# ABSTRACT

Contagion, Trajectory, and Turnover:
Exploring Network Factors Influencing Turnover Over Time

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Organizations use a large portion of their budget on building and maintaining human resources. Losing an employee, especially a good one, can be expensive. While turnover has been studied using a network lens, it has traditionally viewed network characteristics as a property of the particular individual, and the majority of research that has examined social network position and its outcomes has focused on a cross-sectional view of an individuals' position. We consider that an individual's network position changes over time: moving toward the center of the network becoming more embedded, away from the center becoming less embedded, or staying relatively static. We call this an individual's Structural Trajectory. We build a research model using Structural Trajectory, and social contagion, to explore the drivers of turnover in a dataset containing employee email metadata. The results show a strong contagion effect, and a relationship between large network movements (Structural Trajectory) and turnover.

Contagion, Trajectory, and Turnover:
Exploring Network Factors Influencing Turnover Over Time

by

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A Thesis

Approved by the Department of Information Systems

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## ACKNOWLEDGMENTS

I completed my enlistment in the Air Force in 2010 and then began pursuing an education. I found employment in the Information Technology industry but did not stay at any one organization for long. I kept quitting because I felt disconnected. I was accustomed to being a part of something in the military, and now I was just an employee with a timecard. Soon after completing my undergraduate program, I began considering going to graduate school to find something more meaningful in my life.

I ended up living in Waco, TX, employed at an organization that just so happened to be experiencing a high rate of turnover. It was during this time that I first met Dr. Trower to talk about Baylor University and possibly completing a thesis. He introduced me to Dr. Tripp. Dr. Tripp mentored me, and helped develop this thesis from a general idea out about my own life to a full paper. Dr. Tripp was both demanding and understanding throughout the entire process.

I have many people to thank for the success of this project. First, I would like to thank the company for providing us with data and fully supporting the project. I would like to thank Wallace Chipidza and Aarti Swadi for helping prepare the data for analysis. I would like to thank Ben Bernard, Whitney Burrow, and Gabriel Odom for their assistance with cleaning the data, building our model, and conducting statistical analysis. Finally, I would like to thank my wife, Luisa Villafranca, for taking up the slack at home all of those long nights that I was working on this project. I could not have completed this without her support.

# DEDICATION

To my loving wife for pushing me to follow my dreams

# CHAPTER ONE

## Introduction

Organizations use a large portion of their budget on building and maintaining human resources. Losing an employee, especially a good one, can be expensive. When an employee quits, the organization must acquire, train, and socialize new employees, or pay for over-time for existing employees. Too much overtime can lead to decreased performance, loss of production, and decreased employee morale which can also lead to more turnover. Additionally, new employees tend to turnover sooner than the employee that they replaced (Tziner and Birati 1996). Clearly, organizations can benefit from understanding and possibly eliminating the root causes of turnover.

One method of understanding the turnover phenomenon is to study the relationships of employees. Feeley et al. (2010) defines organizations as a group of employees who are voluntarily and involuntarily spun together in webs of relationships through work and relational communication. This "web" of communication, also known as a network, acts as a host for the spread of ideas, influence, and behaviors such as turnover intentions. Turnover intentions may spread similar to the contagion mechanism that spreads disease across a population, with infected individuals making contact with non-infected individuals. Therefore, uncovering network ties of employees may offer many clues as to who is susceptible to turnover.

While turnover has been studied using a network lens, it has traditionally viewed network characteristics as a property of the particular individual (degree, centrality, etc.), and the majority of research that has examined social network position and its outcomes has focused on a cross-sectional view of individuals' position. However, network position is constantly evolving, with individuals developing new ties, breaking ties, and modifying the strength of ties. Specifically, individuals' structural position has a trajectory. Individuals may move toward the center of the network and become more embedded, away from the center and become less embedded, or stay relatively static in a central or peripheral location. In this study, we call this an individual's Structural Trajectory.

The goal of this study is to explore the drivers of turnover in our dataset of employee emails. In addition, this study seeks to explore the relationship between Structural Trajectory and turnover. We achieve these goals by answering the following two research questions:

1) How does an employee's Structural Trajectory affect their odds of turnover?
2) How does the exit of an employee affect the odds of other employees to turnover?

We use employee email communication as a proxy of their social network to track their network position over time. In addition, we determine if a turnover contagion effect is present in the organization. This knowledge may help practitioners determine which employees require turnover intervention.

This paper proceeds as follows. The next section presents a literature review of current research in employee turnover, social networks, social contagion, as well as literature on predicting turnover. We then develop a research model of turnover. The methodology and results are next, followed by the discussion and conclusion.

# CHAPTER TWO

## Literature Review

### *Introduction*

In this study, we use literature from social networks, social contagion, and turnover to develop a research model of turnover. We based this research model on employee position within their social network, their ties to turned over employees, and their Structural Trajectory. This section begins with a literature review on social networks to describe the fundamental elements of Structural Trajectory. Next, we review literature on social contagion, because we predict that a contagion effect is present in our dataset. A literature review on turnover then describes some of the antecedents to turnover, which should be included in our model in future studies. We end this chapter with a review on current literature on predicting turnover.

### *Social Networks*

Borgatti and Halgin (2011) define a network as a set of actors or nodes along with a set of ties of a specific type that link them. Patterns of ties form structures. Structures contain embedded nodes that tie to other nodes through interconnected endpoints. There are two basic types of ties: states and events. States have continuity over time, while events are discrete, transitory, and counted over periods-of-time. Ties can be seen as roads or pipes for flow between nodes. Flows are what passes between nodes during interaction. See figure 2.1 for a depiction of a basic network.

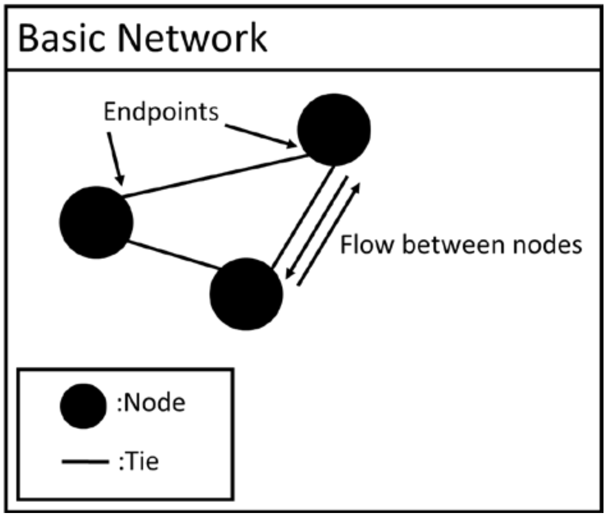


Figure 2.1. A basic network.

There are two highly influential network theories: Granovetter's (1973) Strength of Weak Ties (SWT), and Burt's (1992) Structural Holes Theory (SH). Strength of Weak Ties theory states that the stronger the ties between two people, the more likely they will have ties with the same third parties because people have stronger ties with similar people. In social networks, network ties are defined as the social relationships of members. These ties run along a continuum of strength: weak relationships on one end and strong ties on the other. Tie strength is a function of the amount of interaction, emotional intensity, and reciprocity that occurs between two individuals of the network. Weak ties are characterized as relationships where two individuals interact very little, have low emotional closeness, and one-way communications. Strong ties are characterized as relationships where two individuals in a network have frequent interactions, high emotional closeness, and reciprocity (Perry-Smith and Shalley 2003). Bridging ties, or ties linking a person to someone not connected to his/her friends, are sources of novel ideas. The person from the other network introduces ideas that the original person and group has not heard. Strong ties are unlikely to be the sources of novel information because people tend to form tightly-bound cliques within their network. See figure 2.2 for a depiction of a basic network with a bridging tie.

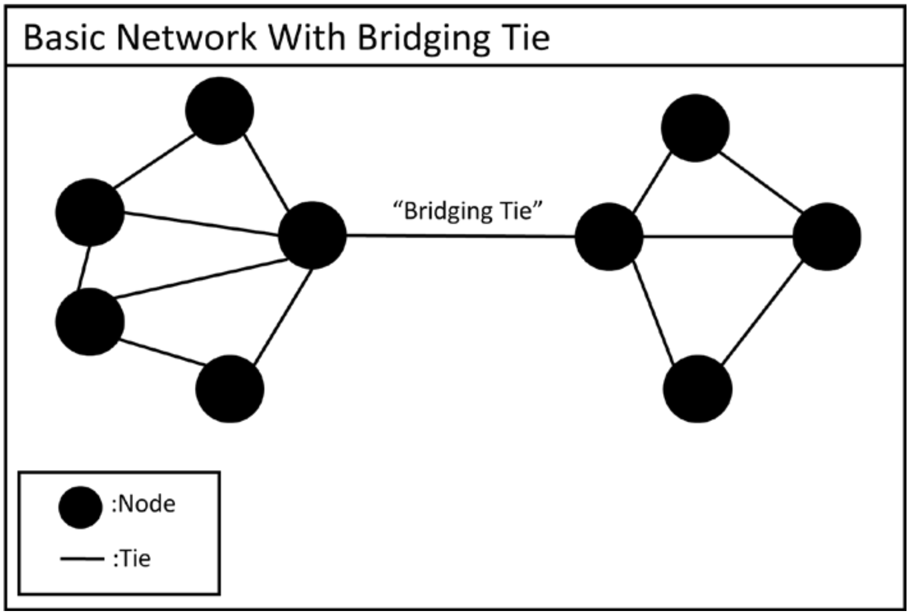


Figure 2.2. Basic network with bridging tie.

Structural Holes (SH) theory is concerned with ego networks, which are the cloud of nodes surrounding a given node, along with the associated ties. A node with fewer direct ties is more likely to receive non-redundant information, which allows that node to perform better. Structural holes are similar to weak ties, in that they are both sources of novel information. In addition, SH theory is very similar to SWT theory, except that Granovetter views tie strength as the determining factor of the tie serving as a bridge, while Burt views non-redundancy as the determining factor. The network in figure 2.3 depicts the Structural Holes theory in our basic network. The figure depicts three networks labeled A, B, and C. Network A is connected to network C by one connection, and network C is connected to network B by that same single connection. The structural hole in this network structure refers to the missing connection between network A and network B. Network A can only receive information about Network B through Network C. Network B is also a weak tie of network A, since they are not directly connected.

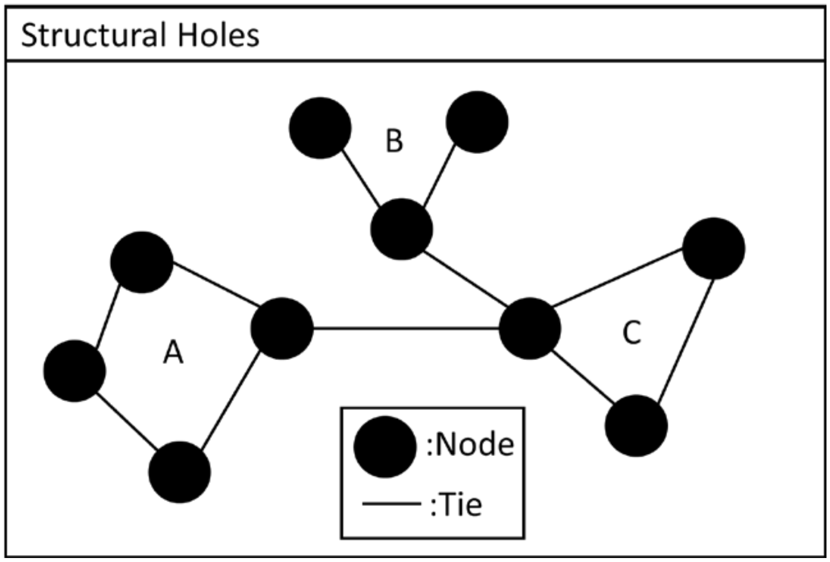


Figure 2.3. Structural holes.

Another important concept in social network analysis is centrality. Central nodes are characterized as being “in the thick of things”, meaning they are more relatively focal in the network than others. There are three formal measures of centrality: degree, closeness, and betweenness. A node’s degree simply refers to how many other nodes it is connected to. A node’s closeness refers to the shortest distances to all other nodes in the network. Finally, a node’s betweenness refers to the degree to which it lies on the shortest path between two other nodes acting as a funnel of information flow in the network (Opsahl et al. 2010). In social network analysis, a tie is also known as an edge. Figure 2.4 depicts these concepts with our basic network structure. In this figure, network A is connected to network B through one interconnecting edge. Network A is a 4-degree network because it contains 4 connected nodes. Network B is a 3-degree network because it contains 3 connected nodes. The node that connects network A to network B has a higher betweenness centrality than the others because it is the shortest path to network A. The nodes in network B have higher closeness centralities than the nodes in network A because they are located physically closer to each other on the network. Degree measures a nodes participation level in a network, while closeness measures the quality of the connection, and betweenness measures the importance of the node. A final measure of centrality is called eigenvector centrality. This measure is a weighted sum of both direct and indirect connections, which is important because it takes into account the entire pattern in the network (Bonacich 2007).

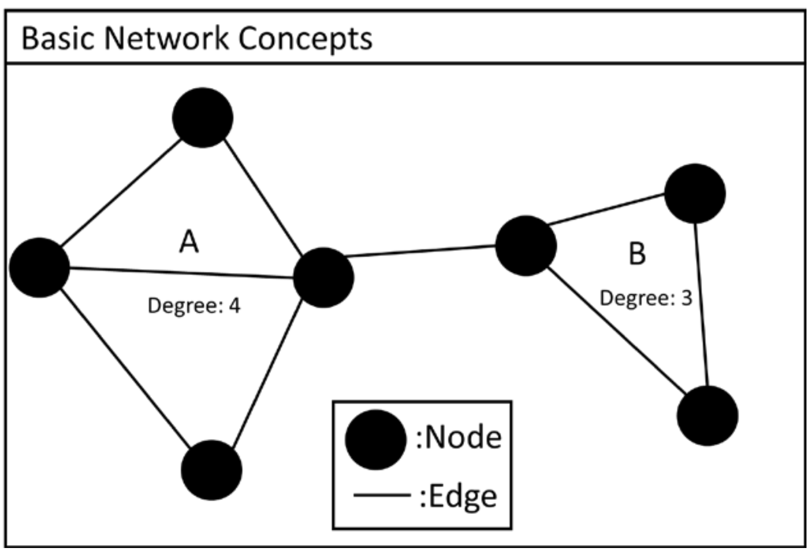


Figure 2.4. Basic network concepts.

Members of social networks are not randomly selected: they usually share sociodemographic dimensions such as age, sex, and education. This is the underlying principle of Blau's (1977) Homophily Principle. The Homophily Principle states that people of similar sociodemographic dimensions are more likely to interact than people who are dissimilar. Homophily often leads to group homogeneity, because people are normally chosen to be included in social networks where they are similar to the current members. In addition, members who are at the fringes of the network often drop out, leading to even less member variance and increased homogeneity.

McPherson et. al. (1992) describes the dynamic behavior of group composition using Darwin's simple evolutionary model of variation, selection, and retention. Group members are selected through recruitment of similar people through homophilous network ties between members and nonmembers. Members are retained when the group replicates the member's characteristics over time, and when lost members are replaced by equivalent new recruits. Groups evolve over time through the selection process, leading to variation. Directional selection occurs when the mean of a group moves to the left or right along some dimension, such as education. This occurs when new members are added who shift the mean of the dimension, while attrition occurs at the opposite end. Stabilizing selection occurs when recruitment and retention are both zero along the edges of the niche. Stabilizing selection leads to group specialization. Disruptive selection occurs when there is more gain of new members than there is loss. Over time, disruptive selection leads to group generalization. Regardless of the selection mechanism, groups are initially formed from contact between members and nonmembers, also known as social ties. The more connections a nonmember has to members of a group, the greater the probability that the person will join the group. This creates overlapping social circles that cause membership turnover, but also adds new members to groups. It also creates cross-pressures and conflicting demands on individual members to leave some groups while joining others.

*Social Contagion*

Contagion refers to the process by which information, trends, behaviors, and other entities spread between individuals in a social network (Hill et. al. 2010). The concept is used heavily in epidemiological studies for infectious disease modeling. In these studies, individuals are either susceptible to infection, or infected with a disease. A susceptible individual becomes infected after coming into contact with an infected individual, and then recovers at a constant rate. Recovered individuals are immune to further infection in the SIR model (susceptible-infected-recovered). Individuals return to a susceptible state in the SIS model (susceptible-infected-susceptible). Psychological and behavioral phenomena can also spread similar to a disease as a result of face-to-face or electronic communication (Alshamsi et. al. 2015). A key difference between epidemiological contagion and behavioral contagion is that traditional modeling ignores individual personality traits as well as the situational factors surrounding the potential infection. Each person is unique and may or may not be susceptible to infection. In addition, traditional contagion modeling focuses on two states: infected and susceptible. Individual personality cannot be modeled in two states: personality states occupy a continuum. An individual can be more or less susceptible to infection depending on where they lie on the continuum at that time. It is not as simple as determining who a person has been in physical contact with, because individual circumstances also dictate whether or not they are susceptible to the behavioral contagion.

In innovation research, infected individuals are known as adopters and susceptible individuals are known as non-adopters. The contagion process occurs when adopters transmit information during interactions with non-adopters, or when management observes other organizations adopting an innovation. The effects of contagion are heterogeneously experienced by non-adopters because they vary in their susceptibility and immunity to infection. In addition, physical or social proximity to infected individuals determines susceptibility. The closer a person is to an infected individual, physically or socially, the greater their odds of adoption. Finally, the individual characteristics of each employee determines susceptibility (Agarwal et. al. 2010), just as in behavioral contagion.

Social structure is important for the spread of new ideas (Burt 1987). There is a certain risk associated with adopting an innovation, and people draw on others to define a socially acceptable interpretation of the risk. In social contagion, people use one another to manage uncertainty through interpersonal ties. The more frequent the communication between a potential adopter and an adopter, the more likely innovations will diffuse in a process called cohesion. In addition, competition between adopters and potential adopters can increase the likelihood of diffusion in a process called structural equivalence.

Research suggests that an obesity contagion may exist over large social networks (Christakis and Fowler 2007). In a time-series study, known as the Framingham Heart Study, of a social network containing 12,067 individuals over the period 1971-2003, it was found that obesity clusters formed over time. The clusters were not the results of homophily, smoking cessation, or any other unknown influence. The culprit of the spread of obesity was individual connections to obese individuals. Similar results were found using the same study to investigate smoking cessation contagion (Christakis and Fowler 2008). Smoking cessation was spread through interconnected ties, with large discernible clusters quitting in concert. In addition, those who continued to smoke were slowly marginalized and drifted to the periphery of the network over time. Networks became increasingly polarized with clusters of smokers and clusters of non-smokers, and few interconnected nodes.

A criticism of social contagion is the difficulty in discerning between influence-based contagion and homophily-driven diffusion. In true contagion, ideas are spread in a network through interactions with heterogeneous individuals. However, most individuals join networks because they are similar to the current members. In homophilous networks, adoption patterns may arise simply because of similarities between individuals. Therefore, it becomes difficult to distinguish between true contagion, or influence-based contagion, and homophily-driven diffusion (Aral et. al. 2009).

### *Turnover*

On the macro-level, employee turnover is defined as the rotation of workers around the labor market. Employees are constantly moving between firms, jobs and occupations, and between the states of employment and unemployment (Abbasi and Hollman 2000). On the micro-level, employee turnover is the voluntary or involuntary exit of an employee from an organization. Involuntary turnover is caused by factors outside the control of management, such as death or incapacity of staff. Voluntary turnover is caused by the volition of the employee due to push and/or pull factors. An example of a push factor would be an employee leaving due to lack of interest in the job. An example of a pull factor would be an employee leaving due to being attracted to another job by incentives (Booth and Hamer 2007). Organizations determine their turnover rate by taking the number of employees who have left during a specified period and dividing it by the average number of employees during the period (Ongori 2007).

Involuntary turnover is nearly impossible to predict and is therefore nearly impossible to prevent. Voluntary turnover can be decreased if organizations can recognize turnover behaviors and intentions of employees beforehand.

Employees typically withdraw before voluntarily leaving an organization. Withdrawal behaviors, such as job searching, are dependent upon withdrawal cognitions, such as turnover intentions (Holtom et. al. 2008). The antecedents to turnover intention are of particular importance in employee turnover research. Antecedents to turnover can be broken down into job related factors and organizational factors. Job related factors include job stress, lack of commitment, job dissatisfaction, personal agency, and role ambiguity. Organizational factors include organizational instability, high levels of inefficiency, low levels of communication, mismanagement of policies, inadequate financial incentives, poor hiring practices, poor managerial style, lack of recognition, and toxic workplace environments (Ongori 2007).

Climate-personality mismatch may also lead to turnover. Downey et. al. (1975) found that an employee's job satisfaction is a function of the interaction between their personality characteristics and the organizational climate. If an organization does not fit the personality of an employee, he/she may become dissatisfied and eventually turnover.

Some researchers have considered an employee's commitment to the organization in search of factors that decrease turnover. Meyer and Allen (1991) describe commitment as reflective of three general themes: affective attachment to the organization, perceived costs associated with leaving, and obligation to remain. Affective commitment refers to the emotional attachment to the organization. Perceived costs associated with leaving refer to the loss of "side bets", such as pension and seniority, that would be lost if the employee leaves. Finally, obligation to remain refers to moral obligations and normative pressures to remain that employee's feel. These themes are not mutually exclusive, and employees may experience all three forms in varying degrees. In addition, an employee's organizational attachment may decrease their odds of turnover. O'Reilly and Chatman (1986) state that organizational attachment is the psychological attachment that a person feels for an organization. The predications of psychological attachment are compliance, identification, and internalization. Compliance refers to the instrumental involvement for specific, extrinsic rewards. Identification refers to involvement based on a desire for affiliation. Internalization refers to involvement predicated on congruence between individual and organizational values.

Other possible causes of turnover are job dissatisfaction (Locke 1968), mental strain (Karasek 1979), and emotional exhaustion (Wright and Cropanzano 1998). The more satisfied an employee is with their organization and/or job position, the less likely they are to withdraw. In addition, the combination of low decision latitude (decision authority or skill level) and heavy job demands leads to mental strain in employees, and possible job dissatisfaction. Finally, the chronic state of physical and emotional depletion due to excessive job demands, known as emotional exhaustion, can lead to turnover intentions in employees.

### *Predicting Turnover*

Studying the role of a social network in turnover intentions requires an organizational view of turnover, rather than an individual view. Feeley and Barnett (1997) studied the the communication network of a firm to determine its usefulness as a predictor of employee turnover. They found that an employee on the fringes of the network is more likely to turnover than others. However, the study did not answer whether the turnover was due to centrality, or to the individual employee's connectedness. In addition, peers may be influencing employees on the fringes of the network to leave.

The Erosion Model (EM) is useful for predicting employee turnover using network centrality instead of structural equivalence. Network Centrality is defined as an individual's position in the network relative to others. Feeley (2000) tested the EM, while including organizational commitment as a mediator between network centrality and turnover. The results showed support for the EM: employees with higher centrality were less likely to leave their positions. Surprisingly, the author also found in a post-hoc t-test that employees who stayed were less committed to the organization than those who left.

Soltis et. al. (2013) explored the influence of formal and informal workplace relationships on employee turnover intentions. They found that employees who were sought after for advice became overextended, and did not feel like they were adequately rewarded for their extra effort, increasing their potential to turnover.

Ng and Feldman (2010) examined how job embeddedness, or the extent to which an individual is enmeshed in their current job, effects their career over time. Specifically, they wanted to know how job embeddedness effected an individual's social capital. Social capital is defined as the relationships that create wealth. The results showed that highly embedded employees were less likely to continue social capital building behaviors over time. While high levels of job embeddedness may lower turnover in the short term, it may be harmful in the long term.

# CHAPTER THREE

## Research Model and Hypothesis Development

### *Structural Trajectory*

We began this project with the notion that an individual's network position and trajectory changes over time. Social networks are constantly growing and shrinking through tie forming and cutting. In addition, individuals are more or less important (central) to their social network over time, depending upon their role in current social situations. While many researchers have considered network position (centrality), few have considered how a change in network position over time effects individual odds of turnover. We considered change in network position over time and call it Structural Trajectory.

Formally, we define Structural Trajectory as the change in a person's structural position in a social network over a given period of time. Change occurs when a person moves from the periphery to the center (positive trajectory), the center to the periphery (negative trajectory), or remaining in a static position in the network. Figure 3.1 depicts this concept. We used betweenness centrality to measure each individuals network position. Betweenness centrality is most appropriate because it measures the degree to which an individual lies on the direct path between two other individuals in the network. Individuals on the direct path between two others are very important because they control the flow of information between networks.

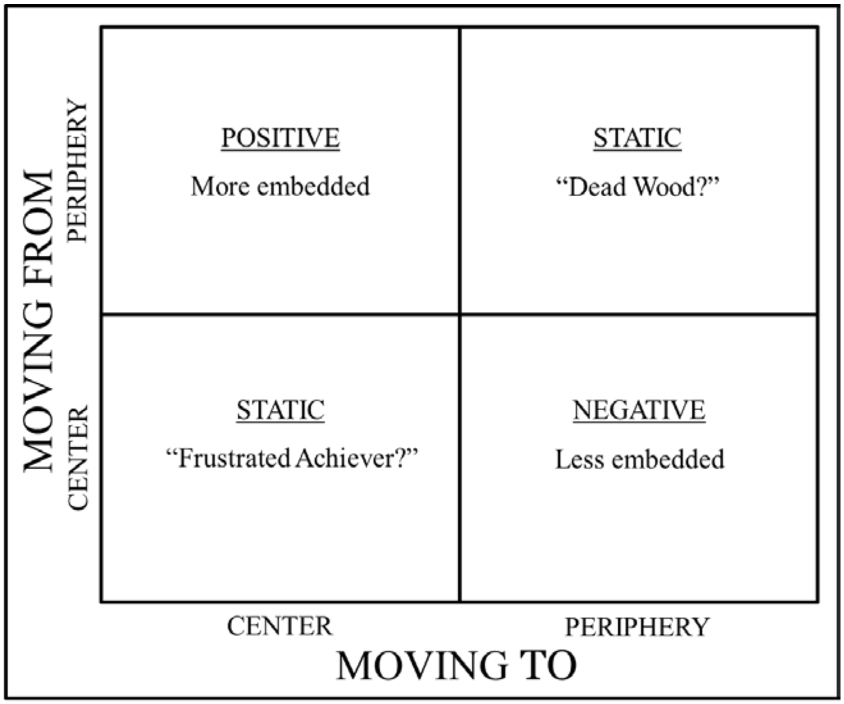


Figure 3.1. Structural Trajectory.

*Research Questions Exploration*

After defining Structural Trajectory, we developed research question number one: how does an employee's Structural Trajectory affect their odds of turnover? To answer question one, we hypothesized about the relationship between Structural Trajectory and turnover. If an employee moves from the periphery to the center, their betweenness centrality increases, giving them a positive trajectory. We predict that the odds of turnover for an employee with a positive trajectory are low, because they are possibly experiencing personal and professional growth within the company and are satisfied with their situation. If an employee moves from the center to the periphery, their betweenness centrality decreases, giving them a negative trajectory. We predict that the odds of turnover for an employee with a negative trajectory are high because they may possibly be withdrawing from the company. Withdrawal behaviors are antecedents of turnover intention. If an employee does not move over time, their betweenness centrality change is very small, and their Structural Trajectory is static. A static employee that begins and ends in the periphery is considered “dead wood” because they are likely making no efforts in their social network and are content with merely existing in the organization. We predict that the odds of dead wood employees turning over is low, because they are possibly content with their situation. Finally, an employee that begins and ends in the center is considered a “frustrated achiever”. These individuals may have reached the pinnacle of their social network and cannot climb any higher. One possible explanation is that these employees may have outgrown their role with the company, thus their odds of turnover are likely to be higher.

A network study would not be complete without exploring the contagion effect. This is especially true of social networks in organizations. This led us to develop research question number two: how does the exit of an employee affect the odds of other employees to turnover? We hypothesize that there is a turnover contagion effect in our dataset, where an individual’s odds of turnover increase as their ties to turned over employees increase. Additionally, we hypothesize that Structural Trajectory will act as a moderator on the social contagion effect. An employee with a positive Structural Trajectory may not be as susceptible to the turnover contagion as an employee with a negative Structural Trajectory. The reasoning behind our hypothesis, is that an employee that is becoming more important to their social network, measured with betweenness centrality, will be less likely to want to leave that network. This should hold true even if their social ties are turning over. While an employee that is becoming less important to their network might be more susceptible to turnover as their ties turnover.

*Research Model*

Our research model consists of Network Centrality, Structural Trajectory, and Ties to Turned Over Employees, leading to Turnover. In summary, the more central an employee is, the lower their odds of turnover (H1). The more ties an employee has to turned over employees, the higher their own odds of turnover (H2). Positive Structural Trajectory decreases the odds of turnover (H3). Static Structural Trajectory increases the odds of turnover for an employee with a central network position (H4A), and decrease the odds for an employee that has a peripheral position (H4B). Finally, Structural Trajectory acts as a moderator of the social contagion effect on turnover (H5). See figure 3.2 below, for a depiction of the research model and the relationships from which we built our hypotheses. See table 3.1 at the end of the section, for a table that summarizes the hypotheses in more detail.

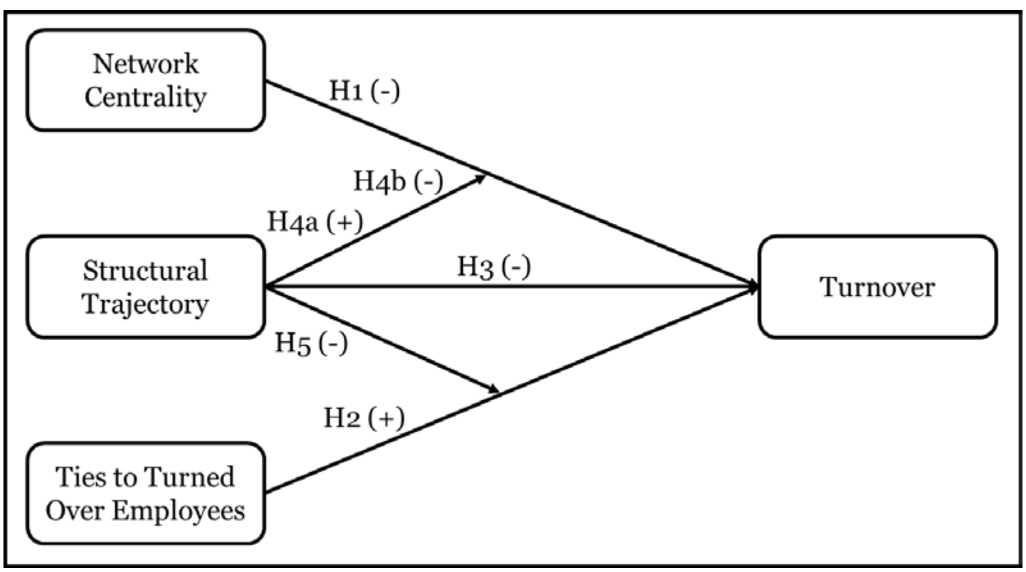


Figure 3.2. Research model.

*Hypothesis 1: Network Centrality*

Employees who are highly central to their network are likely to have many strong ties. Strong ties are characterized as having frequent interactions, high emotional closeness, and reciprocity (Perry-Smith and Shalley 2003). Therefore, employees connected by strong ties are likely happy working together. It is also likely that highly central individuals are acting as a bridge to other networks, making them very important to others in their network. In addition, central employees are likely more connected to the influential individuals of their network. Influential employees may provide such benefits as career progression, information access, and social status, among other things. The network of a central employee is likely homophilous, with many employees thinking and acting in similar ways. McPherson et al. (1992) said that groups evolve over time through the selection process. New members with similar characteristics are added while those with different characteristics move toward the fringes of the network. Eventually, employees on the fringes leave and join networks with members sharing their characteristics. O'reilly and Chatman (1986) explain that as individuals become more psychologically attached to an organization, they are less likely to turnover. We consider that group homogeneity likely increases psychological attachment, since employees share similar beliefs and ideals. In consideration of the likely characteristics of central employees, as well as the likely characteristics of their network, it is counterintuitive that they would want to leave the organization. This led us to hypothesize that highly central employees will have lower odds of turning over.

*H1: Employees with higher levels of network centrality will have lower odds of turnover.*

*Hypothesis 2: Social Contagion*

In diffusion research, the closer a person is to an innovation adopter, physically or socially, the greater their own odds of adoption (Agarwal et al. 2010). The more frequent communication that exists between a potential adopter and an adopter, the more likely innovations will diffuse (Burt 1987). In our study, we consider adopters to be the individuals that have left the company, and potential adopters to be those that had ties with adopters before leaving. The mechanism behind social contagion/innovation diffusion works much like that of a viral contagion. Viruses spread when infected individuals come into contact with uninfected individuals (susceptible). In social contagion, behaviors can be transmitted when people communicate with one another. In our dataset, employees communicate with one another through email. Employees display withdrawal behaviors before turning over and they may communicate these withdrawal behaviors with others in their social network (Holtom et. al. 2008). This could cause a contagion effect, where other employees surrounding the turned over employee may also begin withdrawing. Employees who have many connections to turned over employees are more likely to become "infected" themselves because they are more exposed to withdrawal behaviors than others. In addition, since individuals use each other to manage uncertainty (Burt 1987), employees who are considering quitting may be using their turned over connections as a litmus test for success in a new organization. This led us to hypothesize that the more connections employees have to employees who have turned over, the higher their odds of also turning over.

*H2: Employees with a higher number of ties to turned over employees will have higher odds of turnover.*

*Hypothesis 3-5: Structural Trajectory*

Employees with a positive Structural Trajectory have network positions that move toward the center over time. These employees are likely building their network by adding new connections, and becoming closer to other employees over time. In addition, these individuals are likely becoming more important to their network, since they are acting more and more as a bridge of communication between their network and others. Conversely, central employees who are moving to the periphery over time are likely losing connections, becoming more distant to other employees, and becoming less important to their network over time. They may or may not be withdrawing from the company, but they are certainly becoming less central to their network. This led us to hypothesize that Structural Trajectory and turnover are likely inversely related. Employees with a positive Structural Trajectory are less likely to show withdrawal behaviors, and will likely have a decreased probability of turning over. On the other end of the spectrum, employees with a negative Structural Trajectory are more likely to show withdrawal behaviors, and likely have a higher probability of turning over.

*H3: Employees with a positive Structural Trajectory will have lower odds of turnover, while employees with a negative Structural Trajectory will have higher odds of turnover.*

The network position of an employee with a static Structural Trajectory moves very little over time. This means that they are not gaining or losing ties, becoming closer or more distant to other employees, or changing in importance to their network over time. We hypothesize that his may make an employee feel that their position has “gone stale” and they may need a change in their work-life. This is more likely to be true of employees who are more central to their network. We call these individuals “frustrated achievers" because they have likely "climbed" the social ladder and have hit a "glass-ceiling" in the network. Frustrated achievers could eventually withdraw from the organization and turnover. This is the worst case scenario, because the organization has likely invested a lot of money into acquiring and training frustrated achievers. The withdrawal behaviors that frustrated achievers likely display led us to hypothesize that central employees with a static Structural Trajectory are more likely to turn over.

*H4A: Static Structural Trajectory will increase the odds of turnover for employees with a central position.*

Many employees on the periphery of the network are likely not happy with their position and status, and are likely less committed to remain with the organization (Meyer and Allen 1991). However, not all employees wish to become more central. Many employees are complacent with simply "clocking-in" and "clocking-out", and participate very little in the core social network of the organization. We call these individuals "dead wood". The analogy is obvious, they "float" through the social network "taking up space", but adding very little value. Additionally, dead wood employees could possibly decrease employee morale. Since it would appear that employees with a static structural trajectory are not taking action to become more central, we hypothesize that they are likely content with being on the periphery. This led us to hypothesize that individuals with a peripheral position and a static Structural Trajectory have lower odds of leaving the company.

*H4b: Static Structural Trajectory will decrease the odds of turnover for employees with a peripheral position.*

Finally, we consider the effect that Structural Trajectory has on the relationship between an employee's number of ties to turned over employees and their odds of turnover (turnover contagion effect). Employees with a positive Structural Trajectory are likely content with their network movement over time making them less likely to turnover. This led us to hypothesize that employees with a positive Structural Trajectory are less susceptible to turnover contagion than those with a negative Structural Trajectory.

*H5: Structural Trajectory moderates the turnover contagion effect, where the turnover contagion effect will be decreased if an employee's Structural Trajectory is positive.*

Table 3.1. Summary of hypotheses.

| Hypothesis | Related to | Summary |
|---|---|---|
| H1 | Social Networks | Employees with higher levels of network centrality will have lower odds of turnover. |
| H2 | Social Contagion | Employees with a higher number of ties to turned over employees will have higher odds of turnover. |
| H3 | Structural Trajectory | Employees with a positive Structural Trajectory will have lower odds of turnover, while employees with a negative Structural Trajectory will have higher odds of turnover. |
| H4A | Structural Trajectory | Static Structural Trajectory will increase the odds of turnover for employees with a central position. |
| H4B | Structural Trajectory | Static Structural Trajectory will decrease the odds of turnover for employees with a peripheral position. |
| H5 | Structural Trajectory/Social Contagion | Structural Trajectory moderates the turnover contagion effect, where the turnover contagion effect will be decreased if an employee's Structural Trajectory is positive. |

# CHAPTER FOUR

# Methodology

## *Dataset Description*

Our dataset consists of email metadata from employees in the consulting arm of a large Indian IT company. We used email communication as a proxy for network ties to determine the social network within the organization. Email metadata was analyzed for a 12-month period beginning June 1, 2014 and ending May 31, 2015. Many of the details were not included in the dataset for privacy concerns. The details we were provided included:

- anonymized sender identification number
- anonymized receiver identification number
- inbound or outbound indicator
- date
- last email inbound date
- last email outbound date
- Strength measure of the relationship between the sender to all others in the network

## *Network Statistics*

We conducted social network analysis on the variables to determine each node's network statistics. The statistics included betweenness, degree, closeness, and eigenvector centrality. A node's betweenness indicates the degree to which it lies on the shortest path between two other nodes in the network. Degree indicates the number of other nodes that it is connected to. Closeness indicates the shortest distance to all other nodes in the network. Finally, eigenvalue centrality indicates the importance of the nodes network connections. Strength was provided to us by the organization. Strength is a variable that measures the “strength” of the relationships between one node and all others. The values for Strength in our dataset range from 1-10. The algorithm that determines the Strength is proprietary. We then imported these values into a SQL server database.

### *Survival Analysis*

Survival analysis, also known as event history analysis, was appropriate to investigate the drivers of turnover because we wanted to predict the variables of importance to a turnover event. The risk set consisted of 1,740 employees who were present on June 1, 2014. We did not include employees who began sending outbound emails during any other period because the statistical techniques become much more difficult when people entered the period at different times. This was a limitation to our results, however we still had enough individuals remaining that we could make inferences. To calculate the hazard rate (h), or the rate at which events occurred during the period, we tracked the outbound emails for each employee for every month. An employee survived if they had any outbound emails during each period. An event occurred when an employee turned over. We made the assumption that employees who did not have an outbound email for over 30 days had turned over. We created a column in the database with a binary dummy variable with 0 indicating survival and 1 indicating a turnover event occurred. This was done in preparation for analysis using a semiparametric model named Cox Proportional-Hazards regression. We exported the database into an excel spreadsheet, and then used R to conduct survival analysis.

We tested hypothesis number one using betweenness percentage, calculated as a percentile of betweenness in the dataset, in place of the raw betweenness score ($\beta_{\text{Betweenness}}$*Betweenness). To test hypothesis number two, we had to first take into account the lag effect in our dataset. We defined someone who turned over as someone who did not send an email for greater than 30 days. This caused an issue when we proceeded to “normalize” contagion. We normalized contagion by dividing an employee’s turnover count by their degree. In some cases, employee turnover count was higher than their degree. This was because the turnover count was actually for the previous month. Therefore, we had to divide a person’s current month’s turnover count by the previous month’s degree ($\beta_{\text{TurnoverPercentage}}$*TurnoverPercentage). To test hypothesis number three, we used the direction of change in the raw betweenness score ($\beta_{\text{H3}}$* $\Delta$ Betweenness). Basically, we tested to see if any increase in betweenness would increase odds of turnover. To test hypothesis number four, we had to first define what “static” meant. We define a static structural trajectory as a very low percentage change in betweenness (less than 1%). Next, we had to define a “central” position. We defined the top quartile of betweenness, in the 75th percentile and above, as central individuals (($\beta_{\text{H4A}}\left||\Delta\text{Betweenness}|\right|$*I(Betweenness>$P_{.75}$)). We define a “periphery” position as people in the bottom quartile of betweenness, in the 25th percentile and below (($\beta_{\text{H4B}}\left||\Delta\text{Betweenness}|\right|$*I(Betweenness< $P_{.25}$)). We tested hypothesis number five as an interaction between turnover percentage (contagion) and change in betweenness ((betweenness)+($\beta_{\text{H5}}\left||\Delta\text{Betweenness}|\right|$*TurnoverPercentage)). Finally, we added closeness centrality ($\beta_{Closeness}$*Closeness), eigenvalue centrality ($\beta_{\mathrm{EigenvalueCentrality}}$*EigenvalueCentrality), and Strength ($\beta_{\mathrm{Strength}}$*Strength) to consider all possible significant predictors of turnover. Closeness centrality was removed from the final model because the values in our dataset were not normally distributed. We built one model of turnover to test all of our hypotheses

Full model:

$$\ln(\mathrm{h}) = \alpha(\mathrm{t}) + (\beta_{\mathrm{Betweenness}}*\mathrm{Betweenness}) + (\beta_{\mathrm{Degree}}*\mathrm{Degree}) +$$

$$(\beta_{\mathrm{EigenvalueCentrality}}*\mathrm{EigenvalueCentrality}) + (\beta_{\mathrm{TurnoverPercentage}}*\mathrm{TurnoverPercentage}) +$$

$$(\beta_{\mathrm{Strength}}*\mathrm{Strength}) + (\beta_{\mathrm{H4A}}\left||\Delta\mathrm{Betweenness}|\right|*\mathrm{I}(\mathrm{Betweenness}>\mathrm{P}_{.75})) +$$

$$(\beta_{\mathrm{H4B}}\left||\Delta\mathrm{Betweenness}|\right|*\mathrm{I}(\mathrm{Betweenness}<\mathrm{P}_{.25})) +$$

$$(\beta_{\mathrm{H3}}*\Delta\ \mathrm{Betweenness}) + (\beta_{\mathrm{H5}}\left||\Delta\mathrm{Betweenness}|\right|*\mathrm{TurnoverPercentage}) +$$

$$(\beta_{11}*\mathrm{I}(\left||\Delta\mathrm{Betweenness}|\right|<\mathrm{Q}_1))$$

Hypotheses:

$H1$: $\beta_{Betweenness} < 0$

$H2$: $\beta_{TurnoverPercentage} > 0$

$H3$: $\beta_{H3} < 0$

$H4A$: $\beta_{H4A} > 0$

$H4B$: $\beta_{H4B} < 0$

$H5$: $\beta_{H5} < 0$

# CHAPTER FIVE

## Results

### *Introduction*

The results showed that our data did not support many of our hypotheses. Nonetheless, the results are significant and important to future research. The results of survival analysis on our model are shown below in Table 5.1.

Table 5.1. Survival analysis results.

| Variable | Exp(Coefficient) | P-Value |
|---|---|---|
| Betweenness | 1.54 | 0.03061 |
| Degree | 0.980 | 0.00032 |
| EigenvalueCentrality | 15.5 | 0.00745 |
| TurnoverPercentage | 6.16 | 0.03065 |
| ΔBetweenness | 1.00 | 0.02948 |
| Strength | 0.516 | < 2e-16 |
| Betweenness > $P_{.75}$ | 1.00 | 0.14115 |
| Betweenness < $P_{.25}$ | 1.00 | 0.02265 |
| ΔBetweenness*TurnoverPercentage | 1.00 | 0.69388 |

The survival curve shows that odds of turnover for the employees in our dataset increase in general over time. The survival probability is roughly 91% by month six of employment, falling to around 89% by month nine. Survival probability levels off at just under 88% after 11 months of employment. This is intuitive, however, it is interesting to see evidence. Please see figure 5.1 below for a depiction of the survival curve.

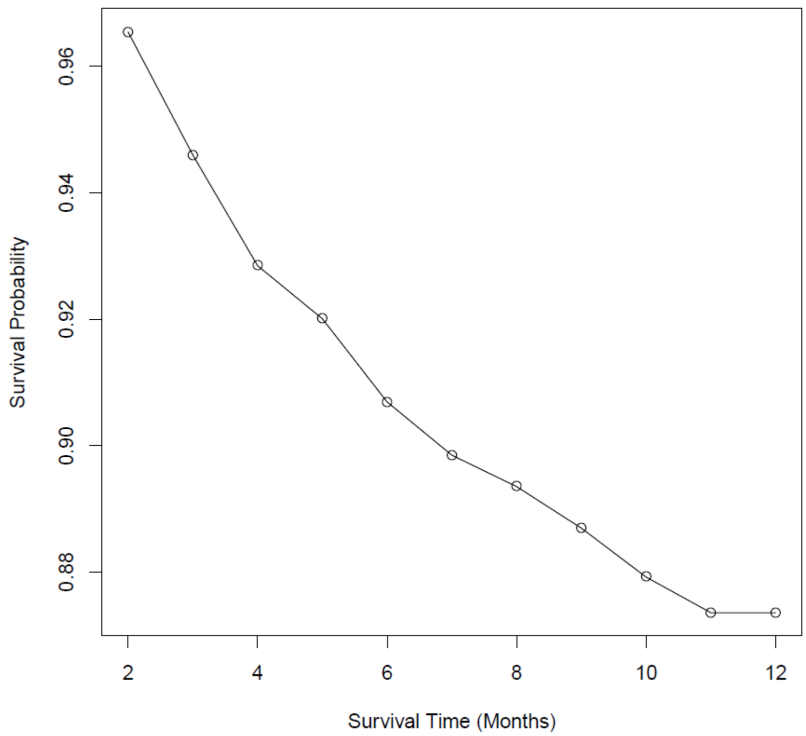


Figure 5.1. Survival curve.

*H1 Results*

$H1$: $\beta_{Betweenness} < 0$: No support

At the 5% significance level, there is evidence to suggest that Betweenness is a significant predictor of turnover (p = 0.03). For each one percent increase in Betweenness, an employee is 1.54 times more likely to turnover, holding all other predictors constant. The sign of the coefficient indicates that the relationship is opposite of what we expected. Clearly, this requires further investigation. We suspect that the limitations on our data caused these unexpected results. One explanation may be that employees may appear more central just before they turnover because they increase their email communication. They may be sending their salutations and/or turnover instructions to other employees, increasing their network centrality statistics. Without the proper context surrounding a turnover event, we cannot distinguish the exact reason for the counterintuitive results.

### *H2 Results*

$H2$: $\beta_{TurnoverPercentage} > 0$: Support

At the 5% significance level, there is evidence to suggest that TurnoverPercentage is a significant predictor of turnover (p = 0.03). For each one percent increase in TurnoverPercentage an employee is 6.16 times more likely to turnover, holding all other predictors constant. Our data fully supports the hypothesis, indicating that there is a turnover contagion present and that TurnoverPercentage is a significant predictor of turnover in the organization. The results are intuitive and consistent with prior research.

### *H3 Results*

$H3$: $\beta_{H3} < 0$: No support

At the 5% significance level, there is evidence to suggest that ΔBetweenness is a significant predictor of turnover (p = 0.029). For each 4,330-unit increase in ΔBetweenness, an employee is 1.186 times more likely to turnover, holding all other predictors constant. The sign of the coefficient indicates that the relationship between ΔBetweenness and turnover is opposite of our prediction. The data does not support this hypothesis. We used a 4,330-unit increase because the resulting change in odds of turnover for a single unit increase in ΔBetweenness is very small (almost 1.00). In addition, 4,330 was equal to one quartile of betweenness, indicating that the employee has a trajectory. Further, the relationship between trajectory (positive or negative) and turnover is only significant to people with large network movements: those with a 4,330-

unit ΔBetweenness and above. Again, we suspect that the limitations in our dataset caused results opposite of what we predicted. The results for hypothesis one showed highly central employees are more likely to turnover than others. One explanation for those results was that the employee merely appeared more central to the network because they increased their email communication before turning over. This would likely happen over a very short period of time, maybe even during the two-week notice period. This would give a person a highly positive Structural Trajectory. Without the context of the turnover event, it is impossible to give a definitive reason for these results. This is another relationship that should be further studied in a dataset with fewer limitations.

*H4A Results*

$H4A$: $\beta_{H4A} < 0$: No support

At the 5% significance level, there is no evidence to suggest that the interaction of a small ΔBetweenness and Betweenness>$P_{.75}$ significantly predicts turnover (p = 0.141). This does not mean that the interaction should be ignored. Again, we suspect the results are not as predicted due to the limitations in our dataset. Further testing in a dataset with fewer limitations is required to fully understand the interaction between a static Structural Trajectory and a central position on turnover odds.

*H4B Results*

$H4B$: $\beta_{H4B} > 0$: Support

At the 5% significance level, there is evidence to suggest that the interaction between a small ΔBetweenness and Betweenness<$P_{.25}$ significantly predicts turnover (p = 0.022). For each one percent decrease in ΔBetweenness, an employee is just slightly over 1.00 times more likely to turnover, holding all other predictors constant. What this means is that an employee in the very bottom of the last quartile of betweenness with a static trajectory is slightly more likely to turn over than those in other quartiles. This relationship is significant only if the employee is on the very fringes of the network. We suspect that data limitations caused this small coefficient. Further testing on a dataset with fewer limitations may clarify the results so that we may fully understand the interaction between static Structural Trajectory and a peripheral position on turnover odds

### *H5 Results*

$H5\colon \beta_{H5} < 0$:

At the 5% significance level, there is no evidence to suggest that the interaction between ΔBetweenness and TurnoverPercentage is a significant predictor of turnover (p = 0.693). Again, we stress that this may be due to the limitations in our dataset. The results for the hypotheses related to Structural Trajectory were not as expected. Structural Trajectory is a component of this interaction term, which leads us to suspect that this interaction is not significant due to the same limitations on the dataset. Again, further testing on a dataset with fewer limitations should yield more accurate results.

Table 5.2. Summary of results.

| Hypothesis | Description | Results |
|---|---|---|
| H1 | Employees with higher levels of network centrality will have lower odds of turnover: $\beta_{Betweenness} < 0$. | No Support |
| H2 | Employees with a higher number of ties to turned over employees will have higher odds of turnover: $\beta_{TurnoverPercentage} > 0$. | Support |
| H3 | Employees with a positive Structural Trajectory will have lower odds of turnover, while employees with a negative Structural Trajectory will have higher odds of turnover: $\beta_{H3} < 0$. | No support |
| H4A | Static Structural Trajectory will increase the odds of turnover for employees with central position: $\beta_{H4A} < 0$. | No Support |
| H4B | Static Structural Trajectory will decrease the odds of turnover for employees with peripheral position: $\beta_{H4B} > 0$. | Support |
| H5 | Structural Trajectory moderates the turnover contagion effect, where the turnover contagion effect, will be decreased if the employees Structural Trajectory is positive: $\beta_{H5} < 0$. | No support |

# CHAPTER SIX

## Discussion

### *Findings*

Our results were promising, even with data that does not support many of our hypotheses. Counter to past literature, we found that the more central an employee is, the more likely they are to turnover. This is possibly due to the limitations in our dataset. We have no context for the situation surrounding a turnover event at the organization. It is possible that employees communicate much more frequently before they turnover to hand over their responsibilities to successors, and/or to give their salutations to friends and colleagues. This increase in communication could cause an increase in their betweenness centrality. This scenario is further supported by the results for hypothesis number three: employees with a positive Structural Trajectory will have increased odds of turnover. In addition, employees with a negative Structural Trajectory have decreased odds of turnover. The combination of the counterintuitive results from hypothesis number one and hypothesis number three indicate that this warrants further research on a dataset with fewer limitations.

Next, we found that a static Structural Trajectory is only a significant predictor of turnover in our dataset for those employees on the very periphery of the network. These results make sense, because these employees are the least involved in the social network. It is possible that these employees quit very soon after starting at the organization. They never attempted to make more connections and were there for such a short time that they had a static Structural Trajectory. We need more context surrounding the turnover event of employees with a static Structural Trajectory to make an accurate inference.

Finally, we found a very high turnover contagion effect in our dataset. Employees are much more likely to turnover when they have ties to others that have turned over. This is very intuitive and consistent with past research. We considered the effect of a positive Structural Trajectory on the contagion effect, however the data did not support this relationship. We think this is also due to the limitations and lack of context in our dataset. In addition, the organization is in an industry with very high turnover. This is likely skewing our results, and we recommend testing this relationship on organizations in different industries with varying turnover rates.

### *Limitations*

We limited our analysis to employees who were present at the beginning of the period. New people joined the organization at various times throughout the 12 months that we tracked emails. For the sake of consistency of analysis, we only concentrated on the employees who were present at the beginning of the period. There were a total of 2,424 employees present on June 1st, 2014. By the end of the period, 983 turned over, and 1,441 remained. Out of the 2,424 employees who began, we had to remove 684 due to missing data, leaving us with a total of 1,740 employees to use for analysis. We may be able to produce more fine-tuned results if we could analyze turnover data for the entire dataset of employees, which includes those who were hired at the various times during the 12-month period.

Our results were limited due to the privacy restrictions on the dataset. We could not discern voluntary turnover from involuntary turnover because we were only given a small amount of information about each employee. If we were given a reason for the turnover event, we could separate the dataset into voluntary and involuntary turnover and make better assessments of the predictors. In addition, we were only given the email metadata, which did not include the text from the body of the email. The body of the email would tell us a great deal about the relationships between employees and give us a complete picture of the social network in the organization.

The accuracy of our results are limited due to the restrictions on the dataset, as well as the characteristics of the organization. The organization of study is in an industry with a relatively high rate of turnover. In addition, the dataset provider was not completely confident with the quality of the data due to a recent system migration. The data quality may be the reason why we have a high number of counterintuitive results. It is nearly impossible to assess the true quality of the dataset with such little information. These limitations were known well before undertaking the study, however we feel confident that the results are useful for exploring the relationships in other, more complete datasets.

### *Future Research*

In the future, we will apply this research model to a dataset with such information as email body, sender and receiver demographics, and employee position in the organizational hierarchy. This will give us a more complete picture of the social network in the organization and the underlying turnover phenomenon. These details would have likely changed the outcome to this study.

Future researchers should consider adding the antecedents of turnover, such as withdrawal behaviors, to the model. Studying antecedents to turnover would make the model very complicated and difficult to test. However, adding them would likely yield more accurate results. This is due to the differences between social contagion and viral contagion. We tested for contagion in a similar manner as testing for viral contagion, however individual differences determine susceptibility. Social contagion should not be considered dyadic because people are usually on a continuum of susceptibility. In addition, antecedents of turnover would add another degree of context to the relationship between Structural Trajectory and turnover. This is especially true for those with a negative Structural Trajectory.

# CHAPTER SEVEN

## Conclusion

### *Structural Trajectory Significance*

While many researchers have attempted to predict turnover using social network analysis, we did not find any that considered the change in network position over time, we call this concept Structural Trajectory. The main contribution of this study is to introduce the concept of Structural Trajectory and to explore its significance to the turnover phenomena. We found it to be an important consideration in determining the odds of turnover for an employee. However, due to our dataset limitations, further research is required to determine the true relationship between Structural Trajectory and turnover.

### *Implications*

Practitioners may be able to use this information to develop turnover reduction plans. The results of this study are applicable to any organization. The methods can be applied to any organization that saves employee emails along with the metadata. Second, we hope this study opens the channels of discussion on the concept of Structural Trajectory. We did not find any research that considered a person's network position over time, and the results indicate a possible relationship that should be further investigated. Third, we hope to add to the literature on predicting turnover using social networks and social contagion. The literature on turnover is rich, however, our study is novel in that we use Structural Trajectory as a predictor. In addition, this study is novel in that we use email communication as a proxy of an organizations social network. Using email communication has limitations, however when combined with other forms of communication, researchers may be able to obtain a more complete picture of the underlying social network.

APPENDIX

# APPENDIX

## A.1. Table of definitions.

| Term | Definition |
|---|---|
| Turnover (Macro Scale) | The rotation of workers around the labor market; between firms, jobs and occupations; and between the states of employment and unemployment (Abbasi and Hollman 2000). |
| Voluntary Turnover | Push factors, such as staff leaving due to lack of interest in the job, or pull factors, such as being attracted to another job by incentives (Booth and Hamer 2007). |
| Network Ties | The social relationships of members in a social network (Perry-Smith and Shalley 2003). |
| Tie strength | A function of the amount of interaction, emotional intensity, and reciprocity that occurs between two individuals of the network (Perry-Smith and Shalley 2003). |
| Network | A set of actors or nodes along with a set of ties of a specific type that link them (Borgatti and Halgin 2011). |
| Contagion | The process by which information, trends, behaviors, and other entities spread between individuals in a social network (Hill et. al. 2010). |
| Betweenness Centrality | The degree to which a node lies on the shortest path between two other nodes (Opsahl et al. 2010). |
| Degree Centrality | The number of nodes the specific node is connected to (Opsahl et al. 2010). |
| Closeness Centrality | The shortest distances from a particular node to all other nodes (Opsahl et al. 2010). |
| Eigenvector Centrality | The weighted sum of direct and indirect connections of a node, taking into account the entire pattern in the network (Bonacich 2007). |
| Structural Trajectory | The change in a person’s structural position in a network over a given period of time- either from the periphery to the center (positive trajectory), from the center to the periphery (negative trajectory), or remaining in a static position. |

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