Abstract

Corruption is a global bad that comes in many forms. It is pervasive in developing countries, and persists in developed countries, where wide-ranging corruption scandals regularly shake public opinion. This study looks at these wide-ranging scandals. It explains why we sometimes see small-scale, petty corruption, and sometimes wide-ranging scandals of grand corruption.

Because grand corruption is often a collective enterprise involving large, sophisticated conspiracies, it resists our traditional tools of analysis and policy-making: methodological individualism and institutional rules. Grand corruption resists these tools because the vast conspiracies that support it manage to subvert these very institutions and avert law-enforcement, even in countries where strong institutions impose swift and harsh punishment on corrupt acts.

This work examines corruption from the perspective of organizations. Its departure point is that corruption is “organized crime within an organization.” It proposes and tests a theory of how corruption is organized; that is, why we observe petty or grand corruption, and how this depends on the structure of the organization where corruption occurs. This approach provides a simple, easily expandable formal-theoretic framework that unifies, sharpens, and expands upon previous work.

I find that corrupt individuals have an incentive to form vast conspiracies when the help provided by additional accomplices offsets their cost in terms of resources. Organizations affect these incentives by embedding corrupt individuals into social networks. Those networks are a double-edged sword: they provide corrupt individuals with opportunities to recruit additional accomplices among close colleagues, but also expose them to the monitoring of those colleagues. Corruption persists in developed countries in the form of grand corruption supported by large conspiracies because stronger institutions make engaging into corruption costlier. Since corruption is costlier, the protection provided by additional accomplices become more desirable.
However, compensating these additional accomplices comes with higher costs that can only be borne by more profitable ventures. As such, less profitable, petty corruption disappears, leading to the survival of grand corruption alone. Testing these propositions using cross-country comparisons, a lab-in-the-field experiment conducted in Morocco, and a field study with a large Moroccan company, I find strong support for the theoretical predictions.
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To Didier and Zaky.
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“A man who has never gone to school may steal a freight car; but if he has a university education, he may steal the whole railroad.”

Theodore Roosevelt (1858 – 1919)

1

Introduction

Although we know little about corruption, one thing we know for certain is that it is bad. Corruption decreases economic growth (Mauro 1995), and bribery alone costs about two percent of global GDP (International Monetary Fund, 2016). It creates political instability, by undermining the legitimacy and capacity of the government (Rothstein 2011; Rose-Ackerman and Palifka 2016). It is pervasive in developing countries, and persists in developed countries, where wide-ranging corruption scandals regularly shake public opinion.

This study looks at these wide-ranging scandals. It explains why we sometimes see small-scale, petty corruption, and sometimes wide-ranging scandals of grand cor-
ruption. As we will see, grand corruption resists our traditional tools of analysis and policy-making: methodological individualism and institutional rules. As such, this work examines corruption from the perspective of organizations. Its departure point is that corruption is a form of organized crime that occurs within an organization. It proposes and tests a theory of how corruption is organized; that is, why we observe petty or grand corruption, and how this depends on the structure of the organization where corruption occurs.

1.1 Of freight cars and railroads

Corruption, “the abuse of entrusted power for private gain” (Transparency International), comes in many forms, including bribery, embezzlement, fraud, extortion, and favoritism (Andvig et al. 2002). When Theodore Roosevelt says that corruption may target freight cars or railroads, he distinguishes between less profitable acts of petty corruption and more profitable acts of grand corruption. Grand corruption is more profitable than petty corruption; by definition, it is more harmful than petty corruption. Because grand corruption is often collective, it is also substantially harder to analyze and combat.

Grand corruption is harder to study, because it is often a collective enterprise. Extending Roosevelt’s metaphor, stealing a freight car is a relatively simple crime, that can be achieved by a few individuals. Conversely, stealing a railroad is a more complicated enterprise, requiring the cooperation of many. In other words, while petty corruption usually takes the form of crimes involving few individuals, such as a police patrol pocketing a traffic bribe, grand corruption typically involves larger, more sophisticated conspiracies, often with connections between politicians, bureaucrats, business interests, and mafias. Considering Chicago in the Roaring Twenties, Landesco (1929) documents these connections by examining funerals. For instance,
the funerals of James "Big Jim" Colosimo, a major figure of the Chicago mob, were attended by three judges, nine aldermen, an assistant state’s attorney, two congressmen, and a state senator. Collective corruption is harder to study, for the researcher has to understand not only how a corrupt individual interacts with law enforcement, but also how she interacts with other corrupt individuals.

Grand corruption is also harder to combat, because the large conspiracies it features usually cooperate to thwart law enforcement. While petty corruption typically enjoy few protections from law enforcement, grand corruption is often designed with the intention of thwarting law enforcement. Grand corruption often manages to appear legal and avoid prosecution by including only but a few strategic individuals in the conspiracy. Colosimo’s contacts in the municipal council were facilitating access to a variety of licenses, while his contacts in the judiciary and at the Department of Justice were protecting his gang from prosecution.

Because grand corruption is harder to prevent and detect, it is more harmful than petty corruption, and plagues developing and developed countries alike. Corruption is pervasive in developing countries, both in the form of petty corruption such as traffic bribes, and grand corruption, like the multi-million dollars procurement scandal that Wrong (2009) documents in Kenya under President Kibaki. Although they have largely eliminated petty corruption, developed countries still witness grand corruption (Kaufmann 2004). As recently as during the 2017 French presidential campaign, François Fillon, the candidate of the right-wing party Les Républicains, was put under investigation for embezzlement and influence peddling.

1.2 From rules to organizations

Since the neo-institutionalist turn (North 1991), studying and changing the “rules of the game” that governs corrupt interactions has come to occupy the forefront of
the agenda for political scientists, economists, and policy-makers. Existing work on corruption gives a nuanced picture of how a variety of institutions, such as compensation policies (Besley and McLaren, 1993) or monitoring technologies (Becker and Stigler, 1974; Banerjee, Hanna and Mullainathan, 2013) may affect corruption. Similarly, governments in developing countries often resort to large scale institutional change in order to tackle corruption. These institutional reforms sometimes prove to be successful: Brazil’s program of municipal audits, started in 2003, successfully reduced corruption by exposing the corrupt practices of politicians to voters, making them more accountable (Ferraz and Finan, 2008, 2011a).

While the dominant institutional approach is very good for understanding and designing effective policies against petty corruption, it is not as well equipped for tackling grand corruption. This rich perspective on institutions comes at the expense of an “under-socialized” (Granovetter, 1985) view of the corrupt man. As we will see, standard approaches to corruption usually consider atomized agents. By sidestepping the social, collective dimension of corruption, the institutional approach overlooks the large conspiracies underpinning grand corruption, and their capacity to subvert those very institutions. This leaves us in the uncomfortable position of not being able to explain the most egregious forms of corruption. Ironically, Brazil, the country that implemented several model institutions to fight pettier forms of corruption, such as the above-mentioned municipal audits, or the OECD Anti-Bribery Convention of 1997, also fell prey to a corruption scandal large enough to lead to the impeachment of Dilma Roussef in 2015.

Given the limitations of the institutional approach, I look at grand corruption from the perspective of organizations for two reasons. First, since grand corruption is often collective, understanding why grand corruption emerges and persists requires

\[^1\text{I discuss this in more details in chapter 2.}\]
considering how corruption is organized; that is, why individual criminals sometimes act alone, and sometimes form vast conspiracies.

Second, just as institutions, organizations affect behavior; they are an actionable policy instrument, and policy-makers have taken notice. Organizational reforms are a relatively common, if understudied, response to corruption. For instance, the creation of one-stop shops for public service delivery has proven increasingly popular, with examples in Ghana (Hausman 2011), Liberia (Friedman 2012), Brazil (Majeed 2014), or Senegal (Gainer, Chan and Skoet 2016). One-stop shops regroup previously disparate functions into a single organizational unit. They are meant to reduce corruption by streamlining processes and limiting the number of transactions between citizens and service-providers. These reforms are, however, seldom evaluated.

Studying corruption and organizations is challenging. Measuring petty corruption is difficult (Olken and Pande 2011). Measuring grand corruption is more difficult, for it entails larger networks, that are better able to avoid detection (Sparrow 1991). Studying how organizations affect corruption is complicated because, like institutions, organizations vary in a myriad of ways, which makes evaluating these reforms difficult. Although some policies, such as one-stop shops, are relatively standardized, most organizational reforms are not. Many reforms introduce large changes to the organizational chart that are hard to compare across organizations for they are highly contingent on idiosyncrasies of the existing organization. For instance, as part of a decade-long reform process, Morocco’s National Social Security Fund (CNSS) underwent substantial regionalization, and local field offices specialized in handling commercial functions, with the headquarters handling administrative functions (Fer-rali 2013).

Given these difficulties, it is unsurprising that we know little about corruption in organizations. Although organizational approaches to the state and the firm are old research traditions in political science (Weber 1948, Crozier 1964, Migdal 1988, Moe...
Carpenter, 2001), and in economics (Coase, 1937; Williamson, 1985; Gibbons and Roberts, 2013), the two disciplines have done little to explore the implications for corruption, save for notable exceptions (Gambetta, 1996; Vannucci and Della Porta, 2013; Carpenter and Moss, 2013; Patacchini and Zenou, 2008; Baccara and Bar-Isaac, 2009). As such, this review also includes work from a wide array of disciplines; in particular, ethnographic studies of corruption cases, sociology of deviance, criminology of organized and white-collar crime, and management. Existing work falls into two broad categories, depending on whether they consider how corruption is organized, or how organizations affect corruption. Lacking the consistency of an integrated framework, they both yield important, albeit incomplete insights.

One approach to corruption and organizations studies organized crime: how corrupt individuals, and other kinds of criminals—e.g., mafias, gangs, or terrorist cells—cooperate. While forty years ago, Shapiro (1980) could say that “we [knew] a great deal about criminals [...] but very little about the activity itself,” this is much less true today. On corruption specifically, numerous ethnographies document particular instances of grand corruption (Wade, 1982; Vaughn, 1983; Baker and Faulkner, 1993; Bako-Arifari, 2001). Theoretical work highlights that organized crime differs from other kinds of organizations because it is illegal and must be kept secret (Raab and Milward, 2003). Secrecy imposes important transaction costs to cooperation among criminals: criminals cannot use the state to enforce their contracts. To alleviate these costs, criminals have to establish trust, and resort to variety of informal mechanisms to do so (Gambetta, 1996; Vannucci and Della Porta, 2013). Additionally, secrecy forces criminals to adopt specific organizational structures that mitigate the risk of detection. The tradeoff is one between secrecy and efficiency: the organizational structures that facilitate achieving the criminal enterprise are also the ones that are more prone to detection. As such, criminals should resort to relatively sparser organi-
zational structures, such as a set of independent cells, in order to mitigate the risk of detection (Lindelauf, Borm and Hamers 2009; Baccara and Bar-Isaac 2008, 2009).

While establishing a solid set of micro-foundations for cooperation among criminals, the literature on organized crime suffers from two major shortcomings that make it less relevant for studying corruption in organizations. First, the approach ignores pre-existing organizations, and typically considers the formation of criminal networks in a vacuum. The assumption seems to be a reasonable simplification for criminal gangs and terrorist networks where, as documented for the 9/11 network (Krebs 2002), criminals often manage to hide from the outside world in the conduct of their operations. The assumption, however, is much less reasonable for corruption, which occurs within a pre-existing organization, in which hiding from colleagues seems much more difficult. Second, the approach has mixed empirical findings. While some find that criminals are relatively isolated (Aven 2015; Morselli, Giguère and Petit 2007), others have found that they are relatively more connected, presumably because they have better access to criminal opportunities (Nyblade and Reed 2012; Callen and Long 2015; Khanna, Kim and Lu 2015). Along similar lines, Bruinsma and Bernasco (2004) compare criminal networks that vary in the amount of risk they face, and finds that the densest networks are the ones that are most at risk of detection, arguably because denser networks facilitate contract enforcement.

Another approach studies how organizational structure affects corruption. In seminal work, Evans (1995) considers relationships between an organization and the rest of society. He shows that to best resist corruption, an organization should neither be “underembedded” nor “overembedded” in society. Underembedded organizations lack control from the outside world. Overembedded organizations end up captured by it. The literature on regulatory capture expands upon this agenda (Carpenter and Moss 2013). For instance, Kwak (2013) argues that close collaboration ties between the regulator and some interest group may induce the regulator to favor that group.
While this approach offers predictions as to which organizational structures are more prone to corruption, it also suffers from several shortcomings. First, because the approach typically refers to organizational structure and networks as a “metaphor” (Ward, Stovel and Sacks 2011), it is difficult to turn these claims into testable predictions. In particular, it is unclear what constitutes the boundaries of an organization, nor what defines network ties. Second, these macro-level predictions about the incidence of corruption in organizations are not grounded in the micro-foundations for cooperation among criminals pinpointed by the rest of literature. As such, it is hard to know whether the predictions made by this approach are consistent with what we know about how criminals cooperate.

Overall, work on corruption and organizations gives important but incomplete insights, because it lacks the consistency of an integrated framework. Existing work on organized crime gives robust micro-foundations for how criminals cooperate, but ignores the impact of a pre-existing organization. Existing work on how organizational structure affects corruption points out a series of features that make organizations more or less prone to corruption, but the predictions are somewhat imprecise, and not rely on the micro-foundations highlighted by the literature on organized crime.

### 1.3 Corruption as a criminal network

This study looks at corruption from the perspective of organizations. Because grand corruption is usually collective and designed to thwart formal institutions, the standard individualist, institutional approach is poorly equipped to understand and fight it. As a result, organizations are a doubly interesting starting point. Framing corruption as “organized crime in an organization” allows understanding both how the large conspiracies that often sustain grand corruption come to be, and how they are affected by the structure of the organization where the crime is occurring.
I propose a framework to understand how corrupt accomplices cooperate, and how this is affected by the structure of the organization it takes place in. Existing work on corruption in organizations offers limited insights because it either studies how criminals cooperate, or how corruption is affected by organizational structure. I integrate both perspectives into a unified framework that I test empirically.

Exposed in part I, the theory rests on a simple idea: corruption is “organized crime in an organization.” Chapter 2 lays out the micro-foundations and grounds them in the literature. Similar to other forms of organized crime, corruption is illegal and must be kept secret. Forming a large conspiracy entails a tradeoff. On the one hand, additional accomplices may extract more resources and provide additional protection against detection by closing their eyes or lying. On the other, they cost resources and may increase the amount of risk: passively, by getting caught, or actively, by reporting their peers to law-enforcement.

Corruption occurs within an organization. Organizations matter because they embed agents into a set of pre-existing social ties: authority, collaboration, or friendship. Those ties complicate the tradeoff criminal face when organizing crime. On the one hand, they deter corruption: colleagues and managers monitor corrupt behavior within the organization. On the other, corrupt individuals may take advantage of these ties to approach potential accomplices among their colleagues.

Chapter 3 explores formally the macro-implications of these micro-foundations. After reviewing existing approaches to modelling collective corruption, I formalize the idea that corruption is organized crime in an organization by considering the formation of a corrupt subnetwork on an organizational network. This setup allows considering three series of questions: within an organization, who becomes corrupt, and how much do they steal? Which organizational structures minimize corruption? How do the informal institutions that sustain cooperation among criminals and the formal institutions that govern their detection affect the incidence of corrup-
tion? Combining network analysis with formal theory is a particularly appropriate exercise, because it spells out exactly how the macro-implications follow from the micro-foundations, and because the network-analytic approach allows characterizing precisely the organizational structures that best mitigate corruption.

I find that corruption takes root in the most enclaved portions of the organization. Because they are isolated from the rest of the organization, enclaves minimize exposure to witnesses, and face lower risks of detection. Organizations have subtle effects on corruption. Increasing oversight at the margin by making the organization more connected 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. Better formal institutions reduce corruption but do not eliminate it, because accomplices adapt: petty corruption disappears because it is not profitable enough; grand corruption survives but relies on larger conspiracies, because they provide better protection. Finally, the lawless environment in which accomplices operate 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. The extent of the inefficiency depends on accomplices’ ability to strike Pareto-improving informal contracts.

The findings of part I have important implications. Findings on organizational structure suggest it would be sensible to redesign government agencies to puncture the isolation of enclaves. They also suggest that such reforms must be conducted carefully, since they may make matters worse. Findings on formal institutions provide a testable rationale for why corruption persists in developed countries in the form of grand corruption supported by large conspiracies.

Part II of this study submits the theoretical framework laid out in part I to empirical testing. Given the novelty of the framework and of its predictions, confronting
it to data is important if we are to establish a solid foundation to study corruption in organizations. This is a difficult problem. Organizational networks are typically hard to measure, and so is corruption. The availability of high-quality data on both corruption and organizational networks, as well as the availability of exogenous variation on the latter poses serious restrictions as to finding research designs that allow making causal claims on how organizational structure affects corruption. I address the problem by combining a series of tests that have either high external validity, or high internal validity.

In chapter 4, I examine cross-country patterns. This test, with relatively high external validity, but relatively lower internal validity ascertains that theoretical predictions are consistent with correlations observed in the data. I investigate correlations between country-level measures of corruption and country-level measures of the organizational structure of the bureaucracy. I also consider evidence at a finer level of aggregation and compare more than a hundred corruption cases in a developed country, the United States, and a developing country, India.

Chapters 5 and 6 consider micro-evidence from Morocco. I consider Morocco because it is a mid-income country with median levels of corruption. Considering a country in the middle of the distribution of both corruption and one of its important correlates, namely per capita income, increases our confidence that the findings travel to either tail of the distribution.

Chapter 5 considers a lab-in-the-field experiment. This test, with high internal validity, but lower external validity checks whether the micro-foundations of the theory do result in the macro-level implications predicted by the model. I introduce a minimal experimental design that allows examining empirically the relationship between corruption and organizations. The lab tests the robustness of the main theoretical predictions to behavioral factors that are assumed away in the model, while solving

\[\text{In Transparency International’s Corruption Perceptions Index 2016, Morocco is ranked 90 out of 176 countries.}\]
the measurement problems associated with studying networks and corruption. The field setting bolsters external validity. Besides holding the experiment in Morocco, I compare a subject pool of service sector employees to a subject pool of undergraduate students.

Chapter 6 turns to field evidence, and considers real cases of corruption within a large firm in Morocco. This setting combines relatively high external validity, and relatively high internal validity. Indeed, this unique setting, combining highly structured work processes and high-resolution data, allows measuring networks of interactions among colleagues and individual occurrences of corrupt behavior, and leveraging natural experiments to make causal claims. I use this opportunity to test the micro-foundations of the theory; specifically, I test whether social ties within the organization serve the dual function of deterring corrupt behavior through monitoring, and facilitating corrupt behavior by allowing corrupt employees to approach new accomplices.

In the conclusion (chapter 7), I highlight how the framework I develop in this study relates to existing work and explains some of its puzzling empirical findings. I offer policy recommendations to better detect existing corrupt individuals and to design organizations that are more resilient to corruption. Doing so, I also examine how existing policies that aim at tackling corruption through organizational reform conform to these recommendations, providing initial thoughts to guide future, more rigorous evaluations of these policies. Finally, because this framework aims at providing a foundation for studying corruption in organizations, I offer directions as to how to expand this framework to consider dimensions it is currently silent upon; in particular, the preferential ties of friendship or kinship that often permeate organizations.
Part I

Theory
The micro-foundations of corruption in organizations

Corruption may take many different forms. Like other forms of organized crime, such as terrorism, gangs of mafias, corruption varies in the extent to which it is organized. On one end of the spectrum, we have individual acts of petty corruption; for instance, a lone policeman pocketing a traffic bribe. On the other end, we have large conspiracies engaging in more profitable acts of grand corruption, like the wide-ranging corruption scandal that led, in 2016, to the impeachment of Dilma Rousseff.
in Brazil. Yet, being “the abuse of entrusted power for private gain,” corruption differs from other forms of organized crime in that it takes place within a pre-existing organization: public organizations, such as bureaucracies and political bodies, and private ones, such as firms and non-profits, that each entrust their members with some kind of power. Understanding why grand corruption is so pervasive, resisting the enforcement efforts of even the most developed nations, requires understanding how corruption is organized; that is, how it varies in form.

In this chapter, I show that the literature on corruption has little to say about this variation: focusing on a handful of representative agents, it sidesteps the question of the form of corruption (section 2.1). Conversely, a vast literature on organized crime, originating from fields as diverse as criminology, sociology, and economics, attempts to explain the functioning of criminal networks, and the relationship between the structure of those networks and the level of criminal activity. This literature, however, ignores the existence of a pre-existing organization and misses important issues of strategy, which makes transposing its insights to corruption problematic (section 2.2). Borrowing from this approach, I lay out the micro-foundations of a theory of the emergence of corruption in organizations. I use three simple simple micro-level hypotheses to account for the formation of corruption networks. Corruption networks form by including additional accomplices into an existing coalition to illegally extract resources from the organization. Like other forms of organized crime, additional accomplices pose a tradeoff between efficiency and secrecy. Organizations complicate this tradeoff by granting agents access to such resources, and embedding them in networks that constrain the recruitment of accomplices and exposes them to witnesses, and in institutions that affect their risk of detection (section 2.3).

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1 Transparency International. The emphasis is mine.
2.1 From individuals to markets: dominant views on corruption

2.1.1 The principal-agent framework

The principal-agent approach typically frames corruption as the interaction between two actors: a welfare-maximizing government, who monitors a potentially corrupt bureaucrat. The assumption of a welfare maximizing government may seem excessively naïve, especially if one considers the behavior of predatory states, but is not as simplistic as it first seems. A weaker, more realistic understanding of this assumption is that while the bureaucrat maximizes his own welfare, the government cares about a broader constituency. As such, it wants to constrain the behavior of bureaucrats (Banerjee, Hanna and Mullainathan, 2013). Under this framework, corruption arises because of asymmetric information: the agent has some hidden knowledge – typically, whether she is of the honest, or corrupt type –, or can take some hidden action, such as to embezzle or not.

The principal faces two problems: adverse selection and moral hazard. Adverse selection results from hidden knowledge. The question is of how the principal can screen out the corrupt types. Moral hazard results from hidden action. The corresponding question is of how the principal can design an incentive scheme that makes bureaucrats behave honestly.

The principal-agent is well-suited to analyze how a variety of formal institutions affect corruption. Indeed, in this class of models, the government optimizes the design of some formal rule—that is, an institution—in order to maximize social welfare, taking into account corruption arising through the channels of adverse selection, and moral hazard. The institutions considered include various policy instruments, such as compensation schemes, which may both reduce adverse selection, and moral hazard;
as well as various strategies of monitoring and punishment, which may reduce moral hazard.

Theorizing the conditions under which compensation schemes can successfully reduce corruption is certainly the contribution that has received most attention. Intuitively, increasing the salary of bureaucrats could both reduce the incentives to take bribes (moral hazard), and attract non-corrupt agents into the bureaucracy (adverse selection). The first formal treatment of the idea dates back to Becker and Stigler (1974) who show that in order to deter moral hazard, bureaucrats must be paid their efficiency wage—that is, above the market rate. While Besley and McLaren (1993) acknowledge that higher salaries do deter corruption, they spell out the conditions under which this policy is optimal; namely, when the government detects corruption well-enough, but there are many corrupt bureaucrats.

Empirical evidence shows that higher wages decrease corruption, but the effect is small. Cross-country studies show either weak correlations (Van Rijckeghem and Weder, 2001), or effects limited to some forms of corruption, such as red-tape, but not others (Rauch and Evans, 2000). More robust, micro evidence shows results that are broadly consistent with the cross-country approach. Exploiting a corruption crackdown in hospitals’ procurement departments in Buenos Aires, Di Tella and Schargrodsky (2003) show that higher wages do reduce input prices paid by hospitals, but only when the probability of an audit is low. Considering adverse selection, Ferraz and Finan (2011) show that higher wages attract higher quality municipal candidates in Brazil.

Similarly, principal-agent models show that better monitoring reduces the extent of corruption (Becker and Stigler, 1974). The empirical literature uses micro evidence to assess the impact of various types of monitoring schemes on corruption. Olken (2007) considers road construction projects in Indonesia. He finds that increasing the probability of top-down monitoring increases the quality of the road. On the other
hand, bottom-up, community-based monitoring, has mixed effects on reducing corruption, as the monitors may end up being captured by elites, subjected to threats, or free ride on monitoring. As a result, the extent, and target of improvements depends on the exact form of the intervention (Björkman and Svensson [2009]; Olken [2007]). In democracies, electoral sanctions contribute to reducing corruption through multiple channels. First, they act in complementarity with top-down monitoring: Ferraz and Finan [2008] find that in Brazil, audits exposing corrupt practices of mayors before elections reduce their chance of being re-elected. Second, the opportunity for re-election also reduces the extent of corruption (Ferraz and Finan [2011]). In autocracies, the press seems to play a similar role, by threatening corrupt bureaucrats to expose their malpractices publicly, and subject them to governmental sanction (Distelhorst [2012]).

Although valuable in its own right, the principal-agent approach is ill-equipped when it comes to accounting for the existence of corruption networks. Indeed, the strength of the principal-agent approach is that it gives an institutional account of corruption. The most sophisticated models, such as Banerjee, Hanna and Mullainathan (2013), are able to consider an immense variety of institutional mechanisms through which government can control the bureaucrat, and through which bureaucrats may engage in corruption. The price of this complexity, however, is that those models consider a very stylized organization, where a handful of representative principals govern a handful of representative agents. By design, the principal-agent approach is unable to consider the sophisticated forms of collusion – either between many bureaucrats, or between many bureaucrats and many clients – that characterize collective, embedded corruption.
2.1.2 The market approach

Another strand in the literature treats corruption as a market, where several corrupt bureaucrats (the offer) control access to a government resource, for which there is demand. Bureaucrats charge a bribe to maximize their private benefit. The approach transfers to corruption concepts borrowed from industrial economics.

In a seminal contribution, Shleifer and Vishny (1993) look at the amount of corruption when bureaucrats act as a single monopoly, as independent monopolies, and as competitors. They predict that corruption should be high in the case of independent monopolies, intermediate in the case of a single monopoly, and low in the competitive case. Bureaucrats’ incentive to collude should be at its highest when price-deviations are easy to detect, and when they are easy to sanction.

Finally, Burgess et al. (2012), and Olken and Barron (2009) discuss the implications of Cournot and Bertrand competition, respectively. Under both forms, increasing the number of bureaucrats increases the level of competition, which results in cheaper bribes, compared to the monopoly case. Furthermore, Olken and Barron (2009) show that if bureaucrats cannot contract on the ex-post division of the surplus, then hold-up situations will occur, leading to an unequal division of the surplus.

The market approach to corruption performs well empirically. Olken and Barron (2009) exploit exogenous variation in market structure, and objective measures of corruption. They show that an exogenous reduction in the number of checkpoints on a road in Aceh, Indonesia, leads to an increase in the total bribes paid by truckers. Consistently with their argument on hold-up, they also show that checkpoints located at the end of the road extract higher bribes than the ones located further up. Similarly, Burgess et al. (2012) exploit the fact that decentralization in post-Suharto Indonesia transferred the power to deliver logging permits in forests to districts. They show that increasing the number of districts leads to an increase in deforestation, due to an increased amount of permits delivered.
The market approach does a better job than the principal-agent approach in explaining the collective nature of corruption. Bureaucrats do not act independently, in the sense that the global level of corruption can be considered as the sum of local levels of corruption. In the market approach, bureaucrats are a multitude. The extent to which they internalize each other’s behavior, and are able to enforce agreements determines in turn the global amount of corruption.

Although the market approach takes into account the collective dimension of corruption, it is still unsatisfying. First, it does explain why, for a given level of state capacity, some market structures may prevail over others in different settings. Shleifer and Vishny (1993) do argue that strong states, such as the USSR, are better able to monitor their bureaucracy, and therefore more able to enforce cartel arrangements. By contrast, weak states, such as Zaire, are less able to monitor their bureaucrats, and therefore more likely to have their bureaucracy acting as independent monopolies. Although the argument may explain cross-country variation, it does not explain within-country variation.

Second, when equating corruption to a market, the approach makes oversimplifying assumptions. In particular, it assumes complete information, and uses a crude metaphor for organizations. In the market approach, although they are many, bureaucrats and clients are interchangeable and operate in an open market. The complete information makes little sense, for it neglects that corruption is characterized by secrecy: in most settings, bureaucrats and clients do not meet in an open marketplace to jointly determine the market-clearing bribe. Although this assumption could easily be relaxed, doing so would still ignore an important tenet of organizational economics itself: markets and organizations are very different [Williamson, 1985]. Because organizations feature a hierarchy, markets are a poor representation of what occurs within them.
2.2 The formation of criminal networks

While dominant approaches to corruption have little to say about how corruption is organized, a large literature considers organized crime more broadly, and examines how covert networks are structured. Most collective activities in life can be thought of as open network. Open networks are public, out in the open; they are legal, and the people participating in its activities are not facing risks such as imprisonment, injury, or death. Conversely, covert networks are “mostly illegal; that is, their activity is contrary to the law that is enacted in the geographic area where the activity takes place. The members of covert networks have to hide their activities, and face constant risks if discovered” (Raab and Milward 2003). This approach argues that covert networks are structured to arbitrate between competing imperatives of efficiency and secrecy: the structure of those networks balances carrying out their activity efficiently with the risk of being detected.

2.2.1 The tradeoff between secrecy and efficiency

Covert networks need to be kept secret, and this imperative gives rise to a tradeoff between secrecy and efficiency. Because covert networks must remain secret, they are more inclined to adopt structures that mitigate the risk of detection. Yet, while those structures which may help shielding the network against discovery, they may also hinder its ability to carry out its task.

Krebs’ (2002) work on the Al-Qaida cell that carried out 9/11 is illustrative of the secrecy-efficiency tradeoff. The 9/11 network was sparse, flat, and had no ties with outsiders. Those features all increase secrecy. A sparse network has few ties. As such, if one node is discovered, and investigators follow the ties originating from this node, they will only discover a few other nodes. A flat network has no highly central nodes. As such, no node is the key to discovering many other nodes. Finally, no ties
with outsiders implies that investigators have little chance of discovering the network if they scan the population at random. Yet, the same features that make the 9/11 network robust to detection by law enforcement also hinder efficiency. Because this network is sparse and flat, its members are far apart from each other: the network has has high average path length. Consequently, information takes time to circulate within the network.

The literature has explored how the optimal network structure varies in function of several parameters, including (1) the degree of risk, (2) the detection technology, (3) the nature of the task to be accomplished by the network, and (4) the types of nodes that compose the network. The relationship between the degree of risk and network structure is straightforward. The more risk of discovery, the more binding the security imperative. As a result, as risk increases, the network should become increasingly sparse and decentralized. Although intuitively appealing, this hypothesis seems to have received little empirical support. Bruinsma and Bernasco (2004) study three international criminal networks, and find support for the opposite conclusion: as risk increases, the network becomes denser.

The structure of covert networks is very sensitive to changes in the detection technology (Baccara and Bar-Isaac, 2008, 2009; Lindelauf, Borm and Hamers, 2009; Easton and Karaivanov, 2009). For instance, Lindelauf, Borm and Hamers (2009) examine formally how variation in the detection policy affects optimal network structure. They compare the optimal responses to three detection technologies, and show that the resulting structures are very different. Under all scenarios, a node is detected with some probability. Then, under the first scenario, all the neighbors of that node are detected as well. Under the second scenario, the neighbors of that node are detected with some probability. Under the third scenario, the probability of detecting the initial node is an increasing function of that node’s centrality. The resulting network structures vary widely with the enforcement strategy: under the first scenario,
the optimal network is a star; under the second, it is the complete graph for a low
detection probability, and a star for a high detection probability; under the third, it
is a ring, for a low number of players; as the number of players increases, they show
computationally that the optimal network structure converges to a non-standard type
of graph: the reinforced wheel.

The type of task accomplished by the network also affects its structure, with more
demanding tasks requiring denser structures (Erickson 1981; Morselli, Giguère and
Petit, 2007). The argument is that more demanding tasks require more coordination
than simpler tasks, which makes the efficiency imperative supersede the security im-
perative. Morselli, Giguère and Petit (2007) compare a criminal network—the Caviar
network, involved in a drug trafficking case in 1990s Montreal—to a terrorist network,
the 9/11 cell. They argue that the Caviar network is denser than the 9/11 network
because while a terrorist action needs to only be carried out once, drug trafficking
requires high-frequency action than the terrorist cell, leading to increased demand for
cooperation, and denser network structures.

Different types of nodes also affect the structure of the network (Krebs 2002;
Bakker, Raab and Milward, 2012). Within a covert networks, nodes have different
types, in the sense that they perform different tasks, some of which are critical to
the success of the operation. For instance, the 9/11 network could not have operated
without pilots. From an efficiency perspective, because those nodes are crucial to
each operation, they should be more central. However, this creates a potential source
of vulnerability for the network, since increased centrality makes those crucial nodes
more likely to be detected. In the 9/11 network, the pilots were precisely the most
central nodes. Bakker, Raab and Milward (2012) argue that in order to maintain
secrecy, covert networks tend to encourage redundancies in types, in order to avoid
structures where the crucial types are too central.
Yet, these insights do not immediately travel to corruption, because they assume that criminal networks form in a vacuum, isolated from the rest of society. The assumption seems reasonable for gangs or terrorist networks, where criminals can hide from the rest of society. Krebs (2002), for instance, shows that members of the 9/11 network were communicating online, and avoided contact with the rest of the world. The assumption seems much less reasonable for organizational settings, where members are forced to interact with assigned colleagues.

2.2.2 Trust and strategic agents

Covert networks are illegal, which implies that disputes between parties cannot be resolved by a hierarchy or a legal system (Gambetta, 1996; Raab and Milward, 2003). Because covert networks operate in a lawless environment, their members have to address a fundamental problem: they need to establish trust; in particular, trust that one will not violate the terms of the venture, and will protect its secrecy (von Lampe and Ole Johansen, 2004).

Criminals resort to a variety of informal institutions to build up trust and mitigate the commitment problems inherent to lawlessness. Solutions include holding one another hostage by sharing compromising evidence, repeated interactions that allow trust to build up over time, or “brokers,” trusted intermediaries who vouch for new accomplices (Gambetta, 2009). The extent to which accomplices are able to secure cooperation crucially depends on the extent to which they are able to establish efficient informal institutions. While these solutions prevent accomplices from denouncing each other prior to detection, they typically make the whole coalition unravel when one member gets caught: former accomplices begin denouncing each other, ultimately leading to the demise of the entire coalition (Gambetta, 1996).

Preferential, strong social ties (Granovetter, 1973) act as grease in the wheels of these informal institutions, because they embed some pre-existing trust. While
kin and the local community are often sources of individualized trust, while ethnic groups are often a source of trust based on reputation (von Lampe and Ole Johansen, 2004). As such, covert networks often cluster along these strong ties, in order to facilitate cooperation among criminals. For instance, Erickson (1981) shows how membership in the San Antonio heroin market, in the 1970s, was bounded to the Hispanic community.

Strong ties put additional constraints on network formation, and complicate the solution to the secrecy-efficiency tradeoff. The benefits of strong ties come with a cost: they restrict the pool of potential members of a network. As such, only the networks that face relatively high risk should rely on them. Bruinsma and Bernasco (2004) provide evidence of this by comparing three covert networks facing increasingly high risk: stolen cars trafficking, women trafficking, and heroine trafficking. They show that as risk increases, the network clusters increasingly along strong ties.

If existing theoretical work on trust and informal institutions has examined in depth how lawlessness affects the behavior of strategic criminals within dyadic relationships, it has paid much less attention to how those dyadic relationships then aggregate in larger covert networks. The problem is twofold. First, given a network structure, criminals interact strategically with each other. Second, the structure itself is determined strategically.

Many models allow for strategic interactions on a given network, considering how commitments problems and strategic interactions with law enforcement affect interactions among criminals (Baccara and Bar-Isaac, 2008, 2009; Easton and Karaivanov, 2009).

Fewer work has considered strategic coalition formation. Most models of criminal networks are models are models of network formation. They characterize, among the set of all networks that can be formed among $N$ criminals, the ones that criminals would likely form. Instead, they characterize the efficient network, that is, the network
that optimally responds to the tradeoff between efficiency and secrecy (eg. Baccara and Bar-Isaac 2008, 2009).

Baker and Faulkner (1993) delineate the problem of strategic network formation informally. Moved by concerns that echo the aggregate-level tradeoff, criminals also balance between efficiency and security considerations when deciding upon the structure of the coalition. From an efficiency point of view, they prefer more central positions, that presumably give them more control over their peers. From a security point of view, however, they prefer less central positions, in order to decrease their exposure to law enforcement.

Game theory has long-highlighted the problems induced by strategy in network formation. The standard approach to apprehend how strategic agents may form a network is to use the concept of pairwise stability (Jackson and Wolinsky 1996). Pairwise stable networks are robust to single deviations by their members: a network is pairwise stable if no one agent would like to sever one of her existing ties, and no two agents would both like to establish a tie between them.

A notable exception, Calvó-Armengol and Zenou (2004) examine pairwise stability in a model of peer effects in crime, but the setup seems ill-adapted to corruption. First, they acknowledge that thinking of pairwise stability in a model of learning among peers seems odd: how could an aspiring criminal discern, ex-ante, who makes up for the best mentor? More importantly, models of network formation seem ill-equipped to transfer to corruption, because they assume that network formation occurs ex nihilo. Doing so, these models suffer from the pitfall highlighted in the previous subsection: they are, by design, unable to account for the existence of an exogenous organization.
2.3 The micro-foundations of corruption in organizations

Existing work on covert networks tells use that organized crime faces a tradeoff between efficiency and secrecy. Yet, insights from organized crime require significant amending to describe corruption, because they neglect organizations. In what follows, I describe how the secrecy-efficiency tradeoff applies to corruption, and detail how organizations matter. I articulate this into a few micro-level hypotheses that form the foundation of the framework, and describe how this allows conceptualizing the difference between petty and grand corruption.

2.3.1 The tradeoff between efficiency and secrecy applied to corruption

Like other forms of organized crime, corruption is illegal, which makes creating the coalition of accomplices that make up the crime result in a tradeoff between encouraging efficient resource extraction and avoiding detection by law enforcement (Raab and Milward, 2003). Indeed, illegality has two consequences. First, because crime is illegal, it must be kept secret (Shleifer and Vishny, 1993). Second, illegality makes criminals operate in a lawless environment, in the sense that they cannot rely on the state as a neutral third-party to enforce corrupt deals, often termed contracts (Gambetta, 1996; Vannucci and Della Porta, 2013). Together, the risks of detection and defection make recruiting accomplices a mixed blessing.

On the one hand, accomplices fulfill some task that ultimately provides the coalition with benefits, in the form of resource extraction or protection. Studying cases of corruption in Hungary, Jávor and Jancsics (2013) show how the employees of a swimming pool in Budapest extract resources:
The gatemen can hack the entry system. These guys have a special technique to keep the gates open with their leg and do not let it measure the number of visitors. When the customer brings a ticket, which is actually an electronic card, to the entrance gates the gatemen takes the card but does not scan it. So, the customer is not registered electronically either by the scanner and nor by the gate’s mechanical counter. Then, the gatekeepers bring back the “unused” tickets to me and I resell them, but this time it is pure money for us.

Accomplices may also provide the coalition with increased protection against detection. Increased protection sometimes materializes in direct collusion, when law-enforcement joins the coalition. (Ledeneva 2006, 106) shows how judges in Russia may get away with offenses by having their colleagues refuse to prosecute. Studying a case of Medicaid provider fraud, (Vaughn 1983) argues that accomplices usually provide protection by increasing the complexity of the scheme, which makes the coalition harder to detect, because evidence is diluted. Wade (1982, 297) shows how the numerous accomplices involved in a canal irrigation scheme in India dilute potential evidence against their bribery scheme:

The Assistant Engineer may tell the Supervisor to ask the farmers to pay the money directly to a named contractor, or the Supervisor may take the money and immediately pass it to the contractor. The only person with any money (evidence) on his hands is thus the contractor. If by chance he should be investigated by the police and large sums of money found in his possession he can say he has taken out loans for his works.

On the other hand, accomplices also hurt the coalition. First, they cost resources. In Wade’s example, each of the many members of the coalition were taking a share of the bribe.
Second, accomplices may compromise the secrecy of the coalition. Similar to other forms of organized crime, corruption operate in a lawless environment, forcing criminals to resort to a variety of informal institutions to build up trust and mitigate the ensuing commitment problems, including the risk of defection to law enforcement. Informal institutions include holding one another hostage by sharing compromising evidence (Ledeneva 1998; Yang 2002), repeated interactions that allow trust to build up over time (Malesky and Samphantharak 2008), or “brokers,” trusted intermediaries who vouch for new accomplices (Vannucci and Della Porta 2013). Well-functioning formal institutions like the judiciary may even help accomplices, guaranteeing that potential defectors will be punished (Gambetta 2018). Ability to secure cooperation depends on the extent to which accomplices manage to establish efficient informal institutions.

The organizational setting of corruption makes accomplices pose an additional risk compared to other forms of organized crime: accomplices may attract the attention of witnesses among the colleagues they interact with. Witnesses hurt the conspiracy by increasing the risk of detection: they may act as whistle-blowers and report corruption, or be summoned as part of investigations conducted by a third-party. Examining three cases of price-fixing in the heavy electrical equipment industry, Baker and Faulkner (1993) show that during trials, eyewitnesses provided evidence that was critical to the downfall of these cartels.

2.3.2 Embeddedness: organizations as resources, networks and institutions

Unlike other forms of organized crime, corruption takes place within a pre-existing organization: a bureaucracy, a political body, a firm, or a non-profit. I argue that organizations matter because they define the exact terms of the tradeoff between efficiency and secrecy. Organizations play two functions. First, they determine in-
dividual opportunities for corruption, by granting access to illegal streams of rent. Second, they embed their members in a set of formal institutions and a social network. Formal institutions define monitoring processes that affect the risk of detection. Social networks play three functions: they provide previous acquaintances that allow recruiting accomplices, they establish relationships of monitoring that determine who witnesses whom, and they supply pre-existing bonds of trust that may be exploited to prevent whistle-blowing and defection. Members of the organization may interact strategically with those networks and institutions, and may amend them at the margin. Nevertheless, such networks and institutions are largely exogenous to individual members, who typically have little leeway in choosing their managers and colleagues, and in deciding on internal monitoring procedures.

Organizations matter because they determine access to opportunities that may be turned into streams of rent (Jávor and Jancsics 2013; Jancsics 2014). Organizations give their members control over processes that they may exploit to their advantage. For instance, in bureaucracies, front-line providers like police patrolmen are more regularly in contact with the public and can more easily extract bribes. These resources are the starting point for including additional accomplices into the coalition.

Organizations also matter because they embed their members in a set of institutions and social networks. This has been oft-noted by political scientists, but rarely articulated into an explicit theoretical framework. Carpenter (2001) discusses how the state-formation literature construes the state as a collection of organizations. Skocpol (1979) defines the state as a “set of administrative, policing, and military organizations;” Skowronek (1982) as an “integrated organization of institutions, procedures, and human talents;” and Tilly (1975) as an “organization which controls the population occupying a definite territory.”

That organizations feature institutions is apparent in those definitions, and has been largely re-emphasized by the neo-institutionalist turn (North 1991). Taking
a closer look at these organizations, some political scientists have also highlighted that they are overlaid with social relationships: formal relationships of authority and collaboration, as well as more informal social ties, such as friendship, political, or ethnic ties (Evans 1995; Carpenter 2001; Van de Walle 2001).

Economic sociology articulates the institutional and social aspects of organizations into the theory of *embeddedness*. In a seminal article, Granovetter (1985) posits that economic agents are embedded in social life. He rejects both under- and oversocialized views of economic agents which hold, respectively, that agents operate freely of social constraints, or are completely governed by them. He argues instead that economic agents are embedded in ongoing networks of social relationships that both constrain them—for instance, through peer pressure—and provide them with benefits, such as information. Zukin and DiMaggio (1990) expand upon the concept and argue that economic agents are indeed embedded within networks of relationships—what they call *social* embeddedness—but also within a set of institutions (institutional embeddedness), and a specific culture (cultural embeddedness).

The embeddedness approach tells us that organizations endow their members with a set of social relationships and formal institutions that are partly endogenous, and partly exogenous. These relationships, such as managers, colleagues, subordinates, or friends are often exogenous to agents’ choices: employees seldom choose their managers, or their office-mates. Nevertheless, Small (2009) shows that agents partially endogenize these relationships, by modifying them at the margin. For instance, office-mates may end up striking friendship ties, or use promotions opportunities to join specific divisions within the organization, leading to the formation of new ties. Similarly, formal institutions are largely exogenous to individual agents. Some of these institutions, such as accounting procedures, are imposed by law, an institution.

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2 Political science has also paid attention to organizational culture, as exemplified by Kaufman’s (1960) proverbial forest ranger. Because a large literature focuses on the cultural aspects of corruption (e.g., Granovetter 2007; Blundo and De Sardan 2013), I set this dimension aside to emphasize its institutional and social aspects.
tional framework that is exterior to the institution. Others, such as internal auditing procedures, are often decided by top management, and are exogenous to lower-level members. Yet, as this last example illustrates, these institutions are also partially endogenous, since they are decided within the organization. Similarly, lower-level employees interact strategically with these institutions, sometimes completely deviating them from their intended purpose. In a famous case-study, Roy (1952) highlights how a group of factory workers deliberately shades on productivity to avoid a downward revision of piece rates by management.

If embeddedness tells us what organizations are—a set of formal institutions and social ties—, it does not tell us immediately what they do to corruption. I argue that they specify the exact terms of the tradeoff between efficiency and secrecy entailed by corruption. The role of formal institutions is immediate: they directly affect the risk of detection.

Specifying how the social networks that constitute organizations affect corruption require distinguishing between the types of relationships captured by network ties and the function of such ties (Larson and Lewis, N.d.). The social network of an organization has many types of ties: authority, collaboration, friendship, ... These ties are relevant to corruption because they have three functions: communication, monitoring, and trust.

Ties affect corruption by determining acquaintances within the organization. Acquaintances include all the people that one usually interacts with in the organization. Almost tautologically, if two accomplices cooperate, or if one recruits the other as an accomplice, then they must have been acquainted to each other; that is, have preexisting knowledge of each other. This function is undirected, in the sense that if person $i$ is acquainted with person $j$, then $j$ is also acquainted with $i$. Within the organization, virtually any type of tie may fulfill this function.
Ties may also affect corruption by allowing for monitoring. The monitoring function simply captures whether, in a relationship, one party knows the activities of the other party enough to provide evidence of her guilt, should she be corrupt. Ties of collaboration and of authority often fulfill this function: employees that share office space often have detailed knowledge of the activities of their colleagues, and so do managers with their employees. This function is directed, in the sense that while $i$ may monitor $j$, $j$ may not monitor $i$. For instance, while managers often closely monitor their employees, employees may not monitor their managers.

Finally, ties affect corruption when they establish trust, both by facilitating cooperation among accomplices, and weakening the monitoring of witnesses. Ties of trust may arise from a variety of sources: friendships struck within the organization, or pre-existing ties coming from shared educational, ethnic (Van de Walle 2001), or political backgrounds. Trust facilitates cooperation among members of the coalition. Documenting corruption among customs agents at the Cotonou harbor, Bako-Arifari (2001) shows how members were exclusively recruited through pre-existing social ties to ensure that they would not defect and redistribute. The pattern is confirmed in the lab: one is more likely to mimic unethical behavior from a peer when that peer is an in-group member, or a strong tie (Gino and Galinsky 2012; Gino and Pierce 2009; Gino, Ayal and Ariely 2009). Conversely, lack of trust reinforces witnesses’ deterring effect: when an in-group member engages in unethical behavior in the presence of an out-group member, other in-group members are more likely to compensate and behave overly ethically (Gino and Pierce 2009).

So far, this discussion has not explicitly tackled the notion of authority. This may seem surprising; since Weber (1948), political science has long-emphasized that bureaucracies are large centralized hierarchies. Organizational economics also argues that organizations provide hierarchies that substitute to markets (Williamson 1985).

\[^{3}\text{See Bourdieu (1989) for educational ties, Van de Walle (2001) for ethnic ties, and Chubb (1981) for political ties.}\]
I argue that conceptualizing organizations as resources, formal institutions, and networks of acquaintance, monitoring, and trust is a sufficiently rich representation for the purposes of understanding the formation of corruption networks. The representation would be too parsimonious if ties of authority affected corruption in a way that the framework does not capture. Networks matter because they define relationships that affect accomplices’ or witnesses’ behavior. Regarding accomplices’ behavior, one may fear that higher-level employees may be able to coerce lower-level employees into joining the coalition. Jávor and Jancsics (2013) show that this is hardly the case: lower-level employees are often critical to some task within the coalition, and know of the wrong-doing of their managers, which gives them leverage. Regarding witnesses behavior, hierarchy would matter if it affected witnesses’ ability to report corruption. A meta-analysis (Mesmer-Magnus and Viswesvaran, 2005) shows that hierarchy matters little after controlling for holding evidence, which is accounted for by monitoring ties. The balance of accomplices and witnesses matters: larger coalitions face less risk of being reported because whistleblowers face a higher risk of retaliation.

2.3.3 The anatomy of corruption

Corruption networks form by including additional accomplices into an existing coalition to extract some illegal stream of rent from the host organization. Like other forms of organized crime, additional accomplices pose a tradeoff between efficiency and secrecy. On the one hand, they benefit the criminal activity, protecting it against detection by “covering up” and extracting more resources. On the other, they cost resources because they need to be compensated for their own risk. They may also increase the risk of defection, making the ability to establish trust and other informal institutions preventing defection an important determinant of success. Finally, they
Organizations complicate the tradeoff between efficiency and secrecy. They grant their members access to the rents that the coalition may extract. They also embed their members in a pre-existing network of social relationships and a set of institutional rules that structure their interactions. Institutions affect the risk of detection faced by the coalition. Networks constrain the recruitment of additional accomplices: they establish the necessary ties of acquaintance that predate recruitment. They also define ties of monitoring that specify which of the accomplices’ peers would know enough about the crime to turn into witnesses and increase the risk of detection. Finally, they establish ties of trust that accomplices may exploit to facilitate cooperation, or to weaken the monitoring of potential witnesses.

Thinking of corruption as a covert network embedded in an organization allows painting a more precise picture of different form of corruption, and defining how petty and grand corruption fit into a broader anatomy of corruption. Figure 2.1 shows a
schematic representation of the corruption scandal that surfaced at the Fédération Internationale de Football Association (FIFA). In 2015 and 2016, major officials of FIFA and its affiliated regional federations were receiving kickbacks from sports marketing companies to be awarded the marketing rights of various soccer tournaments, and selling their votes for the selection of the host nation of soccer tournaments, including the 2010 World Cup.

The framework allows representing FIFA as a network. The organization is pyramidal, with an executive committee sitting on top of the various regional federations. Members of the executive committee (ComEx) monitor each other, and so do members of regional federations.

In this environment, one can describe corruption by asking whether there is a coalition, how does its network structure fit within the broader organization, and how much resources do individual member obtain. In figure 2.1, the coalition includes Blatter and other members of the ComEx, as well as some of the regional federations: CONMEBOL and CONCACAF, which is permeated by ties of trust. It creates witnesses among members of the ComEx and within three regional federations.

I conceptualize the form of corruption in three dimensions: frequency, the likelihood that some corruption occurs; 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. Note that up until now, our discussion of petty and grand corruption was conflating scale and scope corruption. In reality, those are two different dimensions that are often correlated, as suggested by the casual observations that motivated this investigation, and confirmed by the more systematic cross-country evidence I examine in Chapter 4. I define grand corruption as more profitable corruption, which often results in larger coalitions. Petty corruption is less profitable, and this often correlates with smaller coalitions.
Establishing these micro-foundations is the first step to understanding why grand corruption persists, and how organizations affect corruption. The next chapter formalizes them into a formal model of strategic diffusion on a network, in order to understand the macro-level implications of those micro-patterns. Another important step is to revisit some of these micro-foundations empirically. At heart, the framework relies on the micro-level assumption that relationships within the organization play a dual, opposite function: they may hurt accomplices by making them exposed to witnesses, or they may help by allowing them to expand the coalition. Available evidence documents both behavior but, being qualitative or coming from the lab, cannot calibrate their relative importance, hindering our theoretical effort. Chapter 6 investigates this question using quantitative evidence from the field.
A theory of corruption in organizations

We saw in the previous chapter that corruption networks emerge in organizations by including additional accomplices into an existing coalition to illegally extract resources from the organization. Additional accomplices pose a tradeoff between efficiency and secrecy: on the one hand, they extract resources and may protect the coalition; on the other, they may compromise the coalition and cost resources. Organizations complicate this tradeoff by granting agents differential access to such resources, and embedding them in networks that constrain the recruitment of accomplices and expose them to witnesses, and in institutions that affect their risk of detection.
These micro-foundations delineate an anatomy of corruption, allowing to describe the form of corruption across cases using three dimensions: frequency, the likelihood that some corruption occurs; 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.

Armed with these patterns and definitions, we can answer the questions that motivated this investigation: When should we expect to see grand corruption? Can we harness organizational structure to fight it? To do so, this chapter develops a formal model of strategic diffusion on a network. In what follows, I first introduce the model informally, justify the main modeling assumptions, and give an overview of the main results (section 3.1). I then present the model and main results formally, and consider a few extensions (section 3.2). I finally discuss the results informally and highlight their implications (section 3.3).

3.1 Modelling corruption in organizations

3.1.1 Formalizing the micro-foundations: strategic diffusion

Modelling the formation of corruption networks requires formalizing our micro-foundations into a setup that is general enough to yield robust insights, yet simple enough to be tractable. Formalizing the micro-foundations requires making coalition formation feature a tradeoff between secrecy and efficiency. Both the (network) structure of the coalition, and the interactions that occur within this structure should be determined by strategic agents, but also be affected by an exogenous organizational structure. I show how considering a process of strategic diffusion on a network satisfies these requirements. In the next subsection, I specify the particular assumptions I make to turn this process into a tractable model.
Existing models of criminal networks do make coalition formation a result from a tradeoff between efficiency and secrecy, but often neglect these issues of strategies. Worse, being games of network formation, they are, by design, ill-equipped when it comes to accounting for an exogenous organization. In other words, because they aim at characterizing, among the set of all networks that can be formed among N criminals, the ones that criminals would likely form, they cannot account for how a pre-existing network would affect the process without substantial amendments.

I depart from this approach and model coalition formation as a process of strategic diffusion on a network. Standard models of diffusion on networks examine how, on a given network, a fad or a disease spreads from a randomly chosen node, the seed. Standard models (e.g., Watts, 2002; Centola and Macy, 2007) are non-strategic, in the sense that diffusion occurs either at random, when a node infects its neighbors with some probability, or according some threshold rule, when a node is infected if some fraction of its neighbors is infected. I make diffusion strategic, and consider a setting where $i$ infects her neighbor $j$ if and only if both of them agree to diffusion.

I consider a process of strategic diffusion for corruption in organizations. In the model, bureaucrats are the nodes of a network representing their agency. A seed 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 spend shares of the rent to turn those witnesses into accomplices. The nodes that accept the rent become accomplices. They create witnesses among their neighbors, but may also use their resources to turn those into accomplices. When the process is over, an exogenous enforcer detects the coalition with some probability.

This setup matches the micro-foundations of coalition formation we identified in the previous chapter. We saw that coalitions grow by by including additional accomplices to illegally extract resources from the organization. A diffusion process

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1See chapter 2 for a detailed review.
captures the essence of this idea, by having the seed discover some illegal stream of rent.

We saw that additional accomplices pose a tradeoff between efficiency and secrecy: on the one hand, they extract resources and may protect the coalition; on the other, they cost resources, and may compromise the secrecy of the coalition. This setup can account for this tradeoff: additional accomplices may increase the amount of rent extracted, and affect the probability of detection. The coalition is built by strategic agents who, starting from the seed, carefully decide whether to extend or accept offers to enter the coalition, and how much of their resource they should spare.

We also saw that organizations complicate the tradeoff between efficiency and secrecy by granting agents differential access to resources, and embedding them in a set of networks and institutions. To capture unequal access to resources, one may want to make the probability of being a seed vary across nodes. The exogenous enforcer captures formal institutions, allowing one could consider arbitrarily sophisticated detection policies. To match how social networks affect opportunities for corruption, one may consider a multiplex network; that is, a network where two nodes may be linked by types of different types. The discussion in the previous chapter tells us the ties to consider. An acquaintance network determines who can offer whom to be can be made. A monitoring network determines which neighbors turn into witnesses when a node joins the coalition, where witnesses affect the probability of detection. Finally a trust network, that interacts with the detection technology and informal institutions.

We finally saw that trust, and the capacity of members of the coalition to devise informal institutions are key to cooperation in a lawless environment. Specifics of the diffusion process may be exploited to explore the effect of trust and informal institutions: accomplices may agree on different ways of splitting the rent; ties of trust can facilitate these arrangements, or feed into the monitoring technology, making
some accomplices better cooperators than others, and some witnesses less likely to report.

3.1.2 A model of corruption in organizations

Conceiving coalition formation as a process of strategic diffusion on a network, where a seed recruits accomplices by sharing an illegal rent with her neighbors gives a setup that is sufficiently rich to accommodate strategic criminals and an exogenous organization. I make several assumptions to turn this broad setup into a tractable model, and discuss the most important ones below. Some of these assumptions are largely innocuous, and mostly simplify the interpretation. Others have important substantive implications that I partially address in extensions. Those substantive assumptions are grounded in the best of our knowledge of corruption networks. They aim at making as few restrictions as possible on network structure, the area where the model is most innovative, at the cost of assumptions in areas that have received more attention in previous work, such as the monitoring technology, or defection problems within the coalition.

I simplify the tradeoff posed by including additional accomplices in important ways. Accomplices benefit the coalition by extracting additional resources or providing protection against detection by covering up. For ease of interpretation, I make their positive contribution come exclusively from the second channel. I consider a rent of a fixed size, normalized to 1. Additional accomplices do not increase the size of the rent. They cost resources, governed by their individual cost of corruption $\epsilon \leq 1$.

Together with the rest of the setup, this assumption allows to recover the dimensions of corruption highlighted in the previous chapter. The diffusion process leads to the formation of a coalition, which of accomplices: a corrupt subnetwork within the organization, whose features are dimensions of corruption. The likelihood that some corruption occurs—whether the seed takes the rent captures the frequency of corrup-
tion. The number of accomplices captures the *scope* of corruption. The quantity $1 - \epsilon$ captures the *scale* of corruption; that is, its profitability, on a continuum from less profitable, petty corruption to more profitable, grand corruption. For a rent of size 1 and a cost of corruption $\epsilon$, the quantity $1 - \epsilon$ 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.

Second, I use a simple, all-or-nothing probability of detection. The enforcer detects the coalition with probability $p$. Accomplices always pay their cost of corruption $\epsilon$. If they succeed, members of the coalition earn their share of the rent. Otherwise, they earn 0. This models, in a reduced form, a commonly observed pattern of criminal networks: members of the coalition devise informal institutions that prevent defection but when one gets caught, the institution unravels and all members denounce each other.

The structure of the coalition affects secrecy through the probability of detection. I assume that the probability of success depends on features of the coalition: it is increasing in the number of accomplices, but decreasing in the number of witnesses. In other words, I assume that accomplices help the coalition, to the extent that they do not create witnesses that hurt the coalition. This assumption also implies that witnesses are not strategic: they do not strategically choose whether to report corruption, but mechanically decrease the probability of success instead.

The probability of detection also depends on a parameter for the monitoring technology, that captures in a reduced form how all formal institutions inside and outside the organization affect detection, capturing how good, is the organization at detecting and punishing corruption, net of the effect of organizational structure.

Because it plays such an important role in the model, I consider flexible functional forms for the probability of detection. The probability of detection embodies
in a reduced form assumptions on witnesses’ behavior relative to reporting corruption, accomplices’ behavior relative to preventing defections to law-enforcement, and institutional capacity to detect corruption. Available evidence gives relatively few guidance as to how to make more specific assumptions. As such, to consider whether results are robust to the myriad of ways in which those behaviors could unfold in more realistic models, I make few assumptions on the functional form of the probability of detection (see assumptions 1 and 2). In particular, I do not assume any kind of concavity or convexity.  

Finally, I explore how informal institutions affect accomplices’ ability to cooperate through the rent-division process. Because such informal institutions can be extraordinarily diverse, I triangulate their effect 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. I do not, however, consider how pre-existing ties of trust may affect cooperation nor reporting: we saw how the model should include a multiplex network featuring acquaintance, monitoring, and trust networks. I consider only the first two, and ignore the trust network.

Overall, the model captures the main features of the micro-foundations of coalition formation. In order to consider network structures that are as general as possible, it makes a few simplifying assumptions. While most of them either simplify interpreta-

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2Because the probability of detection might also depend on the scale corruption, I consider this possibility in an extension (Appendix A.4).

3I consider equal-sharing in the main specification, and examine the other rules in an extension (section 3.2.4).
tion or embody in a reduced form the conclusions of previous work, some limit the scope of the model; in particular, that witnesses’ reporting behavior is not strategic, and that the model does not feature an exogenous trust network. I discuss directions for future research in the conclusion).

3.2 Formal model and results

This section presents the model formally, derives equilibrium and comparative statics. It also considers an extension with endogenous division of the rent. Proofs, as well as an extension where the probability of detection depends on the profitability of corruption, are available in Appendix A.

3.2.1 Setting

I model corruption as a dynamic game of complete information. Bureaucrats are the nodes of the exogenous multiplex graph $g = (N, G_c, G_m)$ 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 acquaintance network, with $ij \in G_c$ denoting that $i$ and $j$ are acquaintances and may communicate. 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 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)

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4 A graph is the mathematical term used to refer to a network. A multiplex graph is a graph that contains several types of ties.

5 That is, that there is a path on $G_c$ between any $i, j \in N$. 

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Figure 3.1: **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.

she makes the vector of offers $t_s$ to her acquaintances. The sunk cost $\epsilon_s$ represents the seed’s cost of corruption, incorporating dimensions such as effort, risk, or a moral cost. Conversely, $1 - \epsilon_s$ represents the scale of corruption.

Once the seed has made her offers, the nodes that have been made a strictly positive offer 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 and holds the transfer $t_{si}$. 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 offers $t_i$ to her susceptible neighbors; that is, her non-pending, non-accomplice acquaintances. 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 3.1).

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

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Note that this under this setup, offers are being answered sequentially, which eliminate possibilities for multiple equilibria. Future research could usefully relax this assumption.
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 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 \( p = p(a, w, q) : \{1, \ldots, N\} \times \{0, \ldots, N\} \times (0, 1) \rightarrow (0, 1) \) 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 \( p(a + 1, w, q) - p(a, w, q) > 0 \), \( p(a, w + 1, q) - p(a, w, q) < 0 \), 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 \( \epsilon \), and holds some share of the rent \( \pi_i \geq 0 \).

Suppose \( i \) accepted offer \( t_{ki} \); let \( r_{ij} = 1 \) if \( j \) accepted an offer \( t_{ij} \) from \( i \), and \( r_{ij} = 0 \) otherwise; then \( \pi_i = t_{ki} - \sum_{j \in P_i} t_{ij} r_{ij} \), where \( P_i \) is the set of \( i \)'s susceptible neighbors.

\(^7\)That is, the set of nodes \( j \) such that \( j \to i \in G_m \).

\(^8\)Note that the probability of detection does not depend on the scale of corruption, \( 1 - \epsilon \), which might be problematic. I relax this assumption in an extension (Appendix A.4).
when she made her offers $t_i$. With probability $p$, agent $i$ gets her share $\pi_i$, and gets 0 otherwise. I first assume that agents divide bribe equally, and schedule transfers such that $\pi_i = \frac{1}{a_c}$ for any member of coalition $c$. Section 3.2.4 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 $v : \{1, \ldots, N\} \times \{0, \ldots, N\} \times (0, 1) \to \mathbb{R}$ is defined for an arbitrary number of accomplices and witnesses, 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:

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

(3.1)

3.2.2 Characterization of equilibrium coalitions

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 the problem is more complicated: in principle, because incentives are dynamic, there is no guarantee that accomplices will cooperate to realize $c^*$. However, because accomplices divide the rent equally, incentives within the coalition are sequentially aligned: all accomplices value the same coalitions equally, and as such, 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 $c \in C^*_gq$ is realized.

Saying more about which coalitions are realized in equilibrium requires characterizing the coalitions that the seed prefers. To do so, I characterize the frontier; that is, the coalitions that lie in $C^*_gq$. Comparing same-sized coalitions, one prefers the one with fewer witnesses. Two additional assumptions give more traction, by allowing comparisons between coalitions of different sizes:

**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 $a_1 \leq a_2$, $w_1, w_2 \in \{0, \ldots, N\}$, $q \in (0, 1)$. Then $\frac{\partial p(a_2, w_2, q)}{\partial q} > \frac{\partial p(a_1, w_1, q)}{\partial q}$ 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

$$|v(a, w + 1, q) - v(a, w, q)| > v(a^*, w, q) - \max\{v(1, w, q), v(N, w, q)\},$$

where $a^* \in \arg\max_{a \in \{1, \ldots, N\}} v(a, w, q)$.

Assumption 1 bounds the probability of success as the size of the coalition grows. It implies that $\frac{\partial p}{\partial a}$ 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 $(\epsilon_s, q) \in (0, 1)^2 \setminus U$, where $U$ has measure zero.

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9That is, $v$ satisfies $v(a, w, q) \geq \max\{v(a_1, w, q), v(a_2, w, q)\}$ for any $a_1 \leq a \leq a_2 \in \{1, \ldots, N\}$.
Figure 3.2: **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).

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 3.2). 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 3.2 provides an illustration).

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

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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:

**Proposition 2** (Equilibrium coalitions are minimal). If $c \in C^{*}_{qq}$ 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 the next section how this reconciles previous mixed findings.

### 3.2.3 Comparative statics

Having pinned down equilibrium behavior allows characterizing how corruption varies across organizations. Two lines of inquiry seem particularly relevant. First, keeping organizational structure constant, how does corruption change as organizations adopt better formal institutions? Second, keeping formal institutions constant, how does corruption vary as the organization changes?

Examining how corruption varies as organizations adopt better monitoring technologies, I show that corruption is less frequent but has a higher scale and a broader scope under better monitoring (Figure 3.3). Because detection is more likely, the seed now prefers giving away resources to benefit from the protection of additional accomplices, hence increasing the scope of corruption. Because larger coalitions are more costly, accepting the rent requires the project’s scale to be high enough to offset
Figure 3.3: **Equilibrium outcomes for any** \((q, \varepsilon)\). As \(q\) increases, the rejection area grows, weeding out low-scale corruption, and coalitions of increasing size are realized (Proposition 3).

this increase in costs: only projects with a high enough scale can now be sustained. As such, 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. 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 \(q_1 < q_2 \Rightarrow \hat{\varepsilon}_s(g, q_1) \geq \hat{\varepsilon}_s(g, q_2)\) and \(a_{c_1^*} \leq a_{c_2^*}\).

I then investigate how corruption varies as organizational structure changes. Comparing across networks, however, is a difficult exercise, because two networks can differ in a variety of ways. As such, I conduct two comparisons. First, I look at the impact of marginal changes to an existing organization, by examining analytically the impact of adding one tie to a network. Second, I use simulations to compare across a large number of organizations.

Examining the impact of marginal changes to an existing organization shows that making organizations more connected is no cure-all. Intuitively, proposition 2 shows that enclaves are good for corruption. Adding ties should make enclaves more ex-
posed, 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 acquaintance 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.

Formally, I compare the graph \( g = (N, G_c, G_m) \) to \( g' = (N, G'_c, G'_m) \), that I construct by adding an acquaintance or a 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. The results spell out the conditions under which additional ties have a non-zero effect on corruption:

**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 be that \( j \in c \), and \( i \notin c \cup W_c \) for some minimal coalition \( c \in M_g \) and all coalitions essentially equal to \( c \).

**Proposition 5** (Adding acquaintance 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.

I use simulations to compare across organizations and explore an immediate implication of enclaves. If enclaves are more corrupt, then organizations that contain

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\( ^{10} \)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, \( c' \) cannot satisfy \( w_{c'} < w_{c^*} \).
more enclaves should be more corrupt. In particular, more vertical organizations, as epitomized by Ford or General Motors in the 1930s should contain more enclaves than flatter organizations, like Google or Facebook. As such, more vertical organizations should be more corrupt. Network analysis provides a metric that allows capturing the extent to which an organization is vertical: modularity (Newman, 2006). 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 and within communities. As $m$ increases, more ties fall within communities, and fewer across. More modular graphs represent more vertical organizations.

Simulations examine the extent to which a randomly chosen seed takes the rent for graphs of varying modularity; that is, I consider the expected area under the $\hat{\epsilon}_s$ curve for a random seed $s$. For a given seed $s$ and a graph $g$, the Area Under the Curve is $AUC_{sg} = \int_0^1 \hat{\epsilon}_s(g, q) dq$ (Figure 3.3). Simulations examine the quantity $AUC_g = \mathbb{E}(AUC_{1g})$, where higher values of $AUC_g$ denote more corruption.

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. 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: $ij \in G_c \iff i \to j, j \to i \in G_m$. 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. Simulations assume equal-sharing and use the following probability of
success:

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

(3.2)

This function has several properties that make it appealing. In the absence of social structure, detection depends only on the monitoring technology: \( p(1, 0, q) = 1 - q \). It is linear in \( a \) and \( w \). Success is certain when the whole organization is corrupt, with \( p(N, 0, q) = 1 \). Symmetrically, detection is certain when the organization is a witness, with \( p(1, N-1, q) = 0 \). I show in appendix refsub:pass that \( p \) satisfies assumptions 1 and 2.

Figure 3.4 shows the results. More vertical organizations, as captured by more modular graphs, are more corrupt (left panel) because communities are more enclaved. When the organization becomes flatter, as captured by decreasing modularity, communities disenclave: cross-community ties reduce modularity and make them more exposed to each other, hence 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.

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 1 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 acquaintance 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.

### 3.2.4 Bargaining over the distribution of the rent

Up to now we maintained the assumption of equal-sharing. Underlying this approach are the assumptions that accomplices are able to strike an informal contract that specifies the distribution of the rent ex-ante, and that accomplices are maximally egalitarian. Relaxing these assumptions raises new interrogations. How would accomplices distribute the bribe endogenously? Does the structure of corrupt coalitions change if accomplices distribute the rent differently? I answer these questions by considering two alternative division rules: another contractual arrangement, \textit{monopoly}, where the seed pockets all the surplus, and \textit{bargaining} which assumes that accomplices operate in a lawless environment where they cannot strike contracts. Under bargaining, accomplices divide the bribe endogenously, which allows discussing the distribution of the rent within corrupt coalitions. In contrast with equal-sharing, monopoly assumes that accomplices are maximally unegalitarian, and that the seed
pockets all the surplus. Comparing equal-sharing to monopoly gives a sense of how equity concerns, or other factors affecting the bargaining power of accomplices may affect the results. Furthermore, it turns out that under monopoly, the seed realizes the most extractive coalition. As such, comparing this environment to the others gives a sense of how they perform against an efficient benchmark. In this extension, I assume 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 $\min_{c \in C^m} a_c \leq \min_{c \in C^e} a_c$, and $\max_{c \in C^m} a_c \leq \max_{c \in C^e} a_c$.

I finally examine the robustness of the findings to these new division rules. I show in Appendix 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.

3.3 Discussion

This chapter analyzed a formal model that treats corruption as the outcome of a process of strategic diffusion on a network representing the organization. This simple, easily expandable idea provides a framework to think about the macro-implications of the micro-foundations we highlighted in the previous chapter. Thinking of relationship between corruption, organizations, and institutions, the model provides insights that echo, reconcile, and precise previous findings. I discuss these in turn.

We first fixed the network and the monitoring technology and wondered where corruption would take root. We saw that corruption is more likely to occur in enclaves—subgraphs with relatively few monitoring ties pointing to them—because they generate fewer witnesses (proposition 2).

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 cor-
rupt (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.

We then fixed the monitoring capacity but varied the organizational structure.
Analytically, we modified the network at the margin, and considered the addition of
a single tie to the network. We showed that additional monitoring ties weakly de-
crease the frequency of corruption, while additional acquaintance ties weakly increase
the frequency of corruption (propositions 4 and 5). In the real world, separating
acquaintance and monitoring in relationships might be difficult. A practical inter-
pretation of the result is that in organizations, some ties prevent corruption, while
others facilitate it, depending on whether they facilitate monitoring more than reach-
ing better accomplices. Yet, most ties should have little effect, because they do not
target enclaves, and are therefore affecting “clean” portions of the organization.

Using simulations, we compared across a wide array of networks, and showed that
corruption should be more frequent in more siloed organizations. Intuitively, siloed
organizations have more enclaves; as such they should be more corrupt. A standard
network-analytic concept, modularity (Newman 2006) captures the notion notion of
silos, by describing the extent to which a network can be partitioned in independent
“modules” with many ties within modules, and few ties across them. I use simulations
to compare the frequency of corruption across graphs of various levels of modularity,
and show that corruption is more frequent on more modular networks.

These results ground and expand upon previous findings. They rationalize 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. Results also expand upon Evans, in that while acknowledging that the amount of ties matters, they show that their direction also matters: comparing two organizations with the same amount of ties, the more modular organization will be more corrupt.

These results also 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.

We also fixed the network and considered the impact of better formal institutions, as captured by better monitoring technologies. We saw that as organizations adopt better monitoring technologies, corruption becomes less frequent, but increases in scope and selects on high-scale projects. Because detection is more likely, corruption requires the protection of additional accomplices. The additional costs they impose on the coalition selects out petty corruption, thereby decreasing total corruption, but allow grand corruption to survive (proposition 3).

This finding confirms and provides a theoretical rationale to the intuition that guided this investigation: corruption persists and selects on grand corruption in developed countries, although it is less frequent than in developing countries. The second part of this study evaluates the claim empirically.

Finally, we investigated the impact of informal institutions on accomplices’ ability to cooperate by considering how different ways of dividing the rent among accomplices affects their behavior. Results show that commitment problems induced by corruption’s lawless environment may introduce significant noise and inefficiencies (proposition 8), that agents would presumably partially solve using informal self-enforcing contracts. Commitment problems benefit brokers—accomplices who recruit
other accomplices, who exploit their control over the diffusion process to extract larger shares of the rent (propositions 6).

Findings on informal institutions also precise earlier work. That lawlessness generates inefficiencies that benefit brokers, but may be alleviated by informal contracts is in line with the literature on trust in organized crime (eg. Gambetta 1996; Vannucci and Della Porta 2013). The model’s contribution to this line of research is in pinpointing a testable mechanism: brokers extract more of the surplus because the lack of commitment device allows them to veer diffusion according to their preferences.
Part II

Empirics
The first part of this study constructed a framework to describe how corruption networks form in organizations. Starting from the simple idea that corruption is “organized crime in an organization,” the framework builds on a small set of micro-foundations (Chapter 2): corruption networks emerge in organizations by including additional accomplices into an existing coalition to illegally extract resources from the organization. Additional accomplices pose a tradeoff between efficiency and secrecy: on the one hand, they extract resources and may protect the coalition; on the other, they compromise the coalition and they cost resources. Organizations complicate this tradeoff by granting agents differential access to such resources, and embedding
them in networks that constrain the recruitment of accomplices and expose them to witnesses, and in institutions that affect their risk of detection.

We then derived some macro-level implications from these micro-foundations by analyzing a model that treats corruption as the outcome of a process of strategic diffusion on a network (Chapter 3). In particular, we saw that as organizations adopt better monitoring technologies, corruption becomes less frequent, but increases in scope and selects on high-scale, grand corruption: because detection is more likely, corruption requires the protection of additional accomplices, but their increasing cost selects out small-scale, petty corruption, thereby decreasing total corruption. More isolated subgraphs form enclaves that are more corrupt, because they generate fewer witnesses. Some ties make corruption less frequent, some increase corruption, and others have no effect, depending on whether they enable additional monitoring, or reaching better accomplices. Commitment problems induced by corruption’s lawless environment may introduce significant noise and inefficiencies, that agents would presumably partially solve using informal self-enforcing contracts.

The second part of this study submits the framework to empirical testing. The framework unifies a large body of previous work into a single, parsimonious formal model that can be easily amended. It yields novel insights as to why grand corruption persists in developed countries, and how organizational structure can be harnessed to fight it. Submitting this framework to rigorous empirical testing is particularly important, if it is to serve as a foundation for future research, or if these new predictions are to be used to design policies to fight corruption.

Testing arguments about how organizational structure affects the structure of corruption networks is very challenging. The enterprise compounds a measurement problem and an identification problem. Corruption and networks are hard to measure. While a large share of the literature on corruption uses subjective indicators, or objective indicators aggregated, at best, at the organization level (Olken and Pande).
A faithful test of the argument requires more fine-grained data: ideally, the amounts stolen by individual members of the coalition, as well as the network structure of that coalition. Furthermore, the exercise requires measuring not only networks among members of the coalition, but also their ties with other members of the organization. Compounded with this measurement problem is the problem of identifying the causal effect of organizational structure on corruption. Ideally, one would want to exploit exogenous variation on organizational structure. While solving each issue separately is problematic, addressing them all at once is even more challenging.

I circumvent this difficulty by breaking it down into a series of tests that focus on different stages of the argument, and vary in how much emphasis they put on internal and external validity. Chapters 5 and 6 conduct tests with relatively higher internal validity. While Chapter 5 tests the macro-implications of the framework in a lab experiment, Chapter 6 revisits its micro-foundations using field data from a large company.

In this chapter, I evaluate the macro-implications of the theory by conducting a test that has high external validity, but low internal validity. I examine cross-country data on aggregate corruption levels and aggregate features of the bureaucracy, as well as data on corruption cases in a developed country, the United States, and a developing country, India.

The goal is to submit these macro-level implications to an easy test: do theoretical predictions match the correlations we observe in the data, after controlling for obvious confounders? The evidence is highly tentative. The observed correlations could be driven by unobserved confounders. Furthermore, conducting the analysis at such a high level of aggregation forces us to rely on proxy measures for the concepts of interest, introducing measurement error. Yet, even though this analysis will not be able to ascertain whether the theory explains the variation we observe at the global
level, it will at least be able to tell us whether the theory is consistent with the observed variation.

Together these comparisons lend support to the predictions that corruption occurs in enclaves, and that as states adopt better monitoring technologies, corruption becomes less frequent, but increases in scope and selects on high-scale, grand corruption. I first examine cross-country comparisons (section 4.1), then corruption data from the US and India (section 4.2).\footnote{All models used to construct the figures in this Chapter are available in Appendix B.1}

### 4.1 Corruption across countries

Cross-country datasets have proliferated over the past two decades, often providing long-running panels that measure many aspects of a country’s social, economic, and political environment. A particularly important source is the 2017 Quality of Government dataset (QoG) and its related 2015 Expert Survey (QoGEx, Dahlström et al., 2015) that compile a comprehensive source of cross-country data relevant to the quality of governance. Although this dataset comprises a large number of indicators, very few measure precisely the concepts of interest to the theory. I detail below which predictions can be tested, and how the chosen indicators map back to the theory (see Table 4.1 for a description of these indicators).

The QoG/QoGEx datasets allow testing some of our predictions on how corruption varies with the quality of the monitoring technology. I first examine whether as the monitoring technology gets better, corruption decreases by selecting on cases of grand corruption. The cross-country counterpart to this prediction is that states that have stronger institutions should be, overall, less corrupt that states with weaker institutions. Additionally, they should feature less petty corruption, but comparable amounts of grand corruption. Because these relationships are consistent with
quotidian experience and have been well-documented elsewhere\textsuperscript{2}. I only examine this relationship superficially, as a way to ascertain that this data reproduces relationships that we know are true.

Throughout these tests, I proxy for institutional strength using GDP per capita in PPP USD 2011. Levels of development highly correlate with institutional strength, and GDP per capita is a measure that is widely available, and comparable over time and across space.

I proxy for levels of petty and grand corruption using perceptions of corruption in institutions that are typically associated with each kind. I use perceptions of corruption in the legislature to measure grand corruption, and perceptions of corruption in the police for petty corruption. Of course, not all corruption in the police is petty

\textsuperscript{2}The relationship between institutional strength and overall levels of corruption has been well-documented since Mauro [1995]. See Kaufmann [2004] for evidence on petty and grand corruption in developing and developed countries.

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

Table 4.1: Variables used in cross-country comparisons
Figure 4.1: **Petty and grand corruption across countries.** Higher levels of development correlate with lower amounts of petty corruption, as proxied by corruption in the police. There is little correlation with amounts of grand corruption, as proxied by corruption in the legislature. Shaded areas represent 95 percent heteroskedastic confidence intervals.

corruption. Yet, it is definitely the case that if legislators engage in corruption, they engage in grand corruption. As such, these indicators seem reasonable proxies for the concepts of interest.

Figure 4.1 confirms the prediction: while developed countries feature little petty corruption, they are still plagued by high levels of grand corruption. There is a clear negative correlation between levels of development and corruption in the police, while there is about no correlation between between levels of development and corruption in the legislature.

The data allows testing another prediction related to the monitoring technology: as the monitoring technology gets better, corruption increases in scope; that is, the same corruption case should involve more accomplices under better monitoring. Again, the cross-country counterpart of this prediction is that the same corruption case in a country with strong institutions should involve more accomplices than the average corruption case in a country with weak institutions.
To test this prediction, I use the following hypothetical scenario from QoGEx: if a bureaucrat were tasked to give $1000 to the poor, (a) how much would eventually reach the poor, (b) how much would the bureaucrat keep to herself, and (c) how much would she give to her manager or to middlemen. I use the fraction of the amount embezzled that goes to accomplices—here, manager or middlemen—as a proxy for the number of accomplices.\(^3\) Mechanically, for a rent of a fixed size, if the number of accomplices increases, then the share of the rent that goes to accomplices should also increase.

Figure 4.2 supports the prediction that corruption increases in scope under better monitoring technologies. Accomplices pocketing larger shares of the rent correlate with higher levels of development.

Using the fraction of the rent as a proxy for the number of accomplices has both an advantage and a disadvantage. On the one hand, using a fraction controls for the fact that in reality, cases of grand corruption, which have larger rents, also tend to involve more accomplices. A fraction alleviates concerns that our findings will be driven

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\(^3\)In other words, I use the ratio \(c/(b+c)\).
by the fact that more developed countries exhibit more grand corruption. On the other hand, the model also tells us that in a lawless environment, corruption benefits brokers—accomplices who recruit other accomplices—, who exploit their control over the diffusion process to extract larger fractions of the rent. Stronger formal institutions may prevent accomplices from successfully implementing informal institutions that alleviate the commitment problems induced by lawlessness. As a result, the observed correlation may capture the distributive implications of stronger formal institutions, instead of their implications for the scope of corruption.

The data allows testing one final implication of the theory; namely, that corruption occurs in enclaves. I show in the previous chapter that corruption occurs in enclaves; that is, more isolated portions of the organization. Using simulations, I also show that organizations that contain more such enclaves are more corrupt. Taking this to cross-country comparisons, we should see that all other things equal, a country that exhibits a more enclaved bureaucracy should be more corrupt.

I proxy for the degree of enclavation of a bureaucracy using QoGEx’s index of bureaucratic closedness. The index includes three components that capture the extent to which recruitment in public sector jobs is flexible, transparent, and comparable to the private sector. Although the index does not directly measure enclavation within the bureaucracy, it captures, at least, how much the bureaucracy as a whole is isolated from the rest of society.

Table 4.2 supports the prediction that more enclaved bureaucracies exhibit more corruption. The correlation is robust to using different indicators of corruption, and controlling for a few obvious confounders; namely, the level of development and regime type.
Table 4.2: Corruption and bureaucratic closedness across countries. More closed bureaucracies are more corrupt. Higher closedness values indicate more enclaved bureaucracies. Each model uses a different indicator of corruption as the dependent variable. In model 1, higher values of the dependent variable indicate more corruption; they indicate less corruption in models 2 and 3. Models are estimated using OLS. Heteroskedastic standard errors in parenthesis.

### 4.2 Corruption in the US and India

While cross-country comparisons had the advantage of identifying patterns at the global scale, they also suffer from relatively poor measurement. The indicators used in these comparisons are admittedly crude proxies for the quantities of interest. Furthermore, the approach relates cases of corruption aggregated at the country-level to measures of the quality of the monitoring technology, and other features of the bureaucracy that are also aggregated at the country-level. Making inferences about individual cases of corruption using aggregated data exposes the analysis to the well-known risk of ecological fallacy (Gelman, 2009).

To alleviate these concerns, I consider data at a finer level of aggregation: instead of focusing on countries as the unit of analysis, I consider individual corruption cases. In order to ensure that there is a sufficient amount of variation in the quality of the monitoring technology across cases, I compare cases in a country that has allegedly strong institutions for fighting corruption, the US, to a country that has allegedly weaker institutions for fighting corruption. I test whether corruption patterns in
the two countries conform to the prediction that corruption decreases under better monitoring technologies but increases in scope and selects on grand corruption.

I collected data on corruption cases 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 ran this 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. I then went through each article to identify the ones actually covering corruption cases. For each selected article, I collected the amount stolen, the number of accomplices, and whether the case involved strong ties; that is, whether at least two accomplices shared any affiliation other than professional (see Table 4.3 for descriptive statistics). 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.

<table>
<thead>
<tr>
<th></th>
<th>India</th>
<th>USA</th>
</tr>
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<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 4.3: **Descriptive statistics on corruption cases in India and the US.** Cases of corruption are less frequent in the US than in India, but involve more accomplices and larger amounts stolen than in India, and comparable amounts of strong ties.
Figure 4.3: **Cumulative distribution of amounts stolen in India and the US.** Cases of corruption select on grand corruption in the US. The distribution of amounts stolen is more skewed towards higher amounts in the US than in India.

While using newspaper data to measure corruption is not uncommon (see, for instance Glaeser and Goldin [2008]), this kind of data has several well-known pitfalls that the research design addresses to some extent. Most importantly, different newspapers may have different editorial lines that push them to select differently on the topics they cover. Differences across newspapers could then be attributable not to different levels of corruption, but to variation in the willingness to report on cases of corruption. Comparing the US and India addresses this concern to some extent. The NYT and the TOI are both major generalist, 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. If these newspapers were to differ in their willingness to cover corruption, then selection should only dampen the findings. Indeed, 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.
Comparing the US and India also partially addresses another concern of this approach; namely that the design attributes all differences in corruption cases across countries to differences in the quality of the monitoring technology alone. Yet, countries presumably differ on additional dimensions. Again, comparing the US and India alleviates some of these concerns, for it selects countries that are similar in some well-known determinants of corruption. Specifically, the design controls for regime type, as well as some demographic and institutional features, since both countries are large federal states with vivid democracies. Those two countries still differ in other dimensions; most importantly, levels of development, and culture. These differences may certainly affect the incidence of corruption, by governing the profitability of corruption, and willingness to engage in it. This should not be too concerning, because the claim that stronger institutions curtail corruption is a well-established fact (Svensson 2005; Olken and Pande 2011). It is more difficult to argue that economic and cultural differences between the US and India affect how corruption is organized, conditional on corruption occurring. If anything, cultural differences would dampen our findings. If corruption hinges on a culture of gift-giving (Granovetter 2007; Blundo and De Sardan 2013), then coalitions should involve more accomplices in India, whose more traditional values would presumably put more weight on gift-giving.

Results support the prediction that that corruption becomes less frequent under better monitoring technologies but increases in scope and selects on grand corruption. The descriptive statistics in table 4.3 confirm our casual intuition that corruption is less frequent in the US than in India: it takes about fifteen years of NYT data to collect 55 cases of corruption, while it takes about two months of TOI data to collect 55 cases of corruption. Comparing the distribution of amounts stolen across countries (Figure 4.3) also shows that while the India features both grand and petty corruption, the US feature only grand corruption: the distribution of amounts stolen
Figure 4.4: **Scope of corruption in India and the US.** Cases of corruption in the US have more accomplices than in India for similar amounts stolen. Shaded areas represent 95 percent confidence intervals.

is more skewed towards higher amounts in the US than in India. While the US have no corruption cases where less than 10 percent of GNI p/c was stolen, those cases represent about 40 percent of corruption cases in India. Finally, figure 4.4 controls for the scale of corruption, and shows that comparable corruption cases involve more accomplices in the US than in India.

\[\text{A one-sided Mann-Whitney test is significant at the 1 percent level.}\]
In the previous chapter, we saw that patterns of corruption across countries are broadly consistent with the macro-implications of the theoretical model I analyze in chapter 3. Specifically, they support the predictions that corruption occurs in enclaves, and that as countries acquire stronger institutions, corruption decreases, but selects on grand corruption, and involves more accomplices. Although this analysis lends support to the theory, it suffers from a number of weaknesses. First, this analysis is only suggestive, showing correlations that are consistent with the theory,
and might be driven by unobserved confounders. Second, most of the concepts of interest, such as organizations, the structure of corruption networks, and the quality of the monitoring technology, are not measured precisely. These data limitations also prevent us from testing other implications of the theory, such as predictions on how changes to the organizational structure may curtail corruption.

This chapter takes the model to the lab, submitting it to a test that has comparatively high internal validity, but lower external validity. The lab is particularly advantageous in that it allows solving the thorny measurement and inferential issues associated with studying corruption and networks through experimental manipulation. Although the lab has comparatively lower external validity, several features of the design are meant to increase it. The experiment uses face-to-face interactions, in order to mimic the interpersonal interactions that occur in real organizations. Taking the lab to the field, I hold the experiment in Morocco, a mid-income country with median levels of corruption\(^1\) and compare a subject pool of students to a subject pool of service sector employees.

The experiment tests the robustness of the main theoretical predictions to behavioral factors that are assumed away in the model. Doing so, I submit the theory to a minimal test: if predictions are not verified in this highly controlled environment, where the only sources of noise are behavioral traits, then there is little reason to believe that they would hold outside the lab. Although the main goal of the experiment is to test the main predictions of the theory, I also examine an important set of model assumptions: the division rule used by accomplices. Examining these assumptions is particularly important, for different division rules may prompt for different coalitions.

In what follows, I situate this experiment within a broader literature that studies corruption in the lab (section 5.1), then introduces the experimental design and the main hypotheses (section 5.2). I then analyze the results, and show that they

\(^1\)Morocco is ranked 90 out of 176 countries in the Transparency International Corruption Perception Index 2016.
strongly support the main predictions of the model: corruption occurs in enclaves, and changing the organizational structure may decrease corruption if done carefully: while increasing the amount of connections within the organization may decrease corruption, many ties have no effect. Furthermore, increasing the quality of the monitoring technology decreases corruption, but selects on grand corruption and increases in scope. Of course, the data are no perfect match the theoretical prediction. Examining the division rule used by subjects, I identify one systematic deviation that has important substantive implications: for cognitive reasons, subjects have difficulties coordinating to form large coalitions. This provides an additional reason as to why developed countries are less corrupt than developing countries. In developed countries, better monitoring technologies prompt for larger coalitions, which often fail to form because they require more coordination from their members (section 5.3). Finally, I conduct a few important robustness check, and show that results were not biased by poor comprehension, learning, or pooling effects, and that students and employees behaved comparably (section 5.4).

5.1 Studying corruption in the lab

The experimental design introduced in this paper relates to a burgeoning literature that studies corruption in the lab (see Serra and Wantchekon, 2012, for a review). The lab allows for careful measurement of the concepts of interest while maintaining the ability to make causal claims, and controlling for important confounders. An important such confounders is the ethical considerations that surround corruption. A common practice—which this experiment follows—is to use a neutral framing as a baseline; that is, make no mention of corruption to participants, and then investigate in additional experiments the impact of a loaded framing.
Most related to this paper is the work of Berninghaus et al. (2013), who study a collective corruption experiment: bureaucrats simultaneously decide whether to accept a bribe, their probability of detection decreases with the amount of bureaucrats that accepted the bribe. I add to this experiment by providing the simplest setting that allows to test for the the relationship between organizational structure and corruption. I add to Berninghaus et al.’s design an exogenous network structure that affects the probability of detection: as in their paper, the probability of detection decreases with the amount of corrupt bureaucrats, but it also increases with the amount of witnesses, which depends on the network. I also add a diffusion element, so as to account for the formation of a criminal ring: only one bureaucrat is offered the bribe, and may share it with her neighbors. This, in turn, poses a tradeoff between secrecy and efficiency, which was absent from Berninghaus et al.’s experiment: increasing the probability of detection is done at the expense of reducing one’s share of the bribe.

Introducing network structure places this experiment within a growing literature that studies networks experimentally. Closest to this paper are Charness, Corominas-Bosch and Fréchette (2007), who study simultaneous bargaining on a network, and Centola (2010), who examines an online experiment on diffusion, without the bargaining component.

5.2 Design

The experiment tests whether the main substantive implications of the theoretical model analyzed in Chapter 3 are verified empirically, in a setting with relative ecological validity. 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: because detection is more likely, corruption requires the protection of additional accom-
plices, but their increasing cost selects out petty corruption, thereby decreasing total corruption. More isolated subgraphs form enclaves that are more corrupt, because they generate fewer witnesses. Some ties make corruption less frequent, some increase corruption, and others have no effect, depending on whether they enable additional monitoring, or reaching better accomplices. Commitment problems induced by corruption’s lawless environment may introduce significant noise and inefficiencies, that agents would presumably partially solve using informal self-enforcing contracts.

Participants play the diffusion game analyzed in the model: a participant is offered a rent that she may share with her neighbors on a pre-determined network. Neighbors may, in turn, share their holdings with their neighbors. Once the process is over, accomplices get detected with probability $1 - p$. The probability of success $p = p(a, w, q)$ depends on three parameters. It is increasing in $a$, the number of accomplices that composes the coalition, to capture the idea that accomplices protect the coalition from detection. It is decreasing in $w$, the number of witnesses—that is, the non-corrupt neighbors of accomplices—to capture the idea that accomplices hurt the coalition by creating witnesses among their peers within the organization. Finally, the probability of success is decreasing in $q$, a parameter that captures the quality of the monitoring technology; in other words, how good the organization is at detecting and punishing corruption, net of the effect of social structure.

Following standard practice, I use a neutral framing, to control for social desirability bias and other moral considerations related to corruption that may affect sharing behavior in the lab. Supplementing the neutral framing with a loaded framing was not feasible due to security concerns for respondents. Available secondary evidence suggests, however, that framing effects should not impact the result. Analyzing a bribery experiment, Abbink and Hennig-Schmidt (2006) find no framing effects. Barr and Serra (2009) and Lambsdorff and Frank (2010) do find framing effects, but only

See chapter 2 for an informal discussion of the setup, and chapter 3 for a formal analysis of the model.
Table 5.1: **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 (column 5) use a t-test; *p<0.05; **p<0.01; ***p<0.001.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Sample</th>
<th>Students</th>
<th>Employees</th>
<th>Δ</th>
</tr>
</thead>
<tbody>
<tr>
<td>age</td>
<td>24.85</td>
<td>20.44</td>
<td>26.17</td>
<td>5.73***</td>
</tr>
<tr>
<td>% females</td>
<td>0.21</td>
<td>0.16</td>
<td>0.23</td>
<td>0.07</td>
</tr>
<tr>
<td>% secondary education</td>
<td>0.75</td>
<td>0.95</td>
<td>0.69</td>
<td>-0.26***</td>
</tr>
<tr>
<td>income</td>
<td>1.65</td>
<td>1.83</td>
<td>1.59</td>
<td>-0.23**</td>
</tr>
<tr>
<td>% urban</td>
<td>0.94</td>
<td>1.00</td>
<td>0.93</td>
<td>-0.07***</td>
</tr>
<tr>
<td>% Arabs</td>
<td>0.94</td>
<td>0.95</td>
<td>0.94</td>
<td>-0.01</td>
</tr>
<tr>
<td>risk-taking</td>
<td>2.78</td>
<td>2.59</td>
<td>2.83</td>
<td>0.25</td>
</tr>
<tr>
<td>altruism</td>
<td>1.54</td>
<td>1.83</td>
<td>1.45</td>
<td>-0.37**</td>
</tr>
<tr>
<td>extroversion</td>
<td>2.96</td>
<td>2.69</td>
<td>3.04</td>
<td>0.36**</td>
</tr>
<tr>
<td>N</td>
<td>272</td>
<td>63</td>
<td>209</td>
<td></td>
</tr>
</tbody>
</table>

on the client side, not on the bureaucrat side. Since this experiment focuses on the bureaucrat side, there is little reason to expect that framing effects would bias the result.

The protocol takes advantage of the field setting to increase ecological validity. The experiments were all conducted in Mohammedia, Morocco, a mid-income country with median levels of corruption. Considering a country in the middle of the distribution of both corruption and one of its important correlates, namely per capita income, increases our confidence that the findings travel to either tail of the distribution.

I used a convenience sample of 272 subjects with one quarter undergraduate students, and three quarters employees of the service industry. While conducting the experiment with bureaucrats proved unfeasible, service-sector employees are a reasonable proxy, since the argument extends to private organizations. Undergraduate students, the standard subject pool of laboratory experiments, are very different from employees (Table 5.1). As such, comparing between subject pools tests whether behavior is driven by some characteristic held only by students or employees.

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3Even if a subject pool of service-sector employees may not capture all the features of bureaucrats, this subject pool proxies, at the very least, for an adult, urban, and employed population.
thermore, the protocol uses face-to-face interactions. Face-to-face interactions mimic the interpersonal interactions that arise in organizations. They provide participants with opportunities for cheap talk that they may leverage to solve the commitment problem through informal mechanisms.

To test the main predictions, the experiment examines behavior in a baseline condition with a less profitable rent (petty corruption) and a more profitable one (grand corruption), and compares this baseline to two treatment conditions. The first, “hard” treatment increases the level of monitoring while keeping the network constant. It examines how corruption changes in form as organizations get better at detecting it. Compared to the baseline, the seed should reject less profitable rents at a higher rate, and recruit more accomplices under grand corruption (proposition 3). The second, “exposing tie” treatment manipulates the network structure and keeps the level of monitoring constant, to test whether organizational structure affects corruption. I add a specific tie to the baseline and test whether ties that make enclaves more exposed reduce the frequency of corruption (proposition 4). I also add and remove “irrelevant” ties to verify that ties that do not affect enclaves have no effect (propositions 4 and 5). Corruption should occur in enclaves, because they are less monitored. Within treatment condition, I examine whether realized coalitions are relatively more enclaved. Although the main goal of the experiment is to test the main predictions of the theory, I also examine an important set of model assumptions: the division rule used by accomplices. Examining these assumptions is particularly important, for different division rules may prompt for coalitions. As such, I examine the distribution of the rent within coalitions and compare it to the hypotheses considered in the model: bargaining on the one hand, which assumes that agents are unable to solve commitment problems, and equal-sharing and monopoly on the other, which assume that agents solve commitment problems using, in turn, a perfectly egalitarian and a perfectly unegalitarian contract (proposition 8).
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 paper handout listing the probability of success $p$ of each feasible coalitions. The probability of success rescales the function used in the simulations (equation 3.2) by a factor of .83: $\tilde{p}(a, w, q) = .83p(a, w, q)$. Each player is endowed with $\epsilon$ discrete experimental units (EU). One player is the seed. An enumerator offers her a rent of 12 EU that she may take to initiate a diffusion game akin to the model. If players accept an offer, they give up their endowment, to represent the loss from corruption. Once the process is over, non-accomplices keep their endowment. To determine whether accomplices won or lost, the enumerator rolls a hundred-sided dice and compares it to the probability of success of the realized coalition, using the paper handout on the table. If the outcome is smaller than the probability of success, the outcome is a success, and accomplices earn their holdings. Otherwise, the outcome is a failure, and accomplices earn 0. 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. All interactions are public, to reproduce the environment of complete information that features in the model. Furthermore, while cheap talk is otherwise allowed, the enumerator mediates communication related to offers between players, to implement the sequential, take-it-or-leave-it offers that feature in the model. As discussed earlier, the protocol uses a neutral framing, and makes no mention of corruption to participants.

Table 5.2 details the experimental parameters and equilibrium outcomes in the baseline and the main treatment conditions. The baseline sets the monitoring technology $q$ to .1 and uses a star network. The hard treatment uses the same network.

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4 Without rescaling, the probability of success is $p(N, 0, q) = 1$ for the grand coalition. The rescaling has $\tilde{p}(N, 0, q) = .83$, which prevents this outcome from being focal.

5 The enumerator would mediate communication around offers by 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.
### Table 5.2: 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.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Capacity ((q))</th>
<th>Predicted equilibrium coalition</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Grand corruption ((\epsilon = 2))</td>
<td>Petty corruption ((\epsilon = 4))</td>
</tr>
<tr>
<td>Baseline</td>
<td>.1</td>
<td><img src="image1.png" alt="Diagram" /></td>
</tr>
<tr>
<td>Hard</td>
<td>.75</td>
<td><img src="image3.png" alt="Diagram" /></td>
</tr>
<tr>
<td>Exposing tie</td>
<td>.1</td>
<td><img src="image5.png" alt="Diagram" /></td>
</tr>
</tbody>
</table>

but increases the strength of monitoring to \(q = .75\). The exposing tie treatment keeps a monitoring technology of .1, but adds to the star network a tie that should decrease corruption. In all conditions, I 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. Experimental parameters were chosen to yield the same equilibrium coalition in the lawless environment, and under the monopoly and equal-sharing division rules.\(^6\) 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).

Subjects played the experiment in groups of four, with a total of 68 groups. Before participating in the experiment, subjects took a short, individual pre-experiment survey. After participating in the experiment, subjects were administered a short, individual post-experiment survey. They were then paid their earnings, with the

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\(^6\)See Appendix C.1 for equilibrium predictions.
average payment amounting to daily minimum wage, comprising an average gain of $2.6 average gain and a $5 show-up fee.

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. The twelve rounds were divided in three “blocks” of four rounds, corresponding to the baseline and the two treatments. Within each block, 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, according to the ordering in figure 5.1. 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.

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, for instance by incentivizing subjects to pool across games. Several features of the design discourage adverse learning and pooling effects. First, 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. Second, 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.

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.

I show in section 5.4 that subjects displayed satisfactory levels of comprehension, that learning effects are insignificant and mixed, and that there are no pooling effects. I provide additional details about the protocol in Appendix C.2.
5.3 Results

5.3.1 Testing the main propositions

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? To test these hypotheses, I compare three outcomes across treatment conditions: whether the seed accepts the rent (Figure 5.2), the mean size of realized coalitions (Figure 5.3), and the distribution of these coalitions (Figure 5.4). Since the model’s assumptions are not a perfect match to reality, taking the model to the lab introduces significant noise. As such, testing whether the realized outcomes match the equilibrium predictions in each treatment may be too strict a test. Instead, I test whether the estimated treatment effects go in the same direction as the predicted variation, then examine in more details the effects whose size most differs from the theory. Treatment effects on acceptance behavior and on coalition size are estimated using OLS: I regress the corresponding outcomes—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. When examining the size of realized coalitions and their distribution, I restrict the analysis to grand corruption, because predictions on the structure of corrupt coalitions are conditional on the seed taking the rent in equilibrium, which only happens with grand corruption.

Behavior in the baseline condition matches equilibrium predictions reasonably well. In equilibrium, the seed should take the rent and keep it to herself under both petty and grand corruption (Table 5.2). Observed acceptance rates in the baseline

\footnote{Appendix B.2 shows the models used to construct all the figures in this chapter.}
Figure 5.2: **Frequency of corruption in all treatments.** Errors are clustered at the group level. Full circles are point estimates with their 95 percent confidence interval. Empty circles are equilibrium predictions. 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 5.3: **Scope of corruption in all treatments with grand corruption.** Errors are clustered at the group level. Full circles are point estimates with their 95 percent 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.

Figure 5.4: **Distribution of realized coalitions in all treatments with grand corruption.** Bar labels correspond to the coalitions that include the black nodes. Grey bars indicate the equilibrium. More isolated nodes are more likely to be corrupt (panel 5.4c second and third bars). Most realized coalitions correspond to the equilibrium prediction, except for the hard treatment.
are high—around 90 percent—and do not differ significantly under petty or grand corruption (Figure 5.2). Looking at the structure of realized coalitions, coalitions have a mean size of 1.7 under grand corruption (Figure 5.3), which is slightly larger than the prediction, but the equilibrium coalition is realized in more than 70 percent cases.

Comparing the baseline to the hard treatment shows support for our hypotheses on how corruption changes in form as organizations get better at detecting it (proposition 3). Because getting caught becomes more likely, the seed should be more willing to give away fractions of the rent to recruit additional accomplices. However, the seed can only afford the cost entailed by additional accomplices when corruption is profitable enough. As such, in equilibrium, the seed should reject the rent under petty corruption. Under grand corruption, she should accept it and recruit the other three participants. Figure 5.2 shows that under grand corruption, the seed accepts the rent at rates that are comparable to the baseline—the difference in means is marginally significant. However, those rates drop sharply—by about 40 percentage points—when moving to petty corruption, confirming that better monitoring technologies reduce the frequency of corruption by selecting on grand corruption. Grand corruption also involves more accomplices: compared to the baseline, better monitoring increases the mean size of the coalition increases by about 1.1 accomplices (Figure 5.3). While the observed variation goes in the same direction as the theory, it is in this treatment that we observe most deviation between the realized coalitions and the equilibrium prediction: in this treatment, the equilibrium coalition accounts for only 28 percent of realized coalitions, while other treatments align better with predictions (Figure 5.4). I show in the next subsection that this is due to subjects making mistakes when engaging in bargaining for long chains of backward induction.

The exposing tie treatment confirms that corruption occurs in enclaves (proposition 2), and that changing organizational structure may reduce corruption (proposi-
In this treatment, the additional tie makes the seed more exposed, to the point that she should reject the bribe under petty corruption. Under grand corruption, she should accept it, and recruit her more enclaved neighbor. Similar to the hard treatment, Figure 5.2 shows that ties that make enclaves more exposed reduce corruption, and the frequency of corruption by selecting on grand corruption: under grand corruption, the seed takes the rent at rates that are comparable to the baseline, but that those rates drop sharply when moving to petty corruption. Realized coalitions also align well with the predictions. Figure 5.3 shows that compared to the baseline, the mean size of the coalition increases to about 2.1 accomplices, matching the equilibrium prediction very closely. The figure also shows that the ordering of effects is consistent with predictions: the coalition is largest in the hard treatment, and second largest in the exposing tie treatment. Looking at the distribution of realized coalitions confirms that corruption occurs in enclaves. In the exposing tie treatment, the seed overwhelmingly favors the more enclaved 2-people coalition (Figure 5.4c): the equilibrium coalition accounts for 45 percent of realized coalitions.

Comparing within all treatments, I show that ties that do not make enclaves more exposed have no effect on corruption (propositions 4 and 5). I first examine the effect of such irrelevant ties on the seed’s acceptance behavior. I estimate this effect within treatment, by adding an indicator variable for irrelevant ties to our main specification. Figure 5.2 shows that adding irrelevant ties has little effect on the incidence and the scale of corruption, with a marginally significant difference in means. I adopt a similar approach to estimate the effect of irrelevant ties on realized coalitions, and 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.

Results available from the author upon request.

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5.3.2 Division rule

Having shown support for the main theoretical predictions, I now investigate the division rule used by participants. In section 3.2.4 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.

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 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.
Figure 5.5: **Seed’s share of the rent under grand corruption in equilibrium coalitions.** All: much of the mass lies above the monopoly prediction. Right: The seed’s payoff is closer to the predictions under bargaining and monopoly in the exposing tie treatment.

![Graph showing observed and predicted frequencies for hard treatment and exposing tie treatment.]

<table>
<thead>
<tr>
<th>Payoff</th>
<th>Observed frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 2 3 4 5 6 7 8 9 10 12</td>
<td>0.00 0.10 0.20 0.30</td>
</tr>
</tbody>
</table>

**Prediction**
- all environments
  - mean = 4.69
  - median = 4

- equal-sharing
  - mean = 7.96
  - median = 8

<table>
<thead>
<tr>
<th>Payoff</th>
<th>Observed frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 2 3 4 5 6 7 8 9 10 12</td>
<td>0.00 0.10 0.20 0.30</td>
</tr>
</tbody>
</table>

**Table 5.3: Observed behavior compared to predicted behavior under bargaining.** Numbers denote observed frequencies. Subjects over-share and over-accept: errors (italicized cells) are overwhelmingly false positives.

<table>
<thead>
<tr>
<th>Share</th>
<th>Did</th>
<th>Not Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>.07</td>
<td>.50</td>
<td>.42</td>
</tr>
</tbody>
</table>

(a) Sender’s decision

<table>
<thead>
<tr>
<th>Accept</th>
<th>Did</th>
<th>Reject</th>
</tr>
</thead>
<tbody>
<tr>
<td>.24</td>
<td>.51</td>
<td>.23</td>
</tr>
</tbody>
</table>

(b) Recipient’s decision

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 5.5). The observed distributions align more closely with bargaining and equal-sharing in the exposing tie treatment.

More importantly, figure 5.5 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. Table 5.3 shows that for both decisions, most errors are false positives: offerers over-share, and consistently, recipients over-accept.9

Looking at amounts offered pinpoints the irrationality (Figure 5.6): about 75% offers are greedy—they would leave the recipient with negative surplus; yet, they have a very high chance of being accepted.10 Proposition 7 implies that under bargaining, all agents have threshold strategies: \( i \) should accept offer \( t_{ji} \) 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 5.6 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 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,

---

9 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.

10 The right panel of figure 5.6 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.
Figure 5.6: 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 percent confidence intervals. History 1 is the seed’s decision, and is omitted. Footnote [10] provides details about estimation.

the problem is easier. As such, offers get closer to the equilibrium prediction, and recipients are more likely to reject greedy offers.

5.4 Robustness checks

5.4.1 Learning and pooling effects

As mentioned in section 5.2, learning and pooling effects are an important challenge in this experiment. Although the experimental design incorporates several features to minimize such effects, they might still bias the results. 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, undesirable 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
Figure 5.7: **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.

This and adjust their strategies accordingly, hence deviating from equilibrium strategy over time.

Figure 5.7 shows that subjects displayed satisfactory levels of comprehension. On average, the percent of correct answers to a given comprehension question never went below 80 percent, and reached 94 percent by the end of a session.

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 5.1). 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 5.8 shows that both in early and late rounds, results go in the expected directions. Effect size never varies significantly. The effect of capacity
Figure 5.8: 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 percent confidence intervals. There is little evidence for learning and pooling effects: behavior never differ significantly between the late and early blocks.

Pooling effects could explain why bribe offerers engage overly greedy in bargaining (Section 5.3.2). Subjects might tacitly agree on reciprocal exploitation. Recipient $i$ accepts to be exploited by bribe-offerers in some round of the game because she knows that she will exploit others when she will get to be an offerer in later round. If this is true, then we should observe an end-game effect: recipients in the last rounds would be less inclined to accept greedy bargaining because there is no further opportunity to reciprocate.

There are no pooling effects. Recall that the exposing tie block was administered last and that within block, the order of games was randomized. I compare the first
two rounds of the exposing tie block to the last two. In particular, I look at the
distribution of offers as deviation from the equilibrium offer. A Kolmogorov-Smirnov
test fails to reject the null that these distributions are similar. Figure 5.8 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.

5.4.2 Individual-level characteristics

Investigating potential heterogeneous treatment effects, I find that the behavior of
employees does not significantly differ from that of students, despite their very different
characteristics. I first show that group-, and individual-level heterogeneity have
little influence, and that group-level heterogeneity is larger than individual-level het-
erogeneity. I re-estimate our quantities of interest, using linear mixed models with
individual-level random effects, group-level effects, and both. Figure 5.9 shows that
the quantities of interest are virtually unchanged. Furthermore, random effect specifi-
cations fit the data marginally better than a specification without pooling, suggesting
that there is little heterogeneity across groups, or across groups (Table B.2). Fur-
thermore, 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.

Second, I show that although they have very different characteristics, students
and employees have very similar behavior. Sample descriptive statistics revealed that
employees are poorer, less educated, more rural, less altruistic, and more extroverted
than students (Table 5.1). Yet, students and employees behaved very similarly in
the experiment. I reestimate the quantities of interest separately for students and
employees (Figure 5.10): predictions for students are more noisy than for employees,
because of they represent a smaller fraction of the sample, but they largely overlap
Figure 5.9: **Random effect specifications.** The specifications without random effects is estimated using a Gaussian GLM; RE specifications use linear mixed models. Bars indicate 95 percent confidence intervals. The main quantities of interest are robust to adding random effects.
with that of employees. This makes the results more credible, suggesting that behavior is not driven by some characteristic held only by students or employees.
Figure 5.10: Students vs. employees. “All” reports the estimates from the main specification (Table B.3). Bars indicate 95 percent confidence intervals. Students and employees have similar behavior.
In the first part of this study, we derived several micro-foundations for corrupt behavior in organizations. These micro-foundations informed the assumptions of a formal model that, in turn, derived a few macro-level implications. The previous chapter analyzed a lab experiment that showed support for the macro-implications of the theoretical model analyzed in chapter 3. Yet, this experiment was taking these micro-foundations for granted. One such micro-foundations is that accomplices pose a tradeoff between efficiency and secrecy. The experiment imposed this tradeoff by
design: following the model, it imposed a functional form for the probability of detection where additional accomplices decrease the probability of detection, to the extent that they do not create witnesses among their neighbors, who increase the probability of detection.

In this chapter, I assess some of these micro-foundations empirically, in order to verify that the model rests on realistic assumptions. We saw in Chapter 2 that corruption networks emerge in organizations by including additional accomplices into an existing coalition to illegally extract resources from the organization. Additional accomplices pose a tradeoff between efficiency and secrecy: on the one hand, they extract resources and may protect the coalition; on the other, they compromise the coalition and they cost resources. Organizations complicate this tradeoff by granting agents differential access to such resources, and embedding them in networks that constrain the recruitment of accomplices and expose them to witnesses, and in institutions that affect their risk of detection.

At the heart of these micro-foundations is the idea that in organizations, honest colleagues play a dual role: on the one hand, they deter unethical behavior from “bad apples” by subjecting them to some informal monitoring; on the other, they may end succumbing to their influence, and turn into bad apples themselves.

Evaluating empirically this simple assertion empirically faces formidable measurement problems. The task faces two challenges. First, it requires data that are granular enough to allow separating honest and dishonest behavior, and keeping track of interactions among all agents. Second, as is the case with many network studies, the set of neighbors that may influence an individual’s actions is hard to define (Pietryka and DeBats, 2017).

Existing evidence is partial or has relatively low ecological validity, because it addresses these challenges using either partial field studies, or lab experiments. Field studies typically consider past cases of fraud (Gambetta, 1996; Vannucci and Della...
This approach has detailed information on the “bad apples,” but much less information on the good ones. It makes nuanced claims on how corrupt agents interact with each other, highlighting the importance of trust in an environment where contracts cannot be enforced by a neutral third-party. It has, however, much less to say about relationships between good and bad apples. Other field studies consider a large number of organizations, but have little information on relationships inside each of them, which severely restricts the range of inferences they can make. For instance, Khanna, Kim and Lu (2015) considers the top executives of about 2,700 US firms, and construct interactions based off whether an executive was appointed during the CEO’s tenure. They show that better connected boards are more likely to commit financial fraud. Finally, lab experiments solve the measurement problems by trading off ecological validity for the control afforded by the lab (Gino and Pierce 2009; Gino, Ayal and Ariely 2009; Gino and Galinsky 2012; Pitesa and Thau 2013). Although the approach allows measuring precisely the concepts of interest and making solid causal claims, it is unclear how much the social relationships and dishonest behavior that are engineered in contrived lab settings reflect the durable, multi-layered relationships, and the variety of dishonest behaviors that may occur in real organizations.

To address this difficulty, I exploit a unique dataset on the daily operations of a call-center company in which clerks allocate incoming claims to a network of service providers. The data records the interactions of clerks with the internal company software used to allocate claims to service providers. This allows the detection of suspicious behavior during claim allocation, revealing suspicious deviations from company policy and potential preferential allocation of claims to specific service providers. The data also measures rich networks of interactions among clerks, enabling an investigation of how interpersonal relationships affect corrupt behavior.
Of course, it is difficult to simply observe an organization and find corruption. The setting combines features that allow detecting statistically likely instances of dishonest behavior among clerks. This is because clerks perform a standardized task where fraud is well-defined: instead of allocating claims to the best service provider, clerks may allocate them to their chosen provider, in return for a kickback. The company software governs the allocation of claims by randomly drawing the provider to which it should be allocated, according to a weighting defined by management. Clerks check whether the provider is available. If the provider is not available, they may skip; that is, ask for another draw. Clerks may also force; that is, they may opt out of random drawing, and manually select a provider. For management, verifying whether past skipping and forcing behavior was legitimate is costly, requiring them to manually match phone records to claims and listening to the recorded call. This gives an opportunity for dishonest clerks to use these tools wrongfully: they may pretend that the randomly drawn provider was unavailable and allocate the claim a favored provider instead. As such, dishonest clerks should have disproportionately high skipping and forcing rates.

I exploit these features to test the first part of the proposition: do good apples deter the unethical behavior of the bad apples they interact with? I leave the other part of the proposition—that is, whether bad apples infect good apples—to future research. I report three core findings that show that interpersonal interactions deter corrupt behavior.

The first finding shows statistical evidence for dishonest behavior among clerks. Because the task is standardized, if all clerks were honest, they should behave similarly. This allows pinning down the distribution of skipping rates if all clerks were honest. I show that the claims of a small amount of clerks are awarded after significantly more draws that what would be expected under honest behavior. This
suggests that these clerks behaved dishonestly, by deliberately skipping selected service providers.

The other findings establish that interpersonal interactions deter corrupt behavior. Using a series of natural experiments, I show that plausibly exogenous variation in the number of colleagues monitoring one’s task caused some clerks to reduce their skipping and forcing rates. I exploit two plausibly exogenous events: first, new hires, whose type is yet unknown to their more senior colleagues, and may trigger additional caution; second, temporary allocations of clerks to markets they seldom operate in, due to unforeseen peaks in demand. I show that both events have heterogeneous effects: while they have no effect for most clerk-provider dyads, they lead to decreases in skipping and forcing rates for some dyads. I also document that a milder form of unethical behavior may be widespread within the organization. Results show that most clerks reduce their forcing behavior when other colleagues are present, suggesting that they may unduly force when left to their own device, presumably to avoid the time-consuming process of random draws.

Finally, I use a structural model to unpack the patterns that natural experiments identified in a reduced form. The natural experiments label as dishonest the clerks who reduce their suspicious behavior when surrounded by other clerks. Doing so, they may conflate identifying dishonest types with the behavioral hypotheses attached to such types. This approach may be spurious if our assumptions on the behavior of honest and dishonest types are wrong. The structural model separates the two components of the problem, by estimating the latent probability that a provider is unavailable, and that a claim has been unduly skipped. This allows assigning honest and dishonest types to clerk-provider dyads, and identifying the behavior of dishonest types. Results confirm and sharpen the causal evidence. I confirm that dishonest clerks are more likely to skip unduly when subjected to less monitoring from their peers. I also show that dishonest types are sophisticated, in the sense that they are
more likely to skip unduly for high-value claims, since those transfer more revenue to the providers they are colluding with.

In what follows, I first provide additional details about the context and the data (section 6.1), then show descriptive evidence of fraudulent behavior (section 6.2). I finally provide causal evidence that additional monitoring by peers deters corrupt behavior (section 6.3), as well as comparable structural evidence (section 6.4).

6.1 Context and data

The data describes the daily operations of a call-center company based in Casablanca, Morocco, between November 1st, 2016 and March 10th, 2017. This call-center operates a network of 325 partnering service providers. When calling, customers file claims to the company, who dispatches a service provider to satisfy the customer’s demand. These claims are typically urgent, and need to be serviced within the shortest amount of time—5 minutes on average for urgent services, and 30 minutes on average for non-urgent services. The company compensates providers for their service, with the subscriptions of its customers. In our sample, average monthly compensation is $2,337.

The data is a backup of the database of the company’s internal software. The database contains all interactions of clerks with the company software, as well as characteristics of the 69,445 claims awarded during the period. Table 6.1 shows descriptive statistics.

This context has the advantage that corruption is well-defined. Clerks can behave dishonestly by either creating fictitious claims, or misallocating them. Creating fictitious claims is virtually impossible, for management monitors all claims that involve financial transactions. As such, the only kind of corrupt behavior is the preferential allocation of claims to service providers, in return for a kickback. Some of such

\footnote{All OLS models used to construct figures in this Chapter are reported in Appendix B.3}
### Table 6.1: Sample descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable</td>
<td></td>
</tr>
<tr>
<td>Forcing rate</td>
<td>0.23</td>
</tr>
<tr>
<td>Mean chain length</td>
<td>1.44</td>
</tr>
<tr>
<td>Claim characteristics</td>
<td></td>
</tr>
<tr>
<td>Number of claims</td>
<td>69,445</td>
</tr>
<tr>
<td>Revenue</td>
<td>$2.90m</td>
</tr>
<tr>
<td>Daily number of claims</td>
<td>534</td>
</tr>
<tr>
<td>Daily revenue</td>
<td>$22,333</td>
</tr>
<tr>
<td>Beginning of period</td>
<td>11/1/2016</td>
</tr>
<tr>
<td>End of period</td>
<td>3/10/2017</td>
</tr>
<tr>
<td>Number of markets</td>
<td>238</td>
</tr>
<tr>
<td>Number of service providers</td>
<td>325</td>
</tr>
<tr>
<td>Number of clerks</td>
<td>177</td>
</tr>
<tr>
<td>Clerk characteristics</td>
<td></td>
</tr>
<tr>
<td>Monthly wage</td>
<td>$424</td>
</tr>
<tr>
<td>Percent females</td>
<td>0.57</td>
</tr>
<tr>
<td>Age</td>
<td>28.29</td>
</tr>
<tr>
<td>Turnover rate</td>
<td>0.70</td>
</tr>
</tbody>
</table>

Mean chain length reports the mean chain length of claims that were not forced. Salary represents about 1.7 times minimum wage. Turnover rate is computed for year 2016.

Some schemes have been detected by company management in the past, with the last prominent incident dating back to 2012: a couple was colluding with several providers, and got caught after they approached an honest provider, who signaled the incident to management.\(^2\)

The incident highlights a weakness in managerial processes: manually detecting instances of collusion between a clerk and a service provider is a daunting task. The call-center processes an average of 534 claims daily; monitoring their allocation would require listening to hours of recordings of phone conversations. Such lack of oversight leaves room for fraudulent behavior.

To address the problem, the company rolled out in November 2016 an update to its internal software, to limit clerks’ discretion when selecting service providers. Under the new system, called the rotation, clerks request services in a given market—defined as a type of services in a city. The software randomly draws a provider

---

\(^2\)Evidence collected from interviews with management. Interview transcripts are available upon request to the author.
Figure 6.1: **Observed distribution of chain lengths under the rotation.** The distribution is skewed to the left: 92 percent of claims are allocated after at most two draws.

within the market, using weights set by management. Clerks must call the selected provider and check whether it is available. If it is, then they should allocate the claim to that provider. If not, they must input a reason, and may *skip*—ask for another draw. The process ends when they reach an available provider. Reasons for unavailability include inability to reach the provider, the provider already operating at full capacity, or incapacity to service particular claims for technical reasons, such as lack of adequate equipment. Through this process, it takes an average of 1.4 draws to award a claim (Figure 6.1). Clerks may also *force* out of the rotation, i.e. terminate the random draw, and select a provider manually, which occurs in 23 percent claims. Clerks should force in three instances: when instructed to do so by management, for recurring claim where one customer always deals with the same provider, and when a customer jointly files two claims that could be serviced by the same provider. In this case, the provider should be selected through the rotation for the first claim, and is forced for the second claim.

Although the rotation does not completely eliminate discretion during provider selection, it makes collusion bear clear empirical implications. Because it is costly, management seldom verifies the reasons clerks invoke for skipping or forcing. Suppose
Figure 6.2: **Schematic floor plan of the call-center.** Desks sit one person. The space has an area of 4,725 squared feet. Clerks operate in a single room. They are separated in two functionally, and spatially distinct divisions.

that clerk $i$ colludes with provider $j$. Then $i$ may pretend that providers other than $j$ were unavailable, and skip to $j$. Although it is more risky, $i$ may also pretend that she was following an instruction from management, and force to $j$. So if $i$ colludes with $j$, then $i$ should skip non-$j$ providers more than honest clerks, and/or $i$’s rate of services forced to $j$ should be higher than that of honest clerks.

The call-center operates 24-7 and employs about 177 clerks. As is typical of call-centers in developing countries, clerks are relatively young (28 years old on average), and well-educated, with virtually all clerks having completed some tertiary education, and there is high turnover (70.3 percent in 2016). Clerks are paid an average of $424, which represents 1.7 times minimum wage.

Combined with features of the company, the internal software allows reconstructing interactions between clerks. Clerks all work in one room, on a single floor of 4,725 squared feet. (Figure 6.2), and can only access the company software from that room. Clerks log into the software as they start their shift, and close their session when they leave, for this information is used by management to monitor their presence, and pay them accordingly. As such, although the company software does not record the physical location of employees, interactions with the software allow deriving which clerks are in the room at any given time.
Since the goal is to assess how the presence of colleagues affects incidences of fraudulent behavior, I use interactions with the software to construct an indicator of attendance: the number of clerks that are present in the room at some point in time. Other features of the company allow making finer distinctions: clerks are separated in two divisions, that operate in two non-overlapping industries, and are also spatially distinct. While clerks rarely collaborate across divisions, they regularly do so within division, where clerks often grant claims within the same market. As such, I consider two finer measures of attendance, that capture closer professional relationships. While (total) attendance tallied the number of clerks on the floor, within-division attendance counts, for clerk $i$, the number of clerks currently operating in her division, and within-market attendance counts the number of clerks that are currently operating in her market.

Finally, I construct an indicator of tie strength [Granovetter, 1973]. The software allows reconstructing the amount of time two clerks spent together in a given time-period. I use a cutoff to separate weak ties from stronger ones, and define as a weak tie two clerks that have spent less that some time operating on the same markets in the past 30 days. Because most clerks work series of 8-hour shifts, I use alternatively a cutoff of one or two shifts. While Granovetter’s notion of tie strength referred to an emotional bond that distinguished friends from acquaintances, I take a broader view of the concept, separating familiar colleagues from unfamiliar ones.

6.2 Descriptive evidence

This section devises a novel, simple test to show statistical evidence of fraud in the allocation of claims. The test considers only claims allocated through the rotation, and examines the distribution of chain lengths, ie the number of draws before awarding a claim. Assuming that all clerks are honest, I pin down the theoretical distribution
of chain lengths, and compare it to the observed distribution. I show that overall, chains are longer than expected under the null distribution, which suggests that some dyads did behave dishonestly. I also identify the dyads that are most unlikely to conform to the null distribution, and hence more likely to be dishonest.

6.2.1 Theoretical distribution of chain lengths

A market is a pool of $N$ companies. At each period, company $i$ is drawn without replacement from the pool, with initial weight $p_i$, such that $\sum_{i \in N} p_i = 1$. Each company has a probability of being available $q_i \in (0, 1)$. The process stops at the first occurrence of an available company. When the pool is empty, all companies are put back in the pool.

The distribution of $L$, the length of a chain, has discrete support from 1 to infinity, with parameters $p = (p_i)_{i=1}^N$, and $q = (q_i)_{i=1}^N$. I first pin down the distribution of $L$ before the pool is empty; that is, for $L \leq |N|$. This distribution is defined by recursion. Let $V_t \subseteq N$ be the (random) subset of companies that are in the pool at draw $t$. Suppose that the pool is full; that is, $V_t = N$. The probability that the process stops at the next draw is simply the probability of picking an available company: $\Pr(l = 1|V_t = N) = \sum_{i \in N} p_i q_i$. Deriving the probability that the process stops at the next draw given any pool amounts to rescaling the weights to the companies that are left in the pool: $\Pr(l = 1|V_t) = \frac{\sum_{i \in V_t} p_i q_i}{\sum_{i \in V_t} p_i}$. The probability that the process ends in more than one draw is defined recursively. Conditional on company $i$ being drawn and unavailable at draw $t$, the pool contains $V_{t+1} = V_t \setminus \{i\}$ at draw $t + 1$, and the probability that the process ends at draw $t + 1$, $\Pr(l = 1|V_{t+1})$ is given by our previous result. Company $i$ is unavailable given pool $V_t$ with probability $p_i (1 - q_i) / \sum_{j \in V_t} p_j$. As such, the probability of the process ending after two draws is $\Pr(l = 2|V_t) = \frac{\sum_{i \in V_t} p_i (1 - q_i) \Pr(l = 1|V_t \setminus \{i\})}{\sum_{i \in V_t} p_i}$. More
generally, the probability of observing exactly \( l \leq |V_t| \) additional draws is:

\[
\Pr(l|V_t) = \begin{cases} 
\frac{\sum_{i\in V_t} p_i q_i}{\sum_{i\in V_t} p_i} & \text{if } l = 1 \\
\frac{\sum_{i\in V_t} p_i (1-q_i) \Pr(l-1|V_t\setminus\{i\})}{\sum_{i\in V_t} p_i} & \text{otherwise}
\end{cases}
\]

For \( L > |N| \), it suffices to decompose the event in the number of times the pool has been refilled, and the number of additional draws after the last refill. The pool is refilled after \(|N|\) successive failures. This event, \( R \), occurs with probability \( \Pr(R) = \prod_{i\in N} (1-q_i) \). Let \( L = m|N| + l \) be the Euclidean division of \( L \) by \(|N|\); \( m \) is the number of times the pool needs be refilled, and \( l \) the number of additional draws to realize a chain of length \( L \). Then, the distribution of \( L \) is:

\[ \Pr(L) = \Pr(R)^m \Pr(l|N). \]

While the weights \( p \) are directly available, the parameters \( q \) for a company being available need to be estimated. Assuming that all clerks are honest, we can easily estimate them from the data, since all skips then correspond to instances where the company was unavailable. I estimate \( q_i \) with \( \hat{q}_i \), the mean skip rate on draws involving company \( i \).

Estimating the unavailability rate \( q_i \) from the data makes the approach conservative. If some clerks are dishonest, then they have higher skip rates than their honest colleagues, which overestimates the true unavailability rate. As a result, the estimated distribution of chain lengths biased towards longer chains. Since only deviations towards longer chains are evidence of suspicious behavior, bias goes against the expected effect, making the approach more conservative.
6.2.2 Results

Using the procedure described above, I derive the null distribution of chain lengths for all markets. Suppose \( n \) claims were awarded in a market. In each market, I then derive the expected frequencies of chain lengths for \( n \) claims. To get a sense of uncertainty, I also simulate 1000 times \( n \) draws from the null distribution.

Aggregating all markets, Figure 6.3 shows that observed chains are longer than expected under the null, suggesting that some clerks did behave dishonestly by pretending that providers were unavailable. Chains of length 2 to 3 are less frequent than expected, while chains of length 5 to 7 are significantly more frequent. A Chi-squared test confirms the pattern, rejecting the that observed frequencies are drawn from the null distribution.

I then preform a comparable test within markets, to identify the clerks whose distribution of skips differs from the null. Suppose that clerk \( i \) awarded \( n \) claims in some market, with a mean chain length of \( \bar{l}_i \). I examine the probability of obtaining a mean chain length \( \bar{l} > \bar{l}_i \) after \( n \) draws from the null, to derive the following one-tailed
Figure 6.4: **Deviation from the null distribution at the individual level.** Distribution of Benjamini-Hochberg corrected p-values for the probability of obtaining mean chain length larger than observed in the data under the null distribution for a given clerk-market. For a few clerk-markets, it is very unlikely that their mean chain length comes from the null distribution.

p-value: $\Pr(\bar{l} > \bar{l}_i)$. I estimate this p-value by simulating 1000 times $n$ draws from the null distribution. I obtain 582 such p-values, one per clerk-market, that I correct for multiple testing using the Benjamini-Hochberg procedure.

Figure 6.4 shows the distribution of such p-values for all clerk-markets. Most clerk-markets seem to conform to the null distribution: 92 percent of them have a p-value above 10 percent. However, 4 percent have a p-value below 1 percent. This result tells us that while the overwhelming majority of clerks seem to behave honestly, with chain lengths in line with what is to be expected if all clerks were honest, a small minority seem to behave dishonestly, with longer chains than expected.

Overall, the evidence in this section suggests that the null hypothesis of honest behavior fails to perfectly describe the observed distribution of chain lengths. Observed chains are significantly longer than expected under the null, suggesting that some clerks pretended that some providers were busy, in order to skip to their preferred provider. These deviations owe to a small number of clerk-markets, suggesting that some clerks may be regularly engaging in dishonest behavior in selected markets.
6.3 Causal evidence

Analyzing the distribution of the number of skips preceding the allocation of claims revealed significant deviations from what would be expected if all clerks were honest, suggesting that some clerks may behave dishonestly in selected markets. In this section, I investigate how interpersonal relationships among clerks may cause such deviations.

6.3.1 Identification strategy and hypotheses

Identifying the causal effect of interpersonal relationships on dishonest behavior faces two main challenges. First, one needs to credibly label behavior as honest or dishonest. Second, as with all studies of social influence, we face issues of endogeneity: social relationships are not random. In this case, some markets feature more relationships than others, because the services awarded in those markets are more costly, and more complex. Such markets require more collaboration among clerks, but their increased complexity also opens up more opportunities for fraud. Furthermore, clerks might have a tendency to cluster by type, with dishonest types in one cluster, and honest types in another.

The identification strategy addresses the issue of measuring dishonest behavior by taking advantage of the highly structured nature of claim allocation. The claim allocation process makes dishonest behavior bear clear empirical implications that allow isolating suspicious behavior. Compared to their honest counterparts, dishonest clerks should have higher skipping and forcing rates, ceteris paribus. As such, I consider two outcomes for claim \( i \): whether it was forced or not (force\(_i\) = 1, 0 respectively) and, if the claim was not forced, the number of draws leading to its allocation, skips\(_i\) > 0.
Ideally, to circumvent the endogeneity issue and identify the causal effect of social interaction on dishonest behavior, one would randomly assign social interactions during claim allocation, and observe the impact of such interactions on outcomes.

The identification strategy takes advantage of the size of the data to make comparisons within very small units, and consider only events where variation in social interactions is plausibly exogenous to dishonest behavior. I compare outcomes within dyad, within day of the week, and within hour, and control for the dollar value of the claim, as well as the level of business within market; that is, the number of claims awarded within that market within the past hour. Indeed, providers might be less available if there is more activity within the market, which would drive up skipping and forcing rates. I consider three events whose as-if-random nature is increasingly plausible, that I detail in the next subsection. The first is variation in attendance levels that owes to minor perturbations in how management schedules shifts and assigns clerks to markets. The second considers the same variation, but focuses on colleagues who do not know one another, which addresses concerns of selection by type. The third is recent hires, whose type is yet unknown to the rest of their colleagues.

Taking advantage of these events where variation in the number of interactions is plausibly exogenous, I first examine the average effect of the event. That is, for claim \( i \) in dyad \( j \) awarded at hour \( h \) of day \( d \), I examine the following linear model:

\[
Y_{ijhd} = \beta_0 j + \beta_1 \text{event}_i + \beta_2 \log(\text{amount}_i) + \beta_3 \text{business}_i + \beta_4 h + \beta_5 d, \tag{6.1}
\]

where \( Y_{ijhd} \in \{\text{force}_i, \text{skips}_i\} \) is the outcome of interest.

Knowing that most clerks are honest, if they clerks deter dishonest behavior, then their presence should have no impact on other honest clerks, but decrease the incidence of fraudulent behavior by dishonest clerks, leading to lower skipping and forcing rates overall. That is:
Hypothesis 1. If honest clerks deter dishonest behavior, then $\beta_1 < 0$.

In our setting, however, the average effect may not be very indicative. If most clerks are honest, then the negative contribution of dishonest clerks to the average effect should be dwarfed by the null effect of honest clerks, leading us to observe $\beta_1 = 0$ instead.

As such, I look into heterogeneous effects, and examine a mixture model where dyad $j$ can take one of two latent types $t_j \in \{H, L\}$, and let the intercept and coefficient on the event vary by type. Slightly adapting the previous approach, I now compare within provider instead of within dyad, and use some arbitrary provider as the reference category. That is, for claim $i$ awarded by clerk $j$ to company $c$ on day $d$ at hour $h$, with type $t_{jc} = t \in \{H, L\}$, I estimate the following model:

\[ Y_{ijchd} = \beta_0 t + \beta_1 t \text{ event}_i + \beta_2 \log(\text{amount}_i) + \beta_3 \text{ business}_i + \beta_4 h + \beta_5 d + \beta_6 c, \quad (6.2) \]

where I set $\beta_6 c = 0$ for some arbitrary company $c$ that serves as a reference category. I estimate this model with the EM algorithm ([Dempster, Laird and Rubin] [1977]).

I identify the high type ($H$) as the one with the highest coefficient, and the low type ($L$) as the one with the lowest coefficient; that is, I define $H$ and $L$ such that $\beta_{1L} < \beta_{1H}$. Again, if honest clerks deter dishonest behavior, then their presence should have no impact on honest clerks, but decrease the incidence of fraudulent behavior by dishonest clerks, leading to lower skipping and forcing rates:

Hypothesis 2. If honest clerks deter dishonest behavior, then there are dyads of type $L$ and $\beta_{1L} < \beta_{1H} = 0$.

6.3.2 Results

The first event I consider is variation in attendance levels: I use variation in the number of clerks present in the room when the claim was awarded. The strategy exploits
Figure 6.5: **Average marginal effect of attendance on force and skip rates.** Points are average marginal effects of one additional attendee, estimated using the specification in model 6.1. Bars represent 95 percent confidence intervals. Errors are clustered at the dyad level. On average, increased attendance decreases forcing behavior. It has no significant effect, or decreases skipping behavior.

small shocks in attendance levels that owe to minor variations in how management schedules shifts. Because the model includes hourly, and daily fixed effects, and the level of business, I control for the most obvious confounders; that is, temporality and business driving both attendance levels and our outcomes of interest. As detailed in section 6.1 I measure attendance at three levels, corresponding to increasingly close professional interactions. While total attendance is the number of clerks on the floor, I also consider attendance within division and and within market.

Figure 6.5 shows partial support for hypothesis 1: on average, increases in attendance decrease forcing behavior, suggesting that interpersonal interactions deter fraudulent behavior among clerks. Furthermore, the effect is stronger for closer forms of professional interactions. In particular, market attendance has a markedly larger effect than division, or total attendance. However, such increases in attendance have either no effect, or increase skipping behavior.

Figure 6.6 considers heterogeneous treatment effects, and shows support for hypothesis 2. The mixture model shows that for the low type, increasing attendance decreases fraudulent behavior. In contrast, the high type has effect sizes that are
Figure 6.6: **Heterogeneous effects of attendance on force and skip rates.** Panel a represents the density of the posterior probability $\Pr(t_j = L|X,Y)$. The mixture models are separating. In panel b, points are average marginal effects of one additional attendee for each type, estimated using the specification in model 6.2. Bars are 95 percent confidence intervals. Increased attendance decreases forcing behavior for the low type, and has much smaller effects on the high type. The effect of increased attendance on skipping behavior is similar across types.

statistically indistinguishable from zero, or have much smaller magnitude than the high type. As before, types become increasingly differentiated for closer forms of interactions, with the gap in effect size broadening as we move from total attendance to market attendance. Furthermore, a significant number of dyads compose the low type. The model classifies about a third of all dyads as low type for skipping behavior, and 80 percent as low type for forcing behavior. This suggests that undue forcing might be a milder, more widespread form of unethical behavior: instead of going through the cumbersome process of random drawing, clerks save time and force to some provider. When surrounded by colleagues, clerks quickly adjust their behavior and go back to normal. Finally, both models pick up the same dyads: for each kind of attendance, the correlation between the posterior probability of a dyad being of the low type for skipping and for forcing never goes below .23. This, in turn, suggests
that the clerks that do engage in more serious forms of fraudulent behavior use both forcing and skipping.

Although this first result suggests that interpersonal relationships do reduce the suspicious behavior of some clerks, one challenge threatens identification: clerks may select into attendance. In particular, it might be that dishonest clerks cluster together on certain shifts, or on certain markets.

To address the issue of selection, I consider another event: the within-market attendance of unfamiliar colleagues, defined as the colleagues with whom one has spent less than some threshold of time operating on the same markets in the past 30 days. Unfamiliar colleagues alleviate our concern of selection. Consider a dishonest clerk. Although unfamiliar colleagues may also be dishonest, their type is still unknown to the clerk under consideration, who will therefore behave as if those colleagues had been randomly selected. As detailed in section 6.1, I use two cutoffs, defining as unfamiliar the colleagues with whom one has spent less than 8, or 16 hours in the past 30 days.
Figure 6.8: Heterogeneous effects of unfamiliar colleagues on force and skip rates. Panel a represents the density of the posterior probability $\Pr(t_j = L|X,Y)$. The mixture models are separating. In panel b, points are average marginal effects of one additional attendee for each type, estimated using the specification in model 6.2. Bars are 95 percent confidence intervals. Increased attendance decreases forcing and skipping behavior for the low type, and has smaller effects on the high type.

Figure 6.7 considers average effects, and shows no support for hypothesis 1: the average marginal effect of unfamiliar colleagues is statistically indistinguishable from zero. As discussed in the preceding subsection, this likely owes to average effects pooling honest and dishonest types.

Conversely, Figure 6.8 considers heterogeneous effects, and shows support for hypothesis 2 with results that are very similar to considering both familiar, and unfamiliar colleagues. This confirms that there is a substantial fraction of clerks for which interpersonal relationships reduce the incidence of suspicious behavior, and that forcing behavior seems to be a milder, more widespread form of unethical behavior. Finally, results are stronger when using a cutoff of two shifts, and globally have a smaller magnitude than when considering both strong, and weak ties. This suggests that there is little concern for selection. Indeed, if selection was driving the results, then they should become weaker when considering stronger ties, who should be clustered together, hence exerting less monitoring on dishonest types.
Since there may still be concerns that our measure of familiarity does not measure perfectly relationships among colleagues—especially relationships outside the workplace—the third event considers the impact of new hires on the behavior of current employees. This event addresses in a more convincing way the issue of selection: in this high-turnover environment, new hires are typically unknown of current employees. Because new hires may take some time to “settle in,” and become familiar to current employees, I use different windows to define the event of being a new hire, ranging from the first day of a clerk, to her first week. As for attendance, I define the event at three different scales: the entire call-center, the division, and the market, counting, respectively, the number of new hires currently operating in the room, the division, or the market of the claim under consideration.

However, this event comes with two major drawbacks. First, it is less frequent than the previous two, increasing our uncertainty about the estimates. Second, the behavioral implications are not as clear-cut as for the other events. By definition, new hires are inexperienced. As such, dishonest types may not alter their behavior in the presence of new hires, for the latter might be too inexperienced to notice suspicious behavior. When the new hire is experienced enough to notice this such behavior and have an impact on dishonest types, she has been working for long enough that her type becomes known to her colleagues.

Unsurprisingly, I find mixed results, that are reported in section D.1 of the Appendix. On average, new hires have little effect on forcing and skipping behavior, and such effect is indistinguishable across types.

Overall, interpersonal relationships cause reductions in suspicious behavior for low-type dyads, increasingly so as we consider closer forms of monitoring: results are stronger for colleagues that interact on the same market, and that share a stronger tie. Furthermore, results suggest that a majority of clerks might engage in mildly unethical
behavior: a majority of clerks reduce their forcing rates when other colleagues are present.

6.4 Structural evidence

The analysis in the previous section showed that interpersonal relationships cause reductions in suspicious behavior by dishonest clerks. It exploited on a reduced-form implication of the data generating process–dishonest clerks should have higher skipping and forcing rates than honest clerks, and reduce such dishonest behavior when surrounded with honest clerks.

This reduced-form approach, however, suffers from two major drawbacks. First, since this implication only holds *ceteris paribus*, it forced to make comparisons within very small units, potentially wasting a lot of power. Second, the analysis conflates identifying clerks’ types with identifying properties about such types. In other words, the mixture models estimated in the preceding section define as dishonest the clerks that do reduce their forcing and skipping rates when surrounded with more clerks. A better analysis would first identify dishonest clerks, then examine how such clerks behave, and test whether their behavior is sensitive to monitoring from honest colleagues.

I estimate a structural model that takes advantage of the highly structured process defined by the rotation to recover this missing information–the probability that a provider is unavailable and the probability that a clerk is dishonest–and to describe the behavior of dishonest clerks. The model considers only claims allocated through the rotation, and ignores claims that were forced.
6.4.1 Model

Consider draw $i$ from the rotation. The econometrician only observes the clerk $j[i]$ that requested the draw and the company $c[i]$ that was drawn, as well as the outcome $y_i = 0$ if the claim was awarded to $c[i]$, or $y_i = 1$ if the company was skipped. The clerk, on the other hand, knows her type, and observes whether the company was available ($b_i = 0$), or busy ($b_i = 0$).

To identify dishonest clerks, the model exploits the same implications of the data generating process as in the preceding section, but does so at the micro-level: a dishonest clerk may only unduly skip if the company was available. In other words, the model defines types at the dyad level. Consider the dyad between clerk $j$ and company $c$. If that dyad is honest, it has type $t_{jc} = H$, and the clerk only skips when the company is busy. That is, $b_i = y_i$ for all draws from dyad $jc$. If the dyad is dishonest, it has type $t_{jc} = L$. In this case, the clerk may pretend that company $c[i]$ was unavailable and skips ($y_i = 1$), although it was not ($b_i = 0$). That is, $b_i \leq y_i$ for all draws from dyad $jc$.

Defining types at the dyad level has important implications for model estimation and interpretation. First, since the dependent variable $y_i$ is binary, the model reduces to a mixture of binomials, which are generically not identified. Defining types at the dyad level pools claims within dyads, which identifies the model. Second, this approach impacts interpretation; in particular, it labels as honest the providers that dishonest clerks collude with, but labels as dishonest the providers that such clerks take revenue from. Suppose that clerk $j$ is colluding with company $c^*$. Then $j$ will only unduly skip when companies $c \neq c^*$ are drawn. That is, $j$ will appear as type $H$ for dyad $jc^*$, and as type $L$ for dyads $jc, c \neq c^*$.

This suffices to define the model. Consider dyad $jc$ and draw $i$ from that dyad. Suppose that $jc$ is dishonest with probability $\pi$. Let $p_i$ be the probability that the provider is available, and $1 - q_i$ the probability that an undue skip occurs, given that
dyad jc is dishonest and provider c is available. I make $p_i$ and $q_i$ depend covariates using probit regressions. Let $x_i$ and $z_i$ be vectors of covariates that affect availability and dishonest skipping respectively, and $\beta$ and $\gamma$ associated vectors of parameters. With $\Phi(.)$ the cumulative density function of the standard normal distribution, we have the following model:

$$
\pi = \Pr(t_{ij} = L) \\
p_i = \Pr(b_i|x_i) = \Phi(x_i^t \beta) \\
q_i = \Pr(y_i|z_i, b_i, t_{ij||c|i} = L, b_i = 0, t_{ij||c|i}) = \begin{cases} \\
\Phi(z_i^t \gamma) & \text{if } t_{ij||c|i} = L \text{ and } b_i = 0 \\
b_i & \text{otherwise}
\end{cases}
$$

I estimate the model using a collapsed Gibbs sampler (Holmes and Held, 2006, see Appendix D.2 for details) with the following conjugate priors:

$$
\pi \sim \text{Beta}(\alpha_0, \alpha_1) \\
\beta \sim \text{N}(0, \sigma_0^2) \\
\gamma \sim \text{N}(0, \varsigma_0^2)
$$

### 6.4.2 Specification and results

The model requires specifying covariates for the probability of being unavailable, $\Pr(b_i|x_i)$, and the probability of a dishonest type unduly skipping, $\Pr(y_i = 0|z_i, b_i = 0, t_{ij||c|i} = L)$. The chosen specification follows closely the specifications used for causal inference. I model the probability of being available using company, hour, and day of the week fixed effects, and control for claim value, as well as the level of business. Even without collusion, providers might be more willing to service high-value claims, and pretend they are unavailable for claims that are not profitable.
enough. Furthermore, at times of peak activity, all providers within a given market are more likely to be unavailable. As in the causal inference section, I also control for the level of business within the market. With $\Phi(.)$ the cdf of the standard normal distribution, the specification for being unavailable writes:

$$\Pr(b_i|x_i) = \Phi(\beta_0 c[i] + \beta_{\text{hour}} + \beta_{\text{day}} + \beta_3 \log(\text{amount}_i) + \beta_4 \text{business}_i)$$

Dishonest clerks have a baseline probability of skipping unduly, but may also adjust their behavior according to circumstances. In particular, they should be more inclined to unduly skip high-value claims, since those claims bring more revenue to the provider they are colluding with. If interpersonal relationships affect dishonest behavior, they should also adjust their behavior when other clerks are present. As such, I control for the value of the claim, and the level of market attendance, which has been shown in the previous section to trigger the strongest deterrence effect. I also include hour and day of the week fixed effects:

$$\Pr(y_i|z_i, b_i = 0, t_{j[i,c[i]} = L) = \Phi(\gamma_0 + \gamma_{\text{hour}} + \gamma_{\text{day}} + \gamma_1 \log(\text{amount}_i) + \gamma_2 \text{market attendance}_i)$$

The discussion yields two core hypotheses about the behavior of dishonest types. First, these types should be more inclined to behave dishonestly for high-value claims:

**Hypothesis 3.** There are dyads of type $L$ and $\gamma_1 > 0$.

Second, if honest clerks deter dishonest behavior, then market attendance should reduce the extent of undue skipping.

**Hypothesis 4.** If honest clerks deter dishonest behavior, then there are dyads of type $L$ and $\gamma_2 < 0$.

Empirical results confirm the hypotheses. Panel (a) of Figure 6.9 shows that while most dyads are likely honest, some have a very high probability of being dishonest.
Figure 6.9: **Structural model, results.** Panel a represents the density of the lower bound of the 95 percent credible interval around the posterior probability of being a low type. The model isolates a few dyads that are very likely to be of the low type. In panel b, points are posterior mean parameter values; thick bars are 80 percent credible intervals, thin bars are 95 percent credible intervals. Low types skip more higher value claims, and skip less when there is high attendance. The model is estimated using 1000 iterations of the Gibbs sampler, with a burn-in of 100 iterations.

I use a conservative estimate for identifying dishonest types: instead of considering the mean posterior probability of a dyad being dishonest, I only consider the lower bound of the 95 percent credible interval. By this metric, .7 percent of dyads have a 99 percent chance of being dishonest, while 96 percent have less than 90 percent chance of being dishonest.

Panel (b) of Figure 6.9 confirms hypotheses relative to the behavior of low types. As expected, they are more likely to skip high-value claims, since those transfer more revenue to the provider they are colluding with. They are, however, less likely to behave dishonestly when more clerks are present, which implies that interpersonal relations within the organization deter dishonest behavior.
“Knowledge is not for knowing: knowledge is for cutting.”

Michel Foucault (1926 – 1984)

Conclusion

This study started with a question: why does corruption persist in developed countries in the form of wide-ranging corruption scandals? Distinguishing between more profitable acts of grand corruption, and less profitable acts of petty corruption, we saw that grand corruption, although more harmful than petty corruption, has received less attention from academics and policy-makers alike. Because grand corruption is more often than not a collective enterprise involving large, sophisticated conspiracies, it resists our traditional tools of analysis and policy-making: methodological individualism and institutional rules. Grand corruption resists these tools precisely because the vast conspiracies that support it manage to subvert these very institutions and
avert law-enforcement, even in countries where strong institutions impose swift and harsh punishment on corrupt acts, such as the United States or China.

Acknowledging the limitations of our current focus on individuals and institutions, I approached corruption from the perspective of organizations, and turned our original interrogation into two more specific questions. If corrupt individuals sometimes act alone, and sometimes form vast conspiracies, then how is corruption organized? In other words, to understand how grand corruption emerge and persists, we need to understand the incentives for corrupt individuals to act alone or form these vast conspiracies. Relatedly, if grand corruption resists institutions, then we need to find another instrument to fight it. Just like institutions, organizations are an actionable policy instrument that can potentially be used to curtail corruption. This, in turn, calls for our second question: how do organizations affect corruption?

To answer these questions, I developed an organizational approach that treats corruption as “organized crime within an organization,” and tested its main predictions and assumptions empirically. This approach provides a simple, easily expandable formal-theoretic framework that unifies, sharpens, and expands upon previous work. In a nutshell, the framework tells us that corrupt individuals have an incentive to form vast conspiracies when the help provided by additional accomplices offsets their cost in terms of resources. Organizations affect these incentives by embedding corrupt individuals into social networks. Those networks are a double-edged sword: they provide corrupt individuals with opportunities to recruit additional accomplices among close colleagues, but also expose them to the monitoring of those colleagues. Corruption persists in developed countries in the form of grand corruption supported by large conspiracies because stronger institutions make engaging into corruption more costly. Since corruption is more costly, the protection provided by additional accomplices become more desirable. However, compensating these additional accomplices comes with higher costs that can only be borne by more profitable ventures.
As such, less profitable, petty corruption disappears, leading to the survival of grand corruption alone.

In what follows, I discuss the results in light of the literature (Section 7.1), then provide policy recommendations and directions for future research (Section 7.2).

7.1 Taking stock: a framework for corruption in organizations

The proposed framework for analyzing corruption in organizations rests on a small number of micro-foundations (Chapter 2). Corruption networks emerge in organizations by including additional accomplices into an existing coalition to illegally extract resources from the organization. Additional accomplices pose a tradeoff between efficiency and secrecy: on the one hand, they extract resources and may protect the coalition; on the other, they may compromise the coalition and cost resources. Organizations complicate this tradeoff by granting agents differential access to such resources, and embedding them in networks that constrain the recruitment of accomplices and expose them to witnesses, and in institutions that affect their risk of detection.

These micro-foundations delineate an anatomy of corruption, allowing to describe the form of corruption across cases using three dimensions: frequency, the likelihood that some corruption occurs; 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.

These patterns and definitions allow constructing a formal model that treats corruption as the outcome of a process of strategic diffusion on a network representing the organization (Chapter 3). This simple, easily expandable idea allows exploring the macro-level implications of these micro-foundations while preserving the ability
to make specific network-analytic claims relative to the structure of the coalition, and how it is affected by changes in the structure of its host organization.

Characterizing how corruption is organized, we saw that corruption occurs in *enclaves*; that is, relatively isolated portions of the organization, because they generate fewer witnesses. Enclaves shift the unit of analysis from the individual to the coalition. 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.

We also characterized which organizational structures are more prone to corruption. Analyzing marginal changes to the organization, we saw that some of the social ties provided by organizations decrease the frequency of corruption, while others increase it, depending on whether they facilitate monitoring more than reaching better accomplices. Yet, most ties should have little effect, because they do not target enclaves, and are therefore affecting “clean” portions of the organization. Comparing across a wide array of organizations, we saw that corruption should be more frequent in more siloed organizations. Intuitively, siloed organizations have more enclaves, which makes them more corrupt.

Findings on how organizational structure affects corruption ground and expand upon previous findings. They rationalize Evans’ (1995) claim that corruption is more frequent in under- and over-embedded bureaucracies. 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. Results also expand upon Evans, in that
while acknowledging that the amount of ties matters, they show that their direction also matters: comparing two organizations with the same amount of ties, the more modular organization will be more corrupt.

Considering the impact of better formal institutions, we saw that as organizations adopt better monitoring technologies, corruption becomes less frequent, but increases in scope and selects on high-scale projects. Because detection is more likely, corruption requires the protection of additional accomplices. The additional costs they impose on the coalition selects out petty corruption, thereby decreasing total corruption, but allow grand corruption to survive. This finding provides a theoretical rationale to the question that motivated this investigation: corruption persists and selects on grand corruption in developed countries, although it is less frequent than in developing countries because corrupt individuals adapt to better enforcement by recruiting more accomplices.

Finally, we investigated how accomplices’ ability to establish informal institutions to govern their interactions impact their ability to cooperate. We saw that commitment problems induced by corruption’s lawless environment may introduce significant noise and inefficiencies, that agents would presumably partially solve using informal self-enforcing contracts. Additionally, commitment problems benefit brokers—accomplices who recruit other accomplices—who exploit their control over the diffusion process to extract larger shares of the rent.

Findings on informal institutions also precise earlier work. That lawlessness generates inefficiencies that benefit brokers, but may be alleviated by informal contracts is in line with the literature on trust in organized crime (eg. [Gambetta, 1996; Vannucci and Della Porta, 2013]). The model’s contribution to this line of research is in pinpointing a testable mechanism: brokers extract more of the surplus because the lack of commitment device allows them to veer diffusion according to their preferences.
The empirical part of this study largely confirmed the predictions of the theoretical framework. Examining broad patterns of corruption across countries, as well as individual corruption cases in India and the US (Chapter 4), we confirmed our casual starting observation, and earlier work by Kaufmann (2004): developed countries are less corrupt because they managed to get rid of petty corruption but, similar to their less developed counterparts, are still plagued by grand corruption. Those comparisons also lent initial support to other theoretical predictions: corruption has a broader scope in developed countries, and is more frequent in more enclaved bureaucracies.

Findings from a lab experiment also strongly supported the main predictions of the model (Chapter 5). Observed deviations from the theoretical predictions also provided an additional reason as to why more developed countries are less corrupt than developing countries. In the lab, subjects had difficulties to coordinate when tasked with forming larger coalitions. This suggests that developed countries should be even less corrupt than predicted by the theory: corruption in developed countries requires larger coalitions, which are more difficult to sustain.

We finally turned to an observational setting in order to assess empirically some of the micro-foundations of the framework (Chapter 6). The framework posits that interpersonal interactions within organizations are a double-edged sword for members of the coalition: they provide them with opportunities to turn colleagues into accomplices, but also expose them to their monitoring. Using data from the daily activity of a large firm, we considered the second part of this proposition, and saw that interpersonal interactions among colleagues do deter unethical behavior by dishonest members of the organization.
7.2 Looking ahead: using organizations to fight corruption

These results have important policy implications. Ex-ante, they show that organizational structure may substitute for better enforcement in order to prevent corruption. Ex-post, they suggest ways for law-enforcement to detect corruption more efficiently once it has occurred. Yet, these recommendations are to be taken with a grain of salt, for two reasons. First, this study shows that organizations are no miracle cure, and may end up doing more harm than good. Second, when deriving macro-implications, the study ignored a few potentially important dimensions of corruption in organizations, which prompt for additional research.

Organizations may help curtailing corruption, but they are no cure-all. Organizational change may help curtailing corruption to the extent that it makes enclaves more connected to the rest of the organization, exposing them to the scrutiny of additional monitors. Organizational change hurts, however, when it enables enclaves to reach additional accomplices. Finally, organizational change has no effect at all when it does not target enclaves.

While the subtle effects organizations have on corruption prompt for careful policy-making, even careful policy-makers may have difficulties harnessing organizational structure in the fight against corruption. Enclaves are hard to identify. Identifying which individual members are isolated within an organization is a comparatively easy task, for it requires enumerating the connections of each of its $n$ members. Identifying which groups of members of the organization are isolated is a much more difficult task, requiring to enumerate the connections of each of the $2^n$ groups that can be formed with $n$ members. In other words, because enclaves may not neatly map onto the formal layout of the organization, identifying them requires going through an enormous amount of candidates.
The difficulties associated with leveraging organizational structure to fight corruption call into question the effectiveness of existing organizational reforms, and prompt for more careful evaluation. We saw in the introduction that such policies are gaining increasing traction in the policy world. On the one hand, some standards start to emerge, with one-stop shops\(^1\) being one such popular examples. On the other, many such reforms are large-scale changes that are tailored to the particular organization they target. Yet, none of these interventions have been submitted to careful evaluation. Given the risks highlighted by this study, future research should evaluate more carefully such interventions. In this regard, one should focus on those large-scale, *sui generis* changes, because they are the ones that have the most dramatic impact on the organization. A difficulty here will be to devise research designs that allow estimating the effect of a treatment administered to a single organization when no other obvious comparable organization is available. Consider, for instance, the reform of Social Security in Morocco: it is unclear which organization one could compare this agency to.

While the framework also yields policy implications related to how law-enforcement may best detect corruption, sharpening these requires additional research. The framework suggests that since corruption occurs in enclaves, then law-enforcement should prioritize auditing such enclaves. This recommendation rests on the assumption that corrupt individuals will not respond strategically to this change in the detection technology, which makes it rather fragile. Indeed, extant work on criminal networks shows that criminals are highly strategic, and swiftly adapt to changes in the detection policy (Baccara and Bar-Isaac 2008, 2009). The model considered in Chapter 3 used a simple, all-or-nothing detection policy\(^2\). In the spirit of existing work on criminal networks, future research should consider a larger

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\(^1\)A one-stop shop regroups previously disparate functions into a single organizational unit.
\(^2\)That is, the model assumed that either all accomplices got detected, or none.
set of detection policies, and spell out the policy that minimizes corruption taking into account the response of criminals to that policy.

Finally, although micro-foundations suggest that strong ties play an important role in facilitating cooperation within the coalition and between the coalition and witnesses, the formal model sidesteps those. Future research should include strong ties in the model for several reasons. First, this might provide a rationale for some organizational policies that make no sense within the current framework. For instance, staff rotation is an old, popular policy—dating back, in France, to Napoleonic times—that prevents staff from forging too strong relationships in their environment. Within the current framework, this policy makes little sense, because new staff would hold the same position within the organization. Second, strong ties will allow speaking of patronage-ladden bureaucracies, which are often divided into ethnic monopolies (Van de Walle, 2001). From the micro-foundations, strong ties should play a dual role. On the one hand, they should increase the amount of trust within the coalition, and facilitate cooperation among accomplices. On the other, they should make witnesses less likely to report corruption. Strong ties, in this sense, pose a tradeoff to existing members of the coalition, for it is unclear whether the coalition would benefit more from the additional help strong ties provide as accomplices, or the diminished monitoring they provide as witnesses. As such, future research should consider extensions to the current framework that allow for strong ties, and for endogenous reporting by witnesses.
Part III

Appendices
A.1 Proofs of section 3.2.2

Proof of lemma 1. Suppose $u(c^*, g, q) < \epsilon_s$. Then, no coalition gives $s$ a positive payoff. She 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:

\[
\nabla_x u_2 - u_1 = \frac{\partial u_2 - u_1}{\partial \epsilon} x_\epsilon + \frac{\partial u_2 - u_1}{\partial q} x_q = \left( \frac{\partial p_1}{\partial q} / a_{c_1} - \frac{\partial p_2}{\partial q} / a_{c_2} \right) x_q \tag{A.1}
\]

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 \( v(a_c, w_c, q) \leq \max\{v(a_1, w_1, q), v(a_2, w_1, q)\} \).
Note that \( v(a_2, w_2, q) \geq v(a_2, w_1, q) \). Therefore,

\[
\max\{v(a_1, w_1, q), v(a_2, w_1, q)\} \leq \max\{v(a_1, w_1, q), v(a_2, w_2, q)\},
\]

which implies \( v(a_c, w_c, q) \leq \max\{v(a_1, w_1, q), v(a_2, w_1, q)\} \).

Suppose \( v \) is non-monotonic in \( a \) and \( |v(a, w_1 + 1, q) - v(a, w_1, q)| > v(a^*, w_1, q) - \max\{v(1, w_1, q), v(N, w_1, q)\} \), where \( a^* \in \arg \max_{a \in \{1, \ldots, N\}} v(a, w_1, q) \). Then,

\[
v(a^*, w_1, q) - |v(a, w_1 + 1, q) - v(a, w_1, q)| < \max\{v(1, w, q), v(N, w, q)\}.
\]

Since \( w_c \geq w_1 \), we have \( v(a_c, w_c, q) \leq v(a_c, w_1, q) - |v(a, w_1 + 1, q) - v(a, w_1, q)| \leq v(a^*, w_1, q) - |v(a, w_1 + 1, q) - v(a, w_1, q)| \). 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,

\[
v(a_c, w_c, q) \leq \max\{v(a_1, w_1, q), v(a_2, w_1, q)\}.
\]

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

A.2 Proofs of section 3.2.3

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

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, if 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
Proof. The proof is immediate.

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:

\[
    w_{cg'} = \begin{cases} 
    w_{cg} + 1, & \text{if } g' = g+i \rightarrow j \text{ and } j \in c \text{ and } i \notin c \\
    w_{cg} & \text{otherwise.}
    \end{cases} \quad (A.2)
\]

Proof. The proof is immediate.

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 \( c'_{nf} \) be the set of such nodes. Its complement, \( c'_{f} = c' \setminus c'_{nf} \), is feasible on \( g \). I show that \( c'_{f} = c \). By construction, we have \( a_{c'_{f}} < a_{c'} \). Note that \( i \in c'_{f} \Longleftrightarrow j \in c'_{nf} \). Without loss of generality, suppose that \( i \in c'_{f} \).

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

\[
    w_{cg'} = |W_{cg'}| = |W_{c'_{f}g'} \setminus c'_{nf}| + |W_{c'_{nf}g'}| - |(W_{c'_{f}g'} \setminus c'_{nf}) \cap W_{c'_{nf}g'}| \quad (A.3)
\]

By construction, \( W_{c'_{f}g'} \setminus c'_{nf} = W_{c'_{nf}g'} \). Indeed, if node \( k \in W_{c'_{f}g'} \cap c'_{nf} \), then \( k \) is the neighbor of some \( l \in c'_{f} \) on \( g_u \). So the path \( s, ..., l, k \) 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 $|W_{c'f_g}| = w_{c'g}$. Also note that witnesses of coalition $c'_{nf}$ cannot be in $c'_{nf}: c'_{nf} \cap W_{c'_{nf}g'} = \emptyset$. As such, $(W_{c'f_g} \setminus c'_{nf}) \cap W_{c'_{nf}g'} = W_{c'f_g} \cap W_{c'_{nf}g'}$. Plugging back into equation A.3, we get $w_{cg'} = w_{c'g} + |W_{c'_{nf}g'}| - |W_{c'_{nf}g'} \cap W_{c'f_g}| \geq w_{c'g}$.

Proof of proposition 4. By lemma 3, we have $C_{g'} = C_g$ and for any $c \in C_g$, $w_{cg} \leq w_{cg'} \leq w_{cg} + 1$. This implies $u(c, g', q) \leq u(c, g, q)$. So $\hat{\epsilon}_s(g', q) \leq \hat{\epsilon}_s(g, q)$. 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 $i \rightarrow j$ 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 $i \in c \cup W_{cg'}$. Then by lemma lemma 3, $c$ on $g'$ that is essentially equal to $c^*$ on $g$. As such, $u(c, g', q) = u(c^*, g, q)$.

Proof of proposition 3. By lemma 3, we have that for any $c \in C_g$, $u(c, g, q) = u(c, g', q)$, which implies that $\hat{\epsilon}_s(g', q) \geq \hat{\epsilon}_s(g, q)$. Let’s show the second part of the proposition. Suppose that there is $q \in (0, 1)$ such that $\hat{\epsilon}_s(g', q) \geq \hat{\epsilon}_s(g, q)$. Using proposition 2, this means that there is $c \in M_g, c' \in M_{g'}$ such that $u(c', g', q) > u(c, g, q)$. For this to be true, it must be that $c' \in C_{g'} \setminus C_g$ 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 $w_{c^*g} = w_{c'g'}$ for otherwise, lemma 2 implies $u(c', g', q) < \max\{u(c^*, g, q), v(N, 0, q)\}$. Suppose $c^* \notin M_g$. Then there is $c \in C_g$ such that $a_c \leq a_{c^*}$ and $w_{cg} < w_{c^*g}$. This implies $a_c \leq a_{c'}$ and $w_{cg} < w_{c'g}$. Then lemma 2 implies $u(c', g', q) < \max\{u(c, g, q), v(N, 0, q)\}$, a contradiction.

A.3 Proofs of section 3.2.4

In this section, we denote the three environments (equal-sharing, lawlessness, and monopoly) using the subscripts $e, l, m$ respectively. In particular, $u^e(c, g, q, \epsilon) = \frac{p(a_c, w_{cg}, q)}{a_c} - \epsilon$ 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 $\max_{c \in \Gamma} u^e(c, g, q, \epsilon) = p(a_c, w_{cg}, q) - \tau(c, g, q, \epsilon)\epsilon < 0$, 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 $\frac{\partial \tau}{\partial \epsilon} = 0$. Otherwise, $s$ accepts the rent and some coalition in $C_{gq\epsilon}^e = \arg \max_{c \in \Gamma} u^e(c, g, q, \epsilon)$ 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 \( \max_{c \in \Gamma_{ih}} t_{ji}p(a_c, w_{cg}, q) - \tau_i(c, g, q, \epsilon) \epsilon \geq 0 \), for some \( \tau_i : \Gamma_{ih} \times (0, 1)^2 \rightarrow \mathbb{R}^+ \) that satisfies \( \tau_i(c, g, q, \epsilon) \geq a_i^i + 1 \), where \( a_i^i \) is the number of accomplices in \( c \) hired in transfers using money from \( i \)'s transfer, and \( \frac{\partial \tau_i}{\partial \epsilon} = 0 \). Otherwise, \( i \) accepts the transfer and some coalition in \( \arg \max_{c \in \Gamma_{ih}} t_{ji}p(a_c, w_{cg}, q) - \tau_i(c, g, q, \epsilon) \epsilon \) 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 \( a_i^i \geq 0 \) transfers in such coalition, her payoff is \( u_i^i(c, g, q, \epsilon) = (t_{ji} - a_i^i \frac{\epsilon}{p(a_c, w_{cg}, q)})p(a_c, w_{cg}, q) - \epsilon = t_{ji}p(a_c, w_{cg}, q) - (a_i^i + 1)\epsilon. \)

Setting \( \tau_i(c, g, q, \epsilon) = a_i^i + 1 \) proves the claim. We have \( \frac{\partial \tau_i}{\partial \epsilon} = 0 \). In equilibrium, \( i \) rejects \( t_{ji} \) if \( \max_{c \in \Gamma_{ih}} u_i^i(c, g, q, \epsilon) < 0 \). Otherwise, she accepts and makes the transfers that realize some coalition in \( \arg \max_{c \in \Gamma_{ih}} u_i^i(c, g, q, \epsilon) \).

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, \( t_{ik} = \frac{\tau_k(c,g,q,\epsilon)}{p(a_c,w_{cg},q)} \epsilon \). Suppose \( j \)'s best outside option is to accept and make some other transfer resulting in coalition \( c' \). Then \( t_{ik} \) solves \( t_{ik}p(c,g,q,\epsilon) - \tau_k(c,g,q,\epsilon)\epsilon = t_{ik}p(c',g,q) - \tau_k(c',g,q,\epsilon)\epsilon \), which gives \( t_{ik} = \frac{\tau_k(c,g,q,\epsilon) - \tau_k(c',g,q,\epsilon)}{p(a_c,w_{cg},q) - p(c',g,q)}\epsilon \). In equilibrium, \( i \)'s payoff from \( c \in \Gamma_{ih} \) is \( u'_i(c,g,q,\epsilon) = (t_{ji} - \sum_k t_{ik})p(a_c,w_{cg},q) - \epsilon = t_{ji}p(a_c,w_{cg},q) - (1 + \sum_k t_{ik})p(a_c,w_{cg},q)/\epsilon\epsilon \). Setting \( \tau_i(c,g,q,\epsilon) = 1 + \sum_k t_{ik}p(a_c,w_{cg},q)/\epsilon \) proves the claim. Replacing \( t_{ik} \) by their equilibrium values and using the inductive hypothesis on \( \tau_k \), it is easy to show that \( \frac{\partial}{\partial \epsilon} t_{ik}p(a_c,w_{cg},q)/\epsilon = 0 \), which implies \( \frac{\partial \tau_i}{\partial \epsilon} = 0 \). 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 \( C^m_{g\epsilon} = \arg \max_{c \in C_g} u^m(c,g,q,\epsilon) \) is realized.

**Proof.** Under monopoly, non-seed members of a coalition have \( u_i(c,g,q) = \pi_ip(a_c,w_{cg},q) - \epsilon = 0 \). Solving for \( \pi_i \), we have \( \pi_i = \epsilon/p(a_c,w_{cg},q) \). So \( u^m(c,g,q,\epsilon) = (1 - \sum_{i \neq S} \pi_i)p(a_c,w_{cg},q) - \epsilon = p(a_c,w_{cg},q) - a_c \epsilon \). Consider \( c^m \in C^m_{g\epsilon} \). 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 \( c \notin C^m_{g\epsilon} \) 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 \( \epsilon = \max_{c \in C} \frac{p(a_c, w_{c,g}, q)}{a_c} = 0 \). I show that \( \hat{\epsilon} = \max_{c \in C} \frac{p(a_c, w_{c,g}, q)}{a_c} \). We have \( \frac{\partial u_m}{\partial \epsilon} < 0 \), so \( \frac{\partial}{\partial \epsilon} \max_{c \in C} u(c, g, q, \epsilon) < 0 \). \( s \) 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 \( \max_{c \in \Gamma} p(a_c, w_{c,g}, q) - \tau(c, g, q, \epsilon) = 0 \); that is, when \( \epsilon = \max_{c \in \Gamma} \frac{p(a_c, w_{c,g}, q)}{\tau(c, g, q, \epsilon)} = 0 \). We show as under monopoly that \( \hat{\epsilon} = \max_{c \in \Gamma} \frac{p(a_c, w_{c,g}, q)}{\tau(c, g, q, \epsilon)} \).

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

That \( \hat{\epsilon}_m = \hat{\epsilon} \geq \hat{\epsilon} \) follows from lemma \[1\] and the proof of proposition \[7\]; we have \( \hat{\epsilon}_m = \hat{\epsilon} = \max_{c \in C} \frac{p(c, g, q)}{a_c} \), while \( \hat{\epsilon} = \max_{c \in \Gamma} \frac{p(c, g, q)}{\tau(c, g, q, \epsilon)} \). Lemma \[5\] tells us that \( \tau(c, g, q, \epsilon) \geq a_c \), which implies \( \hat{\epsilon}_m \geq \hat{\epsilon} \).

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

Consider the case where \( \epsilon < \hat{\epsilon}_m \). Lemma \[1\] tells us that \( C_{gq}^e \) does not vary with \( \epsilon \). Conversely, the following lemma shows that as \( \epsilon \) decreases, the coalitions in \( C_{gq}^m \) 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 \( \epsilon_{1m} \in C_{gq1}^m \) and \( \epsilon_{2m} \in C_{gq2}^m \). We have \( \epsilon_1 < \epsilon_2 \Rightarrow a_{1c} \geq a_{2c} \).
Proof. Let $c_1$ be the smallest coalition in $C_{gq\epsilon_1}^m$, and $c_2$ the largest in $C_{gq\epsilon_2}^m$ 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 $c_1 \in C_{gq\epsilon_1}^m$ and $c_2 \in C_{gq\epsilon_2}^m$, 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.

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 $\frac{\partial p(a_2, w_2, q)}{\partial q} / \frac{\partial p(a_1, w_1, q)}{\partial q} < 1$ 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

$$|v^m(a, w + 1, q, \epsilon) - v^m(a, w, q, \epsilon)| > v^m(a^*, w, q, \epsilon) - \max\{v^m(1, w, q, \epsilon), v^m(N, w, q, \epsilon)\},$$

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. This proposition proves as under equal-sharing, with the exception that equation \[A.1\] becomes:

\[
\nabla_x u_2 - u_1 = \frac{\partial u_2 - u_1}{\partial \epsilon} x_\epsilon + \frac{\partial u_2 - u_1}{\partial q} x_q = \left( \frac{\partial p_1}{\partial q} - \frac{\partial p_2}{\partial q} \right) x_q - (a_{c_2} - a_{c_1}) x_\epsilon \quad \text{(A.4)}
\]

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. \(\square\)

Lemma \(2\) and propositions \(2, 3, 4\) and \(5\) prove as in equal-sharing, but consider \(C_{gq\epsilon}^m\) instead of \(C_{gq}^*\), \(u_m(c, g, q, \epsilon)\) instead of \(u(c, g, q)\), and \(\hat{\epsilon}_m(g, q)\) instead of \(\hat{\epsilon}_s(g, q)\).

### 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:

$$p(a, w, q, \epsilon) = \rho(\epsilon)p(a, w, q), \quad (A.5)$$

where $\rho : (0, 1) \to (0, 1)$ 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. The utility function now writes:

$$u_i(c, g, q, \epsilon) = \begin{cases} u(c, g, q, \epsilon) - \epsilon = \frac{p(a_c, w_{cg}, q; \epsilon)}{a} - \epsilon, & \text{if } i \in c \\ 0, & \text{otherwise} \end{cases} \quad (A.6)$$

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 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 and 2, and lemma 2 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 9 (Threshold strategy, extension). Consider $\epsilon, \epsilon' \in (0, 1)$. We have $C^*_g = \arg\max_{c \in C_g} u_s(c, g, q, \epsilon) = \arg\max_{c \in C_g} u_s(c, g, q, \epsilon')$. There is a threshold $\hat{\epsilon}_s(g, q) \in (0, 1)$ such that if $\rho'(\epsilon) \leq \frac{a_c + 1}{p(c, g, q, \epsilon)}$ 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 $\epsilon > \hat{\epsilon}_s(g, q)$. Otherwise, she accepts it, and some coalition $c^* \in C^*$ is realized. If $\rho'(\epsilon) > \frac{a_c}{p(c, g, q, \epsilon)}$ 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, she 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 $\frac{p(a_c, w_{c', g, q, \epsilon})}{a_c} \leq \frac{p(a_c, w_{c', g, q, \epsilon})}{a_c}$. As such, $u_s(c, g, q, \epsilon') \leq u_s(c', g, q, \epsilon')$, proving the point.

Let’s show the rest of the lemma. Note that $\frac{\partial u_s}{\partial \epsilon} = \frac{\rho'(\epsilon)p(c, g, q, \epsilon)}{a_c} - 1$. 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 $\hat{\epsilon} \in (0, 1)$ such that $u_s(c^*, g, q, \hat{\epsilon}) = 0$. Note that $\frac{\partial u_s}{\partial \epsilon} = \frac{\rho'(\epsilon)p(c, g, q, \epsilon)}{a_c} - 1$. So if $\rho'(\epsilon) \leq \frac{a_c}{p(c, g, q, \epsilon)}$ for any $c \in C, q \in (0, 1), \epsilon \in (0, 1)$, $s$ rejects the bribe for $\epsilon > \hat{\epsilon}$. Conversely, if $\rho'(\epsilon) > \frac{a_c}{p(c, g, q, \epsilon)}$ for any $c \in C, s$ rejects the bribe for $\epsilon < \hat{\epsilon}$. If $u_s(c^*, g, q, \hat{\epsilon}) > 0$ for any $\epsilon \in (0, 1)$ then the seed always accepts (rejects) the bribe, so define some $\hat{\epsilon} \in \{0, 1\}$.
If $u_s(c^*, g, q, \hat{\epsilon}) \geq 0$, we show as in lemma 1 that $s$ accepts the bribe and $c^*$ is an equilibrium outcome.

Proposition 3 becomes:

**Proposition 9.** Let $c^*_1 \in C_{gq_1}^*$, $c^*_2 \in C_{gq_2}^*$. If $\rho'(\epsilon) \leq \frac{a_c+1}{p(c,g,q,\epsilon)}$ for any $c, g, q, \epsilon$, we have $q_1 < q_2 \Rightarrow \hat{\epsilon}(g, q_1) \geq \hat{\epsilon}(g, q_2)$. If $\rho'(\epsilon) > \frac{a_c+1}{p(c,g,q,\epsilon)}$ for any $c, g, q, \epsilon$, we have $q_1 < q_2 \Rightarrow \hat{\epsilon}(g, q_1) \leq \hat{\epsilon}(g, q_2)$. For any $\rho'(\epsilon)$, we have $a_{c^*_1} \leq a_{c^*_2}$.

**Proof of proposition 9.** From lemma 9, $\hat{\epsilon}(g, q)$ 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, $\hat{\epsilon}(g, q_1) \geq (\leq) \hat{\epsilon}(g, q_2)$ if $\rho'(\epsilon) \leq (>) \frac{a_c+1}{p(c,g,q,\epsilon)}$. The rest of the proposition proves as in proposition 3.

Proposition 4 becomes:

**Proposition 10.** Suppose $g' = g+i \rightarrow j$. Then if $\rho'(\epsilon) \leq (>) \frac{a_c}{p(c,g,q,\epsilon)}$ 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 $i \not\in c \cup W_{cg}$ 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 $\rho'(\epsilon) \leq (>) \frac{a_c}{p(c,g,q,\epsilon)}$ 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 5 becomes:

**Proposition 11.**
Proposition 11. Suppose \( g' = g + ij \). Then if \( \rho'(\epsilon) \leq (>) \frac{\alpha_c}{p(c,g,q,\epsilon)} \) 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 \( \rho'(\epsilon) \leq (>) \frac{\alpha_c}{p(c,g,q,\epsilon)} \) for any \( c,g,q,\epsilon \).

The second part of the proposition proves as in proposition 5 if \( \rho'(\epsilon) \leq \frac{\alpha_c}{p(c,g,q,\epsilon)} \) for any \( c,g,q,\epsilon \). If \( \rho'(\epsilon) \geq \frac{\alpha_c}{p(c,g,q,\epsilon)} \) for any \( c,g,q,\epsilon \), then suppose that there is \( q \in (0,1) \) such that \( \hat{\epsilon}(g',q) \leq \hat{\epsilon}(g,q) \) and use the same argument as in proposition 5.

A.5 Simulations and experiment

In this section, I prove that the functional form for the probability of success \( p \) in equation 3.2 used in simulations and in the experiment satisfies assumptions 1 and 2.

\( p \) satisfies assumption 1. 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

\[
\frac{\partial p(a_2,w_2,q)}{\partial q} / \frac{\partial p(a_1,w_1,q)}{\partial q} \leq \frac{a_2}{a_1} \iff (N-w_1)a_2 - (N-w_2)a_1 \geq 0
\]

Note that since \( \frac{\partial p}{\partial q} < 0, a_1 = a_2 \) 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 2. We have \( \frac{\partial v}{\partial a} \propto (N-w_c)q - (N-1-w_c) \). That is, \( \frac{\partial v}{\partial a} \geq 0 \iff q \geq 1 - \frac{1}{N-w} \), which is not a function of \( a \). So \( v \) is monotonic in \( a \).
This appendix includes the models used to create all the figures included in this dissertation.

B.1 Chapter 4
Table B.1: Models used to construct figures 4.1 and 4.2. Models are estimated using OLS with heteroskedastic standard errors.

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<th>Dependent variable:</th>
<th>Corruption (police)</th>
<th>Corruption (Parliament)</th>
<th>Share of accomplices</th>
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<tr>
<td>log(GDP p/c), $ PPP 2011</td>
<td>$0.029 (0.060)</td>
<td>$0.349*** (0.051)</td>
<td>0.010*** (0.002)</td>
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<tr>
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<td>6.893*** (0.485)</td>
<td>0.421*** (0.020)</td>
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Note: *p<0.1; **p<0.05; ***p<0.01

Table B.2: Models used to construct Figure 4.4. Amount is measured as a fraction of GNI p/c. For similar amounts stolen, corruption in the more capable US involves more accomplices than in India.

B.2 Chapter 5
Table B.3: **Main models of the experiment.** Standard errors are in parentheses, and errors are clustered at the group level. Models 1, 2, and 4 use OLS, and all their variables are binary. Model 3 is a logistic generalized additive model (see footnote 10 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 5.2. Model 3 is used to construct figure 5.6 panel b. Model 4 is used to construct figure 5.3.
Table B.4: 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 5.8.
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*Note:* *p<0.05; **p<0.01; ***p<0.001

Table B.5: **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 5.8.
**Table B.6: 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 5.9.

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<td>635.124</td>
<td>1,772.321</td>
<td>1,739.139</td>
<td>1,741.139</td>
<td></td>
</tr>
</tbody>
</table>

**Note:** *p<0.05; **p<0.01; ***p<0.001
### Table B.7: 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 5.10.

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>Pr(accept)</th>
<th>N accomplices</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Hard, Grand</td>
<td>-.172</td>
<td>-.074</td>
<td>-.172</td>
</tr>
<tr>
<td>Exposing, Grand</td>
<td>-.034</td>
<td>.072**</td>
<td>-.034</td>
</tr>
<tr>
<td>Baseline, Petty</td>
<td>-.142</td>
<td>-.070</td>
<td>-.148</td>
</tr>
<tr>
<td>Hard, Petty</td>
<td>-.377***</td>
<td>-.526***</td>
<td>-.383***</td>
</tr>
<tr>
<td>Exposing, Petty</td>
<td>-.348**</td>
<td>-.309**</td>
<td>-.354**</td>
</tr>
<tr>
<td>With irrelevant tie</td>
<td>-.075</td>
<td>-.044</td>
<td>(C)</td>
</tr>
<tr>
<td>Constant</td>
<td>.966***</td>
<td>.896***</td>
<td>1.007***</td>
</tr>
</tbody>
</table>

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

### B.3 Chapter 6
<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>Force Division</th>
<th>Market</th>
<th>Total</th>
<th>N Skips Division</th>
<th>Market</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>attendance</td>
<td>-0.001***</td>
<td>-0.001***</td>
<td>-0.006***</td>
<td>0.005***</td>
<td>0.004***</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.0005)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>business</td>
<td>0.0004*</td>
<td>0.001**</td>
<td>0.004**</td>
<td>-0.002**</td>
<td>-0.002**</td>
<td>-0.003**</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0003)</td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>log(amount)</td>
<td>0.003**</td>
<td>0.003**</td>
<td>0.003**</td>
<td>0.024***</td>
<td>0.024***</td>
<td>0.026***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.040*</td>
<td>0.035*</td>
<td>0.028</td>
<td>-0.060</td>
<td>-0.050</td>
<td>-0.050</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.020)</td>
<td>(0.020)</td>
<td>(0.067)</td>
<td>(0.067)</td>
<td>(0.067)</td>
</tr>
<tr>
<td>Observations</td>
<td>54,120</td>
<td>54,120</td>
<td>54,120</td>
<td>38,979</td>
<td>38,979</td>
<td>38,979</td>
</tr>
<tr>
<td>R²</td>
<td>0.007</td>
<td>0.007</td>
<td>0.008</td>
<td>0.006</td>
<td>0.006</td>
<td>0.005</td>
</tr>
</tbody>
</table>

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

Table B.8: Average marginal effect of attendance on force and skip rates. All models use OLS. Standard errors clustered at the dyad level in parentheses. All models include day of the week and hour fixed effects. Models estimate the effect of total, division, and market attendance on forcing behavior and skipping behavior (models 1-3 and 4-6 respectively). These models are used to construct Figure 6.5.

<table>
<thead>
<tr>
<th></th>
<th>Force</th>
<th>N Skips</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 shift</td>
<td>2 shifts</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>N attending weak ties</td>
<td>-0.00004</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>business</td>
<td>-0.0003*</td>
<td>-0.0003</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>log(amount)</td>
<td>0.003*</td>
<td>0.003*</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.036</td>
<td>0.037</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Observations</td>
<td>36,667</td>
<td>36,667</td>
</tr>
<tr>
<td>R²</td>
<td>0.009</td>
<td>0.009</td>
</tr>
</tbody>
</table>

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

Table B.9: Average marginal effect of unfamiliar colleagues on force and skip rates. All models use OLS. Standard errors clustered at the dyad level in parentheses. All models include day of the week and hour fixed effects. Models estimate the effect unfamiliar colleagues, defined using a threshold of 1 and 2 shifts spent together in the past 30 days on forcing behavior and skipping behavior (models 1-2 and 3-4 respectively). These models are used to construct Figure 6.7.
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 C.1 show equilibrium in the unscaled model.
Figure C.1: 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 Experimental protocol

C.2.1 Location

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

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with relative privacy. The experiment room contained two circular tables, each with five chairs for the enumerator and four subjects to play the game.

We held 17 sessions of 16 respondents each. 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.2.2 Enumerators

Our partner selected two male and two female enumerators, three of them students from the Hassan II University in Mohammedia and one from our partner’s company. Having uploaded our pre-experiment survey, experiment survey, and post-experiment survey to Qualtrics, we trained our enumerators to administer the Qualtrics surveys on handheld tablets. We trained all four enumerators to administer the pre- and post-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.2.3 Subjects

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

Invitation to participate in a study session

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

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

C.2.4 Prompts and material

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

Prompt of the first block (control or hard)

You are about to participate in an experiment on behavior in uncertain situations. The experiment looks like a game in which you will have to
Figure C.2: **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]

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.
Additional evidence from the firm

D.1 Causal evidence

Figure D.1 shows that on average, new hires have little effect on skipping and forcing behavior, and that this effect vanishes as the length of the window increases. The effect, however, seems more pronounced for forcing: new hires significantly decrease forcing behavior for windows of length 1, 5, 6, and 7. Yet, Figure D.2 shows that such effect is largely indistinguishable across types, irrespective of the window length.
Figure D.1: **Average marginal effect of attendance on force and skip rates.** Points are average marginal effects of one additional new hire, estimated using the specification in model 6.1. Shaded areas are 95 percent confidence intervals. Errors are clustered at the dyad level. On average, increased attendance decreases forcing behavior. It has no significant effect, or decreases skipping behavior.

Figure D.2: **Heterogeneous effects of new hires on force and skip rates.** Panel a represents the density of the posterior probability $\Pr(t_j = L | X, Y)$. The mixture models are separating. In panel b, points are average marginal effects of a new hire for each type, estimated using the specification in model 6.2. Bars are 95 percent confidence intervals. Irrespective of the window length, the effect of new hires is indistinguishable across types.
### D.2 Gibbs sampler

Note that $p_i$ and $q_i$ are probit regressions of $b_i$ and $y_i$ on $x_i$ and $z_i$ respectively. I use the standard latent utility representation, with

$$ u_i = x_i' \beta + \epsilon_i $$

$$ v_i = z_i' \gamma + \eta_i $$

$\epsilon_i, \eta_i \sim N(0,1)$

$u_i \geq 0 \iff b_i = 1$

$\forall i \leq N$ for $i = 1, \ldots, n$.

$u_i \geq 0 \iff y_i = 1$.

The Gibbs sampler proceeds as follows:

1. Update $p|\beta = \Phi(x' \beta)$, and $q|\gamma = \Phi(z\gamma)$

2. Update $\tau_{ij} = \Pr(t_{ij}|\pi, p, q, y) = \frac{\pi \prod_{k \in C_{ij}} (p^L_k)^{y_k} (1-p^L_k)^{1-y_k}}{\pi \prod_{k \in C_{ij}} (p^L_k)^{y_k} (1-p^L_k)^{1-y_k} + (1-\pi) \prod_{k \in C_{ij}} p^L_k (1-p^L_k)^{1-y_k}}$

3. Update $\pi|p, q, \tau, y \sim \text{Beta}(\sum_{ij} \tau_{ij} + \alpha_0, D - \sum_{ij} \pi_{ij} + \alpha_1)$

4. Update $b_i|\pi, p_i, q_i, y_i \sim \text{Binom\left(} y_i \left[ (1 - \pi) + \pi \frac{p_i}{p_i + (1-p_i)q_i} \right] \right)$

5. Update $\beta, \sigma^2|b, x$ using a collapsed Gibbs sampler [Holmes and Held (2006)]

6. Update $\gamma, \varsigma^2|y, z, b, \tau$ using Holmes and Held (2006), with weights $w_i = \Pr(b_i = 0, t_{j[i]|c[i]} = L|p_i, q_i, \tau_{j[i]|c[i]}) = \tau_{j[i]|c[i]} \frac{(1-p_i)q_i}{\pi (p_i + (1-p_i)q_i)}$


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