise in our paper is to study how citizens connected to local elected leaders change their tax remitting behavior. In our study, we focus on the connections to GP ward members. We determine whether a property owner is connected to a GP ward member

[5] In our data, property numbers seem to change year on year for property owners. As a result, our analysis follows property owners instead of properties.

by examining if they share the same last name. From our election dataset, we first isolate the last names of the contestants for the ward member elections. We then translate these last names from English to Marathi. While translating these names, where applicable, we tried to match the Marathi translation of the last name with one of the commonly occuring last names of the property owners from the GP.

Second, for each GP, we went through the list of the last names of the property owners, and for those that matched with a leader's last name, we tried to standardize their spellings. For example, let's say Bhalerav is the last name of an election contestant for GP Ann Arbor. We match this with all the Bhaleravs in the GP. In addition, we go through the list of last names that sound the same as Bhalerav, for example Bhalerao, Balerav and standardize their spelling to Bhalerav. This allows us to code all the property owners whose last name is Bhalerav as being connected to the leader with the last name Bhalerav.

Our third data source is the Namuna 8 property register. This is another novel administrative data source that include in our analysis. Namuna 8 (Form 8) is an official government form that records the parcel area owned by all the property owners in the GP. We have access to the cross-sectional N8 data maintained by the land records department of Pune. This gives us a snapshot of property ownership records in our study area. Parcel area is one of the determinants of the property tax assessment and is supposed to be recorded for every property owner in the GP. In our data, in some of the cases we see multiple recorded parcel areas for a property owner. In this case we take the max of all the property areas recorded for that property owner[6] as the relevant parcel area in our analysis.

We use parcel area as a control in our regressions and also use it for heterogeneity analysis. We use it as a proxy for wealth of property owners in our heterogeneity analysis to understand who the government leaders target in weak capacity states. We merge the Namuna 8 data with the property tax data on the basis of property number in a GP[7]. After merging the two datasets, for a subset of the sample, we verified that the property owners' names in Namuna 8 match with the property owners' names in the tax data.

3.2 Sample Selection

We impose two types of sample selection restrictions. In our property tax data, we observe property owners, property tax outstanding from the previous year, property tax levied in the current

[6]We also conducted robustness checks with the mean of the recorded parcel areas instead of the max and it doesn't significantly change our results.

[7]In our data the property numbers for a given property seem to change every year. To merge with the Namuna 8 data, we use the property numbers assigned in 2021 as we have the most coverage for the 2020-2021 financial year.

Table 2: Summary Statistics

Variables	Mean	SD	N
Remit any	.487	.5	33718
Remit Completely	.26	.438	33718
Tax Remitted	818.465	36000	33718
Tax Levied	798.433	4085.542	33718
Fine	305.64	36000	33718
Probability of fine	.342	.474	33718

Notes: Remit any is a binary indicator for whether any amount of property tax is remitted. Remit completely is a binary indicator which takes the value 0 if there is any oustanding amout of property tax. Tax remitted is the amount of tax remitted and tax levied is the amount of property tax levied in the current year. Fine is the amount of fine reported. Tax remitted, tax levied and fine are all bottom coded so they take non-negative values. Probability of fine is a binary indicator for whether a fine is levied on the property owner. All the amounts are in nominal INR terms.

year, total property tax owed which is the sum of property tax from the previous year and property tax from the current year and fines levied. In our data, since we only see the amounts owed, in order to determine how much property tax was not remitted in year t, for a given property owner, we use the property tax owed from previous year value in year $t+1$ and use that to infer how much was not remitted in year t. Since we directly observe the tax levied in year t, we can subtract tax not remitted in year t to determine the tax remitted in year t. Since we need to observe a property owner for two consecutive years (t and $t+1$) to determine the amount of property tax remitted in a given year t, we restrict our sample to property owners who we consecutively observe for atleast two years. For all our analysis, we restrict our sample to those observations for which we have data on all the outcome variables[8].

One major drawback of our data is that property numbers seem to change from one financial year to next. So, instead of properties, we will be tracking property owners using their names and their GP of residence to identify them. To make sure we are not tracking two different property owners with the same name, we restrict our sample to property owners who we observe only once per year. In other words, we are restricting our analysis to property owners who appear only once every year during our sample years.

We also restrict our analysis to those ward elections where the winner and loser have unique last names amongst all the ward election winners and losers. For example if we see two leaders with last name Kale compete for different ward seats or the same ward seat in a GP, we drop all the seats where the winner or loser has the last name Kale. We do this because a citizen may be connected to more than one winner or may be connected to one winner and one loser. In our current analysis, we focus on citizens who share a connection with one elected leader. In

[8]We run analysis on observations in year t but exclude year $t+1$ if we don't observe data for year $t+2$. This is because we cannot construct property tax remitted in $t+1$ if we don't observe year $t+2$

future versions, we will redefine connectedness in a less coarse manner to capture different types of connections.

4 Empirical Strategy

In typical close elections regression discontinuity designs (RDD), margin of victory between the winner and loser, as defined in equation (1), is used as a running variable. In equation (1), $ValidVotesCandidate_{nvt}$ are the valid votes received by candidate with last name n in village v at time t and $ValidVotesCandidate_{n'vt}$ are the valid votes received by candidate with last name n' in village v at time t. In our study, we define the treatment group as those citizens in a GP who share the same last name as an elected ward member. The control group is defined as those citizens who share the same last name as the loser of the ward member election. In other words, our treatment variable is as defined in (2).

$$margin_{nvt} = \frac{ValidVotesCandidate_{nvt} - ValidVotesCandidate_{n'vt}}{ValidVotesCandidate_{nvt} + ValidVotesCandidate_{n'vt}} \tag{1}$$

Table 3: Balance Table

VARIABLES	(1) Log Parcel Area
Margin	0.00529
	(0.0329)
Treat	0.173**
	(0.0801)
Margin × Treat	-0.0440
	(0.0572)
Observations	8,570
GP FE	YES
Num GPs	98
Dependent variable mean	6.070

Notes: The dependent variable is the log of parcel area recorded for the property owners from property register data. We restrict the sample to the property owners who live in the same property and to whom we can assign a single parcel area. There are a few cases (5% of the data) where different property owners living in the same property report different parcel areas. We drop these cases from the analysis in the table. Including these cases doesn't change the conclusions of the analysis in the table. Margin and Treat are as defined in (1) and (2). The regression includes GP fixed effects, year fixed effects and standard errors are clustered at the GP level. *p<0.1, **p<0.05, ***p<0.01

To prove validity of the identification strategy, we are required to show a balance table with a host of covariates between the treatment and control groups. In our data, the only covariate we observe is property parcel area from the property register. Table 3 suggests that parcel area is not balanced between those connected to the winner of a ward member election and those connected to the loser. While we do have data on pre-election tax outcomes, we don't know who the incumbent was at the time of election that we observe in our data. So we cannot assert that both treatment and controls groups were similar before the observed election.

To overcome these issues, we use close elections difference-in-discontinuities or regression discontinuity difference-in-differences design as in Grembi et al. (2016) and Persson and Rossin-Slater (2019). Close elections RD-DD net out systematic pre-existing differences between the winner connections (treatment group) and the loser connections prior to the election (control group). While our preferred specification is difference-in-discontinuities, we show the RDD results in tables A1 and A2 in Appendix A. We find that the RDD results are qualitatively in line with our difference-in-discontinuities results.

In our set up, we will assume that there are pre-existing differences between the control and treatment groups. To simplify, let's assume that on average control and treatment groups only differ in terms of the parcel area that they own (as seen in table 3); average parcel area differs systematically with the last name even prior to election. So two treatments sharply change at the cut-off threshold. To be consistent with notation in Grembi et al. (2016), we define L_{nvt} as the first treatment for citizen with last name n in village v at time t, which is equal to 1 if parcel area is large and 0 otherwise. We also define $Treat_{nvt}$ as the second treatment, equal to 1 if the citizen shares the same last name as winner of a ward member election and 0 if the citizen shares the same last name as loser of a ward member election[9].

Following Grembi et al. (2016), the assignment mechanism for two treatments can be described as follows:

$$Treat_{nvt} = \begin{cases} 1 \text{ if } margin_{nvt} \geq 0 \text{ and } Post_t = 1 \\ 0 \quad \text{otherwise} \end{cases} \tag{2}$$

$$L_{nvt} = \begin{cases} 1 \text{ if } \quad margin_{nvt} \geq 0 \\ 0 \quad \text{otherwise} \end{cases} \tag{3}$$

We define $Post_t$ as a binary variable that takes the value 1 post-election and 0 pre-election. Define $Y_{nvt}(l,t)$ as the potential policy outcomes if $L_{nvt} = l$ and $Treat_{nvt} = t$. The observed outcome can then be defined as $Y_{nvt} = L_{nvt}Treat_{nvt}Y_{nvt}(1,1) + L_{nvt}(1 - Treat_{nvt})Y_{nvt}(1,0) + (1 - L_{nvt})Treat_{nvt}Y_{nvt}(0,1) + (1 - L_{nvt})(1 - Treat_{nvt})Y_{nvt}(0,0)$. In our setting we want to identify the causal effect of $Treat_{nvt}$ on Y_{nvt}. As in Grembi et al. (2016), we need to make three assumptions for causal identification.

1. Assumption 1: All potential outcomes $E[Y_{nvt}(l,t)|margin_{nvt} = 0, Post_t = 0]$ and $E[Y_{nvt}(l,t)|margin_{nvt} =$

[9]Due to our set-up of close elections RD-DD design, those who aren't connected to either the winner or loser drop out of our analysis as we cannot assign a margin variable for them.

$0, Post_t = 1]$, with $l = 0,1$ and $t = 0,1$, are continuous in $margin_{nvt}$ at 0.

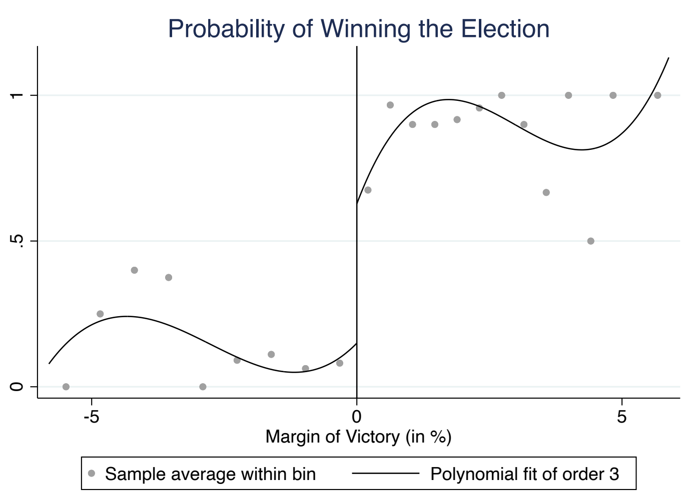
2. Assumption 2: The effect of the confounding policy L_{nvt} at $margin_{nvt}$, in case of no treatment, $(Treat_{nvt} = 0)$ is contant over time: $Y_{nvt}(1,0) - Y_{nvt}(0,0) = \tilde{Y}(1,0) - \tilde{Y}(0,0)$. In our context, this implies difference in parcel area between treatment and control groups is constant over time.

3. Assumption 3: The effect of $Treat_{nvt}$ at $margin_{nvt} = 0$ does not depend on the confounding policy $L_{nvt} : Y_{nvt}(1,1) - Y_{nvt}(0,0) = Y_{nvt}(0,1) - Y_{nvt}(0,0) = Y_{nvt}(1) - Y_{nvt}(0,0)$. In our setting, this implies tax compliance and remittance shouldn't depend on pre-existing differences in land area.

The first two assumptions are sufficient to show that differences-in-discontinuity estimator identifies the average treatment effect $E[Y_{nvt}(1,1) - Y_{nvt}(1,0)|margin_{nvt} = 0]$. To identify a more general estimand, similar to the one estimated by RD designs, we need to incorporate the third assumption as well. For more details on exact identification, please refer to Grembi et al. (2016).

In a sharp regression discontinuity design, as the running variable goes from below to above the cut-off, the probability of treatment should discontinuously jump from 0 to 1. In our setting, this means as the margin of victory (as defined in equation (1)) becomes positive, the probability of a citizen who has the last name n being connected to elected ward member with last name n should jump from 0 to 1. However in the data while we see a discontinuous jump at the cut-off 0, the probability of being connected to winner jumps approximately from 0.2 to 0.7 as can be seen in figure 3.

Figure 3



Notes: This figure presents an RD plot of margin of victory (in percent), as defined in equation (1), on the x-axis and probability of being declared as the winner of ward election on the y-axis.

There are 2 reasons why we don't see a jump from 0 to 1 at the 0 threshold for margin. First, out of the 137 close elections[10] that we see in our data, there are 5 elections where a winner is declared when the margin of victory is 0. These seem to be cases where there is a tie and there was either a re-election or some other factor (that we don't observe) that determines the winner. There are 11 elections where the contestant for whom the margin is negative is declared the winner. In such cases, there was either an error in reporting this information or something else that happened at the time of the election which we don't observe. We deal with such elections in two ways. First, we drop the cases where a contestant is declared as the winner when the margin is 0 or negative and run a sharp difference-in-discontinuities. We are left with 121 close elections once we drop these elections. Sharp difference-in-discontinuities is our preferred specification and we present the results of this specification in our main paper. Second, we don't drop these cases and instead use margin of victory as an instrument for probability of being connected to the winner and run a fuzzy difference-in-discontinuities. The results of this specification are displayed in tables B1 and B2 in Appendix B. Though not significant, results for tax outcomes (apart from probability of remitting completely) and enforcement outcomes are in line with our main results.

Following the regression specification from Grembi et al. (2016), the sharp difference-in-discontinuities specification is as follows:

$$\begin{aligned} y_{invt} = \beta_0 + \beta_1 X_i + \beta_2 Treat_{nvt} + \beta_3 Treat_{nvt} \times margin_{nvt} + \beta_4 Post_t + \beta_5 Post_t \times \\ margin_{nvt} + \beta_6 Post_t \times Treat_{nvt} + \beta_7 margin_{nvt} \times Treat_{nvt} \times Post_t + \eta_v + \delta_t + \epsilon_{invt} \end{aligned} \tag{4}$$

In the above equation, y_{invt} is the property tax outcome of property owner i with last name n in GP v at time t. X_i refers to property owner level controls which include the property parcel area. $Treat_{nvt}$ and $margin_{nvt}$ are as defined in equations (1) and (2) respectively. $Post_t$ is a binary indicator for the financial year t starting after the GP election date. η_v and δ_t are GP and year fixed effects. ϵ_{invt} is a mean zero error term. β_6 is our coefficient of interest and captures how connections of the elected GP leaders change their property tax remitting behaviour post election. We use the optimal bandwidth as proposed by rdbwselect command from Calonico et al. (2014a,b) as is standard in the RD literature. We use clustered standard errors at the GP level.

5 Results

Table 4 shows the results for β_6 from equation (4). These results show that those who are connected to the ward member are 44.9 percentage points more likely to remit any taxes and 30.6 percentage points less likely to completely remit their taxes compared to connections of the contestant with the second highest votes in the ward election. We also find that connections of the ward member

[10] absolute value of margin of victory is less than 6%

face 100% more in property taxes levied and remit 351% more in taxes. Comparing the coefficient for log property tax levied and log property tax remitted, we find that increase in property tax remittance is not completely driven by higher amount of taxes being levied.

Table 4: Property Tax Outcomes

VARIABLES	(1) Remit Any	(2) Log Property Tax Levied (Current)	(3) Log Property Tax Remitted
Post × Treat	0.449**	0.693***	1.508**
	(0.176)	(0.208)	(0.697)
Observations	5,926	8,516	6,841
GP FE	YES	YES	YES
Year FE	YES	YES	YES
Bandwidth	.334	.494	.436
Num GPs	13	20	17
Num Seats	13	20	17
Dependent variable mean	0.270	5.560	1.840

Notes: The table displays regression coefficient β_6 from equation (4) with property tax outcomes as main dependent variables. Remit any is a binary indicator for whether any amount of property tax is remitted. Remit completely is a binary indicator which takes the value 0 if there is any outstanding amount of property tax. Log property tax levied (current) is the log of property tax levied in the current year. Property tax levied in the current year is bottom coded to be non-negative. Log property tax remitted is the log of amount of tax remitted. Amount of tax remitted is also bottom coded to be non-negative. We select the bandwidths reported in the table according to the optimal bandwidth selection procedure from Calonico et al. (2014b,a). When selecting the optimal bandwidths, we control for GP fixed effects, year fixed effects and clustering of standard errors. The regression includes GP fixed effects, year fixed effects and standard errors are clustered at the GP level. *p<0.1, **p<0.05, ***p<0.01

As discussed in the introduction, it's possible that citizens who feel affinity towards their leader are more likely to remit taxes as they may believe that leader is better at targeting public goods towards them or is more efficient with fiscal revenues. It's also possible that leaders use their local information to enforce tax collection better for their co-network members. To disentangle whether this is citizen driven or enforcement driven, we look at fines that are levied on property owners who are delinquent on their property taxes.

We use the same equation as in (4) where y_{invt} refer to fines levied or probability of facing a fine. In table 5, we show the results for fines. We find that our results are atleast partially being driven by enforcement as those who are connected to the GP ward-member face 247% more in fines and are 30.8 percentage points more likely to be fined.

These estimation results are consistent with two types of descriptive graphs shown in figures 4 and 5. Following Grembi et al. (2016), to examine if there is a discontinuity at the threshold, we draw scatters and polynomials of each post-election and each pre-election value in figure 4. We can see that there are discontinuous jumps for all the property tax outcomes and fines. The

Table 5: Fines

VARIABLES	(1) Log Fine Amount	(2) P(Fine)
Post × Treat	1.259**	0.308*
	(0.584)	(0.151)
Observations	8,516	8,516
GP FE	YES	YES
Year FE	YES	YES
Bandwidth	.5	.52
Num GPs	20	20
Num Seats	20	20
Dependent variable mean	1.180	0.320

Notes: The table displays regression coefficient β_6 from equation (4) with log fine and probability of being fined as main dependent variables. Log fine amount is the log of fine amounts recorded in the property tax dataset. Fine amounts are bottom coded so they take non-negative values. Probability of fine is a binary indicator for whether a fine is levied on the property owner. We select the bandwidths reported in the table according to the optimal bandwidth selection procedure from Calonico et al. (2014b,a). When selecting the optimal bandwidths, we control for GP fixed effects, year fixed effects and clustering of standard errors. The regression includes GP fixed effects, year fixed effects and standard errors are clustered at the GP level. *p<0.1, **p<0.05, ***p<0.01

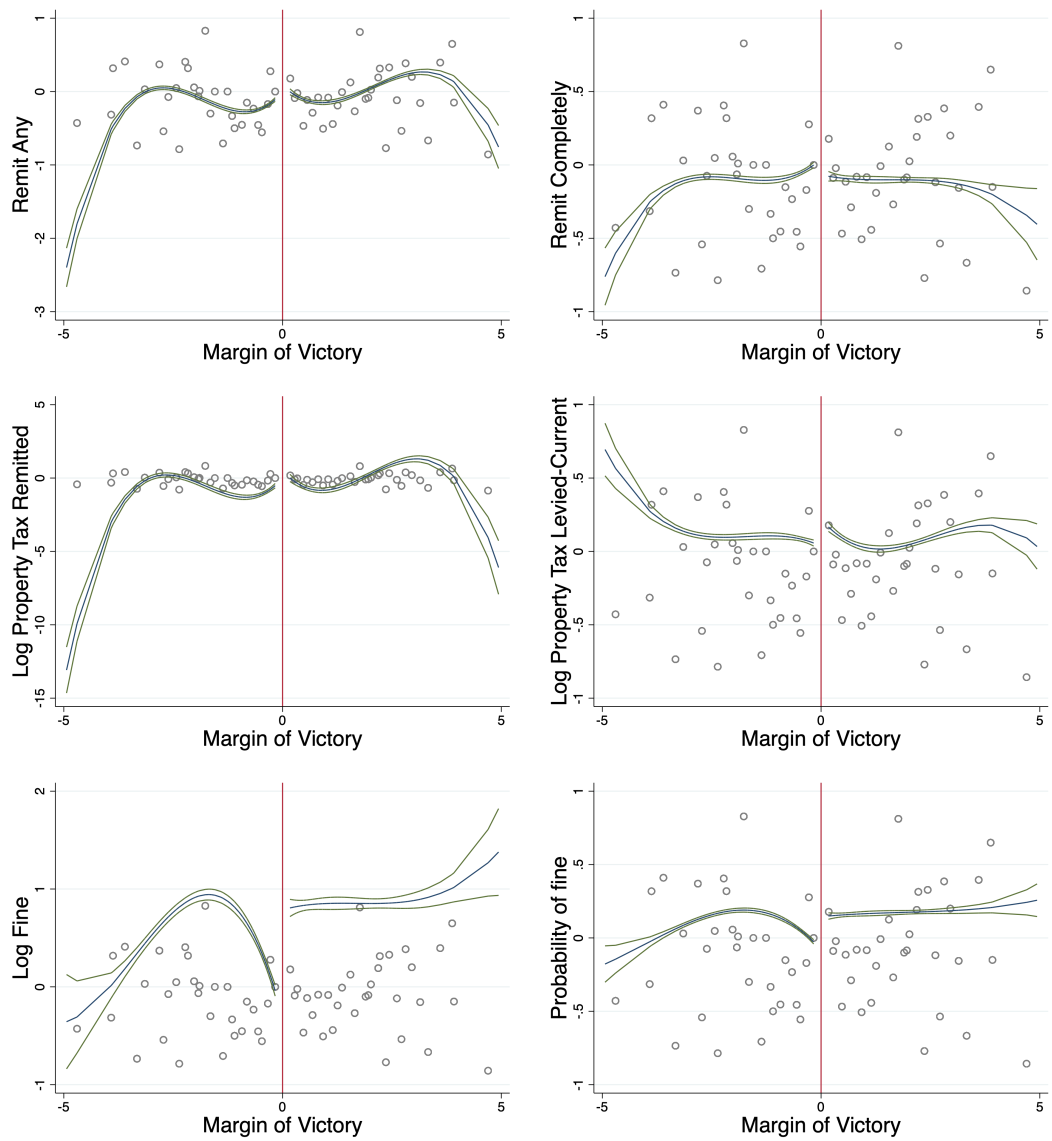
discontinuity in jump and difference in slopes are most evident for the enforcement variables; log fine levied and probability of fine.

Next, to examine whether the citizens connected to the winner and citizens connected to the loser are on similar tax remitting trends prior to the election, we conduct analysis with individual fixed effects (as shown in specification in equation (5)). In equation (5), y_{invt} refers to property tax outcomes or fines of individual i with last name n in village v at time t belonging to group g, where g refers to either control or treatment groups. The second and third terms refer to full set of event-time and year dummies. ϕ_i refer to property owner fixed effects and ν^g_{invt} refer to mean 0 error term. As individuals' property tax remitting behaviour within a GP may be correlated (for example due to general tax morale or perceived level of evasion), we cluster the standard errors at the GP level. We normalize the coefficients relative to the immediate period prior to the election. For this analysis, instead of choosing different bandwidths as dictated by Calonico et al. (2014b), we choose a margin of 1% for all the graphs. For this reason, the graphs in figure 5 should be interpreted as descriptive results.

$$y^g_{invt} = \gamma_0 + \sum_{j \neq -1} \gamma^g_j \cdot \mathbb{I}[j = s] + \sum_t \gamma^g_z \cdot \mathbb{I}[z = t] + \phi_i + \nu^g_{invt} \tag{5}$$

In figure 5, citizens connected to winners and citizens connected to losers do seem to be on parallel trends prior to the election in terms of their tax remitting behaviour. Post election, the results for probability of remitting any tax, log property tax remitted, log fines and probability of

Figure 4: Descriptive difference-in-discontinuity plots

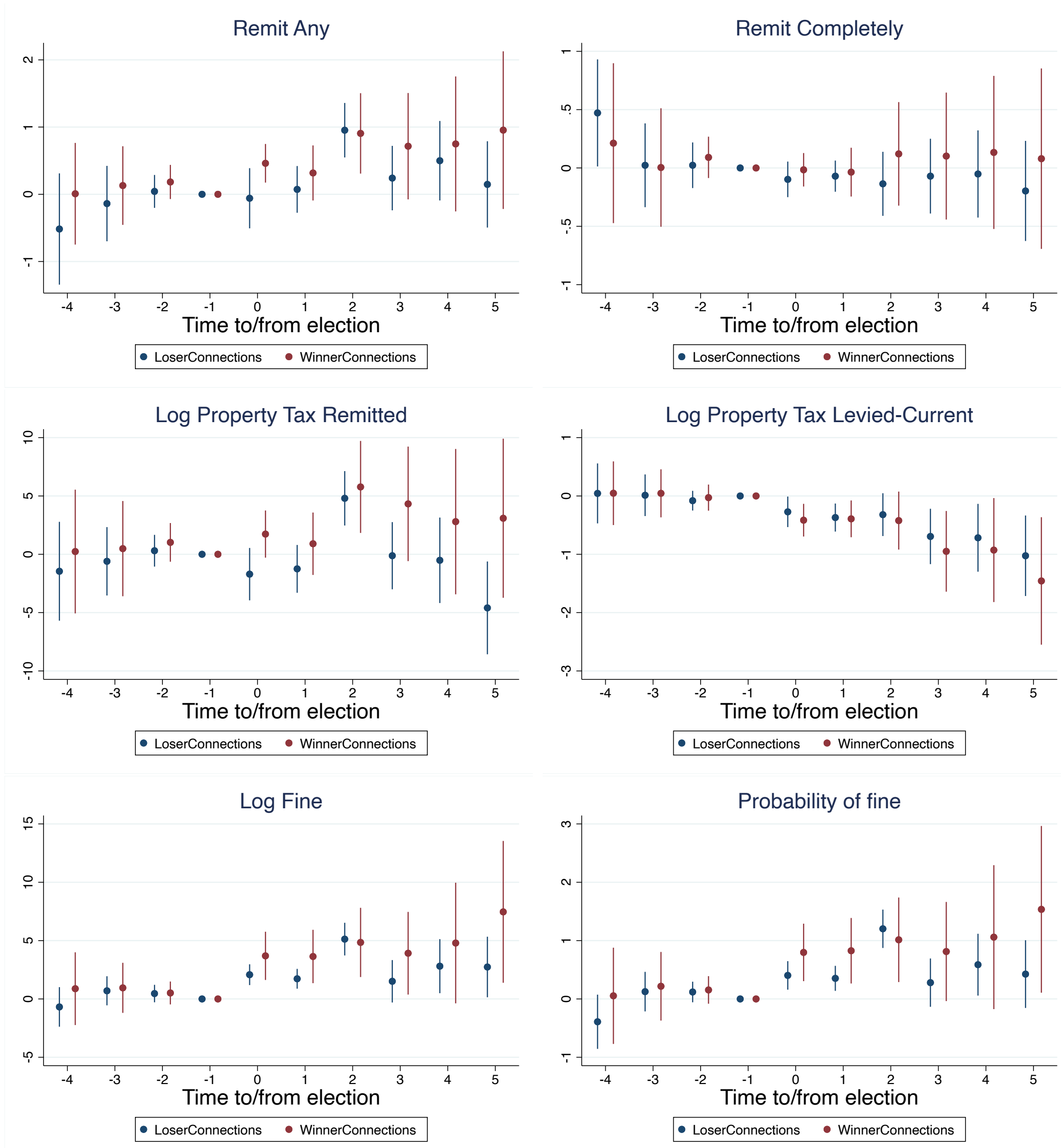


Notes: The vertical axis is the difference of each post-election outcome value and each pre-election outcome value for each of the dependent variables. The horizontal axis is the margin of victory variable. The central line is a spline third-order polynomial fit; the green lines represent the 95 percent confidence interval. Scatter points are averaged over intervals of 0.1 margin of victory.

being fined are consistent with those that we see in tables 4 and 5.

We test the sensitivity of our results to the choice of bandwidth. As in typical RDD analysis, with smaller bandwidths the coefficients are accompanied by larger standard errors due to smaller sample sizes, but there is also lower selection bias. With larger standard errors, precision is more likely to be achieved but with larger bias. We plot our RD-DD estimates over different bandwidths for margin of victory ranging from 0.2 to 5 (with an interval of 0.2) for all our outcome variables of interest. We show these results in figure 6.

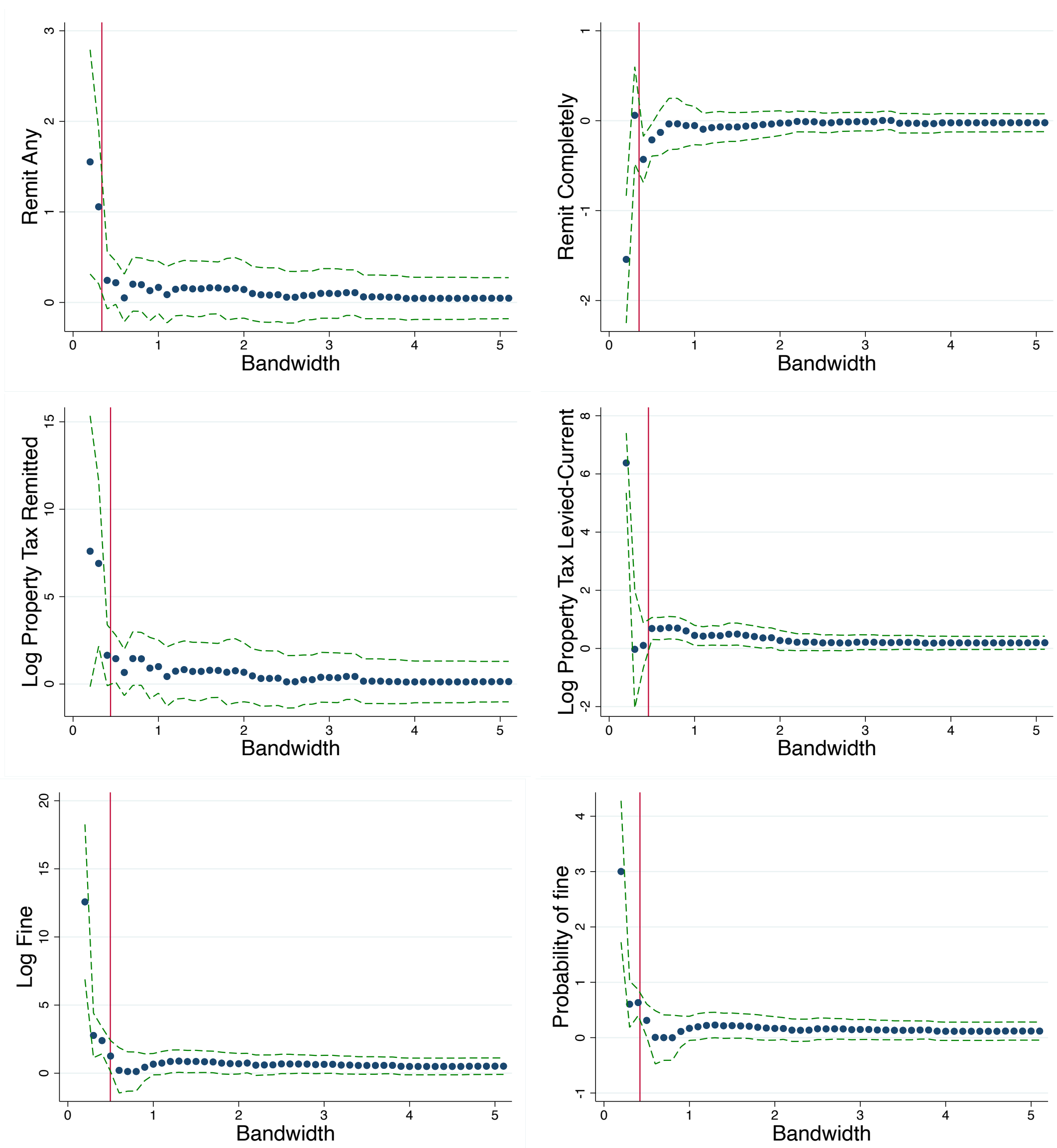
Figure 5: Event study for connections of winner and loser of ward member election



Notes: The vertical axis of graphs plot γ_j^g from equation (5) separately for citizens connected to loser (blue) and winner (red) of a ward member election for each of the dependent variables. The horizontal axis is the time to and from election for the citizens. The margin of victory is fixed at 1% for all the graphs and the coefficient for the period immediately before ward election is normalized to 0.

We do find that our results are sensitive to the choice of bandwidth. However, we find our results to be significant at smaller bandwidths. While most of the property tax outcomes lose significance around 0.5% margin bandwidth, we find these effects remains significant for log property tax levied and log fines levied over a range of different bandwidths for margins. Across various causal and descriptive estimates, results on enforcement show up to be economically and statistically significant.

Figure 6: Difference-in-discontinuity estimates for different bandwidths



Notes: The graphs plots the β_6 coefficients (i.e. coefficient of $Post \times Treat_{nvt}$) from equation (4) for margin of victory bandwidths ranging from 0.2% to 5.1% with 0.2% intervals. The blue circles represent the coefficient estimates and green lines represent 95% confidence interval. The red vertical lines mark the "optimal" bandwidths estimated using Calonico et al. (2014b,a) method. The blue circles that coincide with the red line represent the coefficients shown in tables 4 and 5.

5.1 Heterogeneity test

In this section, we ask who within connections of a GP ward member are driving the results? More specifically, we ask whether it is those citizens who are connected and relatively wealthy or those who are connected and relatively poor. We are interested in this heterogeneity because discussions on field suggest that in general, it is the poorer property owners that remit taxes: *"Poor families have already paid the taxes. The rich do not pay the tax. Middle class and poor people pay the tax. Poor families know that if they do not pay the tax this year then the next year they have to pay the tax with an interest rate which they can't afford. Therefore, poor families pay on time. Rich people have not yet paid tax for the last 10 years."*

- Quote from a Self Help Group member on field

More generally, if the wealthier connections of the ward member are remitting more and facing higher fines, then the GPs are levying property taxes progressively. In addition, if the tax revenues are directed towards public goods that are targeted at poorer connections within the GP, then the results we find on targeting wealthier connections are most likely welfare enhancing. On the other hand, if we find that poorer connections of the leaders are bearing the burden of the tax, there could be two possible scenarios. One, the poorer connections may be paying for public goods but in the form of taxes. Two, they may be remitting more taxes, but if the revenues go towards public goods for the wealthier households, then that's possibly worse for overall welfare.

To perform our heterogeneity analysis, amongst all the connections of the winner (loser) in a GP, we calculate the median log parcel area. We then generate an indicator for whether the connection has above the median log parcel area or below the median log parcel area and run a triple difference approach by interacting each of the variables in equation (4) with the above median indicator.

The results of this exercise are displayed in tables 6 and 7. From this table we can see that increases in tax remittance and higher levying of property taxes are driven by the property owners with below median parcel area. Interestingly, for those property owners with above the median parcel area, we find clientelistic behaviour. We can rationalize these results if we take into account that larger parcel area owners likely have more political power and may affect re-election probability more compared to property owners with lower parcel area.

So while those who are connected to the local GP ward member have a higher probability of remitting taxes, remit more in taxes, face higher taxes and face more enforcement, the results are being driven by poorer connections. At this point, with our current set of data we are not able to disentangle whether these tax revenues go towards supplying public goods for these poorer connections or for the village in general. In future iterations of our paper, we hope to supplement

Table 6: Property Tax Outcomes

VARIABLES	(1) Remit Any	(2) Log Property Tax Levied (Current)	(3) Log Property Tax Remitted
Post × Treat × Below Median	0.532**	0.945*	1.820*
	(0.185)	(0.524)	(0.871)
Post × Treat × Above Median	-0.151*	-0.540	-0.758
	(0.0766)	(0.799)	(0.893)
Observations	5,926	8,516	6,841
GP FE	YES	YES	YES
Year FE	YES	YES	YES
Bandwidth	.334	.494	.436
Num GPs	13	20	17
Num Seats	13	20	17
Dependent variable mean	0.270	5.560	1.840
Above med == Below med	0.0110	0.266	0.117

Notes: Remit any is a binary indicator for whether any amount of property tax is remitted. Remit completely is a binary indicator which takes the value 0 if there is any outstanding amount of property tax. Log property tax levied (current) is the log of property tax levied in the current year. Property tax levied in the current year is bottom coded to be non-negative. Log property tax remitted is the log of amount of tax remitted. Amount of tax remitted is also bottom coded to be non-negative. We select the bandwidths reported in the table according to the optimal bandwidth selection procedure from Calonico et al. (2014b,a). When selecting the optimal bandwidths, we control for GP fixed effects, year fixed effects and clustering of standard errors. Amongst the connections of a ward member within a GP, we calculate the median log parcel area. We then generate a binary indicator for whether a connected property owner has above median log parcel area or below median log parcel area and interact this indicator with $Post \times Treat$ to conduct a heterogeneity analysis. The coefficients of this interaction are displayed in the above table. The last line of the table displays the p-value for the t-test with the null hypothesis that the coefficient for the below median interaction is statistically indifferent from the coefficient for the above median interaction. The regression includes GP fixed effects, year fixed effects and standard errors are clustered at the GP level. *p<0.1, **p<0.05, ***p<0.01

this analysis with data on public goods to better understand how these tax revenues are utilized.

5.2 Discussion of results

We believe our results can be rationalized by either of the following models. The set up of the models is the same but they differ in what the voters use as a signal to infer the ward member's type. Let's assume politicians are of two different types, good and bad (i.e. type of politician $\theta \in \{b, g\}$). All politicians in our model care about re-election. The politicians can undertake an action a (for example, collect taxes, enforce fines, build public goods) to signal their type but this is observed by the voters with a noise. Voters observe $a + \epsilon$. Voters will vote and re-elect leaders they perceive to be of the good type.

Use property tax remittance behaviour of connections as a signal of ward member type: In the first type of model, let's say the voters observe the property tax remittance behaviour of those connected to an elected ward member and use this to infer the type (θ) of the ward member. For the ward member to be perceived of the good type, the connections have to be more likely

Table 7: Fines

VARIABLES	(1) Log Fine Amount	(2) P(Fine)
Post $\times$ Treat $\times$ Below Median	1.428**	0.304*
	(0.645)	(0.154)
Post $\times$ Treat $\times$ Above Median	-0.368	-0.00343
	(0.430)	(0.0920)
Observations	8,516	8,516
GP FE	YES	YES
Year FE	YES	YES
Bandwidth	.5	.52
Num GPs	20	20
Num Seats	20	20
Dependent variable mean	1.180	0.320
Above med == Below med	0.0640	0.129

Notes: Log fine amount is the log of fine amounts recorded in the property tax dataset. Fine amounts are bottom coded so they take non-negative values. Probability of fine is a binary indicator for whether a fine is levied on the property owner. We select the bandwidths reported in the table according to the optimal bandwidth selection procedure from Calonico et al. (2014b,a). When selecting the optimal bandwidths, we control for GP fixed effects, year fixed effects and clustering of standard errors. Amongst the connections of a ward member within a GP, we calculate the median parcel area. We then generate a binary indicator for whether a connected property owner has above median log parcel area or below median log parcel area and interact this indicator with $Post \times Treat$ to conduct a heterogeneity analysis. The coefficients of this interaction are displayed in the above table. The last line of the table displays the p-value for the t-test with the null hypothesis that the coefficient for the below median interaction is statistically indifferent from the coefficient for the above median interaction. The regression includes GP fixed effects, year fixed effects and standard errors are clustered at the GP level. *p<0.1, **p<0.05, ***p<0.01

to remit taxes and remit more in taxes. Otherwise, the ward member may be perceived as displaying favouritism towards connections and hence corrupt. As a result, the ward member may be enforcing fines more strictly for connections in order to increase their tax remittance to increase the likelihood of being perceived as 'good' and as result increase the re-election probability. It's likely that it is less costly for the elected leaders to target the less wealthy connections for this stringent enforcement as they have less political power and as a result are less likely to mobilize and retaliate.

Use enforcement of fines on connections as a signal of ward member type: In the second type of model, let's say the voters observe the enforcement actions undertaken by the ward member to infer the ward member's type. For the ward member to be perceived as the good type, the connections have to face higher fines and a higher probability of being fined. The ward member may as a result be enforcing fines more strictly for connections. As the penalties for tax evasion become more salient for connected citizens, they increase their tax remittance. Similar to the above model, the elected leaders may target this stricter enforcement towards less wealthy connections as they hold less political power.

Use public good provision as a signal of ward member type: In the third type of model, let's say the voters observe the building of public goods by the ward member to infer the ward member's type. For the ward member to be perceived as the good type, the ward member needs to raise sufficient revenues in order to build the public goods. Since we are in a low compliance environment, the ward member may target their enforcement efforts towards their connections to increase the chances of raising revenues without severely damaging re-election probability. Once again it's possible that they target the enforcement efforts towards the less wealthy connections as they hold less power. It's also possible that they target the enforcement efforts towards the less wealthy connections as they are more likely to benefit from access to new public goods.

We believe any of the above mentioned models can help rationalize our results. In future work, we hope to incorporate data on re-election probabilities and public goods to disentangle which of the above models may be able to explain our results best.

6 Conclusion

Our study provides valuable insights into the dynamics of tax compliance in developing countries by examining the impact of social connections with local elected leaders. We provide novel evidence from an understudied setting - rural areas in developing countries - that individuals connected to elected officials are more likely to remit property taxes, face higher tax assessments, and ultimately remit larger amounts. Our findings suggest that these effects are largely driven by increased enforcement, such as higher fines and a greater likelihood of being fined. Additionally, we observe that these outcomes are primarily driven by less wealthy individuals who are connected to local leaders, further highlighting the role of socioeconomic status in shaping tax compliance dynamics within these communities.

This behavior underscores the role of enforcement and social networks in shaping tax compliance, particularly among poorer property owners. The observed discrepancies in tax compliance between connected and non-connected individuals highlight the potential of leveraging local political structures to enhance fiscal capacity and improve revenue collection. By demonstrating that connections to local leaders can lead to substantial increases in tax compliance, our research not only contributes to the understanding of tax behavior but also informs policy discussions on enhancing local government autonomy and effectiveness in poverty alleviation.

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Appendices

Appendix A

Table A1: Property Tax Outcomes - RDD Estimates

VARIABLES	(1) Remit Any	(2) Log Property Tax Levied (Current)	(3) Log Property Tax Remitted
RD_Estimate	0.490	0.111	1.850
Observations	10590	10590	10590
Robust 95% CI	[-2.245 ; 2.932]	[-.6 ; 1.069]	[-7.432 ; 6.755]
Kernel Type	Triangular	Triangular	Triangular
BW Type	mserd	mserd	mserd
Conventional Std. Error	0.058	0.106	0.453
Conventional p-value	0.000	0.294	0.000
Robust p-value	0.795	0.582	0.926
Order Loc. Poly. (p)	1.000	1.000	1.000
Order Bias (q)	2.000	2.000	2.000
BW Loc. Poly. (h)	0.268	0.633	0.310
BW Bias (b)	0.538	0.771	0.505

Notes: The table shows the RD estimate computed using Calonico et al. (2014b,a). Remit any is a binary indicator for whether any amount of property tax is remitted. Remit completely is a binary indicator which takes the value 0 if there is any outstanding amount of property tax. Log property tax levied (current) is the log of property tax levied in the current year. Property tax levied in the current year is bottom coded to be non-negative. Log property tax remitted is the log of amount of tax remitted. Amount of tax remitted is also bottom coded to be non-negative. The regression includes GP fixed effects, year fixed effects and standard errors are clustered at the GP level. *p<0.1, **p<0.05, ***p<0.01.

Table A2: Fines - RDD Estimates

VARIABLES	(1) Log Fine Amount	(2) P(fine) Amount
RD_Estimate	0.904	0.156
Observations	10590	10590
Robust 95% CI	[-1.011 ; 3.709]	[.038 ; .388]
Kernel Type	Triangular	Triangular
BW Type	mserd	mserd
Conventional Std. Error	0.162	0.024
Conventional p-value	0.000	0.000
Robust p-value	0.263	0.017
Order Loc. Poly. (p)	1.000	1.000
Order Bias (q)	2.000	2.000
BW Loc. Poly. (h)	0.363	0.476
BW Bias (b)	0.613	0.691

Notes: The table shows the RD estimate computed using Calonico et al. (2014b,a) method. Log fine amount is the log of fine amounts recorded in the property tax dataset. Fine amounts are bottom coded so they take non-negative values. Probability of fine is a binary indicator for whether a fine is levied on the property owner. The regression includes GP fixed effects, year fixed effects and standard errors are clustered at the GP level. *p<0.1, **p<0.05, ***p<0.01

Appendix B

Table B1: Property Tax Outcomes - Fuzzy Differences-in-Discontinuity Estimates

VARIABLES	(1) Remit Any	(2) Log Property Tax Levied (Current)	(3) Log Property Tax Remitted
Connected Winner × Post	1.055	1.231	0.821
	(2.776)	(3.250)	(2.107)
Observations	11,087	12,762	10,172
GP FE	YES	YES	YES
Year FE	YES	YES	YES
Bandwidth	.456	.529	.353
Num GPs	24	27	20
Num Seats	24	27	20
Dependent variable mean	0.460	5.720	2.640

Notes: The table shows $Post \times Treat$ estimates for instrumental variable difference-in-discontinuity estimates. We instrument with sharing the same last name as a ward member (treatment) with margin of victory variable. The dependent variables are property tax outcomes. Remit any is a binary indicator for whether any amount of property tax is remitted. Remit completely is a binary indicator which takes the value 0 if there is any outstanding amount of property tax. Log property tax levied (current) is the log of property tax levied in the current year. Property tax levied in the current year is bottom coded to be non-negative. Log property tax remitted is the log of amount of tax remitted. Amount of tax remitted is also bottom coded to be non-negative. We select the bandwidths reported in the table according to the optimal bandwidth selection procedure from Calonico et al. (2014b,a). When selecting the optimal bandwidths, we control for GP fixed effects, year fixed effects and clustering of standard errors.The regression includes GP fixed effects, year fixed effects and standard errors are clustered at the GP level. *p<0.1, **p<0.05, ***p<0.01

Table B2: Fines - Fuzzy Differences-in-Discontinuity Estimates

VARIABLES	(1) Log Fine Amount	(2) P(Fine)
Connected Winner × Post	1.186	0.346
	(2.267)	(0.441)
Observations	10,520	10,172
GP FE	YES	YES
Year FE	YES	YES
Bandwidth	.373	.36
Num GPs	21	20
Num Seats	21	20
Dependent variable mean	1.020	0.280

Notes: The table shows $Post \times Treat$ estimates for instrumental variable difference-in-discontinuity estimates. We instrument with sharing the same last name as a ward member (treatment) with margin of victory variable. The dependent variables are enforcement outcomes.Log fine amount is the log of fine amounts recorded in the property tax dataset. Fine amounts are bottom coded so they take non-negative values. Probability of fine is a binary indicator for whether a fine is levied on the property owner. We select the bandwidths reported in the table according to the optimal bandwidth selection procedure from Calonico et al. (2014b,a). When selecting the optimal bandwidths, we control for GP fixed effects, year fixed effects and clustering of standard errors. The regression includes GP fixed effects, year fixed effects and standard errors are clustered at the GP level. *p<0.1, **p<0.05, ***p<0.01