The Effects of Corruption on Individual Communication Behavior

Brandy Aven
Carnegie Mellon University
Tepper School of Business
5000 Forbes Avenue
Pittsburgh, PA 15213
Tel. (412) 532-6756
aven@cmu.edu

I am particularly grateful to Walter Powell, Henning Hillmann, Karen Cook, Mark Granovetter, Linda Argote, Kaisa Snellman, David Krackhardt, and Donald Palmer for their extensive comments and suggestions. I also wish to thank the seminar participants at Carnegie Mellon and Stanford University for their helpful critiques. For all remaining errors, I alone am responsible. Direct correspondence to Brandy Aven, Tepper School of Business, Carnegie Mellon University. E-mail: aven@cmu.edu.
ABSTRACT
In the past decade, the U.S. has seen an unprecedented rise in corruption at Fortune 500 firms, particularly in the form of organizational crime. Despite the prevalence of organizational crime and renewed academic interest in corruption, the coordination of corrupt activities remains under-theorized. This study uses longitudinal data based on the organizational crimes at Enron Corporation prior to its demise, and couples qualitative coding techniques with social network analysis to understand the effects of corruption on communication behavior. By contrasting corrupt and non-corrupt projects, I examine how corruption influences the way individuals mobilize to accomplish a goal. In contrast to non-corrupt project members, members of corrupt projects share less communication, have fewer reciprocal relations, and have lower amounts of relational transitivity. These different patterns hold for between- and within-subject analyses. This study provides insight into how corruption is coordinated within firms and highlights the role of information in understanding the emergent properties of communication behaviors.
ABSTRACT
In the past decade, the U.S. has seen an unprecedented rise in corruption at Fortune 500 firms, particularly in the form of organizational crime. Despite the prevalence of organizational crime and renewed academic interest in corruption, the coordination of corrupt activities remains under-theorized. This study uses longitudinal data based on the organizational crimes at Enron Corporation prior to its demise, and couples qualitative coding techniques with social network analysis to understand the effects of corruption on communication behavior. By contrasting corrupt and non-corrupt projects, I examine how corruption influences the way individuals mobilize to accomplish a goal. In contrast to non-corrupt project members, members of corrupt projects share less communication, have fewer reciprocal relations, and have lower amounts of relational transitivity. These different patterns hold for between- and within-subject analyses. This study provides insight into how corruption is coordinated within firms and highlights the role of information in understanding the emergent properties of communication behaviors.
In the past decade, the U.S. has seen an unprecedented rise in the number of Fortune 500 firms committing organizational crimes, a form of corruption wherein members of an organization coordinate to commit an illegal activity primarily for the benefit of the organization (Clinard and Yeagar, 1980). In 2011, the FBI investigated 726 cases of corporate fraud, a 37% increase since 2007, with estimated overall losses to public investors exceeding $1 billion dollars (FBI, 2011). Despite its cost and prevalence, organizational scholars know relatively little about the implementation of organizational crime within firms and have made calls for more empirical research of the phenomenon (Brass et al, 1998; Greve et al, 2010; Palmer and Maher, 2006). Consequently, the social organization of corruption within firms is an area of study that warrants attention for both its implications for corporate governance and its significance for organization studies.

Whereas there are a number of recent studies that have enriched our understanding of organizational opportunism, these studies have primarily focused either on corrupt acts committed by individuals or organizational cultures that foster corruption (Kish-Gephardt et al, 2010; Greve et al, 2010). Although both perspectives are instructive, neither approach addresses the communication and coordination dynamics of implementing an organizational crime. A key to explaining the phenomenon of an organizational crime resides with understanding how members orchestrate corrupt activity. The social network perspective provides a means to understand how individuals in a firm organize to commit an organizational crime. Yet, with the exception of Baker and Faulkner’s (1993) original work on criminal networks, little work has followed that explicates corrupt networks, and the coordination of criminal activities remain under-theorized (Brass et al., 1998; Greve et al, 2010). In their seminal paper Baker and Faulkner (1993) examined the network characteristics of market collusion, where individuals illegally cooperated across firm boundaries and predicted criminal convictions based on individual network positions.

This paper extends Baker and Faulkner’s (1993) classic analysis of corrupt networks by examining individual communication behaviors for both corrupt and non-corrupt activities. Baker and Faulkner (1993) contend that the corrupt networks take the form that they do to solve the challenge of
remaining secret while simultaneously ensuring the necessary coordination and control of their members. Underscoring Simmel’s (1950) conclusion that not all secrets are corrupt activities, but all corrupt activities are secrets, I argue that it is the secretive nature of corrupt information that influences the communication strategies of organizational crime members. However, my model differs from traditional social network analysis, in which the relations are the primary focus and from which information flows may be inferred. By contrast, in this model, the information that is conveyed between individuals informs the relations and is examined as a determinant of network relations. When individuals are faced with different types of content, such as information about organizational crime, they must make subjective decisions about whether to share information, with whom to share information, and what information to share. By comparing the behaviors of individual communications across ethical contexts, I take into account the individual’s subjective communication decisions to share secret information about organizational crime. Rather than investigate the antecedents of corruption, I examine how the illegal endeavors are communicated and organized by firm employees. I treat the decision to participate in fraud as exogenous, and instead focus on communication patterns that emerge when members share information about the organizational crime.

This study examines organizational crime that took place at Enron Corporation to uncover the effect of corrupt information on communication behavior patterns. Enron provides a unique opportunity to understand the organization of corruption because the firm was eventually indicted for several counts of large-scale organizational crime. Using government documents and employee testimonies, I identify three projects at Enron as organizational crimes and then matched them to non-criminal projects with similar organizational objectives and firm-wide coordination requirements. I utilize a unique dataset comprised of email communications from Enron. These data provide both an excellent opportunity to observe corrupt communication behaviors, which are historically difficult to obtain, and have a richness not normally found in network analysis. This email dataset allows me to couple qualitative coding of the electronic messages with social network analysis, which strengthens the research by permitting a finer examination of organizational communication networks.
SOCIAL ORGANIZATION OF CORRUPTION

Information is a key factor for understanding network behavior, especially if we consider it in terms of being either covert or overt. Simmel (1906) argued that all social relationships, whether between two individuals or among a group, can be largely characterized by the amount of secrecy within and surrounding them (p 330). His conclusion was that individuals alter their relations based on the amount of secrecy the information being conveyed requires. When information is meant to be kept secret, the process by which people share or discuss the information leads to different communication choices and strategies than if the information is public (Richardson, 1988; Simmel, 1906). Studies of illegal groups generally find that the communication networks share particular characteristics, such as hierarchical structures, but the mechanisms by which these network form are not clear (Gambetta, 2009; Goffman, 1970; Simmel, 1950). Research in sociology also finds that when certain types of information are deemed illegitimate or counter-normative, individuals attempt to alter their communication behavior to keep the information secret (Goffman, 1970; Granovetter, 2007; Lee, 1969). Recent studies on terrorist networks suggest that individuals deliberately structure communications to evade detection and maintain close-knit control (Baccara and Bar-Isaac, 2008; Cruickshank and Ali, 2007). For groups engaging in an organizational crime, secrecy is a particularly crucial element (Fine and Holyfield, 1996). Taken together, these earlier studies suggest that the secrecy required for organizational crime will alter the communications patterns of participants.

As opposed to crimes committed by a lone individual, such as embezzlement, organizational crime requires that members keep the activity secret while simultaneously ensuring that the members receive the necessary information. Corrupt information and the network members’ communications must be tightly restricted in order to limit exposure and possible detection. This issue is compounded by a general trade-off for groups between the interests of the group versus the interests of the individual. When individuals share information, it generally provides coordination benefits for the group but also entails a cost or effort for the individual who conveys the information (Bonacich, 1987; Hansen, 1999). Sharing corrupt information greatly increases the cost of sending information because of the added risk of
detection and punishment for the individual. Even though organizational crime members must also manage similar project objectives and coordinate among themselves for a successful implementation, they share the added burden of concealing the organizational crime and each member’s involvement. To effectively implement organizational crime, members require some level of information to coordinate activity, but at the same time, individuals are motivated to reduce information flow to limit the risk of detection. Conversely, for groups engaged in non-corrupt activities, the information need not be constrained and members may communicate unencumbered by secrecy (Goffman, 1970).

The prediction here is that organizational crime requires secrecy, which will countervail group coordination patterns common to organizational project groups. The challenge for organizational crime members is that the behaviors that coincide with trust and coordination for complex tasks make the group more vulnerable to detection. The knowledge transfer literature provides insights into the individual motivations and factors that promote information sharing among organizational members. In particular, three network characteristics that encourage knowledge transfer commonly cited as benefiting groups are communication frequency, reciprocal relations, and transitivity (Brass et al., 1998; Hansen, 1999). Paradoxically, although these three measures capture communication factors that contribute to project success, they also make concealment difficult. Although knowledge transfer benefits the group or organizational as a whole, knowledge transfer can be costly for the information source (Hansen, 1999; Reagans and McEvily, 2003). The challenge for project members is that the behavior that coincides with effective coordination makes the group members more vulnerable to detection. Because organizational crime increases the cost of information sharing for the individual, corrupt members will be motivated to limit relational features that are positively associated with information sharing. In turn, the micro-communication strategies of organizational members will differ between corrupt and non-corrupt projects. This is not to suggest that the non-corrupt groups arrive at the optimal amounts of frequency, reciprocity and transitivity, but rather that they are unencumbered by secrecy. The secrecy that corruption requires can act as a dampening factor on all of these communication behaviors.
THEORY AND HYPOTHESES

Communication Frequency

For projects with complex tasks and uncertain outcomes, as those investigated here, frequent communication amongst the project members supports information access and group coordination. Tie strength, which often corresponds with frequent interactions, increases motivations to share information (Granovetter, 1973). Greater amounts of communication also facilitate knowledge transfer between members and enable learning that can help accelerate group goal attainment (Hansen, 1999; Reagans and McEvily, 2003; Tortoriello et al, 2012). Frequent communications also improve coordination through the development of shared heuristics (Katz, 1982). Members who share heuristics are more likely to understand one another even when discussing abstract or complex topics, and in turn, this understanding increases the likelihood of the team’s success (Lim and Klein, 2006). In addition, frequent communication assists individuals in clarifying issues, resolving problems, and expediting the project’s goals (Eisenhardt, 1989). Therefore, assuming purposive communication and a shared group objective of effective implementation, the non-corrupt projects should be conducive to frequent communications among their members. Clearly, the patterns identified above reflect ideal cases, and non-corrupt projects will vary in the extent to which members communicate. Nevertheless, these variations will not be equivalent to the effects on communication imposed by the secrecy required for participating in organizational crime.

Organizational crime participants must strike a balance between coordinating members to complete the project’s goal and shielding members from detection (Baker and Faulkner, 1993). The participants must accomplish a task similar to the non-corrupt projects, which requires the comparable amount of coordination and information sharing among members while simultaneously restraining communication frequency. The trade-off comprises of members either over-communicating, which increases risk of discovery, or under-communicating and potentially failing in their collective endeavor. In the corrupt projects, each time a member shares information, both the sender and the receiver run the risk of being discovered by nonmembers. I assume that corrupt project members are equally purposive in
their communication as the non-corrupt members, but the corrupt members have the additional risk of detection to account for in their communications. Therefore, secret information leads members to decrease communication frequency to the lowest amount possible to in order to minimize risk (Goffman, 1970). Since it behooves the individual to restrict communication to only the most essential sharing of information, I expect that the sharing of corrupt information will depress the frequency of communication as compared to sharing non-corrupt information, when all else is equal. In other words, the communication frequency will be more constrained in corrupt than the non-corrupt networks. Formally,

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

**Reciprocity**

Individuals generally feel obliged to respond to other’s communications, and norms of reciprocity compel individuals to return an interaction in kind (Gouldner, 1960). For example, when one employee shares critical information with another employee, the receiving employee will commonly reciprocate with equivalent information. Beyond its normative framework, reciprocity is critical for coordinating groups and developing effective channels of communication (Argote et al., 2003; Reagans and McEvily, 2003). Reciprocal communications permit discourse between the members to help them clarify, extend, and refine ideas. Reciprocity also reduces uncertainty between individuals by promoting trust and shared understanding (Molm et al., 2007). Additionally, the act of reciprocating itself engenders commitment and positive affect among group members, which then benefits group coordination (Molm, 1997). Given its normative strength and its benefits for coordination, I expect reciprocity of communication to be generally unrestricted in non-corrupt project networks.

In spite of its advantages, reciprocity poses a challenge for those involved in an organizational crime. Reciprocity is an act of acknowledgement, which makes it difficult for a member who responds to information about a corrupt project to plausibly deny being involved in it (Palmer and Mahr, 2006). Thus, reciprocal communication increases the risk of incrimination. Moreover, reciprocity necessitates greater amounts of interaction; more interactions, in turn, further enmesh the culpable individuals into the corrupt
The Effects of Corruption on Individual Communication Behavior

project. Individuals engaged in corruption may be motivated to sacrifice reciprocity in order to limit interactions and potentially shift blame to others who are involved in the organizational crime (Baker and Faulkner, 1993). For these reasons, I expect that when all else is equal, reciprocity will be lower for corrupt networks as compared to their non-corrump counterparts. Hence,

Hypothesis 2: Corrupt information networks will have lower amounts of reciprocal relations than non-corrump information networks.

**Connectedness**

Connectedness refers to the extent to which members of a group share relations with each other (Krackhardt, 1994). Group connectedness is important for projects particularly because connected structures allow members to consult and gain complex information from one another through established ties and relations (Hansen, 1999; Uzzi, 1999). A well-connected group permits more individuals to be uniformly and adequately informed (Burt, 1992). Multiple links between members makes the transfer of information more likely, and across various settings, connectedness has been found to positively affect knowledge transfer (Argote et al., 2003). Sharing multiple connections also serves to align individual behavior with the goals and objectives of the group (Ingram and Roberts, 2000). In cases where the task is complex, even the information redundancy that high connectedness generates can benefit the project and its participants by allowing members to validate information and diffuse information rapidly (Coleman, 1988; Obstfeld, 2005). In general, connectedness proves optimal for sharing information, encouraging cooperation, and reducing conflict (Simmel, 1950).

In addition to the advantages of connectedness for the group, psychological research suggests that individuals also encourage those they are connected with to also be connected (Heider, 1958). The basis for such interpersonal connectedness may stem from psychological tendencies to prefer “balanced” relations (Granovetter, 1973; Heider, 1958; Simmel, 1950). When the focal actor is strongly connected to two others who themselves are not connected, it creates a tension for the focal actor (Krackhardt, 1999). The focal actor can endure the tension, drop one relation, or foster a connection between the two alters (Heider, 1958). Balance theory suggests the latter is preferred, that when two individuals share a
connection to a common third person, they will eventually become tied to each other (Davis, 1963; Holland and Leinhardt, 1971). When actors promote connections between their alters, the level of connectedness surrounding them increases. Thus I expect non-corrupt members to prefer connections between members.

Despite the advantages of connectedness, the secrecy required of organizational crime networks may hinder an individual’s willingness to foster connections among others with whom she shares a connection. When the objectives of a project include secrecy, individuals may be motivated to intentionally obstruct or limit relations between the other members, creating communication barriers that limit information transfer and validation (Simmel, 1950; Goffman, 1970). By discouraging ties between members, individuals enhance their local control and power over the information and the separated others (Cook and Emerson, 1978; Fernandez-Mateo, 2007; 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 a degree of power over them (p162). Without a known connection, the alters are not able to confirm information or form a coalition against the focal actor. The absence of connections not only provides opportunities to play members against each other, it also reduces the possibility that alters are aware of each other’s involvement (Burt, 1992). Consequently, these cleavages in the network make it difficult for members to corroborate evidence against the shared third and may help to protect the focal actor from recrimination (Granovetter, 2007). Further, poorly connected networks limit the individual’s ability to effectively monitor others and undermine individual’s ability to identify the other corrupt members (Burt, 1992; Mitchell, 2003; Vaughan, 1999). Hence, all other things being equal, I expect that information about corruption will undermine motivations to create linkages among alters and these groups will have fewer connections than their non-corrupt counterparts. Therefore,

Hypothesis 3: Corrupt information networks will be lower in connectedness than non-corrupt information networks.
METHOD

Research Setting: Organizational Crime Networks at Enron Corporation

Prior to coming under investigation, Enron Corporation was a world leader in energy production and distribution. After many years of dramatic success, record-making profits, public acclaim, and favored status on Wall Street, Enron was brought under investigation by two federal agencies. On October 22, 2001, the Security and Exchange Commission (SEC) announced that it was exploring several suspicious deals at Enron. While under investigation by the SEC, the Federal Energy and Regulatory Commission (FERC) also brought charges against Enron for manipulating energy markets. 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, namely the Sarbanes-Oxley Act of 2002. As part of the investigation, FERC seized Enron’s email servers, which contained five years of email correspondence from top management. The data were later made available as the Enron Email Corpus (EEC). The EEC data is used here for a retrospective analysis of corrupt and non-corrupt projects via their communication networks.

In order to mislead investors about the financial health of the firm prior to its collapse, Enron’s managers employed complex accounting methods that were common to other projects at Enron. These financial misdeeds were not localized to a few top executives in the firm, but included the involvement of many organizational members from various departments in order to implement the accounting fraud. In this way, the organizational crimes mirrored the legitimate activities at Enron, which largely entailed coordinating organizational members to successfully implement financial projects in order to maximize

---

1 Under applicable accounting rules, an SPE could receive off-balance-sheet treatment only if independent third party investors contributed a minimum of 3 percent of the SPE’s capital and the third party investments were genuinely independent. If these criteria were not met, then Enron was required to consolidate the SPEs onto its balance sheets (Section 10(b) of the Exchange Act).
the profit for the company—except that in the case of organizational crime, the means were, of course, illegal. In other words, although the corrupt projects were similar to the non-corrupt projects in their organizational requirements and undertaking, they were employed illegally to hide Enron’s large amounts of debt.

**Project Selection and Data Sources**

Multiple sources, such as corporate documents, government reports, media coverage, testimonies, and autobiographies from employees were used to distinguish an appropriate set of corrupt projects and comparable non-corrup projects for systematic comparison. The identification strategy used here is a variant of the case/non-case sample selection common to clinical trials (Mann & Andrews, 2007). This method entails that, once the corrupt projects were identified, they were matched on relevant dimensions to comparable non-corrup projects. Six commensurate projects were finally selected for analysis. These six projects permit a critical test of the effect of corrupt versus non-corrupt information on communication patterns. By focusing on similar organizational projects within Enron, I am able to examine the social organization of organizational crime and its influence on communication arrangements.

The three corrupt projects were identified as organizational crimes that enabled fraudulent misrepresentation of the organization’s accounts. The corrupt projects examined in this study purposefully violated existing accounting principles and intentionally misrepresented Enron’s accounts (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). Corrupt projects were also identified through testimonies and reports provided to the U.S. Department of Justice (DOJ) concerning charges brought against Enron and its management. For example, a former Enron 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 from Enron managers provided evidence that corrupt project 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 earlier 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-corrupt projects were selected based on their legality and comparability to the corrupt projects at the Enron along several key dimensions. The first criterion was to identify non-corrupt projects.² These projects had to be both publicly documented in Enron’s press releases and annual reports and not identified as fraudulent in any government agency reports or individual testimonies against Enron by the DOJ, SEC, or FERC (Enron, 1998-2000). Table 1 presents the six projects and the corresponding documentation that was used to determine corrupt versus non-corrupt projects. Only non-corrupt projects that had partnerships with other organizations were selected as matches because all of the corrupt projects were based on limited partnership agreements (McLean and Elkind, 2004; Swartz and Watkins, 2003). Next, project valuation, such as capital under management and projected earnings, was used to select comparably sized non-corrupt projects. This identification was particularly challenging given that for the corrupt projects, the SEC was only able to determine the approximate amount of debt concealed and since the non-corrupt projects were relatively new, Enron only published their projected value. In addition, non-corrupt projects were limited to those that had similar project durations to the corrupt projects, lasting from two to three years between 1998 and 2002 (Eichenwald, 2005; Mclean and Elkind, 2004). Finally, similar to the corrupt projects, the non-corrupt projects were conducted across departments and required information sharing among functional groups.

² This is not to suggest that corruption is an absolute dichotomous state and that the non-corrupt projects were without corruption or that the corrupt projects were without legitimate activity. Here, I only speak to the available evidence as gathered by federal agencies and reported in news outlets and biographies.
In addition, I limited this study to projects that began within the observation time permitted by the seized dataset so as to capture communication shared at the onset of the group. New projects also provide an opportunity to understand the emergence of social networks, because by their nature, these projects are not already integrated into the existing practices of the organization (Rogers, 1962). In the case of a new project, participants need to communicate with each other to acquire pertinent information and to develop a shared understanding of the project’s objectives (Eisenhardt, 1989). Inchoate projects require organizational members to develop new channels to share and access information from other members, and the roles and relations of new organizational projects have not yet begun to calcify into a fixed system of relations. This is particularly relevant when the project is novel and the tasks for project completion are not defined (Bunderson and Boumgarden, 2010).

Research Design
As mentioned, this study analyzes archival data from the Enron Email Corpus, which are comprised of electronic messages sent between the years 1998 to 2002. Recently researchers have begun to employ large electronic communication databases to understand social networks across organizational settings (Aral and Van Alstyne, 2011; Kleinbaum, 2012). Email exchange provides a useful means to understand individual communication behavior and social networks within an organization. Evidence also indicates that email exchanges closely parallel organizational work relations (Hinds and Kiesler, 1995). Moreover, 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 (Bernard, Killworth, and Sailer, 1980). Most important for this analysis, behavioral measures allow observation of corruption information communications that individuals would be reluctant to report.

The dataset consists of professional and personal electronic messages and contains both incoming and outgoing emails. Each email includes the following information: sender, recipients, date, 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. The remaining sample of emails corresponds to the actual population of Enron employees.

This research design incorporates both quantitative and qualitative analysis to generate robust results and enrich our understanding of communication behavior in organizational crime networks (Edmondson and McMannus, 2007; Jick, 1979). First, to understand the effect of organizational crime on communication, I use the qualitative codings of email messages to identify corrupt information. The qualitative method used in this study parallels recent work on email topic coding; however, the keyword list was predetermined based on the project names rather than emerging from the corpus (Aral and Van Alstyne, 2011). As mentioned, earlier project selection was based on documents external to the EEC archive, such as annual reports, individual interviews, public statements, and testimonies from the SEC and the DOJ. A structured keyword list search across a large archival dataset ensures consistent identification and improves generalizability (Maxwell, 2004; Miles and Huberman, 1984). The primary objective was to identify and code a complete set of emails containing information specific to one of the six projects. Coding was done with the assistance of software, using keyword list searches based on the unique project names. The resulting coded subset of emails was then reviewed and validated iteratively, as is common in qualitative analysis (Strauss and Corbin, 1990). This process continued until the complete subset of the appropriate email messages was identified.

Next, the set of coded emails were used to generate the project-specific communication networks. As is common in network analysis of emails, the networks were constructed from the email headers, which identify the messages’ senders and recipients, and the email messages represent ties between individuals in each project (Aral and Van Alstyne, 2011). Six different directed weighted networks were generated. Weights were used to reflect email frequency between members. Directed networks are critical

---

3 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.”
to this analysis in order to determine the reciprocity of communication between organizational members (Wasserman and Faust, 1994). To permit longitudinal analysis of behavior, the networks were partitioned by year. Annual project networks only include communications within the given year.

VARIABLES

This study examines three different dependent variables to compare the behavioral consequences for communication when the information is either corrupt or non-corrupt.

Dependent Variables

*Communication Frequency* The frequency of communication captures the volume of discourse between project members. Frequency of communication is a common measure in network studies as a dimension of tie strength (Hansen, 1999; Tortoriello et al, 2012; Uzzi, 1999). Although I expect the measure to be a reliable indicator of tie strength, the focus of this study is on the amount of communication itself. Since only coded messages where included in this measure, the measure indicates the number of project-related messages sent. For each member of a project, the mean frequency of communication was calculated as the number of both incoming and outgoing project-related messages divided by the total number of the individual’s alters in the project network. Communication frequency is used as a test for hypothesis 1.

*Reciprocity* I use a measure of reciprocity to examine the likelihood of symmetrical communication behavior as a test for Hypotheses 2. Reciprocity is the proportion of ego’s communications that receive a reply and is commonly used to understand information flow (Brass, 1995; Hansen, 1999). Reciprocity is treated as a dichotomous outcome here rather than a proportion of the symmetrical communications. A reciprocity index equal to 1 means that all communications are symmetrical. Alternatively, a reciprocity score of 0 indicates that none of ego’s communications, either sent or received, obtained a response.

*Transitivity* To address connectedness for individuals, I use a measure of transitivity in line with earlier work (Snijders, 2011). Transitivity measures the extent to which the individual is embedded within triadic relations, or “balanced” relations. The transitivity measure for an individual is the ratio of closed triads that are connected to the individual. In other words, this is the proportion of ego’s alters that share a tie
between themselves to those alters that do not share ties (Wasserman and Faust, 1994). Transitivity scores do not reflect for the direction of ties. I examine transitivity as a test of hypothesis 3.

**Independent Variables**

**Corruption Information** As discussed above, emails were coded as having information pertaining to one of the six projects, and the projects were classified as either organizational crimes or not. Thus, if the email conveyed information about one of the three projects engaged in organizational crime, it would be identified as containing corrupt information. Corrupt information is a dichotomous variable set equal to 1 if the message was coded as containing information about an organizational crime and 0 if it was not. The measure is time-invariant because I assume that the corrupt intent of the projects did not change over time.

**Control Variables**

Network size is a common and basic measure in social network research that reflects the number of alters of the focal actor, and is used here as a control in the all the models (Reagans and McEvily, 2003; Tortoriello et al., 2012). In addition to predicting communication frequency, reciprocity, and transitivity, I also control for these variables in the models where they are not the dependent variables because they can influence dyadic and triadic relations (Wasserman and Faust, 1994).

**ANALYSIS**

Two different analyses are conducted in this study. In the first analysis, I examine all 1,571 individuals who were members of any of the six different projects over the four-year observation period. The majority of Enron employees (53%) only participated in two projects. I use this sample to compare the communication behavior of the all the members of the corrupt and non-corrupt projects. Next, from the original sample of 1,571 individuals involved in the six projects, a subset of 114 was indentified who participated in both non-corrupt and corrupt projects. I use this sample in a second analysis to mitigate the possibility of omitted variable bias, since the same individual can be compared across the two types of projects. The benefit of this design is that it helps to rule out the possibility of certain individuals having a predilection for both corruption and certain communication patterns.
In the first analysis of all project members’ communications, I have repeated observations for individuals across project and year observations, and I begin by using a linear mixed model (Rabe-Hesketh and Skrondal, 2005). I adjusted for individual differences by using a random effect estimator to account for member-specific tendencies to communicate in a particular manner. In my setting, allowing the intercepts to vary by member is important, since increasing evidence suggests that formal roles or individual differences may generate variations in behavior aside from content (Burt, 2012; Sasovova et al., 2010). More importantly, the consequence of random effects is that the residuals for a given person are correlated across periods. 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. I added a two-way fixed effect for the project-year to address any form of temporal heterogeneity across the projects that might affect patterns of communication and absorb the effects of project differences in size, density, money under management, and objectives. This allows the comparison of all the project members’ communication behavior across the corrupt and non-corrupt projects.

For the second analysis of individual behavior of the 114 individuals who participated in both corrupt and non-corrupt projects, I employ fixed-effects estimates for individuals in the analyses to compare the effects of corrupt information on communication behavior. A Hausman test confirmed that fixed-effects specification was more appropriate than random-effects for this sample. As with the random-effect models, the fixed-effect models also included a project-year fixed effect to account for project and temporal variation. This model also holds constant individual level differences and corrects for non-independence common to network samples. The results should be interpreted as explaining within-individual variations, and a significant corrupt information estimator suggests that the information alters individual communication behavior.

RESULTS

-----------------------------------
Insert Table 2 about here
-----------------------------------
Presented in table 2 are the descriptives for both the corrupt and non-corrupt projects and their members. The comparisons of individual member measures show significantly lower means for communication frequency, reciprocity, and transitivity in the corrupt projects. Table 3 provides descriptive statistics and a correlation matrix of all 1,571 project members with 5,009 project-year observations. The three dependent variables—communication frequency, reciprocity, and transitivity—are presented across the six models in a step-wise fashion in table 4. Models 1, 3, and 5 are the control models for the three dependent variables examined, and models 2, 4, and 6 present the effects of the explanatory variable, corrupt information. In all of the models except the fifth and sixth, network size is significant and positive; however, for the sixth model, network size is negative and significant. In other words, as the number of alters increases, communication frequency and reciprocity increase but transitivity decreases. Communication frequency was also included as a control variable in models 3 through 6 and has the reverse effect on the dependent variables than that of corrupt information. Frequent communication increases reciprocity and transitivity in relations. These control models highlight the way frequency of communication helps to strengthen relations and connectedness in the group, and this finding parallels earlier research on strong ties that suggests all three of these constructs commonly co-occur (Granovetter, 1973; Uzzi, 1997, 1999). As to be expected, models 1 and 2 demonstrate that reciprocity increases communication frequency. A bit more surprising is the negative relationship between reciprocity and transitivity in models 3-6. This evidence suggests that symmetrical communications are less likely to occur within triads across both corrupt and non-corrupt information networks.
The parameter of fundamental interest is corrupt information. In Model 2, corrupt information significantly reduced communication frequency (-3.320; p < 0.000), providing support for hypothesis 1. Thus, when individuals were participating in organizational crime, they sent fewer messages per relation. Next, model 4 shows that when an individual was engaged in a corrupt project, the number of his reciprocal relations decreased (-0.114; p < 0.000). This result provides evidence for hypothesis 2, that corrupt information reduces the likelihood of symmetrical communications. Model 6 provides evidence that transitivity was also lower when individuals communicated corrupt information (-0.132; p < 0.000). Members of projects engaged in organizational crimes were less likely to share connected alters than those who were members of a project not engaged in organizational crime. Thus, I find support for hypothesis 3.

Taken together, these results indicate that corrupt information is a strong determinant of the three communication behaviors that coincide with both knowledge sharing and secrecy. The corrupt projects’ members communicated less than their non-corrupt counterparts, despite having to overcome similar coordination challenges. Members of corrupt projects were also far less likely to reciprocate a message, which is counter to the observed behavior in the non-corrupt projects. Lastly, participation in a corrupt project meant individuals were less likely to be embedded in triadic relations. That is, a corrupt project member’s alters were less likely to be connected to one another than a non-corrupt project member’s alters.

Even though the communication behavior between the two groups differs significantly, this analysis cannot rule out an omitted variable that might determine both the willingness to participate in an organizational crime and communication behavior. To address this concern, in the following analysis individuals who participated in both corrupt and non-corrupt of projects are examined. This helps us to rule out a self-selection bias of the individuals in the organizational crime projects and control for individual differences. In the following models, hypotheses one through three are examined again with this subsample.
In table 5, I present the fixed-effects regression models for the communication behavior of the 114 individuals who were involved in both corrupt and non-corrupt projects, with a total of 838 project-year observations. Hypothesis 1 predicted that individuals would have less frequent communication when sharing corrupt information. Model 2 shows that the effect of corrupt information significantly reduces the frequency of communication (-2.739; p < 0.000). Hypothesis 2 predicted that corrupt information would reduce reciprocal communications for an individual’s relations. The estimates from model 4 support this hypothesis; corrupt information decreases reciprocal communications for individuals (-0.154; p = 0.001). Hypothesis 3 predicted that, for individuals, corrupt information reduces transitivity among relations. The results in model 6 indicate that when individuals share corrupt information, triads are less likely (-0.152; p < 0.000). This finding suggests that in corrupt information networks, individuals are more tolerant of open triads than in the non-corrupt projects. In sum, corrupt information appears to alter behavior for the individual, leading to less frequent communication, fewer reciprocal exchanges, and fewer triadic relations.

**Sensitivity Analysis**

To evaluate the robustness of these results, I conducted several additional analyses. I included controls for individual characteristics to the random-effects models examined in the first analysis, such as gender, organizational tenure, and the individual’s proclivity for the behavior that may influence communication behavior. Although individuals’ genders were not available in the original Enron dataset, it was inferred through a matching process of the members’ first names.\(^4\) This matching technique allowed for the gender identification of 1,145 of the 1,571 employees who participated in both corrupt

---

\(^4\) 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.
and non-corrupt projects. Approximately 35% of the matched sample was identified as female, and this percentage accurately reflects Enron’s gender composition at the management level.

Organizational tenure was also not part of the original data; however, a variable was constructed to approximate organizational tenure based on the observations of communication in the EEC data. This variable is the difference in years between first email communication and last for the individual. The range for organizational tenure using this method is between 2 to 5 years. Finally, global measures of frequency, reciprocity, and transitivity were calculated over all of an individual’s communications, not selecting on information, to rule out an individual’s proclivity for a communication behavior.

The findings from the earlier analyses remain robust when I include the variables listed above. None of the measures are significant across the models except for the effect of gender on transitivity (0.035; p < 0.098). This indicates that although corrupt information greatly reduces transitivity (-0.141; p < 0.000), gender only slightly counteracts the effect. Importantly, the global measures of frequency, reciprocity, and triad density, which are meant to test the individual’s proclivity towards certain behaviors, did not significantly influence the individual behavior in the projects.

DISCUSSION & CONCLUSION

Corrupt Communication Behavior and Network Forms

Overall, I find communication behaviors of corrupt project members differ structurally in the dimensions of communication frequency, reciprocity, and transitivity from those of comparable non-corrupt project members. When individuals communicate within a corrupt project, they communicate less often and share fewer reciprocal ties than those involved in non-corrupt projects. Transitivity is also lower when members share corrupt project information versus non-corrupt project information. The within individual analysis of communication behavior across the corrupt and non-corrupt networks suggests that the findings are not due to an unobserved variable but instead to the secretive nature of the corrupt information. These results enrich our empirical understanding of corrupt information networks by demonstrating how individual decisions to maintain the secrecy of an organizational crime influence
coordination behavior. Additionally, these findings extend Baker and Faulkner (1993) earlier research to the case of organizational crime and individual behavior while also permitting systematic comparisons to non-corrupt behavior not present in earlier studies.

A central challenge of organizational criminals is to remain undetected while simultaneously addressing the challenges of group coordination. In contrast to non-corrupt project members, corrupt project members must account for the additional risk of detection. Because organizational crime increases the cost of information sharing for the individual, corrupt members are motivated to limit relational features that are positively associated group coordination and knowledge transfer—communication frequency, reciprocal relations, and transitivity (Brass et al., 1998; Hansen, 1999). Consequently, communication and coordination behaviors differ between corrupt and non-corrupt project members.

This work makes three contributions. First, by developing my account of corrupt projects, I hope to shed light on the dark side of networks. Despite the growing ubiquity of organizational crime and the calls for more empirical research on corrupt networks, organization theorists have a poor understanding of how corruption in organizations is coordinated and managed (Brass et al., 1998; Greve et al., 2010). Moreover, sociologists have theorized a great deal about the coordination of corruption, but empirical examinations have been rare given the secretive nature of the phenomenon. This is in part due to the challenge of studying clandestine structures because of the scarcity of reliable data (Carley, 2006). In particular, a strength of this study is that it uses behavioral data to understand corrupt communication behavior. These findings present the underlying communication patterns that facilitate organizational crime, which can have meaningful implications for both managers and policy-makers (Brass et al, 1998; Vaughan, 1999). Finally, understanding how corruption is coordinated may help to detect, intervene, and mitigate its occurrence.

Second, by comparing individuals’ communication patterns, this study addresses the call for more theories of agency in social network research (Ibarra, Kilduff, and Tsai, 2005; Sasovova et al., 2010). The underlying premise of social network research is that the system of relations and individual positions facilitates information sharing (Burt, 1992; Krackhart, 1992; Podolny and Baron, 1997). Extant models of
social structure generally assume that the presence of a relation determines the transmission of information and bypasses the social-psychological motivations of individuals to share information. (Marsden, 1983; Podolny and Baron, 1997). Despite the plethora of network studies, individual communication decisions regarding information have largely been eschewed in favor of structural explanations of network dynamics. Yet, individuals choose what information to share and with whom to share it, thus altering their interactions and associations (Monge and Contractor, 2003). Ignoring the actor’s subjectivity toward information limits our ability to understand the interplay of social action and social structure. The evidence provided here demonstrates that micro-communication strategies of individuals lead to different relational patterns, which, in turn, can have cumulative effects on the emergent social structure. By investigating individual motivations to convey certain types of information, researchers may gain new insights into the dynamics of tie-formation and network reproduction.

Third, the analysis used here departs from conventional social network analysis to consider the effect of information type on relational patterns. To date, network research has emphasized the effect of relations on information sharing rather than the converse, the effect of information on the pattern of relations. For example, earlier studies show greater relational strength improves the likelihood of the complex or private information transmission (Centola and Macy, 2007; Hansen, 1999; Uzzi, 1997). Understanding the effect of certain information types on communication behavior is critical to conceptualizing both organizational processes and networks. I find evidence for endogenous mechanisms that lead to divergent characteristics when communication is parsed by corrupt and non-corrupt information. The results presented here indicate that social interactions hinge, in part, on information content. Thus, the results 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 characteristics.

Despite significant advantages, the data used here impose some limitations on the study of information 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 potential 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.

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.
REFERENCES


The Penguin Group, New York.


Doubleday.


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. Project Selection Overview

<table>
<thead>
<tr>
<th>Project</th>
<th>Example Quotes Used in Indentifying Corrupt and Non-Corrupt Projects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corrupt 1</td>
<td>“As a result of these various machinations, &lt;Corrupt 1&gt; was improperly kept off Enron's balance sheet because it did not have the third-party equity at risk required by the applicable accounting rules” (SEC Filing complaint 17762).</td>
</tr>
<tr>
<td>Corrupt 2</td>
<td>“In connection with the January 20, 2000 analyst conference, Enron and &lt;Corrupt 2&gt; purportedly executed a series of transactions, known as &quot;Project &lt;Corrupt 2&gt;&quot;, that allowed &lt;Corrupt 2&gt; ’s income to increase as the price of Enron’s stock increased. Project &lt;Corrupt 2&gt; allowed Enron to recognize, through its partnership interest in &lt;Corrupt 2&gt;, approximately $85 million in earnings as a result of the manufactured increase in Enron stock from the false and misleading presentation at the analyst conference.” (SEC Filing complaint 18582).</td>
</tr>
<tr>
<td>Non-corrupt 1</td>
<td>“In April 2000 Enron signed an agreement with a U.S. ... retailer to deliver over the Enron Intelligent Network” (Enron Annual Report 2000 p17)</td>
</tr>
<tr>
<td>Non-corrupt 2</td>
<td>“In its first two-and-a-half months of operation &lt;Non-Corrupt 2&gt; did approximately $9 billion of business” (Enron Annual Report 1999 p6)</td>
</tr>
<tr>
<td>Non-corrupt 3</td>
<td>“The &lt;Non-Corrupt 3&gt; in the state of ... is the cornerstone of Enron’s activities in India and is expected to be a strong contributor to Enron’s earnings in 1999 and beyond.” (Enron Annual Report 1998)</td>
</tr>
</tbody>
</table>
Table 2. Descriptives by Project Type Type (N=6)*

<table>
<thead>
<tr>
<th></th>
<th>Non-Corrupt Projects (N=3) Mean</th>
<th>Corrupt Projects (N=3) Mean</th>
<th>All Projects Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Network Measures</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Duration (Years)</td>
<td>2.667</td>
<td>2.667</td>
<td>2.2857</td>
</tr>
<tr>
<td>Network Size</td>
<td>676</td>
<td>118</td>
<td>340.2857</td>
</tr>
<tr>
<td>Network Diameter</td>
<td>8.250</td>
<td>4.667</td>
<td>5.4286</td>
</tr>
<tr>
<td>Average Path Length</td>
<td>2.884</td>
<td>1.979</td>
<td>2.0317</td>
</tr>
<tr>
<td>Graph Density</td>
<td>0.004</td>
<td>0.017</td>
<td>0.0090</td>
</tr>
<tr>
<td><strong>Individual Member Measures</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Network Size (00s)</td>
<td>4.452</td>
<td>0.258</td>
<td>3.783***</td>
</tr>
<tr>
<td>Frequency</td>
<td>8.894</td>
<td>2.769</td>
<td>7.918***</td>
</tr>
<tr>
<td>Reciprocity</td>
<td>0.954</td>
<td>0.831</td>
<td>.935***</td>
</tr>
<tr>
<td>Transitivity</td>
<td>0.156</td>
<td>0.104</td>
<td>0.148***</td>
</tr>
</tbody>
</table>

*** p<0.001, ** p<0.01, * p<0.05; Significant differences compare means (t-statistic).

*t-statistic in parentheses.
Table 3.  
Descriptive Statistics and Correlations (1,571 Individuals with 5,009 Observations)

<table>
<thead>
<tr>
<th>Variable</th>
<th>mean</th>
<th>sd</th>
<th>min</th>
<th>max</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corrupt Information</td>
<td>0.160</td>
<td>0.366</td>
<td>0</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Network Size (00s)</td>
<td>3.783</td>
<td>3.641</td>
<td>0.03</td>
<td>11.54</td>
<td>-0.422***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td>7.917</td>
<td>4.548</td>
<td>1.000</td>
<td>38.348</td>
<td>-0.493***</td>
<td>0.473***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reciprocity</td>
<td>0.934</td>
<td>0.097</td>
<td>0.167</td>
<td>1</td>
<td>-0.465***</td>
<td>0.544***</td>
<td>0.410***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transitivity</td>
<td>0.148</td>
<td>0.101</td>
<td>0.000</td>
<td>0.750</td>
<td>-0.190***</td>
<td>-0.170***</td>
<td>0.118***</td>
<td>-0.347***</td>
<td></td>
</tr>
<tr>
<td>Year</td>
<td>2000</td>
<td>0.868</td>
<td>1999</td>
<td>2002</td>
<td>0.214***</td>
<td>-0.073***</td>
<td>-0.414***</td>
<td>-0.091***</td>
<td>-0.023</td>
</tr>
</tbody>
</table>

*Note:*** Significant at the 0.1% level.*
Table 4.
Results of Random Effects Models Predicting Corrupt Information Effects on Communication Behaviors* (1,571 Individuals with 5,009 Observations)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Frequency 1 (1)</th>
<th>Reciprocity 2 (3)</th>
<th>Transitivity 3 (4)</th>
<th>Transitivity 6 (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corrupt Information</td>
<td>-3.320***</td>
<td>-0.114***</td>
<td>-0.132***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.275)</td>
<td>(0.015)</td>
<td>(0.010)</td>
<td></td>
</tr>
<tr>
<td>Network Size (00s)</td>
<td>0.321***</td>
<td>0.241***</td>
<td>0.010***</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.026)</td>
<td>(0.000)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Frequency</td>
<td>0.006***</td>
<td>0.003***</td>
<td>0.006***</td>
<td>0.003***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Reciprocity</td>
<td>15.599***</td>
<td>9.878***</td>
<td>-0.384***</td>
<td>-0.516***</td>
</tr>
<tr>
<td></td>
<td>(1.170)</td>
<td>(1.287)</td>
<td>(0.084)</td>
<td>(0.085)</td>
</tr>
<tr>
<td>Transitivity</td>
<td>12.719***</td>
<td>8.076***</td>
<td>-0.292***</td>
<td>-0.383***</td>
</tr>
<tr>
<td></td>
<td>(1.030)</td>
<td>(1.204)</td>
<td>(0.069)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-9.566***</td>
<td>-2.743*</td>
<td>0.897***</td>
<td>0.465***</td>
</tr>
<tr>
<td></td>
<td>(1.128)</td>
<td>(1.325)</td>
<td>(0.010)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Pseudo R² (between)</td>
<td>0.430</td>
<td>0.466</td>
<td>0.473</td>
<td>0.512</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.272</td>
<td>0.327</td>
</tr>
<tr>
<td>Pseudo R² (overall)</td>
<td>0.327</td>
<td>0.358</td>
<td>0.419</td>
<td>0.499</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.204</td>
<td>0.302</td>
</tr>
</tbody>
</table>

*** p<0.001, ** p<0.01, * p<0.05
* Robust standard errors in parentheses. All models include project-year fixed effects.
Table 5.
Results of Fixed Effects Models Predicting Corrupt Information Effects on Communication Behaviors* (114 Individuals with 838 Observations)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Frequency</th>
<th>Reciprocity</th>
<th>Transitivity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Corrupt Information</td>
<td>-2.739***</td>
<td>-0.154***</td>
<td>-0.152***</td>
</tr>
<tr>
<td></td>
<td>(0.478)</td>
<td>(0.025)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Network Size</td>
<td>0.624***</td>
<td>0.459***</td>
<td>0.011***</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.053)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Frequency</td>
<td>0.010***</td>
<td>0.004***</td>
<td>0.010***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Reciprocity</td>
<td>9.441***</td>
<td>4.280**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.192)</td>
<td>(1.337)</td>
<td></td>
</tr>
<tr>
<td>Transitivity</td>
<td>9.127***</td>
<td>4.050*</td>
<td>-0.427**</td>
</tr>
<tr>
<td></td>
<td>(1.516)</td>
<td>(1.705)</td>
<td>(0.148)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-5.551***</td>
<td>1.420</td>
<td>0.863***</td>
</tr>
<tr>
<td></td>
<td>(1.111)</td>
<td>(1.379)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Pseudo-R²</td>
<td>0.521</td>
<td>0.554</td>
<td>0.421</td>
</tr>
</tbody>
</table>

*** p<0.001, ** p<0.01, * p<0.05
* Robust standard errors in parentheses. All models include project-year fixed-effects.