The Political Economy of Progressive Tax Reform: Experimental Evidence from Pakistan
Extended Abstract.

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Abstract

This study explores the political feasibility of progressive tax reform by examining the preferences of citizens, politicians, and bureaucrats regarding the level and progressivity of property taxation. In Experiment 1, we use a series of survey vignettes combined with six experimental treatments to identify the determinants of citizen support for higher and more progressive property taxes. These interventions test leading explanations for resistance to reform, including lack of information, perceived revenue leakages, weak tax-benefit linkages, deficits in public goods provision, and elite capture. In Experiment 2, we assess whether the preferences of local politicians and tax bureaucrats align more closely with those of rich or poor citizens. We also implement a field experiment that uses a costly measure to test whether political and bureaucratic decision-makers make policy endorsements that are more responsive to party directives or to the preferences of affluent versus low-income citizens. Our findings aim to inform the design of tax systems that are both effective and politically sustainable, and to advance understanding of the political economy dynamics that impede the adoption of progressive taxation in low-income countries.

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1 Introduction

Progressive taxes are the primary means through which rich countries redistribute from rich citizens to poor citizens. However, political decision-makers are frequently reluctant to levy high taxes on the rich. Why? Candidate explanations include political capture or over-representation of the preferences of the rich, a lack of salience of taxes, or the difficulty of collecting taxes on the rich.

Moreover, property taxes, the primary own-source revenues of local governments around the world, tend to be systematically lower in low- and middle-income countries than in rich countries (Brockmeyer *et al.*, 2023). This is even more puzzling considering the urgency of the need for increased spending on local public goods and services in increasingly urbanized low- and middle-income countries.

This extended abstract summarizes our ongoing work on the political economy of property tax reform in low- and middle-income countries using the case of Lahore, Pakistan as a case study.

We partnered with the Excise & Taxation department of the government of Punjab, Pakistan and with the Public Accounts Committee and Speaker of the Punjab Provincial Assembly to bolster the evidence base on which upcoming property tax reforms, to be presented in the June/July 2025 Punjab budget, will be based. We conducted a sequence of two survey experiments, with citizens, and with bureaucrats and local politicians, to understand the preferences of these three key stakeholders and their determinants.

Summary aggregates of the finings of the two surveys will be presented to the leadership in both the bureaucracy and the provincial assembly as they discuss the formulation of the upcoming budget. Through our analysis of the results of the experiment, we aim to trace out the contours of a set of politically and administratively feasible reforms to the property tax that both increase revenues and improve the progressivity of the property tax.

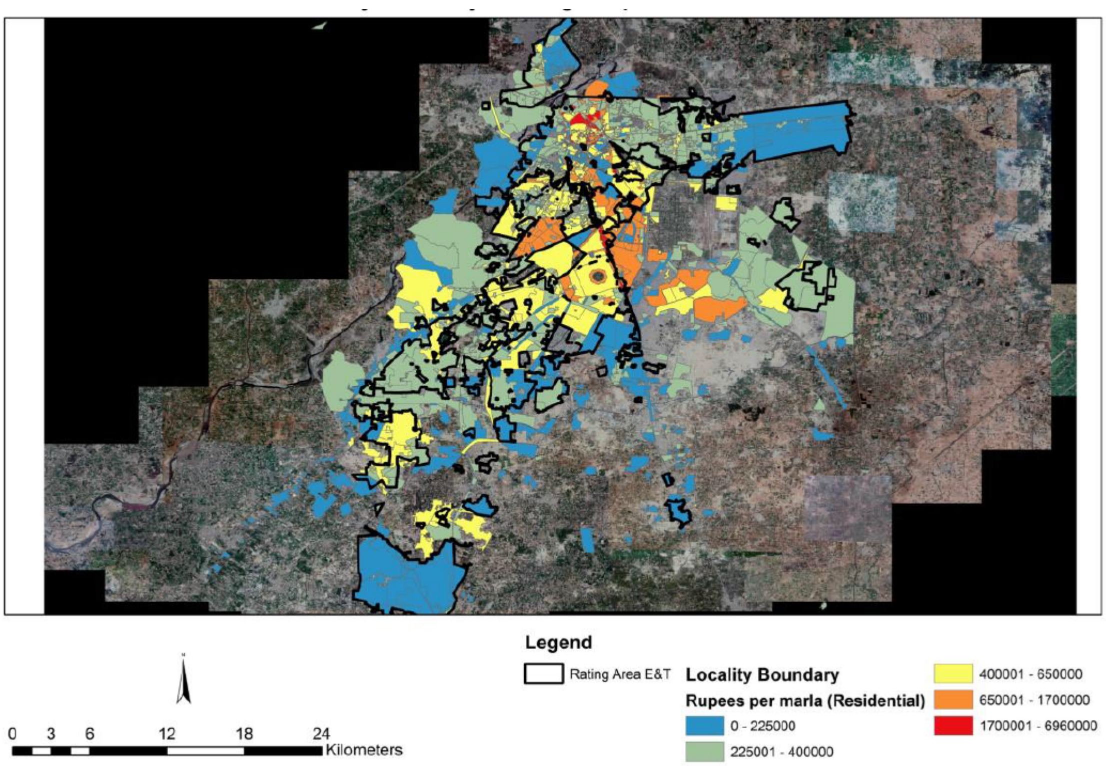
This extended abstract proceeds as follows. Section 2 describes the context in which our project takes place. Section 3 presents our first experiment exploring the preferences of citizens over the property tax schedule and their determinants. Section 4 presents our second experiment exploring the preferences of bureaucrats and politicians and their responsiveness to citizen preferences. Finally, section 5 discusses our preliminary findings and next steps before the conference.

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.

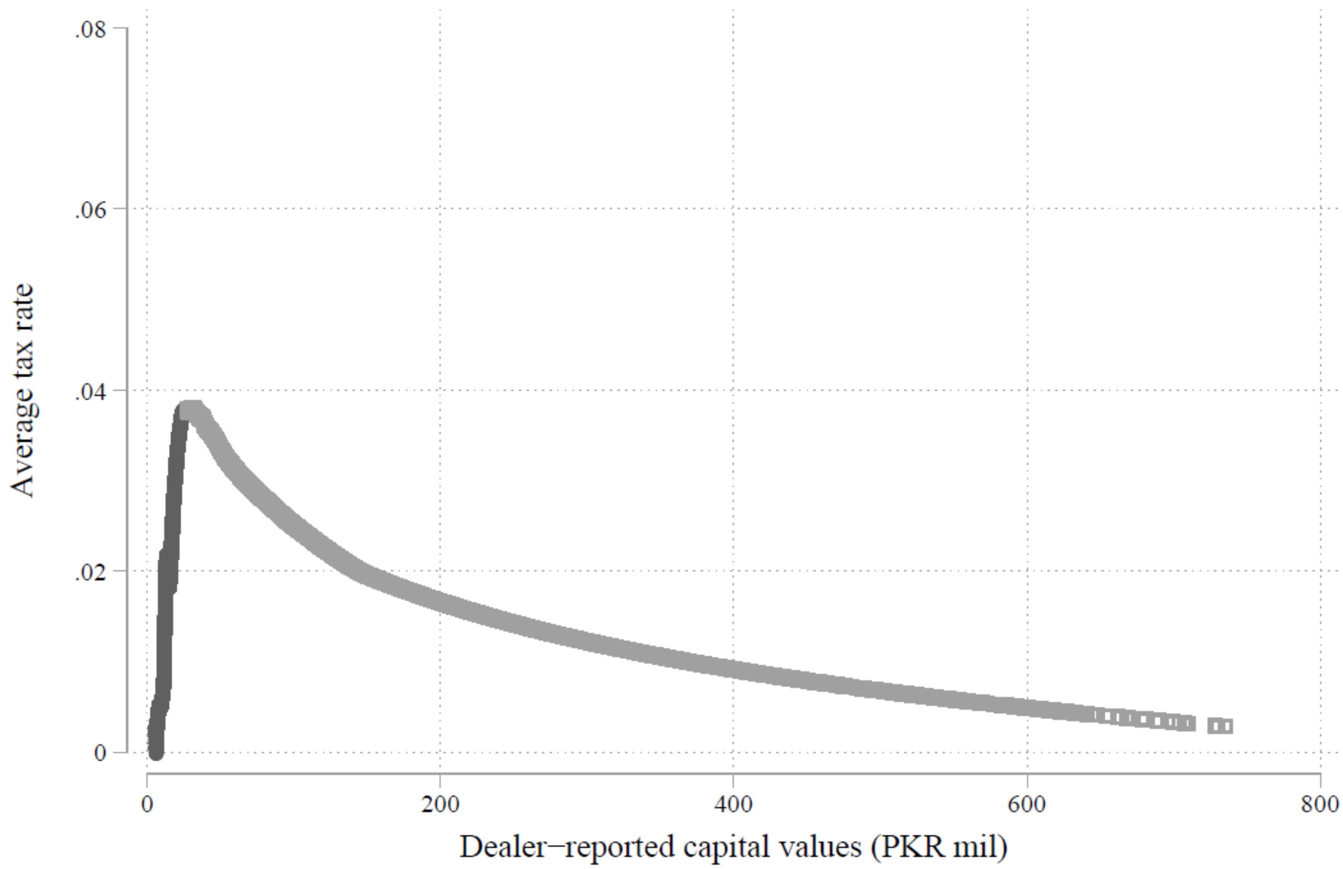


Figure 2: Current Tax Schedule in Lahore, Punjab Pakistan

Source: E&T property 2021-2022 tax demand data; IDEAS-LUMS property valuation survey.
Notes: Figure shows average tax rate against property value. x-axis shows market values assessed by real estate agents in 2023. The exchange rate is £1 = PKR 350. Y-axis shows average tax rate which is tax liability expressed as a percentage of market capital values. Total properties number of properties = 842000

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.

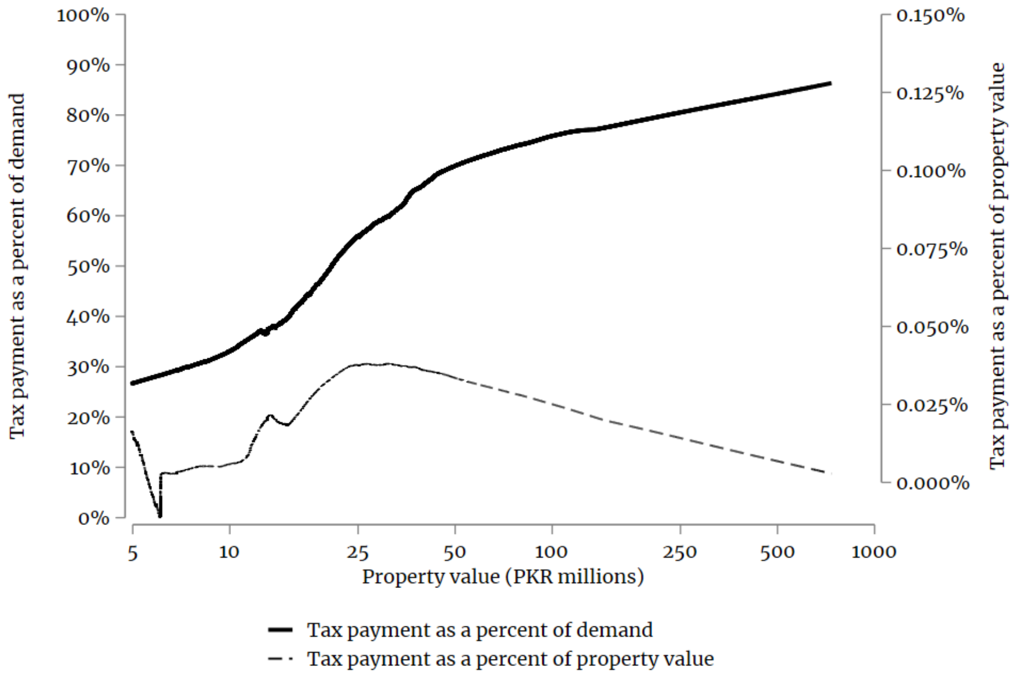


Figure 3: Compliance and regressivity in Lahore, Punjab Pakistan

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 3 shows compliance and the effective property tax rate by property value. The figure shows that 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. Consequently, the government is drafting proposals for inclusion in the provincial budget, to be presented in June 2025.

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.

3 Experiment 1: Citizens

3.1 Sampling

We draw our required sample of 7,577 residential properties using multiple data source as given in Table 1. We reach our required sample through a two-stage sampling strategy. In the first stage, a locality-level sample was drawn from the "common list" of localities that appear in both FBR 2022 and DC 2019 public lists, and a property-level sample was drawn in the second stage from the E&T cadaster based on the localities picked in the first stage sample.

Table 1: Description of Auxiliary Data Sources

Term	Details
FBR 2022 list	• Publicly available locality-level list of 1,270 localities of Lahore. • These are capital property rates that were estimated in 2021-22. The list contains: locality, town, residential land rate, commercial land rate.
DC 2019 public list	• Publicly available locality-level list of 1,325 localities of Lahore. • The rates are estimated through a DC-based valuation system that was done in 2018-19. The list contains: locality, town, residential land rate, commercial land rate, residential structure rate, commercial structure rate.
UU's DC mapping list	• A locality-level list, which was exported from ArcMap, of DC areas for which the Urban Unit has digitized maps. The list contains: locality, residential DC land rate, commercial DC land rate.
E&T's GIS data	• A property-level subset of E&T's cadastral that has property geocoordinates and DC locality information entered into it.

FBR: Federal Board of Revenue; DC: Deputy Commissioner's Office; E&T: Excise and Taxation Department.

3.1.1 First-stage

In the first stage we sample neighborhoods (localities) stratifying by property values. However, the Excise & Taxation cadaster only contains assessed values, which deviate strongly from market values. To overcome this, we relied on the Federal Board of Revenue's (The federal government's tax authority) 2022 publicly available list of residential and commercial rates for each locality. At the time of sampling, this was the most recent, and most reliable list of locality-level property values and so this was our primary reference for locality values. One challenge this list posed was that it doesn't contain geographic information on the location of the localities and it was difficult to merge it with property-level data from Excise and Taxation. To overcome this challenge, we used auxiliary locality-level data from the District Administration (DC) along with geo-coded maps provided by Urban Unit (UU) - a semi-private institution aimed to provide Geographic Information System information for key policy reforms (see Table 1).

Figure 4: Data Matching Process for Auxiliary Data Sources

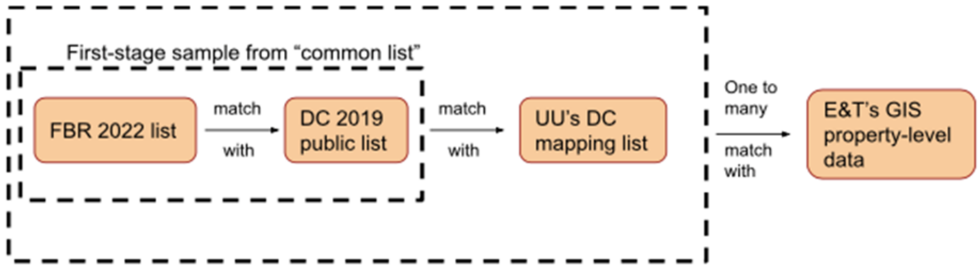


Figure 4 summarizes how the first stage sample was drawn and how it was linked to the second-stage property level data. In order to link FBR 2022 data with Urban Unit's digitized dataset, we first created a "common list" of localities that appear in both FBR and DC lists. To do this, we match the localities by name using STATA's fuzzy matching command to string match locality names across both lists followed by a manual audit to ensure that we match maximum localities across both lists. This common list contained a sampling frame of 1,114 of Lahore as shown Figure 4. This list was further cleaned to drop localities administered by Military and Cantonment Establishment to arrive at a final sampling frame of 1,002 localities that are common across FBR and DC lists.

We use the sampling frame of 1,002 localities from the "common" list to divide the frame into 5 value bins based on the distribution of FBR commercial rates first.[1] All localities within the highest-value bin were randomly ranked and the first 20 localities from this bin were drawn to our sample. Following this, the remaining localities were divided into 5 value bins based on the distribution of residential FBR capital value rates. Within each bin, we intended to draw a random sample of maximum 20 localities from each of the 5 bins to have a total sample of maximum 100 residential localities. All remaining localities, within each bin, were added to our replacement sample as per their respective rank(s). Out of the total sample of 105 localities, we could only map 82 localities from the UU digitized maps list. The remaining 23 localities were replaced by 20 next-in-line mapped localities giving a first-stage sample of 102 FBR/DC localities (see Table 2).

[1]We categorize locality into lowest bin if it was less 20th percentile; low if it was between 20th and 40th percentile; Medium if it was between 40th and 60th percentile; High if it was between 60th and 80th percentile and Highest if it was greater than 80th percentile based on the the FBR commercial/residential capital value rate in the full FBR list (not just the 1,002 localities in the common list).

Table 2: Distribution of Localities by Value Bin and FBR Rate

Distribution of Localities by Value Bin and FBR Rate			
Value Bin	**FBR Rate**	**# in Population**	**# in Sample**
Commercial			
Highest	Commercial	22	19
Total (Commercial)	–	**22**	**19**
Residential			
Lowest	Residential	73	20
Low	Residential	409	20
Medium	Residential	439	20
High	Residential	54	20
Highest	Residential	5	3
Total (Residential)	–	**980**	**83**

These 102 FBR/DC localities with digital maps were then merged with E&T administrative data by overlaying property geo-coordinates from E&T on the digital maps of the localities. Whenever at least 1 property with coordinates in the E&T cadaster fell inside a geo-coded DC locality, we assigned all properties in that E&T locality to that DC locality. Using this method, we merged 66 DC localities with E&T data. The remaining 36 DC localities were merged by showing DC maps to the relevant E&T inspectors who identified the localities manually. 5 localities were subsequently replaced with next-in-line localities as these localities fell out of the E&T's rating area.

3.1.2 Second-stage

The Excise and Taxation Department, Government of Punjab, Pakistan provided us with an anonymized cadaster of 1 million properties and contains information on property use (residential or commercial), ownership status (owned or rented), and property location (main or off-road). In addition, the cadaster contains information on the property's valuation category, which captures the quality of facilities and infrastructure in the property's locality. Each property is assigned a valuation category ranging from A to G. The second stage of our sampling consisted of drawing properties within each locality drawn in the first-stage sample from the E&T property cadaster. Thus, the second-stage sampling frame comprised 179,641 properties corresponding to the 102 DC/FBR localities from the first-stage sample. Only fully residential and fully commercial properties were retained to get this frame. Residential properties were stratified using land area (above and below median). Commercial properties were stratified using a covered area (above and below the median).

The following target sample sizes were set to be drawn from each locality:

- Residential:
  - Lowest-valued: 90 properties (20 localities)
  - Low-valued: 90 properties (20 localities)

  - Medium-valued: 120 properties (20 localities)
  - High-valued: 150 properties (20 localities)
  - Highest-valued: 150 properties (3 localities)
- Commercial:
  - Highest-valued: 150 properties (19 localities)

Since some localities did not have enough properties to meet their sample targets, it was decided to oversample from localities in bins where bin target size $\leq$ bin sample size. Once these bins were determined, localities with at least 30 unsampled properties were identified and picked randomly to meet target sizes. Samples from all 4 strata were drawn from each locality so that their total added up to the target locality sample size and each sample strata size was proportional to actual strata size. A stratified random sample of 12,363 properties was drawn, including 7,577 residential properties and 4,786 commercial properties. The remaining 167,278 properties in the sampling frame make up the replacement sample.

As explained in Section 3.4 below, following rigorous piloting, we decided that surveying commercial properties was untenable, so we dropped them from our survey sample and focus exclusively on 7,577 residential properties.

3.2 Survey and Experimental Design

In order to elicit preferences over the level and progressivity of property taxes, and to understand their determinants, we implement a survey with a sample of citizens of Lahore. Section 3.1 above outlines our sampling strategy. At the beginning of the survey, we provide respondents with a brief overview of property taxes, focusing on the concept of the average tax rate (which underlies our measures of progressivity) and its use to assess the tax burden borne by different classes of property holders. This is followed by a battery of questions that will allow us to assess citizens' comprehension of this concept. Figure B.1 shows the vignette we use to guide respondents through these concepts. To anchor beliefs about the overall level of property taxation in Lahore, all respondents were also shown the overall average tax rate of properties in Lahore: 0.04%

To understand the determinants of citizens' preferences over property taxes, we randomly assign survey respondents to receive combinations of 6 survey-experimental interventions. The implementation of the randomization is described in section 3.2.8 below.

3.2.1 Correcting Misperceptions

In the Correcting Misperceptions treatment respondents are shown photographs of 5 properties[2] that are representative of Lahore's regressive schedule and we ask citizens to assess the tax liability associated with each property through an interactive dashboard shown in Figure B.2. Respondents' answers are then used to estimate the shape of the average tax rate schedule implied by their answers which is shared with the respondents.

[2] We reduce the number of vignettes to 3 for greater than 7 marlas properties for reasons explained in Section 3.4

We then provide respondents with the actual average tax rates faced by each of the properties and show them the actual shape of the tax schedule in Lahore. Figure B.3 shows the exhibit used to present this information.

This intervention allows us to (a) measure the inaccuracy of citizen beliefs and (b) correct them by providing respondents with true information about the level of taxes paid by different properties and the distribution of the property tax burden across Lahore's properties.

3.2.2 Placebo

The placebo intervention acts as a placebo for the interventions discussed in sections 3.2.3 – 3.2.6 below. This group receives an informational video message (Please see exhibits from the video in Figure B.4) about the different tiers of government and the assignment of revenue and spending functions to each tier. The placebo message does not contain any information about the fiscal relationship between the citizen and the state but provides information about general government functions and takes a similar amount of time in the survey as the interventions in sections 3.2.3 – 3.2.6 below.

3.2.3 Public Goods

The Public Goods intervention provides respondents with information on local public good deficits in Lahore and argues that the lack of financing, which is a consequence of low property tax utilization is a big constraint on the government's ability to meet the public service delivery needs of citizens (Please see exhibits from video in Figure B.5).

3.2.4 Revenue Leakage

The Revenue Leakage intervention provides respondents with information on the magnitude of the property tax compliance challenge in Lahore and the potential financing that can become available if there was full compliance. It ends with the message that raising adequate financing for local public good provision in the city will be difficult for government in the absence of improved compliance (Please see exhibits from video in Figure B.6).

3.2.5 Spending Leakage

The Spending Leakage intervention provides respondents with information on citizen perceptions in Lahore about tax reciprocity, i.e. the proportion of taxes that are spent on the provision of public services in the city. It ends with the message that raising adequate financing for local public good provision in the city will be difficult for government in the absence of measures that can strengthen tax reciprocity (Please see exhibits from video in Figure B.7).

3.2.6 Elite Capture

The Elite Capture intervention provides respondents with examples of recent cases where opposition from high value property owners in Lahore successfully delayed the introduction of reforms designed to raise more property taxes from the wealthy. It ends with the message that raising adequate financing for local public good provision in the city will be difficult for government in the absence of cooperation from the wealthy elite of the city (Please see exhibits from video in Figure B.8).

3.2.7 Preference Elicitation

Following these interventions we collect our 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 9 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.9 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].

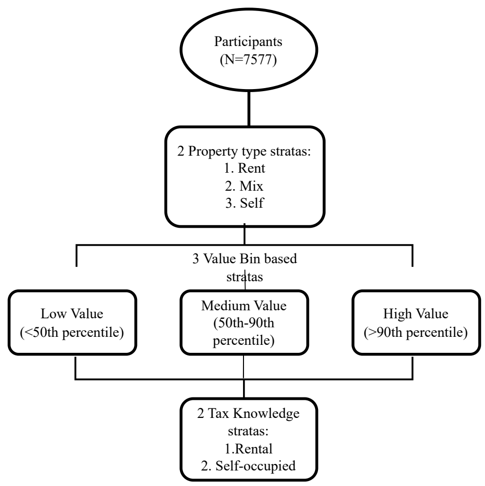
We then compute the total revenue from the tax schedule implied by the respondents' answers using the method described in Appendix D by extrapolating from the respondents' answers to the universe of properties in Lahore (see Figure B.10 for a screenshot of the graph generated and follow-up questions). When the respondent's preferred schedule raises more revenue than the current system, we ask the respondents how they would like to spend it (questions spending, budget_support, international_debt, property_tax in the attached survey instrument), choosing between 1) increasing spending on public services, 2) reducing budget support from provincial/federal government, 3) paying back debt owed to international donors, 4) lowering property taxes. Similarly, whenever the respondent's preferred schedule raises less revenue than the current system, we ask respondents how they would like to cover the shortfall, choosing between 1) reducing spending on services, 2) requesting more budget support from provincial/federal government, 3) raising more debt from international donors, 4) raising property taxes.

[3] For greater than 7 property sample, we reduced the number of properties to two from each strata and six in total to reduce survey-based fatigue

3.2.8 Treatment Assignment

All participants were interviewed at residential properties. Participants were allocated into distinct groups using a three-tiered stratification process based on property type, property value, and elicitation category. Property types were classified as rented, self-occupied, or mixed. Property values were classified as Low (0 - 50th percentile), Medium (50th - 90th percentile), and High (Above 90th percentile) according to predicted wealth percentiles for each property type (using the predicted property values from the estimation described in appendix C). The third set of strata assigned respondents to view either owner-occupied or rented properties during the preference elicitation module described in section 3.2.7.

Figure 5: Treatment Assignment Stratification



This resulted in 18 strata formed from the combination of the three property types, three value categories, and two elicitation groups ($3 \times 3 \times 2$) as shown in Figure 5. The residential sample of 7,577 was then evenly distributed across each stratum, ensuring that at least 420 properties were sampled into each of the 18 strata. These 420 properties in each stratum were subsequently randomly assigned to one of six treatment statuses, leading to a treatment status assignment for 7,560 properties. The remaining 17 properties were randomly sorted and assigned a treatment status, resulting in a sample of 1,263 properties assigned to five treatment arms and 1,262 properties to the "pure control" group.

Table 3 summarizes the randomization design, treatment assignment, and assigned sample within each stratum to be surveyed.

Table 3: Sample by type of treatment

Tax Knowledge	**Policy Preferences**	**Sample N**
None	placebo	1,262
Correcting misperceptions	placebo	1,263
Correcting misperceptions	public goods	1,263
Correcting misperceptions	revenue leakage	1,263
Correcting misperceptions	spending leakage	1,263
Correcting misperceptions	elite capture	1,263
	Total N	**7,577**

3.3 Outcomes

3.3.1 Tax Progressivity

Our most important primary outcome is survey respondents' desired degree of tax progressivity. We use four measures of progressivity that are commonly used in the literature.[4] 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:

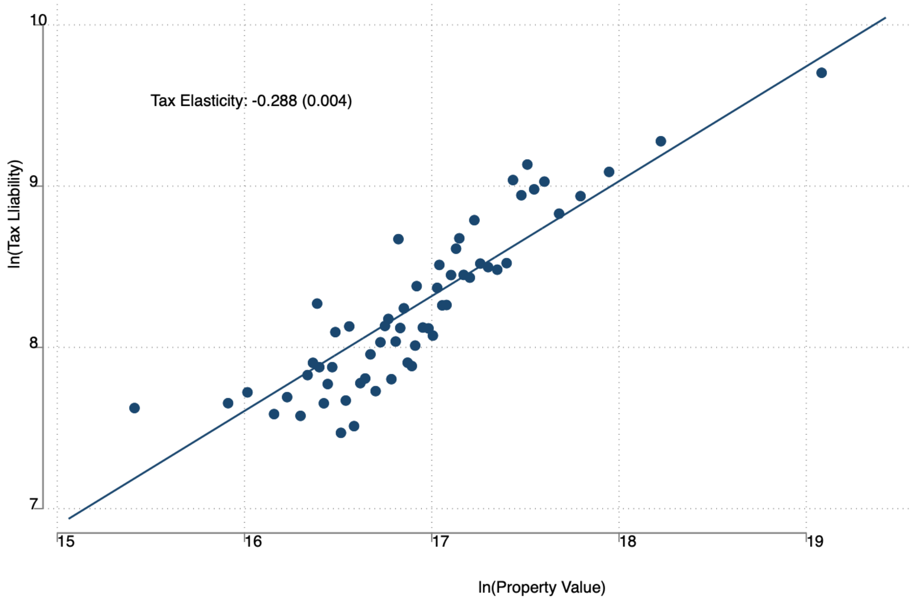
1. ***Tax Elasticity:*** The tax elasticity is $\hat{\beta}_1 - 1$ from the regression of log tax liability on log property value shown in equation (3.1). This measure is admirably simple and fits well with the spirit that "A rate structure is progressive where the average rate of tax (i.e., tax liability as a percentage of income) rises when moving up the income scale" (Musgrave & Thin, 1948, p. 498).

$$\ln\left(\text{tax liability}_i\right) = \beta_0 + \beta_1 \ln\left(\text{property value}_i\right) + \varepsilon_i \tag{3.1}$$

   Figure 6 shows a binned scatterplot (using the stata implementation of the `binsreg` command (Cattaneo *et al.*, 2024)) of the tax elasticity in the Excise & Taxation cadaster. We find that the tax elasticity is -0.288, indicating that the system is regressive.

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

Figure 6: 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:

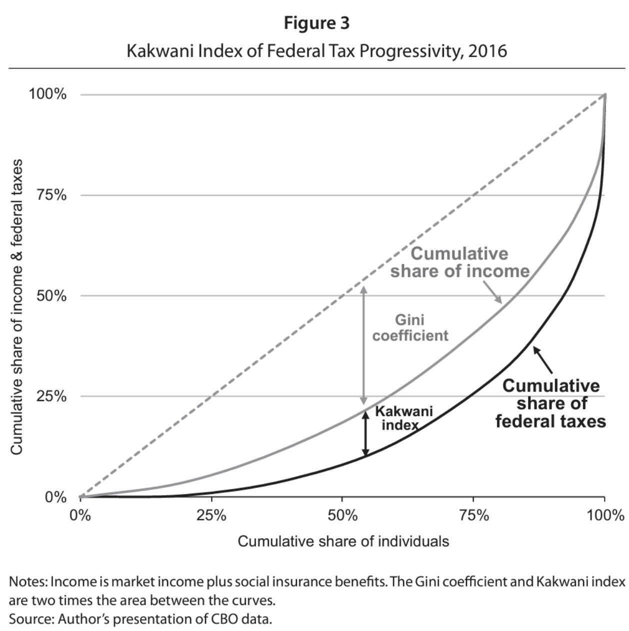
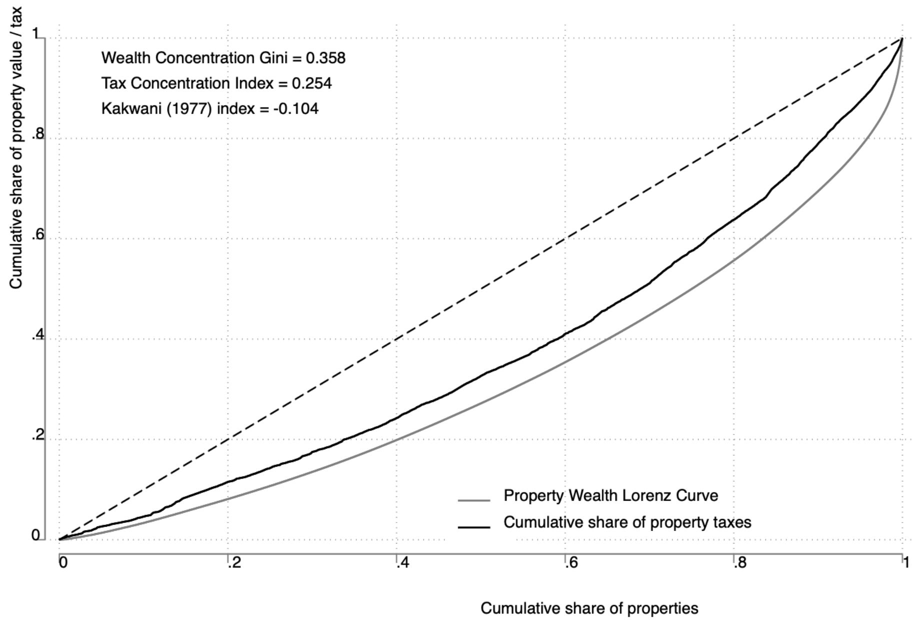


Figure 7 presents the Kakwani index in Lahore estimated from the Excise & Taxation cadaster. We find that the residential property wealth concentration gini coefficient is 0.358 while the concentration index for taxes is only 0.254, so that the Kakwani index, at -0.104, also indicates that the property tax in Lahore is regressive.

Figure 7: Baseline Kakwani Index

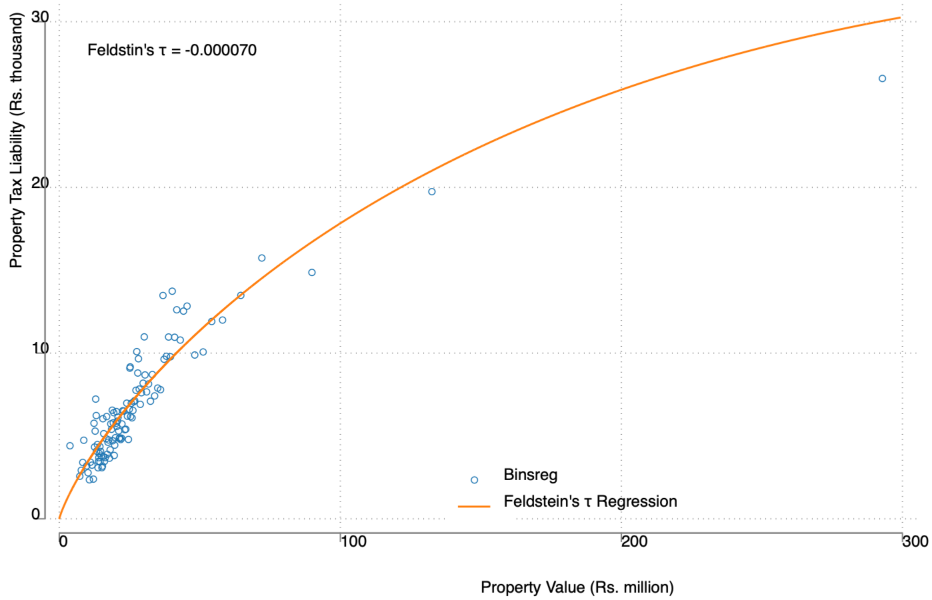


3. ***Feldstein-τ***. This measure derives from Feldstein (1969) and has been widely used in macro public finance, for e.g. Heathcote *et al.* (2017). The measure is the estimated $\hat{\tau}$ from the non-linear regression (3.2):

$$\text{tax liability}_i = \text{property value}_i - \lambda \text{property value}_i^{1-\tau} + \varepsilon_i \tag{3.2}$$

Figure 8 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 8: Baseline Feldstein's τ

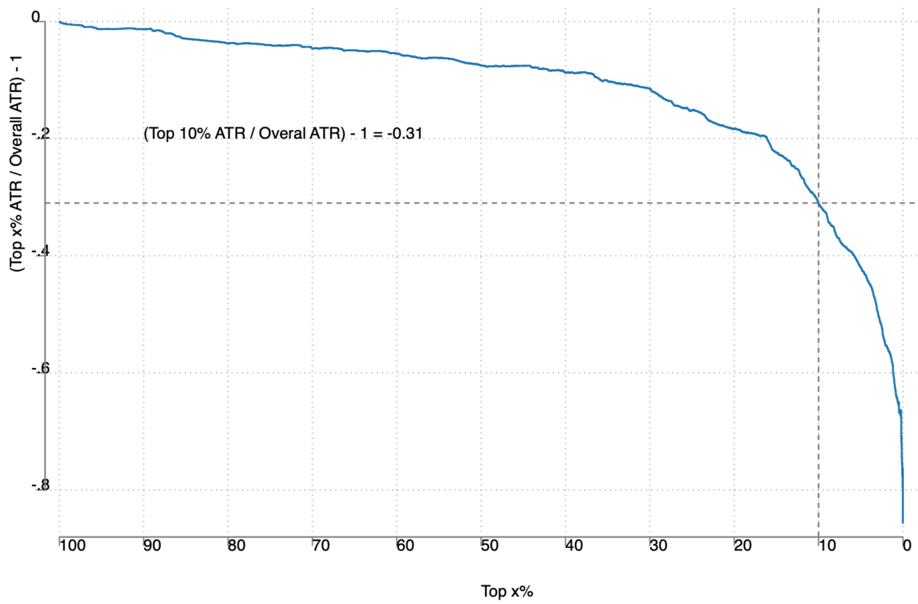


4. ***Top Tax Rate***. Since much of the literature focuses on progressivity at the very top of the distribution (e.g. Piketty & Saez, 2007), our fourth measure focuses on the top 10% of the property value distribution:

$$\text{Top 10\% Progressivity} = \frac{\text{Top 10\% ATR}}{\text{Overall ATR}} - 1 \tag{3.3}$$

Figure 9 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 9: 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

$$\tilde{Y}_i = \frac{1}{4} \sum_{k=1}^{4} \frac{Y_{ki}}{\mathsf{sd}\left(Y_k\right)} \tag{3.4}$$

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.[5] 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.

[5]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.

3.3.2 Tax Revenue

Our second primary outcome is the level of property taxation preferred by the survey respondent. For this, we take the 9 elicited preferred property tax rates, and use them to estimate a restricted cubic spline.[6] This gives us an estimate of the respondents' full preferred tax schedule.

With the respondents preferred tax schedule we can compute the revenue that would be raised by applying this schedule to the full cadaster of properties in Lahore. Since we only show respondents residential properties, we assume that the respondents' preferred commercial tax rates are such that the proportions of overall revenue raised by residential and commercial properties are the same under the respondents' preferred tax schedule as under the current tax schedule. See Appendix D for technical details.

3.3.3 Secondary Outcomes

Our secondary outcomes fall into 11 categories.

1. Current property tax' fairness (s8_q18, s8_q20, s8_q21)
2. Tax morale (s8_q13 s8_q14 s8_q15 s8_q17)
3. Representation (s5_q1, a3_q1_1, a3_q1_2, a3_q1_3)
4. Property tax rationale (s8_q5, s8_q7)
5. Behavioral responses to taxing high-value properties (s6_q1, s6_q2, s6_q3, s6_q4, s6_q5)
6. Incidence of taxing high-value properties (b1_q1, b1_q2, b1_q3, b3_q1, b3_q2)
7. Uses of deficit/surplus from preference elicitation. (spending, budget_support, international_debt, property_tax)
8. Behavioral responses to overall tax increases (s6_q6, s6_q7, s6_q8, s6_q9, s6_q10)
9. Incidence of taxing average-valued properties. (b2_q1, b2_q2, b2_q3, b3_q3, b3_q4)
10. Inequality views (s8_q1, s8_q3, s8_q4)
11. Payment behavior in subsequent fiscal year. (s4_q3)

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.

3.4 Survey Rollout

Over time, the study faced several design challenges due to external shocks and a tense political climate. Our initial pilots showed notably low response rates, especially among commercial units. Consequently, we dropped the 4,786 sample commercial properties from the study, as respondents from these units were unwilling to engage with our surveyors.

[6] 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.

For residential properties, we divided the sample by land area, as the first two pilots indicated considerable differences in response rates between properties smaller than 7 marlas and those larger (1,575 sq. ft.). The response rate for properties under 7 marlas was 44%, while those over 7 marlas had a response rate of only 10%. We therefore decided to split the survey into two phases. In the first phase we surveyed the 4,897 sample properties below 7 marlas, and in phase 2 we surveyed the remaining 2,680 larger properties.

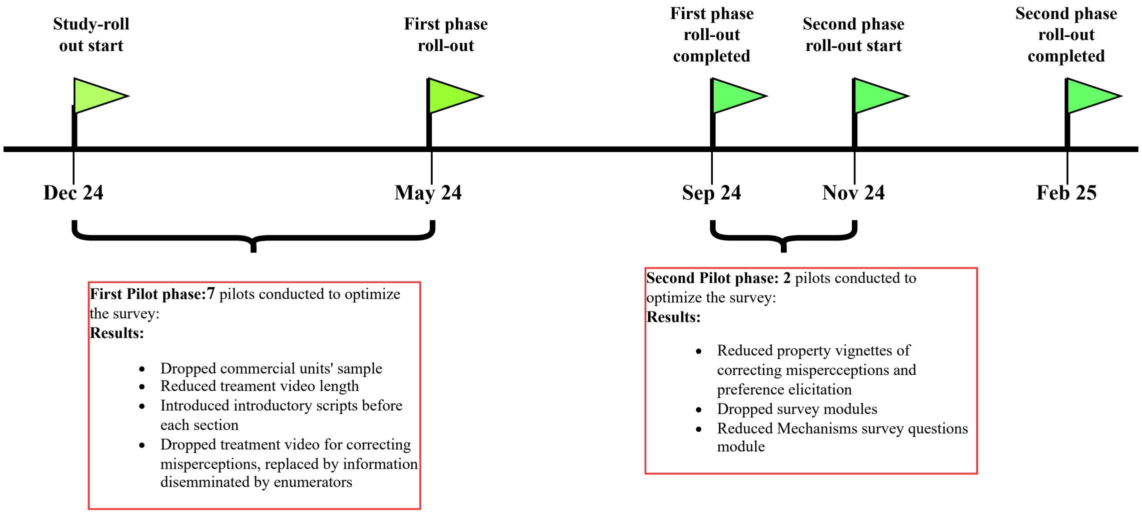
Before rolling-out the phase 1 survey, we performed rigorous piloting and incorporated feedback to revise survey structure, shorten the treatment videos, add introductory scripts before each survey section, and streamlined information to enhance clarity and participation. The first phase of the survey for properties under 7 marlas was rolled-out in the last week of May 2024, and data collection for 4,897 households concluded by the first week of September 2024. The response rate with replacements for this first phase was 53.5%.[7] The second phase started in November 2024 and was completed in February 2025.

When moving to the second phase, our pilots encountered critically low response rates for the larger properties over 7 marlas, prompting us to implement further strategies to improve engagement. Subsequent pilots revealed that to achieve a satisfactory response rate, the total survey length, inclusive of treatment videos and the interactive dashboard, should not exceed 30 minutes. To meet this goal, we reduced the number of property vignettes for correcting misconceptions module from 5 to 3, and for preference elicitation, from 9 to 6. Additionally, we dropped sections on tax knowledge, political participation, and general preferences, and significantly condensed the mechanisms section. Both the longer and the shorter versions of the survey are included with our experiment's registration at https://www.socialscienceregistry.org/trials/15393.

Furthermore, since a substantial portion of the second phase sample was from gated communities, we secured access through the management committees of these societies. The management leadership aided our surveys by connecting us with respondents. The timeline below outlines the main changes.

[7] The response rate is defined as total surveys completed including main and replacement properties expressed as a percentage of total properties attempted.

Figure 10: Timeline of survey roll-out



3.5 Descriptive Findings from Citizen Survey

Demographics

Table 4: **Demographics**

Education	Freq	Percent
Less than class 1	586	7.7
class 1-5	943	12.4
class 6-8	1,189	15.7
secondary	2,020	26.6
higher secondary	1,328	17.5
Graduate/MBBS/BDS/LLB	875	11.5
MA/MPhil//MS	414	5.5
Diploma/Vocational	23	0.3
Hafiz (those who have no formal education but have memorized the entire Quran)	4	0.1
No formal education but have basic literacy/numeracy	53	0.7
Have never been to school	143	1.9
Don't know	2	0.0
Refused to answer	6	0.1
Do you live in a joint family system?	Freq	Percent
Yes	3,025	39.9
No	4,542	59.9
Prefer not to say	19	0.3

Table 5: **Number of years living in property**

Living in the property	Count	Mean	St. Dev.	Min	Max	Median
How long lived/used property	7547	24.32	12.37	0.00	60.00	25

Tax Knowledge

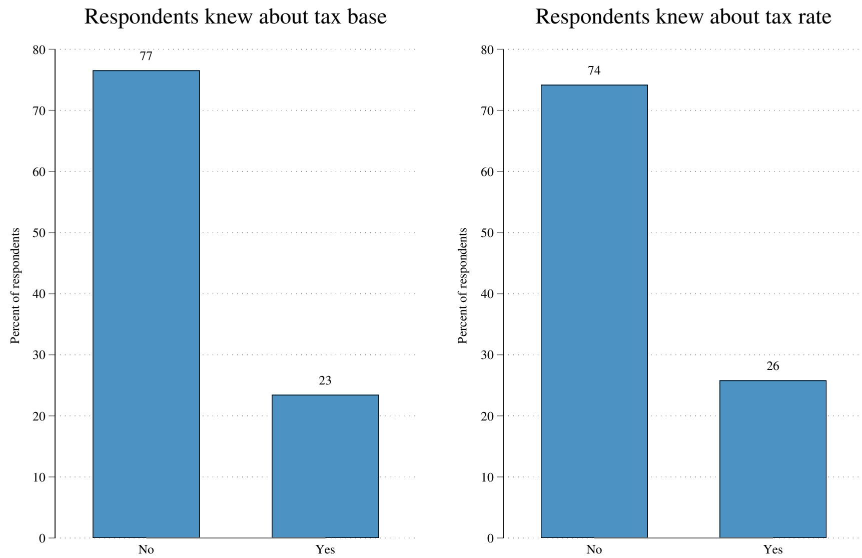


Figure 11: Citizens' knowledge about tax schedule

Source: IDEAS-LUMS citizens property tax survey.

Trust in Government

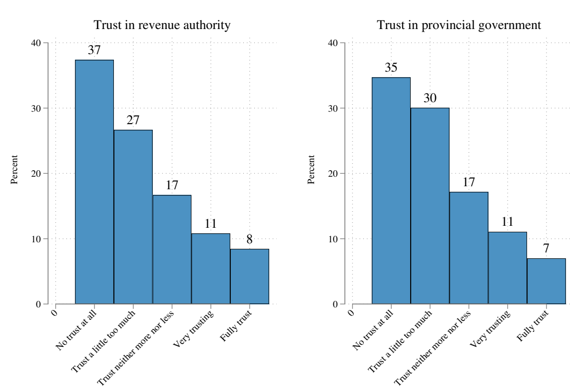


Figure 12: Citizens' trust in government

Source: IDEAS-LUMS citizens property tax survey.

Correcting Misperception

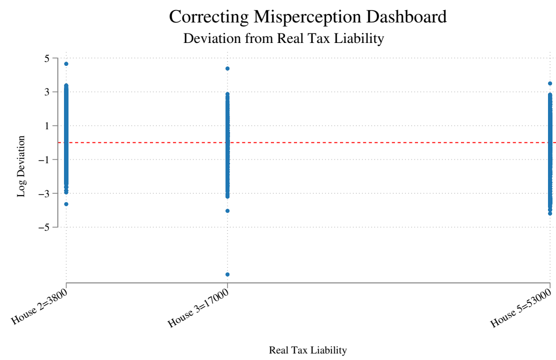


Figure 13: Citizens' tax liability estimates

Source: IDEAS-LUMS citizens property tax survey.
Notes: Citizens were asked to estimate the tax liability of three different properties. The figure shows a log of the difference between the citizens' estimated tax liability and the actual liability.

The figure reveals that citizens have substantial misperceptions about their property tax liabilities. These misperceptions are not limited to any specific property type or value; instead, they persist across all three example houses shown in the dashboard. The wide dispersion of responses indicates that the inaccuracies are systematic rather than tied to particular tax amounts or property characteristics.

Preference Elicitation

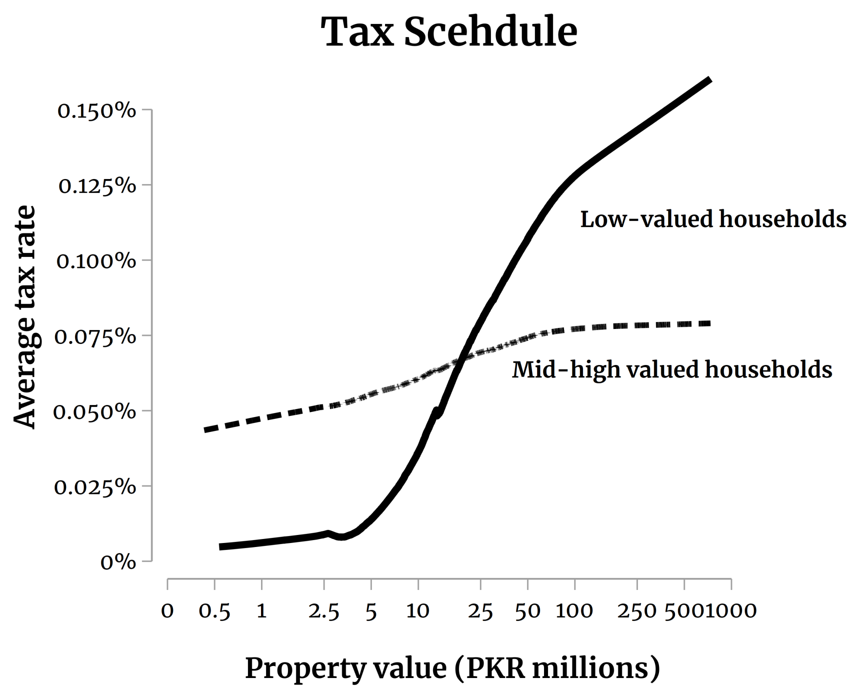


Figure 14: Citizens preferred tax schedule

Source: IDEAS-LUMS citizens property tax survey.
Notes: We used k-means clustering to divide the citizens into two groups by property value. Figure shows preferred tax rate by the two groups against property value. Properties valued less than 7 million were characterized as low-value households and comprised of 51% of the sample while those above 7 million were characterized as “medium-high” valued households. The horizontal axis shows market values assessed by real estate agents in 2023. The exchange rate is £1 = PKR 350. Vertical-axis shows citizens preferred tax rate.

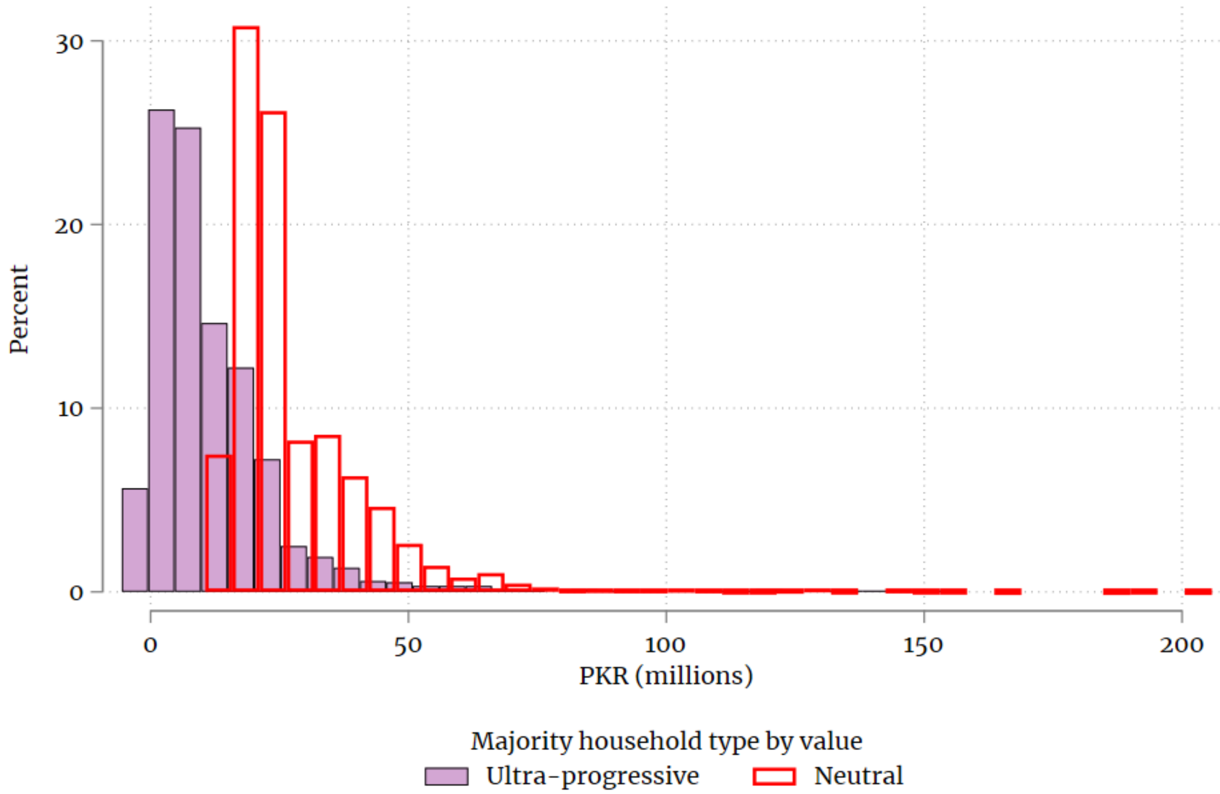


Figure 15: Citizens characteristics by preferred tax schedule type

Source: IDEAS-LUMS citizens property tax survey.
Notes: We used k-means clustering to divide the citizens into two groups by property value. Figure shows that citizens who prefer a progressive tax schedule (shown by solid line in Figure 14) live in low-valued households where as citizens who prefer a neutral schedule (shown by dotted line in Figure 14) live in middle to high value households.

4 Experiment 2: Bureaucrats and Politicians

4.1 Sampling

The experiment works with two samples of decision makers:

1. **Bureaucrats**: As described in section 2, the administration of the property tax in Lahore is divided into 179 geographic jurisdictions—tax circles. Each tax circle is administered by an inspector (the senior bureaucrat), a constable (the inspector's deputy), and a clerk (the most junior bureaucrat in the circle). We work with the universe of inspectors and constables for a total of 358 bureaucrat respondents.
2. **Politicians**: For political and administrative purposes, Lahore is divided into 274 Union Councils. In our experiment, we exclude 14 Union Councils from the Lahore Cantonment area and select a sample of 884 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.

4.2 Survey and Experimental Design

The flow of the survey in our second experiment is much like the flow in the first experiment. Hence, to avoid repetition, here we focus on the main differences between the citizen experiment and the bureaucrat/politician experiment.

4.2.1 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 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 E shows an example of the Policy Recommendations form.

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

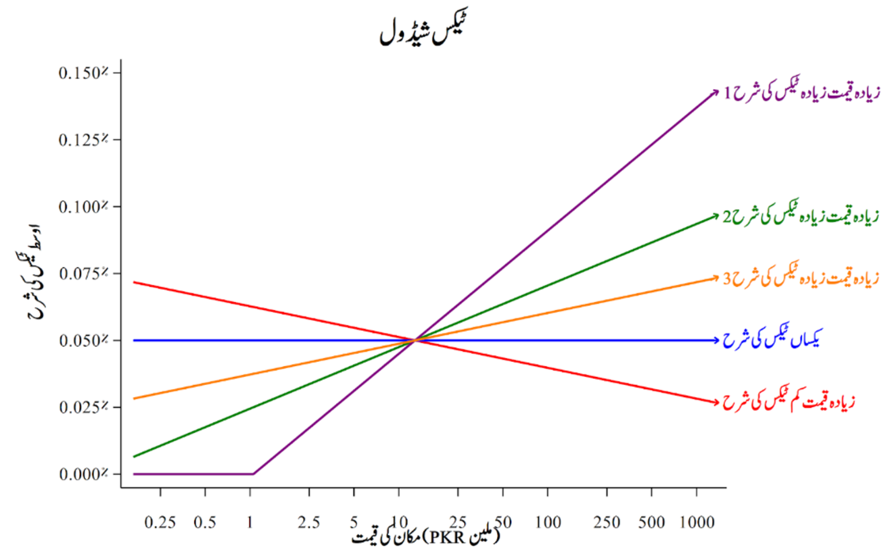
Since a critical part of our respondents' work involves aggregating citizens' preferences (especially for politicians), we elicit respondents' beliefs about the shape of the preferred tax schedules of four different groups by showing respondents the set of tax schedules in figure 16 and asking them which of them would be most preferred by members of each group. The four groups we elicited are:

1. Low-value property holders;
2. Medium/high-value property holders;
3. Bureaucrats in the government of Punjab; and
4. The government of Punjab

4.2.3 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.

Figure 16: Eliciting Respondents' Priors About Other Groups' Tax Preferences



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 and/or compliance information as follows.

For politicians, we randomly assigned politicians to 6 groups:

1. Control
2. low and med/high-value properties citizens' preferences
3. low-value properties citizens' preferences and government proposal with compliance information
4. low-value properties citizens' preferences and government proposal without compliance information
5. med/high-value properties citizens' preferences and government proposal with compliance information
6. med/high-value properties citizens' preferences and government proposal without compliance information

Since the sample of bureaucrats is slightly smaller, for them we did not use treatment arm 3.

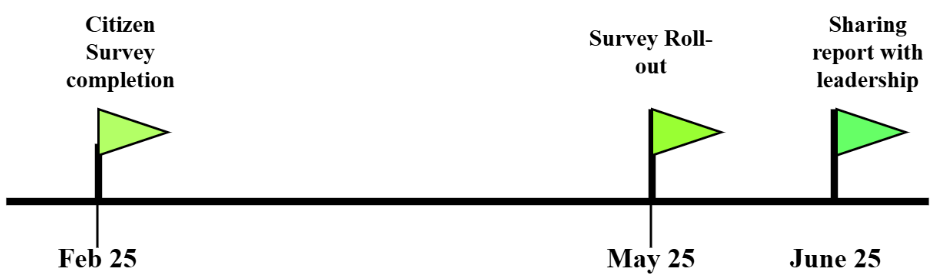
4.3 Outcomes

We focus on 2 main outcomes we focus on in experiment 2. First, the preferences over the tax schedule elicited in the same way we elicited preferences from citizens as described in section 3.2.7. Second, which tax schedule the respondent endorses in their Policy Recommendation form. In the Policy Recommendation form, respondents are asked to choose between the two tax schedules they were randomly assigned plus the status quo tax schedule (as shown in figure E).

By studying how respondents' policy preferences and endorsements differ between the treatment arms, we will be able to learn about how responsive politicians' and bureaucrats' preferences are to information about the preferences of citizens, political leadership, and bureaucrats.

4.4 Rollout

Figure 17: Roll-out timline



5 Discussion and Next Steps

In this extended abstract we have sketched the work we are doing in order to learn about the political economy of progressive property tax reform, using the city of Lahore, Pakistan as a case study. We are conducting a sequence of two experiments. First, we have conducted a large survey experiment with 7,500 citizens to learn about their preferences and the determinants of their preferences over the tax schedule. Using the outputs of the first experiment, we then conduct a second experiment with bureaucrats and local politicians, the two other key stakeholders in the policymaking process.

Our immediate next step is to conclude the second experiment and present the findings to senior policymakers in the civil service and the provincial assembly so that they may inform the formulation of property tax reform options to present in the upcoming budget at the end of June. Following that, and before the conference, we will analyze the results of the two experiments which will teach us what the determinants of the three stakeholders' preferences are, how responsive their preferences are to those of the other stakeholders, and whether the intersection of the three groups' preferences for reform contains politically feasible property tax reforms to both raise more revenues and engage in more effective redistribution.

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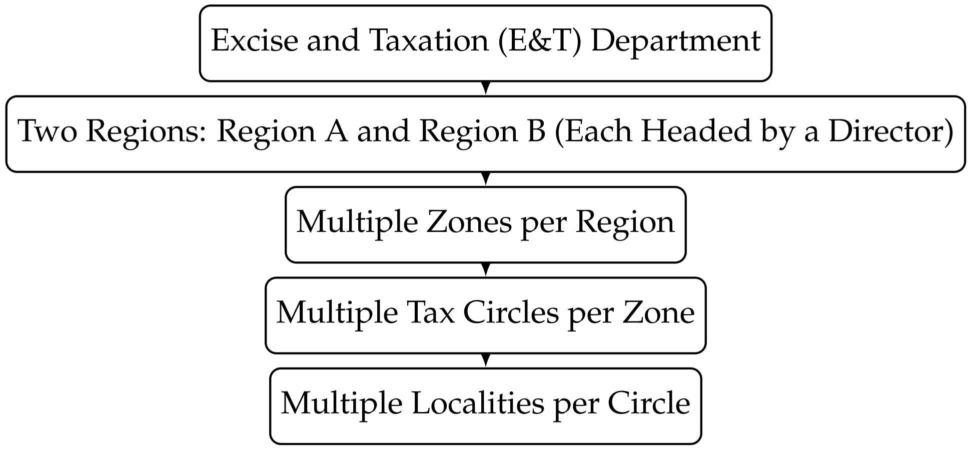
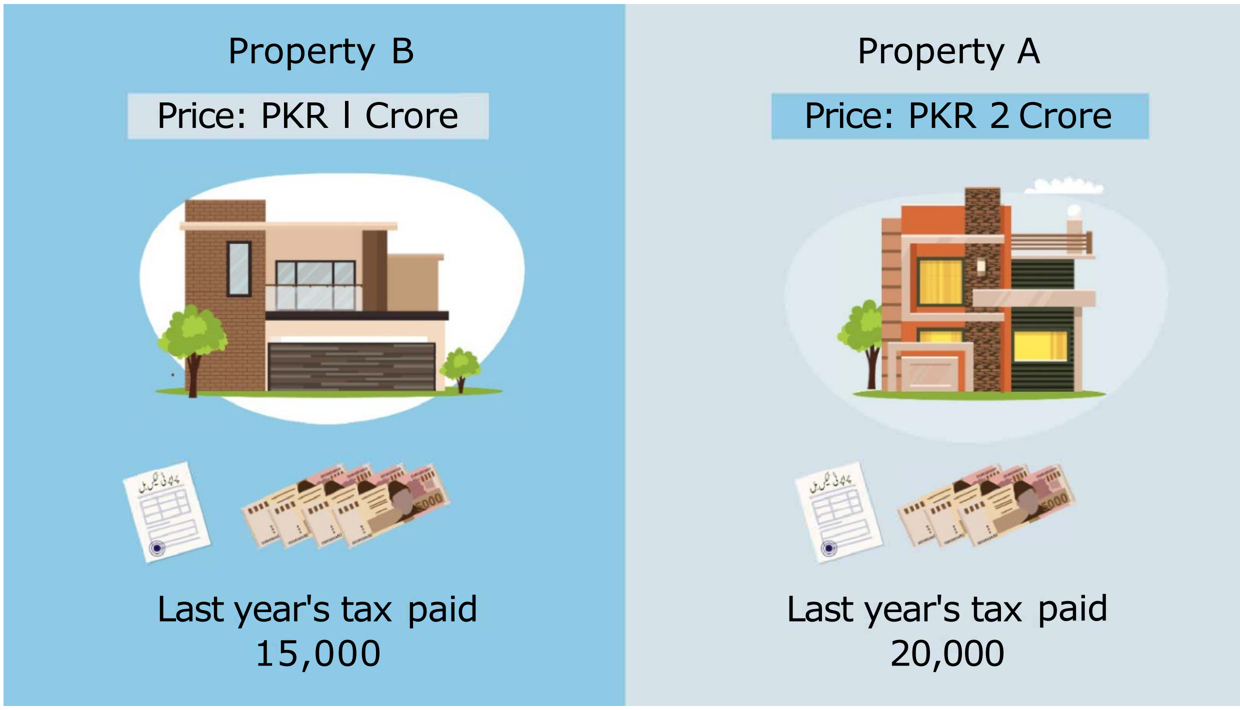
A Excise and Taxation Hierarchy

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



B Treatment Vignettes and Exhibits

Figure B.1: Manipulation checks vignette for ATR comprehension

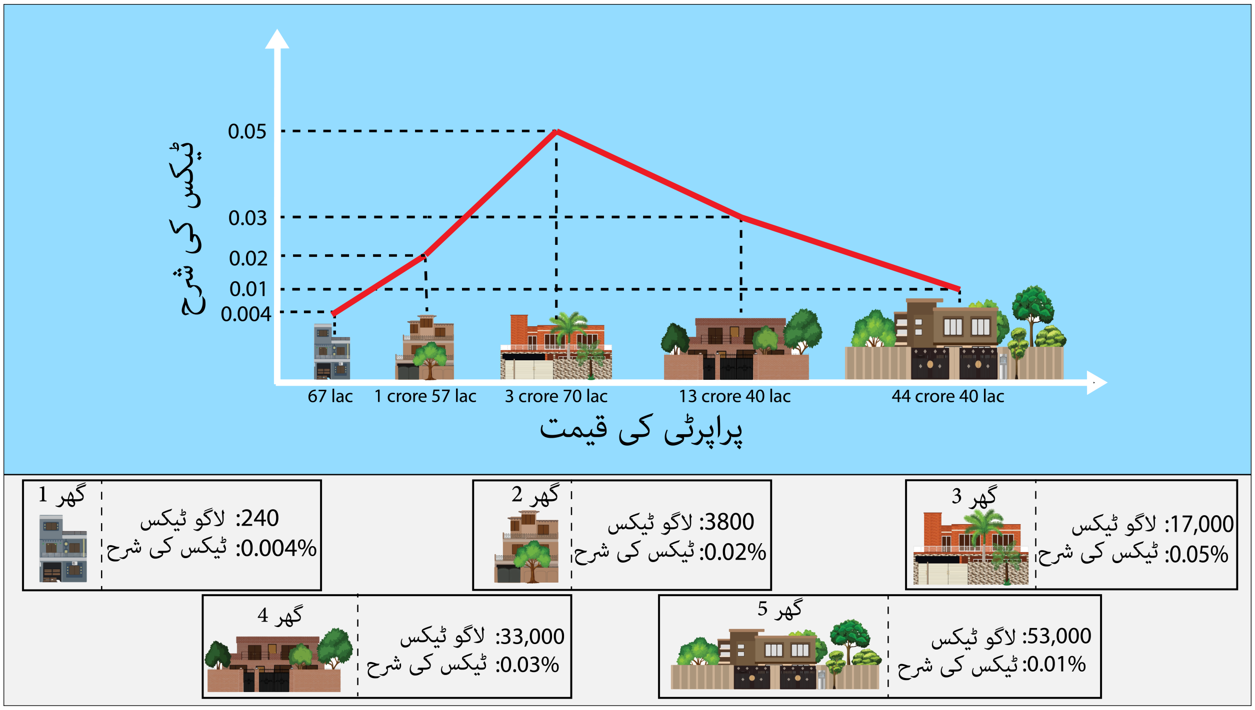


Source: IDEAS-LUMS Property Valuation Survey 2024-2025
Notes: Figure shows vignette to check respondents' comprehension of Average Tax Rate. The respondents were shown a video before this vignette and were then asked to calculate ATRs for both properties. The correct answer was for Property A was 0.1% and Property B was 0.15%. The purpose of the vignette was to show that even though Property A is paying a higher tax in rupees, but its tax burden (tax rate) was lower than that of Property B.

Figure B.2: Correcting Misperceptions Dashboard

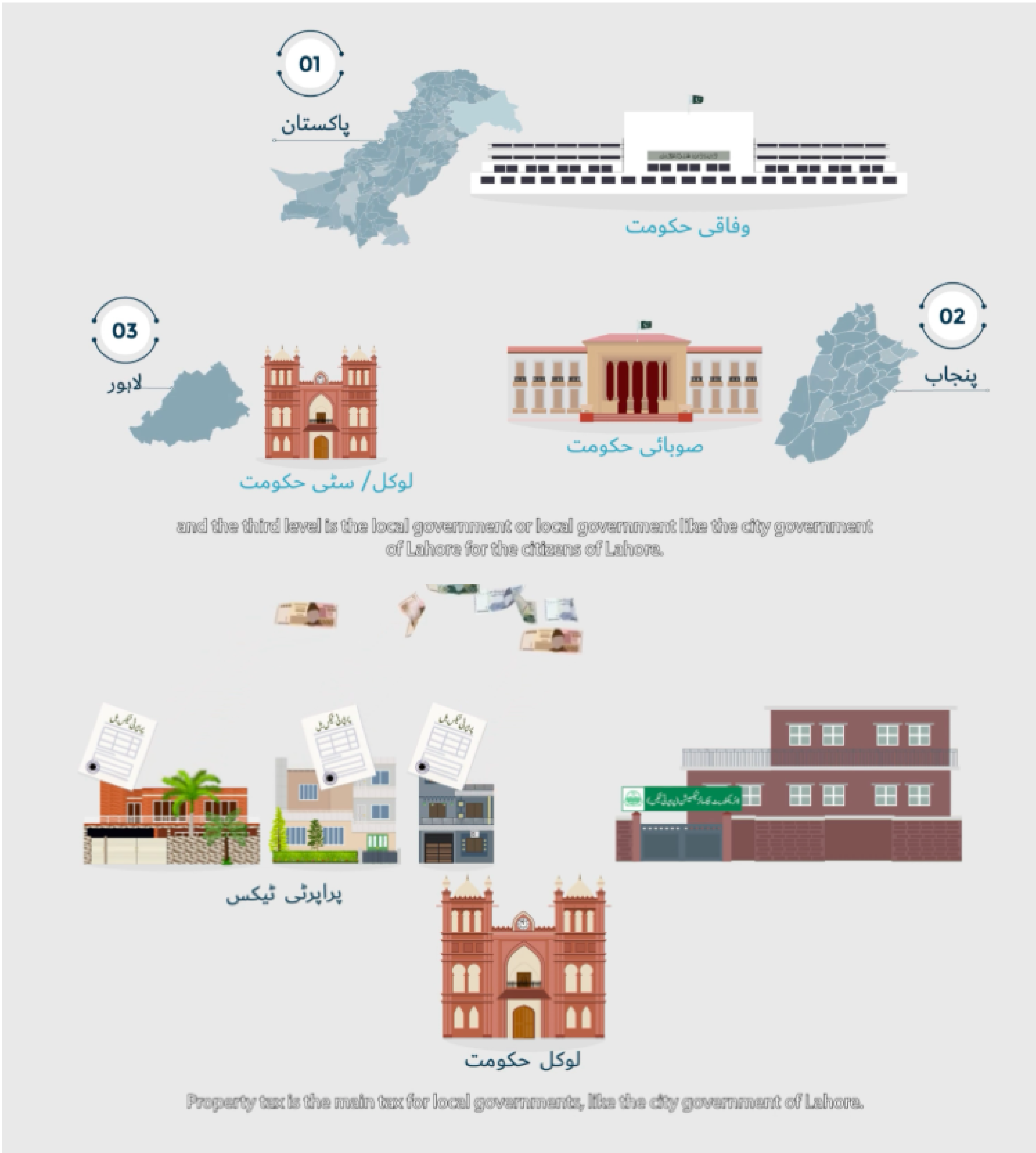
Source: IDEAS-LUMS Property Valuation Survey 2024-2025
Notes: Figure shows screenshot from Android Application developed to capture respondents' reported tax liabilities before revealing actual tax liabilities of the 5 properties. For greater than 7 marlas properties' sample, we reduce the number of properties shown to 3 keeping property 3, 4 and 5 only.

Figure B.3: Correcting Misperceptions Treatment Exhibit



Source: IDEAS-LUMS Property Valuation Survey 2024-2025
Notes: Figure shows the exhibit which was shown to the respondents by enumerators. The figure shows property tax rates decreasing after an initial peak at mid-range property values, indicating a regressive tax pattern where higher-value properties have lower effective tax rates.

Figure B.4: Placebo Video Information Exhibit



Source: IDEAS-LUMS Property Valuation Survey 2024-2025
Notes: Figure shows an exhibit from the placebo informational video. The exhibit shows tiers of the government and property tax being the main revenue source for the third tier i.e. local government.

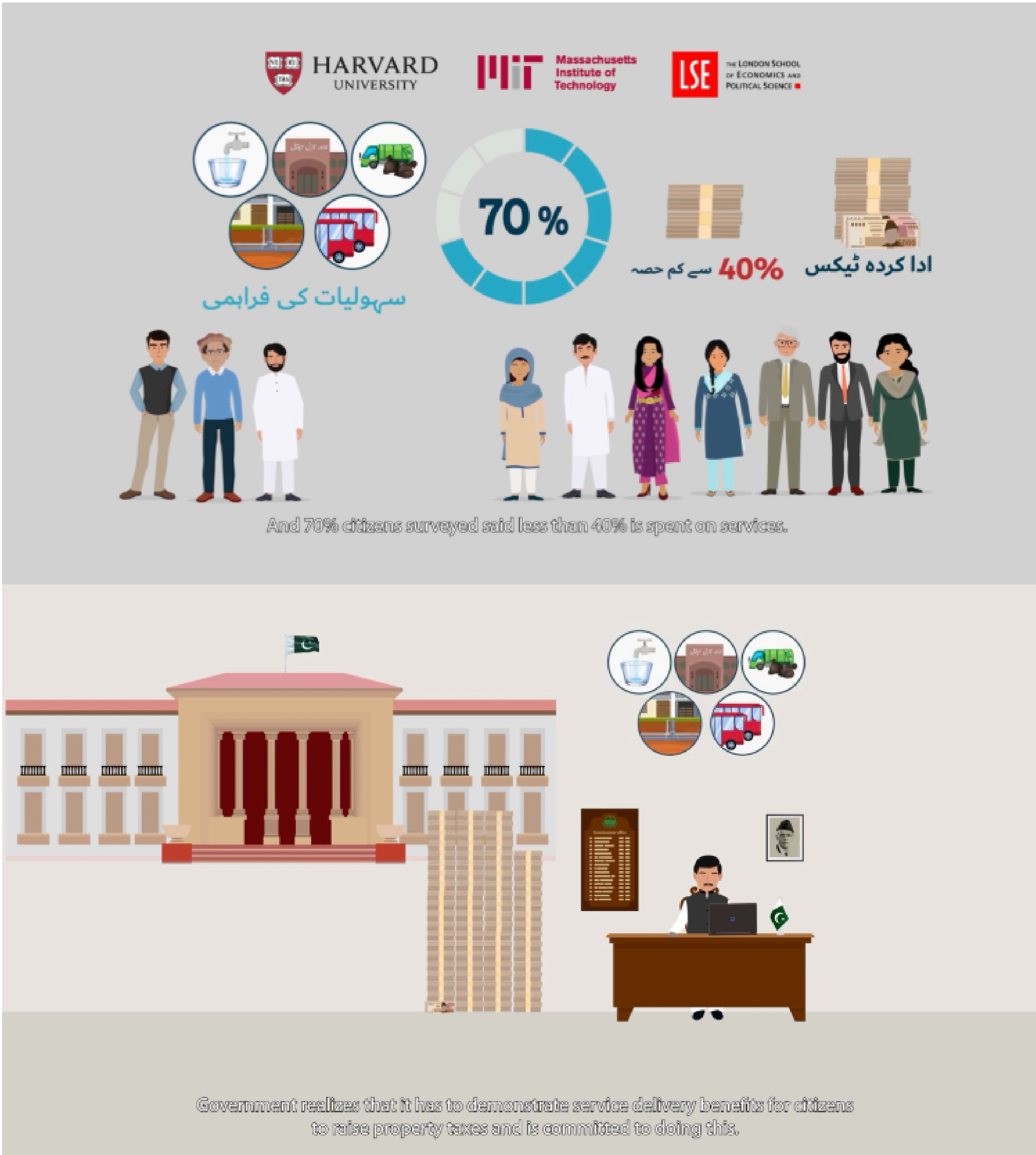
Figure B.5: Public Goods Treatment Video Exhibit

Source: IDEAS-LUMS Property Valuation Survey 2024-2025
Notes: Figure shows an exhibit from the Public Goods Treatment video. The exhibit shows low property tax utilization is a big constraint on the government's ability to meet the public service delivery needs of citizens.

Figure B.6: Revenue Leakages Treatment Video Exhibit

Source: IDEAS-LUMS Property Valuation Survey 2024-2025
Notes: Figure shows an exhibit from the Revenue Leakages Treatment video. The exhibit shows implications of low revenue collection on public goods service provision and ends with the message that raising adequate financing for local public good provision in the city will be difficult for government in the absence of improved compliance

Figure B.7: Spending Leakages Treatment Video Exhibit



Source: IDEAS-LUMS Property Valuation Survey 2024-2025
Notes: Figure shows an exhibit from the Spending Leakages Treatment video. The exhibit shows citizens' perception of utilization of revenue collected from property taxes and ends with a message reinforcing the message that local public good provision in the city will be difficult for government in the absence of measures that can strengthen tax reciprocity

Figure B.8: Elite Capture Treatment Video Exhibit

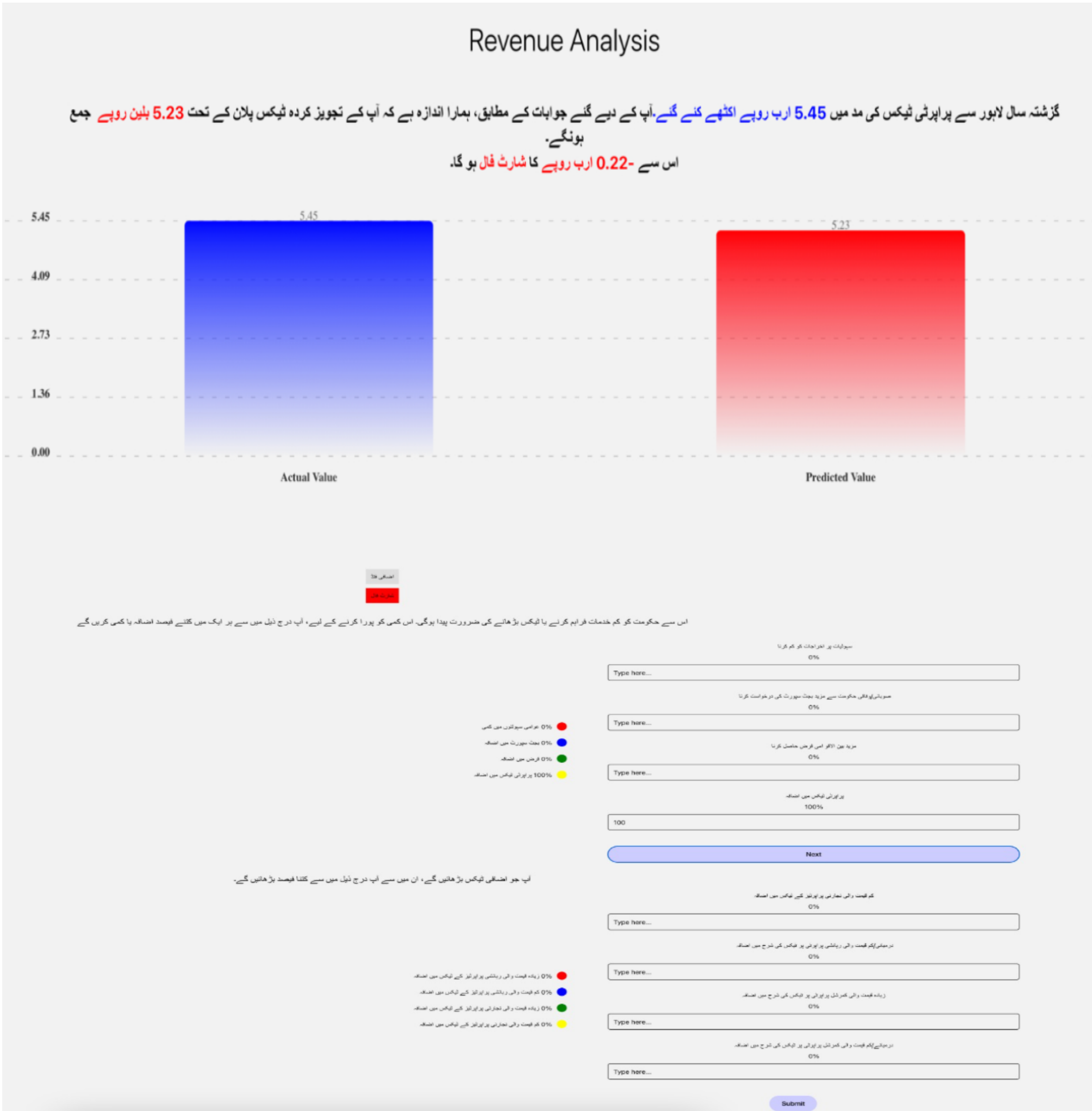
Source: IDEAS-LUMS Property Valuation Survey 2024-2025
Notes: Figure shows an exhibit from the Elite Capture Treatment video. The exhibit shows recent cases where opposition from high value property owners in Lahore successfully delayed the introduction of reforms designed to raise more property taxes from the wealthy. It ends with the message that raising adequate financing for local public good provision in the city will be difficult for government in the absence of cooperation from the wealthy elite of the city.

Figure B.9: Preference Elicitation Dashboard

Source: IDEAS-LUMS Property Valuation Survey 2024-2025

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 (Panel A). Once all 9 properties were asked, the respondent was show a summary table (Panel B), followed by the shape of the curve based on their preferred schedule and whether their response generated a progressive, neutral or a regressive schedule (Panel C). Respondents were then given a chance to revise their preferred tax rate the updated graph was shown to them as well (Panel D).

Figure B.10: Revenue Calculations and Posterior Questions



Source: IDEAS-LUMS Property Valuation Survey 2024-2025

Notes: Figure shows screenshot from Android Application developed for eliciting respondents' preferred tax schedule. Based on the final responses for preferred tax schedule, respondents were shown how much their preferred tax schedule will raise in revenue. If the revenue was greater than the current revenue, the respondents were asked where they wanted to spend and if it was less than the current revenue, they were asked from where they will source the deficit from. These questions were not asked for greater than 7 marlas properties to reduce survey time as explained in Section 3.4

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

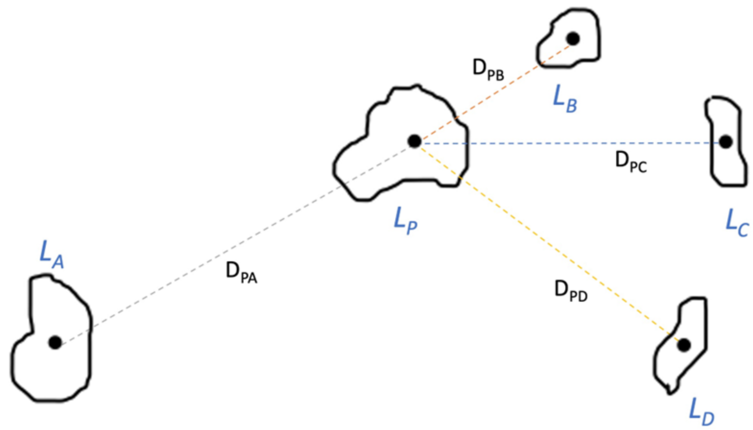
We get 2023 market value data from real-estate experts. For every property assessed, participating dealers were requested to provide estimates on the capital value, potential value as an open plot, and the rental value. Dealers were also asked about their own confidence levels in the reported values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

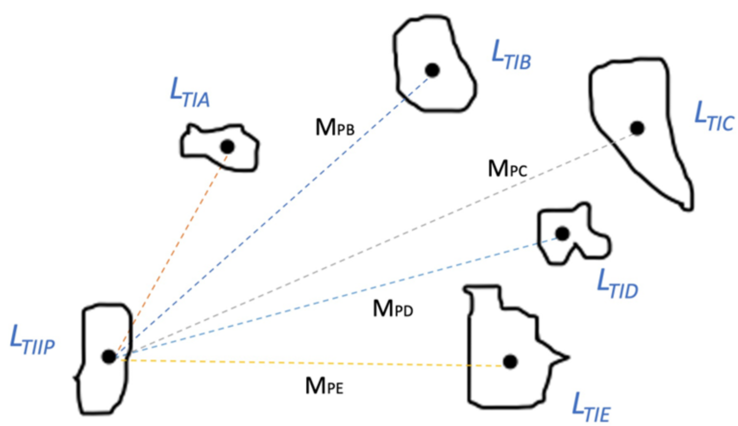
Figure C.1: Assigning DC values to a TI locality using location attributes



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

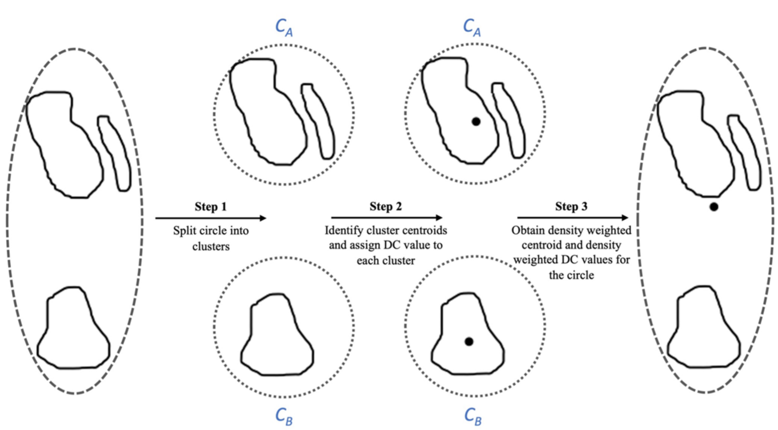


Source: IDEAS-LUMS Property Valuation Survey 2023
Notes: Figure shows out-of-sample L_{TIIP} locality was matched to L_{TIA} due to its proximity in terms of Mahalanobis distance.

- **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.

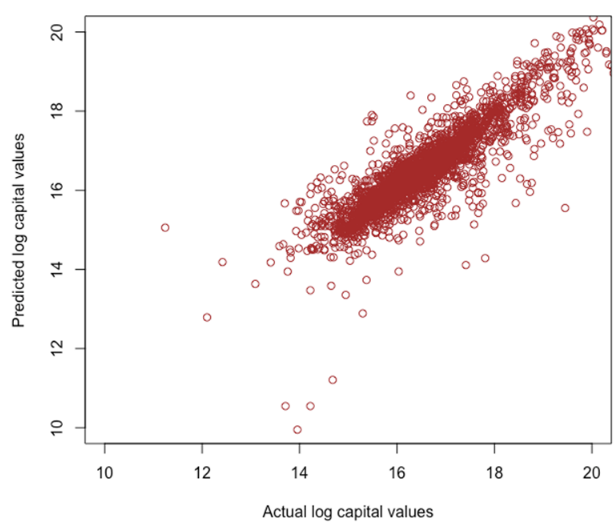
For the current context, property value is a function of land area (L), built area (B), residential use dummy (R), and a vector of cluster dummies (C) such that:

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

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.

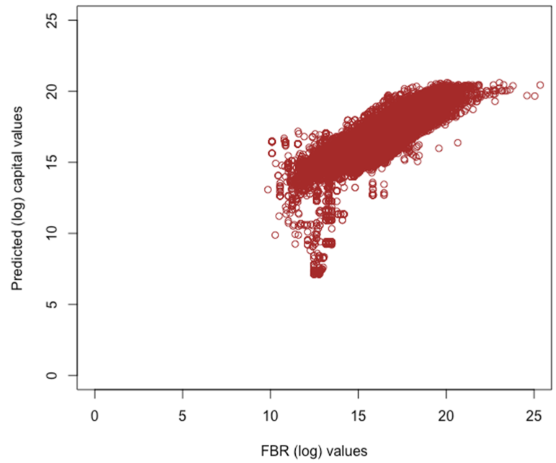
The results of this cross-validation (Figures C.4) show a high correlation between the predicted and actual capital values within the cross-validation sample. The results are robust with actual values as well. (See Figure B.5).

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

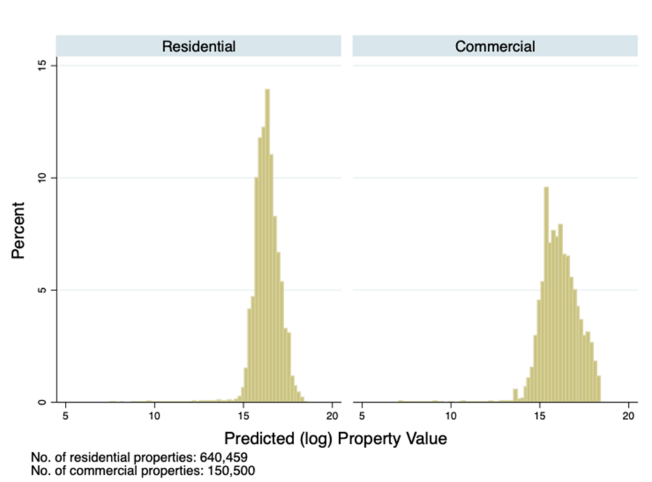


Source: IDEAS-LUMS Property Valuation Survey 2023

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.

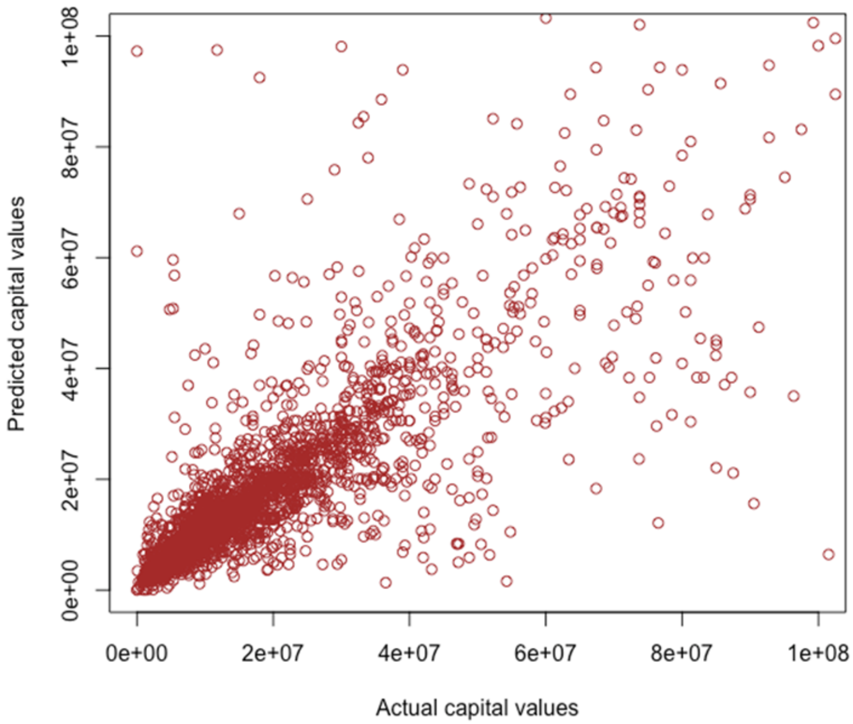
As expected, both residential and commercial property value distributions are right-skewed with few very highly valued properties (see Figure C.6).

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



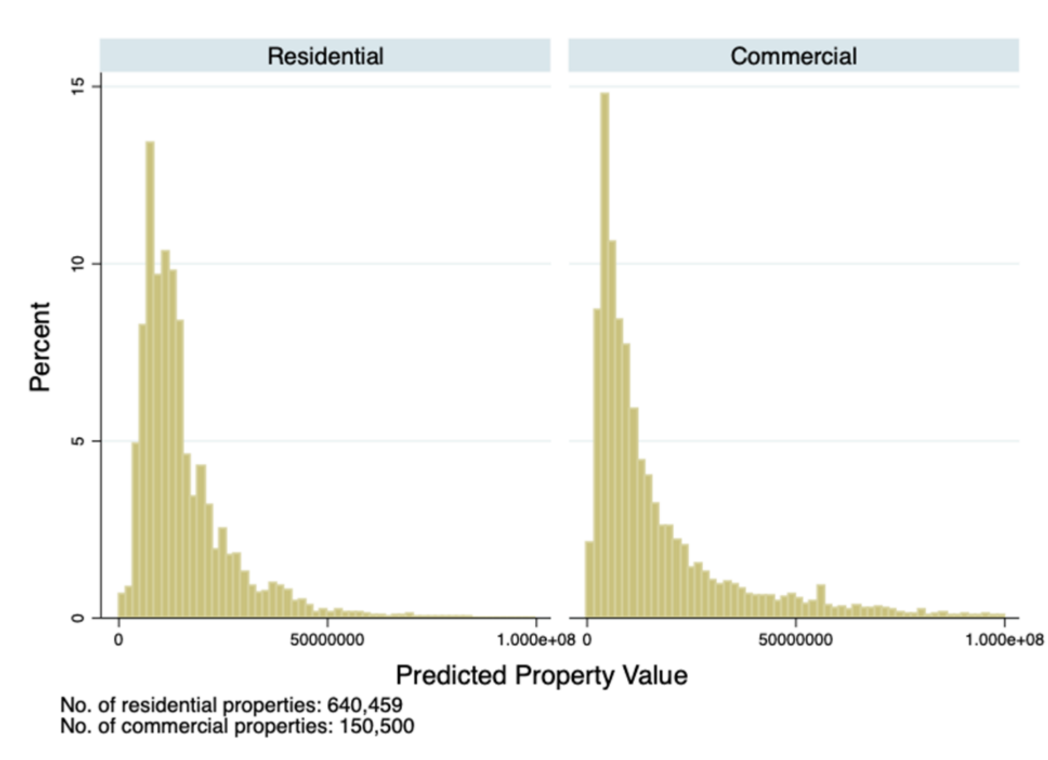
Source: IDEAS-LUMS Property Valuation Survey 2023
Notes: Values restricted to PKR 800 million for better visualization

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

D Total Revenue from Survey Responses

This section show how we calculated the revenue value from preferred ATR from survey responses. The calculated revenue value caters for the tax demand from the cadaster as well as the tax complaince.

D.1 Setup

We aim to take the 9 survey responses on desired ATRs for 9 properties and return an estimate of the total revenue raised by that tax schedule using the following setup.

Each property i is of one of 2 property types:

1. Residential, self-occupied: $t(i) = (r, s)$
2. Residential, rented: $t(i) = (r, r)$

The respondents j are randomly assigned one of these property types: $t(j) \in \{(r, s), (r, r)\}$. They see 9 properties from this property type (and none of the other type).

Properties also fall into 3 type-specific value strata:

1. $\mathcal{S}_1^t$: The property's log value $v_i \leq k_1^t$. Where k_1^t is the 50th percentile of the distribution of residential self-occupied log property values.
2. $\mathcal{S}_2^t$: $k_1^t < v_i \leq v_2^t$. where k_2^t is the 90th percentile of the distribution of residential self-occupied log property values.
3. $\mathcal{S}_3^t$: $k_2^t < v_i$.

D.2 Restricted Spline

Using respondent j's survey responses, we ran a 3-piece linear spline of the ATR y_i^j on the log of the property value v_i. This can be done in two steps.

1. Create 3 variables:
   (a) $v_{1i}^{t(j)} = \min\{v_i, k_1^{t(j)}\}$
   (b) $v_{2i}^{t(j)} = \max\{\min\{v_i, k_2^{t(j)}\}, k_1^{t(j)}\} - k_1^{t(j)}$
   (c) $v_{3i}^{t(j)} = \max\{v_i, k_2^{t(j)}\} - k_2^{t(j)}$

   where we
2. Run a restricted OLS regression of y_i^j on a constant, $v_{1i}^{t(j)}$, $v_{2i}^{t(j)}$, and $v_{3i}^{t(j)}$:

$$y_i^j = \beta_0^j + \beta_1^j v_{1i}^{t(j)} + \beta_2^j v_{2i}^{t(j)} + \beta_3^j v_{3i}^{t(j)} + \varepsilon_i^j$$

   with the restrictions that it should never predict an ATR lower than 0 or higher than 100

With the $\hat{\boldsymbol{\beta}}^j$ in hand, we compute predicted ATRs for any property:

$$\hat{y}_i^j (v_i) = \hat{\beta}_0^j + \hat{\beta}_1^j v_{1,i}^{t(j)} + \hat{\beta}_2^j v_{2,i}^{t(j)} + \hat{\beta}_3^j v_{3,i}^{t(j)} \tag{D.1}$$

Since the spline is piecewise linear, to impose the restrictions that it never predicts less than 0 or more than 100, we imposed the restrictions at each of the knots and at the extremes. Specifically, there are 8 constraints:

1. $\hat{y}(\underline{\mathrm{v}}) = \hat{\beta}_0 + \hat{\beta}_1 \underline{\mathrm{v}} \geq 0$
2. $\hat{y}(\underline{\mathrm{v}}) = \hat{\beta}_0 + \hat{\beta}_1 \underline{\mathrm{v}} \leq 100$
3. $\hat{y}(k_1) = \hat{\beta}_0 + \hat{\beta}_1 k_1 \geq 0$
4. $\hat{y}(k_1) = \hat{\beta}_0 + \hat{\beta}_1 k_1 \leq 100$
5. $\hat{y}(k_2) = \hat{\beta}_0 + \hat{\beta}_1 k_1 + \hat{\beta}_2 (k_2 - k_1) \geq 0$
6. $\hat{y}(k_2) = \hat{\beta}_0 + \hat{\beta}_1 k_1 + \hat{\beta}_2 (k_2 - k_1) \leq 100$
7. $\hat{y}(\bar{v}) = \hat{\beta}_0 + \hat{\beta}_1 k_1 + \hat{\beta}_2 (k_2 - k_1) + \hat{\beta} (\bar{v} - k_2) \geq 0$
8. $\hat{y}(\bar{v}) = \hat{\beta}_0 + \hat{\beta}_1 k_1 + \hat{\beta}_2 (k_2 - k_1) + \hat{\beta} (\bar{v} - k_2) \leq 100$

where $\underline{\mathrm{v}}$ is the lowest (log) property value for which we need to predict and $\bar{v}$ is the highest (log) property value we need to predict.

The `restriktor` package in `R` lets us implement this. But it wants the constraints in the syntax $\mathbf{R}\hat{\boldsymbol{\beta}} \geq rhs$ which in our case is

$$\begin{pmatrix} 1 & \underline{\mathrm{v}} & 0 & 0 \\ \text{-1} & -\underline{\mathrm{v}} & 0 & 0 \\ 1 & k_1 & 0 & 0 \\ \text{-1} & -k_1 & 0 & 0 \\ 1 & k_1 & (k_2 - k_1) & 0 \\ \text{-1} & -k_1 & -(k_2 - k_1) & 0 \\ 1 & k_1 & (k_2 - k_1) & (\bar{v} - k_2) \\ \text{-1} & -k_1 & -(k_2 - k_1) & 0 \end{pmatrix} \hat{\boldsymbol{\beta}} \geq \begin{pmatrix} 0 \\ \text{-100} \\ 0 \\ \text{-100} \\ 0 \\ \text{-100} \\ 0 \\ \text{-100} \end{pmatrix} \tag{D.2}$$

D.3 Total Revenue Estimates

We estimate how much total revenue would be raised by the respondent's preferred tax schedule. To do this we have to overcome three challenges:

1. We only ask the respondents about 9 properties, so we need to extrapolate to all other properties.
2. We only ask the respondents about one type of property (either residential self-occupied or residential rented).
3. Not all of the tax demanded from households is actually paid i.e. less than 100% tax payment compliance.

We will go through these one by one:

D.3.1 Tax demand for "my" property type

Each respondent is either type $t(j) = (r, s)$ or type $t(j) = (r, r)$ and their type determines the cutoffs of the value bins (low/middle/high) for them. In general, the tax demand for the respondent's property type is

$$R_1^j = \sum_{t(i)=t(j)} \hat{y}_i^j v_i \tag{D.3}$$

That is, we sum across all properties whose type $t(i)$ is the same as that assigned to the respondent ($t(j)$). For each property, we use the spline predictions of the ATR $\hat{y}_i^j$ and the log value of the property v_i to predict the tax demand for that property.

We compute this for all the properties in the cadaster and then add them all up to get total revenue via a shortcut as follows: note that in equation (D.3), we can break open the predicted ATR:

$$\hat{y}_i^j v_i = \left(\hat{\beta}_0^j + \hat{\beta}_1^j v_{1,i}^{t(j)} + \hat{\beta}_2^j v_{2,i}^{t(j)} + \hat{\beta}_3^j v_{3,i}^{t(j)}\right) v_i \tag{D.4}$$

and so,

$$\begin{aligned} R_1^j =& \hat{\beta}_0^j \sum_{t(i)=t(j)} v_i + \hat{\beta}_1^j \sum_{t(i)=t(j)} v_{1,i}^{t(j)} v_i + \hat{\beta}_2^j \sum_{t(i)=t(j)} v_{2,i}^{t(j)} v_i + \hat{\beta}_3^j \sum_{t(i)=t(j)} v_{3,i}^{t(j)} v_i && \text{(D.5)} \\ =& \left[\hat{\beta}_0^j V^{t(j)} + \hat{\beta}_1^j V_1^{t(j)} + \hat{\beta}_2^j V_2^{t(j)} + \hat{\beta}_3^j V_3^{t(j)}\right] && \text{(D.6)} \end{aligned}$$

where

$$V^{t(j)} = \sum_{t(i)=t(j)} v_i \tag{D.7}$$

$$V_1^{t(j)} = \sum_{t(i)=t(j)} v_{1,i}^{t(j)} v_i \tag{D.8}$$

$$V_2^{t(j)} = \sum_{t(i)=t(j)} v_{2,i}^{t(j)} v_i \tag{D.9}$$

$$V_3^{t(j)} = \sum_{t(i)=t(j)} v_{3,i}^{t(j)} v_i \tag{D.10}$$

Note that we pre-compute all of the sums in (D.7)–(D.10). There are two types of properties and four numbers, so this is eight "V" numbers. Finally, we multiply the "V" numbers by our coefficients and add them to get $R_1^{j,t(j)}$.

D.3.2 Other property types

We also need to deal with the fact that we only asked people about one property type $t(j) \in \{(r,r), r(s)\}$. Other property types also have a share in the total revenue which should be catered in our revenue estimation. This means we will have to scale up our revenue estimate from the proportion of revenue calculated from two property types used in survey questions. To cater for other property types, we use the cadaster.

We compute the total tax demand of the two property types we ask respondents about:

$$D_1^\tau = \sum_{t(i)=\tau} d_i \tag{D.11}$$

where d_i is the tax demanded from property i and $\tau \in \{(r,r),(r,s)\}$ are the two property types we are interested in. Then, also calculate total tax demanded from the entire cadaster

$$D = \sum_{i=1}^{N} d_i \tag{D.12}$$

and use these to scale our revenue estimate up:

$$R_2^j = R_1^j \frac{D}{D_1^{t(j)}}. \tag{D.13}$$

D.3.3 Noncompliance

Finally, to deal with the fact that not all of the tax demanded is actually paid, we again use the aggregate amounts to scale the revenue estimate. For this get the total amount paid by everyone from the cadaster:

$$T = \sum_{i=1}^{N} t_i \tag{D.14}$$

and we use this to scale our revenue estimate down:

$$R^j = \frac{T}{D} R_2^j = \frac{T}{D_1^{t(j)}} R_1^j \tag{D.15}$$

D.4 Dealing with Non-response of 9 "main" properties

In what's outlined above, we are assuming that each respondent answers 9 preference elicitation questions. But they may refuse/not know how to answer for all 9. If there is a non-response, we continue until we have asked all 9 properties. At the end of the 9 properties, we check how many responses we have for the various types of properties the respondent saw.

The respondent is randomly assigned a type $t(j) \in \{(r,s),(r,r)\}$. For that type, they saw 9 properties: 3 low-value, 3 medium-value, and 3 high-value. If

1. They gave a response for ≥ 1 low-value property; AND
2. They gave a response for ≥ 1 medium-value property; AND
3. They gave a response for ≥ 1 high-value property

Then

1. fill in the missing responses with the average of the obtained responses in that category (low/medium/high-value).
2. Continue as normal

If they do not satisfy all 3 criteria above, abort the revenue estimation.

E Sample Policy Recommendation Form

Name: ____

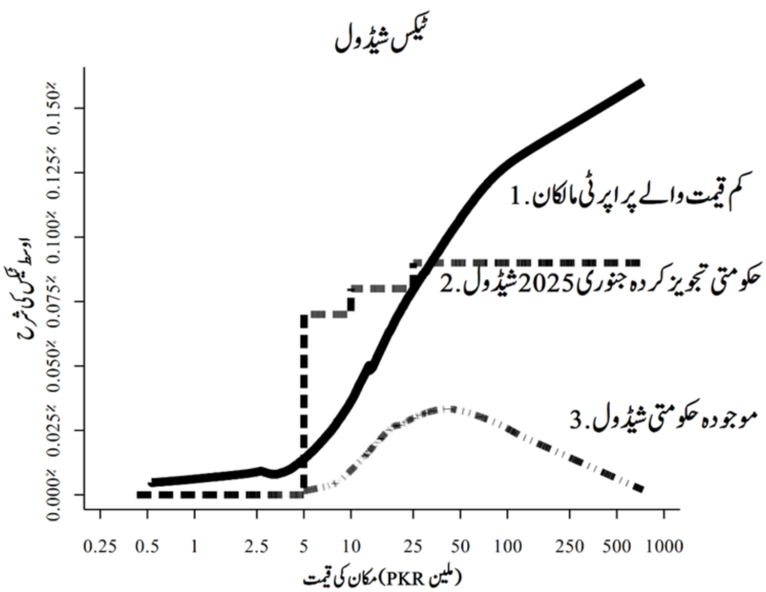
Position: ____

Union Council: ____

Phone: ____

This figure shows three possible policies that are currently under discussion that the government could pursue regarding the property tax schedule. The first solid line shows the property tax schedule preferred by citizens living in low-value properties. The second dashed line shows the proposed property tax schedule presented to the Punjab Assembly in January 2025. The third dotted line shows the current tax schedule.

Which of these tax schedules is closest to what you recommend the government adopts as a reform to Lahore's property tax for residential properties? Please select just one option:



☐ The tax schedule preferred by the occupants of low-valued homes.

☐ The tax schedule presented to the Punjab Assembly in January 2025 for consideration.

☐ The tax schedule that currently exists.

Why did you pick this tax schedule?

Signature Date