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I am particularly grateful to Walter Powell, Henning Hillmann, Karen Cook, Mark Granovetter, and Linda Argote for their extensive comments and suggestions. I also wish to thank Kaisa Snellman and seminar participants at Carnegie Mellon and Stanford University for their helpful critiques. For all remaining errors, I am alone responsible. Direct correspondence to Brandy Aven, Tepper School of Business, Carnegie Mellon University. E-mail: aven@cmu.edu.
ABSTRACT

Previous research on diffusion networks has focused predominately on the final step in diffusion, adoption, rather than the primary phase of information acquisition. To explain the information spread, I propose a theory of information transfer based on the characteristics of the dyad and the characteristics of the sender. To understand information transfer, I examine the transmission of project information within a large corporation. I posit that diffusion patterns differ based on the relational embeddedness and characteristics of the sender. In an empirical analysis of the transfer of information shared between individuals within Enron between 1998-2003, I find that the probability that information will be transferred between sender and recipient is influenced by several factors: (1) the attributes of the relationship between the sender and recipient, (2) social structure surrounding the sender and the recipient, (3) and previous sharing behavior of the sender.
INTRODUCTION

Although not examined directly, a critical mechanism for social network research is how networks facilitate the transfer of information (Monge and Contractor, 2002). Granovetter (1985) identified that weak relations often provided access to novel information, such as where to find a job. Burt (1992) later argued that individuals with low-closure networks are better able to access information and therefore better able to assess opportunities within an organization. The network literature abounds with arguments that explain the link between particular relational patterns and improved performance outcomes by the increase in information attainment. Whether focusing on relationships between individuals within an organization, such as sharing complex knowledge (Hansen, 1999), promotion information (Podolny and Baron, 1997), political information (Krackhardt, 1990), or on inter-organizational relationships, such as pricing information (Roberts and Ingram, 2000), and research findings (Powell, Koput, and Smith-Doerr, 1996), these studies point to information attainment as a key reason they observe individual network positions influencing performance outcomes.

Even though it is understood that certain positions may enhance the likelihood of receiving particular types of information, such as private, complex, or tacit information (Hansen, 1999; Uzzi, 1996; 1997; Centola and Macy, 2007), we still understand relatively little about how information spreads within an organization (for a review, see Borgatti and Halgin, 2011 and Argote, McEvily, and Reagans, 2003). Extant network diffusion research focuses primarily on the problem of decision-making rather than the spread of the information (for examples, see Wejnert, 2002). Diffusion studies commonly examine precursors to what may be considered the final step in the process of diffusion, when the
behavior or attitude can be observed (Rogers, 2003; Centola, 2010). Information attainment, the primary step in diffusion, remains to be investigated empirically (Rogers, 2003; Abrahamson and Rosenkopf, 1997). The most salient shortcoming in the network literature pertains to a theory that can explain the transmission of information between actors. The purpose of this study is to examine dyadic information transfer.

Moreover, a puzzle emerges if we consider the four most prevalent mechanism of diffusion in networks cited by organizational sociology literature: proximity, tie strength, cohesion, and structural equivalence. These forces conspire to produce total convergence of information throughout the network when two actors are closely linked (proximity), when actors share strong relationships (tie strength), when actors share ties with others who also share strong ties (cohesion), and when individuals find themselves in similar networks positions (structural equivalence). However, if these forces alone accounted for the diffusion of information, the information in the network would eventually reach all members. Roger and Kincaid (1981) refer to these models as examples of the convergence model of communication. Krackhardt and Brass (1994) noted that such models lead to equilibrium wherein everyone in the network will converge in their information, attitudes, and actions. And yet, empirically, network theorists find knowledge, beliefs, and behaviors diffuse unevenly in networks (Podolny, 1994; Gulati, 1995; Walker, Kogut and Shan, 1997; Stuart, 1998). Existing micro-level (individual position) theories of information diffusion therefore imply macro-level diffusion patterns inconsistent with those that we observe empirically. I posit this is due in part to the fact that these theories do not account for the differences in information transfer. In fact, scholars of knowledge networks find knowledge disparities throughout organizational networks, despite the benefit of
knowledge transfer for the firm (Reagans et al., 2005; Reagans and McEvily, 2003). Within
and among organizations, information sharing has been argued to improve routines and
practices (Baum and Ingram, 1999; Epple et al., 1991; Zander and Kogut, 1995; Reagans et
al., 2005), and lead to product innovations (Hansen, 1999) and increased learning rates
(Argote, Beckman, and Epple, 1990).

To understand diffusion in networks most theories focus on social influence
processes that affect the potential adopter (Friedkin, 1990; Ibarra and Andrews, 1993;
March and Simon, 1958). These studies seek to explain individual conformity given the
attributes of the individual’s surrounding network (Centola, 2010; Granovetter, 1978).
Although the adopter’s surrounding relationships undoubtedly influence decisions to act, I
focus here on information attainment as the precursor to the adoption of a behavior,
attitude, or practice. In other words, in order for an individual to make a decision, she must
first be made aware of her choice set, because, for obviously reasons, lack of information
thwarts her ability to decide. In Rogers’ (2003) model of the innovation-decision process,
the first exposure to an innovation’s existence is the initial stage of the five-stage model (p
164). Coleman et al. (1957) concluded that in the early stages of diffusion, members first
learned of the innovation through communication channels and did not actively seek out
the information.¹ Thus, innovation diffusion commences with information transfer and
particular attention should be allotted to the role of the sender.

To identify mechanism of information spread in networks, I focus specifically on
the determinants of dyadic transfer – the sharing of information between a sender and a

¹ This is not to suggest that the recipient is a passive agent, because in later stages, the
doctors actively sought out information from network peers.
receiver nested in a social structure. Extant social contagion studies have primarily sought to explain individual and system-level influences (Valente, 1999). Theories of contagion are based on the assumption that communication networks in organizations serve to expose people to information (Burt, 1980; 1987; Monge and Contractor, 2003). The transfer of information largely occurs between dyads. The relation between sender and receiver in the network provides a distinct channel for communication. This makes the dyad the most appropriate level of analysis for information transfer. Dyadic transfers also occupy center stage in models of social network diffusion (e.g., Watts and Strogatz, 1998), explaining the spread of innovations, attitudes, diseases, and so forth (Bearman, Moody, and Stovel, 2004; Dezso and Barabasi, 2002; Moody et al., 2003). The determinants and frequency of dyadic transfer within a network therefore appear vitally important to outcomes of scholarly concern.

Whereas prior studies have treated either the actor or the system as the unit of analysis and developed mechanisms relevant to those levels, this theory and methodology expands the analysis of diffusion to include the dyadic transfer. I analyze the transfer of project information via emails at Enron from 1998 to 2002. In particular, I investigate the conditions under which an initial email is transmitted regarding unique project facts. Similar to earlier studies of diffusion, my models estimate the likelihood that transmission occurs. My data has a structure common in directed communication networks: they comprise a source (the email sender), target (the email recipient), and tie-content (the message shared between parties). To date, the research has privileged the role of the recipient and not sought to understand either the role of the sender or the interpersonal transmission dynamic of the pair. My theorizing and modeling differ from past research
because, although I model the probability of an individual’s receipt of information in replication of earlier work, I also explicitly examine dyadic transfer of information. I incorporate both the relational attributes of the pair of actors and the structural role of the sender in my estimation of the probability that a sender will transmit information to a recipient.

THE DIFFUSION OF PROJECT INFORMATION WITHIN ORGANIZATIONS

Social networks emerge within organizations because they provide individuals with a setting in which to develop contacts and ties (McPherson and Smith-Lovin, 1982; 1987). Organizational communication networks are comprised of the interactions shared between members and can reveal the underlying social structure within an organization (Monge and Contractor, 2003). These emergent communication structures are important determinants of an organization’s performance (Bavelas et al., 1950; Guetzkow and Simon, 1955; Leavitt, 1951; Tushman, 1979; Argote and Ophir, 2002). The research on organizational networks generally assumes that these social network ties act as conduits for social processes and information (Borgatti and Halgin, 2011; Monge and Contractor, 2002; Reagans and McEvily, 2003). Yet, little empirical research has directly investigated information spread via network ties. By studying the transfer of discrete facts about projects within a firm, I test the predominant mechanisms for network effects on information spread.

Information is a fundamental concept for studying both social networks and organizations (Kilduff and Tsai, 2003). Network theorists have long held insights regarding information spread but have yet to empirically investigate it. It is well accepted among organizational theorists that various network positions provide differing amounts of
exposure to information within an organization (Stuart, 1998). Location in a dense cluster may provide access to complex or tacit knowledge but limit exposure to novel information (Hansen, 1999; Granovetter, 1985; Uzzi 1996; 1997). Conversely, a position that bridges such dense clusters may create opportunities to discover new or exclusive information (Burt, 1992).

Conceptually, studies of diffusion within networks typically depend on two assumptions. First, that transmission will not be at random but follow a relational pattern as either a pathway within the network (as in Coleman, Katz, and Menzel, 1957) or as in the case of Burt’s (1987) structurally equivalent agents, spread between those in similar roles. Second, because individuals must be aware of the set of behaviors and attitudes to be adopted, social contagion hinges on information attainment. Thus, once introduced into the system of relationships, the transmission operates endogenously within the network. Studies in this tradition include Granovetter’s (1978) threshold model of diffusion, Abrahamson and Rosenkopf’s (1997) examination of network innovation diffusion, and Macy and Centola’s (2007) theory of complex contagions.

Early studies on diffusion of social contagions investigated the structural determinants of adoption, focusing mainly on the network structure that surrounds an individual (Burt, 1987; Coleman, Katz, and Menzel, 1957; Rogers, 2003). These scholars developed actor-level explanations of adoption; the predictions related the actor’s position to the probability of behavior spread. The most familiar hypotheses from this perspective is that social cohesion in the form of dense, strong network clusters, leads individuals to receive redundant messages from multiple sources, which creates social pressure to adopt. Empirical studies, for example, explored how dense patterns of relationships among
professionals determine the acceptance of certain practices (e.g., Coleman, Katz, and Menzel, 1957).

The majority of both individual-level and system-level studies of network diffusion examine the structural factors that would lead an individual to adopt a belief or exhibit a behavior (for similar conclusions, Krackhardt and Brass, 1994; Roger and Kincaid, 1981). In individual-level studies, researchers investigate characteristics of the potential adopter that lead to conversion, such as the number of alters who themselves previously adopted. These predictions focus on the kinds of social arrangements that lead the uninitiated individuals to conform, but not on the initiated’s likelihood of transmitting information. Similarly, the system-level analysis of network diffusion investigates the rate of transmission via distant ties (Watts and Strogatz, 1998). These distant ties cut across local clusters in the network to increase the speed of transmission with the social system.

In this way, my theory of information transfer parallels the concept of knowledge transfer or knowledge networks (Baum and Ingram, 1998; Darr and Argote, 1995; Epple et al., 1991; Phelps et al., 2012; Reagans et al., 2005; Zander and Kogut, 1995). However, I examine specific content that presents a potential opportunity for the recipient, rather than sophisticated routines or practices. Here, information transfer is the transmission of discrete valuable facts between a pair of individuals. Specifically, I examine the sharing of new project information within the firm.

Within modern firms, projects are increasingly the most influential organizing logic (Catalado and Ehrlich, 2012). While firms continue to maintain group distinctions by functional role, such as legal or accounting, increasingly professionals are members of
cross-functional project teams (Wang and He, 2008). The participation in such teams is not always straightforward because project assignments tend not to be centrally managed (Hinds and Bailey, 2003). Instead, managers of projects are left to seek out members, particularly those with valuable information (Menon and Pfeffer, 2003). These projects commonly have their own resources, strategic plan, and task assignment structure. Projects, as such, create an internal market for labor where each project competes for members within the firm (Pfeffer and Cohen, 1984). Therefore it is up to the both the project leaders and the potential project members to identify talent and opportunities, respectively. Participation in a successful project can provide professional recognition, bonuses, promotions, and, of course, more opportunities within the organization (Obstfeld, 2008). Pre-existing relations in the network between organizational members serve as important conduits for information about these opportunities (Hansen, 2002).

ANTECEDENTS OF INFORMATION TRANSFER

The social network literature is replete with examples that relate information to social structures. For example, early on, Granovetter (1973) posited that members of densely knit groups share similar information. In such dense groups, information also diffuses more rapidly because the members share many direct connections to one another, creating information echo chambers. Information within dense clusters tends to be more trustworthy, since members of the cluster can validate the information via redundant contacts in the group (Newman, 1999; Watts and Strogatz, 1998). Hence, information tends to be more reliable but homogenous within groups. Although these information echo chambers have been cited as producing benefits such as trust and solidarity (Coleman, 1988; Greif, 1993; Uzzi, 1996; 1997), in the organizational literature it is the network
position that connects disconnected sub-groups that is most cited for benefiting the actor (Burt, 1992; Hargadon and Sutton, 1997; Podolny and Baron, 1997; Zaheer and Bell, 2005; Shipilov and Li, 2008).

Burt (1992) conceptualizes network ties in terms of the information and resources that individuals can acquire, and he describes the benefits of brokerage, where an individual has the ability to span structural holes (i.e., when one member is connected to many other members who themselves are not connected to each other). Individuals with networks rich in structural holes have greater access to distinct information flows. Therefore, people who share ties across clusters have better access to more diverse information sources and are more likely to be aware of novel information in the organization (see Burt, 2002 for a review). Evidence for this argument can be found for both managers and firms (Fernandez and Gould, 1994; Mehra, Kilduff, and Brass, 2001; Mizruchi and Stearns, 2001; Stuart and Podolny, 1999). Since the majority of individual-level network studies cite information attainment as a central explanation for the brokerage position’s benefit (Hargadon and Sutton, 1997; Podolny and Baron, 1997; Zaheer and Bell, 2005; Shipilov and Li, 2008), I explicitly test the effects of brokerage for the receipt of information. Formally,

Hypothesis 1: Increases in brokerage ability will increase the odds of receiving information.

Particular individual-level positions may be advantageous, but do not tell the complete story of information transmission between parties. The explanatory focus here is
on the role of the sender and how relations between sender and receiver influence information transmission.

**DYADIC INFORMATION TRANSFER**

For network analysts, diffusion is largely determined by the structural concept of social proximity (Brass et al., 2004). Increased social proximity of two individuals in a social network is associated with greater interpersonal sharing and influence between the two individuals (Cartwright and Zander, 1968; Friedkin, 1990; Granovetter, 1985). Within organizations, proximate connections are easier to maintain and more likely to be strong (Monge and Eisenberg, 1987). I define social proximity within a network as the fewest possible intermediaries between two actors; the most proximate actors are those that are not separated by a third party. Social proximity models also posit that the stronger the tie between ego and alter, the more likely ego will disseminate information to alter (Festinger, Schachter, and Beck, 1950; Friedkin, 1990), the argument being that individuals are motivated to share information with those that they share direct ties with, and therefore, the information ego has will be shared with his alter. In lieu of these earlier theories, I expect social proximity to facilitate information transfer for dyads.

**Hypothesis 2:** Information transfer will occur at a higher rate for dyads that are socially proximate than for dyads that are not socially proximate.

Some network scholars have argued that social cohesion is the necessary structural element for predicting innovation spread (Coleman, Katz, and Menzel, 1957; Valente, 1995). In the networks literature, cohesion implies networks that are dense, with strong ties among members (Festinger, 1950; Wasserman and Faust, 1994). Network scholars assume
that greater interconnectedness increases the amount of information flowing through the system, as well as the rate at which information diffuses (Rogers, 2003). In this sense, the argument reflects the level of embeddedness in which the dyad is situated (Granovetter, 1985). When dyads are ensconced within triads, the dyad’s tie is reinforced and more likely to see information sharing (Krackhardt, 1999; Simmel, 1950). Kossinets and Watts (2006) showed in communication networks of emails at a large research university that triadic closure increased the likelihood of communicating. Coleman, Katz, and Menzel (1957) found that physicians who shared many ties to other physicians were more likely to adopt the use of tetracycline than those with fewer connections. Hence, I expect the number of associates the dyad members share to influence information transfer. I therefore predict:

**Hypothesis 3:** The greater the dyad’s number of shared associates, the higher the odds the dyad will transfer information.

The focus on the dyad should not come at the cost of ignoring individual differences. Rather, the purpose here is to illuminate all the structural characteristics that may promote information transfer. When studying how information spreads from one person to the next through a social system, past diffusion research has largely focused on the receiver’s decision to adopt (Abrahamson Rosenkopf, 1997; Rogers 1966; Granovetter, 1978) and not the sender’s willingness to share information.

Without investigating the role of the sender, network research has neglected the possibility that certain individuals may have a greater proclivity for sharing information either due to personal preferences or prescribed roles. As a counterpart to the broker, I introduce the concept of the *information dispatcher*. In many settings, a dispatcher is
organizational member who is responsible for coordinating information and transmitting important messages. This is not to imply that an information dispatcher is necessarily an organizational role, because willingness to dispatch information may also be an individual characteristic or trait. Substantial evidence from psychology indicates that social motivations vary greatly across individuals (for a review, see John, Robins, and Pervin, 2008, Sasovova et al., 2010). With this in mind, I argue that the willingness to transmit information about opportunities is largely at the discretion of the sender and the varying motivations of senders is most likely shaped by individual differences, which have been found to alter relational patterns (Flynn et al., 2006; Casciaro and Lobo, 2008; Sasovova et al., 2010). Therefore, I expect that the sender’s propensity to share information will be an observable trait and increase information transfer.

**Hypothesis 4:** The greater the sender’s proclivity to act as an information dispatcher, the higher the odds the dyad will transfer information.

As previously mentioned, the broker’s advantage over non-brokers is primarily cited as being due to their access and control over information (Burt, 1992; Hargadon and Sutton, 1997; Hillman and Aven, 2012; Podolny and Baron, 1997; Zaheer and Bell, 2005; Shipilov 2006). As compared to non-brokers, brokers generate better ideas (Burt, 2004), are better compensated (Burt, 1997; 2002), acquire more resources (Cook and Emerson, 1978), possess greater influence over community and political elites (Padgett and Ansell, 1993), obtain better evaluations and organizational advancement (Burt, 2004; Podolny and Baron, 1997), and get more deals done (Mizruchi and Stearns, 2001). Although benefits to brokerage have been confirmed, what is not certain is if brokers are more likely to receive information transfers than non-brokers, and conversely, whether brokers are more apt than
non-brokers to pass information on to others. The argument that I put forward here is that the benefits to brokerage found in previous research may be derived from the both the broker’s access to information and, in part, her willingness to forward it to others. In other words, brokers may readily share information in exchange for other resources within the organization. Hence, I expect higher transfer rates when either the receiver or the sender occupies a brokerage position.

**Hypothesis 5**: Increases in the sender’s brokerage capacity will increase the odds of information transfer within the dyad.

**Hypothesis 6**: Increases in the receiver’s brokerage capacity will increase the odds of information transfer within the dyad.

*DATA SOURCE: The Email Corpus*

This study examines longitudinal data taken from Enron between the years 1998 and 2002. The network information and correspondence were drawn from the Enron Email Corpus (EEC), a collection of emails subpoenaed and made public record by the Federal Energy Regulation Commission. The EEC dataset is comprised of professional and personal email messages sent by individuals over a five-year period. As is typically found within organizations, email was used predominantly at Enron to monitor project statuses, coordinate member efforts, and exchange relevant information (McLean and Elkind, 2004; McKenney, Zack, and Doherty, 1993). Two factors in particular make this dataset valuable and appropriate for the systematic study of information diffusion. First, this setting permits the systematic study of communication networks and organizational information. Second,
the EEC provides a unique opportunity to capture the explicit spread of information, as emails include specific details about communications.

**METHOD**

The research design used here incorporates content analysis and social network analysis. Although both are common methods in social science, this study integrates techniques from each to improve our understanding of communication networks. Combining quantitative and qualitative methods generates results that are more reliable and enriches the findings (Edmondson and McMannus, 2007; Jick, 1979). Incorporating these two methods facilitates this study in two significant ways: (1) it allows the actual information assumed to be shared in most social network models to be observed, and (2) coding content rather than relying on informant reports provides more reliable accounts of diffusion (Bernard, Killworth, and Sailer, 1982).

Content analysis permits quantitative analysis of large numbers of text to indentify certain words or concepts used or referred to in the corpus (Carley, 1993). To conduct a content analysis of the emails, I use a structured approach with a keyword search, which helps to ensure the comparability of data across the documents and improves generalizability (Maxwell, 2004). The coding of the email was iterative and based on a “start list” generated from the archival data (Miles and Huberman, 1984).

I began by first synthesizing the email documents and supplemental archival data, as is common in qualitative research (Eisenhardt, 1989). Each project had a unique name, which aided in the task of automating the identification of project specific facts and emails (Carley, 1993). These names were used as search terms in the EEC to identify pertinent emails. The subset of emails was then reviewed and non-pertinent emails were excluded.
This is not unusual given the iterative nature of content analysis (Strauss and Corbin, 1990).

Recent studies have begun to investigate large electronic communication databases to understand the evolution of social networks (Kossinets and Watts, 2006; Marmaros and Sacerdote, 2006). Following similar techniques, the communication networks were constructed from all the email correspondence. Each email in the corpus includes the following information: sender; recipients; recipient form: to, carbon copy (CC), and blind carbon copy (BCC); transmission form: original, reply, and forward; date; subject; and message content. Within the EEC, there are over 13,957 unique senders and recipients, after the data were normalized to remove redundant email addresses (one individual can have several email accounts throughout their tenure at Enron), group emails, and distribution lists. From these emails a cumulative bipartite graph was created in which all individuals associated with an email message would share a connection to that email. The two-mode networks were then projected onto one-mode networks with the shared emails as links between individuals (Wassermann and Faust, 1994). Email links were coded with project facts based on the content analysis, permitting an analysis of both the individual-level and dyad-level transmission patterns.

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2 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.”

3 A small number of non-Enron emails were included as they were a part of the communication structure at Enron; however, these, emails were not considered candidates for information transmission.
**Analysis and Measures**

The analysis was restricted to messages that unambiguously name the project and were the first email message that the individual received regarding the project. To conform to this distinction, only the transmissions in which the project was specifically mentioned were included. This provided a stringent requirement to be included in the data. It is possible that relevant information could have been shared about the projects without naming the project directly. Therefore, restricting the data in this way limits the study to a more conservative estimation of the information diffusion process.

Based on employee interviews, investigative journalists’ accounts, and corporate reporting, four projects were identified and selected that shared similar qualities in terms of objective, money under management, and duration (Eichenwald, 2005; Swartz and Watkins, 2004; Mclean and Elkind, 2004). The email messages themselves also corroborated the individual reports, since they contained information regarding the projects. The projects coded for this analysis were publicly documented in Enron’s press releases and annual reports (Enron, 1998-2000). Each of the projects was a limited partnership, which sought to introduce a new service to the market (Eichenwald, 2005). Projects were limited to those that started after 1998, the beginning of the observation period. One project from the initial set was excluded from the sample because it shifted its objective mid-course.

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4 Even though Enron was involved in many illegal projects, the projects investigated in this study were all deemed legitimate by either the Securities and Exchange Commission and/or the Department of Justice (Aven 2012).
An event history graph is presented for each project at Enron in Figure 1. Lines in the figure represent one of the three individual networks. The y-axis is the total number of individuals who received a transmission over all possible information recipients. It is evident from Figure 1 that they actively transmitted information at varying rates.

Researchers have studied information diffusion primarily at the individual-level (Abrahamson and Rosenkopf, 1990; 1997; Granovetter, 1978; Rogers, 2003). Individual-level models are designed to understand which individual network characteristics determine information attainment. To investigate the relational qualities that promote transmission, I also examine transmission at the dyad-level. Dyad-level analysis has been primarily used to study relationship formation (Sorenson and Stuart, 2008; Mizruchi, 1989; Podolny, 1994; Gulati, 1995). Dyad models address questions regarding how the relationship between two actors affects the likelihood of transmission. Performing the analysis at both the individual and dyad level helps to clarify the mechanisms and reinforce the findings.

I limited the analysis to the first information transmission to individuals who had not previously received a transmission. Therefore, the dependent variable for both individual-level and dyad-level analysis excludes subsequent transmissions from any sender. For each transfer event, the panel data includes the date of transfer, sender ID, receiver ID, and the project. With regard to this paper’s research purpose, the data permits the verification of the effect of structural factors for individuals and dyads on information transfer.
**Modeling Individual-level Information Receipt.** The dependent variable for the individual-level models is a binary variable. The variable is zero for individuals who have not received a project fact. Once an individual receives project information, the variable is coded as one.

In the individual-level analysis, I test the likelihood of receiving project information given the member’s structural position in the network and proximity others who are involved. Only individuals who had ever received an email in the current or previous year were included in the sample to account for new hires and attrition. I used random effects logistic regression to test my individual-level hypothesis. Logistic regression is appropriate because the dependent variable (information receipt or not) is a dichotomous variable (Rabe-Hesketh and Skrondal, 2008). Since I have repeated observations for each individual, I introduced a random effect to adjust the standard errors. The random effects estimator differs from the usual logistic because it allows the error terms across project-year to be correlated. A fixed effects approach is not feasible because some variables, including the dependent variable, do not vary for all or some observations. The individual panel was not balanced as more individuals entered the sample but the variation was nominal. The initial sample included 8,878 people and increased to 9,658 in the final year, representing an 8% increase in 5 years.

**Modeling Dyad-level Information Transfer.** The dyad-level models address binary outcomes in which the dyad has two distinct and mutually exclusive states—information transfer or not. The dependent variable is an indicator denoting the presence (=1) or absence (=0) of project information transfer.
Commonly, dyadic analysis yields large sample sizes because it comprises the set of all potential pairs (Sorenson and Stuart, 2008). However, for this analysis, tie-formation is not the focus but the specific transmission of information between pairs. Rather than examining all the potential dyads in the analysis, I limit the sample to only the dyads for which a tie exists in the cumulative five-year network. The dyad enters the panel sample at the first shared email and then is included in the analysis of subsequent years. Again, this accounts for normal organization hiring and turnover that might bias the sample. I do not assume that project facts are endogenous to the network and therefore do not restrict the sample to dyads in which I observe the sender as having project information. This yields a sample of 22,104 unique pairs with 87,649 total observations.

To estimate the dyad models, I used a conditional logistic regression with fixed effects for project-year to account for the non-independence of observations and the binary dependent variable. This model is appropriate since it accounts for the combined effects of omitted characteristics or unobserved heterogeneity for dyads (Rabe-Hesketh and Skrondall, 2005). The conditional logit model, which is similar to the fixed-effects logit for panel data predicts the transfer of information. Since my data do not include demographics of the organizational members, I am not able to control for such characteristics as tenure, gender, and formal role. This model controls for unobserved heterogeneity while examining the influence of the covariates on dyadic transfer (Allison, 2005). Conditional logit models measure within-dyad variation. Restricting the analysis to within-dyad variation eliminates the possibility of contamination and is much more likely to produce unbiased estimates.

**Independent Measures**
**Individual-Level**

All the network measures are based on the individual’s preceding email communications prior to gaining information about the project.

*Network Constraint.* I use the network constraint of structural holes as defined by Burt (1992) as a measure of the focal members’ ability to broker information across different organizational constituencies within the email network. The measure captures the degree to which the focal actor’s alters are themselves connected (e.g., Burt, 1992; 2002; Reagans and McEvily, 2003). A low measure of network constraint indicates that the individual has a higher ability to receive information from disparate or non-connected individuals (e.g., Granovetter, 1985; Burt, 1992; Uzzi, 1996; 1997). The network constraint index was standardized, where zero indicates low connectivity between the alters of ego and one reflects high connectivity between ego’s alters.

*Dyad-Level*

All independent measures from the email network were calculated on the characteristics of the dyad and its members prior to the information transfer.

*Social Proximity.* To operationalize proximity in the network, I used two different measures. The first is existence of prior communications and the second is how frequently the communications occurred. A *prior tie* indicates that the two employees have communicated via email before the transfer of information. Prior ties are commonly included in network research to account for proximity (Baker, 1990; Gulati, 1995; Guimera et al., 2005). The *frequency of communication* is the number of emails exchanged between the parties before the event of project information transfer. Frequency of communication is
based on all communication prior to the transfer event. Frequent communications between ego and alter have been found to increase the likelihood of shared evaluations (Galawskieze, 1985). Frequency of communication was transformed to the square root to correct for variable skew.

*Mutual Associates.* I operationalize cohesion for the dyad by the number of individuals that the sender and the recipient have in common. Measuring cohesion in this way is similar to estimating triadic closure counts. The number of shared third parties is a basic measure of dyadic embeddedness. Dyads nested within triads tend to have stronger connections (Simmel, 1950; Krackhardt, 1999).

*Information Dispatcher.* The purpose of dyad analysis is not to ignore individual difference but to examine the characteristics of the relationship that promotes information sharing; however, certain individuals may be more disposed to sharing information either due to personality or formal roles. Therefore, I employ a measure, *information dispatcher*, to account for the sender’s proclivity to disseminate information. The information dispatcher measure captures if the dyad’s sender generally has a higher propensity to share project information. I base this measure on the sender’s past information transfers to different receivers by project and year. The mean number of transfers is calculated for each project-year and then subtracted from each sender’s total transmission in a project-year. This measure represents the number of transmissions that surpass the average number of transfers for each project annually. On average, senders transfer project information 6.81 times a year.
Network Constraint of Sender and Receiver. Network constraint for the members of the dyad were measured in the same manner as for the individual-level models.

Controls Variables. The models control for a number of individual network attributes that prior research has singled out as possible factors that influence information diffusion for both individuals and dyads. All of the control variables were constructed with one-year lags. Indegree, measured as the number of incoming communications to the focal actor, was added to the individual-level models. Indegree represents the willingness of other individuals to send information to the focal actor. Typically, indegree is used by network scholars to indicate an individual’s power and status in a network (Podolny, 1994; Wasserman and Faust, 1994). The individual-level models also included outdegree as a control for the amount of information that the individual shares with other organizational members. Outdegree is the number of outgoing communications by the focal actor and is a common control in network models (Hansen, 1999).

Closeness centrality measures the proximity of the individual to all other individuals in the communication network. Hence, this measure reflects the efficiency with which this member may obtain information from all other individuals within the network (Bonacich, 1987; Wasserman and Faust, 1994). Therefore, I chose to control for the closeness centrality of individuals. Closeness centrality was measured using Freeman’s (1979) formulation (Wasserman and Faust, 1994). I standardized the measure so that a member is the most proximate to other members when the index is one and the most distant when the index is near zero.
For the dyad-level models, I included an *indirect tie* as a control. Although not directly linked, nodes commonly share an indirect tie. If the sender and receiver were connected through another individual, they share an indirect link. Kossinets and Watts (2006) found for a communication network of emails at a large research university that indirect links increased likelihood of communicating. Indirect connections through multiple third parties increase the probability of two individuals becoming connected in the future (Newman, 2001). Thus, I include a dummy variable for pairs of senders and receivers that were indirectly linked by third actor.

**RESULTS**

Table 1 provides a means and correlation matrix for all the measures modeled for the individual-level analysis. The independent variables, with the exception of receiver’s constraint, show a positive relationship with receiving information. Table 2 reports the estimates of the random effects logistic regression of information transmission to an individual. The base models (1) and (2) in Table 4 contain only the control variables. The baseline results show that both indegree and outdegree significantly increase the likelihood of receiving information, albeit nominally. Closeness centrality is only significant for the base model (2) but not for the final model. Hypothesis 1 predicted that a brokerage position with low network constraint would increase the likelihood of an individual receiving information. According to the model 3 estimates, network constraint reduced the receipt of information. These results are in line with previous theories and indicate that brokers more commonly receive information than non-brokers.

<INSERT TABLE 1 ABOUT HERE>
Table 3 reports the means, standard deviations, and correlations for the variables used in the dyad-level models. As expected, the bivariate descriptives for information transfer and all the independent variables indicate a positive relationship, with the exception of sender’s and receiver’s constraint. Model 1 in Table 4 is the base model with an indirect tie between dyads. In model 2, I present the conditional logit estimates for project information transfer with the inclusion of a previous communication and frequency of previous communications to the base model. The coefficients in model 2 provide partial support for social proximity increasing the likelihood of sharing information, since only frequency of communication significantly increases the odds of information transfer. However, in the subsequent models that include attributes of the sender and the characteristics of the dyad, the effect of communication frequency remains significant but becomes negative. Hence, the estimates from model 2 do not provide support for Hypothesis 2. This suggests that the previous communications serve as a poor predictor of future information transmission for dyads.

Model 3 adds to model 2 the number of mutual associates that the dyad members share. By comparing the results of model 2 with those of model 3, we can see that including shared associates improves the model. The log-likelihood increases by more than 1,500, and the increased pseudo-R² suggests that the inclusion of this measure improves the accuracy of the model. Mutual associates shared by the sender and receiver significantly
increased the odds of dyadic transfer in this model and the estimates provide support for Hypothesis 3, that dyads where the two parties share contacts are more likely to transfer information between them. Although mutual associates are also positively significant in the final model, the effect size is greatly diminished with the inclusion of the sender’s attributes and the related interaction terms, thus indicating the effect of shared third parties takes a reduced role when sender characteristics are also considered.

Model 4 adds the information dispatcher variable to the model with tie characteristics and mutual associates. The positive and significant parameter estimate on this variable supports Hypothesis 4, that the sender’s proclivity to share information increases the odds of transmission and appears to be an important factor for predicting future transmissions. Model 5 in Table 4 presents the test of Hypothesis 5, that network constraint of the sender will reduce the likelihood of dyadic information transfer. The results from model 5 support Hypothesis 5; a sender’s network constraint reduces the transfer of project facts. In other words, dyads in which the sender has an increased capacity to broker have a greater likelihood of information transmission. In model 6, I include a test for Hypothesis 6, which posits that receivers with low network constraint (i.e. brokers) increase information transfer. Given the individual-level analysis, it is not surprising that the effects of receiver’s constraint are negative and significant in model 6. Thus, I also find support for Hypothesis 6 for dyads. In sum, mutual associates, low network constraint for both the receiver and the sender, and the sender’s propensity to share information all increase the odds of dyadic transfers.

In models not shown here, the geodesic distance for the dyad before transfer was included but was not significant. In other unreported models, I included the number of
alters who already had project information prior to the transfer event for both the sender and the receiver. Including these variables did not change the results of information transmission for the variables shown here and the variables were not statistically significant.

DISCUSSION AND CONCLUSION

Most theories of diffusion imply that actors have little agency when deciding whether to transfer information to another actor, but actual decisions to share information vary on one or more social dimensions. To explain how information is acquired, I advance a theory of information transfer based on the characteristics of the dyad and the characteristics of the sender. I find that the probability that information will be transferred between sender and recipient is influenced by several factors: (1) the attributes of the relationship between the sender and recipient, (2) social structure surrounding the sender and the recipient, (3) and previous sharing behavior of the sender.

The individual-level analysis, which focuses on the recipient of the information, replicates findings from previous research (Burt, 1992; Hargadon and Sutton, 1997; Hillmann and Aven, 2012; Podolny and Baron, 1997; Zaheer and Bell, 2005; Shipilov and Li, 2008), specifically, that brokers are more likely to obtain novel project information. For the dyad-level analysis, the inclusion of the shared associates between the sender and receiver vastly improved the models. Although this is in line with previous theories of embeddedness and simmelian ties (Granovetter, 1985; Krackhardt, 1999), it has not been examined for information transfer. By highlighting the importance of the dyad for
diffusion, I call attention to two explanations of information transfer: the social structure surrounding the relationship and the role of the sender.

Two key insights that emerge from the dyad-level results are the prominent affects of the sender’s predilection for sharing information and the sender’s low network constraint. The effect of information dispatchers, as I term them, demonstrates that individual characteristic is an important determinant for information transfer. This highlights, once again, the need for network studies to account for personality and individual factors (Labianca and Brass, 2006). The second finding, which merits further investigation, is that dyadic transfer occurs more often when the sender is in a brokerage position. Rather than leading individuals to amass information for control and power, occupying a brokerage position leads to the greater dissemination of information. At first examination, this may seem counterintuitive, since extensive research has suggested that the benefits afforded to brokers emerges from a position that increases access to novel information and their ability to control it. Perhaps the benefits to brokerage do not come from limiting access to novel information but from passing it along to others. It is possible that brokers transfer information in order to obtain resources, social or otherwise.

Information and its transfer are fundamental concepts to various areas of research, including social networks, organization theory, economics, sociology, and social psychology. Understanding the mechanisms that lead one individual to share information may help existing work in multiple domains, such as Burt’s (1992) concept of brokerage and social capital, knowledge sharing in networks (Phelps, 2012), link-prediction models (Liben-Nowell and Kleinberg 2007; Newman et al., 2006), and theories of innovation diffusion (Rogers, 2003; Valente, 1995). This study also addresses specific calls from
organizational theorists for the development of more research and theory for dyadic knowledge transfer (Argote et al., 2002; Borgatti et al., 2009). Albeit this study takes a narrow perspective of knowledge and examines a distinct information type, new project information, it nevertheless lays the groundwork from which to examine more complex information transfers. In addition, explaining the initial conditions for social contagion effects, dyadic transfer may also help to answer basic questions of social network evolution. How ties form, change, and dissolve poses an important puzzle for network theorists (Rosenkopf & Padula, 2008). For example, information transfer may serve as a precursor to tie-formation.

The methods and results shown in this study may provide insights for social contagion and diffusion research. Recent social contagion and network diffusion models that posit social proximity and cohesion increase the likelihood that individuals share similar information, attitudes, and behaviors have been challenged due to endogeneity issues (Shalizi and Thomas, 2010). Addressing the acquisition of information, as I do here with longitudinal data, may help to determine the accurate sample of potential adopters, which then helps to precisely identify the antecedents to adoption. By not analyzing information transfer separately from adoption, diffusion research has been stymied because the studies cannot differentiate the time when an individual becomes a potential adopter from when adoption actually occurs. By only analyzing adoption and not parsing out the time of dyadic transfer, these studies cannot explicate the exact social mechanisms that predict who will adopt and when.

To generate diffusion patterns consistent with those seen at the macro-level, micro-level theories of social contagions must address the origins of dyadic information transfer.
Since information transfer sets the initial conditions for diffusion, I expect that it may have profound effects on diffusion rates. Small variations early in the diffusion process greatly alter diffusion outcomes, such as leading certain innovations to prevail (David, 1991). Minute differences in the initial distribution of individual adoption preferences have been found to have large effects on the extent of innovation diffusion (Granovetter, 1978). Moreover, differences in the social network configurations can exert major influence on the timing and extent of innovation diffusion. Abrahamson and Rosenkopf (1997) suggest a theory that the social structure through which potential adopters find information regarding innovations affects diffusion patterns and showed through computer simulations that information transfer prior to the adoption was an important factor to consider for diffusion studies. Following research might examine how the dyadic transfer of information culminates in decisions to adopt.

The two major limitations of this study are brought about by shortcomings of the data. First, the data examined here does not contain demographic information for the organizational members, such as tenure, gender, and organizational role. Organizational role in particular would be useful to explore. For instance, within projects, informing other individuals about the project may have been tied to a formal role assignment. Even though the individual’s demographics may influence the transfer, the research on informal networks suggest that even when two individuals share the same organizational role, their social relationships often have divergent patterns (Burt, 1992). Next, it is possible that the individuals could have received information about the projects outside email, such as phone conversations or in person. In general, the literature suggests that the email networks closely parallel other social networks (Kleinbaum et al., forthcoming; Marmaros and
Sacerdote, 2006). Although earlier research suggests that these issues may be trivial, it should be empirically confirmed for this theory. Specifically, this poses a concern for future research; does the medium of transfer, such as email or phone, influence adoption and diffusion patterns? Future studies may incorporate interviews with recipients to identify whether the medium affects the diffusion process.

The second limitation is that although I account for three of the four network mechanisms for diffusion in this study, I do not examine the role of structural equivalence. Diffusion by structural equivalence, where information spreads across actors that share similar network positions but are not themselves connected, is a powerful mechanism for understanding diffusion (Burt, 1987; Galaskiewicz and Burt, 1991; Abrahamson and Fombrun, 1994; Lorraine and White, 1971). Structurally equivalent actors observe similar others and commonly imitate each other (Burt, 1987; DiMaggio and Powell, 1983). The information transferred between structurally equivalent actors does not occur via behavioral communication but rather through symbolic information sharing (Galaskiewicz and Burt, 1991). Give this theory’s specific grounding in the communication channels of discrete information, the method used here did not extend to included the study of symbolic information. The examination of structural equivalence mechanisms therefore was beyond the scope of this paper but merits study.

Last, there is a question about the generalizabilty of this study. The study examines multiple projects, but for a single organization. It would be advisable to replicate the findings in other organizations. In addition, the information that I examined had unique characteristics. I investigated discrete project information that provided organizational members with pertinent facts. It is uncertain if this study’s findings would hold for all types
of information. Nevertheless, while the findings of discrete facts may not be replicable for complex information, transmission of this simple type of information is neither uncommon nor trivial.
APPENDIX A:

The sample is based on egocentric data, which over time is similar to a snowball sample. The seed sample consisted of 129 individuals, from which a snowball sample of email recipients and senders was created. The data were normalized to identify unique senders and recipients by removing redundant emails (one individual may have had several email accounts throughout their tenure at Enron), group emails, and distribution lists. As individuals communicate with more individuals over time and the individuals that they communicate with also communicate more, the sample grows. This results in the eventual observed network of 14,272 employees, which was 65% of Enron’s 22,000 total population for 2001 (see Table 3.a) (Standard and Poor’s Compstat 2009). Even though only Enron employee email addresses are used in the analysis, the EEC includes emails from those outside Enron. The nature of the data results in a limited sample in the initial years. This is a common issue for panel data (although usually in the reverse, with larger populations that dwindle in subsequent periods) and can be addressed with statistical techniques discussed later in this paper.

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5Email 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.”

6Individuals outside of Enron are included in the analysis to calculate aggregate network measures for Enron employees because having relationships outside the organization may change the effects of the relationships with individuals from within the company. For example, individuals with many ties outside the organization may receive different or less information than those with many ties within the organization and therefore may be less likely to participate in either type of innovation.
REFERENCES


Jackson, M. O., & Yariv, L. (2010). Diffusion, strategic interaction, and social structure. In J. Benhabib, M. O. Jackson, & A. Bisin (Eds.), *Handbook of Social Economics*. San Diego, Ca: Elsevier.


Fig. 1. Time-series by project showing the transmission rates of information. The percent is the fraction all possible information recipients who receive project-specific transmissions.
### TABLES

**Table 1**

Descriptive Statistics and Correlations for Variables in Individual-level Models (45,546 Observations and 9,658 Receivers)

<table>
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<tr>
<th>Variable</th>
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<th>(2)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<td>0.175</td>
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<td></td>
<td></td>
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* *p < .10; **p < .05; ***p < .01*
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<td>(0.103)</td>
<td>(0.213)</td>
<td>(0.425)</td>
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<td>Insig2u</td>
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* p < .10; ** p < .05; *** p < .01
### Table 3

Descriptive Statistics and Correlations for Variables in Dyad-level Models  
(87,649 Observations of 22,104 Dyads)

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(+ Variable was transformed to the square root.)
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Project-Year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Pseudo R-sq</td>
<td>0.828</td>
<td>0.925</td>
<td>0.978</td>
<td>0.984</td>
<td>0.986</td>
<td>0.986</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-7,504.536</td>
<td>-2,746.709</td>
<td>-950.855</td>
<td>-584.135</td>
<td>-525.225</td>
<td>-517.194</td>
</tr>
</tbody>
</table>

* p < .10; ** p ≤ .05; *** p ≤ .01

(+ Variable was transformed to the square root.)