Trust and Taxation: Pre-Analysis Plan

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This text represents the intentions of the research team at the time it is filed. We may deviate from this plan if unexpected issues arise, but we will report a "populated PAP" if we materially deviate from it (Duflo et al., 2020).

Abstract

This study aims to trace out the contours of politically feasible property tax reforms. Experiment 1 focused on eliciting citizens' preferences for the level and progressivity of property taxes and their determinants through a series of vignettes. That experiment's pre-registration and pre-analysis plan are available at https://www.socialscienceregistry.org/trials/15393. Experiment 2 focuses on the preferences of local politicians and bureaucrats in the Excise & Taxation department. This Pre-analysis plan presents the details of our experimental design and survey and our plan for how to analyze the resulting data.

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1 Introduction

This project focuses on the political economy of progressive property tax reform. Property taxes are beloved by economists and widely derided by politicians and taxpayers. Economists like the tax's efficiency: the base is easy to identify, immobile, and a good signal of taxpayers' wealth and income (Abbas *et al.*, 2023); (Ahmad & Brosio, 2022); (Collier *et al.*, 2018). Politicians dislike the tax's salience (Cabral & Hoxby, 2012); (Nathan *et al.*, 2020) and fear the political consequences of trying to raise taxes on property, partly because wealthy elites could suffer from such reforms and sway politicians' future electoral prospects. Governments thus often struggle politically to reform property taxes. Correspondingly, property taxes are often regressive.

In our previous experiment, we traced out the determinants of citizens' policy preferences. However, there are two other key stakeholders in property tax reforms: Local politicians, and the bureaucrats who work at the Excise & Taxation department that administers the tax. This second experiment works with them to understand the determinants of their preferences and, in particular, how responsive their preferences are to learning citizens' preferences.

The impetus for this study comes from provisions of Punjab's Property Tax Act (1958), which require the Government of the Punjab to notify updated property valuations implying a resetting of the tax rate and a change in the policy parameters that determine the distribution of tax liabilities across taxpayers. The Government of Punjab has engaged the research team to conduct a prospective evaluation that allows it to formulate strategies to increase support for higher and more progressive taxes. It has also engaged the team to test the relative efficacy of different models of mass valuation. For this exercise, Punjab's Excise and Taxation Department entered into a MOU with the research team and the Punjab Urban Unit in September 2021. The study context is Punjab, a rapidly urbanizing province with over half of Pakistan's population. Its capital city, Lahore, the site of the study, is home to over 11 million people. Lahore's current effective property tax rate (0.04%) is significantly lower than in comparators (0.5-1% in the US and Europe, 1-2% in China and the Philippines, and 0.65% in Mexico). Property taxes in Lahore generate very low levels of revenue and they are also regressive. These challenges remain despite improvements in tax capacity because of recent initiatives and the digitization of property records.

1.1 Research Questions

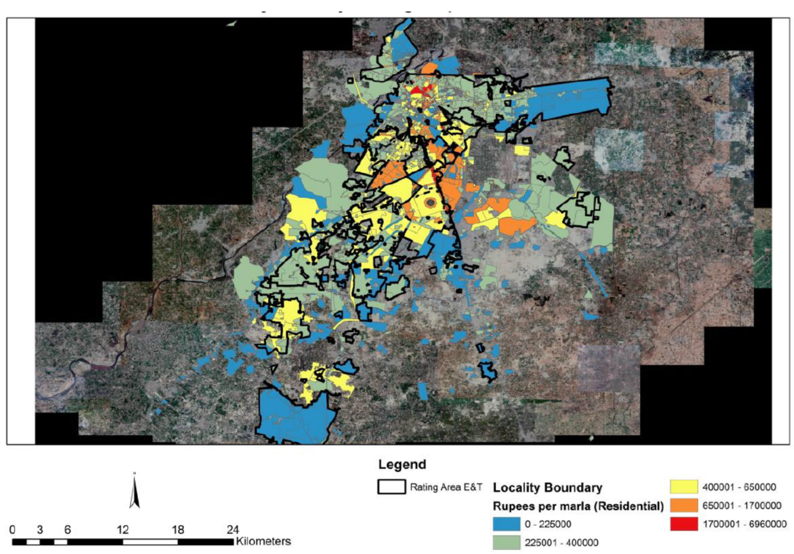
We aim to understand politicians' and bureaucrats' preferences over the level and progressivity of property taxes. As critical stakeholders, they play key information aggregation and agenda-setting roles in all property tax reform discussions. As such, we aim to understand how responsive their policy preferences and recommendations to their superiors are responsive to citizens' preferences and to the views of the government. We test for this through the random provision of information about the policy preferences of subsets of citizens and the government as described in section 3.

2 Property Taxes in Lahore

Our study site is Lahore, the provincial capital of the province Punjab, Pakistan. With a population of 110 million, Punjab is the most populous province of Pakistan. Lahore, the provincial capital, is home to 11 million people.

We work with the Excise and Taxation (E&T) Department, a provincial government revenue authority that administers the collection and billing of property taxes in metropolitan cities. Excise and Taxation administers tax from almost 1 million properties in Lahore. To administer the property tax, the E&T department has divided its rating area in Lahore into two regions headed by a director. A region is subdivided into zones. A zone is comprised of multiple tax circles. A circle is further divided into multiple localities. Localities vary in value due to a variety of reasons such as amenities etc as shown in Figure 1. Appendix A shows a flow chart of the hierarchy in jurisdictions along with the total number.

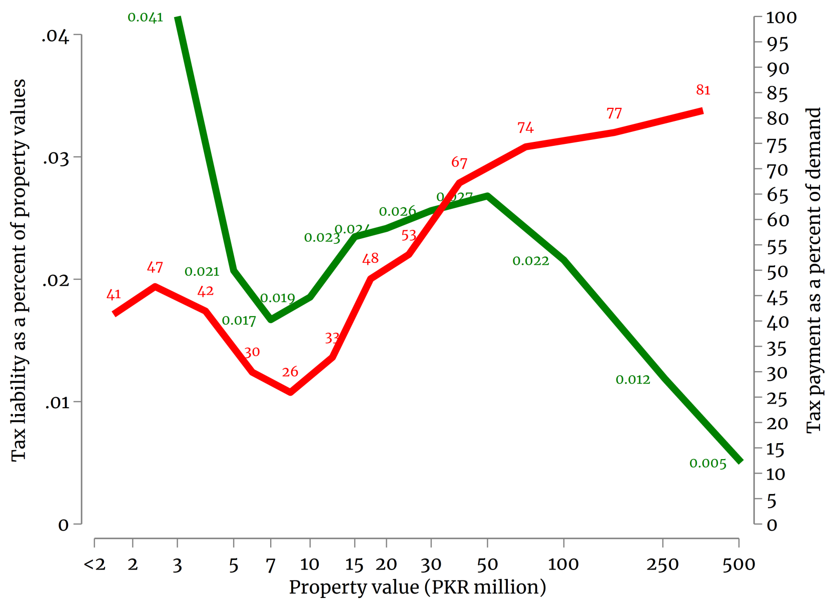
Figure 1: Locality boundary coverage of residential areas by capital value in Lahore



The current property tax system in Lahore is presumptive. A formula based on observable property attributes (including land area, covered area, number of stories, and geographic location) generates a proxy for the gross annual rental value (GARV) of the property. A table of rates is then applied to the GARV based on location and usage.

To assess the structure of the current system, we worked with real estate agents and used machine learning models to estimate the values of all residential properties in Lahore (see appendix C for details). Figure 2 shows the average property tax rate by property value in Lahore in 2022. Two key findings emerge from these data. First, Lahore's current average property tax rate (0.04%) is significantly lower than in comparators (0.5-1.5% in the US and Europe, 1-2% in China and the Philippines, and 0.65% in Mexico). Second, the property tax is mostly regressive. Exemptions of very low-valued properties make the tax progressive at the very bottom, but for the bulk of the distribution, the tax is regressive.

Figure 2: Compliance and regressivity in Lahore, Punjab Pakistan



Source: E&T property 2021-2022 tax demand data; IDEAS-LUMS property valuation survey.
Notes: Figure shows average tax rate and compliance against property value. x-axis shows market values assessed by real estate agents in 2023. The exchange rate is £1 = PKR 350. Right Y-axis shows average tax rate which is tax liability expressed as a percentage of market capital values. Left y-axis shows total tax liability as a percent of the total tax demand.

Compliance with the property tax is also imperfect. The total tax liability from Lahore for the year 2021-2022 was PKR 7.44 billion while the total collection was PKR 5.45 billion (an overall compliance rate of 76%). However, compliance is progressive: Higher value properties are more compliant with the property tax, somewhat offsetting the regressivity of the statutory schedule. Figure 2 shows compliance and the effective property tax rate by property value. While compliance is progressive, it remains the case that the effective property tax rate is regressive.

The property tax in Punjab is governed by the Punjab Urban Immovable Property Tax Act of 1958. Under the law, the government is required to update the property tax every 5 years. However, due to political instability, the property tax code for properties built prior to 2025 was last updated in 2014 and is hence urgently in need of updating.

As part of this mandatory reform process, we partnered with the Excise & Taxation department and with the provincial assembly to conduct surveys of citizens, bureaucrats, and local political workers to aggregate views on how the property tax should be set. As described below, our surveys start with a strong prompt from senior decision-makers urging respondents to take the survey very seriously and committing to using the aggregated survey responses in decision-making in the run-up to the provincial budget.

2.1 Respondents

We surveyed individual respondents who play a key role in the property tax policy of the province.

1. **Local Tax Officials**: As described in Section 2, the administration of the property tax in Lahore is divided into 198 geographic jurisdictions—tax circles. In Punjab's UIPT system, a tax circle is the basic local administrative unit responsible for property tax assessment, billing, and collection. Each circle is typically overseen by one inspector (the senior bureaucrat) and one constable (the inspector's deputy). However, in practice, some inspectors and constables are assigned to more than one circle. We work with the full universe of inspectors and constables covering all tax circles in Lahore, yielding a total of 291 bureaucrat respondents.
2. **Local Political Workers**: For political and administrative purposes, Lahore is divided into 274 Union Councils. A Union Council in Lahore, Punjab, Pakistan, is the smallest administrative unit of local government responsible for basic municipal services, civic representation, and community-level governance within a defined neighborhood or locality. In our experiment, we exclude 14 Union Councils from the Lahore Cantonment area and select a sample of 844 political workers from the remaining 260 Union Councils. For each UC, we identified at least 3 male or female political workers who actively campaigned for local members of parliament during the last General Elections in 2024.

3 Survey and Experimental Design

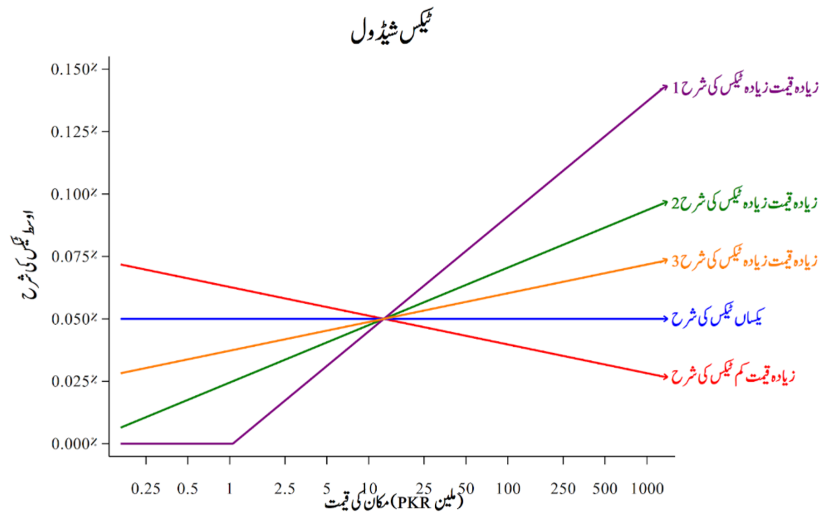
The flow of the survey in our second experiment is much like the flow in the first experiment with citizens (see the pre-registration and pre-analysis plan available at https://www.socialscienceregistry.org/trials/15393 for details). Hence, to avoid repetition, here we focus on the main differences between the citizen experiment and the bureaucrat/politician experiment.

3.1 Introductory Prompt

Even more than with citizens, the experiment was designed to ensure that it is incentive compatible for respondents to answer the survey thoughtfully and honestly. To achieve this, we introduced two distinctive features of the experiment. First, respondents were given a letter from their senior management (in the case of bureaucrats, the Director General of the Excise & Taxation department; in the case of politicians, the chairman of the Public Accounts Committee in the provincial assembly and the speaker of the assembly) explaining that the government is due to reform the property tax in the upcoming budget and that the insights gleaned from the responses to the survey will form an important part of the discussions around the formulation of the property tax proposals.

Second, respondents were asked to complete a "Policy Recommendations Form". In the form, which is referred to directly in the letter from the respondent's senior management, the respondents are asked to make an explicit endorsement of a property tax reform, and to sign and date it. This is intended to make it highly salient to

Figure 3: Eliciting Respondents' Priors About Other Groups' Tax Preferences



the respondent that the responses are being collected, aggregated, and transmitted directly to their superiors who are committed to engaging with the material and using it in their discussions around the property tax. Appendix **??** shows an example of the Policy Recommendations Form.

3.2 Beliefs about citizens', politicians' and bureaucrats' preferences.

Since a critical part of our respondents' work involves aggregating citizens' preferences (especially for politicians), we elicit respondents' beliefs about the shape of the preferred tax schedules of seven different groups by showing respondents the set of tax schedules in figure 3 and asking them which of them would be most preferred by members of each group. The seven groups we elicited are:

1. Low-value property holders;
2. Medium-value property holders;
3. High-value property holders;
4. Bureaucrats in the government of Punjab;
5. Members of the government of Punjab;
6. Opposition members of the Punjab Assembly; and
7. International donors.

3.3 Information Provision Treatments

Given the smaller sample size in experiment 2, we focused our information treatments on the main mechanism we are interested in: the responsiveness of decision-makers to the preferences of citizens, political leadership, and bureaucrats. To represent citizens' preferences, we summarized the preferences expressed by 2 groups of citizens in experiment 1:

1. low-value property occupants
2. medium/high-value property owners

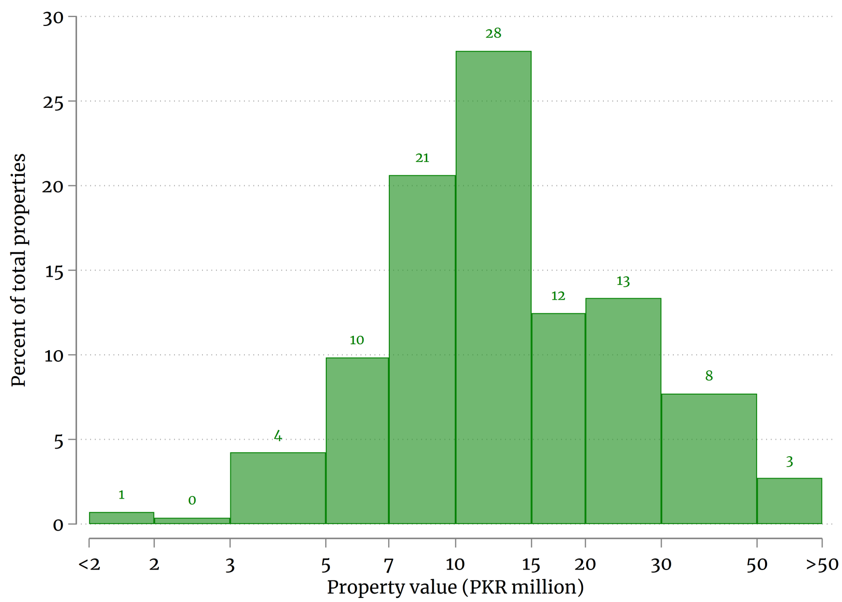
To represent the political leadership's preferences, we used a proposed reform presented to the Punjab assembly in January 2025 for use in the taxation of newly constructed properties. Finally, to represent bureaucrats' preferences, we focused on the ease of enforcement, and showed respondents the compliance rates with the property tax at different property values.

In the experiment, respondents were randomly assigned to be shown two groups' preferred tax schedules with or without property tax compliance information as follows.

3.3.1 Property value distribution

71% of the respondents were first shown a standardized introduction describing the distribution of residential property values across the 645,000 taxed properties in Lahore, based on recent survey and administrative data (see Appendix C). This introductory card highlighted the share of properties in different valuation bands (e.g., 5—7 million, 10—15 million, 30-–50 million PKR), helping respondents situate themselves and citizens within the wealth distribution (see Figure 4).

Figure 4: Distribution of residential property values in Lahore, Punjab, Pakistan

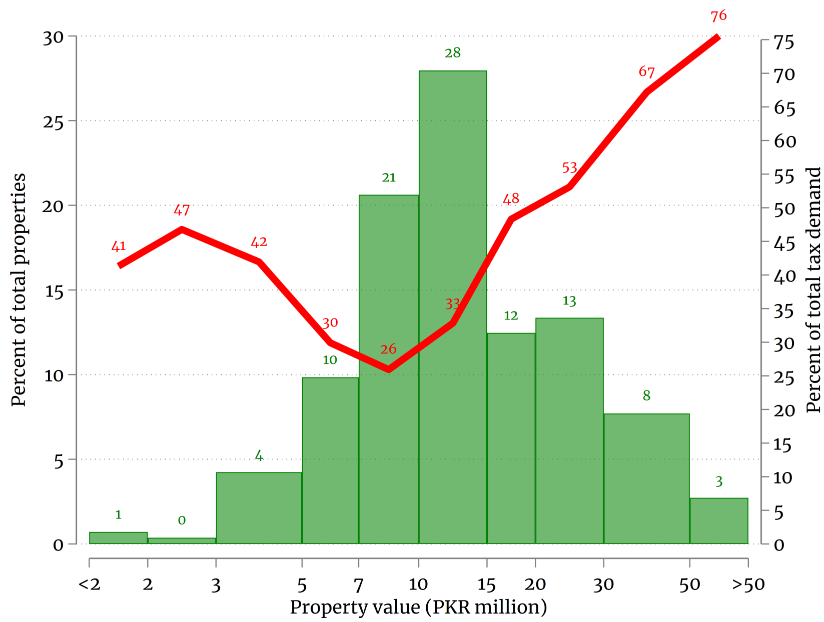


Source: IDEAS-LUMS Pol-Bur Survey 2025
Notes: Figure shows distribution for all residential properties registered with E&T in Lahore subject to the property tax based on large survey survey of property owners and real estate experts in Lahore between August 2024 and February 2025. It shows 10% of properties, with values between 5 and 7 million Rupees. We also see that there are approximately 28% of properties, with values between 10 and 15 million Rupees and that there are approximately 8% of properties, with values between 30 and 50 million Rupees.

3.3.2 Property value distribution with compliance rates

In addition to the property distribution as shown in Figure 4, 29% of respondents were also shown compliance rates measured by total tax payment as a percent of total tax demand for various property value bins. This information treatment served as a way to highlight the gap between the statutory and effective tax rates to test how important compliance rates are in determining preferences over the *statutory* tax schedule.

Figure 5: Distribution of residential property values and compliance rates in Lahore, Punjab, Pakistan



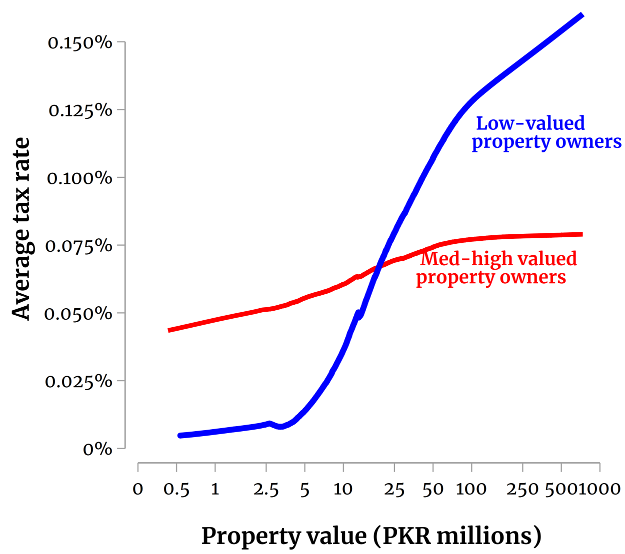
Source: IDEAS-LUMS Pol-Bur Survey 2025
Notes: The figure shows property value distribution overlaid with how much of the tax demanded from properties in each bin was actually paid (shown by red line). It shows that about 10% of properties in Lahore have values between 5 and 7 million Rupees. These properties paid around 30% of the tax demanded from them. Approximately 28% of properties in Lahore have values between 10 and 15 million Rupees and they paid around 26% of the total tax demanded. We also see that approximately 8% of properties in Lahore have values between 30 and 50 million Rupees, and these property owners pay around 76% of the total tax demanded.

Furthermore, participants were randomly allocated to receive information on two out of three of the schedules preferred by low-value property owners, medium-/high-value property owners, and a Government schedule that was implemented in January 2025, which is currently being levied on properties constructed after January 2025. Respondents were shown three benchmark property values—PKR 1 million, PKR 5 million, and PKR 100 million—and the corresponding tax rates under each group's preferred schedule. After reviewing the side-by-side comparison, respondents were asked to endorse one of the two schedules or to choose neither, in which case they were informed that this would imply support for the status quo, i.e., the existing ARV-based property tax system. The three types of comparisons included:

3.3.3 Low vs medium-to-high valued households

In this treatment arm, respondents were presented with a direct comparison between two property tax schedules derived from a large-scale survey of residents in Lahore. The first schedule reflected the average tax preferences of citizens living in low-value properties (valued under PKR 7 million), who comprise approximately 49% of the city's property-owning population. The second schedule reflected the preferences of citizens living in medium- and high-value properties (valued above PKR 7 million), representing the remaining 51% (see Figure 8).

Figure 6: Comparison of low vs medium-to-high households' tax preferences

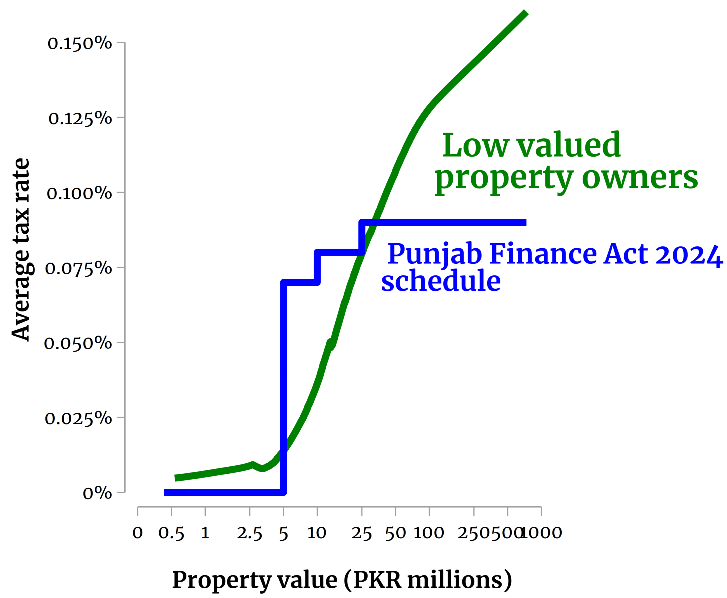


Source: IDEAS-LUMS Pol-Bur Survey 2025
Notes: The figure shows preferred property tax schedules of citizens aggregated by property value. In the citizens' survey, we asked citizens for their views on what they thought the property tax schedule should look like. We split the citizens up into two groups. The first group lives in low-value homes (under 7 million Rupees). 49% of properties are in this group. The second group resides in medium- to high-value homes (above 7 million Rupees). 51% of properties are in this group. The figure shows that low-valued households prefer a more progressive tax schedule than medium- to high-valued households.

3.3.4 Low valued households vs. the Government's tax schedule

In this treatment arm, respondents were presented with a direct comparison between average tax preferences of citizens living in low-value properties and the official tax proposal introduced by the Government of Punjab in January 2025, which moved the property tax system from an annual rental value (ARV) basis to a capital value (CV) system with progressive slabs.

Figure 7: Comparison of low vs medium-to-high households' tax preferences

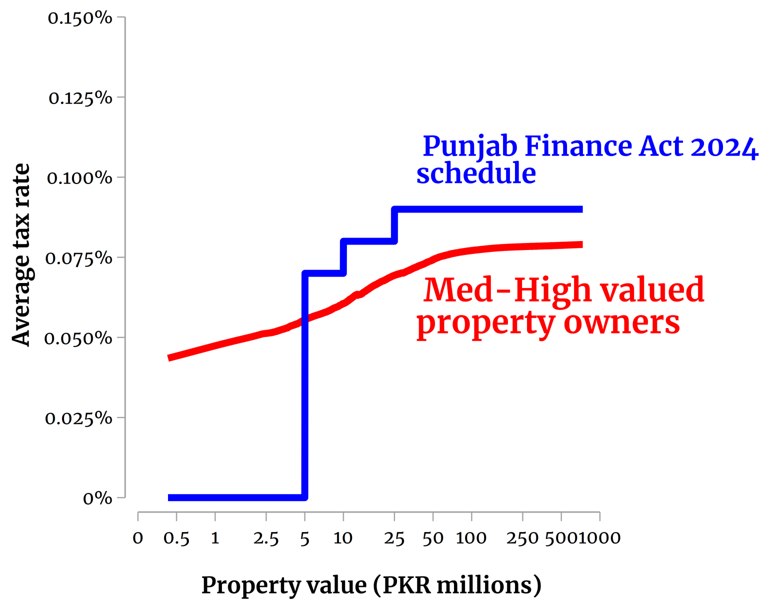


Source: IDEAS-LUMS Pol-Bur Survey 2025
Notes: The figure shows the preferred property tax schedule of citizens living in low-valued households (Below 7 million and comprising 49% of the total sample) and the new tax schedule sanctioned under the Punjab Finance Act 2024. The figure shows that for property values above PKR 25 million, low-valued households prefer a higher tax rate and a much progressive tax schedule than the government-sanctioned tax schedule.

3.3.5 Medium-to-high valued households vs. the Government's tax schedule

In this treatment arm, respondents were presented with a direct comparison between average tax preferences of citizens living in medium-to-high-value properties (valued above PKR 7 million), who make up approximately 51% of Lahore's property-owning population and the official tax proposal introduced by the Government of Punjab in January 2025.

Figure 8: Comparison of medium-to-high households' vs the Government's tax preferences



Source: IDEAS-LUMS Pol-Bur Survey 2025
Notes: The figure shows the preferred property tax schedule of citizens living in medium-to-high valued households (Above 7 million and comprising of 51% of the total sample) and the new tax schedule sanctioned under the Punjab Finance Act 2024. The figure shows that medium- to high-valued households prefer a lower tax rate than the government-sanctioned tax schedule.

3.3.6 Control

Respondents assigned to the control treatment arm were only shown the property value distribution in Lahore (see Figure 4)

Table 1: Experimental Design for Politicians and Bureaucrats

Respondent Type	Group	Prop. Val. Dist.	Compliance Info	Comparative Tax Schedule
Politicians	Control (1)	Yes	No	–
	Treatment 1 (2)	Yes	No	Low vs. Govt.
	Treatment 2 (3)	Yes	Yes	Low vs. Govt.
	Treatment 3 (4)	Yes	No	Med-High vs. Govt.
	Treatment 4 (5)	Yes	Yes	Med-High vs. Govt.
	Treatment 5 (6)	Yes	No	Low vs. Med-High
Bureaucrats	Control (1)	Yes	No	–
	Treatment 1 (2)	Yes	No	Low vs. Govt.
	Treatment 3 (3)	Yes	No	Med-High vs. Govt.
	Treatment 4 (4)	Yes	Yes	Med-High vs. Govt.
	Treatment 5 (5)	Yes	No	Low vs. Med-High

Notes: Politicians were randomly assigned to one of six groups. Since the sample of bureaucrats is slightly smaller, for them we did not use treatment arm 2.

3.4 Preference Elicitation

Following the interventions and endorsements, we collect our first main outcome by asking respondents in the experiment about their preferred tax structure. This is done by presenting respondents with information on a series of 6 residential properties, similar to (Fisman *et al.*, 2020). Respondents are then asked what they believe the current average tax rate the property tax is bearing and what they think is the appropriate average tax rate for the property. Rigorous piloting showed that the most effective method for accurately eliciting respondents' preferences involved using the average ATR of Lahore as a benchmark. Respondents were first asked whether the current rate or their preferred rate was above or below this average, followed by questions regarding the magnitude of deviation from the benchmark, either higher or lower.

Figure B.1 shows a screenshot of the Android dashboard developed for the preference elicitation module. Respondents are shown the properties' lot size, built area size, usage, the predicted market value of the property, and the number of stories. The property value predictions come from a random forest algorithm applied to data we gathered from real estate agents on their expert opinions on the values of 12,363 properties (see appendix C for details). Respondents are shown three randomly picked low-value properties (below the 50th percentile of the value distribution), three randomly picked medium-value properties (between the 50th and the 90th percentile of the value distribution), and three randomly picked high-value properties (above the 90th percentile of the value distribution).

3.5 Endorsements

After respondents are shown the pair of proposed tax schedules as detailed in section 3.3, but before we elicit respondents' preferences over the shape of the tax schedule as described in section 3.4, we ask our respondents for a provisional answer on our second main outcome. Respondents are asked whether they would be willing to endorse either of the two schedules they were shown for possible implementation during the upcoming budget. They are also asked which proposal they believe would have the highest chance of being successfully implemented.

After we have elicited respondents' preferences over the shape of the tax schedule, we ask respondents to fill in, sign and date a *"Policy Recommendation Form"*. The Form shows the respondents three tax schedules. The two reform proposals that they were randomly assigned, and the status quo. They are then asked which, if any, of the three tax schedules they endorse and the reason for their endorsement. Control group respondents are also shown three tax schedules, but they are not told whose preferences the reform schedules represent, only the status quo schedule is identified to them.

3.6 Willingness to Pay for Citizen Preferences

Near the end of the survey, we elicit respondents' willingness to pay for information about citizens' preferences about taxation. At the beginning of the survey, respondents are told that they will be given ten tickets for a lottery to win one of five Samsung tablets if they complete the survey. They can also earn up to five additional tickets if they correctly answer factual questions about the current tax system. Near the end of the survey respondents are given the opportunity to spend some of their lottery tickets on learning more about the preferences of groups of citizens.

We grouped citizens into six groups based on whether their property was low-value, medium-value, or high-value and based on whether they lived in the same area as the survey respondent or in a different part of the city. If the respondent is willing to give up 1 ticket, we tell them which of the six groups' preferences are closest to the ones that they just gave in the preference elicitation dashboard (this is computed automatically in the backend during the survey) and display that group's preferences to the respondent. Respondents then face a linear price schedule to learn the preferences of more groups, where each subsequent tax schedule revelation results in a deduction of 1 additional ticket.

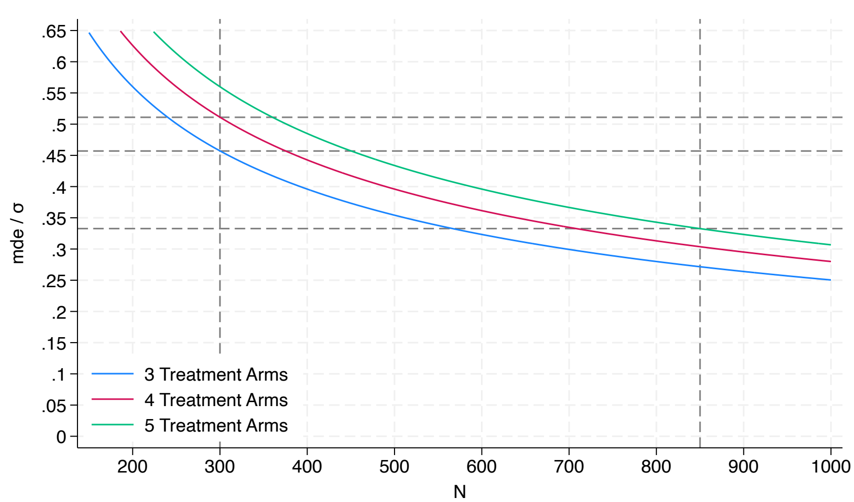
3.7 Statistical Power

Figure 9 shows the minimum detectable effect for our survey experiment as a function of the sample size, showing that we are powered to detect even relatively small effects. As described in detail in section 3.8 below, we assign respondents evenly to each of our treatment arms. This means that the minimal detectable effect comparing any two treatment arms when the total number of treatment arms (excluding the control arm) is T is given by

$$\frac{\text{MDE}}{\sigma} = \left(t_\kappa + t_{\alpha/2}\right) \cdot \sqrt{\frac{2(T+1)}{N}} \tag{3.1}$$

We aim to survey 850 politicians, assigning them to 5 treatment arms, and 300 bureaucrats, assigning them to 4 treatment arms. In the event that we are underpowered, we will pool together the treatments with and without compliance information to economize on power, leading to only 3 treatment arms. Figure 9 shows the minimal detectable effects in the two subsamples.

Figure 9: Power Calculations for Experiment

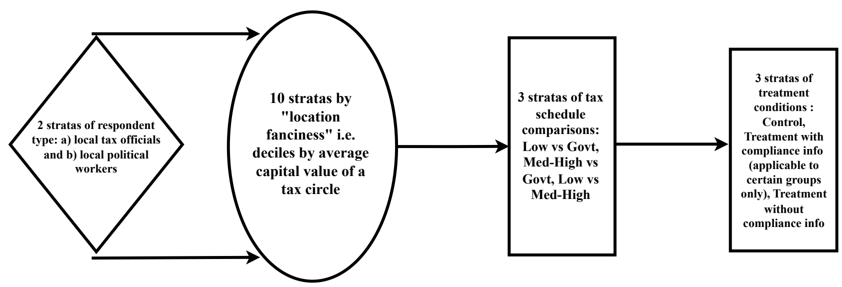


As the figure shows, for bureaucrats, at our sample size of 300, we can expect to detect effects of at least 0.51 (residual) standard deviations, while if we pool treatments this will drop to 0.46 residual standard deviations, somewhat better. For politicians, we can expect to detect effects of at least 0.33 residual standard deviations giving us confidence that the experiment is well-powered.

3.8 Treatment Assignment

Local politicians were interviewed at their offices or residential properties whereas all bureaucrats were interviewed in their respective offices. Participants were randomly assigned into treatment arms stratifying by respondent type (local politician vs bureaucrat) and deciles of the average property value in the respondent's jurisdiction (tax circle for bureaucrats, Union Council for local politicians). Figure 10 shows the four-step procedure used to implement the randomization.

Figure 10: Treatment Assignment Stratification



3.8.1 Local political workers

Within each decile stratum, politicians were randomly assigned to one of three primary comparison groups:

1. **Poor vs. Government**
2. **Med-High vs. Government**
3. **Poor vs. Med-High**

The randomization process followed a nested two-step structure:

- **Step 1**: Each respondent was randomly assigned to one of the three comparison groups (termed `group3`) with the following probabilities:
  - $\frac{7}{18}$ to **Poor vs. Government**
  - $\frac{7}{18}$ to **Med-High vs. Government**
  - $\frac{2}{9}$ to **Poor vs. Med-High**
- **Step 2**: Within each group, respondents were further assigned to treatment arms:
  - **Poor vs. Government** and **Med-High vs. Government**:
    * $\frac{1}{7}$ to Control
    * $\frac{3}{7}$ to Treatment (No Compliance Info)
    * $\frac{3}{7}$ to Treatment (With Compliance Info)

- **Poor vs. Med-High**:
  - $\frac{1}{4}$ to Control
  - $\frac{3}{4}$ to Treatment (No Compliance Info)

3.8.2 Local tax officials

Bureaucrats were stratified and randomized using the same decile-based approach, but assigned to five treatment arms due to the exclusion of the **Poor vs. Government with compliance information** treatment arm.

- **Step 1**: Assignment to one of three comparison groups (`group3`) with the following target shares:
  - $\frac{4}{15}$ to **Poor vs. Government**
  - $\frac{7}{15}$ to **Med-High vs. Government**
  - $\frac{4}{15}$ to **Poor vs. Med-High**
- **Step 2**: Assignment to treatment conditions:
  - **Poor vs. Government** and **Poor vs. Med-High**:
    - $\frac{1}{4}$ to Control
    - $\frac{3}{4}$ to Treatment (No Compliance Info)
  - **Med-High vs. Government**:
    - $\frac{1}{7}$ to Control
    - $\frac{3}{7}$ to Treatment (No Compliance Info)
    - $\frac{3}{7}$ to Treatment (With Compliance Info)

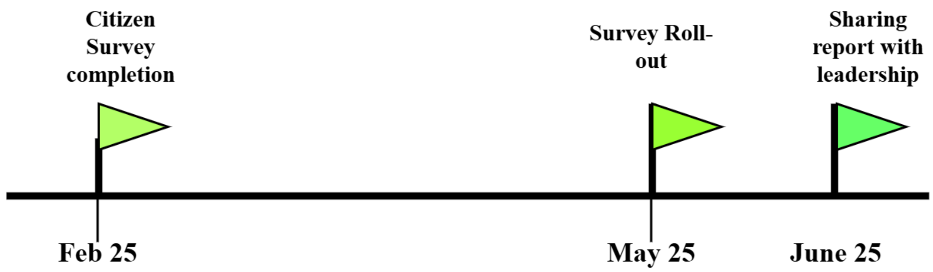
Table 2: Treatment Assignment Summary for Politicians and Bureaucrats

Comparison Group	Treatment Type	Assignment Share
Panel A: Politicians		
Comparison Group	**Treatment Type**	**Assignment Share**
Poor vs. Government	Control	1/7
	Treatment: No Compliance Info	3/7
	Treatment: With Compliance Info	3/7
Med-High vs. Government	Control	1/7
	Treatment: No Compliance Info	3/7
	Treatment: With Compliance Info	3/7
Poor vs. Med-High	Control	1/4
	Treatment: No Compliance Info	3/4
Panel B: Bureaucrats		
Comparison Group	**Treatment Type**	**Assignment Share**
Poor vs. Government	Control	1/4
	Treatment: No Compliance Info	3/4
Med-High vs. Government	Control	1/7
	Treatment: No Compliance Info	3/7
	Treatment: With Compliance Info	3/7
Poor vs. Med-High	Control	1/4
	Treatment: No Compliance Info	3/4

For each decile-based stratum, we calculated how many observations it contained, and then identified the largest number divisible by 18 (for politicians) or 15 (for tax officials) that was still smaller than or equal to the stratum size. This allowed us to assign treatment in exact proportions across groups. Any remaining respondents who did not fit into these exact blocks were assigned treatment using a second randomization step, based on a new randomized ranking. This method ensured balanced treatment assignment while making full use of the available sample.

3.9 Survey Timeline

Figure 11: Roll-out timline



4 Outcomes

4.1 Primary Outcomes

4.1.1 Endorsements

As described in section 3.5, we elicit respondents' endorsements of several tax reform proposals. We ask respondents for a preliminary endorsement before they give us their own preferences over the tax schedule, and then we ask them to complete a Policy Recommendations Form afterwards with their final endorsement that we then use as the first of our primary outcomes.

4.1.2 Tax Progressivity

Our second primary outcome is survey respondents' desired degree of tax progressivity. We use four measures of progressivity that are commonly used in the literature.[1] Each measure is normalized so that 0 means a proportional tax system, positive numbers mean progressive tax systems, and negative numbers mean regressive tax systems. We also combine the four measures into an index of progressivity since they each capture slightly different aspects of the progressivity of the overall tax schedule, and so that we can use a single measure of progressivity when we explore heterogeneity of the treatment effects.

Our progressivity measures are:

1. ***Tax Elasticity:*** The tax elasticity is $\hat{\beta}_1 - 1$ from the regression of log tax liability on log property value shown in equation (4.1). This measure is admirably simple and fits well with the spirit that "A rate structure is progressive where the average rate of tax (i.e., tax liability as a percentage of income) rises when moving up the income scale" (Musgrave & Thin, 1948, p. 498).

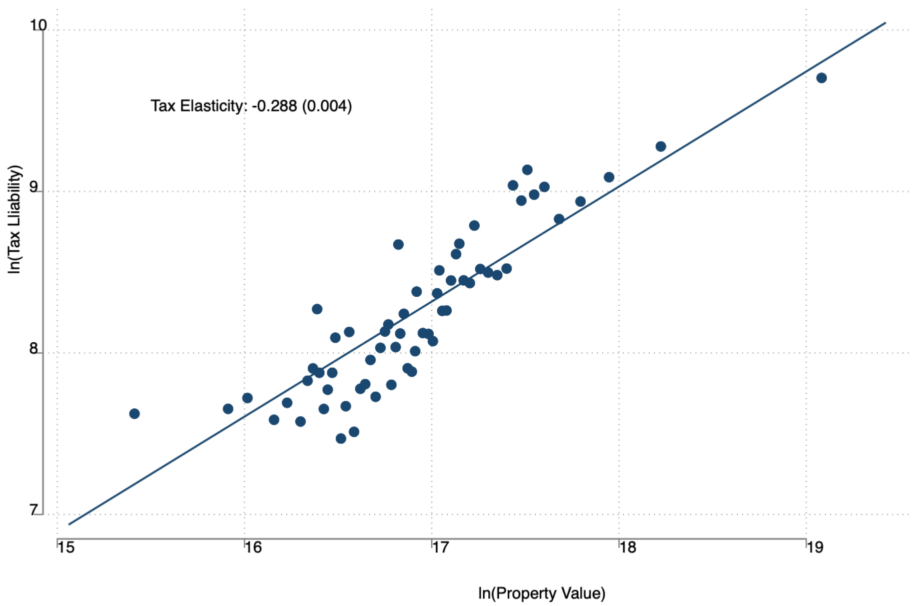
$$\ln\left(\text{tax liability}_i\right) = \beta_0 + \beta_1 \ln\left(\text{property value}_i\right) + \varepsilon_i \tag{4.1}$$

Figure 12 shows a binned scatterplot (using the stata implementation of the `binsreg` command (Cattaneo *et al.*, 2024)) of the tax elasticity in the Excise &

[1]See e.g. Thomas (2023) for a review focusing on low-income countries.

Taxation cadaster. We find that the tax elasticity is -0.288, indicating that the system is regressive.

Figure 12: Baseline Tax Elasticity



2. ***Kakwani Index:*** This index is based on the Lorenz curves of property wealth and of taxes paid (Kakwani, 1977). The index is easiest to understand visually, as presented by Splinter (2020) for the US income tax:

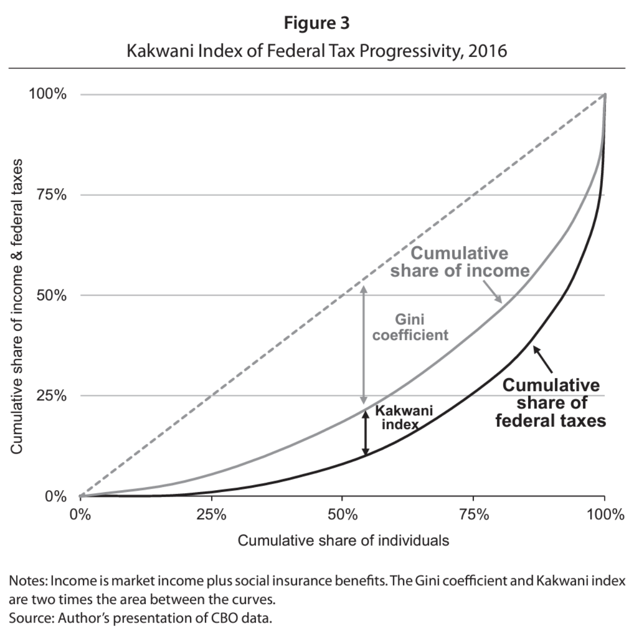
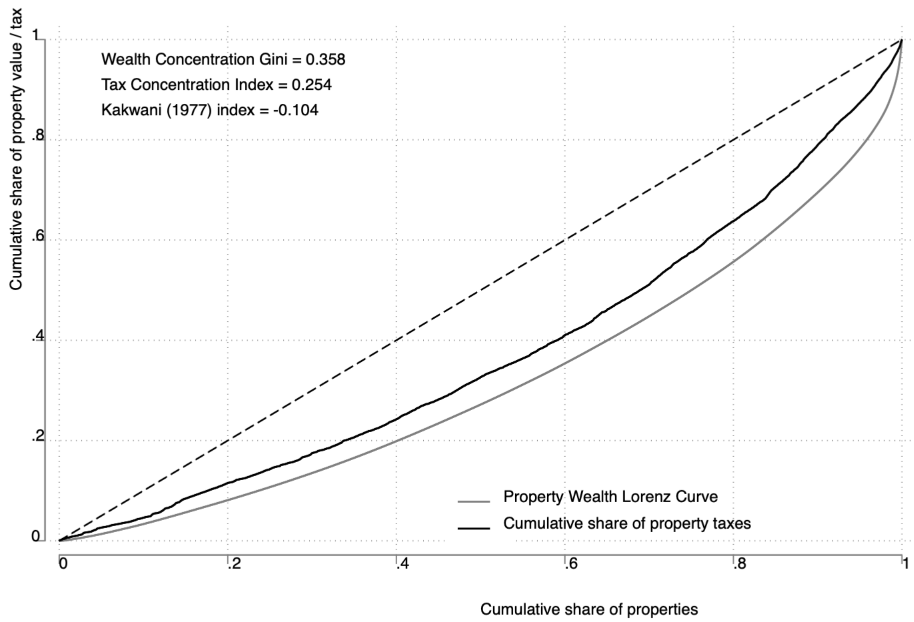


Figure 13 presents the Kakwani index in Lahore estimated from the Excise & Taxation cadaster. We find that the residential property wealth concentration gini coefficient is 0.358 while the concentration index for taxes is only 0.254, so that the Kakwani index, at -0.104, also indicates that the property tax in Lahore is regressive.

Figure 13: Baseline Kakwani Index

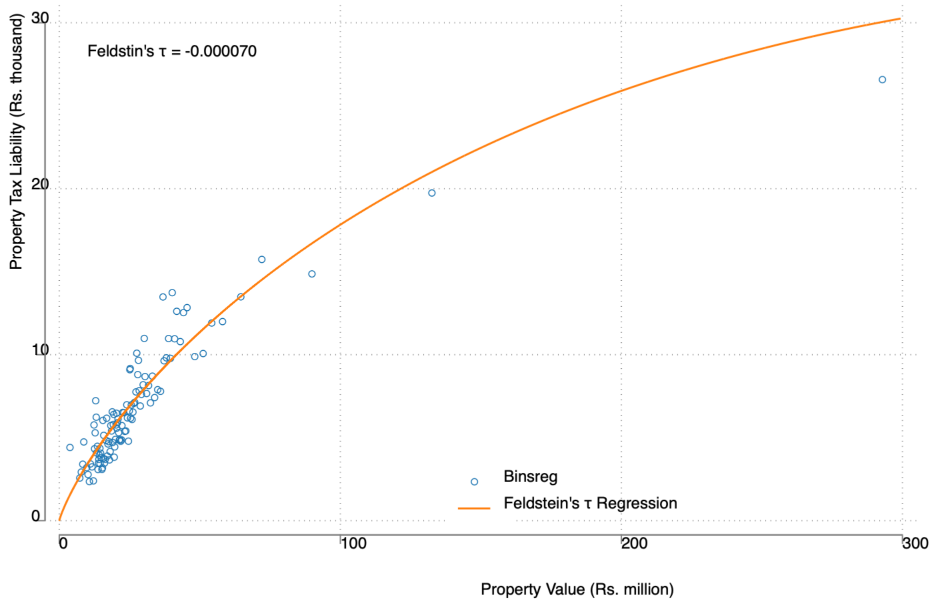


3. ***Feldstein-τ***. This measure derives from Feldstein (1969) and has been widely used in macro public finance, for e.g. Heathcote *et al.* (2017). The measure is the estimated $\hat{\tau}$ from the non-linear regression (4.2):

$$\text{tax liability}_i = \text{property value}_i - \lambda \text{property value}_i^{1-\tau} + \varepsilon_i \tag{4.2}$$

Figure 14 presents our estimation of Feldstein's τ from the Excise & Taxation cadaster. We estimate Feldstein's τ to be equal to -0.00007, again indicating a regressive system.

Figure 14: Baseline Feldstein's τ

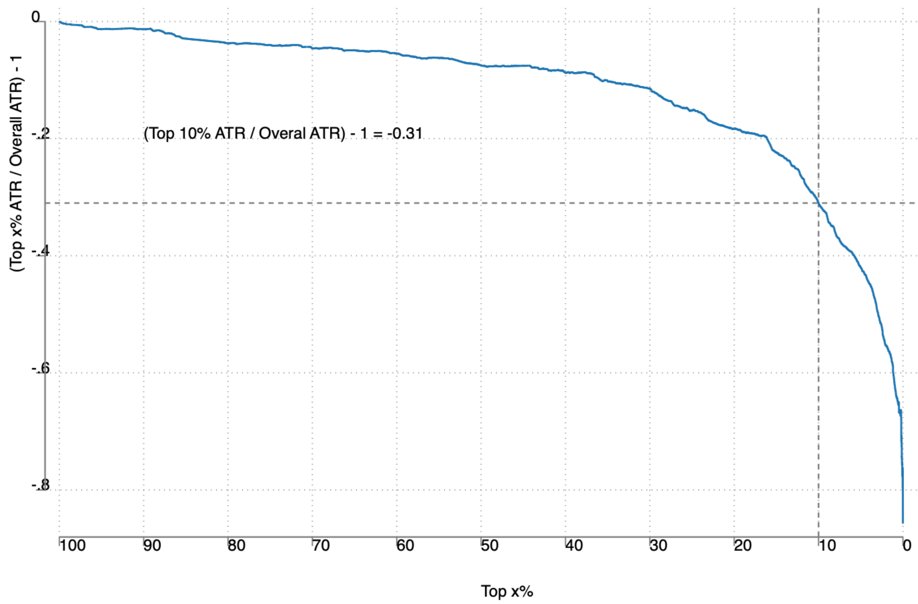


4. ***Top Tax Rate***. Since much of the literature focuses on progressivity at the very top of the distribution (e.g. Piketty & Saez, 2007), our fourth measure focuses on the top 10% of the property value distribution:

$$\text{Top 10\% Progressivity} = \frac{\text{Top 10\% ATR}}{\text{Overall ATR}} - 1 \tag{4.3}$$

Figure 15 presents our estimation of The Average Tax Rate throughout the wealth distribution. For each percentile of the wealth distribution we compute the average tax rate (total tax liabilty / total wealth) of properties above that percentile in the wealth distribution. We normalize this by dividing by the overall ATR and subtracting 1 (so that mechanically our index is equal to zero at the bottom of the distribution). We estimate that the normalized average tax rate of the top 10% is equal to -0.31 again indicating a regressive system.

Figure 15: Baseline Top ATR



5. ***Progressivity Index***. Following Kling *et al.* (2007), our final progressivity measure is an equally-weighted index of our four measures. Denoting the four measures above $Y_1, \ldots, Y_4$, the index is

$$\tilde{Y}_i = \frac{1}{4} \sum_{k=1}^{4} \frac{Y_{ki}}{\mathsf{sd}\left(Y_k\right)} \tag{4.4}$$

where the standard deviations $\mathsf{sd}\left(Y_k\right)$ are computed from the control group.

Measures 1. & 3. don't depend on the distribution of property values, but measures 2. & 4. do. To apply these measures to a constant distribution of property values, we take the distribution of residential property values we observe in the baseline data. To apply a respondent's preferences to this full distribution, we estimate a restricted cubic spline using the respondent's 9 responses.[2] With this we have an estimate of the respondent's full tax function to apply to the full property value distribution.

When we study progressivity, we will study all five of these measures separately. However, as mentioned above, when exploring heterogeneity of the treatment effects, we will favor our progressivity index. This way of constructing the index has the virtue of being simple and transparent. But it gives equal weights to all four measures, and some may capture variation across respondents more faithfully than others. If, using our equally-weighted index, it seems that this does not adequately capture the variation in the responses, we will also use the first principal component of the four (normalized) progressivity measures (as in Kling *et al.*, 2007). Additionally, for robustness, we will also study each item individually for robustness.

[2]Specifically, we place knots at the 50th, 75th, and 90th percentiles of the overall residential property value distribution, and then fit a cubic spline restricted to remain between 0 and 100% within the observed range of property values.

In the survey we also elicit respondents' beliefs about the degree of compliance by each property, and so for each of our progressivity measures we will also construct an effective tax rate measure by multiplying the preferred average tax rate by the respondent's belief about the baseline compliance of the property (implicitly assuming that there are no behavioral responses to the tax rate as a first pass).

4.2 Secondary Outcomes

Our secondary outcomes are

1. **Efficacy beliefs**. We ask respondents three questions (s12_q1, s12_q20a, s12_q20b) about how likely they believe it is that their recommendations will be taken into account during propoerty tax reform discussions by senior stakeholders.
2. **Willingness to pay for information**. We measure this using the number of tickets the respondent is willing to forego to learn about citizens' preferences as discussed in section 3.6.
3. **Behavioral responses to tax increases**. We ask respondents two questions (s70_q3 and s70_q4) about how low-valued property owners and medium-/high-valued property owners would respond to tax increases.
4. **Perceived compliance rates**. We measure this using the respondents' answers to the questions about their beliefs about the baseline compliance rates of the six randomly selected properties they are shown to elicit their preferences over the shape of the tax schedule.

For each outcome, we study each outcome separately, and also create an index of the outcomes in that category to summarize respondents' overall view on that topic.

5 Heterogeneity

We use six characteristics of our respondents to explore the heterogeneity of the treatment effects (using the methods described in section 6.3). As our outcomes for the heterogeneity analysis we consider two outcomes: The reform endorsements defined in section 4.1.1 and the progressivity index defined in section 4.1.2.

1. **Prior beliefs about citizens' tax preferences**. Near the beginning of the survey we ask respondents which of five tax schedules they think various types of citizens would prefer (s5_q1 – s5_q3). The five schedules are calibrated to have the same average tax rate but to vary in their degree of progressivity. We ask respondents their beliefs about the preferences of

   (a) owners of low-value properties

   (b) owners of medium-value properties

   (c) owners of high-value properties

   We also ask respondents which aspects of a proposed reform they believe are most important to citizens when forming their opinions (s12_q2). The aspects considered are enforcement, progressivity, revenue, the expansion of public goods, and political opposition.

2. **Beliefs about bureaucrats' and politicians' tax preferences**. When asking respondents what they think citizens would prefer, we also ask about other stakeholders (s5_q4 – s5_q7). Specifically, we ask respondents their beliefs about the preferences of

   (a) civil servants in the government of Punjab
   (b) members of the Punjab assembly belonging to the government's party
   (c) opposition members of the Punjab assembly
   (d) international donors.

   We also ask respondents about which aspects of proposed reforms they believe other stakeholders value most, in addition to citizens (s12_q3, s12_q5, s12_q6, s12_q7). We ask respondents about their beliefs about the views of local politicians, excise & taxation officers, and the Government of Punjab. We also ask respondents to consider three local politicians or bureaucrats whose primary motivations are their own interest, the interests of their superiors, or the interests of citizens. We then ask respondents to tell us which will make better decisions, which citizens will prefer, which will have a more successful career, and which is most prevalent in Pakistan (s30_q1–s30_q5). Finally, we create experience indices using s33_q1 – s33_7 for bureaucrats and s34_q1 – s34_q7 for politicians.

3. **Views about fairness**. We ask respondents two questions (s12_q14, s12_q15a) about whether the property tax leads the rich to pay their fair share and about how much of a propblem they feel that wealth inequality is.

4. **Views about the efficacy of the state**. We ask respondents to rank five reasons why more property tax isn't collected from low-value properties and from medium-/high-value properties (s70_q1, s70_q2). The five reasons are tax inspectors' human capital, political influence, insufficient penalties, lack of spending on public goods, and corruption.

5. **Respondents as citizens**. We ask respondents various questions to elicit their congruence with various types of citizens so that we can place them in the distribution of citizens. We create a wealth index using s35_q1 –s35_q5 and s31_q1 – s31_q6. We also ask respondents about their priors about the topics covered in the four experimental information provision treatments embeded in our citizen survey (see the pre-registration at https://www.socialscienceregistry.org/trials/15393 for details) about government spending efficiency, the property tax gap, elite capture, and local public goods provision. We ask respondents in this experiment for their priors about these same four items (s10_q1, s10_q3, s10_q4, s10_q6).

6. **Knowledge of Tax Policy**. The questions `s2_q1, s2_q3b, s2_q5, s3_q3`) assess respondents' knowledge of property tax policies in Lahore, covering topics such as the base for tax calculation, changes in tax upon renting, and prevailing tax rates. We will use these questions to construct an index of property tax knowledge, using the first component from a Principal Component Analysis (PCA) to capture the underlying understanding of property tax regulations among respondents.

6 Statistical Procedures

6.1 Continuous Outcomes

For outcomes that are continuous (e.g. the progressivity of the respondent's elicited tax schedule, or the progressivity of the reform proposal they endorse) we will use a regression model

$$Y_i = \beta_0 + \mathbf{X}_i\boldsymbol{\beta}_1 + \sum_{g=1}^{5} D_{gi}\left(\delta_g + \eta_g E_i\right) + \gamma_{\text{Stratum},i} + \varepsilon_i \tag{6.1}$$

where the D_{gi} are indicators for whether the respondent was shown the reform proposal based on the preferences of group g (low-value property owners, medium-/high-value property owners, or the government), E_i is an indicator for whether the respondent was shown the baseline compliance rates of properties, $\gamma_{\text{Stratum},i}$ are randomization stratum fixed effects, and we use heteroskedasticity-robust standard errors. The $\mathbf{X}_i$ are post-lasso controls for precision (Wager *et al.*, 2016).

For the lasso variable selection we will include demographics of the respondent and the area where they work. For any categorical variables, we will include all levels of the variable as a group in a grouped-lasso procedure. For robustness, we will also estimate a saturated model as suggested by Lin (2013).

We will perform the analysis separately for bureaucrats and politicians. If specification 6.1 does not show any effects of the compliance information, we will drop the E_i interactions.

6.2 Discrete Outcomes

One of our primary outcomes is the tax reform proposal the respondent endorses. Since this is a discrete choice, we will use discrete choice models to analyze the individual choices (as well as using the progressivity of the endorsed schedule as a continuous outcome as discussed in section 6.1 above).

We will do this in two ways.

1. Holding choice sets fixed. Here we restrict to the subsample of respondents who were offered the same choice of three tax schedules to endorse. Then we compare treated respondents (who were told whose preferences the two reform schedules were based on and discussed the differences between the two) to control respondents (to whom only the status quo schedule was identified).

2. Pooling choice sets. Here we use all choice sets together. This increases the sample sizes involved dramatically, but comes at the slight disadvantage of relying on stronger structural assumptions about the way that respondents make choices.

In both cases we will use mixed logit models to model the utility of each possible endorsement as a function of controls and the coefficients of interest: coefficients on an indicator for (randomly) being told the preferences of the group of citizens the reform is based on.

6.3 Heterogeneous Treatment Effects

We follow the approaches in Guess *et al.* (2023) that builds on Semenova & Chernozhukov (2020); Kennedy (2023) to estimate treatment effect heterogeneity. This can be implemented using the `tidyhte` library in R. We use a non nonparametric two-stage regression procedure that has been proven to be statistically optimal under weak conditions (Kennedy 2020) – and under essentially no conditions in an experiment. The DR-Learner first constructs a doubly robust pseudo-outcome and then regresses this pseudo-outcome on moderators of interest; cross-fit sample splitting is used to prevent overfitting and reduce bias.

There are three main pre-specification choices:

1. how to estimate the pseudo-outcome
2. how to estimate the second-stage regression of the pseudo-outcome
3. how to do sample splitting

The definition of the pseudo-outcome is:

$$\hat{\varphi}(Z) = \frac{A - \pi(X)}{\pi(X)[1 - (X)]}[Y - \hat{\mu}_A(X)] + \hat{\mu}_1(X) - \hat{\mu}_0(X)$$

where X denotes a covariate, A is a binary treatment (we will break the data into subsets with binary treatments, or extend this model to allow for multiple treatments), Y is the outcome of interest, $\pi(X)$ are the (known) propensity scores, $\hat{\mu}_a(x)$ is a regression prediction of the outcome $\mathbb{E}\left[\hat{Y}|X = x, A = a\right]$. This pseudo-outcome is a double-robust mimic of the difference in the potential outcomes.

The regression predictions will be built using standard machine-learning models (for example those available in the `superlearner` package in R)

The second-stage regression of the pseudo-outcome on the covariate of interest will depend on the type of the covariate:

1. For discrete covariates (with five or fewer levels) we will use within-group averages.
2. for continuous covariates we will use local polynomial regression.

We will use 10-fold cross-validation for tuning parameter selection, both for regression predictions and second-stage pseudo-outcome regression, with 12-fold cross-fitting to separate building of regression predictions from the second-stage regression and second-stage model selection. This ensures efficient use of the data, as each observation will separately contribute to regressions in both first and second stages.

6.4 Adjustment for multiple comparisons

We will implement a sharpened FDR adjustment (Benjamini *et al.*, 2006) in a hierarchical manner building on Anderson & Magruder (2022); Guess *et al.* (2023). Our analysis proceeds sequentially in descending order of the priority of our analysis. Each step tests a set of hypotheses, and only the treatments for which we do not reject the null of no treatment effect proceed to the next step, economizing maximally on power.

1. Study P primary outcome tests. Adjust FDR for P comparisons. Continue to the next step only for treatments rejecting the null of no effect on the index of progressivity.

2. Add S_1 step-1 secondary outcome comparisons and H_1 step-1 heterogeneity comparisons. Adjust FDR for $P + S_1 + H_1$ comparisons.

3. Add S_2 step-2 secondary outcome comparisons and H_2 step-2 heterogeneity comparisons. Adjust FDR for $P + S_1 + H_1 + S_2 + H_2$ comparisons.

4. Add S_3 step-3 secondary outcome comparisons and H_3 step-3 heterogeneity comparisons. Adjust FDR for $P + S_1 + H_1 + S_2 + H_2 + S_3 + H_3$ comparisons.

5. Add S_4 step-4 secondary outcome comparisons and H_4 step-4 heterogeneity comparisons. Adjust FDR for $P + S_1 + H_1 + S_2 + H_2 + S_3 + H_3 + S_4 + H_4$ comparisons.

6. Add S_5 step-5 secondary outcome comparisons and H_5 step-5 heterogeneity comparisons. Adjust FDR for $P + S_1 + H_1 + S_2 + H_2 + S_3 + H_3 + S_4 + H_4 + S_5 + H_5$ comparisons.

7. Add S_6 step-6 secondary outcome comparisons and H_6 step-6 heterogeneity comparisons. Adjust FDR for $P + S_1 + H_1 + S_2 + H_2 + S_3 + H_3 + S_4 + H_4 + S_5 + H_5 + S_6 + H_6$ comparisons.

We group our secondary outcomes and heterogeneity dimensions into the seven sequential groups as shown in table 3.

Table 3: Sequential Groups of Secondary Outcomes and Heterogeneity Dimensions

Group	Secondary Outcomes	Heterogeneity
1		Citizen preferences
2	Influence on decision makers	Bureaucrat / politician preferences
3	WTP for citizen preferences	Fairness
4	Behavioral responses to taxation	Efficacy of the state
5	Compliance rates	Beliefs as citizens
6		Tax knowledge

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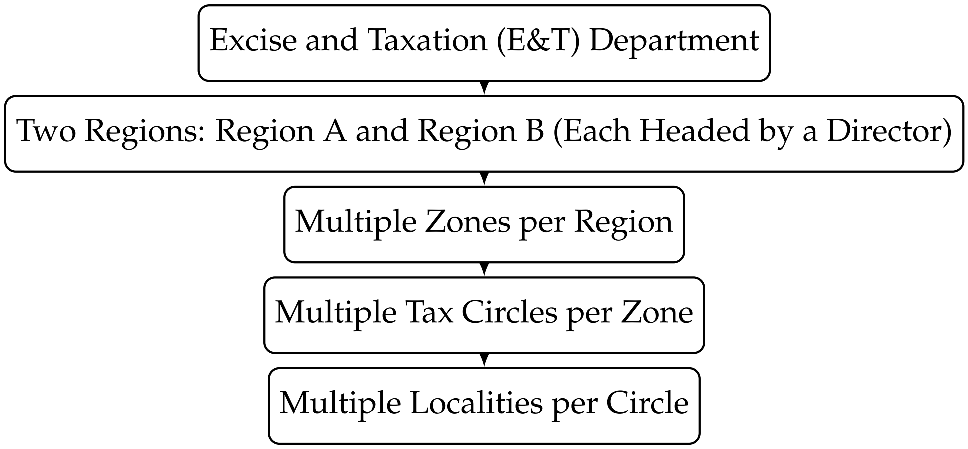
A Excise and Taxation Hierarchy

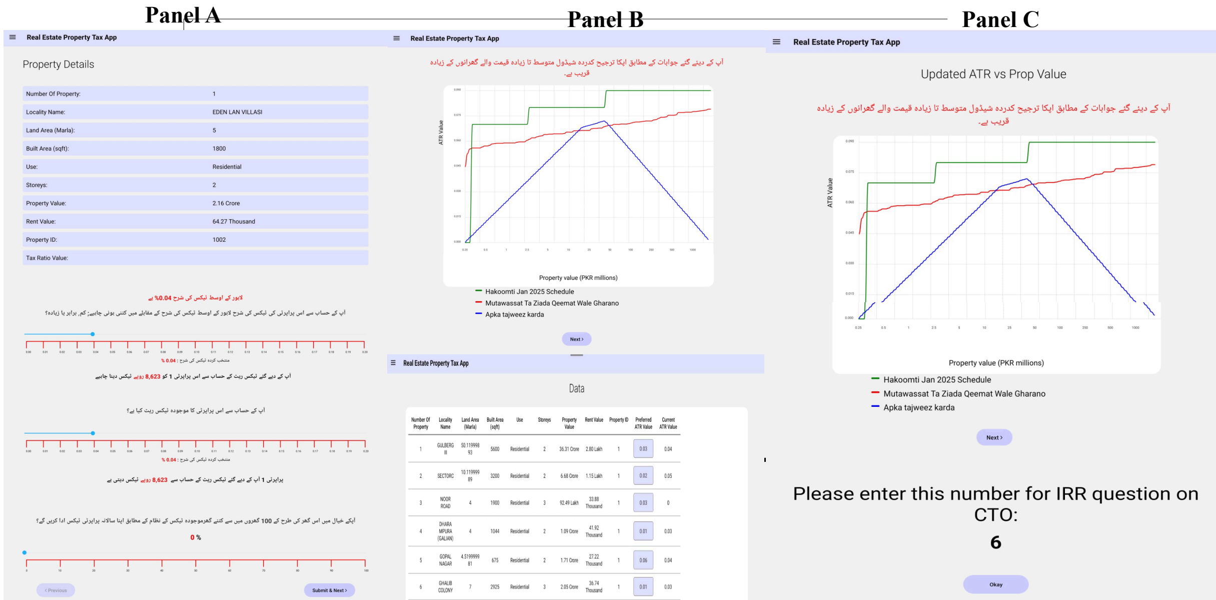
Figure A.1: Flowchart of Property Tax Administration in Lahore



B Survey Exhibits

B.1 Preference Elicitation

Figure B.1: Preference Elicitation Dashboard

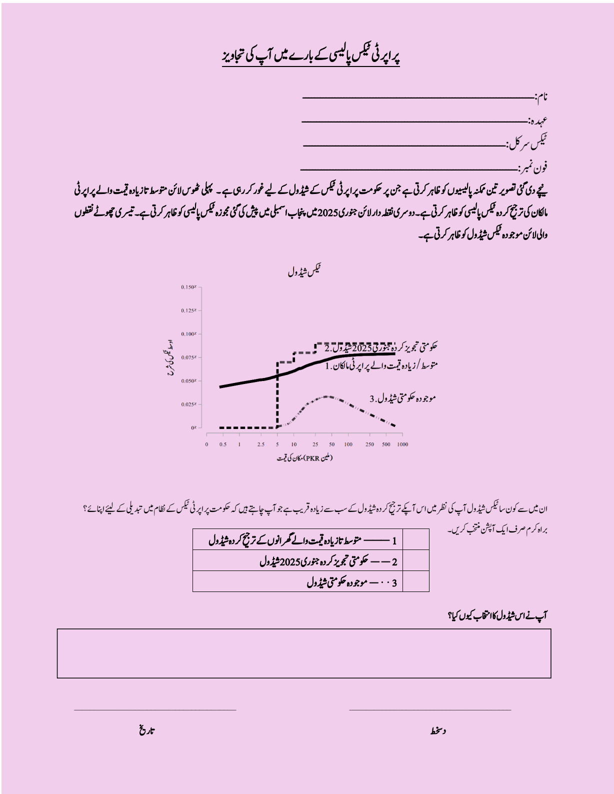


Source: IDEAS-LUMS Local Tax Officials and Political Workers Survey 2025
Notes: Figure shows screenshot from Android Application developed for eliciting respondents' preferred tax schedule. Respondents were shown property characteristics along with a scale with a default value at Lahore's average tax rate of 0.04%. Respondents were then asked whether they preferred a higher or a lower tax rate than Lahore's average on this property and they the scale was adjusted based on respondents response and their perceptions about tax compliance (Panel A). Once all 6 properties were asked, the respondent was shown a summary table and the shape of their preferred tax schedule (blue line) overlaid with tax schedules of the type of treatment group they belonged to e.g. in the current vignette, the respondent was assigned to see comparsion of tax schedules of Medium-to-High valued property owners (red line) against Govt. sanctioned Jan 2025 tax schedule (green line) (Panel B). Respondents were then given a chance to revise their preferred tax rate the updated graph was shown to them as well (Panel C).

B.2 Policy Recommendation Form

Figure B.2: Policy Recommendation Form Exhibit

(a) Treatment Group



پراپرٹی ٹیکس پالیسی کے بارے میں آپ کی تجاویز

نام:______

عہدہ:______

ٹیکس سرکل:______

فون نمبر:______

نیچے دی گئی تصویر تین ممکنہ پالیسیوں کو ظاہر کرتی ہے جن پر حکومت پراپرٹی ٹیکس کے شیڈول کے لیے غور کر رہی ہے۔ پہلی ٹھوس لائن متوسط تا زیادہ قیمت والے پراپرٹی مالکان کی ترجیح کردہ ٹیکس پالیسی کو ظاہر کرتی ہے۔ دوسری نقطہ دار لائن جنوری 2025 میں پنجاب اسمبلی میں پیش کی گئی مجوزہ ٹیکس پالیسی کو ظاہر کرتی ہے۔ تیسری چھوٹے نقطوں والی لائن موجودہ ٹیکس شیڈول کو ظاہر کرتی ہے۔

ان میں سے کون سا ٹیکس شیڈول آپ کی نظر میں اس آپکے ترجیح کردہ شیڈول کے سب سے زیادہ قریب ہے جو آپ چاہتے ہیں کہ حکومت پراپرٹی ٹیکس کے نظام میں تبدیلی کے لیئے اپنائے؟

براہ کرم صرف ایک آپشن منتخب کریں۔

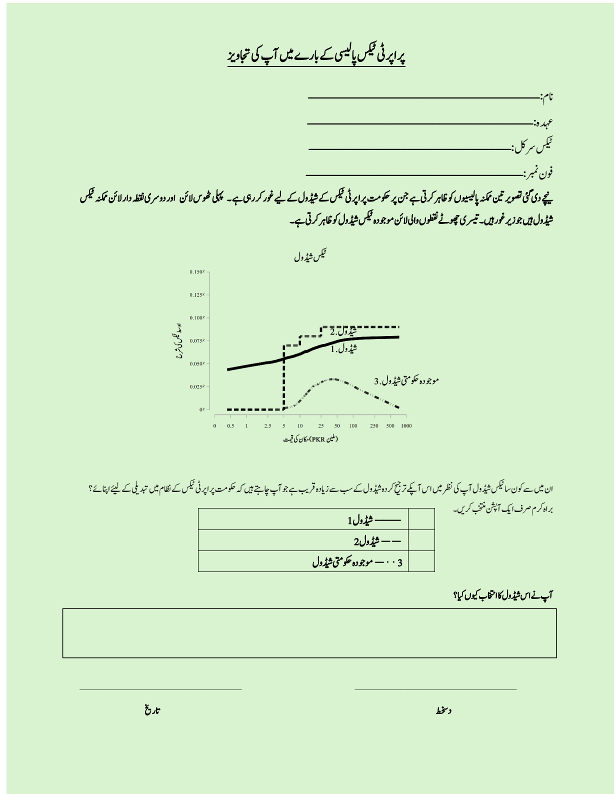
1 —— متوسط تا زیادہ قیمت والے گھرانوں کے ترجیح کردہ شیڈول	
2 – – حکومتی تجویز کردہ جنوری 2025 شیڈول	
3 · · — موجودہ حکومتی شیڈول	

آپ نے اس شیڈول کا انتخاب کیوں کیا؟

دستخط

تاریخ

(b) Control Group



پراپرٹی ٹیکس پالیسی کے بارے میں آپ کی تجاویز

نام:______

عہدہ:______

ٹیکس سرکل:______

فون نمبر:______

نیچے دی گئی تصویر تین ممکنہ پالیسیوں کو ظاہر کرتی ہے جن پر حکومت پراپرٹی ٹیکس کے شیڈول کے لیے غور کر رہی ہے۔ پہلی ٹھوس لائن اور دوسری نقطہ دار لائن ممکنہ ٹیکس شیڈول ہیں جو زیر غور ہیں۔ تیسری چھوٹے نقطوں والی لائن موجودہ ٹیکس شیڈول کو ظاہر کرتی ہے۔

ان میں سے کون سا ٹیکس شیڈول آپ کی نظر میں اس آپکے ترجیح کردہ شیڈول کے سب سے زیادہ قریب ہے جو آپ چاہتے ہیں کہ حکومت پراپرٹی ٹیکس کے نظام میں تبدیلی کے لیئے اپنائے؟

براہ کرم صرف ایک آپشن منتخب کریں۔

1 —— شیڈول 1	
2 – – شیڈول 2	
3 · · — موجودہ حکومتی شیڈول	

آپ نے اس شیڈول کا انتخاب کیوں کیا؟

تاریخ

دستخط

Source: IDEAS-LUMS Local Tax Officials and Political Workers Survey 2025
Notes: Figure shows Policy Recommendation Form exhibit for Treatment (Light Purple) and Control (Light Green) groups, which received comparison of preferred tax schedule of med-to-high valued property owners (labeled as 1.) against government-sanctioned property tax schedule in January 2025 (labeled as 2.) and government's old ARV based tax schedule (labelled as 3.). This exhibit was presented to bureaucrats where they were asked to provide basic information including their name, rank, tax circle they are appointed to and phone number. Secondly, they had to choose between the two tax schedules they were randomly assigned plus the status quo tax schedule and provide reasons for their choice. They were also asked to sign this form. For Control group, we removed the labels of the schedule. For local political workers we used the same form except they were asked to provide information about the Union Council where they mainly worked and networked.

C Property Value Prediction

This appendix describes the procedures we followed to estimate predicted property values for all 802,000 properties in the Excise & Taxation cadaster. Section C.1 describes our survey with real estate agents to create the training data used for our estimation. Section C.2 describes how we impute localities for the parts of the cadaster missing locality information. Section C.3 describes the random forest algorithm and its performance.

C.1 Training Data: Real Estate Agent Valuation

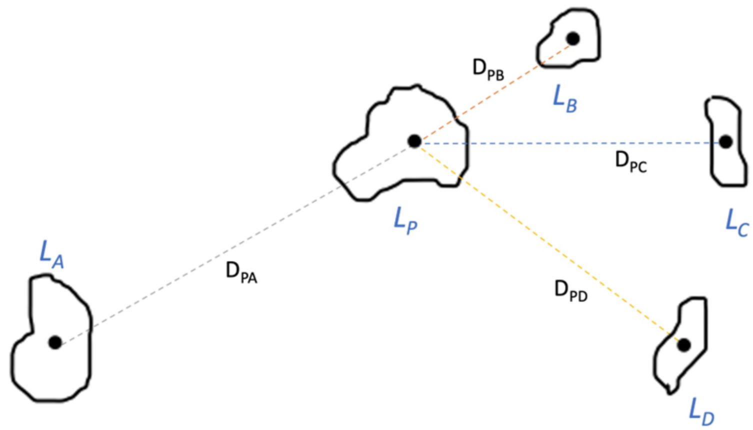
We get 2023 market value data from real-estate experts. For every property assessed, participating dealers were requested to provide estimates on the capital value, potential value as an open plot, and the rental value. Dealers were also asked about their own confidence levels in the reported values and their observations regarding property trends over the past six months, as well as their expectations for the next six months.

C.2 Imputing Missing Locality Data

One of the key inputs into our property valuation algorithm is the neighborhood a property is located in. However, the Excise & Taxation cadaster only contains the names of localities, not geocoded data on their location. To impute this missing data we follow the following procedue. Localities were categorized into one of four distinct groups.

- **Type I (TI):** This category included localities that were present in the valuation sample. Property geocodes obtained during the valuation exercise were utilized for these localities to determine a quasi-centroid in cases where the cadastre lacks geocodes. Once the quasi-centroids were obtained for all TI localities, the localities where the rates were missing were assigned DC residential and commercial rates from nearest possible locality using Mahalanobis distances

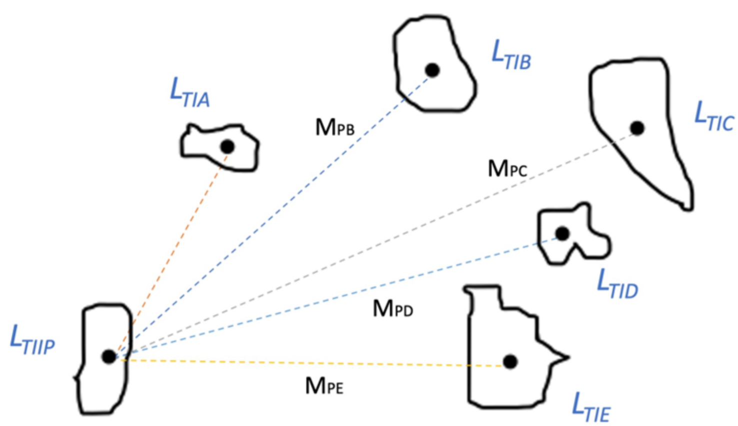
Figure C.1: Assigning DC values to a TI locality using location attributes



Source: IDEAS-LUMS Property Valuation Survey 2023
Notes: Figure shows if rates were missing from locality L_p, commercial and residential locality rates were assigned from locality L_B as its nearest to L_P. The distance was determined using Mahalanobis distance.

- **Type II (TII):** This category included localities which were not drawn in the main sample but had geo-codes and commercial and residential locality-level rates from the DC 2018-19 list. For each TII locality, Mahalanobis distances were computed for their proximity with all TI localities using location (i.e. longitude and latitude) and fanciness (i.e. DC residential and commercial rates) attributes. They were then linked to the closest TI locality (see Figure C.2) for the prediction model.

Figure C.2: Linking a TII locality to a TI locality using location and fanciness attributes

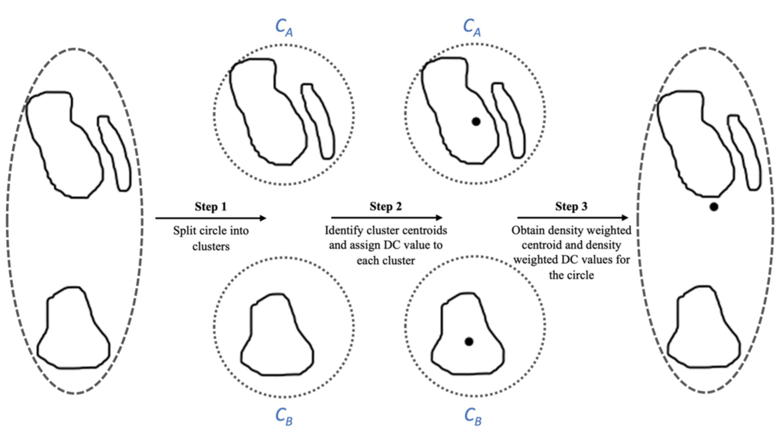


Source: IDEAS-LUMS Property Valuation Survey 2023
Notes: Figure shows out-of-sample L_{TIIP} locality was matched to L_{TIA} due to its proximity in terms of Mahalanobis distance.

- **Type III (TIII):** These types of localities were not drawn into the sample but had location geo-codes, and at least one of the residential and commercial DC rates was missing. For each TIII locality Mahalanobis distances were computed to all TI and TII localities using location attributes (i.e. longitude and latitude). Each TIII locality was then assigned DC rates of the closest TI or TII locality. If the TIII locality was assigned DC rates of a TI locality, then it was also linked to the same TI locality for the prediction model. Otherwise, location and "estimated" fanciness measures were used to link this TIII locality to a TI locality.

- **Type IV (TIV):** These localities were not drawn in the sample and did not have geocoded location information or DC rates. TIV localities were first split into two subtypes: a) locality lies in E&T defined circle that has geocodes and DC rates; and b) locality lies in a E&T defined circle that has no geocodes property and no DC rates. For a), missing information was filled using the strategy employed for TII localities. The only change was that circle centroids and average DC rates at the circle level were assigned to type a) localities. For localities from sub-sample b), 37 circle boundaries were plotted on QGIS. 14 of these circles were scattered around different parts of the city. It was decided that these circles would be (manually) split into clusters and cluster centroids and densities were computed using AsiaPop data. Each cluster was assigned DC rates of the closest TI, TII or TIII locality. These values were then computed using a density-weighted centroid and density-weighted DC residential and commercial rates for each circle (see Figure C.3). Mahalanobis distances were computed in the final step to link each type b) locality to a TI locality using density-weighted centroid and density-weighted DC rates.

Figure C.3: Dealing with a circle that has clusters in different parts of the city



Source: IDEAS-LUMS Property Valuation Survey 2023

C.3 Random forest property value data

This section details the procedures adopted to generate the random forest data. One source of estimating baseline levels of progressivity is administrative data. For this purpose, rental and capital market values for 2023 were obtained by surveying a sample of 12,363 commercial and residential properties from real estate experts. This 12,363 sample was then expanded to 802,592 properties using random forest. The random forest data was then merged with the property tax collection data obtained from E&T to create a unique dataset that contains information on 2022-2023 capital and rental market values and actual tax liabilities from FY 2021-2022.

The E&T property cadastre has 2,069 localities, of which only 407 were sampled. Predicting the property values for 1,662 out-of-sample localities was crucial because the neighbourhood is one of the key determinants of property value.

For this purpose, the location and average value of the locality were used to predict the property values. For location, an average of the property geocodes in the locality was taken to get a quasi-centroid (with latitude and longitude). Secondly, DC 2018-19 land rates (and not structure rates) served as a measure of fanciness for that locality. Both residential and commercial DC land rates were used to link the localities as they significantly differ even within a locality.

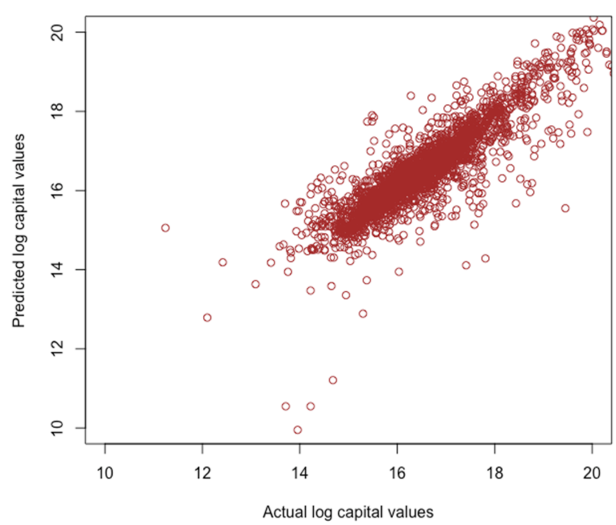
For the current context, property value is a function of land area (L), built area (B), residential use dummy (R), and a vector of cluster dummies (C) such that:

$$V = f(L, B, R, C)$$

To predict V, random forest model was set up where 75% of the data was used to predicted log of V using the logs of L, B, R and C. The remaining 25% of the sample was reserved for cross-validation, a technique used to assess the model's predictive performance on unseen data, thus providing insights into its generalizability.

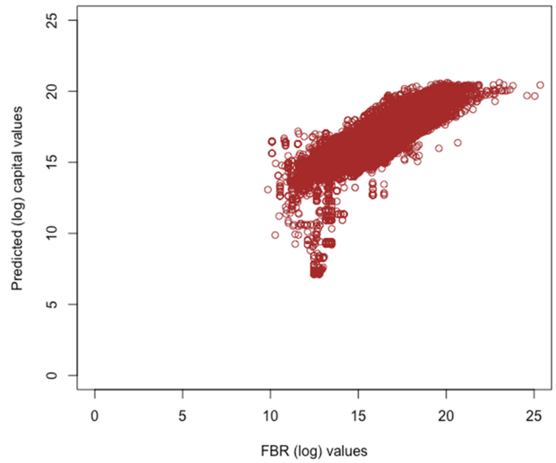
The results of this cross-validation (Figures C.4) show a high correlation between the predicted and actual capital values within the cross-validation sample. The results are robust with actual values as well. (See Figure **??**).

Figure C.4: Relationship between predicted and actual capital values



The entire valuation sample was then used to train the random forest model and predictions were made for the full valuation sampling frame where we had FBR values. Figure C.5 shows that the correlation between predicted values and FBR values was positive but not as strong as with the cross-validation sample in Figure C.4.

Figure C.5: Relationship between predicted and FBR capital values for the valuation sampling frame

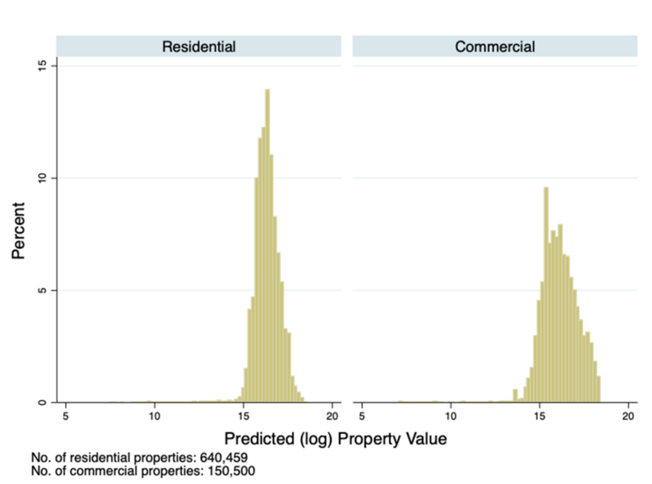


Source: IDEAS-LUMS Property Valuation Survey 2023

The final step in this process was to set up a random forest model and predict values for all residential and commercial properties in the cadastre. This was done by fixing the number of trees to 100 in the final specification and the number of variables used at each split to 2.

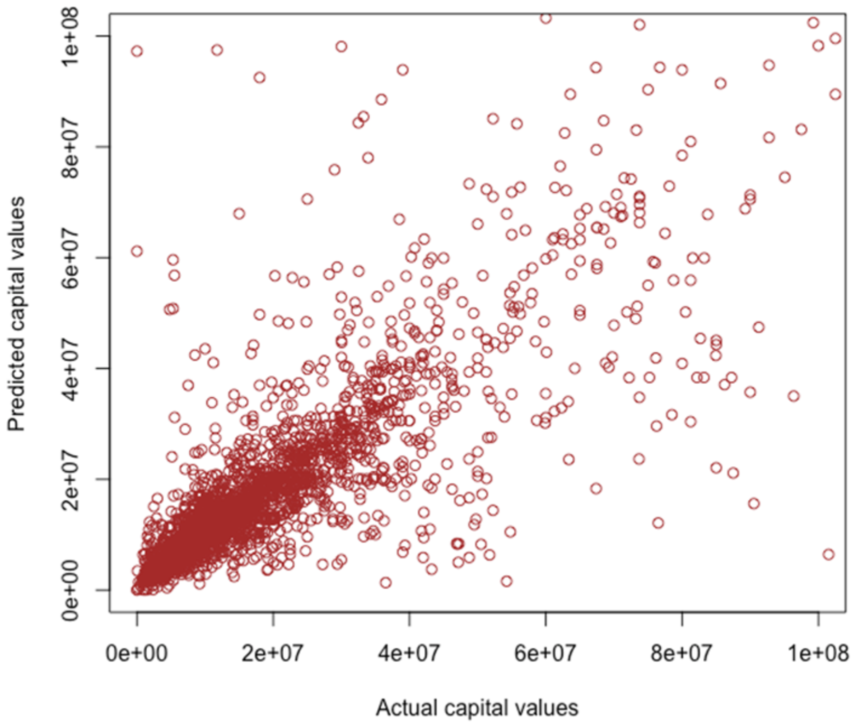
As expected, both residential and commercial property value distributions are right-skewed with few very highly valued properties (see Figure C.6).

Figure C.6: Distributions of predicted property values by property use



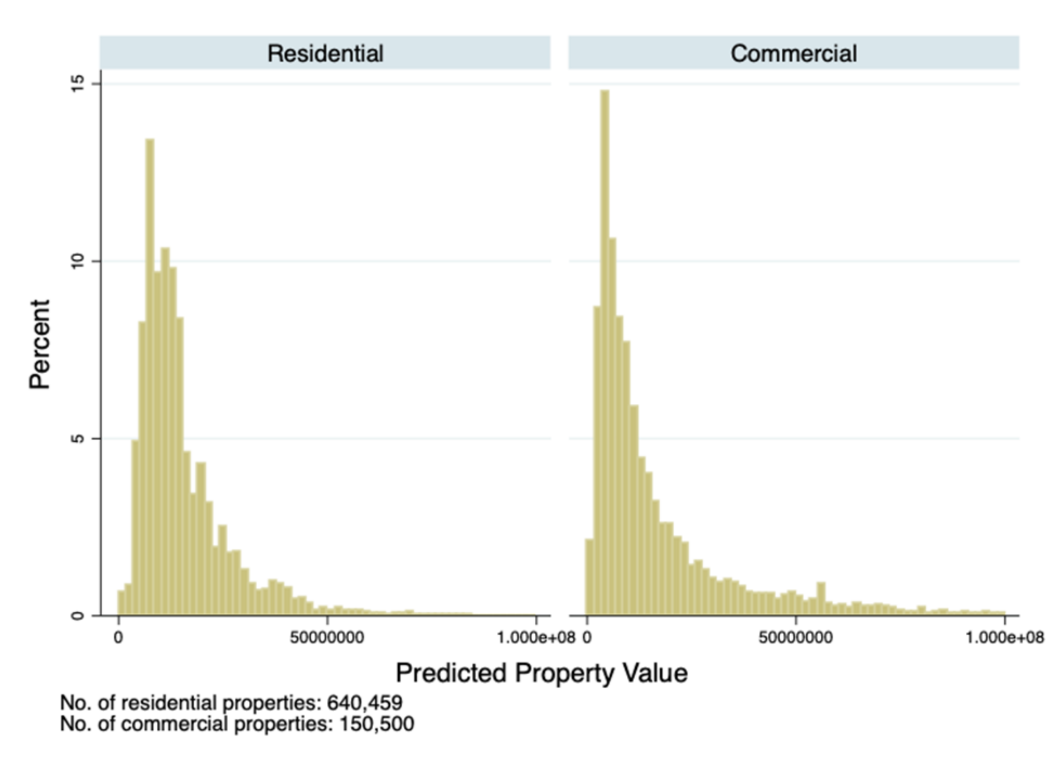
Source: IDEAS-LUMS Property Valuation Survey 2023
Notes: Values restricted to PKR 800 million for better visualization

Figure C.7: Relationship between predicted and actual (log) capital values for the cross-validation sample



Source: IDEAS-LUMS Property Valuation Survey 2023

Figure C.8: Distributions of predicted (log) property values by property use



Source: IDEAS-LUMS Property Valuation Survey 2023
Notes: Values restricted to PKR 800 million for better visualization