The Policy Preferences of Deputy Ministers*

Shaheen Naseer, Sultan Mehmood, Shachar Kariv, and Raymond Fisman†

July 12, 2025

Abstract

Policymakers balance priorities like poverty reduction, infrastructure development, healthcare, and education. We examine how nearly 1,000 high-level Pakistani officials across federal and regional governments navigate these trade-offs through a budget line experiment, allocating resources between their top two policy priorities (selected from nine) while varying the relative price of reallocation. Choices are generally consistent with maximizing a policymaking (constant elasticity of substitution) objective function. While there is considerable heterogeneity in policy prioritization—ranging from perfect complements to perfect substitutes—most subjects view their top priorities as complements rather than substitutes. Certain individual attributes predict policy preferences in largely expected ways.

JEL Classification Numbers: C91, D61, P43

Keywords: policy priorities, policymaking preferences, revealed preference, civil service, deputy ministers, Pakistan, experiment.

---

*We are grateful to the National School of Public Policy (NSPP) in Lahore—the premier institution for training and continuing education of civil servants in Pakistan—for partnering with us in conducting this study, and particularly its Rector, Dr. Ijaz Munir, for his support and invaluable suggestions. We also thank Frederico Finan, Daniel Markovits, and Matthew Polisson for their useful discussions, as well as numerous seminar audiences for their helpful suggestions. Yaroslav Prokhorskoy provided excellent research assistance. The experiments in this paper were conducted online using the budget line experimental interface of the Understanding America Study (UAS) at the University of Southern California (USC). Any opinions, findings, conclusions, or recommendations expressed herein are those of the authors and do not necessarily reflect the views of NSPP or any other institution.

†Authors listed in reverse alphabetical order. Naseer: University of Oxford (shaheen.naseer@oxfordmartin.ox.ac.uk); Mehmood: New Economic School (smehmood@nes.ru); Kariv: University of California, Berkeley (kariv@berkeley.edu); Fisman: Boston University (rfisman@bu.edu).

1 INTRODUCTION

Policymakers play a fundamental role in setting government priorities and allocating resources effectively, navigating difficult trade-offs: Should the focus be on reducing rural poverty or enhancing infrastructure? Should investments prioritize education or disaster preparedness? Understanding these trade-offs requires an appreciation of what policymakers' priorities are—poverty versus infrastructure—but also whether they view these objectives as substitutes or complements when distributing scarce funding, e.g., focus all resources on the policy objective with the highest return, or to distribute spending across a range of potentially complementary objectives.

In this paper, we conceptualize policymakers as having a policy "objective function" composed of priorities and explore its underlying structure as revealed through choices in an experiment involving high-level government officials in Pakistan. Our study population consists of nearly 1,000 Deputy Ministers (hereafter, *DM*s), who play a central role in policy design and implementation across various government functions at the national and regional levels.

We collected our experimental data through the participation of *DM*s in a mandatory training program required for promotion, held 2–3 times per year and lasting 3–4 months. The programs are managed by the National School of Public Policy (NSPP), within dedicated Management Institutes located in five cities across the country.

The *DM* subjects in our study serve in both federal and regional governments, playing critical roles in state policy in various domains, ranging from climate change to infrastructure. Many are senior members of Pakistan's Administrative Service (PAS), Police Service of Pakistan (PSP), Pakistan Customs Service, and various other sectors within the federal and regional governments. All participants in our study are under consideration for promotion to grades 19-21—just below the highest attainable grade of 22. To provide some sense of *DM*s' responsibilities, a *DM* serves as the top police officer for the Lahore division of the PSP—a region encompassing Pakistan's second-largest city, with a population of 23 million.

At the beginning of the experiment, *DM*s were asked to select their top *two* priorities from a list of *nine* policy priorities/objectives that reflect key national challenges—including education, law and order, healthcare, and pollution—roughly based on the priorities outlined in Pakistan's Planning Commission Vision 2025.[1]

[1] Vision 2025 aimed to make Pakistan an upper-middle-income economy by 2025 and one of the world's ten largest economies by 2047. For our purposes, it identifies seven "pillars" to development, including human development, governance reforms, energy security, private sector growth, knowledge economy, infrastructure modernization, and regional connectivity.

The DMs were then asked to allocate (hypothetical) resources between their two selected priorities by presenting them with a standard economic decision problem—the selection of a bundle from a two-dimensional budget line. These decision problems were presented using a graphical experimental interface. A choice of the allocation (x, y) from the budget line represents an allocation of resources between priorities x and y (corresponding to the usual horizontal and vertical axes).[2,3]

In addition to the large and heterogeneous sample of high-level government officials, another distinctive feature of our study is the use of a revealed—rather than stated—preference framework to examine how these officials navigate real-world policy trade-offs. Previous studies of policymaking preferences (as described below) have relied for the most part on questionnaires, which are tailored to answering questions about specific policy concerns and thus relatively limited in the information they can uncover. In particular, heterogeneity is typically constrained to a few categories, making it difficult to derive the parameters of underlying preference relations from survey responses. Compared to these experiments, the choice of a bundle from a budget constraint reveals more about preferences than a typical binary (or discrete) choice. Moreover, because choices are drawn from standard budget sets, we can apply classical revealed preference analysis to assess whether behavior is consistent with rationality, and use classical demand analysis to recover information about the underlying policymaking preferences.

Without essential loss of generality, assume the resources to allocate to the two priorities are normalized to 1. The budget line is then given by $p_x x + p_y y = 1$ and the DM can choose any allocation $(x, y) \geq 0$ that satisfies this constraint. One may conceive of the relative price of allocating resources p_x/p_y as reflecting, for example, the presence of funding from international organizations or a higher level of government that, say, makes it 'cheaper' to pursue education rather than healthcare goals. Or it may reflect the country's relative efficiency in delivering education relative to healthcare.

We assume—and subsequently verify the validity of this assumption—that the underlying policymaking preferences can be represented by an objective function $u_{DM}(x, y)$ that is a member of the constant elasticity of substitution (CES) family, commonly used in demand analysis:

[2]The experimental interface was developed by Choi et al. (2007b) and first utilized by Fisman et al. (2007) to analyze social preferences, and by Choi et al. (2007a) to study risk preferences. We are therefore building on expertise gained through previous work across various individual choice problems.

[3]Using the experimental interface, subjects can make many choices within a single experimental session, allowing for analysis at the individual level without the need to pool data or assume homogeneity among subjects. However, due to the limited availability of DMs for the study, we administered fewer choices than in prior work. Below, we discuss how we adjusted our analysis accordingly.

$$u_{DM}(x, y) = [\alpha x^{\rho} + (1-\alpha) y^{\rho}]^{1/\rho}.$$

The $0 \leq \alpha \leq 1$ parameter measures skewness—the indexical weight on priority x versus y—and the $-\infty < \rho \leq 1$ parameter measures substitutability. The CES function contains several well-known functions as special cases, depending on the value of the substitutability parameter ρ—the linear form ($\rho = 1$), the Cobb-Douglas form ($\rho \to 0$), and the Leontief form ($\rho \to -\infty$). Note that if $\rho > 0$ (resp. $\rho < 0$), a decrease in the relative price of allocating resources to priority x (p_x/p_y) increases (resp. decreases) the expenditure share ($p_x x$) of the resources allocated to the now-cheaper priority x (recall that resources are normalized to 1). Thus, any $\rho > 0$ indicates policymaking preferences weighted towards increasing the total resources collectively allocated to priorities x and y, while $\rho < 0$ indicates policymaking preferences weighted toward ensuring comparable allocations to both priorities. This is how the CES specification captures policymakers' views on substitutability, enabling a flexible and parsimonious assessment of whether they perceive policy priorities as substitutes ($\rho > 0$) or complements ($\rho < 0$) .

The conclusions from our theoretical-experimental exercise can be summarized under five headings:

[1] **The choices of policy priorities.** There is considerable heterogeneity in priority choices, with Education being the most common selection by far (63.1%), followed by Health (36.4%), Food (28.7%), and Law and Order (22.4%). This heterogeneity extends to the pairings of top priorities—the most frequent combination is Education and Health (24.1%), followed by Education and Law and Order (13.6%) and Education and Food (7.6%). Despite this heterogeneity, the priority choices vary systematically in anticipated ways with *DM*s' attributes, as detailed below.

[2] **The consistency of allocations across policy priorities.** With very few exceptions, the choices made by subjects in our experiment exhibit a high level of consistency with the Generalized Axiom of Revealed Preference (GARP)—far exceeding what would be expected from random choices—so there exists a policymaking preference ordering for each subject that can rationalize their choices. Further revealed preference tests suggest minimal loss when representing these policymaking preferences using the CES form.

[3] **The CES skewness parameter (α).** There is considerable heterogeneity in the indexical weights that *DM*s assign to their top two priorities. However, for all priorities, the average weights remain close to 0.5—the mean ranges from 0.39 to 0.61, and

the medians fall between 0.41 and 0.59. Only 10%, 5%, and 1% of subjects assign a weight exceeding 0.72, 0.76, and 0.82, respectively, to one of their top two policy priorities. This reflects *DM*s' belief that effective policymaking requires contributions across multiple priorities, as improvements in one area can potentially reinforce and amplify progress in others.

[4] **The CES substitutability parameter (ρ).** There is also substantial heterogeneity in the *DM*s' substitutability between their top two priorities, indicating that policymaking preferences vary widely, ranging from linear ($\rho \to 1$) to Leontief ($\rho \to -\infty$). Nevertheless, the vast majority (81.3%) of *DM*s perceive their top two policy priorities as complements, with a substantial fraction (10.7%) exhibiting preferences that approach perfect complements. This finding reinforces the idea that *DM*s view development as requiring multiple inputs, even at a considerable "efficiency" cost.

[5] **The correlates of policy priorities.** Some individual attributes predict *DM*s' selection of policy priorities in largely expected ways: women are more likely to prioritize addressing the underrepresentation of women, *DM*s employed by the police service tend to prioritize law and order, and younger *DM*s are more likely to select environmental concerns. In this exploratory analysis, we also identify some less obvious patterns: younger *DM*s and women are significantly less likely to prioritize law and order, while those with engineering backgrounds prior to joining the Civil Service tend to place less emphasis on environmental concerns as a top priority. [4]

The stability of these relationships across multiple waves of data collection, combined with the diversity of *DM*s in our study—spanning various departments, educational backgrounds, and a representation of both men and women—helps mitigate concerns that they may be statistical artifacts.

The policymakers we study—Deputy Ministers—hold significant influence in Pakistan at both national and regional levels, and their policy priorities/preferences likely shape government decisions and outcomes. Our results emphasize the importance of understanding how government resource allocation is driven by policymakers with heterogeneous priorities/preferences. The substantial heterogeneity we observe in these priorities/preferences provides insight into the potentially idiosyncratic nature of policy formulation.

[4] While there is substantial variation in the estimated CES parameters both within and across professional and socio-demographic categories. It is less clear that we would find predictors of skewness (α) or substitutability (ρ) in policymaking preferences, and indeed, we do not observe any variation explained by the attributes of *DM*s.

The potentially idiosyncratic nature of policymaking may also, of course, result from inter-government bargaining. The graphical experimental interface can accommodate multi-player interactive games, enabling numerous extensions that can deepen our understanding of interpersonal interactions. Combining our experimental interface's ability to represent non-linear choice sets with a bargaining game creates a unique opportunity to study inter-government bargaining using axiomatic bargaining solutions that are foundational to game theory. This presents a promising venue for further research with the same subject pool.

Relationship to prior literature

Our findings contribute first and foremost to a large and growing research effort that explores the beliefs and preferences of higher-level government officials. Much of this work has focused on canvassing politicians on particular policy objectives – how they feel about, for example, reducing corruption (Ferroni et al., 2024) or promoting education (Blesse et al., 2023), and how these beliefs and preferences compare in turn to those of citizens (e.g., Walgrave et al., 2023; Sheffer et al., 2018), and exploring their preferences mostly via surveys and also through lab experiments (see Kertzer and Renshon, 2022 for a survey of the literature). Our approach is distinct from this earlier work, in the sense that we are focused on the particular *structure* of preferences over policy priorities, rather than a simple rank ordering of them.

We also link to the much larger research enterprise on the personnel economics of the state, which looks at factors like incentives, monitoring, and selection that drive organizational performance (see Finan et al., 2017 for an overview). While much of this research focuses mostly on lower-ranked government officials and front-line service delivery (see, e.g., Khan et al., 2016 and Callen et al., 2025 for work looking specifically at Pakistani officials, focused on tax collectors and healthcare workers respectively), we share with a handful of studies a focus on high-level civil servants. Whereas we study policy preferences, these papers focus instead on career incentives and bureaucratic performance (e.g., Iyer and Mani, 2012; Gulzar and Pasquale, 2017). And while these studies tend to focus on specific branches of the civil service (e.g., the Indian Administrative Service in Bertrand et al., 2020), our sample spans a wide range of branches within Pakistan's civil service.

A related body of work examines the role of individuals in driving realized policy decisions and outcomes, a literature that was launched by the work of Bertrand and Schoar (2003) (and later extended by Lazear et al., 2015) to examine the role of individual managers in driving organizational decision-making. Again, the outcomes in this literature tend to emphasize organizational performance rather than the adjudication of trade-offs among various desirable policies, as is our focus. This is in part because it is difficult to link an individual to any particular policy agenda, even for senior officials, since policy formulation is the outcome of the collective preferences and negotiations of many officials (a point that we return to discuss in more detail in our conclusion). This point is underscored by the findings of Jones and Olken (2005), which suggest that, at least in democracies, an exogenous change in the leader's identity has no effect on macro policies or outcomes – even a president or prime minister cannot shift policy in their own. The challenge is even more extreme in our setting, as we wish to study the preferences of officials who engage in policymaking in various domains, ranging from national security to revenue collection to foreign relations, so it would be difficult even to define an outcome that can be compared across study participants.

Finally, relative to prior work that studies government leaders, a distinctive feature of our paper is the combination of experimental methods, microeconomic tools, and econometric techniques for analyzing policymaking preferences. Our approach is built on the techniques developed by Choi et al. (2007a), who developed a graphical interface in which subjects see a standard consumer decision problem on a computer screen, and select a bundle of commodities from a standard budget set. Subsequent work has applied this approach to understanding individual preferences for personal and social consumption, as well as attitudes toward risk, ambiguity, and inequality.[5]

The rest of the paper proceeds as follows. Section 2 provides background on the civil service in Pakistan, along with a description of our specific sample of DMs. Section 3 outlines the experimental design and procedures, Section 4 presents the conceptual framework for our analysis, and Section 5 summarizes our results. Section 6 concludes by emphasizing the key takeaways of the paper.

[5] Following Fisman et al. (2007), a series of papers employ this methodology to study social preferences across different subject pools, including Fisman et al. (2015a), Fisman et al. (2015b), Fisman et al. (2017), Fisman et al. (2023), Li et al. (2017), and Li et al. (2022). Ahn et al. (2014) extended the work of Choi et al. (2007a) and Choi et al. (2014) on risk (known probabilities) to settings involving ambiguity (unknown probabilities). The datasets of Choi et al. (2007b) and Choi et al. (2014) have been analyzed extensively, including in Halevy et al. (2018), Polisson et al. (2020), and de Clippel and Rozen (2023). Other related studies have developed experimental methods for testing consistency with different theories Dembo et al. (2025) and exploring the linkages between preferences for personal and social consumption and attitudes toward risk and inequality Zame et al. (2025). Since all experimental designs share the same graphical interface, our work builds on the datasets and expertise accumulated through previous research.

2 BACKGROUND AND SAMPLE

2.1 Background

> "The Civil Service of Pakistan is the successor to the (British) Indian Civil Service, which was the most distinguished Civil Bureaucracy in the world." —Sir Eric Franklin, Careers in the Pakistan Central Superior Services, 1980.

The *DM*s in our sample occupy the highest ranks within Pakistan's civil service, which runs the country's bureaucracy. As such, the *DM*s we study are not only policy implementers but also key architects of policy, often described as the "steel frame" of the government (Bertrand et al., 2020). The civil service has been described as a "state within a state" (Lieven, 2011), underscoring its independence from politics. It is regarded as a stabilizing force, defined by meritocracy and professionalism (Wilder, 2013). Its reputation as a meritocratic institution is upheld by its rigorous and impartial selection processes.

Pakistan employs a centralized recruitment system, selecting generalists through a single competitive exam, which spans over several months. Successful candidates are placed into 12 broad occupational groups, each managed by a specific government department. The Establishment Division oversees the Pakistan Administrative Service (PAS), Police Service (PSP), and Office Management Group, while other groups are managed by their respective ministries.

Competition for entry-level civil service positions is fierce—each year, over 15,000 aspirants from diverse educational backgrounds compete for just 200–400 highly selective slots, with the number of available positions varying based on the staffing needs of ministries and departments. The PAS and PSP are the most sought-after groups, typically allocated to top-performing candidates, followed by the Foreign Service and other occupational groups.

Because the Pakistani civil service prioritizes recruiting generalists and does not require a specific academic background, civil servants come from a wide range of fields. Consequently, the *DM*s in our sample represent diverse disciplines (more below). A gender quota introduced in 2007 ensured that at least 10% of selected candidates were women, slightly lower than the 14% share of our sample that is female.[6]

Joining the civil service is restricted to applicants in their twenties, who typically commit to a lifelong career until mandatory retirement at age 60. [7] All admitted candidates

[6] The quota is no longer binding, more recent cohorts have seen over a third of successful applicants being women, who compete on an equal footing with male candidates. However, since our sample is comprised of more senior officials, the gender composition reflects that of earlier entry cohorts.

[7] There are some exceptions to these age constraints, though as revealed by the narrow age range of

undergo a six-month pre-service training conducted collectively, followed by specialized training upon entering the civil service. This training prepares selected generalists for careers in specific areas—for example, those in the Pakistan Audit and Accounts Service receive additional training in accounting and finance.

Due to stringent educational requirements and rigorous screening, civil servants enter at relatively high grades under Pakistan's Basic Pay Scale (BPS) system, with BPS-17 as the entry-level position. The highest rank in the civil service (and public employment more broadly) is BPS-22, occupied by top officials such as provincial and federal ministry heads. To contextualize the seniority of the civil servants in our sample, the *DM*s who participated in our study are undergoing mandatory training for promotion to grades 19–21. Those in *DM* positions typically provide strategic guidance at the highest levels of government—including advising the Prime Minister, President, and Chief Ministers—and thus play a vital role in national policymaking.[8]

2.2 Sample

At senior ranks for promotion to grade 19–21 (recall that the highest level is 22), civil servants must complete mandatory training before promotion, with sessions held at dedicated management institutes in Islamabad, Karachi, Lahore, Peshawar, and Quetta. Our study was conducted during the training of *DM*s, who participate in high-level career development courses at these institutes. We gathered data across three sessions in 2023—the first was entirely anonymous, limiting the background information available to us. In the subsequent two sessions, we collected the *DM*s' names, allowing us to obtain their personnel and professional details.

To ensure participation, we embedded the survey within the *DM*s' training time. An email invitation was sent to 1371 *DM*s, of whom 1011 (73.7%) logged into the experiment. A total of 929 (67.8%) completed at least 8 out of the 10 decision rounds, forming our subject pool. Among them, 883 (95%) completed all 10 rounds, 39 completed 9, and 7 completed 8. Of the 929 *DM*s in the subject pool, 567 (61%) participated in the second and third sessions. Of those, we successfully matched 494 (87.1%) to personnel and professional records based on name and year of civil service entry.[9] Table 1 presents sum-

participants in our experiment, they are sparingly applied.

[8]Following the training program we study, *DM*s have gone on to serve as Secretary to the Chief Minister (the top aide to the provincial government leader), Additional Secretary to federal ministries such as Finance, Planning, and Interior (senior civil servants assisting in formulation of national policies for their respective ministries); ambassadors to major world capitals; superintendent of the national police; and so forth.

[9]Appendix Table A1 shows that matching subjects to personnel records is largely uncorrelated with their

mary statistics on the attributes of these 494 *DM*s.

[Table 1 here]

The mean *DM* listed in Table 1 has just over 16 years of civil service experience and is approximately 44 years old. Most *DM*s fall within a narrow range in age and experience—the interquartile age range is 39–47, and the interquartile years of employment range is 12–19. These patterns are expected, given that the program in which we conducted our research targets government officials at a specific career stage. Women make up 13.6% of these *DM*s, a higher proportion than the overall 10% female representation in Pakistan's civil service. Turning to educational backgrounds, 27.9% of the 494 *DM*s in Table 1 hold a degree in the sciences (defined as having a B.Sc. or an M.Sc., if only recorded as a graduate degree), 10.9% in engineering, and 11.3% in medicine. Nearly half have a graduate degree of some kind.

The data in Table 1 also confirm that our sample captures the diverse backgrounds of *DM*s participating in these training programs. Representation is roughly proportional to provincial populations—for example, Punjab accounts for 53% of Pakistan's population, and 54% of our sample is from there. Finally, we list the departments of matched *DM*s, whose distribution is broadly reflective of *DM*s' representation in the civil service. About a quarter of *DM*s come from the Pakistan Administrative Service (PAS), which consists of generalists playing a crucial role in policy formulation and implementation at all levels of government, with a particularly strong presence in federal ministries. We also highlight the three other departments with at least 10% of the *DM*s—Police, Foreign Service, and Income Tax—while the remainder are spread across nine additional departments.

3 The Experiment

Our experiment builds on our previous work, motivated by the need to provide a conceptually well-motivated, positive account of policy preferences. To provide that account, we need a choice environment that is rich enough to allow a general characterization of the patterns of individual behavior. In addition, to characterize behavior at the level of the individual subject, it is necessary to generate sufficiently many observations per subject over a wide range of choice sets. Choi et al. (2007b) developed a graphical interface

selection of priorities. Of the nine priorities, only Education is marginally significant at the 10% level as a positive predictor of missing information. Given that we evaluate 9 separate hypotheses, the probability of at least one appearing significant at this threshold is high—the result would not withstand correction for multiple hypothesis testing.

for exactly this purpose. With the interface, subjects see on a computer screen a geometrical representation of a standard economic decision problem (selection of a bundle from a standard budget set) and choose allocations through a simple "point-and-click" interface. [10]

Our graphical interface and experimental protocol are integrated with the Understanding America Study (UAS) survey instrument, enabling us to conduct the experiment online, as we did with other subject pools in previous work. In all 3 waves of data collection, the *DM* subjects were informed before the decision tasks that they would be asked to:

> "...allocate a budget according to your personal policy preferences, reflecting what you think would be the best allocation of resources at the national level. Remember, you are not being asked to select budget allocations based on your departmental preferences, but rather what you believe would be the best allocation for the country."

The *DM* subjects were then asked to select their top two priorities from 9 options, designed to reflect the key categories emphasized in Pakistan's Planning Commission Vision 2025, the country's most recent ten-year plan. These included the following:

(1)	Climate change	(2)	Education	(3)	Food scarcity and malnutrition
(4)	Health	(5)	Infrastructure	(6)	Law and order
(7)	Pollution	(8)	Power sector	(9)	Underrepresentation

While we list these in alphabetical order here, the participants were presented these options in a random order.[11]

[10] The study was conducted during training sessions organized by the NSPP across Pakistan. All data collection took place with prior approval from NSPP leadership and following its ethical guidelines for research and training activities. *DM*s were informed that participation was entirely voluntary, the stakes were hypothetical with no material payoffs, responses would be used solely for academic research, and they could withdraw at any point. A dedicated helpline was available during the experimental sessions for *DM*s to raise questions. All queries were handled in real time by the research team solely to support informed participation, and no records of these interactions were retained. The experiment was conducted online using the UAS budget line interface, developed for prior work and used with multiple subject pools across multiple decision domains. The study was deemed exempt as it involved only minimal risk and was not federally or non-federally funded. Data were securely stored and de-identified prior to analysis. No personally identifiable information is reported in this paper.

[11] Using the exact wording from the experimental instructions: (1) Climate change policy – forestation, dike building, other flood prevention efforts; (2) Education – school construction, school supplies; (3) Food scarcity and malnutrition – nutrition, food subsidies, agricultural outreach, food security; (4) Health – vaccinations, hospitals, public health insurance; (5) Infrastructure – building roads, housing, IT infrastructure, etc.; (6) Law and order – giving more access to justice to citizens, maintenance of courts, police service de-

Each decision problem was presented as a choice from a two-dimensional budget line. A choice of the allocation (x, y) from the budget line represents an allocation between accounts x and y (corresponding to the horizontal and vertical axes) that comprised feasible allocations to the two priorities selected. Without essential loss of generality, assume the total resources to be allocated is normalized to 1. The budget set is then $p_x x + p_y y = 1$ and the subject could choose any allocation $(x, y) \geq 0$ that satisfies this constraint. Put precisely, the budget line is given by $x/\bar{x} + y/\bar{y} = 1$ where $(\bar{x}, \bar{y})$ are the endpoints of the budget line so the price ratio is $p_x/p_y = \bar{y}/\bar{x}$.

Each decision problem began with the computer randomly selecting a budget line from the set of budget lines that intersect with at least one of the axes, $\bar{x}$ and/or $\bar{y}$, at 50 lakh or more (1 lakh = 100,000 PKR, approximately 350 USD at the time of the experiment), with no intercept below 10 lakh or above 100 lakh. The resulting changes in relative prices p_x/p_y cause the budget lines to intersect frequently. The budget lines selected for each subject in different decision problems were independent of each other and of the sets selected for any of the other subjects in their decision problems.

This variation in budget lines—and thus in the relative prices p_x/p_y of reallocating resources from one priority to another—is crucial for a thorough assessment of subjects' underlying policymaking preferences (as discussed further below). The relative price p_x/p_y of reallocating resources was presented to subjects as reflecting, "for example, the different efficiencies of the two departments overseeing the policies."

The experiment included 10 decision rounds (and 2 practice rounds), fewer than in our prior work due to limits on the time we could demand from *DM*s during their training period. At the start of each round, the setup refreshed, with the pointer randomly repositioned on the budget line. Subjects selected allocations using the mouse, restricted to points on the budget constraint.[12] Full experimental instructions are available in the Appendix.

livery; (7) Pollution – air pollution, water pollution, sanitation and sewerage issues, garbage collection; (8) Power sector – electricity generation and delivery, provision of fuel to industry and citizens; (9) Underrepresentation – woman representation, social mobility, inter-generational mobility, provincial harmony.

[12] In Fisman et al. (2007), subjects selected points on a graph representing a budget set, allowing disposal of payoffs via strictly interior allocations. Since the vast majority adhered to budget balancedness, future experiments restricted choices to the budget constraint, simplifying decision-making and improving usability.

4 Template for Analysis

4.1 Nonparametric

Let $\{(\mathbf{p}^i, \mathbf{x}^i)\}_{i=1}^{10}$ be the data generated by some individual's choices, where $\mathbf{p}^i = (p_x^i, p_y^i)$ denotes the i-th observation of the price vector and $\mathbf{x}^i = (x^i, y^i)$ denotes the associated allocation. We first test whether DMs' choices in the experiment are consistent with the essence of all traditional models of economic decision-making—utility maximization. If a well-defined objective function $u_{DM}(x, y)$ that the choices maximize exists, it becomes natural to explore the structure of the objective functions that rationalize the observed data.

Following Afriat (1967a), we employ the Generalized Axiom of Revealed Preference (GARP) to test whether the finite set of observed price and quantity data that our experiment generated may be rationalized by a utility function. GARP (which is a generalization of various other revealed preference tests) requires that if $\mathbf{x}^i$ is indirectly revealed preferred to $\mathbf{x}^j$, then $\mathbf{x}^j$ is not strictly directly revealed preferred to $\mathbf{x}^i$, i.e., we cannot have $\mathbf{p}^j\mathbf{x}^i \geq \mathbf{p}^j\mathbf{x}^j$. It is clear that if the data are generated by a non-satiated utility function, then they must satisfy GARP. Conversely, Afriat (1967a) theorem tells us that if a finite data set generated by an individual's choices satisfies GARP, then the data can be rationalized by a well-behaved (piecewise linear, continuous, increasing, and concave) utility function.

We assess how nearly the data complies with GARP by calculating Afriat (1972) Critical Cost Efficiency Index (CCEI). This measures the amount by which each budget constraint must be relaxed in order to remove all violations of GARP. The CCEI is bounded between zero and one. The closer it is to one, the smaller the perturbation of budget sets required to remove all violations and thus the closer the data are to satisfying GARP. To generate a benchmark against which to compare these CCEI scores, we use the test designed by Bronars (1987), which employs the choices of a hypothetical subject who chooses randomly among all allocations on each budget line as a point of comparison.

As noted above, we were limited to just 10 individual decisions per subject, whereas our previous experiments using the same design allowed for 25 or 50 decisions.[13] Consequently, our study has less power to rule out the possibility that observed consistency might stem from random behavior. To illustrate this, we calibrated the choices of 25,000 hypothetical subjects across 10, 25, and 50 randomly generated budget sets, as human subjects have done in the present and past experiments. With only 10 choices, 20.2%

[13] The power of Bronars (1987) test is defined as the probability that a random subject violates GARP, which depends on two key factors: the extent to which the range of choice sets generates frequent budget line crossings and the number of decisions made by each subject.

of subjects were perfectly consistent, 37.3% had CCEI scores above 0.95, and 50.6% had scores above 0.90. In contrast, with 25 choices, only 4.3% of subjects were perfectly consistent, 14.3% had CCEI scores above 0.95, and 28.9% had scores above 0.90. At 50 choices, all 25,000 hypothetical subjects violated GARP at least once, and only about a dozen had CCEI scores above the 0.90 threshold. Notably, the Bronars (1987) test has been applied by Harbaugh et al. (2001) and Andreoni and Miller (2002a) , among many others, to experimental data with similar or lower power than ours.

Beyond consistency with GARP, extensions of Afriat (1967b) theorem allow us to test whether choices can be rationalized by a utility function with more specific properties. In the case of two goods—as in our experiment—consistency with GARP and budget balancedness implies that the demand function is homogeneous of degree zero. Separability and homotheticity further entail that the underlying utility function takes the CES form. Building on Nishimura et al. (2017), Polisson et al. (2020) developed the Generalized Restriction of Infinite Domains (GRID) test, which assesses consistency with the maximization of specific families of utility functions.

In our experiment, individual-level choice data is said to be CES-rationalizable if it can be rationalized by a (utility) function taking the CES form. The GRID method replaces the bundle space ($\mathbb{R}^2_+$ in our case) with a finite set of allocations in $\mathbb{R}^2_+$ constructed in a specific manner such that an individual-level dataset is CES-rationalizable if and only if it can be rationalized by a CES function over allocations in this subset, rather than over all possible bundles. Accordingly, the method developed by Polisson et al. (2020) is referred to as the Generalized Restriction of Infinite Domains (GRID) because it focuses on a finite grid of constructed allocations.

We apply this test to examine whether choices align with the constant elasticity of substitution (CES) utility function, a common specification in demand analysis. Since the CES utility function family is a subset of the broader class of well-behaved utility functions, the CCEI score for consistency with CES maximization must be no greater than the CCEI score for consistency with GARP. Among others, the CES utility function is the parametric form chosen by Andreoni and Andreoni and Miller (2002a) and Fisman et al. (2007) for recovering social preferences. It is also employed by Cox et al. (2008) for analyzing preferences in simple binary choice ultimatum games and Stackelberg duopoly games.

4.2 Parametric

Because, as we show below, assuming the CES form involves minimal to no consistency loss for most subjects, we will assume that $u_{DM}(x, y)$ belongs to the CES family given by:

$$u_{DM}(x, y) = [\alpha x^{\rho} + (1-\alpha) y^{\rho}]^{1/\rho}$$

where α measures skewness—the indexical weight on priority x versus y—ρ measures substitutability—the curvature of the indifference curves—and $\sigma = 1/(\rho - 1)$ is the (constant) elasticity of substitution. Expressed in terms of budget share, the CES demand function is given by

$$p_x x = \frac{g}{(p_x/p_y)^r + g}$$

where

$$g = [\alpha/(1-\alpha)]^{1/(1-\rho)} \text{ and } r = \rho/(\rho - 1)$$

which generates the following individual-level econometric specification for each subject:

$$p_x^i x^i = \frac{g}{(p_x^i/p_y^i)^r + g} + \epsilon^i$$

where $i = 1, ..., 10$ and ϵ^i is assumed to be distributed normally with mean zero and variance σ^2. Note that the demands are estimated as budget shares, which are bounded between zero and one, with an *i.i.d.* error term.

Before proceeding with parameter estimation, we emphasize that our objective is to obtain individual-level estimates for each subject separately. Given that each subject makes only 10 decisions, and we aim to include those who made at least 8 decisions, we will approximate the CES parameter α by the average fraction of tokens allocated to x (i.e., $x/(x + y)$ and estimate ρ directly, rather than first estimating g and r and then inferring both CES parameters α and ρ.[14]

To better understand how the CES specification fits the individual-level data in the econometric analysis presented in the next section, Figure 1 (reproduced from Fisman et al. (2015a)) illustrates the relationship between the log-price ratio and the optimal demand share for different values of the CES parameters: $\alpha = 0.5$ (top panel), $\alpha = 0.75$ (middle

[14]In their preference-for-giving experiment with 8-11 budget lines, Andreoni and Miller (2002b) grouped subjects into three categories—selfish, Leontief, and perfect substitutes—by minimizing the distance of their choices from these prototypical preferences. Due to the substantial variation in our subjects' behaviors, we opted not to pool the data, as this would suppress the observed heterogeneity. By focusing on individual-level estimates using classical demand analysis, we can investigate the extent to which differences in choice can be explained by demographic and economic variables.

panel) and $\alpha = 0.9$ (bottom panel), and $\rho = -2$ (dotted gray), $\rho = -0.5$ (solid gray), $\rho \approx 0.0$ (dotted black) and $\rho = 0.5$ (solid black). An increase in the indexical weight parameter α shifts each curve upwards (when comparing the curve for each ρ across panels), and an increase in the substitutability parameter ρ makes the curve steeper. The optimal demand share approaches a step function as $\rho \to 1$ and a horizontal line at α as $\rho \to -\infty$.

[Figure 1 here]

5 RESULTS

5.1 Policy prioritization

Column (1) of Table 2 presents the fraction of subjects selecting each priority. The priorities are ranked from most to least frequently chosen. Since each DM selects two priorities, this column sums to 2. The superdiagonal entries of the matrix in columns (2)-(9) of Table 2 summarize the frequencies with which pairs of priorities were selected by our subjects. Columns (10) and (11) present, respectively, the average *demand* and *budget* shares of each priority when selected—that is, if the priority is x, then $x/(x+y)$ and $p_x x$ respectively (recall that the endowment is normalized to 1).

[Table 2 here]

Column (1) in Table 2 highlights the prevalence of specific policy priorities and their combinations, though there is considerable heterogeneity. Education was the most frequently selected priority, chosen by a majority of DMs, while Pollution and Underrepresentation were rarely selected. Among the 929 DMs in our sample—those who made at least 8 of the 10 decisions—588 (63.3%) selected Education, 339 (36.5%) selected Health, 267 (28.7%) selected Law and Order, and 208 (22.4%) selected Food. Three other priorities—Power, Climate, and Infrastructure—were selected by 163 (17.5%), 118 (12.7%), and 106 (11.4%) DMs, respectively. Finally, Pollution and Underrepresentation were selected by only 43 (4.6%) and 26 (2.8%) DMs, respectively.

There is considerable heterogeneity in the pairs of policy priorities selected, as reported in columns (2)-(9). Among the 588 DMs who chose Education—the most frequently selected priority—225 (24.2%) paired it with Health, 127 (13.7%) with Law and Order, and 71 (7.6%) with Food. Additionally, 165 DMs (17.8%) selected Education alongside one of the other policy priorities (with percentages in parentheses representing shares of the full sample of 929 DMs). The heterogeneity in selected pairs reflects underlying differences in policy emphasis considered by DMs.

Interestingly, the average demand shares reported in column (10) show little variation across policy priorities, ranging from 0.463 to 0.559. Curiously, Education—the most frequently selected priority—has the lowest average demand share (0.463), while Climate, one of the less popular choices, has the highest (0.559); as expected, average budget shares reported in column (11) are nearly identical to average demand shares. However, as we will see below, these averages mask a lot of individual heterogeneity.

If policymaking preferences are *symmetric*—obey $(x, y) \sim (y, x)$ for all (x, y)—then the average demand share will be (close to) $1/2$. But symmetric perfect complements, $u_{DM}(x, y) = \min\{x, y\}$, always results in demand shares of $1/2$, whereas perfect substitutes, $u_{DM}(x, y) = x + y$, yields demand shares of either 1 or 0. For symmetric Cobb-Douglas preferences, $u_{DM}(x, y) = x \cdot y$, both average demand and budget shares equal $1/2$, though it always results only in a budget share of $1/2$. In our estimation of the CES parameters, we use the average demand share as a proxy for the CES parameter α. We find that using budget shares instead of demand shares yields virtually identical results, further strengthening the reliability of the estimation presented in the next section.

5.2 Policymaking preferences

To convey the individual heterogeneity we find, Figure 2 provides a scatterplot of the demand share of policy priority x—that is, $x/(x + y)$—on the vertical axis and the demand share of the *cheaper* policy priority—that is, $x/(x + y)$ when $(p_x < p_y)$ and $y/(x + y)$ otherwise—on the horizontal axis. The histogram on the right (resp. on the top) shows the distribution of the demand share of policy priority x (resp. the cheaper policy priority), with the line representing the corresponding kernel density function. Figure 2 reveals striking heterogeneity in policymaking preferences across DMs, which is consistent with our prior work that finds significant heterogeneity in individuals' social preferences across various subject pools (e.g., Fisman et al., 2015b).

[Figure 2 here]

The distribution of the demand share for policy priority x (vertical axis) is symmetric around $1/2$, as expected given the random assignment of priorities to each axis. However, it is quite spread out, indicating that many DMs assign different weights to their two selected priorities. By contrast, the distribution of the demand share for the cheaper policy priority (horizontal axis) is almost entirely to the right of $1/2$, as expected, but it is noticeably skewed to the left. This suggests that DMs tend to weight their policymaking preferences toward ensuring comparable allocations across both priorities, viewing them more as complements than substitutes.[15]

Table 3 below presents below a population-level summary, reporting summary statistics and percentile values for the distributions of CCEI scores, demand shares, and CES parameter estimates in our data. Columns (1) and (2) summarize the distribution of the CCEI scores of the *DM*s and compare it to the distribution of scores of simulated random subjects. Column (3) reports our *DM*s' consistency scores for CES maximization, analogous to the CCEI scores reported in column (1). Column (4) reports the corresponding scores for simulated subjects whose choices are uniformly distributed over each budget set, conditional on perfect consistency with GARP, as explained in further detail below.

Columns (5) and (6) report the distribution of the demand share of policy priority x and the demand share of the cheaper policy priority—that is, $x/(x+y)$ when $(p_x < p_y)$ and $y/(x+y)$ otherwise. Recall that we use the demand share of policy priority x to proxy for the CES skewness parameter α —the indexical weight on priority x versus y—as explained above. The other columns report the distribution of the estimated CES substitutability parameter ρ for all *DM*s across all policy priorities and for the subset of *DM*s who selected each of the top five priorities: Education, Health, Law and Order, Food, and Power.

[Table 3 here]

Examining columns (1) and (2) of Table 3, the mean and median CCEI scores of the *DM*s are 0.981 and 1.000, respectively, compared to 0.944 and 0.906 for the simulated random subjects. Although the differences are small—given that we could only confront *DM*s with 10 budget lines— our *DM*s are, on average, more consistent with GARP. Additionally, the distribution of the *DM*s' CCEI scores has a much shorter left tail, with scores of 0.993, 0.934 and 0.883 compared to 0.854, 0.750 and 0.677 for the simulated random subjects at the 25$^{\text{th}}$, 10$^{\text{th}}$ and 5$^{\text{th}}$ percentile values.

We interpret these numbers as confirmation that *DM*s' choices are not inconsistent with GARP. However, we note the caveat that if maximization is not the correct model, an experiment with only 10 budget lines may not be sufficiently powerful to detect such inconsistencies. In multiple prior studies with real stakes and thousands of subjects across

[15]For *DM*s whose average demand shares are nearly equal, the average demand share of the cheaper policy priority—as well as the budget shares—serves as a useful proxy for substitutability in their policy-making preferences. However, many *DM*s assign greater indexical weight to one of their selected priorities, necessitating a structural model to recover their willingness to substitute between the two priorities as a function of their relative price, p_x/p_y. This relationship is captured by the CES substitutability parameter ρ.

diverse samples—including broad representations of general populations—and various preference domains with predominantly 50 budget sets, we found a high level of consistency. There is no evidence to suggest that the DMs in this study, who are all highly educated, would exhibit lower consistency with GARP, even if the stakes are hypothetical.

Column (3) reports measures of consistency with CES-maximization that are analogous to CCEI scores, computed using the purely nonparametric GRID method developed by Polisson et al. (2020). Because CES-maximization imposes a stricter consistency requirement than GARP—rationalizing choices through a specific functional form rather than any function, the distribution of CES consistency scores for the DMs in column (3) must, by definition, be left-shifted relative to the corresponding figures in column (1): The mean and median CCEI scores reported in column (1) are 0.981 and 1.000, whereas the mean and median scores for consistency with CES-maximization reported in column (3) are 0.898 and 0.930.

We argue that most DMs' scores are still sufficiently close to their CCEI scores —- and close enough to 1 -— that we may not wish to reject the hypothesis that their choices are consistent with CES-maximization. To give this notion greater precision, we generate benchmark levels of consistency against which to compare the DMs' CCEI-type scores for CES-maximization. To that end, we simulate a sample of subjects making choices on the same budget lines faced by the DMs. These simulated choices are uniformly distributed over each budget set, conditional on *perfect consistency* with GARP. Hence, there exists a utility function that rationalizes the choices of each simulated subject, but its functional form is arbitrary.[16]

The summary statistics of the CES-maximization consistency scores for the simulated subjects are reported in column (4). Comparing these with the scores of the DMs in column (3), we see that the DMs' scores are substantially higher -— the distribution of their consistency scores is skewed to the right, with a mean of 0.90 (median 0.93) compared to 0.80 (median of 0.82), despite the fact that the simulated subjects are perfectly consistent with GARP. Overall, the data support the view that most DMs exhibit behavior that is sufficiently close to CES-maximization, that the violations are minor enough to recover their policymaking preferences using the CES form.

Shifting our focus to policy demand, in columns (5) and (6) of Table 3, we provide the the mean and median demand shares of policy priority x, which are 0.519 and 0.511,

[16]To be precise, the simulated datasets are generated as follows. First, pick allocations uniformly at random from the first and second budget sets. If the data are inconsistent with GARP, continue drawing allocations from the second budget set until there is no violation. Repeat this procedure for all subsequent budget sets, selecting a random allocation until there is no GARP violation with the previously generated data. The resulting datasets are perfectly consistent with GARP and otherwise arbitrary.

respectively. The distribution of the demand share of x across subjects is symmetric, with an interquartile range (25$^{\text{th}}$–75$^{\text{th}}$ percentiles) of $0.430 - 0.615$ and a decile range (10$^{\text{th}}$–90$^{\text{th}}$ percentiles) of $0.349 - 0.691$. We use the demand share of policy priority x as a proxy for the CES skewness parameter α when estimating the substitutability parameter ρ. Turning to the demand share of the cheaper policy priority, the mean and median values are 0.606 and 0.563, respectively. The distribution is almost entirely above $1/2$, with the 10$^{\text{th}}$ percentile at 0.481, but is noticeably skewed to the left, as discussed above. However, a substantial number of DMs exhibit significantly higher average demand for the cheaper priority, with the 90$^{\text{th}}$ and 95$^{\text{th}}$ percentiles at 0.872 and 0.913, respectively.

Finally, columns (7)-(12) of Table 3 show the distribution of the estimated CES substitutability parameter ρ across all DMs for all policy priorities, as well as for the subset of DMs who selected each of the top five priorities. If $\rho > 0$ (resp. $\rho < 0$), a decrease in the relative price p_x/p_y increases (resp. decreases) the expenditure share $p_x x$ of the resources allocated to policy priority x. Therefore, $\rho > 0$ indicates that policymaking preferences lean toward viewing priorities as *substitutes*, increasing the total resources allocated to both. Conversely, $\rho < 0$ suggests that priorities are seen as *complements*, reducing resource disparities between them.

Column (7) of Table 3 shows that among our 929 DMs, the vast majority have negative estimated ρ parameters (to be precise, 754 or 81.2%). The mean and median estimated ρ are -3.647 and -1.072, respectively. That said, there is a substantial number of DMs with policymaking preferences heavily weighted towards increasing the total resources, as indicated by the 90$^{\text{th}}$ and 95$^{\text{th}}$ percentiles of the distribution of estimated ρ parameters of 0.579 and 0.705, respectively. Although there are some differences in the distributions of the estimated ρ parameters across the top five priorities—Education, Health, Law and Order, Food, and Power—as shown in columns (6)-(10) of Table 3, all distributions are weighted towards reducing the difference in resources between the two priorities. The means of the estimated ρ parameters range from -3.108 (Law and Order) to -4.399 (Health), and the medians range from -1.011 (Law and Order) to -1.273 (Education).[17]

5.3 Individual correlates

Next, we correlate DMs' policy priorities—as well as their policymaking preferences—with their characteristics, focusing on a core set of personal and professional attributes. We include age and gender but exclude years of civil service experience due to its high

[17] To avoid computational issues or convergence failures, the estimation of the CES parameter $-\infty < \rho \leq 1$ is bounded at -20, a value that implies near-perfect complementarity, approaching the Leontief function.

collinearity with age (0.89). Additionally, we examine whether *DM*s are generalists in the PAS—the elite cadre of the Civil Services of Pakistan assigned to various government departments—as well as their education type (Engineering, Medical, Science) and whether they hold a graduate degree (Master). The analysis is based on 494 out of 567 (87.1%) *DM*s who participated in the second and third waves of the study and were successfully matched to personnel and professional records based on their name and year of civil service entry.

[Table 4 here]

We begin by examining whether *DM*s' attributes predict their views on Pakistan's top policy priorities. In columns (1)–(3) of Table 4, we present the correlates of selecting priorities that have natural constituencies among *DM*s—specifically, Law (law and order), Health, and Underrep (underrepresentation of women). We also view these specifications as a test case for assessing whether choices in our experiment plausibly reflect *DM*s' underlying policy preferences. We conjecture that police officers—given their role in legal enforcement—would be most likely to prioritize law and order, those trained as physicians would be most inclined to select health, and women would be most acutely aware of under-representation as a pressing concern.

Starting with Law and Order in column (1), we find that the coefficient on Police is large, positive, and marginally significant ($p = 0.06$), suggesting that *DM*s in the police are nearly 50% more likely to select law and order as a priority than others. The coefficient on Female is even more striking, indicating that women are less than half as likely to prioritize law and order ($p < 0.001$). Additionally, older *DM*s are significantly more likely to prioritize this issue ($p < 0.01$).

Turning to Health in column (2), we observe that medical training is positively correlated with selecting health as a priority; however, the coefficient on Medical does not reach statistical significance. Serving in the PAS and training as an engineer are both positive predictors of selecting health, with point estimates of 0.118 for PAS and 0.162 for Engineering—substantial magnitudes relative to the mean proportion of 0.36.

In column (3), we observe that *Female* is the only significant predictor of selecting under-representation of women as a priority. While the coefficient is marginally significant ($p = 0.07$), its magnitude is substantial—only about 2% of male *DM*s selected under-representation, meaning the 0.069 estimate represents a several-fold difference.

In columns (4) and (5) of Table 4, we examine Education and Environment, with the latter capturing whether a participant selected Climate (climate change) or Pollution as a priority. For Education—recall that a substantial majority of *DM*s selected it—there is no significant predictor of prioritization, as it is universally regarded as important among DMs. The patterns for Environment, however, are more intriguing: age emerges as a significant negative predictor of selecting environmental concerns as priorities, consistent with previous research showing stronger environmental concerns among younger individuals.[18] Also interestingly, the second strongest and most significant association ($p < 0.001$) with selecting Climate or Pollution as a priority is an engineering background. Given that only 17.3% of participants selected Climate or Pollution as a priority, the point estimate of -0.155 for Engineering suggests a strong negative relationship between the two variables.[19]

Finally, in column (6), we examine the relationship between DMs' attributes and the extent to which they perceive policy priorities as complements or substitutes, as measured by the CES ρ parameter. Due to its highly skewed distribution, we apply the transformation $-\log(1-\rho)$ for negative ρ values. We find no significant predictor among the covariates considered. This suggests that, despite substantial variation in these estimates—reflecting wide heterogeneity in how DMs approach trade-offs between policy priorities—we do not identify any consistent predictor.[20]

5.4 Discussion and interpretation

Before concluding, we comment on two elements of the interpretation of our experiment: experimenter demand effects and external relevance.

The variant on demand effects that is most relevant for our study stems from the possibility that DMs choose the policies that they perceive their government prioritizes. We note, however, that the full set of 9 policy priorities that they chose from were selected precisely to reflect the policy objectives of Pakistan's government, based on the Vision 2025 goals. Further, Vision 2025 deliberately does not place any particular policy objective above another. For example, the term "education" appears twice in the Vision 2025

[18] Liere and Dunlap (1980) provide an early and widely cited review identifying age as the "predominant" individual attribute correlated with environmental concerns. We do not, however, observe a significant relationship with gender, despite prior research noting its correlation with environmental concerns, as highlighted by Xiao and McCright (2015).

[19] Appendix Table A2 presents the correlation between DMs' attributes and the selection of priorities not included in Table 4—specifically, Food (food scarcity and malnutrition), Infrastructure, and Power (power sector)—as well as Climate and Pollution separately. Additionally, since these results are exploratory, Appendix Table A3 provides a version that accounts for multiple hypothesis testing. As expected, in these specifications, most of the previously reported results are no longer significant based on the estimated q-values (Benjamini et al., 2006).

[20] In practice, any transformation that compresses the distribution of negative ρ values yields the same results. We similarly find no significant predictor of α among any of the covariates, despite the results indicating a link from DM attributes to choice of top policy priorities.

executive summary, the same number of times as "environment" (in references to environmentalism) and "gender."[21] Further, to the extent that such demand effects were in fact a dominant consideration, we should observe a much greater consensus in policy priorities – while there is considerable agreement on education as a priority, there is generally a lot of heterogeneity in the policy pairs chosen by DMs.[22]

Given that we do observe such a strong consensus around education as a priority, it then begs the question of why education receives so little support from the Pakistani government. Pakistan spent under 2% of GDP on education in 2023, down from 2.5% a decade prior. As one point of comparison, in India, education as a fraction of GDP increased from 3.3% to around 4.5% over the same period.[23]

There are multiple reasons for this seeming mismatch between preferences and realized policies. First, it is important to observe that it need not reflect any mismatch at all – while education is frequently selected as a priority, its average demand share is actually less than 50%, since our DMs also show at least symmetric concern for other competing priorities. Second, and relatedly, policymaking is not a simple average of individual policy preferences but rather the outcome of a potentially complex negotiation. Bureaucrats interface with politicians to develop policies that serve electoral purposes as well. And to the extent that voters hold similar views on education but a diversity of perspectives on, say, religion and gender equality, the latter may be more useful electorally as "wedge" issues when facing a polarized electorate. Understanding why preferences do not line up with realized policies (if that is indeed the case) is an important topic for future work, but lies beyond the scope of our current paper.

6 CONCLUSION

Our subjects in this study are nearly 1,000 high-ranking Pakistani government officials—Deputy Ministers—who are deeply involved in policy prioritization and implementation across various government functions. We present them with a decision problem that can be interpreted as a standard economic problem: the selection of a bundle from a standard budget set. These decision problems are presented using a graphical experimental interface, allowing us to frame them in a way that is representative both statistically

[21] `https://pc.gov.pk/uploads/vision2025/Vision-2025-Executive-Summary.pdf`, last accessed June 25, 2025.

[22] Similarly, if there were such agreement on education as a dominant concern, we would expect to see a high demand share for education, conditional on its selection. Instead, we see considerable heterogeneity in both CES parameters, α and ρ.

[23] There is a range of estimates from various sources. These figures come from data accessed via `https://data.worldbank.org/`, last accessed June 25, 2025.

and economically, rather than narrowly tailored to capture a specific trade-off. The rich dataset generated by this design enables analysis at the individual level. The budget sets presented to subjects are structured around policy priorities, providing extensive data on policymaking preferences.

Our paper departs from prior work by combining a broad sample of high-level officials with an experimental technique that, while well-established, has never before been used to analyze policymakers' preferences. A further distinguishing feature is the modeling—and testing—of the existence of underlying policymaking preferences (in the sense of a complete and transitive preference ordering over policy priorities) and their representation through an objective function within the CES family, commonly employed in demand analysis. The broad range of budget lines used in our experiment allows us to test this assumption and estimate a structural econometric model at the individual level. In doing so, we present the first systematic experimental study of the policymaking preferences of leading policymakers.

To recap our results, our analysis reveals substantial heterogeneity in policy priority choices, with Education being the most commonly selected (by more than 60% of DMs), followed by Health, Food, and Law and Order (each chosen by 20–30% of DMs). The experimental data exhibit strong consistency with GARP, supporting the existence of complete and transitive policymaking preferences, which can be effectively represented using the CES framework.

While indexical weights assigned to top priorities vary, they remain centered around 1/2, reinforcing the view that effective policymaking requires contributions across multiple priorities. The CES substitutability parameter ρ shows considerable variation, yet the majority of DMs perceive their top policy priorities as complements, underscoring the notion that development depends on multiple inputs. Certain attributes, such as gender and professional background, predict policy preferences in expected ways, while exploratory findings uncover additional unexpected patterns. The robustness of these results across multiple waves mitigates concerns that they are statistical artifacts.

Many open questions remain about policymakers' preferences and policy formulation more generally. One promising direction is to study decision-making over non-linear budgets. Our graphical experimental interface allows us to test any set, theoretically yielding richer data about choices than a simple linear budget line. The linear budget constraint assumes constant substitution between investing in different policy priorities. However, nonlinearities may arise, for example, when policymakers have an initial allocation of resources and face different price ratios in each direction relative to the status quo. Another promising direction is to study interactive games between policymakers, since much policy (especially given the diversity of priorities) is the outcome of negotiation rather than a reflection of individual preferences. Our graphical interface can accommodate two- and three-player interactive games, where policymakers can bargain. Various axiomatic solutions have been proposed for this bargaining problem, which is fundamental to policymaking. Combining our sample with the experimental setup's capacity provides a unique opportunity to study these questions.

References

Afriat, Sydney N, "The construction of utility functions from expenditure data," *International Economic review*, 1967, *8* (1), 67–77.

Afriat, Sydney N., "The Construction of Utility Functions from Expenditure Data," *International Economic Review*, 1967, *8* (1), 67–77.

__ , "Efficiency Estimates of Production Functions," *International Economic Review*, 1972, *8*, 568–598.

Ahn, David, Syngjoo Choi, Douglas Gale, and Shachar Kariv, "Estimating ambiguity aversion in a portfolio choice experiment," *Quantitative Economics*, 2014, *5* (2), 195–223.

Andreoni, James and John Miller, "Giving according to GARP: An experimental test of the consistency of preferences for altruism," *Econometrica*, 2002, *70* (2), 737–753.

__ **and** __ , "Giving According to GARP: An Experimental Test of the Consistency of Preferences for Altruism," *Econometrica*, 2002, *70* (2), 737–753.

Benjamini, Yoav, Abba M Krieger, and Daniel Yekutieli, "Adaptive linear step-up procedures that control the false discovery rate," *Biometrika*, 2006, *93* (3), 491–507.

Bertrand, Marianne and Antoinette Schoar, "Managing with style: The effect of managers on firm policies," *The Quarterly Journal of Economics*, 2003, *118* (4), 1169–1208.

__ **, Robin Burgess, Arunish Chawla, and Guo Xu**, "The glittering prizes: Career incentives and bureaucrat performance," *The Review of Economic Studies*, 2020, *87* (2), 626–655.

Blesse, Sebastian, Philipp Lergetporer, Justus Nover, and Katharina Werner, "Transparency and policy competition: Experimental evidence from German citizens and politicians," 2023.

Bronars, Stephen G., "The Power of Nonparametric Tests of Preference Maximization," *Econometrica*, 1987, *55* (3), 693–698.

Callen, Michael, Saad Gulzar, Ali Hasanain, Muhammad Yasir Khan, and Arman Rezaee, "Personalities and public sector performance: Evidence from a health experiment in Pakistan," *Economic Development and Cultural Change*, 2025, *73* (3), 1439–1474.

Choi, Syngjoo, Raymond Fisman, Douglas Gale, and Shachar Kariv, "Consistency and Heterogeneity of Individual Behavior under Uncertainty," *American Economic Review*, 2007, *97* (5), 1921–1938.

__ , __ , Douglas M Gale, and Shachar jakiela, "Revealing preferences graphically: an old method gets a new tool kit," *American Economic Review*, 2007, *97* (2), 153–158.

__ , Shachar Kariv, Wieland Müller, and Dan Silverman, "Who is (more) rational?," *American Economic Review*, 2014, *104* (6), 1518–1550.

Cox, James C., Daniel Friedman, and Sadiraj Vjollca, "Revealed Altruism," *Econometrica*, 2008, *76* (1), 31–69.

de Clippel, Geoffroy and Kareen Rozen, "Relaxed Optimization: How Close Is a Consumer to Satisfying First-Order Conditions?," *Review of Economics and Statistics*, 2023, *105* (4), 883–898.

Dembo, A., Shachar jakiela, Matthew Polisson, and John K.-H. Quah, "Ever Since Allais," *Journal of Political Economy*, 2025. Forthcoming.

Ferroni, Matteo F, Raymond Fisman, and Miriam Golden, "Corruption as a Shared Dilemma: Survey Evidence from Legislators and Citizens in Three Countries," 2024.

Finan, Frederico, Benjamin A Olken, and Rohini Pande, "The personnel Economics of the developing state," *Handbook of Economic Field Experiments*, 2017, *2*, 467–514.

Fisman, Raymond, Pamela Jakiela, and Shachar Kariv, "How did distributional preferences change during the great recession?," *Journal of Public Economics*, 2015, *128*, 84–95.

__ , __ , and __ , "Distributional preferences and political behavior," *Journal of Public Economics*, 2017, *155*, 1–10.

__ , __ , __ , and Daniel Markovits, "The distributional preferences of an elite," *Science*, 2015, *349* (6254), aab0096.

__ , __ , __ , and Silvia Vannutelli, "The distributional preferences of Americans, 2013–2016," *Experimental Economics*, 2023, *26* (4), 727–748.

__ , Shachar jakiela, and Daniel Markovits, "Individual preferences for giving," *American Economic Review*, 2007, *97* (5), 1858–1876.

Gulzar, Saad and Benjamin J Pasquale, "Politicians, bureaucrats, and development: Evidence from India," *American Political Science Review*, 2017, *111* (1), 162–183.

Halevy, Yoram, Dotan Persitz, and Lanny Zrill, "Parametric recoverability of preferences," *Journal of Political Economy*, 2018, *126* (4), 1558–1593.

Harbaugh, William, Kate Krause, and Timothy Berry, "GARP for Kids: On the Development of Rational Choice Behavior," *The American Economic Review*, 2001, *91* (5), 1539–1545.

Iyer, Lakshmi and Anandi Mani, "Traveling agents: political change and bureaucratic turnover in India," *Review of Economics and Statistics*, 2012, *94* (3), 723–739.

Jones, Benjamin F and Benjamin A Olken, "Do leaders matter? National leadership and growth since World War II," *The Quarterly Journal of Economics*, 2005, *120* (3), 835–864.

Kertzer, Joshua D and Jonathan Renshon, "Experiments and surveys on political elites," *Annual Review of Political Science*, 2022, *25* (1), 529–550.

Khan, Adnan Q, Asim I Khwaja, and Benjamin A Olken, "Tax farming redux: Experimental evidence on performance pay for tax collectors," *The Quarterly Journal of Economics*, 2016, *131* (1), 219–271.

Lazear, Edward P, Kathryn L Shaw, and Christopher T Stanton, "The value of bosses," *Journal of Labor Economics*, 2015, *33* (4), 823–861.

Li, Jing, Lawrence Casalino, Raymond Fisman, Shachar Kariv, and Daniel Markovits, "Experimental Evidence of Physician Social Preference," *Proceedings of the National Academy of Sciences*, July 2022, *119* (28), 1–11.

_ , William Dow, and Shachar jakiela, "Preferences of Future Physicians," *Proceedings of the National Academy of Sciences*, November 2017, *114* (48), 10291–10300.

Liere, Kent D Van and Riley E Dunlap, "The social bases of environmental concern: A review of hypotheses, explanations and empirical evidence," *Public Opinion Quarterly*, 1980, *44* (2), 181–197.

Lieven, Anatol, *Pakistan: A Hard Country*, New York: Public Affairs, 2011.

Nishimura, Hiroaki, Efe A. Ok, and John K.-H. Quah, "A Comprehensive Approach to Revealed Preference Theory," *American Economic Review*, 2017, *107* (4), 1239–1263.

Polisson, Matthew, John K-H Quah, and Ludovic Renou, "Revealed preferences over risk and uncertainty," *American Economic Review*, 2020, *110* (6), 1782–1820.

Sheffer, Lior, Peter John Loewen, Stuart Soroka, Stefaan Walgrave, and Tamir Sheafer, "Nonrepresentative representatives: An experimental study of the decision making of elected politicians," *American Political Science Review*, 2018, *112* (2), 302–321.

Walgrave, Stefaan, Arno Jansen, Julie Sevenans, Karolin Soontjens, Jean-Benoit Pilet, Nathalie Brack, Frédéric Varone, Luzia Helfer, Rens Vliegenthart, Toni van der Meer et al., "Inaccurate politicians: Elected representatives' estimations of public opinion in four countries," *The Journal of Politics*, 2023, *85* (1), 209–222.

Wilder, Andrew R., "The Politics of Civil Service Reform in Pakistan," Special Report 349, United States Institute of Peace 2013.

Xiao, Chenyang and Aaron M McCright, "Gender differences in environmental concern: Revisiting the institutional trust hypothesis in the USA," *Environment and Behavior*, 2015, *47* (1), 17–37.

Zame, William, Bertil Tungodden, Erik Sørensen, Shachar jakiela, and Alexander W. Cappelen, "Linking Social and Personal Preferences: Theory and Experiment," *Journal of Political Economy*, 2025. Forthcoming.

7 TABLES AND FIGURES

TABLE 1: Sample characteristics

	Mean Fraction	**SD**
Years Employment	16.26	4.928
Age	43.59	5.337
Female	0.136	0.343
Education		
Engineering	0.11	0.312
Medical	0.11	0.317
Science	0.28	0.449
Masters	0.47	0.499
Provinces		
Balochistan	0.071	0.257
Punjab	0.54	0.499
KP	0.13	0.334
Sindh	0.21	0.408
Other	0.051	0.219
Departments		
PAS	0.25	0.434
Police	0.08	0.276
Foreign Service	0.08	0.276
Income Tax	0.08	0.273
Other Dept	0.50	0.501

Notes: Data on 494 of the 929 *DM*s in the subject pool (53.2%) who participated in the second and third sessions and could be matched to personnel and professional records based on name and year of civil service entry. Masters refers to *DM*s who hold a graduate degree. Pakistan consists of four provinces: Punjab, Sindh, Khyber Pakhtunkhwa (KP), and Balochistan. The Other category primarily includes the Islamabad Capital Territory, along with the two regions of Pakistan-administered Kashmir. The Pakistan Administrative Service (PAS) is equivalent to the Indian Administrative Service (IAS) and serves as the highest ranking civil service in Pakistan.

TABLE 2: Policy prioritization

	Frequency (1)	Health (2)	Law (3)	Food (4)	Power (5)	Climate (6)	Infrastr (7)	Pollution (8)	Underrep (9)	Demand (10)	Budget (11)
Education	0.633	0.242	0.137	0.076	0.058	0.047	0.052	0.008	0.013	0.463	0.458
Health	0.365	.	0.041	0.034	0.018	0.010	0.011	0.009	0.000	0.513	0.524
Law	0.287	.	.	0.038	0.032	0.014	0.015	0.004	0.006	0.552	0.544
Food	0.224	.	.	.	0.031	0.025	0.010	0.006	0.003	0.492	0.490
Power	0.175	.	.	.	.	0.014	0.016	0.002	0.003	0.482	0.483
Climate	0.127	.	.	.	.	.	0.005	0.012	0.000	0.559	0.560
Infrastr	0.114	.	.	.	.	.	.	0.004	0.001	0.479	0.488
Pollution	0.046	.	.	.	.	.	.	.	0.001	0.541	0.550
Underrep	0.028	.	.	.	.	.	.	.	.	0.564	0.552

Notes: Data on all 929 *DM*s in the subject pool. Column (1) shows the fraction of *DM*s that selected each priority. Since each *DM*s elects two priorities, this column sums to 2. The superdiagonal in Columns (2)-(9) provides the fraction of *DM*s that selected each priority pair. The final columns (10) and (11) present the average demand $x/(x+y)$ and budget shares p_xx (recall that resources are normalized to 1) of each priority, say it is x, when selected.

TABLE 3: A population-level summary of the individual-level results

	CCEI		CES		Demand shares		ρ	CES ρ estimate by priority				
	*DM*s (1)	Simulated (2)	*DM*s (3)	Simulated (4)	x (5)	Cheaper (6)	(7)	Education (8)	Health (9)	Law (10)	Food (11)	Power (12)
Mean	0.981	0.906	0.898	0.801	0.519	0.606	-3.647	-4.282	-4.399	-3.108	-3.168	-3.524
SD	0.050	0.110	0.096	0.099	0.133	0.138	6.270	6.759	6.973	5.773	5.539	5.910
Percentile												
5	0.883	0.677	0.689	0.603	0.305	0.449	-20	-20	-20	-20	-20	-20
10	0.934	0.750	0.770	0.660	0.349	0.481	-20	-20	-20	-12.105	-12.105	-14.052
25	0.993	0.854	0.859	0.746	0.431	0.509	-2.917	-3.672	-3.971	-2.412	-2.888	-3.473
50	1	0.945	0.930	0.815	0.511	0.563	-1.072	-1.273	-1.216	-1.011	-1.050	-1.149
75	1	1	0.964	0.875	0.615	0.662	-0.260	-0.353	-0.223	-0.200	-0.295	-0.363
90	1	1	0.987	0.913	0.691	0.872	0.579	0.444	0.664	0.662	0.307	0.485
95	1	1	0.993	0.935	0.737	0.913	0.705	0.683	0.725	0.822	0.713	0.674
N	929	10,000	929	1,000	929	929	929	588	339	267	208	163

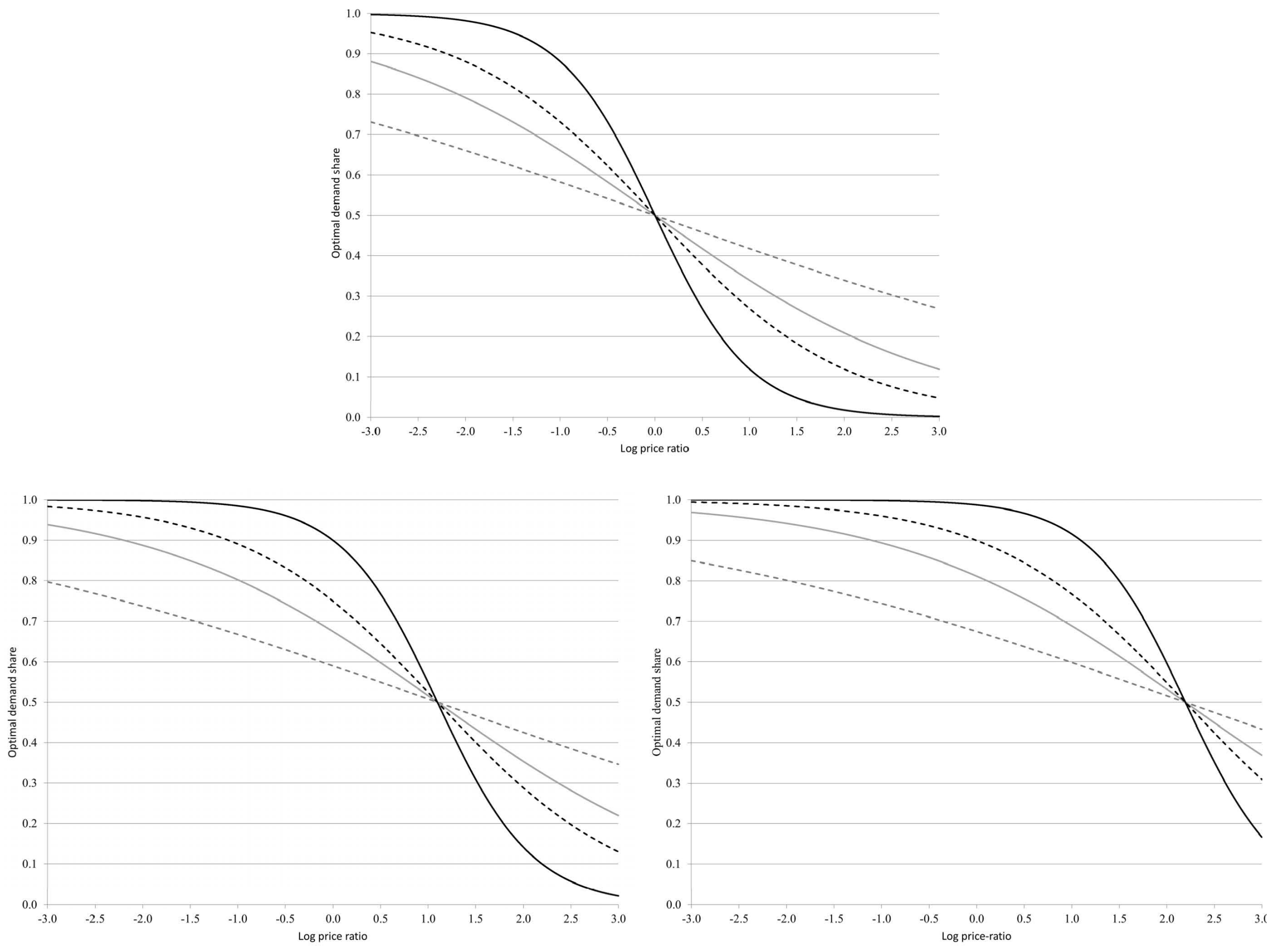
Notes: Columns (1) and (2) provide the CCEI score for the *DM*s in our sample and for the choices of simulated subjects whose choices are uniformly distributed on the budget line, respectively. Columns (3) and (4) provide the CCEI score for consistency with maximizing the CES function for the *DM*s and for simulated subjects whose choices are uniformly distributed on each budget set, subject to *perfect* consistency with GARP, respectively. Obviously, the CCEI score for consistency with CES-maximization can be no greater than the CCEI score for consistency with GARP. Columns (5) and (6) provide, respectively, the average demand share of the priority randomly assigned to the x -axis $x/(x+y)$ and the cheaper priority—that is, $x/(x+y)$ when $(p_x < p_y)$ and $y/(x+y)$ otherwise. Column (7) reports the distribution of the CES ρ parameter for all 929 *DM*s in the subject pool *DM*s, and the remaining columns (8)-(12) report it for the *DM*s who selected each of the top five most-chosen priorities. N is the number of individuals in each column. We calculated the CCEI for 10,000 simulated subjects (column 2), and the CCEI for consistency with CES-maximization for only 1,000 simulated subjects (column 3), due to its computational complexity.

TABLE 4: Correlates of policy priorities and policymaking preferences

	Law	Health	Underrep	Educ	Env	ρ
	(1)	(2)	(3)	(4)	(5)	(6)
Log of Age	0.412**	-0.091	0.048	-0.026	-0.303**	0.252
	(0.174)	(0.191)	(0.078)	(0.190)	(0.136)	(0.433)
Female	-0.174***	-0.057	0.066*	-0.003	0.032	-0.083
	(0.050)	(0.062)	(0.036)	(0.063)	(0.050)	(0.139)
PAS	0.005	0.118**	-0.005	-0.072	0.037	0.015
	(0.049)	(0.052)	(0.019)	(0.052)	(0.039)	(0.125)
Engineering	0.002	0.162**	-0.007	-0.010	-0.155***	-0.218
	(0.070)	(0.078)	(0.026)	(0.076)	(0.045)	(0.191)
Medical	0.009	0.087	0.049	-0.121	-0.066	-0.068
	(0.070)	(0.077)	(0.037)	(0.078)	(0.056)	(0.191)
Science	0.060	0.014	-0.011	-0.001	-0.032	-0.170
	(0.050)	(0.051)	(0.016)	(0.051)	(0.039)	(0.114)
Masters	0.037	-0.025	0.013	-0.050	-0.049	-0.160
	(0.046)	(0.048)	(0.018)	(0.048)	(0.039)	(0.112)
Police	0.146*					
	(0.079)					
R^2	0.041	0.028	0.024	0.012	0.026	0.010

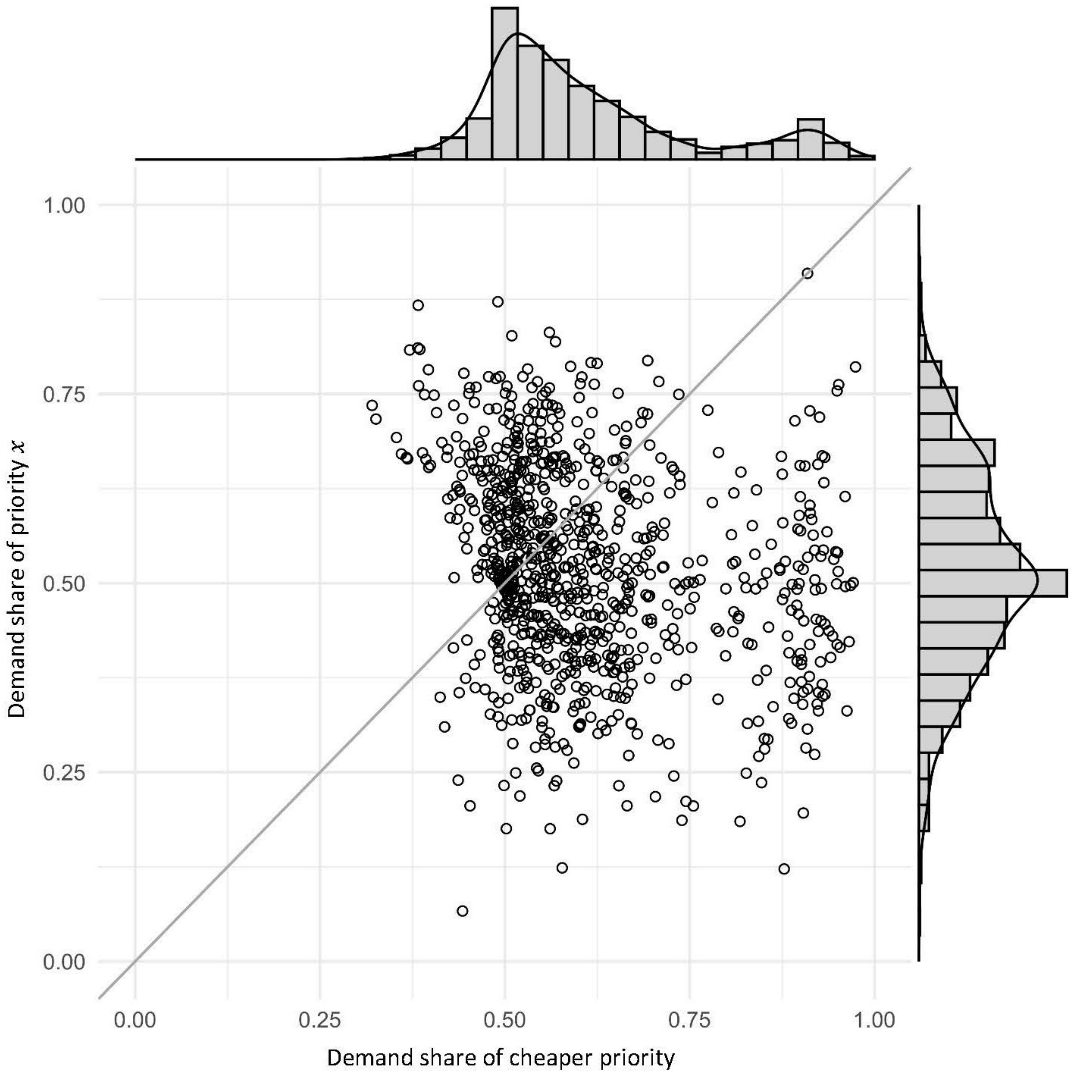
Notes: In columns (1)-(5), the dependent variable is whether a priority was selected. The dependent variable Environment in column (5) captures selecting Climate or Pollution as a priority. The correlation between *DM*s' attributes and the selection of priorities not included here is presented in Appendix Table A2. The dependent variable in the last column (6) is a transformation of the CES parameter ρ to reduce negative outliers (refer to the text for a detailed explanation). In addition to (log) age and gender, we indicate whether *DM*s are generalists in the PAS, their education type (Engineering, Medical, Science) and whether they hold a graduate degree (Masters). Police indicates that a *DM* is a member of the Police Service Group (PSP). We include the 494 *DM*s that were successfully matched to personnel and professional records based on their name and year of civil service entry. Robust standard errors are reported throughout. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Figure 1: The optimal demand share by log price ratio for different CES parameter values



Note: The relationship between the $\log(p_x/p_y)$ (horizontal axis) and the optimal demand share $x/(x+y)$ (vertical axis) for different values of the CES parameters α and ρ. Panels represent different levels of α, and lines indicate different levels of ρ: $\alpha = 0.5$ (top panel), $\alpha = 0.75$ (bottom left panel) and $\alpha = 0.9$ (bottom right panel). $\rho = -2$ (dotted gray), $\rho = -0.5$ (solid gray), $\rho \approx 0.0$ (dotted black) and $\rho = 0.5$ (solid black).

Figure 2: A scatterplot of the individual-level demand shares



Notes: Vertical axis: The demand share of policy priority x—that is, $x/(x+y)$. Horizontal axis: The demand share of the cheaper policy priority—that is, $y/(x+y)$ when $(p_x < p_y)$ and $y/(x+y)$ otherwise. The histogram on the right shows the distribution of the demand share of policy priority x, and the histogram on the top shows the distribution of the demand share of the cheaper policy priority. The lines are the corresponding kernel density functions.

TABLE A1: Correlates of missing personal data

	Missing Personal Info						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Law	0.013						
	(0.031)						
Health		0.036					
		(0.030)					
Underrep			-0.076				
			(0.056)				
Educ				0.049*			
				(0.028)			
Env					-0.004		
					(0.039)		
ρ						0.018	
						(0.011)	
α							-0.073
							(0.177)
R^2	0.000	0.003	0.002	0.005	0.000	0.003	0.000

Notes: The dependent variable in all columns is an indicator variable denoting that a *DM* could not be matched to personnel and professional records based on their name and year of civil service entry. The first set of covariates are indicator variables denoting that a %*DM*s elected that priority. We include the five priorities that are also listed in Table 4 where Environment captures selecting Climate or Pollution as a priority. The ρ covariate is a transformation of the CES ρ parameter estimate, adjusted to reduce negative outliers (refer to the text for a detailed explanation). The α covariate is the average fraction of the tokens allocated to the priority—either x or y—with the higher demand share. Robust standard errors are reported throughout. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. Of the 929 *DM*s in the subject pool, we included the 567 (61%) who participated in the second and third sessions (the first was conducted entirely anonymously).

TABLE A2: Correlates of policy priorities

Priority	Food (1)	Infra (2)	Climate (3)	Pollution (4)	Power (5)
Log of Age	-0.085	0.102	-0.301**	-0.086	0.036
	(0.148)	(0.120)	(0.129)	(0.068)	(0.148)
Female	0.043	-0.020	0.040	0.022	0.076
	(0.055)	(0.039)	(0.047)	(0.033)	(0.058)
PAS	-0.013	-0.006	0.050	-0.010	-0.051
	(0.040)	(0.033)	(0.037)	(0.021)	(0.038)
Engineering	0.003	-0.049	-0.114***	-0.057***	0.063
	(0.061)	(0.052)	(0.042)	(0.020)	(0.057)
Medical	-0.020	-0.087*	-0.061	-0.003	0.148**
	(0.057)	(0.047)	(0.050)	(0.037)	(0.064)
Science	0.042	-0.064**	-0.009	-0.028	-0.011
	(0.043)	(0.031)	(0.036)	(0.022)	(0.040)
Masters	-0.014	-0.048	-0.056	0.014	0.133***
	(0.039)	(0.032)	(0.036)	(0.024)	(0.037)
R^2	0.006	0.016	0.027	0.015	0.036

Notes: In each column, the dependent variable is whether a priority not included in Table 4 was selected, as well as Climate and Pollution separately. In addition to (log) age and gender, we indicate whether *DM*s are generalists in the PAS, their education type (Engineering, Medical, Science) and whether they hold a graduate degree (Masters). We include the 494 *DM*s that were successfully matched to personnel and professional records based on their name and year of civil service entry. Robust standard errors are reported throughout. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

TABLE A3: Correlates of policy priorities correcting for multiple hypothesis testing

	Law	Health	Underrep	Educ	Env
Log of Age	0.412**	-0.091	0.048	-0.026	-0.303**
	(0.018)	(0.632)	(0.537)	(0.892)	(0.026)
	[0.213]	[1.000]	[1.000]	[1.000]	[0.213]
Female	-0.174***	-0.057	0.066*	-0.003	0.032
	(0.001)	(0.355)	(0.065)	(0.962)	(0.520)
	[0.012]	[1.000]	[0.332]	[1.000]	[1.000]
PAS	0.005	0.118**	-0.005	-0.072	0.037
	(0.926)	(0.024)	(0.776)	(0.172)	(0.352)
	[1.000]	[0.213]	[1.000]	[0.876]	[1.000]
Engineering	0.002	0.162**	-0.007	-0.010	-0.155***
	(0.977)	(0.039)	(0.797)	(0.900)	(0.001)
	[1.000]	[0.253]	[1.000]	[1.000]	[0.012]
Medical	0.009	0.087	0.049	-0.121	-0.066
	(0.902)	(0.264)	(0.183)	(0.118)	(0.237)
	[1.000]	[0.909]	[0.876]	[0.582]	[0.896]
Science	0.060	0.014	-0.011	-0.001	-0.032
	(0.233)	(0.789)	(0.502)	(0.991)	(0.412)
	[0.896]	[1.000]	[1.000]	[1.000]	[1.000]
Masters	0.037	-0.025	0.013	-0.050	-0.049
	(0.419)	(0.602)	(0.443)	(0.295)	(0.210)
	[1.000]	[1.000]	[1.000]	[0.994]	[0.896]
Police	0.146*				
	(0.066)				
	[0.332]				
R^2	0.041	0.028	0.024	0.012	0.026

Notes: In all columns, the dependent variable is whether a priority was selected. We include the five priorities that are listed in Table 4 where Environment captures selecting Climate or Pollution as a priority. In addition to (log) age and gender, we indicate whether *DM*%s are generalists in the PAS, their education type (Engineering, Medical, Science) and whether they hold a graduate degree (Masters). Police indicates that a *DM* is a member of the Police Service Group (PSP). We include the 494 *DM*s that were successfully matched to personnel and professional records based on their name and year of civil service entry. p-vlaues in parentheses and q-values in square brackets throughout. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.