Northwestern | INSTITUTE FOR POLICY RESEARCH

IPR Working Paper Series

WP-22-28

Selective Bribery:

When Do Citizens Engage in Corruption?

Aaron Erlich
McGill University

Jordan Gans-Morse
Northwestern University and IPR

Simeon Nichter
University of California, San Diego

Version: June 30, 2022

DRAFT

Please do not quote or distribute without permission.

Abstract

Corruption often persists not only because public officials take bribes, but also because many citizens are willing to pay them. Yet even in countries with endemic corruption, few people always pay bribes. Why do citizens bribe in some situations but not in others? Integrating insights from both principal-agent and collective action approaches to the study of corruption, the authors develop an analytical framework for understanding *selective bribery*. Their framework reveals how citizens' motivations, costs, and risks influence their willingness to engage in corruption. A conjoint experiment conducted in Ukraine in 2020 provides substantial corroboration for 10 of 11 pre-registered predictions. By shedding light on conditions that dampen citizens' readiness to pay bribes, the researchers' findings offer insights into the types of institutional reforms that may reduce corruption.

The authors thank John Bullock, James Druckman, Timothy Frye, Marko Klasnja, Irfan Nooruddin, Salvatore Nunnari, Michael Peress, and Andrew Saab, as well as participants in the "Drivers of Prosocial Behavior in Ukraine" Panel at the 2021 ASN Convention, the Georgetown University Current Research on Issues and Topics in Comparative Scholarship workshop and the Northwestern University Institute for Policy Research Fay Lomax Cook Colloquium, for input and advice on this project. They also thank Annie Chen and Anna Marukhnyak for outstanding research assistance.

In many countries, widespread corruption undermines political institutions and stifles economic development (Fisman and Golden 2017, ch. 4; Olken and Pande 2012, pp. 491–495; Svensson 2005, pp. 36–39). Corruption, moreover, regularly affects the lives of everyday people. In recent years, approximately one in four citizens globally report paying a bribe to obtain public services in the last year. Its prevalence is often far higher: In Mexico and Egypt, over half of citizens report paying a recent bribe; in India, over two-thirds.[1] Yet even where corruption is endemic, few people *always* pay bribes. Why do citizens choose to bribe in some situations, but refrain from paying bribes in others?

The present study investigates this important topic, building on a novel wave of research that draws attention to citizens' role in sustaining corruption. Unlike earlier principal-agent approaches that predominantly focused on public officials (e.g., Klitgaard, 1988; Rose-Ackerman, 1978), a more recent body of literature emphasizes the importance of citizens' collective choices (e.g., Mungiu-Pippidi, 2006; Persson et al., 2013). Scholars contributing to this increasingly influential research agenda argue that conceptualizing corruption as public officials' deviations from norms or rules ignores its frequently systemic nature — corruption *is* the norm rather than a deviation in many societies. Accordingly, these scholars focus on the collective action problem facing citizens: Once corruption is endemic, even citizens who detest the phenomenon face strong incentives to bribe. Otherwise, they may experience longer wait times or receive inferior public services than their bribe-paying peers. These collective action problems often create vicious cycles of expectations and social norms that are challenging to disrupt, leading some scholars to suggest that countries with endemic corruption may require extensive societal and political transformations to escape high-corruption equilibria (Rothstein, 2011).

This collective action approach offers many important insights, but sheds little light on why many people choose to bribe in some situations but not in others — engaging in what

[1] For the global bribe rate, see Transparency International's 2017 Global Corruption Report, p. 7. Bribe rates by country are available at https://www.transparency.org/en/gcb/global/global-corruption-barometer-2017/press-and-downloads, downloaded on 11/24/21.

we term *selective bribery*. By contrast, we advance the study of corruption by unpacking how and why citizens often make distinct choices about partaking in corrupt transactions. We tackle this fundamental question by drawing not only on the collective action approach's focus on citizens, but also on the principal-agent approach's attention to institutional mechanisms and cost-benefit calculations. When appropriate, our analyses build on prior research that exclusively focuses on officials' bribe-taking in order to generate insights into citizens' bribe-giving. Our findings shift attention from questions about *whether* some types of citizens give bribes to questions about *why* citizens' propensity to give bribes varies from one context to another. A deeper understanding of the institutional incentives shaping citizens' willingness to bribe is crucial for developing effective reforms to mitigate corruption's pernicious consequences.

To guide our empirical analyses, we develop a simple theoretical framework that integrates numerous factors that may affect citizens' propensity to engage in selective bribery. Our decision-theoretic model conceptualizes bribe choices as analogous to a consumer demand problem, in which citizens decide how to allocate resources across a corruptly provided service and non-corrupt alternatives. Formal analyses yield 11 predictions about how motivations, costs, and risks influence citizens' willingness to bribe public officials. Regarding motivations, the model predicts that citizens pay fewer bribes when a service: (a) can be obtained with minimal red tape; (b) is less urgently needed; and (c) can be obtained from multiple providers. Regarding costs, it predicts that citizens pay fewer bribes when: (a) expected bribe prices are high; (b) they are uncertain bribes will yield preferential treatment; (c) they have no prior interactions with an official; (d) they expect no future interactions with an official; and (e) they must obtain additional permits or signatures. Regarding risks, it suggests that citizens pay fewer bribes when: (a) the probability of detection by authorities increases; (b) an official does not proactively request bribes; and (c) they believe that few other citizens engage in corruption. Overall, our theoretical framework yields a rich set of hypotheses about how institutional and situational factors affect citizens' willingness to bribe officials, even in countries with endemic corruption.

Another key contribution of our study is that it rigorously tests these theoretical predictions about selective bribery. In 2020, we conducted a pre-registered conjoint experiment in Ukraine — a country that prior to Russia's 2022 invasion had conducted extensive anti-corruption efforts to address widespread corruption. This approach establishes causality and circumvents numerous empirical challenges that bedevil observational analyses. For example, while many valuable studies use survey data to suggest a link between citizens' propensity to bribe and demographic characteristics such as income, gender and education (see, e.g., Hunt, 2010; Hunt & Laszlo, 2005; Miller, 2006; Mocan, 2008; Truex, 2011), their findings may suffer from omitted variables bias and reverse causality.[2] By contrast, our conjoint experiment with over 3,000 Ukrainian participants overcomes these challenges by randomly assigning treatments designed to isolate and test each of the 11 hypotheses derived from our theoretical model.[3] In addition to corroborating 10 of these hypotheses, the experiment reveals that institutional and situational factors can have substantial effects on bribe-giving: Our analyses suggest, for instance, that a citizen is over 20 percentage points less likely to bribe a doctor at a public clinic if she can obtain treatment elsewhere, expects no future interactions with the doctor, and is uncertain the doctor can expedite treatment if bribed. Whereas a handful of laboratory experiments discussed below examine one or two specific aspects of bribe transactions, our conjoint experiment simultaneously considers a far broader range of factors (Hainmueller et al., 2014), and deepens our understanding of the relative impact of these factors on selective bribery.

The next section introduces our analytical framework and situates our approach within

[2]While recent conjoint experiments examine citizens' willingness to elect corrupt politicians (for a meta-analysis, see Incerti, 2020), our study is the first to investigate a distinct question: What factors influence citizens' willingness to pay bribes? Our question is less susceptible to Abramson et al.'s (2021) critique about conjoint experiments' applicability for analyzing majority preferences in elections.

[3]We pre-registered all hypotheses with Open Science Framework on 8/21/2020, before data collection commenced (see Online Appendix Section E).

the existing literature. We then elaborate our research design and discuss experimental tests of theoretical predictions. At the outset, we emphasize that our focus on citizens' role in petty corruption should not detract attention from the important topic of grand corruption, or from the key role of public officials and firms in various types of bribe transactions. Nevertheless, our focus is crucial for addressing the highly persistent equilibria that underlie systemic corruption, as it aims to clarify how various factors shape the extent to which citizens pay bribes in their everyday interactions with officials. Our findings offer insights into the types of institutional reforms that may help to reduce citizens' willingness to engage in corruption when obtaining public services.

1 Institutional Incentives for Bribe-Giving

Although scholars and policymakers have devoted extensive attention to corruption, the conditions that dampen citizens' willingness to bribe remain understudied. Whereas numerous studies analyze national-level correlates of corruption (for a review, see Treisman, 2007) or factors affecting public officials' propensity to take bribes (for a review, see Gans-Morse et al., 2018), far less is known about citizens' readiness to engage in corruption.

To the extent that corruption research focuses on citizens, it primarily investigates how individuals' demographic or socioeconomic characteristics explain why some types of people are more or less likely than others to bribe. While evidence is mixed, some studies suggest that women may be less likely engage in bribe transactions (Mocan, 2008; Swamy et al., 2001), wealthier citizens may be more likely to face bribe requests from public officials (Hunt, 2010; Hunt & Laszlo, 2005; Mocan, 2008),[4] and citizens with greater education may be more likely to express negative views about paying bribes (Truex, 2011). One limitation of such studies is their frequent reliance on observational survey data, raising well-known concerns including spurious correlation and reverse causality. And, crucially for our research question, studies on demographic or socioeconomic characteristics are not

[4]By contrast, Fried et al. (2010) suggest bribe-seeking traffic police in Mexico target lower-class drivers.

designed to explain why the same citizen might choose to offer bribes in some contexts but not in others — or how institutional incentives might affect such decisions.[5] As discussed in the Introduction, another key strand of literature focused on citizens is the collective action approach. Influential studies by Persson et al. (2013) and Corbacho et al. (2016), for example, examine the important issue of how citizens' propensity to bribe depends on individual beliefs about others' willingness to bribe. But, as noted above, the collective action approach offers far more insights into why high levels of corruption persist than into why — even in countries where corruption is endemic — few people *always* pay bribes.

In contrast to such studies, we advance the literature by illuminating why citizens' propensity to give bribes often varies from one context to another. The analytical framework we introduce below incorporates important insights from the collective action literature; for example, we explore how individuals' willingness to bribe depends on whether they believe many others engage in corruption. But in developing this framework, we also incorporate lessons from the principal-agent literature on corruption among public officials, inverting its focus to investigate not why officials take bribes but rather why citizens give bribes. To date, the handful of studies that adopt a similar approach focus narrowly on how only one or two factors affect citizens' bribe-giving, such as laboratory experiments analyzing the effects of increased penalties or monitoring (Banuri & Eckel, 2015; Serra, 2012). By contrast, we consider a far broader range of straightforward yet essential concerns central to the principal-agent approach — such as bribe prices, costs of overcoming bureaucratic red tape, and detection risks — that may account for variation in citizens' bribe choices even in societies where corruption is widespread.

Beyond institutional incentives central to principal-agent models, the framework we introduce below also considers unique transaction costs that citizens incur when paying bribes, given that illicit exchanges typically inhibit deceived individuals from turning to

[5] Similarly, studies of bribe-giving by firms focus more on variation in bribe levels across sectors or types of firm (e.g., Svensson, 2003), or on whether bribes can enhance efficiency (e.g., Kaufmann & Wei, 1999), than on how institutional and situational factors affect willingness to bribe.

courts and other formal means of contract enforcement (Lambsdorff, 2002). The framework also incorporates considerations about effects of bureaucratic structures, such as whether public services are provided monopolistically or competitively, and whether the value of public services provided by one official depends on access to complementary services provided by other officials (a common situation when citizens must receive permits or authorization from multiple agencies). While such questions about the "industrial organization" of corrupt bureaucracies are central to canonical studies about public officials' propensity to take bribes (see Klitgaard, 1988; Rose-Ackerman, 1978; Shleifer & Vishny, 1993), our study is among the first to examine how the structure of corrupt bureaucracies affects citizens' willingness to give bribes.

Building on these important insights from the corruption literature, we next develop an analytical framework focused on how institutional incentives and situational factors shape citizens' willingness to engage in selective bribery. We elaborate a formal model that ties together these diverse considerations, clarifies the logic underlying hypotheses tested in our empirical application, makes explicit underlying assumptions, and confirms the internal consistency of our predictions.

Analytical Framework

As discussed above, the present study focuses on how institutional and situational factors influence why an individual might bribe more in some contexts than in others. Accordingly, we conceptualize a citizen's decision about when to engage in bribery as an intertemporal consumer demand problem. More specifically, a citizen who needs government services chooses how to allocate her budget across three options: (1) obtain services from corrupt officials, making facilitating payments for expedited treatment; (2) obtain services from corrupt officials, with costly delays and no grease payments; and (3) obtain substitute services by searching for honest officials.

Formalizing these three options, let x_b represent services obtained from corrupt officials while paying bribes, x_{nb} represent services obtained from corrupt officials without bribes, and x_s represent substitute services provided by honest officials. Paying bribes $b > 0$ enables the citizen to receive expedited services x_b at time t. By contrast, citizens face bureaucratic obstacles when obtaining services x_{nb} or x_s, such that they receive these services at time $t+1$ (see also the discussion of red tape costs below).[6] We employ a standard constant elasticity of substitution (CES) utility function to represent the citizen's utility over these three services:

$$U(x_b, x_{nb}, x_s) = (x_b^\eta + \delta(x_{nb}^\eta + x_s^\eta))^{\frac{1}{\eta}} \tag{1}$$

where η is the substitution parameter.[7] The assumption that $0 < \eta < 1$ ensures that x_b, x_{nb}, and x_s are substitutes. To reflect the citizen's preference for receiving the service in time t instead of $t+1$, $\delta \in (0,1)$ represents a discount factor: higher values of δ reflect less urgently needed services.

Of primary interest is the uncompensated demand function $x_b^*(c, \delta, \gamma, n_s)$ for services obtained via bribery, where x_b^* is the solution to the constrained optimization problem:

$$\max_{x_b, x_{nb}, x_s} U(x_b, x_{nb}, x_s) \;\; \text{s.t.} \;\; cx_b + \gamma x_{nb} + \frac{1}{n_s}(1+\gamma)x_s \leq M \tag{2}$$

The M in the budget constraint shown represents the citizen's budget for government services, and the official price of x_b, x_{nb}, and x_s is normalized to 0. Other parameters in the budget constraint capture additional costs of each option. First, to obtain expedited services x_b through bribery, the citizen incurs cost $c > 0$. We unpack this cost such that $c = b + \tau + z$, where all three disaggregated cost parameters are strictly positive. The first term, b, is the bribe amount. Transaction costs τ capture the fact that bribe exchanges are difficult to enforce, as the citizen lacks legal recourse if a bribed official reneges on expediting the service. Given the risk involved when bribing officials, z is a cost reflecting

[6] We assume the market for bribes is sufficiently competitive such that corrupt officials are price takers who cannot adjust the asking price of b.

[7] Following the standard CES utility function, $\eta = \frac{(\sigma-1)}{\sigma}$, where σ is the elasticity of substitution.

the expected disutility from any punishments (such as fines when corruption is exposed).[8] Second, when obtaining services x_{nb} from corrupt officials without paying a bribe, the citizen incurs red tape costs $\gamma > 0$. Red tape costs represent opportunity costs of time spent waiting and effort exerted to overcome bureaucratic hurdles, such as needing to return repeatedly or filling out numerous forms. Third, when the citizen seeks an honest service provider to obtain x_s, she expends costly effort $e > 0$, which includes search and transportation costs. We assume that such costs decline in the number $n_s > 0$ of providers in the vicinity who offer service x_s, such that $e = \frac{1}{n_s}$. The citizen also incurs red tape costs γ_s when obtaining x_s. We assume $\gamma_s = \frac{\gamma}{n_s}$, because some aspects of red tape costs — such as queue length — decrease with more nearby service providers.[9]

Formal analyses presented in Section D of the Online Appendix derive comparative statics from the uncompensated demand function. These comparative statics reveal how changes in parameters just discussed affect the citizen's demand for corruptly provided services x_b. The model's empirical predictions motivate our experimental research design and can be classified into three categories of institutional and situational factors that structure bribe transactions: (1) motivations to bribe, (2) costs to bribe, (3) and punishment risks.

Empirical Predictions

As summarized in Table 1, our first three hypotheses pertain to factors affecting citizens' *motivations to bribe*. The first hypothesis considers a fundamental reason citizens engage in corruption — avoiding red tape — and offers insights into how bribe-giving should be expected to rise or fall as bureaucratic hurdles become more or less extensive. The second hypothesis emphasizes how the urgency with which a citizen needs a given service influences propensity to engage in corruption. A third hypothesis summarizes the model's predictions

[8]We do not distinguish between punishment size and the probability of detection, so z can be considered an expected cost incorporating both considerations.

[9]In line with evidence that corrupt officials intentionally maintain bureaucratic hurdles to encourage grease payments (Klitgaard 1988, pp. 87–89; Shleifer and Vishny 1993, p. 601), we assume a greater number of service providers reduces red tape costs such as queue length for honest but not for corrupt providers.

about a key aspect of the industrial organization of corrupt bureaucracies, formalizing how access to competing service providers (or lack thereof) affects bribe levels:

- Hypothesis 1 (*Red Tape*): As red tape (γ) increases, demand for corruptly provided services x_b increases.
- Hypothesis 2 (*Need*): As a service becomes more urgently needed (i.e., as δ decreases), demand for corruptly provided services x_b decreases.
- Hypothesis 3 (*Access to Substitutes*): As more providers (n_s) offer access to substitute services, demand for corruptly provided services x_b decreases.

Our second set of hypotheses pertain to factors affecting citizens' *costs to bribe*. We consider not only how expected bribe sizes affect citizens' willingness to engage in corruption, but also present three hypotheses based on our model's prediction for transaction costs (τ). Drawing on the institutional economics literature, we emphasize that transaction costs of corruption are lower when officials: (a) can credibly commit to expedite services in exchange for bribes; (b) have a reputation for providing expedited services for bribes, which can be inferred from a history of past interactions; and/or (c) have disincentives to cheat bribers, such as expectations of future bribe interactions (Lambsdorff 2002, pp. 226–227, 230–232; Rose-Ackerman 1990, pp. 99–104). Accordingly, our formal analyses predict:

- Hypothesis 4 (*Bribe Size*): As expected bribe prices b increase, demand for corruptly provided services x_b decreases.
- Hypothesis 5 (*Enforceability*): As the enforceability of bribe transactions increases (thereby decreasing τ), demand for corruptly provided services x_b increases.
- Hypothesis 6 (*Past Interactions*) As past interactions between an official and citizen increase (thereby decreasing τ), demand for corruptly provided services x_b increases.
- Hypothesis 7 (*Future Interactions*): As expected future interactions increase (thereby decreasing τ), demand for corruptly provided services x_b increases.

Our third set of hypotheses involve factors affecting citizens' *punishment risks*. We consider not only how increased detection affects citizens' willingness to bribe, but also provide two hypotheses based on our model's prediction for penalty z. First, we examine whether officials act as first movers by asking for bribes, which reduces citizens' expected penalty. As Lambsdorff (2002, pp. 223–225) discusses, the party who initiates a bribe transaction asymmetrically exposes herself to risk, given difficulties of determining whether the other party is corruptible. Second, we consider whether citizens believe many other people engage in bribery. After all, studies on citizens' collective action problem underscore that pervasive corruption lowers a given individual's probability of punishment (see, e.g., Corbacho et al., 2016, pp. 1079–1981). By extension, our model predicts:

- Hypothesis 8 (*Detection*): As the risk of law enforcement detecting corruption rises (thereby increasing z), demand for corruptly provided services x_b decreases.
- Hypothesis 9 (*First Mover*): When public officials initiate bribe transactions (thereby decreasing z), demand for corruptly provided services x_b increases.
- Hypothesis 10 (*Collective Action*): When citizens expect that many other people pay bribes (thereby decreasing z), demand for corruptly provided services x_b increases.

Complementary Services

Beyond our analysis of substitute services, our theoretical framework yields insight about complementary services. In some instances, the value of services just discussed (x_b, x_{nb}, and x_s) may partially depend on obtaining one or more services y at price p_y offered by another service provider. For example, a citizen may need an additional signature or permit from a different official (Shleifer & Vishny, 1993, pp. 605–606). To examine this possibility, we build on the model by employing a nested CES utility function, which facilitates analysis of both substitutes and complements in a unified framework. More specifically, the citizen's utility over x_b, x_{nb}, x_s and y is represented as follows:

$$U(x_b, x_{nb}, x_s, y) = \left[\left((x_b^\eta + \delta(x_{nb}^\eta + x_s^\eta))^{\frac{1}{\eta}}\right)^\rho + y^\rho\right]^{\frac{1}{\rho}} \tag{3}$$

In addition to parameters in Equation (1), this utility function includes the substitution parameter ρ. The assumption that $\rho < 0$ ensures y is a complement to x_b, x_{nb}, and x_s. Following Equation (2), the constrained optimization problem is thus:

$$\max_{x_b, x_{nb}, x_s, y} U(x_b, x_{nb}, x_s, y) \quad \text{s.t.} \quad cx_b + \gamma x_{nb} + \frac{1}{n_s}(1+\gamma)x_s + p_y y \leq M$$

Table 1: Summary of Hypotheses

	Change in Incentives to Bribe	Change in Model Parameter	Predicted Effect on Bribery
Motivation to Bribe			
Red Tape (H1)	Red Tape When Not Bribing Increases	Increase in γ	Bribery Increases
Need (H2)	Immediate Need for Service Increases	Decrease in δ	Bribery Increases
Access to Substitutes (H3)	Access to Substitutes Increases	Increase in n_s	Bribery Decreases
Cost to Bribe			
Bribe Size (H4)	Bribe Size Increases	Increase in b	Bribery Decreases
Enforceability (H5)	Bribe Enforceability Increases	Decrease in τ	Bribery Increases
Past Interactions (H6)	Past Interactions Increase	Decrease in τ	Bribery Increases
Future Interactions (H7)	Future Interactions Increase	Decrease in τ	Bribery Increases
Required Complement (H11)	Need for Ancillary Services Increases	Increase in n_c	Bribery Decreases
Risk of Punishment			
Detection (H8)	Detection of Bribery Increases	Increase in z	Bribery Decreases
First Mover (H9)	Official Asks for Bribe	Decrease in z	Bribery Increases
Collective Action (H10)	Others' Bribery Increases	Decrease in z	Bribery Increases

Comparative statics analysis in the appendix shows all 10 hypotheses presented above continue to hold when using this model to consider both substitute and complementary services. Moreover, it yields an additional hypothesis that we test experimentally:

- Hypothesis 11 (*Required Complement*): When costlier complementary services are needed (i.e., p_y increases), demand for corruptly provided services x_b decreases.

More broadly, our analytical framework generates 11 empirical predictions, which shed light on how motivations, costs and punishments shape citizens' bribe choices. By inverting the more traditional focus on officials' bribe-taking, we offer novel predictions such as how substitutes and complements, as well as the urgency with which a service is needed, affect citizens' bribe-giving. Moreover, the model offers testable implications that are consistent with existing studies of officials, but that are rarely analyzed with respect to citizen behavior, investigated in a unified framework, or subjected to empirical scrutiny. To date, no study has offered a rigorous evaluation of the effects of such a wide range of factors in the integrative context of a conjoint experiment, which allows subjects to consider simultaneously a comprehensive set of institutional and situational factors that potentially influence citizens' willingness to bribe. The next section introduces our experimental design.

2 Experimental Design

To investigate whether this analytical framework provides meaningful predictions about human behavior, we developed a conjoint experiment to test the pre-registered hypotheses summarized in Table 1. We employ a paired conjoint design, in which respondents view and compare two profiles shown next to each other, as this design performs best with respect to external validity (Hainmueller et al., 2015).

Implementation

We conducted the conjoint experiment described below in Ukraine in 2020. Prior to Russia's February 2022 invasion, Ukraine battled endemic corruption with mixed success, providing a fitting context for our study. Transparency International ranked Ukraine 122nd out of 180 countries in its 2021 Corruption Perception Index. According to its latest Global Corruption Barometer data for the country (in 2016), 38% of Ukrainians reported paying a bribe in the last 12 months.[10] There are two key advantages to conducting our study in a context with widespread corruption. First, we enhance external validity and experimental realism given that many of our subjects have either direct familiarity with the types of corruption our conjoint experiment examines, or indirect information from family members and friends with such familiarity. Second, the topic is frequently far from taboo in societies where corruption is prevalent. Ukrainians openly and regularly discuss corruption, partially mitigating risks to inference from social desirability bias. In related work utilizing a similar sample of Ukrainians, we find that responses to direct questions about willingness to bribe were nearly identical to responses elicited via indirect response methods designed for studying sensitive topics.[11] We nevertheless recognize that the measurement of illicit

[10] See www.transparency.org/cpi and www.transparency.org/research/gcb/overview.

[11] In Erlich and Gans-Morse (2022) we examine a different topic — anti-corruption messaging's effectiveness — but use an identical recruitment strategy. We queried respondents via both direct questions and list experiments about willingness to bribe, using the same scenarios examined in the present study.

phenomena entails inherent challenges, and we accordingly employ a range of approaches discussed below to measure survey respondents' willingness to engage in corruption.

Subjects were recruited via Facebook advertisements between August 21 and October 6, 2020. Facebook's extensive reach in Ukraine heightens its usefulness for recruiting research participants. At the time of our study, Facebook was by far Ukraine's most popular social media application: over half of Ukrainians were registered Facebook users.[12] To incentivize participation, we informed prospective respondents they would be entered into a lottery for an Apple Watch. Following our pre-registered sample-size target, we recruited 3,060 respondents. Respondents who clicked on our Facebook ads were redirected to a consent form and survey instrument on the Qualtrics platform. Subjects could choose to complete the survey in Russian or Ukrainian; 64% chose Ukrainian. The median time for survey completion was 22 minutes. While we make no claims regarding representativeness, our sample includes a wide range of demographic groups. The sample is 52% male versus 48% female. Respondents' ages are distributed normally, with a mean and median age of 48 and 49, respectively. Subjects' self-reported place of residence is not limited to the capital (Kyiv) or other large cities: 33% indicated living in a small city or town and 19% in a village or rural area. The sample also displayed considerable geographic diversity, including many respondents from all of Ukraine's regional administrative units (excluding Russian-occupied Crimea).[13]

Conjoint Experiment

Our conjoint experiment employed two distinct scenarios in which a hypothetical citizen seeks a service from a public service provider — one about obtaining a driver's license and the other about receiving treatment at a state-run healthcare clinic. We focus on these spheres because they often involve corruption in Ukraine and are emphasized in

[12] In September 2020, Facebook Ads reported that ads reached 21.1 million unique Ukrainian users aged 18 or older. Ukraine's population was 44.1 million. For Facebook's share of Ukraine's social media market, see: gs.statcounter.com/social-media-stats/all/ukraine/2020.

[13] As shown in Online Appendix Section A, the sample slightly overrepresents males and underrepresents young and elderly citizens relative to population benchmarks from Ukraine's 2021 census extrapolations.

Table 2: Attributes for Corruption Profiles

(Driver's License Scenario/Healthcare Scenario)

	Attribute	Levels
Motivation to Bribe		
H1: Red Tape	Wait time without bribe	1 month, 4 months, 8 months/1 day, 1 month, 4 months
H2: Need	Commute to work using public transportation/Seriousness of injury	10 minutes, 1 hour, 2 hours/Can walk, Can walk with crutches, Needs wheelchair
H3: Access to Substitutes	Are there other nearby driving schools to obtain a license/nearby clinics to obtain treatment?	No other schools/clinics; Yes, 5 other schools/clinics; Yes, 10 other schools/clinics
Cost to Bribe		
H4: Bribe Size	Typical bribe size	250 UAH, 500 UAH, 1000 UAH, 2000 UAH, 4000 UAH, 8000 UAH
H5: Enforceability	If bribed, is instructor/doctor certain to speed up license/treatment?	Not certain; Yes, certain
H6: Past Interactions	Have used same instructor/doctor in the past?	No, never; Yes, several times already
H7: Future Interactions	Will use same instructor/doctor again?	No, never; Yes, several times more
H11: Required Complement	Receiving license/treatment requires more than one instructor/doctor?	No, Yes
Risk of Punishment		
H8: Detection	Probability police will catch bribe payment	1% chance, 10% chance, 20% chance
H9: First-Mover	Instructor/doctor hinted at bribe?	No, Yes
H10: Collective Action	Percent of other drivers/patients giving bribes at this school/clinic	0%, 25%, 50%

prior corruption research (e.g. Bertrand et al., 2007; Ryvkin & Serra, 2018).[14] For the driver's license scenario, we employed the following vignette: "Nina is tired of taking public transportation to work and wants a driver's license. When she goes to the driving school, the instructor, Ivan, informs her that there will be a considerable wait time to receive a license. Please read the additional information below about scenario A and scenario B and then indicate in which scenario – A or B – Nina would be more likely to pay a bribe in order to receive a license more quickly." The Ukrainian government mandates testing at official driving schools before granting licenses, and extensive anecdotal evidence indicates driving school instructors regularly take bribes to ease or accelerate passing of driving tests.[15] The parallel healthcare vignette reads as follows: "Petro has hurt his leg and needs a doctor. He goes to a state-run healthcare clinic. The doctor, Ruslana, informs him that there will be a considerable wait in order to receive treatment. Please read the additional information below about Scenario A and Scenario B and then indicate in which scenario – A or B – Petro would be more likely to pay a bribe in order to receive treatment more quickly." All names were randomized, using 40 common male and female names.[16]

Employing a paired conjoint design, the experiment sequentially showed eight screens. In each screen, respondents viewed and answered questions about a table that compared two side-by-side profiles. Each profile showed randomly assigned permutations of the 11 attributes in Table 2, which each operationalize one of the 11 hypotheses derived from our model.[17] Half of respondents were randomly assigned to first see four screens about the driver's license scenario and then four about the healthcare scenario; for the other half, the order was reversed. To further mitigate potential order effects, we randomized the order of attributes in conjoint tables shown to each respondent (while holding the order constant across all eight screens presented to a given respondent to facilitate comparison and reduce cognitive burden). Our paired conjoint design produces evaluations of 24,480

[14]In a 2015 national poll, 66% of Ukrainians considered the State Auto Inspectorate to be "very corrupt," tied with the judiciary as the most corrupt institution in Ukraine. Healthcare ranked fifth, rated by 58.0% of respondents as "very corrupt." See Kiev International Institute of Sociology, "Corruption in Ukraine: Comparative Analysis of National Surveys," 2015, p. 33 (http://kiis.com.ua/).

[15]See, e.g., Violetta Ryabko, " 'Vsya sistema postroena na unizhenii': pochemu tak tyazhelo poluchit prava, ne davaya vzyatku" [" 'The whole system is built on humiliation': Why it is so hard to get driver's licenses without giving a bribe"], *Afisha Daily*, March 16, 2021; Olesya Arkhipskaya, "Tenevoj rynok voditelskikh prav v Ukraine sostavlyet 17,5 mln doll." ["The 17.5 million dollar shadow market for driver's licenses in Ukraine"], *Internet Agency "Istochnik"*, January 22, 2019.

[16]Names were randomized both by gender and by Ukrainian versus Russian ethnicity. We find neither gender nor ethnicity of the official or citizen in vignettes affects respondents' answers.

[17]See Online Appendix Section B for a screenshot of the conjoint profiles. Recent research demonstrates no undue strain on subjects' cognitive capacity using 11 attributes; research finds estimates remain robust (Jenke et al., 2021) and survey satisficing minimal even with far more attributes (Bansak et al., 2021).

profiles for each of the two scenarios: per scenario, 3,060 subjects viewed four screens with two profiles each.

To assess respondents' beliefs about how institutional and situational attributes affect willingness to bribe, we employed several approaches. Our primary outcome variable asks respondents to assess whether the hypothetical citizen would be more likely to pay a bribe in scenario A or scenario B. One advantage of this paired design is that forcing respondents to make comparisons may sharpen concentration (Hainmueller et al. 2015, p. 2396; Hainmueller and Hopkins 2015, p. 533). Additionally, its focus on a hypothetical citizen reduces the question's sensitivity, mitigating potential concerns about social desirability bias.[18]

We also consider two secondary rating variables, each measured on a seven-point scale. After the forced-choice question, we asked respondents to rate each independent profile on the screen: "On a [7-point] scale from 'definitely no' to 'definitely yes,' how likely would Nina be to pay a bribe to the instructor [doctor] to receive the license [treatment] more quickly?" We do so in part because conjoint experiments commonly include a rating question after a forced-choice question as a robustness check (see, e.g., Hainmueller & Hopkins, 2015, p. 533), not least because rating questions circumvent debates about how to interpret forced-choice designs (Abramson et al., 2021).[19] Moreover, for our study it serves an additional purpose: it enables us to compare respondents' estimates of their *own* willingness to offer bribes with their estimates of the willingness of hypothetical citizens. Accordingly, we next posed the question: "Using the same scale, if you were in Nina's position, how likely would you be to pay a bribe to the instructor [doctor] to receive the license [treatment]

[18]Note our predictions pertain to how changes in attributes increase or decrease bribe activity, rather than to the aggregate level of bribery. To test our predictions, social desirability would only threaten inference in the unlikely case that certain combinations of attribute levels in the conjoint experiment trigger concerns about providing honest answers more than other combinations. Preliminary evidence also suggests conjoint designs generally reduce social desirability bias, making this threat unlikely (Horiuchi et al., 2021).

[19]See Costa (2021) for a similar discussion of using ratings in conjoint experiments.

more quickly?"[20] Ultimately, our use of multiple approaches to measurement reveals that results are robust across several similar yet distinct outcome indicators. Furthermore, it serves to balance concerns about the sensitivity of direct questions about respondents' own willingness to engage in illicit behavior with the important goal of ascertaining whether we glean insights about respondents when asking how they believe others will act.

3 Results

Figures 1 and 2 present our primary results for the driver's license and healthcare scenarios, respectively. All results are based on OLS regressions of the three outcome variables introduced in the preceding section on sets of indicator variables for each level of each attribute, omitting the reference categories, with standard errors clustered at the respondent level. Circles represent point estimates; lines represent 95% confidence intervals. Attribute levels without lines serve as reference categories.

Panel A in each figure shows results using the forced-choice conjoint design, in which respondents were asked in which of the paired profiles the hypothetical citizen would be more likely to bribe. Following Bansak et al. (2020) and Hainmueller et al. (2014), we estimate average marginal component effects (AMCEs), which reflect the average effect taken over all possible combinations of the other attributes in the corruption scenario. For the forced-choice question — our primary outcome variable — the AMCE estimates the change in probability that a citizen will bribe when a profile includes the indicated attribute level instead of its baseline level. Panels B and C, meanwhile, show results for our secondary outcome variables, involving ratings of how likely a hypothetical citizen and the respondent (respectively) would bribe, with the 7-point outcomes rescaled to range from 0 ("definitely no") to 1 ("definitely yes") for comparability with the forced choice design. For these two outcomes, the AMCE estimates the change in the rating when a profile includes the indicated attribute level instead of its baseline level.

[20]We did not present respondents with a forced-choice question about their own likeliness to bribe, given concerns respondents could be averse to a design in which refusing to bribe is not an option.

As is common in studies of corruption and other similarly illicit phenomena (see, e.g., Bicchieri & Fukui, 1999; Hoffmann & Patel, 2017), respondents on average indicate they are less likely to bribe than their peers (in this case, a hypothetical citizen). For the driver's license scenario, the mean rating for the hypothetical citizen was 0.60 versus 0.30 for respondents' rating of themselves; for the healthcare scenario, 0.60 versus 0.36. Despite differences in levels of hypothetical versus self ratings, respondent's hypothetical ratings significantly predict their self ratings for both scenarios.[21] We explore this point further with regards to specific predictions using conjoint analyses below.

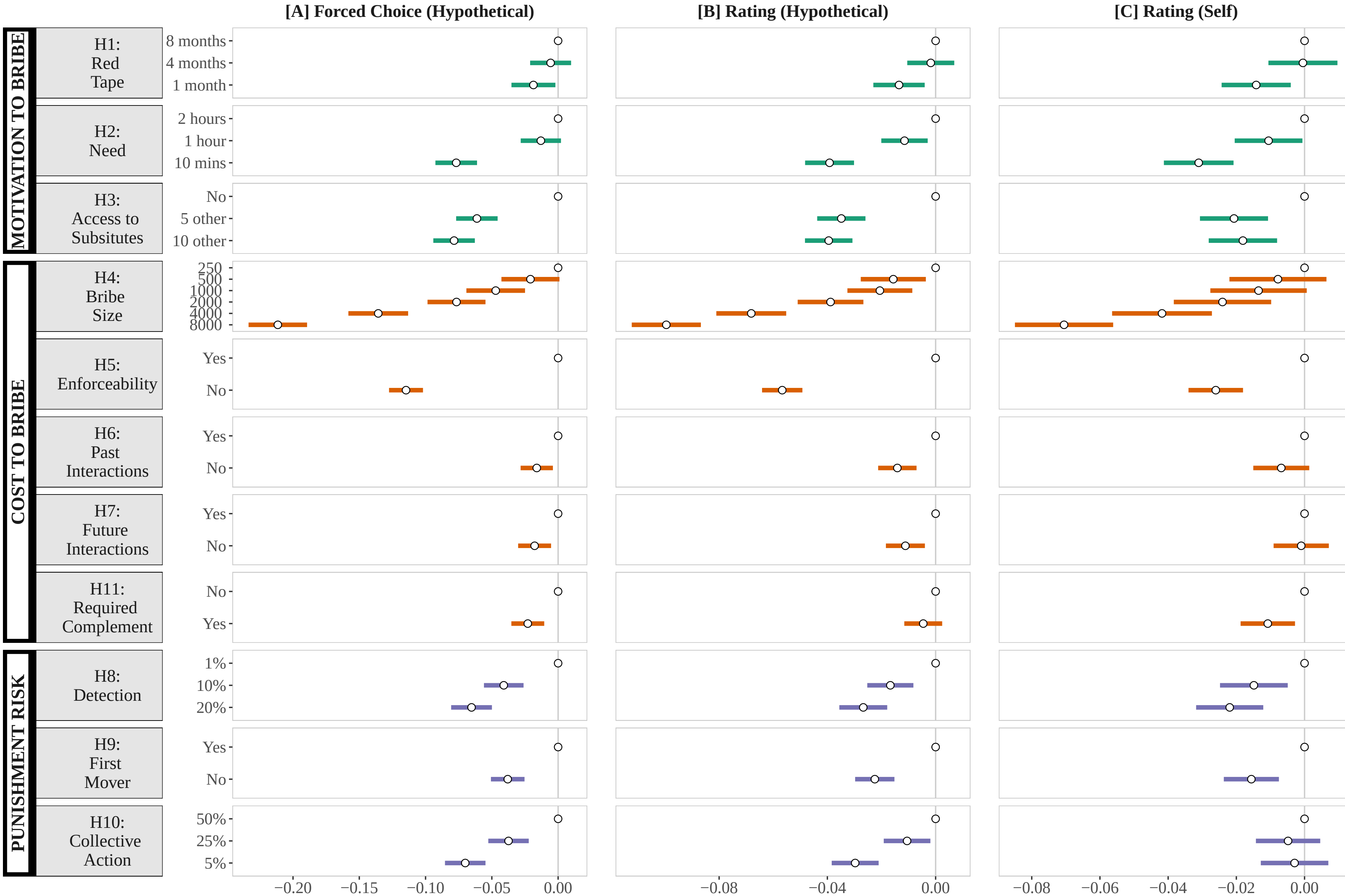
Motivation to Bribe

Findings in Figures 1 and 2 corroborate all three hypotheses that pertain to citizens' motivations for bribing. Consistent with H1, reducing red tape decreases citizens' bribery. For a driver's license, bribes are 1.9 percentage points ($p = .028$) less likely if the wait time is one month versus eight months, as can be seen in Panel A. And for healthcare, bribes are 1.6 percentage points ($p = .070$) less likely if the wait time is one day versus four months.[22] Meanwhile, Panels B and C show that our predictions for H1 are also confirmed using our secondary outcome variables, with substantially greater effect sizes for healthcare. Although red tape is a frequently cited motivation for bribing, its effects — though statistically significant and in line with predictions — are smaller than several other factors with the same number of attributes in Figures 1 and 2. For example, consider H2, which posits that bribery falls as citizens' need for services declines. Findings conform with theoretical expectations and are relatively large in magnitude. For a driver's license, bribes are 7.7 percentage points ($p < .001$) less likely if a citizen's commute without the license is 10 minutes versus two hours. And for healthcare, bribes are 5.6 percentage

[21]Pooling all attributes, a regression with respondent fixed effects shows that each 0.1 point increase in hypothetical ratings on the 1 point scale is associated with a 0.04 (0.05) point increase in respondents' self rating for the driver's license (healthcare) scenario; both are significant at the .001 level.

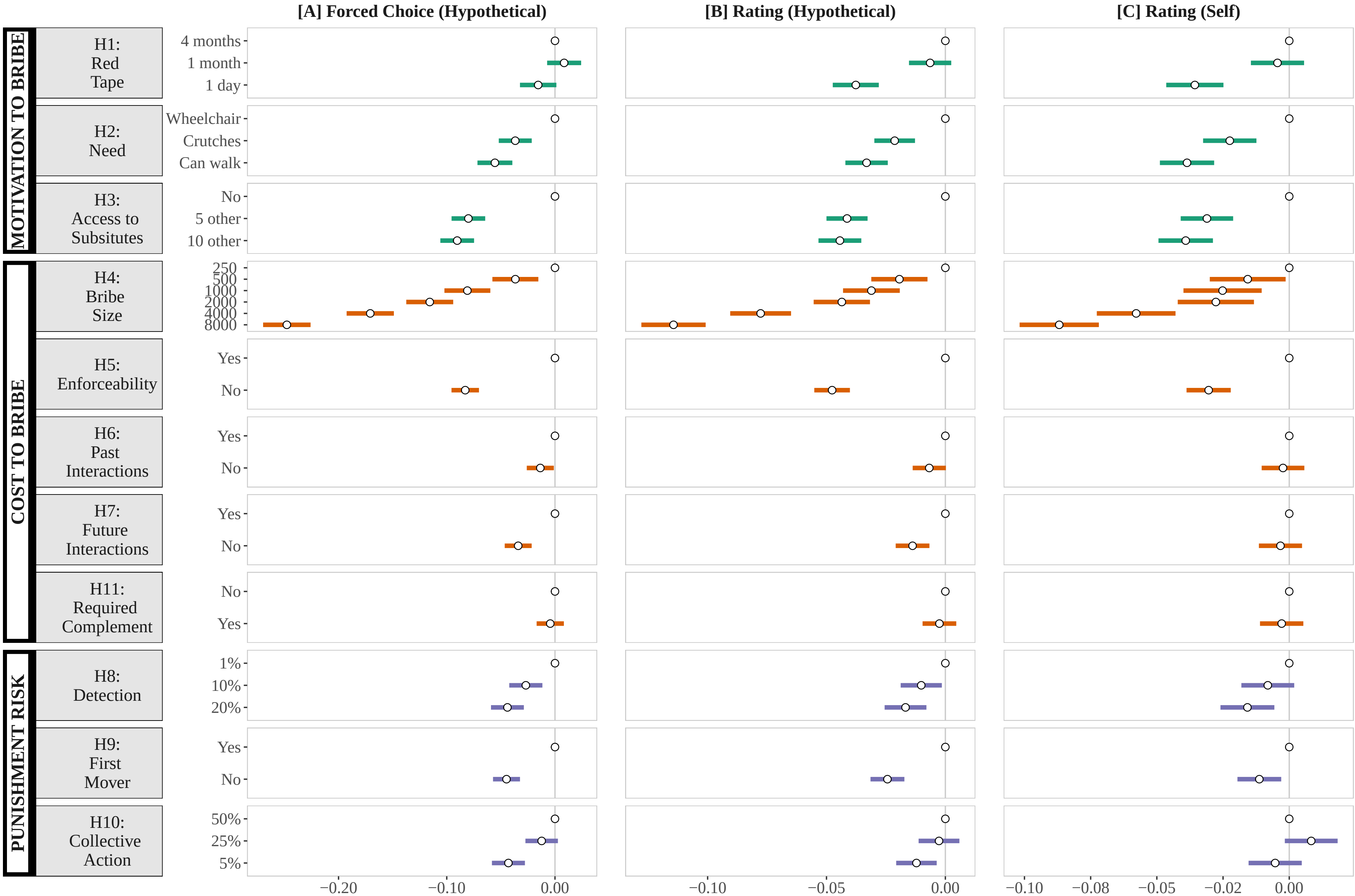
[22]All p-values reported are from two-tailed significance tests.

Figure 1: Conjoint Experiment: Driver's License Scenario (AMCE Estimates)



Note: Panel A shows our primary outcome measure using the forced-choice design. AMCEs in Panel A estimate the change in probability that a citizen will bribe when a profile includes the indicated attribute level instead of its baseline level. Panels B and C show secondary outcomes. For those panels, AMCEs estimate the change in the rating of how likely a hypothetical citizen and the respondent (respectively) would bribe, when a profile includes the indicated attribute level instead of its baseline level. Ratings are rescaled to range from 0 ("definitely no") to 1 ("definitely yes"). Estimates based on OLS regressions with standard errors clustered at the respondent level. Bars represent 95% confidence intervals. Points without lines denote attribute values serving as the reference category.

Figure 2: Conjoint Experiment: Healthcare Scenario (AMCE Estimates)



Note: Panel A shows our primary outcome measure using the forced-choice design. AMCEs in Panel A estimate the change in probability that a citizen will bribe when a profile includes the indicated attribute level instead of its baseline level. Panels B and C show secondary outcomes. For those panels, AMCEs estimate the change in the rating of how likely a hypothetical citizen and the respondent (respectively) would bribe, when a profile includes the indicated attribute level instead of its baseline level. Ratings are rescaled to range from 0 ("definitely no") to 1 ("definitely yes"). Estimates based on OLS regressions with standard errors clustered at the respondent level. Bars represent 95% confidence intervals. Points without lines denote attribute values serving as the reference category.

points ($p < .001$) less likely if a citizen is ambulatory versus in need of a wheelchair before receiving treatment. Again, results are consistent when using secondary outcome variables.

Findings also corroborate H3, which suggests that bribery decreases as access to substitutes rises, again with large effect sizes. For a driver's license, bribes are 7.8 percentage points ($p < .001$) less likely if a citizen can reach 10 alternative driving schools versus none. Similarly for healthcare, bribes are 9.0 percentage points ($p < .001$) less likely if a citizen can reach 10 alternative medical clinics versus none. Interestingly, the decrease in bribes from expanding access from no alternative schools (or clinics) to five is almost as large as that from expanding access from none to 10. Monopolization of service provision, rather than the number of alternative service providers, is what appears to affect citizens' propensity to engage in corruption.

Overall, results from the conjoint experiment conform with our model's predictions for all three factors pertaining to citizens' motivation to bribe: red tape, urgency of needing public services, and access to substitute service providers. Of these three factors, red tape appears to be relatively less consequential.

Costs to Bribe

Turning to our second set of theoretical predictions, experimental results support most hypotheses regarding costs of bribing. Consistent with H4, citizens' bribe choices are highly sensitive to information about the typical bribe size. As shown in Figures 1 and 2, results are comparable across both scenarios and robust across all three outcomes. For driver's licenses, bribes are 7.7 percentage points ($p < .001$) less likely if the bribe price is 2,000 versus 250 UAH (∼\$75 versus ∼\$10) — and 21.1 percentage points ($p < .001$) less likely if the bribe price is 8,000 versus 250 UAH (∼\$300 versus ∼\$10).[23] Effects are greater for healthcare: relative to the 250 UAH baseline, bribes are 11.6 percentage points ($p < .001$) less likely with a 2,000 UAH bribe price, and 24.8 percentage points ($p < .001$) less likely with an 8,000 UAH bribe price. While findings for bribe size conform with theoretical

[23] At the time of the study, 1 USD ≈ 28 UAH.

predictions, we consider results for this attribute to be suggestive; as discussed in Section 4, bribe price is the one attribute in the experiment for which we observe carryover effects.

Findings are also consistent with H5, which predicts that bribes fall as the enforceability of corrupt transactions declines. For the driver's license and healthcare scenarios, citizens are 11.5 and 8.3 percentage points, respectively, less likely to bribe when they are uncertain the official can guarantee to expedite service provision in exchange for informal payments. These effects are robust (with $p < .001$) across both scenarios for all three outcome variables. As mentioned, citizens may have concerns about officials' ability to commit to providing services when bribed, as parties engaging in illicit transactions cannot rely on formal institutions for resolving contract violations.

Section 1 discussed how reputational histories (H6) and expectations of ongoing future relationships (H7) are informal mechanisms than can mitigate this commitment problem. Evidence corroborates both predictions, though the magnitude of effects is relatively small. Having no past interactions with the official renders a bribe 1.6 percentage points ($p = .010$) less likely in the driver's license scenario — and 1.4 percentage points ($p = .034$) less likely in the healthcare scenario — than the baseline of having past interactions. If no future interactions with the official are expected, a bribe is 1.8 and 3.4 percentage points less likely for the driver's license and healthcare scenarios ($p = .005$ and $p < .001$), respectively, compared to the baseline of expecting future interactions. Findings for these two hypotheses are relatively less robust than others discussed: for both scenarios, they remain significant using only one of our secondary measures (the hypothetical but not self ratings).

Considering another factor that contributes to bribery costs, results only partially corroborate the model's prediction that bribery decreases when complementary services are required (H11). For a driver's license, the probability of a bribe falls by 2.3 percentage points ($p < .001$) when an additional instructor is required to receive the license. This finding also holds with one secondary measure; more specifically, with the self but not hypothetical ratings. For healthcare, no effects are observed with any outcome variables.

Altogether, the conjoint experiment provides strong support for many but not all hypotheses related to costs. For bribe size (H4) and enforceability (H5), predictions are confirmed at statistically significant levels using all three outcomes for both scenarios. For past interactions (H6) and future interactions (H7), predictions are confirmed with our primary outcome (i.e., forced-choice), as well as with one of two secondary outcomes. In contrast, the prediction for complementary services (H11) finds only mixed empirical support with one scenario.

Risks of Punishment

We now assess evidence about our final set of hypotheses, which involves punishment risks. The experiment confirms all three hypotheses, suggesting that even where corruption is endemic, citizens' bribe choices are influenced by factors emphasized by principal-agent approaches, such as institutional mechanisms for monitoring and punishing illicit behavior. Regarding the prediction that bribery falls as detection increases (H8), Figure 1 shows that for the driver's license scenario, bribes fall by 6.5 percentage points ($p < .001$) when there is a 20% instead of 1% chance that bribery will be detected. For healthcare, the effect is a 4.4 percentage point decline ($p < .001$) in bribes. Across all three outcome variables for both scenarios, results conform with predictions and are statistically significant.

Figures 1 and 2 also present evidence in favor of two other predictions concerning bribe-givers' risk of punishment. First, consider our "first mover" hypothesis (H9), which predicts citizens will be less likely to bribe when they are the initiator and thus face heightened risks. Consonant with this prediction, bribe payments are approximately 4 percentage points less likely when the instructor or doctor does not first hint at the need for a bribe.[24] These results are statistically significant across all three outcome variables for both scenarios.

Our final hypothesis predicts a citizen is more willing to bribe when others' bribery

[24]The effects are 3.8 percentage points ($p < .001$) and 4.5 percentage points ($p < .001$), respectively.

increases (H10), as argued by the collective action approach. This prediction finds considerable support, even when accounting for the numerous institutional and situational attributes incorporated in the experiment. For a driver's license, Figure 1 shows bribes fall by 7.0 percentage points ($p < .001$) when a citizen believes that 5% instead of 50% of her peers offer bribes at the driving school. For healthcare, Figure 2 shows a significant but more muted effect of 4.3 percentage points ($p < .001$) for this comparison. Results are robust when examining one secondary measure (the hypothetical but not self rating).

In summary, results from our conjoint experiment strongly support empirical predictions of our analytical framework. Using our preferred outcome variable based on the forced-choice design, analyses of the driver's license scenario reveal statistically significant corroboration for *all* 11 hypotheses, though the magnitude of effects varies. Similarly, for the healthcare scenario, analyses yield statistically significant results consistent with 10 of 11 hypotheses. Regarding our secondary measures, for both scenarios we observe statistically significant findings consistent with 10 of 11 hypotheses for the ranking of how likely it is that a hypothetical citizen would pay a bribe. Numerous statistically significant results also emerge for analyses based on direct questions about respondents' own willingness to bribe, although unlike the other two measurement approaches, results for self ratings are not robust for three hypotheses: "past interactions" (H6), "future interactions" (H7), and "collective action" (H10). Notably, all three of these hypotheses pertain to beliefs about whether other citizens' actions affect the bribe choices of a given individual. Arguably, while evidence suggests that respondents recognize the influence of social norms and expectations when considering others' behaviors, they may be less receptive to believing that they too are susceptible to such social influences.

Beyond the overall robustness of support for the analytical framework's predictions, our findings draw attention to institutional and situational factors' substantial impact: For the driver's license scenario, the probability of bribing is 21.1 percentage points lower for citizens who have access to 10 driving schools, expect no future interactions with the instructor, and are uncertain a bribe will expedite receipt of a license relative to citizens with baseline levels of these attributes. For the healthcare scenario, the comparable circumstances result in a 20.7 percentage point decrease in the probability of bribing.

The relative effect sizes of several institutional attributes in particular are also noteworthy. For both scenarios, we observe especially large magnitudes for the impact of access to substitutes (H3), expectations about typical bribe prices (H4), and uncertainty about whether officials will provide expedited services if bribed (H5). For the driver's license scenario, we observe large effects for risk of detection (H8) and for expectations about others' bribery (H10); however, these effects' magnitudes are smaller (though still significant) for the healthcare scenario. It may be that when confronted with health concerns, citizens prioritize timely service far more than when in need of a driver's license, perhaps even to the point of placing less emphasis on risks associated with corruption. It should be noted that our analyses are designed to test our pre-registered hypotheses — not to assess whether effect sizes are statistically different across attributes or scenarios.[25] Nevertheless, the observations in this paragraph suggest that a rigorous investigation of such differences and their underlying causes would be a worthy endeavor for future research.

Stepping back, broader results from the conjoint experiment across both scenarios are strikingly similar. As discussed below, further research should explore a wider range of public service sectors, but our largely comparable results across the driver's license and healthcare scenarios offer promising evidence with respect to generalizability.

4 Robustness Checks

To confirm our results' robustness, we assess: (1) diagnostic indicators for AMCE estimators, (2) whether respondents' attentiveness affects findings, and (3) whether results hold when limiting our sample to respondents who admit to personally paying a recent bribe.

Our first set of robustness checks follows Hainmueller et al. (2014)'s suggested diagnos-

[25] Additionally, Ganter (2021, p. 7) underscores that effect sizes of attributes with different numbers of levels are not directly comparable.

tics tests for the identification assumptions of the AMCE estimator. In particular, analyses in the Online Appendix examine whether subjects' responses are affected by the placement of paired profiles, or the order in which scenarios or profiles are shown. First, we confirm that profiles' placement does not affect responses: it does not matter whether profiles appear on the left or right side of the screen (see Table C.1). Furthermore, we confirm responses are not influenced by whether subjects view the driver's license or healthcare scenarios first (Table C.2). We detect modest carryover effects; i.e., the order in which subjects view profiles in a scenario affects some responses (Table C.3). To demonstrate robustness, we show that results are similar if we only use data from the first screen viewed by each respondent (Figure C.1). Analyses demonstrate carryover effects stem from one attribute — bribe prices — presumably because prices viewed on the first screen serve as a reference point for prices shown subsequently.[26]

Second, given we recruited subjects via Facebook, we also examine whether inattentive subjects might influence our results. Following Berinsky et al. (2014)'s recommendations, we included screener questions to measure attentiveness, but do not exclude respondents who failed screeners from main results. For each of two screener questions, approximately 60 percent of respondents answered correctly. As shown in the Online Appendix, if we limit analyses to attentive subjects, the magnitude of effects is generally amplified and findings are even more significant (Figures C.2 and C.3).

Finally, we investigate the experimental realism of our study by examining the subset of respondents who admitted paying a bribe in the past 12 months. If findings only hold among citizens with no such experience, one might be concerned they reflect stereotypes absorbed from secondhand reports about corruption, with potentially little relation to actual behavior. Much to the contrary, we find that qualitatively similar patterns hold among respondents who admitted paying a recent bribe (Figures C.4 and C.5).[27]

[26] No carryover effects are observed, and all other results hold, in analyses omitting the bribe price attribute.

[27] Of 3,060 overall respondents, 1,694 (55 percent) reported interacting with a public official in the past 12 months. Of these, 448 (29 percent) admitted to paying a bribe.

5 Discussion

The present study integrates insights from principal-agent and collective action approaches to corruption to investigate an important, understudied question: Why do people choose to bribe in some situations, but not in others? Even in countries where corruption is endemic, few people always pay bribes. Our analytical framework yields 11 hypotheses about how motivations, costs and risks explain in part why citizens often make distinct, context-specific choices about engaging in selective bribery.

Our conjoint experiment in Ukraine largely corroborates these hypotheses, which we derive from formal analysis. Indeed, all 11 hypotheses are confirmed when we show respondents paired scenarios and ask them to choose when a hypothetical citizen would be more likely to pay a bribe for an expedited driver's license. Similarly, 10 of 11 hypotheses are confirmed when we present respondents with paired scenarios involving bribes for expedited medical treatment. Consistent with our model's predictions regarding motivations, the conjoint experiment shows that respondents pay fewer bribes when a service: (a) can be obtained with minimal red tape; (b) is less urgently needed; and (c) can be obtained from multiple providers. In line with predictions for costs, respondents pay fewer bribes when: (a) expected bribe prices are high; (b) they are uncertain bribe takers will fulfill promises to provide preferential treatment; (c) they have no prior interactions with an official; (d) they expect no future interactions with an official; and (e) they must obtain additional permits or signatures. And consonant with predictions for risks, respondents pay fewer bribes when: (a) the probability of detection by authorities increases; (b) an official does not proactively request bribes; and (c) they believe that few other citizens engage in corruption. Furthermore, these findings are mostly robust when using secondary outcome variables.

These results are particularly illuminating because a more nuanced understanding of why individuals choose to pay or not pay bribes — and how this decision is sensitive to context — is crucial for developing effective institutional reforms to combat corruption.

Notwithstanding the importance of fighting corruption by transforming citizens' norms and values (e.g., through educational campaigns), many practitioners suggest that institutional reforms may be more feasible in the short run: a perspective pithily summarized by the suggestion to "reform situations rather than people" (Miller, 2006, p. 378). Yet many such measures proposed or even employed by anti-corruption experts have faced minimal empirical scrutiny (Gans-Morse et al., 2018), especially with regards to their proposed mechanisms for changing citizens' behavior. By rigorously testing how particular factors can reduce citizens' propensity to pay bribes, the present study sheds light on numerous levers that may be effectively applied through institutional reforms.

To illustrate, consider that our results offer empirical support for a number of common policy prescriptions. Some findings, such as the importance of increasing the risk of detection by authorities, may hold little promise in countries with endemic corruption, given that law enforcement and others tasked with oversight may themselves be corrupt. But other findings suggest policies that should be feasible to implement even where corruption is widespread. With respect to motivations for bribing, the impact of long wait times and the lack of alternative public service providers point to the importance of reducing red tape and limiting monopolistic service provision, although we find red tape's effects to be smaller than might be expected. In terms of bribery costs, our study also offers support to Lambsdorff and Teksoz's (2005, p. 149) suggestion that reforms should be designed to "aggravate the enforcement of corrupt deals" via measures such as conflict of interest policies that undermine long-term relationships. For instance, our finding that repeated interactions between citizens and officials increase propensity to bribe suggests that regularly rotating public employees across geographic or functional postings may be well-founded. Yet another example of how our study sheds empirical light on potential policy levers: our respondents' sensitivity to bribe prices suggests it may be worth exploring informational campaigns to drive up citizens' beliefs about how expensive it is to bribe officials.

Moreover, the present study offers a fruitful research agenda for further investigation of factors that influence citizens' propensity to give bribes. One important avenue is to explore how corruption might lead citizens to forgo public services, perhaps by using conjoint experiments that provide respondents that option, instead of just a binary decision about whether to bribe. Some anti-corruption measures that reduce citizens' willingness to bribe may potentially also reduce willingness to seek public services, raising difficult but intriguing questions about whether some corrupt behavior should be tolerated in order to limit the outright marginalization of citizens who might otherwise avoid interactions with public officials. Second, further research should explore the role of incomplete or uncertain information in citizens' bribe decisions. Realistically, citizens seeking public services may not have as much information about the institutional context and other factors as provided in our experiment. Another productive line of research would involve comprehensive analyses of potential variation in institutional and situational factors' effects on bribe-giving across policy domains. As noted above, strikingly similar results across the driver's license and healthcare scenarios in our conjoint experiment offer promising evidence with regards to generalizability, but broader testing is an important next step.

Ultimately, as researchers and practitioners have increasingly recognized in recent years, corruption persists not only because public officials take bribes, but also because citizens are willing to pay them. Our study demonstrates that unpacking this demand side of bribery can further our understanding of why corruption occurs, as well as inform policy debates about anti-corruption reforms.

References

Abramson, S. F., Koçak, K., & Magazinnik, A. (2021). What do we learn about voter preferences from conjoint experiments? [https://www.korhankocak.com/publication/cp/CP.pdf].

Bansak, K., Hainmueller, J., Hopkins, D. J., & Yamamoto, T. (2020). Using conjoint experiments to analyze elections: The essential role of the average marginal component effect (AMCE). *SSRN Electronic Journal*.

Bansak, K., Hainmueller, J., Hopkins, D. J., & Yamamoto, T. (2021). Beyond the breaking point? Survey satisficing in conjoint experiments. *Political Science Research and Methods*, *9*(1), 53–71.

Banuri, S., & Eckel, C. (2015). Cracking down on bribery. *Social Choice and Welfare*, *45*(3), 579–600.

Berinsky, A. J., Margolis, M. F., & Sances, M. W. (2014). Separating the shirkers from the workers? Making sure respondents pay attention on self-administered surveys. *American Journal of Political Science*, *58*(3), 739–753.

Bertrand, M., Djankov, S., Hanna, R., & Mullainathan, S. (2007). Obtaining a driver's license in India: An experimental approach to studying corruption. *The Quarterly Journal of Economics*, *122*(4), 1639–1676.

Bicchieri, C., & Fukui, Y. (1999). The great illusion: Ignorance, informational cascades, and the persistence of unpopular norms. *Business Ethics Quarterly*, *9*(1), 127–155.

Corbacho, A., Gingerich, D. W., Oliveros, V., & Ruiz-Vega, M. (2016). Corruption as a self-fulfilling prophecy: Evidence from a survey experiment in Costa Rica. *American Journal of Political Science*, *60*(4), 1077–1092.

Costa, M. (2021). Ideology, not affect: What Americans want from political representation. *American Journal of Political Science*, *65*(2), 342–358.

Erlich, A., & Gans-Morse, J. (2022). Making Anti-Corruption Information Campaigns Work: Evidence from Three Experiments in Ukraine [McGill University & Northwestern University Working Paper].

Fisman, R., & Golden, M. (2017). *Corruption: What everyone needs to know*. Oxford University Press.

Fried, B. J., Lagunes, P., & Venkataramani, A. (2010). Corruption and inequality at the crossroad: A multimethod study of bribery and discrimination in Latin America. *Latin American Research Review*, *45*(1), 76–97.

Gans-Morse, J., Borges, M., Makarin, A., Mannah-Blankson, T., Nickow, A., & Zhang, D. (2018). Reducing bureaucratic corruption: Interdisciplinary perspectives on what works. *World Development*, *105*, 171–188.

Ganter, F. (2021). Identification of preferences in forced-choice conjoint experiments: Reassessing the quantity of interest. *Political Analysis*, 1–15 (FirstView).

Hainmueller, J., Hangartner, D., & Yamamoto, T. (2015). Validating vignette and conjoint survey experiments against real-world behavior. *Proceedings of the National Academy of Sciences*, *112*(8), 2395–2400.

Hainmueller, J., & Hopkins, D. J. (2015). The hidden American immigration consensus: A conjoint analysis of attitudes toward immigrants. *American Journal of Political Science*, *59*(3), 529–548.

Hainmueller, J., Hopkins, D. J., & Yamamoto, T. (2014). Causal inference in conjoint analysis: Understanding multidimensional choices via stated preference experiments. *Political Analysis*, *22*(1), 1–30.

Hoffmann, L. K., & Patel, R. N. (2017). Collective action on corruption in Nigeria: A social norms approach to connecting society and institutions [Chatham House Report (May 2017)].

Horiuchi, Y., Markovich, Z., & Yamamoto, T. (2021). Does conjoint analysis mitigate social desirability bias? *Political Analysis*, 1–15 (FirstView).

Hunt, J. (2010). Bribery in health care in Uganda. *Journal of Health Economics*, *29*(5), 699–707.

Hunt, J., & Laszlo, S. (2005). Bribery: Who pays, who refuses, what are the payoffs? [National Bureau of Economic Research Working Paper 11635].

Incerti, T. (2020). Corruption information and vote share: A meta-analysis and lessons for experimental design. *American Political Science Review*, *114*(3), 761–774.

Jenke, L., Bansak, K., Hainmueller, J., & Hangartner, D. (2021). Using eye-tracking to understand decision-making in conjoint experiments. *Political Analysis*, *29*(1), 75–101.

Kaufmann, D., & Wei, S.-J. (1999). Does "grease money" speed up the wheels of commerce? [National Bureau of Economic Research Working Paper 7093].

Klitgaard, R. (1988). *Controlling corruption*. University of California Press.

Lambsdorff, J. G. (2002). Making corrupt deals: Contracting in the shadow of the law. *Journal of Economic Behavior & Organization*, *48*(3), 221–241.

Lambsdorff, J. G., & Teksoz, S. U. (2005). Corrupt relational contracting. In J. G. Lambsdorff, M. Taube, & M. Schramm (Eds.), *The new institutional economics of corruption* (pp. 138–151). New York, NY: Routledge.

Miller, W. L. (2006). Corruption and corruptibility. *World Development*, *34*(2), 371–380.

Mocan, N. (2008). What determines corruption? International evidence from microdata. *Economic Inquiry*, *46*(4), 493–510.

Mungiu-Pippidi, A. (2006). Corruption: Diagnosis and treatment. *Journal of Democracy*, *17*(3), 86–99.

Olken, B. A., & Pande, R. (2012). Corruption in developing countries. *Annual Review of Economics*, *4*(1), 479–509.

Persson, A., Rothstein, B., & Teorell, J. (2013). Why anticorruption reforms fail – systemic corruption as a collective action problem. *Governance*, *26*(3), 449–471.

Rose-Ackerman, S. (1978). *Corruption: A study in political economy*. New York, NY: Academic Press.

Rose-Ackerman, S. (1990). *Corruption and government: Causes, consequences, and reform* (First edition). Cambridge University Press.

Rothstein, B. (2011). Anti-corruption: The indirect 'big bang' approach. *Review of International Political Economy*, *18*(2), 228–250.

Ryvkin, D., & Serra, D. (2018). Corruption and competition among bureaucrats: An experimental study. *Journal of Economic Behavior & Organization*, *175*, 439–451.

Serra, D. (2012). Combining top-down and bottom-up accountability: Evidence from a bribery experiment. *The journal of law, economics, & organization*, *28*(3), 569–587.

Shleifer, A., & Vishny, R. W. (1993). Corruption. *The Quarterly Journal of Economics*, *108*(3), 599–617.

Svensson, J. (2003). Who must pay bribes and how much? Evidence from a cross section of firms. *The Quarterly Journal of Economics*, *118*(1), 207–230.

Svensson, J. (2005). Eight questions about corruption. *Journal of Economic Perspectives*, *19*(3), 19–42.

Swamy, A., Knack, S., Lee, Y., & Azfar, O. (2001). Gender and corruption. *Journal of Development Economics*, *64*(1), 25–55.

Treisman, D. (2007). What have we learned about the causes of corruption from ten years of cross-national empirical research? *Annual Review of Political Science*, *10*, 211–244.

Truex, R. (2011). Corruption, attitudes, and education: Survey evidence from Nepal. *World Development*, *39*(7), 1133–1142.

Online Appendix
"Selective Bribery: When Do Citizens Engage in Corruption?"

A Survey Descriptive Statistics and Population Benchmarks **1**

B Screenshot of Conjoint Profiles **3**

C Robustness Tests **4**

C.1 Diagnostic Tests of Identification Assumptions 4

C.2 Attentiveness 5

C.3 Experimental Realism 5

D Proofs **11**

E Pre-Analysis Plan **20**

A Survey Descriptive Statistics and Population Benchmarks

This section provides descriptive statistics for our survey sample and, where possible, population benchmarks from 2021 census extrapolations estimated by the Census Bureau of the State Statistics Service of Ukraine.[1] Our analyses include data from all respondents who completed at least 90 percent of the survey instrument and who reported being located in Ukraine at the time of the survey, which yields an N of 3,060.[2]

While we make no claims regarding representativeness, our sample includes a wide range of demographic groups. The sample is 52% male versus 48% female. Respondents' ages are distributed normally, with a mean and median age of 48 and 49, respectively. Overall, relative to Ukraine's population, the sample slightly overrepresents males and underrepresents young and elderly citizens. Subjects' self-reported place of residence is not limited to the capital (Kyiv) or other large cities: 33% indicated living in a small city or town and 19% in a village or rural area. The sample also displayed considerable geographic diversity, including many respondents from all of Ukraine's regional administrative units (excluding Russian-occupied Crimea). While there are disproportionately fewer respondents from the east, this may reflect the inability of recent census extrapolations to properly account for internal migration resulting from the war in Donbas that has been ongoing since 2014.

Table A.1: Benchmarking Survey Sample to Census Data

	Census		Survey	
	N	%	N	%
Gender				
Men	15,353,209	45.2%	1,576	51.5%
Women	18,605,831	54.8%	1,482	48.5%
Age groups				
18-29	5,300,461	15.6%	327	10.7%
30-39	6,849,855	20.2%	501	16.4%
40-49	6,079,955	17.9%	829	27.2%
50-59	5,607,145	16.5%	729	23.9%
60-69	5,286,715	15.6%	524	17.2%
70 and older	4,834,909	14.2%	142	4.7%
Regions				
East	11,747,035	40.3%	768	25.1%
North/Central	8,317,520	28.5%	1,277	41.7%
South	2,996,401	10.3%	297	9.7%
West	6,078,390	20.9%	718	23.5%

Note: Census data are from the January 1, 2021 census extrapolations conducted by the Census Bureau of the State Statistics Service of Ukraine.

[1] We rely on extrapolations because Ukraine has not conducted a census since 2001.

[2] The difference between completing 90 percent and fully completing the survey was whether respondents clicked through the final informational screens. All but 83 respondents fully completed the survey.

Table A.2: Additional Descriptive Statistics from Survey Sample

		N	%
City Size	Capital (Kyiv)	509	16.6%
	Large City	1,055	34.5%
	Small City	957	31.3%
	Village/Rural	538	17.6%
	DK/RA	1	0.0%
Education	B.A or higher	2,281	74.5%
	Secondary or Less	263	8.6%
	Technical/Professional Degree	515	16.8%
	DK/RA	1	0.0%
Income	< 2,500 hryvna	502	16.4%
	2,500-4,999 hryvna	699	22.8%
	5,000-9,999 hryvna	929	30.4%
	10,000-14,999	456	14.9%
	15,000-19,999 hryvna	191	6.2%
	20,000-29,999 hryvna	118	3.9%
	>= 30,000 hryvna	147	4.8%
	DK/RA	18	0.6%
Native Language	Other Language	26	0.8%
	Russian	483	15.8%
	Ukrainian	1,636	53.5%
	Ukrainian/Russian equally	914	29.9%
	DK/RA	1	0.0%
Survey Language	Russian	1,118	36.5%
	Ukrainian	1,942	63.5%
Any Contact w/ Officials	No	1,011	33.0%
	Yes	1,694	55.4%
	DK/RA	355	11.6%
Bribed Official	No	1,244	40.7%
	Yes	448	14.6%
	No Contact	1,011	33.0%
	DK/RA	357	11.7%

B Screenshot of Conjoint Profiles

Screen Shot of Profiles for Medical Scenario (in Ukrainian)

Уявіть, будь ласка, таку ситуацію. **Федора Мізенова** травмувала ногу. Їй необхідний лікар. Вона прийшла до державної поліклініки. Її прийняла лікар **Світлана Чаркова**. Вона повідомила, що зачекати треба буде досить довго. Будь ласка, прочитайте додаткову інформацію про сценарії А та Б нижче. **Потім вкажіть в якому з цих двох сценаріїв Федора Мізенова з більшою ймовірністю дасть хабар лікарю за швидший прийом.**

	Сценарій А	Сценарій Б
Чи є інші поліклініки для лікування поруч	Так, 10 інших поліклінік	Так, 5 інших поліклінік
Відсоток пацієнтів, які дають хабарі у цій поліклініці	50%	50%
Чи звертався(лась) до того ж лікаря в минулому?	Так, вже кілька разів	Так, вже кілька разів
Шанс бути спійманим поліцією на хабарі	Шанс 10%	Шанс 1%
Чи натякнув лікар на хабар?	Ні	Ні
Чи буде звертатися ще раз до того ж лікаря?	Так, ще кілька разів	Так, ще кілька разів
Типовий розмір хабаря	500 грн	4000 грн
Чи необхідний для лікування ще один лікар?	Так	Так
Серйозність травми	Може пересуватись	Може пересуватись з милицями
Час очікування без хабаря	1 місяць	1 день
Чи точно хабар прискорить лікування?	Так, точно	Так, точно

	Сценарій А	Сценарій Б
В якому з цих двох сценаріїв Федора Мізенова з більшою ймовірністю дасть хабар?	◉	○

Будь ласка, дайте відповідь на кожне з наступних запитань відносно Сценарію А та Сценарію Б.

	Сценарій А	Сценарій Б
За шкалою від «абсолютно так» до «абсолютно ні», яка ймовірність, що Федора Мізенова дасть хабар лікарю, щоб пришвидшити час прийому?	Скоріше всього ні	Абсолютно так
За тією самою шкалою, якби Ви були на місці Федори Мізенової, яка була б ймовірність, що Ви дасте хабар лікарю, щоб пришвидшити час прийому?	Напевно так	Напевно ні

C Robustness Tests

C.1 Diagnostic Tests of Identification Assumptions

Following Hainmueller et al. (2014), we conduct diagnostic tests for the identification assumptions of the AMCE estimator. First, we confirm profiles' placement does not affect responses: it does not matter whether profiles appear on the left or right side of the screen. As observed in Table C.1, ANOVA tests show no evidence of statistically significant differences resulting from profile placement. This is true for tests including the full set of profiles and for tests when we subset the data based on whether the driver's license or medical scenario was shown first. Second, we consider the possibility that viewing scenarios related to one sphere of corruption biases respondents' answers for scenarios related to a distinct sphere of corruption. Table C.2 shows no statistically significant effects; that is, we confirm responses are not influenced by whether subjects view the driver's license or healthcare scenarios first. Third, we investigate in Table C.3 whether the order in which subjects view profiles in a scenario affects responses. We observe some evidence of carryover effects, more so for the driver's license scenario (see odd-numbered rows). The effect is concentrated in the first scenario viewed by subjects (compare rows 3-6). Further inspection of marginal means by task order suggests these effects stem from one attribute: bribe prices. An ANOVA test confirms no carryover effects once bribe price is removed from the model. We posit these effects exist because prices viewed on the first screen serve as a reference point for prices shown subsequently. To demonstrate robustness to these carryover effects, we show results are similar if we only use data from the first screen viewed by each respondent (Figure C.1). Furthermore, findings for all other attributes hold in analyses omitting the bribe price attribute. This robustness is expected: given attribute levels were randomized independently, carryover effects on one attribute in expectation would not affect overall results.

Table C.1: Profile Order Effects

Scenario	F	Pr(>F)
Driver's License Scenario (All)	1.020	0.433
Healthcare Scenario (All)	1.138	0.298
Driver's License (Driver's License 1st)	0.836	0.677
Healthcare Scenario (Driver's License 1st)	1.123	0.314
Driver's License (Healthcare 1st)	0.688	0.849
Healthcare Scenario (Healthcare 1st)	1.104	0.334

Table C.2: Conjoint Order Effects

Scenario	F	Pr(>F)
Driver's License Scenario	1.023	0.430
Healthcare Scenario	1.151	0.285

Table C.3: Carryover Effects

Scenario	F	Pr(>F)
Driver's License Scenario (All)	1.764	0.000
Healthcare Scenario (All)	1.314	0.049
Driver's License Scenario (Driver's License 1st)	1.615	0.002
Healthcare Scenario (Healthcare 1st)	1.225	0.109
Driver's License Scenario (Driver's License 2nd)	1.239	0.097
Healthcare Scenario (Healthcare 2nd)	0.941	0.609

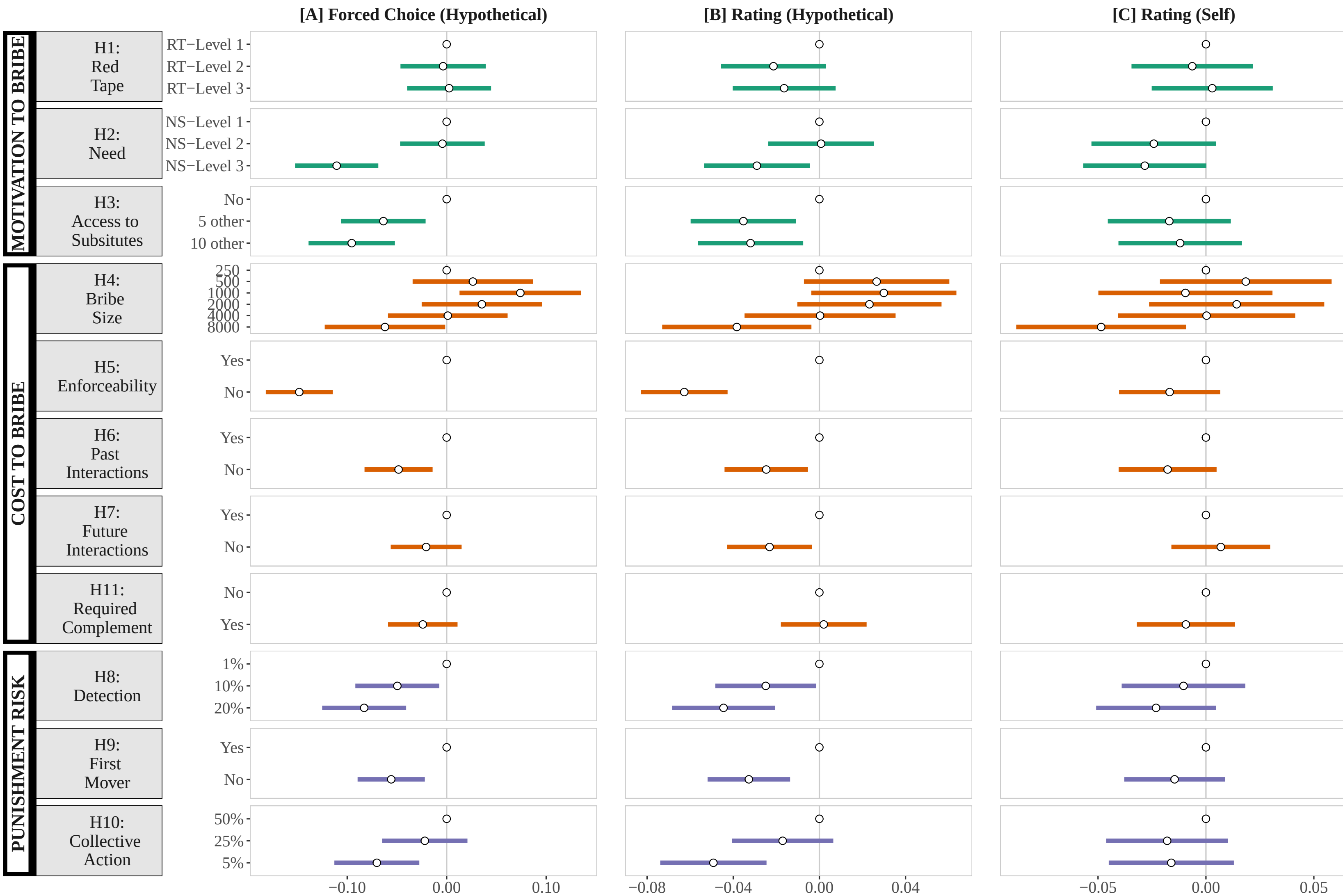
C.2 Attentiveness

Following Berinsky et al. (2014), we employed two screener questions to measure subjects' attentiveness. The first, a translation of the screener shown in Figure S1 in Section 2 of Berinsky et al.'s (2014) Online Appendix, was asked directly before the conjoint scenarios. The second, based on the screener shown in Figure S2 in Section 2 of Berinsky et al.'s (2014) Online Appendix, was asked after the conjoint scenarios. In our sample, 60% answered the first screener correctly and 59% answered the second correctly. These rates are comparable to the passage rates in studies discussed by Berinsky et al. (2014, p. 745). Most importantly, Figures C.2 and C.3 show that limiting our analyses to respondents who passed the first screener — i.e., the screener preceding the conjoint experiment — the magnitude of effects is generally amplified and even more findings are significant.

C.3 Experimental Realism

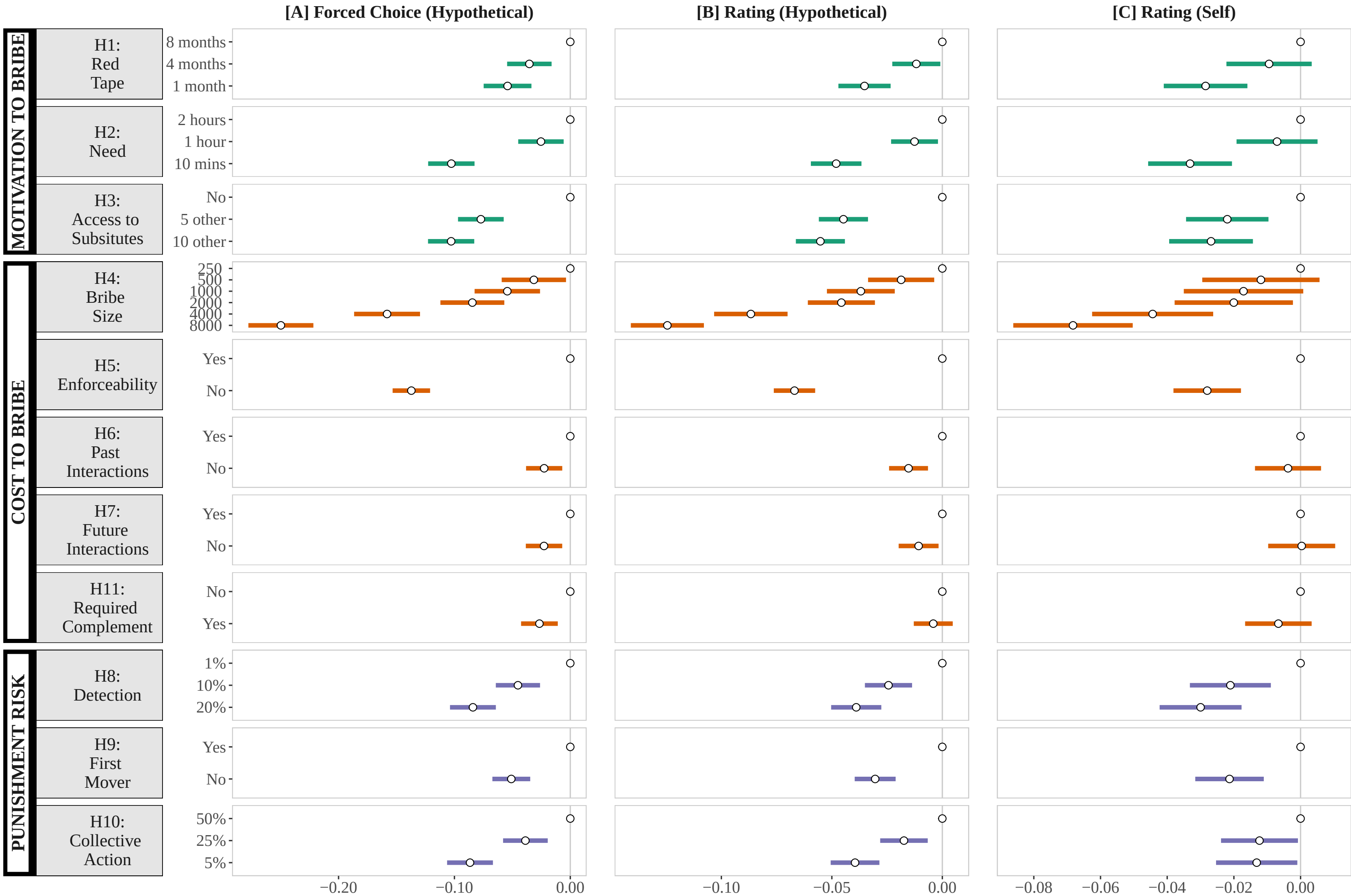
Of our 3,060 respondents, 1,694 reported interacting with public officials in the past 12 months. Of these, 448 admitted to paying a bribe. To investigate the experimental realism of our study, we re-conducted our analyses on this subset of 448 respondents, who have recent firsthand experience with bribe-giving. As shown in Figures C.4 and C.5, results based on this subset are qualitatively similar to those based on the full sample.

Figure C.1: AMCE Estimates: First Task Only Pooled for Both Scenarios



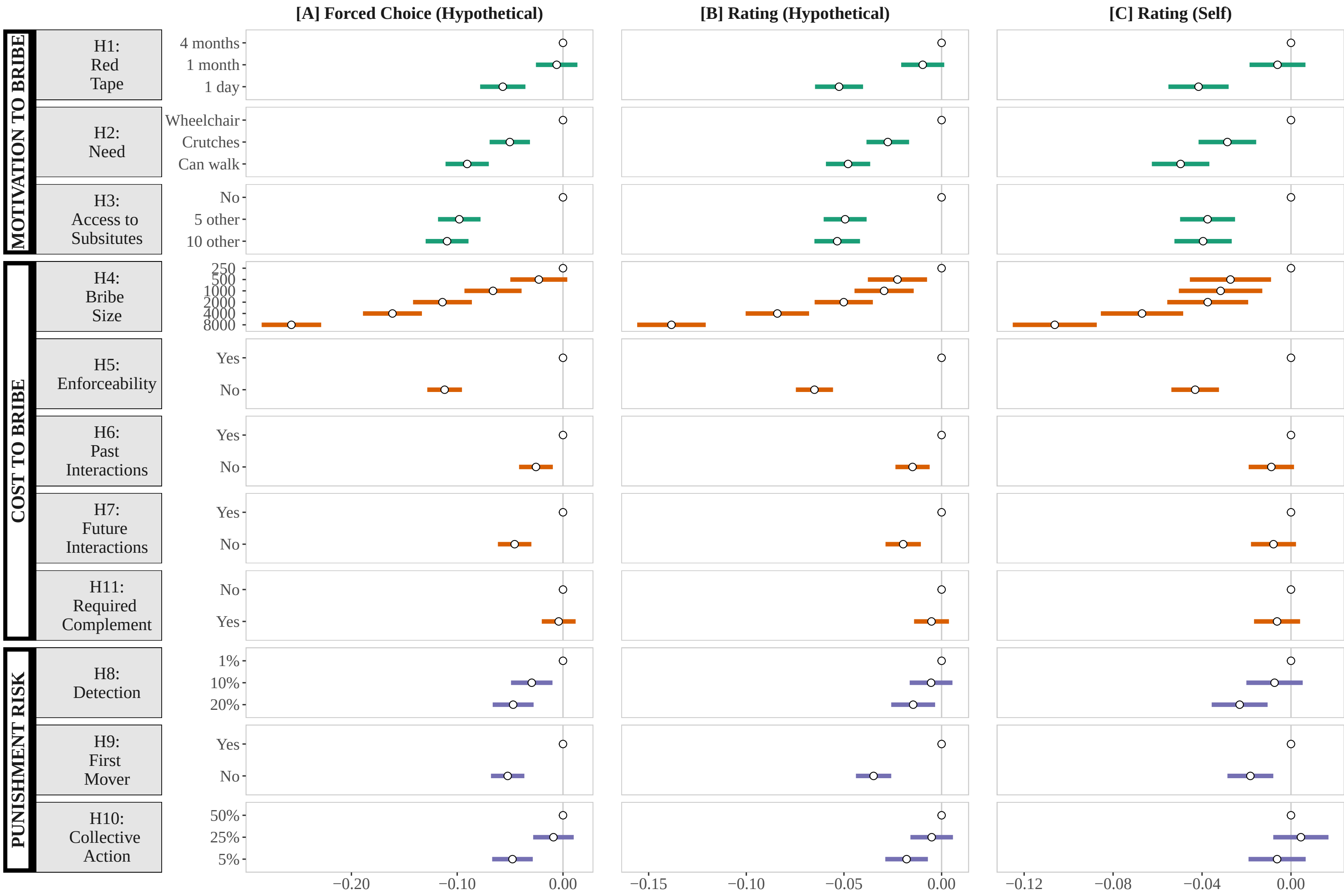
Note: Panel A shows our primary outcome measure using the forced-choice design. AMCEs in Panel A estimate the change in probability that a citizen will bribe when a profile includes the indicated attribute level instead of its baseline level. Panels B and C show secondary outcomes. For those panels, AMCEs estimate the change in the rating of how likely a hypothetical citizen and the respondent (respectively) would bribe, when a profile includes the indicated attribute level instead of its baseline level. Ratings are rescaled to range from 0 ("definitely no") to 1 ("definitely yes"). Estimates based on OLS regressions with standard errors clustered at the respondent level. Bars represent 95% confidence intervals. Points without lines denote attribute values serving as the reference category.

Figure C.2: AMCE Estimates for Attentive Only: Driver's License Scenario



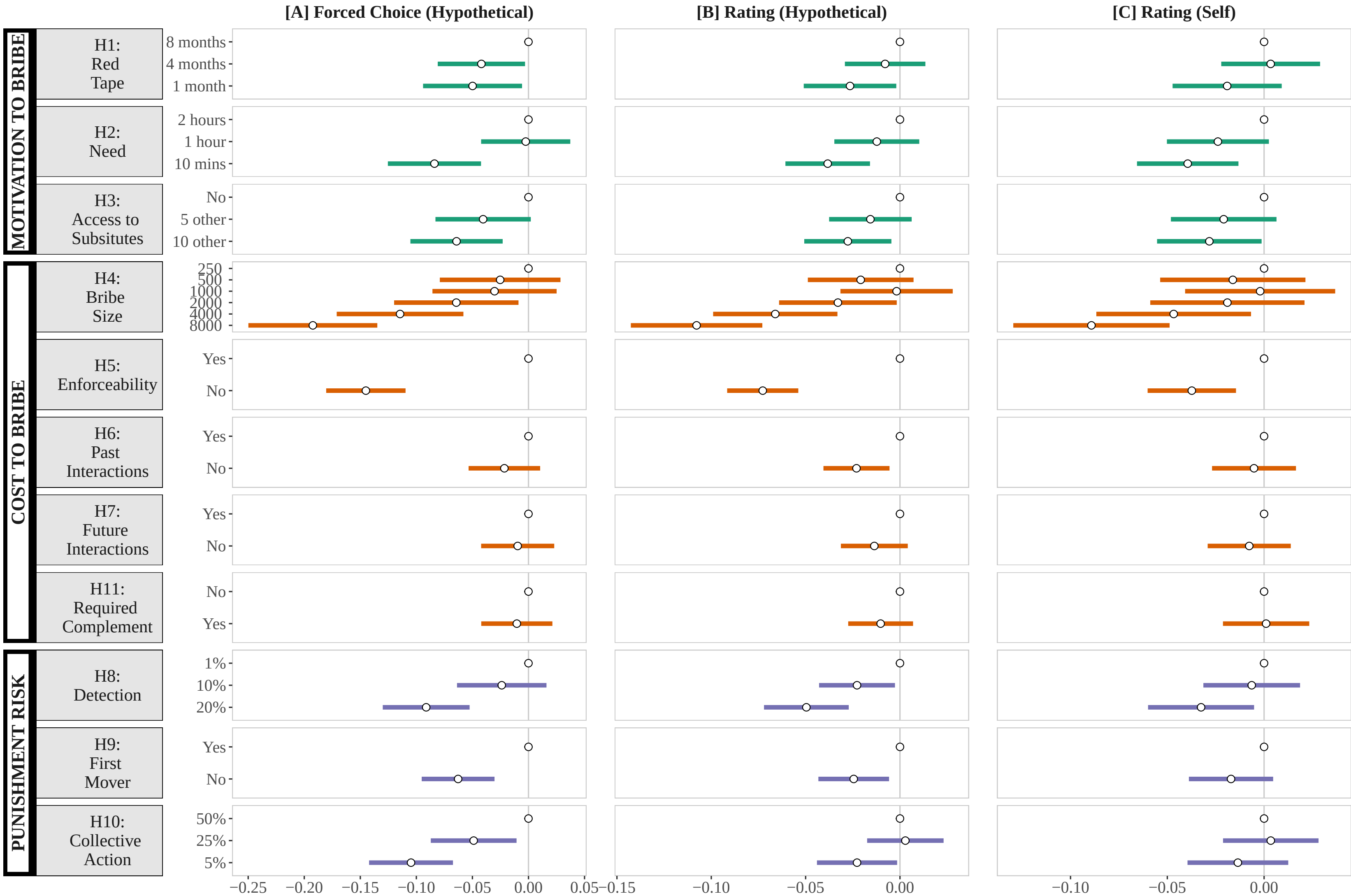
Note: Panel A shows our primary outcome measure using the forced-choice design. AMCEs in Panel A estimate the change in probability that a citizen will bribe when a profile includes the indicated attribute level instead of its baseline level. Panels B and C show secondary outcomes. For those panels, AMCEs estimate the change in the rating of how likely a hypothetical citizen and the respondent (respectively) would bribe, when a profile includes the indicated attribute level instead of its baseline level. Ratings are rescaled to range from 0 ("definitely no") to 1 ("definitely yes"). Estimates based on OLS regressions with standard errors clustered at the respondent level. Bars represent 95% confidence intervals. Points without lines denote attribute values serving as the reference category.

Figure C.3: AMCE Estimates for Attentive Only: Healthcare Scenario



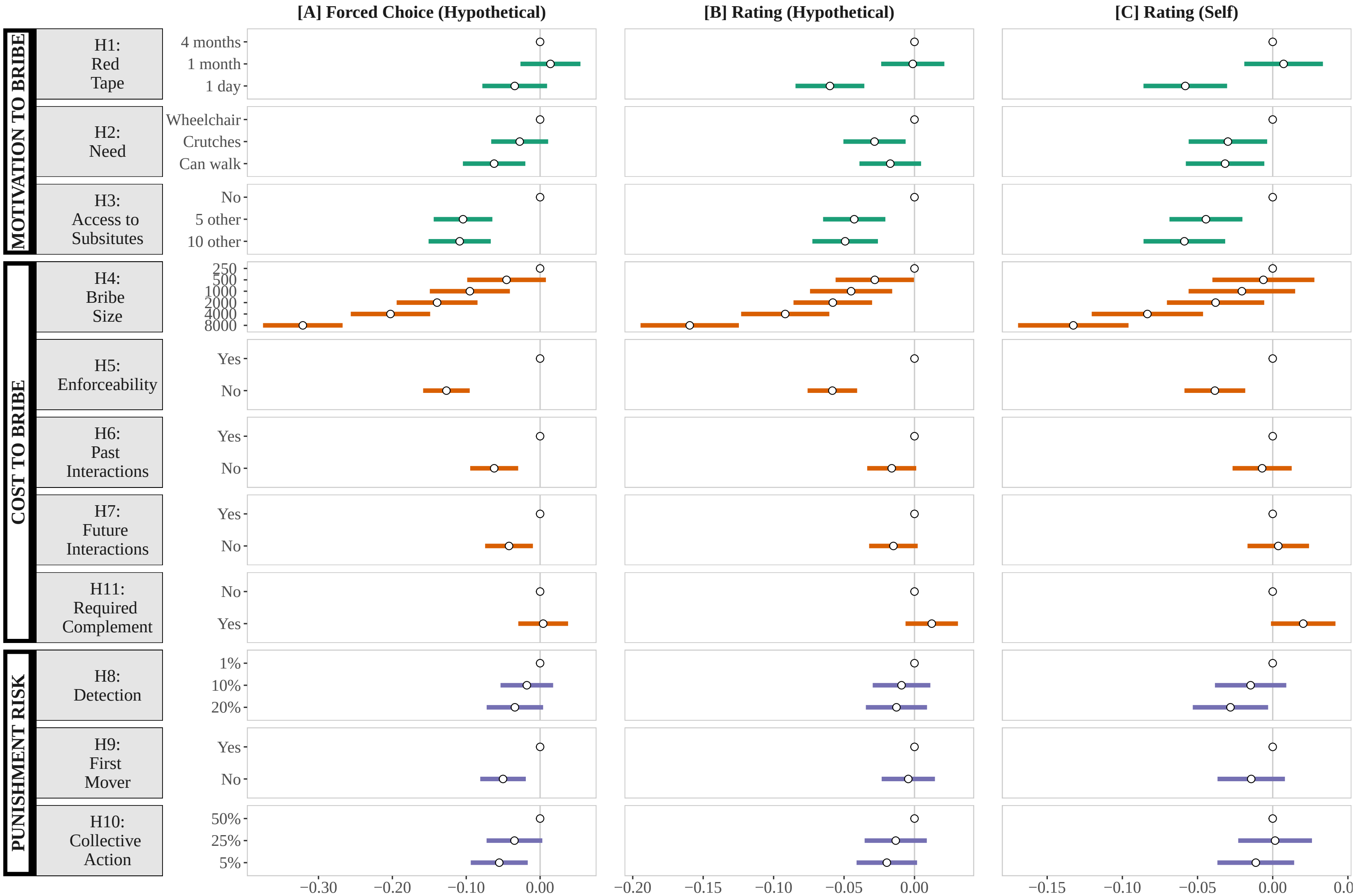
Note: Panel A shows our primary outcome measure using the forced-choice design. AMCEs in Panel A estimate the change in probability that a citizen will bribe when a profile includes the indicated attribute level instead of its baseline level. Panels B and C show secondary outcomes. For those panels, AMCEs estimate the change in the rating of how likely a hypothetical citizen and the respondent (respectively) would bribe, when a profile includes the indicated attribute level instead of its baseline level. Ratings are rescaled to range from 0 ("definitely no") to 1 ("definitely yes"). Estimates based on OLS regressions with standard errors clustered at the respondent level. Bars represent 95% confidence intervals. Points without lines denote attribute values serving as the reference category.

Figure C.4: AMCE Estimates for Bribers Only: Driver's License Scenario



Note: Panel A shows our primary outcome measure using the forced-choice design. AMCEs in Panel A estimate the change in probability that a citizen will bribe when a profile includes the indicated attribute level instead of its baseline level. Panels B and C show secondary outcomes. For those panels, AMCEs estimate the change in the rating of how likely a hypothetical citizen and the respondent (respectively) would bribe, when a profile includes the indicated attribute level instead of its baseline level. Ratings are rescaled to range from 0 ("definitely no") to 1 ("definitely yes"). Estimates based on OLS regressions with standard errors clustered at the respondent level. Bars represent 95% confidence intervals. Points without lines denote attribute values serving as the reference category.

Figure C.5: AMCE Estimates for Bribers Only: Healthcare Scenario



Note: Panel A shows our primary outcome measure using the forced-choice design. AMCEs in Panel A estimate the change in probability that a citizen will bribe when a profile includes the indicated attribute level instead of its baseline level. Panels B and C show secondary outcomes. For those panels, AMCEs estimate the change in the rating of how likely a hypothetical citizen and the respondent (respectively) would bribe, when a profile includes the indicated attribute level instead of its baseline level. Ratings are rescaled to range from 0 ("definitely no") to 1 ("definitely yes"). Estimates based on OLS regressions with standard errors clustered at the respondent level. Bars represent 95% confidence intervals. Points without lines denote attribute values serving as the reference category.

D Proofs

In this section, we derive the comparative static results on which our empirical predictions are based. Consider the citizen's optimization problem:

$$\max_{x_b, x_{nb}, x_s} U(x_b, x_{nb}, x_s) = (x_b^\eta + \delta(x_{nb}^\eta + x_s^\eta))^{\frac{1}{\eta}} \qquad \text{s.t.} \tag{4}$$

$$cx_b + \gamma x_{nb} + \frac{1}{n_s}(1+\gamma)x_s \leq M \tag{5}$$

where $c = \tau + z + b$.

We first derive the marginal utilities of U' with respect to x_b, x_{nb} , and x_s:

$$\frac{\partial U'}{\partial x_b} = (x_b^\eta + \delta(x_{nb}^\eta + x_s^\eta))^{\frac{1-\eta}{\eta}} x_b^{\eta-1} \tag{6}$$

$$\frac{\partial U'}{\partial x_{nb}} = (x_b^\eta + \delta(x_{nb}^\eta + x_s^\eta))^{\frac{1-\eta}{\eta}} \delta x_{nb}^{\eta-1} \tag{7}$$

$$\frac{\partial U'}{\partial x_s} = (x_b^\eta + \delta(x_{nb}^\eta + x_s^\eta))^{\frac{1-\eta}{\eta}} \delta x_s^{\eta-1} \tag{8}$$

Per the first order conditions for a constrained consumer optimization problem, the marginal rate of substitution (MRS) of any two services must equal the price ratio of the two services for an allocation of budget resources to be optimal. Setting $\frac{\partial U'/\partial x_b}{\partial U'/\partial x_{nb}}$, the MRS of x_b for x_{nb}, as derived in equations 6 and 7, equal to the price ratio for x_b to x_{nb} (see the budget constraint in equation 5) produces:

$$\frac{x_b^{\eta-1}}{\delta x_{nb}^{\eta-1}} = \frac{c}{\gamma} \qquad \Longleftrightarrow$$

$$\left(\frac{x_{nb}}{x_b}\right)^{1-\eta} = \frac{\delta c}{\gamma} \qquad \Longleftrightarrow$$

$$x_{nb} = \left(\frac{\delta c}{\gamma}\right)^{\frac{1}{1-\eta}} x_b \tag{9}$$

Setting $\frac{\partial U'/\partial x_b}{\partial U'/\partial x_s}$, the MRS of x_b for x_s, as derived in equations 6 and 8, equal to the price ratio for x_b to x_s analogously produces:

$$x_s = \left(\frac{n_s \delta c}{1+\gamma}\right)^{\frac{1}{1-\eta}} x_b \tag{10}$$

We next insert these identities for x_{nb} and x_s from equations 9 and 10 in an optimal budget allocation into the budget constraint from equation 5, which, given that U' is strictly increasing in all three choice variables, will be binding:

$$\begin{aligned}
cx_b + \gamma x_{nb} + \frac{1}{n_s}(1+\gamma)x_s &= M && \iff \\
cx_b + \gamma\left[\left(\frac{\delta c}{\gamma}\right)^{\frac{1}{1-\eta}} x_b\right] + \frac{1}{n_s}(1+\gamma)\left[\left(\frac{n_s\delta c}{(1+\gamma)}\right)^{\frac{1}{1-\eta}} x_b\right] &= M && \iff \\
\left(c + \gamma\left(\frac{\delta c}{\gamma}\right)^{\frac{1}{1-\eta}} + \frac{1}{n_s}(1+\gamma)\left(\frac{n_s\delta c}{(1+\gamma)}\right)^{\frac{1}{1-\eta}}\right) x_b &= M && \iff \\
\left(c + (\delta c)^{\frac{1}{1-\eta}}\left(\gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}}\right)\right) x_b &= M && (11)
\end{aligned}$$

Rearranging equation 11 produces the uncompensated demand function $x_b^*(c, \delta, \gamma, n_s)$:

$$x_b^* = \left[c + (\delta c)^{\frac{1}{1-\eta}}\left(\gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}}\right)\right]^{-1} M \qquad (12)$$

Comparative Statics

We now turn to the model's empirical predictions and derive comparative statics. To simplify notation, let $\Omega = c + (\delta c)^{\frac{1}{1-\eta}}\left(\gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}}\right)$ and $\Pi = \gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}}$, such that x_b^* can be rewritten as either $x_b^* = \Omega^{-1}M$ or $x_b^* = \left[c + (\delta c)^{\frac{1}{1-\eta}}\Pi\right]^{-1} M$. Recall that c, δ, γ, and n_s are all strictly positive, which implies that $\Omega > 0$ and $\Pi > 0$.

Hypothesis 1 (*Red Tape*): As red tape costs (γ) increase, demand for corruptly provided services x_b increases ($\frac{\partial x_b}{\partial \gamma} > 0$).

Note that $\frac{-\eta}{1-\eta}$, the exponent term on γ and $(1+\gamma)$ in Ω, is negative, given that $0 < \eta < 1$. Then:

$$\frac{\partial x_b}{\partial \gamma} = -\Omega^{-2}\left(\frac{-\eta}{1-\eta}\right)\left[\delta c^{\frac{1}{1-\eta}}\left(\gamma^{\frac{-\eta}{1-\eta}-1} + (1+\gamma)^{\frac{-\eta}{1-\eta}-1} n_s^{\frac{\eta}{1-\eta}}\right)\right] M > 0$$

Hypothesis 2 (*Need*): As a service becomes less urgently needed (i.e., as δ increases), demand for corruptly provided services x_b decreases ($\frac{\partial x_b}{\partial \delta} < 0$).

Note that $\frac{1}{1-\eta}$, the exponent term on δ in Ω, is positive, given that $0 < \eta < 1$. Then:

$$\frac{\partial x_b}{\partial \delta} = -\Omega^{-2}\left(\frac{1}{1-\eta}\right)\left[\delta^{\frac{1}{1-\eta}-1} c^{\frac{1}{1-\eta}}\Pi\right] M < 0$$

Hypothesis 3 (*Access to Substitutes*): As more providers (n_s) offer access to substitute services, demand for corruptly provided services x_b decreases ($\frac{\partial x_b}{\partial n_s} < 0$).

Note that $\frac{\eta}{1-\eta}$, the exponent term on n_s in Ω, is positive, given that $0 < \eta < 1$. Then:

$$\frac{\partial x_b}{\partial n_s} = -\Omega^{-2}\left(\frac{\eta}{1-\eta}\right)\left[(\delta c)^{\frac{1}{1-\eta}}\left(\gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}-1}\right)\right] M < 0$$

Hypothesis 4 (*Bribe Size*): As expected bribe prices b increase, demand for corruptly provided services x_b decreases ($\frac{\partial x_b}{\partial b} < 0$).

Recall that we defined $c = \tau + z + b$, where τ, z, and b are strictly positive. It is therefore straightforward to see that the sign of the partial derivative $\frac{\partial x_b}{\partial c}$ will be in the same direction as the signs for the partial derivatives $\frac{\partial x_b}{\partial b}$, $\frac{\partial x_b}{\partial \tau}$, and $\frac{\partial x_b}{\partial z}$. Note that the exponent terms on c in Ω are 1 and $\frac{1}{1-\eta}$, both of which are strictly positive given $0 < \eta < 1$. Then:

$$\frac{\partial x_b}{\partial c} = -\Omega^{-2}\left[\left(1 + \frac{1}{1-\eta}\delta^{\frac{1}{1-\eta}-1} c^{\frac{1}{1-\eta}}\right)\Pi\right] M < 0$$

Hypotheses 5 - 7

Comparative statics for hypotheses 5 - 7 pertain to the model's prediction that $\frac{\partial x_b}{\partial \tau} < 0$. As noted in the derivation of comparative statics for hypothesis 4, the derivation of $\frac{\partial x_b}{\partial \tau} < 0$ follows directly from the derivation of $\frac{\partial x_b}{\partial c} < 0$, where $c = \tau + z + b$.

Hypothesis 5 (*Enforceability*): As the enforceability of bribe transactions increases (thereby decreasing τ), demand for corruptly provided services x_b increases.

Hypothesis 6 (*Past Interactions*) As past interactions between a citizen and public official increase (thereby decreasing τ), demand for corruptly provided services x_b increases.

Hypothesis 7 (*Future Interactions*): As expected future interactions increase (thereby decreasing τ), demand for corruptly provided services x_b increases.

Hypotheses 8 - 10

Comparative statics for hypotheses 8 - 10 pertain the model's prediction that $\frac{\partial x_b}{\partial z} < 0$. As noted in the derivation of comparative statics for hypothesis 4, the derivation of $\frac{\partial x_b}{\partial z} < 0$ follows directly from the derivation of $\frac{\partial x_b}{\partial c} < 0$, where $c = \tau + z + b$.

Hypothesis 8 (*Detection*): As the risk of law enforcement detecting corruption rises (thereby increasing z), demand for corruptly provided services x_b decreases.

Hypothesis 9 (*First Mover*): When public officials initiate bribe transactions (thereby increasing z), demand for corruptly provided services x_b increases.

Hypothesis 10 (*Collective Action*): When citizens expect that many other people pay bribes (thereby increasing z), demand for corruptly provided services x_b increases.

Complementary Services

We next derive comparative statics for the version of the model that incorporates complementary services. We show that the results for hypotheses 1 through 10 hold in the augmented version of the model. We then derive comparative statics for hypothesis 11.

Consider the citizen's optimization problem:

$$\max_{x_b, x_{nb}, x_s, y} U(x_b, x_{nb}, x_s, y) = \left[\left((x_b^\eta + \delta(x_{nb}^\eta + x_s^\eta))^{\frac{1}{\eta}} \right)^\rho + y^\rho \right]^{\frac{1}{\rho}} \qquad \text{s.t.} \tag{13}$$

$$c x_b + \gamma x_{nb} + \frac{1}{n_s}(1+\gamma) x_s + p_y y \leq M \tag{14}$$

where $c = \tau + z + b$.

To begin, we rewrite the citizen's utility function in a more tractable form, employing monotonic transformations to preserve preference relations:[3]

$$U'(x_b, x_{nb}, x_s, y) = \frac{1}{\rho} \left[\frac{1}{\eta} \left(x_b^\eta + \delta(x_{nb}^\eta + x_s^\eta) \right)^\rho + y^\rho \right] \tag{15}$$

We then derive the marginal utilities of U' with respect to x_b, x_{nb} , x_s and y:

$$\frac{\partial U'}{\partial x_b} = \Psi^{\rho-1} x_b^{\eta-1} \tag{16}$$

$$\frac{\partial U'}{\partial x_{nb}} = \Psi^{\rho-1} \delta x_{nb}^{\eta-1} \tag{17}$$

$$\frac{\partial U'}{\partial x_s} = \Psi^{\rho-1} \delta x_s^{\eta-1} \tag{18}$$

$$\frac{\partial U'}{\partial y} = y^{\rho-1} \tag{19}$$

where $\Psi = \frac{1}{\eta}(x_b^\eta + \delta(x_{nb}^\eta + x_s^\eta))$.

[3] Specifically, let $V = (x_b^\eta + \delta(x_{nb}^\eta + x_s^\eta))^{\frac{1}{\eta}}$ and define the function $f(V)$ as $f(V) = \frac{1}{\eta} V^\eta$ and the function $g(U)$ as $g(U) = \frac{1}{\rho} U^\rho$. Then $U' = g(U(f(V), y))$.

Per the first order conditions for a constrained consumer optimization problem, the marginal rate of substitution (MRS) of any two services must equal the price ratio of the two services for an allocation of budget resources to be optimal. Setting $\frac{\partial U'/\partial x_b}{\partial U'/\partial x_{nb}}$, the MRS of x_b for x_{nb}, as derived in equations 16 and 17, equal to the price ratio for x_b to x_{nb} (see the budget constraint in equation 14) produces:

$$\begin{aligned}
\frac{\Psi^{\rho-1}x_b^{\eta-1}}{\Psi^{\rho-1}\delta x_{nb}^{\eta-1}} &= \frac{c}{\gamma} && \iff \\
\left(\frac{x_{nb}}{x_b}\right)^{1-\eta} &= \frac{\delta c}{\gamma} && \iff \\
x_{nb} &= \left(\frac{\delta c}{\gamma}\right)^{\frac{1}{1-\eta}} x_b && (20)
\end{aligned}$$

Setting $\frac{\partial U'/\partial x_b}{\partial U'/\partial x_s}$, the MRS of x_b for x_s, as derived in equations 16 and 18, equal to the price ratio for x_b to x_s analogously produces:

$$x_s = \left(\frac{n_s \delta c}{1+\gamma}\right)^{\frac{1}{1-\eta}} x_b \tag{21}$$

Finally, setting $\frac{\partial U'/\partial x_b}{\partial U'/\partial y}$, the MRS of x_b for y, as derived in equations 16 and 19, equal to the price ratio for x_b to y produces:

$$\begin{aligned}
\frac{\Psi^{\rho-1}x_b^{\eta-1}}{y^{\rho-1}} &= \frac{c}{p_y} && \iff \\
\left(\frac{y}{\Psi}\right)^{1-\rho} &= \frac{c}{p_y} x_b^{1-\eta} && \iff \\
y &= \left(\frac{c}{p_y}\right)^{\frac{1}{1-\rho}} x_b^{\frac{1-\eta}{1-\rho}} \Psi \\
&= \left(\frac{c}{p_y}\right)^{\frac{1}{1-\rho}} x_b^{\frac{1-\eta}{1-\rho}} \left[\frac{1}{\eta}(x_b^\eta + \delta(x_{nb}^\eta + x_s^\eta))\right] \\
&= \left(\frac{c}{p_y}\right)^{\frac{1}{1-\rho}} x_b^{\frac{1-\eta}{1-\rho}} \left[\frac{1}{\eta}\left(x_b^\eta + \delta\left(\left(\left(\frac{\delta c}{\gamma}\right)^{\frac{1}{1-\eta}} x_b\right)^\eta + \left(\left(\frac{n_s \delta c}{1+\gamma}\right)^{\frac{1}{1-\eta}} x_b\right)^\eta\right)\right)\right] \\
&= \frac{1}{\eta}\left(\frac{c}{p_y}\right)^{\frac{1}{1-\rho}} \left(x_b^{\frac{1-\eta}{1-\rho}}\right) x_b^\eta \left[1 + \delta\left(\left(\frac{\delta c}{\gamma}\right)^{\frac{\eta}{1-\eta}} + \left(\frac{n_s \delta c}{1+\gamma}\right)^{\frac{\eta}{1-\eta}}\right)\right] \\
&= \frac{1}{\eta}\left(\frac{c}{p_y}\right)^{\frac{1}{1-\rho}} \left[1 + \delta^{\frac{1}{1-\eta}} c^{\frac{\eta}{1-\eta}} \left(\left(\frac{1}{\gamma}\right)^{\frac{\eta}{1-\eta}} + \left(\frac{n_s}{1+\gamma}\right)^{\frac{\eta}{1-\eta}}\right)\right] x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}} \\
&= \frac{1}{\eta}\left(c^{\frac{1}{1-\rho}} + p_y^{\frac{-1}{1-\rho}} \delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}} \left(\gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}}\right)\right) x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}} && (22)
\end{aligned}$$

where the substitutions for x_{nb} and x_s in the fourth to last line follow from equations 20 and 21, respectively.

We next insert these identities for x_{nb}, x_s, and y from equations 20, 21, and 22 in an optimal budget allocation into the budget constraint from equation 14, which, given that U' is strictly increasing in all four choice variables, will be binding:

$$\begin{aligned}
cx_b + \gamma x_{nb} + \frac{1}{n_s}(1+\gamma)x_s + p_y y &= M \iff \\
cx_b + \gamma\left[\left(\frac{\delta c}{\gamma}\right)^{\frac{1}{1-\eta}} x_b\right] + \frac{1}{n_s}(1+\gamma)\left[\left(\frac{n_s\delta c}{(1+\gamma)}\right)^{\frac{1}{1-\eta}} x_b\right] + & \\
p_y\left[\frac{1}{\eta}\left(c^{\frac{1}{1-\rho}} + p_y^{\frac{-1}{1-\rho}}\delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}}\left(\gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}}\right)\right) x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}}\right] &= M \iff \\
\left(c + \gamma\left(\frac{\delta c}{\gamma}\right)^{\frac{1}{1-\eta}} + \frac{1}{n_s}(1+\gamma)\left(\frac{n_s\delta c}{(1+\gamma)}\right)^{\frac{1}{1-\eta}}\right) x_b + & \\
\frac{1}{\eta}\left(p_y c^{\frac{1}{1-\rho}} + p_y^{\frac{-\rho}{1-\rho}}\delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}}\left(\gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}}\right)\right) x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}} &= M \iff \\
\left(c + (\delta c)^{\frac{1}{1-\eta}}\left(\gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}}\right)\right) x_b + & \\
\frac{1}{\eta}\left(p_y c^{\frac{1}{1-\rho}} + p_y^{\frac{-\rho}{1-\rho}}\delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}}\left(\gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}}\right)\right) x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}} &= M \qquad (23)
\end{aligned}$$

Comparative Statics

We now rewrite equation 23 as an implicit function, $G(x_b; c, \delta, \gamma, n_s, n_c)$, and employ the inverse function theorem to derive comparative statics:

$$\begin{aligned}
G(x_b; c, \delta, \gamma, n_s, n_c) = \left(c + (\delta c)^{\frac{1}{1-\eta}}\left(\gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}}\right)\right) x_b \; + & \\
\frac{1}{\eta}\left(p_y c^{\frac{1}{1-\rho}} + p_y^{\frac{-\rho}{1-\rho}}\delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}}\left(\gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}}\right)\right) x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}} - M = 0 \qquad (24)
\end{aligned}$$

We first determine the sign of $\frac{\partial G}{\partial x_b}$. Let $\Gamma = \left(c + (\delta c)^{\frac{1}{1-\eta}}\left(\gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}}\right)\right)$ and $\Phi = \frac{1}{\eta}\left(p_y c^{\frac{1}{1-\rho}} + p_y^{\frac{-\rho}{1-\rho}}\delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}}\left(\gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}}\right)\right)$, such that G can be rewritten as $G = \Gamma x_b + \Phi x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}} - M$. Recall that γ, δ, n_s, and p_y are strictly positive. We earlier defined $c = \tau + z + b$, where τ, z, and b are all strictly positive. It is therefore straightforward to see that Γ and Φ are strictly positive. Finally, note that the exponent term $\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}$ is also strictly positive, given that $0 < \eta < 1$ and $\rho < 0$. Accordingly, the derivative of G with respect to x_b will be positive:

$$\frac{\partial G}{\partial x_b} = \Gamma + \frac{(1-\eta)+\eta(1-\rho)}{1-\rho}\Phi x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}-1} > 0$$

We now turn to the model's empirical predictions:

Hypothesis 1 (*Red Tape*): As red tape costs (γ) increase, demand for corruptly provided services x_b increases ($\frac{\partial x_b}{\partial \gamma} > 0$).

Note that $\frac{-\eta}{1-\eta}$, the exponent term on γ and $(1+\gamma)$ in G, is negative, given that $0 < \eta < 1$. Then, by the implicit function theorem, $\frac{\partial x_b}{\partial \gamma} = -\frac{\partial G}{\partial \gamma} / \frac{\partial G}{\partial x_b}$. We have already shown that $\frac{\partial G}{\partial x_b} > 0$ and will now show that $\frac{\partial G}{\partial \gamma} < 0$, which implies that $\frac{\partial x_b}{\partial \gamma} > 0$:

$$\begin{aligned}
\frac{\partial G}{\partial \gamma} &= \left((\delta c)^{\frac{1}{1-\eta}} \left(\frac{-\eta}{1-\eta}\gamma^{\frac{-\eta}{1-\eta}-1} + \frac{-\eta}{1-\eta}(1+\gamma)^{\frac{-\eta}{1-\eta}-1} n_s^{\frac{\eta}{1-\eta}} \right) \right) x_b \; + \\
&\quad \frac{1}{\eta}\left(p_y^{\frac{-\rho}{1-\rho}} \delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}} \left(\frac{-\eta}{1-\eta}\gamma^{\frac{-\eta}{1-\eta}-1} + \frac{-\eta}{1-\eta}(1+\gamma)^{\frac{-\eta}{1-\eta}-1} n_s^{\frac{\eta}{1-\eta}} \right) \right) x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}} \\
&= \frac{-\eta}{1-\eta}\left(\gamma^{\frac{-\eta}{1-\eta}-1} + (1+\gamma)^{\frac{-\eta}{1-\eta}-1} n_s^{\frac{\eta}{1-\eta}} \right) \left[(\delta c)^{\frac{1}{1-\eta}} x_b + \frac{1}{\eta} p_y^{\frac{-\rho}{1-\rho}} \delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}} x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}} \right] < 0
\end{aligned}$$

Hypothesis 2 (*Need*): As a service becomes less urgently needed (i.e., as δ increases), demand for corruptly provided services x_b decreases ($\frac{\partial x_b}{\partial \delta} < 0$).

Let $\Pi = \gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}} > 0$, such that G can be written as $G = \left(c + (\delta c)^{\frac{1}{1-\eta}} \Pi \right) x_b + \frac{1}{\eta}\left(c^{\frac{1}{1-\rho}} + p_y^{\frac{-\rho}{1-\rho}} \delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}} \Pi \right) x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}} - M$. Note that $\frac{1}{1-\eta}$, the exponent term on δ in G, is positive, given that $0 < \eta < 1$. By the implicit function theorem, $\frac{\partial x_b}{\partial \delta} = -\frac{\partial G}{\partial \delta} / \frac{\partial G}{\partial x_b}$. We have already shown that $\frac{\partial G}{\partial x_b} > 0$ and will now show that $\frac{\partial G}{\partial \delta} > 0$, which implies that $\frac{\partial x_b}{\partial \delta} < 0$:

$$\begin{aligned}
\frac{\partial G}{\partial \delta} &= \frac{1}{1-\eta} c^{\frac{1}{1-\eta}} \delta^{\frac{1}{1-\eta}-1} \Pi x_b + \frac{1}{1-\eta}\frac{1}{\eta} p_y^{\frac{-\rho}{1-\rho}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}} \delta^{\frac{1}{1-\eta}-1} \Pi x_b^{\frac{(1-\eta)+\rho(1-\rho)}{1-\rho}} \\
&= \frac{1}{1-\eta} \delta^{\frac{1}{1-\eta}-1} \Pi \left(c^{\frac{1}{1-\eta}} x_b + \frac{1}{\eta} p_y^{\frac{-\rho}{1-\rho}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}} x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}} \right) > 0
\end{aligned}$$

Hypothesis 3 (*Access to Substitutes*): As more providers (n_s) offer access to substitute services, demand for corruptly provided services x_b decreases ($\frac{\partial x_b}{\partial n_s} < 0$).

Note that $\frac{\eta}{1-\eta}$, the exponent term on n_s in G, is positive, given that $0 < \eta < 1$. By the implicit function theorem, $\frac{\partial x_b}{\partial n_s} = -\frac{\partial G}{\partial n_s} / \frac{\partial G}{\partial x_b}$. We have already shown that $\frac{\partial G}{\partial x_b} > 0$ and will now show that $\frac{\partial G}{\partial n_s} > 0$, which implies that $\frac{\partial x_b}{\partial n_s} < 0$:

$$\frac{\partial G}{\partial n_s} = \left(\frac{\eta}{1-\eta}(\delta c)^{\frac{1}{1-\eta}}(1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}-1}\right) x_b + \left(\frac{\eta}{1-\eta}\frac{1}{\eta} p_y^{\frac{-\rho}{1-\rho}} \delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}} (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}-1}\right) x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}}$$

$$= \frac{\eta}{1-\eta} n_s^{\frac{\eta}{1-\eta}-1} \left((\delta c)^{\frac{1}{1-\eta}}(1+\gamma)^{\frac{-\eta}{1-\eta}} x_b + \frac{1}{\eta} p_y^{\frac{-\rho}{1-\rho}} \delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}} (1+\gamma)^{\frac{-\eta}{1-\eta}} x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}}\right) > 0$$

Hypothesis 4 (*Bribe Size*): As expected bribe prices b increase, demand for corruptly provided services x_b decreases ($\frac{\partial x_b}{\partial b} < 0$).

Recall that we defined $c = \tau + z + b$, where τ, z, and b are strictly positive. It is therefore straightforward to see that the sign of the partial derivative $\frac{\partial x_b}{\partial c}$ will be in the same direction as the signs for the partial derivatives $\frac{\partial x_b}{\partial b}$, $\frac{\partial x_b}{\partial \tau}$, and $\frac{\partial x_b}{\partial z}$. As in the derivation of comparative statics for hypothesis 2, let $\Pi = \gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}} > 0$, such that G can be written as $G = \left(c + (\delta c)^{\frac{1}{1-\eta}}\Pi\right) x_b + \frac{1}{\eta}\left(p_y c^{\frac{1}{1-\rho}} + p_y^{\frac{-\rho}{1-\rho}} \delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}} \Pi\right) x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}} - M$. Note that the exponent terms on c in G are 1, $\frac{1}{1-\eta}$, $\frac{1}{1-\rho}$, and $\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}$, all of which are strictly positive given $0 < \eta < 1$ and $\rho < 0$. By the implicit function theorem, $\frac{\partial x_b}{\partial c} = -\frac{\partial G}{\partial c} / \frac{\partial G}{\partial x_b}$. We have already shown that $\frac{\partial G}{\partial x_b} > 0$ and will now show that $\frac{\partial G}{\partial c} > 0$, which implies that $\frac{\partial x_b}{\partial c} < 0$, and, accordingly, that $\frac{\partial x_b}{\partial b} < 0$:

$$\frac{\partial G}{\partial c} = \left(1 + \frac{1}{1-\eta}\delta^{\frac{1}{1-\eta}} c^{\frac{1}{1-\eta}-1}\Pi\right) x_b + \frac{1}{\eta}\left(\frac{1}{1-\rho} p_y c^{\frac{1}{1-\rho}-1} + \frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)} p_y^{\frac{-\rho}{1-\rho}} \delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}-1}\Pi\right) x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}} > 0$$

Hypotheses 5 - 7

Comparative statics for hypotheses 5 - 7 follow from the model's prediction that $\frac{\partial x_b}{\partial \tau} < 0$. As noted in the derivation of comparative statics for hypothesis 4, the derivation of $\frac{\partial x_b}{\partial \tau} < 0$ follows directly from the derivation of $\frac{\partial x_b}{\partial c} < 0$, where $c = \tau + z + b$.

Hypothesis 5 (*Enforceability*): As the enforceability of bribe transactions increases (thereby decreasing τ), demand for corruptly provided services x_b increases.

Hypothesis 6 (*Past Interactions*) As past interactions between a citizen and public official increase (thereby decreasing τ), demand for corruptly provided services x_b increases.

Hypothesis 7 (*Future Interactions*): As expected future interactions increase (thereby decreasing τ), demand for corruptly provided services x_b increases.

Hypotheses 8 - 10

Comparative statics for hypotheses 8 - 10 follow from the model's prediction that $\frac{\partial x_b}{\partial z} < 0$. As noted in the derivation of comparative statics for hypothesis 4, the derivation of $\frac{\partial x_b}{\partial z} < 0$ follows directly from the derivation of $\frac{\partial x_b}{\partial c} < 0$, where $c = \tau + z + b$.

Hypothesis 8 (*Detection*): As the risk of law enforcement detecting corruption rises (thereby increasing z), demand for corruptly provided services x_b decreases.

Hypothesis 9 (*First Mover*): When public officials initiate bribe transactions (thereby increasing z), demand for corruptly provided services x_b increases.

Hypothesis 10 (*Collective Action*): When citizens expect that many other people pay bribes (thereby increasing z), demand for corruptly provided services x_b increases.

Hypothesis 11 (*Required Complement*): When costlier complementary services are needed (i.e., p_y increases), demand for corruptly provided services x_b decreases ($\frac{\partial x_b}{\partial p_y} < 0$).

Let $\Sigma = \left(c + (\delta c)^{\frac{1}{1-\eta}} \left(\gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}}\right)\right) x_b$ and, as in the derivation of comparative statics for hypotheses 2 and 4, let $\Pi = \gamma^{\frac{-\eta}{1-\eta}} + (1+\gamma)^{\frac{-\eta}{1-\eta}} n_s^{\frac{\eta}{1-\eta}} > 0$, such that G can be written as $G = \Sigma + \frac{1}{\eta}\left(p_y c^{\frac{1}{1-\rho}} + p_y^{\frac{-\rho}{1-\rho}} \delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}} \Pi\right) x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}} - M$. Note that Σ does not contain the parameter p_y, Π is strictly positive, and the exponent terms on p_y — 1 and $\frac{-\rho}{1-\rho}$ — are strictly positive given $\rho < 0$. By the implicit function theorem, $\frac{\partial x_b}{\partial p_y} = -\frac{\partial G}{\partial p_y} / \frac{\partial G}{\partial x_b}$. We have already shown that $\frac{\partial G}{\partial x_b} > 0$ and will now show that $\frac{\partial G}{\partial p_y} > 0$ is positive, which implies that $\frac{\partial x_b}{\partial p_y} < 0$:

$$\frac{\partial G}{\partial p_y} = \frac{1}{\eta}\left(c^{\frac{1}{1-\rho}} + \frac{-\rho}{1-\rho} p_y^{\frac{-\rho}{1-\rho}-1} \delta^{\frac{1}{1-\eta}} c^{\frac{(1-\eta)+\eta(1-\rho)}{(1-\rho)(1-\eta)}} \Pi\right) x_b^{\frac{(1-\eta)+\eta(1-\rho)}{1-\rho}} > 0$$

E Pre-Analysis Plan

We filed a pre-analysis plan on August 21, 2020 with the Open Science Framework, prior to beginning data collection. Our research process and analyses adhered to the pre-registered plan. Please note we reordered hypotheses in the present manuscript, so hypothesis numbers differ from the pre-analysis plan. An anonymized version of the pre-analysis plan can be viewed via this link:

https://osf.io/j7wg5?view_only=77a62fcc76f14c70ad0d737ad9633b7f

References

Berinsky, A. J., Margolis, M. F., & Sances, M. W. (2014). Separating the shirkers from the workers? Making sure respondents pay attention on self-administered surveys. *American Journal of Political Science*, *58*(3), 739–753.

Hainmueller, J., Hopkins, D. J., & Yamamoto, T. (2014). Causal inference in conjoint analysis: Understanding multidimensional choices via stated preference experiments. *Political Analysis*, *22*(1), 1–30.