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HOW ORGANIZATIONAL TURBULENCE SHAPES THE BROKER VISION ADVANTAGE

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DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
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ABSTRACT OF DISSERTATION

HOW ORGANIZATIONAL TURBULENCE SHAPES THE BROKER VISION ADVANTAGE

Research on social networks has established that those who bridge the gaps between dense social groups (i.e. structural holes) are granted a "vision advantage" compared to those who are embedded in dense groups. A common explanation for the advantage is that bridging a structural hole provides the broker with access to diverse information. What is less clear is how this process performs when the organizational context is turbulent. I propose that in a turbulent organizational context, when the organization is experiencing dramatic changes, employees benefit less from building a repertoire of diverse information and instead benefit more from adopting socially distant information. Information discussed by members of the organization which are several steps away from an employee would be more valuable in a turbulent context. Socially distant information would be more rare as people become rigid in response to threat, and it would be more relevant as local information becomes obsolete.

To explore this idea, I study the case of two large organizations undergoing a merger integration. The members of the higher-status, acquiring organization experience relative stability compared to members of the target firm, who experience a great deal more uncertainty. The higher-status firm dominated the merger, the top management of the target firm was replaced, supervisory structures are changed, employees are forced to develop new routines, learn new technologies, and had to uproot their social support networks and move across the country. This case provides an opportunity to examine how two information flow mechanisms, which mediate the relationship between broker positions and individual career benefits, are altered in the presence of organizational turbulence.

I measure information variance and the adoption of socially distant information of 612 organizational members by fitting a topic model on a dataset of email content covering a 14-month period immediately following the merger of two large consumer product firms. I test my hypotheses using a latent difference score model to test the impacts of increases in information variance, constraint, and adoption of socially distant information on increases in employee salary. I find that organizational turbulence alters the ways in which information flows provides benefits. Within turbulent contexts the pathways between access to diverse information and improved career outcomes are destroyed. Instead adopting socially distant information and information associated with power and status provides more benefits to the individual than incrementally improving a repertoire of diverse information. This study contributes to research on M&As, organizational change, and social network theory by expanding our understanding of the impact of organizational turbulence on the information mechanisms driving advantage in open networks.

KEYWORDS: Social Network Analysis, Email Data,
Mergers and Acquisitions,
Career Outcomes, Big Data

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DEDICATION

To best family a doctoral student could have:
my wife Teresa and my sons, Finn and Felix.

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CHAPTER ONE: INTRODUCTION

Transferring a bit of information between two people is cheap and easy, especially with modern communication technology. In dense social network groups, where everyone in the group communicates with every other member, it doesn't take long before a new bit of information (e.g. product ideas, news of someone's promotion, new terminology for an obscure concept, etc.) is shared by nearly every member of the group. It's less likely for that information to move between groups, and thus each group has its own distinct pool of information. Those who bridge structural holes (the gaps between individuals, typically in different groups) are referred to as brokers. Brokers gain a 'vision advantage' from the exposure to the diversity of information, ideas, and perspectives of the groups they bridge. As a result brokers are seen as more creative and innovative (Brass, 1995; Jen, 2014), they control the flows of information between groups (Brass, 1984; Rodan, 2010; Rodan & Galunic, 2004), and they are able to see opportunities earlier than those who are embedded within groups (Arenius & De Clercq, 2005; Burt, 2004, 2005; Ozgen & Baron, 2007). They are seeded with new ideas, they recombine knowledge and information from multiple groups, and they have better control over how these new ideas are seen and understood.

This study builds on previous research on the advantages provided by knowledge heterogeneity or diverse information (Argote & Miron-Spektor, 2011; Borgatti & Cross, 2003; Rodan, 2010; Rodan & Galunic, 2004; Szulanski, 1996; Tortoriello & Krackhardt, 2010; Tortoriello, Mcevily, & Krackhardt, 2014) and extends it by directly observing and measuring information flows within a network of email communications. This follows the work of Aral and Van Alstyne (2011) by developing a "modern weak tie theory" (Aral, 2016) which digs into the different antecedents and consequences of a variety of different information flows and how those flows provide benefits to individuals, groups, and organizations. For instance, different network structures provide better access to diverse information in different situations. Aral and van Alstyne (2011) found that strong ties, with a high bandwidth of information, provide better access to diverse information when the information in the employee's immediate neighborhood is changing rapidly. This study intends to extend network theory by identifying which features of information flows are important to employees when the organizational context is turbulent. By directly observing information flows in the digital traces of communication behavior, I hope to provide a more precise understanding of how networks provide access to information and how that information can lead to individual or group advantages.

This study will builds on previous research on knowledge and information flows in organizations (Aral & Van Alstyne, 2011; Borgatti & Cross, 2003; Reagans & McEvily, 2003; Tortoriello, Reagans, & McEvily, 2012). Most research in the area has focused on stable organizational contexts and have inferred information flows. I directly observe information exchanged between employees by extracting topics from the organization's email corpus using a probabilistic topic model (Blei, 2012; Blei, Ng, Jordan, & Lafferty, 2003). I extend research on social networks and information flows by studying the advantageous career benefits of two different conceptualizations of information flows, information variance and socially distant information, and how the beneficial effects of information change when the organizational context is either turbulent or stable.

This research was conducted during a dynamic post-merger integration process. Organizational mergers and acquisitions (M&As) are critical strategic moves designed to increase organizational competitiveness by decreasing costs, consolidating or extending markets, creating synergy, or accessing new knowledge, products, or technology (Cartwright, 2012). M&As are still very common, with $4-5 trillion dollars' worth of deal value occurring in both 2015 and 2016[1]. However, this popularity obscures the human toll on the organizational members who are asked to endure the synthesis of two previously independent organizations. M&As can be immensely disruptive to employees' existing work, as well as their interpersonal relationships, both of which can affect their career outcomes dramatically (Amiot, Terry, Jimmieson, & Callan, 2006; Cartwright & Cooper, 1993; Cartwright & Schoenberg, 2006; van Dick, Ullrich, & Tissington, 2006). The merger can completely change how work is conducted in the organization, including rewiring and transforming the interpersonal network of flows for critical knowledge and information.

In the case presented in this research two large organizations from the same industry are undergoing an integration. For the members of the acquiring, higher-status organization there are relatively few changes. For the members of the target organization the situation is very different: they were expected to move across the country, their upper management was either removed or completely rearranged, they are expected to use new technologies and new systems, and they have to adapt to new supervision procedures. This turbulence produces a great deal of uncertainty for the members of the target organization, while the dominance of the acquirer created relative

1 CNBC, accessed June 23, 2017. http://www.cnbc.com/2017/06/21/outbound-merger-and-acquisition-deals-by-japanese-firms-are-growing-jpmorgan.html

stability for its members. This case provides an opportunity to compare how network position provides different kinds of access to information flows, how the benefits of those information flows change depending on the turbulence of the organizational context.

While there may be many different ways of conceptualizing information flows in organizational communication networks, I primarily consider two different forms of information flows: changes in information variance and adoption of socially distant information. The concept of nonredundant information used by social network researchers often conflates the idea of adopting information that is rare in the local network (Granovetter, 1973; Rosenkopf & Nerkar, 2001), and the idea of synthesizing multiple different bits of information into novel combinations (Burt, 2004; Fleming, Mingo, & Chen, 2007). Here information variance is understood to be the use or exposure to multiple organizational topics in novel combinations (e.g. the use of topics related to logistics and planning along with topics related to IT or sales) (Brass, 1995; Fleming & Sorenson, 2004). The broker's conversations are a blend of diverse topics. I expect that information variance will have a larger impact in a stable organizational context and less of an impact in the turbulent organizational context. In the turbulent context it's unclear which information is important; information is quickly becoming obsolete, and because most people are becoming rigid from threat relative value socially distant information is increased. For those in the turbulent context, I propose that adopting socially distant information will be more important than information variance for individual advantage (Baum, Rowley, Shipilov, & Chuang, 2005; Rosenkopf & Nerkar, 2001).

The concept of information variance is orthogonal to socially distant information. It is possible for an individual to explore the organization and adopt new, previously distant information, without creating new combinations with the information they found. It is also possible for the individual to create new combinations of disparate bits of information which are rarely used together just by searching the local network and never exploring more distant information in the organization. I examine how each of these aspects information flows grants an advantage to an employee dependent on the degree of organizational turbulence. I expect the target firm would be more turbulent than the acquirer. The emphasis for members of the turbulent context would be on seeking out new information in use by people distant from their personal network. In a turbulent context individuals benefit more from finding the *right* information rather than incrementally developing a varied repertoire information.

This study elaborates structural hole theory by showing how organizational turbulence affects the mediating information flow mechanism that provides a vision advantage to brokers. While I expect structural holes will facilitate access to both information variance and socially distant information in both contexts, the benefits of these information flows will differ depending on organizational turbulence. Further, consistent with the learning hypothesis of brokerage (Burt, 2008; Kleinbaum, 2012; Perry-Smith, 2014), I expect that it is the *adoption* of new information into one's cognitive schema which is important, not just access or exposure to the information. By adopting and using new patterns of language the employee has also altered the way they think. The use of new modes of expression is an indication that the broker has developed skills of translation, which indicates an expansion of cognitive abilities.

In this study I directly examine the digital traces of information flows in an organizational network. I measure the mediation processes of different forms of information flows which link brokerage positions to positive individual outcomes. I then use the case of an organizational merger between two equally-sized organizations in the same industry, but with wide differences in industry status, as an opportunity to compare the relative changes in the benefits of information flows. I expect that information variance will have a stronger effect on individual increases in salary for employees in the stable organizational context. And socially distant information will have a stronger effect on individual increases in salary for employees in the turbulent organizational context. This work extends structural hole theory by examining the different mediating information flow mechanisms which provide a vision advantage. It contributes to research on mergers and acquisitions and organizational change by explaining another way in which stress and turbulence affects the individual employees during the merger process.

CHAPTER TWO: LITERATURE REVIEW AND THEORY

Complex organizations are composed of multiple dense groups where people all know and communicate with one another frequently, and between the groups there are gaps with few people bridging in between. In tightly knit groups with dense ties, new information quickly reaches every member of the group. A bit of information (e.g. a perspective on the day's events, or new idea for a product) is likely to circulate around the group many times until everyone is familiar with the information. People with ties to people in other groups are brokers for new information. They listen for novel information from different groups and broker the flow of information between groups. This network form, where multiple dense groups are connected by a peppering of bridging ties, is often referred to as a small-world network (Fleming & Marx, 2006; Watts & Strogatz, 1998) or sometimes a 'caveman' network, since it mimics the idea of different caves of people with the occasional explorer who ventures between caves. The brokers control the flow of diverse ideas, synthesize the new and different ideas into innovations, and strategically introduce the ideas to other groups. This gives the broker an advantage over other members of the organizational network who are otherwise exposed only to redundant information.

The ties within groups tend to be strong, close ties which provide trust and support among members of the group (Coleman, 1988), while the ties which bridge between groups tend to be weaker, infrequent relationships. In his landmark paper, Mark Granovetter (1973) described the important role of weak ties in connecting groups and providing access to novel information. When a member of a dense group receives information from a strong tie, because strong ties tend to be embedded within dense groups, it's likely the information is redundant to what the person already knows. The person had heard it before from another member of the group. But weak ties tend to bridge groups or reach out to distant parts of the network where people have different perspectives and different information. Ronald Burt extended the idea and introduced the structural hole, an absence of a tie (Burt, 1992). Rather than focusing on how distant parts of the network are connected (Brass, 1984), Burt focuses on the local structure of the person's network (Burt, 2007). A broker is connected to many people who themselves are not connected to each other. The result is that each alter would be more likely to have unique perspectives and information compared to the brokers other alters, and the broker would have access to a wealth of nonredundant information.

Nonredundant information provides the broker with a "vision advantage" - the ability to see opportunities and leverage an improved perspective to produce good ideas. Burt showed that individuals who bridge structural holes tend to be promoted faster, are more likely to get positive performance reviews, generate better ideas, and have a higher compensation compared to their colleagues who were embedded in dense groups (Burt, 1992, 2001, 2005). In Seibert, Kraimer, and Liden's study (2001) of an alumni network, brokerage positions provided access to information and resources which led to improved career success, higher salaries and improved career satisfaction. In a study of networks and personality at a technology firm, brokerage positions were found to improve supervisor-rated performance (Mehra, Kilduff, & Brass, 2001). At the inter-organizational level, Zaheer and Bell (2005) find that structural holes was predictive of firm performance. In each of these studies the theorized mechanism which provides a network position with advantage is some form of information flow, either the control of information, improvements to innovation and creativity through diverse information, or early recognition of opportunities.

Interpersonal communications remain an influential source of information. In this research I study the ways in which the structure of direct communication with other members of the organization impacts flows of information. To do this I deconstruct the vision advantage into two different concepts, information variance and socially distant information. These two aspects of information flows separately provide benefits to individual advantage.

Deconstructing the Vision Advantage

There has been a great deal of success in using structural hole theory to empirically predict performance, however these models have "far outstripped our understanding of the way information flow in networks is responsible for network effects" and the "substance of advantage, information, is almost never observed" (Burt, 2008: 953). In this study I have the opportunity to directly examine the substance of advantage, flows of information in the organization, and to develop and test precise concepts of information flows.

Concepts of nonredundant are a mix of different concepts of information flows. It is frequently stated that nonredundant information is discovered from distant sources. Granovetter explained that weak ties are "the channels through which ideas, influences, or information socially distant from ego may reach him" (Granovetter, 1973:1370). But research has shown that nonredundant information can come from sources close to the individual and not necessarily from socially distant sources (Fleming & Sorenson, 2004). Aral and van Alstyne showed that in some situations nonredundant information can come from close, high-bandwidth ties and not just weak or bridging ties (Aral & Van Alstyne, 2011). And for the transfer of complex information it may be necessary to have multiple redundant sources of the same information (Centola, 2010; Hansen, 1999). Not all nonredundant information comes from socially distant sources. I intend to separate the *information variance*, the recombination of multiple different topics, from the adoption of socially distant information. *Socially distant information* is information that is commonly shared among people who are many steps away in the social communication network. This is a temporal concept wherein the ego adopts information by the second time point that was discussed by employees socially distant from the ego at the first time point.

The two concepts of information variance and socially distant information are orthogonal and independent to each other. Both information flow concepts can be mapped on a continuum between exploitation and exploration (March, 1991). While both concepts of information flow involve some element of exploration, the adoption of socially distant information should involve much higher amount of exploration than increases in information variance. The increasing information variance can be the result of exploration, but to a lesser degree than socially distant information. Increasing information variance, as discussed previously, *can* be achieved through local network contacts, and thus, compared to adopting socially distant information, is more related to exploiting existing social resources rather than exploring the network. Ambidextrous employees who integrate of both socially distant information and information variance should be rare (Prieto, Revilla, & Rodriguez, 2007; Rogan & Mors, 2014). Nonlocal search is costly and risky and the process would consume time and resources that aren't available to develop a diverse repertoire of information. I expect it would be common that while an employee may integrate socially distant information, the employee would have a lower variance in the information that they use. The employee would find new, distant information which is radically valuable to her, but she would remain focused in one particular topic-area rather than adopting multiple information topics from multiple areas, at least in the short term. Each behavior has a different set of skills associated with them, and, as I argue later, are differentially beneficial depending on the organizational situation.

Directly separating information variance and socially distant information in empirical work requires examining the content of ideas that are exchanged within the social relationships. As Burt (2005: 61) points out, "I have no tools that provide novel insights into idea content (relative to the network analysis tools that can pry open the link between ideas and social structure)." Yet the payoffs of doing so are very high. Separating the two information use behaviors can help advance "modern weak tie theory" (Aral, 2016), the emerging research agenda which seeks to understand the micro-mechanisms behind the relationships between tie strength and achievement. One of the pillars of this movement is the study of how networks and information co-evolve. By looking at the relationship between an individual's network position, their information content and the individual's career success we can better understand how network positions matter and under what conditions brokerage matters for the individuals' career outcomes.

Brokerage as a Teacher

In this study I examine information variance and socially distant information *adopted into use* by each employee and not simply exposure to the information. Concretely this would be indicated by the individual authoring emails consistent with the different topics of communication within the organization. Cognitive processes are plastic and frequently change based on behavior and interactions (Bandura, Adams, & Beyer, 1977), and when an individual adopts information it implies that the individual is engaging with the ideas. In some small way, the cognitive structure of the individual has changed. Constantly interacting with different groups, different ways of seeing the world, and the requirement of constantly translating complex ideas forces the broker to cognitively develop skills of analogizing. Evidence from childhood and language researchers support this idea. There is some evidence that bilingual children tend to outperform monolingual children in executive function tasks such as ignoring irrelevant information, task switching, and resolving conflict (Kroll & Bialystok, 2013). The same cognitive systems in the brain "involved in switching between languages are the same as those generally used for selective attention to non-verbal executive function tasks" (Kroll & Bialystok, 2013). Thus for bilingual children important cognitive systems are constantly being exercised and developed. In organizational networks, each subgroup possesses its own unique local languages. Burt (2008: 963) suggests a "teaching hypothesis of brokerage" by suggesting that:

> … brokerage is not valuable for the information it provides so much as it is valuable as a forcing function for the cognitive and emotional skills required to communicate across divergent views. It is the cognitive and emotional skills produced as a by-product of bridging structural holes that are the proximate source of competitive advantage.

The cognitive and emotional skills give the individual broker improved "cosmopolitan" skills to reach out between social worlds and transfer ideas between them (Reagans &

Zuckerman, 2008). Reagans and McEvily (2003) found that those who had a broader network range found it easier to adopt new ideas than those whose range was limited. Using a diverse set of ideas is also akin to having a rich and diverse cognitive toolkit available to call upon when it could be strategically useful (DiMaggio, 1997; Rindova, Dalpiaz, & Ravasi, 2011). Different groups have different perspectives, protocols, and frames through which they understand the world. Successful transfer of good ideas relies on the ability to use different framing techniques to emphasize the importance of a concept with different contexts (Cornelissen & Werner, 2014; Perry-Smith, 2014). Ideas need to be framed and transformed in such a way that they are more likely to transfer from one group to another and stick in the minds of the recipients (Szulanski, 1996; Tortoriello & Krackhardt, 2010). Those who hold these cosmopolitan translator positions are valuable to the organization, and the people filling this role often benefit.

If an employee authors an email message and sends information within a topic, then I consider the topic as having been *adopted* into use by the employee. In this study I consider the variance and social distance of the information that is authored by the employee rather than just the information the employee is exposed to. By writing within the same language patterns of others who converse within a topic it is implied that the thought processes of the employee have changed. Thus I propose that the information variance and socially distant information adopted by the employee will be preceded by an advantageous network position rich in structural holes, and succeeded by positive increases in that employee's salary.

Information Variance

There are many ways in which using a large variance of information could provide an advantage to the employee. Rodan (Rodan, 2010) identified five potential mechanisms from the existing literature on structural holes which explain the advantage granted to brokers. All but one of them[2] involved some form of "knowledge heterogeneity". Being exposed to a varied set of information allows a broker to see opportunities sooner than non-brokers (Arenius & De Clercq, 2005; Ozgen & Baron, 2007). Having access to varied information allows the broker to arbitrage information from one dense group to another group and extract the benefits of providing the information (Brass, 1984). Another advantage stems from keeping potential competitors divided from one another (Reagans & Zuckerman, 2008). And lastly knowledge heterogeneity improves

2 Autonomy, provided by a bridging position, allows the broker to act and speak as necessary without social constraints.

impact on creativity and innovativeness (Brass, 1995; Burt, 2004, 2005; Perry-Smith, 2014). What this study, and the research it is based on, demonstrates is access to and use of varied information is a key mechanism linking broker positions in social networks to individual advantage.

The recombination of ideas into new concepts can provide considerable advantage to employees and managers within an organization. The variance of information and perspectives that brokers are exposed to induces them to be more creative (Jen, 2014; Perry-Smith & Shalley, 2003). Being exposed to a variance of perspectives and ideas is a way of using the wisdom of the crowd where a collection of attempts to solve a problem can converge on the optimal solution (Page, 2007). A broker will provide better ideas and solutions to a problem because they have experienced multiple views of the problem. In Burt's study connecting brokerage to idea generation (Burt, 2004), the employees were asked to provide ideas to improve the company. Those who had many structural holes in their personal network were more likely to synthesize useful ideas and gain a career advantage. The ideas offered by brokers focused on unique transformations which would provide a competitive advantage, and non-brokers instead focused on transactional, task-based ideas which emphasized consistency and uniformity and allow them to more easily accomplish tasks. I expect that increasing information variance, expressed through the variance of topics combined in the communications authored by an individual, will mediate the relationship between the network position an individual occupies and career success, expressed as salary growth. Thus I present this hypothesis:

> *H1a. Increases in adopted information variance will mediate the relationship between increases in structural holes and increases in salary.*

Adopting Socially Distant Information

While the local network maintains some opportunities for recombination, individuals and firms often have to search beyond their local network to find new information and solutions to problems. In large, complex organizations finding useful information can be difficult, and those who can find the right information in the organization and bring it into use will gain an advantage. The processes of social network formation, and formal processes of the organization, are likely to sort people according to their interests, background, and expertise (Feld, 1981; McPherson, Smith-Lovin, & Cook, 2001). As a result distance between two people in a social network can provide a clue to the potential cognitive distance of the information and perspectives they discuss with others (Watts, Dodds, & Newman, 2002). In order to infuse new, nonredundant ideas into her department, a manager might benefit most from searching somewhere distant in the organization. By communicating and socializing with socially distant members of the organization she would learn more about the different processes, problems, and routines in use throughout the organization. She would see her own role and her department's role in the organization differently, and she would better understand which new ideas are feasible and important and which ideas should be shelved (Arenius & De Clercq, 2005). Non-local search is contrasted by a more local search in which she only approaches others in her own department, or even adjacent departments in the workflow. Although it is possible with some effort to find locally nonredundant information, socially distant information is less likely to be redundant to what she already knows.

In the strategic management literature, socially distant information is acquired through nonlocal search. Nonlocal search is more costly and comes at greater risk, but it has the potential for radically-beneficial payoffs (Katila & Ahuja, 2002; Laursen, 2012; Rosenkopf & Nerkar, 2001). Firms understand the potential returns from crossing organizational and technological boundaries, but they understand the difficulties in communicating across knowledge boundaries. Two firms in different knowledge spaces have different languages, goals, timelines, and perspectives dictated by different industry demands and technological needs. Also many firms believe there are still benefits in searching the local knowledge space to find elements which have not yet been combined into new innovations (Fleming & Sorenson, 2004; Laursen, 2012).

Employees within a firm are likely to have an analogous experience. There is a greater difficulty and risk in nonlocal search for socially distant information, and so they often search for nonredundant information through their local contacts, or by focusing their attention to the information that is discussed between pairs of nearby alters (Katila & Ahuja, 2002). Nonlocal search is a "conscious effort to move away from current organizational routines and knowledge base" (2002: 1184) and to find new knowledge which could better provide an advantage. Katila and Ahuja (2002) found that the wider the scope of knowledge search, the more new product ideas that a firm produced. Within organizational research teams, brokering new ideas from outside of a social group and bringing them into use is a key aspect of catalyzing team innovation (Tortoriello et al., 2014). Socially distant information is more likely to be useful for recombination since the information is rare in the local network.

Thus I believe that the adoption of socially distant information, regardless of the changes in information variance, will provide an advantage and mediate the relationship between network position and salary growth:

H1b. Adopting socially distant information will mediate the relationship between increases in structural holes and increases in salary.

Information Flows in Turbulent Organizational Contexts

The differences in turbulence between the two organizational contexts in this study are induced by organizational restructuring following a merger integration. Mergers and acquisitions are undertaken to accomplish a wide variety of goals, including infusing a stagnating firm with new life and diversity, allowing a struggling smaller firm to reach new markets, adding to the firm's capabilities, or helping them achieve their growth targets. Regardless of the reasons underlying mergers, they are risky endeavors and frequently fail to meet the initial goals set out by their architects (Cartwright & Schoenberg, 2006). Psychological stress, lack of cultural fit, or lack of compatibility among employees are commonly cited causes of the failures (Levinson, 1970). Mergers are a stressful and turbulent experience for employees (Amiot, Terry, & Callan, 2007; Cartwright, 2012; Oreg, Vakola, & Armenakis, 2011), and they may have difficulty adjusting to the changes (Dane, 2010; Gilbert, 2005; Leroy & Ramanantsoa, 1997). Organizations need their employees to be adaptable and engaged throughout the turbulent and stressful organizational changes that occur. When individuals feel as though their future is under threat they could seize up and resist the changes (Fugate, Prussia, & Kinicki, 2012; Staw, Sandelands, & Dutton, 1981), while those who reach out and adopt new information are likely to benefit (Fleming et al., 2007).

Members of both organizations would experience some level of threat from the merger restructuring, but the feeling of uncertainty and threat should be much higher for members of the target organization (Giessner, Viki, Otten, Terry, & Täuber, 2006; Paruchuri, Nerkar, & Hambrick, 2006; Terry & O'Brien, 2001). When two organizations begin a merger integration the status difference of the two organizations can impact the behavior and outcomes of the employees in the integrated firm. Even when both organizations have similar size and market presence, these "mergers of equals" rarely proceed as though both organizations are equal (Cowen, 2012; Fried, Tiegs, Naughton, & Ashforth, 1996). The routines, standards of operation, perspectives, and ideas of the higher status organization tend to dominate while the elements of the lower status organization tend to be replaced (Kaplan, 2008). Members of the lower status organization still have to face new policies, technologies, reporting relationships, and work locations (Buono & Bowditch, 2003). The high-status organization “is much more likely to define the character of the merged company” and a consequence members of the high-status organization are more likely to “feel a sense of continuity of their premerger identity in the postmerger identity and maintain their premerger position” (Paruchuri et al., 2006: 340). As a consequence of the changes the low-status organization will feel much more turbulent and uncertain to its members, while the members of the high-status organization will feel relatively stable.

While I expect both information variance and socially distant information to provide career advantages regardless of situation, the strength of the effects will be impacted by the stability of the organizational context. Organizational turbulence increases feelings of threat and uncertainty (Jackson & Dutton, 1988), which elicits an emotional response from each individual (Amiot et al., 2006). Two such responses are for the individual to withdraw to protect gains (Fugate et al., 2012; George, Chattopadhyay, Sitkin, & Barden, 2006; Staw et al., 1981), or they take risks for the potential of a large payoff (Baum et al., 2005; Kahneman & Tversky, 1979; Tversky & Kahneman, 1977). In stable organizational contexts incremental changes through local search are preferable since they are less costly and less risky. Employees can find nonredundant information in their local network and still gain enough of an advantage (Aral & Van Alstyne, 2011; Rosenkopf & Almeida, 2003). In turbulent organizational contexts the risks of reaching out to distant parts of the network may be justified. For an employee in the turbulent context, the information in the local network may no longer be relevant or useful (Aral & Van Alstyne, 2011; Fleming & Sorenson, 2004; S. B. Srivastava, 2015). In order to find valuable information the employee will have to look further than their local network (Baum et al., 2005; Katila & Ahuja, 2002; Laursen, 2012). Also, because most employees in the turbulent context are likely to react by withdrawing (Fugate et al., 2012; Romero, Uzzi, & Kleinberg, 2016; Staw et al., 1981), those who take risks will find socially distant information to be more valuable since it will be more rare. As a result of the effects of the potential obsolescence of information and the local rarity of useful nonredundant information, I expect organizational turbulence would increase the effectiveness of socially distant information to provide career advantages

Threat-induced Withdrawal

While I expect that socially distant information is more valuable in the turbulent context, I expect that organizational members in the turbulent context are actually less likely to adopt socially distant information than those in the stable context. When experiencing threat, the employee experiences stress and anxiety, and then they fixate on a narrow range of behaviors and information (Staw et al., 1981). Instead of seeking out risk, an employee perceiving threat would narrow their focus to their most well-learned and dominant routines and behaviors. It is less likely that the employee would explore new information or synthesize anything new. At the same time, people weigh potential losses greater than potential gains (Pettit, Yong, & Spataro, 2010) and would focus on the potential loss of security, identity, or status with the upcoming merger (Sung et al., 2017). The individual would be risk averse and they would cope by attempting to protect their existing position and the gains they've accumulated.

Threat narrows the breadth of information search behavior and focuses it towards more well-rehearsed routines of communication. Andersen and Nichols (2007) found the breadth of information search reduced feelings of threat, while the time spent searching for information increased feelings of threat. This is similar to what Gilbert (2005) found at an organizational level; organizations under threat were able to free up resources, but they increasingly relied on existing strategies and reduced experimentation. Researchers have also found individual creativity decreases when employees are under threat (Long, 2013; Zhou, Shin, & Cannella, 2008). Long (2013) found that threatening situations had a strong negative effect on perceptions of creativity. Zhou, Shin, and Cannella (2008) conducted research on employees who had experienced a merger in the previous two years and found that those who perceived threat from the merger experienced a drop in creativity compared to those who perceived opportunity from the merger. Overall the effect of threat on reaching out and searching for new ideas and new connections is consistent with threat-rigidity.

In addition to being less intellectually curious and creative, the personal networks of those under threat also close up (Romero et al., 2016). During the integration of two firms, employees and managers are expected to form new relationships with members of the other firm. Even after the members of the acquired firm are moved across the country to a new location, they are still more likely to form ties with members of their legacy firm rather than form new ties with those in the new firm (Briscoe & Tsai, 2011). They also found that employees with a closed network in their legacy firm were much less likely to form ties with the new firm, and those with open networks found it easier. In a longitudinal study of a global IT department, the researchers found that employees expanded their networks when they received positive feedback and retracted their network and increased activity with their strongest ties when they received negative feedback (Parker, Halgin, & Borgatti, 2016). In a study of the instant messaging communication patterns among personnel at a hedge fund, researchers found that during periods of uncertainty, the personnel reduced their communication with members outside their group (Romero et al., 2016). The researchers demarcated different teams in the organization based on the stocks they actively tracked. External shocks, such as the dramatic rise or fall of stock prices, forced the network to "turtle-up." The fraction of boundary crossing ties dropped, and the amount of closure increased, regardless if the shock was a negative or positive change. The common response to organizational turbulence is to withdraw; which can be reflected both in the closure of personal networks and in the reduced use and recombination of new information.

Taking Risks for Information

Emotional reactions to situations can be very strong, and while the general response to threat is withdrawal, it is likely this response is not the most advantageous strategy for the situation. Those who are well-positioned or successful in overcoming the feelings of threat can reach out and adopt new ideas and will experience an advantage over those who withdraw. A minority of the employees in the turbulent context are likely to believe the risks involved from adopting socially distant information are justified (Barberis, 2013; George et al., 2006). Different framing narratives, individual perspectives, and individual differences will induce a diversity of responses to the merger. While withdrawal is the typical response in the turbulent organizational context, many will choose to take the risks and pay the costs associated with adopting socially distant information.

In the turbulent context information churn is greater than the information in the stable context. Information in a turbulent context will quickly become obsolete, and thus local search quickly loses its benefit (Aral & Van Alstyne, 2011; Fleming & Sorenson, 2004; Rosenkopf & Almeida, 2003; Rosenkopf & Nerkar, 2001). The landscape of information in the turbulent organizational context is changing rapidly. The information available in the local network of the turbulent organization is less likely to be relevant to the organization following the changes and thus socially distant information is more likely to be useful. Because the local information landscape is less valuable, employees would be best served by seeking out information and relationships with socially distant members of the organization (Baum et al., 2005; Rosenkopf & Nerkar, 2001; S. B. Srivastava, 2015). Obsolescence and refresh rates are not necessarily the only reason socially distant information would be more beneficial in a turbulent context. Rosenkopf and Nerker (2001) found that even while controlling for obsolescence, non-local search provided more impact than local search. Socially distant information should be valuable regardless of the contextual stability, but it should be more valuable when the local context is turbulent.

While the research on threat-rigidity suggests that in the presence of turbulence and threat, the organizational members will withdraw, other studies have found that threat induces risk-seeking behavior (Baum et al., 2005; S. Srivastava, 2015; Tversky & Kahneman, 1981, 1992). Srivastava (2015) found that during an ambiguous organizational change, people reduced communication with their formal ties and increased communication with their informal contacts. The author theorizes that during ambiguous events, employees begin gathering information, and because close formal ties will have very similar information, they prefer to activate informal or more distant ties, which will have greater informational value. Research on bank relationships through underwriting found that firms with performance consistent with their aspirations were less likely to take a risk and form relationships with distant firms (Baum et al., 2005). Significant threat, conceptualized as underperformance, was an indication that a firm would take a risk and search a new domain in hopes of a payoff. These studies tend to suggest that risk-seeking behaviors are still expected under conditions of threat and turbulence.

The net effect of threat-rigidity behaviors is that socially distant information would be relatively more rare in the turbulent context. This would increase the relative value of socially distant information for members in the turbulent context (Barney, 1991; Lavie, 2006). Those who broker socially distant information into the turbulent context would enjoy a greater advantage than if they had brought that socially distant information into a stable context.

Ambidexterity is Costly

It would be rare and difficult to both spend the time and effort exploring distant parts of the social network while simultaneously exploiting local network contacts for nonredundant information (Kane & Alavi, 2007; March, 1991). Socially distant information comes with costs and risks that aren't justified compared to the relative ease of finding information in the local network. In the stable organizational context, there is still a great deal of value in the local network since the local information is more likely to be relevant in the future and provide a reliable benefit. Much of the research establishing the advantage associated with exposure to diverse information has been conducted in stable organizational contexts where there is an advantage to *maintaining* a diverse repertoire of information (Burt, 1992, 2004; Fleming et al.,

2007) and, in a stable context, the benefits of the incremental strategy of searching the local network are likely to outweigh the benefits of spending time and resources to find single bits of valuable information that may be a long distance away:

> *H2a. The effect of increases in information variance on increases in salary will be strongest in the stable organizational context.*

In a turbulent context where the landscape of information is changing quickly and unpredictably, the information in the local network is less likely to be useful to the individual than socially distant information. Furthermore, because most employees in the turbulent organizational context would become rigid and withdraw, those who take the risks would be rewarded proportionally more due the rarity of useful, nonredundant information in the local network. For these reasons I believe that socially distant information will have a greater effect on increases on salary in the turbulent organizational context than in the stable organizational context:

> *H2b. The effect of adopting socially distant information on increases in salary will be strongest in the turbulent organizational context*

CHAPTER THREE: METHODS

Research Setting

I conducted the data collection along with a team of other researchers from the University of Kentucky. The data collection effort was approved by the IRB at the University of Kentucky under protocol number 13-0467-P4J. The data was collected at a large consumer product company immediately following the ratification of a merger of two firms: Luxury, Inc. and Standard, Inc. The companies were rivals in the same consumer product industry. Standard's products ranged from very basic to above average, but had not penetrated the high end of the industry. Luxury had premium products, yet it wanted to expand its market share without sullying its premium brand. In 2013, Luxury acquired Standard in order to cover the entire industry category, reduce costs, and integrate R&D. The pressure to integrate was higher for employees of Standard (the target). Nearly all non-manufacturing professionals of Standard were relocated to Luxury's home city, while Luxury employees remained in place. Standard employees were more likely to be transferred into new departments, while Luxury employees maintained their existing supervisory and job roles. Standard's employees and managers were expected to adapt to Luxury's scoring and performance review system. Standard employees were forced to do most of the adaptation to the newly integrated company, while Luxury employees were tasked with ensuring a smooth transition.

In the month immediately following the ratification of the merger the structure of the communication networks of each company were notably different. Standard's network had a dense, core-periphery structure, while Luxury's network was more siloed, functional, and clustered. Further corroborating the dominance of Luxury's identity over the postmerger organization (Dackert, Jackson, Brenner, & Johansson, 2003; Sung et al., 2017), at the end of the study period, the integrated company had adopted Luxury's clustered, siloed network structure.

The HR department gave us access to their database with appropriate anonymization to secure the privacy of individuals. I used email data collected at two time points. Time 1 (T1) represents emails exchanged over a 30-day period starting ~40 days after the merger was ratified and the individuals in two companies could start communicating with one another, and emails exchanged over a 30-day period one year after (Time 2, T2).

I was asked, along with other members of the research team, to join the firm's Organizational Development Leadership Council, a high-level problem solving and organizational design group which met bi-weekly. We discussed internal HR issues which involved restructuring the postmerger company, improving hiring practices, and developing programs to retain and train leadership talent. This provided the research team with valuable insights into the operations of the company, its goals and leadership, and how operations were managed.

Dependent Variable.

I am interested in examining how information flows impact individual career development. For this study I focus on the changes in salary. Within-individual changes in salary was chosen as the outcome measure since it is a relatively unambiguous marker of achievement. Specifically, I am interested in the magnitude and direction of change in salary that the individual experiences between T1 (June 2013) and T2 (June 2014). This data was provided by the company's HR department. The salary data had a log-normal distribution, so it was transformed using a natural log, to more closely match a normal distribution. The transformed salary was standardized within each year and across the company. Therefore, if an employee received a salary increase during the study period, but had the mean salary of the company in both time points, then the increase in the z-score for that individual's salary would be zero. If the employee received a raise, but it was smaller than the average raise the rest of the company received, then they would likely have a negative change in their standardized salary.

Using Email Data to Construct Networks

In the past decade organizational researchers have increasingly used email data for studying social networks and other phenomena (Aral & Van Alstyne, 2011; Goldberg, Srivastava, Manian, Monroe, & Potts, 2016; Kleinbaum & Stuart, 2014). Email data provides a behavioral reality of the organization compared to the perceptual reality provided by survey data (Quintane & Kleinbaum, 2011). The reality captured through email data is not necessarily more "true" than the perceptual reality captured by the survey data. Rather I argue that this source of data is appropriate for testing ideas related to information flows. I am not interested in the perceptions of information variance or the perception that the information a person uses was once socially distant, instead I'm concerned with the actual behavior of adopting information into use.

Quintane and Kleinbaum (2011) contend that the recall of ties in a survey depends on the ties' salience to the respondent. Also the personal attributes of the ego and their alters can impact how the tie is understood. This means that email data "may provide a more genuine representation of the organizational communication process," although it represents a different "reality" than a network collected through traditional contact recall methodology.

To study the network communications at newly merged Luxury-Standard, I requested a corpus of emails from the company. Interviews with key informants and participant observation in the organization suggested that email was the most preferred method of communication, particularly for interdepartmental communication. Other potential sources of digital communication (e.g., texting and instant messaging) were not actively utilized at Luxury-Standard. In fact, many employees would use email as a form of instant messaging and would exchange multiple single word or single sentence emails in a very short time period.

A third party firm stored the company's emails for the purposes of creating an easy-to-search database that can facilitate legal discovery in the event of a lawsuit. This entity stored all of the company's email traffic, i.e. incoming and outgoing messages, along with all content and attachments. To avoid compromising the security of the data when transmitting it over the Internet, I obtained the data by parcel service on encrypted hard drives. The data comprised nearly 1,500 compressed zip archive files, each containing a single Microsoft PST file that contained 10,000 messages each. I extracted messages from each PST file using the *readpst* program into EML formatted text files. The text files were parsed using custom R code and stored in an intermediate SQLite database with the fields and their values stored as key-value pairs. I stored email addresses in the "from", "to", "cc", and "bcc" fields, the message body, the subject lines, the date and time stamp, and the information necessary to reconstruct conversation threads. I removed other data, such as attachments.

Social Network Data The dyadic information (email addresses attached to each message), were stored in one database table; message level data (such as content and date/time of the message), were stored in another database table; and attachment information (such as the type of attachment, not the actual attachment itself) in a third database table. For privacy reasons, I de-identified the email addresses using a cryptographic algorithm to obfuscate the original email address while maintaining a consistent identity to match across tables and other sources of data (such as performance, demographics, and surveys).

To determine which email addresses were part of the company and which were outsiders, the human resources department provided us a list of company email addresses, and the IT department gave us a list of registered and aliased email addresses from their email system. Some employees, especially in sales, used accounts that were issued by third party email providers (e.g., Gmail, Yahoo) and other employees in the network had multiple addresses. These email addresses were recoded to reflect one primary email address per employee. This was done using an email alias system provided by the company network administrators, in combination with information provided by human resources.

I created social network edgelist data by treating the email addresses in the “from” field as a source and the email addresses in the “to”, “cc”, and “bcc” fields as targets. Each tie represents the number of messages sent from one person to another in a thirty-day period. The network was thus a valued network where the weight of a tie represents the number of messages exchanged within each period. To find the appropriate cutoff for dichotomizing the network, a sensitivity analysis showed that network statistics stabilized after removing ties with fewer than four messages exchanged between them.

The total list of approximately 10,000 unique email addresses (after primary email recoding) were hand coded by the research team as a “person” or “nonperson” (e.g. of the email addresses belonged to various systems, such as accounting and logistics), or as a “meeting room” email address (the scheduling system through Outlook uses emails to transfer data). Emails sent from nonperson addresses (such as ordering systems sending updates, or meeting room messages) were removed first. I also removed policy broadcast emails that didn’t involve direct meaningful interpersonal communication. I focused on emails involving only the sender and no more than two targets; messages with few targets (at most 3) had the best association with perceived closeness measured through surveys (Quintane & Kleinbaum, 2011). Next I filtered out any message that included someone from outside the formal boundaries of the company and not listed in databases provided by the HR or IT departments. This filter also removed all the spam messages.

Constraint. I computed Burt’s (Burt, 1992) constraint measure for each individual employee at each time point using the dichotomized social network data described above. Constraint varies according to the size and density of the network of other employees immediately connected to the employee. Constraint is high if the employee’s direct communication partners also talk a lot to one another. A higher constraint indicates fewer structural holes in the personal network.

Cleaning the Content. Next I needed to process the content of the email messages to create the information flow measures. I cleaned up the content of emails in several steps. First, to avoid duplication of text when individuals reply to the previous messages, I remove reply text using a number of indicators provided by the different email systems that indicated the beginning of a previous message. Second, I removed signature text by detecting the proportion of terms in a region of the text that were proper nouns. Third, I focused on English language content only by comparing the words to an English dictionary.

To protect respondent and organizational identity, I applied a sanitization process which used the Stanford Named Entity Recognizer[3]. This process recoded names, organizations, and locations to a token (e.g. Arthur Dent could be replaced with PERSON_42, and AT&T could be replaced with ORGANIZATION_65). Finally, since only the semantic content was needed, all numbers were removed from the content and replaced with a pound sign (e.g., 867-5309 would become ###-####) which removed anything resembling a phone number, social security number, PIN, or any other secure numeric information. After cleaning and processing, there were approximately 4 million English language messages that could be used for the study. The raw, unsanitized text data was destroyed. The resulting sanitized content data were used to calculate the information measures

Identification of Topics in Emails

I extracted topics from the cleaned and sanitized email data using a probabilistic topic model with Latent Dirichlet Allocation (LDA) (Blei, Carin, & Dunson, 2010). This approach allows me to analyze the contents of emails without human coders, which means that the task of reading the specific emails was given to the machine, and I did not "look over each employee's shoulder" and respected privacy. The use of unsupervised text classification methods such as LDA (Blei et al., 2003) allow organizational researchers to understand the dynamics of conversations (Bail, 2014). For example, one study used LDA to analyze the framing behaviors of political parties in the United States Congress (Tsur, Calacci, & Lazer, 2015). The authors assigned ownership of each topic by the relative frequency with which it appears in public statements made by the offices of each representative. They measured framing behavior by which topics were mixed within the representative's communications. For example, a topic on budget issues could be combined in a public statement with a topic discussing national defense.

DiMaggio, Nag, and Blei (2013) use LDA models to analyze how arts funding was framed over a ten-year period. The authors treat the topics extracted from text using LDA as

3 http://nlp.stanford.edu/software/CRF-NER.shtml

semantic frames. The authors argue that topics extracted using LDA capture two important aspects of language: polysemy and heteroglossia. Polysemy refers to the varied meanings a word may adopt when used in different contexts. Many terms appear highly weighted in many different topics suggesting that those terms' meanings are fluid and change based on the context of the surrounding terms in each topic. Each document can also belong to multiple topics, which captures the heteroglossia, or existence of multiple perspectives or "voices" within a single document. Based on these advantages, topic models are a powerful tool for the analysis of the different meaningful topics being discussed in the organization.

I fit the topic model on the entire corpus across all time points and across all divisions of the merged organization. The LDA attempts to estimate the distribution of topics in each email message. Each email has an associated probability distribution across all of the topics (say 60% chance of topic 5, and 30% chance of topic 2, and a small chance of all other topics combined such that the sum equals 1). Thus each email is a mixture of topics. Each topic is a probability distribution across all terms in the entire corpus. Thus each topic is a mixture of terms. These probabilities can be treated as scalar weights of attachment between a document and a topic, and a topic and term. The number of topics is chosen by the researcher. In this study I fit the LDA with 100, 150, and 200 topics and assess the quality of the topics according to how meaningful the topics appear considering my contextual knowledge of the organization. Tsur et al. (2015) take a similar approach and choose the number of topics for which the topics are both specific and coherent. Too many topics and each topic becomes too specific, and too few and they lack coherence. In this case, the 200 topic fit seemed to have the best trade-off between specificity and coherence. I use the results of the topic models to quantify information variance and socially distant information, along with controls such as Luxury topics and topic change.

Measuring Information Flows. There are N people in the dataset, L is number of topic. Each email message E_{il} (where l is the index of the email and i is the index of the employee) has a corresponding probability distribution across all the topics which indicates the estimated probability that the email belongs to each topic. Thus each email could be represented as an L-dimensional vector of topic probabilities in a topic space,

$$\mathbf{E}_{il} = \langle k_{i1}, k_{i2}, \ldots, k_{iL} \rangle$$

Since E_{il} is a probability distribution, the magnitude of each E is equal to 1. However, due to parameters of the Dirichlet distribution, which provides the prior distribution for LDA, the vast majority of the values in this vector are equal and very close to zero. For purposes of this study I subtracted the minimum value of each E from the values of E_{il} so that the minimum probability was 0:

$$\mathbf{E}_{il} = \mathbf{E}_{il} - min(\mathbf{E}_{il})$$

The mean topic vector m was computed for each employee where m_{ik} represents the mean weight of attachment for employee *i* to topic *k*. The mean vector is calculated separately for the two 30-day time periods such that each employee has two mean topic vectors, one for each occasion.

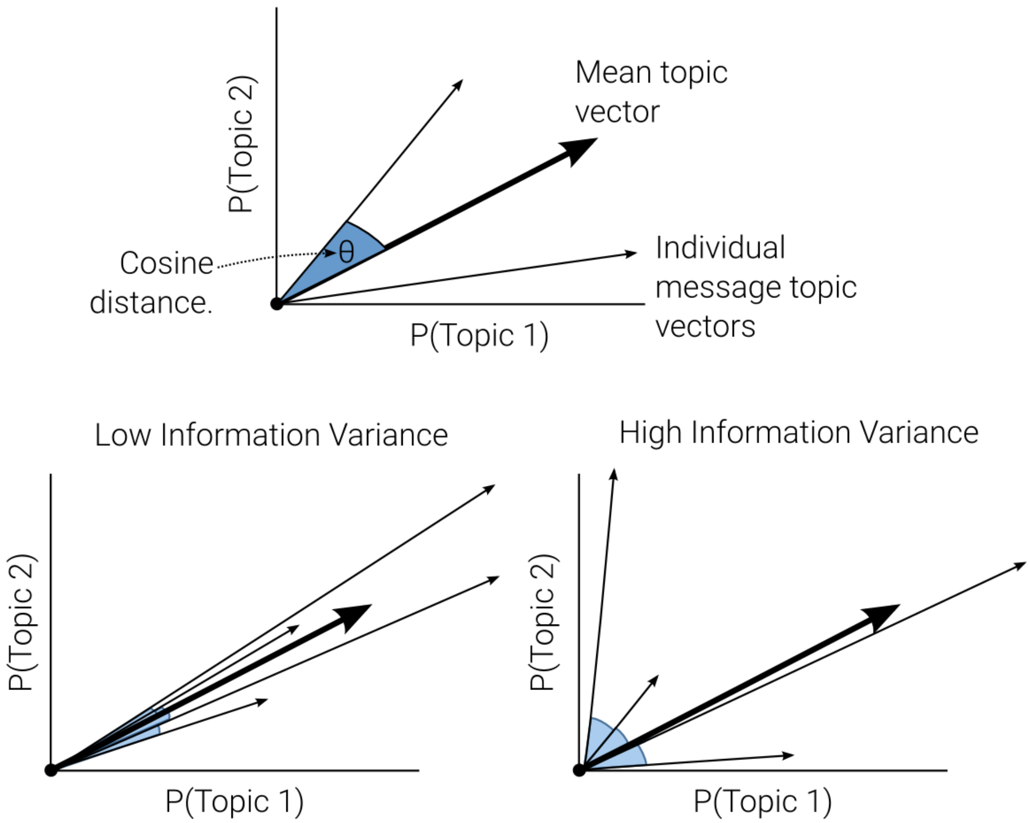

Figure 3.1 Using a vector space model, information variance is the mean cosine distance between a mean topic vector and the document topic vectors of either the sent or received messages. The angle between the vectors is of interest, not distance between the points in the vector space. If a document topic vector for an email message is parallel to the mean topic vector, it would indicate that the document is semantically the same to the mean of the existing discussions. Movement parallel to the mean topic indicates the use of the same

mixture of topics, only more or less strongly. After calculating the mean, the value is multiplied by the total volume of messages sent (or received) by the employee in the measurement period.

Information Variance. When measuring information variance, I use Aral and van Alstyne's (2011) approach of summing the cosine distances between each outgoing email topic vector and the mean topic vector. See *Figure 3.1* for a graphical description of the vector space model implemented here. The formula is:

$$InfoVariance_i(t) = \sum_{j=1}^{N} \frac{[1 - cos(E_{ij}, m(t))]^2}{N}$$

where *N*, in this calculation, is the number of documents sent by the employee. The resulting value is then multiplied by the total volume of messages sent by the employee within the given period. The higher variance the greater the range of combinations of different topics the employee uses or is exposed to in their communications.

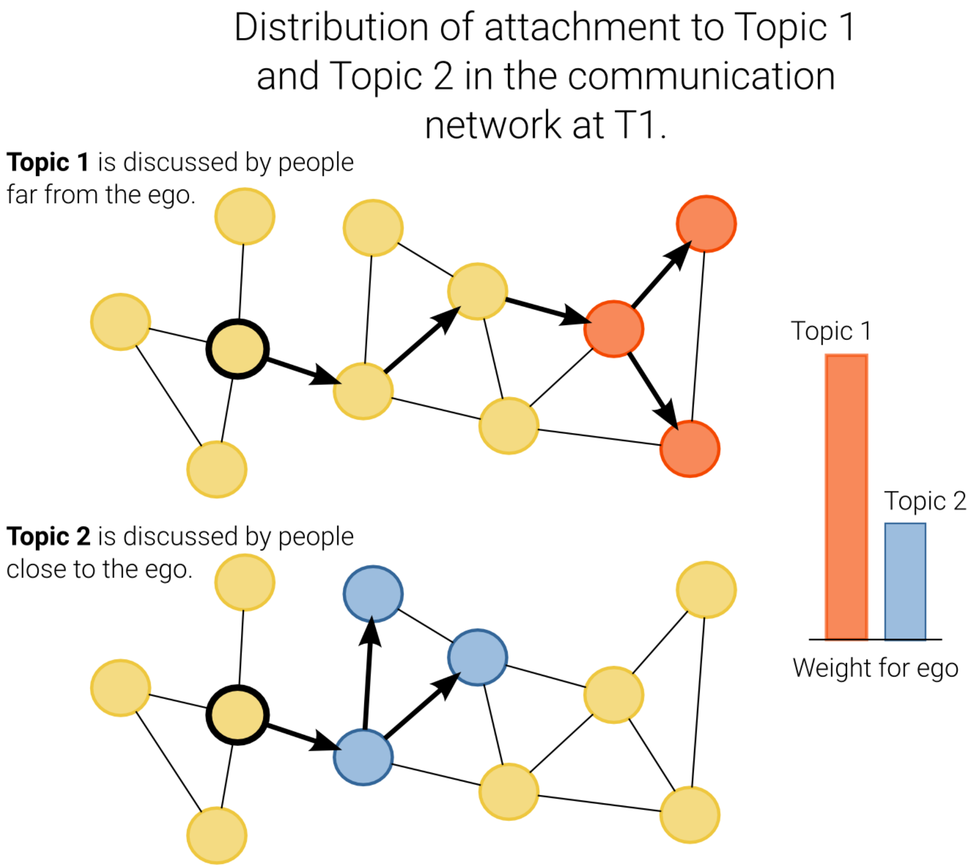

Figure 3.2. This diagram illustrates how the topics are weighted when calculating socially distant information. Note that the distances are normalized to [0, 1] so that the distance weights are all relative to the individual's current position.

Socially Distant Information. Socially distant information is the extent that an employee adopts topics that were previously socially very distant from them. I examine the change in the mean topics vectors of each employee, weight the changes based on the average distance from the employee to others discussing that topic at T1 (see *Figure 3.2.*), then sum the results. Socially distant information for an employee, i, from time t_1 to time t_2, is expressed as

$$SociallyDistantInfo_i(t_1, t_2) = \mathbf{d_i}(t_1) \cdot \mathbf{\Delta m_i}(t_1, t_2) = \sum_{k=1}^{L} d_{ik}(t_1)\Delta m_{ik}(t_1, t_2)$$

where $d_{ik}(t_1)$ is the mean geodesic distance in the communication network of discussions concerning topic k from the individual i. The change in mean topic is the per-topic change from t_1

to t_2.

$$\mathbf{\Delta m_i}(t_1, t_2) = \langle m_1(t_2) - m_1(t_1), m_2(t_2) - m_2(t_1), \ldots, m_L(t_2) - m_L(t_1) \rangle$$

The distance function $d_i(t)$, which measures the distance between an individuals' position in the topic space and other topics in the organization, can be defined in many different ways. The approach I use is the mean geodesic distance in the underlying organizational social network to other people who are discussing that topic.

$$d_{ik}(t) = \mathbf{D}_i(t) \cdot \mathbf{m}_k(t) = \sum_j^N D_{ij}(t) m_{jk}(t)$$

The distance from an individual *i* to topic *k* at time *t* is the sum of the products of the geodesic distance from the ego to each node *j* at time *t* in the social network and the weight of attachment of each individual *j* to a topic *k* at time *t*.

Some members of the organization may be distant from the core. I'm interested in how socially distant the information may be relative to the individual, and how the individual experience of change impacts outcome. To adjust for interindividual changes in position, the geodesic distances were normalized to the range [0,1] within each individual before calculating the socially distant information measure, such that the largest distance weight for any individual was 1 removing any effect due to the interindividual differences in global position in the network.

Controls

I control for the effects of gender, tenure, and organizational rank. An employee's rank was coded by examining the supervisory hierarchy and titles of each individual and assigning them a number between 1 and 8, where 7 and 8 are members of the top management team and 1 is the lowest ranking employee. Gender was dummy coded as 1 is Male and 0 is Female. Tenure was coded as the number of years the focal employee has worked for either organization, Luxury or Standard.

Received Information Variance. Being exposed to information is more consistent to the existing theorized concepts of nonredundant information (Burt, 1992; Rodan & Galunic, 2004). Thus I create another latent difference score for the information variance received by an employee.

Topic Change. It is possible that breaking out of one way of thinking and changing to another way of thinking would be related to beneficial outcomes (Dane, 2010; Labianca, Gray, & Brass, 2000). One such explanation would be that the ability to make dramatic change in the topic use is an indication of some latent ability to adapt and learn, and this latent ability would be responsible for individual advantage. To account for this possibility, I use each individual's the cosine distance between the mean topic vectors at each time point. The highest value for this measure would indicate that the person had dropped every topic they were using and adopted the set of topics they weren't using at all. This measure is similar to Aral and van Alstyne's refresh rate (2011: 126)

$$TopicChange_i(t_1, t_2) = 1 - cos(\mathbf{m}_i(t_1), \mathbf{m}_i(t_2))$$

Luxury-Weighted Topics. During a merger the higher-status organization tends to dominate and assert its perspectives and identity over the postmerger organization (Cowen, 2012; Kaplan, 2008). It is possible that distant topics are valuable simply because they are commonly used by people in the higher-status organization. I created weights for each of the topics as they were used in Time 1. Using the mean topic vectors of individual employees as the independent variables, I fit a model of legacy membership of the employee (using a binary logistic model, where Luxury is 1 and Standard is 0). Because of the large number of predictors in the model (200 topics) I use a cross-validated elastic net regularization model with α = 0.2 (Zou & Hastie, 2005). This model is uniquely-suited to variable selection with a large number of features. The fitted model correctly predicted legacy membership for 93% of the observations based on their mean topic vector (sensitivity: 0.95, specificity: 0.92). The model produces coefficients representing the log-odds that a person is a member of the Luxury organization based on their average use of each topic. Due to the regularization most of the beta weights were 0.

Similar to the calculation of socially distant information, I use the difference in the mean topics for each individual then weight each difference by the betas from the model, and finally sum the result. For the *Luxury-weighted topic change* a positive value indicates that the new topics that the employee was adopted were associated with the Luxury organization, and a negative value means they adopted topics associated with the Standard organization. I will use this measure as a control to better argue that the social distance of information is important and not the peculiarities of this specific case.

$$LuxuryWeightedTopics(t_1, t_2) = \mathbf{l} \cdot \mathbf{\Delta m_i}(t_1, t_2) = \sum_{k=1}^{L} l_k \cdot \Delta m_{ik}(t_1, t_2)$$

Where l is the vector of weights produced by the elastic net model. I left the weights as their raw log-odds coefficients when calculating this measure.

Analysis

Structural Equation Modeling is a collection of different statistical techniques designed to tease apart causality and account for the complex research questions posed in the social sciences. One such class of techniques within SEM are intended to study longitudinal phenomena. Latent Difference Score (LDS) modelling (Gollwitzer, Christ, & Lemmer, 2014) was developed to make reliable estimates of intra-individual changes between exactly two waves of data collection. LDS models improve upon direct difference scores by partialling out potential sources of measurement errors in each time point and creating a latent difference score for each individual (Newsom, 2015). I created latent difference scores for changes in network constraint, changes in information variance (sent and received), and changes in salary. Socially distant information is treated as a single exogenous, rather than latent, variable since the change is measured prior to being modeled as described above. Due to the complexity of moderation effects in this framework, for the analyses I split the samples between the turbulent and stable organization and estimate LDS path models for each context, as well as the overall integrated organization. The models are estimated using the *lavaan* package (Rosseel, 2012) in R (R Core Team, 2015).

A latent difference score uses two occasions of observed values for estimation. The autoregressive path between the first measurement and the second measurement is assumed to be 1. As an example, consider salary at two time points. A fixed autoregressive path of 1 would mean we assume that an individual's salary earned this year they will be the same next year. The mean and variance of the second observation is fixed to 0, and the true latent difference is thus the remaining variation after accounting for the fixed autoregression. The latent difference score is unobserved, but the moments of the score are estimated: the mean change ($\mu_{\Delta \text{Salary}}$), interindividual differences in change ($\sigma_{\Delta \text{Salary}}$), and covariance of change to the initial level ($\sigma_{\text{Salary13},\Delta \text{Salary}}$). Because the model partials out the sources of measurement error within each time point and separately estimates interindividual differences, the latent difference score produces a more reliable estimation of the true change.

There regression of change on change is represented by the causal path between the two latent difference scores ($\beta_{\Delta \text{Constraint}, \Delta \text{Salary}}$). I will focus on these terms in each model for my hypothesis testing. A covariance term is added between the initial values of both LDS ($\sigma_{\text{Constraint13, Salary13}}$) to account for the possibility that starting conditions might be a cause of the relationship from change to change.

I add an additional path from the initial level of the first effect to change in the second (e.g. $\beta_{\text{Constraint13}, \Delta \text{Salary}}$) for *∆ Information Variance (sent and recv)* and *∆ Constraint*. This accounts for the possibility that the initial conditions are responsible for the change (Hausknecht, Sturman, & Roberson, 2011; Ployhart, Cooper-thomas, & Anderson, 2011). In a way this asks the question, is it where you are that's more important or what you do? If the initial level is significant than where the employee is matters, there's something lucky or advantageous about maintaining a position. If it's the latent difference score that predicts change than it was moving positions that drove the change. It's possible both would be related to change, in which case initial position provides the employee an advantage, but the employee can move positions and gain further advantage as well.

There is a great number of methods for assessing the fit of a SEM model fit. I provide a χ^2 statistic for each model for consistency with previous research on SEM, but χ^2 will nearly always indicate a poor fit when the sample sizes are large (greater than 200). Thus I don't consider it directly as a fit statistic, but other measures include it in their calculation. RMSEA, for example, which considers the ratio of χ^2 to the degrees of freedom and sample size. When assessing the fit of a model I consider three fit indices: the root mean square error of approximation (RMSEA), the squared root-mean residual (SRMR), and the comparative fit index (CFI). Each of these consider fit differently, and I consider the overall fit of a model acceptable if 2 of the 3 indices are within acceptable ranges. For RMSEA I consider an acceptable fit to be below 0.10 (Browne, Cudeck, & Others, 1993). For CFI I consider an acceptable fit to be a value of 0.90 or greater (Bentler, 1990). And for SRMR I consider a value of 0.08 or less to be acceptable (Hu & Bentler, 1999).

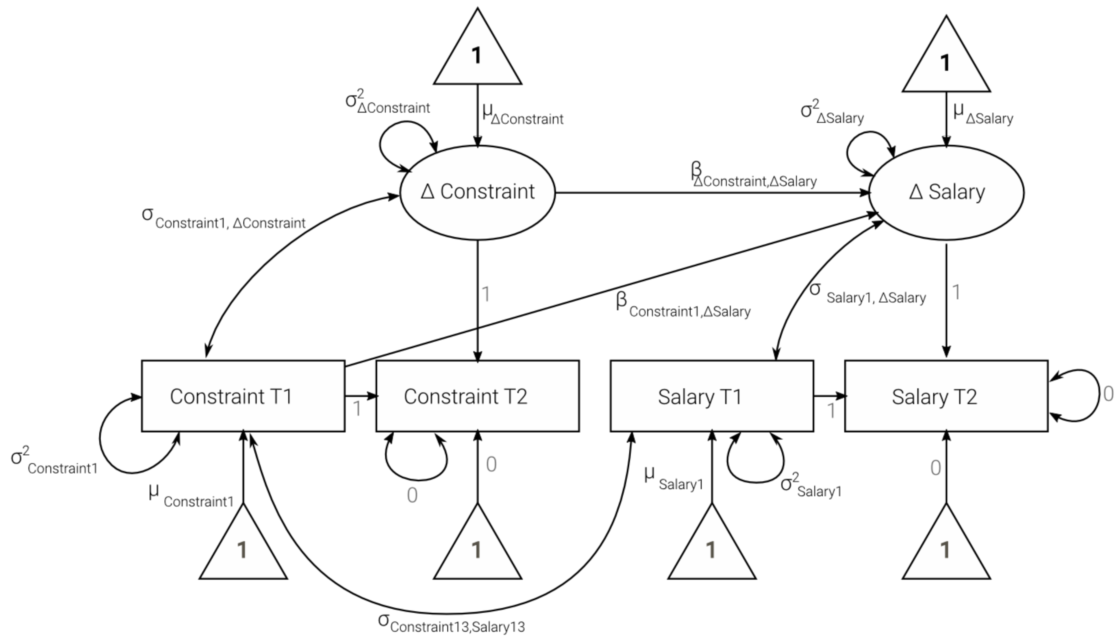

Figure 3.3. Path diagram of the estimation of two latent difference scores (∆) for constraint and salary. Change on change regression is estimated with a causal path between ∆Constraint and ∆Salary.

CHAPTER FOUR: RESULTS

Many sections of the results are split into three samples: overall, stable context, and turbulent context. Overall refers to both contexts together: the integrated, postmerger organization. Throughout this section *(sent)* refers to variables derived from messages authored by the person, while *(recv)* refers to variables derived from messages in the person's inbox. The Δ indicates an estimated latent difference score, and T1 refers to the initial value of the variable at Time 1.

Means, Distributions, and Comparisons

The sample consists of 612 salaried employees at Luxury-Standard, Inc. There were 250 from Luxury Inc., the stable context, and 362 from Standard Inc., the turbulent context. The means and standard deviations of each of the variables in each context are shown in *Table 4.1*. The results of a two tailed t-test, comparing the value in the stable and turbulent contexts, is indicated by the number of stars next to each variable name. The results in this table represent the sample used in the full model of the data (shown in *Table LDS6, N* = 607). This data was used so that the results could be presented along with the estimated latent difference scores (i.e. Δ *Constraint*). The variables were all standardized within year and across the whole company, with the exceptions of rank and gender. The small variations from 0 for each variable are due to standardizing the variables prior to using them in analysis and then some observations dropping during the model selection and creation process.

There were several differences between the two companies. The sample from Luxury had a higher proportion of women (49%) compared to Standard (38%). Standard Inc. was a much older company than Luxury so the average tenure among members of the turbulent context was significantly higher. There were many Standard legacy members who had been at the company longer than it was possible to be a member of Luxury. Employees in the stable context received larger increases in salary compared to those in the turbulent context. This is largely a correction since the members of the turbulent, lower-status Standard Inc. were paid more on average than the members of Luxury. At T1, the untransformed salary had a mean across the company of \$74k (SD \$49k), Standard's was \$76k (SD \$34k), and Luxury was 70K (SD \$66K). There was a much larger variation in salaries at Luxury. The difference can be seen visually in the salary distributions in *Figure 4.1*.

Those in the stable context had lower constraint on average, and had a higher initial information variance (*T1 Constraint)*. The network in the turbulent context started denser and more centralized compared to the network in the stable context, which was more open. Consistent with threat-rigidity those in the turbulent context adopted less socially distant information (although this difference suggested by the results, not statistically significant). While these differences may impact the overall results, it shouldn't influence analyses within each context.

A smoothed density area plot is shown for each variable in *Figure 4.1.* The distributions are shown for each context and the overall integrated company. The visualization in the figure truncates the distribution of rank so that greater detail can be seen in the remaining variables.

Table 4.1. The means, standard deviations for each variable within each context. The significance of a two-tailed t-test between the stable and turbulent contexts is shown by the stars by each variable name.

Variable	**Stable** mean (sd)	**Turbulent** mean (sd)	**Overall** mean (sd)
1. Δ Salary ***	0.03 (0.09)	-0.02 (0.07)	-0.00 (0.04)
2. T1 Salary ***	-0.27 (1.24)	0.23 (0.76)	0.02 (1.01)
3. T2 Salary ***	-0.24 (1.24)	0.21 (0.76)	0.02 (1.01)
4. Δ Constraint **	0.02 (0.34)	-0.08 (0.43)	-0.04 (0.38)
5. T1 Constraint ***	-0.23 (0.67)	0.09 (1.05)	-0.04 (0.93)
6. T2 Constraint ***	-0.21 (0.68)	0.01 (0.95)	-0.08 (0.85)
7. Δ Info. Variance (recv) ***	-0.14 (0.47)	0.11 (0.88)	0.01 (0.56)
8. T1 Info. Variance (recv) ***	0.22 (0.92)	-0.12 (0.96)	0.02 (0.96)
9. T2 Info. Variance (recv)	0.07 (0.90)	-0.01 (1.04)	0.03 (0.99)
10. Δ Info. Variance (sent)	-0.01 (1.11)	0.06 (0.59)	0.03 (0.73)
11. T1 Info. Variance (sent) **	0.08 (0.69)	-0.09 (0.82)	-0.02 (0.77)
12. T2 Info. Variance (sent)	0.07 (1.16)	-0.02 (0.93)	0.01 (1.03)
13. Soc. Distant Information (sent) †	0.07 (0.81)	-0.07 (1.15)	-0.01 (1.03)
14. Luxury Info. (sent) ***	-0.41 (0.93)	0.30 (0.95)	0.00 (1.00)
15. Topic Change (sent) *	-0.13 (0.90)	0.04 (1.02)	-0.03 (0.97)
16. Org. Rank *	2.16 (1.71)	2.48 (1.38)	2.35 (1.53)
17. Tenure ***	-0.50 (0.49)	0.34 (1.06)	-0.00 (0.97)
18. Gender (male) *	0.51 (0.50)	0.62 (0.49)	0.57 (0.50)

t-tests for difference in means between the Stable and Turbulent contexts
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Correlations

The correlations for the data are presented in three tables, one for each sample: overall, turbulent context, and stable context. Latent difference scores (e.g. *⊿Salary*) are included in the tables by estimating their value using the full model presented in *Table LDS6*. These are unobserved latent variables, yet I've included them to provide a simple sense of how the estimated latent change relates to other variables.

The control for *Luxury Information* was added because it was expected that *Socially Distant Information* might be beneficial to members of the turbulent context simply because it was associated with the dominant organization. However, the correlation appears be the reverse of this expectation for those in the turbulent context. The correlation between adopting *socially distant information* and adopting *Luxury weighted information* was (r = -0.22, $p < 0.001$) and positive but not significant for the stable context (r = 0.11, *n.s.*). Similarly, the covariance within the turbulent context between *socially distant information* and *Luxury Information* estimated in the socially distant information model (Table LDS5) was r = -0.24 ($p < 0.001$). A scatterplot of the relationship is shown in *Figure 4.2*. Since negative values of *Luxury Information* imply that the person is adopting topics associated with Standard, this correlation implies that socially distant information tends to come from *within* the turbulent context.

Some scatterplots of key variables regressed against *⊿ Salary* are shown in *Figures SalaryVarSent*, *SalaryVarRecv*, *SalarySocDist*, and *SalaryTopicChange*. These scatterplots show the dramatic differences between the two contexts in the relationship between *⊿ Information Variance*, both sent and received, and *⊿ Salary*. Within the stable context increases in received and sent information variance were both positively related to increases in salary (recv: r = 0.67, $p < 0.001$, sent: r = 0.73, $p < 0.001$). In the turbulent context the exact opposite was true. Increases to information variance, sent and received, resulted in reduction to salary (recv: r = -0.66, $p < 0.001$, sent: r = -0.43, $p < 0.001$).

Figure 4.1. Density distribution plots of the variables

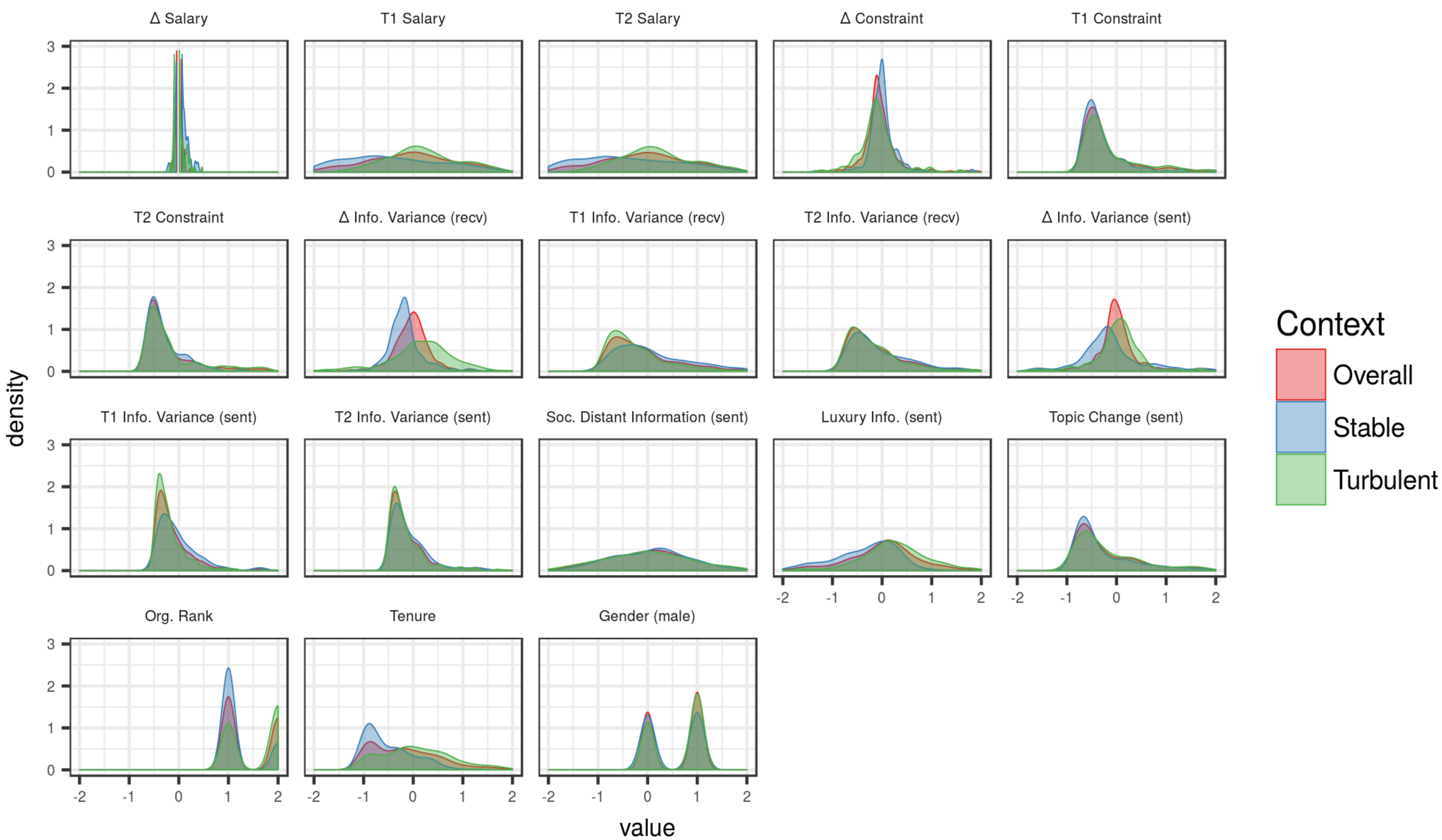

Table 4.2. Correlations of variables for the overall context.

Variable	1	2	3	4	5	6	7	8
1. Δ Salary								
2. T1 Salary	-0.06							
3. T2 Salary	0.04	0.99***						
4. Δ Constraint	-0.16***	-0.02	-0.02					
5. T1 Constraint	0.01	-0.14***	-0.16***	-0.04				
6. T2 Constraint	-0.14***	-0.16***	-0.17***	0.63***	0.69***			
7. Δ Info. Variance (recv)	0.09*	0.06	0.05	-0.21***	0	-0.04		
8. T1 Info. Variance (recv)	-0.03	0.23***	0.25***	0.11**	-0.42***	-0.35***	-0.04	
9. T2 Info. Variance (recv)	0.16***	0.25***	0.27***	-0.14***	-0.34***	-0.37***	0.59***	0.72***
10. Δ Info. Variance (sent)	0.49***	0.02	0.05	-0.17***	0	-0.08	0.70***	0
11. T1 Info. Variance (sent)	-0.04	0.05	0.07	0.07	-0.26***	-0.21***	-0.10*	0.65***
12. T2 Info. Variance (sent)	0.15***	0.08*	0.10*	-0.08	-0.20***	-0.22***	0.43***	0.51***
13. Soc. Distant Information (sen	0.04	-0.03	-0.02	-0.35***	0.08	-0.06	0.18***	-0.08
14. Luxury Info. (sent)	-0.02	-0.01	-0.02	-0.04	0.10*	0.09*	0.01	-0.13**
15. Topic Change (sent)	-0.05	-0.11**	-0.12**	0.02	0.45***	0.48***	-0.01	-0.14***
16. Org. Rank	-0.08	0.87***	0.87***	0	-0.20***	-0.21***	0.02	0.28***
17. Tenure	-0.16***	0.13***	0.11**	-0.07	0.17***	0.12**	0.04	-0.04
18. Gender (male)	-0.04	0.41***	0.40***	-0.02	0.16***	0.16***	0.01	-0.08*

Variable	9	10	11	12	13	14	15	16	17
9. T2 Info. Variance (recv)									
10. Δ Info. Variance (sent)	0.39***								
11. T1 Info. Variance (sent)	0.54***	-0.05							
12. T2 Info. Variance (sent)	0.70***	0.62***	0.74***						
13. Soc. Distant Information (sen	0.08*	0.08*	0	0.05					
14. Luxury Info. (sent)	-0.10*	-0.01	0.04	0.02	-0.13**				
15. Topic Change (sent)	-0.09*	0	0.08*	0.09*	-0.05	0.03			
16. Org. Rank	0.26***	-0.02	0.11**	0.10*	-0.03	-0.04	-0.13**		
17. Tenure	0.08	-0.03	-0.02	0.06	-0.03	0.13***	0.09*	0.05	
18. Gender (male)	-0.12**	-0.01	-0.09*	-0.10*	0.01	-0.03	0.08*	0.37***	0.08

Table 4.3. Correlations of variables within the *stable* context.

Variable	1	2	3	4	5	6	7	8
1. Δ Salary								
2. T1 Salary	-0.08							
3. T2 Salary	0.03	0.99***						
4. Δ Constraint	-0.09	-0.03	-0.03					
5. T1 Constraint	0	-0.25***	-0.26***	-0.04				
6. T2 Constraint	-0.08	-0.25***	-0.27***	0.67***	0.68***			
7. Δ Info. Variance (recv)	0.67***	0.01	0.07	-0.1	0	-0.01		
8. T1 Info. Variance (recv)	0.01	0.35***	0.37***	0.11	-0.48***	-0.39***	0.05	
9. T2 Info. Variance (recv)	0.20**	0.42***	0.45***	-0.13*	-0.38***	-0.42***	0.55***	0.76***
10. Δ Info. Variance (sent)	0.73***	-0.03	0.05	-0.11	0	-0.07	0.85***	0.09
11. T1 Info. Variance (sent)	-0.03	0.15*	0.18**	0.09	-0.33***	-0.27***	-0.05	0.69***
12. T2 Info. Variance (sent)	0.17**	0.17**	0.20**	-0.06	-0.20**	-0.22***	0.54***	0.53***
13. Soc. Distant Information (sent	0.03	-0.04	-0.03	-0.37***	0.15*	-0.02	0.18**	-0.14*
14. Luxury Info. (sent)	-0.02	-0.23***	-0.23***	-0.16*	0.06	-0.02	-0.05	-0.12
15. Topic Change (sent)	-0.04	-0.20**	-0.19**	0.33***	0.38***	0.53***	-0.03	-0.15*
16. Org. Rank	-0.1	0.92***	0.91***	0.01	-0.26***	-0.24***	-0.04	0.38***
17. Tenure	-0.09	0.01	0	0.05	-0.06	-0.01	-0.04	-0.03
18. Gender (male)	-0.05	0.41***	0.40***	0.06	0.02	0.08	-0.02	-0.05

Variable	9	10	11	12	13	14	15	16	17
9. T2 Info. Variance (recv)									
10. Δ Info. Variance (sent)	0.38***								
11. T1 Info. Variance (sent)	0.59***	0.01							
12. T2 Info. Variance (sent)	0.73***	0.66***	0.60***						
13. Soc. Distant Information (sent	0.02	0.07	-0.05	0.03					
14. Luxury Info. (sent)	-0.15*	-0.02	-0.13*	-0.09	0.11				
15. Topic Change (sent)	-0.19**	-0.05	0.01	0.02	0.02	-0.12			
16. Org. Rank	0.40***	-0.06	0.18**	0.16*	-0.08	-0.21**	-0.16**		
17. Tenure	-0.02	-0.06	-0.08	0.04	0	-0.07	-0.08	-0.06	
18. Gender (male)	-0.04	-0.03	-0.14*	-0.08	0.01	-0.11	-0.02	0.35***	0.08

Table 4.4. Correlations of variables within the *turbulent* context.

Variable	1	2	3	4	5	6	7	8
1. Δ Salary								
2. T1 Salary	-0.02							
3. T2 Salary	0.07	1.00***						
4. Δ Constraint	-0.15**	0.02	0.02					
5. T1 Constraint	0.01	-0.18***	-0.19***	-0.04				
6. T2 Constraint	-0.13*	-0.18***	-0.19***	0.61***	0.68***			
7. Δ Info. Variance (recv)	-0.66***	0	-0.06	-0.26***	0	-0.06		
8. T1 Info. Variance (recv)	-0.03	0.23***	0.24***	0.12*	-0.37***	-0.32***	-0.09	
9. T2 Info. Variance (recv)	0.05	0.14**	0.15**	-0.14**	-0.32***	-0.35***	0.37***	0.71***
10. Δ Info. Variance (sent)	-0.43***	0.01	-0.03	-0.29***	0.01	-0.09	0.89***	-0.11*
11. T1 Info. Variance (sent)	-0.02	0.03	0.03	0.06	-0.21***	-0.18***	-0.07	0.62***
12. T2 Info. Variance (sent)	0.01	0	0	-0.09	-0.21***	-0.22***	0.24***	0.51***
13. Soc. Distant Information (sent	0.03	0.01	0.02	-0.34***	0.07	-0.06	0.12*	-0.07
14. Luxury Info. (sent)	-0.01	0.03	0.04	0.08	0.04	0.08	-0.03	-0.05
15. Topic Change (sent)	-0.06	-0.1	-0.10*	-0.14**	0.48***	0.46***	0.15**	-0.11*
16. Org. Rank	-0.02	0.84***	0.84***	0.01	-0.21***	-0.22***	0.01	0.25***
17. Tenure	-0.14**	0.06	0.04	-0.06	0.14**	0.09	0.13*	0.07
18. Gender (male)	0.02	0.41***	0.41***	-0.04	0.21***	0.19***	-0.01	-0.08

Variable	9	10	11	12	13	14	15	16	17
9. T2 Info. Variance (recv)									
10. Δ Info. Variance (sent)	0.36***								
11. T1 Info. Variance (sent)	0.51***	-0.09							
12. T2 Info. Variance (sent)	0.69***	0.36***	0.86***						
13. Soc. Distant Information (sent	0.1	0.09	0.01	0.06					
14. Luxury Info. (sent)	-0.05	-0.05	0.19***	0.14**	-0.22***				
15. Topic Change (sent)	-0.03	0.16**	0.13*	0.16**	-0.07	0.08			
16. Org. Rank	0.17**	0.01	0.08	0.04	0.01	0.03	-0.12*		
17. Tenure	0.14**	0.09	0.06	0.12*	0	0	0.10*	0.04	
18. Gender (male)	-0.16**	0	-0.05	-0.1	0.02	-0.04	0.13*	0.37***	0.02

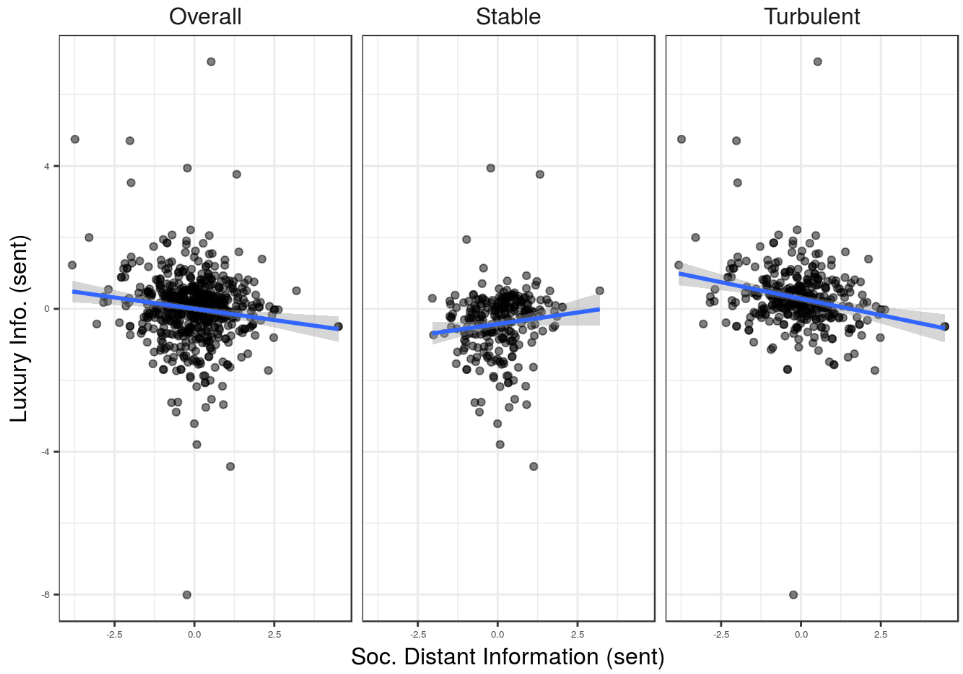

Figure 4.2. Two scatterplots of *socially distant information* plotted against *Luxury information*. The correlation was significant and negative for the turbulent context (r = -0.22, $p < 0.001$) and positive but not significant for the stable context (r = 0.11, *n.s.*).

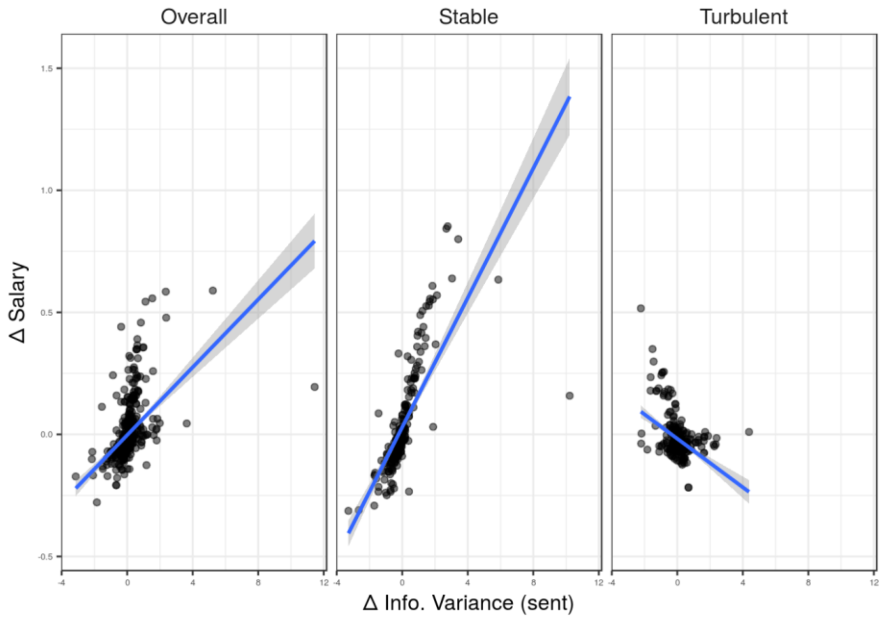

Figure 4.3. Scatterplot of the estimated *⊿ Salary* by *⊿ Info. Variance (sent)* using the model presented in LDS6. The regression line and confidence interval from an OLS regression line is overlaid..

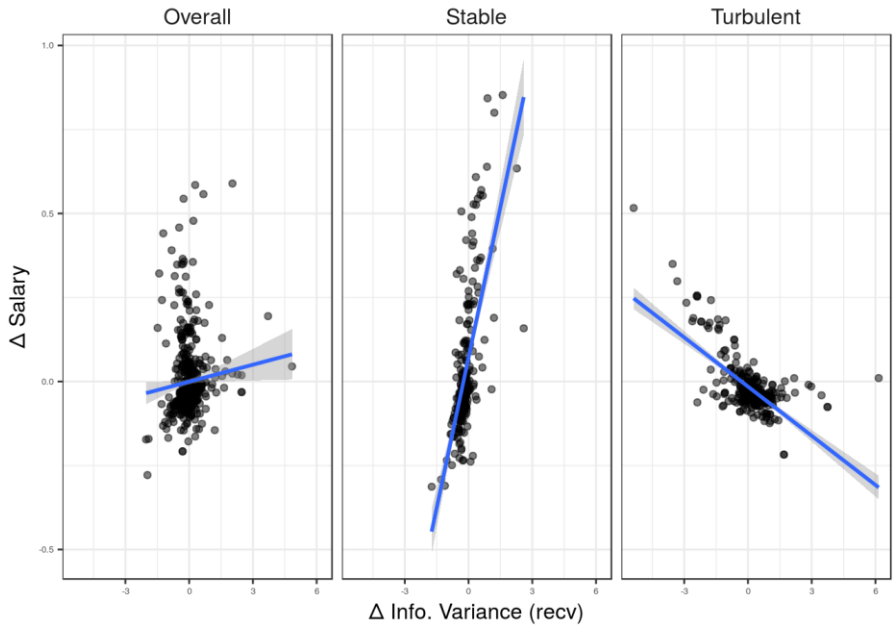

Figure 4.4. Scatterplot of the estimated *Δ Salary* by *Δ Info. Variance (recv)* using the model presented in LDS6. The regression line and confidence interval from an OLS regression line is overlaid..

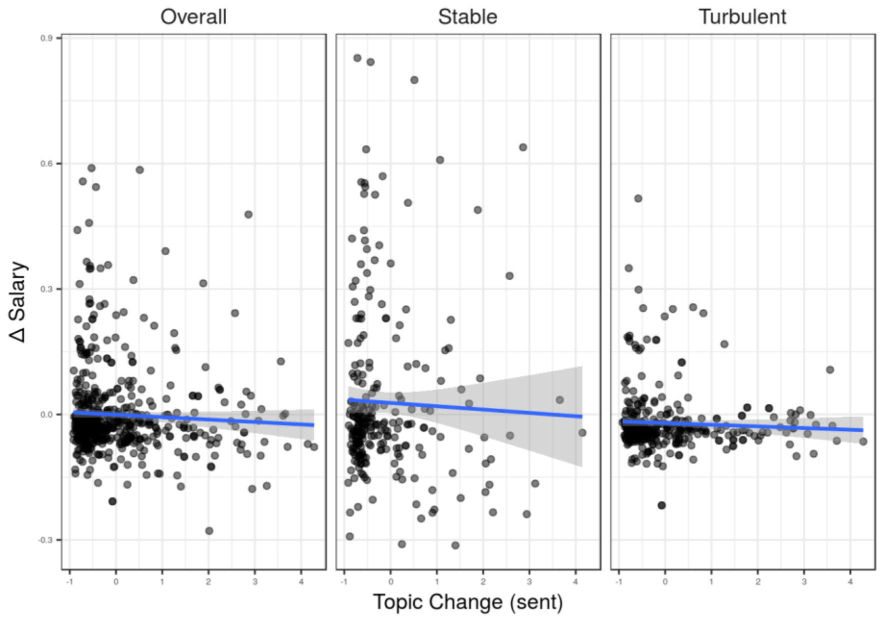

Figure 4.5. Scatterplot of the estimated *Δ Salary*, using the model presented in LDS6, by *Topic Change (sent)*. The regression line and confidence interval from an OLS regression line is overlaid.

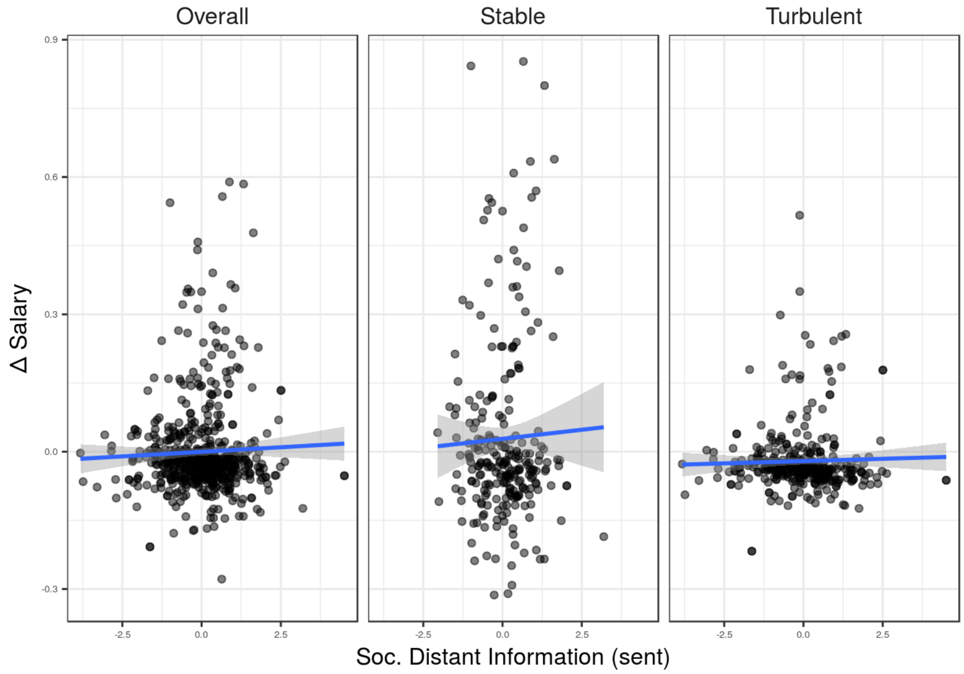

Figure 4.7. Scatterplot of the estimated *Δ Salary*, using the model presented in LDS6, by *Socially Distant Information (sent)*. The regression line and confidence interval from an OLS regression line is overlaid.

Network Descriptive Statistics

After the research team trawled 10,000+ email addresses and descriptions to code the addresses as either person or nonperson to identify addresses associated with active human persons rather than an automated system (such as those who track inventory and logistics), the full network of the combined contained 2,372 nodes at T1 and 2,529 nodes at T2. The whole network descriptive statistics for the networks used for calculations are presented in *Table 4.5*. The reduced network, filtered for only the organizational members included in the analysis, is visualized in *Figures 4.9* and *4.10* (N_1 = 626, N_2 = 624).

The network variables and topics used in this study were calculated using the full organizational communication network. Many of the email accounts still include everything from the salaried home-office employees, to consultants (myself and other members of the research team received email accounts with the firm), to buyers and retailers who had their own accounts. A great deal of people had email accounts, communicated frequently with many members of the organization, but were not directly on the payroll of the organization. For testing hypotheses, this study focuses only on the North American salaried employees from each legacy firm who have data at both time points. Restricting the network range to only members directly on the payroll may exclude important, frequent working relationships and conversations. The conversations and networks of the entire organization should impact outcomes (whether they are overseas, a regular purchaser who visits frequently, etc.). Constraint is calculated using the full organizational network of employee communications, not simply the sample of individuals used here for hypothesis testing.

Table 4.5. Whole network statistics for the overall communications network.

Statistic	T1	T2
Number of Nodes	2,372	2,529
Number of Edges	32,937	29,049
Density	0.0059	0.0045
Diameter	12	11
Degree Centralization	0.0412	0.0382

Topic Model Results

Not all the topics and their highest weighted terms can be displayed to protect privacy. Three example topics, whose subject matter was general enough to share, are shown in *Figure 4.8.* Many of the topics were composed of collections of names, suggesting that many discussions were about the roles, responsibilities, and relationships of other members of the organization and that particular sets of names co-occurred frequently in the same messages. When assessing the weights for computing *Luxury Information*, some of the topics most associated with Luxury discussed groups of people, product specifics, scheduling lunch or break, logistics (shipping questions), and a topic for asking and posing questions (top words: questions, answer, quick, give, survey, asked, concerns, etc.). The topics most associated with Standard discussed specific products, managing manufacturing, logistics (truck transportation), label printing, and pricing for catalogues.

Hi PERSON_391123,

I saw you were preparing the space for the show in Vegas next week. Let PERSON_318923 know that his bonus will come through after we process the taxes for this quarter. There will be some adjustments we need to make after the show. Let me know how it all goes and we can grab some lunch when you return. Somewhere other than Chinese place this time. lol

finance	**trade shows**	**breaks**
tax	show	lunch
amount	market	break
balance	vegas	dinner
pay	week	bring
bonus	showroom	food
cash	space	eat
paid	coming	lol
total	shows	grab
...	...	...

Figure 4.8. An example of a topic model applied to an email message. The email was fabricated for this example, but the topics presented come directly from the 200-topic model used in the study.

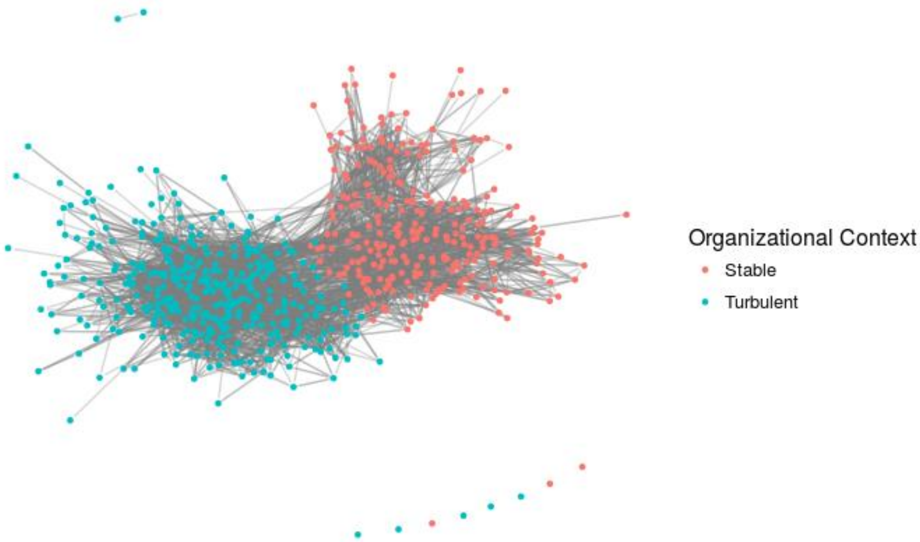

Figure 4.9. The communication network at Time 1. The nodes are colored by organization context. Ties represent frequent, direct email communications. Only nodes included in the analyses are included in this visualization (N = 626, edges = 7,479)

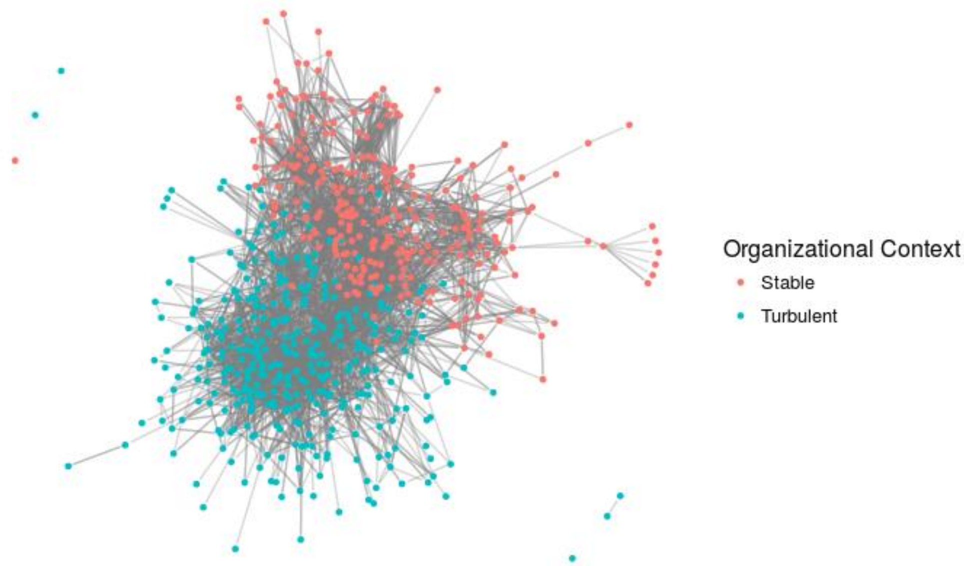

Figure 4.10. The communication network at Time 2. The nodes are colored the membership in the organizational context. Ties represent frequent, direct email communications. Only nodes included in the analyses are included in this visualization (N = 624, edges = 6,229)

Hypothesis Testing

The tables for the LDS path models are shown below. The same model was estimated for samples split by the context. I do not show full path diagrams because the fully estimated diagram would be too complex to show within this document. Instead I report each of the regression paths in a table for each segment of the data. The results for each model are shown in three tables: one for the regression paths, the second for the fit statistics of the model, and finally all but one model shows the estimated indirect and total mediation effects of information flows between increases in constraint and increases in salary. The models, overall, had a good fit, suggesting the differences between the implied covariance matrix and sample covariance matrix were relatively small throughout. None of the models had a fit index that was outside the acceptable bounds.

The first model (presented in Table LDS1.1.) tests the direct impacts of constraint on salary. I found no detectable direct effect of *⊿ Constraint* on *⊿ Salary*. There is a direct negative effect from *T1 Constraint* which would suggest an open network at the beginning of the merger process is a benefit for people in the stable context. In a separate, cross sectional analysis I estimated logged salary at T1 using constraint, which was negative and significant. But when controlling for rank, the relationship was no longer significant. There are strong cross-sectional correlations in the data between rank and constraint, those with a higher rank had more structural holes in their network, and higher rank was strongly associated with salary. But rank was not related to increases in structural holes.

In the second model (Table 4.6.1) I test the classical structural hole argument that an open network will provide *access* to a variety of information, and information variation will provide an advantage. I find that increases in structural holes positively relates to increases in received information variance for both the stable and turbulent contexts ($\beta = -0.17$, $p < 0.05$ for stable, and $\beta = -0.12$, $p < 0.05$ for turbulent). The changes in information variance correspond to increases in salary ($\beta = 0.06$, $p < 0.001$), but only for the stable context, not for the turbulent context. The test for mediation path (see Table 4.6.3) is significant for the stable context ($\beta = -0.01$, $p < 0.05$) but only suggestive for the turbulent context ($\beta = -0.01$, $p < 0.10$). These results support the idea that organizational turbulence impacts how information flows provide an advantage. There is still no detectable direct effect or total effect of structural holes on *⊿ Salary*, but the indirect mediation path for structural holes through *⊿ Information Variance (recv)* ($\beta = -0.01$, $p < 0.05$) supports the structural hole argument that structural holes provide access to diverse information which then provide a benefit.

The third model (Table 4.7.1) adds two controls *Luxury Info. (sent)* and *Topic Change (sent)*. Neither variable impacted the effects of *⊿ Info. Variance (recv)*. For *Luxury Info (sent)*, the way the weights were calculated a positive coefficient suggests that adopting topics which are dominantly discussed by people in the Luxury organization provides an advantage, while a negative coefficient would suggest that adopting topics from the Standard organization provides an advantage. If the individual adopts Standard topics, Luxury Info will be negative, and multiplied by a negative coefficient would imply an increase in salary. The individual would also see a positive coefficient if they dropped Standard topics without actually adopting Luxury topics (for instance a Standard employee could stop discussing topics associated with Standard and start discussing general topics that aren't concretely associated with either organization).

The other information control variable *Topic Change*, the cosine distance between mean topic vectors at T1 and T2, considers how much a person has changed in terms of the kinds of things they discuss in their communications, regardless of how far away that information was, who it belonged to, etc. Within the stable organizational context there is a positive impact from *Topic Change (sent)* on *⊿ Salary* ($\beta = 0.03$, $p < 0.01$). There was also a very strong positive relationship between increases in closure, *⊿ Constraint*, and *Topic Change* within each context (stable: $\beta = 0.68$, $p < 0.001$, turbulent: $\beta = 0.26$, $p < 0.001$). The net effect, indicated in the mediation paths in *Table 4.7.3.*, suggests that closure can be more beneficial (mediation path through *Topic Change*: $\beta = 0.02$, $p < 0.05$, mediation path through *⊿ Information Variance (recv)*: $\beta = -0.01$, $p < 0.05$). Although the relationship between *⊿ Information Variance (recv)* is stronger than *Topic Change*, there is a much stronger relation between *⊿ Constraint* and *Topic Change* than there is between *⊿ Information Variance (recv)* and *⊿ Constraint*.

Hypothesis 1a and *2a* are tested with tables LDS4.1 and LDS4.3. for *⊿ Info. Variance (sent)*. The mediation path for increases in sent information variance is not significant. This provides no support for the hypothesis. However, due to the very high correlation between sent and received increases in information variance, this could be a problem of multicollinearity. Increases in constraint was negatively related to increases in sent information variance (∆ *Info. Variance (sent)*, $\beta = -0.09$, $p < 0.01$), but only in the turbulent context. Network position did not result in an increase in sent information variance for members in the stable context ($\beta = -0.18$, n.s.). Initial Information Variance at T1 provided an increase in salary to members of the stable context, but sent information variance did not provide any benefit to members in the turbulent context.

Hypothesis 1b and *2b* are tested with tables LDS5.1 and LDS5.3. There is only partial support for H1b. The indirect effect of *Socially Distant Information* was not significant at the 0.05 level, but there is the suggestion of an effect for the turbulent and overall contexts ($\beta = -0.002$ $p < 0.10$). Hypothesis 2b was supported. There was a detectable impact of *Socially Distant Information* on *⊿ Salary* within the turbulent context ($\beta = 0.01$, $p < 0.05$), but no effect was found within the stable context ($\beta = 0.01$, *n.s.*). This effect was robust to inclusion of the effect of *Luxury Information* suggesting that the distance of the information from the subject had an independent effect beyond the status effects of adopting topics associated with the dominant organization.

All of the relevant variables are included in the full model, and the results are presented in *Table LDS6*. These results show that the information flow mechanisms that benefit individuals differ depending on the stability of the organizational context. There is a demarcation of effects: in the stable context information variance and topic change are important, in the turbulent context socially distant information and topics from the dominant organization are important. Within stable organizational contexts incremental measures of nonredundant information, such as the variance of information sent and received, were beneficial. Within turbulent organizational contexts radical measures of nonredundant information, socially distant information, were more relevant.

Due to the high correlation for the stable context between *⊿ Information Variance (sent)* and ⊿ *Information Variance* (recv) (r = 0.85, p < 0.001), I fit another model without ⊿ *Information Variance (recv)* (*Table 6a*). The results showed little difference except that ⊿ *Information Variance (sent)* now has a significant impact on ⊿ *Salary* (β = 0.02, p < 0.05). The effects of initial information variance (β = 0.05, p < 0.001) suggests that members of stable context gained an advantage by being in a strong information-rich position at the start of the merger. Those who were conversant in wide variety of topics at the start of the merger were better able to position themselves in the postmerger organization.

Model Selection. I consider the model in *Table LDS5* to be the best representative model of this study. I do not think that ⊿ *Information Variance (sent)* should be included in the model due to the high correlation with its ⊿ *Information Variance (recv)*. The effects ⊿ *Information Variance (recv)* is more robust to the addition and removal of controls variables, and the model AIC for the received variance (Table LDS5: AIC_{stable} = 5479) was better than the model which just included sent variance (Table LDS6a: AIC_{stable} = 5634). Because of the correlation only one pair of variables can be included in a model. The evidence suggests that received increases in information variance (∆ *Information Variance (recv))* is a more robust, stronger predictor of ⊿ *Salary*, thus I consider the model in LDS5 to be the best model.

Sent or Received Socially Distant Information

While the effects of information variance tended to be stronger for received messages compared to sent messages, is this difference in the effect the same for socially distant information? The correlation between sent and received socially distant information was r = 0.27 (p < 0.001). Those in the stable context received significantly greater amount of socially distant information compared to those in the turbulent context (μ_{stable} = 0.11, $\mu_{turbulent}$ = -0.08, p < 0.05). The model results (found in *Table LDS7.*) suggest the opposite is true for socially distant information. The relationship from *Soc. Distant Information (recv)* and ⊿ *Salary* was only suggested and not significant (β = 0.01, p < 0.01). From this I infer that socially distant information provides an advantage if it's adopted into use and represented in authored messages rather than through exposure and reading socially distant information.

Table 4.6.1. Regression paths for the Information Variance (recv) model.

	Dependent	Independent	Stable	Turbulent	Overall
1	Δ Info. Variance (recv)	Gender (male)	-0.002 (0.084)	-0.147 (0.093)	-0.095 (0.065)
2	Δ Info. Variance (recv)	Tenure	0.052 (0.079)	0.077 (0.037)*	0.108 (0.030)***
3	Δ Info. Variance (recv)	Org. Rank	0.028 (0.039)	-0.062 (0.050)	-0.007 (0.032)
4	Δ Info. Variance (recv)	Δ Constraint	-0.171 (0.072)*	-0.122 (0.054)*	-0.120 (0.043)**
5	Δ Info. Variance (recv)	T1 Constraint	0.096 (0.065)	-0.047 (0.047)	-0.002 (0.037)
6	Δ Salary	Δ Info. Variance (recv)	0.058 (0.015)***	0.000 (0.005)	0.014 (0.006)*
7	Δ Salary	T1 Info. Variance (recv)	0.035 (0.012)**	0.004 (0.004)	0.017 (0.005)**
8	Δ Salary	Δ Constraint	0.008 (0.018)	-0.009 (0.005)†	-0.006 (0.007)
9	Δ Salary	T1 Constraint	-0.011 (0.016)	-0.009 (0.004)*	-0.012 (0.006)*

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 4.6.2. Model fit statistics for the Information Variance (recv) model

	Fit Statistic	Stable Fit	Turbulent Fit	Overall Fit
1	N	250	361	611
2	χ^2	27.63**	21.14*	49.12***
3	df	9	9	9
4	RMSEA	0.091	0.061	0.085
5	CFI	0.991	0.996	0.992
6	TLI	0.965	0.983	0.967
7	SRMR	0.016	0.018	0.017
8	AIC	3417	5470	9612

Table 4.6.3. Mediation paths for the Information Variance (recv) model.

	Mediation Path	Stable	Turbulent	Overall
1	Constraint > Info. Var. (recv) Indirect Effect	-0.010 (0.005)*	-0.000 (0.001)	-0.002 (0.001)†
2	Constraint > Info. Var. (recv) Total Effect	-0.002 (0.018)	-0.009 (0.005)†	-0.008 (0.007)

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 4.7.1. Regression paths for the information controls model.

	Dependent	Independent	Stable	Turbulent	Overall
1	Luxury Info. (sent)	Gender (male)	-0.028 (0.124)	-0.186 (0.117)	-0.100 (0.091)
2	Luxury Info. (sent)	Tenure	-0.150 (0.116)	-0.014 (0.048)	0.128 (0.042)**
3	Luxury Info. (sent)	Org. Rank	-0.176 (0.057)**	0.092 (0.063)	-0.007 (0.045)
4	Luxury Info. (sent)	Δ Constraint	-0.183 (0.114)	0.122 (0.071)†	0.046 (0.064)
5	Luxury Info. (sent)	T1 Constraint	-0.062 (0.097)	0.118 (0.061)†	0.108 (0.053)*
6	Topic Change (sent)	Gender (male)	-0.089 (0.104)	0.068 (0.109)	-0.002 (0.077)
7	Topic Change (sent)	Tenure	-0.125 (0.098)	0.038 (0.044)	0.016 (0.036)
8	Topic Change (sent)	Org. Rank	-0.017 (0.048)	-0.021 (0.059)	-0.018 (0.038)
9	Topic Change (sent)	Δ Constraint	0.685 (0.096)***	0.260 (0.066)***	0.371 (0.054)***
10	Topic Change (sent)	T1 Constraint	0.718 (0.081)***	0.545 (0.056)***	0.604 (0.045)***
11	Δ Info. Variance (recv)	Gender (male)	-0.002 (0.084)	-0.147 (0.094)	-0.094 (0.065)
12	Δ Info. Variance (recv)	Tenure	0.052 (0.079)	0.080 (0.038)*	0.111 (0.030)***
13	Δ Info. Variance (recv)	Org. Rank	0.028 (0.039)	-0.062 (0.051)	-0.007 (0.032)
14	Δ Info. Variance (recv)	Δ Constraint	-0.171 (0.072)*	-0.121 (0.055)*	-0.120 (0.044)**
15	Δ Info. Variance (recv)	T1 Constraint	0.096 (0.065)	-0.044 (0.048)	0.002 (0.038)
16	Δ Salary	Δ Info. Variance (recv)	0.061 (0.015)***	0.001 (0.005)	0.013 (0.006)*
17	Δ Salary	T1 Info. Variance (recv)	0.035 (0.011)**	0.005 (0.004)	0.016 (0.005)**
18	Δ Salary	Topic Change (sent)	0.030 (0.011)**	-0.004 (0.004)	0.005 (0.005)
19	Δ Salary	Luxury Info. (sent)	0.011 (0.009)	0.006 (0.004)†	-0.002 (0.004)
20	Δ Salary	Δ Constraint	-0.009 (0.019)	-0.008 (0.005)	-0.008 (0.007)
21	Δ Salary	T1 Constraint	-0.034 (0.018)†	-0.007 (0.005)	-0.015 (0.007)*

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 4.7.2. Model fit statistics for the information controls model.

	Fit Statistic	Stable Fit	Turbulent Fit	Overall Fit
1	N	250	357	607
2	χ^2	35.04**	37.36**	70.59***
3	df	15	15	15
4	RMSEA	0.073	0.065	0.078
5	CFI	0.991	0.992	0.989
6	TLI	0.967	0.972	0.960
7	SRMR	0.024	0.025	0.025
8	AIC	4661	7307	12761

Table 4.7.3. Mediation paths for the information controls model.

	Mediation Path	Stable	Turbulent	Overall
1	Constraint > Luxury Info. Indirect Effect	-0.002 (0.002)	0.001 (0.001)	-0.000 (0.000)
2	Constraint > Luxury Info. Total Effect	-0.011 (0.020)	-0.007 (0.005)	-0.008 (0.007)
3	Constraint > Topic Change Indirect Effect	0.021 (0.008)*	-0.001 (0.001)	0.002 (0.002)
4	Constraint > Topic Change Total Effect	0.012 (0.018)	-0.009 (0.005)†	-0.006 (0.007)
5	Constraint > Info. Var. (recv) Indirect Effect	-0.010 (0.005)*	-0.000 (0.001)	-0.002 (0.001)
6	Constraint > Info. Var. (recv) Total Effect	-0.020 (0.020)	-0.008 (0.005)	-0.010 (0.007)

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 4.8.1. Regression paths for the Information Variance (sent) model.

	Dependent	Independent	Stable	Turbulent	Overall
1	Luxury Info. (sent)	Gender (male)	-0.028 (0.124)	-0.187 (0.117)	-0.100 (0.091)
2	Luxury Info. (sent)	Tenure	-0.150 (0.116)	-0.014 (0.048)	0.128 (0.042)**
3	Luxury Info. (sent)	Org. Rank	-0.176 (0.057)**	0.092 (0.063)	-0.007 (0.045)
4	Luxury Info. (sent)	Δ Constraint	-0.181 (0.114)	0.121 (0.069)†	0.047 (0.064)
5	Luxury Info. (sent)	T1 Constraint	-0.062 (0.097)	0.118 (0.061)†	0.108 (0.053)*
6	Topic Change (sent)	Gender (male)	0.046 (0.166)	0.150 (0.163)	0.013 (0.088)
7	Topic Change (sent)	Tenure	-1.159 (0.848)	0.877 (0.527)†	-0.459 (0.280)
8	Topic Change (sent)	Org. Rank	-0.075 (0.075)	-0.114 (0.102)	0.021 (0.049)
9	Topic Change (sent)	Δ Constraint	0.631 (0.100)***	0.155 (0.092)†	0.421 (0.063)***
10	Topic Change (sent)	T1 Constraint	0.648 (0.113)***	0.390 (0.125)**	0.700 (0.076)***
11	Δ Info. Variance (sent)	Gender (male)	-0.061 (0.125)	-0.063 (0.058)	-0.064 (0.063)
12	Δ Info. Variance (sent)	Tenure	0.226 (0.117)†	0.057 (0.023)*	0.078 (0.029)**
13	Δ Info. Variance (sent)	Org. Rank	0.071 (0.058)	-0.038 (0.031)	0.015 (0.031)
14	Δ Info. Variance (sent)	Δ Constraint	-0.183 (0.115)	-0.091 (0.035)**	-0.109 (0.045)*
15	Δ Info. Variance (sent)	T1 Constraint	-0.025 (0.098)	-0.063 (0.030)*	-0.055 (0.037)
16	Δ Info. Variance (recv)	Gender (male)	-0.003 (0.088)	-0.148 (0.092)	-0.094 (0.066)
17	Δ Info. Variance (recv)	Tenure	0.059 (0.080)	0.079 (0.037)*	0.124 (0.030)***
18	Δ Info. Variance (recv)	Org. Rank	0.029 (0.040)	-0.062 (0.050)	-0.008 (0.033)
19	Δ Info. Variance (recv)	Δ Constraint	-0.173 (0.072)*	-0.132 (0.054)*	-0.125 (0.044)**
20	Δ Info. Variance (recv)	T1 Constraint	0.096 (0.068)	-0.045 (0.048)	-0.001 (0.039)
21	Δ Salary	Δ Info. Variance (recv)	0.056 (0.019)**	0.010 (0.007)	0.008 (0.008)
22	Δ Salary	T1 Info. Variance (recv)	0.012 (0.017)	0.008 (0.006)	0.006 (0.007)
23	Δ Salary	Δ Info. Variance (sent)	-0.000 (0.012)	-0.017 (0.011)	0.006 (0.008)
24	Δ Salary	T1 Info. Variance (sent)	0.042 (0.018)*	-0.003 (0.006)	0.016 (0.008)*
25	Δ Salary	Topic Change (sent)	0.026 (0.012)*	-0.003 (0.004)	0.003 (0.005)
26	Δ Salary	Luxury Info. (sent)	0.011 (0.009)	0.006 (0.004)	-0.004 (0.004)
27	Δ Salary	Δ Constraint	-0.008 (0.019)	-0.008 (0.005)	-0.008 (0.007)
28	Δ Salary	T1 Constraint	-0.031 (0.018)†	-0.007 (0.005)	-0.014 (0.007)*

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 4.8.2. Model fit statistics for the Information Variance (sent) model.

	Fit Statistic	Stable Fit	Turbulent Fit	Overall Fit
1	N	250	357	607
2	χ^2	49.02***	43.45**	82.84***
3	df	20	20	20
4	RMSEA	0.076	0.057	0.072
5	CFI	0.989	0.994	0.990
6	TLI	0.957	0.977	0.961
7	SRMR	0.029	0.029	0.028
8	AIC	5588	8137	14811

Table 4.8.3. Mediation paths for the Information Variance (sent) model.

	Mediation Path	Stable	Turbulent	Overall
1	Constraint > Luxury Info. Indirect Effect	-0.002 (0.002)	0.001 (0.001)	-0.000 (0.000)
2	Constraint > Luxury Info. Total Effect	-0.010 (0.019)	-0.007 (0.005)	-0.008 (0.007)
3	Constraint > Topic Change Indirect Effect	0.016 (0.008)*	-0.000 (0.001)	0.001 (0.002)
4	Constraint > Topic Change Total Effect	0.008 (0.018)	-0.009 (0.005)†	-0.006 (0.007)
5	Constraint > Info. Var. (sent) Indirect Effect	0.000 (0.002)	0.002 (0.001)	-0.001 (0.001)
6	Constraint > Info. Var. (sent) Total Effect	-0.008 (0.019)	-0.007 (0.005)	-0.008 (0.007)
7	Constraint > Info. Var. (recv) Indirect Effect	-0.010 (0.005)†	-0.001 (0.001)	-0.001 (0.001)
8	Constraint > Info. Var. (recv) Total Effect	-0.018 (0.019)	-0.010 (0.005)†	-0.009 (0.007)

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 4.9.1 Regression paths for the Socially Distant Information (sent) model.

	Dependent	Independent	Stable	Turbulent	Overall
1	Luxury Info. (sent)	Gender (male)	-0.028 (0.124)	-0.186 (0.117)	-0.100 (0.091)
2	Luxury Info. (sent)	Tenure	-0.150 (0.116)	-0.014 (0.048)	0.128 (0.042)**
3	Luxury Info. (sent)	Org. Rank	-0.176 (0.057)**	0.092 (0.063)	-0.007 (0.045)
4	Luxury Info. (sent)	Δ Constraint	-0.183 (0.114)	0.122 (0.071)†	0.046 (0.064)
5	Luxury Info. (sent)	T1 Constraint	-0.062 (0.097)	0.118 (0.061)†	0.108 (0.053)*
6	Topic Change (sent)	Gender (male)	-0.089 (0.104)	0.068 (0.109)	-0.002 (0.077)
7	Topic Change (sent)	Tenure	-0.125 (0.098)	0.038 (0.044)	0.016 (0.036)
8	Topic Change (sent)	Org. Rank	-0.017 (0.048)	-0.021 (0.059)	-0.018 (0.038)
9	Topic Change (sent)	Δ Constraint	0.685 (0.096)***	0.260 (0.066)***	0.371 (0.054)***
10	Topic Change (sent)	T1 Constraint	0.718 (0.081)***	0.545 (0.056)***	0.604 (0.045)***
11	Soc. Distant Information (sent)	Gender (male)	0.073 (0.109)	0.048 (0.142)	0.059 (0.093)
12	Soc. Distant Information (sent)	Tenure	0.017 (0.102)	-0.018 (0.057)	-0.047 (0.043)
13	Soc. Distant Information (sent)	Org. Rank	-0.055 (0.050)	-0.005 (0.077)	-0.043 (0.046)
14	Soc. Distant Information (sent)	Δ Constraint	-0.296 (0.100)**	-0.257 (0.086)**	-0.269 (0.066)***
15	Soc. Distant Information (sent)	T1 Constraint	0.069 (0.085)	-0.026 (0.073)	-0.020 (0.055)
16	Δ Info. Variance (recv)	Gender (male)	-0.002 (0.084)	-0.147 (0.094)	-0.094 (0.065)
17	Δ Info. Variance (recv)	Tenure	0.052 (0.079)	0.080 (0.038)*	0.111 (0.030)***
18	Δ Info. Variance (recv)	Org. Rank	0.028 (0.039)	-0.062 (0.051)	-0.007 (0.032)
19	Δ Info. Variance (recv)	Δ Constraint	-0.171 (0.072)*	-0.121 (0.055)*	-0.120 (0.044)**
20	Δ Info. Variance (recv)	T1 Constraint	0.096 (0.065)	-0.044 (0.048)	0.002 (0.038)
21	Δ Salary	Δ Info. Variance (recv)	0.061 (0.015)***	-0.001 (0.005)	0.011 (0.006)†
22	Δ Salary	T1 Info. Variance (recv)	0.035 (0.012)**	0.005 (0.004)	0.016 (0.005)**
23	Δ Salary	Topic Change (sent)	0.030 (0.011)**	-0.003 (0.004)	0.005 (0.005)
24	Δ Salary	Soc. Distant Information (sent)	0.004 (0.011)	0.007 (0.003)*	0.007 (0.004)†
25	Δ Salary	Luxury Info. (sent)	0.010 (0.009)	0.008 (0.004)*	-0.001 (0.004)
26	Δ Salary	Δ Constraint	-0.008 (0.020)	-0.007 (0.005)	-0.007 (0.007)
27	Δ Salary	T1 Constraint	-0.034 (0.018)†	-0.007 (0.005)	-0.015 (0.007)*

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 4.9.2. Model fit statistics for the Socially Distant Information (sent) model.

	Fit Statistic	Stable Fit	Turbulent Fit	Overall Fit
1	N	250	357	607
2	χ^2	45.29***	57.89***	96.22***
3	df	18	18	18
4	RMSEA	0.078	0.079	0.085
5	CFI	0.988	0.987	0.985
6	TLI	0.956	0.952	0.944
7	SRMR	0.025	0.026	0.026
8	AIC	5270	8407	14502

Table 4.9.3. Mediation paths for the Socially Distant Information (sent) model.

	Mediation Path	Stable	Turbulent	Overall
1	Constraint > Luxury Info. Indirect Effect	-0.002 (0.002)	0.001 (0.001)	-0.000 (0.000)
2	Constraint > Luxury Info. Total Effect	-0.010 (0.020)	-0.006 (0.005)	-0.007 (0.007)
3	Constraint > Topic Change Indirect Effect	0.020 (0.008)*	-0.001 (0.001)	0.002 (0.002)
4	Constraint > Topic Change Total Effect	0.012 (0.018)	-0.008 (0.005)	-0.005 (0.007)
5	Constraint > Soc. Dist. Info. Indirect Effect	-0.001 (0.003)	-0.002 (0.001)†	-0.002 (0.001)
6	Constraint > Soc. Dist. Info. Total Effect	-0.009 (0.019)	-0.009 (0.005)†	-0.009 (0.007)
7	Constraint > Info. Var. (recv) Indirect Effect	-0.010 (0.005)*	0.000 (0.001)	-0.001 (0.001)
8	Constraint > Info. Var. (recv) Total Effect	-0.018 (0.020)	-0.007 (0.005)	-0.008 (0.007)
9	Cons > SocDistInfo + Cons > Luxury Info Indirect	-0.003 (0.004)	-0.001 (0.001)	-0.002 (0.001)
10	Cons > SocDistInfo + Cons > Luxury Info Total	-0.011 (0.020)	-0.008 (0.005)	-0.009 (0.007)
11	Cons > InfoVar (recv) + Cons > Topic Change Indirect	-0.003 (0.008)	0.002 (0.001)†	-0.002 (0.002)
12	Cons > InfoVar (recv) + Cons > Topic Change Total	-0.011 (0.021)	-0.005 (0.005)	-0.009 (0.007)
13	Constraint > all info vars > Salary Indirect	0.007 (0.010)	-0.001 (0.002)	-0.001 (0.002)
14	Constraint > all info vars > Salary Total	-0.001 (0.018)	-0.008 (0.005)†	-0.008 (0.007)

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 4.10.1. Regression paths for the full model.

	Dependent	Independent	Stable	Turbulent	Overall
1	Luxury Info. (sent)	Gender (male)	-0.028 (0.124)	-0.187 (0.117)	-0.100 (0.091)
2	Luxury Info. (sent)	Tenure	-0.150 (0.116)	-0.014 (0.048)	0.128 (0.042)**
3	Luxury Info. (sent)	Org. Rank	-0.176 (0.057)**	0.092 (0.063)	-0.007 (0.045)
4	Luxury Info. (sent)	Δ Constraint	-0.181 (0.114)	0.121 (0.069)†	0.047 (0.064)
5	Luxury Info. (sent)	T1 Constraint	-0.062 (0.097)	0.118 (0.061)†	0.108 (0.053)*
6	Topic Change (sent)	Gender (male)	0.052 (0.168)	0.149 (0.163)	0.012 (0.088)
7	Topic Change (sent)	Tenure	-1.203 (0.860)	0.874 (0.525)†	-0.452 (0.277)
8	Topic Change (sent)	Org. Rank	-0.077 (0.076)	-0.114 (0.101)	0.021 (0.049)
9	Topic Change (sent)	Δ Constraint	0.629 (0.100)***	0.155 (0.092)†	0.421 (0.063)***
10	Topic Change (sent)	T1 Constraint	0.645 (0.114)***	0.391 (0.125)**	0.698 (0.075)***
11	Soc. Distant Information (sent)	Gender (male)	0.073 (0.109)	0.048 (0.142)	0.059 (0.093)
12	Soc. Distant Information (sent)	Tenure	0.017 (0.102)	-0.018 (0.057)	-0.047 (0.043)
13	Soc. Distant Information (sent)	Org. Rank	-0.055 (0.050)	-0.005 (0.077)	-0.043 (0.046)
14	Soc. Distant Information (sent)	Δ Constraint	-0.296 (0.100)**	-0.257 (0.086)**	-0.269 (0.066)***
15	Soc. Distant Information (sent)	T1 Constraint	0.069 (0.085)	-0.026 (0.073)	-0.020 (0.055)
16	Δ Info. Variance (sent)	Gender (male)	-0.061 (0.125)	-0.063 (0.058)	-0.064 (0.063)
17	Δ Info. Variance (sent)	Tenure	0.226 (0.117)†	0.057 (0.023)*	0.078 (0.029)**
18	Δ Info. Variance (sent)	Org. Rank	0.071 (0.058)	-0.038 (0.031)	0.015 (0.031)
19	Δ Info. Variance (sent)	Δ Constraint	-0.183 (0.115)	-0.091 (0.035)**	-0.109 (0.045)*
20	Δ Info. Variance (sent)	T1 Constraint	-0.025 (0.098)	-0.063 (0.030)*	-0.055 (0.037)
21	Δ Info. Variance (recv)	Gender (male)	-0.002 (0.088)	-0.148 (0.092)	-0.094 (0.066)
22	Δ Info. Variance (recv)	Tenure	0.058 (0.080)	0.079 (0.037)*	0.124 (0.030)***
23	Δ Info. Variance (recv)	Org. Rank	0.029 (0.040)	-0.062 (0.050)	-0.008 (0.033)
24	Δ Info. Variance (recv)	Δ Constraint	-0.173 (0.072)*	-0.132 (0.054)*	-0.126 (0.044)**
25	Δ Info. Variance (recv)	T1 Constraint	0.096 (0.068)	-0.045 (0.048)	-0.001 (0.039)
26	Δ Salary	Δ Info. Variance (recv)	0.055 (0.019)**	0.007 (0.007)	0.006 (0.008)
27	Δ Salary	T1 Info. Variance (recv)	0.012 (0.017)	0.008 (0.005)	0.006 (0.007)
28	Δ Salary	Δ Info. Variance (sent)	-0.000 (0.012)	-0.015 (0.011)	0.007 (0.008)
29	Δ Salary	T1 Info. Variance (sent)	0.042 (0.018)*	-0.005 (0.006)	0.015 (0.008)†
30	Δ Salary	Topic Change (sent)	0.026 (0.012)*	-0.002 (0.004)	0.004 (0.005)
31	Δ Salary	Soc. Distant Information (sent)	0.003 (0.011)	0.007 (0.003)*	0.007 (0.004)
32	Δ Salary	Luxury Info. (sent)	0.011 (0.009)	0.008 (0.004)*	-0.003 (0.004)
33	Δ Salary	Δ Constraint	-0.007 (0.019)	-0.007 (0.005)	-0.007 (0.007)
34	Δ Salary	T1 Constraint	-0.031 (0.018)†	-0.008 (0.005)†	-0.015 (0.007)*

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 4.10.2. Model fit statistics for the full model.

	Fit Statistic	Stable Fit	Turbulent Fit	Overall Fit
1	N	250	357	607
2	χ^2	59.52***	70.10***	111.72***
3	df	25	25	25
4	RMSEA	0.074	0.071	0.076
5	CFI	0.987	0.989	0.986
6	TLI	0.953	0.959	0.950
7	SRMR	0.029	0.030	0.029
8	AIC	6197	9232	16551

Table 4.10.3. Mediation paths for the full model.

	Mediation Path	Stable	Turbulent	Overall
1	Constraint > Luxury Info. Indirect Effect	-0.002 (0.002)	0.001 (0.001)	-0.000 (0.000)
2	Constraint > Luxury Info. Total Effect	-0.009 (0.020)	-0.006 (0.005)	-0.007 (0.007)
3	Constraint > Topic Change Indirect Effect	0.016 (0.008)*	-0.000 (0.001)	0.002 (0.002)
4	Constraint > Topic Change Total Effect	0.009 (0.018)	-0.008 (0.005)	-0.005 (0.007)
5	Constraint > Soc. Dist. Info. Indirect Effect	-0.001 (0.003)	-0.002 (0.001)†	-0.002 (0.001)
6	Constraint > Soc. Dist. Info. Total Effect	-0.008 (0.019)	-0.009 (0.005)†	-0.008 (0.007)
7	Constraint > Info. Var. (sent) Indirect Effect	0.000 (0.002)	0.001 (0.001)	-0.001 (0.001)
8	Constraint > Info. Var. (sent) Total Effect	-0.007 (0.020)	-0.006 (0.005)	-0.007 (0.007)
9	Constraint > Info. Var. (recv) Indirect Effect	-0.009 (0.005)†	-0.001 (0.001)	-0.001 (0.001)
10	Constraint > Info. Var. (recv) Total Effect	-0.017 (0.020)	-0.008 (0.005)	-0.007 (0.007)
11	cons_nrir_nri_indirect	-0.010 (0.010)	-0.003 (0.003)	0.002 (0.004)
12	cons_nrir_nri_total	-0.017 (0.021)	-0.011 (0.006)†	-0.004 (0.008)
13	Constraint > all info vars > Salary Indirect	0.004 (0.010)	-0.002 (0.002)	-0.001 (0.003)
14	Constraint > all info vars > Salary Total	-0.003 (0.018)	-0.009 (0.005)†	-0.008 (0.007)

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 4.11.1. Regression paths for the full model with only sent information variance.

	Dependent	Independent	Stable	Turbulent	Overall
1	Luxury Info. (sent)	Gender (male)	-0.030 (0.124)	-0.188 (0.117)	-0.100 (0.091)
2	Luxury Info. (sent)	Tenure	-0.151 (0.116)	-0.015 (0.048)	0.128 (0.042)**
3	Luxury Info. (sent)	Org. Rank	-0.176 (0.057)**	0.093 (0.063)	-0.007 (0.045)
4	Luxury Info. (sent)	Δ Constraint	-0.164 (0.114)	0.104 (0.071)	0.040 (0.065)
5	Luxury Info. (sent)	T1 Constraint	-0.062 (0.097)	0.117 (0.061)†	0.108 (0.053)*
6	Topic Change (sent)	Gender (male)	0.041 (0.164)	0.077 (0.149)	0.007 (0.080)
7	Topic Change (sent)	Tenure	-1.078 (0.833)	0.150 (1.026)	-0.223 (0.236)
8	Topic Change (sent)	Org. Rank	-0.074 (0.075)	-0.033 (0.129)	-0.000 (0.043)
9	Topic Change (sent)	Δ Constraint	0.615 (0.102)***	0.224 (0.130)†	0.376 (0.060)***
10	Topic Change (sent)	T1 Constraint	0.652 (0.111)***	0.524 (0.196)**	0.650 (0.065)***
11	Soc. Distant Information (sent)	Gender (male)	0.073 (0.109)	0.048 (0.142)	0.059 (0.093)
12	Soc. Distant Information (sent)	Tenure	0.017 (0.102)	-0.018 (0.057)	-0.047 (0.043)
13	Soc. Distant Information (sent)	Org. Rank	-0.055 (0.050)	-0.005 (0.077)	-0.043 (0.046)
14	Soc. Distant Information (sent)	Δ Constraint	-0.296 (0.101)**	-0.257 (0.087)**	-0.269 (0.066)***
15	Soc. Distant Information (sent)	T1 Constraint	0.069 (0.085)	-0.026 (0.073)	-0.020 (0.055)
16	Δ Info. Variance (sent)	Gender (male)	-0.061 (0.126)	-0.063 (0.058)	-0.064 (0.063)
17	Δ Info. Variance (sent)	Tenure	0.226 (0.118)†	0.057 (0.023)*	0.079 (0.029)**
18	Δ Info. Variance (sent)	Org. Rank	0.071 (0.058)	-0.038 (0.031)	0.015 (0.031)
19	Δ Info. Variance (sent)	Δ Constraint	-0.182 (0.117)	-0.086 (0.035)*	-0.105 (0.045)*
20	Δ Info. Variance (sent)	T1 Constraint	-0.025 (0.098)	-0.063 (0.030)*	-0.055 (0.037)
21	Δ Salary	Δ Info. Variance (sent)	0.019 (0.009)*	-0.008 (0.008)	0.010 (0.006)
22	Δ Salary	T1 Info. Variance (sent)	0.046 (0.014)***	0.001 (0.005)	0.019 (0.006)**
23	Δ Salary	Topic Change (sent)	0.019 (0.012)	-0.002 (0.004)	0.003 (0.005)
24	Δ Salary	Soc. Distant Information (sent)	0.008 (0.011)	0.007 (0.003)*	0.007 (0.004)
25	Δ Salary	Luxury Info. (sent)	0.005 (0.010)	0.007 (0.004)†	-0.004 (0.004)
26	Δ Salary	Δ Constraint	-0.013 (0.020)	-0.008 (0.005)	-0.007 (0.007)
27	Δ Salary	T1 Constraint	-0.028 (0.018)	-0.010 (0.005)*	-0.016 (0.007)*

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 4.11.2. Model fit statistics for the full model with only sent information variance.

	Fit Statistic	Stable Fit	Turbulent Fit	Overall Fit
1	N	250	357	607
2	χ^2	19.50	30.01**	44.06***
3	df	14	14	14
4	RMSEA	0.040	0.057	0.059
5	CFI	0.997	0.995	0.994
6	TLI	0.987	0.977	0.972
7	SRMR	0.015	0.014	0.012
8	AIC	5425	7990	14355

Table 4.11.3. Mediation paths for the full model with only sent information variance.

	Mediation Path	Stable	Turbulent	Overall
1	Constraint > Luxury Info. Indirect Effect	-0.001 (0.002)	0.001 (0.001)	-0.000 (0.000)
2	Constraint > Luxury Info. Total Effect	-0.013 (0.020)	-0.008 (0.005)	-0.007 (0.007)
3	Constraint > Topic Change Indirect Effect	0.011 (0.008)	-0.000 (0.001)	0.001 (0.002)
4	Constraint > Topic Change Total Effect	-0.001 (0.018)	-0.009 (0.005)†	-0.006 (0.007)
5	Constraint > Soc. Dist. Info. Indirect Effect	-0.002 (0.003)	-0.002 (0.001)†	-0.002 (0.001)
6	Constraint > Soc. Dist. Info. Total Effect	-0.015 (0.019)	-0.010 (0.005)†	-0.009 (0.007)
7	Constraint > Info. Var. (sent) Indirect Effect	-0.003 (0.003)	0.001 (0.001)	-0.001 (0.001)
8	Constraint > Info. Var. (sent) Total Effect	-0.016 (0.020)	-0.008 (0.005)	-0.008 (0.007)
9	Cons > SocDistInfo + Cons > Luxury Info Indirect	-0.003 (0.004)	-0.001 (0.001)	-0.002 (0.001)
10	Cons > SocDistInfo + Cons > Luxury Info Total	-0.016 (0.019)	-0.009 (0.005)†	-0.009 (0.007)
11	Constraint > all info vars > Salary Indirect	0.008 (0.008)	-0.001 (0.001)	-0.001 (0.002)
12	Constraint > all info vars > Salary Total	-0.004 (0.018)	-0.010 (0.005)†	-0.008 (0.007)

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 4.12.1. Regression paths for the Socially Distant Information (recv) model.

Table LDS7.1. Regression paths for the Socially Distant Information (recv) model.

	Dependent	Independent	Stable	Turbulent	Overall
1	Luxury Info. (sent)	Gender (male)	-0.028 (0.124)	-0.186 (0.117)	-0.100 (0.091)
2	Luxury Info. (sent)	Tenure	-0.150 (0.116)	-0.014 (0.048)	0.128 (0.042)**
3	Luxury Info. (sent)	Org. Rank	-0.176 (0.057)**	0.092 (0.063)	-0.007 (0.045)
4	Luxury Info. (sent)	Δ Constraint	-0.183 (0.114)	0.122 (0.071)†	0.046 (0.064)
5	Luxury Info. (sent)	T1 Constraint	-0.062 (0.097)	0.118 (0.061)†	0.108 (0.053)*
6	Topic Change (sent)	Gender (male)	-0.089 (0.104)	0.068 (0.109)	-0.002 (0.077)
7	Topic Change (sent)	Tenure	-0.125 (0.098)	0.038 (0.044)	0.016 (0.036)
8	Topic Change (sent)	Org. Rank	-0.017 (0.048)	-0.021 (0.059)	-0.018 (0.038)
9	Topic Change (sent)	Δ Constraint	0.685 (0.096)***	0.260 (0.066)***	0.371 (0.054)***
10	Topic Change (sent)	T1 Constraint	0.718 (0.081)***	0.545 (0.056)***	0.604 (0.045)***
11	Soc. Distant Information (recv)	Gender (male)	-0.027 (0.109)	-0.041 (0.136)	-0.029 (0.090)
12	Soc. Distant Information (recv)	Tenure	0.090 (0.102)	-0.050 (0.055)	-0.065 (0.042)
13	Soc. Distant Information (recv)	Org. Rank	0.010 (0.050)	0.010 (0.073)	-0.007 (0.045)
14	Soc. Distant Information (recv)	Δ Constraint	-0.289 (0.100)**	-0.454 (0.082)***	-0.411 (0.064)***
15	Soc. Distant Information (recv)	T1 Constraint	0.012 (0.085)	-0.174 (0.070)*	-0.144 (0.053)**
16	Δ Info. Variance (recv)	Gender (male)	-0.002 (0.084)	-0.147 (0.094)	-0.094 (0.065)
17	Δ Info. Variance (recv)	Tenure	0.052 (0.079)	0.080 (0.038)*	0.111 (0.030)***
18	Δ Info. Variance (recv)	Org. Rank	0.028 (0.039)	-0.062 (0.051)	-0.007 (0.032)
19	Δ Info. Variance (recv)	Δ Constraint	-0.171 (0.072)*	-0.121 (0.055)*	-0.120 (0.044)**
20	Δ Info. Variance (recv)	T1 Constraint	0.096 (0.065)	-0.044 (0.048)	0.002 (0.038)
21	Δ Salary	Δ Info. Variance (recv)	0.062 (0.015)***	-0.000 (0.005)	0.011 (0.006)†
22	Δ Salary	T1 Info. Variance (recv)	0.035 (0.011)**	0.005 (0.004)	0.016 (0.005)**
23	Δ Salary	Topic Change (sent)	0.030 (0.011)**	-0.004 (0.004)	0.005 (0.005)
24	Δ Salary	Soc. Distant Information (recv)	-0.001 (0.011)	0.006 (0.003)†	0.007 (0.004)†
25	Δ Salary	Luxury Info. (sent)	0.011 (0.009)	0.006 (0.004)†	-0.002 (0.004)
26	Δ Salary	Δ Constraint	-0.009 (0.020)	-0.006 (0.005)	-0.005 (0.007)
27	Δ Salary	T1 Constraint	-0.034 (0.018)†	-0.006 (0.005)	-0.014 (0.007)*

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 4.12.2. Model fit statistics for the Socially Distant Information (recv) model.

	Fit Statistic	Stable Fit	Turbulent Fit	Overall Fit
1	N	250	357	607
2	χ^2	57.93***	65.74***	113.74***
3	df	18	18	18
4	RMSEA	0.094	0.086	0.094
5	CFI	0.982	0.984	0.981
6	TLI	0.935	0.942	0.932
7	SRMR	0.027	0.030	0.028
8	AIC	5270	8397	14477

Table 4.12.3. Mediation paths for the Socially Distant Information (recv) model.

	Mediation Path	Stable	Turbulent	Overall
1	Constraint > Luxury Info. Indirect Effect	-0.002 (0.002)	0.001 (0.001)	-0.000 (0.000)
2	Constraint > Luxury Info. Total Effect	-0.011 (0.020)	-0.005 (0.005)	-0.006 (0.007)
3	Constraint > Topic Change Indirect Effect	0.021 (0.008)*	-0.001 (0.001)	0.002 (0.002)
4	Constraint > Topic Change Total Effect	0.011 (0.018)	-0.007 (0.005)	-0.004 (0.007)
5	Constraint > Soc. Dist. Info. Indirect Effect	0.000 (0.003)	-0.003 (0.002)	-0.003 (0.002)
6	Constraint > Soc. Dist. Info. Total Effect	-0.009 (0.019)	-0.008 (0.005)	-0.008 (0.007)
7	Constraint > Info. Var. (recv) Indirect Effect	-0.011 (0.005)*	0.000 (0.001)	-0.001 (0.001)
8	Constraint > Info. Var. (recv) Total Effect	-0.020 (0.020)	-0.006 (0.005)	-0.007 (0.007)
9	Cons > SocDistInfo + Cons > Luxury Info Indirect	-0.002 (0.004)	-0.002 (0.002)	-0.003 (0.002)†
10	Cons > SocDistInfo + Cons > Luxury Info Total	-0.011 (0.020)	-0.008 (0.005)	-0.009 (0.007)
11	Constraint > all info vars > Salary Indirect	0.008 (0.010)	-0.003 (0.002)	-0.002 (0.003)
12	Constraint > all info vars > Salary Total	-0.001 (0.018)	-0.008 (0.005)†	-0.008 (0.007)

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

CHAPTER FIVE: Discussion

The goal of this study was to understand how organizational turbulence impacts the information flow mechanisms which link network positions rich in structural holes to individual advantage. The organizational turbulence in Standard Inc. erased the advantages of information variance so the employees sought new information from new places. Two consistent themes were present in the results: network position impacted access and adoption of different forms of information flows, and that the benefits of information flows were altered by the presence of organizational turbulence. Different concepts of information flows provided a benefit when the organizational context was stable compared to when it was turbulent. Employees in the stable organizational setting, consistent with structural hole theory, benefitted from increasing the variance of their repertoire of information. In the turbulent organizational setting, at best there were almost no benefits of increasing information variance, and at worst it could be a liability. Instead benefits came from searching the organizational topic space for the right kind of information.

I found partial support for H1a and H1b. The results showed a mediation path for *⊿ Information Variance (recv)* but a mediation path for *⊿ Information Variance (sent)* never materialized. I was specifically interested in the information variance authored by the individual, but it was a worse predictor than, and highly correlated with the information variance of messages in the individual's inbox. This result confirms existing theories regarding the intervening role of access to diverse information, linking brokerage to individual advantage. For *Socially Distant Information* the mediation results fail to reject the null hypothesis that it does not mediate brokerage and increases in salary, but the results were very suggestive of a path. Both component paths of the mediation are significant, but the effect from *Socially Distant Information* and ∆ Salary is somewhat weak, and, as a result, the indirect effect was weak.

I had expected that *Socially Distant Information* and *⊿ Information Variance*, both received and sent, would provide an advantage in both contexts, but the differences in the contexts were strong. The effect of turbulence meant that the theorized mediating mechanism from structural hole theory of being exposed to information variance did not provide any detectable benefit to those in the turbulent context, and, at worst, information variance may even become a liability for those in a turbulent context. That does not mean that structural holes were not beneficial to people in the turbulent context. Although the significance of the mediation path was only suggestive of the indirect or total effect, structural holes improved the adoption of socially distant information, and socially distant information was found to have a positive impact on changes in salary.

As mentioned, organizational turbulence had a strong impact on the effects of information flows on changes in salary. Under organizational turbulence employees behave differently than they would in stable situations. They may perceive the restructuring changes as a threat and respond by become rigid or taking risks, which changes the ways in which employees and managers search for and use information (Andersen & Nichols, 2007; Baum et al., 2005). I found support for both H2a and H2b. The effect of organizational turbulence shut down some paths from ⊿ *Information Variance* and opened paths through *Socially Distant Information* and information tied to the dominant organization.

There is some evidence to support the idea that members in the turbulent context became rigid. The adoption of socially distant information was, on average, lower in the turbulent setting compared to the stable setting, although this difference was only suggestive, not significant. There appears to be more evidence that members in the turbulent context became risk seeking and sought out new information. The changes in information variance (received) and topic change were both higher for the members in the turbulent context. This could be the effect of regression to the new postmerger mean. The initial levels of information variance were higher in the stable context, and thus in order to adapt to the new postmerger context there should be some movement towards the new global average.

Closure and Topic Change.

The controls offered some puzzling interactions with other variables in the models. The results of the analyses indicated that closed networks induce greater change to the topics the employee discusses than open networks. This effect was present in all contexts, but appears strongest in the stable context. Also, topic change itself and the mediation path through topic change was significant. Due to the strong effect between increases in constraint and topic change, the results suggest that a 1 s.d. increase in constraint is more beneficial than a 1 s.d. decrease in constraint due to the indirect advantages from topic changes.

The relationship between closure and topic change may be evidence for the difficulty of transferring complex ideas (Centola & Macy, 2007; Reagans & McEvily, 2003). In order to significantly change the topics of the emails someone authors, it helps if there is pressure from multiple embedded alters. Complex knowledge transfer, such as inducing large changes in an individual's topic space, is costlier and complex to transfer than simple contagions. The new knowledge is thought to be beneficial to the recipient (although the direct benefit of topic change in this setting was not found), but this is at a cost paid by the sender in time to educate, train, and correct. Embedded relationships reduces the resulting "competitive and motivational impediments" (Reagans & McEvily, 2003: 242). Closed networks of trust and norms reduce the potential transaction costs in the transfer of complex information (Uzzi, 1997).

In the stable context, employees could form either closed or open networks. Both benefit the individual through different information mechanisms. The closed network comes with trust, and norms, and influence from others to help induce complex changes when necessary. Or the employee can choose to create an open network and benefit from access to diverse information.

During organizational turbulence, it pays to be adaptable. This effect may be from that those in the stable context see opportunities where those in the turbulent context saw threats (Dutton & Jackson, 1987; Jackson & Dutton, 1988; Krueger, 2007). Many employees may be deeply embedded in their own routines (Dane, 2010; Labianca et al., 2000), integrations are rare events and they conjure mindfulness about one's current position, routines, and schema (Bauer, King, & Matzler, 2016; Weick et al., 2005). Organizational routines can become habits, a set of operations that individuals perform with little cognitive effort. The interruption of the routine can drive attention and mindfulness towards those routines, perhaps lead an individual to more advantageous ways of working. The integration of two firms is a turbulent experience in which habits and routines are disrupted, and "when routines are disrupted, the resulting void is similar to the void induced by meditation. When either void is created, past experience no longer serves as a firm guide, and the disruption stirs the cognitive pot. Because the void is momentarily tough to categorize and label, it serves as a moment of nonconceptual mindfulness. This means that during this moment more is seen, and more is seen about seeing" (Weick & Sutcliffe, 2006: 516).

The integration process presents an opportunity to form new ideas, create new structures, and codify the organizational environment in new ways. Previous routines, scripts, and schema become less relevant, people become more receptive to the patterns offered by others subject to their own selective attention, biases, and interpretations. This is a highly cognitive and emotional process that can be shaped by previous biases, as well as perceptions of the merger event. Dense networks of ties benefit from trust and safety, which could support individuals as they make changes.

Distant, but Close to Home

I found a negative correlation between adopting *Socially Distant Information* and *Luxury Information* within the turbulent context. Members of the turbulent context who adopted socially distant information tended to adopt information from within their own legacy organization. This could indicate a process of sensemaking in the face of a disrupting organizational change (Bartunek & Rousseau, 2006; Weick et al., 2005). A logical next step in the analysis would be to investigate the interaction between *Socially Distant Information* and *Luxury Information*. It might be possible that adopting socially distant information within the dominant organization is especially beneficial, or perhaps the information is unusable because it is too different from what is known in the local network.

Socially distant information may suffer from the “liability of newness” (Stinchcombe & March, 1965); it’s too different from existing information and is rejected by others. Even when adopting socially distant information the Standard employees didn’t want to adopt information that was *too* different from what they already knew. When employees adopted socially distant information in the turbulent context it tended to come from their own organization. By adopting distant information from within the legacy organization the searcher may be trying to reduce this liability. A study of the interactions between social distance and legacy ownership of adopted information may provide some evidence that a liability exists. However, I did find that those who adopted from the other context, Luxury, experienced an additional boost to salary, contraindicating the existence of that liability in this setting.

The Uniqueness of the Situation

Almost every whole network study is in some way a case study of a unique organization, and there are a number of unique aspects to the case I study here that can make generalizing the results difficult. I focused this research on the adoption of social distance rather than the adoption of information from the opposing organizations so that the results would be more generalizable to other situations where there are large organizational changes. By controlling for the adoption of Luxury weighted topics I have helped achieve that goal by showing that socially distant information is independently beneficial to individuals when controlling for the adoption of dominant topics. I expected that the socially distant topics that people adopt are distant simply because the come from the other organization. I showed that there was only a weak or negative relationship between adopting socially distant information and adopting topics from the opposite organization.

It’s possible that the turbulence within Standard Inc. was not the cause of changes, but rather something characteristic about the organization that lead to the difference in effect from information flows to increases in salary. I’ve controlled for three of the major demographic differences between the two firms, but it’s possible there are other differences which were missed. Further study in new organizational settings would help solve this question.

Future Study

On a scale between exploration and exploitation, socially distant information is more related to exploration, and changes in information variance is more related to exploitation. This leaves open the question of ambidexterity (Mom, van den Bosch, & Volberda, 2009; Rogan & Mors, 2014). There is only so much time and resources that can be spent on search, thus the increased cost of non-local search is likely to reduce incremental local search efforts. However, the payoff could be great. If an employee discusses a wide variance of topics and she is writing emails on topics typically discussed by people outside the local network, there could be additional benefits. Research on managerial ambidexterity could be extended by the range of causes and benefits of employees adopting both varied and distant information.

One improvement to the socially distant information measure is to a decay parameter which reduces the marginal impact of distance as it grows. The difference of impact to advantages of adopting information from three steps away vs. two steps away should not be equal to the differences of the impact of adopting information from 12 steps way vs. 11 steps away. A one step increase is not equal at all distances from the individual. The introduction of a decay parameter would allow the researcher to tune the measure to the peculiarities of a network, such as unusually high rates of information transfer where long distances are still important.

This study represents only two 30-day time points in a very dynamic process. It could be that there are periodic surges of searches for distant, powerful, or unique information similar to network oscillations (Burt & Merluzzi, 2016). Trends such as these are only detectable using more than two time points. A more comprehensive look at turbulent and stable organizations as they respond to organizational changes could help further our understanding of the dynamic and interacting benefits of information flows, brokerage, and closure.

CHAPTER SIX: Conclusion

More data, bigger datasets can be like using bigger telescope or higher powered microscope. We can use it as a way of peering into processes that were understood, but never precisely measured and observed. In this study I use a large corpus of email content to deep our understanding of the ways in which network position influences employee information flows, and how the pathways of the broker vision advantage are transformed in the presence of overwhelming organizational turbulence. The difference in organizational contexts was found to have a dramatic impact on the value of different forms of interpersonal information flows. While the paths linking network position to information were somewhat stable, the paths linking features of information flows to increases in salary were very different. For those in a relative stable, albeit still changing, environment the theorized relationships between structural holes, access to diverse information, and individual advantage has been supported. This path is destroyed in the turbulent context, and instead members in the turbulent context had to search the organization for the right information: information distant from where they are, and information that is associated with power and status. This dissertation reveals a number of new avenues for research and lays the groundwork for several future studies.

APPENDIX ONE: Inter-Legacy Ties

Routines of communication can be difficult to break (Allatta & Singh, 2011; Briscoe & Tsai, 2011). Briscoe and Tsai (2011) found that the employees with a closed network in their legacy firm were much less likely to form ties with the new firm, and those with open networks found it easier. But what is the effect of reaching out? In this appendix I test a different structural source of information, increases in reaching out to the other side. To create the variable, I measured the number of alters in each individual's network that were from the opposite legacy organization at each time point, then created a LDS from the change.

The strongest key variable ∆ *Inter-Legacy Ties* correlates with the ⊿ *Info. Variance (recv)*. The results of the LDS model are presented in *Table 7.1.1*. I found that among the members of the lower-status organization, forging ties with the dominant organization was directly related to ⊿ *Salary* ($\beta = 0.01$, $p < 0.05$). There was also a significant partial mediation path in the turbulent context ($\beta = 01$, $p < 0.01$): forming inter-legacy ties provides an advantage both directly and indirectly through improved access to diverse information.

Table 7.1.1. Regression paths for the Inter-Legacy Ties model.

	Dependent	Independent	Stable	Turbulent	Overall
1	Luxury Info. (sent)	Gender (male)	-0.029 (0.120)	-0.164 (0.117)	-0.101 (0.091)
2	Luxury Info. (sent)	Tenure	-0.158 (0.112)	-0.016 (0.047)	0.129 (0.042)**
3	Luxury Info. (sent)	Org. Rank	-0.213 (0.055)***	0.073 (0.063)	-0.007 (0.045)
4	Luxury Info. (sent)	Δ Constraint	-0.215 (0.110)†	0.135 (0.071)†	0.045 (0.064)
5	Luxury Info. (sent)	T1 Constraint	-0.072 (0.093)	0.126 (0.060)*	0.107 (0.053)*
6	Luxury Info. (sent)	Δ Inter-legacy ties	-0.255 (0.059)***	0.112 (0.062)†	-0.010 (0.047)
7	Topic Change (sent)	Gender (male)	-0.089 (0.104)	0.071 (0.109)	0.001 (0.077)
8	Topic Change (sent)	Tenure	-0.124 (0.098)	0.037 (0.044)	0.014 (0.036)
9	Topic Change (sent)	Org. Rank	-0.010 (0.048)	-0.024 (0.059)	-0.018 (0.038)
10	Topic Change (sent)	Δ Constraint	0.691 (0.096)***	0.262 (0.066)***	0.375 (0.054)***
11	Topic Change (sent)	T1 Constraint	0.719 (0.081)***	0.546 (0.056)***	0.607 (0.045)***
12	Topic Change (sent)	Δ Inter-legacy ties	0.046 (0.051)	0.016 (0.058)	0.034 (0.040)
13	Soc. Distant Information (sent)	Gender (male)	0.073 (0.109)	0.063 (0.141)	0.061 (0.093)
14	Soc. Distant Information (sent)	Tenure	0.017 (0.102)	-0.019 (0.057)	-0.048 (0.043)
15	Soc. Distant Information (sent)	Org. Rank	-0.059 (0.050)	-0.017 (0.076)	-0.044 (0.046)
16	Soc. Distant Information (sent)	Δ Constraint	-0.299 (0.101)**	-0.249 (0.086)**	-0.266 (0.066)***
17	Soc. Distant Information (sent)	T1 Constraint	0.068 (0.085)	-0.020 (0.073)	-0.018 (0.055)
18	Soc. Distant Information (sent)	Δ Inter-legacy ties	-0.029 (0.054)	0.073 (0.076)	0.022 (0.048)
19	Δ Info. Variance (recv)	Gender (male)	-0.002 (0.082)	-0.115 (0.092)	-0.080 (0.064)
20	Δ Info. Variance (recv)	Tenure	0.056 (0.077)	0.077 (0.037)*	0.102 (0.030)***
21	Δ Info. Variance (recv)	Org. Rank	0.052 (0.038)	-0.090 (0.050)†	-0.008 (0.032)
22	Δ Info. Variance (recv)	Δ Constraint	-0.142 (0.068)*	-0.105 (0.054)†	-0.106 (0.043)*
23	Δ Info. Variance (recv)	T1 Constraint	0.102 (0.064)	-0.032 (0.048)	0.013 (0.038)
24	Δ Info. Variance (recv)	Δ Inter-legacy ties	0.161 (0.036)***	0.160 (0.047)***	0.150 (0.031)***
25	Δ Salary	Δ Info. Variance (recv)	0.058 (0.016)***	-0.003 (0.005)	0.010 (0.007)
26	Δ Salary	T1 Info. Variance (recv)	0.035 (0.012)**	0.004 (0.004)	0.016 (0.005)**
27	Δ Salary	Topic Change (sent)	0.030 (0.011)**	-0.003 (0.004)	0.005 (0.005)
28	Δ Salary	Δ Inter-legacy ties	0.003 (0.010)	0.011 (0.004)*	0.005 (0.005)
29	Δ Salary	Soc. Distant Information (sent)	0.004 (0.011)	0.006 (0.003)*	0.007 (0.004)†
30	Δ Salary	Luxury Info. (sent)	0.011 (0.010)	0.007 (0.004)†	-0.002 (0.004)
31	Δ Salary	Δ Constraint	-0.007 (0.020)	-0.006 (0.005)	-0.006 (0.007)
32	Δ Salary	T1 Constraint	-0.034 (0.018)†	-0.006 (0.005)	-0.015 (0.007)*

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 7.1.2. Model fit statistics for the Inter-Legacy Ties model.

	Fit Statistic	Stable Fit	Turbulent Fit	Overall Fit
1	N	250	357	607
2	χ^2	68.66***	86.54***	110.19***
3	df	30	30	30
4	RMSEA	0.072	0.073	0.066
5	CFI	0.985	0.983	0.986
6	TLI	0.954	0.949	0.957
7	SRMR	0.031	0.031	0.025
8	AIC	6400	10069	17370

Table 7.1.3. Mediation paths for the Inter-Legacy Ties model.

	Mediation Path	Stable	Turbulent	Overall
1	Constraint > Luxury Info. Indirect Effect	-0.002 (0.002)	0.001 (0.001)	-0.000 (0.000)
2	Constraint > Luxury Info. Total Effect	-0.010 (0.020)	-0.005 (0.005)	-0.006 (0.007)
3	Constraint > Topic Change Indirect Effect	0.021 (0.008)*	-0.001 (0.001)	0.002 (0.002)
4	Constraint > Topic Change Total Effect	0.013 (0.018)	-0.006 (0.005)	-0.004 (0.007)
5	Constraint > Soc. Dist. Info. Indirect Effect	-0.001 (0.003)	-0.002 (0.001)†	-0.002 (0.001)
6	Constraint > Soc. Dist. Info. Total Effect	-0.009 (0.020)	-0.007 (0.005)	-0.008 (0.007)
7	Constraint > Info. Var. (recv) Indirect Effect	-0.008 (0.005)†	0.000 (0.001)	-0.001 (0.001)
8	Constraint > Info. Var. (recv) Total Effect	-0.016 (0.020)	-0.005 (0.005)	-0.007 (0.007)
9	Cons > SocDistInfo + Cons > Luxury Info Indirect	-0.004 (0.004)	-0.001 (0.001)	-0.002 (0.001)†
10	Cons > SocDistInfo + Cons > Luxury Info Total	-0.011 (0.020)	-0.006 (0.005)	-0.008 (0.007)
11	Cons > InfoVar (recv) + Cons > Topic Change Indirect	-0.000 (0.008)	0.002 (0.001)†	-0.002 (0.002)
12	Cons > InfoVar (recv) + Cons > Topic Change Total	-0.008 (0.021)	-0.004 (0.005)	-0.008 (0.007)
13	Constraint > all info vars > Salary Indirect	0.009 (0.010)	-0.001 (0.002)	-0.001 (0.002)
14	Constraint > all info vars > Salary Total	0.001 (0.018)	-0.007 (0.005)	-0.007 (0.007)
15	InterLegacyTies > all info vars > Salary Indirect	0.008 (0.004)†	0.001 (0.001)	0.002 (0.001)
16	InterLegacyTies > all info vars > Salary Total	0.011 (0.010)	0.012 (0.004)**	0.007 (0.005)

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

APPENDIX TWO: High-Ranking Information

An individual can find herself among power, but fail to learn to use power. The upper echelons of the organization can have unique personalities or ways of thinking (Chatterjee & Hambrick, 2011), and altering one's cognitive schema to match could have a benefit (Magee & Galinsky, 2008). I use a similar process that I used for creating Luxury-weighted information to create rank-weighted information. I attempt to predict the rank of each individual in T1 using the mean topic weights of the information that person sends. Again, because of the number of predictors (200 topics), I use an elastic net model with an $\alpha = 0.2$ (Zou & Hastie, 2005). Due to the regularization, most of the weights for the model are equal to 0. A positive weight indicates that the topic is more indicative of higher ranks in the organization, while small or negative weights are likely to predict a lower rank. The resulting model was a good fit with an $R^2 = 0.78$. A plot of the predicted value vs. actual value is shown in *Figure 4.11*. The weights are then multiplied on the change in topics from T1 to T2, and then summed. This creates measure which indicates the degree to which a person has adopted topics into use that are typically associated with high ranks in the organization.

There is a strongest correlation with the resulting *High-Rank Info. (sent)* index is with *Social Distance Information* ($r = 0.46$, $p < 0.001$). It seems that when employees reach out for information, they are seeking information that the higher ranked employees and managers know. The results of an LDS model based on LDS5 is presented in *Table AppRWI*. When controlling for *High-Rank Info. (sent)* the effect of *Social Distance Information* in the turbulent context is wiped out. Nearly all of the variance contributed by adopting socially distant information is subsumed by adopting high-ranking information. There was a significant impact of increases in structural holes on adopting high-ranking information in the turbulent context ($\beta = -0.24$, $p < 0.01$), but this did not result in a significant mediation. In the stable context I did not find an advantage to adopting high-ranking information.

But are they adopting high-ranking information from the dominant organization or adopting information from high-ranking members of their own organization? I created an interaction between *Luxury Info.* and *High-Rank Info.* and added it to the model. The results are presented in *Table AppRTC-LTC*. The interaction is not significant suggesting that it doesn't matter which organization the high-ranking information comes from, adopting high-ranking information is beneficial.

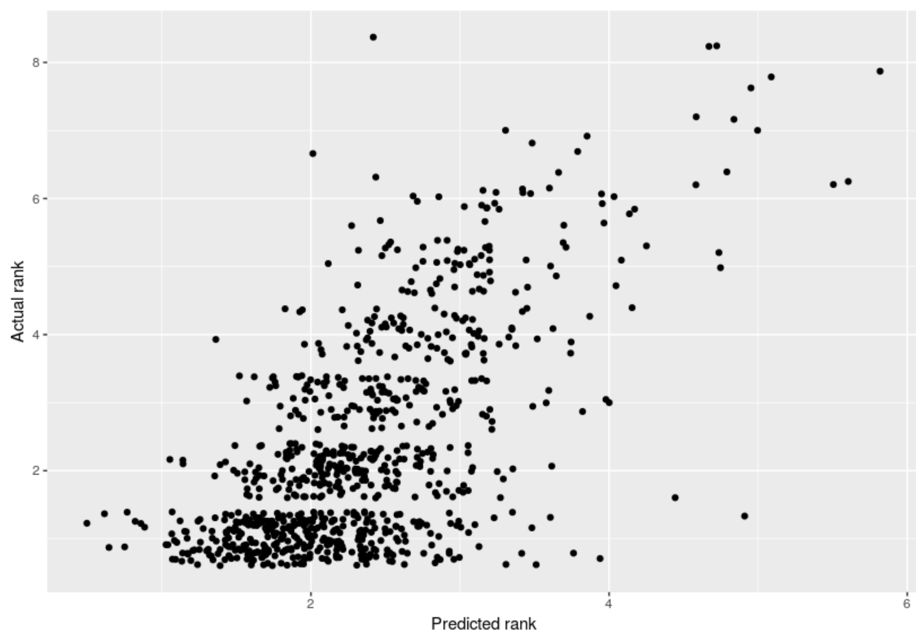

Figure 4.11. This plot shows the predicted vs. actual rank employees based on their mean topic vector (R^2 = 0.78). The rank-weights indicates an increased in the expected rank of the individual given the topics they discuss. Most of the weights are 0 due to regularization.

Table 7.2.1. Regression paths for the High-Rank Information model.

	Dependent	Independent	Stable	Turbulent	Overall
1	Luxury Info. (sent)	Gender (male)	-0.028 (0.124)	-0.186 (0.117)	-0.100 (0.091)
2	Luxury Info. (sent)	Tenure	-0.150 (0.116)	-0.014 (0.048)	0.128 (0.042)**
3	Luxury Info. (sent)	Org. Rank	-0.176 (0.057)**	0.092 (0.063)	-0.007 (0.045)
4	Luxury Info. (sent)	Δ Constraint	-0.183 (0.114)	0.122 (0.071)†	0.046 (0.064)
5	Luxury Info. (sent)	T1 Constraint	-0.062 (0.097)	0.118 (0.061)†	0.108 (0.053)*
6	High-rank Info. (sent)	Gender (male)	0.058 (0.125)	0.013 (0.125)	0.044 (0.089)
7	High-rank Info. (sent)	Tenure	-0.110 (0.118)	-0.057 (0.051)	-0.093 (0.042)*
8	High-rank Info. (sent)	Org. Rank	-0.221 (0.058)***	-0.041 (0.067)	-0.144 (0.044)**
9	High-rank Info. (sent)	Δ Constraint	-0.180 (0.115)	-0.239 (0.076)**	-0.234 (0.063)***
10	High-rank Info. (sent)	T1 Constraint	-0.075 (0.098)	-0.006 (0.064)	-0.043 (0.052)
11	Topic Change (sent)	Gender (male)	-0.089 (0.104)	0.068 (0.109)	-0.002 (0.077)
12	Topic Change (sent)	Tenure	-0.125 (0.098)	0.038 (0.044)	0.016 (0.036)
13	Topic Change (sent)	Org. Rank	-0.017 (0.048)	-0.021 (0.059)	-0.018 (0.038)
14	Topic Change (sent)	Δ Constraint	0.685 (0.096)***	0.260 (0.066)***	0.371 (0.054)***
15	Topic Change (sent)	T1 Constraint	0.718 (0.081)***	0.545 (0.056)***	0.604 (0.045)***
16	Soc. Distant Information (sent)	Gender (male)	0.073 (0.109)	0.048 (0.142)	0.059 (0.093)
17	Soc. Distant Information (sent)	Tenure	0.017 (0.102)	-0.018 (0.057)	-0.047 (0.043)
18	Soc. Distant Information (sent)	Org. Rank	-0.055 (0.050)	-0.005 (0.077)	-0.043 (0.046)
19	Soc. Distant Information (sent)	Δ Constraint	-0.296 (0.100)**	-0.257 (0.086)**	-0.269 (0.066)***
20	Soc. Distant Information (sent)	T1 Constraint	0.069 (0.085)	-0.026 (0.073)	-0.020 (0.055)
21	Δ Info. Variance (recv)	Gender (male)	-0.002 (0.084)	-0.147 (0.094)	-0.094 (0.065)
22	Δ Info. Variance (recv)	Tenure	0.052 (0.079)	0.080 (0.038)*	0.111 (0.030)***
23	Δ Info. Variance (recv)	Org. Rank	0.028 (0.039)	-0.062 (0.051)	-0.007 (0.032)
24	Δ Info. Variance (recv)	Δ Constraint	-0.171 (0.072)*	-0.121 (0.055)*	-0.120 (0.044)**
25	Δ Info. Variance (recv)	T1 Constraint	0.096 (0.065)	-0.044 (0.048)	0.002 (0.038)
26	Δ Salary	Δ Info. Variance (recv)	0.061 (0.015)***	-0.001 (0.005)	0.011 (0.006)†
27	Δ Salary	T1 Info. Variance (recv)	0.035 (0.012)**	0.004 (0.004)	0.016 (0.005)**
28	Δ Salary	Topic Change (sent)	0.029 (0.012)*	-0.004 (0.004)	0.004 (0.005)
29	Δ Salary	Soc. Distant Information (sent)	0.003 (0.012)	0.002 (0.004)	0.004 (0.005)
30	Δ Salary	Luxury Info. (sent)	0.011 (0.010)	0.010 (0.004)**	-0.000 (0.004)
31	Δ Salary	Δ Constraint	-0.008 (0.020)	-0.005 (0.005)	-0.005 (0.007)
32	Δ Salary	T1 Constraint	-0.033 (0.018)†	-0.007 (0.005)	-0.015 (0.007)*
33	Δ Salary	High-rank Info. (sent)	0.003 (0.010)	0.013 (0.004)**	0.008 (0.005)†

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 7.2.2. Model fit statistics for the High-Rank Information model.

	Fit Statistic	Stable Fit	Turbulent Fit	Overall Fit
1	N	250	357	607
2	χ^2	45.96**	66.66***	104.98***
3	df	21	21	21
4	RMSEA	0.069	0.078	0.081
5	CFI	0.989	0.986	0.984
6	TLI	0.960	0.946	0.941
7	SRMR	0.023	0.028	0.026
8	AIC	5896	9324	16040

Table 7.2.3. Mediation paths for the High-Rank Information model.

	Mediation Path	Stable	Turbulent	Overall
1	Constraint > High-rank Info. > Salary Indirect	-0.002 (0.002)	0.001 (0.001)	-0.000 (0.000)
2	Constraint > High-rank Info. > Salary Indirect	-0.010 (0.020)	-0.004 (0.005)	-0.005 (0.007)
3	Constraint > Luxury Info. Indirect Effect	-0.002 (0.002)	0.001 (0.001)	-0.000 (0.000)
4	Constraint > Luxury Info. Total Effect	-0.010 (0.020)	-0.004 (0.005)	-0.005 (0.007)
5	Constraint > Topic Change Indirect Effect	0.020 (0.008)*	-0.001 (0.001)	0.002 (0.002)
6	Constraint > Topic Change Total Effect	0.012 (0.018)	-0.007 (0.005)	-0.004 (0.007)
7	Constraint > Soc. Dist. Info. Indirect Effect	-0.001 (0.004)	-0.000 (0.001)	-0.001 (0.001)
8	Constraint > Soc. Dist. Info. Total Effect	-0.008 (0.020)	-0.006 (0.005)	-0.006 (0.007)
9	Constraint > Info. Var. (recv) Indirect Effect	-0.010 (0.005)*	0.000 (0.001)	-0.001 (0.001)
10	Constraint > Info. Var. (recv) Total Effect	-0.018 (0.020)	-0.005 (0.005)	-0.007 (0.007)
11	Constraint > all info vars > Salary Indirect	0.005 (0.011)	0.001 (0.002)	-0.001 (0.002)
12	Constraint > all info vars > Salary Total	-0.003 (0.018)	-0.004 (0.005)	-0.006 (0.007)

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 7.3.1. Regression paths for the High-Rank, Luxury Information model.

	Dependent	Independent	Stable	Turbulent	Overall
1	High-Rank-Luxury Info.	Gender (male)	0.132 (0.179)	0.099 (0.236)	0.071 (0.155)
2	High-Rank-Luxury Info.	Tenure	-0.445 (0.168)**	-0.009 (0.096)	-0.100 (0.072)
3	High-Rank-Luxury Info.	Org. Rank	0.142 (0.082)†	-0.152 (0.128)	0.008 (0.077)
4	High-Rank-Luxury Info.	Δ Constraint	-0.059 (0.165)	-0.523 (0.143)***	-0.394 (0.110)***
5	High-Rank-Luxury Info.	T1 Constraint	0.040 (0.140)	-0.238 (0.122)†	-0.143 (0.091)
6	Luxury Info. (sent)	Gender (male)	-0.028 (0.124)	-0.186 (0.117)	-0.100 (0.091)
7	Luxury Info. (sent)	Tenure	-0.150 (0.116)	-0.014 (0.048)	0.128 (0.042)**
8	Luxury Info. (sent)	Org. Rank	-0.176 (0.057)**	0.092 (0.063)	-0.007 (0.045)
9	Luxury Info. (sent)	Δ Constraint	-0.183 (0.114)	0.122 (0.071)†	0.046 (0.064)
10	Luxury Info. (sent)	T1 Constraint	-0.062 (0.097)	0.118 (0.061)†	0.108 (0.053)*
11	High-rank Info. (sent)	Gender (male)	0.058 (0.125)	0.013 (0.125)	0.044 (0.089)
12	High-rank Info. (sent)	Tenure	-0.110 (0.118)	-0.057 (0.051)	-0.093 (0.042)*
13	High-rank Info. (sent)	Org. Rank	-0.221 (0.058)***	-0.041 (0.067)	-0.144 (0.044)**
14	High-rank Info. (sent)	Δ Constraint	-0.180 (0.115)	-0.239 (0.076)**	-0.234 (0.063)***
15	High-rank Info. (sent)	T1 Constraint	-0.075 (0.098)	-0.006 (0.064)	-0.043 (0.052)
16	Topic Change (sent)	Gender (male)	-0.089 (0.104)	0.068 (0.109)	-0.002 (0.077)
17	Topic Change (sent)	Tenure	-0.125 (0.098)	0.038 (0.044)	0.016 (0.036)
18	Topic Change (sent)	Org. Rank	-0.017 (0.048)	-0.021 (0.059)	-0.018 (0.038)
19	Topic Change (sent)	Δ Constraint	0.685 (0.096)***	0.260 (0.066)***	0.371 (0.054)***
20	Topic Change (sent)	T1 Constraint	0.718 (0.081)***	0.545 (0.056)***	0.604 (0.045)***
21	Soc. Distant Information (sent)	Gender (male)	0.073 (0.109)	0.048 (0.142)	0.059 (0.093)
22	Soc. Distant Information (sent)	Tenure	0.017 (0.102)	-0.018 (0.057)	-0.047 (0.043)
23	Soc. Distant Information (sent)	Org. Rank	-0.055 (0.050)	-0.005 (0.077)	-0.043 (0.046)
24	Soc. Distant Information (sent)	Δ Constraint	-0.296 (0.100)**	-0.257 (0.086)**	-0.269 (0.066)***
25	Soc. Distant Information (sent)	T1 Constraint	0.069 (0.085)	-0.026 (0.073)	-0.020 (0.055)
26	Δ Info. Variance (recv)	Gender (male)	-0.002 (0.084)	-0.147 (0.094)	-0.094 (0.065)
27	Δ Info. Variance (recv)	Tenure	0.052 (0.079)	0.080 (0.038)*	0.111 (0.030)***
28	Δ Info. Variance (recv)	Org. Rank	0.028 (0.039)	-0.062 (0.051)	-0.007 (0.032)
29	Δ Info. Variance (recv)	Δ Constraint	-0.171 (0.072)*	-0.121 (0.055)*	-0.120 (0.044)**
30	Δ Info. Variance (recv)	T1 Constraint	0.096 (0.065)	-0.044 (0.048)	0.002 (0.038)
31	Δ Salary	Δ Info. Variance (recv)	0.064 (0.015)***	-0.001 (0.005)	0.011 (0.006)†
32	Δ Salary	T1 Info. Variance (recv)	0.037 (0.011)**	0.004 (0.004)	0.016 (0.005)**
33	Δ Salary	Topic Change (sent)	0.035 (0.012)**	-0.004 (0.004)	0.006 (0.005)
34	Δ Salary	Soc. Distant Information (sent)	-0.001 (0.012)	0.002 (0.004)	0.004 (0.005)
35	Δ Salary	Luxury Info. (sent)	0.012 (0.009)	0.010 (0.004)**	-0.000 (0.004)
36	Δ Salary	Δ Constraint	-0.009 (0.020)	-0.005 (0.005)	-0.005 (0.007)
37	Δ Salary	T1 Constraint	-0.036 (0.018)*	-0.007 (0.005)	-0.015 (0.007)*
38	Δ Salary	High-rank Info. (sent)	0.011 (0.011)	0.013 (0.004)**	0.007 (0.005)
39	Δ Salary	High-Rank-Luxury Info.	0.013 (0.007)†	-0.000 (0.002)	0.003 (0.003)

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 7.3.2. Model fit statistics for the High-Rank, Luxury Information model.

	Fit Statistic	Stable Fit	Turbulent Fit	Overall Fit
1	N	250	357	607
2	χ^2	54.01***	67.78***	106.37***
3	df	24	24	24
4	RMSEA	0.071	0.071	0.075
5	CFI	0.988	0.986	0.985
6	TLI	0.953	0.949	0.942
7	SRMR	0.025	0.027	0.026
8	AIC	6678	10741	18375

Table 7.3.3. Mediation paths for the High-Rank, Luxury Information model.

	Mediation Path	Stable	Turbulent	Overall
1	Constraint > High-rank Info. > Salary Indirect	-0.002 (0.002)	0.001 (0.001)	-0.000 (0.000)
2	Constraint > High-rank Info. > Salary Indirect	-0.011 (0.020)	-0.004 (0.005)	-0.005 (0.007)
3	Constraint > Luxury Info. Indirect Effect	-0.002 (0.002)	0.001 (0.001)	-0.000 (0.000)
4	Constraint > Luxury Info. Total Effect	-0.011 (0.020)	-0.004 (0.005)	-0.005 (0.007)
5	Constraint > Topic Change Indirect Effect	0.024 (0.009)**	-0.001 (0.001)	0.002 (0.002)
6	Constraint > Topic Change Total Effect	0.015 (0.018)	-0.007 (0.005)	-0.003 (0.007)
7	Constraint > Soc. Dist. Info. Indirect Effect	0.000 (0.004)	-0.000 (0.001)	-0.001 (0.001)
8	Constraint > Soc. Dist. Info. Total Effect	-0.009 (0.020)	-0.006 (0.005)	-0.006 (0.007)
9	Constraint > Info. Var. (recv) Indirect Effect	-0.011 (0.005)*	0.000 (0.001)	-0.001 (0.001)
10	Constraint > Info. Var. (recv) Total Effect	-0.020 (0.020)	-0.005 (0.005)	-0.006 (0.007)
11	Constraint > all info vars > Salary Indirect	0.009 (0.011)	0.001 (0.002)	-0.000 (0.002)
12	Constraint > all info vars > Salary Total	-0.000 (0.019)	-0.004 (0.005)	-0.005 (0.007)

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

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VITA

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EDUCATION

Colorado State University, Fort Collins CO

M.A. in *Sociology* May 2011

Thesis: Evolution of Community Structure in the Global System of Environmental Governance.

B.A. Double Major *Mathematics* and *English* May 2007

PROFESSIONAL EXPERIENCE

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Graduate Research and Teaching Assistant

University of Kentucky, Gatton College of Business and Economics

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August 2012 – July 2017

Research Associate II

OMNI Institute

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July 2008 – July 2012

Network Evaluation of Albuquerque Safe Schools Healthy Students (SSHS) Grant

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March 2010 – August 2011

FELLOWSHIPS AND AWARDS

2016 UK Researcher/Faculty Award for OpenEddi software program SPARK Bluegrass Showcase of Emerging Entrepreneurs and University Researchers, University of Kentucky, 2016

2016 Gatton Fellowship

2015 Max Steckler Fellowship

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PEER REVIEWED PUBLICATIONS

Sung, W., Woehler, M., Fagan, J. M., Floyd, T., Grosser, T. J., Labianca, G. 2017. Employees' Responses to an Organizational Merger: Intraindividual Change in Organizational Identification, Attachment, and Turnover. *Journal of Applied Psychology*, 102(6): 910–934.

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