The Effects of Corruption on Organizational Networks and Individual Behavior

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ABSTRACT
In this study, I examine the effects of corruption on patterns of relations in a well-known case of organizational crime. By contrasting corrupt and non-corrupt projects within an organization, I am able to examine how fraudulent endeavors alter the way individuals mobilize to accomplish a goal. This study examines longitudinal data and couples qualitative coding techniques with social network analysis to understand the effects of corruption on social structure. In contrast to non-corrupt projects, corrupt networks have lower connectivity, fewer reciprocal relations, and communicate less frequently. These different patterns also hold for between- and within-subject studies. For individuals, corrupt communications, as compared to non-corrupt communications, are less frequent, less likely to be reciprocated, and have reduced transitivity, meaning that message recipients are not as likely to share a communication link. This study highlights the role of content in understanding the emergent properties of communication networks.
Between 2000-2011, the U.S. saw an unprecedented rise in organizational crime, particularly in the form of fraudulent accounting practices by Fortune 500 firms. Organizational crime is a crime wherein members of an organization commit the illegal action primarily for the benefit of the organization (Clinard and Yeagar, 1980). Enron typified such forms of organizational crime and corporate deception as one of the first of the U.S.’s major corporations to come under investigation for accounting fraud. In 2001, Enron publicly admitted to overstating its earnings by $586 million and hiding $3 billion in debt (McLean and Elkind, 2003). Not long thereafter, it was found that WorldCom, the second largest phone company in the United States, misreported profits by $3.8 billion by improperly shifting certain expenses to capital funds (Patsuris, 2002). Following the financial crisis of 2008, the Securities and Exchange Commission (SEC) levied a $550 million penalty against Goldman Sachs Group, the largest ever against a Wall Street firm, for misleading investors in collateralized debt obligations (Hurtado and Harper, 2010). Recently in 2011, a court-appointed examiner’s report determined that Lehman Brothers had reshuffled $50 billion off the firm’s balance sheet to help the investment bank appear less financially troubled than it was before its collapse in 2008 (Merced and Werdigier, 2011). Though these cases of accounting fraud abound, organizational scholars know relatively little about the implementation of organizational crime.

At each of these large corporations, managers employed complex accounting methods to mislead investors about the financial health of their firms. However, these financial misdeeds were not localized to a few executives in the firm; they required the involvement of many organizational members from various departments in order to implement such accounting malfeasance. The looming question from these incidents is how these managers were able to organize and carry out criminal activity that required participation from multiple members. In this way, organizational crime in the form of accounting fraud mirrors the regular activities of a for-profit firm, which largely entail coordinating organizational members to successfully implement projects in order to maximize the profit for the company – except that in the case of organizational crime the means used to meet the objectives are, of course, illegal. This leads to second question: are the structures in organizations used to implement legitimate projects the same as
those that are meant to deceive monitoring agencies and investors? This study examines the case of organizational crime at Enron to understand how such fraudulent activity is organized. As one the first Fortune 500 firms to commit such large scale accounting fraud, Enron provides an excellent setting to understand how corruption takes form.

To address these questions, I utilize an important and unique dataset for understanding the social structure of deviance. Using email communication from Enron, I couple qualitative coding of message contents with social network analysis to permit a finer examination of organizational relations and behavior. These data provide an excellent opportunity to gather behavioral measures on corruption, which have been historically difficult to obtain. Email messages also have a qualitative richness not normally found in network analysis. Additionally, by examining networks at both the group level and the individual level, I am able to speak to the micro-macro linkages often lacking in network research (Ibarra, Kilduff, and Tsai, 2005).

Rather than investigate the antecedents of corruption, I examine how illegal endeavors come to be organized. I treat the decision to participate in fraud as exogenous in this study. Instead, I focus on network forms that emerge when members cooperate to implement an organizational crime. By identifying non-corrupt and corrupt projects at Enron, I am able to compare the networks of complex projects. This study design also permits me to examine the behavior of individuals that lead to different structures. I show that micro-level communication behaviors concerning the criminal activity create a characteristically different network form – a hub-and-spoke structure with concentric rings of information access.

**CORRUPT NETWORK TRADE-OFFS**

Research in sociology suggests that when certain types of content are deemed illegitimate or counter-normative, individuals alter their communication behavior. For example, in Lee's (1969) *The Search for an Abortionist*, which was set at a time when abortions were illegal and neither the doctors who performed abortions nor the women who sought them could do so openly, individuals were careful and strategic with whom they could discuss the procedure. In their seminal work on collusion networks,
Baker and Faulkner (1993) found that individuals involved in illegal networks appeared to arrange their communications in order to evade detection. Thus, the motivations of individuals in communications can have cumulative effects on the emergent social system.

As Goffman (1970) originally noted, the constraint of secrecy distinguishes illegal communication networks from legitimate communication networks. In his view, corrupt networks have the additional challenge of remaining secret while simultaneously ensuring the necessary coordination and control of their members. This trade-off hinges on information access for the network members. Members require some level of information to efficiently and effectively organize, but limiting information throughout the network helps shield members from possible detection and maintains concealment. The puzzle for corrupt networks is that the behavior that coincides with effective coordination – frequent communications, reciprocity, and cohesion – makes the group more vulnerable to detection. And generally, non-corrupt projects do not face this trade-off.  

**FREQUENCY OF COMMUNICATION**

In the instance of novel and complex endeavors, frequency of communication assists individuals in clarifying issues, resolving problems, and expediting the project’s goals (Eisenhardt, 1989). Frequency is not simply the volume of communication but it also indicates greater information sharing between two members. Frequency of interaction is a commonly used measure of relational strength, with increased communications leading to increased tie-strength (Wasserman and Faust, 1994). Close interpersonal links facilitate knowledge transfer and are more likely to coincide with a greater motivation to assist (Granovetter, 1985; Reagans and McEvily, 2003). Hence, for projects where the task is complex and its outcome uncertain, frequent communication amongst the project team members serves to improve information access and group coordination.

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1 This is not to suggest that the non-corrupt groups arrive at the optimal network form. Rather that they are unencumbered by secrecy, and the assumption here is that criminal activity requires covert communication behaviors.
In the case of corrupt networks, each time members share information about the illicit endeavor, they run the risk of being discovered. The corrupt group must strike a balance between coordinating members to complete its goals and shielding its members from detection. Members may attempt to minimize risk by decreasing communication to the lowest amount possible without jeopardizing the goals of the project (Goffman, 1970; p78). Since it behooves the individual and the group to reserve communication to only the most essential sharing of information, the effects of corruption on frequency should be found at both the network and the individual. Formally,

Hypothesis 1a: Corrupt information networks will have lower communication frequency than non-corrupt information networks.

Hypothesis 1b: Sharing corrupt information reduce communication frequency for the individual.

**RECIPROCAL COMMUNICATION**

Norms of reciprocity are commonly found among groups across various settings (Gouldner, 1960). In addition to its prevalence in groups, reciprocity is also critical for coordinating projects and developing effective channels of communication. A network rich with reciprocal communications permits discourse between the members to help them clarify, extend, and refine ideas. Reciprocity also reduces uncertainty between individuals by promoting trust and solidarity (Molm, Schaefer, and Colletti, 2007). Additionally, the act of reciprocating itself engenders commitment and positive affect among group members, which benefits group coordination (Molm, 1990, 1997). Given the norm of reciprocity and its benefits to group coordination, I propose that complex project networks will be characterized by reciprocal communication.

On the other hand, reciprocity can also be less efficient and increase the risk of detection. Structures that contain a high number of nonreciprocal or asymmetrical relations tend to be more efficient for information transmission with fewer redundant channels to detect (Guetzkow and Simon, 1955). Greater reciprocity necessitates greater amounts of interaction, since the receiver must respond to the sender. This, in turn, creates more opportunities for the group and its members to be discovered. Systems with low levels of reciprocity also inherently lead to differences in information acquisition, with
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information commonly flowing to the most powerful or highest status members (Brass, Butterfield, and Skaggs, 1998). In an asymmetrical communication network, receiving information from well informed others contributes more to the individual’s knowledge (Bonacich, 2001). And this pattern can serve to aggregate information toward certain actors making them structurally central. Thus, asymmetrical or hierarchical structures heighten control over information particularly for central members (Bonacich, 1987; Freeman, 1979). Finally, there is evidence to suggest that illegal activities tend to yield centralized, hierarchical networks (Baker & Faulkner 1993; Simmel 1950). Hence,

Hypothesis 2a: Corrupt information networks will have more asymmetrical relations than non-corrupt information networks.

Hypothesis 2b: Sharing corrupt information will increase asymmetrical relations for the individual.

GROUP COHESION

Group cohesion generally refers to the extent to which group members are inter-connected with each other. Cohesion is important for project groups particularly because a connected structure allows members to consult and gain complex information from one another through established ties and relations (Hansen, 1999; Uzzi, 1999). A well-connected, cohesive group permits more individuals to be uniformly and adequately informed because in such projects, members are more likely to share similar information (Burt, 1987). Information also diffuses more rapidly in these groups (Coleman, 1988).

Despite the advantages of group cohesion, the secrecy required in corrupt networks may hinder connectivity within the network. Corrupt project participants may seek to create graduated divisions of labor that serve as organizational buffers, sealing off members from one another (Simmel, 1950; Goffman, 1970). Consequently, these cleavages in the network render it difficult to implicate the entire group (Granovetter, 2007). Lastly, sparse networks permit more opportunities for malfeasance and organizational deviance because of the group’s inability to effectively monitor all of its members (Burt, 2004; Mitchell, 2003; Vaughan, 1999).

2 Therefore, I do not assume that all members had complete knowledge of the illicit undertaking but were simply aware that the project was surreptitious.
Transitivity refers to the tendency of two individuals, who both share a connection to a common third person, to also become tied to each other (Davis, 1963; Feld, 1981; Holland and Leinhardt, 1971). When actors promote connections between their alters, the level of cohesion surrounding them is increased. This localized cohesion is generally optimal for sharing information, encouraging cooperation, and reducing conflict (Simmel, 1950). In addition, dyadic relations embedded within closed triads are more stable and more likely to produce consensus (Krackhardt, 1999). In cases where the task is complex, such as those investigated here, even the redundancy of information that high cohesion promotes can benefit the project and its participants (Obstfeld, 2005).

However, when the objectives of the group include secrecy, individuals may intentionally obstruct or limit relations between alters. By discouraging ties between alters, actors enhance their local control and power over the separated others (Emerson, 1962; Pfeffer and Salancik, 1978). This parallels Simmel’s (1950) concept of Divide et Impera, “divide and conquer”, where the third actor strategically keeps two actors separate to maintain some degree of power over them (p162). Open triads also reduce the possibility that alters are aware of each other’s involvement or the network in its entirety. The absence of connections that characterizes open triads also leads to a network rich with structural holes or unconnected constituents, which in turn provides opportunities to play members against each other (Burt, 1992; Volker and Flap, 2001). I propose that corrupt information will undermine motivations to create linkages among alters, attenuating group cohesion. Therefore,

Hypothesis 3a: Corrupt information networks will have less cohesion than non-corrupt projects.

Hypothesis 3b: Sharing corrupt information will reduce transitive relationships for the individual.

RESEARCH SETTING

As mentioned earlier, this study is based on emails exchanged at Enron Corporation. Enron was an energy company based out of Houston, Texas and was one of the world’s leaders in electricity, natural gas, and communication. After many years of dramatic success, record-making profits, public acclaim, and favored status on Wall Street, Enron was brought under investigation. On October 22, 2001, the Security and Exchange Commission (SEC) announced that it was exploring several suspicious deals at
Enron. Shortly thereafter, Enron filed for bankruptcy – making it the largest bankruptcy of its time. It was later revealed that Enron hid massive amounts of debt using what were termed “creative accounting practices” and “off-balance-sheet” transactions through projects with special purpose entities (SPEs). These activities not only precipitated the investigation of Enron’s accounting and management practices by the SEC, but also led to the enactment of federal laws to mitigate fraud, such as the Sarbanes-Oxley Act of 2002.

While under investigation by the SEC, the Federal Energy and Regulatory Commission (FERC) also brought charges against Enron for market manipulations. As part of the investigation, FERC seized Enron’s email servers, which contained five years of email correspondence. The data were later made available as the Enron Email Corpus (EEC). The EEC data is used here for a retrospective analysis of the firm and its internal projects via communication networks. Constructing networks from this large body of email text required selecting projects prior to examining the networks. Multiple sources, such as corporate documents, government reports, and media coverage, and testimonies and autobiographies from employees were used to select an appropriate set of projects for systematic comparison. Six projects were finally selected for analysis here.

All of the six projects were conducted at the organizational level and required information sharing across functional groups. I limited this study to new and novel projects within the time frame that the data were collected so as not to miss prior communication shared in the group. Novel projects also provide an opportunity to understand the emergent social networks, because by their nature, these projects are not already integrated into the existing practices of the organization (Rogers, 1962). Organizational members must develop new channels by which to share and access information about the inchoate projects.

The first three projects were identified as organizational crimes that enabled fraudulent misrepresentation of the organization’s accounts. Each project purposefully violated existing accounting principles and was intentionally misleading (McLean and Elkind, 2003). These projects enabled Enron to present itself more attractively to investors, but also led the firm to file “materially false and misleading” annual and quarterly reports (SEC filing complaint 17692). Projects were identified through testimonies
and reports provided to the U.S. Department of Justice (DOJ) concerning charges brought against Enron and its employees. For example, a former treasurer admitted, “he and others at Enron deliberately structured [project one] in a way that appeared to comply with, but in fact violated, applicable accounting rules” (USDOJ Release, 2003). Similar statements provided evidence that members designed the projects with the intention of misleading investors. In testimonies to the DOJ, Enron’s Chief Financial Officer confessed that the projects [two and three] were created to protect Enron’s balance sheet from decreases in the value of certain investments (USDOJ Release, 2003b; USDOJ Release, 2004). Finally, in a report to the SEC, these three projects were found to be in violation of accounting laws and to have misreported Enron’s financial statements (SEC Report, 2001).

The remaining three non-corr upt projects were selected based on their comparability to the corrupt projects at the firm along specific dimensions. The first criterion was to identify non-corr upt projects. These had to be both publicly documented in Enron’s press releases and annual reports and not indentified as corrupt in any government agency reports or individual testimonies against Enron by the DOJ, SEC, or FERC (Enron, 1998-2000). Also, because all of the corrupt projects were based on limited partnership agreements, only non-corr upt limited partnerships projects were selected as matches. Capital under management was used to select comparably sized non-corr upt projects. Due to the misreporting of capital under management for the corrupt projects this was particularly tricky to determine; however, since the corrupt projects were used as vehicles to keep upwards of 100 million off Enron’s debt accounting, only non-corr upt projects estimated to be worth 100 million or more were included. Lastly, non-corr upt projects were limited to those that had similar project durations to the corrupt projects, lasting from two to three years between 1998 and 2002.

3 This is not to suggest that corruption is an absolute dichotomous state and that the non-corr upt projects were without corruption or that the corrupt projects were without legitimate activity. Instead, I suggest that corruption is a continuum. Here, I can only speak to the available evidence as gathered by government agencies and reported in news outlets and biographies. Based on this data, the projects have been incorrectly identified.
Data Sources

The organizational communication network was comprised of EEC emails sent between the years 1998 to 2002. The EEC dataset consists of professional and personal email messages and contains both incoming and outgoing emails. Each email includes the following information: sender; recipients; recipient form: to, carbon copy (CC), and blind carbon copy (BCC); transmission form: original, reply, and forward; date; folder title; subject; and message content. Within the EEC, there are over twenty-seven thousand unique senders and recipients, after the data were normalized to remove redundant emails (one individual can have several email accounts throughout their tenure at Enron), group emails, and distribution lists.4 5

Email exchange provides an ideal setting to understand individual communication behavior and social networks within an enterprise. Notably, Bernard, Killworth, and Sailer (1976; 1979) find that behavioral measures, such as those captured in electronic communication, are less sensitive to biases found in self-reported data, where individuals tend to over-report interactions with high-status actors or under-report misdeeds. Evidence also indicates that email exchanges closely parallel work networks (Hinds and Kiesler, 1995; Kleinbaum, Stuart, and Tushman, forthcoming). Most important for this analysis, behavioral measures allow observation of corruption that individuals would normally be reluctant to report.

The email messages were first qualitatively coded based on information pertinent to the project. The primary objective was to identify a complete set of emails containing information regarding each particular project. In the initial step, coding was done with the assistance of software, using key-word searches for all messages in the EEC. Key-word search term lists were based on the information from

4 The data was extracted from a subset of Enron accounts since the complete set was not available. The unique emails do not therefore represent the total number of accounts.

5 Email addresses have been normalized to represent actual Enron employees in a variety of ways. First list-serve or group email accounts were removed, such as “wholesaleteam@enron.com.” In addition, emails accounts were combined when they belonged to a single individual. For example, Kenneth Lay had both “ken.lay@enron” and “kenneth.lay@enron.”
EEC itself and complemented with additional sources, such as annual reports, individual interviews, public statements, and testimonies from the SEC and the DOJ. The resulting subset was then reviewed and validated using traditional methods. These steps were iterated multiple times to refine the key-word search terms.\(^6\) Through this process, the six different communication networks were derived based on the content of the information exchanged. Next, a directed one-mode network was created based on the email exchanges. The directed networks were constructed from the email headers, which identify the messages’ senders and recipients. Directed networks are critical to this analysis in order to determine the symmetry of information flow between organizational members.

For each project and year, I extracted the individual’s egocentric network 2-degrees from ego (ego’s friends’ friends). Egocentric networks are commonly used to understand individual behavior within networks (Marsden, 1990), as the set of relations defined by an individual and her contacts with others. I limited the egocentric network to only 2-degrees for the following reason; individual egos can know and, to some degree, shape what their alters and their alters’ alters know. After 2-degrees, it would be difficult for ego to alter the amount of information that others may receive or influence their behavior. Further, beyond 2-degrees is considered outside of ego’s “sphere of influence” (Levine, 1972; Marsden, 2002). For each project that an individual was involved in, an egocentric network was derived, which permits the annual observation of different behaviors across the projects. Figure 1 is a stylized representation of the method for disaggregating network relations by content for both the network and individual members.

\(^6\) In most cases, this entailed excluding certain emails that were not relevant. For example, one project shared a similar name with a Houston basketball team, which many Enron employees were fans. These messages were excluded from the analysis.
Measures

This analysis examines three outcomes: communication frequency, reciprocity, and cohesion. Although the measures for frequency and reciprocity are appropriate for sociocentric and egocentric levels of analysis, connectedness is not a suitable measure for egocentric networks (Marsden, 2002). Therefore, I use a different measure, transitivity, to examine cohesion in egocentric networks.

**Communication Frequency** Frequency of communication is a common measure of relation strength and information bandwidth (Reagans and McEvily, 2003; Uzzi, 1999). At the group level, frequency is the average message per observed tie for the project duration. Frequency for individuals is the mean number of messages shared with all of ego’s relations within a year for the project. I use frequency to test Hypothesis 1a and 1b.

**Structural Asymmetry** Structural asymmetry captures the degree of asymmetry or non-reciprocity within the network. A completely asymmetrical network is one in which communication flows in one direction and is not reciprocated by the receivers. By counting the number of pairs that have reciprocated ties relative to the number of observed pairs of ties, I am able to assess the degree to which a structure deviates from complete asymmetry (Krackhardt, 1994). This index is used to measure both the project structure and individual behavior in the ego networks for testing Hypotheses 2a and 2b. An asymmetry index equal to 1 means that none of the pairs share a reciprocated tie; an index equal to 0 means that all ties are reciprocated. Provided below is the formula for asymmetry:

\[
1 - \left[ \frac{V}{\max(V)} \right]
\]

Where \(V\) is the number of symmetrical pairs and \(\max(V)\) is the total number of pairs.\(^8\)

\(^7\) This measure is termed hierarchy by Krackhardt (1994); however, I have renamed the index to parallel egocentric terminology used here.

\(^8\) Dyadic reciprocity is treated as a dichotomous outcome here rather than a proportion of the asymmetrical communications.
Sociocentric Cohesion Cohesion may be measured in a variety of ways, such as by examining graph density or the clustering coefficients; however, these measures are very sensitive to variations in network size, whereas measures like connectedness and transitivity are less sensitive to such variations (Friedkin, 1981). Krackhardt’s (1994) connectedness measure captures the underlying proportion of the network that is a single component and is used to test Hypothesis 3a. Specifically, connectedness reflects the degree to which relations exist between all members of the network (Krackhardt, 1994). A component is a subgroup that is completely connected, meaning all individuals share at least one tie to the group. A connectedness score of 1 indicates that all actors share at least one tie to the social structure. Conversely, a connectedness score of 0 means that all members are isolated from one another and do not share ties. When a social network is comprised of multiple components (un-connected sub-groups), the proportion of unreachable actors can be high and the connectedness index will be low. Below is Krackhardt’s (1994) formula for connectedness:

\[
1 - \frac{V}{N(N-1)/2}
\]

Where \( V \) is the number of pairs that are not mutually reachable, and \( N(N-1)/2 \) is the total number of pairs. Connectedness scores do not account for the direction of ties.

Egocentric Cohesion Transitivity is the ratio of closed triads that are connected to the individual. In other words, this is the ratio of ego’s alters that share a tie between themselves to those alters that do not. Transitivity for each individual was calculated on the undirected graph. Transitivity is used to test Hypothesis 3b.

Independent Variables Corruption information is the independent variable of interest. Corrupt information is a dummy variable set equal to one if the project was found to be an organizational crime and is time-invariant.

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9 The nature of email exchange makes this outcome impossible; however, disconnected sub-groups are likely.
**Controls** Network size is a common and basic measure in social network research that reflects the number of members within a communication structure and is used here as a control in all the models (Marsden, 1990). In addition to predicting frequency, I also control for frequency in the models predicting structural asymmetry and social cohesion because it can affect dyadic and triadic relations (Wasserman and Faust, 1994). The year in project was included to control for variations in project tenure for individuals. The individual’s gender was included as a control since research suggests that it affects information networks in firms (Ibarra, 1997).

**Analysis of Project Structures**

Statistically comparing sociocentric measures such as connectedness and asymmetry can prove difficult given network variation in size and density. For example, all of the networks here have different numbers of participants and ties, which makes direct comparison of network statistics difficult. The application of a classic method of data normalization, z-score transformation, provides a way of standardizing data across a range of networks and allows for comparison of network data independent of the original network size and density (Robins and Alexander, 2004). Population means and standard deviations for each network are based on 100 simulations conditioned on the network’s size and degree distribution. The z-scores were calculated by taking the observed graph indices, such as connectedness, minus the mean of all of the random networks divided by the standard deviation.

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Insert Table 1 about here

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In Table 1, I present the summary statistics and the sociocentric measures for the corrupt and non-corrupt networks. Both sets of projects lasted between two to three years. The number of participants

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10 See Appendix A for how gender was derived for individuals in the models.

11 Network density is the proportion of observed ties over the total number of possible ties (Wasserman and Faust, 1994).
varied between the two groups, with the non-corr upt projects being larger in size. In terms of the z-score comparisons, it is important to note that in Table 1 both sets of observed network types differ substantially on each dimension from the conditional random graph distributions, as well as from each other. This indicates there are underlying social processes operating for the two types of projects and the network forms are not by-products of a random processes. For each relation within a project, I calculated the tie frequency and performed a one-tailed t-test, with corrupt information as the grouping variable. The mean frequency was 2.830 for corrupt information and significantly higher for non-corr upt information, 7.955 ($t = 5.868; \text{df} = 12,409, p<.000$). Thus, the communication between individuals was much higher within the non-corr upt networks, indicating a greater amount of information sharing among members. Next, although the non-corr upt networks were not more connected structures than their simulated counterparts ($z$-score = -20.6273), the corrupt networks were less connected than the non-corr upt networks ($z$-score = -37.0402). This is despite the fact that the non-corr upt networks had far more members. Lastly, non-corr upt networks also appear to be dramatically more reciprocal than the corrupt networks. The $z$-score for asymmetry in the non-corr upt networks was extremely low ($z$-score = -275.423), as compared to the asymmetry in corrupt networks ($z$-score = -49.261). In other words, individuals involved in corrupt communication networks are far less likely to reciprocate communications. This analysis provides evidence in support for all the hypotheses regarding network structures differences (i.e., 1a, 2a, and 3a).

Given these findings, I suggest that organizational crime networks reflect a structure similar to a wheel’s hand-spokes, a central clique surrounded by satellite nodes. The network graphs of all six projects are shown in Figure 2. In the network graphs, all the communications are represented for the duration of the project and node sizes denote the individual’s in-degree standardized for the project.
The above network graphs make apparent that a small clique of members serves as the hub at the center of the corrupt network where the periphery members channel information. Surrounding the hub are spokes, individuals who do not share ties with each other. The spokes provide the hub with access to information and resources throughout the network. Thus, the spokes permit the hub to span structural holes. Maintaining a network full of structural holes not only maximizes access to information, but also allows central members to take advantage of those in the periphery who are less informed (Brass, Butterfield, and Skaggs 1998; Burt 2004; Mitchell 2003). Keeping the spokes isolated also helps to mitigate the risks of either coalitions or whistle-blowers. This structure maximizes power and information control for those residing in the core. Interestingly, individuals in the core were more likely to be found guilty in the trials regarding Enron’s fraud (see Appendix B for trial evidence).

In Figure 3 the density plots for in-degree distributions are given by project type. Peaks and valleys characterize the density plots for the corrupt networks, as opposed to the non-corrupt network plots, in which the distribution is gradual and smooth, indicating that the in-degree communication for non-corrupt pursuits was much more evenly distributed. The graph also suggests that the corrupt networks were partitioned by relational access. Classes of members received varying amounts of incoming communication ties in the organizational crime networks. Thus, the corrupt networks appear to have “compartmental insulation,” which limits exposure of the whole group, as Goffman (1970) suggested (p78). This graduation of information access acts to separate members and may shield the leaders of the system (Simmel 1950; p356). Extending the hub-and-spoke metaphor, this would imply that there were concentric circles of involvement within the system.

\[^{12}\text{Given this particular structure and the aggregation of information at the hub, one might speculate that the spokes were unaware of the full extent of the crime despite having access to enough of the project details to implicate the group.}\]
Analysis of Individual Behavior

For study 2, observations were based on individual behavior within all of the six project networks. The data are a panel of observations for each group member based on project-year. The time-varying variables were measured annually within project. Table 2 provides descriptive statistics and a correlation matrix of all 1,571 project members with 5,009 project-year observations. To examine communication behavior across the corrupt and non-corrupt projects, I used a random effects estimator with two-way fixed effects. I estimate the models with the White/Huber robust estimator, which yields consistent standard errors even when the residuals across individuals are not identically distributed. The three dependent variables – frequency, asymmetry, and transitivity – are presented across the six models in a step-wise fashion in Table 3. Models 1, 3, and 5 are the control models for the three dependent variables examined. The parameter of fundamental interest amongst all the models is corrupt information. In Model 2, corruption significantly reduced communication along communication ties (-3.793; p < 0.000) as hypothesized by 1b. Thus, for each relation in a corrupt network, individuals sent almost 4 fewer messages. From Model 4, we see that corruption also increased asymmetry in relations (0.084; p < 0.000). In other words, a sender of corrupt information was significantly less likely to receive a reciprocal message. Model 6 provides evidence that transitivity was also lower in criminal communications (-0.091; p < 0.000). Therefore, I find support for both Hypotheses 2b and 3b. Although the size of the individual’s network is significant for the all the models, the effect size is small as compared to that of corrupt information. Communication frequency was included as a control variable in Models 3 through 6 and has the reverse effect on the dependent variables than that of corrupt information. It is not surprising that more interactions would both increase reciprocity and transitivity in relations, but the effects size is much smaller than that of corruption. In the complete models, year in project also has the opposite effect than corruption on asymmetry and transitivity but not frequency. This finding indicates that longer project tenure reduced the need for frequent email exchanges, yet led to greater reciprocity and cohesion. In models not shown, gender was included and was not significant in any of the models. Taken together, these results indicate that corruption is a strong determinant of the communication behaviors observed.
In order to examine the effects of corruption more closely, a subsequent analysis of members who participated in both corrupt and non-corrupt networks was conducted. Analyzing the individuals that participated in both types of networks mitigates the possibility of sample selection bias since the same individual can be compared across the two types of projects. From the original sample of 1,571 individuals involved in the six projects, 114 were identified who participated in both non-corrupt and corrupt projects. I use this sample to observe the behavior of individuals across different types of information networks. In order to hold constant individual level differences and correct for non-independence common to network samples, I employ two-way fixed-effects estimates by project-year for the analyses.\(^{13}\) The results should be interpreted as explaining within-individual variations.

In Table 4, I present the descriptive statistics and a correlation matrix of the 114 individuals with 838 project-year observations. In Table 5, the fixed-effects regression models are presented with only the control variables included in the first, third, and fifth models.\(^{14}\) Hypothesis 1b predicted that individuals would have less frequent communication when sharing corrupt information. Model 2 shows that the effect of corrupt information is significant for the frequency of individual level communication \((-3.621; p < \) 0.05).  

\(^{13}\) A Hausman test confirmed that fixed-effects specification was more appropriate than random-effects.  

\(^{14}\) Although year in project was used as a control variable in the random-intercept models, it is not included in the fixed-effect models because project-year observations are within subject.
Corruption reduces how frequently an individual shares information by roughly 4 emails. Hypothesis 2b predicted that corrupt information would reduce reciprocity for an individual's egocentric networks. The estimates from Model 4 support this; corrupt information increases asymmetry for an individual's networks (0.100; p = 0.001), indicating that individuals are less likely to have reciprocal exchanges in fraudulent communication networks. Hypothesis 3b predicted reduced transitivity when individuals shared corrupt information. The results in Model 6 indicate that when individuals share corrupt information, triadic closure is less likely (-0.095; p < 0.000). Corrupt information appears to alter behavior for the individual, causing them to have less frequent and less reciprocal communications, which are also less likely to be embedded in a triad. Thus, the evidence demonstrates that the information type alters individual behavior, which mirror the aggregate network structures observed in study 1.

DISCUSSION & CONCLUSION

This analysis finds evidence for endogenous mechanisms that lead to divergent network characteristics when communication is parsed by corrupt content. In the first study, the topological implications of organizational crime on networks indicate that the structures will be sparse, comprised primarily of asymmetrical connections with infrequent communications. The data strongly suggests that the structure of organizational crimes tends toward a hub-and-spoke shape with members partitioned into concentric circles. Study 1’s findings add greater empirical detail to early theories and case studies of secret and illegal societies, such as the mafia’s powerful cupola or the strategic core of terrorist groups (Cruickshank and Ali, 2007; Gambetta, 1993). The results also support the role of content specification in social network research, and disaggregating networks by information, such as corruption, may present new opportunities to better understand network forms and their emergent forms.

The second study departs from conventional social network analysis to consider the message contents effect on individuals. By providing evidence that members channel non-corrupt and corrupt information differently, the data indicate that social interactions hinge, in part, on information type. Information is a fundamental concept for studying relations between individuals. Individuals communicate to create, share, alter, and validate information and these processes help individuals to reach
a mutual understanding (March and Simon, 1958; Monge and Contractor, 2003). Since social relations are largely based on communication, understanding information is critical to conceptualizing social networks. As evidenced here, individuals choose what information to share and with whom to share it, thus altering their interactions and associations. Subsequently, these decisions have consequences for not only the individual but also the entire social structure.

By comparing individuals’ communication patterns and their surrounding social structure, this study addresses the call for more theories of agency in social network research (Ibarra, Kilduff, and Tsai, 2005; Sasovova et al., 2010). Information content may provide a key to understanding the micro-macro link. Evidence provided here demonstrates that micro-communication strategies of organizational members lead to different relational patterns, which, in turn, have cumulative effects on the emergent social structure.

By developing my account of corrupt projects, I hope to also shed light on the dark side of networks. Clandestine structures are challenging to understand due to the scarcity of reliable data, given their secretive nature (Carley, 2006). Understanding underlying structures that facilitate corruption can have meaningful implications for both organizations and policy-makers (Brass, Butterfield, and Skaggs, 1998). For organizational research, these results demonstrate that information shapes networks to take different topological forms and these resulting communication structures can have consequences for the organization’s information-processing ability (Argote and Ophir, 2002; Bavelas, 1950; Leavitt, 1951). In addition to the implications of having members involved in fraud or corruption, corruption can lead to behaviors that hinder information flow throughout the firm and the fractioning of the communication network. These cleavages can severely handicap the organization’s ability to operate or respond to a crisis (Krackhardt and Stern, 1988).

Particularly since corrupt information may not be common within most organizations, future research need not be limited to the corrupt and non-corrupt typology. A meaningful extension would be to examine overt and covert content. For instance, organizations may have covert projects that prize secrecy
but are not corrupt, such as a confidential research and development team with strict a non-disclosure agreement. Such networks might mirror the interpersonal mechanisms found in corrupt project relations. Studying such cases would help to clarify the differences between the motivations of interactions when the information is fraudulent versus simply secretive.

A potential shortcoming of this analysis is the possibility that corrupt communications were conducted through outside email accounts or other mediums, such as phone calls or meetings. I was very sensitive to these concerns in the qualitative analysis of the emails. The qualitative analysis suggests that corrupt members shared similar amounts of information via email as non-corrupt members. Although the overall email volume was different between corrupt and non-corrupt projects, the word count per email was not significantly different. Further, the criminal emails did not have greater occurrences of phrases that would indicate alternative channels of communication, such as “meet privately” or “discuss over the phone.” In addition, personal email accounts were included if they contained pertinent project information, in case members tried to use non-work email systems. Finally, Enron’s case was the first to include electronic documents in the trial, so individuals may not have considered email as a “paper trail.” Still it is not possible to irrefutably conclude that email captured all the fraudulent conversations. Future research might explore the uses of communication mediums for corrupt ends.

Despite significant advantages, the data used here impose some limitations on the study of content and social networks. The first and most important limitation relates to message censoring. Only messages that were available on the servers were used in the analysis. This poses two issues: I do not know the total volume of emails and certain messages may have been intentionally deleted, causing a bias in the sample. However, since the sender and all recipients would have to delete the email for the message to be lost completely, this appears to be an unusual occurrence. A second limitation is the question of the study’s generalizability to other networks and organizations. Notwithstanding this limitation, a focus on one firm has benefits. Comparing projects within the same organization minimizes variation of other organizational variables, such as culture or norms of communication. However, we cannot completely rule out the moderating effects of Enron’s formal structure and its culture.
APPENDIX A – Determining Gender for Enron Employees

Although individual’s genders were not available in the original Enron dataset, it was inferred through a matching process of the members’ first names. The gender of employees was obtained by parsing first names from emails that followed the format of “FIRSTNAME.LASTNAME@enron.com” and then comparing names to the U. S. social security name database. This public dataset provides the most common first names by year and gender. Emails with ambiguous first names or initials were disregarded. This matching technique allowed for the gender identification of 1,145 of the 1,571 employees who participated in both corrupt and non-corrupt projects. Approximately, 35% of the matched sample was identified as female and reflects Enron’s gender composition at the management level.
APPENDIX B – Replication and Extension of Baker and Faulkner’s (1993) Model for Enron

In Baker and Faulkner (1993) original analysis, they examined an individual’s likelihood of being sentenced based on both the overall centralization of the network and three centrality measures for individual’s position in the network include – degree, betweenness, and closeness.\(^{15}\) However, they did not include individual in-degree nor did they include eigenvector centrality as a determinant of criminal sentence. Degree is aggregate measure of both in-degree and out-degree. By examining in-degree, we can disentangle those who may have sent many messages from those who received many messages. Eigenvector centrality captures the cumulative effect of degree on information. These two measures indicate individuals who had the greatest access to information and were the power hubs as indentified in study 1. I report the descriptives for the variables used in this analysis in table A.1. In Table A.2, I replicate Baker and Faulkner’s analysis with 352 members from the corrupt networks.\(^{16}\) The dependent measure is a guilty plea or sentence based on all the Enron-related trials brought by the DOJ. Both in-degree and eigenvector are significant in the model but eigenvector has a far greater effect size for a guilty conviction. This analysis offers evidence that the powerful actors were centralized in the hub of the network and were possibly orchestrating the crimes.

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Insert Table A.1 about here
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Insert Table A.2 about here
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\(^{15}\) Degree centrality is simply the number of ties to an individual. Betweenness centrality indicates how many paths between others the individual occupied. Closeness centrality measures how proximate the individual is to others in the network.

\(^{16}\) This model differs slightly in that it does not include the manager’s rank (top or middle), which was not available in this study. However, manager’s rank was not significant for the Baker and Faulkner models.
REFERENCES

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Studies." Conflict & Terrorism, 30: 1–14.


U.S Department of Justice (May 1, 2003) Former Enron Treasurer Ben Glisan Pleads Guilty to Conspiracy to Commit Wire and Securities Fraud.

U.S Department of Justice (September. 10, 2003) Justice Department Expands Charges Against Former Enron CFO Andrew Fastow.

U.S Department of Justice (January 14, 2004) Former Enron Chief Financial Officer Andrew Fastow Pleads Guilty to Conspiracy to Commit Securities and Wire Fraud, Agrees to Cooperate with Enron Investigation.

U.S. Securities and Exchange Commission, FORM 8-K CURRENT REPORT Pursuant to Section 13 or 15(d) of the Securities Exchange Act of 1934, November 8, 2001 Commission File Number 1-13159 ENRON CORP.


Table 1.

<table>
<thead>
<tr>
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<th>Corrupt Projects (N=3)</th>
<th>All Projects</th>
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</thead>
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<td></td>
<td></td>
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<td>-37.0402</td>
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<td>Observed Asymmetry</td>
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<td>0.0331</td>
<td>0.0180</td>
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<td>Simulated Distribution for</td>
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<td>Asymmetry (z-score)</td>
<td>-275.4225</td>
<td>-49.2616</td>
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* Standard deviations in parentheses.
Table 2.
Descriptive Statistics and Correlations

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<th>sd</th>
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<th>(3)</th>
<th>(4)</th>
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<td>1.000</td>
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<td>-</td>
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<td>0.000</td>
<td>1.000</td>
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<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Frequency</td>
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<td>1.000</td>
<td>38.350</td>
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<td>0.473</td>
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<td>-</td>
<td>-</td>
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<tr>
<td>Asymmetry</td>
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<td>0.100</td>
<td>0.000</td>
<td>0.830</td>
<td>0.063</td>
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<td>0.465</td>
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<td>-0.405</td>
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<td>Transitivity</td>
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<td>-0.190</td>
<td>0.118</td>
<td>0.347</td>
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* p<0.05, ** p<0.01, *** p<0.001
### Table 3. Random Intercept Effects of Corruption on Individual Communication*

<table>
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<th>Content-Specific Frequency</th>
<th>Content-Specific Asymmetry</th>
<th>Content-Specific Transitivity</th>
</tr>
</thead>
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<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
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<td>Corrupt Information</td>
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<td>0.084***</td>
<td>-0.091***</td>
</tr>
<tr>
<td></td>
<td>(0.208)</td>
<td>(0.015)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Network Size</td>
<td>0.005***</td>
<td>0.003***</td>
<td>-0.000***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Frequency</td>
<td>-0.004***</td>
<td>-0.003***</td>
<td>0.004***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
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<td>Year in Project</td>
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<td>-0.000***</td>
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<tr>
<td></td>
<td>(0.0507)</td>
<td>(0.0457)</td>
<td>(0.001)</td>
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<td>9.503***</td>
<td>9.993***</td>
<td>0.142***</td>
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<td>(0.208)</td>
<td>(0.218)</td>
<td>(0.006)</td>
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<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Individual Random Effects</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
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<td>2.258</td>
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<td></td>
<td>(.068)</td>
<td>(.065)</td>
<td>(.001)</td>
</tr>
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<td>Residual</td>
<td>2.944</td>
<td>2.829</td>
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<td></td>
<td>(.035)</td>
<td>(.034)</td>
<td>(.001)</td>
</tr>
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<td>N(Total Project-Year)</td>
<td>5,009</td>
<td>5,009</td>
<td>5,009</td>
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<tr>
<td>Total Number of Individuals</td>
<td>1,571</td>
<td>1,571</td>
<td>1,571</td>
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<tr>
<td>R-Square (between)</td>
<td>0.323</td>
<td>0.378</td>
<td>0.3255</td>
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<td>R-Square (overall)</td>
<td>0.376</td>
<td>0.436</td>
<td>0.3698</td>
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* p < .10, ** p < .05, *** p < .01.

* Robust Standard errors in parentheses. All models include unreported project-year effects.
Table 4. 
Descriptive Statistics and Correlations

<table>
<thead>
<tr>
<th>Variable</th>
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<th>max</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network Size</td>
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<td>348.510</td>
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<td>1,151.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Corruption</td>
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<td>0.500</td>
<td>0.000</td>
<td>1.000</td>
<td>-0.606</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Frequency</td>
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<td>38.350</td>
<td>0.648</td>
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<td>0.120</td>
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* p<0.05, ** p<0.01, *** p<0.001
Table 5.
Fixed Effects of Corruption on Individual Communication

<table>
<thead>
<tr>
<th>Variable</th>
<th>Content-Specific Frequency</th>
<th>Content-Specific Asymmetry</th>
<th>Content-Specific Transitivity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td>(2)</td>
<td>(3)</td>
</tr>
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<td>0.100***</td>
<td>-0.095***</td>
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<td>(0.452)</td>
<td>(0.029)</td>
<td>(0.034)</td>
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<td>-0.000***</td>
<td>-0.000***</td>
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<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
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<tr>
<td>Frequency</td>
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<td>-0.002</td>
<td>0.007***</td>
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<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.001)</td>
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<tr>
<td>Intercept</td>
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<td>6.170***</td>
<td>0.177***</td>
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<td>(0.0571)</td>
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<td>Project-Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N(Total Project-Year)</td>
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<td>838</td>
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<tr>
<td>Total Number of Individuals</td>
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<td>114</td>
<td>114</td>
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<td>R-Square (within)</td>
<td>0.450</td>
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</tbody>
</table>

* p < .10, ** p < .05, *** p < .01.
* Robust Standard errors in parentheses. All models include unreported project-year effects.
Table A1.
Descriptive Statistics and Correlations

<table>
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<tr>
<th>Variable</th>
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<th>(2)</th>
<th>(3)</th>
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</thead>
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<td>0.000</td>
<td>1.000</td>
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<tr>
<td>Degree</td>
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<td>55.000</td>
<td>-0.008</td>
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<td>In-Degree±</td>
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<tr>
<td>Betweenness±</td>
<td>0.060</td>
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<td>0.000</td>
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<td>0.068</td>
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<tr>
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<td>16.290</td>
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<td>96.310</td>
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<td>-0.237</td>
<td>0.276</td>
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* p<0.05, ** p<0.01, *** p<0.001
† Logged variable.
± Square Root variable.
Table A2.

Logistic Regression on Trial Convictions for Corrupt Network Participants (N=354)

<table>
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<tr>
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<td></td>
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<td>(0.220)</td>
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* p < .10, ** p < .05, *** p < .01.
* Standard errors in parentheses.
† Logged variable.
± Square Root variable.
Figure 1. Stylized depiction of network disaggregation by content.
The Effects of Corruption on Organizational Networks and Individual Behavior

Figure 2. Corrupt and Non-corrupt Project Network Graphs

(Vertices size is the individual’s in-degree standardized for the project; Fruchterman-Reingold Spring Algorithm: repulsion = 3 & iterations =10.)
Figure 3. In-degree Distributions by Corrupt and Non-corrup Project Type.