

Does competition among public officials reduce corruption? An experiment*

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Abstract

Despite the abundance of theoretical and empirical studies on corruption, identifying successful anti-corruption strategies remains a challenge. This paper tests the effectiveness of an anti-corruption policy that is often discussed among practitioners: an increase in competition among officials providing the same good or service. In particular, we investigate whether overlapping jurisdictions reduce extortionary corruption, i.e., bribe demands for the provision of services that clients are entitled to receive. We overcome measurement and identification problems by addressing our research question in the laboratory. We conduct an extortionary bribery experiment where clients apply for a license from one of many available offices and officials can demand a bribe on top of the license fee. Officials decide whether or not to demand a bribe and the size of the bribe simultaneously and clients engage in costly search. By manipulating the number of available offices and the size of search costs we are able to assess whether increasing competition reduces extortionary corruption. We find that, if search costs are unaffected, increasing the number of providers may actually increase corruption. In particular, our results show that increasing competition has either no effect (if search costs are high) or a positive effect (if search costs are low) on bribe demands.

JEL classification codes: D73, D49, C91

Keywords: Competition; Extortionary Corruption; Experiment

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1 Introduction

Over the last three decades, theoretical and empirical studies have generated widespread consensus on the negative effects that corruption has on society.¹ As a consequence, empirical investigations into the causes of corruption, ultimately aimed at identifying policy measures that might be successful in its mitigation, have proliferated.² Similarly, theoretical studies have focused on the design of institutions that, through monetary rewards and penalties, can prevent public officials from abusing their positions and thus causing harm to society.³ Although the existing studies have increased our understanding of why and how corruption occurs, identifying successful anti-corruption strategies remains a challenge. The evidence suggests that the expected returns to corruption can be successfully reduced by increasing formal monitoring and punishment; however, the enforcement of severe deterrence mechanisms might be prohibitively costly, or simply unfeasible in settings where the strategic complementarities associated with corruption render rule enforcement a collective action problem. Changes in the institutional environment that do not rely on external punishment are preferable, especially in settings characterized by systemic corruption. One such change, which is often suggested as a potentially effective anti-corruption policy, concerns the organization of the bureaucracy and the relationship between public offices in charge of providing the same good or service.

Rose-Ackerman (1978, 1999) was the first to state that if officials were given overlapping jurisdictions citizens would be able to choose which official to approach when applying for a given license or service. Consequently, no official would have much monopoly power. The same argument was brought forward by Shleifer and Vishny (1993) which stated that if many officials can provide the same permit, “Bertrand competition in bribes will force the equilibrium bribe on each permit down to zero” (Shleifer and Vishny, 1993, p. 607). According to both Rose-Ackerman (1978, 1999) and Shleifer and Vishny (1993), competition among officials is likely to be effective especially in the fight against *extortionary*, or coercive, corruption, i.e. bribe demands for services that citizens are entitled to, as opposed to *collusive* corruption i.e. bribe demands for the provision of illegal services that citizens are not entitled to receive.⁴ It is on payments generated by extortionary corruption that we focus in this paper; such payments are sometimes referred to as *harassment bribes*. Think for instance of a citizen applying for a passport, going to the closest passport issuing office (which might require long traveling time) and being demanded a bribe on top of the official fee. The citizen can then either pay the bribe and get the passport or refuse to pay and go to a different office hoping to be able to get the passport without having to pay a bribe. If there is no other office to go to, the citizen’s only

¹See Mauro (1995), Meon and Sekkat (2005), Keefer and Knack (1995), Olken (2006), Reinnika and Svensson (2004), Fisman and Svensson (2007), Tanzi and Davoodi (1997), among the others.

²For examples of studies using cross-country data, see Treisman (2000) and Serra (2006). For examples of studies using firm- or household-level data, see Svensson (2003) and Hunt (2007). For examples of studies using direct observation in the field see Olken and Barron (2009) and Sequeira and Djankov (2013). For a review of the different methodologies employed for the empirical study of corruption, see Sequeira (2012).

³For a review of important issues see Bardhan (1997), Banerjee et al. (2012) and Ryvkin and Serra (2012).

⁴Shleifer and Vishny call this kind of corruption, *corruption without theft*.

option is to pay the bribe. The same applies to multiple other environments. Think for instance of the case of a citizen requesting connection to an electrical line or to a water pipe, or the case of a firm applying for a building permit.

Testing whether creating competition among providers of the same government service would negatively affect the demand of harassment bribes is empirically challenging, due to both the difficulty of measuring corruption in the field and the necessity to persuade high level government officials to experiment with the available number of service providers in a scientific way. Unsurprisingly, empirical studies on this matter are scarce. Burgess et al. (2012) investigate the effect of forestry officials' overlapping jurisdictions in the context of logging permits in Indonesia. However, they look at quantity-based rather than price-based competition among officials in the context of collusive rather than extortionary corruption. Kiselev (2012) employs firm-level survey data and regional panel data in Russia and measures region-level competition among officials using the density of government employment in each region. He finds that (self-reported) bribe payments by firms are higher yet the (self-reported) occurrence of corrupt exchanges is lower in more competitive regions.

In this paper we employ a novel laboratory experiment to test whether introducing or increasing competition among public offices would be an effective way to fight *extortionary* corruption. In particular, we designed an experiment that simulates extortionary corruption in a setting where service recipient can obtain the same service from multiple offices. Our experiment represents a novel departure from all the existing corruption experiments (Abbink et al., 2002; Abbink et al., 2014; Barr and Serra, 2010; Banuri and Eckel, 2012; Cameron et al., 2008, among others), which have focused on the interaction between a potential briber, i.e. a firm or a citizen, and a public official with monopoly power over the provision of a government good or service.⁵ Contrary to previous studies, we do not exogenously match each service recipient to a possibly corrupt service provider; instead, we allow service recipients to search among multiple service providers and choose to receive a service or good from any of them. This framework allows us to investigate whether changes in the number of available offices providing the same "license" affect the demand of harassment bribes. Crucially, contrary to both Rose-Ackerman (1978, 1999) and Shleifer and Vishny (1993) we assume that searching for an honest official is costly, as it involves traveling from office to office with no guarantee that searching would pay off.

By employing a laboratory experiment, we are able to both isolate confounding effects - such as the indirect effect of increased number of providers via a decrease in search costs - and overcome implementation and measurement difficulties that would make testing our research question in the field especially problematic. It could be argued that decisions made by student subjects within the controlled environment of the experimental lab are unlikely to reflect the decisions that the same students or that average ordinary citizens would make in outside-the-lab situations. We have two answers to this possible criticism. First, we are not trying to estimate

⁵We know of only one other experimental study (Abbink et al., 2014) that, like us, focuses on extortionary rather than collusive corruption.

“general” corruption preferences. We acknowledge that, of course, levels of corruption are likely to be different when using different subject pools and when moving from the lab to the field. However, like most experimental economists, we are not interested in levels; we are interested in comparative statics regarding the effects of certain incentive systems and contextual situations, and in the mechanisms underlying observed behaviors.⁶ Second, investigating these comparative statics in the field is often prohibitively costly or simply unfeasible. The decision-making context that we are studying is clearly an example of such infeasibility. Indeed, due to the secretive and illegal nature of corruption and the need to persuade a government to experiment with the number of offices and/or providers of the same good or service, it is highly unlikely that our research question could ever be addressed in the field.⁷

Our findings suggest that increasing the number of offices in charge of providing the same license may increase rather than decrease extortionary corruption, depending on the size of search costs. In particular, if search costs are high, increasing the number of offices has no effect on bribe demands, whereas if search costs are low increasing the number of offices leads to higher bribes. On the other hand, a reduction in clients’ search costs, keeping the number of offices fixed, unambiguously leads to lower bribes. In the field, an increase in the number of offices is often accompanied by a reduction in search costs, for example due to a more convenient geographical location of new offices for some clients. Our results suggest that such a change may lead to lower or higher corruption; while the decrease in search costs would push the bribes down, the increase in the number of offices might push the bribes up. The resulting level of corruption would therefore depend on the relative magnitude of the two opposing effects. According to our findings, corruption could be more effectively reduced by implementing policies aimed at reducing clients’ search costs directly,⁸ than by increasing the number of overlapping jurisdictions for the provision of government goods or services.

Given the scarcity of empirical evidence on the more general effect of competition on prices, we also test whether our results extend to a general market setting where multiple buyers can buy a homogeneous good from a low versus a high number of sellers, in the presence of low search

⁶For a general discussion of the external validity of laboratory experiments, see Kessler and Versterlund (2011) and Camerer (2011).

⁷Additionally, while proving the external validity of our design is virtually impossible, some conclusions can be drawn from the study of Barr and Serra (2010), which relies on a bribery game similar to the one used in this paper and on a sample of students coming from over 40 countries characterized by markedly different levels of corruption. Barr and Serra (2010) show that behavior of the undergraduate students in the game could be predicted by the level of corruption in the students’ home countries, as proxied by Transparency International’s Corruption Perception Index. The fact that corruption in the stylized setting of the lab experiment correlates with corruption in the participants’ home countries can be interpreted as an indication that the setting reproduced in the lab is indeed related to corruption decision-making outside the lab. Armantier and Boly (2013) show that corruption “can be studied in the lab” by comparing individuals’ behavior and responses to incentives in a bribery experiment and in an actual field experiment, in which participants, unaware of being part of a study on corruption, had to decide whether or not to engage in bribery. Both experiments were conducted in Burkina Faso. The results show that individuals’ propensities to engage in bribery were virtually identical in the lab and in the field, when controlling for individual characteristics.

⁸For example, search costs can be reduced by improving infrastructures, such as roads or public transportation, or promoting information sharing about the size of bribe demanded by different officials, without changing the number of offices.

costs. Contrary to our corruption results, when replicating the study in a market setting we find that the number of sellers has no impact on prices. Our data provide suggestive evidence that the different results obtained in the two settings might be driven by different search strategies employed by buyers depending on the context.

The paper is organized as follows. Section 2 reviews the related literature. Section 3 describes our extortionary corruption experiment and theoretical predictions. Section 4 presents the empirical results and Section 5 reports results from additional treatments employing a standard market setting. Finally, Section 6 concludes.

2 A review of the literature

In the last decade, a growing number of studies have applied experimental methodologies to the study of corruption. The surge of laboratory experiments, in particular, has followed from the universal desire to identify effective anti-corruption policies while facing severe measurement and identification problems in non-experimental data, as well as the difficulty of convincing (often corrupt) government to scientifically test possible policies in the field through randomization. The existing experimental literature has provided valuable insights into the effectiveness of top-down enforcement mechanisms (Abbink et al., 2002), asymmetric punishment (Abbink et al., 2014), different sets of monetary incentives (Armantier and Boly, 2013), as well as non-monetary factors (Abbink and Hennig-Schmidt, 2006; Barr and Serra, 2009), and bottom-up punishment systems (Banuri and Eckel, 2012; Cameron et al., 2009; Serra, 2011).⁹ Crucially, with the exception of Abbink et al. (2014) all the previous studies have focused on collusive corruption, i.e. the exchange of bribes for the provision of an illegal service. Moreover, in all the existing experiments, to the best of our knowledge, service providers, i.e. “public officials”, are granted monopoly power over the good demanded by the potential bribe-payer. In other words, each service recipient is randomly matched with a provider and given the chance to obtain the desired corrupt good only from that provider, possibly by paying a bribe. There are no experimental studies of corruption, to the best of our knowledge, that analyze bribe demands under the assumption of competition among service providers.

From a theoretical viewpoint, the prediction that increasing the number of officials in charge of providing the same permit would reduce the size of bribe-demands (Rose-Ackerman, 1978, 1998; Shleifer and Vishny, 1993) does not take into account the existence of search costs. We are not aware of any theoretical study of corruption that systematically investigates the effectiveness of competition among public offices in the presence of search costs.¹⁰

The more general theoretical literature on the effect of competition on prices under the assumption that consumers are (at least partly) uninformed about prices and therefore need to

⁹Significant advances have also been made in our understanding of the relationship between gender and corruption (Alatas et al., 2009), and between culture and corruption (Barr and Serra, 2010; Cameron et al., 2009).

¹⁰Drugov (2010) develops a model of competition among public officials in the presence of both extortionary and collusive corruption, but does not employ the framework of equilibrium search theory.

search, where searching is costly, is quite vast. Diamond (1971) was the first to show that when consumers are uninformed about prices and all have nonzero search costs, monopoly pricing can emerge as equilibrium in Bertrand competition of identical sellers of a homogeneous product. Applying Diamond (1971)'s theory to our extortionary corruption setting leads to the prediction that, if all applicants have positive search costs, increasing the number of available offices would not have any effect on bribe demands, since all offices would still demand the highest possible bribe. If instead we adopt an equilibrium search framework, whether increasing competition reduces or increases prices seem to depend crucially on the assumptions of the model with respect to the distribution of search costs and the search algorithm employed by consumers. In particular, we can distinguish between *sequential* (Stahl, 1989) and *nonsequential*, or fixed sample size (Burdett and Judd, 1983; Janssen and Moraga-Gonzales, 2004) search models. Sequential search models assume that consumers search until they find a price at or below a reservation value determined by the equality of their marginal search cost and expected gain from an additional search. Nonsequential search models assume that consumers decide first how many sellers to visit or search from, and then buy from the seller charging the lowest price, out of those visited. Note that the difference between the two search strategies is not the fact that the former assumes that buyers visit one store at a time, while the latter does not. Under the assumption of nonsequential search buyers might still visit each store in a sequential matter. Rather, the difference is that when search is sequential, at any given time the decision to visit an extra store depends on the prices encountered so far, whereas when search is nonsequential it does not, since buyers determine the number of stores to visit before the search process begins.

As we briefly discuss in Section 3.2 and formally show in Appendix B, sequential and non-sequential search models lead to different predictions with respect to the effect of an increase in the number of sellers on prices. This implies that there is no clear answer to whether increasing competition among public offices reduces or increases bribe demands. Instead, the answer seems to depend on the search algorithms employed by citizens, and which algorithm is employed is ultimately an empirical question.¹¹

The empirical evidence on the effect of increased number sellers on pricing is also scarce. The obvious identification difficulty lies in the endogenous nature of the number of firms operating in a market.¹² Experimental studies are less problematic and indeed more common. However, most studies are finalized to test for discrepancies between optimal search and observed buyer behavior while focusing on sequential search (Grether et al., 1988),¹³ or compare different search

¹¹The existing empirical evidence suggests that the search algorithm used by consumers is some mixture of fixed sample size and sequential search. Morgan and Manning (1985) obtain theoretically the conditions under which one of the two search algorithms, fixed size or sequential, is optimal. De los Santos et al. (2012) use detailed web browsing and purchases data and find that sequential search is largely rejected by, while fixed sample size search is mostly consistent with the observed search behavior. See Section 6 for further discussion.

¹²Haynes and Thompson (2004) and Barron et al. (2004) are among the few exceptions.

¹³The experimental studies of Schotter and Braunstein (1981), Harrison and Morgan (1990), Kogut (1990), Sonnemans (1998), Brown et al. (2011), among others, find significant deviations from the predictions of sequential search models. See Camerer (2005) for a review of this literature.

algorithms (see Harrison and Morgan, 1990).¹⁴ There is no study, to the best of our knowledge, that directly investigates the effect of increasing the number of sellers on prices in a context where consumers need to engage in costly search to identify the cheaper seller.¹⁵

3 The Experiment

3.1 Design and implementation

We designed a novel extortionary bribery game, in which we use corruption-loaded language. In the experiment, subjects are randomly assigned either the role of public official or the role of private citizen and keep that role for the duration of the experiment. There are m citizens and n officials in each session. Each public official is in charge of an office that provides a license to private citizens. Public officials receive a lump-sum wage of 130 experimental currency units (ECU). Citizens receive an initial endowment of 80 ECU. When a citizen acquires the license she additionally gains 70 ECU. The official license fee is 20 ECU. Thus, in the absence of corruption both public officials and citizens earn 130 ECU. However, each public official can demand a bribe between 1 and 50 ECU on top of the official fee. If a bribe is demanded, citizens can either pay it and get the license, or refuse to pay and go to a different office by paying a fixed search cost. In the experiment we vary the size of the search cost and the number of available offices.

The experiment proceeds as follows. At the beginning of each of 10 rounds, public officials simultaneously decide whether they want to demand a bribe for the provision of the license on top of the official fee, and the size of the bribe, if any. Then, each citizen is randomly matched with an office and finds out the bribe demanded by the official in that office, if any. The citizen can either get the license by paying the official license fee and the requested bribe, or visit another office by paying a fixed cost c . Each citizen has access to a map showing all available offices; for the offices the citizen visited, the map shows what bribes are demanded there. Citizens can costlessly go back and get the license from any of the previously visited offices by paying the corresponding bribe; they have to get the license eventually. Officials do not know the size of the bribes demanded by other officials; however, as citizens search through the offices, each official can see how many citizens visited his office, how many decided to get the license there and how many decided to leave. The official's payoff at the end of each round is 130 ECU plus all the bribes paid by the citizens who decided to get the license at the official's office. The citizen's payoff at the end of each round is 130 ECU minus the bribe she ends up paying and total search costs, i.e. c multiplied by the total number of searches. At the beginning of each new round,

¹⁴Davis and Holt (1996) and Cason and Friedman (2003) manipulate the size of search costs while assuming different search algorithms and both find that prices increase as search costs are increased. Davis and Holt (1996) employ sequential search, whereas Cason and Friedman (2002) employ a streamlined version of Burdett and Judd (1983)'s noisy search model.

¹⁵Morgan et al. (2006) conduct an experiment where computerized buyers are either fully informed about the prices charged by different sellers, and therefore buy all the desired units from the cheapest sellers, or buy an equal number of unit from each seller. Morgan et al. (2006) vary the proportion of informed buyers and the number of sellers. They find that increasing the number of sellers lowers the price paid by informed consumers and increases the price paid by uninformed consumers, hence resulting in higher price dispersion.

Treatment	n	c	sessions	subjects
low c /low n	3	5	4	40
low c /high n	7	5	2	28
high c /low n	3	10	4	40
high c /high n	7	10	2	28

Table 1: Summary of experimental sessions and treatments.

officials are randomly re-assigned to different offices, so citizens cannot associate location on the map to a particular official.

We set the number of citizens, m , equal to 7 in all sessions. We conduct different treatments where we manipulate the number of offices, n , and the search cost c . In particular, in the *low- n treatments* we set $n = 3$ and in the *high- n treatments* with set $n = 7$. Moreover, in half of the sessions we set $c = 5$ (the *low- c treatments*) and in the remaining half we set $c = 10$ (the *high- c treatments*). The experiment follows a 2×2 between-subject design resulting in four treatments: low c /low n , low c /high n , high c /low n and high c /high n .

A total of 136 subjects participated in the experiment, as summarized in Table 1. Each experimental subject participated in only one session and, hence, one treatment.

Before engaging in the corruption experiment each subject was involved in a task aimed at measuring risk preferences. Following the method first introduced by Holt and Laury (2002), we invited subjects to choose between two lotteries, $A = (\$1.60, \$2.00; p, 1 - p)$ and $B = (\$0.10, \$3.85; p, 1 - p)$, with probability p changing from 0.9 to 0 in decrements of 0.1; therefore, each subject went through a sequence of 10 lottery choices. After all 10 choices were made, one lottery was randomly chosen for payment, although earnings from this task were revealed to subjects only at the very end of the experimental session.

After all subjects completed the risk aversion task, the corruption experiment began. Subjects engaged in the experiment for 10 rounds, and were informed that one of the 10 rounds would be randomly selected for payment at the end of the session. The earnings from the selected round were then converted from ECUs to US\$ at the exchange rate of \$1 for 20 ECU. The session concluded with a short questionnaire.

We conducted all experimental sessions at the XS/FS laboratory at Florida State University between February and March 2012. The experiment was programmed in z-Tree (Fischbacher, 2007) and subjects were recruited among FSU students using ORSEE (Greiner, 2004). In order to guarantee anonymity, at the beginning of each session subjects were randomly assigned an identification number, which they kept for the duration of the experiment. At no point did we ask subjects to reveal their names during the experiment, and although actual names were used during the payment process for accounting purposes, we informed the subjects that we would not register their names and, therefore, we would not be able to link them to the choices made in the experiment. Each session lasted between 60 and 90 minutes, with average earnings of around \$21.60 per subject including a \$10 show-up fee. Instructions were read aloud, with a

printed copy distributed to subjects (see Appendix C).

3.2 Predictions

As briefly discussed in Section 2, when employing a setting where individuals have the possibility to acquire information through searching, the assumption concerning the way people search becomes crucial. Starting from Burdett and Judd (1983), *nonsequential* search models have assumed that individuals first commit to sampling a certain number of sellers (offices in our setting) and then acquire the good (license) from the seller (office) demanding the lowest price (bribe) in the sample. On the other hand, *sequential* search models (Stahl, 1989) assume that individuals re-evaluate their options after each search and continue searching as long as the cost of an additional search is lower than the expected benefit from such search. While the two models generate the same prediction with respect to the effect of search costs on prices (bribe demands), they lead to different predictions with respect to the effect of the number of sellers/providers on prices (bribe demands).

In Appendix B, we formally show that this is the case by applying the models of Burdett and Judd (1983) and of Stahl (1989) to our corruption setting. We, therefore, hypothesize that

Prediction 1 *An increase in c will lead to an increase in bribes.*¹⁶

Prediction 2 *An increase in n will have an ambiguous effect on bribe demands. If citizens search sequentially, an increase in n should lead to an increase in bribes. If citizens search nonsequentially, an increase in n should have a negative effect on bribes if c is low enough, or no effect if c is high.*

The theoretical ambiguity of Prediction 2 makes experimental methods particularly suitable to studying the effect of competition with search costs on corruption.

From a practical viewpoint, it may also be of interest to investigate how bribes are affected by a simultaneous increase in n and decrease in c . Such a combined effect would result, for example, from an increase in the density of public officials in a given area. As seen from the predictions above, the two effects can either work in the same direction, reducing the bribes more than each of the changes in isolation (for nonsequential search), or they can work in opposite directions (for sequential search). This ambiguity will also be addressed empirically in our experiment.

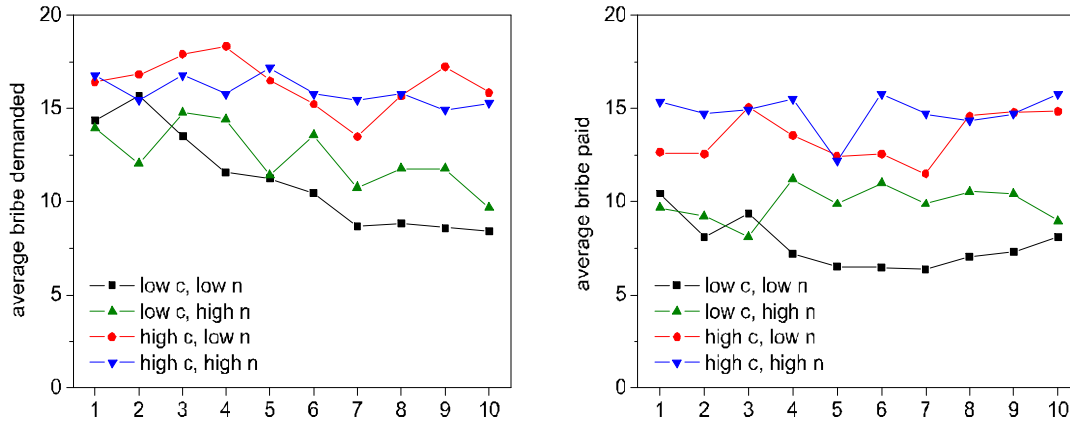


Figure 1: Average bribe demanded by public officials (left) and paid by private citizens (right) in each round, by treatment.

4 Results

4.1 Treatment effects

The left panel in Figure 1 shows the average bribe demanded in each round, by treatment. As the figure suggests, higher bribes are demanded when the search cost is high, both for high and low n . The effect is especially pronounced in later rounds. As for the impact of the number of offices, it appears that higher n leads to higher bribes when the search cost is low, but there is no effect of n on bribes demanded when the search cost is high. The right panel in Figure 1, showing the average bribe paid by citizens, tells essentially the same story. Histograms displaying the entire distributions of bribes demanded and paid – see Figure 4 in Appendix A – show that the distributions are shifted as search costs increase, and also as n increases from low to high, but only under low c .

Table 2 shows the average bribes demanded by public officials, average bribes paid by citizens, the average number of searches per citizen and average citizen’s earnings by treatment. In each case, the averages are shown over the entire sequence of 10 rounds (all t) and over the last 5 rounds ($t > 5$). Table 2 also reports standard errors in parentheses for each of the averages that are clustered at the subject level.

We performed nonparametric Kolmogorov-Smirnov (KS) tests comparing the empirical distributions of bribes demanded and paid across treatments. For these comparisons, we computed average bribes demanded by each public official and average bribes paid by each citizen over all

¹⁶A positive monotonic relationship between search costs and equilibrium prices is common for a variety of basic search models employing both sequential and nonsequential search algorithms, e.g., Stahl (1989), Bakos (1997). It is possible, however, for an increase in search costs to lead to lower equilibrium prices in more complex settings, e.g., in the presence of “local searchers” (Chen and Zhang 2009) or advertisement (Cason and Datta 2006, Janssen and Non 2008, Cason and Mago 2010).

	Bribe demanded		Bribe paid		# of searches		Citizen earnings	
	all t	$t > 5$	all t	$t > 5$	all t	$t > 5$	all t	$t > 5$
low c/low n	11.13 (1.91)	9 (1.19)	7.69 (0.39)	7.06 (0.30)	0.41 (0.07)	0.36 (0.08)	120.24 (0.49)	121.12 (0.44)
low c/high n	12.42 (0.71)	11.51 (0.48)	9.88 (0.53)	10.16 (0.23)	0.36 (0.07)	0.26 (0.06)	118.33 (0.47)	118.56 (0.38)
high c/low n	16.35 (2.07)	15.5 (1.19)	13.47 (0.97)	13.67 (1.07)	0.28 (0.48)	0.21 (0.05)	113.71 (0.73)	114.26 (0.92)
high c/high n	15.92 (1.64)	15.44 (1.62)	14.8 (0.72)	15.07 (0.93)	0.25 (0.06)	0.24 (0.07)	112.69 (0.59)	112.5 (0.83)

Table 2: Summary statistics by treatment (standard errors in parentheses are clustered by subject).

10 rounds (all t) and over the last 5 rounds ($t > 5$), and treated those as independent observations.¹⁷ We found that bribes demanded are higher when c is high under both low n ($p = 0.017$, all t ; $p = 0.017$, $t > 5$) and under high n ($p = 0.003$, all t ; $p = 0.003$, $t > 5$). Also, bribes demanded are higher when n is high for low c ($p = 0.073$, all t ; $p = 0.010$, $t > 5$), but there is no difference in bribes demanded when c is high ($p = 0.725$, all t ; $p = 1.000$, $t > 5$). Similarly, bribes paid are higher when c is high under both low n ($p = 0.000$, all t ; $p = 0.000$, $t > 5$) and high n ($p = 0.000$, all t ; $p = 0.000$, $t > 5$); and bribes paid are higher when n is high for low c ($p = 0.004$, all t ; $p = 0.000$, $t > 5$), but there is no difference in bribes paid when c is high ($p = 0.199$, all t ; $p = 0.488$, $t > 5$).

The statistical support for the treatment effects suggested by Figure 1 can also be seen from Table 3 which shows the results of linear regressions of bribes demanded by public officials and bribes paid by private citizens on the dummy variables *high c* , *low n* , and their interaction, with errors clustered at the subject level. Consistent with the KS tests reported above, Table 3 confirms the following results.

Result 1 *For both high and low n , higher bribes are demanded and paid when c is higher. Both results hold for all rounds and for rounds 6-10.*

Result 2 (a) *When c is low, higher bribes are demanded and paid when n is higher. The result for bribe demands holds for rounds 6-10, and the result for bribe payments holds for all rounds and for rounds 6-10.*

(b) *When c is high, there is no difference in bribes demanded and paid between the treatments with high n and low n .*

Result 3 *Lower bribes are demanded and paid in the low c /high n treatment than in the high c /low n treatment. Thus, there is a reduction in bribes when n increases and c decreases at the same time.*

¹⁷The KS test also allows us to test for first-order stochastic dominance (FOSD) between empirical distributions. The FOSD was identified for bribes demanded and paid in all the cases when significant differences between the distributions were found.

	Bribe demanded		Bribe paid	
	all t	$t > 5$	all t	$t > 5$
high c	3.500** (1.742)	3.929** (1.652)	4.929*** (0.869)	4.914*** (0.931)
low n	-1.288 (1.981)	-2.514** (1.247)	-2.186*** (0.644)	-3.100*** (0.366)
high c & low n	1.717 (3.241)	2.571 (2.771)	0.846 (1.355)	1.700 (1.440)
Constant	12.421*** (0.692)	11.514*** (0.471)	9.879*** (0.515)	10.157*** (0.220)
Observations	520	260	840	420
Clusters	52	52	84	84
R-squared	0.077	0.196	0.184	0.294

Table 3: OLS regression results for average treatment effects. Subject-level robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

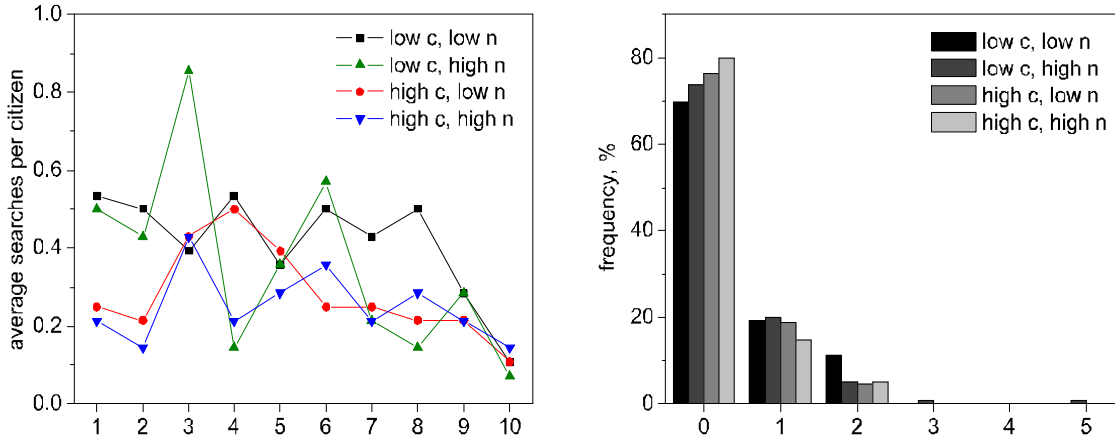


Figure 2: Average number of searches by citizens in each round, by treatment (left) and number of searches by citizens in all rounds, by treatment (right).

Turning to searching behavior, Figure 2 (left) shows the average number of searches per citizen in each round, by treatment. Overall, it appears that citizens search relatively little, and there is no obvious ranking of treatments. Moreover the number of searches converges to zero for all treatments. Figure 2 (right) shows the histogram of the number of searches per citizen for each treatment. The histogram suggests that citizens search more as the search cost goes down, but the difference between treatments is not statistically significant. The reason is, as we show in Section 4.2, that the decision whether or not to search depends strongly on the dynamics of bribes encountered, and those are adjusted by officials across treatments.

4.2 Individual-level analysis

Table 4 reports the results of dynamic individual-level regressions of bribes demanded by officials and paid by citizens. Specification (1) for bribe demands includes the bribe demanded by the official in the previous round (*bribe_lag*), the fraction of citizens who obtained the license from the official relative to the number of citizens who visited his office in the previous round (*%bought_lag*), and the interaction between the two. As seen from the table, bribes are persistent to the extent that the treatment dummies become insignificant. Moreover, the persistence of bribes is higher the higher the fraction of citizens who paid the official’s bribes in the previous round. Specification (2) adds gender, whether the official is economics major, and our experimental measure of risk aversion (the number of “safe” choices, option A, in the Holt and Laury (2002) task) to the specification. We find that female officials demand higher bribes, whereas risk aversion has a negative impact on bribes demanded.

Specifications (3) and (4) explore the determinants of bribes paid by citizens. Both include the treatment dummies, the bribe paid in the previous round (*bribepaid_lag*) and the number of searches in the current round (*#searches*). Specification (4) adds the same demographic characteristics as specification (2) for the officials. We find that there is substantial persistence in the bribes paid, although not to the extent that the treatment dummies are no longer relevant. This can be explained by the fact that citizens do not have that much control, beyond their ability to search, over the bribes they pay. Those bribes are set by the officials and are, therefore, subject to strong treatment effects even when the persistence in bribes paid is accounted for.

As expected, the number of searches has a strong negative effect on the bribes paid. The estimates in columns (3) and (4) suggest that on average one additional search reduces the bribe paid by 1 ECU. Given the size of the search costs, searching does not seem to be beneficial. Further analysis, not reported here, shows that each search lowers average citizens’ earnings by about 8 ECU if the search cost is high and by about 4 ECU if the search cost is low. On the other hand, the higher the frequency of searches in a round, the lower the bribes set by officials in the following round and, consequently, the higher the average earnings of citizens in that round. This suggests that searchers are actually providing a public good, i.e., their searching activity reduces their current earnings but increases the earnings of all citizens in the following rounds; citizens who do not search are those who benefit most.¹⁸ Finally, note that none of the demographic characteristics for citizens emerge as significant factors. We summarize the results as follows.

Result 4 (a) *There is strong persistence in the bribes demanded by officials and paid by citizens. For officials, the persistence is stronger the more successful the official was in receiving the bribe for his service in the previous round.*

(b) *Women officials demand higher bribes than men, and more risk-averse officials demand lower bribes.*

(c) *Citizens who search more pay relatively lower bribes, yet searching lowers total earnings.*

¹⁸Results are available from the authors upon request.

	Bribe demanded		Bribe paid	
	(1)	(2)	(3)	(4)
high c	0.484 (0.703)	0.469 (0.781)	3.408*** (0.700)	3.185*** (0.742)
low n	-0.190 (1.012)	-0.004 (1.012)	-1.793*** (0.377)	-2.093*** (0.509)
high c & low n	1.089 (1.402)	0.193 (1.477)	1.033 (0.956)	1.393 (1.044)
bribe_lag	0.386** (0.170)	0.368** (0.169)		
b_lag x % bought_lag	0.434*** (0.150)	0.407** (0.154)		
% bought_lag	-3.385 (3.002)	-2.780 (3.065)		
# searches			-1.009*** (0.326)	-1.034*** (0.337)
bribepaid_lag			0.285*** (0.057)	0.280*** (0.060)
female		1.803** (0.716)		0.156 (0.525)
econ major		-0.175 (0.594)		-0.609 (1.184)
risk aversion		-0.314** (0.151)		-0.181 (0.130)
Constant	6.576* (3.345)	7.538** (3.542)	7.399*** (0.655)	8.654*** (1.332)
Observations	468	468	756	756
Clusters	52	52	84	84
R-squared	0.430	0.446	0.303	0.307

Table 4: OLS regression results for individual-level decisions on bribes demanded and paid. Subject-level robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Search		
	(1)	(2)	(3)
high c	-0.066 (0.055)	-0.032 (0.061)	-0.032 (0.061)
low n	0.028 (0.047)	0.003 (0.051)	0.003 (0.051)
high c & low n	-0.006 (0.071)	0.002 (0.072)	0.002 (0.072)
lowest bribe		0.004* (0.003)	
bribepaid_lag		-0.010*** (0.002)	-0.006** (0.002)
bribedif			0.004* (0.003)
Observations	1,120	1,004	1,004
Clusters	84	84	84
Controls	No	YES	YES

Table 5: Probit regression results for individual-level decision on search. Marginal effects are reported. Subject-level robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Next, we look at the citizens' search behavior. Table 5 reports the results of probit regressions for the individual-level decision to search by citizens. Specification (1) only includes treatment dummies. The results show, consistent with Figure 2, that there are no significant differences in search intensity across treatments.

Specification (2) includes two additional variables – the lowest bribe encountered so far in the current round (*lowest bribe*) and the bribe paid in the previous round (*bribepaid_lag*). Both have the expected significant effect on the decision to search. Consistent with sequential search models and reservation price-based search, the higher the minimal bribe encountered so far the more likely it is that the citizen will continue searching. The effect of the bribe paid in the previous round on search intensity is negative. One explanation can be that citizens learn about the population of officials they encounter and update their beliefs about the probability of finding a lower bribe. An alternative explanation is suggested by specification (3), which includes, instead of the lowest available bribe, the difference between the lowest available bribe and the bribe paid in the previous round (*bribedif*). The bribe paid previously can serve as the citizen's reference point in deciding whether or not to search further.

Specifications (2) and (3) in Table 5 also include demographic controls, but none of those was found statistically significant.

Result 5 (a) *There are no differences in search intensity across treatments.*

(b) *Citizens are less likely to search in the current round the larger the bribe paid in the previous round, the smaller the minimum bribe they encountered so far, and the smaller the difference between these two bribes.*

5 Increasing competition in a standard market setting

As discussed in Section 2, the difficulty in conducting empirical investigations of the effect of competition on prices applies to the corruption setting studied in this paper but also more generally to standard market settings with multiple buyers and sellers, where sellers offer an homogeneous product and buyers acquire information about prices through costly search.¹⁹

It is, therefore, of interest to test whether our results on the effect of competition in the corruption setting are consistent with those obtained in a standard market setting. As a robustness check, we conducted two additional treatments. In these treatments, we replaced the corruption frame in our experimental instructions with a market frame and test whether and how increasing the number of sellers from 3 to 7 affects sellers' price setting behavior in the presence of costly search. Given that we identified the most interesting and significant effect of competition on corruption for low search costs, we only conducted the market setting treatments with $c = 5$ and manipulated solely the number of sellers n .

In the two additional treatments, *low c/low n/m* and *low c/high n/m*, we employ exactly the same protocols and parameters as in our corruption frame treatments *low c/low n* and *low c/high n*, respectively, except that "Offices" are now called "Stores" and "Public Officials" are now called "Owners of a Store." We still refer to buyers as "Citizens." Recall that in the corruption frame officials had to decide whether or not to demand a bribe for the provision of the license on top of an official fee of 20 ECU, with the fee being transferred to the government and hence not cashed by the officials. In the market frame, we give sellers the possibility to set a price mark-up on top of a fixed production cost of 20 ECU that is then subtracted from the price paid by citizens and hence not included in the sellers' earnings. In this way, we keep monetary incentives identical in the two settings. We conducted two sessions with $n = 7$ (*low c/high n/m* treatment) and four sessions with $n = 3$ (*low c/low n/m* treatment). A total of 68 subjects participated in these treatments.

Figure 3 shows the average price mark-up demanded (left) and paid (right) in each round, by treatment. Table 6 shows the average price mark-ups set by sellers, the average price mark-ups paid by citizens, the average number of searches per citizen and average citizen's earnings under low and high n . In each case, the averages are shown over the entire sequence of 10 rounds (all t) and over the last 5 rounds ($t > 5$). The standard errors in parentheses are clustered at the subject level. As Figure 3 and Table 6 suggest, there seems to be no effect of n on prices.

Similar to Section 4, we performed KS tests comparing the empirical distributions of mark-ups demanded and paid across treatments. For these comparisons, we computed average mark-ups demanded by each public official and average mark-ups paid by each citizen and treated those as independent observations. All the comparisons provide no evidence of statistically significant differences across treatments.²⁰

¹⁹ An important difference between the two settings, however, is that in the case of corruption sellers, i.e. public officials, cannot advertise their bribes, due to their illegal nature; therefore, acquiring information through office visits is even more crucial than in a standard market setting.

²⁰ The KS test shows a weakly significant difference ($p = 0.081$) for mark-ups demanded over all 10 rounds, but

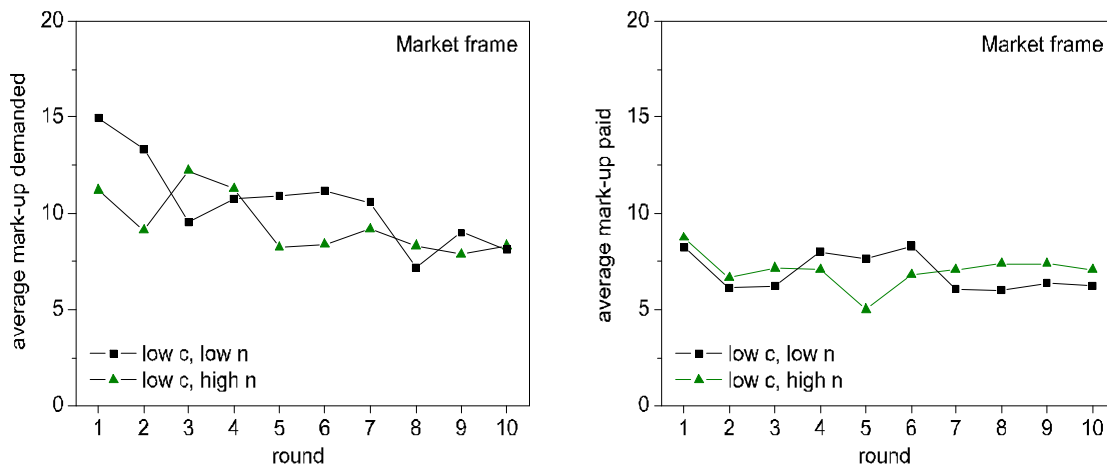


Figure 3: Average price mark-up demanded by sellers (left) and average price mark-up paid by citizens (right) in each round, by treatment.

	Mark-up demanded		Mark-up paid		# of searches		Citizen earnings	
	all t	$t > 5$	all t	$t > 5$	all t	$t > 5$	all t	$t > 5$
low c /low n /m	10.55	9.2	6.9	6.58	0.44	0.36	120.90	121.6
	(1.59)	(1.39)	(0.69)	(0.73)	(0.07)	(0.07)	(0.64)	(0.63)
low c /high n /m	9.4	8.4	7.02	7.12	0.38	0.33	121.09	121.23
	(0.88)	(1.01)	(0.57)	(0.56)	(0.12)	(0.12)	(0.56)	(0.48)

Table 6: Summary statistics in the market frame treatments (standard errors in parentheses are clustered by subject).

Further evidence of no effect of n on prices can be found in columns (1) and (2) of Table 7, which show estimates of linear regressions of price mark-ups set by sellers and paid by citizens on the dummy variable *high n*. When looking at sellers' price setting behavior we also control for the price mark-up set in the previous round and when looking at buyers' behavior we control for the price paid in the previous round and the number of searches conducted in the current round. The estimates in columns 1 and 2 of Table 7 show persistence of both prices set and paid over time, and effectiveness of searching in reducing the price paid.²¹ Finally, column (3) of Table 7 reports results of probit regressions for citizens' decision to search.

The estimates show that there are no significant differences in search intensity across treatments. Moreover, while the price paid by citizens in the previous round affects the decision to search at any given time in the current round, the difference between the lowest price currently encountered and the price previously paid does not affect searching behavior.²² We summarize

not over the last 5 rounds.

²¹However, since on average one additional search reduces the price paid by less than 1 ECU and each search costs 5 ECU, searching is actually not beneficial. Similar to the corruption frame, it has an effect of a public good for other citizens.

²²The lowest price encountered is also not significant when included in the search specification by itself. The results are not reported in Table 7, but are available from the authors upon request.

	Price demanded (1)	Price paid (2)	Search (3)
high n	-0.424 (0.723)	0.089 (0.489)	-0.005 (0.065)
pricedemanded_lag	0.542** (0.229)		
pricepaid_lag		0.360*** (0.082)	-0.012** (0.005)
# searches		-0.735** (0.337)	
pricedif			0.006 (0.005)
Constant	0.458 (4.068)	3.057*** (0.975)	
Observations	234	378	530
Clusters	26	42	42
Controls	YES	YES	YES

Table 7: OLS regressions for price demanded and price paid, and probit regression results for individual-level decision to search. For the probit regressions, marginal effects are reported. Subject-level robust standard errors in parentheses. Significance levels: *** - $p < 0.01$, ** - $p < 0.05$, * - $p < 0.1$.

the results as follows.

Result 6 *In the market setting,*

- (a) *There is no difference in prices set and paid between the treatments with high n and low n .*
- (b) *There is persistence in the prices demanded by sellers and in the prices paid by buyers.*
- (c) *There is no difference in search intensity across treatments.*
- (d) *Citizens are less likely to search in the current round the larger the price paid in the previous round. The lowest price they encountered so far and the difference between such price and the price paid in the previous round do not affect search.*

Comparing the results obtained in the market setting with those in the corruption setting (cf. Tables 2 and 6), we observe that there are no significant differences in averages between the two settings when n is low. However, when n is high (and c is low) bribes are higher than price mark-ups; the latter stay at the same level as under low n . One important conclusion we can draw from these comparisons is that the finding that an increase in the number of offices does *not* lead to a *reduction* in bribes is robust to framing. On the other hand, the result that an increase in n leads to higher prices only applies to the corruption setting. In the remainder of this section, we propose an explanation for the differential effect of n on bribes versus mark-ups.

Recall that an increase in prices with an increase in n is predicted by theory if buyers search sequentially, while there may be no effect, or a negative effect, of n on prices if search is nonsequential. Thus, one possibility is that individuals use different search algorithms in

different settings, i.e., sequential in the corruption setting and nonsequential in the market setting. There is almost no empirical evidence of how individuals search. One notable exception is the recent study by De Los Santos et al. (2012). Using data on web browsing and purchasing of books online, De Los Santos et al. (2012) find that individuals' decision to search does not depend on the outcomes of previous searches, which provides evidence of nonsequential rather than sequential search.²³

The conjecture that individuals search differently in the corruption and in the market settings is supported by the different results that we obtained for individuals' decision to search in the corruption setting, cf. column (3) in Table 5, and in the market setting, cf. column (3) in Table 7. While in both cases the variable `bribepaid_lag` (`pricepaid_lag` in Table 7) has a negative effect on search, the variable `bribemin`, the lowest bribe/price encountered so far, and the variable `bribe_dif` (`price_dif` in Table 7), the difference between the lowest available bribe and the bribe paid in the previous round, is significant in the corruption setting but not in the market setting. Similar to De los Santos et al. (2012), we can interpret the presence of a reaction to the lowest price found from previous searches in the corruption setting as evidence of sequential search, while failure to react to such lowest price in the market setting as evidence of nonsequential search. Therefore, the positive effect of n on bribes obtained in the corruption setting is in line with the predictions of a sequential search model, and the null effect of n on prices in the market setting is in line with the predictions of a nonsequential search model.

While we did not hypothesize the observed differences in search behavior in the two settings, we can advance some speculative explanations of such differences. Since all subjects have had hands-on experience with markets outside the lab, the search patterns in our market setting are more likely to be consistent with those observed in other studies of search behavior using field data, which point in the direction of nonsequential search (De los Santos et al. 2012). The corruption setting, on the other hand, is likely to be less familiar to our subjects. Moreover, despite the structural equivalence of the two settings, individuals might simply not perceive the (possibly corrupt) service delivery environment as a market. Therefore, search patterns in this setting are likely to be more cautious and generally consistent with directional reinforcement learning, thus leading to behavior that looks more like sequential search.

6 Conclusions

Identifying successful anti-corruption policies is challenging. The most common approach is deterrence-based, i.e. it relies on policies aimed at increasing the expected monetary costs of corruption through higher threat of punishment and/or severe sanctions. However, since effective deterrence is dependent upon top-down monitoring and enforcement mechanisms, policies aimed

²³In a specially designed experiment, Harrison and Morgan (1990) found evidence that individuals use a mix of sequential and nonsequential search strategies, referred to as variable-sample-size strategies (Morgan and Manning, 1985). Hong and Shum (2006) and Chen et al. (2007) use data on textbook prices to structurally estimate the distribution of consumer search costs using both the fixed sample size and sequential search models but do not conclude definitively in favor of one of the two models.

at increasing the probability and/or severity of punishment often prove ineffective, especially in countries characterized by systemic corruption.

An alternative approach would be to identify institutional changes that reduce corruption without relying on increased top-down monitoring and enforcement. In this paper, we investigated the effectiveness of one of such possible changes, which concerns the structure and organization of the bureaucracy in charge of providing a given good or service to citizens. In particular, we designed and conducted a laboratory experiment to test whether increasing the number of offices providing the same service – i.e., increasing competition among offices – would reduce the demand of extortionary bribes, i.e. bribes for the provision of goods that clients are entitled to, as first suggested by Rose-Ackerman (1978, 1999) and Shleifer and Vishny (1993).

Addressing our research question in the field is problematic due to identification and measurement problems, and the obvious difficulty to find a cooperating government willing to experiment with alternative ways to provide goods and services to citizens. We were able to overcome these challenges by conducting a specially designed laboratory experiment where, contrary to all previous corruption experiments, we allowed for, and manipulated the extent of, competition among public officials for the provision of the same government service in a controlled setting.

In the experiment, we gave subjects in the role of public officials the task to provide a license to citizens visiting their office. Each public official could demand a bribe for the provision of the license on top of an official fee. Subjects in the role of private citizens could get the license from any available office; however, while visiting the first office (to which they were randomly matched) was free, in order to visit any of the other offices they had to sustain a fixed cost. Citizens had to get the license eventually. In the experiment, we manipulated the number of available offices. Moreover, since increasing the number of offices in the field may or may not cause a reduction in search costs, we conducted half of the sessions with a relatively low search cost and the remaining half with a high search cost.

We found that increasing competition among offices may reduce bribe demands only if it comes with a reduction in search costs, and it is the reduction in search costs that is the driver of the reduction in bribes. Moreover, the *ceteris paribus* effect of an increase in the number of offices may actually go in the opposite direction, i.e., it can lead to an increase in bribes demanded. Specifically, we find that if search costs stay unchanged, increasing the number of offices leads to either no change in corruption (if search costs are high) or an increase in corruption (if search costs are low). On the other hand, reducing search costs alone always results in lower level of extortionary corruption. Further research will investigate the effectiveness of different mechanisms aimed at reducing search costs directly, for example through information sharing among license applicants.

Finally, given the possible applications of our results to general market environments, we tested the robustness of our findings by replicating the study employing a standard market setting, while keeping protocol and payoffs identical to the corruption setting. We found that increasing the number of sellers in a standard market setting while keeping search costs low, has no impact on pricing behavior. Our data provide suggestive evidence that the differential

effects of n on prices in the two settings might be due to different search strategies employed by buyers.

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A Additional graphs

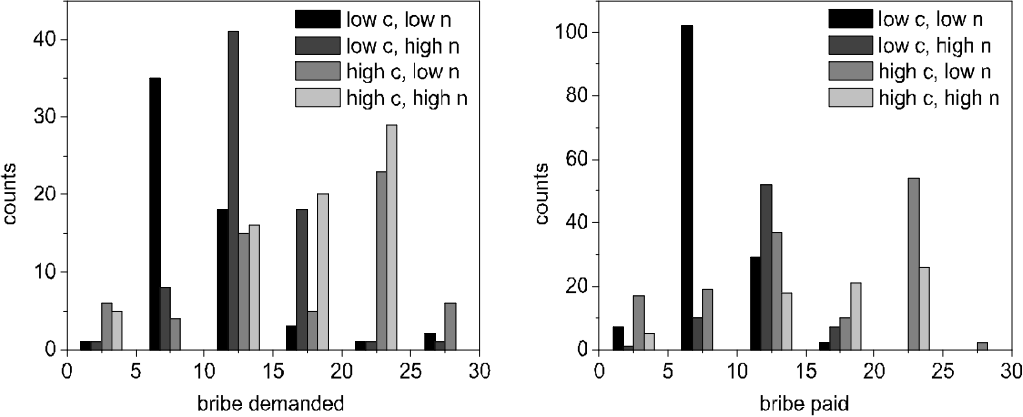


Figure 4: Bribes demanded by public officials in rounds 6-10, by treatment (left) and bribes paid by private citizens in rounds 6-10, by treatment (right).

B Theoretical Framework

In our corruption experiment, we use the following simple framework. There are m citizens indexed by $i = 1, \dots, m$ and n offices indexed by $j = 1, \dots, n$. The offices provide a license that has a net value of V to citizens. Each office j is managed by a public official who decides on the amount of the bribe, $b_j \in [0, B]$, to demand for the provision of the license. Initially, each citizen is randomly matched to an office and learns about the bribe demanded by the official in that office. The citizen can either acquire the license by paying the bribe or *search*, i.e., incur a search cost and visit a different office. All citizens have the same monetary cost of search $c > 0$.

Search is with recall, i.e., a citizen can always acquire the license from any previously visited office at no additional cost. The game ends when all citizens acquire the license. If a citizen searches through all available offices, she has to obtain the license from one of them. Citizen i 's monetary payoff is $V - b_{\bar{j}(i)} - l_i c$, where $\bar{j}(i)$ is the office where citizen i eventually obtained the license, and l_i is the number of searches she undertook. Public official j 's payoff is $k_j b_j$, where b_j is the bribe she demands, and k_j is the number of citizens who acquired the license from office j .²⁴

In addition to the common monetary search cost c , citizens have heterogeneous nonmonetary cost parameters α_i so that citizen i 's total search cost is $c_i = \max\{0, c + \alpha_i\}$. Parameters α_i can be positive or negative and represent, in a reduced form, a combination of unobserved individual-specific factors affecting search behavior, such as general propensity to search, costs of engaging in corruption, costs of time or cognitive costs. We assume parameters α_i are drawn independently from a commonly known distribution, resulting in a distribution $G(\cdot)$ of total search costs c_i . Distribution $G(\cdot)$ will have a mass at zero if there are citizens with $\alpha_i \leq -c$. This corresponds, in the language of consumer price search models, to the presence of “shoppers,” i.e., citizens who will search until they find an office that does not demand a bribe, or exhaust all available offices.

In this paper we are interested in the effect of the number of offices, n , on the level of bribes. We also explore the effect of exogenous variation in search costs which we manipulate by changing the monetary component of search costs, c . The reason is that in the field an increase in the number of available offices may or may not be accompanied by a reduction in search costs, and vice versa, and it is of interest to explore the effects of an increase in n and a reduction in c on corruption in isolation as well as jointly.

The characterization of equilibrium in a market with heterogeneous search costs is a complex problem. First, the results depend crucially on the search algorithm adopted by citizens. Second, even for a fixed search algorithm, the equilibrium distribution of bribes can vary depending on the distribution of total search costs $G(\cdot)$.

In what follows, we briefly present the equilibrium characterization of two models corre-

²⁴In the experiment, citizens additionally incur a fixed official license fee, which is here subsumed in V ; and public officials earn a fixed official wage regardless of the bribes. Parameters are calibrated so that in the absence of corruption public officials and citizens earn the same amount.

sponding to the two prominent search paradigms – nonsequential and sequential search – and summarize their comparative statics predictions related to n and c .

B.1 Nonsequential search

When citizens search nonsequentially, they first commit to sampling a certain number of offices and then acquire the license at the office demanding the lowest bribe in the sample. We adopt the approach of Burdett and Judd (1983). Let $F(b)$ denote the resulting equilibrium distribution of bribes. For a risk-neutral citizen with search cost c_i , the optimal number of offices to visit, $l^*(c_i)$, is given by the following cost minimization problem:²⁵

$$\min_{l \geq 1} c_i(l-1) + \int bl[1-F(b)]^{l-1} dF(b).$$

The first term represents the cost of visiting l offices (including the costless visit to the office with which the citizen is initially matched); the second term is the expected lowest bribe from a random sample of l offices.

Let b_{\min}^l denote the expected minimal bribe in a sample of l offices. Then the citizen's expected gain from visiting one more office after having visited l offices is $D_l = b_{\min}^l - b_{\min}^{l+1}$. It is easy to see that D_l is decreasing in l ; therefore, citizen i will be searching as long as D_l exceeds c_i and will search through all available offices if $D_{n-1} > c_i$. Given F , parameters D_l determine the distribution of citizens by the number of searches. Specifically, the proportion $q_1 = 1 - G(D_1)$ of citizens will acquire the license immediately; proportion $q_2 = G(D_1) - G(D_2)$ will sample two offices, and so on, with the proportion $q_n = G(D_{n-1})$ of citizens visiting all n offices.

Assuming that there are citizens who do not search, the equilibrium distribution of bribes will satisfy the following indifference condition for all b in the support of F :

$$Bq_1 = b \sum_{l=1}^n q_l l [1-F(b)]^{l-1}. \quad (1)$$

The left-hand side represents an official's expected payoff from the citizens who do not search and pay the highest bribe B , while the right-hand side is the official's expected payoff from choosing a bribe using a mixed strategy $F(b)$. Equation (1) is an implicit equation for the equilibrium distribution of bribes F .

An increase in the monetary search cost c will lead to an upward probabilistic shift of the distribution G , which, in turn, will lead to an increase in q_1 and a downward probabilistic shift in the distribution of the number of searches q_l . Thus, the left-hand side of Eq. (1) will increase and, to match the increase, $F(b)$ will have to go down. The prediction, therefore, is an upward probabilistic shift of the distribution of bribes.

Consider now an increase in the number of offices, n . Suppose, first, that search costs are

²⁵Here and below, integration is over the support of F unless specified otherwise.

low enough so there is a mass of citizens who search through all available offices, i.e., $q_n > 0$. An increase in n will allow those citizens to search more, which implies an upward shift in the distribution of the number of searches and, as a result, a downward shift in the distribution of bribes. If, however, search costs are so high that $q_n = 0$, an increase in n will have no effect.

To summarize, the nonsequential search model predicts that an increase in n will lead to more searches and a reduction of bribes if search costs are low enough, and to no change in searches and bribes otherwise, while an increase in c will lead to fewer searches and an increase in bribes.

B.2 Sequential search

Citizens searching sequentially re-evaluate their options after each office visit. Having visited an office, they can acquire the license by paying the lowest bribe encountered so far or undertake an additional search. In this section, we adopt the approach of Stahl (1989). Given a distribution of bribes $F(b)$, the optimal sequential search algorithm for citizen i is to search until a reservation bribe $b_r(c_i)$ is reached, which is defined as $b_r(c_i) = \min\{z(c_i), B\}$, where $z(c_i)$ is the solution of the equation

$$c_i = \int_{b \leq z} (z - b) dF(b). \quad (2)$$

Here, the right-hand side represents the marginal gain from one additional search given that the lowest bribe encountered so far is z . We will use F_r to denote the distribution of reservation bribes in the population of citizens. The proportion of citizens for whom the reservation bribe is B is $\alpha = 1 - F_r(B)$, and $F_r = 0$ at the lower bound of the support of distribution F . An official demanding bribe b will only attract citizens with reservation bribes $b > b_r$. Thus, the proportion of citizens getting the license from an office demanding a bribe b is $\int_b^B [1 - (1 - F(b_r))^n] dF_r(b_r)$. Here, $(1 - F(b_r))^n$ is the probability that all offices demand a bribe above b_r , and the integral gives the probability that there is at least one office with bribe less than b_r averaged over the distribution of reservation bribes with $b < b_r$ (see Hong and Shum, 2006).

Similar to the previous section, a symmetric mixed strategy equilibrium distribution of bribes F must satisfy the indifference condition for all b in the support of F :

$$B\alpha = b \int_b^B [1 - (1 - F(b_r))^n] dF_r(b_r). \quad (3)$$

The left-hand side of (3) is the expected payoff of an official demanding the highest bribe B , while the right-hand side gives the payoff at an arbitrary bribe b . This equation implicitly determines the equilibrium distribution of bribes.

Consider an increase in the monetary search cost c leading to an upward shift of the distribution G . As seen from Eq. (2), $z(c_i)$ is an increasing function of c_i ; therefore, the distribution of reservation bribes F_r will also shift upward, leading to an upward shift in the equilibrium distribution of bribes.

If the number of offices n increases, the right-hand side of Eq. (3) will also increase, for a given F . To compensate that increase, F should decrease, i.e., there will be an *upward* shift of the distribution of bribes (for a detailed discussion, see, e.g., Stahl 1989).

To summarize, the sequential search model predicts that an increase in n and an increase in c will both lead to fewer searches and an increase in bribes.

C Experimental Instructions (treatment low c /high n)

General Instructions

Thank you all for coming today. You are here to participate in an experiment. After playing the game you will be asked to complete a brief questionnaire. In addition to a \$10 participation fee, you will be paid any money you accumulate from the experiment. You will be paid privately, by check, at the conclusion of the experiment. This study has been reviewed and approved by the FSU Human Subjects Committee. If you have any questions during the experiment, please raise your hand and wait for an experimenter to come to you. Please do not talk, exclaim, or try to communicate with other participants during the experiment. Participants intentionally violating these rules may be asked to leave the experiment and may not be paid.

Please read and sign the Consent form that you found on your desk. Please raise your hand if you have any question about any of the information on the Consent form. We will proceed with the experiment once we have collected all signed consent forms.

The number that you have found on your desk is your identification number in the experiment. We won't ask you to write down your name at any time during this experimental session. No one, including the experimenter, will have a way to link your name to the decisions you made in the experiment. At the end of the session, you will need to show your number to the experimenter in order to receive the money that you collected in the experiment.

Earnings during the experiment will be denominated in Experimental Currency Units, or ECU. At the end of the experiment your earnings will be converted to dollars at the exchange rate of \$1 for 20 ECU.

The experiment will consist of several parts and the instructions will be provided separately at the beginning of each part.

Instructions for Part 1

In each round of this series of decisions you will be asked to make a choice between two lotteries that will be labeled A and B. There will be a total of 10 rounds and after you have made your choice for all 10 rounds, one of those rounds will be randomly chosen to be played. Lottery A will always give you the chance of winning a prize of \$2.00 or \$1.60, while lottery B will give you the chance of winning \$3.85 or \$0.10. Each decision round will involve changing the probabilities of your winning the prizes. For example in round 1, your decision will be represented on the screen in front of you:

Your decision is between these two lotteries:

Lottery A: A random number will be drawn between 1 and 100. You will win

\$1.60 if the number is between 1-90 (90 % chance)

\$2.00 if the number is between 91 and 100 (10 % chance)

Lottery B: A random number will be drawn between 1 and 100. You will win

\$0.10 if the number is between 1 and 90 (90% chance)

\$3.85 if the number is between 91 and 100 (10% chance)

If you were to choose lottery B and this turns out to be the round actually played, then the computer

will generate a random integer between 1 and 100 with all numbers being equally likely. If the number drawn is between 1 and 90, then you would win \$0.10 while if the number is between 91 and 100, then you would win \$3.85. Had you chosen lottery A, then if the number drawn were between 1 and 90 you would win \$1.60 while a number between 91 and 100 would earn you \$2.00.

All of the other 9 choices will be represented in a similar manner. Each will give you the probability of winning each prize as well as translate that probability into the numerical range the random number has to be in for you to win that prize.

At the end of the 10 choice rounds, the computer will randomly pick one of the 10 rounds to base your payment on, and draw the random number between 1 and 100 to determine your earnings. You will be informed about your earnings from this part of the experiment at the very end after you complete all parts.

Are there any questions before you begin making your decisions?

You will now start the sequence of 10 choices. You will be able to go through the choices at your own pace, but we will not be able to continue the experiment until everyone has completed this series.

Instructions for Part 2

This part of the experiment will consist of several decision sequences. The instructions will be given separately at the beginning of each sequence. At the end of the experiment one the sequences will be randomly chosen to base your actual earnings on.

SEQUENCE 1

You are going to participate in this experimental task in one of two possible roles. You will be randomly assigned either the role of Public Official or the role of Private Citizen. A total of 7 Public Officials and 7 Private Citizens will participate in the task.

Each Public Official will be in charge of an Office that provides licenses to Private Citizens, and will receive a lump-sum wage of 130 ECU.

Each Private Citizen will start with a monetary endowment of 80 ECU and will have to get a license from one of the 7 Offices. The license will generate a monetary benefit of 70 ECU to the Citizen. The Private Citizen will have to pay a fee in order to get the license. The official license fee is 20 ECU. However, Public Official can refuse to provide the license unless a bribe is paid on top of the official fee. The bribe demanded by a Public Official can be any integer amount between 1 and 50 ECU.

At the beginning, each Public Official will decide whether or not to demand a bribe from the Private Citizens who may visit his or her Office, and the specific amount of the bribe, in the range between 1 and 50 ECU. The decision to demand a bribe and the size of the bribe cannot be changed during the sequence.

Each Public Official will not know if the other Public Officials chose to demand a bribe or the size of their bribes, if any. Private Citizens will also be initially unaware of the bribes demanded by each Public Official, if any, but they will be able to acquire such information by visiting the corresponding Office, at the cost of 5 ECU for every new visit.

The sequence proceeds as follows:

- At the beginning, each Public Official has to decide whether he or she would like to request a bribe, between 1 and 50 ECU, for the provision of the license, on top of the official fee of 20 ECU.

- Each Private Citizen is initially randomly assigned to visit an Office and finds out if a bribe is requested by the Public Official in that Office, and if so, the size of the bribe.

- Then, the Private Citizen has to decide whether to pay the total amount requested by the visited Office, and receive the license there, or leave that Office and choose to visit any of the other 6 available Offices. Every visit to a new Office costs 5 ECU to the Private Citizen.

- The Citizen can visit as many Offices as he or she wishes, at the cost of 5 ECU for any new visit, and can acquire the license from any of the Offices previously visited by paying the amount requested by the Official in that Office.

- The Private Citizen has to get the license eventually.

The payoffs from the sequence are determined as follows:

- Each Public Official earns a lump-sum wage of 130 ECU. On top of the wage, if the Public Official decides to demand a bribe for his or her services, he or she can get additional earnings from the bribes paid by the Private Citizens who visited the Office and decided to obtain the license there, if any.

- Each Private Citizen starts with an endowment of 80 ECU. When the Private Citizen gets the license, he or she additionally receives 70 ECU, but will have to pay the total amount requested by the Public Official (that may or may not include a bribe) and the accumulated cost of office visits, which is equal to 5 ECU x (number of visited offices).

Private Citizens will see the map below, showing the available 7 Offices that they can visit to get the license. By clicking on an Office, Private Citizens will be able to visit that Office and get information about whether a bribe is requested by the corresponding Public Official, and the size of the bribe, if any.

After being initially matched with one Office, each Citizen will be able to visit as many Offices as he or she wishes, at the cost of 5 ECU per new visit. Once an Office has been visited, Citizens will be able to see the requested amount on the map, in the corresponding box. Citizens could decide to get the license from any of the Offices previously visited, or visit a new Office.

You are the Private Citizen P		Initial Endowment: 80.00	Visits Cost: 0.00	Balance: 80.00
		Revenue from License: 70.00	Obtained License: No	

Office 1 Official Fee: 20 Bribe: ? Total: ? <input type="button" value="Visit"/>	Office 2 Official Fee: 20 Bribe: ? Total: ? <input type="button" value="Visit"/>
Office 3 Official Fee: 20 Bribe: ? Total: ? <input type="button" value="Visit"/>	Office 4 Official Fee: 20 Bribe: ? Total: ? <input type="button" value="Visit"/>
Office 6 Official Fee: 20 Bribe: ? Total: ? <input type="button" value="Visit"/>	Office 7 Official Fee: 20 Bribe: ? Total: ? <input type="button" value="Visit"/>
Office 5 Official Fee: 20 Bribe: ? Total: ? <input type="button" value="Visit"/>	

By visiting an Office, you will receive information about whether the Public Official in that Office requests a bribe for the provision of the license, on top of the official fee, and the size of the bribe, if any. You will be able to visit as many Offices as you wish, at the cost of 5 ECU per new visit. You can get the license from any of the Offices previously visited.

Please click continue to proceed with the experiment.

After being initially matched with one Office, each Citizen will be able to visit as many Offices as he or she wishes, at the cost of 5 ECU per new visit. Once an Office has been visited, Citizens will be able to see the requested amount on the map, in the corresponding box. Citizens could decide to get the license from any of the Offices previously visited, or visit a new Office.

Are there any questions? This part of the experiment is about to begin. We ask again that you not look at the screens of those around you or attempt to talk with other participants at any time during the session. You will be able to read through the instructions and click through the screens at your own pace. Each section of the experiment will begin after all participants have finished reading the instructions for that section and have clicked Continue. If you have any question about the instructions that you will receive on your screen, please feel free to raise your hand at any time during the session, and the experimenter will come to answer your questions in private.

Screen 1: Citizen visits the first Office

You are the Private Citizen Q	Initial Endowment: 80.00 Revenue from License: 70.00	Visits Cost: 0.00 Obtained License: No	Balance: 80.00
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You have been randomly assigned to visit **Office 7**

The Public Official in this Office is not willing to provide you with a license for the official fee of 20 ECU.

On top of the official fee, in order to provide the license the Public Official in this Office requests a bribe of **15 ECU**

You will now get back to the map of Offices, where you will be able to see the bribe demanded by this Office, if any. You will have the choice to either get the license by paying the amount requested by this Office or visit a new Office of your choice by paying a visit cost of 5 ECU.

Please click continue to go back to the map.

Continue

Screen 2: Citizen sees the map of Offices

You are the Private Citizen Q	Initial Endowment: 80.00 Revenue from License: 70.00	Visits Cost: 0.00 Obtained License: No			
Office 1 Official Fee: 20 Bribe: ? Total: ? <input type="button" value="Visit"/>			Office 2 Official Fee: 20 Bribe: ? Total: ? <input type="button" value="Visit"/>		
Office 3 Official Fee: 20 Bribe: ? Total: ? <input type="button" value="Visit"/>		Office 4 Official Fee: 20 Bribe: ? Total: ? <input type="button" value="Visit"/>		Office 5 Official Fee: 20 Bribe: ? Total: ? <input type="button" value="Visit"/>	
Office 6 Official Fee: 20 Bribe: ? Total: ? <input type="button" value="Visit"/>			Office 7 Official Fee: 20 Bribe: 15 Total: 35 <input type="button" value="Pay"/>		
WAITING SCREEN					
<p>You must get the license from one of the 7 Offices. The license will generate 70 ECU to you. You have just visited Office 7. On the map, you can see whether the Public Official in this Office requests a bribe, and the total amount you would have to pay to get the license from this Office. You can use your Balance, at the top right corner, to either pay the requested amount or choose to visit a different Office, at the cost of 5 ECU. After you visit a new Office, you will come back to this map and will be able to get the license from any of the previously visited Offices, or visit a new Office at the cost of 5 ECU per new visit.</p>					
Please be patient as other participants make decisions.					

Screen 3: Official sees who visits the Office and who buys the license

You are the Public Official in Office 5		Your Official Wage: 130	Earnings from Bribes: 0
<p>You have decided not to demand a bribe for the provision of the license. Below you will see when a Private Citizen visits your Office and when/if he or she decides to get the license from you. Visits and license acquisitions will be marked with an X for the corresponding Citizen.</p> <p>Citizen S was randomly assigned to visit your Office at the beginning of this sequence.</p>			
	Visted Your Office	Received License from You	
Citizen P			
Citizen Q			
Citizen R			
Citizen S	X		
Citizen T			
Citizen U			
Citizen V			
<p>This sequence will end when all Private Citizens get the license.</p>			