

The Political Economy of Progressive Tax Reform: Experimental Evidence from Pakistan*

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Abstract

The study of policy reform often ignores implementation challenges, despite the central role of the bureaucracy in policy formulation. We embed an experiment into an actual property tax reform to study effects on high stakes recommendations made by local bureaucrats and politicians to senior decision-makers who have legal mandate for policy reform. We show that while both citizens and politicians prefer progressive reform, bureaucrats endorse the regressive status quo. Making political dynamics salient mobilises politicians but retrenches bureaucrats. However, making enforcement salient pushes bureaucrats towards more progressive reform. Our findings suggest that the binding constraint on progressive reform is the implementing bureaucracy, constraining the set of feasible reforms.

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Dear Colleagues,

I have taken the *workshop* element of our conference very seriously. We have been working on this project for a while, but the last phase of data collection is still ongoing.

Nevertheless, I think our findings so far are quite interesting and we're excited to continue exploring them. It's an unusual paper, both methodologically, and in the questions that it asks, sitting somewhat in between disciplines. We thought that this audience, bringing together both legal scholars with a wealth of knowledge and experience of the nitty gritty of how tax reforms really happen, and economics scholars who can grill us on the standard errors ;) would be a great venue to get some feedback on the direction we are heading, and the framing of our study.

We have written up, roughly, what we have so far and indications of where we are heading next. But as you will see, the writing is very rough (you will probably detect some AI-litter there also despite my efforts to clean it all out), and the results are incomplete. Apologies for the confusion that will no-doubt ensue, and thank you in advance for all the helpful comments.

I'm looking forward to the conference very much!

Michael

1 Introduction

The property tax is the most under-used tax in low- and middle-income countries (Brockmeyer *et al.*, 2023). And in both rich and poor countries, it tends to be regressive. In our setting of Lahore, Pakistan, the average tax rate of the top 10% of properties is 31% *below* the city-wide average. This is despite the fact that the property tax is typically seen as a relatively efficient means of raising revenue. This paper asks why we see such low and regressive property taxes in low- and middle-income countries, focusing on the role of the bureaucracy in constraining both the effective tax schedule and the process of reform.

We study this through a series of quantitative and qualitative surveys and information experiments with citizens, local politicians, and tax bureaucrats embedded in a real-world reform to the property tax in Lahore, Pakistan. We ask three questions: First, whose support sustained the status quo as an equilibrium? Second, how do the possible political coalitions that can be assembled around reform proposals and the enforceability of taxation affect their support among local politicians and bureaucrats? Third, once reform has happened, what are the political and bureaucratic determinants of the reform's sustainability?

Our main findings (so far) are that there was limited support for the status quo before the reform among both citizens and politicians. The group that staunchly resisted reform is the bureaucracy. Unsurprisingly, we find that support for reform directions among local politicians is determined primarily by political considerations. For bureaucrats, neither political nor enforceability considerations reduce support for the status quo. However, when considering possible reform directions, political considerations push bureaucrats towards regressive taxes, while enforceability considerations push their support towards progressive taxes. Finally, bureaucrats think the main determinant of sustainability is compliance (in particular delinquency) by the rich, while local politicians think that the main determinant is support among the poor.

We performed a sequence of three data gathering exercises combining quantitative and qualitative surveys, information experiments, and conjoint experiments to study the determinants of preferences for the progressivity of the tax code, reform priorities, and views on the sustainability of the reformed tax code.

First, we surveyed a random sample of 7,577 residential property owners. Our survey walked citizens through the way the status quo property tax worked, including detailed work on the concept of the progressivity of the tax code. We then showed citizens random samples of actual properties with their characteristics, and elicited their beliefs about the current tax rate each property faced and what the respondent thought an appropriate tax

rate for that property would be. From this we are able to construct each respondent's preferred tax schedule and measure the degree of its progressivity.

Second, we surveyed the universe of 292 local tax officers and 831 local political workers. The survey elicited preferences over the tax schedule in the same way as for citizens, and also asked for respondents' high-stakes endorsements of either the status quo tax schedule or one of three potential reforms: the average schedule preferred by low-value property owners; the schedule preferred by medium and high-value property owners; or the schedule proposed by the government a year early for the taxation of newly built residential property. The endorsements were high stakes since the survey started with a message from their superior (the Director General of the Excise & Taxation department in the case of the tax officials, and the chairman of the Public Accounts Committee of the provincial assembly in the case of local politicians) explaining that the survey was an information gathering exercise embedded in the discussions about the imminent reform with their support and at their request.

Embedded in the survey were two information experiments. Control respondents were asked to make their endorsements without being shown the source of the proposals (i.e. to focus entirely on the progressivity or not of the schedule). Respondents in the *proposer* treatment were also shown the group that was supporting the reform, making the political coalitions that might be built around any potential reform more salient. Finally, respondents in the *compliance* treatment were additionally shown the profile of compliance rates with the status quo schedule, making the administrability and enforceability of any potential tax reform more salient. Comparing the endorsements of the three groups allows us to study the determinants of support for plausible reform directions.

Third, after the reform had been passed by the provincial assembly and the Excise & Taxation department had implemented it, we re-interviewed the tax officers and local politicians. We combined a qualitative survey exploring the respondent's experience of the passage of the reform and the subsequent work to implement it with a conjoint experiment studying the determinants of the respondents' views of what would make the reform sustainable in the medium term. In ongoing work, we are also doing qualitative interviews with the mid-level and senior political decision-makers and officials in the Finance, and Excise & Taxation departments.

Our paper introduces political economy considerations, and in particular the focus on the bureaucracy into the study of tax design and tax reform. The classical public finance literature ([Atkinson & Stiglitz, 2015](#)) focuses on the role of asymmetric information and the resultant efficiency cost of raising revenue. Political economy considerations, to the extent they are present, take the form of political constraints modeled as citizens voting

on reforms, requiring the median voter to support any reform (Feldstein, 1976; Bierbrauer *et al.*, 2021). The bureaucracy is notably absent.¹

A large literature in political science and public administration shows that frontline officials operate under binding resource constraints, ambiguous objectives, and substantial discretion, making adaptation and informal rulemaking an unavoidable part of implementation (Lipsky, 1980; Hupe & Hill, 2007). From this perspective, what is commonly labeled as bureaucratic “resistance” is not an anomaly but a predictable response to reforms that alter tasks, monitoring, or discretion without correspondingly changing incentives or operational guidance (Brehm & Gates, 1997). Field-level officials can adjust effort, reinterpret rules, or strategically manage information in ways that are difficult for principals to observe, generating implementation gaps even when reforms are politically endorsed and legally sound (Pressman & Wildavsky, 1973). Importantly, these behaviors need not reflect ideological opposition. They can arise from coping strategies, professional norms, or perceptions that reforms are meaningless or infeasible in day-to-day practice (Tummers, 2012; Tummers & Bekkers, 2014).

Economics has begun to open this black box, particularly in the context of taxation, but the evidence remains thin relative to the scale of the problem. A small number of influential studies demonstrate that tax collectors respond strongly to incentives, postings and assignment rules, and technological tools, and that these responses materially affect revenue outcomes (Khan *et al.*, 2016, 2019; Balán *et al.*, 2022; Augustin Bergeron, 2022; Knebelmann *et al.*, 2023; Okunogbe & Santoro, 2023; Dzansi *et al.*, 2025).

A smaller literature also studies the interaction of policy design and administration in low- and middle-income countries (Best *et al.*, 2015; Bergeron *et al.*, 2024; Best *et al.*, 2025; Basri *et al.*, 2021). We focus on the process of policy formulation and the critical role played by the implementing bureaucracy in policy design.

The paper proceeds as follows. Section 2 describes the setting and the 2024–25 reform. Section 3 describes the three data gathering exercises. Section 4 defines outcomes and the empirical strategy. Section 5 presents the results. Section 6 discusses implications.

2 Setting

Our study site is Lahore, the provincial capital of the province of Punjab, Pakistan. With a population of 13 million people, Lahore is the world’s 15th largest city. Our main project partners are Punjab’s Excise and Taxation (E&T) Department, a provincial government revenue authority that administers the collection and billing of the primary property tax

¹Kato (1994), tracing the role of the bureaucracy in Japan’s 1989 tax reform, is a rare exception.

in metropolitan cities. In Lahore, E&T administers the taxation of almost 1 million properties in Lahore.

To administer the property tax, the E&T department organizes its jurisdictions geographically into a 5-layer hierarchy as shown in figure A.1. There are two key levels of the hierarchy that are relevant for our study. First, the bottom level is a *locality*. Lahore contains 2,069 localities and each locality is assigned a land value loosely linked to the market value of properties in the area which is then an input into the presumptive tax formula. Figure A.2 shows the map of Lahore and its localities.² Second, the localities are organized into 194 tax *circles* which are the primary unit of collection and enforcement. Each tax circle is staffed by a team of three officials: An inspector (with primary responsibility for the circle) and a constable, assisted by a clerk.

As is common throughout the world (Best *et al.*, 2025), Lahore’s property tax system is presumptive. Under the pre-reform system, a formula based on observable property attributes (including land area, covered area, number of stories, and geographic location) generated a proxy for the gross annual rental value (GARV) of the property. A table of rates was then applied to the GARV based on location and usage.

To assess the effective tax rates under the pre-reform system, we worked with real estate agents and used machine learning models to estimate the values of all residential properties in Lahore. Our panel of property dealers provided estimates of the market value of a random sample of 12,363 properties which we used as training data for a random forest model that we can then use to estimate the values of all 802,592 properties in the cadaster (see appendix E for details). Figure 1 shows the average property tax rate by property value in Lahore in 2022. It shows that the property rates under the pre-reform system were low, averaging (0.04%). This 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).

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. We can summarize the regressivity of the schedule in a variety of progressivity indices. Appendix B presents 4 such summary measures and an overall index. All of them confirm that the schedule was regressive. A prominent measure of progressivity is *Feldstein’s* τ (Feldstein, 1969; Heathcote *et al.*, 2017), the estimated $\hat{\tau}$ from the nonlinear regression $\text{tax}_i = v_i - \lambda v_i^{1-\tau} + \varepsilon_i$. Negative values indicate regressivity, and positive values indicate progressivity. The pre-reform schedule had a $\hat{\tau}$ of -0.00007 as shown in figure 2.

²The localities do not span the entire city for two reasons. First, the Cantonment areas of the city are governed by a separate Cantonment Board under the Cantonment act of 1924. Second, peripheral areas must be declared to be urban and “rated” before they fall under the property tax.

Compliance with the property tax is also imperfect. Noncompliance is driven by two margins: delinquency, and underassessment. Delinquency leads to substantial revenue losses: 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.

Underassessment is also widespread. We collected ground-truth values of cadastral inputs during the citizen survey; 39% of residential properties have a discrepancy between cadastral and ground-truth inputs, with an implied tax loss of PKR 190 million (USD 681,000) and undervaluation of PKR 3 billion (USD 10.1 million; Appendix Figures A.3–A.4).

2.1 Tax Reform

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 previously updated in 2014 and was hence, in urgent need of updating. The government was under intense pressure to update the tax, allowing us to partner with the government in advance of the impending reform to inform and study the reform process.

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 Experimental Design and Data Collection

We implemented three data gathering exercises to study how information and institutional constraints shape preferences over property tax reform in Lahore, Punjab. First, through a large-scale *citizen survey*, we elicited residential taxpayers' preferred statutory

property tax schedules across the property-value distribution. Importantly, our goal in the citizen survey is not to estimate downstream behavioral responses (e.g., payment) but to construct *aggregated* citizen-preferred schedules for salient taxpayer groups.

These aggregated schedules serve as empirical policy objects in our second exercise, an *endorsement experiment* with local politicians and citizen-facing tax officials that tests whether decision-makers' reform endorsements respond to (i) citizens' stated preferences, (ii) an existing leadership proposal, and (iii) enforcement constraints proxied by compliance gaps.

Third, after the reform had been approved and began to be implemented we re-interviewed the local politicians and tax officials as well as their superiors and the senior decision-makers directly involved with passing the reform. Qualitative interviews explored their experience with the reform process and the subsequent work to implement it. For local politicians and citizen-facing tax officials, we also embed a conjoint experiment in the survey to elicit respondents' views about what the critical determinants of the reform's sustainability will be.

3.1 Citizen Survey

We surveyed 7,577 residential property owners drawn from a stratified two-stage sample of 83 of 980 surveyable Lahore localities (Appendix D). The survey began with a structured introduction to the average tax rate (ATR) and a comprehension vignette of the authors' design (Appendix Figure C.2); respondents were anchored on the citywide ATR (0.05%).

We elicited preferences using a structured schedule-elicitation module modelled on [Fisman et al. \(2020\)](#): respondents saw nine residential property profiles (three each from the bottom 50%, 50–90%, and top 10% of the value distribution) drawn from their assigned property type, and reported (i) their belief about the property's current ATR and (ii) their preferred ATR. Profiles displayed lot size, covered area, usage, storeys, and an estimated market value generated by the random-forest model (Appendix E). We aggregate respondents' nine answers into a full preferred schedule via a constrained cubic spline. The resulting group-aggregated schedules used in Experiment 2 are the schedule of *low-value owners* (under PKR 7 million; 49% of property owners) and the schedule of *medium-/high-value owners* (above PKR 7 million; 51%). Appendix Figures C.6–C.8 display these schedules against the Government's January 2025 schedule.

3.2 Endorsement Experiment: Local Tax Officers and Political Workers

We surveyed the universe of 292 local tax officers (144 inspectors, 148 constables) and 831 local political workers in Lahore. Officers serve on average 3,424 properties, with 16.5 years of experience. Political workers each represent a Union Council of average population 43,692, with 9.6 years of political experience. Full descriptives are in Appendix Tables G.7–G.8.

Incentive-compatible framing. Two design features make the elicitation high-stakes. First, every respondent receives a *senior management cover letter* (the Director General of E&T for officers; the Speaker of the Punjab Assembly and the Chair of the Public Accounts Committee for politicians), committing to use the aggregated responses in budget deliberations (Appendix Figures C.9–C.10). Second, every respondent completes a *Policy Recommendation Form* (Appendix F) showing three schedules and ticking, signing, and dating one. The form converts the stated preference into an explicit policy stance collected for transmission upward.

Information treatments. The design crosses (i) the pair of tax schedules shown to the respondent for endorsement against (ii) whether compliance information is overlaid on the property-value distribution. All respondents are first shown a baseline distribution of residential property values (Appendix Figure C.3); 71% see only the distribution, 29% see an augmented version overlaying compliance rates by value bin (Appendix Figure C.4). Respondents are then assigned one of three pairwise schedule comparisons drawn from {low-value, medium-/high-value, Government} and endorse one option, the other, or *neither* (the latter framed as support for the status quo). The resulting six-arm design is summarised in Appendix Table C.1.

3.3 Post Reform Survey

Our qualitative survey starts with three modules looking back at the reform. First, we discuss how each respondent experienced the process of information aggregation leading up to the reform proposal. Second, we show respondents summaries of their peers' views elicited in the endorsement experiment survey and ask their opinions on them. Third, we show respondents summaries of the other groups' views (i.e. we show politicians bureaucrats' views and *vice-versa*) and discuss them.

For the respondents in the endorsement experiment, we then move to a conjoint experiment in which we show respondents pairs of scenarios with five, randomly-varying

attributes and ask respondents to pick the scenario that is “*most likely to continue functioning effectively over the next 3–5 years.*” For local politicians, we vary i) support from low-value property owners; ii) support from medium- and high-value property owners; iii) overall compliance; iv) support from political parties; and v) support from the real estate industry. For tax officials, we vary i) compliance by low-value property owners; ii) compliance by medium- and high-value property owners; iii) overall support; iv) the fraction of properties that are delinquent; and v) the fraction of properties that are underassessed. To maximize our statistical power to estimate weights on the attributes, the randomization is performed using a Bayesian Adaptive Choice Experiment (BACE) (Drake *et al.*, 2024).

Finally, for all respondents (both the subjects in the endorsement experiment and the senior bureaucrats and politicians) we have qualitative modules digging into the experiences of the implementation of the reform and beliefs about the future sustainability of the reform.

4 Outcomes and Empirical Strategy

Endorsements. The first primary outcome is the schedule the respondent endorses on the Policy Recommendation Form: one of two reform schedules or the status quo. Because each respondent faces three options, we model endorsements with a conditional logit:

$$U_{ij} = \alpha_j + \beta_{Tj}T_i + \beta_{Cj}C_i + \varepsilon_{ij}, \quad (1)$$

where α_j captures the baseline value of policy j in the placebo arm, $T_i = \mathbf{1}[\text{proposer treat}]$, $C_i = \mathbf{1}[\text{compliance treat}]$, and ε_{ij} is iid extreme value. We report predicted endorsement probabilities and contrasts.

Elicited progressivity. The second primary outcome is the elicited preferred tax schedule, summarised by five progressivity measures (defined in Appendix ??): tax elasticity, Kakwani index, Feldstein- τ , top-10% ATR ratio, and an equally weighted index following Kling *et al.* (2007). Each is normalised to mean zero and SD one in the control group. We estimate

$$Y_i = \beta_0 + \mathbf{X}_i\beta_1 + \sum_{g=1}^5 D_{gi}(\delta_g + \eta_g E_i) + \gamma_{\text{Stratum},i} + \theta_{\text{Enumerator},i} + \varepsilon_i, \quad (2)$$

where D_{gi} are arm indicators, E_i flags the compliance overlay, γ_{Stratum} are randomisation-stratum fixed effects, $\theta_{\text{Enumerator}}$ are enumerator fixed effects, and \mathbf{X}_i contains post-Lasso controls (Wager *et al.*, 2016). Standard errors are heteroskedasticity-robust.

First stage and willingness to pay. As a mechanism check we estimate (2) with respondents’ beliefs about compliance by property type as the outcome. We also elicit willingness to pay for additional citizen-preference information using a lottery-tickets mechanism (Appendix ??).

5 Results

5.1 Status-Quo Preferences

Figure 4 Summarizes the support for the status quo among citizens, local politicians, and tax officials at baseline. Panel A summaries citizens’ views. For each citizen, we summarize their preferences for progressivity using Feldstein’s- τ (from fitting $T = P - \lambda P^{1-\tau}$ to their elicited preferences. Values of τ above 0 indicate progressive preferences, while negative values indicate regressive preferences) and plot them as grey dots. The orange line is a lowess fit; the dashed blue line marks the median voter’s preferred level (0.00016); the dashed red line marks the status quo (-0.000070).

Essentially all citizens prefer schedules more progressive than the status quo, and the median voter’s preferred level is more than twice as progressive. This shows that there is widespread support for greater progressivity among citizens, suggesting that this is not the primary obstacle to progressive tax reform.

Panels (b) and (c) show predicted endorsement probabilities of the four options (status quo plus three reform proposals) for politicians and bureaucrats in the placebo arm in which neither the political nor the enforcement aspects of tax reforms are made salient. Among politicians, only 41% prefer the status quo; among bureaucrats, a majority do. This suggests that the constituency holding back reform at baseline is likely to be the implementing bureaucracy, not the electorate or the political class.

5.2 Politics and Tax Reform: Reform Politics Mobilises Politicians and Retrenches Bureaucrats

We next reveal proposer identities to randomly selected respondents. Figure 5 plots the change in predicted endorsement probabilities from the placebo arm to the proposer-

treatment arm for politicians (panel a) and bureaucrats (panel b).

The two panels point in opposite directions. Politicians treat proposer information as a coalition-formation cue: support for the status quo falls by about half and the largest single gain accrues to the Government. Bureaucrats retrench. Their support for the status quo *rises*, and among the three reform options support shifts away from the Government and the low-value owners' proposal and toward the medium-/high-value owners' proposal – the least progressive of the three.

5.3 Enforcibility and Reform: Compliance Information Flips Bureaucrats

The compliance overlay reverses the bureaucratic picture. Figure 6 plots the change in predicted endorsement probabilities from the proposer-only arm to the proposer-plus-compliance arm.

For politicians, the compliance overlay lowers support for both the status quo and the Government and raises support for both citizen proposals; the shift toward citizens is larger for the more progressive low-value-owners' proposal (+0.05) than for the medium-/high-value-owners' proposal (+0.027). For bureaucrats, the shift is sharper: support moves from the medium-/high-value owners' proposal to the Government's. Because the Government's proposal is more progressive, the net effect is a more progressive endorsement.

The elicited-preference results in Table 1 confirm the same direction. The interaction between the compliance overlay and the Mid/Rich-vs-Govt arm raises bureaucrats' preferred progressivity index by 0.32 standard deviations ($p < 0.01$); the Feldstein- τ effect is 0.69 standard deviations ($p < 0.01$); the top-10%-ATR effect is 0.43 standard deviations ($p < 0.05$). Non-interaction effects are economically and statistically small. The treatment that moves bureaucrats is the conjunction of being shown the Government's schedule *and* being shown that the rich do not currently comply – exactly the configuration P3 highlights.

The corresponding politician table is null on every margin (Appendix Table G.1): politicians, who already prefer progressivity, do not revise their own preferred schedule under the compliance treatment.

First stage: officers update high-value compliance beliefs downward. Table 2 reports the mechanism check that disciplines the framework's interpretation. We regress respondents' *beliefs* about compliance by property type on the treatment indicators. The com-

pliance overlay paired with the Mid/Rich-vs-Govt comparison lowers officers' perceived compliance by high-value households by 6.85 percentage points ($p < 0.05$); the analogous effect on perceived low-value compliance is statistically indistinguishable from zero. Officers update belief about high-value compliance *downward* and react by endorsing higher statutory liability on the same group – the substitution mechanism in P3. The corresponding first stage for politicians is null (Appendix Table G.2).

Bureaucrats' willingness to pay for additional citizen-preference information also rises by 0.87 lottery tickets ($p = 0.003$, control mean 0.37; Appendix Table G.3); politicians', already high at 1.08, does not respond (Appendix Table G.4).

5.4 Reform Sustainability: Conjoint and Qualitative Evidence

Our qualitative work and the analysis of the conjoint experiment is ongoing. However, very preliminary results from the conjoint experiment suggest that for local political workers, the dominant attribute is support from low-value owners ($\beta = 0.151$, $p < 0.001$); support from medium-/high-value owners ($\beta = 0.087$), compliance ($\beta = 0.081$), party support ($\beta = 0.080$), and real-estate-industry support ($\beta = 0.069$) all matter, secondarily. For local tax officers, the two largest coefficients in absolute value are negative – under-assessment ($\beta = -0.111$) and delinquency ($\beta = -0.138$, both $p < 0.001$) – and the largest positive coefficient is high-value compliance ($\beta = 0.109$). Officers read sustainability through enforceability; politicians read it through electoral arithmetic. Full results are in Appendix Tables G.5–G.6.

6 Discussion

We study the obstacles to progressive tax reform in the context of Lahore, Pakistan. We argue that a critical, and underappreciated constraint on reforms is the implementing tax bureaucracy.

Our findings contribute to work that seeks to centre the beliefs and preferences of bureaucrats in determining the effectiveness and success of tax reforms. In our case, we find it is unlikely that the groups opposing tax reforms are either citizens or politicians. Both groups appear to support progressive property taxation and reform over the regressive status quo. The main constituency opposing reforms to the property tax at baseline are tax officials.

This is not because tax officials necessarily have regressive preferences – both bureaucrats and politicians support the most progressive reform schedule proposed by low-

value property owners and are opposed to the least progressive reforms proposed by higher-value property owners. Our treatments reveal that their preferences are driven instead by the costs of reform, and specifically, considerations connected to compliance. Politicians are sensitive to the preferences of different groups of citizens and the imperatives of political coalition-building, while tax officials are most sensitive to information about compliance.

These are not unexpected findings, but they may matter greatly not only to how reforms are designed, but also to how constituencies for them are built within implementing institutions. Unlike politicians, bureaucrats are less concerned with the demand or popularity of a reform and may care little for the pressures that lead governments to institute reforms. What they seem to care about more are all the things that make their jobs harder – reforms that make rules harder to enforce, targets harder to meet, and taxes harder to assess or collect. Building a constituency for reform within the bureaucracy – a core element in ensuring reform success and sustainability – requires highlighting not the progressivity levels of tax reforms, but their ‘implementability’ and the ways in which reforms may make their jobs easier.

This paper empirically unpacks the concept of “capacity” as it relates to frontline officials in the context of policy reforms. Relative to previous literature, we take officials’ behavior as endogenous to the policy process. Future work in this area could investigate further the mechanisms affecting the incentives faced by frontline officials and their resultant choice of policy. Such research could also unbundle and assess political workers’ proclivity to opting for more progressive reforms, as a function of political coalition building and administrative reform.

Next steps. The paper is preliminary. We are extending the qualitative work to senior decision-makers, developing a formal model that maps to the experimental treatments, and tracking ex-post compliance and revenue outcomes through 2027.

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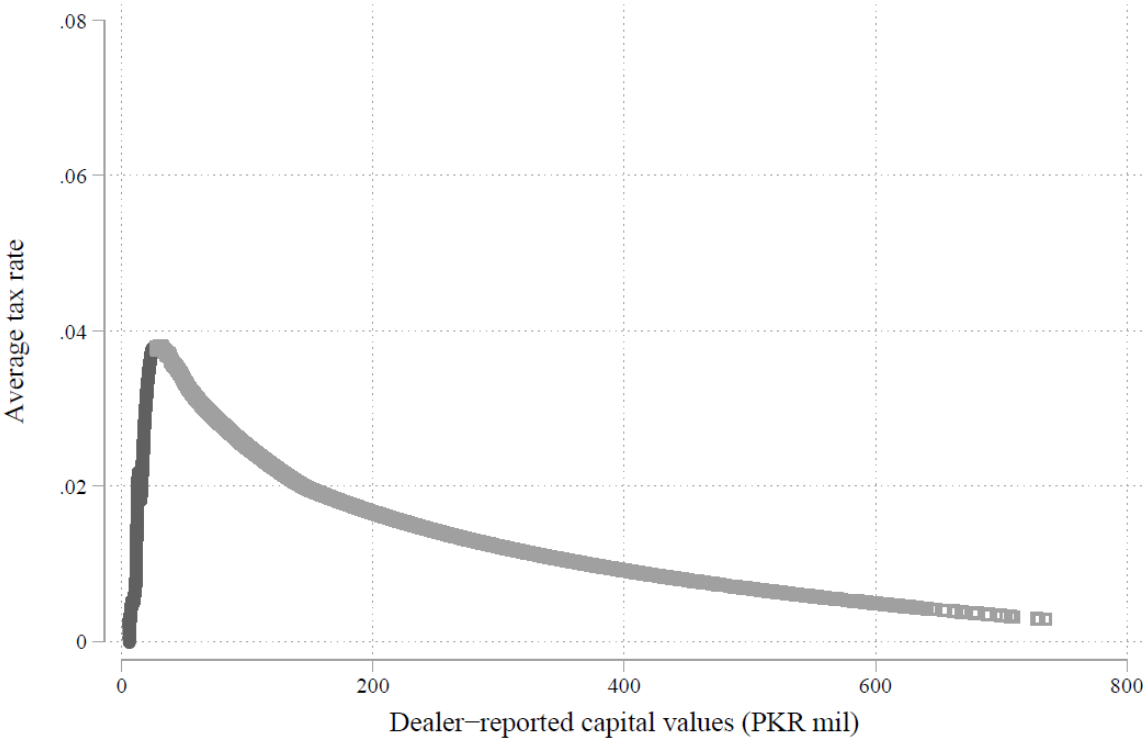
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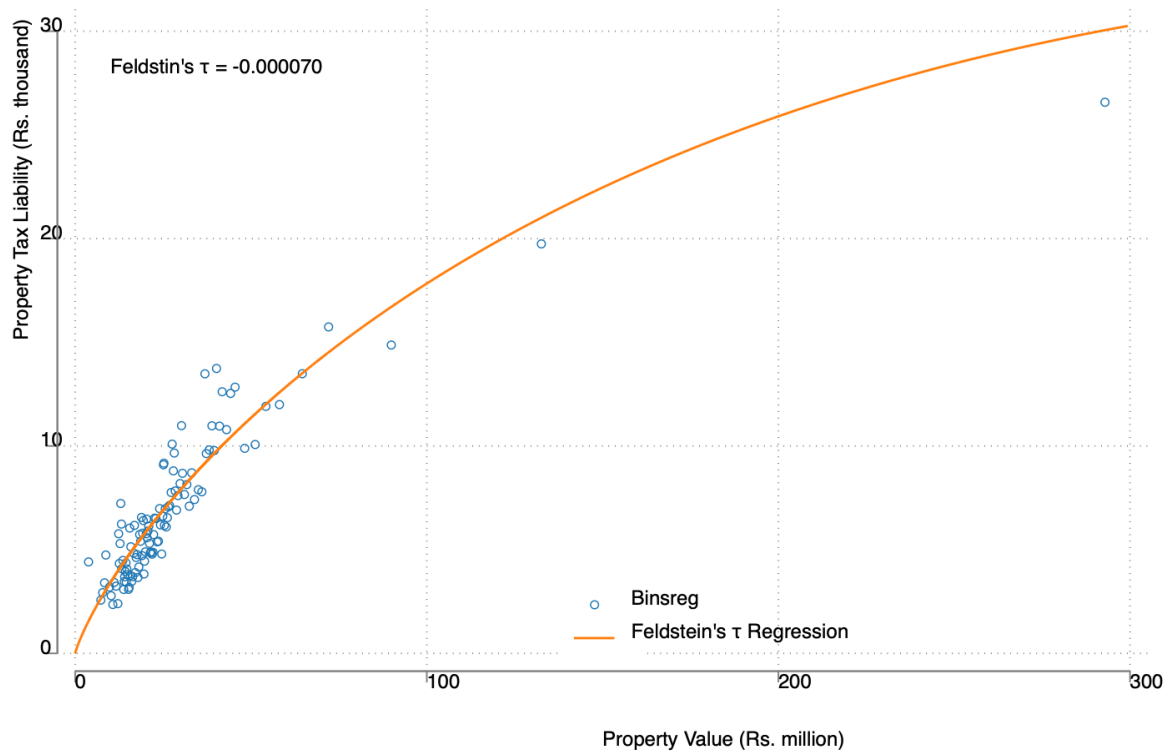
Figures & Tables

FIGURE 1: PRE-REFORM TAX SCHEDULE



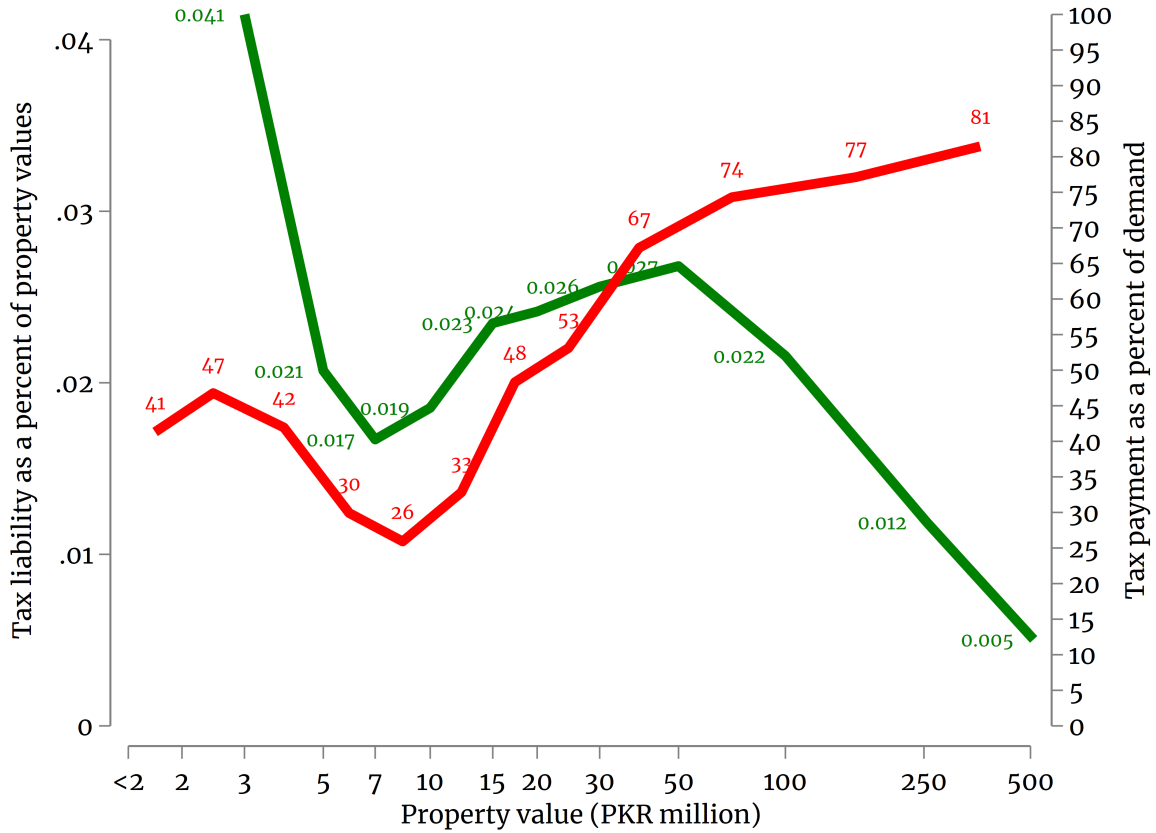
Source: E&T property 2021-2022 tax demand data; IDEAS-LUMS property valuation survey.
Notes: Figure shows average tax rate against property value. x-axis shows market values assessed by real estate agents in 2023. The exchange rate is US\$1 = PKR 275 (£1 = PKR 350). Y-axis shows average tax rate which is tax liability expressed as a percentage of market capital values. Total properties number of properties = 842,000.

FIGURE 2: PRE-REFORM PROGRESSIVITY: FELDSTEIN'S τ



Notes: The figure shows the progressivity of the tax schedule in place before the reform. The progressivity is summarized in the fit of the non-linear regression of tax liability on property value: $\text{tax}_i = v_i - \lambda v_i^{1-\tau} + \varepsilon_i$. The estimated $\hat{\tau}$ summarizes the progressivity of the tax schedule (Feldstein, 1969; Heathcote *et al.*, 2017). Negative values indicate regressivity, and positive values indicate progressivity. The pre-reform schedule had a $\hat{\tau}$ of -0.00007 , indicating a regressive schedule.

FIGURE 3: COMPLIANCE AND REGRESSIVITY IN LAHORE, PUNJAB PAKISTAN

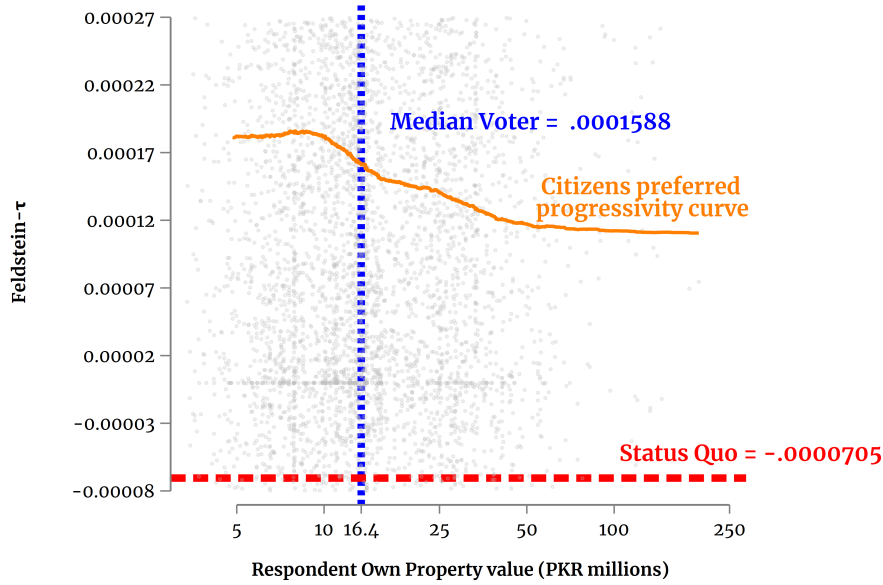


Source: E&T property 2021-2022 tax demand data; IDEAS-LUMS property valuation survey.

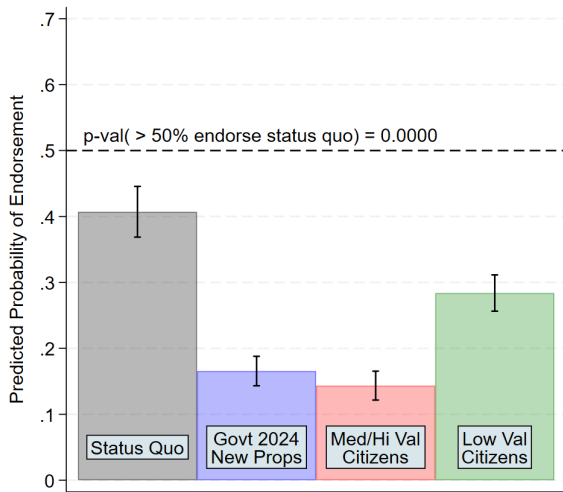
Notes: Figure shows average tax rate and compliance against property value. x-axis shows market values assessed by real estate agents in 2023. The exchange rate is £1 = PKR 350. Right Y-axis shows average tax rate which is tax liability expressed as a percentage of market capital values. Left y-axis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

FIGURE 4: STATUS-QUO PREFERENCES (P1)

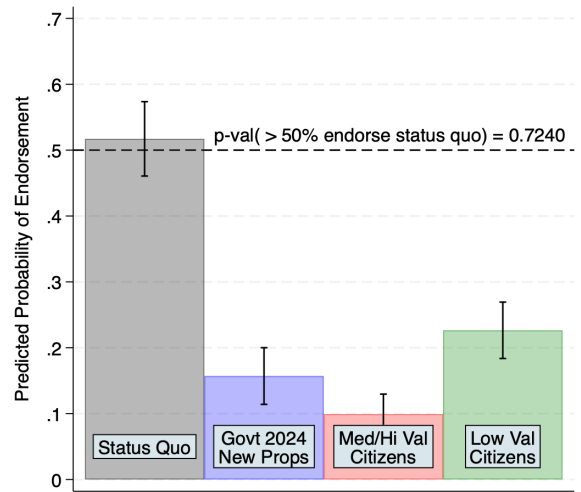
(A) CITIZENS OVERWHELMINGLY PREFER PROGRESSIVITY



(B) POLITICIANS: APPETITE FOR REFORM



(C) BUREAUCRATS: PREFER THE STATUS QUO

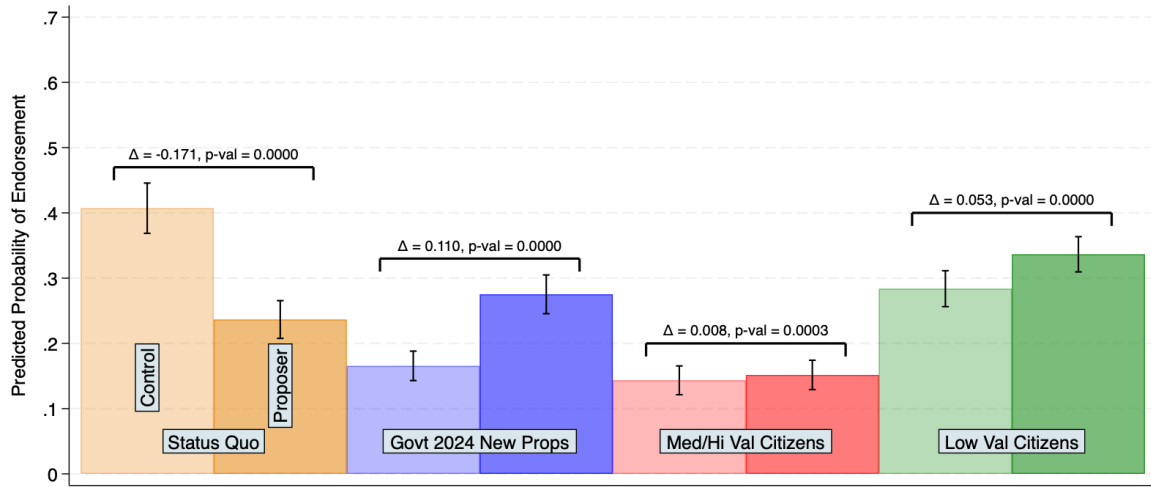


Source: IDEAS-LUMS Property Valuation Survey 2024–25; IDEAS-LUMS Pol-Bur Survey 2025.

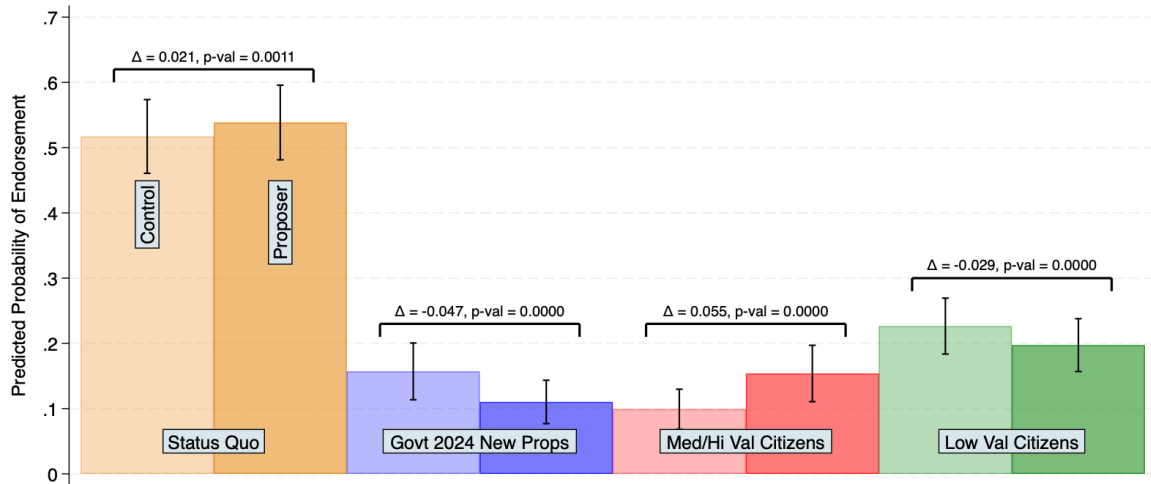
Notes: Panel (a): each gray dot is a citizen respondent; horizontal axis is the respondent’s own property value (log scale); vertical axis is the Feldstein- τ progressivity of the respondent’s elicited schedule applied to the residential value distribution. Orange line is a lowest fit; blue dashed line is the median voter’s preferred τ ; red dashed line is the status quo. Panels (b)–(c): predicted endorsement probabilities from the conditional logit (1) in the placebo arm.

FIGURE 5: PROPOSER TREATMENT EFFECTS (P2)

(A) POLITICIANS: COALITION-BUILDING



(B) BUREAUCRATS: RETRENCHMENT

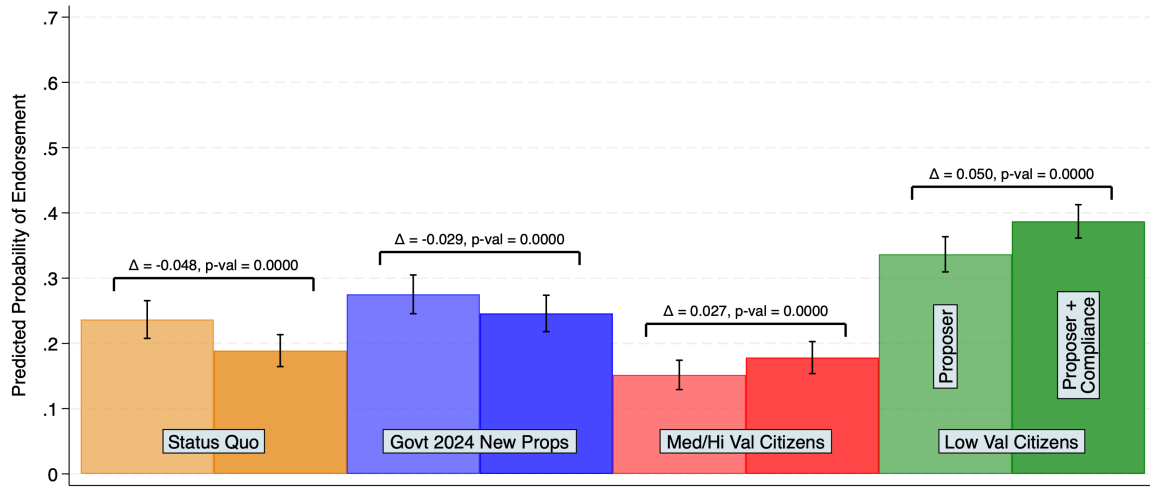


Source: IDEAS-LUMS Pol-Bur Survey 2025.

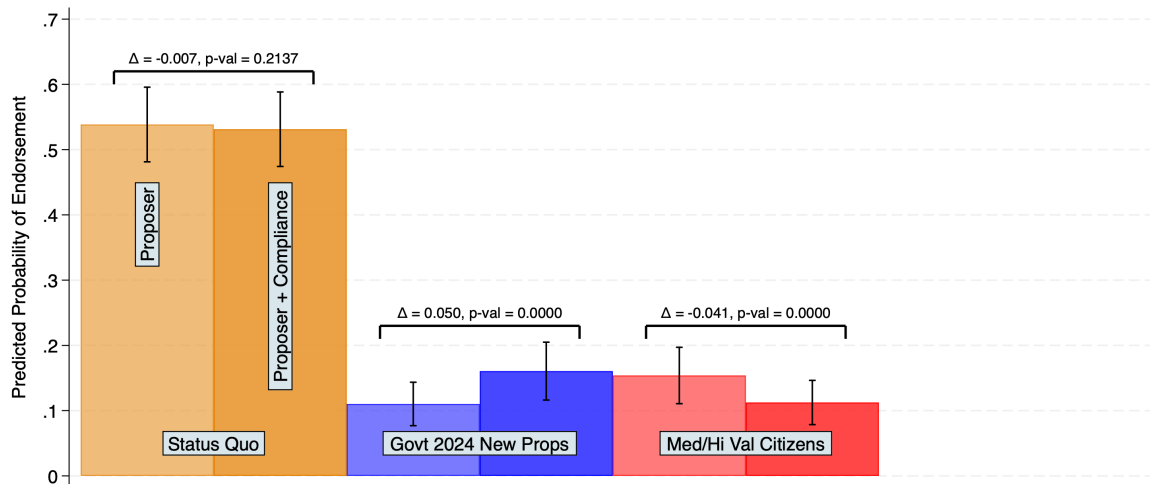
Notes: Predicted change in endorsement probability moving from the placebo arm to the proposer-treatment arm, by reform option. Panel (a) shows that politicians shift away from the status quo, with the largest gain accruing to the Government’s proposal. Panel (b) shows that bureaucrats raise their support for the status quo and, among reform options, tilt toward the proposal of medium-/high-value owners (the least progressive of the three).

FIGURE 6: COMPLIANCE TREATMENT EFFECTS (P3)

(A) POLITICIANS: CLOSER TO CITIZENS



(B) BUREAUCRATS: SUPPORT FOR PROGRESSIVITY



Source: IDEAS-LUMS Pol-Bur Survey 2025.

Notes: Predicted change in endorsement probability moving from the proposer-treatment arm to the proposer-plus-compliance-treatment arm. Panel (a): politicians shift from the Government and the status quo toward both citizen proposals, with the larger shift toward the more progressive low-value-owners' proposal. Panel (b): bureaucrats shift from the medium-/high-value owners' proposal toward the (more progressive) Government proposal.

TABLE 1: BUREAUCRAT ELICITED PROGRESSIVITY: COMPLIANCE TREATMENT INCREASES SUPPORT FOR PROGRESSIVE REFORM (P3)

	Progressivity Index	Tax Elasticity	Kakwani Index	Feldstein- τ	Top-10% Tax Rate
	(1)	(2)	(3)	(4)	(5)
Mid/Rich vs Govt	0.052 (0.103)	-0.023 (0.145)	0.044 (0.159)	-0.040 (0.165)	0.225 (0.146)
Compliance \times Mid/Rich vs Govt	0.322*** (0.116)	0.008 (0.143)	0.167 (0.161)	0.685*** (0.194)	0.429** (0.188)
Poor vs Govt	0.123 (0.102)	0.136 (0.154)	0.144 (0.148)	-0.021 (0.247)	0.232 (0.169)
Poor vs Mid/Rich	0.092 (0.109)	0.023 (0.142)	0.022 (0.164)	0.060 (0.188)	0.264* (0.147)
Obs.	289	289	289	289	289

Notes: OLS estimates of equation (2). Each measure is normalised to mean 0 and SD 1 in the control group. Stratum and enumerator fixed effects, post-Lasso controls (age, education). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 2: FIRST STAGE: COMPLIANCE TREATMENT LOWERS BUREAUCRATS' PERCEIVED COMPLIANCE FOR HIGH-VALUED HOUSEHOLDS

	Perceived Compliance Rate (%)		
	Overall	Low-Valued HHs	High-Valued HHs
Mid/Rich vs Govt	0.499 (3.171)	1.927 (4.214)	-0.914 (3.196)
Compliance × Mid/Rich vs Govt	-4.233 (3.381)	-1.837 (4.322)	-6.846*** (3.297)
Poor vs Govt	-0.833 (3.176)	0.578 (4.212)	-0.318 (3.004)
Poor vs Mid/Rich	3.382 (3.021)	4.283 (3.966)	2.809 (2.871)
Obs.	289	242	287

Notes: OLS estimates with the perceived compliance rate (in percentage points) as the outcome. Stratum and enumerator fixed effects, post-Lasso controls. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Setting

FIGURE A.1: FLOWCHART OF PROPERTY TAX ADMINISTRATION IN LAHORE

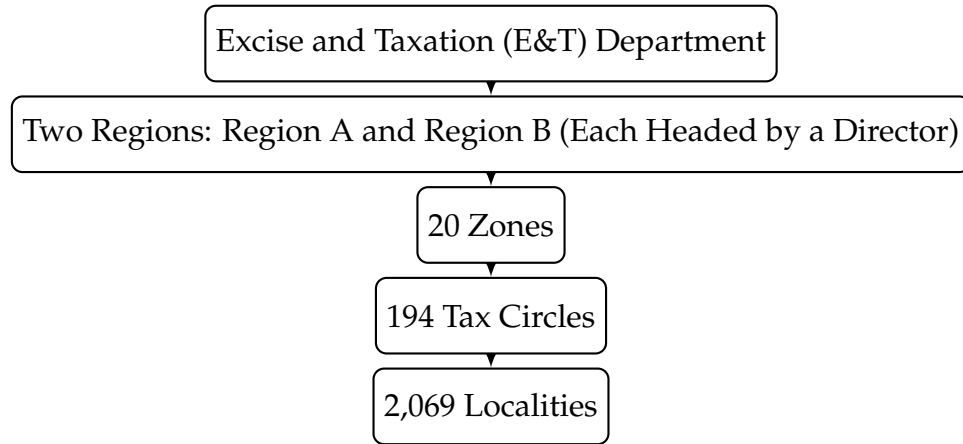
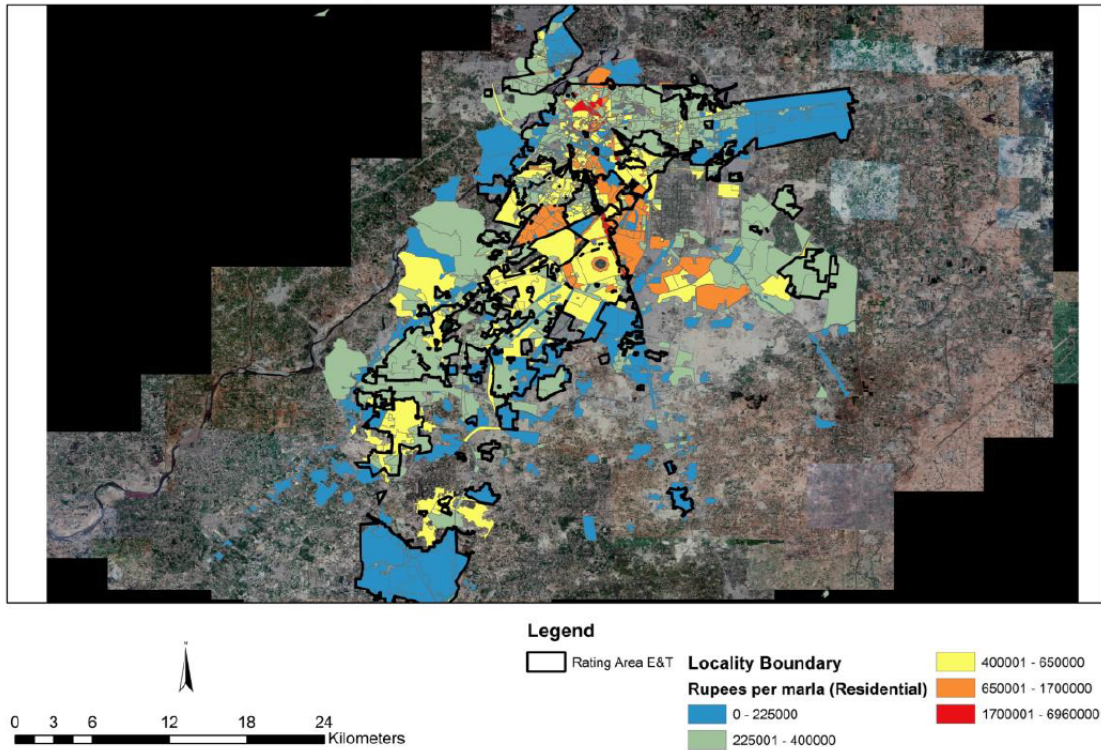


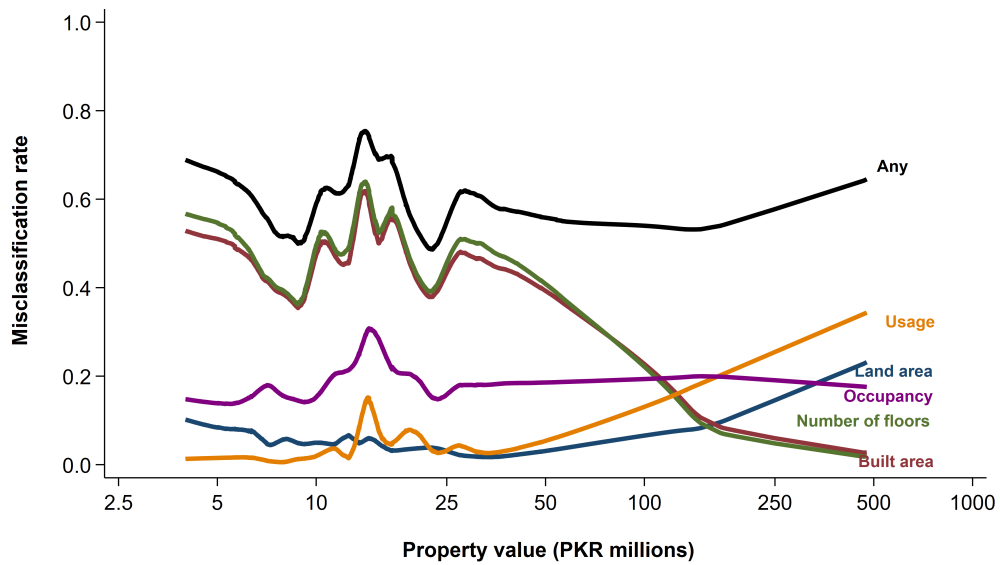
FIGURE A.2: LOCALITY BOUNDARY COVERAGE OF RESIDENTIAL AREAS BY CAPITAL VALUE IN LAHORE



SOURCE: PUNJAB URBAN UNIT 2022

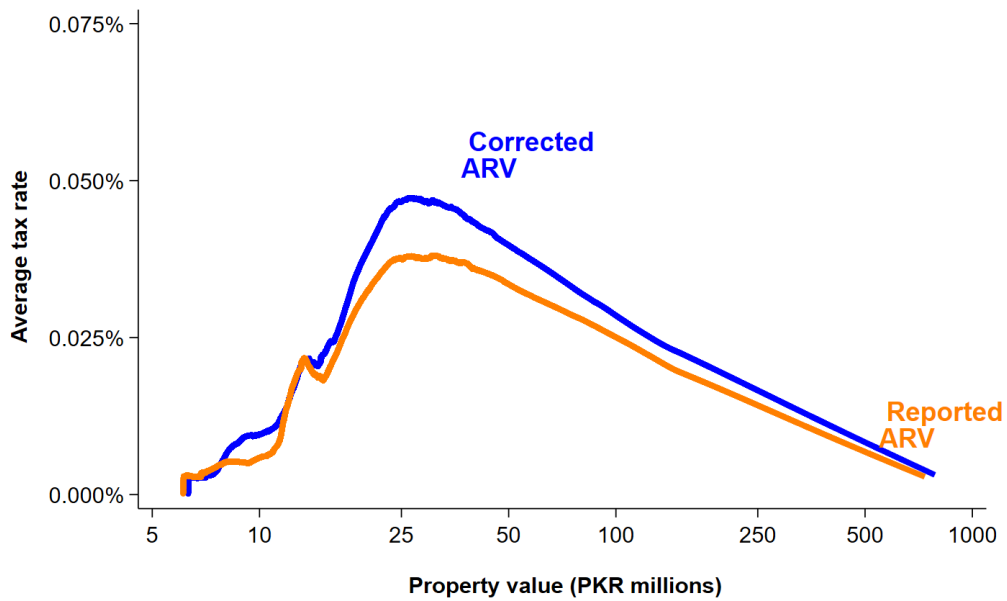
NOTES: THE FIGURE SHOWS VARIATION IN LOCALITY-LEVEL LAND VALUE ACROSS LAHORE. EACH POLYGON SHOWS A DC LOCALITY.

FIGURE A.3: MISCLASSIFICATION INCIDENCE ACROSS THE PROPERTY-VALUE DISTRIBUTION



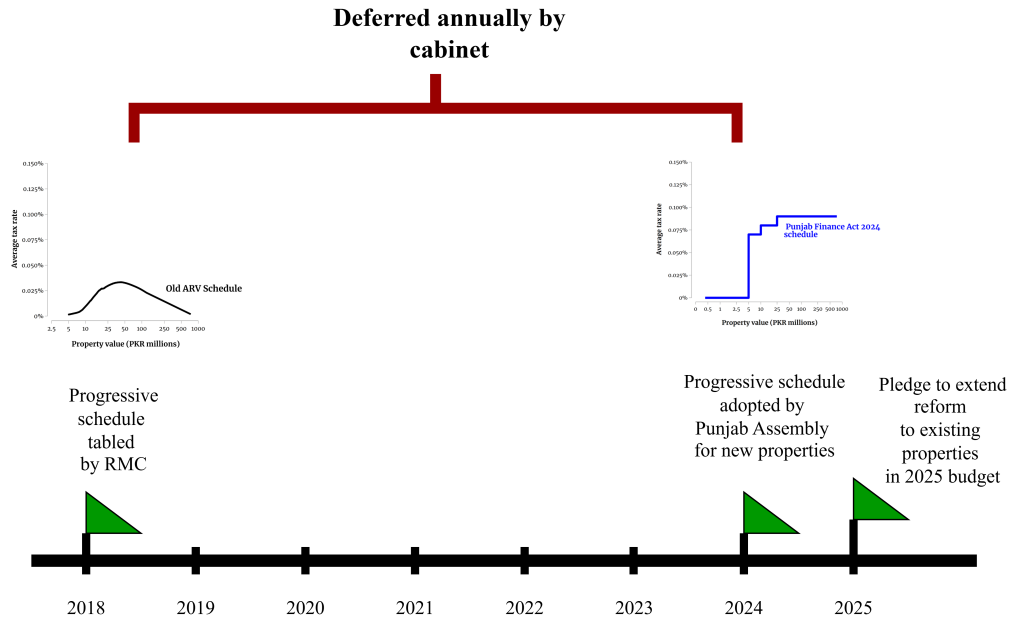
SOURCE: IDEAS-LUMS PROPERTY VALUATION SURVEY 2024–25.

FIGURE A.4: EFFECTIVE TAX RATES: REPORTED VS CORRECTED ARV



SOURCE: E&T PROPERTY TAX DEMAND 2021–22; IDEAS-LUMS PROPERTY VALUATION SURVEY 2024–25.

FIGURE A.5: REFORM TIMELINE



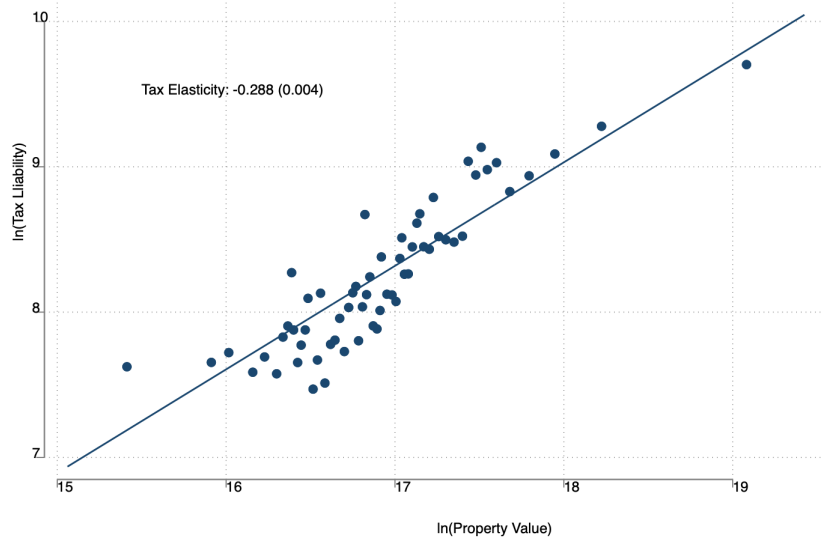
SOURCE: AUTHORS' CONSTRUCTION BASED ON GOVERNMENT OF PUNJAB NOTIFICATIONS AND SENIOR-OFFICIAL INTERVIEWS.

B Progressivity Measures

We use five measures of progressivity, each normalised so that 0 is proportional, positive is progressive, negative is regressive.

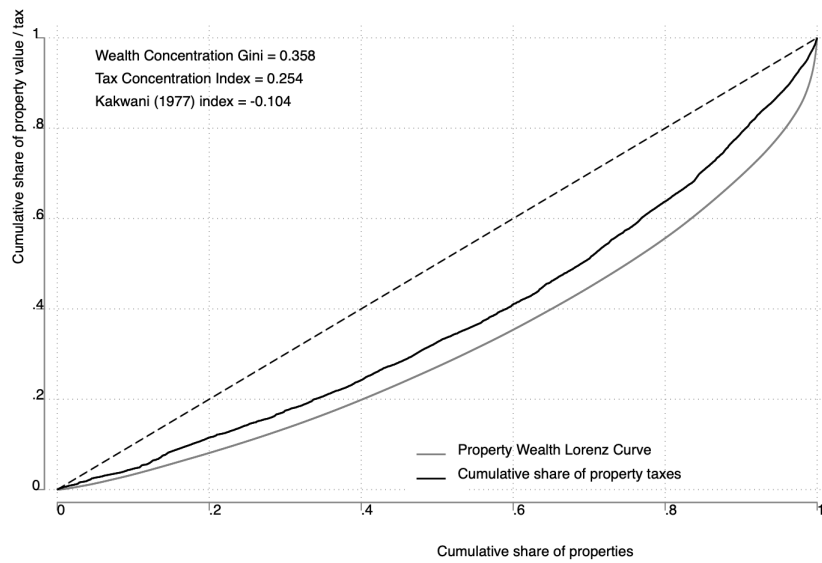
Tax elasticity. $\hat{\beta}_1 - 1$ from $\ln(\text{tax}_i) = \beta_0 + \beta_1 \ln(\text{value}_i) + \varepsilon_i$ (Musgrave & Thin, 1948). Cadaster estimate: -0.288 (Figure B.1).

FIGURE B.1: BASELINE TAX ELASTICITY



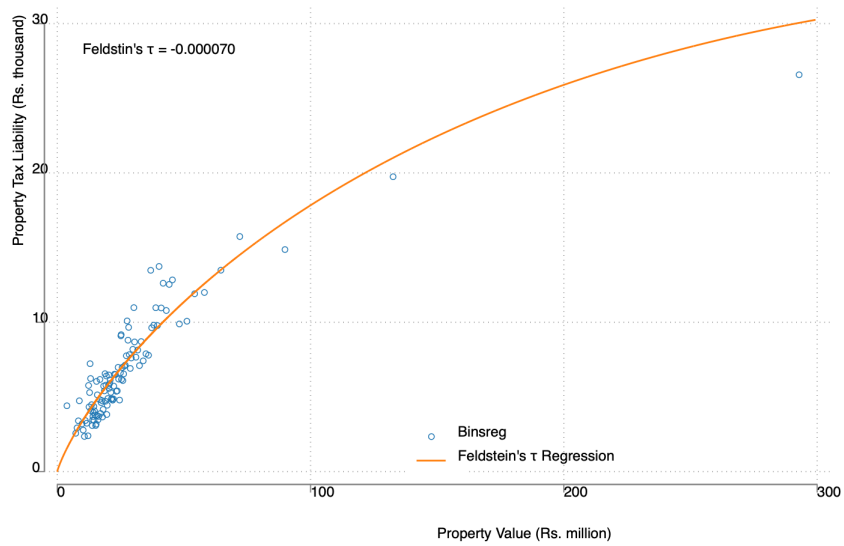
Kakwani index. Concentration index of taxes minus Gini of property wealth (Kakwani, 1977). In Lahore, 0.358 wealth Gini and 0.254 tax concentration index \Rightarrow Kakwani -0.104 (Figure B.2).

FIGURE B.2: BASELINE KAKWANI INDEX



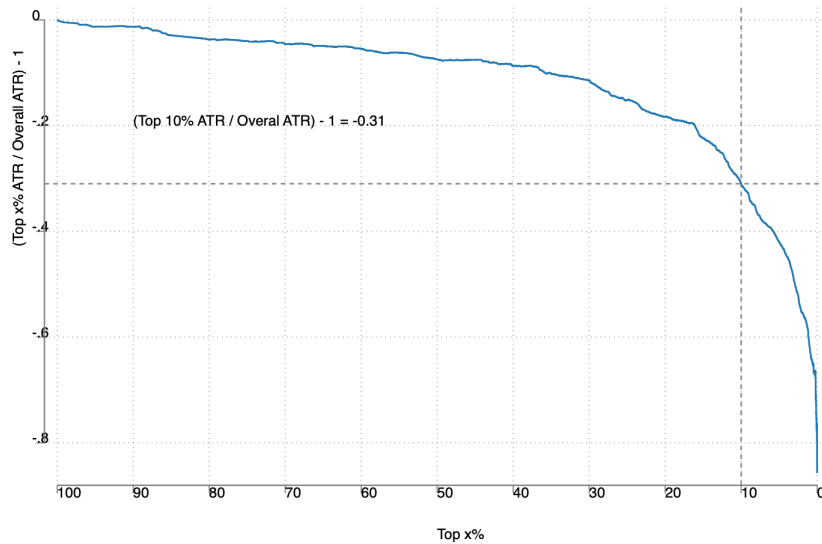
Feldstein- τ . $\hat{\tau}$ from $\text{tax}_i = v_i - \lambda v_i^{1-\tau} + \varepsilon_i$ (Feldstein, 1969; Heathcote *et al.*, 2017). Cadaster estimate: $\hat{\tau} = -0.000070$ (Figure B.3).

FIGURE B.3: BASELINE FELDSTEIN'S τ



Top-10% ATR. $(\text{Top 10\% ATR} / \text{Overall ATR}) - 1$ (Piketty & Saez, 2007). Lahore: -0.31 (Figure B.4).

FIGURE B.4: BASELINE TOP-10% ATR



Progressivity index. Following Kling *et al.* (2007), $\tilde{Y}_i = \frac{1}{4} \sum_{k=1}^4 Y_{ki} / \text{sd}(Y_k)$, with control-group standard deviations.

C Experimental-Design Figures

FIGURE C.1: SURVEY TIMELINE

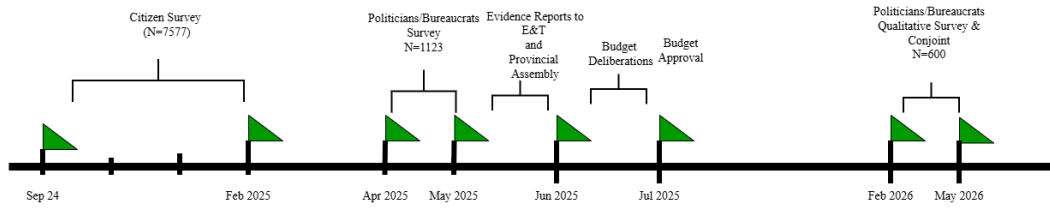


FIGURE C.2: ATR COMPREHENSION VIGNETTE



SOURCE: IDEAS-LUMS PROPERTY VALUATION SURVEY 2024–25.

FIGURE C.3: PROPERTY-VALUE DISTRIBUTION (NO COMPLIANCE OVERLAY)

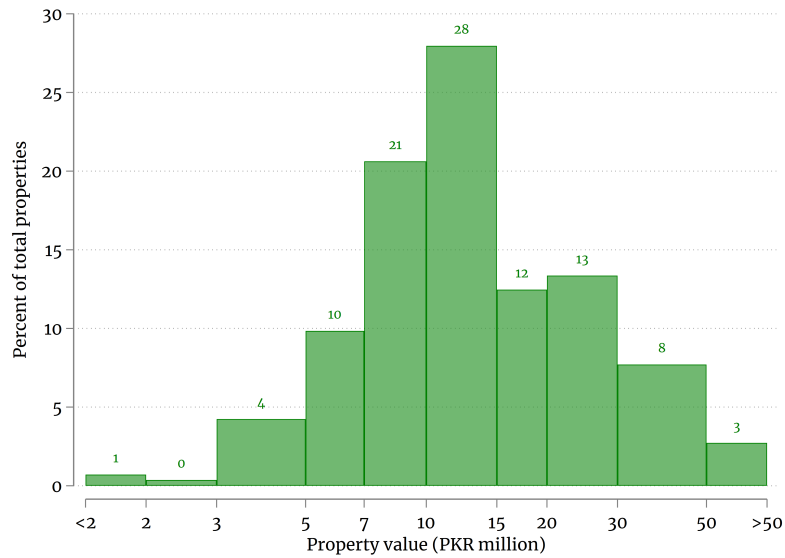


FIGURE C.4: PROPERTY-VALUE DISTRIBUTION WITH COMPLIANCE RATES

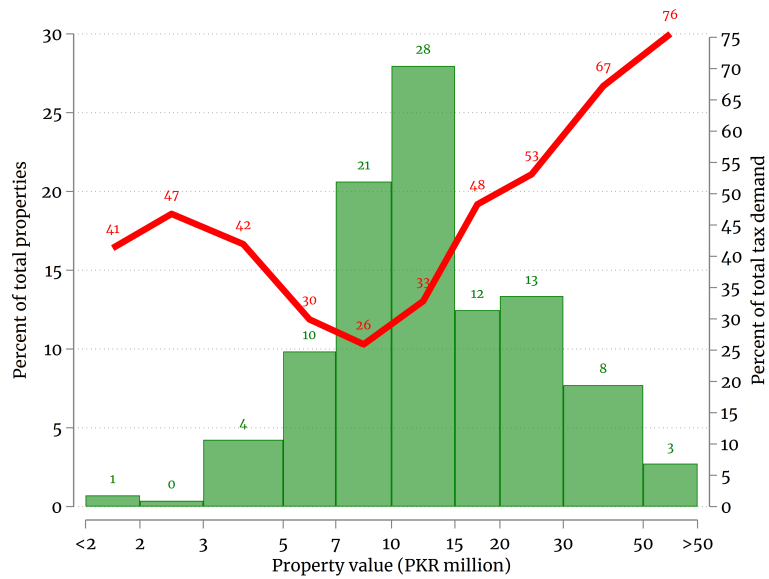
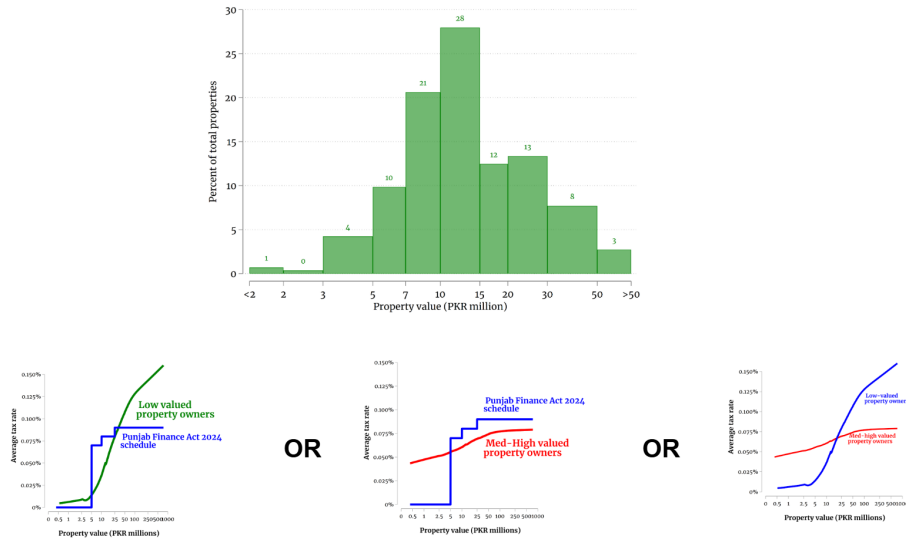


FIGURE C.5: EXPERIMENTAL DESIGN DIAGRAM



Distributional implications of both tax schedules

پراپرٹی کی قیمت	کم قیمت والے گھرانوں کی تجویز کردہ ٹیکس کی شرح	2025 جنوری میں حکومت کی تجویز کردہ ٹیکس کی شرح	کم قیمت والے گھرانوں کی تجویز کردہ ٹیکس کی شرح کے مطابق ٹیکس بل	2025 جنوری میں تجویز کردہ حکومتی ٹیکس کی شرح کے مطابق ٹیکس بل	2025 جنوری میں تجویز کردہ حکومتی ٹیکس کی شرح کے مقابلے میں کم قیمت والے گھرانوں کا تجویز کردہ شرح کے مطابق ٹیکس بل
Rs. 10 lac	0.013%	0% (کوئی ٹیکس نہیں)	Rs. 130	Rs. 0	زیادہ Rs.1 30
Rs. 50 lac	0.014%	0.07%	Rs. 700	Rs. 3,500	کم Rs. 2,800
Rs. 10 crore	0.128%	0.09%	Rs. 128,000	Rs. 90,000	زیادہ Rs. 38,000

FIGURE C.6: SCHEDULE COMPARISON: LOW- VS MEDIUM-/HIGH-VALUE OWNERS

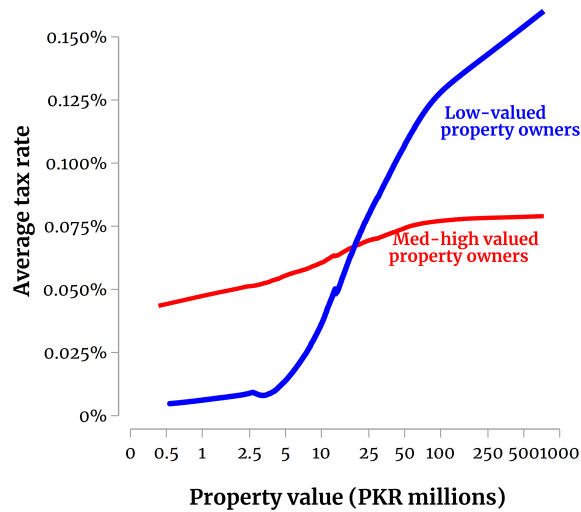


FIGURE C.7: SCHEDULE COMPARISON: LOW-VALUE OWNERS VS GOVERNMENT

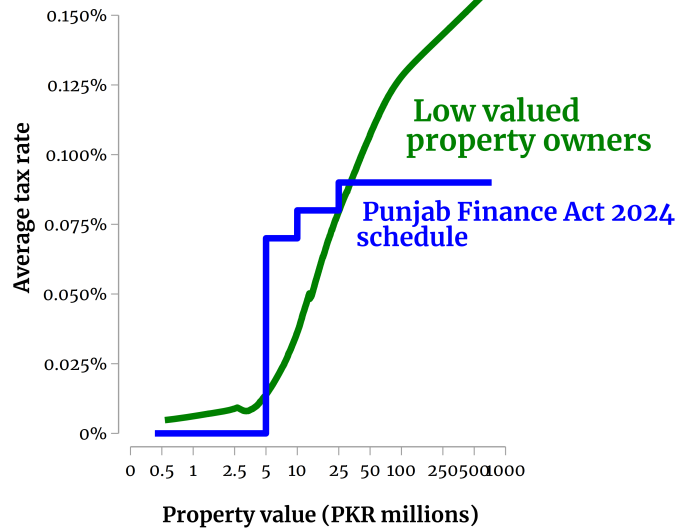


FIGURE C.8: SCHEDULE COMPARISON: MEDIUM-/HIGH-VALUE OWNERS VS GOVERNMENT

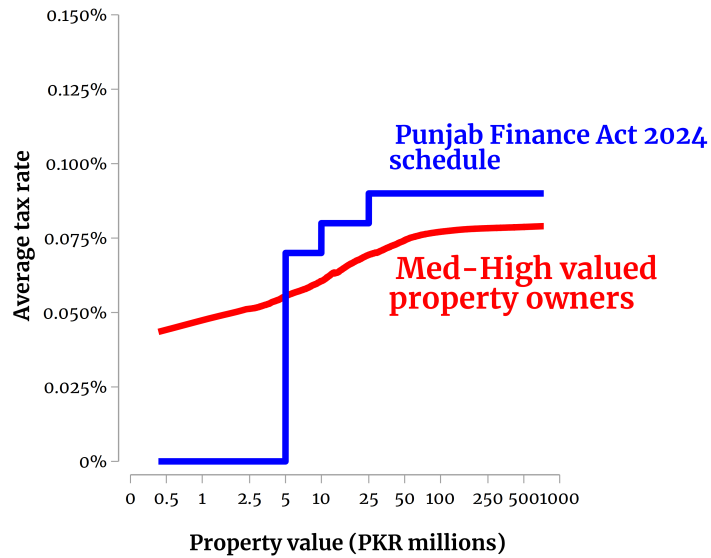


FIGURE C.9: INCENTIVE-COMPATIBILITY COVER LETTER: POLITICIANS

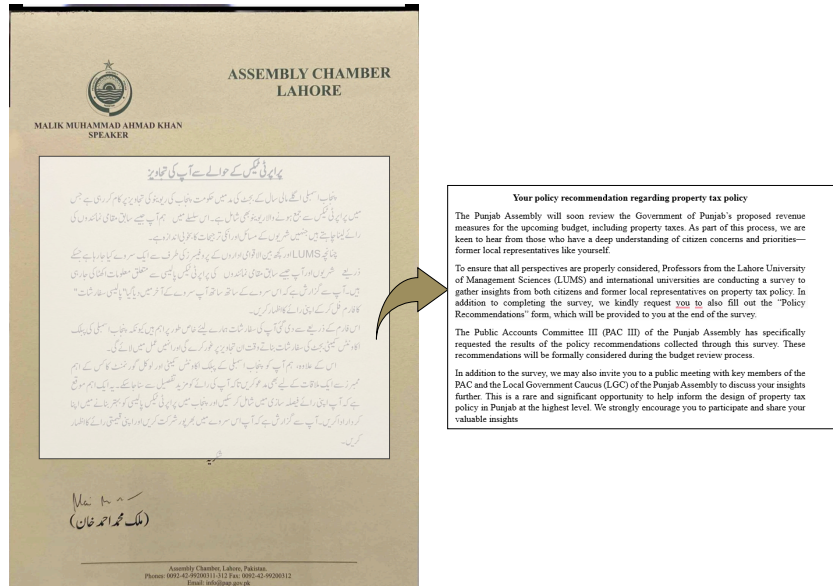
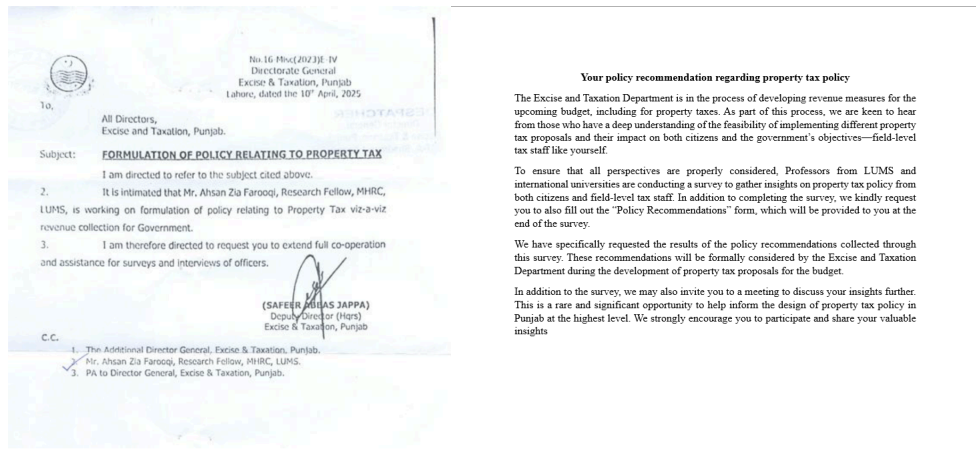


FIGURE C.10: INCENTIVE-COMPATIBILITY COVER LETTER: LOCAL TAX OFFICERS



D Sampling for Experiment 1

We draw our required sample of 7,577 residential properties using multiple data source as given in Table D.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 D.1: DESCRIPTION OF AUXILIARY DATA SOURCES

Term	Details
<i>FBR 2022 list</i>	<ul style="list-style-type: none"> Publicly available locality-level list of 1,270 localities of Lahore. These are capital property rates that were estimated in 2021-22. <p>The list contains: locality, town, residential land rate, commercial land rate.</p>
<i>DC 2019 public list</i>	<ul style="list-style-type: none"> 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. <p>The list contains: locality, town, residential land rate, commercial land rate, residential structure rate, commercial structure rate.</p>
<i>UU's DC mapping list</i>	<ul style="list-style-type: none"> A locality-level list, which was exported from ArcMap, of DC areas for which the Urban Unit has digitized maps. <p>The list contains: locality, residential DC land rate, commercial DC land rate.</p>
<i>E&T's GIS data</i>	<ul style="list-style-type: none"> 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.

D.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 D.1).

FIGURE D.1: DATA MATCHING PROCESS FOR AUXILIARY DATA SOURCES

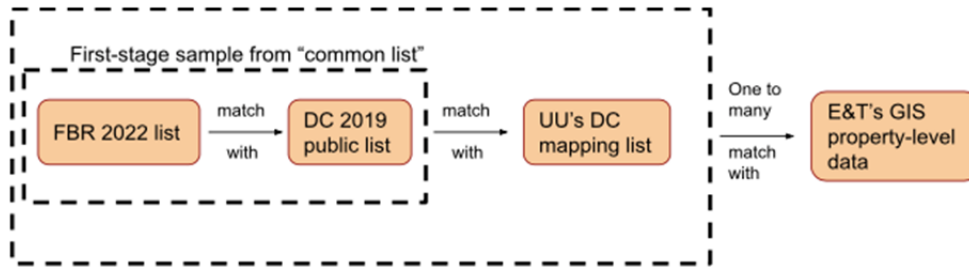


Figure D.1 summarizes how the first stage sample was drawn and how it was linked to the second-stage property level data. In order to link FBR 2022 data with Urban Unit’s digitized dataset, we first created a “common list” of localities that appear in both FBR and DC lists. To do this, we match the localities 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 D.1. 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.³ 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 D.2).

³We 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 D.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.

D.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 ?? 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.

D.3 Weighting

Our survey sample is representative of the areas where it was feasible for us to implement our survey—namely the areas where digital geographic data was either already available or we were able to create it relatively easily (see the discussion of the first-stage sampling in section D.1).

Starting from the universe of tax-liable properties in Lahore, and given our sampling protocol, the probability that a particular household is in our sample is the composite of three probabilities:

$$\Pr(\text{sample property}) = \Pr(\text{sample property}|\text{sample locality}) \times \Pr(\text{sample locality}|\text{locality in sampling frame}) \times \Pr(\text{locality in sampling frame})$$

We can compute these three probabilities and recover each property’s sampling probability. With these we can reweight the survey sample to be representative of the universe of tax-liable properties in Lahore.

E 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 E.1 describes our survey with real estate agents to create the training data used for our estimation. Section E.2 describes how we impute localities for the parts of the cadaster missing locality information. Section E.3 describes the random forest algorithm and its performance.

E.1 Training Data: Real Estate Agent Valuation

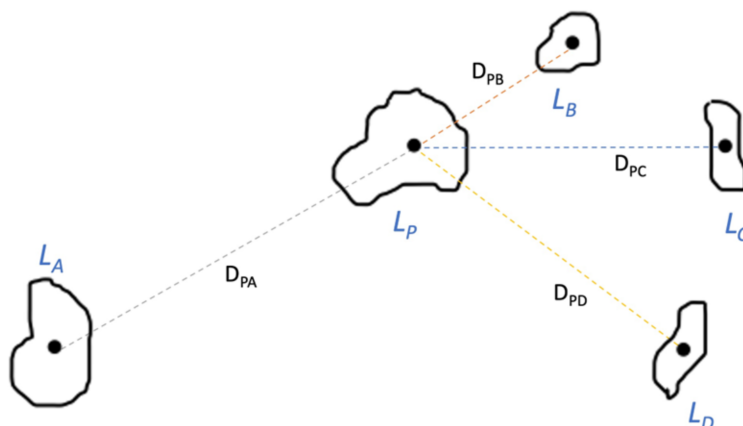
We get 2023 market value data from real-estate experts. For every property assessed, participating dealers were requested to provide estimates on the capital value, potential value as an open plot, and the rental value. Dealers were also asked about their own confidence levels in the reported values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

E.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 procedure. 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 E.1: ASSIGNING DC VALUES TO A TI LOCALITY USING LOCATION ATTRIBUTES

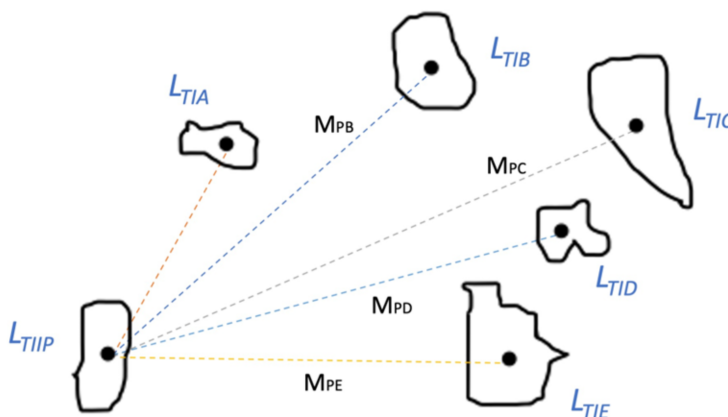


SOURCE: IDEAS-LUMS PROPERTY VALUATION SURVEY 2023

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 E.2) for the prediction model.

FIGURE E.2: LINKING A TII LOCALITY TO A TI LOCALITY USING LOCATION AND FANCINESS ATTRIBUTES

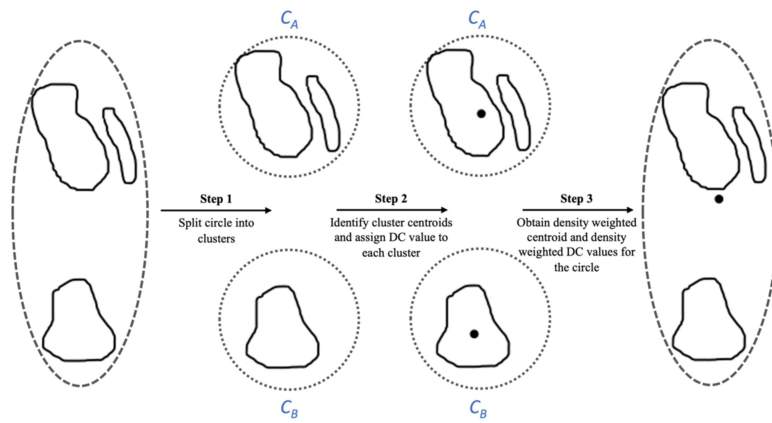


SOURCE: IDEAS-LUMS PROPERTY VALUATION SURVEY 2023

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 E.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 E.3: DEALING WITH A CIRCLE THAT HAS CLUSTERS IN DIFFERENT PARTS OF THE CITY



SOURCE: IDEAS-LUMS PROPERTY VALUATION SURVEY 2023

E.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 pur-

pose, 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.

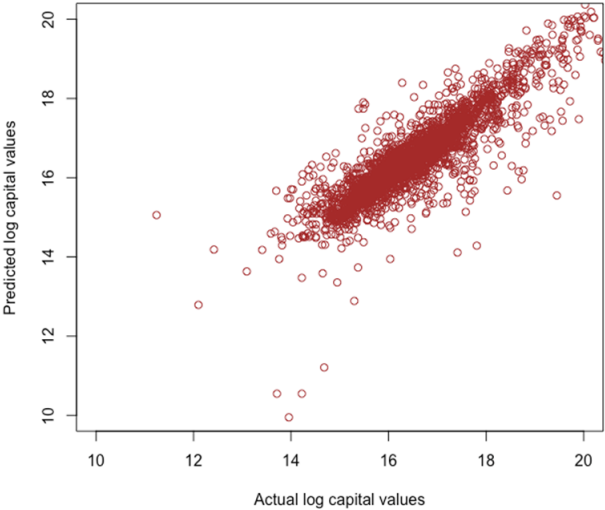
For the current context, property value is a function of land area (L), built area (B), residential use dummy (R), and a vector of cluster dummies (C) such that:

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

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 E.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 ??).

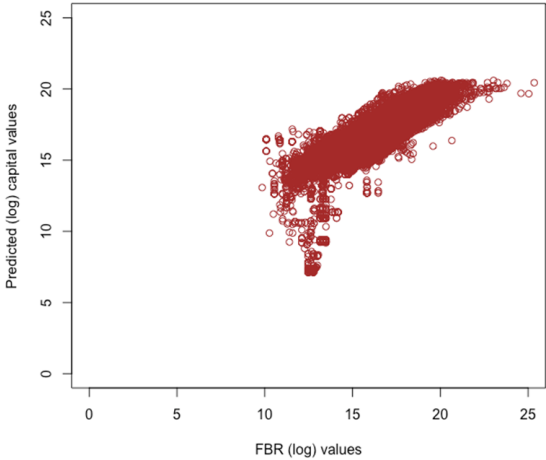
FIGURE E.4: RELATIONSHIP BETWEEN PREDICTED AND ACTUAL CAPITAL VALUES



The entire valuation sample was then used to train the random forest model and pre-

dictions were made for the full valuation sampling frame where we had FBR values. Figure E.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 E.4.

FIGURE E.5: RELATIONSHIP BETWEEN PREDICTED AND FBR CAPITAL VALUES FOR THE VALUATION SAMPLING FRAME

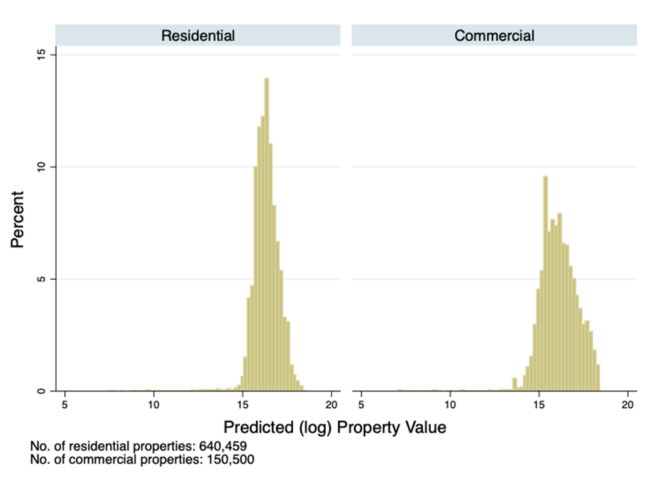


SOURCE: IDEAS-LUMS PROPERTY VALUATION SURVEY 2023

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.

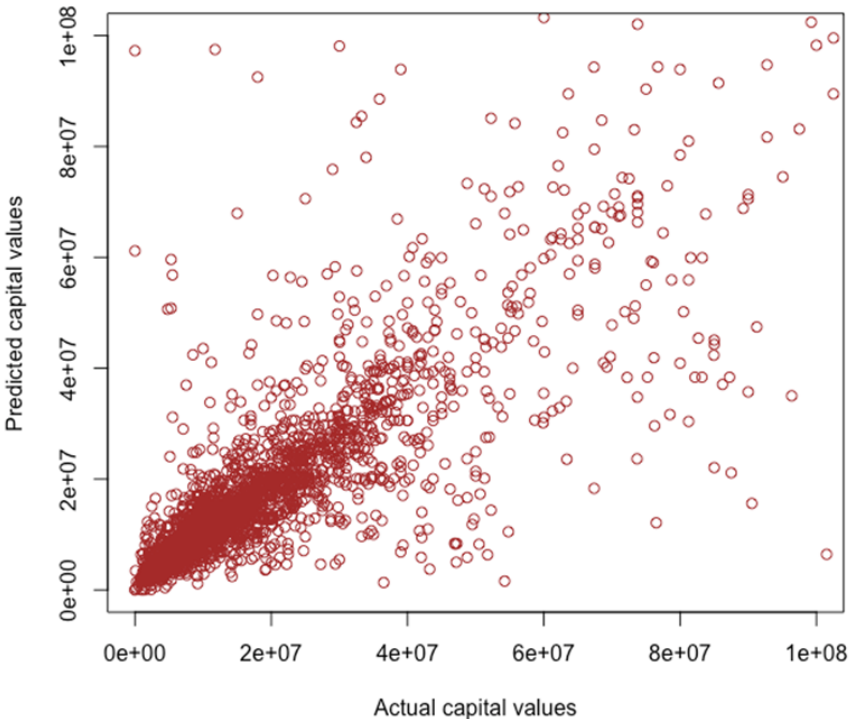
As expected, both residential and commercial property value distributions are right-skewed with few very highly valued properties (see Figure E.6).

FIGURE E.6: DISTRIBUTIONS OF PREDICTED PROPERTY VALUES BY PROPERTY USE



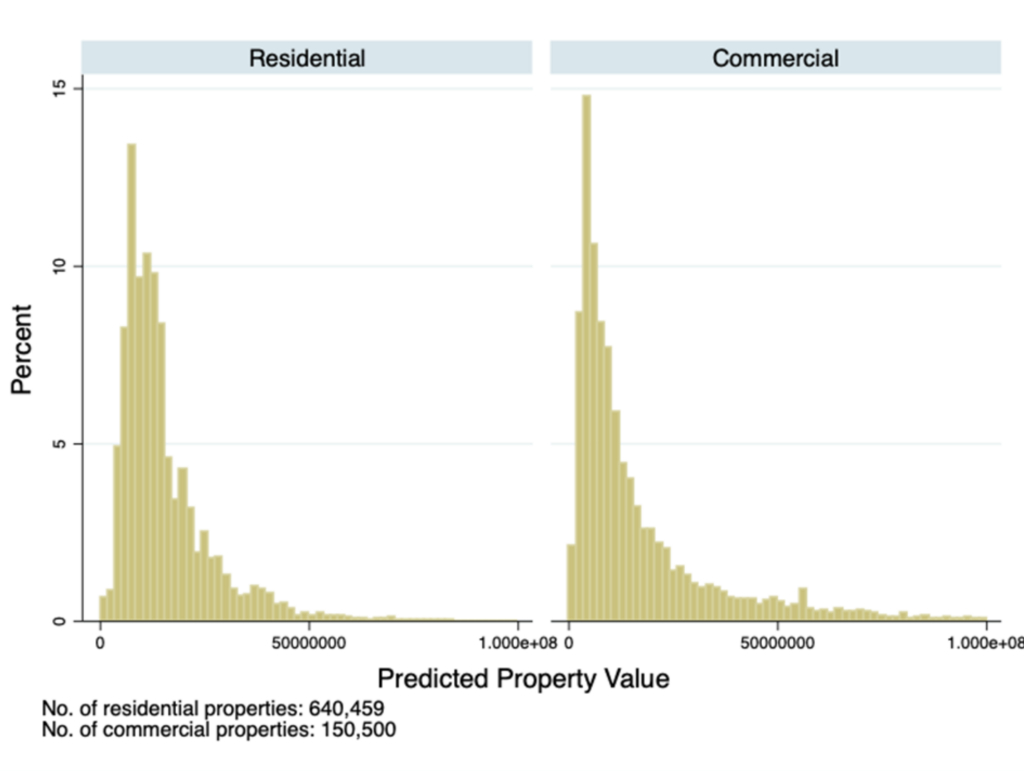
SOURCE: IDEAS-LUMS PROPERTY VALUATION SURVEY 2023
NOTES: VALUES RESTRICTED TO PKR 800 MILLION FOR BETTER VISUALIZATION

FIGURE E.7: RELATIONSHIP BETWEEN PREDICTED AND ACTUAL (LOG) CAPITAL VALUES FOR THE CROSS-VALIDATION SAMPLE



SOURCE: IDEAS-LUMS PROPERTY VALUATION SURVEY 2023

FIGURE E.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

E.3.1 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:

$$T = \sum_{i=1}^N t_i \quad (1)$$

and we use this to scale our revenue estimate down:

$$R^j = \frac{T}{D} R_2^j = \frac{T}{D_1^{t(j)}} R_1^j \quad (2)$$

E.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.

F Sample Policy Recommendation Form

Name: _____

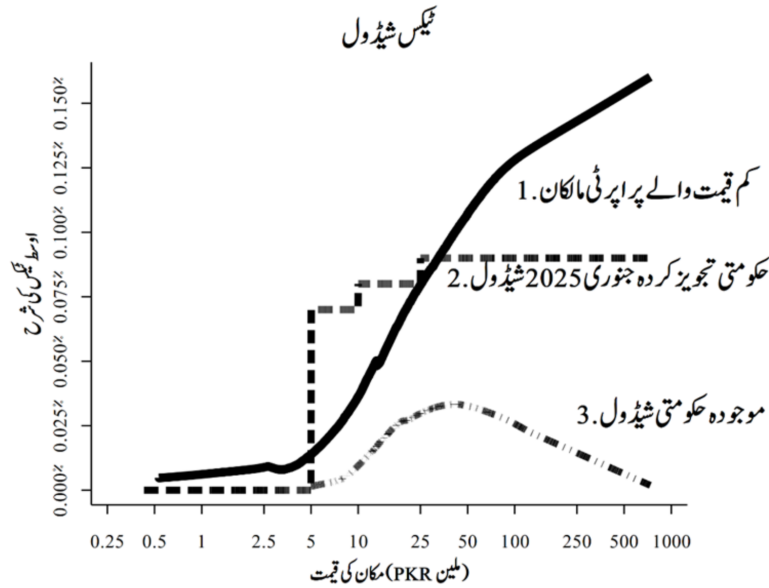
Position: _____

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

G Additional Tables

TABLE G.1: POLITICIAN ELICITED PROGRESSIVITY: NO TREATMENT EFFECT

	Progressivity Index	Tax Elasticity	Kakwani Index	Feldstein- τ	Top-10% Tax Rate
	(1)	(2)	(3)	(4)	(5)
Mid/Rich vs Govt	-0.085 (0.066)	-0.173* (0.091)	-0.183** (0.079)	0.009 (0.108)	0.007 (0.092)
Compliance \times Mid/Rich vs Govt	-0.031 (0.063)	-0.065 (0.090)	-0.080 (0.079)	0.109 (0.101)	-0.088 (0.088)
Poor vs Govt	0.016 (0.068)	0.005 (0.099)	-0.011 (0.076)	0.057 (0.105)	0.012 (0.094)
Compliance \times Poor vs Govt	-0.022 (0.074)	0.056 (0.094)	-0.096 (0.082)	-0.059 (0.114)	0.009 (0.130)
Poor vs Mid/Rich	0.044 (0.070)	0.032 (0.097)	-0.008 (0.085)	0.123 (0.104)	0.027 (0.100)
Obs.	827	827	827	827	827

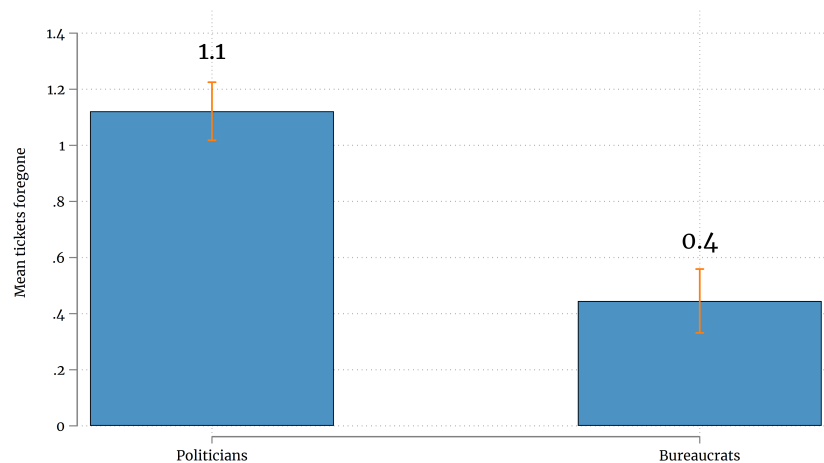
Notes: As Table 1, for the politician sample. Robust standard errors in parentheses.

TABLE G.2: FIRST STAGE: NO EFFECT OF COMPLIANCE TREATMENT ON POLITICIANS' PERCEIVED COMPLIANCE

	Perceived Compliance Rate		
	Overall	Low-Valued HHs	High-Valued HHs
Mid/Rich vs Govt	3.294 (2.078)	0.580 (2.789)	1.853 (2.086)
Compliance × Mid/Rich vs Govt	0.073 (2.062)	1.206 (2.763)	-0.252 (2.122)
Poor vs Govt	3.033 (1.989)	2.895 (2.734)	3.067 (2.058)
Compliance × Poor vs Govt	2.763 (2.019)	2.200 (2.798)	1.443 (2.099)
Poor vs Mid/Rich	3.366*** (1.994)	3.497 (2.767)	1.525 (2.030)
Obs.	828	575	826

Notes: As Table 2, for the politician sample.

FIGURE G.1: WILLINGNESS TO PAY FOR CITIZEN-PREFERENCE INFORMATION



SOURCE: IDEAS-LUMS POL-BUR SURVEY 2025.

NOTES: MEAN TICKETS RESPONDENTS ARE WILLING TO GIVE UP TO LEARN AN ADDITIONAL CITIZEN SUBGROUP'S PREFERRED SCHEDULE, BY RESPONDENT TYPE, IN THE PLACEBO ARM.

TABLE G.3: COMPLIANCE TREATMENT INCREASES BUREAUCRATS' WILLINGNESS TO PAY FOR CITIZEN INFORMATION

Treatment	dy/dx	SE	z	p	CI lower	CI upper	Control mean	Predicted mean
Mid/Rich vs Govt	-0.045	0.124	-0.36	0.717	-0.289	0.199	0.373	0.328
Compliance × Mid/Rich vs Govt	0.871	0.295	2.95	0.003	0.292	1.450	0.373	1.244
Poor vs Govt	-0.006	0.141	-0.05	0.963	-0.283	0.270	0.373	0.367
Poor vs Mid/Rich	-0.154	0.113	-1.36	0.172	-0.375	0.067	0.373	0.219

Notes: Marginal effects from a Poisson regression of tickets traded for citizen-preference revelations. Stratum and enumerator fixed effects, post-Lasso controls. Robust standard errors.

TABLE G.4: POLITICIANS' WILLINGNESS TO PAY: NO COMPLIANCE TREATMENT EFFECT

Treatment	dy/dx	SE	z	p	CI lower	CI upper	Control mean	Predicted mean
Mid/Rich vs Govt	-0.012	0.151	-0.08	0.938	-0.307	0.284	1.080	1.069
Compliance × Mid/Rich vs Govt	-0.004	0.158	-0.03	0.979	-0.311	0.305	1.080	1.076
Poor vs Govt	-0.302	0.171	1.77	0.077	-0.632	0.038	1.080	0.778
Compliance × Poor vs Govt	-0.025	0.142	-0.18	0.860	-0.304	0.254	1.080	1.055
Poor vs Mid/Rich	0.002	0.144	0.01	0.989	-0.279	0.283	1.080	1.082











Notes: As Table G.3, for the politician sample.

FIGURE G.2: CONJOINT DESIGN: LOCAL POLITICAL WORKERS

	CHOICE 1	CHOICE 2
Support from Low-Value Property Owners	80%	50%
Support from Med/High-Value Property Owners	70%	60%
Overall Compliance	40%	60%
Support from MPAs and Party Leadership	50%	50%
Support from Real Estate Developers	80%	50%
Effective Tax Rate	0.018%	0.032%
Total Revenue (PKR Billion)	1.95	3.53

Choice 1 Choice 2

FIGURE G.3: CONJOINT DESIGN: LOCAL TAX OFFICERS

	CHOICE 1	CHOICE 2
Compliance by Low-Value Properties	 30%	 60%
Compliance by High-Value Properties	 80%	 60%
Public Support	 80%	 60%
Percentage of all Properties that are Underassessed	 40%	 20%
Percentage of all Properties that are Delinquent	 30%	 50%
Effective Tax Rate on Low-Value Properties	0.018%	0.043%
Effective Tax Rate on High-Value Properties	0.063%	0.047%
Total Revenue (PKR Billion)	5.770	5.076

Choice 1 Choice 2

TABLE G.5: CONJOINT ATTRIBUTE EFFECTS: LOCAL POLITICAL WORKERS

Attribute	Mean β	95% CI	SD	% Positive	t-stat	p-value
Support (Low)	0.151	[0.140, 0.163]	0.100	92.9%	26.00	< 0.001
Support (High)	0.087	[0.078, 0.096]	0.077	88.9%	19.54	< 0.001
Compliance	0.081	[0.066, 0.095]	0.127	74.0%	10.97	< 0.001
Party Support	0.080	[0.071, 0.089]	0.078	85.8%	17.66	< 0.001
Real Estate Support	0.069	[0.061, 0.077]	0.071	85.5%	16.88	< 0.001

TABLE G.6: CONJOINT ATTRIBUTE EFFECTS: LOCAL TAX OFFICERS

Attribute	Mean β	95% CI	SD	% Positive	t-stat	p-value
Compliance (Low)	0.055	[0.037, 0.074]	0.105	75.8%	5.84	< 0.001
Compliance (High)	0.109	[0.086, 0.131]	0.126	83.9%	9.63	< 0.001
Public Support	0.083	[0.070, 0.096]	0.074	87.1%	12.54	< 0.001
Underassessment	-0.111	[-0.119, -0.102]	0.049	0.0%	-25.48	< 0.001
Delinquency	-0.138	[-0.146, -0.130]	0.046	0.0%	-33.80	< 0.001

TABLE G.7: DESCRIPTIVE STATISTICS: LOCAL TAX OFFICERS

	Mean	SD	Min	Max
<i>Sample composition</i>				
Number of observations	292 (144 inspectors, 148 constables)			
Properties served per officer	3,424			
<i>Individual characteristics</i>				
Age (years)	40.5	11.5	19	60
Education (years)	14.2	3.1	8	18
Experience (years)	16.5	11.8	2	40
Basic Pay Scale	11.0	5.2	5	17
Contacts per week	35.4	42.3	0	200

Source: IDEAS-LUMS Pol-Bur Survey 2025.

TABLE G.8: DESCRIPTIVE STATISTICS: UNION-COUNCIL-LEVEL POLITICAL WORKERS

	Mean	SD	Min	Max
<i>Constituency characteristics</i>				
Population per Union Council	43,692			
<i>Individual characteristics</i>				
Age (years)	41.0	7.1	26	73
Education (years)	11.8	3.0	3	18
Political experience (years)	9.6	5.8	1	37
Contacts per week	12.9	9.0	0	65

Source: IDEAS-LUMS Pol-Bur Survey 2025.