Partners in crime? Corruption as a criminal network

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Abstract

The integrity and efficiency of the bureaucracy are essential to the workings of any government, and bureaucratic corruption undermines both the legitimacy and capacity of the government. Indeed, corruption is among the primary challenges faced by governments throughout the developing world, and in much of the developed world as well. While much of the literature treats corruption as the product of individual miscreants, this paper introduces a model that recognizes the coalitional nature of corruption, which is based on networks of accomplices. The standard prediction that organizationally isolated bureaucrats are most prone to corruption is emended—the model predicts that corruption will arise in isolated bureaucratic enclaves and, surprisingly, that the size of the enclaves will increase when confronted by more effective enforcement effort on the part of the government. The model suggests it would be sensible to redesign government agencies to puncture the isolation of enclaves.

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A corrupt bureaucracy is a challenge to any government. Decreasing the integrity and efficiency of the bureaucracy, bureaucratic corruption undermines the legitimacy and capacity of the government (Rothstein 2011; Rose-Ackerman and Palifka 2016). With a cost of at least 2 percent of global GDP, corruption is rampant in developing countries, and persists in developed countries (International Monetary Fund 2016). This global problem has generated much research. Formal models of corruption and bureaucracy in political science and economics typically use principal-agent models (Olken and Pande 2011; Gailmard and Patty 2012). This parsimonious setting usually considers one dyad, where a welfare-maximizing principal governs a potentially corrupt agent. The metaphor best describes isolated acts of less profitable, petty corruption, such as a policeman pocketing a traffic bribe. It allows making nuanced claims as to how corruption varies across countries, and how institutions, such as monitoring technologies (Banerjee, Hanna and Mullainathan 2013), or wage incentives (Besley and McLaren 1993), may affect outcomes.

Despite its many advantages, the parsimony of principal-agent models misses important aspects of corruption. The dyadic setting cannot readily explain cases of more profitable, grand corruption, which typically involve large conspiracies. Because they are illegal, corrupt deals cannot be enforced in court. As such, cooperation in corrupt coalitions poses additional challenges (Gambetta 2009; Vannucci and Della Porta 2013) that cannot be grasped easily using a single representative agent. Similarly, reducing organizations to a dyad, the principal-agent approach has less to say as to why corruption varies within a bureaucracy, where institutional features are held constant, but the layout of organizational units varies widely both across, and within agencies. As such, it cannot tell us about policies that are frequently observed in practice, where bureaucracies combat corruption through major reforms of their organizational chart (eg. Bennet 2012; Friedman 2012; Hausman 2011).

This paper expands the focus beyond the principal-agent dyad, and introduces a network approach to corruption. It examines a model and a lab experiment that look at corruption as the result of a process of diffusion on a network. In the model, a bureaucrat may take an illegal rent. Corruption is profitable, but exposes her to witnesses, who increase her risk of detection. She has to decide whether to turn those witnesses into accomplices. Accomplices “cover up” for her, but cost resources, and may have other witnesses monitoring them. The bureaucrat faces a tradeoff between efficiency and secrecy: she needs to form the coalition that best protects her against detection, but costs a minimal share of the rent. The organization is the social network that connects bureaucrats. Organizations matter, because they structure opportunities for cooperation among accomplices, and detection by witnesses: ties allow recruiting accomplices, but also allow non-corrupt agents to witness corruption. Organizations also vary in the strength of their monitoring technology, to capture the extent to which formal institutions like formal auditing procedures allow detecting and punishing corruption.

This approach tells us how corruption is organized, and how this depends on organizations.

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1 Political scientists have considered institutions such as appointment power (Hollibaugh, Horton and Lewis 2014), oversight procedures (Shotts and Wiseman 2010), or delegation (Gailmard and Patty under review). Doing full justice to the contributions of this wide literature is beyond the scope of this paper. I mention recent examples, and invite the interested reader to refer to review papers by Olken and Pande 2011 and Gailmard and Patty 2012.
and institutions. Characterizing how corruption is organized, I show that equilibrium coalitions are the most "enclaved" portions of the organization: they minimize exposure to witnesses. This shifts the unit of analysis from the individual to the coalition. Enclaves have few ties to the out-group, although they may exhibit plentiful in-group ties.

Organizations have subtle effects on corruption. Increasing oversight at the margin, by adding ties to the network, is no cure-all. Additional ties may decrease corruption by making enclaves more exposed. However, they have no effect if they do not target enclaves. Worse, they may facilitate access to existing enclaves and increase corruption. Comparing across organizations, I show through simulations that organizations that can be easily separated into independent divisions, as captured by higher levels of modularity (Newman, 2006) are more corrupt, because those divisions form natural enclaves.

The other findings examine institutions. Better formal institutions reduce corruption but do not eliminate it, because accomplices adapt. Better monitoring increases the risk of detection, which makes buying off accomplices more attractive, and drives up the size of the coalition. Less profitable, petty corruption cannot cover the extra cost entailed by more accomplices and disappears; only grand corruption survives, making overall corruption less frequent. I also consider informal institutions. Corrupt deals cannot be enforced in court, but corrupt bureaucrats, as in other forms of organized crime, typically use a wide array of informal institutions to enforce contracts. Because of the nebulous nature of informal institutions, I bound behavior by comparing three extreme cases: the lawless environment, where contracts cannot be enforced, and two contractual environments; one where accomplices agree ex-ante to divide the surplus equally, and one where the initial bureaucrat monopolizes all the surplus. I show that lawlessness introduces inefficiencies that benefit brokers—accomplices that recruits other accomplices, who exploit their control over the diffusion process to extract higher shares of the surplus. Behavior is also largely robust to alternative contractual environments.

I test the model’s predictions by conducting a lab-in-the-field experiment in which subjects play a diffusion game analogous to the model. I focus on a few small networks, and manipulate the monitoring technology and the profitability of corruption. The lab tests the robustness of the main theoretical predictions to behavioral factors that are assumed away in the model, while solving the measurement problems associated with studying networks and corruption. To increase ecological validity, I hold the experiment in Morocco, a mid-income country with median levels of corruption and compare a subject pool of service sector employees to a subject pool of undergraduate students. The experimental data confirm the model’s predictions: enclaves are more corrupt, and only some ties reduce corruption. Consistently with the predictions of the model, the overall incidence of corruption falls in the face of better monitoring, but the corruption that does occur takes place on a larger scale, involving more accomplices. Behavior does not differ across subject pools and thus appears to be largely robust to factors outside the model.

The findings have several implications that I discuss in more details in the conclusion. In particular, shifting the unit of analysis from the individual to the coalition, enclaves reconcile

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2Morocco is ranked 90 out of 176 countries in the Transparency International Corruption Perception Index 2016.
previous puzzling empirical findings about which individuals are more likely to be corrupt. Findings on organizational design may explain why patronage in developing countries often split agencies into ethnic monopolies (Van de Walle 2001). They also suggest that while it would be sensible to redesign government agencies to puncture the isolation of enclaves, this must be done carefully. Organizational reforms may be counterproductive, which is worrying, because these reforms are popular, but rarely subjected to careful evaluation. Finally, findings on institutions provide a testable rationale for why corruption persists in developed countries (Kaufmann 2004).

This paper turns a simple idea— that corruption is organized crime within a bureaucracy— into a framework to understand the relationship between the organization of corruption, and the structure of a bureaucracy. Doing so places the paper within an old tradition in political science that takes an organizational approach to bureaucracies (Weber 1948; Crozier 2009; Moe 1989; Carpenter 2001), and unifies previous work on the organization of corruption (Gambetta 2009; Vannucci and Della Porta 2013) and the impact of organizations (Evans 1995; Carpenter and Moss 2013) into a single formal model. Its comparative advantage is in making precise network-analytic claims as to how corruption is organized, and how organizations affect corruption.

Formally, the model expands our focus beyond the principal-agent dyad, and considers a model of collective corruption. Most related to this approach are market models of corruption (Shleifer and Vishny 1993; Burgess et al. 2012), models of criminal network formation (Baccara and Bar-Isaac 2008; 2009). These models either do not feature a network structure, or are games of network formation (Jackson 2008). As such, they cannot speak of individuals who are embedded in a pre-existing network. Instead, I model corruption as a network diffusion process, and depart from existing probabilistic or threshold models (eg. Centola and Macy 2007) by considering a game of strategic diffusion: corruption diffuses if \( i \) chooses to infect \( j \) and \( j \) chooses to be infected.

The experimental design expands upon work that studies collective corruption in the lab (Azfar and Nelson 2007; Barr, Lindelow and Serneels 2009; Morton and Tyran 2015). I supplement Berninghaus et al’s (2013) design with an exogenous network, hence introducing a minimal design to test for the impact of organizational structure on corrupt behavior.

1 A theory of corruption in organizations

This section first introduces the theory in light of the literature on organizational corruption, then presents the model formally. Although designed with bureaucracies as its primary focus, the theory defines corruption as the “abuse of entrusted power for private gain” (Transparency International). Since the scope extends to any kind of organization, I consider both bureaucracies, and private organizations.
1.1 Organizing corruption

Like terrorist cells or mafias, corruption is a form of organized crime, and typically requires accomplices. Unlike those examples, corruption occurs within a pre-existing organization, where it creates witnesses. The theory treats organized crime as a diffusion problem on a network: a bureaucrat, the seed, finds an illegal rent (e.g. a bribe, or an opportunity for embezzlement); she may take it and form a coalition of accomplices. An exogenous enforcer detects the coalition with some probability. The setup relates how corruption is organized— that is, the network structure of the coalition— to the structure of its host organization, and the effectiveness of other institutions; formal institutions of monitoring, and informal institutions that allow cooperation among criminals.

Additional accomplices pose a tradeoff. They help the coalition, protecting it against detection by “covering up,” (Wade, 1982; Ledeneva, 1998) and extracting more resources (Jávor and Jancsics, 2013). They cost resource because they need to be compensated for their own risk. They create additional witnesses among their colleagues, which increases risk (Baker and Faulkner, 1993). In the model, the probability of detection is increasing in the number of accomplices, and decreasing in the number of witnesses. To simplify interpretation, accomplices do not help extracting resources. The rent is normalized to 1, and additional accomplices cost fractions of the rent.

Organizations matter because the various relationships they feature allow recruiting additional accomplices, or create witnesses. The model separates these functions (Larson and Lewis, under review) into possibly overlapping ties of communication, and monitoring. Communication ties allow existing members of the coalition to recruit new ones. Monitoring ties indicate whether \( i \) would hold incriminating evidence on \( j \) and turn into a witness, should \( j \) be corrupt. Monitoring may not be reciprocal, to capture potential imbalances in information that may arise in hierarchies. Because it has little impact on organizing corruption, hierarchy feeds into the model only through network structure. Coercing lower-level employees to join the coalition is difficult: they are often critical to some task within the coalition, and know of the wrong-doing of their managers, which gives them leverage (Jávor and Jancsics, 2013). Regarding reporting corruption, a meta-analysis (Mesmer-Magnus and Viswesvaran, 2005) shows that hierarchy matters little compared to holding evidence, which stems from close interaction with the wrongdoer. The balance of accomplices and witnesses matters: larger coalitions face less risk of being reported because whistleblowers face a higher risk of retaliation.

Institutions operate through two channels. As examined in details by principal-agent models, formal institutions such as auditing procedures condition the ability to detect and punish accomplices. In the model, the probability of detection depends on a parameter for monitoring technology to capture the extent to which institutions allow for successful detection and punishment of corruption.

Second, informal institutions among accomplices affect the extent to which they are able to cooperate. Corrupt deals cannot be enforced in court, subjecting accomplices to commitment problems; most importantly, the problem of not denouncing each other to law enforcement (Gambetta, 2009; Vannucci and Della Porta, 2013). Criminals resort to a variety of self-enforcing...
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contracts to build up trust and mitigate the commitment problems inherent to lawlessness. Solutions include holding one another hostage by sharing compromising evidence (Ledeneva 1998, Yang 2002), repeated interactions (Malesky and Samphantharak 2008), or “brokers;” trusted intermediaries who vouch for new accomplices (Vannucci and Della Porta 2013). These solutions prevent accomplices from denouncing each other prior to detection, but make the whole coalition collapse if one member gets caught. Accordingly, the model uses an all-or-nothing probability of detection: accomplices solve the commitment problem using some self-enforcing contract, but the entire coalition collapses after one gets detected. The model features another commitment problem: when \(i\) hires \(j\) as an accomplice, \(j\) cannot commit to make the hires that \(i\) prefers. This may prevent \(i\) from hiring \(j\), even when both \(i\) and \(j\) prefer \(j\) following \(i\)’s plan to not hiring \(j\).

I triangulate the effect of informal institutions by comparing three very different division rules, belonging to opposite environments. The first rule, bargaining, supposes a lawless environment, where agents cannot solve the commitment problem, and bargain over the division of the surplus. The other two, monopoly and equal-sharing, suppose a contractual environment, where agents can enforce some pre-determined division of the rent. These two rules are opposite. Monopoly gives all the bargaining power to the seed, and assumes that she pockets all the surplus. Equal-sharing assumes that accomplices split the bribe equally, and reflects more equal distributions of bargaining power.

The diffusion process leads to the formation of a coalition of accomplices: a corrupt subnetwork within the organization. Describing how corruption is organized requires describing what this coalition looks like. I conceptualize the organization of corruption in three dimensions: frequency, the likelihood that some corruption occurs—whether the seed takes the rent; scope, the number of accomplices; and scale, capturing the profitability of corruption on a continuum from less profitable, petty corruption to more profitable, grand corruption. The rent is normalized to 1, but accomplices incur some cost \(\epsilon\) from corruption. The quantity \(1 - \epsilon\) therefore indicates the benefit of corruption relative to its cost; that is, the scale of corruption. When \(\epsilon\) is low, \(1 - \epsilon\) is high, and corruption is very profitable compared to its cost, indicating high-scale, grand corruption. Conversely, high values of \(\epsilon\) indicate low-scale, petty corruption.

1.2 Model

I model corruption as a dynamic game of complete information. Bureaucrats are the nodes of the exogenous multiplex graph\(^6\) \(g = (N, G_c, G_m)\) where \(N\) is a set of nodes indexed from 1 to \(|N|\), and \(G_c\) and \(G_m\) are sets of ties. \(G_c\) is an undirected communication network, 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. \(G_m\) is a directed monitoring network, with \(i \rightarrow j \in G_m\) meaning that \(i\) monitors \(j\). If two people do not interact, they do not know about each others’ activities: \(i \rightarrow j \in G_m \Rightarrow ij \in G_c\).

An arbitrary node \(s \in N\), the seed, discovers an illegal stream of rents of value 1. The seed

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\(^6\) A graph is the mathematical term used to refer to a network. A multiplex graph is a graph that contains several types of ties.

\(^7\) That is, that there is a path on \(G_c\) between any \(i, j \in N\).
can reject the rent or accept it. If she rejects the rent, 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 monitor the seed turn into witnesses; and (3) she makes the vector of transfers $t_s$ to the agents she communicates with. The sunk cost $\epsilon_s$ represents the seed’s expected loss of getting caught, and $1 - \epsilon_s$ the scale of corruption.\(^8\)

Once the seed has made her offers, the nodes that have been made a strictly positive transfer are “pending.” They play sequentially, with lower indices moving first, and face a similar action space. They can reject their offer, or accept it. If node $i$ accepts, she becomes an accomplice. Like the seed, she pays the sunk cost $\epsilon_i$, her non-pending, non-accomplice in-neighbors on $G_m$ turn into witnesses, and she makes the vector of transfers $t_i$ to her susceptible neighbors; that is, her non-pending, non-accomplice neighbors on $G_c$. 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. Once all pending nodes have moved, the players to whom they have 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 a positive offer, or until all nodes in $g$ have become accomplices (Figure 1).

Transfers satisfy a budget constraint. Suppose $i$ makes her offers after she accepted the transfer $t_{ki}$ from node $k$, with $t_{ks} \equiv 1$ if $i = s$. Let $P_i$ her set of susceptible neighbors at that history.\(^7\) Then it must be that $t_{ki} - \sum_{j \in P_i} t_{ij} \geq 0$ and $t_{ij} \geq 0$ for any $j \in P_i$.

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 rent. Together, they form a criminal conspiracy, the coalition. Witnesses are the non-accomplice, non-pending in-neighbors of accomplices on $G_m$. 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 monitoring network induced by graph $g$. The set of witnesses of coalition $c$ on $g$ at

\[^8\]$ may incorporate other costs, such as effort, or a moral cost.

\[^7\]$Note that $P_i$ is simply the neighborhood of $s$ on $G_c$.

\[^9\]$That is, the set of nodes $j$ such that $j \rightarrow i \in G_m$. 

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**Figure 1: Example diffusion process.** Node 1 is the seed. Ties denote communication and mutual monitoring. At the terminal history, nodes 1, 3, 4 are accomplices, and hold .6, .2, and .2 respectively.
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.** Let $C_g \subseteq C$ be the set of feasible coalitions on graph $g$. 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.

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. The probability of success $p$ is a function of $a$, the number of accomplices in the coalition, $w$, its associated number of witnesses, and $q \in (0,1)$, a parameter for the monitoring technology, that captures the ability of an organization to detect and punish corruption. I assume that $p$ is twice-differentiable, with $\frac{\partial p}{\partial a} > 0$, $\frac{\partial p}{\partial w} < 0$, and $\frac{\partial p}{\partial q} < 0$.

If player $i$ is not a member of the coalition at a terminal history her payoff is 0. Otherwise, she pays the sunk cost $\epsilon_i$ and holds some share of the rent $\pi_i \geq 0$. Suppose $i$ accepted transfer $t_{ki}$; let $r_{ij} = 1$ if $j$ accepted an offer $t_{ij}$ from $i$, and $r_{ij} = 0$ otherwise; then $\pi_i = t_{ki} - \sum_{j \in P_i} t_{ij}r_{ij}$. With probability $p$, she gets her share $\pi_i$, and gets 0 otherwise. I first assume that agents divide bribe equally, and schedule transfers such that $\pi_i = \frac{1}{c} \pi$ for any member of coalition $c$.

Section 2 considers other division rules. With risk-neutral agents, 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 analytical 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 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 $u : C_g \times (0,1) \to \mathbb{R}$ 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:

$$u_i(c,g,q) = \begin{cases} u(c,g,q) - \epsilon_i = v(a_c,w_{cg},q) - \epsilon_i = \frac{p(a_c,w_{cg},q)}{a_c} - \epsilon_i, & \text{if } i \in c \\ 0, & \text{otherwise} \end{cases}$$

(1)

**2 Theoretical results**

This section derives equilibrium and comparative statics. It also considers an extension with bargaining. Proofs are available in section A of the appendix.

**2.1 Equilibrium**

When should the seed take the rent? She has a threshold strategy where she rejects the rent below some threshold in scale. Consider her favorite coalition, $c^* \in \arg \max_{c \in C_g} u(c,g,q)$. If $u(c^*,g,q) < \epsilon_s$, then $S$ does not take the rent, since her favorite coalition does not cover her sunk cost. If $u(c^*,g,q) \geq \epsilon_s$, then it is realized in equilibrium because there is no dynamic inconsistency. Since accomplices divide the rent equally, incentives within the coalition are problematic. I relax this assumption in an extension (Section A.4 of the appendix).
sequentially aligned, and members of \(c^*\) have no incentive to deviate to some other coalition. Formally:

**Lemma 1** (Threshold strategy). Let \(C_g^* = \arg \max_{c \in C_g} u(c, g, q)\) and \(c^* \in C_g^*\). 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 rent if \(\epsilon_s > \hat{\epsilon}_s(g, q)\). Otherwise, she accepts it, and some coalition \(c \in C_g^*\) is realized.

Which coalitions does the seed prefer? Answering this question requires characterizing the frontier; that is, the coalitions that lie in \(C_g^*\). Comparing same-sized coalitions, one prefers the one with fewer witnesses. Two additional assumptions give more traction:

**Assumption 1** (Larger coalitions are sufficiently resistant against better monitoring technologies). Suppose \(v(a_1, w_1, q) = v(a_2, w_2, q)\) for some \(a_1 \leq a_2, w_1, w_2 \in [1, N], q \in (0, 1)\). Then \(\frac{\partial g(a_2, w_2, q)}{\partial q} < \frac{\partial g(a_1, w_1, q)}{\partial q}\) for any \(q \in (0, 1)\).

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

Assumption 1 bounds the probability of success as the size of the coalition grows. It implies that \(\frac{\partial g}{\partial q}\) should not be too concave in \(q\): if better monitoring technologies are more effective for larger coalitions, the advantage should be reasonable. The assumption gives an important result: although there are many equilibria, equilibrium coalitions are essentially unique, in the sense that they have the same counts of accomplices and witnesses. Indeed, the assumption implies that two essentially different coalitions may give the same payoff on at most a curve in \((\epsilon, q)\). Formally:

**Proposition 1** (Essential uniqueness). Equilibrium coalitions are essentially unique for any \((\epsilon, q) \in (0, 1)^2 \setminus U\), where \(U\) has measure zero.

Assumption 2 compares coalitions with a fixed number of witnesses and implies that adding witnesses to any such coalitions causes sufficient damage. This allows ruling out the coalitions that are too exposed, and characterizing the frontier. Consider coalitions 1 and 2, where 2 is larger than 1 and has less witnesses. Consider a third coalition \(c\) in between, with more witnesses than either (Figure 2). Because witnesses are sufficiently consequential, coalitions 1 or 2 are always preferred to \(c\):

**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 \(q \in (0, 1)\).

All the coalitions that lemma 2 does not rule out live on the frontier because they are minimal, in the sense that no smaller coalition has fewer witnesses (Figure 2 provides an illustration).

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

Depending on peculiarities of the probability of detection \(p\), some minimal coalitions might be dominated by other minimal coalitions. Proposition 2 tells us that the remaining ones are realized over some interval of institutional strength. Formally:
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Figure 2: **Set of feasible coalitions** $C_g$ for some graph $g$. Points are sets of essentially unique coalitions. Coalitions in black minimize $w$ for a fixed $a$. Because $c$ is above the dashed line and $c_2$ is below, $c_1$ and $c_2$ beat $c$ (Lemma 2). Coalitions on the black line are minimal (Definition 2). By lemma 2, they beat the ones above them. One of them is realized in equilibrium (Proposition 2).

**Proposition 2** (Equilibrium coalitions are minimal). If $c \in C^*_g$ for some $q \in (0,1)$, then $c$ is minimal.

Proposition 2 has an important empirical implication: within an organization, minimal coalitions should be more corrupt. Minimality captures the idea that a coalition is *jointly* isolated from the out-group. The concept shifts the unit of analysis from the individual to the coalition, and is agnostic about tie density within the in-group. I say that a set of nodes that has few monitoring ties pointing to it from the out-group—although there may be many such ties within the in-group—is relatively *enclaved* or *isolated*. Minimal coalitions are the most enclaved coalitions of a graph. I discuss in section 4 how this reconciles previous mixed findings.

### 2.2 Comparative statics

The first comparative static examines how corruption varies as organizations adopt better monitoring technologies. It shows that corruption is less frequent but has a higher scale and a broader scope under better monitoring (Figure 3). Increasing the likelihood that any coalition gets detected makes the seed’s favorite coalition less desirable. Accepting the rent requires the project’s scale to be high enough to offset this loss. Corruption is less frequent in that the seed rejects the rent for a broader range of sunk costs, and higher scale in that it selects on the projects with a low enough sunk cost. Furthermore, the seed’s preferences move towards larger coalitions: because getting caught is more likely, the protection afforded by additional accomplices becomes relatively more attractive than the cost of hiring them. Formally:

**Proposition 3** (Corruption is less frequent under better monitoring technologies but grows in scale and in scope). 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 $a_{c^*_1} \leq a_{c^*_2}$.

I then investigate how corruption varies as organizational structure changes, by examining the impact of adding one tie to a graph. Formally, I compare the graph $g = (N,G_c,G_m)$ to
Figure 3: **Equilibrium outcomes for any** \((q, c)\). As \(q\) increases, the rejection area grows, weeding out low-scale corruption, and coalitions of increasing size are realized (Proposition 3).

\[ g' = (N, G'_c, G'_m), \] that I construct by adding a communication or an monitoring 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. Intuitively, proposition 2 shows that enclaves are good for corruption. Adding ties should
make enclaves more exposed, and hence decrease corruption. The intuition is only partially
true. Additional monitoring ties decrease the frequency of corruption because they expose
existing coalitions to weakly more witnesses, which increases the range in scale for which the
seed rejects the rent. Additional communication ties, however, do not make existing coalitions
more exposed. Worse, they may allow forming new coalitions that may be more enclaved, hence
increasing corruption. Most of the time, however, additional ties have no effect: additional ties
change behavior only if they affect minimal coalitions, which is increasingly unlikely as the
graph gets larger. The results spell out the conditions under which the effect is strict:

**Proposition 4** (Adding monitoring ties weakly decreases the frequency of corruption). If \(g' = g + i \rightarrow j\), then \(\hat{\epsilon}_s(g', q) \leq \hat{\epsilon}_s(g, q)\). For the inequality to hold strictly for some \(q \in (0, 1)\), it must
\(j \in c\), and \(i \notin c \cup W_{cg}\) for some minimal coalition \(c \in M_g\) and all coalitions essentially equal to
\(c\).

**Proposition 5** (Adding communication ties weakly increases the frequency of corruption). If
\(g' = g + ij\), 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 \(w_{c'} = w_{c^*}\).

Note that similar to our result on the monitoring technology (proposition 3), propositions 4
and 5 imply that when the frequency of corruption decreases, it selects on higher-scale projects.

Using simulations, I explore the implications of the findings for comparisons across graphs, and relate our notion of minimality to the standard concept of modularity (Newman, 2006). I
show in section 3 of the appendix that more modular organizations are more corrupt. Specifically, I examine the extent to which a randomly chosen seed takes the rent for graphs of varying
modularity; that is, I consider, for a random \(s\), the area under the \(\hat{\epsilon}_s\) curve, \(\int_0^1 \hat{\epsilon}_s(g, q) dq\) (Figure

\[ 12 \text{ I show in the appendix (lemma 4) that any new coalition has a coalition on the old graph that has strictly less accomplices, and weakly less witnesses. As such, } c' \text{ cannot satisfy } w_{c'} < w_{c^*}. \]
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3. Modularity captures the extent to which the graph can be divided in independent communities. It is a scalar $m$ defined on a graph where nodes are partitioned in $n$ given communities. When $m = 0$, ties are distributed uniformly across communities. As $m$ increases, more ties fall within communities, and fewer across. Simulations show a positive correlation between modularity and the area under the curve. The intuition is simple: as modularity increases, communities become more enclaved, and more corrupt.

Together, analytical results and simulations give a sense of how endogenous network formation may affect the results. They allow deriving the ties a corrupt agent, 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 monitoring ties, and add communication ties. The social planner has opposed preferences: she would rather add monitoring ties, and sever communication ties. Finally, simulations suggest that ties that decrease modularity are more likely to reduce corruption. As such, corrupt agents prefer to add ties within communities, while the social planner prefers to add ties across them.

2.3 Alternative division rules

How do informal institutions affect accomplices’ ability to cooperate? As discussed in section 1.1, I compare equal-sharing to two other division rules: monopoly, where the seed pockets all the surplus, and bargaining. Bargaining allows discussing the distributional implications of corruption. Under monopoly, the seed realizes the most extractive coalition; comparing it to other environments gives a sense of how they perform against an efficient benchmark. In turn, equal-sharing gives a sense of how equity concerns, or other factors affecting the bargaining power of accomplices may affect the results. This extension assumes a constant sunk cost: $\epsilon_i = \epsilon$ for all $i \in N$.

Bargaining benefits brokers. Unlike operatives, who cannot recruit other nodes on equilibrium path—for instance because they only have one neighbor, the one who recruited them—, brokers can recruit other nodes; operatives, or other brokers. The commitment problem implies that while operative cannot extract any of the surplus, brokers can. Equilibrium transfers make operatives indifferent between accepting and rejecting it. Brokers have more outside options, that they leverage to extract more of the surplus. For instance, a broker might have a profitable deviation in not hiring any accomplice. If she recruits accomplices in equilibrium, her share of the surplus needs make her indifferent between keeping her transfer to herself and recruiting those accomplices. Formally:

**Proposition 6** (Brokers extract more surplus). In the lawless environment, if $c$ is an equilibrium coalition, then $u_i(c, g, q) \geq 0$ for any $i \in c$. If $i$ is an operative, then $u_i(c, g, q) = 0$.

Moving further requires defining efficiency. The surplus is the expected benefit from the rent, net of the sunk cost $\epsilon$ paid by each accomplice. A coalition is efficient if it maximizes the surplus, and if such surplus is positive. A division rule is efficient if all of its equilibrium outcomes are efficient coalitions if there are any, and if the seed rejects the rent when there are none. By definition, our diffusion process requires that feasible coalitions $C_g$ include the seed. As such, I use a local notion of efficiency, and only look for efficient coalitions among the
coalitions that are feasible for a given seed:

**Definition 3.** Let $\Pi(c, g, q) = p(a_c, w_{cg}, q) - a_c\epsilon$ be the surplus of coalition $c$ on graph $g$ for monitoring level $q$. A division rule is *efficient* if for any seed $s$, all equilibrium outcomes are coalitions that solve $\max_{c \in C_g} \Pi(c, g, q)$ when $\Pi(c, g, q) \geq 0$ for some $c \in C_g$, and the seed rejects the rent in all equilibrium outcomes otherwise.

Making efficiency claims requires pinning down equilibrium. In all division rules, the seed has a threshold strategy:

**Proposition 7.** Under the monopoly rule and in the lawless environment, the seed has a threshold $\hat{\epsilon} \in [0, 1]$ such that she rejects the rent if $\epsilon > \hat{\epsilon}$. Otherwise, some coalition in $C_g$ is realized.

Only the monopoly rule is efficient because the seed’s objective is always aligned with the efficient coalition. Inefficiencies have different causes in the other rules. Under bargaining, prohibitively expensive brokers may prevent the seed from taking the rent, and make corruption less frequent. Equal-sharing is qualitatively more efficient than bargaining, because corruption is as frequent as under monopoly. It has a smaller scope, however, because the seed’s share is smaller in larger coalitions. Formally:

**Proposition 8.** The monopoly rule is efficient. Let $\hat{\epsilon}^m$, $\hat{\epsilon}^e$, $\hat{\epsilon}^l$ be the seed’s thresholds under monopoly, equal-sharing, and lawlessness respectively. We have $\hat{\epsilon}^m = \hat{\epsilon}^e \geq \hat{\epsilon}^l$. Let $C^m$ and $C^e$ be sets of equilibrium coalitions under equal-sharing and monopoly for some $(q, \epsilon)$. Then $\min_{c \in C^e} a_c \leq \min_{c \in C^m} a_c$, and $\max_{c \in C^e} a_c \leq \max_{c \in C^m} a_c$.

I finally examine the robustness of the findings to these new division rules. I show in section A.3 of the appendix that propositions 1 to 5 and lemma 2 hold in the monopoly rule under similar assumptions. None of the findings travel to the lawless environment, because the cost of a coalition depends on the outside options of all its brokers. Without strong assumptions, there is considerable heterogeneity in how the price of such outside options varies with parameter values, which upsets the regularities we observe in the contractual environment.

Together, results suggest that in reality, corrupt behavior should tend to exhibit the features of the contractual environment, although lawlessness introduces additional noise, and inefficiency. Indeed, contracts can be welfare-enhancing, since both contractual rules are preferable to bargaining. As such, real corrupt agents would try to implement some Pareto-improving contract. Such contracts may be imperfect to some extent, and allow for some of the inefficiency that arises from lawlessness. Although there may be a variety of such contracts, because results are similar under two extreme division rules, they should also travel to other contracts.

### 3 Experiment

This section takes the model to the lab and test experimentally its main predictions. The model has several substantive implications about corrupt behavior in organizations. As organizations adopt better monitoring technologies, corruption becomes less frequent, but increases in scope and selects on high-scale projects (proposition 3). More isolated subgraphs form enclaves that are more corrupt (proposition 2). Some ties make corruption less frequent, some increase
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3.1 Design

The first goal of the experiment is to test the main substantive implications of the theory, in a setting with relative ecological validity. I test the following hypotheses: do better monitoring technologies decrease the frequency of corruption, increase its scope and select on grand corruption? Are enclaves more corrupt? Do exposing ties reduce the frequency of corruption, and do irrelevant ties have no effect? A second-order goal is to identify the division rule used by participants, and see whether agents behave as predicted by any of the division rules—equal-sharing, bargaining, or monopoly—we considered in the model.

I introduce a minimal design to examine the diffusion of corruption in organizations. A group of four sits at a table, with a picture of the network positions they are assigned to, and a table of the probability of success of various coalitions. Each player is endowed with $\epsilon$ discrete experimental units (EU). One player is the seed. She may take a rent of 12 EU, and initiate a diffusion game akin to the model. A dice roll determines whether the coalition won, or lost. An enumerator offers the rent to the seed, and mediates communication between players, to implement sequential, take-it-or-leave-it offers, as in the model (section 1.2). If they accept the rent, players give up their endowment, to represent the expected loss from corruption. The protocol uses a neutral framing, and makes no mention of corruption to participants.

The experiments compared a baseline to two main conditions: (1) increasing institutional strength from $q = .1$ to $q = .75$ (“hard” treatment), and (2) adding a tie that strictly reduces corruption to the baseline graph (“exposing tie” treatment). In all conditions, I also manipulated two dimensions. First, I varied the scale of corruption, by setting the endowment $\epsilon$ to 2 EU (grand corruption), or 4 EU (petty corruption). Second, I added or removed ties that should have no effect on corruption (“irrelevant ties”) to each network. Table 1 shows experimental parameters and equilibria in all conditions. Experimental parameters were chosen to yield the same equilibrium coalition in the lawless environment, and under the monopoly and equal-sharing division rules. This setup separates the two goals of testing whether the main predictions hold, and examining the division rule they used. Due to power considerations, I did not test whether additional ties may increase corruption (proposition 5). For simplicity, all networks used in the experiment collapse the monitoring and the communication network into one undirected network: if two players communicate, they also monitor each other.

The setup allows testing the main substantive predictions. Comparing the hard condition to the baseline tests predictions on the form of corruption when the level of monitoring increases.

---

13 It is common practice in lab experiments on corruption to use a neutral framing as a baseline, and investigate in additional experiments the impact of a loaded framing (see Serra and Wantchekon 2012 for a review). Using a loaded framing was not feasible due to security concerns. Available secondary evidence suggests that framing effects should not impact the result. Abbink and Hennig-Schmidt (2006) finds no framing effects. In a bribery game, Barr and Serra (2009) and Lausen and Frank (2010) find framing effects, but only on the client side, not on the bureaucrat side, which is the focus of the experiment.

14 See section C.1 in the appendix for equilibrium predictions.
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<table>
<thead>
<tr>
<th>Condition</th>
<th>Capacity ($g$)</th>
<th>Predicted equilibrium coalition</th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>grand corruption ($\epsilon = 2$)</td>
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<tr>
<td>Baseline</td>
<td>.1</td>
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<tr>
<td>Hard</td>
<td>.75</td>
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<tr>
<td>Exposing tie</td>
<td>.1</td>
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Table 1: **Experimental parameters and equilibria.** $S$ is the seed. Dashed ties are irrelevant ties, and are added and removed within each condition. Grey nodes represent the coalition. **Hard treatment:** increasing institutional strength eliminates petty corruption, and increases the size of the coalition under grand corruption. **Exposing tie treatment:** adding an exposing tie to the baseline eliminates petty corruption; the less exposed LHS node is preferred over the more exposed RHS node.

The exposing tie condition tests whether more enclaved coalitions are more corrupt; comparing it to the baseline allows testing whether exposing ties reduce corruption. Conversely, adding and removing irrelevant ties checks whether some ties have no effect. Finally, examining how the rent was divided across conditions tests allows examining whether agents behave more as predicted in the lawless environment, or resort to some informal contract.

Two features of the protocol increase ecological validity. First, face-to-face interactions allow for cheap talk that mimics the interpersonal interactions that arise in organizations. Participants operate in a lawless environment, with sequential, take-it-or-leave-it offers, but may use cheap talk to implement informal contracts. Second, the experiments were all conducted in Mohammedia, Morocco, a mid-income country with median levels of corruption. I used a convenience sample of 272 subjects with one quarter undergraduate students, and three quarters employees of the service industry. Undergraduate students, the standard subject pool of laboratory experiments, are very different from employees (Table 2). While conducting the experiment with bureaucrats proved infeasible, service-sector employees are a reasonable proxy, since the argument extends to private organizations. Comparing between subject pools tests whether behavior is driven by some characteristic held only by students or bureaucrats.

Subjects played the experiment in groups of four, with a total of 68 groups. In each group, subjects played twelve rounds of the game in various conditions in a random order. I randomly decided whether the group would play under petty or grand corruption. Assignment to treatment conditions was balanced such that in each group and for each condition, subjects each got to be the seed once, and to occupy each of the other network positions. Subjects were compensated, with the average payment amounting to daily minimum wage ($2.6$ average gain and $5$ show-up fee). Section C in the appendix discusses the protocol further, and conducts several validity checks. I show that participants displayed satisfactory levels of comprehension, discuss concerns for potential learning and pooling effects, and find no evidence of either.
Table 2: **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; \( *p < 0.05; \) \( **p < 0.01; \) \( ***p < 0.001. \)

### 3.2 Results

I first examine support for the main theoretical predictions: do better monitoring technologies decrease the frequency of corruption, increase its scope and select on grand corruption? Are enclaves more corrupt? Do exposing ties reduce the frequency of corruption, and do irrelevant ties have no effect? I examine predictions on the frequency of corruption, then move on to predictions on its scope. The quantities of interest are estimated using OLS: I regress our two outcomes of interest—whether the seed takes the rent, and the size of the resulting coalition—on indicator variables for each treatment, where a *treatment* is the interaction of a main *condition* (baseline, hard, exposing tie), and the scale of corruption (petty, grand). I cluster errors at the group level, to account for within-table correlations. Table 4 in the appendix shows the models used to estimate all quantities of interest in the paper.

**Finding 1.** Support for propositions 3 and 4: increasing capacity and adding exposing ties reduces the frequency of corruption, and selects on grand corruption. In the baseline, the seed is very likely to take both petty, and grand rents: the difference in means is not significantly different from zero (Figure 4). In the hard and exposing tie treatments, the seed is comparably likely to accept grand rents (the differences in means are marginally significant), but her probability of accepting petty rents drops by about 40 percentage points in both treatments.

**Finding 2.** Support for proposition 4: adding irrelevant ties has no effect on the frequency and scale of corruption. I estimate the effect of irrelevant ties within treatment, by adding an indicator variable for irrelevant ties to our main specification. Figure 4 shows that adding irrelevant ties has little effect on the incidence and the scale of corruption (the difference in means is marginally significant).

**Finding 3.** Mixed support for proposition 3: better monitoring increases the scope of corruption, but not as much as expected. The size of the coalition is higher under higher levels of monitoring (Figure 5). I restrict the analysis to grand corruption, because our predictions on the form of corruption are conditional on the seed taking the rent in equilibrium, which only happens with grand corruption. The ordering of effects is consistent with predictions:
Figure 4: **Frequency of corruption in all treatments.** Errors are clustered at the group level. Full circles are point estimate with their 95% confidence interval. Empty circles are equilibrium predictions. The bottom row (irrelevant tie) plots a marginal effect. Corruption becomes less frequent and selects on grand petty corruption in the hard and exposing tie treatments: frequency is comparably high in all treatments under grand corruption (differences in means are marginally significant). Switching to petty corruption has no effect in the baseline, but decreases frequency in the other treatments. Adding irrelevant ties has no effect.

Figure 5: **Scope of corruption in all treatments with grand corruption.** Errors are clustered at the group level. Full circles are point estimate with their 95% confidence interval. Empty circles are equilibrium predictions. Conditional on corruption occurring, the realized coalition involves more accomplices in the hard treatment. Results are closer to equilibrium in the baseline and exposing tie treatment than in the hard treatment.

the coalition is largest in the hard treatment, and second largest in the exposing tie treatment. However, results are furthest away from equilibrium predictions in the hard treatment. I show in the next subsection that this is due to subjects making mistakes when engaging in bargaining for long chains of backward induction.

**Finding 4. Support for proposition 2:** minimal coalitions are more likely to be corrupt. In the exposing tie treatment, the seed overwhelmingly favors the more enclaved 2-people coalition (Figure 6c): the equilibrium coalition accounts for 45 percent of realized coalitions. Consistent with finding 3, most realized coalitions match the equilibrium prediction,
except in the hard treatment, where the complete coalition accounts for only 28 percent of realized coalitions, which is the furthest away from the prediction.

Finding 5. Support for proposition 4: irrelevant ties have no effect on the form of corruption. Our hypothesis is that irrelevant ties should never affect the distribution of realized coalitions. Within a main treatment, for a given kind of rent, I compare the distribution of realized coalitions with and without the extra tie within-treatment using Fisher exact tests. Since we have six treatments, I correct for multiple testing using the Benjamini & Hochberg procedure. The distribution of realized coalitions never differs significantly with and without the irrelevant tie.

Finding 6. The behavior of employees does not significantly differ from that of students, despite their very different characteristics (see section D.2 in the appendix for details). Using random-level specifications, I show that there is little group-, and individual-level heterogeneity, and that group-level heterogeneity is larger than individual-level heterogeneity. I also show students and employees behaved very similarly in the experiment. Their behavior in the baseline is similar, and they show comparable effect sizes. This makes the results more credible, suggesting that behavior is not driven by some characteristic held only by students or employees.

3.3 Division rule

Having shown support for the main theoretical predictions, I now investigate the division rule used by participants. In section 2.3 we considered three different assumptions: first, that agents operate in a lawless environment, where a new accomplice cannot commit to implement transfers to the node who recruited her; second, that agents informally operate in a contractual environment, where they can enforce some division rule; in particular, equal-sharing, and monopoly, where the seed gets all the surplus. The protocol does not give any explicit commitment device to participants, but the face-to-face setting allows them to strike informal contracts using cheap talk. As such, the equal-sharing rule is of particular importance, since it may represent equity norms possibly held by participants.
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I show moderate support for monopoly and bargaining, but mostly identify a deviation from rational behavior that has an important substantive implication: recipients accept transfers that give them negative surplus early on in the diffusion chain, because they do not internalize their future transfers. The problem is more acute in larger coalitions, because they require longer diffusion chains. This suggests an additional reason why corruption better monitoring makes corruption less frequent: better monitoring prompts for larger coalitions, which are more difficult to form. Together, this lends more credibility to the results: all division rules yield comparable insights, and although none of them are a perfect match to the data, their insights are verified empirically. The deviation we identify only makes stronger the substantive implication that better monitoring makes corruption less frequent.

The design does not allow characterizing the division rule easily. In the contractual environment, off-path behavior is not defined for transfers that are inconsistent with the division rule. Second, because treatments yield similar outcomes under all three assumptions, predictions are often identical across rules.

Since off-path behavior may not be defined in the contractual environment, I examine the seed’s payoff in treatments where a multi-player coalition was the equilibrium outcome (hard and exposing tie with grand corruption) and was realized (Figure 7). The observed distributions align more closely with bargaining and equal-sharing in the exposing tie treatment.

More importantly, figure 7 reveals a deviation from rational behavior: in many instances, the seed extracts so much of the surplus that her accomplices end up with negative surplus: the seed’s payoff is above the monopoly allocation in 72 and 40 percent cases in the hard and exposing tie treatments respectively.

Comparing behavior to predictions under bargaining at all histories shows that pattern is more general: subjects often over-accept offers, and over-share their rent. I consider binary decisions first: whether an offerer shares her rent with anyone, and whether a recipient accepts the offer or not. I compare them to the equilibrium prediction under bargaining for that history. Figure 8 shows that for both decisions, most errors are false positives: offerers over-share, and
consistently, recipients over-accept.\footnote{For acceptance, I only examine non-seed nodes. The seed’s decision is discussed in the previous subsection. Furthermore, the seed faces an exogenous offer, which is very different from other offers.}

Looking at amounts offered pinpoints the irrationality (Figure 9): about 75% offers are greedy—they would leave the recipient with negative surplus--; yet, they have a very high chance of being accepted.\footnote{The right panel of figure 9 uses generalized additive logistic regressions with thin plate regression splines, estimated on offers with deviation ranging from -5 to 5, to exclude outliers. Errors are clustered at the group and at the treatment level.} Proposition 7 implies that under bargaining, all agents have threshold strategies: $i$ should accept transfer $t_{ji}$ from $j$ if it is above some threshold $t_{ji}^*$. Comparing the observed offer to the threshold indicates whether an offer is greedy ($t_{ji} - t_{ji}^* < 0$), or generous ($t_{ji} - t_{ji}^* \geq 0$).

Figure 9 also shows that deviations attenuate at later histories. The distribution of offers shifts towards more generosity at later histories. Recipients are less likely to accept greedy offers: the probability of accepting an offer greedy by 1 EU drops by about 20 percentage points between the second and the the fourth history.

The finding is consistent with the commonly observed fact that backward induction problems, such as this experiment, are cognitively taxing, and more so at early histories (Johnson et al., 2002; Spenkuch, Montagnes and Magleby, 2015). 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. As such, offers get closer to the equilibrium prediction, and recipients are more likely to reject greedy offers.

4 Conclusion

We first highlighted that the standard principal-agent models of bureaucratic corruption are, by design, unable to answer two questions: how is corruption organized? how do organizations affect corruption?
Figure 9: Deviation of observed transfers $t_{ji}$ from acceptance threshold $t^*_{ji}$. Left: most offers are greedy ($t_{ji} - t^*_{ji} < 0$), but they become more generous in later histories. Right: 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. Shaded areas denote 95% confidence intervals. History 1 is the seed’s decision, and is omitted. Footnote 16 provides details about estimation.

This paper proposed a model and an experimental design that treat corruption as the outcome of a process of strategic diffusion on a network. This simple, easily expandable idea provides a framework to think about the relationship between corruption, organizations, and institutions. The model provides insights that echo, reconcile, and precise previous findings. The lab experiment confirms most of the model’s predictions, in a field environment with relative ecological validity, and shows divergences that have substantive implications. I now discuss the implication of the findings in light of the literature.

Characterizing how corruption is organized, enclaves shift the unit of analysis from the individual to the coalition (proposition 2). The concept reconciles mixed findings about the structure of criminal networks: Aven (2015) and Morselli, Giguère and Petit (2007) show that criminal networks are sparser than comparable non-criminal networks, but there is also evidence that better connected individuals are more corrupt (Callen and Long 2015; Nyblade and Reed 2012; Khanna, Kim and Lu 2015). Collectively, enclaves are sparsely connected to the rest of the organization. However, accomplices may have many ties with each other, and some of them may be exposed to many witnesses.

Findings on how organizations affect corruption (propositions 4 and 5) provide a microfoundation to Evans’ (1995) claim that under- and over-embedded bureaucracies are more corrupt: under-embedded bureaucracies are more corrupt because they lack monitoring ties. Over-embedded bureaucracies are more corrupt because their numerous communication ties allow forming more enclaved coalitions, or circumventing costly brokers.

Findings on formal institutions (proposition 3) may explain why corruption persists and selects on grand corruption in developed countries, although it is less frequent than in developing countries (Kaufmann 2004). Because detection is more likely when institutions are strong, re-
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cruiting accomplices is more desirable. Yet, only grand corruption is profitable enough to afford additional protection. The lab reveals a behavioral trait that strengthens the result: forming larger coalitions poses a challenging backward induction problem, which makes corruption in those settings all the more unlikely. Section E in the appendix provides further evidence of the mechanism, using cross-country data and a comparison of 110 cases of corruption in India and the US. Controlling for the scale of corruption, instances of corruption in the US involve more accomplices than in India, and accomplices in corruption schemes are better-paid in developed countries.

Findings on informal institutions (propositions 6 to 8) provide micro-foundations to previous work. I find that lawlessness generates inefficiencies that benefit brokers (Vannucci and Della Porta 2013), but may be alleviated by informal contracts (Gambetta 2009). The model pinpoints the mechanism: brokers extract more of the surplus because the lack of commitment device allows them to veer diffusion according to their preferences.

The findings may explain why many African bureaucracies are divided into ethnic monopolies, laden with patronage and cronyism (Van de Walle 2001). Co-ethnicity facilitates cooperation (Habyarimana et al. 2009), and comes with dense social ties. A corrupt principal would staff her agency with coethnics, with whom enforcing informal contracts is easier, and whose pre-existing social networks provide communication ties that facilitate hiring them.

Finally, our results have a major policy implication: they show that organizational responses to corruption may substitute for better enforcement, but may also backfire. This is concerning because such reforms are very common, but have not been subjected to careful evaluation. Results suggest that one should consider whether the proposed policy will reduce modularity, and prevent the creation of new enclaves.
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A Proofs

A.1 Section 2.1

Proof of lemma 7. 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 $C^*_gq$ 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, $\hat{\epsilon}_s(g, q) = u(c, g, q)$.

Proof of proposition 1. For notational simplicity, we denote $\epsilon_s$ by $\epsilon$ in this proof. Consider two essentially different coalitions $c_1, c_2 \in C$ on some graphs $g_1$ and $g_2$ respectively, with probability of success $p_1$ and $p_2$. Let $u_1 = u_s(c_1, g_1, q)$ and $u_2 = u_s(c_2, g_2, q)$ be the seed’s utility from these coalitions, and let $U = \{(\epsilon, q) : u_1 = u_2\} \subset (0, 1)^2$. I show that $U$ has measure 0.

We have $u_2 - u_1 = \frac{p_2}{a_{c_2}} - \frac{p_1}{a_{c_1}}$. Suppose $U$ is non-empty and consider some point $(\epsilon, q) \in U$. The directional derivative of $u_2 - u_1$ at this point writes:

$$\nabla_x u_2 - u_1 = \frac{\partial u_2 - u_1}{\partial \epsilon} x_\epsilon + \frac{\partial u_2 - u_1}{\partial q} x_q = \left( \frac{\partial p_1}{\partial q} / a_{c_1} - \frac{\partial p_2}{\partial q} / a_{c_2} \right) x_q$$

where $x = (x_\epsilon, x_q)$ is a unit-length vector. If the equation $\nabla_x u_2 - u_1 = 0$ has a finite number of solutions in $x$, then $U$ has measure 0. Assumption 1 implies that $\frac{\partial p_1}{\partial q} / a_{c_1} - \frac{\partial p_2}{\partial q} / a_{c_2} \neq 0$, so the only solutions are $(1, 0)$ and $(-1, 0)$.

Since the space for which one is indifferent between any two essentially different coalitions has measure 0, the space for which one is indifferent between any two essentially different equilibrium coalitions also has measure 0.

Proof of lemma 2. Suppose that assumption 2 holds.
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 \( v(a_2, w_2, q) \geq v(a_2, w_1, q) \), 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 \( \frac{\partial v(a, w, q)}{\partial w} > v(a^*, w, q) - \max\{v(0, w, q), v(N-1, w, q)\} \), where \( a^* \in \arg \max_{a \in [1,N]} v(a, w, q) \). Then, \( v(a^*, w, q) \) \( \leq \max\{v(0, w, q), v(N-1, w, q)\} \). Note that \( v(a_c, w_c, q) \leq v(a_c, w_1, q) - \left| \frac{\partial v(a_c, w_1, q)}{\partial w} \right| \leq v(a^*, w_1, q) - \left| \frac{\partial v(a^*, w_1, q)}{\partial w} \right| \). 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 2** I show the contrapositive of \( c' \in C_{gq}^* \Rightarrow c' \in M_g \). 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 \( v(a_{c'}, w_{c'}, q) < \min\{v(a_c, w_c, q), v(N-1, 0, q)\} \) for any \( q \in (0,1) \).

\( \square \)

A.2 Section 2.2

**Proof of proposition 3** Let’s first show that \( q_1 < q_2 \Rightarrow \hat{\epsilon}_s(g, q_1) \leq \hat{\epsilon}_s(g, q_2) \). Let \( c^* \in C_{gq}^* \). 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, \( \hat{\epsilon}_s(g, q_1) \leq \hat{\epsilon}_s(g, q_2) \).

I now show that \( q_1 < q_2 \Rightarrow a_{c_1'} \leq a_{c_2'} \). Let \( c_1' \) be the largest coalition in \( C_{gq_1}^* \), and \( c_2' \) the smallest in \( C_{gq_2}^* \) with sizes \( a_{c_1'} \) and \( a_{c_2'} \). To prove the claim, it suffices to show that \( a_{c_1'} \leq a_{c_2'} \).

Suppose not. Because \( c_1' \in C_{gq_1}^* \) and \( c_2' \in C_{gq_2}^* \), we have \( u(c_2', g, q_1) - u(c_1', g, q_1) \leq 0 \) and \( u(c_2', g, q_2) - u(c_1', g, q_2) \geq 0 \). Since \( u(c_2', g, q_1) - u(c_1', g, q_1) \) is continuous, there must be some \( q \) such that \( u(c_2', g, q_1) = u(c_1', g, q_1) \). Because \( a_{c_1'} > a_{c_2'} \), assumption \( i \) implies that \( \frac{\partial}{\partial q} [u(c_2', g, q) - u(c_1', g, q)] < 0 \). Since \( u(c_2', g, q_1) - u(c_1', g, q_1) \leq 0 \), then \( u(c_2', g, q_2) - u(c_1', g, q_2) < 0 \), a contradiction.

\( \square \)

**Lemma 3** (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:

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

**Proof.** The proof is immediate.

\( \square \)

**Lemma 4** (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 3, 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
be the set of such nodes. Its complement, \( c'_f \setminus c'_{n_f} \), is feasible on \( g \). I show that \( c'_f = c \).

By construction, we have \( a_{c_f} < a_{c'_f} \). Note that \( i \in c'_f \iff j \in c'_{n_f} \). Without loss of generality, suppose that \( i \in c'_f \).

Note that \( W_{c'g'} = (W_{c'_f g'_f} \setminus c'_{n_f}) \cup W_{c'_{n_f} g'} \), which implies
\[
 w_{c'g'} = |W_{c'g'}| = |W_{c'_f g'_f} \setminus c'_{n_f}| + |W_{c'_{n_f} g'}| - |(W_{c'_f g'_f} \setminus c'_{n_f}) \cap W_{c'_{n_f} g'}|.
\]

By construction, \( W_{c'_f g'_f} \setminus c'_{n_f} = W_{c'_{f} g'} \). Indeed, if node \( k \in W_{c'_f g'_f} \setminus c'_{n_f} \), then \( k \) is the neighbor of some \( l \in c'_f \) on \( g'_u \).

So the path \( S, ..., l, k, i \) is such that all nodes between \( s \) and \( k \) are in \( c'_f \), and does not contain \( ij \) which implies, by definition of \( c'_f \), that \( k \in c'_f \).

Lemma 3 implies that \( |W_{c'_f g'}| = w_{c'f} \). Also note that witnesses of coalition \( c'_{n_f} \) cannot be in \( c'_{n_f} \cap W_{c'_{n_f} g'} = \emptyset \).

As such, \((W_{c'_f g'_f} \setminus c'_{n_f}) \cap W_{c'_{n_f} g'} = W_{c'_f g'} \cap W_{c'_{n_f} g'} \). Plugging back into equation 4, we get
\[
 w_{c'g'} = w_{c'f} + |W_{c'_{n_f} g'}| - |W_{c'_{n_f} g'} \cap W_{c'_{n_f} g'}| \geq w_{c'g'}.
\]

**Proof of proposition 4.** By lemma 3, we have \( C_g = C_g \) and for any \( c \in C_g, w_{c'g} \leq w_{c'g} \leq w_{c'g} + 1 \).

This implies \( u(c, g', q) \leq u(c, g, q) \). So \( \epsilon_s(g', q) \leq \epsilon_s(g, q) \).

Let’s show the second part of the proposition. Proposition 2 implies that for any \( q \in (0, 1) \), there is \( c^* \in M_g \) that is realized in equilibrium on \( g \).

Suppose that the condition on \( i \to j \) does not hold. That is, suppose that for all \( c^* \in M_g \), there is some \( c \in M_g \) essentially equal to \( c^* \) such that \( j \notin c \) or \( i \in c \cup W_{c'g} \).

Then by lemma 3, \( c \) on \( g' \) is essentially equal to \( c^* \) on \( g' \). As such, \( u(c, g', q) = u(c^*, g, q) \).

**Proof of proposition 5.** By lemma 3, we have that for any \( c \in C_g, u(c, g, q) = u(c, g', q) \), which implies that \( \epsilon_s(g', q) \geq \epsilon_s(g, q) \).

Let’s show the second part of the proposition. Suppose that there is some \( q \in (0, 1) \) such that \( \epsilon_s(g', q) \geq \epsilon_s(g, q) \). Using proposition 3, this means that there is some \( c' \in C_g \setminus C_g \) such that \( u(c', g', q) > u(c, g, q) \).

For this to be true, it must be that \( c' \in C_g \setminus C_g \) for otherwise, lemma 3 implies \( u(c', g, q) = u(c', g', q) \). So lemma 4 implies that there is \( c^* \in C_g \) such that \( a_{c^*} < a_{c^*}, w_{c'g} \leq w_{c'g} \). It must be that \( w_{c'g} = w_{c'g} \). Then there is \( c^* \in C_g \) such that \( a_{c^*} \leq a_{c^*} \) and \( w_{c'g} = w_{c'g} \). This implies \( a_{c^*} \leq a_{c^*} \) and \( w_{c'g} < w_{c'g} \). Then lemma 2 implies \( u(c', g', q) < \min\{u(c^*, g, q), v(N, 0, q)\} \), a contradiction.

A.3 Section 2.3

In this section, we denote the three environments (equal-sharing, lawlessness, and monopoly) using the subscripts \( c, l, m \) respectively. In particular, \( u^c(c, g, q, \epsilon) = p(a_{c}, q_{c, g}, \epsilon) - \epsilon \) is the seed’s utility under equal-sharing, while \( u^l \) and \( u^m \) are her utility under lawlessness and monopoly.

**Proof of proposition 6.** Suppose coalition \( c \in C_g \) is an equilibrium outcome for some \( (\epsilon, q) \in (0, 1)^2 \). Then it must be that \( u_i(c, g, q) \geq 0 \) for all \( i \in c \) for otherwise, \( i \) has an incentive to deviate and reject her offer. If \( i \) is an operative, then at each of the histories where she moves on equilibrium path, her action space is to accept or reject an offer. Suppose that in equilibrium, \( i \) accepted transfer \( t_{ji} \) from broker \( j \). If \( u_i(c, g, q) > 0 \), then \( j \) has an incentive to deviate and set \( t_{ji} \) such that \( u_i(c, g, q) = 0 \).
Before proving the next propositions, we pin down equilibrium under lawlessness and monopoly. There division rules create multiple equilibria, some of which arise from uninteresting resolution of indifference conditions. In equilibrium, an accomplice is indifferent between her broker’s favorite outcome and her outside option. There is an equilibrium in which she picks her outside option. To rule out this case, I consider equilibria that satisfy deference; that is, equilibria where indifferent nodes defer to their broker’s preference. Formally:

**Definition 4.** A strategy profile $\sigma$ satisfies deference if, whenever some node $i$ that responds to an offer from $j$ is indifferent between two actions, and there are nodes on the path of accepted offers from the seed to $j$ that are not, then $i$ makes the action that is preferred by her closest such node on that path.

All following proofs in this subsection only consider equilibria that satisfy deference.

**Lemma 5.** Under lawlessness, in equilibrium, $s$ rejects the rent if $\max_{c \in \Gamma} u^e(c, g, q, \epsilon) = p(a_c, w_{cg}, q) - \tau(c, g, q, \epsilon) < 0$, for some $\Gamma \subseteq C_g$ and some $\tau : \Gamma \times (0, 1)^2 \rightarrow \mathbb{R}^+$ that satisfies $\tau(c, g, q, \epsilon) \geq a_c$, and $\partial \tau \partial \epsilon = 0$. Otherwise, $s$ accepts the rent and some coalition in $C_{g\epsilon}^e = \arg \max_{c \in \Gamma} u^e(c, g, q, \epsilon)$ is realized.

**Proof.** This proof requires a more specific definition of operatives, and brokers. The definition is inductive. Node $i$ is an operative at history $h$ if in all of $h$’s children histories where $i$ moves, her action space does not contain any transfers. Node $i$ is a level-1 broker at history $h$ if in all of $h$’s children histories where $i$ moves, her action space only includes transfers to operatives. Node $i$ is a level-$n$ broker if in all children histories where $i$ moves, her action space only includes transfers to operatives, and brokers of level $n' < n$.

In equilibrium, if $i$ moves at history $h$, there is a mapping between any of her transfers $t_i$ and all outcome coalitions $\Gamma_{ih} \subset C_g$ that can be formed from that history. I prove the following:

**Lemma 6.** Suppose level-$n$ broker moves at history $h$ after transfer $t_{ji}$. In equilibrium, $i$ rejects the transfer if $\max_{c \in \Gamma_{ih}} t_{ji} p(a_c, w_{cg}, q) - \tau_i(c, g, q, \epsilon) \geq 0$, for some $\tau_i : \Gamma_{ih} \times (0, 1)^2 \rightarrow \mathbb{R}^+$ that satisfies $\tau_i(c, g, q, \epsilon) \geq a^i + 1$, where $a^i$ is the number of accomplices in $c$ hired in transfers using money from $i$’s transfer, and $\partial \tau_{in} \partial \epsilon = 0$. Otherwise, $i$ accepts the transfer and some coalition in $\arg \max_{c \in \Gamma_{ih}} t_{ji} p(a_c, w_{cg}, q) - \tau_i(c, g, q, \epsilon)$ is realized.

**Proof.** I prove the claim by induction on the level of the broker. Suppose $i$ is a level-1 broker. In equilibrium, her transfers make operatives indifferent. Then, under deference, if transfer $t_{i}$ has coalition $c$ as an outcome, then $t_{ik} = \frac{\epsilon}{p(a_c, w_{cg}, q)}$ if $k \in c$, and $t_{ik} = 0$ otherwise. Assuming she makes $a^i \geq 0$ transfers in such coalition, her payoff is $u_i^e(c, g, q, \epsilon) = (t_{ji} - a^i \frac{\epsilon}{p(a_c, w_{cg}, q)}) p(a_c, w_{cg}, q) - \epsilon = t_{ji} p(a_c, w_{cg}, q) - (a^i + 1) \epsilon$. Setting $\tau_i(c, g, q, \epsilon) = a^i + 1$ proves the claim. We have $\partial \tau_{in+1} \partial \epsilon = 0$. In equilibrium, $i$ rejects $t_{ji}$ if $\max_{c \in \Gamma_{ih}} u_i^e(c, g, q, \epsilon) < 0$. Otherwise, she accepts and makes the transfers that realize some coalition in $\arg \max_{c \in \Gamma_{ih}} u_i^e(c, g, q, \epsilon)$. Suppose $i$ is a level-$n$ broker. In equilibrium, her transfers are the cheapest vector of transfers that realize the coalitions in $\Gamma_{ih}$. In particular, her transfers make recipients indifferent between their equilibrium move and their best outside option. Suppose recipient $k$’s best outside option is to reject the transfer. Using the inductive hypothesis, in equilibrium, and under deference, $t_{ik}$ solves $t_{ik} p(c, g, q, \epsilon) - \tau_j(c, g, q, \epsilon) \epsilon = 0$ if $k \in c$ and $t_{ik} = 0$ otherwise. That is, $t_{ik} = \frac{\epsilon}{p(a_c, w_{cg}, q)}$ if $k \in c$, and $t_{ik} = 0$ otherwise.
Suppose \( j \)'s best outside option is to accept and make some other transfer resulting in coalition \( c' \). Then \( t_{ik} \) solves \( t_{ik}(c,g,q,\epsilon) - \tau_k(c,g,q,\epsilon)\epsilon = \tau_k(c',g,q,\epsilon) - \tau_k(c',g,q,\epsilon)\epsilon \), which gives \( t_{ik} = \frac{\tau_k(c,g,q,\epsilon) - \tau_k(c',g,q,\epsilon)}{\tau_k(c',g,q,\epsilon) - \tau_k(c',g,q,\epsilon)} \). In equilibrium, \( i \)'s payoff from \( c \in \Gamma_{ih} \) is 
\[
u_i(c,g,q,\epsilon) = (t_{ji} - \sum_k t_{ik}(p(a_c, w_{cg}, q) - \epsilon = t_{ji}p(a_c, w_{cg}, q) - (1 + \sum_k t_{ik}(a_c, w_{cg}, q))/\epsilon)\epsilon.
\]
Setting \( \tau(c,g,q,\epsilon) = 1 + \sum_k t_{ik}(a_c, w_{cg}, q)/\epsilon \) proves the claim. Replacing \( t_{ik} \) by their equilibrium values and using the inductive hypothesis on \( \tau_k \), it is easy to show that \( \frac{\partial \tau_i}{\partial \epsilon} = 0 \), which implies \( \partial \tau_i / \partial \epsilon = 0 \). Furthermore, in equilibrium, any transfer \( t_i \) must make all the accomplices in \( c \) hired in transfers using money from \( t_i \) better off than rejecting. For \( a^i \) such transfers, it must be that 
\[
\sum_k t_{ik} \geq a^i \frac{\epsilon}{p(a_c, w_{cg}, q)}.
\]
This implies \( \tau_i(c,g,q,\epsilon) \geq a^i + 1 \).

We prove the proposition exactly as in the inductive step of the lemma, setting \( i = S \), \( \tau = \tau_i \), and defining \( t_{ji} = 1 \).

**Lemma 7.** Under monopoly, in equilibrium, \( s \) rejects the rent if \( \max_{c \in C_g} u^m(c,g,q,\epsilon) > p(a_c, w_{cg}, q) - a_c\epsilon < 0 \). Otherwise, \( s \) accepts the rent and some coalition in \( C_{gq}^m = \arg \max_{c \in C_g} u^m(c,g,q,\epsilon) \) is realized.

**Proof.** Under monopoly, non-seed members of a coalition have \( u_i(c,g,q,\epsilon) = \pi_ip(a_c, w_{cg}, q) - \epsilon = 0 \). Solving for \( \pi_i \), we have \( \pi_i = \epsilon/p(a_c, w_{cg}, q) \). So \( u^m(c,g,q,\epsilon) = (1 - \sum_{i \notin S} \pi_i)c(g,q,\epsilon) = p(a_c, w_{cg}, q) - \epsilon = p(a_c, w_{cg}, q) - a_c\epsilon \). Consider \( c^m \in C_{gq}^m \). If \( u^m(c^m,g,q,\epsilon) \geq 0 \), then it is an equilibrium outcome, since non-seed members are indifferent between their equilibrium move and any other move, and \( c^m \) is the seed's favorite coalition. Since we consider equilibria with deference, a coalition \( c \notin C_{gq}^m \) cannot be an equilibrium outcome. If \( u^m(c^m,g,q,\epsilon) < 0 \), then the seed rejects the rent.

**Proof of proposition 7** I first consider monopoly. From lemma 7, the seed is indifferent between taking the rent and rejecting it when \( \max_{c \in C_g} p(a_c, w_{cg}, q) - a_c\epsilon = 0 \); that is, when \( \epsilon = \max_{c \in C_g} p(a_c, w_{cg}, q)/a_c \). We have \( \partial \tau^m / \partial \epsilon < 0 \), so \( \partial \tau^m / \partial \epsilon < 0 \). \( s \) rejects the bribe whenever \( \epsilon > \hat{\epsilon} \). Otherwise, lemma 7 implies that some coalition in \( C_{gq}^m \) is realized. I now consider lawlessness. From lemma 5, the seed is indifferent between taking the rent and rejecting it when \( \max_{c \in \Gamma} p(a_c, w_{cg}, q) - \tau(c,g,q,\epsilon) = 0 \); that is, when \( \epsilon = \max_{c \in \Gamma} \frac{p(a_c, w_{cg}, q)}{c(g,q,\epsilon)} = 0 \). We show as under monopoly that \( \hat{\epsilon} = \max_{c \in \Gamma} \frac{p(a_c, w_{cg}, q)}{c(g,q,\epsilon)} \).

**Proof of proposition 8** Showing that monopoly is efficient is a direct corollary of lemma 7 if \( \epsilon \leq \hat{\epsilon} \), then all equilibrium outcomes are efficient, since they solve \( \max_{c \in C_g} u^m(c,g,q,\epsilon) \). Conversely, if \( \epsilon > \hat{\epsilon} \), then no coalition yields a positive payoff. Corruption is inefficient, and the seed rejects the rent.

That \( \hat{\epsilon}^m = \hat{\epsilon}^e \geq \hat{\epsilon}^l \) follows from lemma 1 and the proof of proposition 7 we have \( \hat{\epsilon}^m = \hat{\epsilon}^e = \max_{c \in C_g} p(c,g,q)/a_c \), while \( \hat{\epsilon}^l = \max_{c \in \Gamma} \frac{p(c,g,q)}{c(g,q,\epsilon)} \). Lemma 5 tells us that \( \tau(c,g,q,\epsilon) \geq a_c \), which implies \( \hat{\epsilon}^m \geq \hat{\epsilon}^l \).

Let's show that for any \((q,\epsilon)\), \( \min_{c \in C^m} c \leq \min_{c \in C^m} a_c \), and \( \max_{c \in C^m} c \leq \max_{c \in C^m} a_c \). Lemmas 1 and 7 tell us that the sets of equilibrium coalitions under equal-sharing and monopoly are, respectively, \( C^e = C^m_{gq} = \arg \max_{c \in C_g} u^e(c,g,q,\epsilon) \), and \( C^m = C^m_{gq} = \arg \max_{c \in C_g} u^m(c,g,q,\epsilon) \). Note that \( u^e(c,g,q,\epsilon) = u^m(c,g,q,\epsilon) \iff \epsilon = p(c,g,q)/a_c \). So when \( \epsilon = \hat{\epsilon}^m = \max_{c \in C_g} p(c,g,q)/a_c \), we have \( C^e_{gq} = C^m_{gq} \). The claim is trivially true.

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Consider the case where $\epsilon < \tilde{\epsilon}^m$. Lemma 1 tells us that $C_{ggq}^c$ does not vary with $\epsilon$. Conversely, the following lemma shows that as $\epsilon$ decreases, the coalitions in $C_{ggq}^m$ get larger. Using this lemma, it is immediate that $\min_{c \in C^e} a_c \leq \min_{c \in C^m} a_c$, and $\max_{c \in C^e} a_c \leq \max_{c \in C^m} a_c$.

**Lemma 8.** Under monopoly, let $c_1^m \in C_{ggq}^m$ and $c_2^m \in C_{ggq}^m$. We have $\epsilon_1 < \epsilon_2 \Rightarrow a_{c_1^m} \geq a_{c_2^m}$.

**Proof.** Let $c_1$ be the smallest coalition in $C_{ggq}^m$, and $c_2$ the largest in $C_{ggq}^m$ with sizes $a_1$ and $a_2$, and probabilities of success $p_1$ and $p_2$ respectively, for a given $q$. To prove the claim, if suffices to show that $a_1 \geq a_2$. Suppose not. Because $c_1 \in C_{ggq}^m$ and $c_2 \in C_{ggq}^m$, we have $u^m(c_2, g, q, \epsilon_1) - u^m(c_1, g, q, \epsilon_1) \leq 0$ and $u^m(c_2, g, q, \epsilon_2) - u^m(c_1, g, q, \epsilon_2) \geq 0$. We have $u^m(c_2, g, q, \epsilon) - u^m(c_1, g, q, \epsilon) = (p_2 - p_1) - (a_2 - a_1)\epsilon$. Then, $\frac{\partial}{\partial q} [u^m(c_2, g, q) - u^m(c_1, g, q)] = a_1 - a_2 < 0$, since $a_1 < a_2$. Since $u^m(c_2, g, q, \epsilon_1) - u^m(c_1, g, q, \epsilon_1) \leq 0$, then $u^m(c_2, g, q, \epsilon_2) - u^m(c_1, g, q, \epsilon_2) < 0$, a contradiction.

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### A.3.1 Robustness of findings under monopoly

Here, I prove that our findings under equal-sharing travel to monopoly. Again, this subsection only considers equilibria that satisfy deference (see definition 4). Similar to equal-sharing, and from lemma 7, let $v^m(a, w, q, \epsilon) = p(a, w, q) - a\epsilon$ be the valuation of a coalition under monopoly. I make the following assumptions, that are analogous to assumptions 1 and 2.

**Assumption 3.** Suppose $v^m(a_1, w_1, q, \epsilon) = v^m(a_2, w_2, q, \epsilon)$ for some $a_1 \leq a_2$, $w_1, w_2 \in [1, N]$, $q \in (0, 1)$, $\epsilon \in (0, 1)$. Then $\frac{\partial v^m(a_2, w_2, q)}{\partial q} \geq \frac{\partial v^m(a_1, w_1, q)}{\partial q} < 1$ for any $q \in (0, 1)$.

**Assumption 4.** $p$ is such that $v^m$ is quasi-concave in $a$ and is either monotonic in $a$ or satisfies $\frac{\partial v^m(a, w, q, \epsilon)}{\partial w} > v^m(a^*, w, q, \epsilon) - \max\{v^m(1, w, q, \epsilon), v^m(N, w, q, \epsilon)\}$, where $a^* \in \arg\max_{a \in [1, N]} v^m(a, w, q, \epsilon)$.

One proposition does not prove in the exact same way:

**Proof of proposition 7** This proposition proves as under equal-sharing, with the exception that equation 2 becomes:

$$\nabla_x u_2 - u_1 = \frac{\partial u_2 - u_1}{\partial \epsilon} x_\epsilon + \frac{\partial u_2 - u_1}{\partial q} x_q = \left(\frac{\partial p_1}{\partial q} - \frac{\partial p_2}{\partial q}\right) x_q - (a_{c_2} - a_{c_1}) x_\epsilon$$

As previously, if the equation $\nabla_x u_2 - u_1 = 0$ has a finite number of solutions in $x$, then $U$ has measure 0. Assumption 3 implies that $\frac{\partial p_1}{\partial q} - \frac{\partial p_2}{\partial q} \neq 0$. If $a_{c_2} = a_{c_1}$, then the setup is similar to the case of equal-sharing. Otherwise, note that the problem is equivalent to solving for $\theta$ in $a \cos \theta + b \sin \theta = 0$, with $a = \frac{\partial p_1}{\partial q} - \frac{\partial p_2}{\partial q}$, $b = a_{c_2} - a_{c_1}$, and $\theta \in [0, 2\pi]$, which has at most four solutions.

Lemma 2 and propositions 2, 3, 4 and 5 prove as in equal-sharing, but consider $C_{ggq}^m$ instead of $C_{ggq}^e$, $u^m(c, g, q, \epsilon)$ instead of $u(c, g, q)$, and $\tilde{\epsilon}^m(g, q)$ instead of $\tilde{\epsilon}_s(g, q)$.
A.4 Extension: detection as a function of the scale of corruption

A.4.1 Results

The model assumes that the probability of detection is independent of the scale 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.

In this extension, I assume again a constant sunk cost: \( \epsilon_i = \epsilon \) for all \( i \), and make the probability of success dependent on \( \epsilon \) by amending our original probability of success as follows:

\[
p(a, w, q, \epsilon) = \rho(\epsilon)p(a, w, q),
\]

where \( \rho : (0, 1) \rightarrow (0, 1) \) is twice-differentiable and rescales the probability of success according to \( \epsilon \). Recall that \( 1 - \epsilon \) measures the scale of corruption, with large values of \( \epsilon \) indicating petty corruption. Assuming that \( \rho'(\cdot) > 0 \) makes grand corruption more likely to be detected, while assuming \( \rho'(\cdot) \leq 0 \) makes petty corruption more likely to be detected. Note that this formulation implicitly assumes that the effect of scale 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 coalition? The utility function now writes:

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

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 scale on detection is independent of the composition of the coalition, the seed’s favorite coalition stays the same for any \( \epsilon \). When grand corruption is less likely to be detected than petty corruption, then that coalition becomes increasingly beneficial as \( \epsilon \) decreases. As such, the seed accepts all projects above some threshold in scale. 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 seed accepts all projects above some threshold in scale. 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 scale.

A.4.2 Proofs

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

Lemma 1 becomes the following:

**Lemma 9** (Threshold strategy, extension). Consider \( \epsilon, \epsilon' \in (0, 1) \). We have \( C_{g q} = \arg \max_{c \in C_g} u_s(c, g, q, \epsilon) = \arg \max_{c \in C_g} u_s(c, g, q, \epsilon') \). There is a threshold \( \epsilon_s(g, q) \in (0, 1) \) such that if \( \rho'(\epsilon) \leq \frac{a_{c, g, q, \epsilon} + 1}{p(c, g, q, \epsilon)} \) for any \( c \in C, q \in (0, 1), \epsilon \in (0, 1) \), then all equilibria have the same outcome that \( s \) rejects the bribe if \( \epsilon > \epsilon_s(g, q) \). Otherwise, \( s \) accepts it, and some coalition \( c^* \in C^* \) is realized. If \( \rho'(\epsilon) > \frac{a_{c, g, q, \epsilon} + 1}{p(c, g, q, \epsilon)} \) for any \( c, g, q, \epsilon \), then all equilibria have the same outcome that \( s \) rejects the bribe if \( \epsilon < u(c^*, g, q, \epsilon) \) for some \( c^* \in C^* \). Otherwise, \( s \) accepts it, and some coalition \( c^* \in C^* \) is realized.

**Proof of lemma 9.** Let’s first show that \( \arg \max_{c \in C_g} u_s(c, g, q, \epsilon) = \arg \max_{c \in C_g} u_s(c, g, q, \epsilon') \). Consider \( c, c' \in C_g \) such that \( u_s(c, g, q, \epsilon) \leq u_s(c', g, q, \epsilon) \). This implies \( \frac{p(a_{c, w, c', q, \epsilon})}{a_{c, w}} \leq \frac{p(a_{c', w, c', q, \epsilon})}{a_{c', w}} \). 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 \( \frac{\partial u_s}{\partial \epsilon} = \frac{\rho'(\epsilon)p(c, g, q, \epsilon)}{a_c} - 1 \). So \( \frac{\partial u_s}{\partial \epsilon} \geq 0 \iff \rho'(\epsilon) \geq \frac{p(c, g, q, \epsilon)}{a_c} \).

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

If \( u_s(c^*, g, q, \epsilon) > 0 \), we show as in lemma 1 that \( s \) accepts the bribe and \( c^* \) is an equilibrium outcome.

Proposition 3 becomes:

**Proposition 9.** Let \( c_1^* \in C_{g q_1}, c_1^* \in C_{g q_2} \). If \( \rho'(\epsilon) \leq \frac{a_{c, g, q, \epsilon} + 1}{p(c, g, q, \epsilon)} \) for any \( c, g, q, \epsilon \), we have \( q_1 < q_2 \Rightarrow \epsilon(g, q_1) \geq \epsilon(g, q_2) \). If \( \rho'(\epsilon) > \frac{a_{c, g, q, \epsilon} + 1}{p(c, g, q, \epsilon)} \) for any \( c, g, q, \epsilon \), we have \( q_1 < q_2 \Rightarrow \epsilon(g, q_1) \leq \epsilon(g, q_2) \).

**Proof of proposition 9.** From lemma 3, \( \epsilon(g, q) \) 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 \( u(c_1, g, q_1, \epsilon) \geq u(c_2, g, q_1, \epsilon) \). 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, \( \epsilon(g, q_1) \geq (\leq) \epsilon(g, q_2) \).

Proposition 4 becomes:
Proposition 10. Suppose \( g' = g + i \rightarrow j \). Then if \( \rho'(\epsilon) \leq (\geq) \frac{ac}{p(c,g,q,\epsilon)} \) for any \( c, g, q, \epsilon \), we have \( \hat{\epsilon}(g', q) \leq (\geq) \hat{\epsilon}(g, q) \). For the inequality to hold strictly for some \( q \in (0, 1) \), it must \( j \in c \), and \( i \notin c \cup W_{cg} \) for some minimal coalition \( c \in M_g \) and all coalitions essentially equal to \( c \).

Proof of proposition 10. By lemma 3 we have \( C_{g'} = C_g \) and for any \( c \in C_g \), \( w_{cg} \leq w_{cg'} \leq w_{cg} + 1 \). This implies \( u(c, g', q, \epsilon) \leq u(c, g, q, \epsilon) \). Using lemma 9 gives that if \( \rho'(\epsilon) \leq (\geq) \frac{ac}{p(c,g,q,\epsilon)} \) for any \( c, g, q, \epsilon \), then \( \hat{\epsilon}(g', q) \leq (\geq) \hat{\epsilon}(g, q) \). We prove the rest of the proposition as in the original proof.

Proposition 11. Suppose \( g' = g + ij \). Then if \( \rho'(\epsilon) \leq (\geq) \frac{ac}{p(c,g,q,\epsilon)} \) for any \( c, g, q, \epsilon \), we have \( \hat{\epsilon}(g', q) \geq (\leq) \hat{\epsilon}(g, q) \). 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 11. By lemma 3 we have that for any \( c \in C_g \) \( u(c, g, q) = u(c, g', q) \), which implies that \( \hat{\epsilon}(g', q) \geq (\leq) \hat{\epsilon}(g, q) \) if \( \rho'(\epsilon) \leq (\geq) \frac{ac}{p(c,g,q,\epsilon)} \) for any \( c, g, q, \epsilon \). The second part of the proposition proves as in proposition 3 if \( \rho'(\epsilon) \leq (\geq) \frac{ac}{p(c,g,q,\epsilon)} \) for any \( c, g, q, \epsilon \). If \( \rho'(\epsilon) \geq (\leq) \frac{ac}{p(c,g,q,\epsilon)} \) for any \( c, g, q, \epsilon \), then suppose that there is \( q \in (0, 1) \) such that \( \hat{\epsilon}(g', q) \leq (\geq) \hat{\epsilon}(g, q) \) and use the same argument as in proposition 5.

B Simulations

Simulations are computationally intensive, for finding the minimal coalitions of a graph of size \( N \) requires enumerating its connected subgraphs, which is \( O(2^N) \). As such, I consider 1000 small graphs \( (N = 16) \), and collapse the multiplex graph into into a simple undirected graph: \( ij \in G_c \iff i \rightarrow j, j \rightarrow i \in G_m \). I use Sah et al. (2014)’s algorithm to generate connected graphs with a specified pattern of communities, while maintaining a structure that least departs from that of a random graph. I sample graphs with a density of .26 with two equal-sized communities, and with modularity (Newman, 2006) ranging from 0, where ties are distributed evenly within and across communities to .4, where ties fall more within communities. I examine expected corruption for a randomly chosen seed. For seed \( i \) on graph \( g \), expected corruption corresponds to I examine the quantity \( AUC_g = \mathbb{E}(AUC_{cg}) \), where higher values of \( AUC_g \) denote more corruption. Simulations assume equal-sharing and use the following probability of success:

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

This function has several properties that make it appealing. It separates social structure from the monitoring technology: \( p(0,0,q) = 1 \). It is linear in \( a \) and \( w \). Success is certain when the whole organization is corrupt \( (p(N,0,q) = 1) \). Symmetrically, detection is certain when the organization is a witness \( (p(0,N,q) = 0) \). I show at the end of the section that \( p \) satisfies assumptions 1 and 2.

Figure 10 shows the results. More modular graphs are more corrupt (left panel) because communities are more enclosed. As modularity decreases, communities disenclave: cross-community
Figure 10: 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 different communities. Lighter nodes are more corrupt.

ties reduce modularity and make them more exposed to each other, hence strictly reducing corruption. The right panel compares low-modularity, low-corruption graph 1 to high-modularity, high-corruption graph 2. Comparing within graphs, lower-degree nodes are more corrupt, confirming that more isolated nodes are more corrupt. Comparing across graphs, 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.

$p$ satisfies assumption \[\PageIndex{2}.\] We have \(\frac{\partial p(a_{2}, w_{2}, q)}{\partial q}/\frac{\partial p(a_{1}, w_{1}, q)}{\partial q} = \frac{N - (a_{2} + w_{2})}{N - (a_{1} + w_{1})}\). This implies that \(\frac{\partial p(a_{2}, w_{2}, q)}{\partial q}/\frac{\partial p(a_{1}, w_{1}, q)}{\partial q} = \frac{a_{2}}{a_{1}} \iff (N - w_{1})a_{2} - (N - w_{2})a_{1} \geq 0\). Note that since \(\frac{\partial v}{\partial q} < 0\), \(a_{1} = a_{2}\) implies that \(v(a_{1}, w_{1}, q) \neq 0\) for any \(q \in (0, 1)\). Suppose \(a_{1} < a_{2}\). We have \(v(a_{2}, w_{2}, q) - v(a_{1}, w_{1}, q) \propto (a_{2} - a_{1}) - (1 - q)(N - w_{1})a_{2} - (N - w_{2})a_{1}\). Since \((a_{2} - a_{1})\) and \((1 - q) > 0\), \(v(a_{2}, w_{2}, q) - v(a_{1}, w_{1}, q) = 0\) requires \((N - w_{1})a_{2} - (N - w_{2})a_{1} > 0\).

$p$ satisfies assumption \[\PageIndex{3}.\] We have \(\frac{\partial v}{\partial a_{c}} \propto (N - w_{c})q - (N - 1 - w_{c})q\). That is, \(\frac{\partial v}{\partial a_{c}} \geq 0 \iff q \geq 1 - \frac{1}{N - w_{c}}\). So \(v\) is monotonic in \(a_{c}\).

C Experimental protocol

I held 17 sessions of 16 respondents. Figure \[\PageIndex{11}\] details the experimental protocol of a session. 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. The rent
amounted to about $1 and was symbolized by 12 red cards. The sunk cost, called the “salary” in the experiment, was represented by 2 or 4 blue cards held by the subjects.

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. I rescale the probability of success used in the experiment (Equation 8) by a factor of 0.83: $\tilde{p}(a,w,q) = 0.83p(a,w,q)$. Without rescaling, the probability of success is 1 for the grand coalition. The rescaling prevents this outcome from being focal.

In order to mimic the interpersonal interactions that arise in organizations, the game used face-to-face interactions. However, to implement take-it-or-leave-it, sequential offers, the enumerator would mediate communication around offers, asking subject $i$ if she wished to offer some amount to $j$, then asking $j$ whether she accepted $i$’s transfer, and if so, have $j$ give up her salary. Cheap talk was otherwise allowed. 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 11. Within each block, two rounds include the irrelevant tie, and two do not. The ordering was designed such that the same two subjects were always assigned to be the seed with the irrelevant tie, while the other two never did. After playing twelve rounds, subjects took a post-experiment survey. They were paid their earnings, which amounted to about daily minimum wage ($2.6 average gain and $5 show-up fee).

In this protocol, 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. To discourage adverse learning and pooling effects, 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. I randomized the order of the games within block, and randomly permuted the first two blocks (baseline and hard). I kept the exposing tie block last, because it was more cognitively demanding. I show in section D.1 that learning effects are insignificant and mixed, and that there are no pooling effects.
Figure 11: **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 irrelevant tie, and two treatments without.

Figure 12: **Average comprehension over time**. 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.
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. For all but the last question, the enumerator would first record the subject’s answer, then correct her publicly so all could learn from her mistake. During a session, mean comprehension was above 80 percent, and reached 94 percent by the end of a session (Figure 12).

C.1 Equilibrium outcomes

I solve the game using backward induction in all treatment conditions, and for all three division rules. Note that the experiment rescaled the bribe to 12 credits, and the probability of success by a factor of .83. Figure 13 show equilibrium in the unscaled model.

Figure 13: Equilibrium outcomes in the unscaled model in all treatments. The figures represent the equilibrium coalition in each region of the ($\epsilon, q$) space. The empty set ($\emptyset$) indicates that the seed rejects the bribe. Points $B, H, E$ correspond to the parameter values in the baseline, hard and exposing tie treatments respectively. The subscript indicates grand ($g$) and petty corruption ($p$).
C.2 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.

C.3 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-experiment 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.

C.4 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
Partners in crime?  

Romain Ferrali

game.

C.5 Prompts and material

Table 3: 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.

Figure 14: Example comprehension question under grand corruption. 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?” [Answer: 0]

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.
D Additional experimental results

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<th>N accomplices</th>
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<td>(3)</td>
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<td>(.023)</td>
<td>(.101)</td>
</tr>
<tr>
<td>Observations</td>
<td>808</td>
<td>808</td>
<td>732</td>
</tr>
<tr>
<td>R²</td>
<td>.158</td>
<td>.163</td>
<td>.214</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>−324.154</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: *p<0.05; **p<0.01; ***p<0.001

Table 4: Models used in the main text. Standard errors are in parentheses, and errors are clustered at the group level. Models 1, 2, 4 use use OLS, and all their variables are binary. Model 3 is a logistic generalized additive model (see footnote 16 in the main text for details about estimation). The variable history ranges from 2 to 4. Models 1 and 2 are used to construct Figure 4. Model 3 is used to construct figure 9 panel b. Model 4 is used to construct figure 5.

D.1 Learning

As mentioned in section C, 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 11 in the main text). 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 15 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 3.3). 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 15 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.

Figure 15: **Learning effects.** Standard errors are in parentheses, and errors are clustered at the group level. 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. Bars indicate 95% confidence intervals with errors clustered at the group-level. There is little evidence for learning and pooling effects: behavior never differ significantly between the late and early blocks. The models used to construct this figure are reported in tables 5 and 6.
### Table 5: Learning effects.
Standard errors are in parentheses, and errors are clustered at the group level. All models use OLS, and all variables are binary. Most learning effects are not statistically different from zero. These models are used to construct Figure 15.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Accept</th>
<th>Irrelevant</th>
<th>N accomplices</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline (1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Hard, Grand</td>
<td>-.156* (.073)</td>
<td>-.156* (.073)</td>
<td>1.250*** (.190)</td>
</tr>
<tr>
<td>Baseline, Petty</td>
<td>-.052 (.093)</td>
<td>-.052 (.093)</td>
<td>-.211 (.118)</td>
</tr>
<tr>
<td>Hard, Petty</td>
<td>-.375** (.134)</td>
<td>-.375** (.134)</td>
<td>.314 (.214)</td>
</tr>
<tr>
<td>With irrelevant tie</td>
<td>-.051 (.034)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Late</td>
<td>-.000 (.049)</td>
<td>0.000 (.053)</td>
<td>.460* (.188)</td>
</tr>
<tr>
<td>Late × (Hard, Grand)</td>
<td>.135 (.106)</td>
<td>.135 (.106)</td>
<td>-.455 (.334)</td>
</tr>
<tr>
<td>Late × (Control, Petty)</td>
<td>-.073 (.122)</td>
<td>-.073 (.122)</td>
<td>-.382 (.237)</td>
</tr>
<tr>
<td>Late × (Hard, Petty)</td>
<td>-.115 (.179)</td>
<td>-.115 (.180)</td>
<td>-.707* (.325)</td>
</tr>
<tr>
<td>Late × With irrelevant tie</td>
<td>-.000 (.045)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>.906*** (.033)</td>
<td>.932*** (.032)</td>
<td>1.333*** (.091)</td>
</tr>
</tbody>
</table>

| Observations | 544 | 544 | 434 |
| R²           | .144 | .148 | .275 |

Note: *p<0.05; **p<0.01; ***p<0.001

### Table 6: Pooling effects.
Standard errors are in parentheses, and errors are clustered at the group level. The model uses Analysis is subsetted to the last block. Late is a dummy variable equal to 1 for the last two games, and 0 otherwise. This model is used to construct Figure 15.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Pr(accept)</th>
</tr>
</thead>
<tbody>
<tr>
<td>bₐ - bₐᵢ × Late</td>
<td>.017 (.046)</td>
</tr>
<tr>
<td>Constant</td>
<td>.834*** (.028)</td>
</tr>
</tbody>
</table>

| Observations | 339 |
| R²           | .134 |

Note: *p<0.05; **p<0.01; ***p<0.001
D.2 Individual-level characteristics

This section shows that individual-level characteristics have little effect. I first show that group- and individual-level heterogeneity have little influence, and that group-level heterogeneity is larger than individual-level heterogeneity. I re-estimate our quantities of interest, using linear mixed models with individual-level random effects, group-level effects, and both. Figure 16 shows that the quantities of interest are virtually unchanged. Table D.2 shows that random effect specifications fit the data marginally better than a specification without pooling, suggesting that there is little heterogeneity across groups, or across groups. Furthermore, individual-level effects add virtually no predictive power. This shows that individual-level effects are very small compared to group-level effects, and further justifies our decision to cluster errors at the group level.

![Graph showing effects on frequency and scope](image)

Figure 16: Random effect specifications. The specifications without random effects is estimated using a Gaussian GLM with errors clustered at the group-level; RE specifications use linear mixed models. Bars indicate 95% confidence intervals. The main quantities of interest are robust to adding random effects. The models used to construct this figure are reported in Table D.2

Second, I show that although they have very different characteristics, students and employees have very similar behavior. Table 2 in the main paper showed that employees are poorer, less educated, more rural, less altruistic, and more extroverted than students. Yet, their behavior
is very similar in the lab. I reestimate the quantities of interest separately for students and employees (Figure 17): the predictions for students are more noisy because of the smaller sample size, but they largely overlap with that of employees.

Figure 17: Students vs. employees. “All” reports the estimates from the main specification (Table 4). The specifications for students and employees are estimated using OLS with bootstrap errors clustered at the group-level. Bars indicate 95% confidence intervals. Students and employees have similar behavior. The models used to construct this figure are reported in Table 8.
<table>
<thead>
<tr>
<th></th>
<th>Pr(accept)</th>
<th>N accomplices</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline</td>
<td>Baseline</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Hard, Grand</td>
<td>−.089*</td>
<td>−.089**</td>
</tr>
<tr>
<td></td>
<td>(.044)</td>
<td>(.036)</td>
</tr>
<tr>
<td>Exposing, Grand</td>
<td>.056*</td>
<td>.056</td>
</tr>
<tr>
<td></td>
<td>(.025)</td>
<td>(.036)</td>
</tr>
<tr>
<td>Baseline, Petty</td>
<td>−.081</td>
<td>−.081</td>
</tr>
<tr>
<td></td>
<td>(.064)</td>
<td>(.048)</td>
</tr>
<tr>
<td>Exposing, Petty</td>
<td>−.306***</td>
<td>−.306***</td>
</tr>
<tr>
<td></td>
<td>(.088)</td>
<td>(.048)</td>
</tr>
<tr>
<td>With irrelevant tie</td>
<td>−.052*</td>
<td>−.052*</td>
</tr>
<tr>
<td>Constant</td>
<td>.906***</td>
<td>.906***</td>
</tr>
<tr>
<td></td>
<td>(.024)</td>
<td>(.026)</td>
</tr>
<tr>
<td>Indiv. RE</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Group RE</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Observations</td>
<td>808</td>
<td>808</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>637.177</td>
<td>668.463</td>
</tr>
<tr>
<td>Note:</td>
<td>*p&lt;0.05; **p&lt;0.01; ***p&lt;0.001</td>
<td></td>
</tr>
</tbody>
</table>

Table 7: **Random effect specifications.** Standard errors are in parentheses. The specifications without random effects is estimated using a Gaussian GLM with errors clustered at the group-level; RE specifications use linear mixed models. All variables are binary. Models have identical point estimates. Random effects have little impact on model fit (AIC), but group effects reduce it more than individual effects. These models are used to construct Figure 16.
### Table 8: Students vs. employees.

Standard errors are in parentheses, and errors are clustered at the group level. All models use OLS, and all variables are binary. Effects for students and employees are comparable. These models are used to construct Figure 17.

<table>
<thead>
<tr>
<th></th>
<th>Pr(accept)</th>
<th>N accomplices</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline</td>
<td>Baseline</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Hard, Grand</td>
<td>−.172</td>
<td>−.074</td>
</tr>
<tr>
<td></td>
<td>(.103)</td>
<td>(.042)</td>
</tr>
<tr>
<td>Exposing, Grand</td>
<td>−.034</td>
<td>.072**</td>
</tr>
<tr>
<td></td>
<td>(.058)</td>
<td>(.027)</td>
</tr>
<tr>
<td>Baseline, Petty</td>
<td>−.142</td>
<td>−.070</td>
</tr>
<tr>
<td></td>
<td>(.102)</td>
<td>(.064)</td>
</tr>
<tr>
<td>Hard, Petty</td>
<td>−.377***</td>
<td>−.526***</td>
</tr>
<tr>
<td></td>
<td>(.098)</td>
<td>(.099)</td>
</tr>
<tr>
<td>Exposing, Petty</td>
<td>−.348**</td>
<td>−.309**</td>
</tr>
<tr>
<td></td>
<td>(.107)</td>
<td>(.098)</td>
</tr>
<tr>
<td>With irrelevant tie</td>
<td>−.075</td>
<td>−.044</td>
</tr>
<tr>
<td></td>
<td>(.056)</td>
<td>(.025)</td>
</tr>
<tr>
<td>Constant</td>
<td>.966***</td>
<td>.896***</td>
</tr>
<tr>
<td></td>
<td>(.033)</td>
<td>(.029)</td>
</tr>
</tbody>
</table>

**Note:** *p<0.05; **p<0.01; ***p<0.001

### E Additional supportive evidence

This section presents preliminary evidence supporting an implication of proposition 3: as institutional strength increases, corruption has a broader scope. Using cross-country comparisons and a comparison of 110 cases of corruption in India and the US, I show that controlling for the scale of corruption, instances of corruption in the US involve more accomplices than in India, and that accomplices in corruption schemes are better-paid in developed countries.

#### E.1 Cross-country comparisons

Cross-country comparisons use the 2017 Quality of Government dataset (QoG) and its related 2015 Expert Survey (QoGEx, Dahlström et al. 2015), to show that accomplices are better paid in developed countries (Figure 18). Institutional strength captures the extent to which formal institutions allow detecting and punishing corruption. I proxy for this concept using a broad indicator for development: GDP per capita in PPP $ 2011, from the World Development Indicators (World Bank, 2016). I construct the share of the rent of accomplices from the following question in QoGEx: “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
Partners in crime? Romain Ferrali

variable amounts to \((b + d)/(b + c + d + e)\).

\[
\text{log(GDP p/c), PPP $ 2011}
\]

\[
\text{Accomplices' share}
\]

\[
1000 
2000 
5000 
20000 
50000
\]

Figure 18: Cross-country comparisons, accomplices’ share vs. GDP p/c. Errors are robust. The shaded area represents the 95% confidence interval. Accomplices pocket higher shares of the rent in more developed countries. The model used for estimation is reported in table 9.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of accomplices</td>
</tr>
<tr>
<td>log(GDP p/c), $ PPP 2011</td>
</tr>
<tr>
<td>(1.805)</td>
</tr>
<tr>
<td>I(closed^2)</td>
</tr>
<tr>
<td>(0.189)</td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td>(4.236)</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>(R^2)</td>
</tr>
</tbody>
</table>

Table 9: Model to construct figure 18. The model is estimated using OLS. Errors are robust.

E.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. While the latter measures the scope of corruption, I normalize the amount stolen by Gross National Income (GNI) per capita to obtain a measure of the scale of corruption indicating its profitability relative to average income. 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 has stronger institutions 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). This data has several pitfalls. Most importantly, 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 10 provides a few descriptive statistics, and table 11 shows the finding: controlling for scale, corruption has a broader scope in the US than in India.

<table>
<thead>
<tr>
<th></th>
<th>India</th>
<th>USA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median amount stolen, fraction of GNI p/c</td>
<td>0.22</td>
<td>1.71</td>
</tr>
<tr>
<td>Mean N accomplices</td>
<td>3.02</td>
<td>10.79</td>
</tr>
<tr>
<td>Percent cases with strong ties</td>
<td>19.23</td>
<td>20.93</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 10: 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>0.197***</td>
<td>0.234***</td>
</tr>
<tr>
<td>(0.031)</td>
<td>(0.051)</td>
<td></td>
</tr>
<tr>
<td>USA</td>
<td>1.021***</td>
<td>1.087***</td>
</tr>
<tr>
<td>(0.201)</td>
<td>(0.305)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.317</td>
<td>-0.408</td>
</tr>
<tr>
<td>(0.172)</td>
<td>(0.229)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>71</td>
<td>71</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-123.553</td>
<td>-105.320</td>
</tr>
<tr>
<td>$\theta$</td>
<td>1.438** (0.497)</td>
<td></td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>253.105</td>
<td>216.640</td>
</tr>
</tbody>
</table>

Table 11: Count regressions for number of accomplices. Amount is measured as a fraction of GNI p/c. Controlling for the amount stolen, corruption in the US involves more accomplices than in India.