Partners in crime? Corruption as a criminal network

Romain Ferrali *

March 13, 2017

Abstract

Bureaucracies are complex organizational structures in which corruption varies in magnitude and in form, from individual acts to vast conspiracies. Extant literature often subsumes structure into a principal-agent relationship, precluding researchers from studying the form of corruption and its relationship to structure. This paper presents a network model of corruption. Agents are embedded in an organizational network on which they form a criminal subnetwork: an agent finds an illegal rent, and decides whether to spend some to recruit accomplices. Accomplices protect the agent but create witnesses among their neighbors, who report corruption. I find that the most isolated portions of the organizations are more corrupt. Increasing network density reduces corruption if it makes isolated parts of the organization more exposed. As enforcement gets tougher, petty corruption disappears, and grand corruption involves more accomplices. Tougher enforcement changes the form of corruption, and organizational design may substitute for better enforcement. I examine the theoretical equilibrium predictions by conducting a lab-in-the-field experiment that compares select network structures.

*Email: ferrali@princeton.edu I thank Michael Bauer, Roland Benabou, Carles Boix, Stefano Caria, Paul DiMaggio, Johannes Haushofer, Robert Gibbons, Matias Iaryczower, Kosuke Imai, Amaney Jamal, Paul Lagunes, Jenn Larson, John Londregan, Joaquin Morales Belpaire, Rebecca Morton, Salvatore Nunnari, Betsy Paluck, Bassel Tarbush, Leonard Wantchekon, Viviana Zelizer, as well as seminar participants at CASBS workshop, CSSO workshop, the Imai Research Group, Oxford University, Sciences Po Aix, Princeton University and the WESSI workshop for their helpful comments. I gratefully acknowledge support from Amaney Jamal, the Center for the Study of Social Organizations and the Mamdouha S. Bobst Center for Peace and Justice.
Why does corruption persist in highly capable states? Corruption in those countries differs widely from the proverbial lone policeman pocketing a bribe to waive a speeding ticket. It often takes the form of vast conspiracies, where several bureaucrats cooperate to extract large amounts of rent and thwart detection. Rampant corruption within the Chicago police force, for instance, has been the subject of numerous movies in popular culture. Cross-country comparisons, and a cursory examination of 110 corruption cases in the US and India confirm the pattern.

Extant research on bureaucratic corruption typically subsumes the complex bureaucratic structures of the modern state into a simple principal-agent relationship. Although very useful to understand many other aspects of bureaucratic corruption, this approach sidesteps, by design, the complex webs of relationships that characterize bureaucracies and, often, corrupt activities. As such, it is unable to explain which bureaucrats become corrupt, how they relate to each other, and, in turn, the emergence of these large conspiracies. In this paper, I consider two questions: how does the frequency, gravity, and scope of corruption vary with the network structure of the bureaucracy? How do those features – the form of corruption – vary as bureaucracies get better at detecting corruption?

This paper proposes a model of corruption diffusion on a network, and examines its predictions in a lab-in-the-field experiment. This new framework allows to move beyond simply asking how many bureaucrats are corrupt, and ask instead which bureaucrats become corrupt, how they relate to each other, and how their incentives to collude is affected by a pre-existing organizational structure.

Although primarily designed to analyze corruption within a bureaucracy, the model encompasses any form of unethical behavior within an organization. Bureaucrats are the nodes of an exogenous graph representing the structure of their organization. A bureaucrat finds an illegal stream of rents, and decides whether to spend some of it in order to recruit accomplices among her neighbors. Rents diffuse through the network according to this process, resulting in a coalition of accomplices that gets detected with some probability.

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1See McCubbins et al. (1987) for a canonical example in political science, and Banerjee et al. (2013) for a recent, general application to corruption.

2A graph is the mathematical term used to refer to a network. I use both terms interchangeably.
bility. Accomplices “cover up” for the coalition, but their non-corrupt neighbors witness corruption, and increase the probability of detection. Recruiting accomplices poses a core tradeoff: on the one hand, they help cover up the illegal activity, but on the other, they cost resources, and the additional witnesses that could observe them may offset the protection they provide. The probability of detection also increases with organizational capacity; that is, how good is an organization at punishing corruption.

The main result is that as capacity increases, less profitable, petty corruption is weeded out, but more profitable, grand corruption remains and involves more accomplices. Since corruption is more risky when capacity is high, buying off accomplices is more attractive, which drives up the size of the coalition. This makes petty corruption not profitable enough to cover the extra cost entailed by more accomplices, leading to the survival of grand corruption only.

The finding provides a testable formal rationale for the observations that (1) more capable states have largely eliminated petty corruption but still feature grand-corruption, and (2) corruption involves more, better paid accomplices in more capable countries.

The equilibrium also generates predictions about how the form of corruption relates to the structure of the organization. The model implies that more isolated subgraphs are more corrupt, because they form enclaves that generate fewer witnesses. This finding echoes the observation that more closed bureaucracies are more corrupt. It may reconcile the contradictory findings that both more isolated (Aven, 2012) and better connected individuals (Nyblade and Reed, 2012) are more likely to be corrupt. Although the enclave is collectively isolated from the rest of the graph, some nodes may be very connected inside of it.

The result makes organizational structure a natural tool of anti-corruption policies. Increasing oversight, by adding social ties to an organization, should reduce corruption. I show that this is not always the case: additional ties do reduce corruption when they make enclaves more exposed. Yet, those additional ties may have no effect. More worryingly, they may even increase corruption, by giving easier access to new enclaves, or by circumventing more costly accomplices. Given that major organizational reshuffling are
a common tool of anti-corruption reforms (for instance, the Los Angeles Police Department under Chief Parker in the 1950s (Buntin, 2010), or the city of Bogota in the 1990s (Devlin and Chaskel, 2010)), the result puts bounds on the effectiveness of such policies. These policies will be effective if the additional ties make enclaves more exposed. I show through simulations that more modular graphs\(^3\) are more enclaved and more corrupt.

I examine the predictions of the model by conducting a lab-in-the-field experiment. The experiments build upon recent work on collective corruption in the lab (Berninghaus et al., 2013), and add to it a network component. In the experiments, I focus on a handful of small graph structures, and vary capacity and the profitability of corruption (petty or grand). The lab allows addressing the severe measurement problems associated with studying jointly social networks and corruption while preserving the ability to make causal claims. The control afforded by the lab allows testing directly the main comparative static implications of the theory, the plausibility of its assumptions, and the robustness of its predictions to behavioral factors that are assumed away in the model.

The experimental data confirms the model’s predictions: more capable organizations feature only grand corruption, with more accomplices. More isolated subgraphs are more corrupt, and only certain ties reduce corruption. Agents’ sharing behavior does not differ across subject pools, and is more consistent with bargaining than equal-sharing, which may seem surprising in light of the equity norms often observed in the lab. Thus, behavior in these complicated environments appears to be largely robust to factors outside the model. The most striking deviation from theoretical predictions is that agents fail more to realize larger equilibrium coalitions, because they are more prone to coordination problems. This provides an additional reason as to why capable organizations are less corrupt: corruption requires larger coalitions, which fail to form because they are cognitively taxing.

The remainder of this paper proceeds as follows: I first review the literature (section 1), then expose a series of stylized facts (section 2). Section 3 presents the model, while section 4 details its main predictions, and considers an extension with bargaining. Section

\(^{3}\)Roughly speaking, graphs that can easily be partitioned into subgraphs with many ties within and few ties across. See Newman (2006) for a specific definition.
details experimental results. Section 6 relates the findings to the stylized facts, and makes a few policy recommendations.

1 Literature review

We have little understanding of how the form of corruption varies, and how organizational structure affects opportunities for corruption. On the one hand, our formal understanding of corruption, and of bureaucracies has largely abstracted away from organizational complexity, and reduced bureaucracies to a principal-agent dyad (see Olken and Pande (2011) for a review). Although the approach is very useful to understand the impact of formal norms, and other institutional features on corruption, it sidesteps, by design, the organizational complexity of bureaucracies and of corruption. On the other hand, informal theoretical effort give us some traction, and posits, for instance, that too dense, or too sparse bureaucracies are more at risk of corruption (Evans 1995), that open-door policies might increase corruption (Carpenter and Moss 2013), and that more Weberian organizations should reduce corruption (Rauch and Evans 2000). This line of argument, however, has made claims that belong more to “metaphorical network analysis” (Ward et al. 2011), and has been unable to make precise claims as to which kinds of organizational structures relate to which form of corruption.

In order to make precise claims relating organizational structure to the form of corruption, the model introduced in the next section combines game theory and network analysis. That is, it pictures a bureaucracy as an organizational network on which bureaucrats are embedded (Granovetter 1985, Zukin and DiMaggio 1990). On this network, corruption is a strategic game of white-collar crime: bureaucrats to form, within the organizational network, a criminal subnetwork. This approach gives enough flexibility to consider arbitrarily complex organizations, and arbitrarily complex criminal subnetworks. In particular, the model distinguishes between ties of communication and ties of observation, allowing to capture, for instance, busy managers that are unable to monitor each of their employees. It allows considering corruption in isolation (one corrupt individual),
or large conspiracies, with a complex architecture of ties.

Most related to this paper is the theoretical literature on criminal network formation. These models are usually games of strategic network formation (Jackson, 2008). They provide useful insight into actors who are unconstrained by existing institutions. However, by design, they cannot answer questions about individuals who are already interconnected in an organization’s network. Consequently, to understand corruption within an existing organization, we need an approach that determines incentives for individuals given an exogenous network. Diffusion models allow speaking about how corruption spreads within an exogenous network. However, because they are either probabilistic or threshold-based, they do not feature strategic agents. I make diffusion strategic: corruption diffuses if an agent chooses to infect her neighbor and that neighbor accepts to be infected.

The paper also relates to a burgeoning literature that studies corruption in the lab (see Serra and Wantchekon (2012) for a review). In particular, Berninghaus et al. (2013) study a collective corruption experiment: bureaucrats simultaneously decide whether to accept a bribe, their probability of detection decreases with the amount of bureaucrats that accepted the bribe. I supplement their design with an exogenous network structure and a diffusion element, hence introducing a minimal design to test for the impact of social structure on corruption.

2 Stylized facts

This section introduces a few empirical regularities on how the form of corruption varies with capacity, and how corrupt individuals cooperate within organizations. While the latter set of facts supports modelling assumptions, the former supports the model’s predictions.


5See, for instance, Centola and Macy (2007).

6Introducing network structure places this experiment within a growing literature that studies games on networks experimentally. Closest to this paper are Charness et al. (2007), who study simultaneous bargaining on a network, and Centola (2010) for an online experiment on diffusion, without the bargaining component.
Figure 1: Corruption decreases in more capable countries by weeding out petty corruption (fact 1). Perceptions of corruption decrease with capacity for the police, but not for Parliament. India features both petty cases and grand cases, while the US features only grand cases.

### 2.1 Forms of corruption

I derive several stylized facts on the form of corruption from cross-country comparisons and a comparison of 110 cases of corruption in the US and India.

Cross-country comparisons use the 2017 Quality of Government dataset and its related 2015 Expert Survey. I use log GDP per capita in PPP $2011 to proxy for state capacity. The US-India comparison uses newspaper articles from the New York Times and the Times of India. It compares a less capable, more corrupt country (India) to the more capable, and less corrupt United States. For each case, I recorded the amount of accomplices involved, and the amounts stolen.

**Fact 1. Corruption decreases in more capable countries by weeding out petty corruption.** Petty corruption corresponds to cases where little amounts of rent are extracted, and grand corruption to large amounts. For cross-country comparisons, I proxy this by perceptions of corruption in institutions typically associated with petty and grand corruption; that is, the police and Parliament respectively, using data from the

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7 see Appendix A for details on data collection, and the models used to construct the figures.
Figure 2: Corruption involves more accomplices in more capable countries (fact 2). The share of rent given to accomplices increases with capacity. The US has more accomplices than India for similar amounts stolen.

Global Corruption Barometer. Figure 1a shows that while police corruption decreases with capacity, Parliament corruption remains constant. Comparing the US to India, figure 1b shows that the distribution of amounts stolen is more skewed to the right in the US than in India: although both countries feature rather high-fly cases, with amounts stolen above $10,000, about 50% cases in India involve amounts below that threshold. The finding is similar to Kaufmann (2004).

Fact 2. Corruption involves more accomplices in more capable countries. Cross-country comparisons use data from the Quality of Government Expert Survey, which asks about the following hypothetical scenario: if a bureaucrat were tasked to give $1,000 to the poor, how much would eventually reach the poor; how much would the bureaucrat keep to herself or to her kin, and how much would she give to her manager or middlemen. Figure 2a plots the percentage that the bureaucrat would give to accomplices; that is, her manager or middlemen, out of the amount she would embezzle. We see that the share given to accomplices increases with GDP per capita. Comparing the US to India reveals a similar pattern: even after controlling for the amount stolen, corruption

A one-sided Mann-Whitney test is significant at the one percent level.
Fact 3. More closed bureaucracies are more corrupt. The organizational structure of a bureaucracy matters. The Quality of Government Expert Survey includes an indicator of bureaucratic closedness, which captures the extent to which bureaucrats are isolated from the rest of society through separated career paths for instance, in the spirit of Evan’s (1995) embeddedness. Table 1 shows that, for similar levels of capacity, more insular bureaucracies are more corrupt.

### Table 1: More closed bureaucracies are more corrupt (fact 3).

<table>
<thead>
<tr>
<th>Corruption indicator</th>
<th>BCI (1)</th>
<th>CPI (2)</th>
<th>WBGI (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(GDP p/c), $ PPP 2011</td>
<td>-13.176***</td>
<td>19.504***</td>
<td>1.057***</td>
</tr>
<tr>
<td>(1.928)</td>
<td>(2.280)</td>
<td>(0.126)</td>
<td></td>
</tr>
<tr>
<td>Polity IV score</td>
<td>-0.496</td>
<td>1.697***</td>
<td>0.083***</td>
</tr>
<tr>
<td>(0.343)</td>
<td>(0.433)</td>
<td>(0.023)</td>
<td></td>
</tr>
<tr>
<td>Closedness</td>
<td>5.170**</td>
<td>-6.676**</td>
<td>-0.328**</td>
</tr>
<tr>
<td>(2.286)</td>
<td>(2.492)</td>
<td>(0.130)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>153.182***</td>
<td>-120.583***</td>
<td>-9.105***</td>
</tr>
<tr>
<td>(22.999)</td>
<td>(26.110)</td>
<td>(1.462)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>44</td>
<td>44</td>
<td>44</td>
</tr>
<tr>
<td>R²</td>
<td>0.568</td>
<td>0.752</td>
<td>0.742</td>
</tr>
</tbody>
</table>

Table 1: More closed bureaucracies are more corrupt (fact 3). Higher closedness values indicate more closed bureaucracies. Each model uses a different indicator of corruption as a dependent variable. In model 1, higher values indicate more corruption; in models 2 and 3, higher values indicate less corruption. Standard errors are robust.

in the US involves more accomplices than in India (figure 2b).

2.2 Organizing corruption

A careful review of the literature on white-collar crime and corruption reveals a few empirical regularities about the functioning of criminal networks within organizations.

First, new accomplices are a mixed blessing to existing criminals. On the one hand, they provide the conspiracy with two kinds of benefits: (1) increased protection against detection through active “covering up,” (Wade 1982, Ledeneva 1998) or (2) increased resource extraction (Jávor and Jancsics 2013). On the other, they hurt the conspiracy chiefly by creating witnesses that make the conspiracy more detectable (Baker and Faulkner 1993).

Second, a fundamental problem of criminal activity is establishing trust among thieves, and chiefly, trust that criminals will not denounce their peers to law enforcement. Crim-
inals resort to various mechanisms to prevent such behavior, including repeated interac-
tions (Malesky and Samphantharak 2008; Coviello and Gagliarducci 2014; Gambetta 1996), sharing compromising evidence (Ledeneva 1998; Yang 2002), and brokers (Gambetta 1996; Vannucci and Della Porta 2013). When one member gets caught, however, trust unravels within the conspiracy, leading to its collapse.

Third, hierarchy does not affect much either recruiting accomplices or whistleblowing. Regarding recruitment, lower-level employees are often critical to some task within the conspiracy, and know of the wrong-doing of their managers, which gives them leverage when deciding whether to join (Jávor and Jancsics 2013). Mesmer-Magnus and Viswes-
varan (2005) show that whistleblowing is more likely when whistleblowers have solid evidence, which is more likely when they closely interact with the wrongdoer. They also show that the balance of accomplices and witnesses matters: whistleblowing is less likely for bigger crime, because the risk of retaliation is higher. However, hierarchy does not have much effect: higher-level employees report hardly more. If they do, it is because their position provides them with evidence rather than because they face a lower risk of retaliation.

The model’s core assumption derive from these regularities. Accomplices help the conspiracy by either (1) extracting more resources, or (2) covering up. To simplify interpretation, the model keeps the first channel constant, by fixing the value of the illegal stream of rent, and makes accomplices’ positive contribution come only from the second channel. Accomplices may denounce their peers to law enforcement, but members of the coalition usually implement mechanisms to prevent this. The model features this in a reduced form, by making the probability of detection all-or-nothing (either all or no accomplices get caught): accomplices implement some mechanism to maintain trust within the coalition, but if one member gets caught, the whole coalition collapses because whoever gets caught first provides incriminating evidence against her peers. Since authority has little impact on recruiting accomplices or reporting them, the model does not feature an explicit notion of authority. Authority only feeds into the model by contributing to the structure of the organizational network.
3 Model

Bureaucrats are the nodes of the exogenous multiplex\textsuperscript{9} graph $g = (N, G_c, G_o)$ where $N$ is the set of nodes, and $G_c$ and $G_o$ are sets of ties, capturing two kinds of relationships within the organization (see figure 3 for an example). $G_c$ captures undirected relationships of communication broadly defined, meaning that agents $i$ and $j$ may talk to each other. The communication network is undirected, with $ij \in G_c$ denoting a channel of communication between $i$ and $j$. Because organizations form a coherent unit, I assume that $G_c$ is connected.\textsuperscript{10} $G_o$ captures directed relationships of observation, representing one’s access to knowledge about another agent’s potentially corrupt activities. The observation network is directed, with $i \rightarrow j \in G_o$ meaning that $i$ observes $j$. I assume that if two people do not interact, they do not know about each others’ activities: if $i \rightarrow j \in G_o$, then $ij \in G_c$.

An arbitrary node $S \in N$, the seed, discovers an illegal stream of rents of value 1, the bribe. The $N - 1$ remaining nodes are indexed by $i \in \{1, \ldots, N - 1\}$. $S$ can reject the bribe or accept it. If she rejects the bribe, the game is over, and all players gain 0. Otherwise, she becomes an accomplice, and (1) she pays a sunk cost $\epsilon_S \in (0, 1)$; (2) all the agents that observe the seed turn into witnesses; and (3) she can share make take-it-or-leave-it (TIOLI) offers to share the bribe with any of the agents she communicates with. The sunk cost $\epsilon_S$ represents the seed’s expected loss of getting caught.\textsuperscript{11} Conversely,

\textsuperscript{9}A multiplex graph is a graph that has several kinds of ties; in our case, ties of communication, and ties of observation.

\textsuperscript{10}That is, that there is a path on $G_c$ between any $i, j \in N$

\textsuperscript{11}$\epsilon_S$ may incorporate other costs, such as effort, or a moral cost.
for a bribe of value 1, the quantity $1 - \epsilon_S$ represents the profitability of corruption, allowing to distinguish between highly profitable, grand corruption, and less profitable, petty corruption.

Once the seed has made her offers, the nodes that have been made an offer are “pending.” They play sequentially. Playing order is determined by lower indices playing first. Pending nodes face a similar action space. They can reject the offer, or accept it. If node $i$ accepts the offer $t_{Si}$, she becomes an accomplice. Like the seed, her non-pending, non-accomplice in-neighbors on $G_o$ turn into witnesses, and she pays a sunk cost $\epsilon_i$. I assume that $0 \leq \epsilon_i \leq \epsilon_S$, to capture the idea that as the instigator, the seed may face tougher a penalty than her accomplices. Because she accepted the bribe, node $i$ can make offers TIOLI offers to her susceptible neighbors; that is, her non-pending, non-accomplice neighbors on $G_c$. Let $P_{ih}$ be the set of susceptible neighbors of $i$ at history $h$. Once all the players whom $S$ has made an offer have played, the players to whom this set of players has made offers (if any) can act. They face the same action space, and their moving order is determined the same way. This process is repeated until no accomplice makes an offer, or until all nodes in $N \setminus \{S\}$ have become accomplices.

Offers satisfy a budget constraint. Let $b_i$ be the share of the bribe owned by $i$ when she makes her offers, $P_i$ the set of susceptible neighbors of $i$ when she makes her offers\footnote{Note that $P_S$ is simply the neighborhood of $S$ on $G_c$.} and $t_{ij} > 0$ an offer from $i$ to $j$, and define $t_{ij} \equiv 0$ if $i$ does not make an offer to $j$. Then it must be that $b_i - \sum_{j \in P_i} t_{ij} \geq 0$.

There are four types of players at any history $h$: pending nodes, accomplices, witnesses and neutral nodes. Pending nodes are all the nodes that have been made an offer prior to history $h$ and will play at, or after $h$. Accomplices are all the nodes that have accepted an offer to share the bribe. Together, they form a criminal conspiracy, that we shall call the coalition. Witnesses are the non-accomplice, non-pending neighbors of accomplices. Finally, neutral nodes are all the remaining nodes, and do not play any role.

Coalition $c$ on graph $g$ has $a_c = |c|$ accomplices. Let $N_i(g)$ be the in-neighborhood of node $i$ on the observation network induced by graph $g$\footnote{That is, the set of nodes $j$ such that $j \rightarrow i \in G_o$.}. The set of witnesses of
coalition $c$ on $g$ at a terminal history is $W_{cg} = \bigcup_{i \in c} N_i(g) \setminus c$, and $w_{cg} = |W_{cg}|$ the amount of witnesses. Let $C$ be the set of coalitions that can be formed on any graph with $N$ nodes. A coalition $c$ is feasible on graph $g$ if it is consistent with some diffusion process originating from the seed; formally:

**Definition 1.** A coalition $c \in C_g$ is feasible on $g$ if for any node $i \in c$, there is a path between $S$ and $i$ on $G_c$ such that all nodes on that path are accomplices. Let $C_g \subseteq C$ be the set of feasible coalitions on graph $g$.

Once the coalition is formed, an exogenous enforcer detects the coalition with probability $1 - p$, where $p = p(a, w, q) : [1, N]^2 \times (0, 1) \to (0, 1)$ is the coalition’s probability of success. Following the discussion in the preceding section, $p$ is a function of $a$, the amount of accomplices in the coalition, and $w$, its associated amount of witnesses. Accomplices help the conspiracy by covering up, and hurt it by creating witnesses. I assume that $p$ is twice-differentiable, and that $\frac{\partial p}{\partial a} > 0$, and $\frac{\partial p}{\partial w} < 0$. Organizations vary in their capacity to detect and punish corruption. I assume that $p$ is decreasing in $q \in (0, 1)$, a parameter for organizational capacity that captures the probability that the organization is subjected to a random audit.\(^{14}\)

If player $i$ is not a member of the coalition at a terminal history her payoff is 0. Otherwise, she pays her sunk cost $\epsilon_i$. Let $r_{ij} = 1$ if $j$ accepted an offer $t_{ij}$ from $i$, and $r_{ij} = 0$ otherwise; then player $i$ has a share of the bribe $\pi_i = b_i - \sum_{j \in P_i} t_{ij} r_{ij}$. With probability $p$, she gets her share $\pi_i > 0$, and gets 0 otherwise. For simplicity, assume that that players are risk-neutral and that the bribe is shared equally between accomplices and the seed. That is, assume that in the diffusion process leading to coalition $c$, agents schedule transfers such that $\pi_i = \frac{1}{a}$ for any $i \in c$. Note that with equal-sharing, the expected utility of a coalition has a common component, $\pi_i p(a, w, q) = \frac{p(a, w, q)}{a}$, and an individual component, the sunk cost $\epsilon_i$. To distinguish between algebraic and graphical considerations, I separate the valuation of a coalition and its expected utility. The *valuation* of a coalition $v : [1, N]^2 \times (0, 1) \to \mathbb{R}$ is defined for an arbitrary

\(^{14}\)Note that the probability of detection does not depend on the profitability of corruption, $1 - \epsilon_S$, which might be problematic. I relax this assumption in an extension (see Appendix D).
number of accomplices and witnesses that need not be integer, with \( v(a, w, q) = \frac{p(a, w, q)}{a} \).

The expected utility of a coalition \( u : C_g \times (0, 1) \rightarrow \mathbb{R} \) is the valuation of existing coalitions on specific graphs: \( u(c, g, q) = v(a_c, w_{cg}, q) \). Under equal-sharing, expected utilities write:

\[
\begin{align*}
\mathbf{u}_i(c, g, q) &= \begin{cases} 
\mathbf{u}(c, g, q) - \epsilon_i = v(a_c, w_{cg}, q) - \epsilon_i = \frac{p(a_c, w_{cg}, q)}{a_c} - \epsilon_i, & \text{if } i \in c \\
0, & \text{otherwise}
\end{cases}
\end{align*}
\]

(1)

4 Theoretical results

This section derives equilibrium and highlights a few comparative statics. Throughout the section, we will use the graph in figure 3 as an illustration. Figure 4 depicts equilibrium. The section will progressively explain it. All proofs are available in Appendix B.

4.1 Equilibrium

When should the seed accept the bribe? If she finds a coalition desirable, will accomplices follow her plan, or will they deviate and form some other coalition? The seed \( S \) has a threshold strategy. Consider \( c^* \in \arg \max_{c \in C_g} u(c, g, q) \). If \( u(c^*, g, q) < \epsilon_S \), then \( S \) rejects the bribe, since no coalition yields a payoff high enough to cover her sunk cost. Conversely, if \( u(c^*, g, q) \geq \epsilon_S \), then coalition \( c^* \) would be most profitable to the seed, since it is in \( \arg \max_{c \in C_g} \). There is no dynamic inconsistency: because players divide the bribe equally, incentives within the coalition are sequentially aligned, and coalition \( c^* \) is realized in equilibrium. Indeed, the equal-sharing assumption implies that all players have the same utility function, up to their sunk cost \( \epsilon_i \leq \epsilon_S \). Then \( c^* \) maximizes the utility of all accomplices in \( c^* \). As such, they all accept the offer, and make the moves that realize that coalition. Figure 4 represents this graphically: the line \( \epsilon_S \) separates, for any level of capacity \( q \), a rejection area from an area where some coalition is realized. Formally:

**Lemma 1** (Threshold strategy). Let \( C_{gq}^* = \arg \max_{c \in C_g} u(c, g, q) \) and \( c^* \in C_{gq}^* \). There is a threshold \( \hat{\epsilon}_S(g, q) = u(c^*, g, q) \in (0, 1) \) such that all equilibria have the same outcome.
that $S$ rejects the bribe if $\epsilon_S > \hat{\epsilon}_S(g, q)$. Otherwise, she accepts it, and some coalition $c \in C_{gg}^*$ is realized.

Further characterization of equilibrium requires characterizing the frontier; that is, the coalitions that lie in $C_{gg}^*$ for some $q$. I look for essentially unique equilibria; that is, equilibria where all equilibrium coalitions have the same counts counts of accomplices and witnesses.  

Figure 4b represents the set of feasible coalitions $C_g$ on graph $g$. Points on this figure correspond to sets of essentially unique coalitions. On that figure, because $\frac{\partial w}{\partial w} < 0$, one
prefers the black points to the ones above them.

I make two additional assumptions:

**Assumption 1** (Larger coalitions are sufficiently impervious to capacity). Suppose \( v(a_1, w_1, q_1) \geq v(a_2, w_2, q_1) \) and \( v(a_2, w_2, q_2) > v(a_1, w_1, q_2) \) for some \( a_1 \leq a_2, w_1, w_2 \in [1, N], q_1, q_2 \in (0, 1) \). Then \( \frac{\partial p(a_2, w_2, q)}{\partial q} < \frac{\partial p(a_1, w_1, q)}{\partial q} \frac{a_2}{a_1} \).

**Assumption 2** (Witnesses are sufficiently consequential). Suppose \( p \) is such that \( v \) is quasi-concave in \( a \) and is either monotonic in \( a \) or satisfies \( \frac{|\partial v(a, w, q)\partial w|}{\partial w} > v(a^*, w, q) - \max\{v(1, w, q), v(N, w, q)\} \), where \( a^* \in \arg \max_{a \in [1, N]} v(a, w, q) \).

Assumption 1 bounds the probability of success as the size of the coalition grows. In particular, it implies that although \( \frac{\partial p}{\partial a} \) may be concave or convex in \( q \), it should not be too concave. The assumption implies that two non-homologous coalitions may yield the same utility for at most one \( q \in (0, 1) \).

Assumption 2 compares coalitions that vary in size but have the same amount of witnesses; that is, it compares coalitions that lie on the same horizontal line in figure 4b. It states that for any \( q \), either (1) one prefers the leftmost or the rightmost coalition, or (2) adding additional witnesses decreases the valuation of a coalition enough: if one prefers some coalition in the middle, then one would never move up from that coalition.

Assumption 1 implies that besides a finite set of knife-edge \( q \)'s, equilibrium outcomes are essentially unique. The result reads:

**Proposition 1** (Essential unicity). *Equilibrium coalitions are essentially unique except in a measure zero set.*

Assumption 2 implies that one would never pick a larger coalition with more witnesses than a smaller one. Since \( G_c \) is connected, one can always form the grand coalition; that is, the coalition that includes all nodes, represented by point \( \gamma_{13} \) on figure 4b. As such, for any \( q \), one prefers the grand coalition or the smaller one to the intermediate one, either because \( v \) is monotonic in \( a \), or because the extra witnesses in the intermediate coalition make it too unattractive. Formally:
Lemma 2. Let $a_1 < a_c < a_2$, and $w_2 \leq w_1 < w_c$. Then $v(a_c, w_c, q) < \max\{v(a_1, w_1, q), v(a_2, w_2, q)\}$ for any $q \in (0, 1)$.

Lemma 2 allows to characterize the frontier: equilibrium coalitions minimize the amount of witnesses in a particular fashion. We call “minimal” a coalition such that no smaller coalition has less witnesses. Those are the coalitions on the black line in figure 4b:

Definition 2. Let $M_g = \{c \in C_g : a_c \leq a_c' \Rightarrow w_{c'} \geq w_c \text{ for any } c' \in C_g\}$ be the set of minimal coalitions on graph $g$.

Note that minimality captures the idea that a coalition jointly generates few witnesses. As such, both individual nodes and sets of nodes can be isolated, depending both on the amount of observation ties pointing towards them, and the location of those ties. Consider, for instance, coalition $\gamma_5$ in figure 4a: although $S$ is exposed within it, the coalition is jointly isolated from the rest. I say that a set of nodes that has few observation ties originating from the rest of the graph and pointing to it–although it may have many such ties between its members–is relatively enclave or isolated. Minimal coalitions are the most enclave coalitions of a given graph.

It follows immediately from lemma 2 that an equilibrium coalition must be minimal. If not, it is beaten either by the smaller coalition that has less witnesses, or the grand coalition. Of course, some minimal coalitions might be dominated by other minimal coalitions, depending on peculiarities of the probability of detection $p$. Combining this with proposition 1 we get that besides the set of knife-edge $q$’s, the remaining, undominated minimal coalitions are realized over some interval of organizational capacity (see example in Figure 4c). Formally:

Proposition 2 (Equilibrium coalitions are minimal). If $c \in C_{gq}^*$ for some $q \in (0, 1)$, then $c$ is minimal. There is a subset of minimal coalitions $M_g^0 \subseteq M_g$ and an increasing sequence of thresholds $(\pi_k)_{k=0}^K$, with $\pi_0 = 0, \pi_K = 1$ such that $c \in C_{gq}^*$ for some $q \notin (\pi_k) \iff c \in M_g^0$. 

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Proposition 2 has an important empirical implication: within an organization, more enclaved subunits should be more corrupt.

4.2 Comparative statics

We begin by asking what happens as capacity increases, allowing us to answer why corruption persists in capable countries. We show that as capacity increases, corruption decreases by weeding out petty corruption, but grand corruption remains. Increasing capacity makes all coalitions less profitable. As such, only the most profitable projects can be sustained in equilibrium; that is, the ones that have a low enough $\epsilon$. Hence, the $\hat{\epsilon}_S$ line is decreasing on figure 4c. Second, equilibrium coalitions grow larger as the size of the coalition increases. The result hinges on assumption 1 because the extra protection afforded by larger coalitions does not decrease too much value as capacity increases, this extra protection comes to offset their higher cost. On figure 4c, increasingly large coalitions (from $\gamma_1$ to $\gamma_{13}$) are realized as $q$ increases. Formally:

**Proposition 3** (As capacity increases, corruption decreases by weeding out petty corruption and coalition size increases). Let $c_1^* \in C_{gq_1}^*$, $c_2^* \in C_{gq_2}^*$. We have $q_1 < q_2 \Rightarrow \hat{\epsilon}_S(g,q_1) \geq \hat{\epsilon}_S(g,q_2)$ and $a_{c_1^*} \leq a_{c_2^*}$.

Proposition 3 exposes the mechanism behind the fact that while less capable states feature both petty and grand corruption with fewer accomplices, more capable states display only grand corruption with more accomplices (section 2.1). Since detection is unlikely in low-capacity states, protection is superfluous, and even petty projects can be sustained. Conversely, getting caught is more likely in high-capacity states. As such, the protection of larger coalitions becomes more attractive. However, only the most profitable ventures afford recruiting those larger coalitions.

We then ask what happens as the organization changes. Although proposition 2 shows that within an organization, more enclaved subunits are more corrupt, this does not tell us which organizations are more likely to be corrupt. Answering this questions requires relating the frontier to some graphical property. Comparing across graphs is
intractable. Instead, I examine the impact of adding a tie to some graph, and show while new observation ties weakly decreases corruption, communication ties weakly increase corruption. I compare the graph \( g = (N, G_c, G_o) \) to \( g' = (N, G'_c, G'_o) \), that I construct by adding a communication or an observation tie between nodes \( i \) and \( j \). We write \( g' = g + ij \) in the first case, and \( g' = g + i \rightarrow j \) in the second case.

Observation ties decrease corruption because they make each coalition weakly more exposed. Therefore, the frontier of \( C_{g'} \) is weakly above that of \( C_g \). As such, the best coalitions on \( g' \) are weakly worse than those on \( g \), and \( g' \) should be less corrupt than \( g \): \( \hat{\epsilon}_S(g', q) \leq \hat{\epsilon}_S(g, q) \) for any \( q \).

That the new graph is weakly less corrupt than the old one means that while the addition of some ties reduce corruption, adding other ties will have no effect. I call “exposing” the ties that strictly reduce corruption. To be exposing, a tie must satisfy a strong condition. Obviously, an exposing tie should make a minimal coalition more exposed since only those are realized in equilibrium. However, many other coalitions may be essentially equal to that coalition. As such, that tie must also make all those coalitions more exposed. The next result encapsulates the discussion:

**Proposition 4** (Adding observation ties weakly decreases corruption). Suppose \( g' = g + i \rightarrow j \). Then \( \hat{\epsilon}_S(g', q) \leq \hat{\epsilon}_S(g, q) \). The inequality holds strictly for some \( q \in (0, 1) \) if and only if there is a minimal coalition \( c^* \in M^0_g \) such that for any coalition \( c \in C_g \) essentially equal to \( c^* \) has \( j \in c \) and \( i \notin c \) and \( i \notin W_{cg} \).

Communication ties may increase corruption because they create new feasible coalitions, which might be more enclaved than old ones. For the additional tie to increase corruption, it must create a new minimal coalition. Furthermore, the utility function must be such that this new coalition is actually more desirable for some level of capacity \( q \). The next result spells out this necessary condition:

**Proposition 5** (Adding communication ties weakly increases corruption). Suppose \( g' = g + ij \). Then \( \hat{\epsilon}_S(g', q) \geq \hat{\epsilon}_S(g, q) \). For the inequality to hold strictly for some \( q \in (0, 1) \), it must be that there is \( c^* \in M_g \) and \( c' \in C_{g'} \) such that \( a_{c'} > a_{c*} \) and \( w_{c'} = w_{c*} \). \(^{16}\)

\(^{16}\)I show in the Appendix (lemma 5) that any new coalition has a coalition on the old graph that has
Together, propositions 4 and 5 show that changing the organizational structure affects corruption in sophisticated ways, providing an explanation to the fact that more closed bureaucracies are more corrupt (section 2.1). Most of the time, such policies will have no effect: additional ties will affect corruption only if they affect minimal coalitions, which is increasingly unlikely as the graph gets larger. These policies can help, if they increase the monitoring of the most enclaved coalitions. These policies can also backfire, because they might create new enclaves. More closed bureaucracies are more corrupt precisely because they are more enclaved.

Since comparing across graphs is intractable, I show through simulations that more modular graphs are more corrupt. Intuitively, modularity (Newman 2006) captures the extent to which the graph can be divided in independent communities. Specifically, it is, for a given community membership, the extent to which the distribution of ties within and across communities differs from their distribution in a random graph. Modularity is a scalar measure \( m \in [-1, 1] \). When \( m = 0 \), the distribution of ties follows a random graph. For \( m = 1 \), all ties fall within communities, and no ties across; and vice versa when \( m = -1 \).

Simulations are computationally intensive, because obtaining the set of minimal coalitions on graph \( g \) with \( N \) nodes requires enumerating the set of connected subgraphs of \( g \), which is \( O(2^N) \). As such, I consider 1000 small graphs \( (N = 16) \), that I collapse into simple undirected graphs: \( ij \in G_c \iff i \to j, j \to i \in G_o \). I use Sah et al. (2014)’s algorithm to generate connected graphs with a specified pattern of communities, while maintaining a graph structure that is as random as possible. The graphs I consider have a density of .26 and a simple community structure, where nodes are split in two equal-sized communities. I sample graphs with modularity ranging from 0 to .4. The right panel of figure 5 shows two such graphs: graph 1 is not modular, while graph 2 is highly modular.

Within each simulation, I examine expected corruption for a randomly chosen seed. For seed \( i \) on graph \( g \), expected corruption for any level of capacity corresponds to the area under the \( \hat{\epsilon}_i \) curve (Figure 4c). This quantity writes \( AUC_{ig} = \int_0^1 \hat{\epsilon}_i(g, q)dq \). For a strictly less accomplices, and weakly less witnesses. As such, \( c' \) cannot satisfy \( w_{c'} < w_{c^*} \).
Figure 5: Simulation results. The left panel shows the area under the curve (AUC) for graphs of varying modularity $m$. Corruption is positively correlated with modularity. The right panel shows detailed simulation results for low modularity, low corruption graph 1 and high modularity, high corruption graph 2. Circles and triangles represent nodes from communities 1 and 2, respectively. Lighter nodes have higher AUC and are more corrupt.

randomly chosen seed, I examine the quantity $AUC_g = \mathbb{E}(AUC_{ig})$, where higher values of $AUC_g$ denote more corruption. For simulations, I use the following probability of success $p$:

$$p(a, c, q) = \frac{a - 1}{N - 1}q + \left(1 - \frac{w}{N - 1}\right)(1 - q) \quad (2)$$

Figure 5 shows the results. The left panel shows that more modular graphs are more corrupt. Intuitively, more modular graphs are more corrupt because communities are more enclaved. As modularity decreases, communities disenclave: when a tie falls between modules, it reduces modularity and is more likely to be exposing. The right panel considers a graph with low modularity and low corruption (graph 1), and a graph with high modularity and high corruption (graph 2). Comparing within graphs, we see that lower-degree nodes are more corrupt, confirming the above result that more isolated nodes are more corrupt. Yet, comparing across graphs, we see that equally isolated nodes are more corrupt on the more modular graph. Indeed, in highly modular graphs, one’s community is more enclaved, and hence more conducive to corruption.
Together, analytical results and simulations give a sense of how endogenous network formation may affect the results. In particular, we can tell which ties corrupt agents, or a social planner would like to add or remove to the graph. Propositions 4 and 5 imply that corrupt agents would like to sever observation ties, and add communication ties. Conversely, the social planner prefers adding observation ties, and severing communication ties. Finally, simulations suggest that ties that decrease modularity are more likely to be exposing. As such, corrupt agents prefer to add ties within modules, while the social planner prefers to add ties across modules.

4.3 Extension with TIOLI bargaining

I now relax the assumption that the bribe is shared equally between members of the coalition. Doing so allows to get a sense of “who gets what” within the coalition, as well as to check the robustness of the results. Indeed, the equal-sharing assumption was crucial to the proof of lemma 1, which in turn allowed to characterize easily the equilibrium coalitions.

I make several simplifying assumptions. As in the simulations, I collapse \( g \) into a simple undirected graph: \( ij \in G_c \iff i \to j, j \to i \in G_o \). Furthermore, I consider the same probability of success \( p \) I used in simulations (equation 2). Finally, I use a particular structure for the graph \( g \): a two-level tree in which \( S \) has two “children,” \( A \) and \( B \), who have, respectively, \( 0 < k_A \leq k_B \) children. (see figure 6a). I call \( A \) and \( B \) first-level nodes, and their children second-level nodes. I also assume that the sunk cost is constant across nodes: \( \epsilon_i = \epsilon \) for all \( i \in N \).

I solve the game by backward induction. Second-level nodes have a threshold strategy: they accept any offer that gives them a positive payoff. At the threshold \( b_j^* \), she is indifferent between accepting and rejecting the offer. For coalition \( c \), the threshold solves \( u_j(c, g, q) = 0 \). This gives

\[
b_j^* = \frac{\epsilon}{1 - p(a_c, w_{cg}, q)}.
\]

Second, let’s pin down the equilibrium behavior of first-level nodes. They also have a
Figure 6: Extension with endogenous sharing of the bribe. Panel a shows the graph $g$ considered in the extension. It follows the conventions of figure 3 and highlights the coalitions $\delta_0, \delta_1, \delta_2, \delta_3$. $A$ and $B$ have $0 < k_A \leq k_B$ children. Panel b shows equilibrium outcomes for any $(q, \epsilon)$. The seed either rejects the bribe or one of $\delta_0, ..., \delta_3$ is realized. As $q$ increases, the rejection area grows, and coalitions of increasing size are realized.

threshold strategy:

**Proposition 6.** First-level node $i$ accepts $S$’s offer to join $c$ if and only if $b_i \geq r_{Si}^* = \frac{\epsilon}{1 - p(a_c, w_{cg}, q)}$. She recruits her $k_i$ children if $b_i \geq b_i^* = (N - 1)\epsilon > r_{Si}^*$, and recruits none otherwise.

Proposition 6 reveals interesting patterns about the distribution of the spoils within the coalition. In particular, in any coalition, brokers (first-level nodes) get a larger share of the spoils than operatives (second-level nodes). This is quite counterintuitive, because second-level nodes are the ones that most reduce the probability of detection, since recruiting them as accomplices does not create new witnesses. This is due to the commitment problem introduced by endogenous sharing of the bribe. Indeed, with endogenous sharing, first-level nodes cannot commit not to pocket what $S$ transfers them. As such, if $S$ wants to recruit second-level nodes, she has to give them a share of the bribe that is so high that they become indifferent between recruiting operatives or not.

We can now compare $S$’s payoffs in every feasible coalition to pin down her equi-
librium behavior. Figure 6b summarizes the findings. Comparing this figure with the case of equal-sharing (figure 4c), we see that most results hold. First, as capacity increases, corruption decreases, in the sense that $\hat{\epsilon}_S(g,q)$ decreases. Second, conditional on $S$ accepting the bribe, as capacity increases, the size of the conspiracy increases. For an intermediate sunk cost $\epsilon$, we see that the equilibrium coalition moves from $\delta_0$ to $\delta_1$ to $\delta_2$.

With endogenous sharing of the bribe, however, the size of the coalition now varies with $\epsilon$. Indeed, since the seed controls the resource, she can extract all the surplus from her accomplices, and compensate them only for their level of risk, $\epsilon$. So, if risk is low enough, protection becomes so cheap that the seed can afford to recruit everyone.

This also introduces slight changes as to who makes up for the best accomplices: although isolation is still first order, more connected brokers are better. Isolation is first order: the seed still picks coalitions that minimize the amount of witnesses. For instance, recruiting node $A$ only dominates recruiting node $B$ only. Similarly, recruiting no node is better than recruiting both $A$ and $B$. Yet, in equilibrium, when the seed picks coalition $\delta_1$, he choses the more connected broker $B$ over broker $A$, while with equal sharing, he would have done the opposite. The reason is that brokers compete against each other. The better connected broker is just as willing to participate in the racket as the less connected one; this is why they both cost $(N - 1)\epsilon$ to the seed. For higher values of $\epsilon$, protection becomes more expensive. The seed fires the least efficient broker and keeps the good one.

Finally, and as in the main specification, adding ties has ambiguous effects on corruption (see example in Appendix C). On the one hand, it may decrease corruption by making coalitions more exposed. On the other hand, it may increase corruption, through a mechanism that is slightly different from the main specification: additional ties may circumvent costly brokers, hence reducing the cost of additional protection.
5 Experimental results

We now take the model to the lab and test experimentally the main predictions of the theory, as well as its main assumptions. The preceding section made several predictions as to how the form of corruption varies in more or less capable organizations. We showed that as capacity increases, corruption decreases by weeding out petty corruption and involves more accomplices (proposition 3). It also made predictions as to how the form of corruption varies with organizational structure. We saw that enclaves are more corrupt (proposition 2), and that while exposing ties reduce corruption, others have no effect (proposition 4). Finally, the main specification of the model assumed that agents divided the bribe equally, while an extension assumed that they bargained over its division. The lab allows testing which assumption is more reasonable.

5.1 Protocol

The experiments were all conducted at MEDA Solutions laboratory in Mohammedia, Morocco, using a convenience sample of 272 subjects, with two thirds employees of the service industry, and one third students. Seventeen sessions of 16 subjects were held. Subjects played the experiment in groups of four, with a total of 68 groups. All sessions assign participants to an exogenous, undirected network. I used a bribe of 12 experimental credits (about $1), and rescaled the probability of success used in equation 2.19

\[ p(a, w, q) = .83 \times \left[ \frac{a - 1}{N - 1} q + \left( 1 - \frac{w}{N - 1} \right) (1 - q) \right] \] (4)

The experiments compared a baseline to two main treatments: (1) increasing capacity from \( q = .1 \) to \( q = .75 \) (the “hard” treatment), and (2) adding an exposing tie to the baseline (the “exposing tie” treatment). In the baseline and each of the treatment condi-

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17 Due to power considerations, I did not test whether some ties increase corruption (proposition 5).

18 Appendix E provides additional details about the protocol, including sample descriptive statistics, recruitment, and experimental material.

19 Without rescaling, the probability of success is 1 for the grand coalition. The rescaling prevents this outcome from being focal.
Condition Capacity ($q$) | Equilibrium
---|---
Baseline | .1
Hard | .75
Exposing tie | .1

Table 2: Experimental parameters and equilibria. $S$ is the seed. Dashed ties correspond to non-exposing ties. They are added and removed within each condition. Grey nodes are accomplices.

tions, I also manipulated two dimensions. First, I varied the profitability of corruption, by setting $\epsilon = 2$ credits (grand corruption), or $\epsilon = 4$ credits (petty corruption). Second, I added or removed non-exposing ties to the network. Table 2 shows experimental parameters and equilibria in all conditions. Experimental parameters were chosen to yield the same equilibrium outcome under bargaining and equal-sharing.

The setup allows testing the main predictions of the theory. Comparing the hard treatment to the baseline tests predictions on the form of corruption when capacity increasing. The exposing tie treatment tests whether more enclaved coalitions are more corrupt; comparing it to the baseline allows testing whether exposing ties reduce corruption. Conversely, non-exposing ties check whether some ties have no effect. Finally, examining how the bribe was divided across treatments tests which assumption on the division rule (equal-sharing or bargaining) is more reasonable.

Figure 7 details the experimental protocol. Before a session, I randomly decided whether it would be played with petty or grand corruption. Subjects entered the lab, and took a short pre-experiment survey. Subjects were then randomly assigned to groups of four. Each group had an enumerator that conducted the session. The enumerator read the instructions aloud, and conducted 12 rounds of the game. For each round, the network was drawn on a board that was placed on the table. The probability of success $p$ associated to each coalition was communicated on a paper handout placed on the table. The 12-credits bribe was symbolized by 12 red cards. The sunk cost, called the “salary” in the
Figure 7: Experimental protocol for group \{1, 2, 3, 4\}. The figure reads from top to bottom. Grey nodes represent the seed. Each full rectangle represents a block of 4 games, and corresponds to a treatment. Within each block, the order of the 4 games was randomly permuted. The first two blocks were randomly permuted. Each block contains two treatments with the non-exposing tie, and two treatments without.

The experiment, was represented by 2 or 4 blue cards held by the subjects. When accepting the bribe, subjects would give up their salary. In order to mimic the interpersonal interactions that arise in organizations, the game used face-to-face interactions. However, to ensure that all offers were take-it-or-leave-it, all communication was mediated by the enumerator. The outcome was drawn by rolling a hundred-sided dice. To prevent framing effects from biasing the results, the experiment used a neutral framing.

The twelve rounds were divided in three “blocks” of four rounds, corresponding to the baseline and the two treatments. Within each block, each subject got to be the seed
once, and to occupy each of the other network positions once according to the ordering in figure 7. Within each block, two rounds include the non-exposing tie, and two do not. The ordering was designed such that the same two subjects were always assigned to be the seed with the non-exposing tie, while the other two never did.

Learning and pooling effects are challenging. On the one hand, the game is cognitively taxing, and was played repeatedly to ensure convergence to equilibrium predictions. On the other hand, repeating the game might bias the results by (1) incentivizing subjects to pool across games, and (2) getting subjects to learn other players’ idiosyncratic strategies over time, making results diverge from the prediction in later rounds. Appendix F.1 shows that learning effects are insignificant and mixed, and that there are no pooling effects.

For comprehension, subjects played practice rounds before each block until the enumerator was confident that at least two out of four understood the rules. In practice, the enumerator usually gave one to two practice rounds, and never more than three. I measured understanding before each block and at the end of the experiment through comprehension quizzes. The enumerator first recorded the subject’s answer, then corrected her publicly if it was wrong so all could learn from her mistake. Throughout the experiment, comprehension never fell below 80 percent, and reached 94 percent at the end of the experiment (see Appendix E).

To discourage learning, enumerators did not tell respondents how many rounds of the game they would play, and did not allow them to keep track of their gains. Within-block, I also randomized the order of the games. To measure potential learning effects, I also randomly switched the order of the first two blocks (baseline and hard). I kept the exposing tie block last, because it was more cognitively demanding.

Each subject then took a post-experiment survey that included a final comprehension quiz. They were paid their earnings, which averaged $2.6, and a show-up fee of $5, for a total of about daily minimum wage.
Figure 8: Incidence of corruption in all conditions. The full circle indicates the point estimate, the empty circle the equilibrium. The top panel plots the raw percentages, the bottom panel plots differences in means. Corruption decreases by weeding out petty bribes in the hard and exposing tie treatments: corruption is comparably high in all treatments for grand corruption (differences in means are marginally significant). Switching to petty bribes has no effect in the baseline, but decreases corruption in the other treatments. Adding non-exposing ties has no effect. 95% confidence intervals are not centered due to the skew introduced by logistic transformation.

5.2 Results

We first examine support for the main theoretical predictions: does increasing capacity decrease corruption by weeding out petty bribe and increase the size of the coalition? Are enclaves more corrupt? Do exposing ties reduce corruption, and do non-exposing ties have no effect? To keep exposition concise, we examine predictions on the incidence of corruption; that is whether the seed accepts or rejects the bribe, then move on to predictions on the form of the coalition. The quantities of interest are estimated using logistic regression for acceptance decision, and OLS for the size of the coalition. Standard errors are clustered at the group level, to account for within-table correlations.

Figure 8 plots the predicted probability that the seed accepts the bribe in all conditions. Appendix F.3 shows all the models used to estimate the quantities of interest in the paper. In Appendix F.2 I also examine random effects specifications, where I add group- and individual-level random effects. Results are robust to including random effects. They also reveal that the contribution of individual-level variance to total variance is minuscule compared to that of group-level variance. This further justifies clustering standard errors at the group level in the main specification, and shows that individual-level covariates have little effect on results.
Finding 1. Support for propositions 3 and 4: increasing capacity and adding exposing ties both reduce corruption by weeding out petty bribes. In the baseline, the seed is very likely to accept both petty and grand bribes: the difference in means is not significantly different from zero. In the hard and exposing tie treatments, the seed is comparably likely to accept grand bribes (the differences in means are marginally significant), but her probability of accepting petty bribes drops by about 40 percentage points in both treatments.

Finding 2. Support for proposition 4: adding non-exposing ties has no effect on the incidence of corruption. I compare within treatment by adding treatment-level fixed effects, where a treatment is defined as the interaction between a main treatment (control, hard, exposing tie) and the kind of bribe (petty, grand). Figure 8 shows that adding non-exposing ties has little effect on the incidence of corruption (the difference in means is marginally significant).

I inspect the mean size of realized coalitions (figure 9), and the distribution of realized coalitions (figure 10). I restrict the analysis to grand corruption, because our predictions on the form of corruption are conditional on the seed accepting the bribe in equilibrium, which only happens with grand corruption.

Finding 3. Mixed support for proposition 3: increasing capacity increases coalition size, but not as much as expected. Figure 9 shows that the size of
Figure 10: Distribution of realized coalitions with grand corruption. Bar labels correspond to the coalitions that include the black nodes. Grey bars indicate the equilibrium. More isolated nodes are more likely to be corrupt (panel 10c, second and third bars). Most realized coalitions correspond to the equilibrium prediction, except for the hard treatment.

the coalition increases when increasing capacity. The ordering of effects is consistent with predictions: the coalition is largest in the hard treatment, and second largest in the exposing tie treatment. However, results are closer to equilibrium prediction in the exposing tie treatment than in the hard treatment. The next subsection shows that this is due to subjects making mistakes when engaging in bargaining for long chains of backward induction.

**Finding 4. Support for proposition 2: isolated nodes are more likely to be corrupt.** Figure 10 shows that in the exposing tie treatment (panel 10c), the seed overwhelmingly favors the coalition including the most isolated node: the equilibrium coalition accounts for 45 percent of realized coalitions. The figure also confirms what we saw earlier: most realized coalitions correspond to the equilibrium prediction, except for the hard treatment. In the baseline, 70 percent of realized coalitions include the seed alone, which is the condition that should be realized in equilibrium. In the hard treatment, the complete coalition account for only 28 percent of realized coalitions, which is further away from the prediction.

**Finding 5. Support for proposition 4: non-exposing ties have no effect on the form of corruption.** Within a main treatment, for a given kind of bribe, I compare the distribution of realized coalitions with and without the extra tie, using Fisher exact tests corrected for multiple testing using the Benjamini & Hochberg procedure. The
distribution of realized coalitions never differs significantly with and without the non-exposing tie.

Having shown support for the main theoretical predictions, we now consider the sharing rule used by subjects. There is little support for equal-sharing. Even for an easy test, predictions are more consistent with bargaining. I examine the seed’s share of the bribe, restricting the analysis to instances where (1) the seed should share the bribe in equilibrium, and (2) the equilibrium coalition was indeed realized. That is, I restrict the analysis to the hard and exposing tie treatments with grand corruption, conditional on the equilibrium coalition being realized. Passing this test should be relatively easy, because it restricts the analysis to cases where subjects did not make errors in the coalition formation process. Figure 11 shows the distribution of the seed’s share of the bribe in those instances. It is not consistent with equal sharing. In the hard treatment (panel 11a), the seed realizes the full coalition in equilibrium. She should get a share of 3 credits under equal sharing. Yet, she has a modal share of 6 credits, and in about 75 percent
Table 3: Deviation from bargaining rule, observed frequencies for binary decisions. The variables $r$ and $t$ correspond to acceptance and sharing behavior, respectively. The * superscript denotes equilibrium behavior under bargaining rule. The value 1 (0) corresponds accepting/sharing (rejecting/not sharing) respectively. When making errors, subjects overwhelmingly over-share and over-accept.

cases, she gets a share of 4 credits or more. In the exposing tie treatment (panel [11b]),
the seed recruits the isolated node in equilibrium. She should get a share of 6 under
equal sharing. Yet, her modal share amounts to 8 credits, and in about 85 percent cases,
she gets a share 7 credits or more. Figure [11] also shows that although payoffs are more
similar to the bargaining prediction, a lot of the mass is even above the bargaining share,
which suggests that the seed is greedier than what bargaining implies. I will now show
that this greediness likely owes to agents struggling to solve long backward induction
problems.

Having ruled out equal-sharing, we can examine deviations from equilibrium under
bargaining. I compute agents’ equilibrium strategy under bargaining at each history.
This gives the equilibrium vector of offers made by bribe-offerers, and the equilibrium
threshold above which bribe recipients should accept the bribe.

Subjects over-accept and over-share. I examine two binary decisions: (1) on the
offerer’s side, whether she shares the bribe with anyone or not ($t = 1, 0$ respectively); (2)
on the recipient’s side, whether she accepts the offer or not ($r = 1, 0$ respectively), and
compare that to the equilibrium move ($r^*$ and $t^*$ for acceptance and sharing respectively).
Table 3a shows that offerers share according to equilibrium behavior in 65 percent cases,
and that they overwhelmingly over-share: most of the error is of type II ($t = 1, t^* = 0$).
Recipients’ behavior is consistent with that of offerers’: they over-accept [21] Table 3b
shows that recipients correctly accept/reject in about 45 percent cases. Again, error is

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21For acceptance, I only examine non-seed nodes, because the previous subsections showed the seed’s
acceptance behavior mostly conformed to equilibrium prediction. Also, since the offer that is made to
the seed is exogenous, she is substantially different from non-seed players.
Figure 12: Offer deviation from equilibrium: $b_i - b_i^*$. Panel 12a shows most offers are greedy ($b_i - b_i^* < 0$), but get closer to equilibrium over time. Panel 12b shows the probability of accepting greedy offers is high, but decreases over time. For ease of interpretation, predicted probabilities at the third history are not shown. Footnote 23 provides details about estimation.

Subjects also make and accept offers that are too greedy but make less errors in later histories. Recall from section 4.3 that bribe-recipients have a threshold strategy. The quantity $b_i - b_i^*$, that is, the offer’s deviation from equilibrium, allows to distinguish greedy offers ($b_i - b_i^* < 0$) from generous ones ($b_i - b_i^* \geq 0$). History 1 corresponds to the seed’s acceptance decision. I consider histories 2 and above. Figure 12a plots the distribution of deviations from the acceptance threshold as received at the second history (offer made by the seed), and at later histories. About 75 percent of the distribution consists of greedy offers ($b_i - b_i^* < 0$). However, offers get less greedy over time: the median offer gets closer to zero for later histories. Figure 12b plots the probability that a non-seed recipient accepts the bribe as a function of the deviation from the acceptance threshold at various histories. In line with individual rationality, recipients have a very high probability of

---

22 This is confirmed by a series of pairwise one-sided Mann-Whitney tests: the distribution of $b_i - b_i^*$ shifts to the right for later histories.

23 This is modeled using generalized additive logistic regressions with thin plate regression splines. The model is estimated on offers with a deviation ranging from -5 to 5, to exclude outliers. To account for correlations within group and within treatment, I cluster standard errors both at the table level and
accepting generous offers (above 90%), irrespective of the history. They also have a high probability of accepting greedy offers. Offers that are greedy by 1 credit have more than 60% chance of being accepted. Nonetheless, the probability of accepting greedy offers decreases over time: while the probability of accepting an offer greedy by 1 credit is significantly lower at the fourth history.

Overall, we have seen that (1) subjects bargain. (2) They over-share and over-accept. (3) They make and accept offers that are too greedy. (4) They make less errors in later histories. Together, this is consistent with the fact that backward induction is cognitively taxing, and more so at early histories. At early histories, both bribe-offerers and recipients underestimate the transfers that recipients will have to make in order to realize the equilibrium coalition. They accept offers that seem generous, because they discount their future transfers. At later histories, the problem is easier. Offers get closer to equilibrium, and recipients are more likely to reject greedy offers.

Cognitive failures with backward induction may explain why, as we saw above, realizations were further away from predictions in the hard treatment. This treatment requires the formation of a larger coalition, which, in turn, requires longer chain of diffusion, and poses a more complicated backward induction problem. This poses a harder problem at early histories, and makes larger coalitions more likely to fail.

6 Discussion

The stylized facts in section 2 highlighted that corruption takes on widely different forms in more or less capable countries, in ways that the standard principal-agent approach is unequipped to explain. This paper presented a model of corruption on a network designed to answer two questions: how does the form of corruption vary as bureaucracies get better at detection corruption? how does it vary with the structure of the bureaucracy? A lab experiment confirmed the main predictions of the model. We now examine how those predictions relate to the stylized facts.

at the treatment level, where a treatment cluster is defined as the interaction between a main treatment and the kind of bribe.
Less capable countries feature both grand and petty corruption, with fewer accomplices. Corruption persists in more capable countries, but features only grand corruption, and involves more accomplices. Proposition 3 provides an explanation: because detection is more likely in capable countries, recruiting accomplices is more desirable. Yet, only grand corruption is profitable enough to afford the cost of recruiting additional protection. Experimental results confirm the mechanism and provide another mechanism: forming larger coalitions poses a challenging backward induction problem, which makes corruption in those settings all the more unlikely.

The stylized facts also revealed that organizational structure matters: in equally capable countries, more insular bureaucracies are more corrupt. Proposition 4 and experimental results suggest that this owes to the fact that corrupt behavior in those bureaucracies is subject to less scrutiny, hence reducing the risk of detection.

The impact of organizational structure on corruption is, however, not straightforward. Proposition 2 shows that enclaves are more likely to be corrupt, because are the most isolated parts of an organization. Isolation, however, is a collective property: although an individual node may be exposed, she might be in a part of the organization that is collectively isolated from the rest. This may reconcile the contradictory findings that both more isolated (Aven, 2012) and better connected individuals (Nyblade and Reed, 2012) are more likely to be corrupt.

Finally, under certain conditions, organizational design can substitute for tougher enforcement. Open plan offices are good examples of such policies, and are commonly implemented in efforts to reduce corruption, for instance by Mayor Bloomberg in New York City, or Mayor Mockus in Bogota. This will be the case if and only if one makes enclaves more exposed, which is more likely when making the organization less modular. On the other hand, such policies can backfire, by creating new enclaves, or by circumventing costly brokers.

These results have important policy implications. First, law-enforcement agencies should audit more isolated subunits of an organization. Second, to prevent corruption through organizational design, one should carefully consider whether the new design will
reduce modularity, and not lead to the creation of new enclaves.

Finally, experimental results showed that the initial assumption of equal-sharing was unwarranted. Further modeling efforts should privilege the more realistic bargaining assumption. Another interesting research avenue is to consider monitoring technologies more sophisticated than the all-or-nothing detection used here.
Appendices

A Data on stylized facts

A.1 Cross-country comparisons

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bayesian Corruption Index (BCI)</td>
<td>An aggregated index of corruption, with data from 20 surveys, and 80 survey questions. It ranges from 0 to 100, with higher values indicating more corruption.</td>
<td>Standaert, 2015</td>
</tr>
<tr>
<td>Corruption Perception Index (CPI)</td>
<td>An index of perceived corruption. It ranges from 0 to 10, with higher values indicating less corruption.</td>
<td>Transparency International, 2015</td>
</tr>
<tr>
<td>World Bank Governance Indicator (WBGI), Control of corruption index</td>
<td>An aggregated index of corruption, with data from 31 sources. Virtually all values range between −2.5 and 2.5, with higher values indicating less corruption.</td>
<td>Kaufmann et al., 2010</td>
</tr>
<tr>
<td>Global Corruption Barometer (GCB)</td>
<td>An index of perceived corruption for various institutions. We focus on the police and Parliament. It ranges from 1 to 5, with higher values indicating more corruption.</td>
<td>Transparency International, 2015</td>
</tr>
<tr>
<td>GDP p/c, PPP $ 2011</td>
<td>Gross Domestic Product per capita in constant US dollar 2011 based on purchasing power parity.</td>
<td>World Development Indicators, World Bank, 2016</td>
</tr>
<tr>
<td>Polity IV score</td>
<td>An indicator of regime type. Ranges from −10 (strongly autocratic) to 10 (strongly democratic)</td>
<td>Marshall et al., 2015</td>
</tr>
<tr>
<td>Closedness</td>
<td>An expert-based index of whether the bureaucracy is more closed or open (private-like). It ranges from 1 to 7, with higher values indicating more closedness.</td>
<td>Dahlström et al., 2015</td>
</tr>
<tr>
<td>Share of accomplices</td>
<td>Constructed from the following question: “Hypothetically, let’s say that a typical public sector employee was given the task to distribute an amount equivalent to 1000 USD per capita to the needy poor in your country. According to your judgment, please state the percentage that would reach” (a) The needy poor, (b) People with kinship ties to the employee, (c) Middlemen/consultants, (d) The public employee’s own pocket, (e) The superiors of the public employee, (f) Others. The variable amounts to ( \frac{(b + d)}{(b + c + d + e)} ).</td>
<td>Dahlström et al., 2015</td>
</tr>
</tbody>
</table>

Table 4: Variables used in cross-country comparisons

<table>
<thead>
<tr>
<th>Dependent variable:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corruption (police)</td>
</tr>
<tr>
<td>(1)</td>
</tr>
<tr>
<td>log(GDP p/c), $ PPP 2011</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>R²</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: Models to construct figures 1a and 2a. Models are estimated using OLS and standard errors are robust.
A.2 US-India comparison

I collected data on corruption cases in the US and India by searching for the words “arrest” and “corruption,” “fraud,” “bribery,” “embezzlement,” or “graft” (as well as their variants, such as “arrested” or “corrupt”) in the National Desk of the New York Times (NYT) and the Times of India (TOI) using Factiva. I then went through each article to identify the ones actually covering corruption cases. For each selected article, I collected the amount stolen and the number of accomplices. In the NYT data, I covered the 2000-2014 time period and ended up with 55 cases. For TOI, I started at December 31, 2014 and stopped collecting data when I obtained a sample of the same size.

I compare the US and India because the former is a more capable state than the latter. I picked the NYT and the TOI because they are both major national dailies in two large democracies with a vivid free press. This lends confidence that both newspapers will cover corruption cases to a similar extent. I ran the above query because using a large vocabulary for corruption would select many articles while looking for the word “arrest” would select the first article on the case to appear in the newspaper, which would usually be the most detailed.

Using newspaper data on corruption is not uncommon (see, for instance, Glaeser and Goldin, 2008). Although this type of data is the best available to provide the kind of evidence required to test the model, it has several pitfalls. The most important one is that different newspapers may select differently on the types of cases they cover. The fact that both newspapers are national, generalist dailies should alleviate this concern. Furthermore, corruption being more widespread in India than in the US should push the TOI to select against petty corruption, which would be less interesting to its readers. As such, selection would only dampen the finding that petty corruption is more prevalent in India. In any case, the stylized facts below should only be taken as tentative evidence.

Table 6 provides a few descriptive statistics, and table 7 shows the Poisson regression used to construct figure 2b. Note that the finding is robust to using a negative binomial regression.
<table>
<thead>
<tr>
<th></th>
<th>India</th>
<th>USA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean amount stolen, m$ PPP 2011</td>
<td>0.93</td>
<td>4.64</td>
</tr>
<tr>
<td>Mean N accomplices</td>
<td>3.02</td>
<td>10.79</td>
</tr>
<tr>
<td>First case</td>
<td>2014-11-04</td>
<td>2000-03-18</td>
</tr>
<tr>
<td>Last case</td>
<td>2014-12-31</td>
<td>2014-10-21</td>
</tr>
<tr>
<td>N</td>
<td>55</td>
<td>55</td>
</tr>
</tbody>
</table>

Table 6: Descriptive statistics on corruption in India and the US.

<table>
<thead>
<tr>
<th></th>
<th>Poisson regression</th>
<th>Negative binomial</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(amount)</td>
<td>0.196***</td>
<td>0.238***</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.051)</td>
</tr>
<tr>
<td>USA</td>
<td>0.656***</td>
<td>0.639*</td>
</tr>
<tr>
<td></td>
<td>(0.215)</td>
<td>(0.330)</td>
</tr>
<tr>
<td>Constant</td>
<td>-2.047***</td>
<td>-2.517***</td>
</tr>
<tr>
<td></td>
<td>(0.366)</td>
<td>(0.559)</td>
</tr>
<tr>
<td>Observations</td>
<td>71</td>
<td>71</td>
</tr>
<tr>
<td>$\theta$</td>
<td>1.434*** (0.493)</td>
<td></td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>253.951</td>
<td>216.520</td>
</tr>
</tbody>
</table>

Table 7: Count regressions for number of accomplices. For similar amounts stolen, corruption in the more capable US involves more accomplices than in India.

**B Proofs**

**Proof of lemma 4.** Suppose $u(c^*, g, q) < \epsilon_S$. Then, no coalition gives $S$ a positive payoff. He rejects the bribe.

Suppose $u(c^*, g, q) \geq \epsilon_S$. Since $c^* \in C_g$, there is at least one strategy profile that has $c^*$ as an outcome. Since all utility functions are the same up to the constant $\epsilon_i$, $c^*$ maximizes the utility of any accomplice $i$ in $c^*$. Because $\epsilon_i < \epsilon_S$, we have $u_i(c^*, g, q) \geq 0$. No accomplice has an incentive to deviate from the profile, since it yields their highest possible payoff. Because $u_S(c^*) \geq 0$, $S$ accepts the bribe.

Showing that profiles that have as outcomes coalitions that do not belong to $C_{gg}^*$ cannot be sustained in equilibrium is straightforward. Consider a strategy profile that such a coalition as an outcome to one that has $c^*$ as an outcome. At the first history where the two profiles diverge, the player that moves at this history has an incentive to deviate to the profile that has $c^*$ as an outcome. As such, $\epsilon_S(g, q) = u(c, g, q)$. \qed
Proof of proposition `[1]` Let $C^* = \bigcup_{q \in (0,1)} C^*_{qq}$ such that no two coalitions are essentially unique. The claim is trivially true if $|C^*| = 1$. Suppose $|C^*| > 1$. Assumption `[1]` implies that \( \frac{\partial}{\partial q} [v(a_2, w_2, q) - v(a_1, w_1, q)] > 0 \). As such, if there is $Q \subset (0,1)$ such that $v(a_2, w_2, q) = v(a_1, w_1, q)$, then $Q$ is a singleton. So for any $c^* \in C^*$, there is a finite amount of $q \in (0,1)$ such that $u(c^*, g, q) = u(c, g, q)$ for some $c \in C^*$. This implies that there is a finite amount of $q \in (0,1)$ such that not all equilibrium coalitions are essentially unique.

\[ \square \]


Suppose $v$ is monotonic in $a$. Then $v(a_c, w_1, q) \leq \max \{v(a_1, w_1, q), v(a_2, w_1, q)\}$. Note that $v(a_c, w_c, q) < v(a_c, w_1, q)$, so $v(a_c, w_c, q) < \max \{v(a_1, w_1, q), v(a_2, w_1, q)\}$. Note that $v(a_2, w_2, q) > v(a_2, w_1, q)$, so $\max \{v(a_1, w_1, q), v(a_2, w_1, q)\} \leq \max \{v(a_1, w_1, q), v(a_2, w_2, q)\}$.

As such, $v(a_c, w_c, q) \leq \max \{v(a_1, w_1, q), v(a_2, w_1, q)\}$.

Suppose $v$ is non-monotonic in $a$ and $\left| \frac{\partial v(a, w, q)}{\partial w} \right| > v(a^*, w, q) - \max \{v(0, w, q), v(N - 1, w, q)\}$, where $a^* \in \arg\max_{a \in [1,N]} v(a, w, q)$. Then, $v(a^*, w, q) - \left| \frac{\partial v(a, w, q)}{\partial w} \right| < \max \{v(0, w, q), v(N - 1, w, q)\}$. Note that $v(a_c, w_c, q) \leq v(a_c, w_1, q) - \left| \frac{\partial v(a, w, q)}{\partial w} \right| \leq v(a^*, w_1, q) - \left| \frac{\partial v(a, w, q)}{\partial w} \right|$. Furthermore, since $u$ is quasi-concave, it must be that $\max \{v(1, w_1, q), v(N, w_1, q)\} \leq \max \{v(a_1, w_1, q), v(a_2, w_1, q)\}$. As such, $v(a_c, w_c, q) \leq \max \{v(a_1, w_1, q), v(a_2, w_1, q)\}$.

\[ \square \]

Proof of proposition `[3]` I show the contrapositive of $c' \in C^*_{qq} \Rightarrow c' \in M_g$. Suppose $c' \notin M_g$. Then there is $c \in C_g$ such that $a_c \leq a_{c'}$ and $w_c < w_{c'}$. Suppose $a_{c'} = a_c$, then $v(a_c, w_c, q) > v(a_{c'}, w_{c'}, q)$. Suppose $a_c < a_{c'}$. Then by lemma `[2]` $v(a_{c'}, w_{c'}, q) < \max \{v(a_c, w_c, q), v(N - 1, 0, q)\}$ for any $q \in (0,1)$.

To construct the sequence $(\pi_k)$, pick all $q$’s such that not all equilibrium coalitions are essentially unique (from proposition `[1]`), sorted by increasing order. Then, define $\pi_0 = 0, \pi_K = 1$. To construct $M^0_g$, discard all elements $c \in M_g$ such that (1) there is $c' \in M_g$ such that $u(c', g, q) > u(c, g, q)$ for any $q \in (0,1)$, or (2) $c \in C^*_{qq}$ for a single $q$. By proposition `[1]` $M^0_g$ is non-empty.

\[ \square \]

Proof of proposition `[3]` Let’s first show that $q_1 < q_2 \Rightarrow \hat{\epsilon}_S(g, q_1) \geq \hat{\epsilon}_S(g, q_2)$. Let $c^* \in C^*_{qq}$.

By lemma `[1]` $\hat{\epsilon}_S(g, q) = u(c^*, g, q)$. We have $u(c^*_1, g, q_1) \geq u(c^*_2, g, q_1)$. Since for a given
coalition, \( u \) is decreasing in \( q \), we have \( u(c_2^*, g, q_1) \geq u(c_2^*, g, q_2) \). This implies \( u(c_1^*, g, q_1) \geq u(c_2^*, g, q_2) \), that is, \( \hat{\epsilon}_S(g, q_1) \geq \hat{\epsilon}_S(g, q_2) \).

To show that \( q_1 < q_2 \Rightarrow a_{c_1} \leq a_{c_2} \), I first prove the following lemma:

**Lemma 3.** Suppose \( v(a_1, w_1, q_1) \geq v(a_2, w_2, q_1) \) and \( v(a_2, w_2, q_2) > v(a_1, w_1, q_2) \) for some \( a_1 \leq a_2, w_1, w_2 \in [0, N-1], q_1, q_2 \in (0, 1) \). Then there is \( \bar{q} \in (0, 1) \) such that \( v(a_1, w_1, q) \geq u(a_2, w_2, q) \iff q \leq \bar{q} \).

**Proof.** Assumption [1] implies that \( \frac{\partial}{\partial q} [v(a_2, w_2, q) - v(a_1, w_1, q)] > 0 \). Since \( v(a_2, w_2, q) - v(a_1, w_1, q) \) is strictly decreasing in \( q \), it must be that (1) \( q_1 < q_2 \), and (2) there is \( \bar{q} \in (q_1, q_2) \) such that \( v(a_1, w_1, q) \geq v(a_2, w_2, q) \iff q \leq \bar{q} \).

Let’s proceed with the proposition. The claim is trivially true if \( c_1^* \in C_{gq_1}^* \) and \( c_2^* \in C_{gq_2}^* \). Suppose not. That is, suppose either \( c_1^* \notin C_{gq_2}^* \), or \( c_2^* \notin C_{gq_1}^* \).

Suppose first that \( c_1^* \notin C_{gq_2}^* \). So we have \( q_1 < q_2 \) such that \( v(a_{c_1^*}, w_{c_1^*}, q_1) \geq v(a_{c_2^*}, w_{c_2^*}, q_1) \) and \( v(a_{c_1^*}, w_{c_1^*}, q_2) < v(a_{c_2^*}, w_{c_2^*}, q_2) \). Suppose \( a_{c_1^*} > a_{c_2^*} \). Then, lemma [3] implies that there is \( \bar{q} \in (0, 1) \) such that \( v(a_{c_1^*}, w_{c_1^*}, q) \geq v(a_{c_2^*}, w_{c_2^*}, q) \iff q \geq \bar{q} \), a contradiction.

We show similarly that if \( c_2^* \notin C_{gq_1}^* \), then \( a_{c_1^*} \leq a_{c_2^*} \).

**Lemma 4** (Old coalitions are weakly dominated). We have \( C_g = C_{g'} \) if \( g' = g + i \rightarrow j \) and \( C_g \subseteq C_{g'} \) if \( g' = g + ij \). Any \( c \in C_g \) satisfies:

\[
w_{cg'} = \begin{cases} 
w_{cg} + 1, & \text{if } g' = g + i \rightarrow j \text{ and } j \in c \text{ and } i \notin c \\
w_{cg} & \text{otherwise.}\end{cases} \tag{5}
\]

**Proof.** The proof is immediate.

**Lemma 5** (New coalitions are weakly dominated). For any coalition \( c' \in C_{g'} \setminus C_g \), there is \( c \in C_g \) such that \( a_c < a_{c'} \) and \( w_{cg} \leq w_{c'g'} \).

**Proof.** By lemma [4] we only need to consider adding communication ties, since \( g' = g + i \rightarrow j \) implies \( C_{g'} = C_g \). Since \( c' \) is not feasible on \( g \), there exists at least one node \( k \in c' \) such that the tie \( ij \) is on all paths between \( k \) and \( S \) in \( g'_u \) such that all nodes on that path are in \( c' \). Let \( c'_{nf} \) be the set of such nodes. Its complement, \( c'_f = c' \setminus c'_{nf} \),
is feasible on \( g \). I show that \( c' = c \). By construction, we have \( a_{c'} < a_c \). Note that \( i \in c' \iff j \in c' \). Without loss of generality, suppose that \( i \in c' \).

Note that \( W_{c'g'} = (W_{c'g'} \setminus c'_{nf}) \cup W_{c'_{nf}g'} \), which implies

\[
w_{c'g'} = |W_{c'g'}| = |W_{c'g'} \setminus c'_{nf}| + |W_{c'_{nf}g'}| - |(W_{c'g'} \setminus c'_{nf}) \cap W_{c'_{nf}g'}|.
\]

By construction, \( W_{c'g'} \setminus c'_{nf} = W_{c'g'} \). Indeed, if node \( k \in W_{c'g'} \setminus c'_{nf} \), then \( k \) is the neighbor of some \( l \in c' \) on \( g' \). So the path \( S, ..., l, k \) is such that all nodes between \( S \) and \( k \) are in \( c' \), and does not contain \( ij \) which implies, by definition of \( c' \), that \( k \in c' \).

Lemma 4 implies that \( |W_{c'g'}| = w_{c'g'} \). Also note that witnesses of coalition \( c'_{nf} \) cannot be in \( c'_{nf} \); \( c'_{nf} \cap W_{c'_{nf}g'} = \emptyset \). As such, \((W_{c'g'} \setminus c'_{nf}) \cap W_{c'_{nf}g'} = W_{c'g'} \cap W_{c'_{nf}g'} \). Plugging back into equation (6) we get \( w_{c'g'} = w_{c'g} + |W_{c'_{nf}g'}| - |W_{c'_{nf}g'} \cap W_{c'g'}| \geq w_{c'g} \).

Proof of proposition 4. By lemma 4 we have \( C_{g'} = C_{g} \) and for any \( c \in C_{g} \), \( w_{cg} \leq w_{cg'} \leq w_{cg} + 1 \). This implies \( u(c, g', q) \leq u(c, g, q) \). So \( \hat{\mathcal{S}}(g', q) \leq \hat{\mathcal{S}}(g, q) \). Let’s show the second part of the proposition. I first show that if the condition on \( i \to j \) holds, then there is \( q \in (0, 1) \) such that \( \hat{\mathcal{S}}(g', q) < \hat{\mathcal{S}}(g, q) \). By propositions 1 and 2 there is an open interval \( U \) such that for any \( q \in U \), \( c^* \) is the essentially unique equilibrium outcome.

Using the same propositions on \( g' \), there is a minimal coalition \( c'' \in M_{g'}^0 \) such that \( c'' \) is the essentially unique equilibrium outcome for any \( q \) in some open interval \( U' \) in \((0, 1)\).

Consider a coalition \( c'' \) such that \( U \cap U' \) is non-empty. Pick \( q \in U \cap U' \). Since \( C_{g'} = C_{g} \), the condition on \( c^* \) implies that no coalition on \( g' \) is essentially equal to \( c^* \) on \( g \). If \( c'' \) on \( g' \) is essentially equal to some coalition \( c \) on \( g \), then \( c \) is not essentially equal to \( c^* \), which implies \( u(c'', g', q) = u(c, g, q) < u(c^*, g, q) \). If no coalition on \( g \) is essentially equal to \( c'' \), then lemma 4 implies that there is \( c \in C_{g} \) such that \( a_{c} = a_{c''} \) and \( w_{cg} = w_{c''g'} - 1 \). As such, \( u(c'', g', q) < u(c, g, q) \leq u(c^*, g, q) \).

Let’s show that if the condition on \( i \to j \) does not hold, then \( \hat{\mathcal{S}}(g', q) = \hat{\mathcal{S}}(g, q) \) for any \( q \in (0, 1) \). Proposition 2 implies that for any \( q \in (0, 1) \), there is \( c^* \in M_{g} \) that is realized in equilibrium on \( g \). Because the condition on \( i \to j \) does not hold, there is a coalition \( c \) on \( g' \) that is essentially equal to \( c^* \). As such, \( u(c, g', q) = u(c^*, g, q) \).
Proof of proposition 5. By lemma 4 we have that for any \( c \in C_g \) \( u(c, g, q) = u(c, g', q) \), which implies that \( \hat{\varepsilon}_S(g', q) \geq \hat{\varepsilon}_S(g, q) \). Let’s show the second part of the proposition. Suppose that there is \( q \in (0, 1) \) such that \( \hat{\varepsilon}_S(g', q) \geq \hat{\varepsilon}_S(g, q) \). Using proposition 2 this means that there is \( c \in M_g, c' \in M_{g'} \) such that \( u(c', g', q) > u(c, g, q) \). For this to be true, it must be that \( c' \subseteq C_{g'} \setminus C_g \). For otherwise, lemma 4 implies \( u(c', g, q) = u(c', g', q) \). So lemma 5 implies that there is \( c^* \subseteq C_g \) such that \( a_{c^*} < a_{c'} \), \( w_{c''} \leq w_{c'''} \). It must be that \( w_{c''} = w_{c''''} \) for otherwise, lemma 2 implies \( u(c', g', q) < \max\{u(c^*, g, q), v(N, 0, q)\} \).

Suppose \( c^* \notin M_g \). Then there is \( c \subseteq C_g \) such that \( a_c \leq a_{c'} \) and \( w_c \leq w_{c'} \). This implies \( a_c \leq a_{c'} \) and \( w_c \leq w_{c'} \). Then lemma 2 implies \( u(c, g', q) < \max\{u(c, g, q), v(N, 0, q)\} \), a contradiction.

\( \square \)

Proof of proposition 6. Suppose that \( S \) made an offer \( t_{S_i} \) to only one first level node, \( i \in \{A, B\} \). Suppose that \( i \) accepted the offer. Let \( \hat{u}_i(k, q) \) be her utility in a coalition \( c^* \) where she makes transfers to \( 0 \leq k \leq k_i \) second-level nodes for capacity \( q \), and \( \hat{p}(k, q) \) the probability of detection of such \( c^* \). We have \( \hat{u}_i(k, q) = (b_i - k b'_j)(1 - \hat{p}(k, q)) - \varepsilon \). Plugging in the equilibrium value of \( b'_j \) from equation 3, we get: \( \hat{u}_i(k, q) = b_i(1 - \hat{p}(k, q)) - (k + 1)\varepsilon \).

Note that since \( \hat{u}_i(k + 1, q) - \hat{u}_i(k, q) = \frac{b_i}{N-1} - \varepsilon \), \( \hat{u}_i \) is increasing in \( k \) if and only if \( b_i \geq (N - 1)\varepsilon \). As a result, conditional on \( i \) accepting \( S \)'s offer, if \( b_i < (N - 1)\varepsilon \), we have that \( k^* = 0 \); that is, \( i \) makes no offer in equilibrium. Conversely, if \( b_i \geq (N - 1)\varepsilon \), \( k^* = k_i \).

That is, \( i \) recruits all her children in equilibrium.

Node \( i \) accepts the bribe whenever \( \hat{u}_i(k^*, q) \geq 0 \). If \( b_i \geq (N - 1)\varepsilon \), then conditional on \( i \) accepting the transfer, the coalition that is realized has one witness, and \( k_i + 2 \) accomplices.

As such, \( \hat{u}_i(k^*, q) = \hat{u}_i(k_i, q) \geq [N - 2 - (N - 3 - k_i)q] \varepsilon > 0 \). That is, \( i \) always accepts the bribe. If \( b_i < (N - 1)\varepsilon \), \( i \) accepts the bribe whenever \( \hat{u}_i(0, q) = b_i\hat{p}(0, q) - \varepsilon \geq 0 \). Solving for \( b_i \), we get that \( i \) accepts the bribe when \( b_i \geq \frac{\varepsilon}{1 - \hat{p}(0, q)} \). That is, \( i \) accepts the bribe for \( b_i \geq \frac{\varepsilon}{1 - \hat{p}(0, q)} \). Note that \( (N - 1)\varepsilon > \frac{\varepsilon}{1 - \hat{p}(0, q)} \). Indeed, \( \frac{\varepsilon}{1 - \hat{p}(0, q)} \) is maximized for \( q = 1 \). In this case, we have \( (N - 1)\varepsilon - \frac{\varepsilon}{1 - \hat{p}(0, q)} = (1 - \frac{1}{a}) (N - 1)\varepsilon \geq 0 \), since the number of accomplices in the coalition \( a \geq 2 \). So for \( q \in (0, 1) \), \( (N - 1)\varepsilon > \frac{\varepsilon}{1 - \hat{p}(c, g, q)} \).

The same reasoning applies when \( S \) makes an offer to both first level nodes. Proceed by backward induction, and suppose that first level nodes \( i \) and \( j \) move first and second
respectively. Player \( j \) behaves exactly as above. Consider now player \( i \). Using the same reasoning as above, she accepts the bribe and recruits all her children if \( b_i \geq (N - 1)\epsilon \). Otherwise, she looks at \( t_{S_j} \) and anticipates \( j \)'s move, conditional on \( i \) accepting the bribe and not recruiting any of her children. Call \( \hat{c} \) the resulting coalition, with \( \hat{p} \) its associated probability of detection. She accepts the bribe and recruits none of her children if her utility in the resulting coalition is greater than 0, that is if \( b_i \geq \frac{\epsilon}{1-\hat{p}} \), and rejects otherwise.

\[ \square \]

C Adding ties under bargaining: an example

\[ \text{Figure 13: Three graphs. The grey node represents the seed. Note that } g_2 = g_1 + 13, \text{ and } g_2 = g_3 + 23 \]

\[ \text{Figure 14: Equilibrium behavior for the graphs in figure 13. The figure follows the conventions in figure 4. The graph } g_2 \text{ is less corrupt than } g_1 \text{ because node 3 is more exposed. It is less corrupt than } g_3 \text{ because the cost of recruiting node 3 is shifted to broker node 2.} \]
Extension: detection as a function of profitability

D.1 Results

The model assumes that the probability of detection is independent of the profitability of corruption. This assumption simplifies the analysis, but may be unrealistic. The effect is unclear. On the one hand, more profitable, grand corruption could be more egregious, hence more likely to be detected. On the other hand, grand corruption might allow agents to spend some of the additional profit to increase protection. I consider both cases and show that assuming that grand corruption is less likely to be detected does not change the results. Assuming that grand corruption is more likely to be detected, I show that results do not change if the effect is sufficiently small. If the effect is sufficiently large, then one result changes: as capacity increases, corruption now decreases by weeding out grand corruption. Because empirical evidence is more supportive of the opposite, I favor the original assumption that the probability of detection either decreases for more profitable schemes, or does not increases by much. The rest of this subsection details changes in the setting, and the intuition behind changes in the results. The next subsection rewrites and proves the propositions that change under this extension.

I make the probability of success dependent on $\epsilon_S$ by amending our original probability of success as follows:

$$p(a, w, q, \epsilon_S) = s(\epsilon_S)p(a, w, q),$$

(7)

where $s : (0, 1) \rightarrow (0, 1)$ is twice-differentiable and rescales the probability of success according to $\epsilon_S$. Recall that $1 - \epsilon_S$ measures the profitability of corruption, with large values of $\epsilon_S$ indicating petty corruption. Assuming that $s'(\cdot) > 0$ makes grand corruption more likely to be detected, while assuming $s'(\cdot) \leq 0$ makes petty corruption more likely to be detected. Note that this formulation implicitly assumes that the effect of profitability on detection is independent of the composition of the coalition. This is in the spirit of the motivating question: how would results change if grand corruption was more or less likely to be detected than petty corruption, independently of the composition of the supporting
coalition? The utility function now writes:

\[
    u_i(c, g, q, \epsilon_S) = \begin{cases} 
    u(c, g, q, \epsilon_S) - \epsilon_i = \frac{p(c, g, q, \epsilon_S)}{a} - \epsilon_i, & \text{if } i \in c \\
    0, & \text{otherwise} 
    \end{cases} 
\]  

Most of the intuition does not change. For a fixed level of capacity \( q \), when considering whether to accept the bribe, the seed looks at \( C_g \) and considers the utility of her favorite coalition. Because the effect of profitability on detection is independent of the composition of the coalition, the seed’s favorite coalition stays the same for any \( \epsilon_S \). When grand corruption is less likely to be detected than petty corruption, then that coalition becomes increasingly beneficial as \( \epsilon_S \) increases. As such, the seed accepts all projects above some threshold in profitability. When grand corruption is more likely to be detected than petty corruption, but the effect is not too strong, then the fact that grand corruption is more profitable offsets the fact that it is more risky. The seed still accepts all projects above some threshold in profitability. Conversely, when that effect is very strong, although grand corruption is more profitable, it is too risky. As such, the seed accepts all projects below some threshold in profitability.

D.2 Proofs

Propositions 1 and 2 and lemmas 2 and 3 compare coalitions for a fixed \( \epsilon \). They are robust to this extension. Similarly, proposition lemmas 4 and 5 are about graphical properties of \( g \). They are unchanged by this extension.

Lemma 6 \textit{(Threshold strategy, extension).} Consider \( \epsilon, \epsilon' \in (0, 1) \). We have \( C_{gq}^* = \arg \max_{c \in C_g} u_S(c, g, q, \epsilon) = \arg \max_{c \in C_g} u_S(c, g, q, \epsilon') \). There is a threshold \( \hat{\epsilon}_S(g, q) \in (0, 1) \) such that if \( s'(\epsilon) \leq \frac{a+\epsilon}{q(c, g, q, \epsilon_S)} \) for any \( c \in C, q \in (0, 1), \epsilon_S \in (0, 1) \), then all equilibria have the same outcome that \( S \) rejects the bribe if \( \epsilon_S > \hat{\epsilon}_S(g, q) \). Otherwise, she accepts it, and some coalition \( c^* \in C^* \) is realized. If \( s'(\epsilon) > \frac{a}{q(c, g, q, \epsilon_S)} \) for any \( c, g, q, \epsilon_S \), then all equilibria have the same outcome that \( S \) rejects the bribe if \( \epsilon_S < u(c^*, g, q, \epsilon_S) \) for some \( c^* \in C^* \).
Consider \( c, c', c, g, q, \epsilon \) for any equilibrium outcome.

Proof of lemma \[6\] Let’s first show that \( \arg \max_{c \in C_{q}} u_{S}(c, g, q, \epsilon) = \arg \max_{c \in C_{q}} u_{S}(c, g, q, \epsilon'). \) Consider \( c, c' \in C_{q} \) such that \( u_{S}(c, g, q, \epsilon) \leq u_{S}(c', g, q, \epsilon). \) This implies \( \frac{p(a, w_{c}, q)}{a_{c}} \leq \frac{p(a, w_{c'}, q)}{a_{c'}}. \) As such, \( u_{S}(c, g, q, \epsilon') \leq u_{S}(c', g, q, \epsilon'), \) proving the point.

Let’s show the rest of the lemma. Note that \( \frac{\partial u_{S}}{\partial \epsilon} = s'(\epsilon)\frac{p(c, g, q, \epsilon)}{a_{c}} - 1. \) So \( \frac{\partial u_{S}}{\partial \epsilon} \geq 0 \iff s'(\epsilon) \geq \frac{p(c, g, q, \epsilon)}{a_{c}}. \)

Let’s show the rest of the proposition. Suppose that for a given \( q, \) there is \( \hat{\epsilon} \in (0, 1) \) such that \( u_{S}(c^{*}, g, q, \hat{\epsilon}) = 0. \) Note that \( \frac{\partial u_{S}}{\partial \epsilon} = s'(\epsilon)\frac{p(c, g, q, \epsilon)}{a_{c}} - 1. \) So if \( s'(\epsilon) \leq \frac{a_{c}}{p(c, g, q, \epsilon)\epsilon} \) for any \( c \in C, q \in (0, 1), \epsilon_{S} \in (0, 1), S \) rejects the bribe for \( \epsilon > \hat{\epsilon}. \) Conversely, if \( s'(\epsilon) > \frac{a_{c}}{p(c, g, q, \epsilon)} \) for any \( c \in C, S \) rejects the bribe for \( \epsilon < \hat{\epsilon}. \) If \( u_{S}(c^{*}, g, q, \hat{\epsilon}) > 0 \) for any \( \epsilon \in (0, 1) \) then the seed always accepts (rejects) the bribe, so define some \( \hat{\epsilon} \in \{0, 1\}. \)

If \( u_{S}(c^{*}, g, q, \hat{\epsilon}) \geq 0, \) we show as in lemma \[1\] that \( S \) accepts the bribe and \( c^{*} \) is an equilibrium outcome.

\[ \square \]

Proposition \[3\] becomes:

**Proposition 7** (As capacity increases, corruption decreases by weeding out petty corruption and coalition size increases, extension). Let \( c_{1}^{*} \in C_{q_{1}}, c_{2}^{*} \in C_{q_{2}}. \) If \( s'(\epsilon) \leq \frac{a_{c_{1}} + 1}{p(c, g, q, \epsilon_{S})} \) for any \( c, g, q, \epsilon_{S}, \) we have \( q_{1} < q_{2} \Rightarrow \hat{\epsilon}_{S}(g, q_{1}) \geq \hat{\epsilon}_{S}(g, q_{2}). \) If \( s'(\epsilon) > \frac{a_{c_{1}} + 1}{p(c, g, q, \epsilon_{S})} \) for any \( c, g, q, \epsilon_{S}., \) we have \( q_{1} < q_{2} \Rightarrow \hat{\epsilon}_{S}(g, q_{1}) \leq \hat{\epsilon}_{S}(g, q_{2}). \) For any \( s'(\epsilon), \) we have \( a_{c_{1}} \leq a_{c_{2}}. \)

Proof of proposition \[7\] From lemma \[6\] \( \hat{\epsilon}_{S}(g, q) \) is one of the bounds of the interval in \( \epsilon \) such that \( S \) accepts the bribe; that is, such that \( u(c^{*}, g, q, \epsilon) \geq \epsilon \) for some \( c^{*} \in \arg \max_{c \in C_{g}} u(c, g, q, \epsilon). \) Pick \( q_{1} < q_{2}, \) and their associated equilibrium coalitions, \( c_{1}, c_{2}. \) Coalition \( c_{1} \) satisfies \( u(c_{1}, g, q_{1}, \epsilon) \geq u(c_{2}, g, q_{1}) \). Since for a given coalition, \( u \) is decreasing in \( q, \) we have \( u(c_{2}, g, q_{1}, \epsilon) \geq u(c_{2}, g, q_{2}, \epsilon). \) This implies \( u(c_{1}, g, q_{1}, \epsilon) \geq u(c_{2}, g, q_{2}, \epsilon). \) As such, the interval such that \( u(c_{1}, g, q_{1}, \epsilon) \geq \epsilon \) has a weakly greater range than the interval such that \( u(c_{2}, g, q_{2}, \epsilon) \geq \epsilon. \) That is, \( \hat{\epsilon}_{S}(g, q_{1}) \geq (\leq)\hat{\epsilon}_{S}(g, q_{2}) \) if \( \epsilon \geq (\epsilon') \frac{a_{c_{1}} + 1}{p(c, g, q, \epsilon_{S})}. \) The rest of the proposition proves as in proposition \[3\] \( \square \)

Proposition \[4\] becomes:
Proof of proposition 8. Suppose \( g' = g + i \rightarrow j \). Then if \( s'(\epsilon) \leq (>) \frac{a_c}{p(c, g, q, \epsilon_S)} \) for any \( c, g, q, \epsilon_S \), we have \( \hat{\epsilon}_S(g', q) \leq (\geq) \hat{\epsilon}_S(g, q) \). The last inequality holds strictly for some \( q \in (0, 1) \) if and only if there is a minimal coalition \( c^* \in M_g^0 \) such that for any coalition \( c \in C_g \) essentially equal to \( c^* \) has \( j \in c \) and \( i \notin c \) and \( i \notin W_{cg} \).

Proof of proposition 8. From lemma 6, \( \hat{\epsilon}_S(g, q) \) is one of the bounds of the interval in \( \epsilon \in (0, 1) \) such that \( S \) accepts the bribe; that is, such that \( u(c^*, g, q, \epsilon) \geq \epsilon \) for some \( c^* \in \arg \max_{c \in C_g} u(c, g, q, \epsilon) \). We show as in proposition 4 that if the condition on \( i \rightarrow j \) holds, then there is \( q \) such that \( \max_{c \in C_g} \{u(c, g, q, \epsilon)\} > \max_{c \in C_g} \{u(c, g', q, \epsilon)\} \). Suppose \( c_g \in \arg \max_{c \in C_g} u(c, g, q, \epsilon) \), and \( c_{g'} \in \arg \max_{c \in C_{g'}} u(c, g', q, \epsilon) \). For that \( q \), the interval such that \( u(c, g, q, \epsilon) \geq \epsilon \) has a weakly greater range than the interval such that \( u(c_{g'}, g', q, \epsilon) \geq \epsilon \). That is, \( \hat{\epsilon}_S(g, q) \geq (\leq) \hat{\epsilon}_S(g', q) \) if \( s'(\epsilon) \leq (>) \frac{a_c}{p(c, g, q, \epsilon_S)} \). If the condition on \( i \rightarrow j \) does not hold, we show as in proposition 4 that \( \hat{\epsilon}_S(g, q) = \hat{\epsilon}_S(g', q) \).

Proposition 9 becomes:

Proposition 9. Suppose \( g' = g + ij \). Then if \( s'(\epsilon) \leq (>) \frac{a_c}{p(c, g, q, \epsilon_S)} \) for any \( c, g, q, \epsilon_S \), we have \( \hat{\epsilon}_S(g', q) \geq (\leq) \hat{\epsilon}_S(g, q) \). For the inequality to hold strictly for some \( q \in (0, 1) \), it must be that there is \( c^* \in M_g \) and \( c' \in C_{g'} \) such that \( a_{c'} > a_{c^*} \) and \( w_{c'} = w_{c^*} \).

Proof of proposition 9. By lemma 4 we have that for any \( c \in C_g \) \( u(c, g, q) = u(c, g', q) \), which implies that \( \hat{\epsilon}_S(g', q) \geq (\leq) \hat{\epsilon}_S(g, q) \) if \( s'(\epsilon) \leq (>) \frac{a_c}{p(c, g, q, \epsilon_S)} \) for any \( c, g, q, \epsilon_S \). The second part of the proposition proves as in proposition 5 if \( s'(\epsilon) \leq \frac{a_c}{p(c, g, q, \epsilon_S)} \) for any \( c, g, q, \epsilon_S \). If \( s'(\epsilon) \geq \frac{a_c}{p(c, g, q, \epsilon_S)} \) for any \( c, g, q, \epsilon_S \), then suppose that there is \( q \in (0, 1) \) such that \( \hat{\epsilon}_S(g', q) \leq \hat{\epsilon}_S(g, q) \) and use the same argument as in proposition 5.

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E Experimental protocol

E.1 Location

The experiment was held in Mohammedia, Morocco from September 9-21, 2015. Working with our local partner, Mhammed Abderebbi of “MEDA Solutions” firm, we rented an apartment in Mohammedia appropriate for our lab. The apartment featured a large salon that we converted into a waiting room, and two bedrooms that we converted into a survey room and an experiment room. The survey room contained a bed, a couch, and a table, thus allowing three surveys to take place simultaneously with relative privacy. The experiment room contained two circular tables, each with five chairs for the enumerator and four subjects to play the game.

Due to unforeseen security threats (local youth demanding to participate in the experiment), we temporarily relocated sessions on September 16, 17, and 21 to our partner’s office, which similarly contained a waiting, survey, and experiment room.

E.2 Enumerators

Our partner selected two male and two female enumerators, three of them students from the Hassan II University in Mohammedia and one from our partner’s company. Having uploaded our pre-experiment survey, experiment survey, and post-experiment survey to Qualtrics, we trained our enumerators to administer the Qualtrics surveys on handheld tablets. We trained all four enumerators to administer the pre- and post-surveys, and trained three of them (one male, and two females) to administer the experiment as well. Enumerators received 200 dirhams per day.

Training was held on Tuesday, September 8, 2015 and lasted half a day. It consisted in having the enumerators administer the pre- and post-experiment surveys to each other, under the author’s supervision. Similarly, they administered the diffusion game to each other, under the author’s supervision.
<table>
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<th>Sample</th>
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<th>Employees</th>
<th>Employees – Students</th>
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<td>20.44</td>
<td>26.17</td>
<td>5.73***</td>
</tr>
<tr>
<td>% females</td>
<td>0.21</td>
<td>0.16</td>
<td>0.23</td>
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<td>0.95</td>
<td>0.69</td>
<td>-0.26***</td>
</tr>
<tr>
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<td>1.83</td>
<td>1.59</td>
<td>-0.23***</td>
</tr>
<tr>
<td>% urban</td>
<td>0.94</td>
<td>1.00</td>
<td>0.93</td>
<td>-0.07***</td>
</tr>
<tr>
<td>% Arabs</td>
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<td>0.95</td>
<td>0.94</td>
<td>-0.01</td>
</tr>
<tr>
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<td>2.83</td>
<td>0.25*</td>
</tr>
<tr>
<td>altruism</td>
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<td>1.83</td>
<td>1.45</td>
<td>-0.37***</td>
</tr>
<tr>
<td>extroversion</td>
<td>2.96</td>
<td>2.69</td>
<td>3.04</td>
<td>0.36***</td>
</tr>
<tr>
<td>N</td>
<td>272</td>
<td>63</td>
<td>209</td>
<td></td>
</tr>
</tbody>
</table>

Table 8: Sample descriptive statistics. Income is measured from asset ownership and ranges from 0 to 3. Risk-taking ranges from 1 (risk-averse) to 4 (risk-lover). Altruism is measured from the donation in a dictator’s game. Extroversion ranges from 1 (introvert) to 4 (extrovert). Tests for differences in means use a t-test; *p<0.1; **p<0.05; ***p<0.01.

### E.3 Subjects

Recruiters solicited subjects from public squares in Mohammedia, presenting them with flyers with the address, time, and following description:

Invitation to participate in a study session

The company MEDA Solutions has the honor of inviting you to a study session that will last about an hour. The topic is one’s financial behavior.

Day: XXX

Time: XXX

Address: Lotissement de la gare. Villa Mounia, no. 82. El Alia, Mohammedia

Phone number: 0668775219

Note: this invitation is personal and cannot be transferred to anyone else. You will not be allowed to participate without this invitation.

In recruiting subjects, we explicitly blocked on occupation, asking recruiters to recruit employees of the service industry, and, if necessary, completing with university students. Recruiters were told to select a diverse range of ages and occupations. Recruiters mentioned that all participants would receive 50 dirhams for their time plus any gains they won in the behavioral game.
E.4 Comprehension

Figure 15: Sample comprehension question, for grand corruption

*Note:* Red and blue rectangles correspond to the bribe and salaries, respectively. Number 62 represents the outcome of the die. The question asked was: “How much as player 1 won?”

Figure 16: Average comprehension over time

*Note:* questions 1, 2, and 3 correspond to the questions asked before the beginning of the first, second and third blocks of the experiment respectively. Question 4 was asked in the post-experiment survey.
E.5 Prompts and material

Table 9: Document displaying the probability of success in each treatment condition, for coalitions of 1 to 4 accomplices. In the exposing tie condition, the one-eyed cell denotes the coalition including the seed and the more isolated node, while the two-eyed cell denotes the coalition including the seed and the more exposed node.

Prompt of the first block (control or hard)

You are about to participate in an experiment on behavior in uncertain situations. The experiment looks like a game in which you will have to make several decisions that may make you win money. We will count the money in credits. One credit is worth a bit less than one dirham.

The experiment is very short. We will repeat it several times. Sometimes, we will change a few details. It is very important that you remain silent during the experiment. You will be able to talk only when I will allow you.

During the experiment, each of you will have a salary of 2 [4] credits, represented by the 2 [4] blue cards. You will have to decide between winning your salary with certainty, or taking a risk to maybe win a higher amount. You will be assigned to positions on a network [draw the star network on the board]. If two people are connected, they are “neighbors,” which allows them to communicate.

I will pick one of you and offer him 12 credits, represented by the 12 red cards. This person will have to decide between taking this sum and giving up her salary, or refusing this sum and keeping her salary. If he refuses it, the
experiment is over, and you will all win your salary. If he takes it, I will offer
him to share this amount with her neighbors. He will announce how much he
wishes to offer to each. I will then allow the neighbors to accept or refuse. If
they refuse, they keep their salary. If they accept, they give up their salary.
The neighbors that have accepted will then be able to share the amount they
have at hand with their neighbors that do not have pending offers and have
not given up their salary. The experiment is over when no further offer can
be made.

In the end, the ones that have held on to their salary win it. The ones
that have given up their salary form a team. I will throw a dice. If the score
is below some threshold, team members win their credits. Otherwise, they
lose them. The threshold is written on this document [show the document].
It depends on the amount of team members.

**Prompt of the second block (hard or control)**

I will now change the probabilities of victory a bit. Note that now, it is
more difficult [easier] for a player on his own to win.

**Prompt of the third block (dense)**

I will now change the network you are playing on [draw the line network
on the board]. I will also change the probabilities of victory. They now not
only depend on the amount of people in the team, but also on the about of
neighbors of the team that have held on to their salary. Now, sharing with
the left hand side player only is better than sharing with the right hand side
player only because the latter has one extra neighbor.
Figure 17: Learning effects. In the top three panel, early and late report estimates for the first and second blocks respectively. In the bottom panel, early and late report estimates for the first and last two rounds of the last block respectively.

F Additional experimental results

F.1 Learning

As mentioned in section 5.1, learning and pooling effects are challenging. Although the experimental design incorporates several features to minimize such effects, they might still occur.

Learning effects might go two ways. On the one hand, learning might have the expected effect: subjects may converge to the equilibrium strategy over time. Learning could also have an unexpected effect: subjects might learn about each others’ types, and further diverge from equilibrium strategy. Suppose that a group contains a subject who never accepts the bribe. Over time, other subjects may progressively learn about this and adjust their strategies accordingly, hence deviating from equilibrium strategy over time.

Learning effects are insignificant and mixed. In early or late rounds, results never significantly vary. Over time, some results converge to the equilibrium prediction, while
others diverge. Furthermore, there is no end-game effect, suggesting that subjects did not pool across games. Recall that the ordering of the control and the hard conditions were administered by blocks of four games, and that the order of these blocks was randomly permuted (Figure 7). I use these blocks to estimate the variation in the effect of increasing capacity over time, and the effect of adding non-exposing ties on the star between the early and the late block using a difference in difference strategy. Figure 17 shows that both in early and late rounds, results go in the expected directions. Effect size never varies significantly. The effect of capacity on size gets marginally closer to the prediction, while its effect on coalition size gets further away from it. The effect of adding non-exposing ties is minuscule.

Pooling effects could explain why bribe offerers engage overly greedy in bargaining (Section 5.2). Subjects might tacitly agree on reciprocal exploitation. Recipient $i$ accepts to be exploited by bribe-offerers in some round of the game because she knows that she will exploit others when she will get to be an offerer in later round. If this is true, then we should observe an end-game effect: recipients in the last rounds would be less inclined to accept greedy bargaining because there is no further opportunity to reciprocate.

There are no pooling effects. Recall that the exposing tie block was administered last and that within block, the order of games was randomized. I compare the first two rounds of the exposing tie block to the last two. In particular, I look at the distribution of offers as deviation from the equilibrium offer. A Kolmogorov-Smirnov test fails to reject the null that these distributions are similar. Figure 17 also shows that facing an equally greedy offer (the median offer, which is greedy by about 1 credit), recipients are equally likely to accept that offer in early and in late rounds.
F.2 Random effects

Figure 18: Clustering: Random effect specifications vs. main specification
### F.3 Regression tables

<table>
<thead>
<tr>
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<th>(1)</th>
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<tbody>
<tr>
<td><strong>Dependent variable:</strong></td>
<td><strong>Pr(accept)</strong></td>
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<td>Hard, Grand</td>
<td>$-0.768^*$</td>
<td>$-0.890^{**}$</td>
<td>$-0.890^{**}$</td>
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<td></td>
<td>(0.353)</td>
<td>(0.335)</td>
<td>(0.335)</td>
<td>(0.519)</td>
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<tr>
<td>Exposing, Grand</td>
<td>$0.962^*$</td>
<td>$1.033^*$</td>
<td>$1.033^*$</td>
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<tr>
<td></td>
<td>(0.413)</td>
<td>(0.477)</td>
<td>(0.477)</td>
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</tr>
<tr>
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<td>$-0.928$</td>
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<td></td>
<td>(0.502)</td>
<td>(0.528)</td>
<td>(0.528)</td>
<td>(0.797)</td>
</tr>
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<td>Hard, Petty</td>
<td>$-2.419^{***}$</td>
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<td>$-2.144^{***}$</td>
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<td>(0.449)</td>
<td>(0.500)</td>
<td>(0.500)</td>
<td>(0.650)</td>
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<tr>
<td>Exposing, Petty</td>
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<td>$-2.266^{***}$</td>
<td>$-2.266^{***}$</td>
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<tr>
<td></td>
<td>(0.454)</td>
<td>(0.497)</td>
<td>(0.497)</td>
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</tr>
<tr>
<td>Late</td>
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<td></td>
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<td>$-0.000$</td>
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<tr>
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<td></td>
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<td>(0.573)</td>
</tr>
<tr>
<td>Late $\times$ (Hard, Grand)</td>
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<td>(0.912)</td>
</tr>
<tr>
<td>Late $\times$ (Control, Petty)</td>
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<td>$-0.495$</td>
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<td>(0.991)</td>
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<tr>
<td>Late $\times$ (Hard, Petty)</td>
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<td>$2.797^{***}$</td>
<td>$2.797^{***}$</td>
<td>$2.269^{***}$</td>
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<td>(0.351)</td>
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<td>-</td>
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<td>Indiv. RE</td>
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<td>634.613</td>
<td>494.731</td>
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*Note:* $^*p<0.05; ^{**}p<0.01; ^{***}p<0.001$

Table 10: Seed’s acceptance behavior. All models are logistic regressions. All Variables are binary. Coefficients are log odds ratios. Model 1 is the main specification (figure 8). Models 2 and 3 are random effects specifications (figure 18 top panel). Model 4 subsets the analysis to the first two blocks (figure 17 top panel). In models 2 and 3, standard errors are not clustered.
Table 11: Size of the coalition. All models are linear models. All variables are binary. All models subset the analysis to games where the seed accepts the bribe. Model 1 is the main specification figures 9. Models 2 and 3 are random effects specifications (figure 18, 2nd panel from top). Model 4 subsets the analysis to the first two blocks (figure 17, middle panel). In models 2 and 3, standard errors are not clustered.

<table>
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<td>Hard, Grand</td>
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<td>1.026***</td>
<td>1.026***</td>
<td>1.250***</td>
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<td>(0.143)</td>
<td>(0.094)</td>
<td>(0.094)</td>
<td>(0.190)</td>
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<td>Exposing, Grand</td>
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<td>0.633***</td>
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<td>(0.091)</td>
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<tr>
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<td>−0.399*</td>
<td>−0.399*</td>
<td>−0.211</td>
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<td>(0.155)</td>
<td>(0.155)</td>
<td>(0.118)</td>
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<td>−0.037</td>
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<td>(0.171)</td>
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Note: *p<0.05; **p<0.01; ***p<0.001
### Table 12: Non-exposing ties. All models are logistic regressions. All variables are binary. Coefficients are log odds ratios. Model 1 is the main specification (figure 8). Models 2 and 3 are random effects specifications (figure 18, top panel). Model 4 subsets the analysis to the first two blocks (figure 17, top panel). In models 2 and 3, standard errors are not clustered.
Table 13: End-game effect. This model is a logistic regression. Coefficients are log odds ratios. Analysis is subsetted to the last block. Late is a dummy variable equal to 1 for the last two games, and 0 otherwise.
References


